

University of Southern Queensland  
Faculty of Health, Engineering and Sciences

# Identification of Cement Manufacturing Raw Materials Using Machine Vision

A dissertation submitted by

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## Abstract

In the mining and manufacturing industry, there is a need for a non-extractive system to identify raw materials on conveying systems. Such a system would allow identification of raw materials on conveying systems preventing cross-contamination when the materials arrive at the final storage location.

This project used machine vision techniques to identify cement manufacturing raw materials (clinker, gypsum and, limestone). Firstly, a representative sample (25 x 10kg samples of each material) was collected using a stratified random sampling procedure. This stratified random sampling procedure ensured the sample accurately represented the raw material in the stockpile.

A dual purpose test bed and controlled lighting camera enclosure (for static model development and future dynamic system implementation) were constructed to minimise the effect of varying ambient light. This test bed and camera enclosure allowed the CMOS global shutter industrial camera to take twenty, 24bit colour images (8bit for each colour) of each sample. These images were catalogued and stored in a database for further model training and verification purposes.

These images were pre-processed by a median filter which allowed any over saturated pixels (due to raw material surface moisture reflection) to have their intensity level reduced by replacing its value by the median value of its local neighbours. From the filtered image the individual red, green and blue (RGB) components were passed to a Histogram function which binned (255 bins for 8-bit colour) the various pixel intensities. The statistical features (weighted mean, skewness and kurtosis) of each colour's histogram were then stored in an array which then passed to the image feature database.

A varying amount of feature arrays were used to train and verify the success of a probabilistic neural network (PNN) model. Initial optimisation of the PNN model was conducted using a local search algorithm which changed the smoothing parameter which achieved 94.83% accuracy. This model was then improved by implementing a Supervised Learning Probabilistic Neural Network (SLPNN). This model added data weight which changed the height of the Gaussian distribution function and input variable vector weight which changes the width of Gaussian distribution function. The implementation of the Supervised Learning Probabilistic Neural Network improved the models accuracy to 99.57%.

Further model field testing will be required to verify the system in an operational environment where the camera enclosure will be subjected to dust, noise, varying temperatures and moisture. The Supervised Learning Probabilistic Neural Network outperforms the standard Probabilistic Neural Network which has been proven by this work. This work supports the claim that Machine Vision can be successfully be used to identify cement manufacturing raw materials with a high success rate. It also contributes to the literature by classifying clinker, gypsum and limestone in one body of work.

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# Contents

Abstract .....	i
Limitations of Use.....	ii
Certification .....	iii
Acknowledgements.....	iv
List of Figures .....	vii
List of Tables .....	ix
Glossary .....	x
1 Introduction.....	1
1.1 Project Realisation .....	1
1.2 Conveying System .....	1
1.3 Raw Materials to be Identified.....	3
1.3.1 Clinker.....	3
1.3.2 Gypsum .....	4
1.3.3 Limestone.....	5
1.3.4 Cement .....	5
1.4 Raw Material Cross Contamination Impacts .....	5
1.4.1 Impact on Finished Concrete .....	6
1.4.2 Operational Impacts .....	7
1.5 Existing Control Measures.....	7
1.5.1 Loader Operator .....	7
1.5.2 Central Control Operator.....	7
1.5.3 Process Attendant.....	8
1.5.4 Conveying System Design .....	8
1.5.5 Conveyor Purge Time.....	8
1.5.6 Quality Testing.....	8
1.6 Problem Statement .....	9
1.7 This Project’s Proposed Contribution to the Gap in the Literature.....	9
1.8 Dissertations Overview .....	10
1.9 Intellectual Property Disclaimer .....	10
2 Background.....	11
2.1 Overview.....	11
2.2 Sample Selection and Collection .....	11
2.3 Image Acquisition.....	11
2.3.1 Camera Sensor Types.....	11
2.3.2 Lighting.....	14
2.4 Image Pre-processing.....	16
2.5 Feature Extraction.....	18
2.5.1 Colour Features .....	18
2.5.2 Shape Features .....	19
2.6 Material Classification .....	20
3 Methodology .....	22
3.1 Project Approach.....	22
3.2 Overview.....	22
3.3 Sample Selection and Collection .....	23
3.4 Training and Verification Image Acquisition .....	23
3.5 Image Pre-Processing.....	23
3.6 Image Feature Extraction.....	23
3.7 Material Classification .....	23
3.8 Model Performance Evaluation and Optimisation.....	24
4 System Development .....	25
4.1 System Design Considerations.....	25
4.2 Overview.....	25
4.3 Raw Material Sampling.....	26
4.3.1 Overview.....	26
4.3.2 Clinker.....	26

4.3.3	Gypsum .....	29
4.3.4	Limestone.....	30
4.4	Camera System Design .....	31
4.4.1	Camera and Lighting Enclosure.....	32
4.4.2	Camera .....	35
4.4.3	Lighting.....	40
4.4.4	Camera Communication Interface Development and Control.....	42
4.5	Image Acquisition.....	43
4.6	Image Pre-processing.....	44
4.7	Image Feature Extraction .....	44
4.7.1	Colour Features (Static Model Development) .....	45
4.7.2	Advanced Shape Feature Extraction (Dynamic Model Development) .....	47
4.8	Probabilistic Neural Network Model Training.....	49
4.9	Probabilistic Neural Network Model Verification Method.....	52
5	Model Optimisation .....	54
5.1	Normalisation of Raw Data.....	54
5.2	Supervised Learning Probabilistic Neural Network.....	55
5.2.1	Overview of implementation.....	55
5.2.2	Smoothness .....	56
5.2.3	Input Variable Vector Weight (Gaussian Distribution Width Modifier) ..	56
5.2.4	Data Weight (Gaussian Distribution Height Modifier).....	57
5.2.5	Supervised Learning Probabilistic Neural Network Optimisation.....	58
6	Results and Analysis .....	59
6.1	Data Analysis .....	59
6.1.1	Review Scatter Plots .....	59
6.1.2	Review Data Spread.....	60
6.2	Probabilistic Neural Network Optimisation Results .....	61
6.2.1	Number of Images Used for Training Effect .....	61
6.2.2	Optimised Smoothing Parameter .....	62
6.3	Supervised Learning PNN Results .....	63
6.3.1	Data Weight (Gaussian Distribution Height Modifier).....	63
6.3.2	Input Variable Vector Weight (Gaussian Distribution Width Modifier) ..	64
6.4	Results Summary .....	65
7	Conclusion .....	66
7.1	Discussion .....	66
7.2	Further Work.....	66
7.3	Closing Statement .....	67
8	References.....	68
	Appendix A – Project Specification.....	71
	Appendix B – Project Management Plan .....	72
	Appendix C – Enclosure Design Drawings .....	75
	Appendix D – Colour Feature Extraction Code.....	77
	Appendix E – Probabilistic Neural Network.....	79
	Appendix F – Feature Normalisation Code.....	82
	Appendix G – Supervised Learning PNN Code .....	84
	Appendix H – Supervised Learning Probabilistic Neural Network Function.....	86
	Appendix I – Supervised Learning Probabilistic Neural Network Optimisation Program	87
	Appendix J – Advanced Shape Feature Extraction .....	90
	Appendix K: Sample Images from Image Database .....	92
	Appendix L – Results Plots.....	93
	Appendix M – Image Vector Database.....	99
	Appendix N – Clinker Sampling Procedure.....	122
	Appendix O – Gypsum Sampling Procedure .....	127
	Appendix P – Limestone Sampling Procedure .....	132

## List of Figures

Figure 1: Cement Manufacturing Raw Materials Transport System Overview.....	1
Figure 2: Tilt Pan Conveying System Raw Material Process Flow .....	2
Figure 3: Tilt Pan Conveyor Drawing obtained and modified from (Aumund, 2016).....	2
Figure 4: Image of Portland Clinker. ....	3
Figure 5: Image of Natural Gypsum .....	4
Figure 6: Image of Limestone .....	5
Figure 7: Pixel Scanning with Rolling Shutter – Image obtained from (Nakamura, 2006) .....	12
Figure 8: Illustration of shape distortion of moving objects in a rolling shutter.....	12
Figure 9: Cross Section of Second Generation Interline Transfer CCD - (Nakamura, 2006) .....	13
Figure 10: CMOS Rolling Shutter Circuitry obtained from (Nakamura, 2006) .....	13
Figure 11: Light Source Relative Intensity Verses Spectral Content obtained from (Martin, 2007) .....	14
Figure 12: Effect of Xeon Lighting obtained from (Cunha, et al., 2015) .....	15
Figure 13: Dome Diffuse, Bright Field and, Dark Field Illumination obtained from (Martin, 2007) .....	16
Figure 14: Operations involved in a median filter, method adopted from (Davies, 2012).....	17
Figure 15: Filter Functions Compared, obtained from (MathWorks, 2016).....	17
Figure 16: Operations Involved in an Average Filter, method adopted from (Davies, 2012) .....	18
Figure 17: Colour Feature Extraction obtained from (Patel & Chatterjee, 2016).....	19
Figure 18: Probabilistic Neural Network, obtained from (Patel & Chatterjee, 2016).....	21
Figure 19: Project Research Cycle adopted from (Maxwell, 2016).....	22
Figure 20: System Development Overview .....	25
Figure 21: Clinker Sampling Station.....	28
Figure 22: 33,000tonne Gypsum Stockpile.....	29
Figure 23: Gypsum Sampling using Stockpile Shield and sample scoop .....	29
Figure 24: Stored Sampled Gypsum .....	30
Figure 25: Limestone conveyor sampling.....	31
Figure 26: Image of Tilt Pan Conveyor .....	32
Figure 27: Support Structure required clearance distance .....	33
Figure 28: Camera Enclosure showing roof clearances .....	34
Figure 29: Tilt Pan Camera Enclosure Design Overview .....	35
Figure 30: Finished Camera Enclosure .....	35
Figure 31: IDS UI Camera, image obtained from (IDS Imaging Development Systems GmbH, 2016b) .....	37
Figure 32: Point Grey Research Grasshopper 3 obtained from (Point Grey Research, 2016) .....	37
Figure 33: Lens selection tool showing Minimum Distance (IDS Imaging Development Systems GmbH, 2016a) .....	39
Figure 34: Lens selection tool showing Maximum Distance (IDS Imaging Development Systems GmbH, 2016a) .....	40
Figure 35: IDS CMOS Sensor Colour Performance obtained from (IDS Imaging Development Systems GmbH, 2016b).....	41
Figure 36: CREE LED Relative Luminous Intensity VS Wavelength obtained from (CREE Inc., 2014).....	41
Figure 37: Image of Machine Vision Imaging Application Workspace .....	42
Figure 38: Image Acquisition Process Sequence .....	43
Figure 39: Image Feature Extraction.....	44
Figure 40: Skewness Explained using theory from (James, 2010) .....	46
Figure 41: Kurtosis Explained using theory from (James, 2010).....	47
Figure 42: Advanced Shape Feature Development Overview .....	48

Figure 43: Distance Transform obtained from (Davies, 2012). .....	48
Figure 44: 3D Plot of Watershed shown in Figure 42.....	49
Figure 45: Probabilistic Neural Network Overview .....	50
Figure 46: Euclidean Distance Function Explained.....	52
Figure 47: ANOVA Statistical Analysis of All Raw Materials, Raw Feature Data showing All Red Components.....	54
Figure 48: Supervised Learning Probabilistic Neural Network Smoothing Parameter Effect of the Gaussian Distribution.....	56
Figure 49: Example of Actual Data Distribution for Red Weighted Mean and Skewness.....	57
Figure 50: Supervised Learning Probabilistic Neural Network Input Variable Vector (Gaussian Distribution Width Modifier).....	57
Figure 51: Supervised Learning Probabilistic Neural Network Data Weight (Gaussian Distribution Height Modifier).....	58
Figure 52: Scatter Plots of the Normalised Colour Features Compared with the Best Match Data.....	60
Figure 53: ANOVA Plot and Statistical Data for all Red Colour Features and Materials .....	61
Figure 54: Effect of Varying the Number of Training Images.....	62
Figure 55: Optimisation of the Probabilistic Neural Networks Smoothing Parameter ( $\sigma$ ) .....	62
Figure 56: Supervised Learning Probabilistic Neural Network Data Weight Optimisation Results.....	63
Figure 57: ANOVA Box and Whisker Expanded View obtained from Figure 57 plot ....	63
Figure 58: Input Variable Weight Optimisation for Red Weighted Mean Colour Feature .....	64
Figure 59: Input Variable Weight Optimisation for Blue Kurtosis Colour Feature.....	64
Figure 60: Camera enclosure Construction Overview .....	75
Figure 61: Camera Enclosure Structure Fabrication Details.....	75
Figure 62: Camera Sliding Mounting Bracket and Enclosure Support Beam Fabrication Details. ....	76
Figure 63: Black Plywood Cutting Guide .....	76

## List of Tables

Table 1: Typical Raw Materials Used to Manufacture Clinker (Hewlett, 2016).....	3
Table 2: Concrete Impact Assessment Overview .....	6
Table 3: Operational Impact Assessment.....	7
Table 4: Case Study’s site 10 Year Clinker Distribution analysis. ....	26
Table 5: Minimum Increment and Sample Mass, Data obtained from (Australian Standards, 2012a).....	27
Table 6: Case Study’s site 10 Year Gypsum Distribution analysis.....	30
Table 7: Case Study’s site 10 Year Limestone Distribution analysis. ....	31
Table 8: Image Pixel Count Related to Field of View Dimensions .....	36
Table 9: Camera Comparison and Selection.....	38
Table 10: Camera Selection Criteria Ranking.....	38
Table 11: Matching Matrix for Probabilistic Neural Network with 500 Training Images (Per Material) and 625 Images Used for Verification.....	53
Table 12: Matching Matrix for Optimised Probabilistic Neural Network with 500 Training Images (Per Material) and 1875 Images Used for Verification.....	55
Table 13: Example of Localised Search for Error Minimum.....	58
Table 14: Optimised Input Variable Vector Weights (Gaussian Distribution Width Modifier) Results .....	64
Table 15: Risk Assessment Matrix .....	72
Table 16: Risk Assessment of those working on the Research Project .....	72
Table 17: Risk Assessment of Research Projects Introduced Technology .....	73
Table 18: Required Resources .....	74

## Glossary

CCD	Charged-Coupled Device
Cement	Raw material used to make concrete
Concrete	Strong building material made using cement, sand and aggregate
CMOS	Complementary Metal-Oxide Semiconductor
Increment	10kg of extracted raw material.
Sample	Made up of 5 x 10kg increments
Particle	in this work particle will be considered a single piece of raw material regardless of its size
PDF	Probability Density Function
PNN	Probabilistic Neural Networks
PoE	Power Over Ethernet
RGB	Red, Green and Blue components of a digital image
RMSE	Root Mean Squared Error
SLPNN	Supervised Learning Probabilistic Neural Networks

# 1 Introduction

## 1.1 Project Realisation

The inspiration for this project came from an operational lifecycle assessment of a cement manufacturing Plant in Tasmania, Australia. An operational risk analysis of existing plant identified the need to positively identify cement manufacturing raw materials as they travel along a conveying system which also transports several other raw materials.

## 1.2 Conveying System

The chosen case study to implement identification of cement manufacturing raw materials using machine vision is on a tilt pan conveyor. This tilt pan conveyor transports clinker, gypsum and limestone to six storage bins which supply two cement mills. These raw materials are reclaimed from under storage sheds or manually loaded using a front end loader (22tonnes a load) into two loading hoppers from outside stockpiles. These two loading hoppers and reclaim conveyors transport raw materials to the tilt pan conveyor via two different conveying systems. These two conveying systems load their contents onto the tail end of the tilt pan conveyor system and the middle as shown in Figure 1. These materials then make their way to the desired bin by the operation of a diverter rail which allows the pans to tilt. The raw material can transfer from the top conveyor to lower conveyor or they can be directed to the desired bin. This system can deliver any two materials via the tail and centre transfer points. Through this clever design 1000 tonnes per hour (2 x 500 tonnes per hour) can be transported to the mill's storage bins.

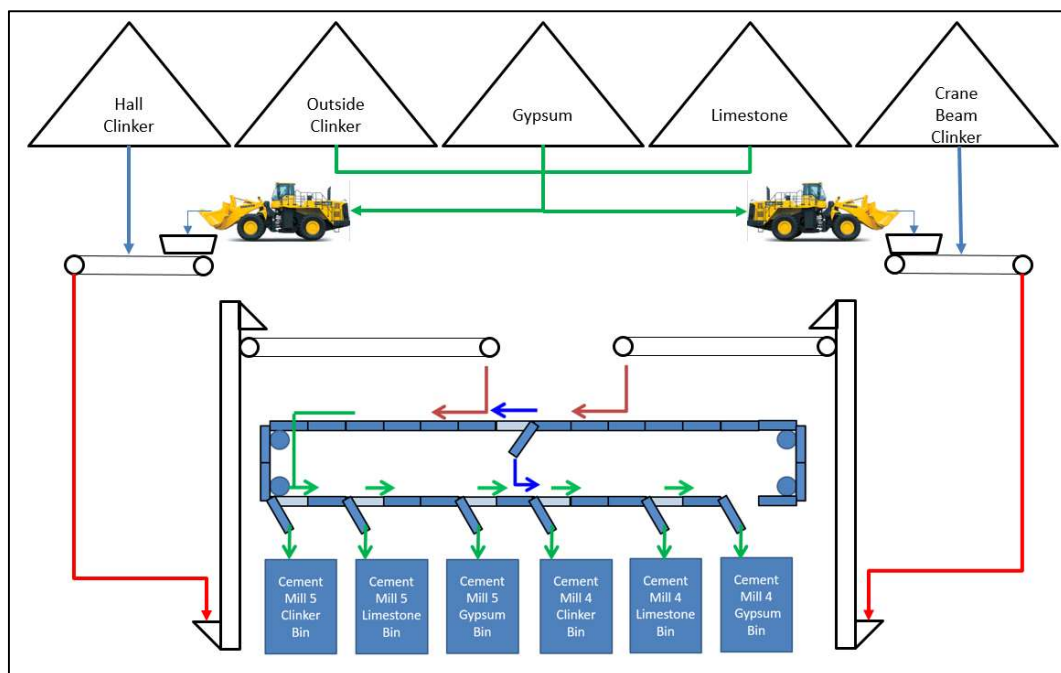


Figure 1: Cement Manufacturing Raw Materials Transport System Overview

Figure 2 and Figure 3 below show a more detailed overview of the tilt pan conveyor. In these figures, it is evident to see that any two materials can be present on the tilt pan conveyor. When two different raw materials are being transported the probability of a cross-contamination increases. A cross-contamination event is where the wrong raw material ends up in the wrong bin.



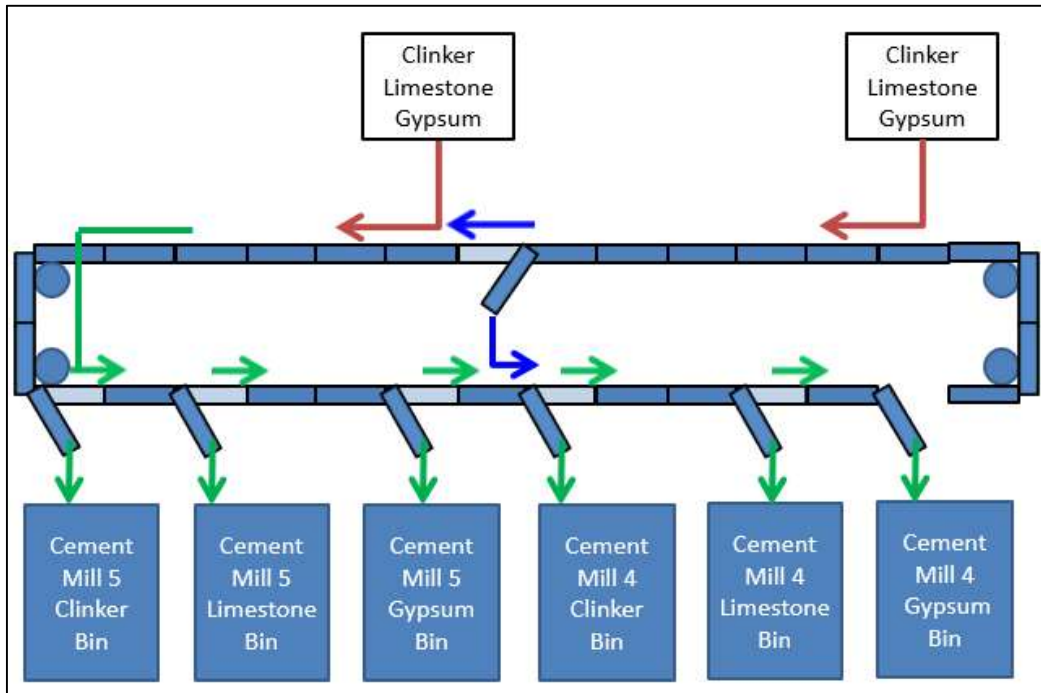


Figure 2: Tilt Pan Conveying System Raw Material Process Flow

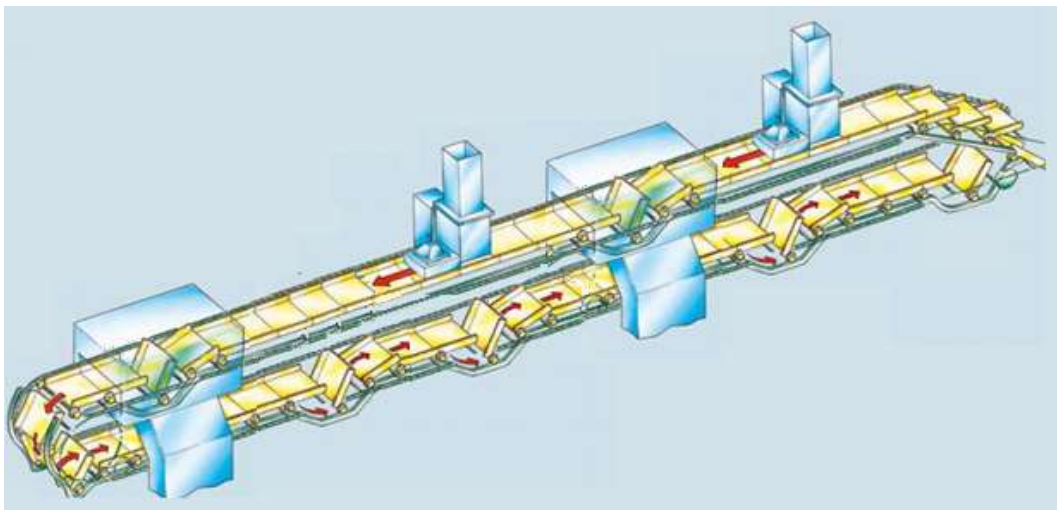


Figure 3: Tilt Pan Conveyor Drawing obtained and modified from (Aumund, 2016)

## 1.3 Raw Materials to be Identified

### 1.3.1 Clinker

Portland clinker (shown in Figure 4) is made up of varying amounts of high-grade limestone, blended stone, silica (sand) and magnetite. Table 1 below shows the typical raw material contributions required to manufacture Portland clinker.



Figure 4: Image of Portland Clinker.

Table 1: Typical Raw Materials Used to Manufacture Clinker (Hewlett, 2016)

Name	Minimum Contribution Clinker	Maximum Contribution to Clinker	Chemical Formula
High Grade Limestone	9%	12%	$\text{CaCO}_3$
Blended Stone (Limestone) and (Clay)	85%	93%	$\text{CaCO}_3$
		7%	$\text{Al}_2\text{Si}_2(\text{OH})_4$
Silica	0%	1.2%	$\text{SiO}_2$
Magnetite	0%	0.6%	$\text{Fe}_3\text{O}_4$

Clinker is manufactured by feeding the three raw materials into a vertical roller mill or a ball mill. These mills grind the material down to the consistency of talcum powder which is called raw meal. This raw meal is transported to a cement kiln where the raw meal enters into the top of four series connected preheater cyclones. The raw meal enters the first riser duct where the hot kiln gasses move this material into enter the first cyclone. This first cyclone then separates the meal from the kiln gasses via a swirling centrifugal force (similar to the Dyson vacuum cleaner bag less dust bin). This meal then leaves the bottom of the first cyclone and drops into the second lower riser duct which leads to the second cyclone. This process repeats until the material enters the fourth cyclone where the meal enters the kiln.

At this point in the process the meal has been preheated to  $600^\circ\text{C}$  as it enters the kiln. At this point, the raw meal continues to be heated until it reaches the liquid phase ( $1250^\circ\text{C}$  to  $1350^\circ\text{C}$ ) in the burning zone. The rotating kiln forces the liquid raw meal to wash up the sides of the kiln in the burning zone which then forces the meal to roll and form clinker nodules. These clinker nodules then leave the kiln and fall into the kiln cooler. This cooler then then rapidly cools the clinker from  $1250^\circ\text{C}$  to  $220^\circ\text{C}$  in about 3 minutes using large volumes of air. The kiln's cooler allows a coarse microscopic grain structure to form. This process overview was obtained from (Hewlett, 2016) and general

knowledge of the topic. This clinker is then stored to be transported to the Cement Mill's when needed.

Clinker's contribution to the manufacture of cement is pivotal as it makes up more than 92.5% of the final cement product (Australian Standards, 2010). This clinker in cement is responsible for the chemical reaction that takes place when water is added to make cement bond the aggregate to form the strong concrete structure. Too much clinker in Cement will cause the concrete to set too quick and not enough will cause the concrete to be too weak (Hewlett, 2016).

It is important to note that clinker contains up to 93% limestone which can makes it very similar in colour to limestone. When oversized clinker leaves the cooler, it also can be broken into shards similar to limestone by the cooler's clinker breaker.

### **1.3.2 Gypsum**

Gypsum used onsite (see Figure 5) is a natural forming raw material supplied from mines in South Australia. They are transported to the site via ship, and then road transport. This raw material is then stored outside in 33,000-tonne stockpile on a concrete pad. This raw material is exposed to the weather which has a continuously varying moisture content. Gypsum is used to manufacture cement because it slows the chemical reaction that the clinker contributes to concrete. If too much gypsum is used the concrete will take too long to set and concrete expansion can occur. If not enough gypsum is used the concrete can flash set and become brittle, offering minimal strength (Hewlett, 2016).

One main point to note is that the chemical formula for gypsum is calcium sulphate dihydrate [ $\text{CaSO}_4 \cdot 2\text{H}_2\text{O}$ ] (Hewlett, 2016), and this has similar concentrations of Calcium as clinker and limestone. The sulphate ( $\text{SO}_4$ ) contributes to the yellow colour which offers a significant visible colour difference.



**Figure 5: Image of Natural Gypsum**

### 1.3.3 Limestone

Limestone used to make both clinker and cement is drilled, blasted, mined and crushed on a daily basis. All mined limestone is crushed then transported to an undercover storage shed in a 15,000-tonne stockpile. The blended stone (previously mentioned) is mined and crushed through the same system but stored in two undercover 35,000-tonne stockpiles. All limestone needed for the Cement Mills is manually transported from the stockpile and loaded into one of the two receival hoppers. The typical formula for limestone is  $\text{CaCO}_3$ . This raw material has a similar colour spectrum to clinker which will contribute to the challenge of identification using colour. Limestone in cement manufacture has been used to improve the grind ability, reduce the thermal and electrical energy per tonne of the finished cement. Limestone is only allowed to be added to the cement process at maximum of concentration of 5% (Australian Standards, 2010).



Figure 6: Image of Limestone

### 1.3.4 Cement

General purpose Portland cement is made by feeding clinker, gypsum and limestone into a wind-swept ball mill. The ball mill is a large cylinder divided into two the crushing chamber and the finishing chamber. These two chambers are filled with two different grades of mill balls varying from 110mm to 30mm. These ball mill rotates at a speed which allows the mill balls to be lifted up to two-thirds of the height of the mill and then drops down crushing the raw material. The raw material passes through the crushing chamber to the finishing chamber by the air passing through the mill. The grinding forces generate particle friction which also generates the heat required heat to dehydrate the raw material. This crushed raw material leaves the mill which is now called cement. This cement is transported to a separator which returns the oversized material to the mill inlet. The correctly sized material passes to the finished product transport system.

## 1.4 Raw Material Cross Contamination Impacts

In cement manufacturing there is always a remote possibility that raw material being loaded into the conveying system could end up in the wrong storage location. This incorrect raw material delivery is called raw material cross contamination. A summary of these impacts has been listed below in the following subsections.

### 1.4.1 Impact on Finished Concrete

Table 2 below shows a brief summary of the impacts to the finished concrete. Some conditions are complexly unacceptable and will lead to an entire day's production being sent to land fill. These events have a severity listed as high. The medium and low impacts can be isolated, tested and blended back into the process at a very low dose rate for reprocessing.

**Table 2: Concrete Impact Assessment Overview**

Condition	Impact on Concrete			Severity
	Consequence	7 Day Strength	28 Day Strength	
Too Much Clinker >98%	Increased Risk of Flash Set Increased Risk of Cracking Not compliant with AS2350.4 Not compliant with AS3250.7	Decrease	Decrease	High
Not Enough Clinker <92.5%	Low Strength Will not Cure Not compliant with AS3972 Not compliant with AS/NZ2350.11	Decrease	Decrease	High
Too Much Gypsum >2.8%	Slow Curing Time May not Cure Increased Risk of Expansion Not compliant with AS2350.14	Decrease	Decrease	High
Not Enough Gypsum <2.6	Increased Risk of Flash Set Increased Risk of Cracking Not compliant with AS2350.4	Decrease	Decrease	High
Too Much Limestone >5%	Low Strength Will not Cure Increased Risk of Sulphate Attack Not compliant with AS3972	Decrease	Decrease	Medium
Not Enough Limestone <5%	Increased Concrete Strength Increased Variability	Increase	Increase	Low

Data obtained from (Australian Standards, 2010) and (Hewlett, 2016)



## 1.4.2 Operational Impacts

A summary of potential operational impacts has been listed below in Table 3. Some effects are completely undesirable for instance an increase in thermal and electrical energy consumption per tonne of cement produced would lead to wasted energy, more CO2 emissions and reduced profit margin.

**Table 3: Operational Impact Assessment**

Condition	Consequence	\$/tonne	Thermal and Electrical Energy
Too Much Clinker >98%	Clinker is the most expensive material Clinker requires most energy to make Open to litigation due to Concrete Fault End User Contract Variability Fine	Increase	Increased
Not Enough Clinker <92.5%	Reduced material costs Reduced energy costs More cement needed to maintain strength End User Contract Variability Fine	Decrease	Decrease
Too Much Gypsum >2.8%	Gypsum is the next most expensive Less energy needed to grind Open to litigation due to Concrete Fault End User Contract Variability Fine	Increase	Decrease
Not Enough Gypsum <2.6	Other materials are harder to grind Open to litigation due to Concrete Fault End User Contract Variability Fine	Decrease	Increase
Too Much Limestone >5%	Open to litigation due to Sulphate Attack End User Contract Variability Fine	Decrease	Decrease
Not Enough Limestone <5%	Other raw materials are more expensive Clinker is harder to grind End User Contract Variability Fine	Increase	Increase
Data has been summarised using sensitive operational data which cannot be shared			

## 1.5 Existing Control Measures

### 1.5.1 Loader Operator

The front end loader operator is one source of cross contamination. As they load the raw materials into the hopper the system informs them what material to load. When they load the hopper with the requested raw material, there may still be another product in the hopper which may have bridged over and not gone through the system. From their position they cannot always see if the hopper is empty due to poor lighting, time constraints or other reasons.

### 1.5.2 Central Control Operator

A single central control operator is responsible for 12 major assets at one time (Crusher, Raw material handling systems, Raw Mill, Kiln system, two Coal Mills, two Cement Mills, Rail loading, road loading, alternative fuel system just to name a few). Several years ago several operators were doing the same job but due to the need for lean manufacturing and improved automation one operator remains. At the same time, new plant is continually being added to handle alternative fuels and alternative raw materials

which can lead to operator overload. With newer technologies operators have high-level control systems helping them cope, but they are still required to monitor 30 conveyor process cameras as a prevention against raw material cross contamination.

### **1.5.3 Process Attendant**

Per shift, there are two process attendants and a shift quality tester. The process attendants conduct hourly walk arounds to inspect the plant and look out for abnormalities in operation. These walk arounds are another form of raw material cross contamination prevention but they are unavailable during abnormal process conditions in other areas.

### **1.5.4 Conveying System Design**

The conveying system design is an important cross contamination prevention system. Systems design should prevent material from bridging over, hanging up but due to legacy designs and process modifications these material hang-ups and material bridging occurs more frequently when raw material moisture changes. The control system is also a control measure which is used to prevent these events. Due to a lack of equipment maintenance due to restricted access time caused by the ever increasing demand for cement, it can be difficult to maintain this equipment at the desired frequency.

### **1.5.5 Conveyor Purge Time.**

The control of the conveying system has a purge timer of 12 minutes between raw materials. This purge time forces the conveyor to run for 12 minutes without any material on the belt. This can waste up to 2 hours per day during peak production times. Not to mention the wasted energy, additional wear on the hardware and lost production opportunity (2 hours x 1000 tonnes per hour = 2000 tonnes in lost raw material delivery tonnes).

### **1.5.6 Quality Testing**

The last line of cross contamination detection is the continuous sampling of cement as it is manufactured. Quality and chemical analysis is completed hourly on these samples. This measure is a feedback control test and results outside the required control bands mean the entire day's production has to be isolated and tested to ensure the required quality is acceptable. If it does not comply the entire batch (6700tonnes) will be sent to landfill or other uses.

## **1.6 Problem Statement**

In the cement manufacturing industry, there is a need for a system which can identify raw materials as they are transported on conveying systems. Such a system will allow automated identification of raw material as they are transported along common conveying. This automated system can prevent cross-contamination before they occur by alerting the operator and sending a command to the control system which will stop the conveying system. The operator will have the opportunity to redirect the incorrectly loaded raw material to the correct storage location hence preventing a cross-contamination event.

An automated raw material identification will need to;

- Identify the raw materials without the need to extract a sample from the conveyor,
- Operate in an environment with varying lighting levels due to artificial lighting and natural lighting,
- Not be affected by fugitive dust, vibration or localised sources of interference.
- The system must not affect conveying systems due to a failure,
- Identify each raw material in an acceptable time frame (less than 30 seconds as 280kg passes through the system every second),
- Able to identify raw materials with a high level of confidence.

## **1.7 This Project's Proposed Contribution to the Gap in the Literature**

During a comprehensive review of the available literature it became apparent that there has been a large amount of machine vision work into the sizing of conveyed materials conducted by (Al-Thyabat, et al., 2007), (Andersson, et al., 2012), (Chen, et al., 2014), (Jemwa & Aldrich, 2012) and, (Thurley, 2011). Also there is extensive work pertaining to several grades of limestone conducted by (Chatterjee, 2013), (Chatterjee, et al., 2010), (DeCost & Holm, 2015), (Isa, et al., 2011) and, (Selver, et al., 2011). From the literature review conducted there appears to be a gap in the literature in the identification of clinker, gypsum and limestone in one body of work.



## **1.8 Dissertations Overview**

### **Chapter One – Introduction**

The opening chapter of this dissertation covers an in-depth overview of the layout of the chosen case study. This overview will help the reader to understand the motivation behind the project and the problem the project intends to resolve.

### **Chapter Two – Background**

A literature review was conducted and continuously reviewed as new problems presented themselves. This continual literature review also identified the way in which this body of work will contribute to the available literature.

### **Chapter Three – Methodology**

The methodology chapter presents the process which was followed to design, build, test, optimise and verify the developed model. This provides an in-depth understanding of how the research cycle was used to ensure the project's objectives were delivered.

### **Chapter Four – System Development**

Chapter four provides an understanding of how the initial model and system was developed and documents the engineering decisions which were made.

### **Chapter Five – Model Optimisation**

The initial systems development was tested, and opportunities were found during a reflection of initial results and a review of the literature. This chapter covers the improvements that were implemented to model.

### **Chapter Six – Results and Analysis**

A reflective review and analysis of the results were documented in this chapter. Critical analysis of the available testing data and comparison of the initial model's performance against the optimised models performance will be presented.

### **Chapter Seven – Conclusion and Further Work**

Finally, a summary of the projects achievements, opportunities for future model improvements and how this body of work can improved in the future.

## **1.9 Intellectual Property Disclaimer**

As this project is an industry sponsored project certain items are of a sensitive nature. These items which will be withheld will be clearly labelled and explained in detail to fulfil the academic requirement.

## 2 Background

### 2.1 Overview

The literature review has been broken down into several subsections which offer a logical breakdown of the primary tasks of this project. The first subject will discuss the importance of sample selection and collection to ensure an accurate representation of all raw material are sampled. The second section discusses the important attributes of camera sensor types which are available for use in the industrial environment. This same section also discusses the different lighting technologies and methods which will offer the best outcome.

The next section will discuss image pre-processing requirements to ensure the image is submitted to the feature extraction system free from noise. From the image, pre-processing feature extraction will be the next section which covers colour and shape features. The last portion of this subsection discusses the ways which raw materials can be classified using statistical and decision ruling algorithms.

### 2.2 Sample Selection and Collection

The importance of sample selection and collection should not be underestimated. To ensure an accurate representative sample is acquired from the raw material sample location work conducted by (Chatterjee & Bhattacharjee, 2011) and, (Hamzeloo, et al., 2014) took their samples from conveyor belts, stockpiles and blast sites using Stratified Random Sampling. This Stratified Random Sampling method divides the total population (total tonnes in the stockpile, total production time or, expected total production tonnage) by the required number of samples required. Once the stratification start and finish points are known a random number is generated to determine the sample location along a stockpile or to sample at a particular produced tonnage.

$$\text{Increment Location} = S \times (I - 1 + R) \quad (2-1)$$

Where S is the stratification size, I is the current sample increment and R is the random generated number between 0 and 1. Equation obtained from (Australian Standards, 2012a). One key point to note is that a random seed be used for the generation of the random number.

### 2.3 Image Acquisition

#### 2.3.1 Camera Sensor Types

The selection of the camera sensor type is a critical aspect of the project as an accurate representation of the raw material must be presented to the feature extraction system. Images submitted to the feature extraction system must be free of shape distortion from a picture taken from a moving conveying system. Shape distortion happens when a Complementary Metal-Oxide Sensor (CMOS) using a rolling shutter samples an image using a pixel array similar to Figure 7 below. This figure shows a simplified pixel array showing Row and Column addressing where the individual pixels are selected and read from then reset (Nakamura, 2006). Also in this figure, we can see a timing chart which indicates that the individual pixels are scanned. There would not be a problem with this imaging sensor if it were taking an image of a stationary target. Figure 8 shows the resultant effect of a moving image sampled using a rolling shutter. Due to the delayed processing of individual rows, the lower half of the circle is distorted providing undesirable results.

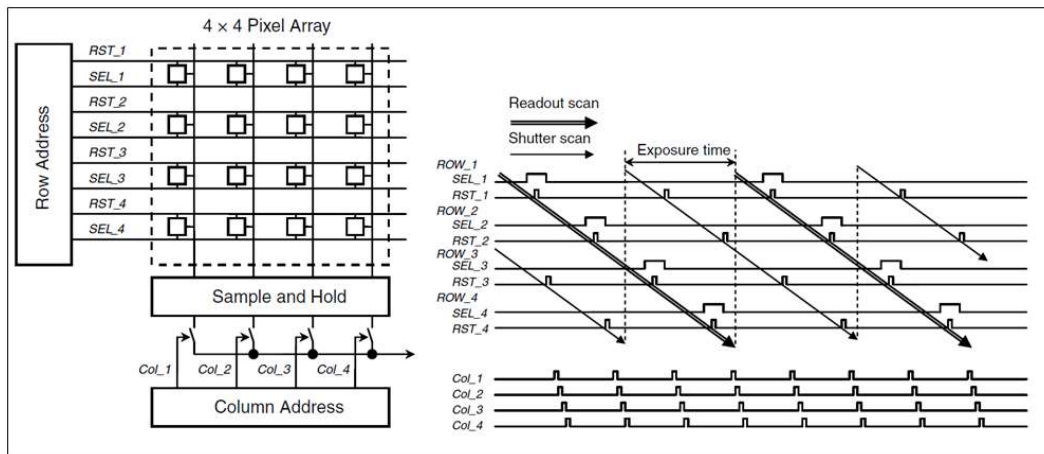


Figure 7: Pixel Scanning with Rolling Shutter – Image obtained from (Nakamura, 2006)

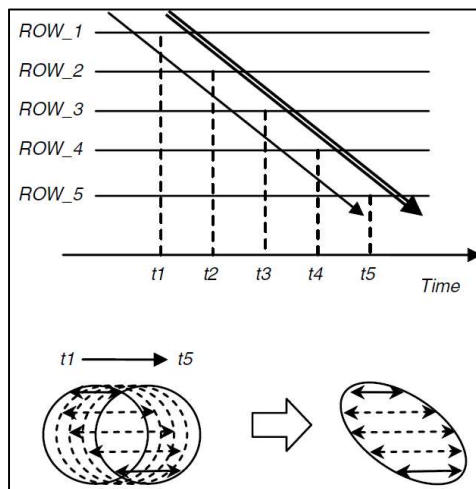


Figure 8: Illustration of shape distortion of moving objects in a rolling shutter

To avoid this situation work conducted by (Mkwelo, 2004), (Selver, et al., 2011) and, (Isa, et al., 2011) selected a camera using charged-coupled device (CCD) camera. To understand the importance of a CCD, a summary of the technical operation obtained from (Nakamura, 2006) has been provided in the following subsection. A comprehensive review has been conducted where we will also investigate the available literature on Complementary Metal-Oxide Semiconductors with global shutter functionality. This design has been created to eliminate the problem with shape distortion.

### Charged Coupled Device (CCD) with Mechanical Shutter

Figure 9 below shows a cross section of a second generation interline transfer CCD for a single pixel. The CCD sensor array is exposed to the light (photons) which passes through the lens to by the opening and closing of a mechanical shutter for a predetermined time. During this period where the shutter is open light (photons) enters the photodiode silicon PN junction (shown by the P+ and, n) structure where electrons are stored in the potential well (demonstrated by p-well in Figure 9). When the lens has been shut these stored electrons are transferred to the positive storage bin also known as the vertical shift register (represented by the p on the side of the PN junction) by the pulse excitation of the Vertical CCD (VCCD) Electrode (Shown in Figure 9 by the VCCD Electrode and the spotted pattern). After each pixel has been moved into the vertical shift register (which has also has been depicted in Figure 9) each row is transferred to serial shift register shown by the blue section. Each row is sent serially to the analogue to digital converter for further handling and storage. After each row has been sent for conversion and processing all rows are shifted down one row, and the next is processed

until all rows have been processed. Once this process is complete, then all components have reverted to a zero state charge ready for the next image (Nakamura, 2006).

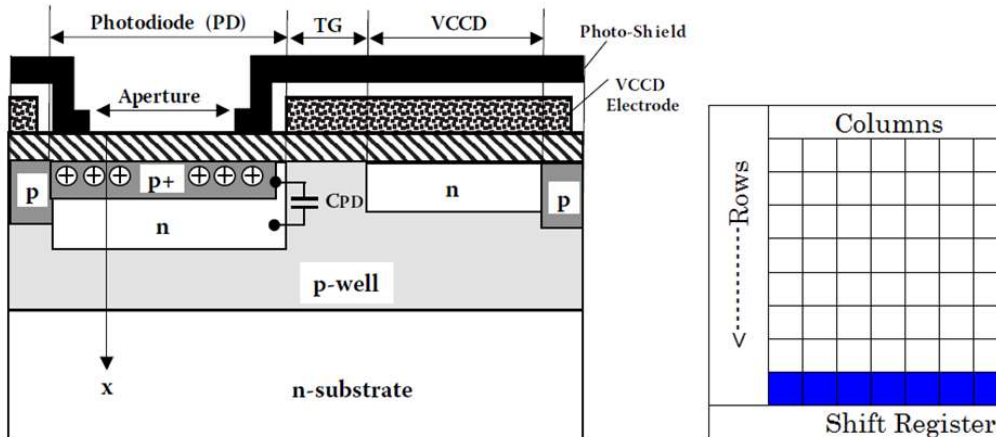


Figure 9: Cross Section of Second Generation Interline Transfer CCD - (Nakamura, 2006)

### Global Shutter Complementary Metal-Oxide Semiconductor (CMOS)

A rolling shutter CMOS sensor has been shown in Figure 7 above. This system can work with a shutter, but typically the shutter is an electronic function where the individual pixel image circuitry is turned on when required. The circuit shown in Figure 10 is a CMOS Rolling Shutter typical circuit. When the shutter/exposure time has been activated a pulse is sent to the Gate of transistor MRS where the photodiode and the Gate of transistor MRD are pulled up to the reset voltage. Then a pulse width of the required exposure time is sent to the gate of Transistor MSEL where the voltage potential from the exposure of light to the photodiode is forwarded to the analogue to digital converter. Each pixel is processed starting with Row 0 Column 0, then Row 0 Column 1 until the end of the row pixel has been processed then the next row will be treated the same way until the full pixel array has been processed. This explanation of the process is the reason why CMOS rolling shutter sensors are subject to shape distortion of moving objects (Nakamura, 2006).

In recent years CMOS sensor manufacturers have found solutions to the shape distortion of moving objects problem by the advent of the CMOS Global Shutter. The CMOS global shutter incorporates technology which allows the individual CMOS pixels to store their electrons similar to CCD sensors (Demant, et al., 2013). With the implementation of this Global shutter technology, more cost effective industrial sensors can be constructed which are less subject to noise and interference.

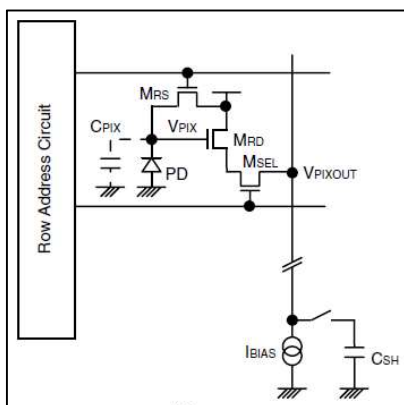


Figure 10: CMOS Rolling Shutter Circuitry obtained from (Nakamura, 2006)

### 2.3.2 Lighting

The chosen lighting method for illuminating the image for raw material identification is an important feature to consider. Machine vision lighting for the application of our application should consider (Martin, 2007);

- Ambient Lighting Contributions,
- Lighting Source (Fluorescent, Quartz Halogen, LED, Metal Halide, Xenon)
- Lighting Wavelength (Visual Range 400 to 650nm)
- Illumination Techniques (Back Lighting, Diffuse Lighting, Bright Field, Dark Field)

With these considerations, we will briefly discuss these items concerning the literature review.

#### Ambient Lighting Contributions

To be able to identify each raw material repeatedly we will need to ensure sources of ambient lighting do not affect our sampled image. These variations in ambient lighting can stem from natural lighting, area lighting and in our case high pressure sodium lighting. Each of these lighting sources offers image variability due to their varying wavelength intensity (Martin, 2007) which can be seen in Figure 11 below.

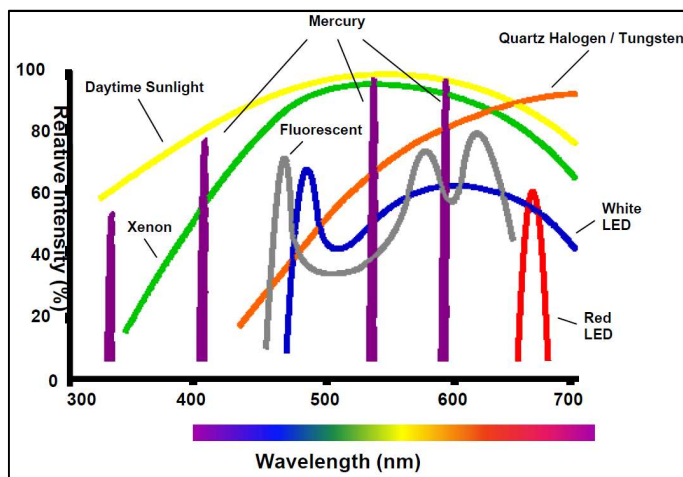


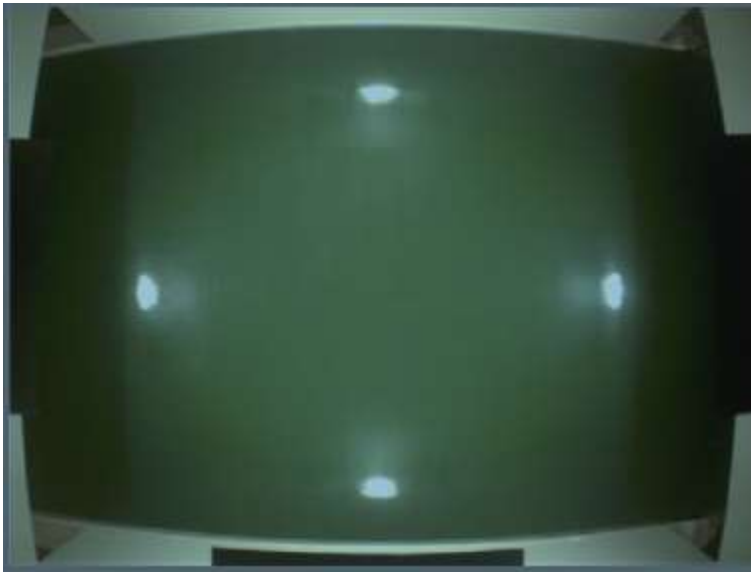
Figure 11: Light Source Relative Intensity Verses Spectral Content obtained from (Martin, 2007)

Work conducted by (Patel & Chatterjee, 2016), (Cunha, et al., 2015) and, (Selver, et al., 2011) managed this ambient lighting variability by installing their camera in a controlled lighting enclosure. This allows lighting to be controlled in a manner which will ensure stable lighting.

#### Controlled Lighting Source

The chosen light source inside the enclosure is an important decision to make. From Figure 11 we can see the spectral content of each light source relative to its intensity. We can see the best choice for colour based applications would be the Xenon lighting as it has fairly consistent relative intensity throughout the visible wavelength spectrum (400-650nm). The next best selection would be White LED and Fluorescent due to their lower cost and availability. The selected lighting in work conducted by (Cunha, et al., 2015) was the Xenon lighting. Figure 12 below shows the effect of the localised lighting which will come from Xenon lighting. The work by (Cunha, et al., 2015) they were able to take a full set of images showing the entire belt and build an image lighting intensity

subtraction model. This lighting intensity model was able to be subtracted from a sampled image to remove this effect. In most lighting source applications there will be sources of non-laminar lighting. This method allows the image to be sampled with minimised effect from the light sources.



**Figure 12: Effect of Xeon Lighting obtained from (Cunha, et al., 2015)**

An additional consideration is the lighting enclosures internal surface preparation. The controlled light source in (Chatterjee, 2013) paper was the use of fluorescent lighting, but they also prepared the inner surfaces of their lighting enclosure with white magnesium oxide. The reasoning behind this was to apply uniform diffuse light to their application which allows an even lighting on their raw material.

In contrast to the diffuse lighting work by (Selver, et al., 2011) their lighting enclosure was painted black to minimise unwanted reflections. The image selection method conducted by (Cunha, et al., 2015) was also replicated in (Chatterjee, 2013) and (Selver, et al., 2011). This image lighting intensity subtraction model negates the importance of internal enclosure finish.

### **Illumination Techniques**

The importance of image illumination technique will become apparent in the following explanation of the various illumination techniques. The common machine illumination techniques obtained from (Martin, 2007) are listed below;

- Backlighting,
- Diffuse Lighting,
- Bright Field
- Dark Field

Each of the above-listed illumination techniques is very different in their application, but the result of the application of these techniques will be further explained below. In our case backlighting will not be considered as it would be near impossible to illuminate our raw material from underneath due to a moving conveyor.

## Diffuse and Dark Field Lighting

The dome diffuse method is the most realistic application of diffuse lighting in which we could implement. Figure 13 shows, an example of dome diffuse lighting. An application of this technique can be seen in (Chatterjee, 2013) which was explained above where they achieved this diffused dome lighting by painting the internals of their lighting enclosure with the white magnesium oxide. This application positioned their lighting in the dark field illumination position. Their intention was to access the benefits of both techniques where the image would not be saturated so a good representation of colour would be available but also the dark field lighting minimises shadows (Chatterjee, et al., 2010).

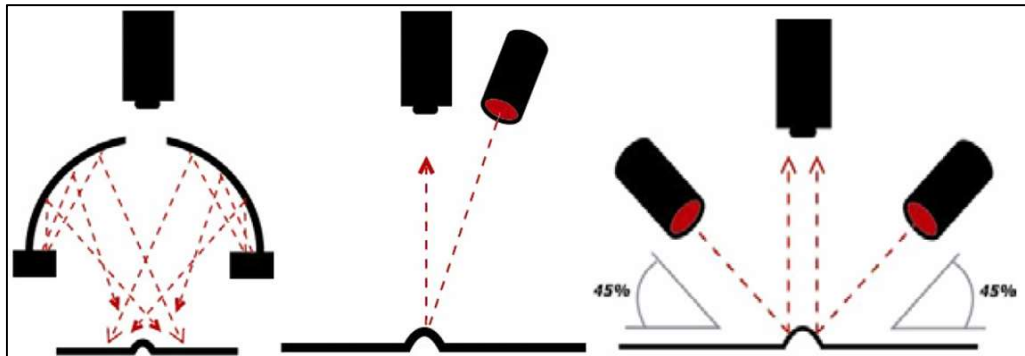


Figure 13: Dome Diffuse, Bright Field and, Dark Field Illumination obtained from (Martin, 2007)

## Bright field Lighting

Bright field lighting applications are usually applied where user wants to enhance topographic detail (Martin, 2007). From Figure 13 we can see the lighting source is nearly perpendicular to the image surface. This method is particularly handy where a watershed image segmentation algorithm will be used to find raw material edges for raw material sizing purposes. This method has been utilised in the work conducted by (Mkwelo, 2004) where he placed his lighting in a high incidence angle to his raw material to encourage the shadows around his limestone to allow better image segmentation.

## 2.4 Image Pre-processing

There are multiple methods to pre-process images before they are presented to the image segmentation and feature extraction. In work by (Chatterjee, et al., 2010) and, (Selver, et al., 2011) they considered the average and median filters to remove unwanted noise in their images. They implemented the median filter which is capable of eliminating input noise values of extremely high values. Due to the importance of a median filter, a brief explanation will be presented in the proceeding sub-section.

### Median Filter

The way in which a median filter works is by assessing a pixel nearest neighbours which are determined by the filters size. Figure 14 below depicts the operations required to perform a 3 x 3 median filter on a 3 x 3 matrix. Each step places the pixel in question in the centre (shown in green) and the pixels being assessed (shown in yellow) are placed in the table in this figure. When no pixels are present, a zero value is substituted in. This process continues until all values have been processed. The point of interest is the zero in the centre of the original matrix. This value was zero, but the resultant value was 33. This filter does not perform well on the edges of an image but its operation is superior in all other areas, this can be seen from the comparison of images in Figure 15. The above explanation was summarised from (Davies, 2012).



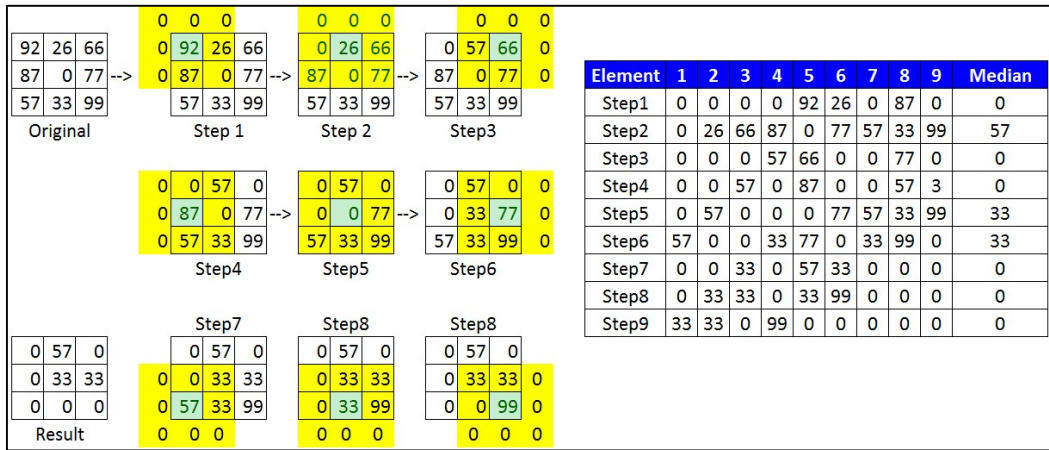


Figure 14: Operations involved in a median filter, method adopted from (Davies, 2012)

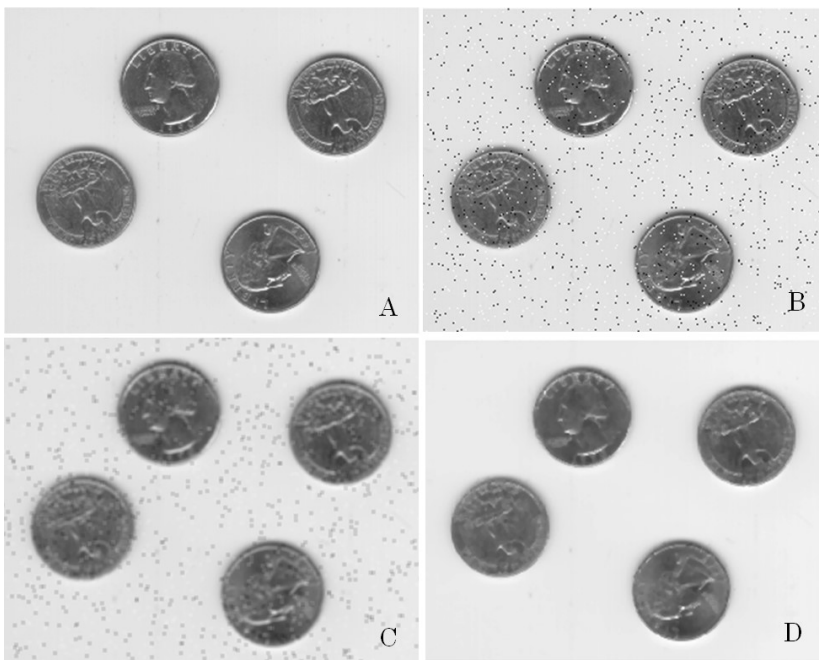


Figure 15: Filter Functions Compared, obtained from (MathWorks, 2016)

### Figure 15 Explanation

- Photo A: MATLAB Original Image
- Photo B: MATLAB Original Image with Salt and Pepper Noise added
- Photo C: MATLAB Noisy image with Average Filter applied
- Photo D: MATLAB Noisy image with Median Filter applied

### Average Filter

An average filter operates the same as a median filter with the only difference is the pixels being assessed are summed up and divided by the total number of pixels being evaluated. This method has also been summarised pictorially in Figure 16 below.



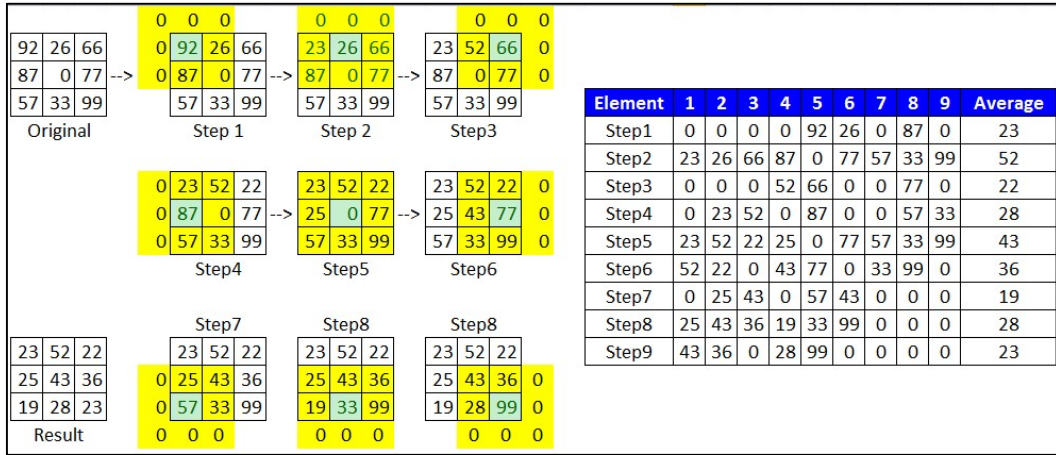


Figure 16: Operations Involved in an Average Filter, method adopted from (Davies, 2012)

## 2.5 Feature Extraction

For the identification of raw materials, there is a broad range of features which we can extract from our pre-processed image. The most relevant feature extraction methods will be explained in detail, and the review literature will support the importance of these methods. To enable an organised presentation of this material all considered features will be categorised under colour and shape properties.

### 2.5.1 Colour Features

From our sampled image we can extract multiple colour features. Work conducted by (Chatterjee, et al., 2010), (Tessier, et al., 2007), (Shanmugamani, et al., 2015) and (Wang & Li, 2015) all used colour in the identification of their raw materials. They achieved this by converting each of the Red, Green and Blue components of a pre-processed image and depending on the image colour depth create a histogram. In these cases, the colour depth was 24bit which means Red, Green and, blue all are represented by 8 bits or 255 intensity levels for each colour. This will require 255 bins to count each of the individual intensity levels. This histogram of each colour was then passed through a statistical algorithm which would determine the weighted average, skewness and kurtosis of each colour. This created nine individual features from three colours (shown in Figure 17 below). The equation to calculate the weighted average, skewness and kurtosis have been listed below in equations ( 2-2 ) to ( 2-6 )

$$\bar{f}_w = \frac{\sum_{f=0}^{L-1} f \times H(f)}{\sum_{f=0}^{L-1} f} \quad (2-2)$$

Where  $\bar{f}_w$  the weighted mean, f is the pixel intensity, H represents the histogram of the image, L is the number of pixels' intensities in the image. Equation obtained from (Patel & Chatterjee, 2016)

$$\bar{f} = \frac{\sum_{f=0}^{L-1} f \times H(f)}{p \times q} \quad (2-3)$$

$$v = \frac{\sum_{f=0}^{L-1} (f - \bar{f})^2 \times H(f)}{p \times q} \quad (2-4)$$

$$S = \frac{\frac{1}{p \times q} (\sum_{f=0}^{L-1} (f - \bar{f})^3 \times H(f))}{(\sqrt{v})^3} \quad (2-5)$$

$$k = \frac{\frac{1}{p \times q} (\sum_{f=0}^{L-1} (f - \bar{f})^4 \times H(f))}{(\sqrt{v})^4} \quad (2-6)$$

Where  $\bar{f}$  is the mean,  $v$  is the variance,  $s$  is the skewness and  $k$  is the kurtosis,  $p$  is the total horizontal pixels,  $q$  is the total vertical pixels. Equations (1.3) to (1.6) also are obtained from (Patel & Chatterjee, 2016)

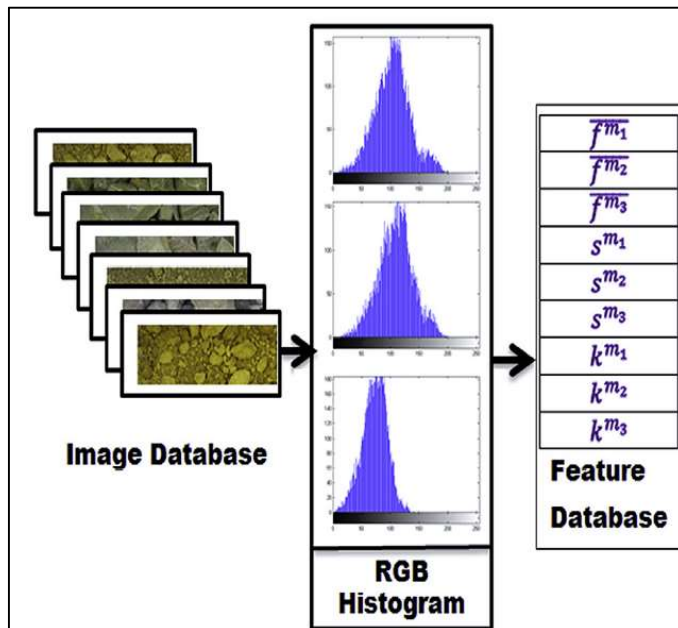


Figure 17: Colour Feature Extraction obtained from (Patel & Chatterjee, 2016)

To add to these colour features (Chatterjee, 2013) also converted the pre-processed images to Hue, Saturation, Intensity and Grey. These additional histograms were then passed through statistical location (median, mode), the measure of spread (variance, standard deviation, range, mean absolute deviation, interquartile range) (Chatterjee, 2013). This work per image would extract a total of individual 70 statistical colour features (7 colour attributes x 10 statistical features). This appears to be excessive, but at the same time, it does allow multiple paths to move on in the event of an unacceptable raw material identification rate.

### 2.5.2 Shape Features

Another method which can be used to identify raw materials is shape features as these features are unique to most raw materials. Shape features are not as readily available as colour features as they need to be passed through an image segmentation process. This process was repeated by (Chatterjee, 2013), (Mehrabi, et al., 2014), (Mkwelo, 2004), (Thurley, 2011) and, (Andersson, et al., 2012) where the image is modified in the order shown below;

- Original Image Sampled
- Filtered
- Grey Scale Conversion
- Image Thresholding
- Image Complement
- Distance Transformation
- Watershed
- Measuring Shape Related Parameters

Steps 1 to 3 are standard functions and have already been explained. The image thresholding is a process where the image is converted from a grey scale image to a binary image. Then the image complement is created using the threshold binary image, and all the ones are changed to a zero and vice versa (Davies, 2012). Finally, the distance transform and the Image Complement are combined and submitted to the watershed algorithm. The watershed transform treats the images as a topographical map where each pixel's grey intensity represents the height of the individual pixel. The lowest point of the image is effectively flooded one intensity level at a time. Points, where the water was to spill into a valley, are marked as an edge/dam wall. This dam wall pixel is set to positive infinity. This will then continue to flood the image to the next spill point where this is also marked as a dam wall. This process continues until the image is fully flooded the maximum field intensity. All the dam walls are declared the watershed image lines (Mkwelo, 2004).

In (Mkwelo, 2004) work he tested a marker-based watershed segmentation process which provided to be far more accurate than the other segmentation methods (e.g. canny filter, Opening and Closing). For more information on the other filter types refer to (Davies, 2012) or (Mkwelo, 2004).

From this segmented image, we can obtain the measurements of the individual raw material particles which will allow us to extract the features listed below which were obtained from (Davies, 2012), (Chatterjee, 2013).

- Area,
- Perimeter
- Area-Perimeter Ratio
- Minimum Radius
- Maximum Radius
- Major and Minor axis lengths

## 2.6 Material Classification

The main methods used to classify raw materials in the reviewed literature are the Probabilistic Neural Networks and, Multiclass support vector machines. Both these methods can operate in the supervised and unsupervised states. The Probabilistic Neural Network (PNN) implemented by (Patel & Chatterjee, 2016) (depicted in Figure 18) consists of a feature database consisting weighted average, skewness and kurtosis of each colour (further explained in section 2.5.1 above) are submitted to the input layer. These features are entered into input vector  $X$  shown in equation (2-7) below. From equation (2-7) the input vector is entered into Equation (2-8) to form the pattern layer where the neurons are divided into a number of classes  $C$  (Patel & Chatterjee, 2016). This result is then fed into equation (2-9) which forms the summation layer classes. Finally, the results of equation (2-9) are passed to the final equation (2-10) which determines the class the input image best represents. This process is repeated for all training photos to ensure the system has the required data to identify each material. Equation (1-7) to (1-10) below were obtained from (Patel & Chatterjee, 2016)

$$X = (\overline{f_w^{m_i}}, S^{m_i}, k^{m_i}), \in R^n, n = 9 \text{ where } m_i = (R, G, B) \quad (2-7)$$

$$F_{c,j}(X) = \frac{1}{(2\pi\sigma^2)^{\frac{n}{2}}} \exp\left(-\frac{\|X-X_{c,j}\|^2}{2\sigma^2}\right) \quad (2-8)$$

$$G_c(X) = \sum_{j=1}^{N_c} F_{c,j}(X), c \in \{1, 2, \dots, C\} \quad (2-9)$$

$$O(X) = \operatorname{argmax}_{1 \leq c \leq C} (G_c) \quad (2-10)$$

Where  $X$  is the image vector;

$\overline{f_w^{m_i}}$  is the weighted mean

- $S^{m_i}$  is the skewness
- $k^{m_i}$  is the kurtosis
- $F_{c,j}(X)$  is the pattern neuron
- $\sigma$  is the smoothing parameter
- $n$  is the number of training images
- $G_c(X)$  is the summation layer
- $O(X)$  is the output layer

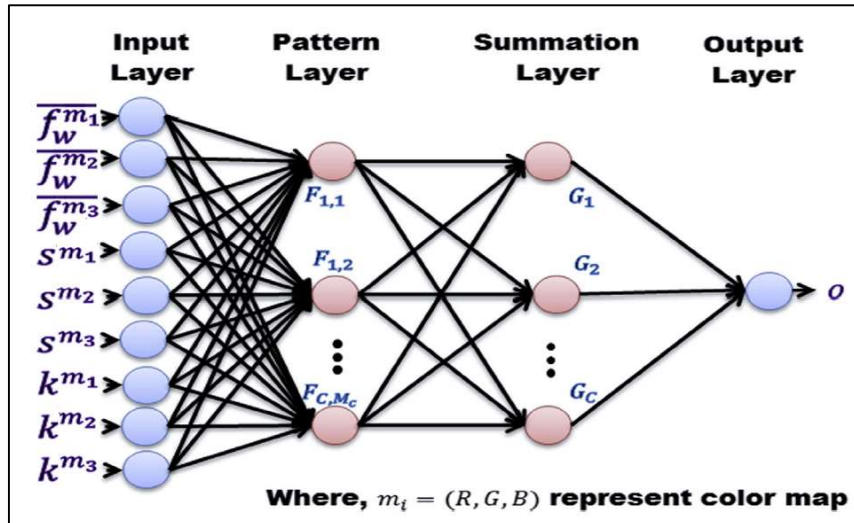


Figure 18: Probabilistic Neural Network, obtained from (Patel & Chatterjee, 2016)

To test the PNN success rate (Patel & Chatterjee, 2016) created a Matching matrix to determine the success rate. This matrix compares the actual image against how many images were miss-classified.

The work conducted by (Chatterjee, 2013) implemented a multiclass support vector machine. He used this method as Probabilistic Neural Networks and other classification algorithms become difficult to manage with the sheer amount of features they chose to classify (189 in total). The workaround (Chatterjee, 2013) developed was using a multiclass classifier approach to minimise the number of features. To achieve this, he used a one versus all algorithm which requires the development of a training set of data. This training set is used to set rules for each desired class. Then these rules are used to select which feature the extracted feature is most like.

## 3 Methodology

### 3.1 Project Approach

This research project will demonstrate a quantitative research approach which will follow the stages of the research cycle shown below in Figure 19. This approach developed the research questions which will be used to guide the literature review. From this literature review, a gap in the literature will be found and potential techniques. This will provide the required information needed to build and test and evaluate a model's performance. Also a test rig or program will provide a quantitative evaluation of the systems resultant data. This evaluation will offer the required data which will allow analysis of the results and which will lead into the critical thinking phase. This critical thinking phase will allow a review of the results to determine if the desired outcome has been delivered. It will most likely lead to a review of the research questions or so a revisit of the literature can occur to find improved ways to optimise the model. This research process can undertake many cycles to deliver the desired result.

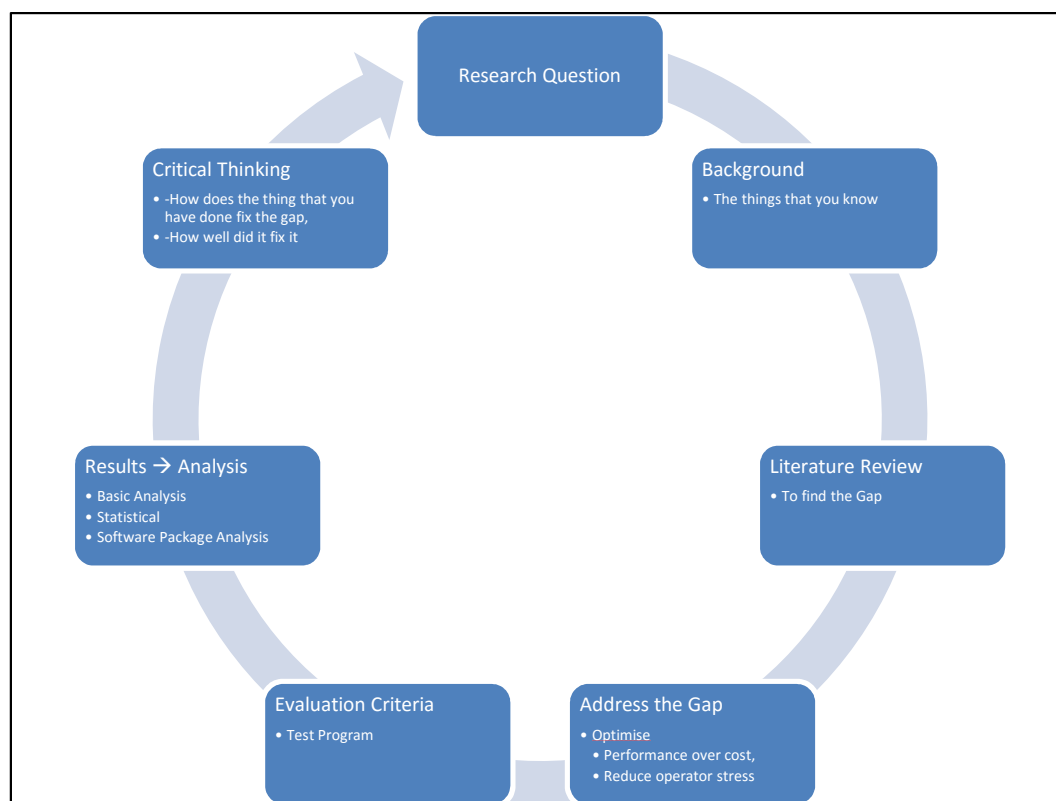


Figure 19: Project Research Cycle adopted from (Maxwell, 2016)

### 3.2 Overview

This project will involve the construction of a camera enclosure and test bed. The camera enclosure and test bed will be used to design a material classification model. This classification model will need to be able to take a significant number of still images with a camera. A computer-based system will be used to extract unique features from the image. These image features will be used to classify the raw material present in the image.

For this research project, the scope is to design, test and optimise a static model with the future intention (after the dissertation is complete) to implement this model on a live conveying system which will be able to optimise itself and operate in the operational environment dynamically. With this in mind, all future design considerations and project work will consider the needs of the static model development and the proposed dynamic functional model.

### **3.3 Sample Selection and Collection**

To be able to take training and verification images the three raw materials will need to be collected. These raw materials will also need to be sampled in a manner which will ensure an accurate cross representative sample is taken from the stockpiles and process which also will represent the total body of raw materials which the process will consume for the development life of the project (May 2016 to October 2016). Sample storage considerations should address ways in which the sample will maintain moisture content present when extracted and can be made available for future quality or physical analysis should this be needed.

### **3.4 Training and Verification Image Acquisition**

To be able to take training images a camera will need to be selected and purchased. A Camera enclosure, camera lighting system will need to be designed and constructed. The design of the camera enclosure and lighting system will need to be developed to address the needs of static operation and meet the needs of the future dynamic system. As well a test bed will be necessary to place the samples on to take the required training and verification image acquisition. Since the future dynamic model will need to operate over the tilt pan conveying system shown in Figure 2 and Figure 3 a spare tilt pan will be used as the test bed. The test bed will hold the raw material samples used to take the training and verification images.

### **3.5 Image Pre-Processing**

Once the training and verification images have been taken, we will need to ensure the images are free from noise and image pixel saturation. It will be important to pass the images through a filter as the wet raw material will be highly reflective and may cause localised image pixels to become saturated.

### **3.6 Image Feature Extraction**

From the taken training and verification images we will need to determine quantifiable features which will be unique to each raw material. For automated classification using these image features, we will require several unique features for all images to improve the classification model's success rate. Additionally, chosen image features will need to consider the processing time taken to extract each images features. This processing time consideration will need to ensure a picture can be classified within the problem statements goal of thirty seconds.

### **3.7 Material Classification**

The image features extracted in section 3.6 will be used as the input to a neural network model, perceptron network or support vector machine. One of these types of classification algorithms will be selected, and the chosen model will be implemented and tested. The intention is to use a program similar to MATLAB for the initial implementation and model development and when the future dynamic system is developed it is intended to be

developed using a mixture of C# programming for the application layer and dotNET coding for the camera control.

### **3.8 Model Performance Evaluation and Optimisation**

At this stage, we will evaluate the model's performance against the projects specification in Appendix A. This evaluation will determine if the static model's performance has delivered the requirements listed in the project's specification. If the model does not comply with the project's specification, we will redefine the problem and conduct a focused review of the literature to determine if a solution can be sourced. If one can be found, then this will allow the static model to be optimised. This entire process from section 3.1 to 3.8 will undergo many cycles until the project specifications can be delivered.

## 4 System Development

### 4.1 System Design Considerations

The system development considered all aspects of the proposed systems lifecycle. For this dissertation, the model developed was a static system used to build, test and optimise the developed model in a controlled environment. This static system will allow the model to be developed free from the operational environment. To minimise waste, the hardware will also be used to conduct static system evaluation and designed to address the dynamic system needs.

The operational environment where the future dynamic system will be installed will subject the system to fugitive dust, varying ambient light, temperature variations and moisture variations. The systems shall not impact the sites conveying system as this will be an unacceptable outcome.

### 4.2 Overview

The first step in this project system development will discuss the method developed to sample the raw materials. The next development discussion point will be the selection of camera, design of the enclosure and discussion surrounding the selection lighting. The following point of discussion will be the way in which the images were taken and then had their features extracted. Finally, the probabilistic neural network model development and verification consideration will have been discussed. An overview of this process has been provided in Figure 20 below.

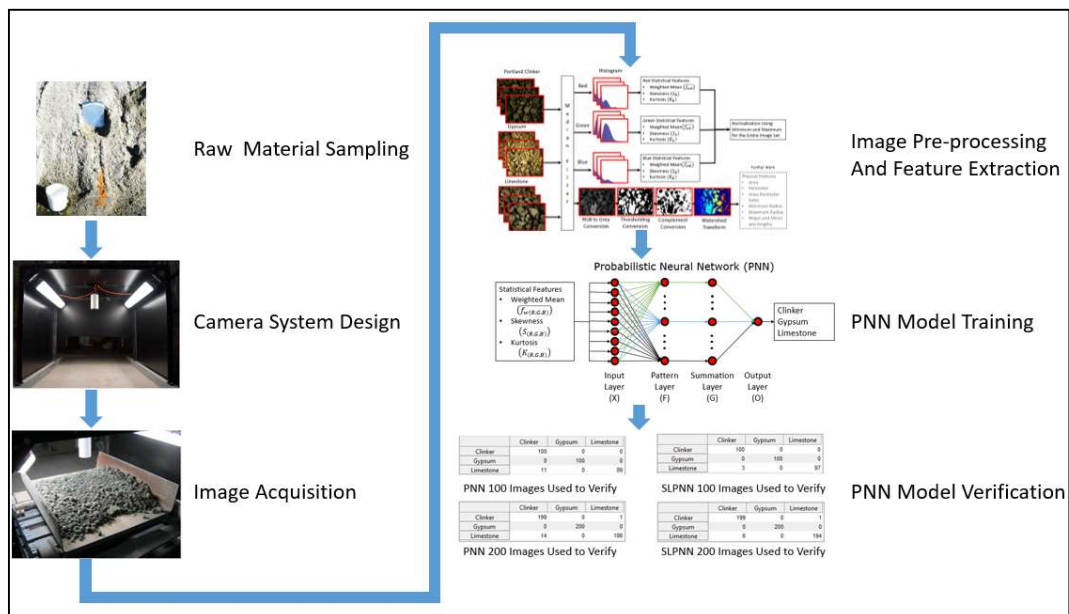


Figure 20: System Development Overview



## 4.3 Raw Material Sampling

### 4.3.1 Overview

The work conducted by (Chatterjee, et al., 2010) and (Hamzeloo, et al., 2014) clearly outlines the importance of developing a sampling plan which will extract a true representative sample of the raw material population your wish to sample. This sampling importance has been explained in detail in section 2.2. In their case, they used Stratified Random Sampling, which is a procedure which divides a total population (Total Length of a Stockpile, Total Production Time or, Total Tonnes Produced) by the number of Increments. ( (Australian Standards, 2012a) states there are five increments per sample). Once the number of required increments and the total population is known, equation (4-1) below can be used to determine the exact location of each increment (length along a stockpile, point in production time or tonnage produced) will need to be extracted from.

$$\text{Increment Location} = S \times (I - 1 + R) \quad (4-1)$$

Where  $S$  is Total length in [m], for Total Length Stratification;  
 $S$  is Total time in [hours], for Total Production Time Stratification;  
 $S$  is Total length in [t], for Total Tonnage Produced Stratification;  
 $I$  is the Increment Number;  
 $R$  is the Randomly Generated Number which will be between 0 and 1.

In (Australian Standards, 2012a) it clearly states that procedures developed using this series is only to be developed by a person who is experienced and qualified in geological engineering. This advice will not be adhered to as access to such an engineer is not available and this standard is only being used for its Stratified Random Sampling procedure. If the samples acquired for this project were to be used for quality analysis, we would need to approach such an engineer. Given the nature of this work we will not consider use of such an engineer and list this item in our project limitations.

Work by (Chatterjee, et al., 2010) claimed that at least 100 images of each sample are needed totalling 500 images per raw material. For this project five samples were extracted for each raw material is based upon the need to generate at least 100 imaged for each sample from the above mentioned work.

### 4.3.2 Clinker

The work by (Chatterjee, et al., 2010) and (Hamzeloo, et al., 2014) was not conducted in Australia. There is a standard for implementing Stratified Random sampling and this standard is (Australian Standards, 2012a). This standard's scope covers all raw material particle sizes up to 63mm. For clinker all historical sizing conducted onsite were obtained and the particle size distributions have been listed in Table 4. This data is obtained by mechanically sifting the raw materials through a series of sieves with the aperture listed below in the table as particle size in millimetre measurements. The number listed under minimum, average and maximum columns are the percentage weight each particle size class is of the total samples weight (e.g. 30.34% represents the maximum portion of particles measured in 10 years were in the 19.1mm particle range).

**Table 4: Case Study's site 10 Year Clinker Distribution analysis.**

Particle Size in (mm)	Clinker		
	Minimum	Average	Maximum
90 - 2D	0.00	0.00	0.00
90 - 1D	0.00	0.00	0.00
38.1	0.00	6.69	30.34
25.4	5.14	15.66	32.97
19.1	8.32	18.14	30.73
12.7	12.00	20.05	36.54
9.5	3.89	9.39	14.69
4.75	4.33	15.53	28.97
2.36	0.69	6.90	15.85
1.17	0.17	3.81	11.38
0	0.07	1.45	7.80
0.3	0.06	0.53	3.75
0.15	0.04	0.57	4.83
0.075	0.06	0.62	4.58

Note: 2D represents greater than 90mm in 2 dimensions and 1D only greater the 90mm in one dimension.

With the use of table 4 we can see that our largest recorded clinker particle size was 38.1mm and according to table 5 from (Australian Standards, 2012a) we can see that the clinker sampling procedure will need a minimum increment mass of 6kg and a sample size minimum of 30kg.

The clinker on site is continuously manufactured and only stored for a short time before it is consumed in the cement mills. For this reason, our sampling procedure will be a tonnes produced stratification. During the projects life time, from May 2016 to October 2016 665,160 tonnes will be produced. So equation ( 4-1 ) will be used to stratify the tonnes produced and it has been decided upon an educated guess that we will require we will require 5 samples which will consist of 25 increments in total.

The detailed procedure, stratification of increments recording and sampling has been provided in Appendix N, O and P.

**Table 5: Minimum Increment and Sample Mass, Data obtained from (Australian Standards, 2012a)**

Nominal Size, mm	90	75	40	28	20	14	10	7	5	<5
Minimum mass per increment, kg	12	10	6	5	4	3	2	2	1	1
Minimum Mass per Sample, kg	59	50	30	25	20	15	10	10	5	5

To find the values for 90 mm which has been highlighted in yellow we will need to extrapolate the data using equations ( 4-2 ) to ( 4-7 ) obtained from (James, 2010).

$$\text{Increment Gradient} = \frac{y_2 - y_1}{x_2 - x_1} = \frac{10 - 6}{75 - 40} = 0.1143 \quad (4-2)$$

$$\text{Sample Gradient} = \frac{y_2 - y_1}{x_2 - x_1} = \frac{50 - 30}{75 - 40} = 0.5714 \quad (4-3)$$

Where  $y_2$  is the highest known y axis value,  
 $y_1$  is the next highest known y axis value,  
 $x_2$  is the highest known x axis value

$x_1$  is the next highest known x axis value

Substitute ( 4-2 ) into ( 4-3 ) to determine  $b$

$$\text{Increment } Y = \text{Gradient} \times x + \quad (4-4)$$

$$10 = 0.1143 \times 75 + b$$

$$b = 1.4275$$

$$\text{Sample } Y = \text{Gradient} \times \quad (4-5)$$

$$50 = 0.5714 \times 75 + b$$

$$b = 7.145$$

Where  $Y$  is the extrapolated data  
 $x$  is the unknown x axis data point  
 $b$  is the  $x=0$  y intercept point.

With this in mind we can generate our linear equation which we will use to extrapolate our increment and sample mass for particle size equals 90mm. This has been shown in equation ( 4-6 ) and ( 4-7 ) below.

$$\text{Increment } Y = \text{Gradient} \times x + b = 0.1143 \times 90 + 1.4275 = 11.7kg \quad (4-6)$$

$$\text{Sample } Y = \text{Gradient} \times x + b = 0.5714 \times 90 + 7.145 = 58.57kg \quad (4-7)$$

The Clinker was sampled directly sampled off the conveyor at the stratified tonnes produced increments listed in Appendix N. The conveyor was not to be stopped as this would lead to a production stop. All materials were sampled at a purpose built sampling station shown in Figure 21 which has all the conveyor draw in hazards engineered out. Another point to note is that the temperature of the Clinker travelling up the conveyor varies from 200°C to 500°C. For this reason, a high temperature protective apron, gloves and face shield were worn during sampling. As well all clinker was placed into a steel bucket using a long handled sample scoop (to minimise the conveyor draw in risk).



Figure 21: Clinker Sampling Station

### 4.3.3 Gypsum

Gypsum is a product which is shipped to site from South Australia in 36,000 tonne shipments. This raw material is delivered to site and stored on a large outdoor concrete pad shown in Figure 22. This stock pile was stratified up into 25 increments using equation (4-1). This has all been recorded in Appendix O – Gypsum Sampling Procedure. The Australian standard (Australian Standards, 2012a) which was used to develop this procedure states that a stock pile is best sampled from the back of the truck as this stockpile is being constructed. In our case this stockpile was constructed before this project started. So to ensure the best representative sample was acquired the sample was extracted from the stock pile using a stockpile shield (see Figure 23) to a depth of 200mm plus the depth of the deepest measured effect of weathering (300mm which can be seen in Figure 22). With this in mind the increment was extracted from a depth of 500mm.



Figure 22: 33,000tonne Gypsum Stockpile



Figure 23: Gypsum Sampling using Stockpile Shield and sample scoop

The gypsum increment size was determined using the maximum sample size from Table 6 and then the recommended sample increment mass and total sample mass from Table 5 was derived. The minimum increment mass will be 6kg and the minimum total sample mass will be 30kg.

**Table 6: Case Study's site 10 Year Gypsum Distribution analysis.**

Particle Size in (mm)	Gypsum		
	Minimum	Average	Maximum
90 - 2D	0.00	0.00	0.00
90 - 1D	0.00	0.00	0.00
38.1	0.00	0.21	8.65
25.4	0.00	1.49	9.01
19.1	0.00	3.85	12.22
12.7	3.00	8.80	23.69
9.5	2.01	7.12	13.92
4.75	4.53	20.14	37.65
2.36	2.03	10.45	18.26
1.17	3.53	12.11	22.16
0	3.01	11.84	17.96
0.3	3.18	11.18	29.79
0.15	1.95	7.03	18.84
0.075	0.39	3.18	6.94

These increments were sampled from the stockpile using two people as risk of engulfment was prevalent due to the piles extreme height of 35.8 meters and an angle of 38°. Another point to note is that the standard requires the stock pile stratification increment point to use length as well as the width of the pile. The length stratification was used but the width was not possible as an elevated work platform was not available for the task and to scale the pile to extract the sample was far too unsafe. All sampling details and considerations have been listed in Appendix O – Gypsum Sampling Procedure.

**Figure 24: Stored Sampled Gypsum**

#### 4.3.4 Limestone

From Table 7 one very important point to note is that limestone has material larger than 90mm. This means that it will not be covered under the scope of (Australian Standards, 2012a) as this standard only covers up to 75mm particle size. Another point for consideration is that the standard which covers these size particles is (Australian Standards, 2012b). This standard covers material greater than 100mm in size and particles are to have a weight above 3.5kg. As well only five particles are needed per sample. In the case of limestone, we will use the data from AS1141.3.1-2012 tables 1 and 2 and extrapolate it to find the ideal increment size for 90mm particles. This extrapolation has been conducted in section 4.3.2 using equation 4-2 to 4-7 and the result has been listed in Table 5. With this in mind we can determine our increment size using Table 7 where our



maximum limestone particle size is 90mm. This can then be used find our increment mass of 12kg and total sample mass of 60kg using Table 5.

**Table 7: Case Study’s site 10 Year Limestone Distribution analysis.**

Particle Size in (mm)	Limestone		
	Minimum	Average	Maximum
90 - 2D	0.00	3.07	15.93
90 - 1D	1.89	8.50	38.38
38.1	5.36	12.37	49.30
25.4	0.95	13.51	23.66
19.1	1.39	11.49	18.34
12.7	1.74	12.56	17.18
9.5	0.77	6.40	9.25
4.75	1.55	13.39	19.25
2.36	0.68	5.93	9.78
1.17	0.51	4.56	8.19
0	0.30	2.90	5.57
0.3	0.19	1.83	3.67
0.15	0.12	1.24	2.81
0.075	0.09	1.01	2.16

The limestone increments were sampled directly of the conveyor similar to the way in which clinker was sampled in subsection 4.3.2. The difference is the limestone increment was taken directly off the belt with the belt stopped and isolated. This allows the best possible sample to be taken as the entire cross section of the belt can be extracted (shown in Figure 25).



**Figure 25: Limestone conveyor sampling**

## 4.4 Camera System Design

As mentioned before in section 4.1 the camera system design must address the needs of the project’s static system requirements needed for model development and address the future needs for the system to be able to operate in the dynamic production environment. To be able to address both the static model’s development and the dynamic model’s development needs the following criteria has been addressed;

- Be capable of being disassembled so it can be safely transported between the training image work area and the tilt pan conveyor by hand,
- No section of the of the disassembled system shall weigh in excess of 10kg due to manual handling issues identified in the risk management plan in section Appendix B – Project Management Plan
- All surfaces must be painted black as per the discussion in section 2.3.
- Camera mount must be adjustable and be able to be locked into position
- Be designed to prevent conveyor material surges from striking the enclosure
- Minimise the effect of fugitive dust problems by ensuring the internals are kept under filtered positive pressure
- Designed to be positioned on the tilt pan conveyor support frame and be positioned on the concrete floor for image training purposes

#### 4.4.1 Camera and Lighting Enclosure

Since the camera enclosure has to be able to operate in both the model development and operational phases the enclosure will need to be able to be installed over the Tilt Pan Conveyor's operational structure shown in Figure 26. To put this figure into prospective the top of the pan to the floor level is 2260mm. The enclosures proposed location has been shown in this image by the red overlay. This location is the only location on this conveyor where such an enclosure can be installed. It would be ideal to be further away from the conveyor transfer point identified by the green ellipse shown below. This transfer point can be a main source of fugitive dust as material is falling from 5 meters above this area on to the Tilt Pan Conveyor. There is dust collection associated with transfer point but it only works when the material flow has been established and coming out the full height of the transfer exit point.

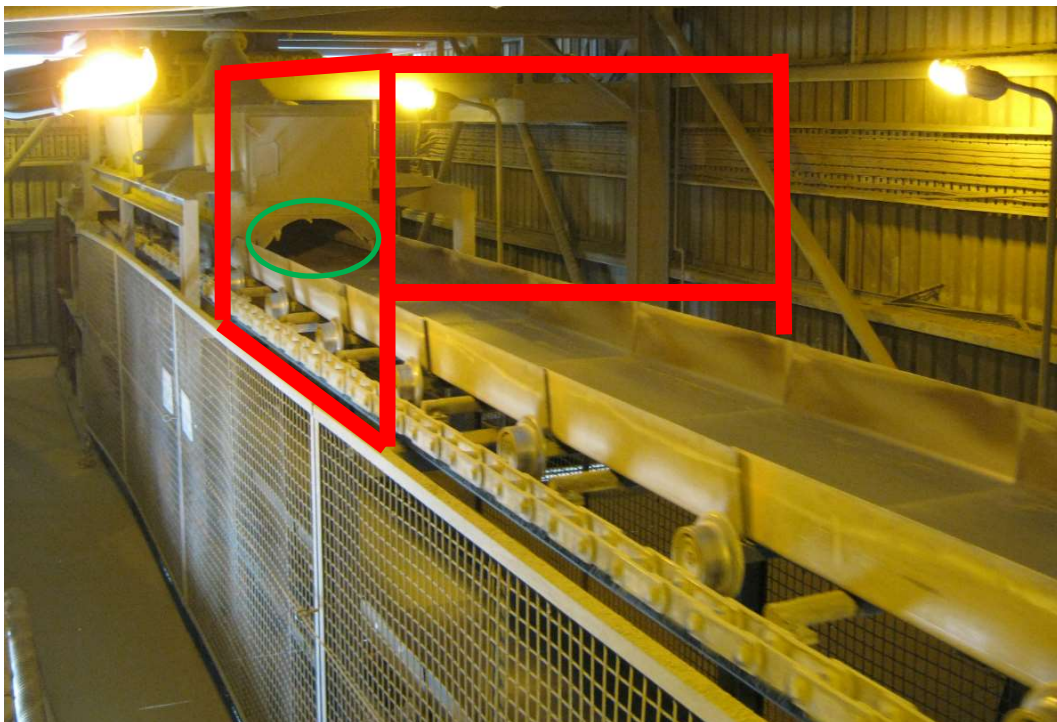
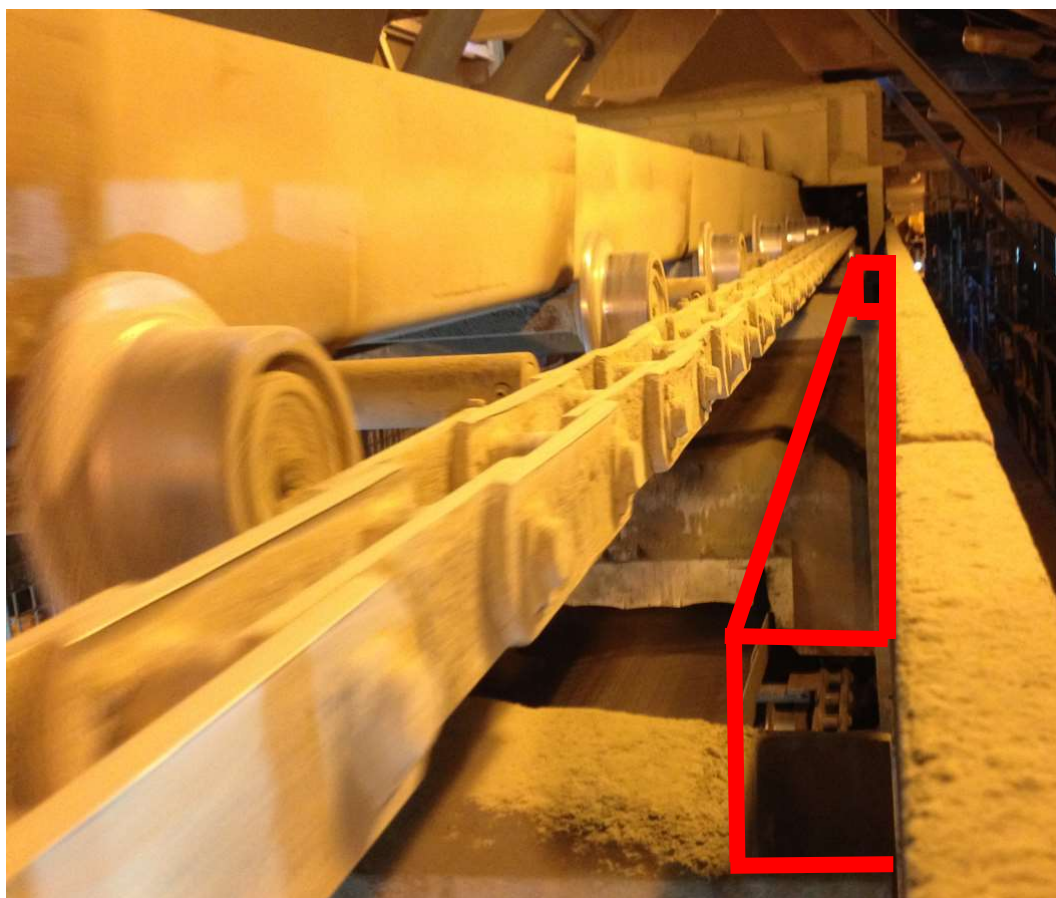


Figure 26: Image of Tilt Pan Conveyor

### Camera Enclosure Support Structure

The proposed support location for the cameras structural channel has been shown in Figure 27. This location has been chosen for two reasons. The first is that it has the largest clearance between the Tilt Pan Conveyors haulage chain and the second is that it has the ideal support structure to mount our structural channel. The main two structural channels were selected using the help of the sites Structural Design Engineer Leigh Wiseman. Leigh's support was requested as the span of 3600mm and the enclosure's total weight was well out of the engineering abilities of the Author. Figure 29 shows two up right support channels where the top section will have a 10mm pad welded onto the top to hold down the camera enclosure's support channel. Full detailed drawings have been provided in Appendix C – Enclosure Design Drawings and an image of the constructed unit can be seen in Figure 30.



**Figure 27: Support Structure required clearance distance**

### Camera Support Bracket

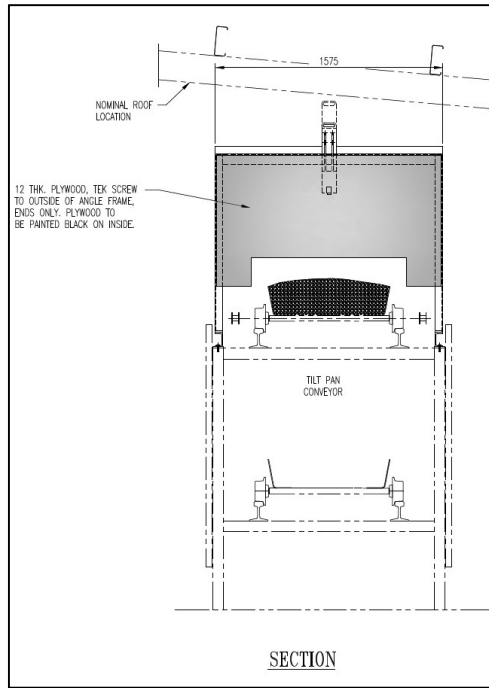
The Camera enclosure design overview can be seen below in Figure 29. From this we can see the importance of the camera's distance to the conveyed raw material. For this reason, the camera's support bracket was stiffened to prevent undue camera vibration, far enough away from the raw material to prevent damage to the camera. Also the camera support bracket was designed to offer 150mm of height adjustment to allow manual camera focusing from outside the enclosure.

### Camera Enclosure Dimensions

The camera enclosure's height was selected to maintain the desired bright field lighting which has been discussed in detail in section 2.3.2. To maintain this bright field lighting



the position of the lights must be as close to the camera and far away as possible from the raw material as possible. The second consideration for enclosure height was the available clearance between the camera and the building's roof (shown in Figure 28). The enclosure height has been made as high as possible without interfering with the roof. Selection of the camera enclosure width is a clear decision to make as it governed by the Tilt Pan Conveyor's dimensions. The length of the camera enclosure is determined by the camera's field of view and the chosen lightings maximum length.



**Figure 28: Camera Enclosure showing roof clearances**

### Enclosure Colour

Since Bright Field lighting (explained in 2.3.2) is being implemented it is important that no lighting reflections come from the enclosures internal surfaces. For this reason, all surfaces and internal materials shall be painted black.

### Enclosure Construction

The enclosures construction will be made up of a steel support frame made from welded angle iron which will give the structure the required strength to support the camera and cladding. To ensure the system is portable (each section less than 10kg and able to fit through a standard doorway) careful design has taken place and each section will bolt together to provide the finished structure. The cladding/panels for the camera enclosure was constructed using black concrete form work plywood for two reasons. Firstly, the panels did not need to be painted and secondly these panels economic and are readily available.

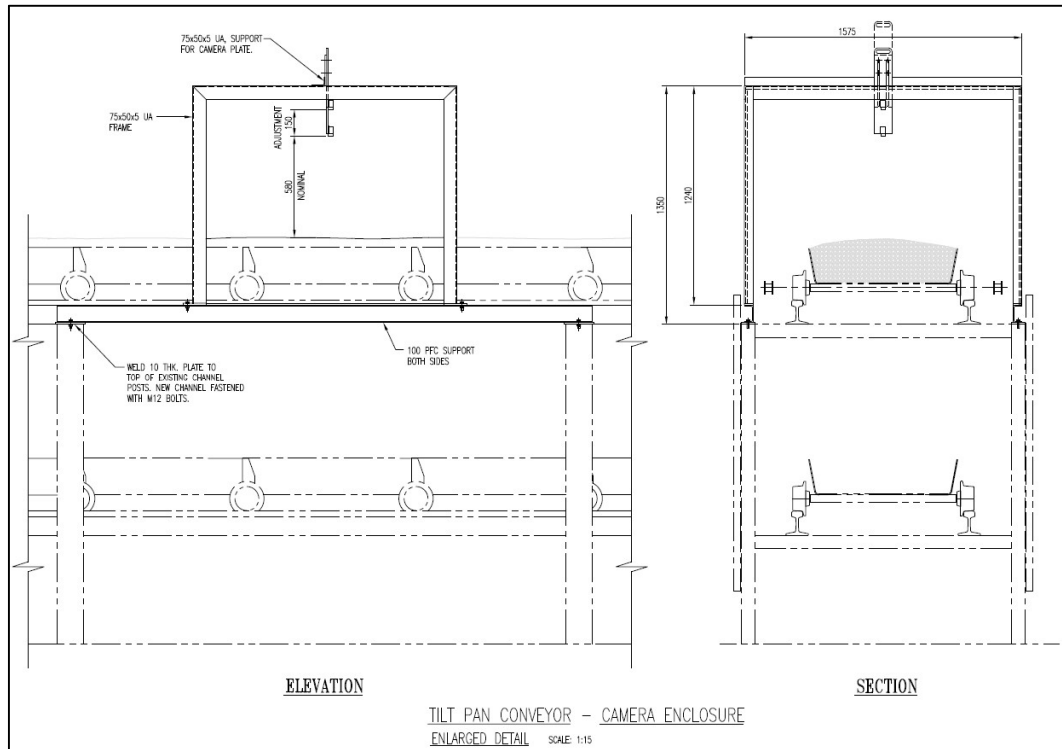


Figure 29: Tilt Pan Camera Enclosure Design Overview



Figure 30: Finished Camera Enclosure

#### 4.4.2 Camera

##### Image Size

Since the tilt pan conveyor pan maximum measured width is 835mm we are able to draw the conclusion that the largest image which can be sampled using a photo with a 4:3 aspect ratio Image dimensions will be 800mm x 600mm. With this in mind we are able to consider the required camera resolution with consideration to the desired Spatial Calibration Resolution. Table 8 below shows the effect of physical image size considering the spatial calibration resolution and the expected image pixel count. Due to project cost constraints and image processing burden we will need to select a camera which will have an image size in the range of 1MP to 3MP in order to maintain a sensible

image which will have the desired resolution yet be able to see enough of the physical raw material for identification purposes.

With the selected lens in subsection 4.4.2 camera lens we selected a lens which should have given us an image 332mm High and 443mm Wide. This was not the case as the provided lens did not screw into the camera body appropriately which modified the desired focal lengths and ended up providing an image with 113mm wide by 150mm high. This is not desired but due to time constraints and the need to progress the project we continued with this modified focal range. Tests using 5mm grid paper were conducted to ensure the image was not distorted. The resultant resolution and image size has been highlighted in yellow below in Table 8: Image Pixel Count Related to Field of View Dimensions.

**Table 8: Image Pixel Count Related to Field of View Dimensions**

Image Height	Image Width	Spatial Calibration	Pixel Count	Image Size (megapixels)
		Resolution (mm/pixel)		
600	800	0.1	4,800,000	4.8MP
		0.15	3,200,000	3.2MP
		0.2	2,400,000	2.4MP
		0.5	960,000	0.96MP
450	600	0.1	2,700,000	2.7MP
		0.15	1,800,000	1.8MP
		0.2	1,350,000	1.35MP
		0.5	540,000	0.54MP
300	400	0.1	1,200,000	1.2MP
		0.15	800,000	0.8MP
		0.2	600,000	0.6MP
		0.5	240,000	0.24MP
112.5	150	0.008789	1,920,000	1.92MP

Camera Selection

To allow the best camera selection can take place for our application we will use a weighted decision matrix which will rank each camera type based upon the desired criteria weighting. From the chosen decision matrix and weightings camera 3 (IDS UI-5250CP-C-HQ) was selected.

**Camera 1: Nikon D40 (Available)**

A Nikon D40 is available for this project but its age, lack of dust protection are key factors which will weigh against this solution. This option has only been considered as a backup option as it has the Charged Coupled Device technology which is capable of taking an image of a moving conveyor without shape distortion which progressive scan CMOS cameras provide (explained in subsection 2.3.1).

Image Size: 6.1MP  
 Sensor: CCD  
 Control: Manual Shutter Control  
 Connection: USB 2.0

### **Camera 2: Axis Q1615-E (Available)**

The Axis Q1615-E is an industrial PoE Ethernet camera which is installed in a weather proof camera enclosure. Camera. This camera is suitable for the environment but its image sensor is unsuitable for taking images of moving conveyors (explained in subsection 2.3.1).

Image Size: 2MP  
Sensor: Progressive Scan CMOS  
Control: Automatic  
Connection: Ethernet

### **Camera 3: IDS UI-5250CP-C-HQ (Need to Purchase)**



**Figure 31: IDS UI Camera, image obtained from (IDS Imaging Development Systems GmbH, 2016b)**

The IDS camera (Figure 31) is a purpose built industrial camera which will be installed in a dust proof enclosure. This camera is ideal for our application as it will provide the correct sensor technology and had the quickest delivery time.

Image Size: 1.92MP  
Sensor: Global Shutter CMOS  
Control: Event Driven by DotNet commands or external trigger  
Connection: Ethernet

### **Camera 4: Point Grey Research Grasshopper 3 GS3-PGE-23S6C-C (Need to Purchase)**



**Figure 32: Point Grey Research Grasshopper 3 obtained from (Point Grey Research, 2016)**

The Point Grey Research camera also is a purpose built industrial camera which will be installed in a dust proof enclosure. This camera is ideal for our application as it will provide the correct sensor technology. Unfortunately, due to Sony's Global Shutter CMOS sensor supply shortage (Due to the April 2016 earth quakes) the delivery time for this item was not reliable.

Image Size: 2.3MP  
Sensor: Global Shutter CMOS  
Control: Event Driven by DotNet commands or external trigger  
Connection: Ethernet

The way in which the cameras were compared has been summarised in Table 9. This comparison has been created using Table 10: Camera Selection Criteria Ranking weightings. The total listed at the bottom of Table 9 is the product sum of each elements weighting and score.

It can be seen from Table 9 that the best camera selection will be camera 3 which is the IDS UI-5250CP-C-HQ. This camera was purchased and implemented.

**Table 9: Camera Comparison and Selection**

	Weighting	Camera 1	Camera 2	Camera 3	Camera 4
Sensor Type	7	4	1	7	7
Delivery Time	6	7	7	6	4
IP Rating	5	1	7	4	4
Noise Immunity	4	1	7	4	4
Cost	3	7	3	5	5
Operation Method	2	1	7	7	7
Local Support	1	1	7	7	1
Total		103	142	157	139

**Table 10: Camera Selection Criteria Ranking**

Score	1	2	3	4	5	6	7
Sensor Type	Progressive Scan CMOS			CCD			CMOS Global Shutter
Delivery Time (Days)	>42	>35	>28	>21	>14	>7	0
IP Rating	N/A	IP1X	IP2X	IP3X	IP4X	IP5X	IP6X
Electrical Noise Immunity	Low			Medium			High
Cost (\$)	<4000	>4000	>3000	>2000	>1500	>1000	>500
Operation Method	Manual						Auto
Local Support	No						Yes

Camera Communication and Connection

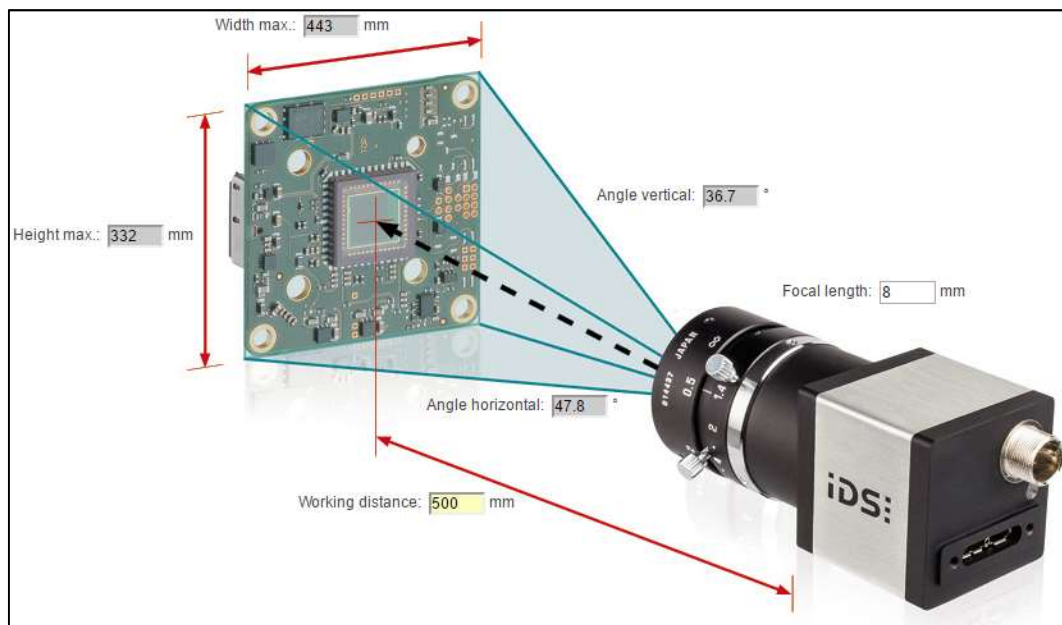
There are two main communication options for the chosen IDS camera and they are USB 3 (5 gigabits per second) and GigE (1 gigabit per second Power Over Ethernet) (IDS Imaging Development Systems GmbH, 2016b). It is obvious that USB 3 is the faster connection but for our application we only wish to sample one image per second at the

highest rate. Additionally, USB 3 is only able to transmit up to 3 meters where GigE can transmit as far as 90 meters with the additional ability to be routed over an Ethernet based network up to infinite distances (IDS Imaging Development Systems GmbH, 2016b). For these reasons we will select and purchase a GigE capable camera.

### Camera Lens Selection

Since the IDS UI-5250CP-C-HQ camera has been chosen we will use IDS lens selection tool (IDS Imaging Development Systems GmbH, 2016a). This tool considers the desired focal attributes where a working distance of 500mm and image size of 332mm x 443mm were entered (Selection tool measurements shown in Figure 33). To understand the effect of moving the cameras working distance to our fully out position of 650mm we can see the cameras resultant image size in Figure 34.

This selection tool recommended several options but the chosen option was selected since its focal settings were lockable, and will offer the least image distortion which we would experience with lens with a shorter focal length. The chosen Lens is the Goyo 2/3” 3MP, 8mm, f/1.4-16, 2/3”, MOD (m): 0.1m, Manual C-Mount.



**Figure 33: Lens selection tool showing Minimum Distance (IDS Imaging Development Systems GmbH, 2016a)**

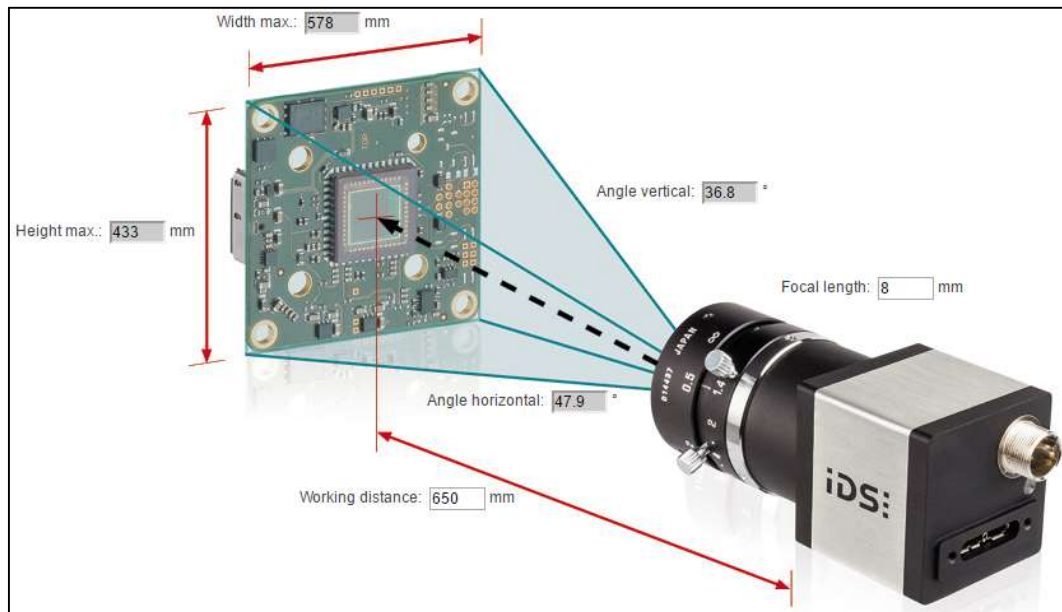


Figure 34: Lens selection tool showing Maximum Distance (IDS Imaging Development Systems GmbH, 2016a)

#### 4.4.3 Lighting

An important element of this machine vision system is the lighting and the control of the varying ambient lighting. The camera enclosure developed in 4.4 will help minimise the effects of varying light by fully enclosing the image area of interest with a black enclosure. This enclosure blocks the majority of the ambient light from entering the enclosure by using a barrier approach. This allows a lighting source to be enclosed inside the camera enclosure which will be able to be used to produce repeatable results with minimised effect from the surrounding ambient lighting (Day/Night light variations, High Pressure Sodium Lighting).

The chosen light source has been selected based upon the considerations listed in section 2.3.2. The desired characteristics for our light source will be;

- Have a dust ingress protection rating of at least IP5X, (Water ingress protection will not need to be considered due to installation location and conditions),
- Have a LED colour between 3000k and 5000k (4000k Optimum),
- Be long enough to light the image area (longer than 800mm)
- Supplied from 240VAC as this is the available power supply,
- Cost less than \$500

Now the enclosure has been constructed we need to match the camera to the proposed light source to the raw materials which need to be identified. Figure 35 shows the IDS camera's sensor sensitivity. This camera appropriately covers the visible colour wavelength range we are interested in (400-650nm).



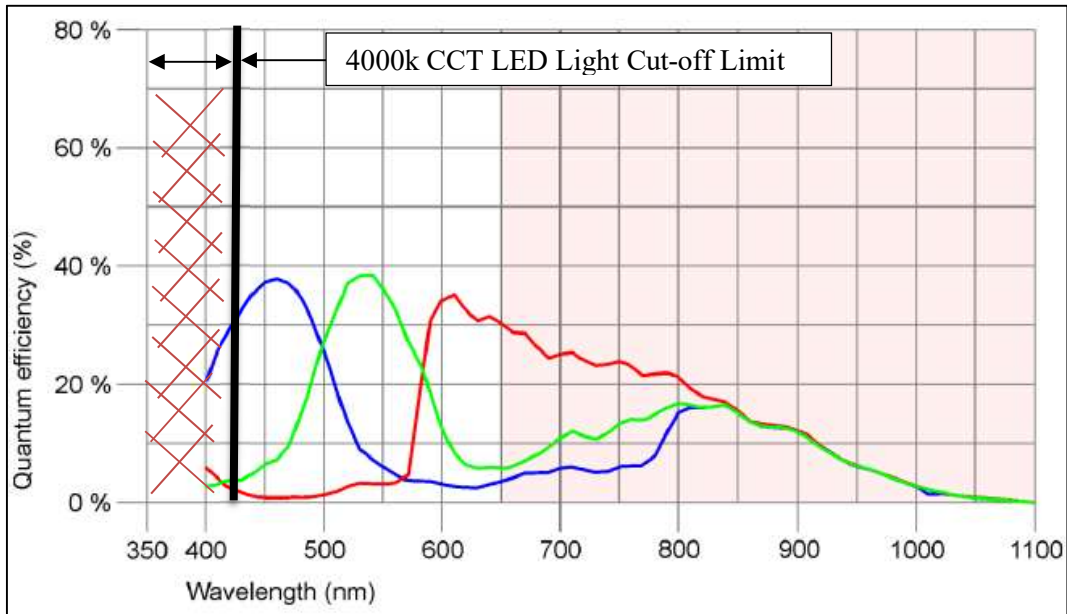


Figure 35: IDS CMOS Sensor Colour Performance obtained from (IDS Imaging Development Systems GmbH, 2016b)

The chosen light which meets the above criteria and can be delivered in the desired time frame will be two Alphilux ALXLEDWP224, 48Watt Weatherproof LED Batten. The LED array which is installed in the light fitting has been designed to deliver 4000 K Correlated Colour Temperature (CCT). The spectrum for this LED has been shown in Figure 36 by the green line. This shows us that this LED light will emit the majority of the camera’s wavelength sensitivity except left of the black line (425nm which is approaching the Violet Light Range (Nakamura, 2006)) shown in Figure 35. This is not ideal but budget constraints will not cover Xenon Discharge Lamps which are the ideal solution as explained in section 2.3.2.

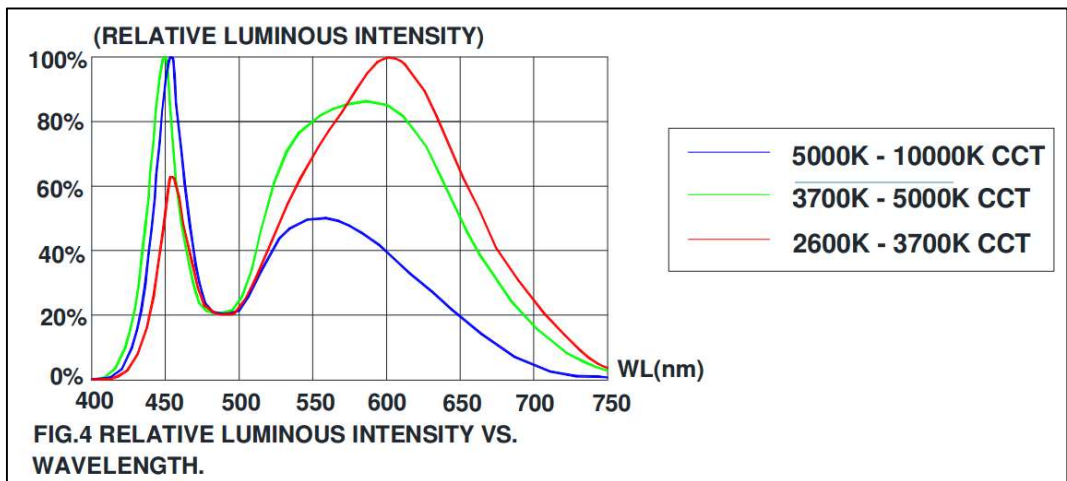


Figure 36: CREE LED Relative Luminous Intensity VS Wavelength obtained from (CREE Inc., 2014)

The Alphilux LED weatherproof batten will be installed inside the Camera enclosure will be parallel to the tilt pan conveyor installed at an angle greater than 45-degrees but less than 90-degrees (as shown in Figure 13) to the conveyor to allow the lighting source to be angled in a way which will provide bright field illumination as discussed in section 2.3.2



#### 4.4.4 Camera Communication Interface Development and Control

As mentioned in subsection 4.4.2 the camera communication and connection method will use Ethernet connectivity. Also power over Ethernet will be used to supply the camera with the required power. With this in mind the Camera requires dotnet commands to initialise, control and take images. Sample application code from (IDS Imaging Development Systems GmbH, 2016c) was modified to add new features listed below;

- Initialise the Camera with predetermined settings,
- Sequentially catalogue all images taken with a unique file name,
- Save the image in a predefined location,

As this software was developed using sponsor equipment source code will not be shared as explanation in section 1.9 Intellectual Property Disclaimer To satisfy the academic requirements screen shots will be provided and explained.

Figure 37 below shows the developed applications workspace when you first open the application. The explanation of each item which has been modified from the original source code has been detailed below;

- 1) The text box is the place where the desired image name goes which will have the photo number automatically added after the image has been taken.
- 2) Item two in this figure establishes a connection with the camera and will send all camera settings to the camera (from a Configuration File stored on the PC) to ensure all images are taken with the same settings. As well this button places the camera into live video mode on start-up.
- 3) Does the same as item 2 but will leave the camera in still mode (takes and image and will not take another image until it is pressed again.

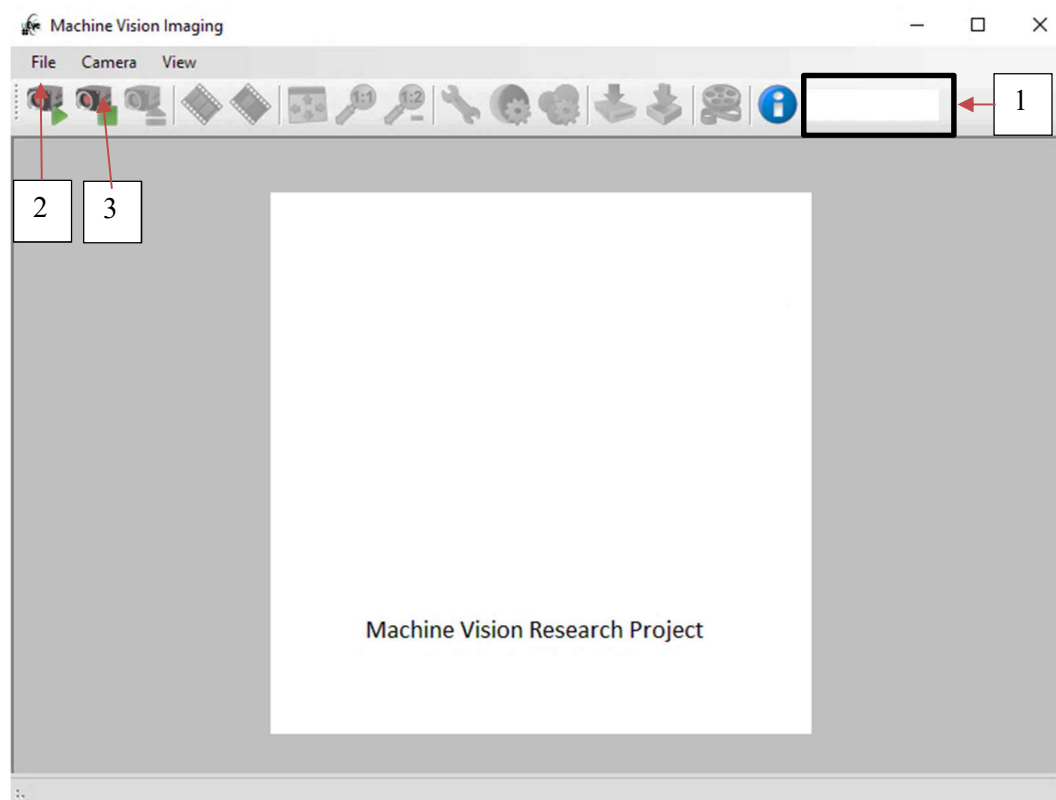


Figure 37: Image of Machine Vision Imaging Application Workspace

## 4.5 Image Acquisition

The process which was used to take the required training and verification imaged has been pictorially represented in Figure 38. Also this process has been explained in detail in the steps listed below which line up with each number in Figure 38. A total of 125 images were taken of each sample and a total of 625 images were taken for each material. A total image set of 1875 images were taken of all three materials.



**Figure 38: Image Acquisition Process Sequence**

### Step 1: Load the Samples

The five increments which make up each sample were loaded onto the test bed. Care was taken when lifting the samples onto the test bed as they all weigh up to 12.5kg.

### Step 2: Prepare and Rotate the Sample

Each sample was then evenly spread out on the test bed similar to the way it would be loaded on the conveyor. Between each pass the sample was completely turned over to ensure a unique image would be created.

### Steps 3, 4 & 5: Position Test Bed, Take the Image and Save

The test bed was position under the camera where at least 10 images were taken with the test bed moved in 100mm between images. Then the test bed was pulled out and step 2 to 5 were repeated until at least 125 images of each material were taken. Images 3 is a picture of the enclosure and Image 4 is the cameras photo and 5 is an image of the developed program capturing and saving the image.

### Steps 6 & 7: Size the Entire Sample

Once the required number of images were taken the sample was passed through a set of mechanical shaker sieves (sizes 12.5mm, 19mm, 26.5mm, 38mm). Image 6 shows the mechanical sieves being loaded before the sample was sorted. This sieving was conducted as the future work for this project will use a watershed transform to conduct online limestone and clinker sizing.

### Step 8: Weigh the Sample

The sieved sample (shown in image 7) was then weighed (Shown in image 8) and recorded to understand the distribution of the raw material particle size and to ensure no material was lost during the process.

## 4.6 Image Pre-processing

All images taken were initially passed through a median filter function which took each pixel and looked up each neighbouring pixels value and returned the median value in that set. This filter minimised the effect from over saturated pixels due to raw material high surface moisture lighting reflections. This median filter function has been explained in more detail in section 2.4.

## 4.7 Image Feature Extraction

For the Raw Material classification to work several unique features for each Raw Material must be extracted from the pre-processed images. There are countless features which can be extracted from these images using, pattern, colour or, shape. During the literature review documented in subsection 2.5 discussed the most successful methods of identifying limestone using colour and shape features. For this reason, we will implement colour features for the static model development and will implement advanced shape features in the future work on the Dynamic Model development.

The static model will be developed using MATLAB code for ease of development and resources. For the future model development, it is intended to modify the C Sharp and DotNet programming mentioned in subsection 4.4.4. Figure 39 below shows an overview of this process for colour feature extraction and the advanced shape feature extraction which was progressed up to the dashed box showing further work.

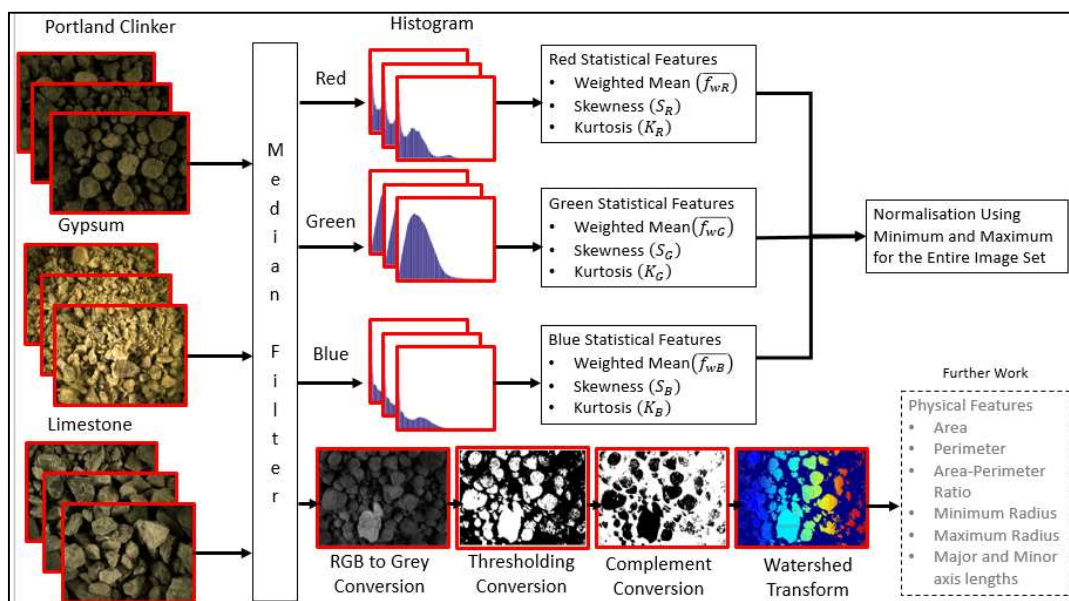


Figure 39: Image Feature Extraction

### 4.7.1 Colour Features (Static Model Development)

The colour features have been extracted using the MATLAB image histogram function and then statistical features were extracted for each colour element. This has been explained in detail in the subsections which follow. A full listing of the MATLAB code has been provided in Appendix D – Colour Feature Extraction Code.

#### Histogram

The first step to extract the colour features is to take the pre-processed image and use the MATLAB image load function. This image is then broken into the individual red, green and blue arrays then passed through to the MATLAB image histogram function. The IDS camera used is a 24-bit camera, this means that for each colour component red, green and blue there is an 8-bit resolution of colour intensity. This means we have  $2^8 = 256$  available intensity levels for each colour. This histogram function bins the number of individual pixel intensities. So the histogram function counts how many pixels have intensity 0 and stores this number in the first position in the resultant array. Then the histogram function it does the same for pixel intensity 1 and goes on until the final intensity level has been processed.

#### Weighted Mean

The weighted mean function uses equation (4-8) below. This measure of weighted mean informs us where the majority of our pixel intensity points lie. A high weighted mean will indicate that the distribution of pixel intensities is more towards the higher intensity levels. The lower the weighted mean number is the more the pixel's distribution is towards the lower intensity level.

$$\bar{f}_w = \frac{\sum_{f=0}^{L-1} f \times H(f)}{\sum_{f=0}^{L-1} f} \quad (4-8)$$

Where  $\bar{f}_w$  is the weighted mean [weighted mean number of pixels' intensity count],  
 $L$  is the number pixel intensities [0 to 255],  
 $f$  is individual intensity level also [0 to 255]  
 $H(f)$  is the array of resultant number of pixels in each intensity class

#### Skewness

Skewness is a measure of how much the general population is to one side and the direction the tail leans to. The larger the number the longer and flatter the skew's tail is. A negative number means the skew's tail travel towards zero and a positive skew will trail off towards positive infinity (shown in Figure 40). Theory summarised from (James, 2010).

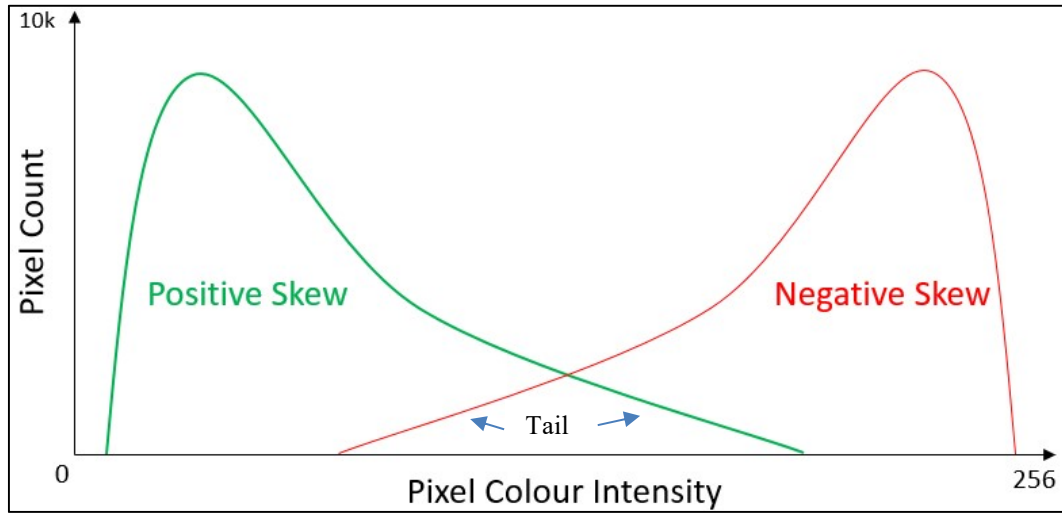


Figure 40: Skewness Explained using theory from (James, 2010)

In order to calculate the skewness, we first need to calculate the mean and variance which has been listed below in equation (4-10 and 4-11) obtained from (Chatterjee & Bhattacharjee, 2011).

$$\bar{f} = \frac{\sum_{f=0}^{L-1} f \times H(f)}{p \times q} \quad (4-9)$$

Where  $\bar{f}$  is the mean [number of pixels]  
 $p$  is the number of pixels in each row  
 $f$  is individual intensity level also [0 to 255]  
 $q$  is the number of pixels in each column  
 $H(f)$  is the array of resultant number of pixels in each intensity class

$$v = \frac{\sum_{f=0}^{L-1} (f - \bar{f})^2 \times H(f)}{p \times q} \quad (4-10)$$

Where  $v$  is the distributions variance in [number of pixels]  
 $f$  is individual intensity level also [0 to 255]  
 $\bar{f}$  is the mean [in pixels]  
 $p$  is the number of pixels in each row  
 $q$  is the number of pixels in each column  
 $H(f)$  is the array of resultant number of pixels in each intensity class

Finally, the skewness can be found using equation (4-11) obtained from (Chatterjee & Bhattacharjee, 2011).

$$S = \frac{\frac{1}{p \times q} (\sum_{f=0}^{L-1} (f - \bar{f})^3 \times H(f))}{(\sqrt{v})^3} \quad (4-11)$$

### Kurtosis

Kurtosis is the measure of how high the peak of the distribution is. The higher the kurtosis number is the higher the peak will be (James, 2010) as shown in Figure 41.

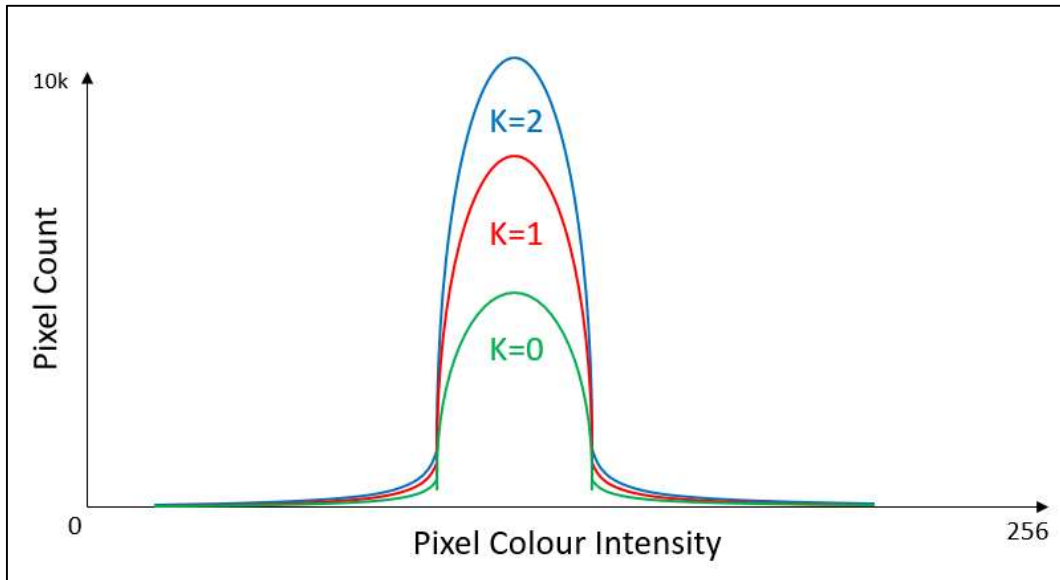


Figure 41: Kurtosis Explained using theory from (James, 2010)

To calculate the kurtosis, we will use equation (4-12) shown below obtained from (Chatterjee & Bhattacharjee, 2011).

$$k = \frac{\frac{1}{p \times q} (\sum_{f=0}^{L-1} (f - \bar{f})^4 \times H(f))}{(\sqrt{v})^4} \quad (4-12)$$

Where  $v$  is the distributions variance in [number of pixels]  
 $f$  is individual intensity level also [0 to 255]  
 $\bar{f}$  is the mean [in pixels]  
 $p$  is the number of pixels in each row  
 $q$  is the number of pixels in each column  
 $H(f)$  is the array of resultant number of pixels in each intensity class

#### 4.7.2 Advanced Shape Feature Extraction (Dynamic Model Development)

During the initial phases of the project time was available whilst waiting for part to arrive the advanced shape image feature extraction work had begun. This work is needed for the future Dynamic Model to provide online raw material analysis using shape and size analysis. This work was progressed to point where the Watershed Transform image array was generated. The philosophy used to generate this code came from (Wang & Li, 2015), (Mkwelo, 2004), (Andersson, et al., 2012) and was developed using programming techniques outlined in (Davies, 2012).

Figure 42 below shows an overview of each step which was used to obtain the final Watershed Transform. All code was modified using MATLAB standard programming examples which have all been referenced in the code (listed in Appendix J). These feature extraction methods have been explained in the subsections which follow.



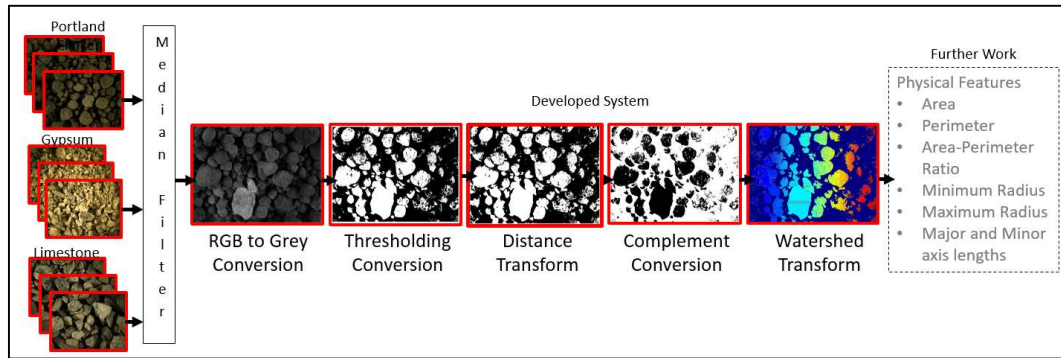


Figure 42: Advanced Shape Feature Development Overview

Red, Green and Blue to Grey Conversion

The red, green and blue to grey conversion uses the removal of the images Saturation and Hue by using equation (4-13) obtained from (Davies, 2012). This equation takes the three colour components and multiplies them against an associated weighting. This procedure is repeated until every pixel of an image is processed.

$$Grey\ Luminance = 0.2989 \times Red + 0.587 \times Green + 0.114 \times Blue \tag{4-13}$$

Where *Red* is the intensity of the Red pixel [0-255]

*Green* is the intensity of the Green pixel [0-255]

*Blue* is the intensity of the Blue pixel [0-255]

Thresholding Conversion

Image thresholding as explained in (Davies, 2012) is the process of selecting an intensity level between 0 and 255. This will then pass through the grey image pixel by pixel and all values greater than the chosen threshold will be saved as 255 and all other values will be returned as 0.

Distance Transform

The distance transform as explained in (Davies, 2012) will make any value greater than 0 which is next to a zero 1. The number goes up the further a pixel is away from zero

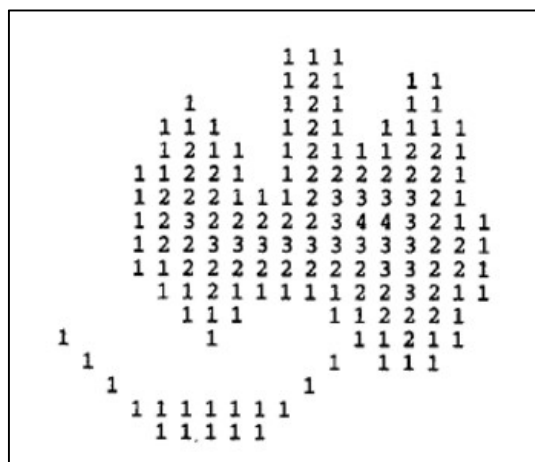


Figure 43: Distance Transform obtained from (Davies, 2012).

### Complement Conversion

The creation of the complement image is the process of taking the distance transform and multiplies it by minus one. Then this image is overlaid by the threshold image where any value equals zero the distance transform image equivalent pixel is replaced with minus infinity (Davies, 2012).

### Watershed Transform

Finally, the complement converted image is fed to the MATLAB watershed algorithm and this treats the image as a topographical map where each pixel's grey intensity represents the height of the individual pixel. The lowest point of the image is effectively flooded one intensity level at a time. Points, where the water was to spill into a valley, are marked as an edge/dam wall. This dam wall pixel is set to positive infinity. This will then continue to flood the image to the next spill point where this is also marked as a dam wall. This process continues until the image is fully flooded the maximum field intensity. All the dam walls are declared the watershed image lines (Mkwelo, 2004). The 3D plot of the image shown in Figure 42 has been plotted below in Figure 44

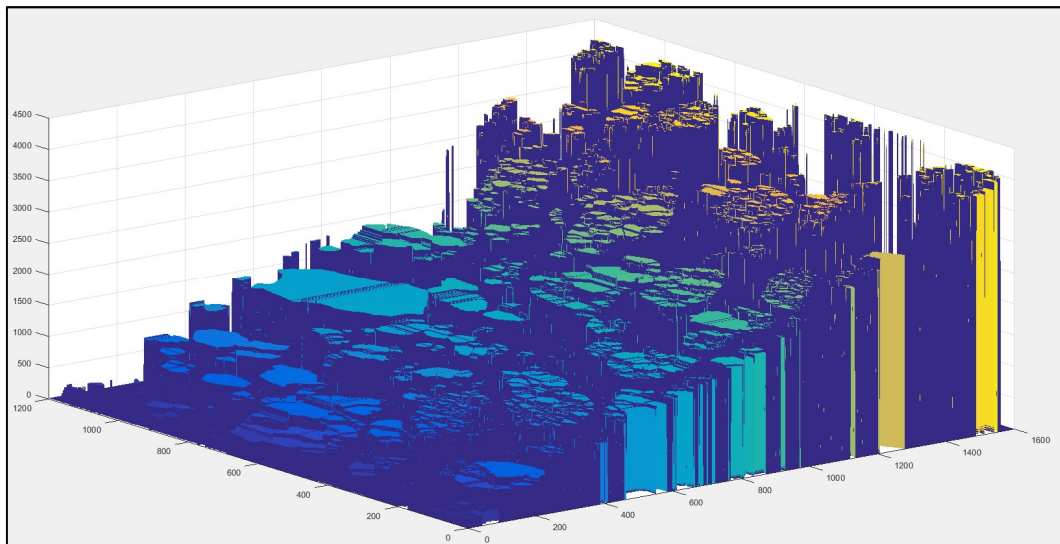


Figure 44: 3D Plot of Watershed shown in Figure 42

## 4.8 Probabilistic Neural Network Model Training

There are many different types of classification models we could have chosen to implement but the most successful algorithm for classifying limestone from the literature review (review in section 2.6) was the Probabilistic Neural Network (PNN). As work classifying clinker, gypsum and, limestone has not been found in the literature this work proposes to contribute to the literature by classifying these cement manufacturing raw materials. The way this Algorithm will be implemented will be using MATLAB to test and build the static model. The proposed future work will implement this tested and optimised classification system will be using C Sharp programming. The static systems probabilistic neural network MATLAB function can be seen in Appendix E – Probabilistic Neural Network .



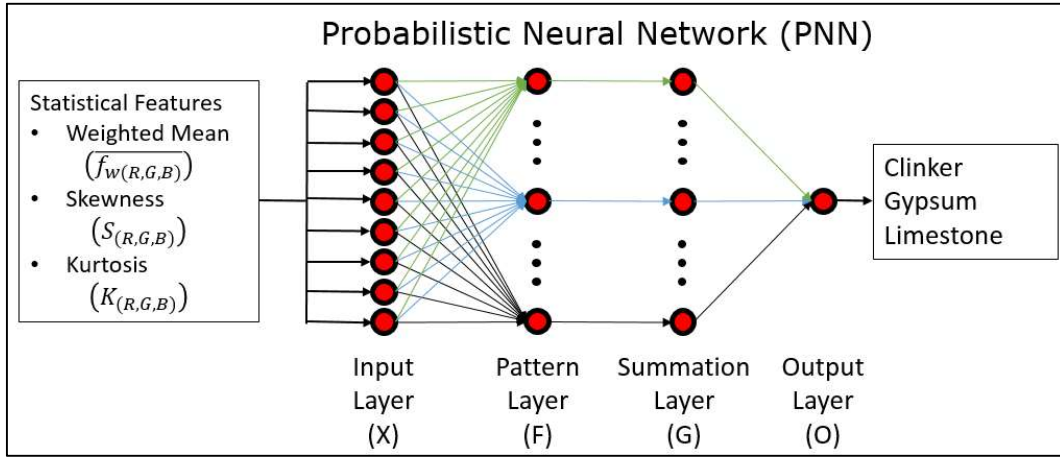


Figure 45: Probabilistic Neural Network Overview

This algorithm consists of four layers which will be explained how they were implemented in the subsections which follow.

### Input Layer

Firstly, the features obtained using the equation from the feature extractions in subsection 4.7.1 have been placed into an array  $X$ . This array has been shown in equation (4-14) which was obtained from (Yeh & lin, 2011).

$$X = (\overline{f_{wR}}, S_R, K_R, \overline{f_{wG}}, S_G, K_G, \overline{f_{wB}}, S_B, K_B) \quad (4-14)$$

Where  $f_{wR}$  is Red Weighted Mean obtained from equation (4-8)  
 $S_R$  is Red Skewness for obtained from equation (4-11)  
 $K_R$  is Red Kurtosis for obtained from equation (4-12)  
 $G$  is for Green  
 $B$  is for Blue

### Pattern Layer

The next layer is the pattern layer which will have an individual neuron for every single training pattern used for this algorithm. These training patterns consist of a desired number of input vectors where the vector is known. This vector can consist of two input image features up to an infinite amount. The important point to note will be the more training patterns you have the better the accuracy of the model but the longer it will take to process.

$$F_{(C,G,L)j} = \frac{1}{(2\pi\sigma^2)^{\frac{n}{2}}} \exp\left(-\left(\frac{\|X-X_{(C,G,L)j}\|^2}{2\sigma^2}\right)\right) \quad (4-15)$$

Where  $\sigma$  is the Gaussian Distribution Smoothness Parameter,  
 $n$  is the number of input features in our case  $n = 9$ ,  
 $X$  is the input Vector to be classified,  
 $X_{C,G,L}$  is the training Vector for each class of material,

### Summation Layer

The summation layer is the layer where all the probability values from each individual neuron in the pattern layer are added together to get the probability the input vector is to each raw material class. This has been achieved by the implementation of equation (4-16) obtained from (Yeh & lin, 2011).

$$\mathbf{G}_{(C,G,L)}(\mathbf{X}) = \sum_{j=1}^{N_{class}} F_{cj}(\mathbf{X}), \text{ class}(C, G, L) \quad (4-16)$$

Where  $C$  is Clinker  
 $G$  is Gypsum  
 $L$  is Limestone  
 $j$  is the index number used to cycle through the array  
 $F_{cj}$  Value from is the  $j$ th of clinker class pattern neuron

### Output Layer

The output layer is purely a comparison of whom has the highest summation layer probability. The highest value wins, this has been mathematically shown in equation (4-17) which has been obtained from (Yeh & lin, 2011).

$$\mathbf{O}(\mathbf{X}) = \text{argmax}(\mathbf{G}_{(C, G, L)}) \quad (4-17)$$

### Total System Simplification

Now that the mathematical expressions for this model have been shared in equations (4-14 to 4-17) we will be able to simplify all layers into one equation for ease of implementation but not ease of understanding.

Simplification of (4-15) can be achieved as there is a large constant on the front of this equation. This constant can be removed to prevent unnecessary CPU operations. Equation (4-18) has been obtained from (Yeh & lin, 2011) and modified to suit the simplifications from (Chatterjee & Bhattacharjee, 2011).

$$h = \frac{1}{(2\pi\sigma^2)^{\frac{n}{2}}} \times \frac{1}{N_A} \quad (4-18)$$

where  $\sigma$  is the Gaussian Distribution Smoothness Parameter,  
 $n$  is the number of input features in our case  $n = 9$ ,  
 $N_A$  is the number of training vectors per class

The next simplification will be the combination of equations (4-15 and 4-16) to form equation (4-19) This has also been obtained from (Yeh & lin, 2011) and modified to suit the simplifications from (Chatterjee & Bhattacharjee, 2011).

$$\mathbf{G}_{(C,G,L)}(\mathbf{X}) = h \sum_{j=1}^{N_{class}} \exp\left(-\frac{\|\mathbf{X}-\mathbf{X}_{(C,G,L)j}\|^2}{2\sigma^2}\right) \quad (4-19)$$

where  $\sigma$  is the Gaussian Distribution Smoothness Parameter,  
 $n$  is the number of input features in our case  $n = 9$ ,  
 $N_A$  is the number of training vectors per class  
 $C$  is Clinker  
 $G$  is Gypsum  
 $L$  is Limestone  
 $j$  is the index number used to cycle through the array

### Euclidean Distance Function

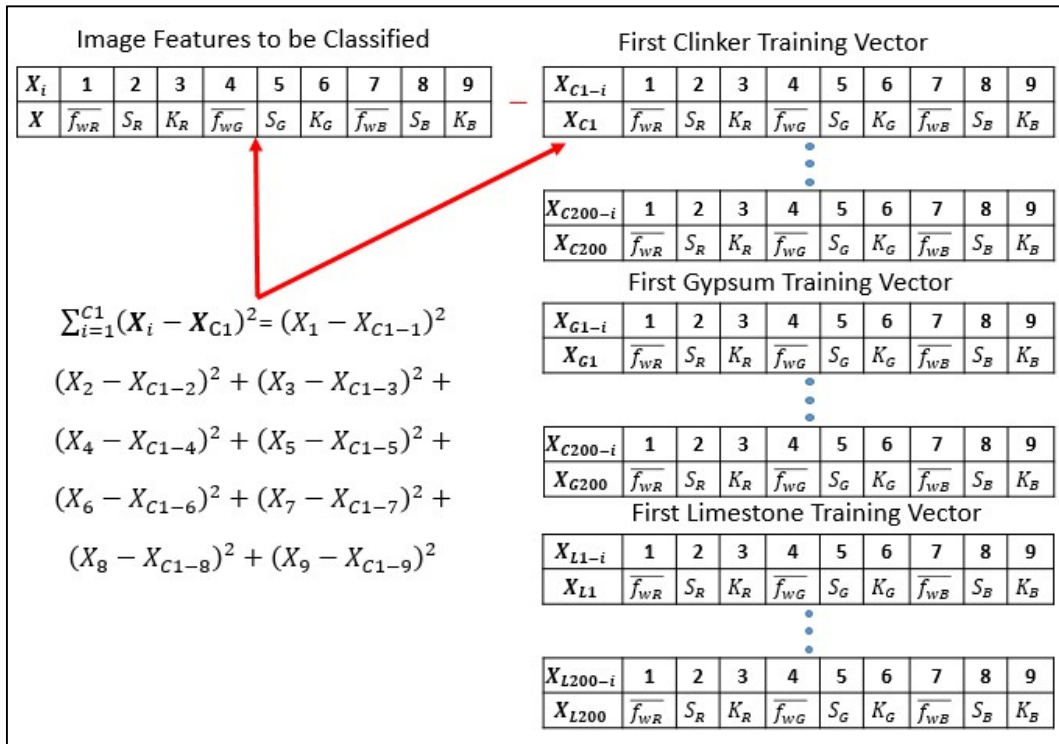
In equation (4-19) there is a Euclidean Distance function which could easily be implemented using a Matlab Function but since this would not be ideal for a final solution a version of this was developed using the work done by (Yeh & lin, 2011). This equation has been expanded in equation 4-20 below.

$$\|X - X_{C,G,L}\|^2 = \sum_{i=1}^n (X_i - X_{C_i,G_i,L_i})^2 \tag{4-20}$$

Where  $\sigma$  is the Gaussian Distribution Smoothness Parameter,  
 $n$  is the number of input features in our case  $n = 9$ ,  
 $X_i$  is the input Vector to be classified Feature  $i$  of  $n$   
 $X_{C_i,G_i,L_i}$  is the training Vector for each class of material,

Figure 46 below attempts to show that equation and (4-20) will subtract the distance between every image feature from the classification image from the training image and square them (to return a positive value). Then this process will be indexed to the second element of both vectors and subtract and square them as well. All individual elements are processed the same until the entire vector has been processed and then their result is added together.

This process is repeated until all training images in the class have been added together and this returns the desired class summation. Each material class is processed the same way passed to equation (4-19) to generate the probability of the classification image to each material class. The final step is to use equation (4-17) to determine the overall maximum class value which determines the winning class.



$$\sum_{i=1}^{C1} (X_i - X_{C1-i})^2 = (X_1 - X_{C1-1})^2 + (X_2 - X_{C1-2})^2 + (X_3 - X_{C1-3})^2 + (X_4 - X_{C1-4})^2 + (X_5 - X_{C1-5})^2 + (X_6 - X_{C1-6})^2 + (X_7 - X_{C1-7})^2 + (X_8 - X_{C1-8})^2 + (X_9 - X_{C1-9})^2$$

Figure 46: Euclidean Distance Function Explained

## 4.9 Probabilistic Neural Network Model Verification Method

The model will be verified by the only possible method. The use of a matching matrix which has been shown in Table 11. This easily shows that the actual material which is known shown on the left hand side. The way in which the material was classified has been correlated to the Top of the table. From this table we can conclude that all clinker and gypsum were correctly classified. Limestone on the other had was miss classified eleven times. This means the classification for limestone is only 89% accurate. This would be an undesirable outcome and will have to be optimised.

**Table 11: Matching Matrix for Probabilistic Neural Network with 500 Training Images (Per Material) and 625 Images Used for Verification**

	Clinker	Gypsum	Limestone
Clinker	490	0	10
Gypsum	125	374	1
Limestone	51	249	200

## 5 Model Optimisation

### 5.1 Normalisation of Raw Data

During the initial probabilistic model testing it became apparent that the work conducted by (Patel & Chatterjee, 2016) had not considered the need to implement data normalisation of the raw feature data obtained from the raw material images. Figure 47 shows AVOVA statistical analysis of all three raw materials, red image feature components (weighted mean, skewness and, kurtosis). From this figure it becomes apparent that the weighted mean features are outweighing all other feature components. The weighted means data range varies from 3655 to 2410, the same range spread for skewness is 4.22 to 0.6852 and finally the kurtosis range spread is 1.4512 to 0.8508. This is visually easy to see when the ANOVA box and whisker plot with all variables on the same plot y axis, the skewness and kurtosis features are flat and very close to zero. This overweighted, weighted mean data causes the model to be model overweighted giving only consideration to the weighted mean data. The same can be seen for all other colour features.

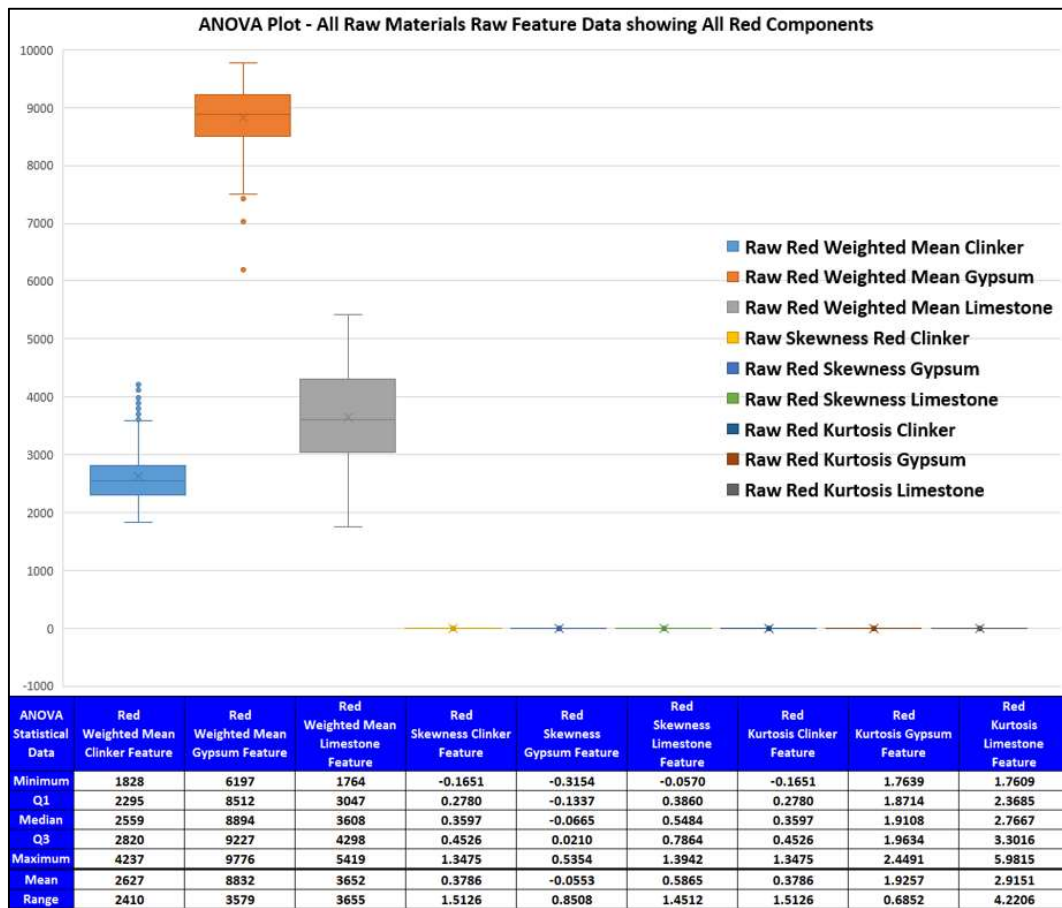


Figure 47: ANOVA Statistical Analysis of All Raw Materials, Raw Feature Data showing All Red Components

This model overweighting has been addressed by the implementation of raw data normalisation. To address this model overweighting the code in Appendix F – Feature Normalisation Code was developed using equation (5-1) below obtained from (Davies, 2012).

$$Normalised\ Data\ Value = \frac{Raw\ Data\ Value - Minimum}{Maximum - Minimum} \quad (5-1)$$

Where *Raw Data Value* is the raw data input to this normalisation equation;  
*Minimum* is the minimum value for that feature for all raw materials;  
*Maximum* is the maximum value for that feature for all raw materials;

## 5.2 Supervised Learning Probabilistic Neural Network

Table 12 listed below shows a Matching Matrix which was the output from the Probabilistic Neural Network which used 500 Training images per raw material and 1875 Verification Images (625 of each Material). The smoothing parameter was optimised using the method explained in subsection 5.2.2 which used the local search algorithm to obtain the optimum smoothing parameter of 0.3501. This Matching Matrix shows us that clinker had ten images incorrectly identified as limestone. gypsum had two incorrectly classified as limestone. Finally, limestone had 85 images incorrectly classified as clinker

**Table 12: Matching Matrix for Optimised Probabilistic Neural Network with 500 Training Images (Per Material) and 1875 Images Used for Verification.**

	Clinker	Gypsum	Limestone
Clinker	615	0	10
Gypsum	0	623	2
Limestone	85	0	540

This optimised Probabilistic Neural Network had a success rate of 94.83% accuracy where work by (Patel & Chatterjee, 2016) had a success rate of 95%. This success rate is comparable with the work mentioned but a focused literature review was conducted to find potential improvements to the Probabilistic Neural Network.

This focused literature review found work conducted by (Yeh & lin, 2011). They implemented a Supervised Learning Probabilistic Neural Network(SLPNN) model. Their model demonstrated a very high success rate of 98%. The Supervised Learning Probabilistic Neural Networks main point of difference was the addition of a data weight which changes the height of the Gaussian distribution and a variable which changes the input variable weight, which changes the Gaussian distributions width. For this reason, these new variables were implemented to allow better optimisation of the Probabilistic Neural Network. This MATLAB code has been provided in Appendix G and H and has been explained in detail in the subsections which follow.

### 5.2.1 Overview of implementation

The Supervised Learning Probabilistic Neural Network equation which will be used has been listed below in ( 5-2). This equation was obtained and modified from (Yeh & lin, 2011). This new equation is equation (4-15) with the distribution height modifier (Data Weight) and width modifier (input variable weight) added.

$$F_{(C,G,L)j} = H \frac{1}{(2\pi\sigma^2)^{\frac{n}{2}}} \exp\left(-\left(\frac{w^2\|X-X_{(C,G,L)j}\|^2}{2\sigma^2}\right)\right) \quad (5-2)$$

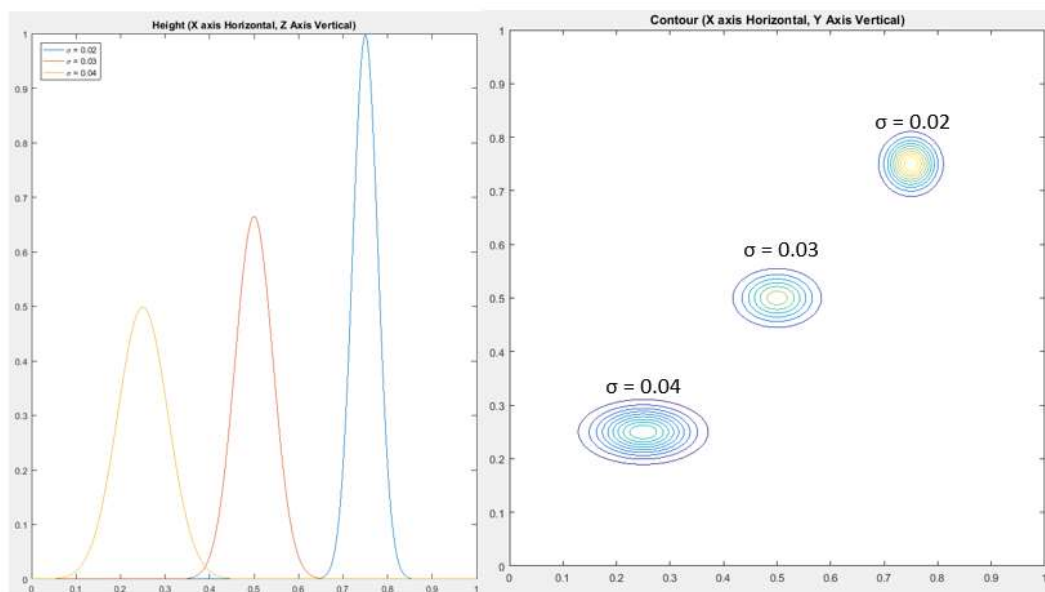
Where  $\sigma$  is the Gaussian Distribution Smoothness Parameter;  
 $n$  is the number of input features in our case  $n = 9$ ;  
 $X$  is the input Vector to be classified;  
 $X_{C,G,L}$  is the training Vector for each class of material;

$H$  is the Data Weight (Gaussian Distribution Height Modifier);  
 $W$  is the Input Variable Vector Weight (Gaussian Distribution Width Modifier).

Each of the Supervised Learning Variables have been explained in detail in subsections 5.2.2 to 5.2.4 below.

### 5.2.2 Smoothness

The smoothness parameter  $\sigma$  is a part of the original Probabilistic Neural Network. It proportionally changes both the height and width of the Gaussian Distribution curve. The way the smoothing parameter changes the Gaussian Distribution curve can be seen in Figure 48. Figure 1 With this figure it is important to note that it has unit less axis. These plots were created using equation (5-2) with the Kernel (centre of the distribution)  $X_{(C,G,L)}$  set to 0.25, 0.5 and 0.75 for both X and Y axis.

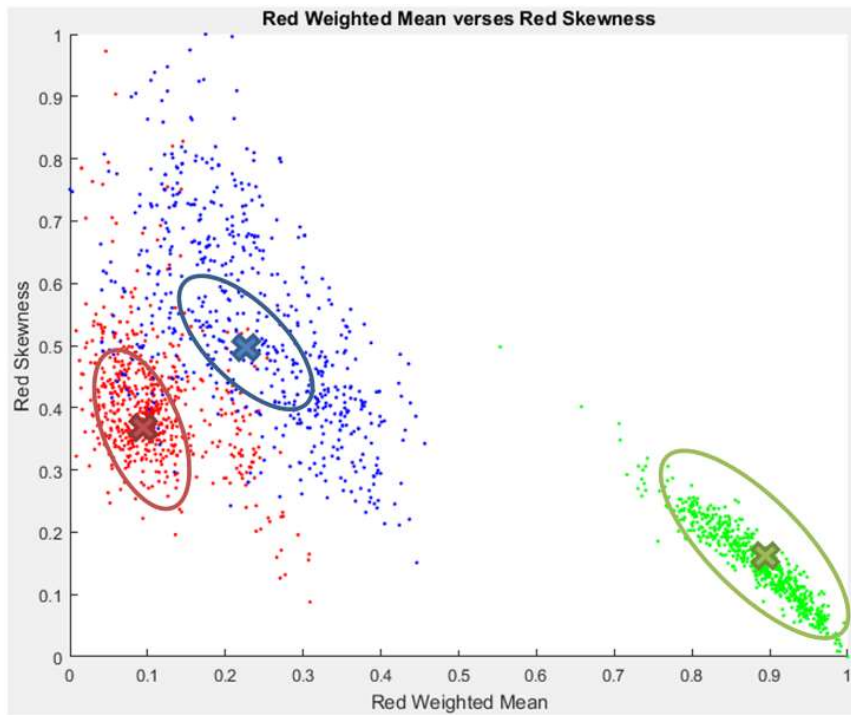


**Figure 48: Supervised Learning Probabilistic Neural Network Smoothing Parameter Effect of the Gaussian Distribution.**

### 5.2.3 Input Variable Vector Weight (Gaussian Distribution Width Modifier)

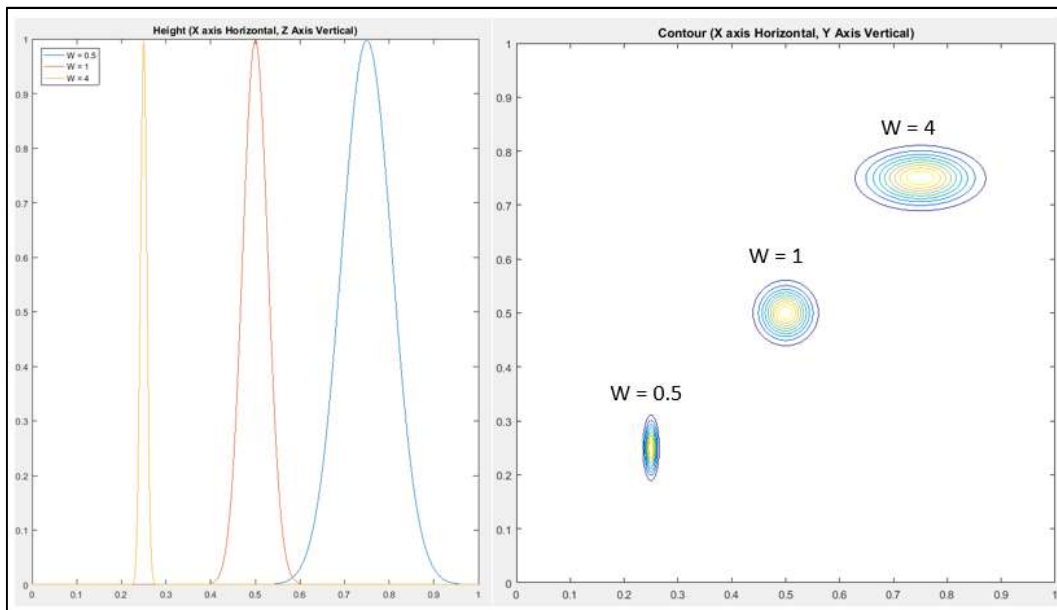
The input variable vector weight is a vector the same dimensions as the classification vector  $\mathbf{X}$ . It is made up of individual weights per feature. The importance of this and the data weight variables can be seen below in Figure 49. In This figure we can see that red scatter points represent clinker, blue represent limestone and green represent gypsum. From this scatter plot that clinker and limestone data is very similar. The median values for each of these datasets have been shown in figure by a coloured cross. The ability for the Gaussian Distribution shape parameters will lead to improved model optimisation.





**Figure 49: Example of Actual Data Distribution for Red Weighted Mean and Skewness**

Changing the weight of the individual input variable vectors weight will change the X Axis width without changing the Z axis height. This has been demonstrated in Figure 50 where the input variable vector weight has been changed from 0.5 to 4 without any change to the Z axis height.

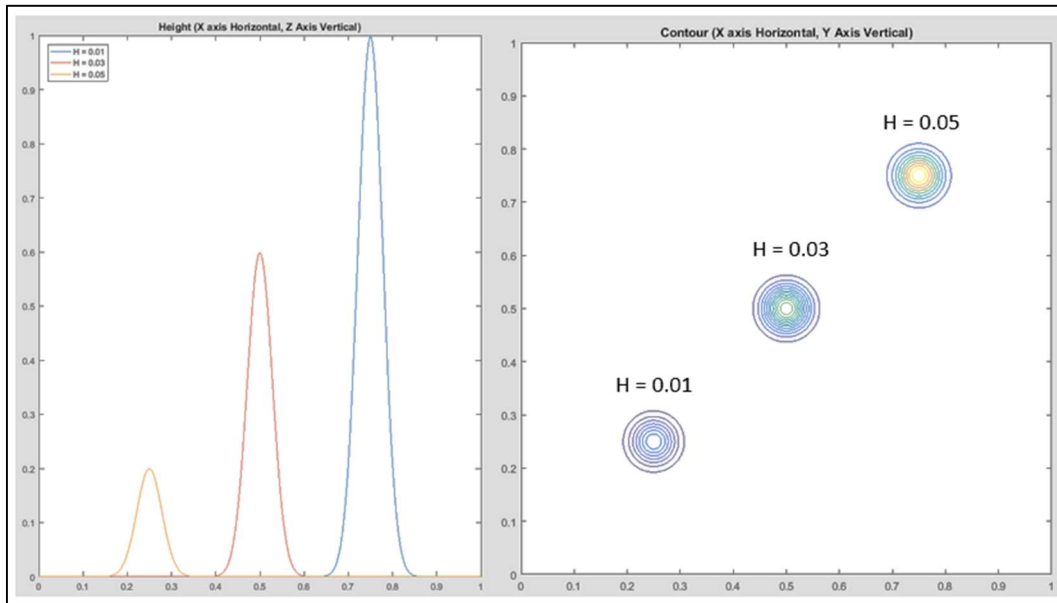


**Figure 50: Supervised Learning Probabilistic Neural Network Input Variable Vector (Gaussian Distribution Width Modifier)**

### 5.2.4 Data Weight (Gaussian Distribution Height Modifier)

The data weight modifier is a single variable which can change the Z Axis height of the Gaussian Distribution without changing the X axis width as the Smoothing parameter does. Figure 51 shows the adjustment of the Data Weight from 0.01 to 0.05 without any change in the X Axis width.





**Figure 51: Supervised Learning Probabilistic Neural Network Data Weight (Gaussian Distribution Height Modifier)**

### 5.2.5 Supervised Learning Probabilistic Neural Network Optimisation

There are two main ways the Supervised Learning Probabilistic Neural Network can be optimised. The first which was conducted by (Yeh & lin, 2011) where they approached the optimisation via an analytical method using steepest decent method. This method is the optimum method to optimise our model but due to the complex maths needed to implement this method and time available we will use this method.

The other method is a localised search algorithm where two of the three variables are fixed and the remaining one is changed with large steps as shown in Table 13. In this table Pass one represents the first large step pass to find the local error minimum. The recorded error minimum in this pass is when our variable is set to 5. The two values either side of this value are then placed as the outer variables and a smaller step is implemented. This pass the error minimum is at variable value 5.25. The same variable values either side of this value become the outer variable limits. The final pass finds that our optimum variable occurs at 5.21. This method was obtained from (Davies, 2012). The developed optimised probabilistic neural network MATLAB code has been provided in Appendix I – Supervised Learning Probabilistic Neural Network Optimisation Program.

**Table 13: Example of Localised Search for Error Minimum.**

Pass 1	Variable	1	2	3	4	5	6	7	8	9	10
	Error	10	8	6	4	2	3	6	8	12	16
Pass 2	Variable	4	4.25	4.50	4.75	5	5.25	5.50	5.75	6	6.25
	Error	4	3.5	3	2.5	2	1.75	2	2.5	3	3.2
Pass 3	Variable	5	5.07	5.14	5.21	5.25	5.32	5.39	5.46	5.53	5.5
	Error	2	1.8	1.6	1.4	1.75	1.77	1.78	1.8	1.98	2

## 6 Results and Analysis

### 6.1 Data Analysis

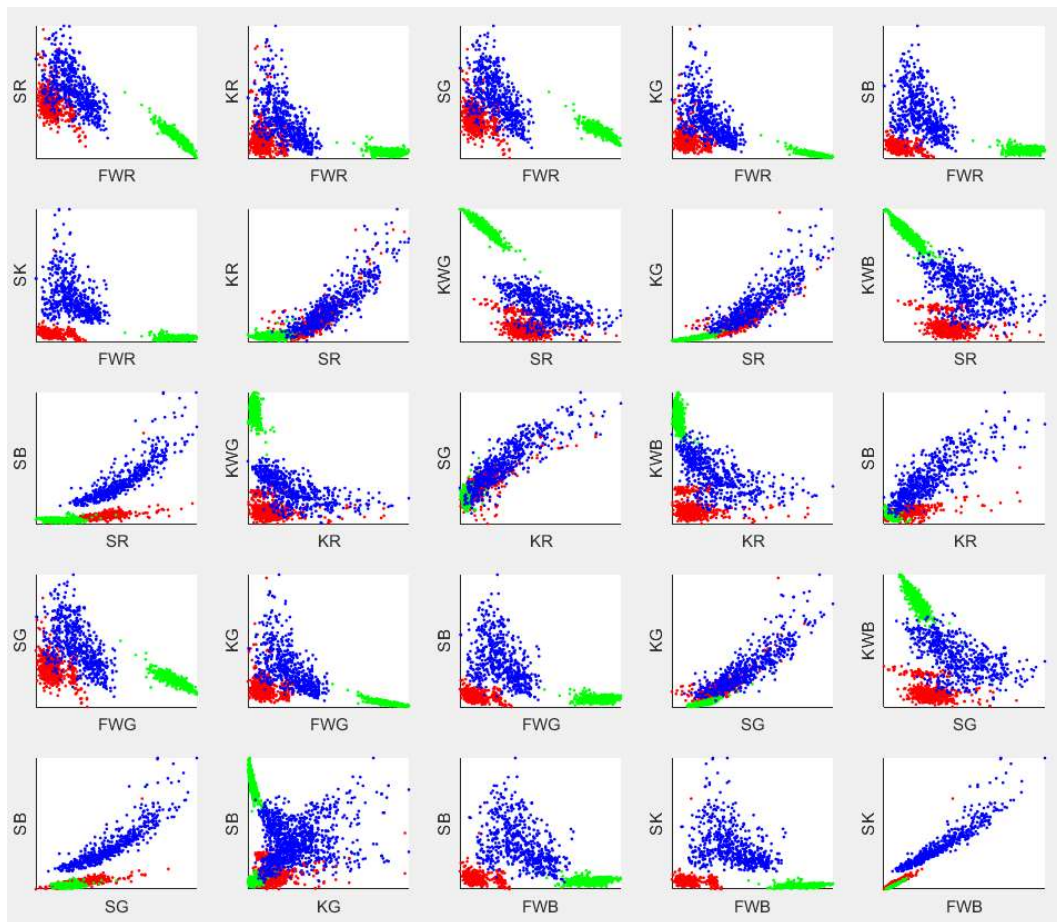
The analysis of the data provided in subsections 6.1.1 and 6.1.2 will provide an understanding of the distribution of the data obtained from the colour features detailed in subsection 4.7.1. This analysis of the available data will provide the justification for using a Probabilistic Neural Network and the optimised Supervised Learning Neural Network.

#### 6.1.1 Review Scatter Plots

Provided below in Figure 52 is a complete comparison of all colour features which were extracted from the image database. In nearly every scatter plot there is convergence between all data. This is not ideal but expected due to the chemical makeup of clinker (red), gypsum (green) and limestone (blue). Clinker and limestone both have very similar concentrations of Calcium Carbonate ( $\text{CaCO}_3$ ) (Hewlett, 2016) as explained in subsections 1.3.1 to 1.3.3. In some features even gypsum approaches clinker and limestone.

The median value for all raw material data sets features are satisfactorily far enough to allow feature classification to occur. The median value has not been shown in this figure as it would be far too difficult to notably see on a scatter plot. For this reason, ANOVA statistical box and whisker plots have been calculated and displayed in the following subsection 6.1.2. Below is a listing of what the abbreviations mean.

Red Points	Clinker
Green Points	Gypsum
Blue Points	Limestone
FWR	Weighted Mean Red
FWG	Weighted Mean Green
FWB	Weighted Mean Blue
SR	Skewness Red
SG	Skewness Green
SB	Skewness Blue
KR	Kurtosis Red
KG	Kurtosis Green
KB	Kurtosis Blue



**Figure 52: Scatter Plots of the Normalised Colour Features Compared with the Best Match Data**

### 6.1.2 Review Data Spread

The data spread analysis can be aided by reviewing Figure 53. This ANOVA box and whisker plot can be interpreted by looking at the red weighted clinker feature which can be identified by looking at the first purple box and whisker which lines up with its table of variables below. This shows us that the minimum value of 0.0080 is the bottom horizontal line. The maximum value is the upper horizontal line which is located at 0.3087. The upper side of the box is the first quartile data point and the lower is the third quartile value. The median value is represented by the middle line in the box and the mean value is represented by the cross. For this plot there are several plots above the maximum line and these plots represent data which is well and truly outside the expected statistical range. This would suggest future work to investigate the cause of these features not being inside the desired range. If reason behind these values were found and they were removed from the dataset we could optimised our model this way.

When comparing different raw materials with the same feature we can see that there is a large amount of overlap between raw materials (e.g. clinker and limestone weighted wean red). The important point to note is that all mean values for each raw material are not within the other raw materials first or third quartile ranges. Statistically this will allow our Supervised Learn Probabilistic Neural Network to be optimised to a point where its accuracy will be able to approach 100% accuracy if enough training images are provided. In Appendix L – Results Plots the green and blue ANOVA plots can be reviewed to come to the same conclusion as the Red ANOVA plot.

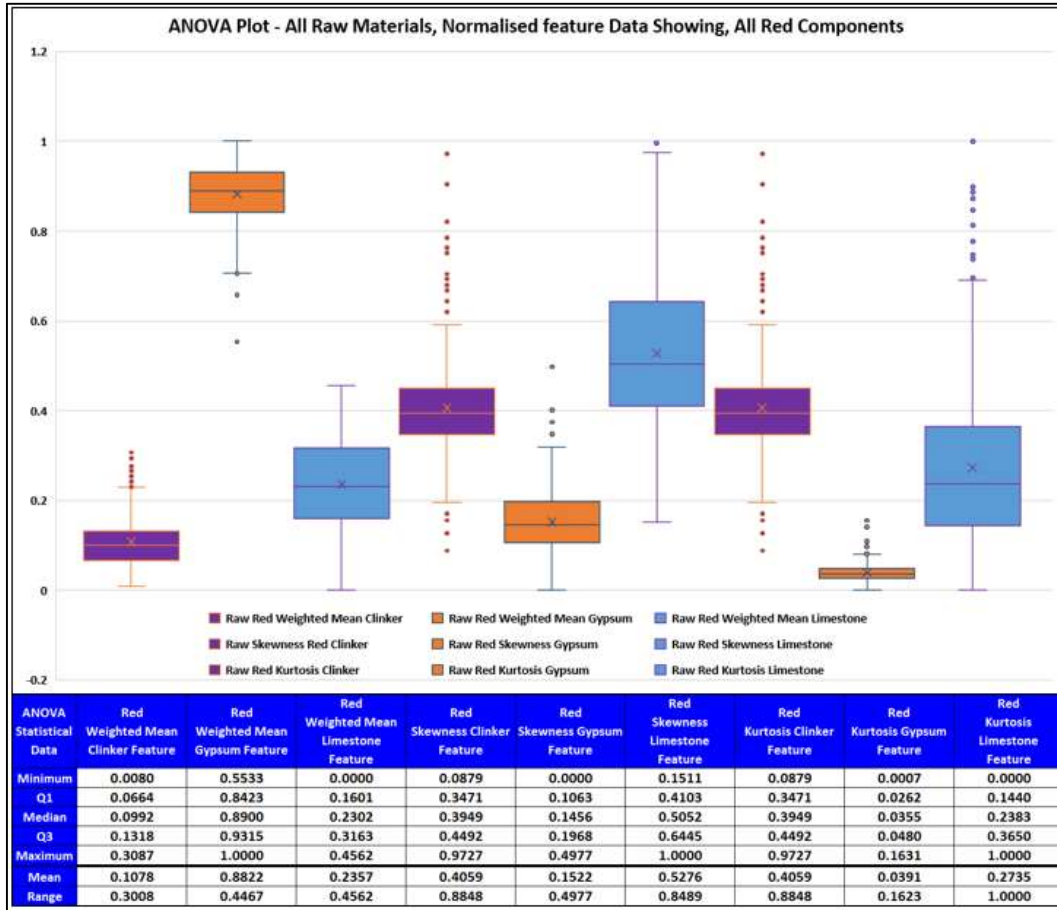


Figure 53: ANOVA Plot and Statistical Data for all Red Colour Features and Materials

## 6.2 Probabilistic Neural Network Optimisation Results

The optimisation of the Probabilistic Neural Networks (PNN) was conducted using the localised search algorithm (discussed in subsection 5.2.5). The results from this optimisation has been detailed in the sub sections which follow. This optimisation process started with the localised search to understand the effect of the number of training images used to train the PNN. Following this the Smoothing Parameter of the PNN was also optimised using the localised search algorithm.

### 6.2.1 Number of Images Used for Training Effect

The effect of the number of training images used to train the Probabilistic Neural Network model can be understood by reviewing Figure 54. As expected the models error decreases as the number of training images is increased. An important point to note is that there was only on set of images acquired for this project. All images are used for verification but varying number of these images are used to train the PNN model. A decrease in model’s performance would be expected on a fresh set of images but work by (Chatterjee, 2013) found their models performance on a fresh set of verification images only decreased their models performance by 2 to 3 %.

With this in mind we will only use 500 images for each raw material out of the available 625 images. This will help reduce the effect of model overfitting which can be seen from Figure 54. The mentioned model overfitting occurs after 600 images, the accuracy continues to rise until we approach 97% accuracy. So 500 images are used for model training should introduce enough error to ensure our model is not over fitted.

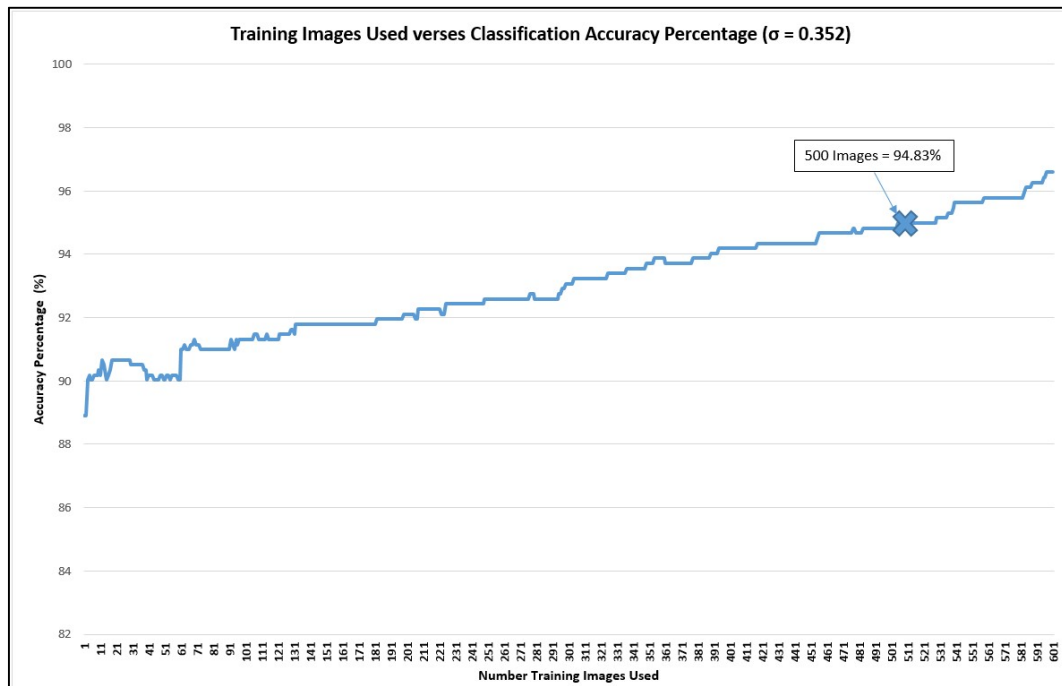


Figure 54: Effect of Varying the Number of Training Images

### 6.2.2 Optimised Smoothing Parameter

The optimisation of the smoothing parameter for our Probabilistic Neural Network also been optimised using the local search algorithm which has been shown in Appendix I – Supervised Learning Probabilistic Neural Network Optimisation Program. The result of this developed MATLAB program can be seen in Figure 55. A low resolution run was done from 0.001 to 10 and then we refined our search to 0.001 to 1.6 with 0.001 steps of the Smoothing Parameter ( $\sigma$ ). The optimum value of 0.352 will be used for all future optimisation of the Supervised Learning Probabilistic Neural Network Model. This optimisation of the smoothing parameter improved our model’s performance from 94.25% accuracy to 94.83%. This improvement may seem insignificant but with our validation image set this equates to 11 images which would have been incorrectly classified.

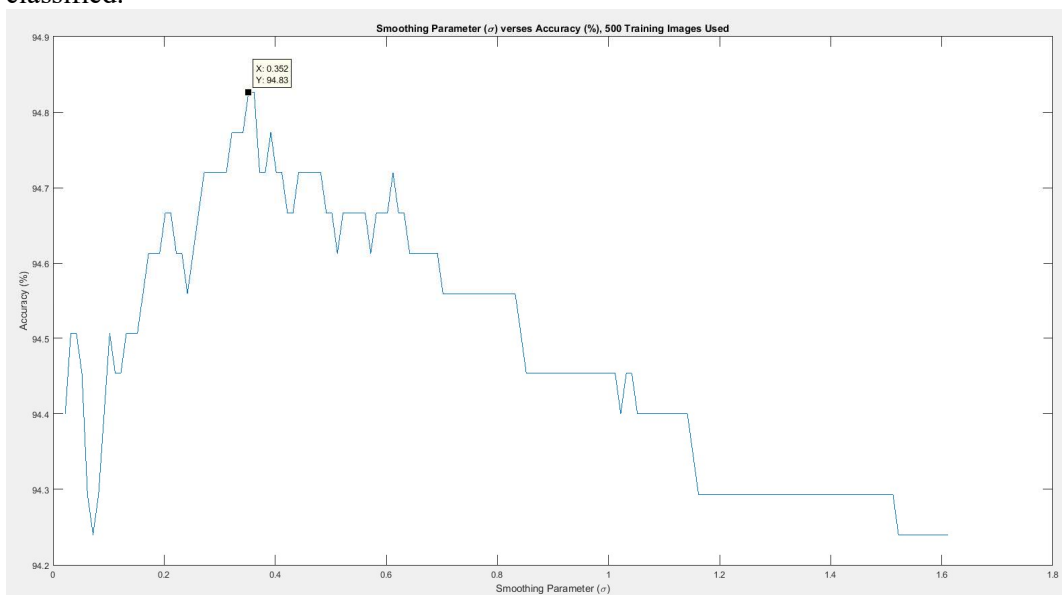


Figure 55: Optimisation of the Probabilistic Neural Networks Smoothing Parameter ( $\sigma$ )

## 6.3 Supervised Learning PNN Results

### 6.3.1 Data Weight (Gaussian Distribution Height Modifier)

The Supervised Learning Probabilistic Neural Network (SLPNN) data weight (Gaussian Distribution Height Modifier) optimisation did not yield any noticeable benefit (seen in Figure 56). A critical review of equation 5-2, the available data and literature revealed that this feature is used for individual training data features which do not contribute to the population in an appropriate manner. An example of this can be seen in Figure 57 where there are 7 data points (Shown above the maximum whisker limit) which do not sit in the acceptable expected data range. Further work could be used to implement an algorithm which decreases the weight for any value which does not sit within the expected data range. This would then be entered into an array which would be the same dimensions as the training image array. That is one height value for every image and every feature. In our case the Data Weight array would be  $H(1500,9)$  or 1500 rows and 9 columns.

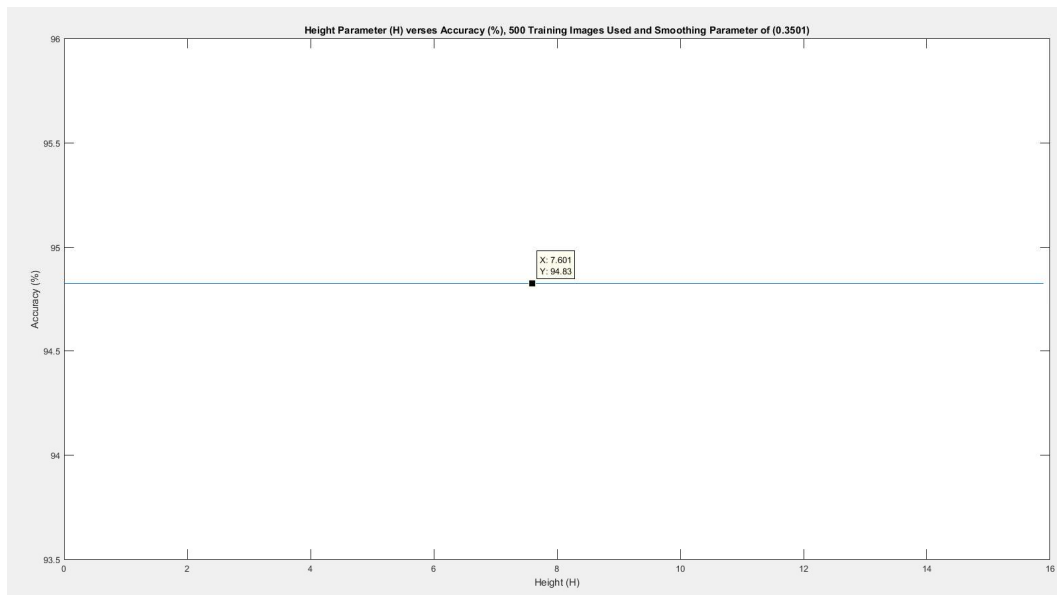


Figure 56: Supervised Learning Probabilistic Neural Network Data Weight Optimisation Results

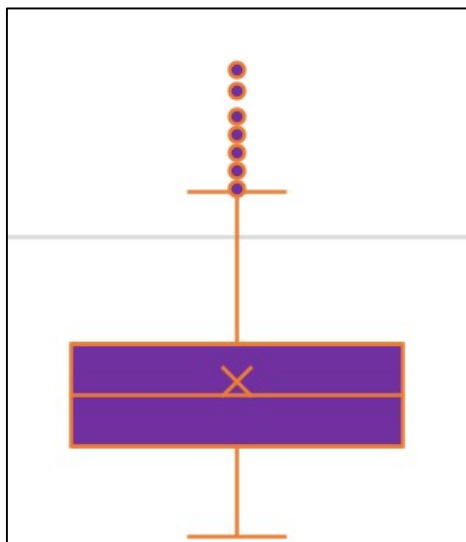


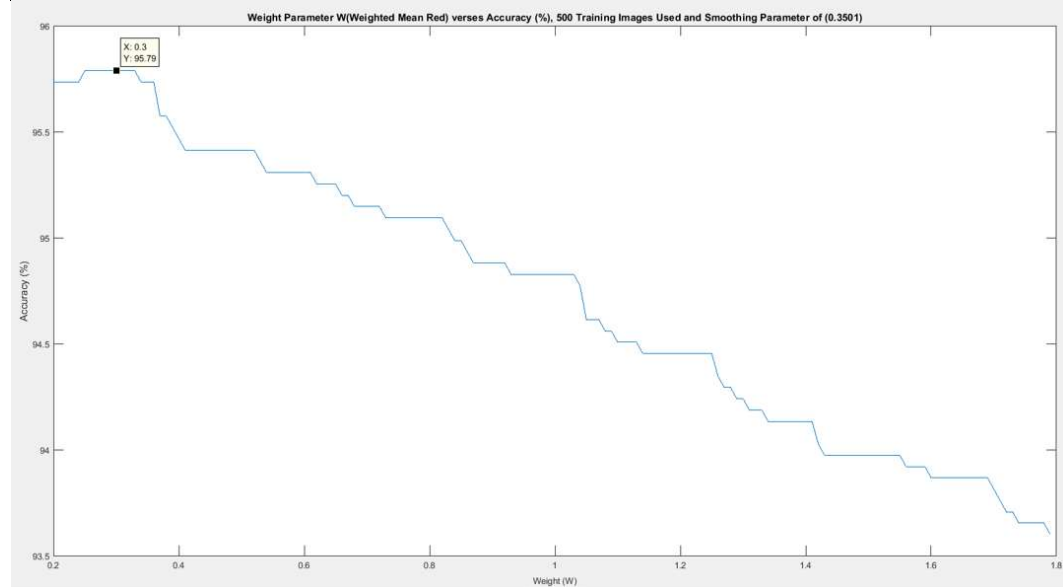
Figure 57: ANOVA Box and Whisker Expanded View obtained from Figure 57 plot

### 6.3.2 Input Variable Vector Weight (Gaussian Distribution Width Modifier)

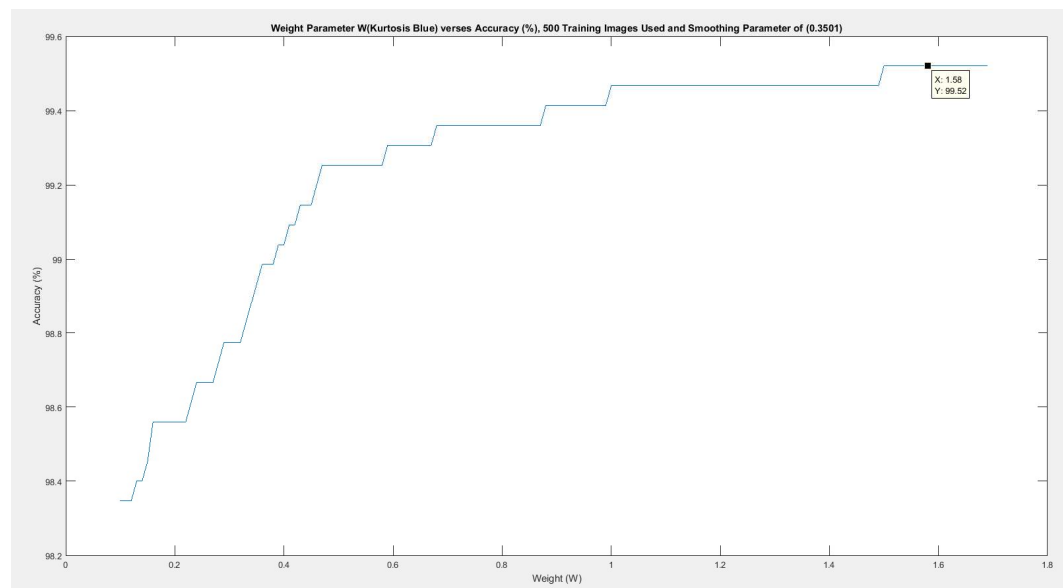
The Supervised Learning Neural Network was successfully optimised. This can be seen in Table 14, Figure 58 and, Figure 59. Weighted mean red was the first value to be optimised and it improved our models accuracy from 94.83% to 95.79%. The model was updated with the optimised weighting and the next feature was optimised which was the skewness red. This process continued through all features until the final models performance was improved to 99.52% accuracy. With our verification image set this equates to 18 images incorrectly classified out of 1875.

**Table 14: Optimised Input Variable Vector Weights (Gaussian Distribution Width Modifier) Results**

Feature	Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue
Optimised Value	0.3	0.1	0.7	0.12	0.82	1.61	0.14	1.51	1.58
Accuracy (%)	95.79	96	96	96.96	96.96	97.01	99.41	99.47	99.52



**Figure 58: Input Variable Weight Optimisation for Red Weighted Mean Colour Feature**



**Figure 59: Input Variable Weight Optimisation for Blue Kurtosis Colour Feature**



## **6.4 Results Summary**

Further future opportunities exist in the implementation of a training data weight optimisation vector which will review all data using ANOVA statistical minimum and maximum values. Any training data which does not lie within the minimum and maximum values could have their weights reduced to minimise their contribution to the final classification. This will help further improve this Supervised Learning Probabilistic Neural Network model.

Future model verification on fresh images would also be needed to ensure the model can work with 100% new images.

Optimisation of the Probabilistic Neural Network was achieved in this work by using a local search algorithm which improved the models accuracy to 94.83%. The introduction of the Supervised Learning Probabilistic Neural Network greatly enhanced the models accuracy to 99.52%.

## 7 Conclusion

### 7.1 Discussion

The research project identification of cement manufacturing raw materials using machine vision involved the development of a series quantitative research question (explained in Chapter 1). These questions were investigated through a comprehensive review of the available literature. This documented review in Chapter 2 identified the technologies in which raw materials could be identified using machine vision techniques. This literature review identified the gap in the literature which this project can contribute. The gap this project intends to bridge is the successful classification of cement manufacturing raw materials (clinker, gypsum and limestone) in one work.

During the literature review, it was identified that there was a need to sample the raw materials in a way which would ensure an accurate representation of the raw material body was acquired.

The next phase of this work was the design and selection of the hardware and software needed to classify the raw materials. A dual purpose camera and lighting enclosure were constructed which could operate in the static model development environment and also operate in the dynamic operational environment (Future work).

The lights were selected to match the camera's sensor sensitivity best to ensure the raw materials had the best opportunity to be successfully classified. The camera's sensor type (Global Shutter CMOS) was chosen to be able to take images of a moving conveyor without distortion to the image.

Once the image sampling hardware was built the image acquisition took place which involved loading the sampled raw materials onto a purposed built test bed. This test bed allowed 625 images to be taken of each raw material which could be then stored in an image database. From these images, the colour features were extracted using a histogram function. This then allowed the weighted mean, skewness and kurtosis to be extracted for the red, green and red elements of the image. From these nine colour features, an image feature database was created which would be used to train and verify a raw material classification Probabilistic Neural Network(PNN). This model was optimised using the inbuilt Gaussian distribution smoothness parameter. This model was then optimised to achieve 94.83% accuracy.

The accuracy optimisation did not achieve the desired accuracy so literature was revisited to find ways to improve the model. This literature review found two improvements. The first was to normalise the data as the weighted mean colour features were causing model over to be overweighted. The second improvement was the implementation of a Supervised Learning Probabilistic Neural Network which through further optimisation the desired classification accuracy of 99.52% was achieved.

### 7.2 Further Work

The project will continue for the next two years to install and optimised the dual purpose camera enclosure on the tilt pan conveyor. This installation will allow further model testing in the production environment to verify all design features will operate in the production environment.

Further work which remains for this project;

- The continuation of the advanced shape features extraction already started in subsection 4.7.2 (raw material particle area, perimeter, length, width),
- Further optimisation of the Supervised Learning Probabilistic Neural Network(SLPNN) training data weight using ANOVA statistical minimum and maximum features,
- Develop a dynamic unsupervised learning algorithm which can be used to allow for the variation in raw materials over time,
- Compare Supervised Learning Probabilistic Neural Network against multiclass support vector machine and multilayer perceptron,
- Investigate the relationship between raw material colour features and raw material quality using X-ray fluorescence chemistry analysis of the training samples.

### **7.3 Closing Statement**

This dissertation researched ways in which raw materials were identified using machine vision techniques. The raw material classification was achieved using carefully selected technologies which were implemented as a complete camera enclosure and lighting system. This system sampled images using a test bed which was able to take 1875 images of the raw materials. These images were then used to successfully build, train and optimise the probabilistic neural network which achieved 94.83% classification accuracy.

The model was further optimised by adding new variables which allowed our model to become a supervised learning probabilistic neural network. This model was optimised and verified to achieve a classification accuracy of 99.52%. This accuracy supports the claim that machine can be successfully be used to positively identify cement manufacturing raw materials.

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## Appendix A – Project Specification

ENG4111/4112 Research Project

### Project Specification

For: Lindsay Notley

Title: Identification of cement manufacturing raw material using machine vision

Major: Electrical and Electronic Engineering

Supervisors: Dr Andrew Maxwell

Sponsor: Cement Australia Pty Ltd

Enrolment: ENG4111 – EXT S1, 2016  
ENG4112 – EXT S2, 2016

Project Aim: To investigate raw material identification techniques using machine vision and develop a system combining several different techniques to correctly identify raw materials with a high success rate.

**Programme: Issue B, 8 April 2016**

1. Research analysis techniques and suitable methods for identifying raw materials.
2. Research appropriate sensor/transducers suitable for use with these methods.
3. Conduct familiarisation with both existing plant systems including previously purchased equipment potentially suitable for implementing the chosen method.
4. Choose a suitable sensor/transducer(s) for use with the existing plant system.
5. Develop a model for analysing the data obtained from the sensor/transducer(s) utilising suitable software packages (for instance Matlab).
6. Create a simulation test-bed to verify the performance of the sensor/transducer(s) and analysis model.
7. Verify the models ability to positively identify different raw materials.

If time and resources permit:

8. Prepare a design specification for the construction of a standalone prototype.
9. Design a economical standalone prototype which can be installed to monitor several locations
10. Investigate, test and implment the additional functionalities such as;
  - a. Cubic Meters passing over the transport system,
  - b. Fill level optimisation
  - c. Product property analysis and the relationship between various visible properties and chemistry



## Appendix B – Project Management Plan

### Safety Management Plan

There are two risk assessments conducted below. The first risk assessment in Table 16 addresses the safety of those working directly on this research project. As per the site rules each task completed on each day will require an individual risk assessment to be completed and approved by the site supervisor.

The second risk assessment manages the risk of the research project introduced technology. These risk assessments will be scored using the risk consequence matrix shown below in Table 17. Tasks which are rated 70 or higher will not proceed without direct management approval. In both Table 16 and Table 17 the headings have been explained below;

- C** Consequence  
**L** Likelihood  
**S** Resultant Score

**Table 15: Risk Assessment Matrix**

Consequence			Very Unlikely	Unlikely	Possible	Very likely	Almost Certain
Asset	Safety	Score	10	20	30	40	50
<\$20k	First Aid	10	20	20	40	50	60
\$20k<X<\$50k	Medically Treated	20	30	40	50	60	70
\$50k<X<\$100k	Permanent Health Issue	30	40	50	60	70	80
\$100k<X<\$500k	Serious Injury	40	50	60	70	80	90
>\$500k	Fatality	50	60	70	80	90	100

Risk Matrix modified from Cement Australia's Risk Matrix

**Table 16: Risk Assessment of those working on the Research Project**

Task	Hazard	C	L	S	Control	C	L	S
Sample Stockpile	Mobile Plant	40	30	70	Communicate with production team, Barricade the area to prevent loaders entering the area	40	10	50
Sample Pan Conveyor	Hot Clinker	20	20	50	Use hot clinker extraction tools, Wear High temperature gloves Follow sampling work instruction	20	10	30
Sample Limestone	Manual Handling of sample	30	20	50	Use correct manual handling techniques. Do not load sample bags greater than 20kg	30	10	40
Access site	Traffic	20	20	40	Walk on designated paths, watch out for traffic, and wear correct PPE.	20	10	30
	Stair Access	20	20	40	Maintain 3 points of contact	20	10	30
	Dust	30	30	60	Wear Dust mask, Access area when plant is off	30	10	40
	Working Alone	20	20	40	Follow site working alone policy and ensure contact is maintained with central control	20	10	30
Equipment Access	Live Plant	40	20	60	Isolate and prove dead.	40	10	50

**Table 17: Risk Assessment of Research Projects Introduced Technology**

Item	Hazard	C	L	S	Control	C	L	S
Camera	Damage to equipment due to bracket failure	20	20	40	Ensure all fixings are captive, Ensure double locking devices are available	20	10	30
Control Cabinet	Damage to equipment due to bracket failure	10	20	30	Ensure all fixings are captive, Ensure double locking devices are available	10	10	20
	Electric Shock	40	20	60	-Ensure earth leakage circuit protection has been provided and tested on the outlets, -Ensure all equipment has been test tagged, -Use Protected Extra low Voltage where possible, -Ensure all equipment has suitable IP ratings, -Ensure all cabling is protected from mechanical vibration and damage, -Keep all leads off the grid floors	40	10	50
Camera Enclosure	Manual Handling	30	30	60	-Design the enclosure to disassemble and ensure all parts are less than 10kg Ensure all parts can be carried up stairs	30	10	40
Relocation from training area								
Camera Enclosure	Machine Collision	20	20	40	- Ensure all parts are at least 100mm away from the tilt pan conveyor	20	10	30
Camera Enclosure	Removal	10	10	20	Provide a decommissioning procedure to ensure safe disposal of equipment	10	10	20

### Communication Plan

For this research project the communication plan will cover multiple parties due to the nature of the proposed installation. The key personnel whom will need to be communicated with have been listed below.

#### **USQ Project Supervisor (Dr Andrew Maxwell),**

The USQ supervisor when confirmed will receive fortnightly project updates or as required. The preferred communication path will be email unless another method is requested by the supervisor. The project updates will provide a summary of key achievements, risks and milestone progress updates.

#### **Cement Australia Supervisor (Andrew Woodward – Electrical Services Manager),**

The Cement Australia supervisor will be provided the same communication as the USQ project supervisor with the addition of a daily safety briefs and updates. Also all project work will be submitted to Andrew Woodward prior to any formal submission to ensure it complies with Cement Australia policies.

#### **Cement Australia Railton Operations Management,**

Will be provided with monthly progress updates and approve all site wide communications before they are shared.

### Cement Australia Railton Staff, Employees and Contractors.

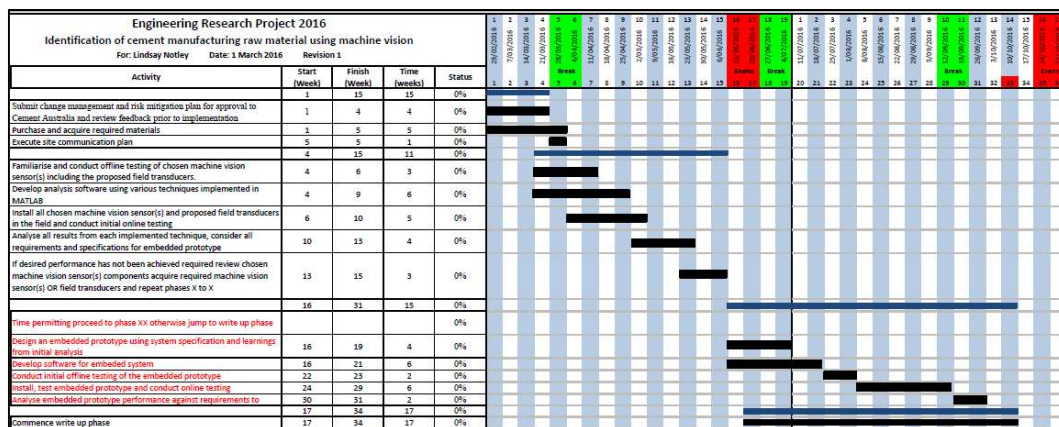
All Cement Australia employees, staff and contractors will receive a project notification.

### Resource Requirements

Table 18: Required Resources

Brand	Part Number	Description	Quantity	Cost	Total
IDC	<u>UI-5250CP-C-HQ</u>	Camera	1	\$1280	\$1,280
Goyo		Lens	1	\$300	\$300
Goyo		F to C Lens Mount Adaptor	1	\$130	\$100
Alphalux	ALXLEDWP224	Twin LED Weather Proof Batten fitting	2	\$254	506
		Plywood	3	\$80	\$240
		Paint Black	1	\$120	\$120
	75 x 50 x5mm	Angle Iron	8m	\$34/m	\$272
	50 x 50 x2.4mm	Angle Iron	8m	\$14/m	\$112
		Raw Material Sample Bag	100	50	50
		Recycled Steel Bucket	10	Loan	Loan
		Information Tags	100	\$0.35	\$35
		Clinker	400kg	Loan	Loan
		Limestone	400kg	Loan	Loan
		Gypsum	250kg	Loan	Loan
		Cable Ties	4 packs	\$4	\$16
		Miscellaneous Electrical	1	\$400	\$400
		Fan and Filter	1	\$300	\$300
		IP Rated enclosure	1	Loan	Loan
		Cat 6 Cable	1	\$300	\$300
		Tilt Pans	3	Loan	Loan
<b>Total</b>					<b>\$4,491</b>

### Project Schedule



## Appendix C – Enclosure Design Drawings

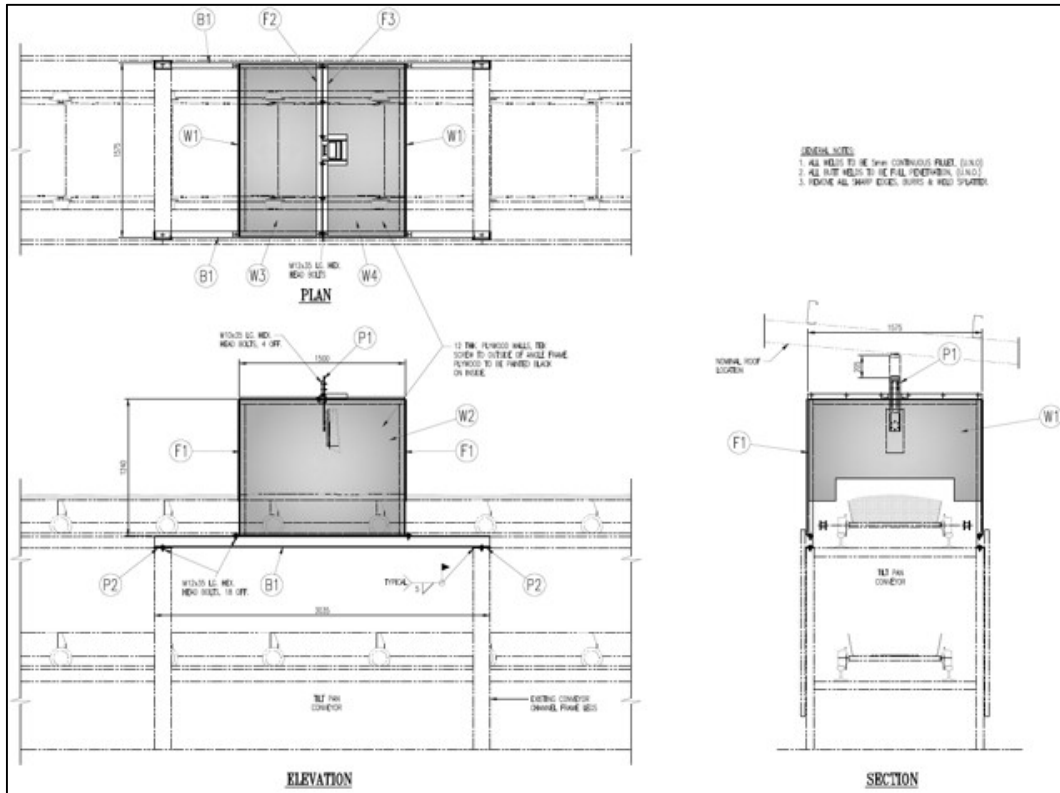


Figure 60: Camera enclosure Construction Overview

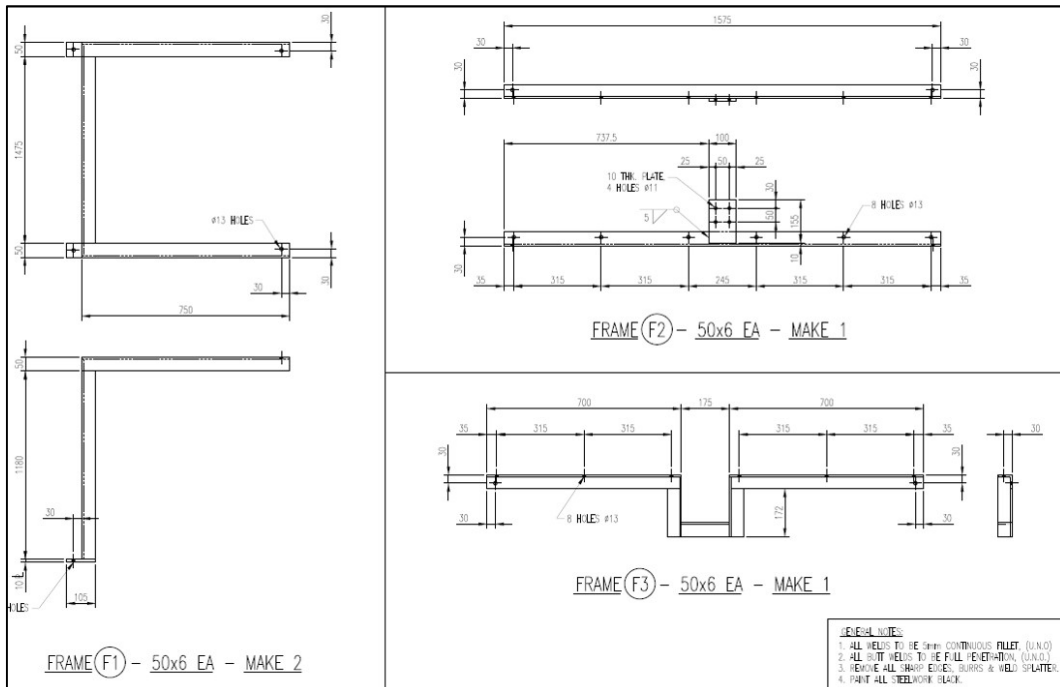


Figure 61: Camera Enclosure Structure Fabrication Details



## Appendix D – Colour Feature Extraction Code

```
% Colour Feature Extraction
% Written By Lindsay Notley
% Version 5 - Improved Comments

% General House Keeping
clc
clear all
close all

% Initialise Constants
NUMBER_OF_FEATURES=9;

% Enter desired Image Directory's Full Path This will obtain all
the
% directory's information Obtained from
% <http://au.mathworks.com/matlabcentral/answers/32038-can-you-
use-dir-to-
% list-files-in-subfolders>
DIRECTORY = dir(['C:\EXTRACT\PREPARED\GYPSUM', '\*.JPG']);
% This will count the number of items in the folder which are not
folders
NUMBER_OF_IMAGES_IN_FILE =
length(DIRECTORY(not([DIRECTORY.isdir])));

%Populate the Storage array with zeros to the size shown below
STORE=zeros(NUMBER_OF_IMAGES_IN_FILE,NUMBER_OF_FEATURES);

%% For Loop to Extract all colour features from the files in the
directory
% Then Store them in the Storage Array

for ii=1:NUMBER_OF_IMAGES_IN_FILE
    % Convert the for loop index number into a string
    A=int2str(ii);
    % Concatenate the sting value so the images will be indexed
according
    % to the index number
    B=strcat('C:\EXTRACT\PREPARED\GYPSUM\G- (' ,A, ').JPG');
    %Load the image into the Image Array
    IMAGE=imread(B);

    % Generate an array from 0 to 255 as a single row
    LEVELS_ROW=(1:256);
    % Generate an array from 0 to 255 as a single cloumn
    LEVELS_COL=LEVELS_ROW';

    % Determine the total pixels in the image
    PIX_IN_IMAGE=numel(IMAGE(:,:,1));

    % Conduct the Histogram function on the Red, Green and Blue
parts of
    % each image
    C_RED_HIST=imhist(IMAGE(:,:,1));
    C_GRN_HIST=imhist(IMAGE(:,:,2));
    C_BLU_HIST=imhist(IMAGE(:,:,3));

    %Weighted Mean
```

```
fwr=(sum(LEVELS_COL.*C_RED_HIST))/sum(LEVELS_COL(:));
fwg=(sum(LEVELS_COL.*C_GRN_HIST))/sum(LEVELS_COL(:));
fwb=(sum(LEVELS_COL.*C_BLU_HIST))/sum(LEVELS_COL(:));

%Mean
fr=(sum(LEVELS_COL.*C_RED_HIST))/(numel(IMAGE(:,:,1)));
fg=(sum(LEVELS_COL.*C_GRN_HIST))/(numel(IMAGE(:,:,2)));
fb=(sum(LEVELS_COL.*C_BLU_HIST))/(numel(IMAGE(:,:,3)));

%Variance
vr=(sum((LEVELS_COL-fr).^2.*C_RED_HIST))/PIX_IN_IMAGE;
vg=(sum((LEVELS_COL-fg).^2.*C_GRN_HIST))/PIX_IN_IMAGE;
vb=(sum((LEVELS_COL-fb).^2.*C_BLU_HIST))/PIX_IN_IMAGE;

%Skewness
SR=((1/PIX_IN_IMAGE)*(sum((LEVELS_COL-
fr).^3.*C_RED_HIST)))/((sqrt(vr))^3);
SG=((1/PIX_IN_IMAGE)*(sum((LEVELS_COL-
fg).^3.*C_GRN_HIST)))/((sqrt(vg))^3);
SB=((1/PIX_IN_IMAGE)*(sum((LEVELS_COL-
fb).^3.*C_BLU_HIST)))/((sqrt(vb))^3);
%Kurtosis
KR=((1/PIX_IN_IMAGE)*(sum((LEVELS_COL-
fr).^4.*C_RED_HIST)))/((sqrt(vr))^4);
KG=((1/PIX_IN_IMAGE)*(sum((LEVELS_COL-
fg).^4.*C_GRN_HIST)))/((sqrt(vg))^4);
KB=((1/PIX_IN_IMAGE)*(sum((LEVELS_COL-
fb).^4.*C_BLU_HIST)))/((sqrt(vb))^4);
% Store current image data in the storage array
STORE(ii,:)= [fwr, SR, KR, fwg, SG, KG, fwb, SB, KB];
end
% Store the array in a CSV File for further processing.
csvwrite('GYPSUM-V2.CSV', STORE);
```



## Appendix E – Probabilistic Neural Network

### Main Program

See below for the developed Probabilistic Neural Network Function

```
% Probabilistic Neural Network Main Program
% Written By Lindsay Notley
% Version 1 - Improved Comments

% ALLDATA is an array where
% Rows 1- 625 are Clinker
% Rows 626-1250 are Gypsum
% Rows 1251-1875 are Limestone
% Column 1 = Red Mean
% Column 2 = Red Skewness
% Column 3 = Red Kurtosis
% Column 4 = Green Mean
% Column 5 = Green Skewness
% Column 6 = Green Kurtosis
% Column 7 = Blue Mean
% Column 8 = Blue Skewness
% Column 9 = Blue Kurtosis

% General House Keeping
clc
clear all
close all

%% Initialise Variables
SMOOTH=0.0009; %Raw Smallest is 0.6, Norm smallest is
0.0009
NUMBER_OF_VARIABLES=9; % 9 Colour Features
NUMBER_OF_CLASSES=3; % 3 Raw Material Classes
HOLDBACK=100; % Number of images to hold back for
verification
CONFUSION=zeros(3); % Create Matching matrix
WRONG=0; % Initialise wrong classification counter
WIN=0; % Set the Material Win count to 0

% Test Raw Data Set OR Test Normalised Data Set
ALLDATA=csvread('ALLDATA_NORM.CSV');
%ALLDATA=csvread('ALLDATA-FINAL.CSV');
% Determine number of images in each Classes Dataset
NUMBER_IN_CLASS=(size(ALLDATA,1))/NUMBER_OF_CLASSES;

%Generate The Training data set by determineign the number to hold
back
%then Vertically concatenate Clinker, Gypsum and Limestone
TRAIN=ALLDATA(1:(NUMBER_IN_CLASS-HOLDBACK),:);
TRAIN=vertcat(TRAIN,(ALLDATA((1+NUMBER_IN_CLASS):(NUMBER_IN_CLASS
*2)-HOLDBACK),:));
TRAIN=vertcat(TRAIN,(ALLDATA((1+NUMBER_IN_CLASS*2):(NUMBER_IN_CLA
SS*3)-HOLDBACK),:));

% Generate the Verification data set by using the number of images
to hold
% back and then Vertically Concateenate Clinker, Gypsum and,
Limestone
```

```
CLASSIFY=ALLDATA(1+(NUMBER_IN_CLASS-  
HOLDBACK):(NUMBER_IN_CLASS),:);  
CLASSIFY=vertcat(CLASSIFY,(ALLDATA((1+(NUMBER_IN_CLASS*2-  
HOLDBACK):(NUMBER_IN_CLASS*2),:)));  
CLASSIFY=vertcat(CLASSIFY,(ALLDATA((1+(NUMBER_IN_CLASS*3-  
HOLDBACK):(NUMBER_IN_CLASS*3),:)));  
  
% Generate the storage array  
RESULT=zeros((HOLDBACK*NUMBER_OF_CLASSES),NUMBER_OF_CLASSES);  
  
%% Process all data using MY_PNN_FUN_V1 to classify the  
verification  
% training set then determine if the images were classified  
correctly. Then  
% store the result in a Matching matrix.  
for ii=1:(HOLDBACK*NUMBER_OF_CLASSES)  
  
[A,B,C]=MY_PNN_FUN_V1(TRAIN,CLASSIFY(ii,:),SMOOTH,NUMBER_OF_VARIAB  
LES,NUMBER_OF_CLASSES);  
  
ACTUAL=(ii<HOLDBACK+1)*1+(HOLDBACK<ii)*(ii<(HOLDBACK*2+1))*2+(ii  
>(HOLDBACK*2))*3;  
MAXIMUM=max(A,(max(B,C)));  
ERROR=(A==0)*(B==0)*(C==0);  
  
if (ERROR>0)  
    % errordlg('Vector not classified','Error');  
elseif (A==MAXIMUM)  
    WIN=1;  
elseif (B==MAXIMUM)  
    WIN=2;  
  
elseif (C==MAXIMUM)  
    WIN=3;  
end  
WRONG=WRONG+(ACTUAL~=WIN)*1;  
CONFUSION(ACTUAL,WIN)=CONFUSION(ACTUAL,WIN)+1;  
RESULT(ii,1:5)=[A,B,C,ACTUAL,WIN];  
  
end  
  
f = figure('Position',[440 500 461 146]);  
% Create the column and row names in cell arrays  
cnames = {'Clinker','Gypsum','Limestone'};  
rnames = {'Clinker','Gypsum','Limestone'};  
  
% Create the uitable  
t =  
uitable(f,'Data',CONFUSION,'ColumnName',cnames,'RowName',rnames);  
  
% Set width and height  
t.Position(3) = t.Extent(3);  
t.Position(4) = t.Extent(4);
```

### Probabilistic Neural Network Function

```
function  
[fAXCLINKER,fAXGYPSUM,fAXLIMESTONE]=MY_PNN_FUN_V1(TRAINDATA,CLASSI  
FYDATA,SMOOTH,NUMBER_OF_INPUT_VARIABLES,NUMBER_OF_CLASSES)
```

```
% Determine the Training Date Set Size and number of rows
TRAINDATASIZE=size(TRAINDATA);
TRAIN_ROWS=(TRAINDATASIZE(1,1))/NUMBER_OF_CLASSES;
% Probabilistic Neural Network Constant (Everything before the
exponential function)
PNN_CONSTANT=((2*pi)^(NUMBER_OF_INPUT_VARIABLES/2))*SMOOTH^NUMBER
_OF_INPUT_VARIABLES*(1/TRAIN_ROWS); %Constant Calculation
% Initialise variables
SUMfApCLINKER=0;
SUMfApGYPSUM=0;
SUMfApLIMESTONE=0;
LL=0;
GG=0;

for mm=1:TRAIN_ROWS
    ii=1;
    SUMOFVECTORELEMENTSCLINKER=0;
    SUMOFVECTORELEMENTSGYPSUM=0;
    SUMOFVECTORELEMENTSLIMESTONE=0;
    for ii=1:NUMBER_OF_INPUT_VARIABLES
        % Calculate euclidean distance for each feature

SUMOFVECTORELEMENTSCLINKER=SUMOFVECTORELEMENTSCLINKER+((TRAINDATA(
mm,ii)-CLASSIFYDATA(1,ii))^2);
        GG=mm+TRAIN_ROWS;

SUMOFVECTORELEMENTSGYPSUM=SUMOFVECTORELEMENTSGYPSUM+((TRAINDATA(GG
,ii)-CLASSIFYDATA(1,ii))^2);
        LL=mm+TRAIN_ROWS*2;

SUMOFVECTORELEMENTSLIMESTONE=SUMOFVECTORELEMENTSLIMESTONE+((TRAIND
ATA(LL,ii)-CLASSIFYDATA(1,ii))^2);
    end
    % Do the exponential function of the PNN Pattern Equation
    fApCLINKER=exp(-1*(SUMOFVECTORELEMENTSCLINKER/(2*SMOOTH^2)));
    SUMfApCLINKER=SUMfApCLINKER+fApCLINKER;
    fApGYPSUM=exp(-1*(SUMOFVECTORELEMENTSGYPSUM/(2*SMOOTH^2)));
    SUMfApGYPSUM=SUMfApGYPSUM+fApGYPSUM;
    fApLIMESTONE=exp(-
1*(SUMOFVECTORELEMENTSLIMESTONE/(2*SMOOTH^2)));
    SUMfApLIMESTONE=SUMfApLIMESTONE+fApLIMESTONE;
end
% Publish the Functions Results
fAXCLINKER=PNN_CONSTANT*SUMfApCLINKER;
fAXGYPSUM=PNN_CONSTANT*SUMfApGYPSUM;
fAXLIMESTONE=PNN_CONSTANT*SUMfApLIMESTONE;
end
```

## Appendix F – Feature Normalisation Code

```
% Colour Feature Normalisation Code
% Written By Lindsay Notley
% Version 2 - Improved Comments

% General House Keeping
clc
clear all
close all

% Load all Colour Feature data from respective CSV Files
CLINKER=csvread('C:\LNOTLEY\UNI\1 - ENG4111-ENG4112 - Final
Project\P4 - Feature Extraction\Take 4\ALL_CLINKER_RAND_V1.CSV');
GYPSUM=csvread('C:\LNOTLEY\UNI\1 - ENG4111-ENG4112 - Final
Project\P4 - Feature Extraction\Take 4\ALL_GYPSUM_RAND_V1.CSV');
LIMESTONE=csvread('C:\LNOTLEY\UNI\1 - ENG4111-ENG4112 - Final
Project\P4 - Feature Extraction\Take
4\ALL_LIMESTONE_RAND_V1.CSV');

% Vertically Concenate All Raw materials into one array called
ALLDATA
ALLDATA=vertcat(CLINKER,GYPSUM);
ALLDATA=vertcat(ALLDATA,LIMESTONE);

% Determine the Minimum and Maximum Values for all materials
indivitual
% feature classes and store them in a mimimum and maximum constant
for
% further processing

ALLDATA_RM_MAX=max(ALLDATA(:,1));
ALLDATA_RM_MIN=min(ALLDATA(:,1));
ALLDATA_RS_MAX=max(ALLDATA(:,2));
ALLDATA_RS_MIN=min(ALLDATA(:,2));
ALLDATA_RK_MAX=max(ALLDATA(:,3));
ALLDATA_RK_MIN=min(ALLDATA(:,3));

ALLDATA_GM_MAX=max(ALLDATA(:,4));
ALLDATA_GM_MIN=min(ALLDATA(:,4));
ALLDATA_GS_MAX=max(ALLDATA(:,5));
ALLDATA_GS_MIN=min(ALLDATA(:,5));
ALLDATA_GK_MAX=max(ALLDATA(:,6));
ALLDATA_GK_MIN=min(ALLDATA(:,6));

ALLDATA_BM_MAX=max(ALLDATA(:,7));
ALLDATA_BM_MIN=min(ALLDATA(:,7));
ALLDATA_BS_MAX=max(ALLDATA(:,8));
ALLDATA_BS_MIN=min(ALLDATA(:,8));
ALLDATA_BK_MAX=max(ALLDATA(:,9));
ALLDATA_BK_MIN=min(ALLDATA(:,9));

% Determine the size of the ALLDATA array
VECTORSIZE=size(ALLDATA);
% Extract the number of rows and store it in the ROW constant
ROW=VECTORSIZE(1,1);
% Extract the number of coloumns and store it in the COLUMN
constant
COLUMN=VECTORSIZE(1,2);
```

```
%% Normalise all data one row at a time
% The formula (Current Value - Mimimum Value)/(Maximum Value -
minimumValue)
% has been used to normalise the data.
for ii=1:ROW
    ALLDATA(ii,1)=(ALLDATA(ii,1)-ALLDATA_RM_MIN)/(ALLDATA_RM_MAX-
ALLDATA_RM_MIN);
    ALLDATA(ii,2)=(ALLDATA(ii,2)-ALLDATA_RS_MIN)/(ALLDATA_RS_MAX-
ALLDATA_RS_MIN);
    ALLDATA(ii,3)=(ALLDATA(ii,3)-ALLDATA_RK_MIN)/(ALLDATA_RK_MAX-
ALLDATA_RK_MIN);

    ALLDATA(ii,4)=(ALLDATA(ii,4)-ALLDATA_GM_MIN)/(ALLDATA_GM_MAX-
ALLDATA_GM_MIN);
    ALLDATA(ii,5)=(ALLDATA(ii,5)-ALLDATA_GS_MIN)/(ALLDATA_GS_MAX-
ALLDATA_GS_MIN);
    ALLDATA(ii,6)=(ALLDATA(ii,6)-ALLDATA_GK_MIN)/(ALLDATA_GK_MAX-
ALLDATA_GK_MIN);

    ALLDATA(ii,7)=(ALLDATA(ii,7)-ALLDATA_BM_MIN)/(ALLDATA_BM_MAX-
ALLDATA_BM_MIN);
    ALLDATA(ii,8)=(ALLDATA(ii,8)-ALLDATA_BS_MIN)/(ALLDATA_BS_MAX-
ALLDATA_BS_MIN);
    ALLDATA(ii,9)=(ALLDATA(ii,9)-ALLDATA_BK_MIN)/(ALLDATA_BK_MAX-
ALLDATA_BK_MIN);
end

% Store All Normalised data in the csv file
csvwrite('ALLDATA_NORM.CSV',ALLDATA);

% Store Clinker Normalised data in the csv file
csvwrite('CLINKER_NORM.CSV',ALLDATA(1:625,:));

% Store Gypsum Normalised data in the csv file
csvwrite('GYPSUM_NORM.CSV',ALLDATA(626:1250,:));

% Store Limestone Normalised data in the csv file
csvwrite('LIMESTONE_NORM.CSV',ALLDATA(1251:1875,:));
```

## Appendix G – Supervised Learning PNN Code

This program uses the Supervised Learning Probabilistic Neural Network Function from Appendix H – Supervised Learning Probabilistic Neural Network Function

```
% Supervised Learning Probabilistic Neural Network
% Main Program
% Written By Lindsay Notley
% Version 1 - Improved Comments
% Need the following functions to work;
% MY_SLPNN_FUN_V1.m

% ALLDATA is an array where
% Rows 1- 625 are Clinker
% Rows 626-1250 are Gypsum
% Rows 1251-1875 are Limestone
% Column 1 = Red Mean
% Column 2 = Red Skewness
% Column 3 = Red Kurtosis
% Column 4 = Green Mean
% Column 5 = Green Skewness
% Column 6 = Green Kurtosis
% Column 7 = Blue Mean
% Column 8 = Blue Skewness
% Column 9 = Blue Kurtosis

% General House Keeping
clc
clear all
close all

%% Initialise Variables
SMOOTH=0.002; % Norm smallest is 0.002
HEIGHT=1; % SPLNN Height Modifier
WEIGHT=[1,1,1,1,1,1,1,1,1]; % SLPNN Individual Input Variable
Vector Weight[FWR,SR,KR,FWG,SG,KG,FWB,SB,KB]
NUMBER_OF_VARIABLES=9; % 9 Colour Features
NUMBER_OF_CLASSES=3; % 3 Raw Material Classes
HOLDBACK=200; % Number of images to hold back for
verification
CONFUSION=zeros(3); % Create confision matrix
WRONG=0; % Initialise wrong classification
counter
WIN=0; % Set the Material Win count to 0

% Test Raw Data Set OR Test Normalised Data Set
ALLDATA=csvread('ALLDATA_NORM.CSV');

% Determine number of images in each Classes Dataset
NUMBER_IN_CLASS=(size(ALLDATA,1))/NUMBER_OF_CLASSES;

%Generate The Training data set by determineign the number to hold
back
%then Vertically concatenate Clinker, Gypsum and Limestone
TRAIN=ALLDATA(1:(NUMBER_IN_CLASS-HOLDBACK),:);
TRAIN=vertcat(TRAIN,(ALLDATA((1+NUMBER_IN_CLASS):(NUMBER_IN_CLASS
*2)-HOLDBACK),:));
TRAIN=vertcat(TRAIN,(ALLDATA((1+NUMBER_IN_CLASS*2):(NUMBER_IN_CLA
SS*3)-HOLDBACK),:));
```

```
% Generate the Verification data set by using the number of images
to hold
% back and then Vertically Concatenate Clinker, Gypsum and,
Limestone
CLASSIFY=ALLDATA(1+(NUMBER_IN_CLASS-
HOLDBACK):(NUMBER_IN_CLASS),:);
CLASSIFY=vertcat(CLASSIFY,(ALLDATA((1+(NUMBER_IN_CLASS*2-
HOLDBACK):(NUMBER_IN_CLASS*2),:)));
CLASSIFY=vertcat(CLASSIFY,(ALLDATA((1+(NUMBER_IN_CLASS*3-
HOLDBACK):(NUMBER_IN_CLASS*3),:)));

% Generate the storage array
RESULT=zeros((HOLDBACK*NUMBER_OF_CLASSES),NUMBER_OF_CLASSES);

%% Process all data using MY_SLPNN_FUN_V1 to classify the
verification
% training set then determine if the images were classified
correctly. Then
% store the result in a confusion matrix.
for ii=1:(HOLDBACK*NUMBER_OF_CLASSES)

[A,B,C]=MY_SLPNN_FUN_V1(TRAIN,CLASSIFY(ii,:),SMOOTH,HEIGHT,WEIGHT,
NUMBER_OF_VARIABLES,NUMBER_OF_CLASSES);

ACTUAL=(ii<HOLDBACK+1)*1+(HOLDBACK<ii)*(ii<(HOLDBACK*2+1))*2+(ii
>(HOLDBACK*2))*3;
MAXIMUM=max(A,(max(B,C)));
ERROR=(A==0)*(B==0)*(C==0);

if (ERROR>0)
    %errorlog('Vector not classified','Error');
elseif (A==MAXIMUM)
    WIN=1;
elseif (B==MAXIMUM)
    WIN=2;

elseif (C==MAXIMUM)
    WIN=3;
end
WRONG=WRONG+(ACTUAL~=WIN)*1;
CONFUSION(ACTUAL,WIN)=CONFUSION(ACTUAL,WIN)+1;
RESULT(ii,1:5)=[A,B,C,ACTUAL,WIN];

end

f = figure('Position',[440 500 461 146]);
% Create the column and row names in cell arrays
cnames = {'Clinker','Gypsum','Limestone'};
rnames = {'Clinker','Gypsum','Limestone'};

% Create the uitable
t =
uitable(f,'Data',CONFUSION,'ColumnName',cnames,'RowName',rnames);

% Set width and height
t.Position(3) = t.Extent(3);
t.Position(4) = t.Extent(4);
```



## Appendix H – Supervised Learning Probabilistic Neural Network Function

```

function
[fAXCLINKER, fAXGYPSUM, fAXLIMESTONE]=MY_SLPNN_FUN_V1 (TRAINDATA, CLAS
SIFYDATA, SMOOTH, HEIGHT, WEIGHT, NUMBER_OF_INPUT_VARIABLES, NUMBER_OF
CLASSES)
% Determine the Training Date Set Size and number of rows
TRAINDATASIZE=size (TRAINDATA);
TRAIN_ROWS=(TRAINDATASIZE(1,1))/NUMBER_OF_CLASSES;
% Probabilistic Neural Network Constant (Everything before the
exponential function)
PNN_CONSTANT=HEIGHT*((2*pi)^(NUMBER_OF_INPUT_VARIABLES/2))*SMOOTH
^NUMBER_OF_INPUT_VARIABLES)*(1/TRAIN_ROWS);      %Constant
Calculation
% Initialise variables
SUMfApCLINKER=0;
SUMfApGYPSUM=0;
SUMfApLIMESTONE=0;
LL=0;
GG=0;

for mm=1:TRAIN_ROWS
    ii=1;
    SUMOFVECTORELEMENTSCLINKER=0;
    SUMOFVECTORELEMENTSGYPSUM=0;
    SUMOFVECTORELEMENTSLIMESTONE=0;
    for ii=1:NUMBER_OF_INPUT_VARIABLES
        % Calculate euclidean distance for each feature

SUMOFVECTORELEMENTSCLINKER=SUMOFVECTORELEMENTSCLINKER+(WEIGHT(1,ii)
)*( (TRAINDATA(mm,ii)-CLASSIFYDATA(1,ii))^2));
        GG=mm+TRAIN_ROWS;

SUMOFVECTORELEMENTSGYPSUM=SUMOFVECTORELEMENTSGYPSUM+(WEIGHT(1,ii)*
((TRAINDATA(GG,ii)-CLASSIFYDATA(1,ii))^2));
        LL=mm+TRAIN_ROWS*2;

SUMOFVECTORELEMENTSLIMESTONE=SUMOFVECTORELEMENTSLIMESTONE+(WEIGHT(
1,ii)*( (TRAINDATA(LL,ii)-CLASSIFYDATA(1,ii))^2));
    end
    % Do the exponential function of the PNN Pattern Equation
    %fApCLINKER=exp(-
1*WEIGHT^2*(SUMOFVECTORELEMENTSCLINKER/(2*SMOOTH^2)));
    fApCLINKER=exp(-1*(SUMOFVECTORELEMENTSCLINKER/(2*SMOOTH^2)));
    SUMfApCLINKER=SUMfApCLINKER+fApCLINKER;
    %fApGYPSUM=exp(-
1*WEIGHT^2*(SUMOFVECTORELEMENTSGYPSUM/(2*SMOOTH^2)));
    fApGYPSUM=exp(-1*(SUMOFVECTORELEMENTSGYPSUM/(2*SMOOTH^2)));
    SUMfApGYPSUM=SUMfApGYPSUM+fApGYPSUM;
    %fApLIMESTONE=exp(-
1*WEIGHT^2*(SUMOFVECTORELEMENTSLIMESTONE/(2*SMOOTH^2)));
    fApLIMESTONE=exp(-
1*(SUMOFVECTORELEMENTSLIMESTONE/(2*SMOOTH^2)));
    SUMfApLIMESTONE=SUMfApLIMESTONE+fApLIMESTONE;
end
% Publish the Functions Results
fAXCLINKER=PNN_CONSTANT*SUMfApCLINKER;
fAXGYPSUM=PNN_CONSTANT*SUMfApGYPSUM;
fAXLIMESTONE=PNN_CONSTANT*SUMfApLIMESTONE;
end

```

## Appendix I – Supervised Learning Probabilistic Neural Network Optimisation Program

This Optimisation program uses the Supervised Learning Probabilistic Neural Network Function from Appendix H – Supervised Learning Probabilistic Neural Network Function

```
% Supervised Learning Probabilistic Neural Network Optimisation
% Main Program
% Written By Lindsay Notley
% Version 1 - Improved Comments
% Need the following functions to work;
% MY_SLPNN_FUN_V1.m

% ALLDATA is an array where
% Rows 1- 625 are Clinker
% Rows 626-1250 are Gypsum
% Rows 1251-1875 are Limestone
% Column 1 = Red Mean
% Column 2 = Red Skewness
% Column 3 = Red Kurtosis
% Column 4 = Green Mean
% Column 5 = Green Skewness
% Column 6 = Green Kurtosis
% Column 7 = Blue Mean
% Column 8 = Blue Skewness
% Column 9 = Blue Kurtosis

% General House Keeping
clc
clear all
close all

%% Initialise Variables
SMOOTH=0.022; % Norm smallest is 0.002 Best is
0.3501
HEIGHT=1; % SPLNN Height Modifier
WEIGHT=[1,1,1,1,1,1,1,1,1]; % SLPNN Individual Input Variable
Vector Weight[FWR,SR,KR,FWG,SG,KG,FWB,SB,KB]
NUMBER_OF_VARIABLES=9; % 9 Colour Features
NUMBER_OF_CLASSES=3; % 3 Raw Material Classes
NUMBER_OF_TRAINING_IMAGES=625;
NUMBER_OF_TRAINING_IMAGES=500;% Number of training images
CONFUSION=zeros(3); % Create confusion matrix
WRONG=0; % Initialise wrong classification
counter
WIN=0; % Set the Material Win count to 0
Iterations=160;
% Test Raw Data Set OR Test Normalised Data Set
ALLDATA=csvread('ALLDATA_NORM.CSV');

% Determine number of images in each Classes Dataset
NUMBER_IN_CLASS=(size(ALLDATA,1))/NUMBER_OF_CLASSES;

%% Generate The Training data set by determineign the number to
hold back
%then Vertically concatenate Clinker, Gypsum and Limestone
```

```
TRAIN=ALLDATA(1:(NUMBER_IN_CLASS-NUMBER_OF_TRAINING_IMAGES),:);
TRAIN=vertcat(TRAIN,(ALLDATA((1+NUMBER_IN_CLASS):(NUMBER_IN_CLASS
*2)-NUMBER_OF_TRAINING_IMAGES),:));
TRAIN=vertcat(TRAIN,(ALLDATA((1+NUMBER_IN_CLASS*2):(NUMBER_IN_CLA
SS*3)-NUMBER_OF_TRAINING_IMAGES),:));

%% Generate the Verification data set by using the number of
images to hold
% back and then Vertically Concateenate Clinker, Gypsum and,
Limestone
CLASSIFY=ALLDATA(1+(NUMBER_IN_CLASS-
NUMBER_OF_VER_IMAGES):(NUMBER_IN_CLASS),:);
CLASSIFY=vertcat(CLASSIFY,(ALLDATA((1+(NUMBER_IN_CLASS*2-
NUMBER_OF_VER_IMAGES):(NUMBER_IN_CLASS*2),:)));
CLASSIFY=vertcat(CLASSIFY,(ALLDATA((1+(NUMBER_IN_CLASS*3-
NUMBER_OF_VER_IMAGES):(NUMBER_IN_CLASS*3),:)));

%% Generate the storage array
RESULT=zeros(Iterations,8); % Change the rows to the same number

%% Process all data using MY_SLPNN_FUN_V1 to classify the
verification
% training set then determine if the images were classified
correctly. Then
% store the result in a confusion matrix.

for mm=1:Iterations
INCREMENT=0.01;

WRONG=0;
WIN=0;
for
ii=1:(NUMBER_IN_CLASS*NUMBER_OF_CLASSES)%(HOLDBACK*NUMBER_OF_CLASS
ES)

[A,B,C]=MY_SLPNN_FUN_V1(TRAIN,CLASSIFY(ii,:),SMOOTH,HEIGHT,WEIGHT,
NUMBER_OF_VARIABLES,NUMBER_OF_CLASSES);

ACTUAL=(ii<NUMBER_OF_VER_IMAGES+1)*1+((NUMBER_OF_VER_IMAGES)<ii)*(
ii<(NUMBER_OF_VER_IMAGES*2+1))*2+(ii>(NUMBER_OF_VER_IMAGES*2))*3;
MAXIMUM=max(A,(max(B,C)));
ERROR=(A==0)*(B==0)*(C==0);

if (ERROR>0)
    %errorldg('Vector not classified','Error');
elseif (A==MAXIMUM)
    WIN=1;
elseif (B==MAXIMUM)
    WIN=2;

elseif (C==MAXIMUM)
    WIN=3;
end
WRONG=WRONG+(ACTUAL~=WIN)*1;
CONFUSION(ACTUAL,WIN)=CONFUSION(ACTUAL,WIN)+1;
ACCURACY=100-
((100/(NUMBER_OF_VER_IMAGES*NUMBER_OF_CLASSES))*WRONG);
%RESULT(ii,1:7)=[A,B,C,ACTUAL,WIN,WRONG,ACCURACY];

end
```

```
RESULT(mm,1:8)=[A,B,C,ACTUAL,WIN,WRONG,ACCURACY,SMOOTH];
SMOOTH=SMOOTH+INCREMENT;
%HEIGHT=HEIGHT+INCREMENT;
%WEIGHT(1,1)=WEIGHT(1,1)+INCREMENT;
end

plot(RESULT(:,8),RESULT(:,7))
xlabel(['Smoothing Parameter (\sigma)'])
ylabel('Accuracy (%)')
title(['Smoothing Parameter (\sigma) versus Accuracy (%)',
',num2str(NUMBER_OF_TRAINING_IMAGES), ' Training Images Used'])
```

## Appendix J – Advanced Shape Feature Extraction

```
% Watershed Transform
% Original code sourced from
% 1) http://au.mathworks.com/matlabcentral/fileexchange/25689-
image-processing/content/thresholding%20image.m
% 2) http://au.mathworks.com/help/images/ref/bwdist.html
% 3) https://au.mathworks.com/help/images/ref/imcomplement.html
% 4) http://au.mathworks.com/help/images/ref/watershed.html

% All Obtained code Modified By Lindsay Notley as per the method
explained
% in Davies, E., 2012. Computer and Machine Vision: Theory,
algorithms,
% practicalities. 4th ed. Burlington: Elsevier Science.
% Version 2 - Improved Comments

% General House Keeping
clc
clear all
close all

%% Load Image
IMAGE=imread('C-1-2.JPG');
figure(1)
imshow(IMAGE, 'InitialMagnification', 'fit');

%% Grey Conversion
GRAY=rgb2gray(IMAGE);

%% Image Threshold
% Code obtained from
% http://au.mathworks.com/matlabcentral/fileexchange/25689-image-
processing/content/thresholding%20image.m

figure(2);
imshow(GRAY, 'InitialMagnification', 'fit');
title('Original Image'); % Display
Image
[ht wd]=size(GRAY);

opim=zeros(ht,wd, 'uint8'); % Take Output
variable

for i=1:ht
    for j=1:wd
        int=GRAY(i,j);
        if int<=45 % Define
Threshold level
            opim(i,j)=0;
        else % Thresholding
            opim(i,j)=255;
        end;
    end;
end;

imwrite(opim, 'C:\temp\clinkerthresh.jpg'); % Create Output Image
& Store
```

```
figure(3)
imshow(opim, 'InitialMagnification', 'fit');
title('Image after Threshold');

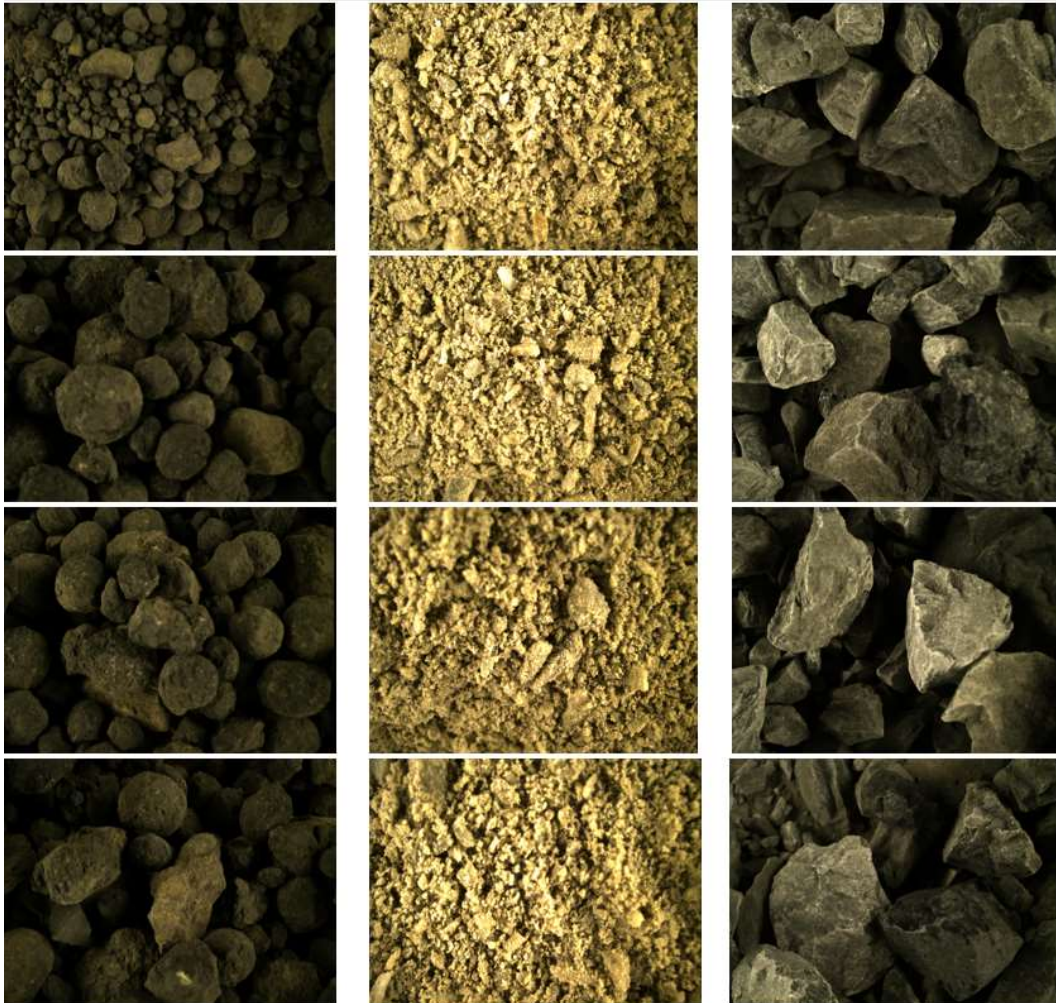
%% Distance Transform
% Code obtained and modified from
% http://au.mathworks.com/help/images/ref/bwdist.html
figure(4)
dist=bwdist(~opim);
imshow(dist, 'InitialMagnification', 'fit')
title('Image after Distance Transform');
imwrite(dist, 'C:\temp\clinkerDistance.jpg'); % Create Output
Image & Store
%% Image Complement
% Code obtained and modified from
% https://au.mathworks.com/help/images/ref/imcomplement.html
D = -dist;
D(~opim) = -Inf;
figure(5)
% Logic to make the array visible when using imshow
n=size(D,2);
DD=zeros(1200,1600);
jj=1;
for jj=1:n
temp=(~isfinite(D(:,jj))*-1)*256;
DD(:,jj)=temp';
end
figure(5)

imwrite(D, 'C:\temp\clinkerComplement.jpg'); % Create Output Image
& Store
imshow(DD, 'InitialMagnification', 'fit')
title('Image Complement');
%% Watershed
% Code obtained and modified from
% http://au.mathworks.com/help/images/ref/watershed.html
L = watershed(D);
rgb = label2rgb(L, 'jet', [.5 .5 .5]);
figure(6)
imshow(rgb, 'InitialMagnification', 'fit')
title('Watershed transform')
imwrite(rgb, 'C:\temp\clnkWtrshdTrans.jpg'); % Create Output Image
& Store

%% 3D Plot of Watershed
figure(7)
[X,Y]=meshgrid(1:1600,1:1200);
h=surf(X,Y,L);
set(h, 'LineStyle', 'none')
```

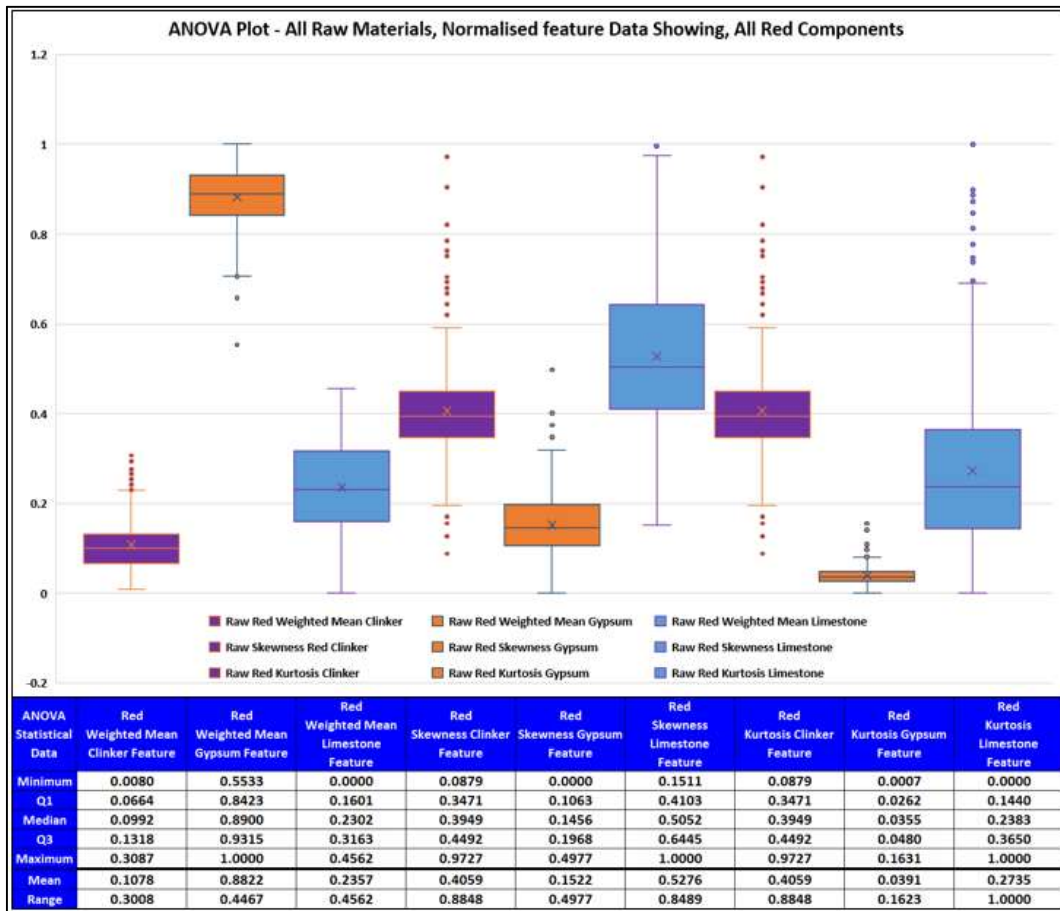
## Appendix K: Sample Images from Image Database

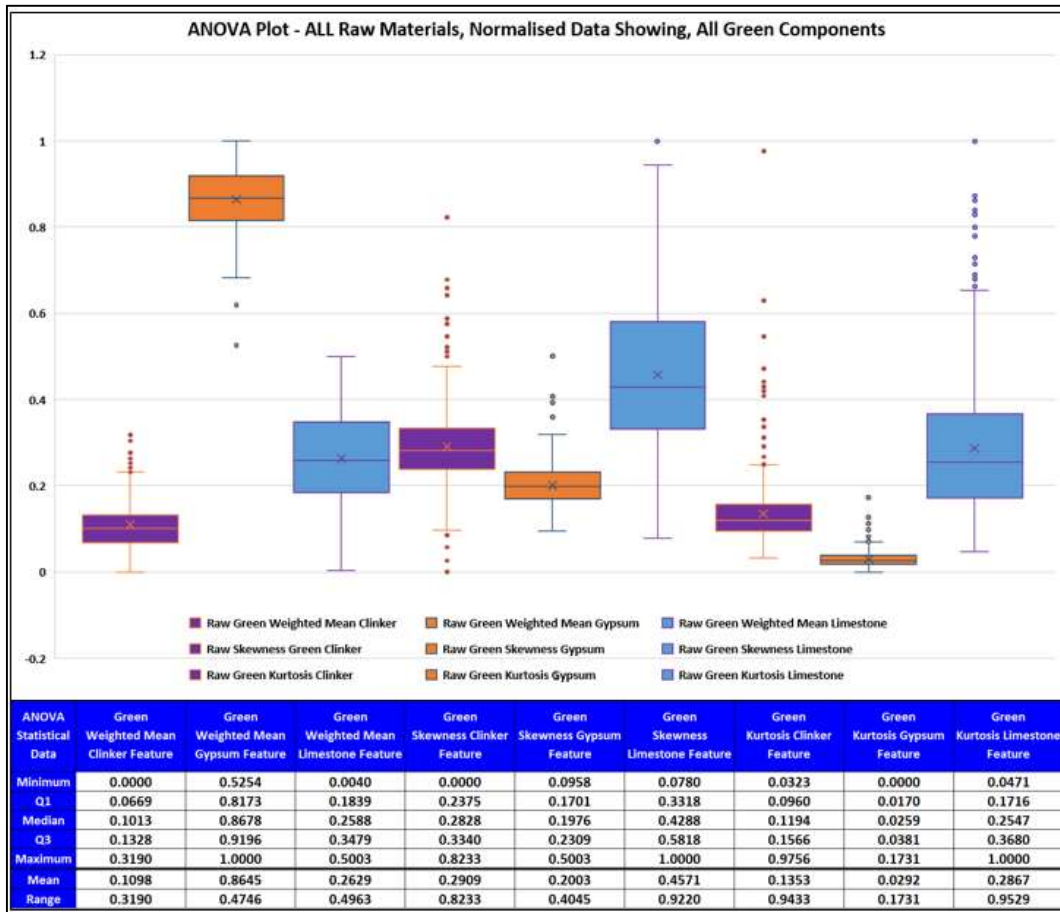
Not all 1875 images can be shown but a few interesting images have been shown.

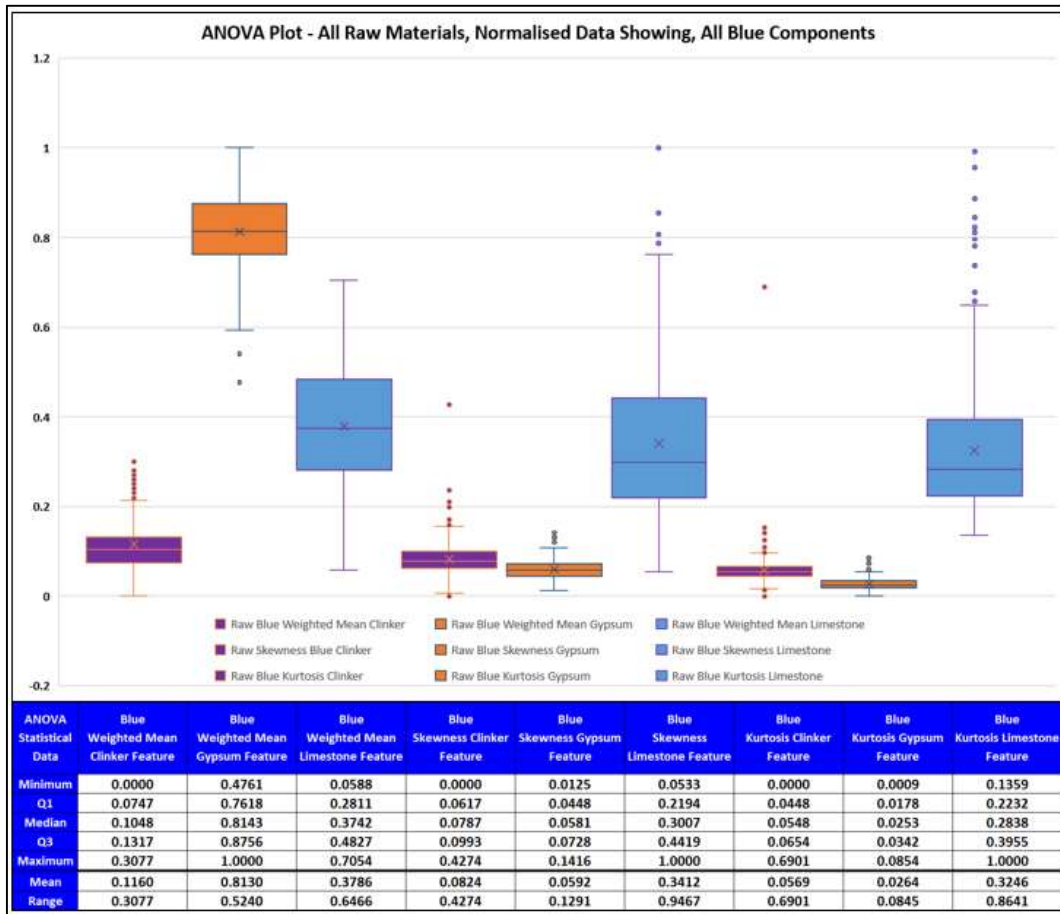


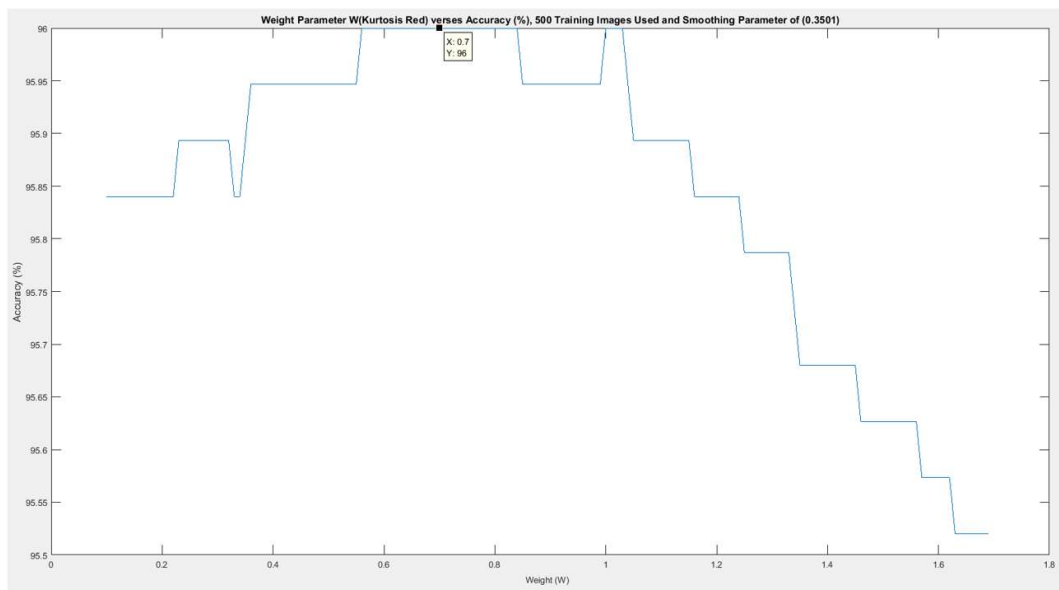
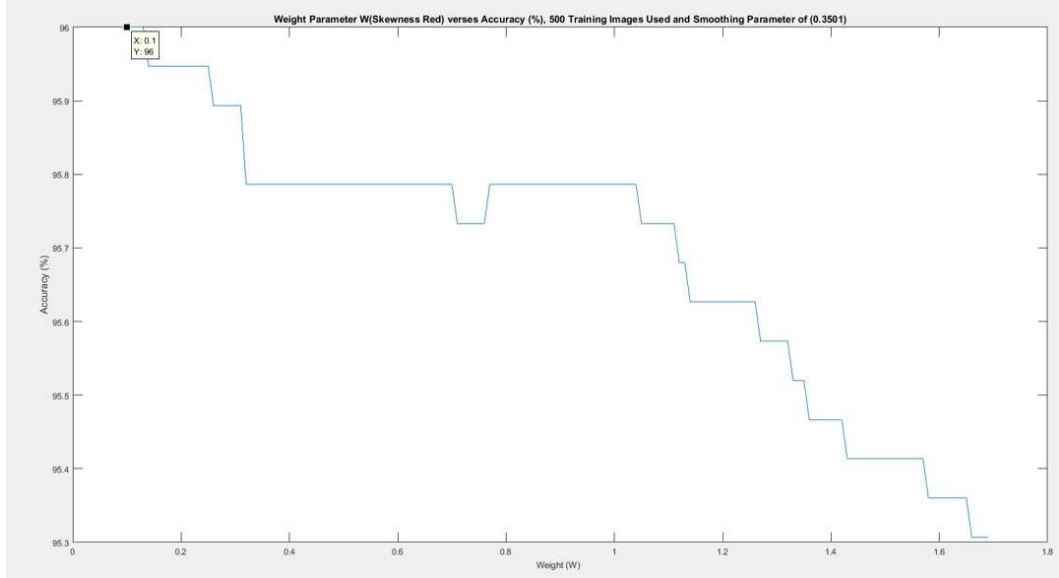
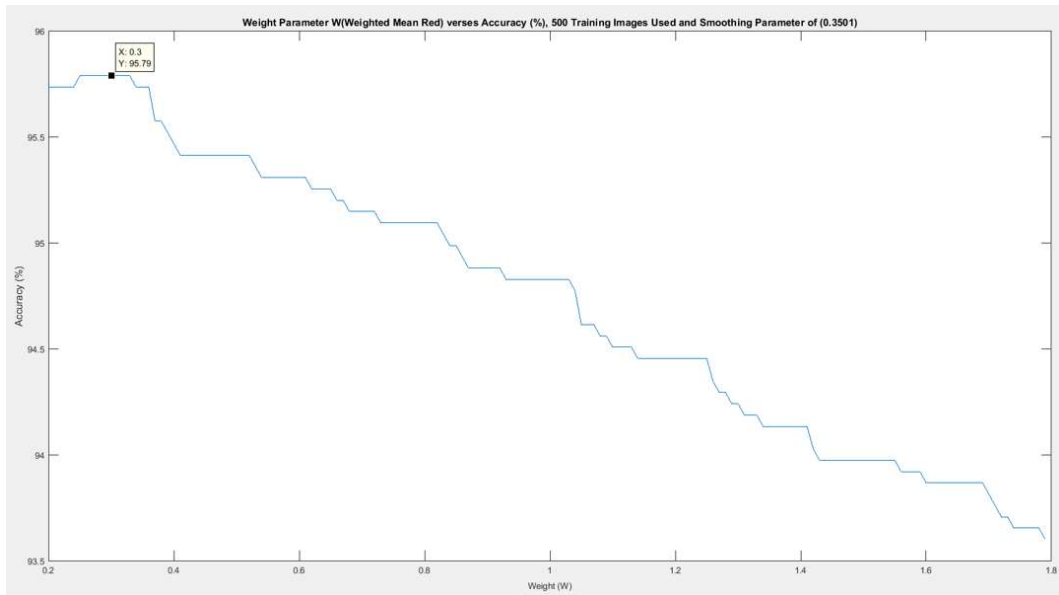


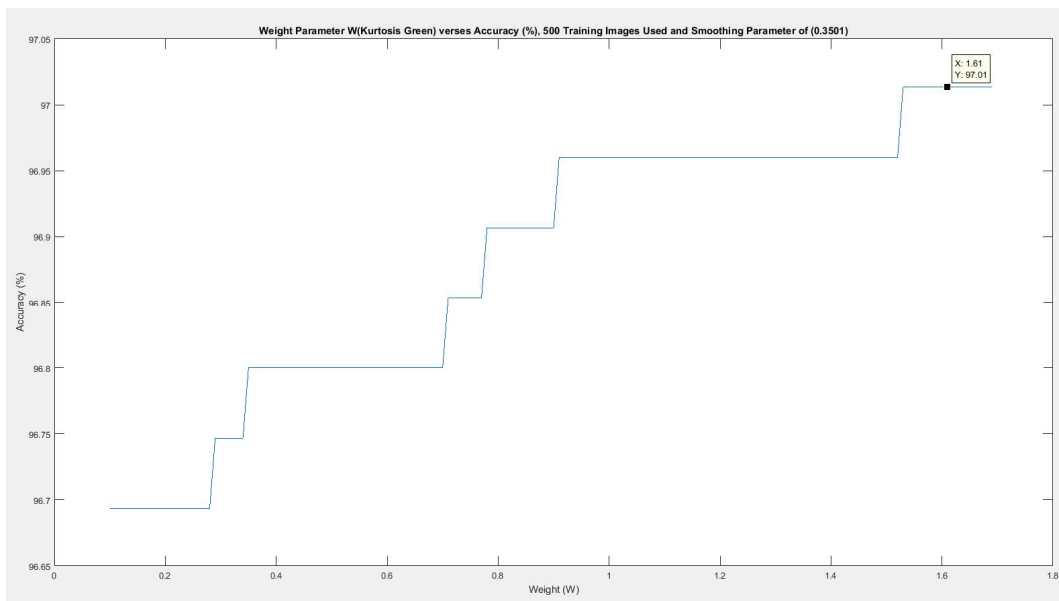
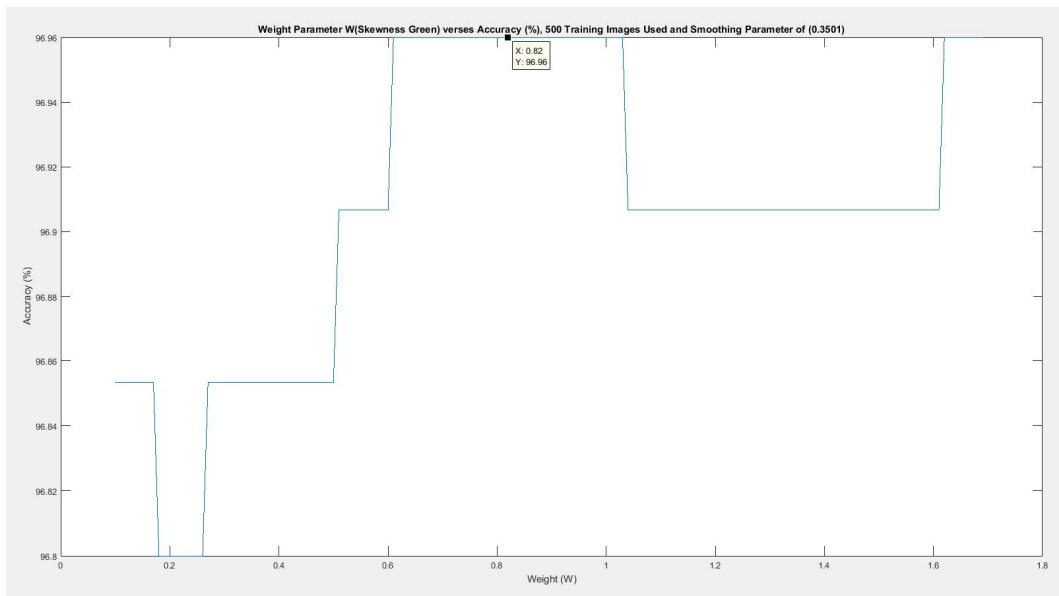
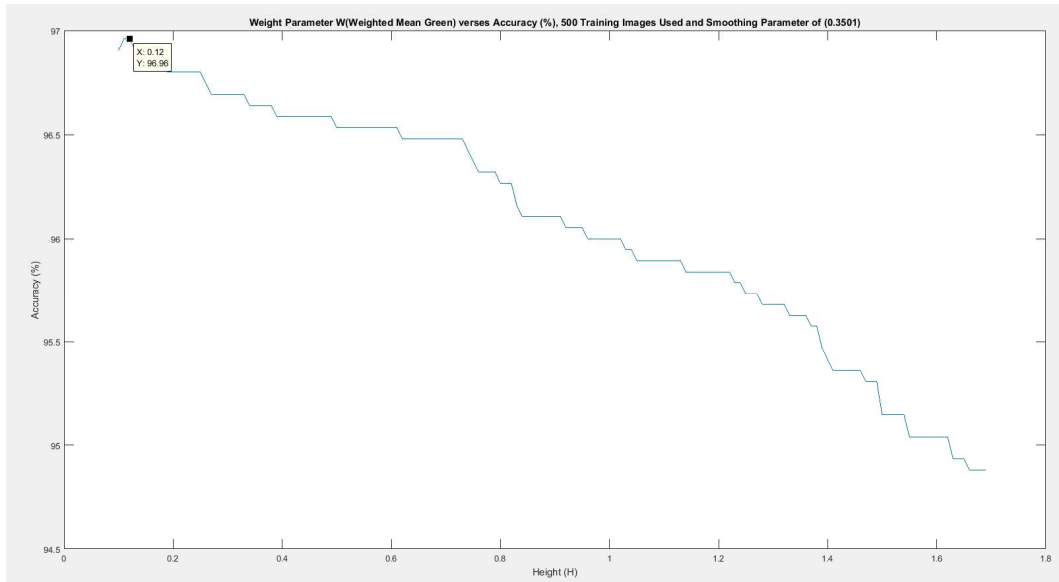
## Appendix L – Results Plots

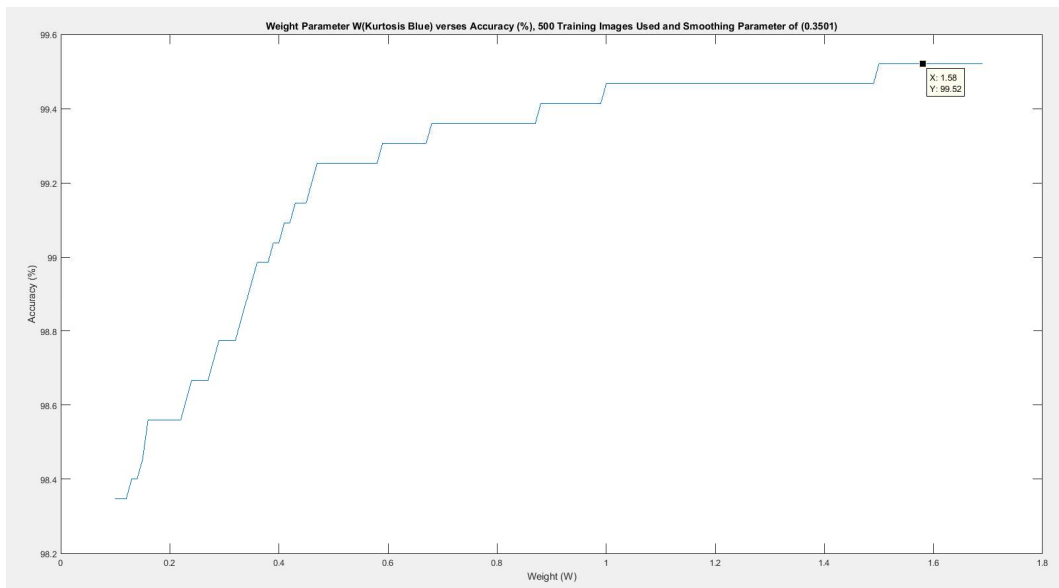
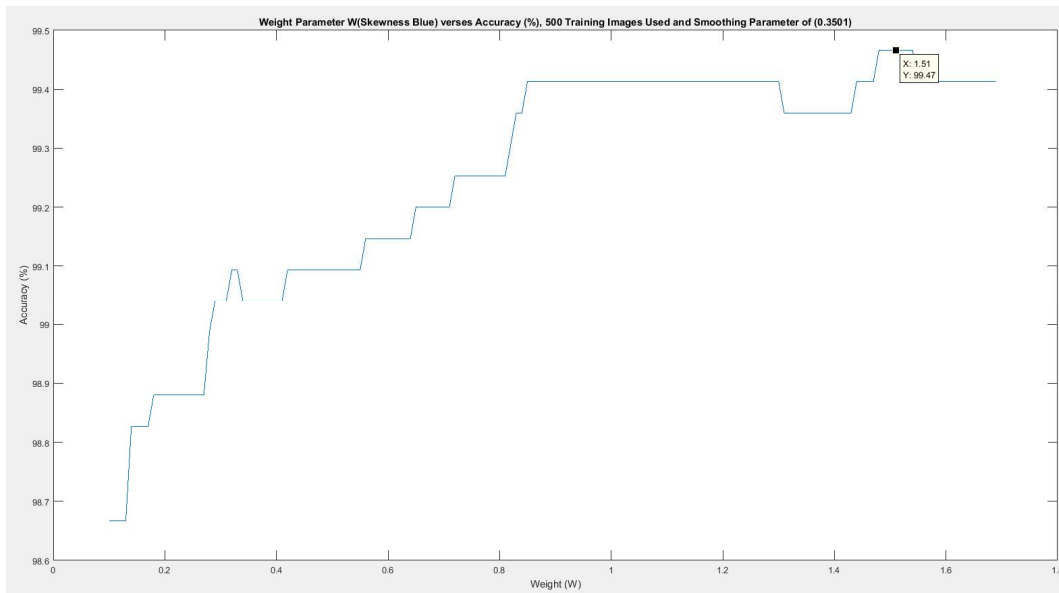
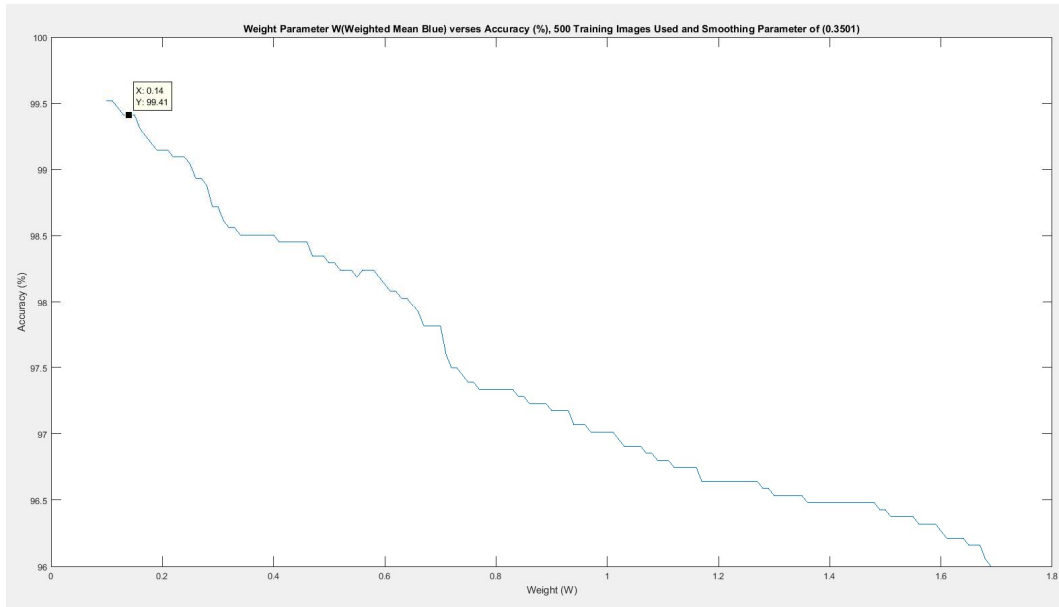












## Appendix M – Image Vector Database

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.098153	0.3946	0.03817	0.095655	0.27574	0.061343	0.10197	0.056259	0.038564	Clinker
0.085297	0.45585	0.19002	0.08436	0.31863	0.16299	0.093173	0.067517	0.050761	Clinker
0.063892	0.38133	0.070725	0.065213	0.26833	0.093501	0.079495	0.083935	0.059107	Clinker
0.058025	0.47939	0.15766	0.058742	0.37772	0.17094	0.073026	0.1305	0.081355	Clinker
0.017149	0.45361	0.090224	0.013978	0.34101	0.10695	0.020878	0.11083	0.063928	Clinker
0.057726	0.39065	0.16228	0.055221	0.27758	0.16458	0.055757	0.078658	0.050834	Clinker
0.10729	0.42859	0.17253	0.10799	0.27629	0.13064	0.11245	0.051505	0.035618	Clinker
0.090077	0.39433	0.11761	0.09206	0.27215	0.12211	0.098876	0.065067	0.043068	Clinker
0.082776	0.37965	0.12764	0.085603	0.25845	0.12711	0.091192	0.069723	0.047148	Clinker
0.072928	0.36364	0.057954	0.074367	0.25362	0.079739	0.088684	0.071294	0.052022	Clinker
0.057214	0.34309	0.039497	0.057483	0.2336	0.068069	0.071045	0.066208	0.050455	Clinker
0.054119	0.30244	0.047695	0.054127	0.17872	0.069997	0.063942	0.042699	0.036607	Clinker
0.028957	0.76336	0.50249	0.052588	0.58764	0.35376	0.033907	0.17934	0.10168	Clinker
0.014915	0.7848	0.50107	0.0068614	0.65903	0.41937	0.0065669	0.19976	0.10974	Clinker
0.014915	0.7848	0.50107	0.0068614	0.65903	0.41937	0.0065669	0.19976	0.10974	Clinker
0.087332	0.32712	0.088945	0.087236	0.21489	0.10441	0.095602	0.054852	0.043879	Clinker
0.086146	0.32618	0.088613	0.086112	0.21415	0.10478	0.094704	0.055256	0.044244	Clinker
0.077484	0.31342	0.072004	0.079551	0.21626	0.10517	0.095127	0.076423	0.059438	Clinker
0.0664	0.42926	0.10423	0.068	0.31857	0.11661	0.084882	0.10034	0.065924	Clinker
0.073739	0.37069	0.10164	0.075775	0.26117	0.12588	0.080842	0.077194	0.056293	Clinker
0.065726	0.33294	0.058049	0.065843	0.22558	0.087368	0.072339	0.061633	0.046223	Clinker
0.057114	0.37758	0.10574	0.056255	0.26585	0.11752	0.06785	0.08344	0.059414	Clinker
0.054319	0.54935	0.24146	0.049139	0.43355	0.22568	0.045797	0.10672	0.063645	Clinker
0.092886	0.31936	0.069303	0.093558	0.20752	0.088558	0.10439	0.055703	0.045395	Clinker
0.091937	0.2799	0.056058	0.093993	0.1688	0.0822	0.10268	0.047037	0.042678	Clinker
0.084336	0.25371	0.041558	0.085798	0.14424	0.071023	0.08768	0.041064	0.036025	Clinker
0.068135	0.33272	0.070061	0.069169	0.22422	0.097541	0.075798	0.074065	0.052568	Clinker
0.071468	0.31444	0.073236	0.072779	0.20511	0.098628	0.081713	0.071493	0.053089	Clinker
0.066937	0.34717	0.034189	0.064944	0.24285	0.065321	0.071864	0.067411	0.04596	Clinker
0.06972	0.44059	0.18613	0.066921	0.30859	0.15835	0.06653	0.067896	0.04223	Clinker
0.088342	0.36862	0.035706	0.086562	0.25984	0.058533	0.094335	0.070999	0.04998	Clinker
0.14362	0.23255	0.013553	0.14451	0.12549	0.043459	0.13722	0.020652	0.022926	Clinker
0.13808	0.32294	0.069706	0.13864	0.20266	0.08298	0.13634	0.038595	0.030591	Clinker
0.11667	0.32493	0.054352	0.11745	0.19908	0.070941	0.11456	0.042383	0.03295	Clinker
0.12112	0.7513	0.61231	0.1179	0.57511	0.42562	0.121	0.13995	0.091127	Clinker
0.12552	0.7548	0.62382	0.12246	0.57562	0.43014	0.12631	0.13653	0.090302	Clinker
0.1357	0.19606	0.024238	0.136	0.086028	0.048032	0.13434	0.017727	0.024258	Clinker
0.11645	0.69275	0.48076	0.11098	0.52171	0.33627	0.11258	0.12997	0.081418	Clinker
0.10207	0.34448	0.17071	0.096824	0.21928	0.14986	0.080446	0.034612	0.022018	Clinker
0.10744	0.46477	0.24781	0.099491	0.32342	0.20312	0.085383	0.046693	0.027406	Clinker
0.054356	0.42248	0.099465	0.052749	0.29953	0.10505	0.06154	0.081431	0.050598	Clinker
0.041288	0.37675	0.069682	0.041783	0.26432	0.092947	0.055572	0.084595	0.06097	Clinker
0.05151	0.24699	0.068853	0.052225	0.12192	0.089317	0.054885	0.035337	0.032263	Clinker
0.040315	0.37247	0.16772	0.040509	0.24025	0.15925	0.047402	0.071728	0.050941	Clinker
0.037956	0.34204	0.14403	0.038082	0.21315	0.13604	0.048548	0.062285	0.051319	Clinker
0.064316	0.5382	0.209	0.059596	0.40888	0.18442	0.058582	0.095497	0.055813	Clinker
0.13193	0.82025	0.44787	0.12424	0.67844	0.34498	0.11031	0.19838	0.1051	Clinker
0.06479	0.50585	0.26319	0.062052	0.38578	0.23967	0.064259	0.096765	0.064639	Clinker
0.049975	0.32547	0.044733	0.050037	0.20556	0.068562	0.060721	0.061658	0.04577	Clinker
0.050499	0.35104	0.026276	0.050532	0.24028	0.057241	0.063784	0.072431	0.04884	Clinker
0.047192	0.33798	0.07724	0.04794	0.22386	0.096823	0.064602	0.073035	0.058467	Clinker
0.049388	0.79411	0.7244	0.050037	0.59418	0.47279	0.056628	0.15791	0.10462	Clinker
0.067748	0.45195	0.21063	0.067251	0.32235	0.1701	0.069884	0.075662	0.051935	Clinker
0.044221	0.35143	0.05113	0.042517	0.25282	0.082385	0.050898	0.084144	0.055426	Clinker
0.093497	0.68036	0.34637	0.088674	0.54577	0.27131	0.089978	0.14715	0.082445	Clinker
0.042224	0.75876	0.58544	0.036584	0.64141	0.47177	0.045295	0.21003	0.14088	Clinker
0.04658	0.35461	0.071814	0.046397	0.23968	0.090301	0.047492	0.057911	0.036188	Clinker
0.06348	0.44504	0.13683	0.063551	0.31857	0.12802	0.071362	0.086081	0.052736	Clinker
0.054156	0.40901	0.073046	0.054217	0.28069	0.08298	0.059321	0.071082	0.044125	Clinker
0.067299	0.40496	0.098849	0.061333	0.27997	0.11036	0.054727	0.07049	0.043492	Clinker
0.020407	0.70444	0.51322	0.016779	0.59621	0.44154	0.019688	0.20362	0.13	Clinker
0.043585	0.40063	0.088992	0.03997	0.28483	0.09912	0.044276	0.068914	0.045692	Clinker
0.066313	0.42606	0.089111	0.064479	0.31399	0.10322	0.067269	0.084361	0.050917	Clinker
0.058075	0.34773	0.088187	0.055326	0.241	0.10903	0.062886	0.061101	0.046126	Clinker
0.052234	0.42346	0.14424	0.047371	0.31979	0.15306	0.053724	0.093716	0.059175	Clinker
0.052234	0.42346	0.14424	0.047371	0.31979	0.15306	0.053724	0.093716	0.059175	Clinker
0.062494	0.45451	0.13699	0.061933	0.33122	0.13152	0.068827	0.085759	0.051665	Clinker
0.052796	0.43767	0.10164	0.05236	0.31567	0.10642	0.058107	0.08202	0.048239	Clinker
0.019995	0.49659	0.11354	0.017993	0.39262	0.13278	0.025969	0.17031	0.094881	Clinker
0.043135	0.49031	0.091409	0.03618	0.39388	0.11099	0.040933	0.12591	0.065189	Clinker
0.01499	0.45464	0.056722	0.0099026	0.33912	0.075227	0.021649	0.10735	0.062883	Clinker
0.055891	0.40377	0.10347	0.053139	0.29722	0.1193	0.061856	0.085455	0.055613	Clinker
0.061308	0.36971	0.093873	0.05621	0.29244	0.12564	0.064655	0.094897	0.059925	Clinker
0.055866	0.41025	0.11577	0.055521	0.29811	0.12869	0.061777	0.078746	0.049495	Clinker
0.036895	0.40439	0.12418	0.038067	0.28505	0.13317	0.043978	0.083266	0.054757	Clinker
0.046168	0.97268	0.82837	0.043326	0.8233	0.6294	0.048284	0.23666	0.15316	Clinker
0.075624	0.46305	0.27866	0.07573	0.28331	0.20017	0.070966	0.045659	0.033858	Clinker
0.02163	0.50442	0.14124	0.018172	0.38478	0.13723	0.023136	0.12107	0.064926	Clinker
0.028832	0.3896	0.079823	0.025633	0.27722	0.096413	0.034783	0.094976	0.061656	Clinker
0.014254	0.43173	0.097688	0.0089738	0.31788	0.11118	0.013332	0.097616	0.057354	Clinker
0.007988	0.52375	0.18393	0	0.42538	0.1917	0	0.13527	0.073459	Clinker
0.094533	0.45836	0.21703	0.092404	0.34197	0.19465	0.0918	0.097086	0.059299	Clinker
0.069808	0.43265	0.13029	0.071041	0.30953	0.12833	0.078386	0.091987	0.058192	Clinker
0.061495	0.40654	0.11314	0.061723	0.27938	0.11063	0.070623	0.063863	0.043324	Clinker
0.070906	0.48899	0.16758	0.06836	0.36337	0.15466	0.074082	0.088148	0.053658	Clinker
0.063305	0.43431	0.10816	0.061169	0.31805	0.11557	0.071653	0.092022	0.05911	Clinker
0.045694	0.38543	0.1029	0.045049	0.27103	0.11241	0.057024	0.08602	0.059643	Clinker
0.032751	0.47182	0.18384	0.02797	0.3526	0.17334	0.026545	0.092856	0.051365	Clinker
0.14305	0.75101	0.61406	0.13984	0.57593	0.42741	0.13901	0.13704	0.082565	Clinker



Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.076173	0.334	0.094252	0.077363	0.20748	0.095593	0.085964	0.051556	0.037149	Clinker
0.072067	0.35143	0.056295	0.072689	0.23786	0.077627	0.083429	0.069768	0.047728	Clinker
0.083774	0.4176	0.13382	0.081678	0.29728	0.13296	0.087179	0.065571	0.047287	Clinker
0.07525	0.36755	0.039994	0.073288	0.25608	0.068213	0.071758	0.067595	0.039859	Clinker
0.064803	0.35397	0.052291	0.065049	0.24705	0.080231	0.079865	0.078737	0.056232	Clinker
0.052746	0.36703	0.067597	0.05197	0.26145	0.093952	0.062965	0.082385	0.055725	Clinker
0.041338	0.44694	0.13005	0.037288	0.34763	0.1465	0.043526	0.10834	0.063906	Clinker
0.12912	0.50255	0.26044	0.1267	0.38669	0.23651	0.12267	0.090615	0.063889	Clinker
0.076435	0.35361	0.030162	0.076075	0.23331	0.055395	0.083192	0.063387	0.043548	Clinker
0.041263	0.43444	0.11427	0.039341	0.3045	0.117	0.048548	0.086541	0.052904	Clinker
0.042649	0.40376	0.08295	0.041768	0.28917	0.1014	0.054542	0.092074	0.058021	Clinker
0.062019	0.44978	0.052765	0.059026	0.34802	0.079288	0.064074	0.11351	0.063083	Clinker
0.070332	0.28015	0.068284	0.064899	0.15674	0.081421	0.060827	0.036325	0.025989	Clinker
0.081553	0.3372	0.18557	0.075521	0.18199	0.14621	0.065976	0.024047	0.016604	Clinker
0.079081	0.55342	0.20218	0.076839	0.44517	0.18913	0.083297	0.13854	0.079918	Clinker
0.035696	0.37146	0.11555	0.033828	0.25258	0.1299	0.033907	0.075397	0.047703	Clinker
0.060896	0.36707	0.071554	0.058532	0.25791	0.095264	0.057156	0.055554	0.037222	Clinker
0.035584	0.39342	0.044235	0.031985	0.28123	0.070449	0.035557	0.078807	0.046764	Clinker
0.032664	0.47124	0.11726	0.030187	0.34034	0.1031	0.038528	0.099979	0.062226	Clinker
0.056403	0.39187	0.074444	0.055266	0.25604	0.080949	0.058529	0.065216	0.045072	Clinker
0.061246	0.39467	0.077335	0.059296	0.2619	0.081975	0.068062	0.06487	0.047596	Clinker
0.077197	0.32271	0.097	0.076509	0.18356	0.098648	0.079653	0.031236	0.03155	Clinker
0.074151	0.32225	0.073331	0.073288	0.20642	0.089296	0.073686	0.042646	0.033741	Clinker
0.077446	0.3639	0.10868	0.07624	0.255	0.12024	0.078307	0.057205	0.041809	Clinker
0.054868	0.66725	0.35763	0.048674	0.55205	0.29613	0.044807	0.1512	0.078029	Clinker
0.035959	0.35105	0.060015	0.032509	0.24158	0.084128	0.034466	0.073207	0.044741	Clinker
0.054656	0.37914	0.079752	0.053678	0.25483	0.094649	0.053724	0.053993	0.034006	Clinker
0.041413	0.51177	0.17455	0.041139	0.38659	0.15673	0.048363	0.099388	0.057634	Clinker
0.029943	0.36198	0.11676	0.02797	0.2641	0.13915	0.035539	0.086793	0.056076	Clinker
0.043984	0.45695	0.21357	0.038262	0.3626	0.21422	0.036584	0.11117	0.06273	Clinker
0.062394	0.4738	0.25432	0.059131	0.34339	0.21859	0.051215	0.075368	0.043852	Clinker
0.045082	0.3583	0.085557	0.038891	0.22214	0.082959	0.031668	0.043848	0.027387	Clinker
0.054805	0.43228	0.21663	0.049318	0.28889	0.17947	0.039578	0.043036	0.024265	Clinker
0.067386	0.57776	0.31057	0.064614	0.41149	0.22642	0.059031	0.076656	0.042873	Clinker
0.075462	0.35907	0.10965	0.07564	0.22067	0.097664	0.083931	0.050317	0.039718	Clinker
0.056827	0.51657	0.21246	0.054816	0.36881	0.17187	0.053301	0.087427	0.04999	Clinker
0.071555	0.30275	0.033313	0.070277	0.19429	0.064501	0.0669	0.04851	0.032494	Clinker
0.020706	0.56669	0.22338	0.01612	0.45561	0.20197	0.023738	0.13288	0.07502	Clinker
0.082152	0.51891	0.32531	0.078352	0.39288	0.26709	0.079521	0.099623	0.068994	Clinker
0.082813	0.5178	0.32367	0.079596	0.39402	0.26889	0.077198	0.10023	0.069179	Clinker
0.062481	0.397	0.13709	0.056704	0.27032	0.12597	0.053512	0.05131	0.033298	Clinker
0.05689	0.46533	0.17526	0.051835	0.33323	0.15191	0.047085	0.058135	0.03415	Clinker
0.071867	0.36261	0.090248	0.072285	0.23681	0.096228	0.078412	0.061958	0.043579	Clinker
0.084136	0.43489	0.1699	0.084584	0.28782	0.1368	0.090242	0.052803	0.03891	Clinker
0.066425	0.46782	0.20483	0.067416	0.32049	0.16551	0.073765	0.070322	0.045473	Clinker
0.1357	0.56052	0.2144	0.13462	0.43988	0.18382	0.12483	0.1055	0.054669	Clinker
0.1324	0.46614	0.15206	0.13308	0.34266	0.13442	0.13642	0.090546	0.057459	Clinker
0.10054	0.40533	0.11686	0.10201	0.29856	0.12461	0.11131	0.084517	0.058849	Clinker
0.095507	0.45437	0.12491	0.096899	0.35389	0.13749	0.10738	0.10615	0.068437	Clinker
0.096742	0.50738	0.17282	0.097213	0.40024	0.16783	0.10439	0.12124	0.073038	Clinker
0.097554	0.43313	0.13636	0.097723	0.32538	0.1403	0.10257	0.096313	0.060509	Clinker
0.085172	0.48957	0.17469	0.085468	0.3632	0.1594	0.098427	0.096001	0.064159	Clinker
0.091013	0.48402	0.18888	0.092105	0.36327	0.17166	0.10315	0.10564	0.071363	Clinker
0.098452	0.39777	0.15495	0.099491	0.27594	0.15027	0.10999	0.075444	0.058533	Clinker
0.10293	0.35998	0.091669	0.10274	0.22165	0.082139	0.10936	0.044971	0.040772	Clinker
0.091712	0.52181	0.23272	0.089873	0.37875	0.18985	0.09143	0.08225	0.049783	Clinker
0.10989	0.3253	0.091788	0.10951	0.20771	0.10158	0.10788	0.045444	0.035489	Clinker
0.10353	0.45828	0.22234	0.10195	0.33339	0.18206	0.10128	0.075034	0.050773	Clinker
0.12458	0.4061	0.10707	0.12587	0.29235	0.10821	0.12861	0.078968	0.052495	Clinker
0.10041	0.46259	0.18692	0.10166	0.33989	0.16461	0.11427	0.11287	0.076091	Clinker
0.077409	0.41373	0.12887	0.078517	0.30245	0.13384	0.086968	0.097017	0.064714	Clinker
0.087019	0.40593	0.13761	0.087925	0.30215	0.14045	0.095444	0.081062	0.055243	Clinker
0.087943	0.40892	0.12148	0.089948	0.2984	0.12859	0.099932	0.098164	0.065644	Clinker
0.098228	0.40843	0.12072	0.10079	0.29727	0.13048	0.11467	0.10285	0.071241	Clinker
0.13586	0.45814	0.14967	0.13684	0.32248	0.12937	0.14234	0.079362	0.05241	Clinker
0.12111	0.48728	0.14015	0.12033	0.37032	0.13239	0.11987	0.090502	0.05258	Clinker
0.13226	0.32751	0.13178	0.13293	0.20912	0.12281	0.12813	0.04297	0.037897	Clinker
0.11664	0.44395	0.16896	0.11946	0.32686	0.15837	0.12383	0.081591	0.053588	Clinker
0.14216	0.64385	0.27063	0.13994	0.51161	0.21945	0.14363	0.13892	0.074842	Clinker
0.058862	0.44374	0.12053	0.057333	0.33496	0.12912	0.063493	0.097677	0.059993	Clinker
0.04839	0.38088	0.083685	0.046172	0.26201	0.096762	0.049869	0.066967	0.044543	Clinker
0.035946	0.42906	0.11972	0.033333	0.30016	0.11809	0.038712	0.075201	0.048651	Clinker
0.06514	0.26871	0.067952	0.066412	0.15276	0.09026	0.074768	0.042193	0.041045	Clinker
0.05498	0.40732	0.1663	0.053468	0.26348	0.13011	0.061434	0.058484	0.04587	Clinker
0.043647	0.56141	0.32128	0.041318	0.40611	0.23438	0.045219	0.11578	0.070825	Clinker
0.13248	0.49885	0.15749	0.13125	0.36622	0.13643	0.12528	0.080246	0.046126	Clinker
0.13864	0.48109	0.15097	0.13766	0.34861	0.13187	0.13315	0.075849	0.045673	Clinker
0.10669	0.35203	0.11704	0.10733	0.23333	0.11417	0.11126	0.051237	0.040285	Clinker
0.031515	0.44156	0.15567	0.028899	0.30931	0.14088	0.030767	0.076315	0.049439	Clinker
0.031603	0.42727	0.15993	0.028779	0.30084	0.14693	0.033173	0.081397	0.053043	Clinker
0.05161	0.48063	0.19656	0.050652	0.36895	0.18438	0.058292	0.12252	0.080464	Clinker
0.075524	0.32071	0.067929	0.074562	0.21146	0.088681	0.07894	0.059658	0.043643	Clinker
0.072466	0.43233	0.19175	0.071086	0.29701	0.16081	0.074399	0.06985	0.046613	Clinker
0.078033	0.3347	0.076032	0.077169	0.20623	0.0846	0.08034	0.046154	0.035022	Clinker
0.089329	0.47085	0.18831	0.088719	0.34208	0.17102	0.09246	0.077134	0.05034	Clinker
0.10815	0.37806	0.13602	0.10935	0.25398	0.12755	0.11461	0.054134	0.044568	Clinker
0.087893	0.37141	0.11136	0.089213	0.25388	0.1128	0.09584	0.066825	0.051616	Clinker
0.071455	0.4338	0.15202	0.073109	0.31571	0.14512	0.086175	0.10461	0.072534	Clinker
0.07495	0.34188	0.071033	0.077648	0.23818	0.098423	0.092275	0.079809	0.06273	Clinker

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.086221	0.37998	0.12738	0.090562	0.26153	0.13173	0.10307	0.07889	0.062934	Clinker
0.085459	0.42981	0.1451	0.08764	0.30835	0.14276	0.10099	0.10239	0.071171	Clinker
0.072841	0.45861	0.12349	0.071041	0.34602	0.12683	0.080472	0.11382	0.070017	Clinker
0.048852	0.44269	0.10501	0.046037	0.31369	0.10646	0.052641	0.084717	0.055587	Clinker
0.059199	0.33843	0.040042	0.058172	0.22638	0.072705	0.062913	0.061266	0.046883	Clinker
0.051136	0.3557	0.066412	0.050487	0.23818	0.08583	0.059242	0.059894	0.048429	Clinker
0.13048	0.44859	0.073354	0.13091	0.33907	0.08138	0.13315	0.081228	0.04764	Clinker
0.13925	0.42833	0.068521	0.13984	0.31625	0.075719	0.13912	0.076919	0.046868	Clinker
0.10402	0.47478	0.21855	0.1031	0.36205	0.19039	0.10476	0.10565	0.066009	Clinker
0.078744	0.58525	0.31678	0.080839	0.44987	0.25815	0.093331	0.14083	0.093311	Clinker
0.075699	0.34603	0.14451	0.078592	0.22422	0.14812	0.086017	0.074045	0.056407	Clinker
0.057851	0.33732	0.12055	0.060674	0.21971	0.13429	0.070016	0.08093	0.059777	Clinker
0.053158	0.36354	0.075297	0.054472	0.25557	0.099346	0.069672	0.095202	0.069264	Clinker
0.068285	0.35916	0.06781	0.069873	0.24786	0.090137	0.081317	0.071965	0.054788	Clinker
0.081128	0.38516	0.15775	0.08433	0.26126	0.15105	0.096658	0.079754	0.061476	Clinker
0.031702	0.3331	0.081221	0.030337	0.21782	0.10195	0.041231	0.063146	0.049398	Clinker
0.081653	0.34669	0.11882	0.082412	0.2058	0.11403	0.087232	0.035914	0.035007	Clinker
0.07661	0.43207	0.1382	0.078367	0.30781	0.13321	0.08937	0.093655	0.063433	Clinker
0.083412	0.48898	0.20082	0.086052	0.37614	0.18768	0.10057	0.122	0.080283	Clinker
0.073952	0.43162	0.16799	0.074607	0.30829	0.15769	0.081845	0.10239	0.067672	Clinker
0.093797	0.22218	0.064019	0.09197	0.10366	0.080888	0.080498	0.023555	0.021531	Clinker
0.075225	0.30543	0.048453	0.072554	0.18981	0.073935	0.066081	0.047432	0.03339	Clinker
0.057239	0.5133	0.15645	0.055131	0.38418	0.1475	0.060563	0.11696	0.068325	Clinker
0.059673	0.45448	0.12989	0.0597	0.33828	0.13821	0.071864	0.1052	0.068692	Clinker
0.073914	0.53772	0.21997	0.075341	0.41219	0.1933	0.091958	0.11331	0.072804	Clinker
0.080916	0.57792	0.27406	0.082831	0.4506	0.23171	0.10307	0.13059	0.088111	Clinker
0.086533	0.6201	0.34417	0.089184	0.47718	0.27501	0.10725	0.1345	0.088011	Clinker
0.080467	0.52372	0.29906	0.084255	0.39081	0.24051	0.10284	0.13975	0.098645	Clinker
0.074601	0.51118	0.25847	0.078202	0.38368	0.2209	0.099695	0.13795	0.097593	Clinker
0.061633	0.48651	0.21995	0.065109	0.36376	0.19955	0.081026	0.13669	0.093998	Clinker
0.051735	0.44517	0.1595	0.053558	0.33143	0.1588	0.075032	0.13362	0.096203	Clinker
0.044733	0.52918	0.21876	0.043551	0.41568	0.20285	0.060087	0.15943	0.10321	Clinker
0.042361	0.51975	0.33469	0.041498	0.40395	0.29024	0.051374	0.15545	0.11118	Clinker
0.038967	0.47762	0.35597	0.038157	0.36419	0.2982	0.053011	0.13664	0.11154	Clinker
0.015814	0.39707	0.12977	0.014951	0.28438	0.14432	0.026392	0.10721	0.070825	Clinker
0.0665	0.45457	0.24885	0.068989	0.32312	0.20365	0.085357	0.096974	0.072166	Clinker
0.055829	0.43311	0.20274	0.058547	0.30785	0.17736	0.076775	0.093308	0.071497	Clinker
0.058225	0.34766	0.10565	0.061708	0.23755	0.12197	0.080921	0.076537	0.064794	Clinker
0.064591	0.53747	0.24416	0.067506	0.41253	0.21028	0.085779	0.13575	0.091319	Clinker
0.066375	0.45282	0.16815	0.069933	0.33131	0.1612	0.087232	0.12196	0.086122	Clinker
0.062893	0.3365	0.073212	0.065633	0.23067	0.1014	0.084433	0.091075	0.073474	Clinker
0.052222	0.39472	0.18121	0.05203	0.29954	0.18448	0.065764	0.10601	0.080717	Clinker
0.040577	0.52828	0.174	0.038157	0.41141	0.16313	0.050159	0.12346	0.075263	Clinker
0.036121	0.5343	0.17687	0.033678	0.41741	0.16588	0.041926	0.13219	0.079132	Clinker
0.039616	0.53336	0.17597	0.036554	0.41726	0.16541	0.048707	0.12952	0.07986	Clinker
0.07012	0.43642	0.26304	0.072464	0.31574	0.23185	0.086888	0.08503	0.064665	Clinker
0.026922	0.47244	0.179	0.029124	0.35876	0.17472	0.047915	0.13102	0.093347	Clinker
0.067049	0.47463	0.22629	0.070577	0.34809	0.20187	0.087179	0.10294	0.073987	Clinker
0.057801	0.42587	0.14313	0.060404	0.30224	0.14379	0.073184	0.099684	0.06934	Clinker
0.041775	0.46335	0.25224	0.043086	0.34937	0.23272	0.054357	0.11343	0.081116	Clinker
0.045282	0.3427	0.1107	0.045243	0.23281	0.12892	0.058054	0.083431	0.065851	Clinker
0.056041	0.31977	0.093186	0.056944	0.20072	0.11424	0.063784	0.059782	0.04801	Clinker
0.05186	0.35535	0.094963	0.05167	0.24339	0.11532	0.0622	0.079023	0.058304	Clinker
0.037668	0.39723	0.17322	0.039371	0.28778	0.17638	0.054648	0.10133	0.072274	Clinker
0.058862	0.90372	0.84538	0.06003	0.67884	0.54659	0.071864	0.17077	0.11159	Clinker
0.083862	0.59137	0.2955	0.085528	0.44845	0.2271	0.10067	0.12567	0.079066	Clinker
0.077983	0.56213	0.31661	0.077753	0.42654	0.24888	0.090664	0.12553	0.083127	Clinker
0.03345	0.48523	0.13489	0.030322	0.38275	0.14153	0.041216	0.12944	0.077206	Clinker
0.058562	0.47458	0.26878	0.060719	0.33677	0.22466	0.073316	0.10223	0.072193	Clinker
0.05166	0.32776	0.09475	0.055041	0.21616	0.11856	0.064602	0.078299	0.061289	Clinker
0.10301	0.39866	0.10837	0.10686	0.27432	0.11206	0.11834	0.074314	0.054041	Clinker
0.07354	0.51737	0.169	0.074697	0.40346	0.16153	0.087126	0.13392	0.08133	Clinker
0.069321	0.49807	0.21547	0.071056	0.37306	0.18058	0.087284	0.12829	0.086871	Clinker
0.071418	0.37429	0.12693	0.074816	0.26199	0.13698	0.093938	0.088252	0.070635	Clinker
0.064416	0.37857	0.09674	0.066787	0.26981	0.11581	0.074795	0.085638	0.06076	Clinker
0.087257	0.35554	0.070653	0.090757	0.24319	0.090629	0.097186	0.070215	0.051433	Clinker
0.07968	0.35678	0.072881	0.081978	0.24964	0.095511	0.095232	0.079023	0.059246	Clinker
0.086108	0.51821	0.32905	0.089678	0.38159	0.2506	0.10397	0.11958	0.08553	Clinker
0.069071	0.41154	0.16727	0.072884	0.28257	0.15355	0.088948	0.092118	0.069917	Clinker
0.036982	0.4249	0.12626	0.038801	0.31325	0.14213	0.049604	0.1081	0.072356	Clinker
0.025	0.30643	0.14351	0.026622	0.17698	0.14943	0.036582	0.056615	0.050686	Clinker
0.029818	0.38648	0.17199	0.030367	0.26072	0.17728	0.037012	0.075246	0.053396	Clinker
0.055292	0.43892	0.14728	0.058172	0.32555	0.15207	0.070834	0.099397	0.069591	Clinker
0.070045	0.33891	0.060797	0.072704	0.22934	0.089419	0.088156	0.062352	0.052431	Clinker
0.090739	0.39923	0.097759	0.094232	0.27983	0.10741	0.10672	0.081928	0.057712	Clinker
0.098452	0.38775	0.11065	0.10244	0.27056	0.11949	0.1195	0.074283	0.057895	Clinker
0.092212	0.47136	0.16931	0.09561	0.34477	0.15285	0.10498	0.10466	0.068551	Clinker
0.065951	0.42972	0.15585	0.068434	0.30842	0.13827	0.082399	0.085412	0.06141	Clinker
0.042312	0.52328	0.18549	0.043625	0.42838	0.19088	0.060774	0.15911	0.101	Clinker
0.042312	0.52328	0.18549	0.043625	0.42838	0.19088	0.060774	0.15911	0.101	Clinker
0.0081128	0.3221	0.036914	0.0082247	0.19863	0.065321	0.0188	0.068368	0.055523	Clinker
0.062731	0.36129	0.055537	0.065768	0.24675	0.081872	0.076062	0.071988	0.051718	Clinker
0.079169	0.34571	0.094584	0.083895	0.23781	0.1177	0.1008	0.077479	0.061863	Clinker
0.077459	0.47179	0.19263	0.082277	0.34777	0.17673	0.09547	0.095853	0.06544	Clinker
0.074688	0.42948	0.22736	0.079281	0.29116	0.17888	0.089951	0.072617	0.057257	Clinker
0.045532	0.4354	0.22047	0.047176	0.3191	0.20679	0.057315	0.092535	0.066146	Clinker
0.045519	0.43309	0.16296	0.046861	0.32893	0.16908	0.057368	0.1131	0.073272	Clinker
0.019483	0.36108	0.076458	0.01976	0.23761	0.091265	0.03171	0.088991	0.062964	Clinker
0.012332	0.4758	0.11242	0.011431	0.35233	0.11631	0.025814	0.12814	0.079241	Clinker

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.070282	0.46143	0.14339	0.07164	0.3547	0.15657	0.077673	0.099692	0.060685	Clinker
0.060534	0.42189	0.085959	0.061363	0.31659	0.10987	0.073131	0.10337	0.064697	Clinker
0.065077	0.45847	0.13647	0.0677	0.34587	0.14266	0.081264	0.1166	0.075334	Clinker
0.062519	0.41917	0.096621	0.064075	0.30691	0.11216	0.074108	0.108	0.070905	Clinker
0.058887	0.51955	0.12704	0.055266	0.39998	0.12796	0.05742	0.099918	0.055672	Clinker
0.03345	0.55021	0.1971	0.029948	0.42621	0.17794	0.035211	0.12219	0.069386	Clinker
0.043298	0.43897	0.10086	0.040404	0.31699	0.10788	0.0382	0.083279	0.049344	Clinker
0.085172	0.3679	0.0081031	0.083491	0.25112	0.038536	0.075191	0.053793	0.033118	Clinker
0.075574	0.31008	0.013008	0.073648	0.1844	0.041592	0.070993	0.038471	0.029517	Clinker
0.075412	0.46956	0.13787	0.076989	0.36497	0.14867	0.087152	0.12375	0.075998	Clinker
0.075374	0.44729	0.10904	0.077933	0.34008	0.12447	0.08945	0.10351	0.064152	Clinker
0.077097	0.38868	0.11133	0.080285	0.27634	0.1239	0.091087	0.072563	0.051711	Clinker
0.072941	0.49431	0.21267	0.077049	0.35965	0.18214	0.085885	0.1079	0.07072	Clinker
0.065826	0.4939	0.15557	0.067745	0.38654	0.1619	0.07931	0.11074	0.072468	Clinker
0.068023	0.40597	0.040421	0.068165	0.29922	0.067782	0.079125	0.086029	0.05621	Clinker
0.072204	0.45257	0.11197	0.073124	0.33681	0.1193	0.081264	0.09005	0.06209	Clinker
0.053882	0.30792	0.10055	0.0557	0.17694	0.11149	0.064655	0.048555	0.04624	Clinker
0.070419	0.58728	0.28003	0.072719	0.45255	0.23561	0.082373	0.11707	0.072123	Clinker
0.074413	0.39713	0.08404	0.076375	0.28491	0.10113	0.091034	0.092083	0.065544	Clinker
0.061633	0.36829	0.066365	0.063985	0.26869	0.098382	0.077145	0.098207	0.070165	Clinker
0.069109	0.41222	0.1057	0.072	0.29607	0.11614	0.083429	0.083831	0.057323	Clinker
0.048989	0.26338	0.030327	0.050172	0.1429	0.059825	0.059929	0.039692	0.041624	Clinker
0.028894	0.50761	0.24203	0.030547	0.35655	0.19075	0.043222	0.1215	0.081471	Clinker
0.037606	0.41739	0.19902	0.039431	0.27619	0.17418	0.053697	0.07589	0.059657	Clinker
0.046256	0.39084	0.10326	0.049154	0.28302	0.12209	0.066688	0.098893	0.072702	Clinker
0.075924	0.49845	0.2154	0.078277	0.36962	0.19215	0.087073	0.090563	0.060901	Clinker
0.081078	0.42243	0.10169	0.0837	0.31369	0.11988	0.093938	0.091423	0.061758	Clinker
0.06187	0.3666	0.077951	0.06391	0.25522	0.096167	0.077937	0.072887	0.053868	Clinker
0.068734	0.46853	0.10913	0.070637	0.35557	0.121	0.083588	0.1197	0.073084	Clinker
0.030879	0.53845	0.27534	0.031835	0.39017	0.22109	0.043566	0.14034	0.090647	Clinker
0.036982	0.40193	0.16223	0.038352	0.27134	0.15408	0.051822	0.076099	0.057834	Clinker
0.15261	0.35791	0.12645	0.15622	0.2548	0.13189	0.15583	0.053166	0.035148	Clinker
0.25691	0.21703	0.2257	0.26443	0.12642	0.16955	0.24355	0.013494	0.0033583	Clinker
0.27426	0.22538	0.22885	0.28238	0.13445	0.16957	0.2694	0.015648	0.0041403	Clinker
0.27148	0.22476	0.22843	0.27957	0.1336	0.17002	0.26562	0.015761	0.0040938	Clinker
0.27359	0.23178	0.23331	0.28208	0.13881	0.17482	0.26813	0.016763	0.00456	Clinker
0.30768	0.16469	0.22717	0.31738	0.066769	0.15632	0.30418	0.0089676	0.0040697	Clinker
0.30685	0.15553	0.21952	0.31727	0.057342	0.15456	0.30037	0.0081103	0.0038097	Clinker
0.27061	0.32811	0.23565	0.28135	0.21526	0.19036	0.28485	0.04454	0.03025	Clinker
0.24284	0.39515	0.23231	0.25431	0.26455	0.17833	0.26694	0.063891	0.045989	Clinker
0.21791	0.29592	0.060015	0.23193	0.18101	0.077422	0.25123	0.051248	0.053398	Clinker
0.20597	0.27893	0.071862	0.21676	0.17426	0.090835	0.23536	0.05664	0.057116	Clinker
0.15538	0.33099	0.095389	0.16142	0.23566	0.11311	0.17199	0.078048	0.060643	Clinker
0.11656	0.35945	0.11994	0.11861	0.26649	0.13308	0.12446	0.093951	0.067351	Clinker
0.11565	0.35934	0.1178	0.11745	0.26743	0.13224	0.12267	0.094368	0.066839	Clinker
0.2393	0.20163	0.091006	0.24706	0.097281	0.091019	0.24498	0.018408	0.021001	Clinker
0.27676	0.13179	0.15131	0.28496	0.032294	0.12291	0.2798	0.0056754	0.0091877	Clinker
0.30874	0.087915	0.1714	0.31897	0	0.1159	0.30721	0	0	Clinker
0.29322	0.1958	0.17744	0.30454	0.1101	0.15948	0.30771	0.018922	0.016093	Clinker
0.23733	0.28731	0.054732	0.25309	0.16986	0.071002	0.27645	0.037524	0.041454	Clinker
0.21306	0.37905	0.091717	0.22801	0.27091	0.1062	0.25691	0.093829	0.07334	Clinker
0.21008	0.40692	0.12671	0.22403	0.30035	0.13335	0.24865	0.10483	0.07714	Clinker
0.20149	0.42785	0.17088	0.21324	0.32619	0.16834	0.23431	0.13872	0.10152	Clinker
0.17072	0.44284	0.15427	0.1785	0.34537	0.15667	0.19729	0.12543	0.086811	Clinker
0.1594	0.43078	0.16372	0.16599	0.33103	0.16202	0.18232	0.12277	0.087989	Clinker
0.15171	0.44241	0.17403	0.15724	0.34259	0.1694	0.17508	0.12682	0.090343	Clinker
0.15505	0.36975	0.12645	0.16081	0.27274	0.13628	0.16716	0.087462	0.063375	Clinker
0.26595	0.1597	0.093115	0.2764	0.060972	0.093788	0.27597	0.01496	0.018123	Clinker
0.27023	0.12639	0.10176	0.28145	0.026145	0.09789	0.28213	0.0094063	0.016224	Clinker
0.27178	0.1709	0.13614	0.28375	0.064474	0.11809	0.28477	0.011681	0.013312	Clinker
0.23613	0.33373	0.12512	0.25167	0.22622	0.12162	0.26679	0.063056	0.047404	Clinker
0.19825	0.28677	0.037601	0.2113	0.18482	0.064214	0.23225	0.053892	0.053953	Clinker
0.21348	0.39392	0.099441	0.22399	0.28995	0.10845	0.24484	0.086741	0.065912	Clinker
0.20844	0.39048	0.0621	0.21834	0.28335	0.079431	0.23354	0.099032	0.070854	Clinker
0.21214	0.33647	0.033526	0.22136	0.23226	0.056297	0.23753	0.080529	0.063738	Clinker
0.21955	0.30681	0.089703	0.23261	0.20655	0.11132	0.24878	0.051066	0.048198	Clinker
0.21901	0.36405	0.14737	0.23164	0.26329	0.15609	0.24928	0.068877	0.054576	Clinker
0.21568	0.36698	0.11257	0.22948	0.25862	0.11448	0.24986	0.079051	0.058408	Clinker
0.18904	0.43038	0.11079	0.20256	0.3124	0.10948	0.22723	0.093221	0.067095	Clinker
0.20813	0.42598	0.065986	0.22015	0.31692	0.081523	0.23798	0.097903	0.066	Clinker
0.23769	0.46637	0.16396	0.24884	0.35204	0.14746	0.26663	0.12359	0.086102	Clinker
0.24428	0.3195	0.021774	0.25407	0.21446	0.046186	0.2751	0.066924	0.060118	Clinker
0.19504	0.38779	0.075819	0.20382	0.28695	0.094854	0.2191	0.090615	0.061946	Clinker
0.21081	0.32139	0.071767	0.22264	0.21307	0.083574	0.2379	0.061113	0.04903	Clinker
0.22238	0.38566	0.13974	0.23347	0.27347	0.13005	0.2501	0.064723	0.047324	Clinker
0.22054	0.33202	0.12249	0.23053	0.24282	0.13585	0.24447	0.057336	0.048203	Clinker
0.22524	0.40021	0.16303	0.23378	0.29193	0.14914	0.244	0.08283	0.058803	Clinker
0.22092	0.29252	0.049637	0.22879	0.1912	0.067803	0.23312	0.046242	0.038401	Clinker
0.22017	0.32275	0.056201	0.22998	0.2251	0.077278	0.24152	0.069057	0.053817	Clinker
0.23087	0.30487	0.047552	0.24264	0.20386	0.068828	0.26137	0.071082	0.06199	Clinker
0.22717	0.29604	0.01687	0.23961	0.19593	0.047663	0.26074	0.059341	0.054513	Clinker
0.20378	0.42427	0.083874	0.21341	0.33034	0.10349	0.23425	0.11263	0.076152	Clinker
0.17061	0.32121	0.061863	0.1773	0.23199	0.090424	0.18395	0.069564	0.053361	Clinker
0.25361	0.47979	0.26101	0.24608	0.28325	0.14764	0.24226	0.067183	0.042009	Clinker
0.21444	0.30268	0.050111	0.22351	0.19131	0.064993	0.23653	0.041181	0.041023	Clinker
0.23155	0.35781	0.097143	0.2418	0.23977	0.096392	0.26	0.05579	0.048013	Clinker
0.23394	0.31263	0.057314	0.24596	0.20609	0.075822	0.26285	0.054208	0.048054	Clinker
0.22056	0.5192	0.21362	0.23261	0.40563	0.18975	0.25195	0.13785	0.092841	Clinker
0.22243	0.4839	0.13117	0.23368	0.37752	0.13042	0.25812	0.1334	0.085452	Clinker

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.23165	0.38891	0.064967	0.24243	0.29323	0.085441	0.25976	0.084569	0.060125	Clinker
0.20198	0.49504	0.18625	0.21088	0.39188	0.17906	0.23021	0.13607	0.090903	Clinker
0.17988	0.37269	0.099085	0.18725	0.27304	0.11506	0.1984	0.071572	0.05211	Clinker
0.19458	0.39705	0.15754	0.2024	0.28846	0.15199	0.20941	0.081085	0.055061	Clinker
0.24532	0.20493	0.13159	0.2539	0.10601	0.11938	0.24865	0.017916	0.012625	Clinker
0.25492	0.22292	0.13181	0.2631	0.12612	0.13433	0.26288	0.024167	0.026797	Clinker
0.2009	0.28726	0.078306	0.20939	0.18952	0.092311	0.21429	0.051377	0.038493	Clinker
0.13653	0.45004	0.11209	0.14049	0.34197	0.11672	0.15293	0.10002	0.067356	Clinker
0.1481	0.42847	0.12958	0.15335	0.33205	0.13641	0.16763	0.10844	0.073011	Clinker
0.13526	0.30888	0.034924	0.13906	0.21241	0.066449	0.14672	0.052823	0.043538	Clinker
0.2238	0.37888	0.092949	0.23474	0.27775	0.10636	0.25424	0.088591	0.062102	Clinker
0.23947	0.24254	0.029901	0.24899	0.13924	0.051334	0.25826	0.031467	0.036215	Clinker
0.22614	0.27554	0.042008	0.2384	0.1782	0.067905	0.26261	0.056298	0.054881	Clinker
0.20603	0.34052	0.088376	0.21817	0.23237	0.10004	0.2403	0.075835	0.062443	Clinker
0.20262	0.52127	0.24018	0.2111	0.40799	0.21153	0.23069	0.14429	0.095074	Clinker
0.24269	0.33649	0.06864	0.25527	0.22328	0.079206	0.27656	0.063655	0.053873	Clinker
0.23999	0.48275	0.21722	0.25258	0.36773	0.19203	0.2784	0.12222	0.090029	Clinker
0.23643	0.51009	0.18966	0.24604	0.4047	0.17424	0.26686	0.13443	0.086538	Clinker
0.22177	0.28666	0.062787	0.23437	0.17839	0.079555	0.25358	0.058954	0.053471	Clinker
0.23555	0.31252	0.063545	0.24659	0.21416	0.082303	0.27341	0.066995	0.065328	Clinker
0.21786	0.32692	0.097143	0.23026	0.21549	0.10624	0.24952	0.060364	0.051896	Clinker
0.21786	0.32692	0.097143	0.23026	0.21549	0.10624	0.24952	0.060364	0.051896	Clinker
0.20931	0.43524	0.1713	0.22142	0.33372	0.16473	0.24487	0.1055	0.077145	Clinker
0.22874	0.52618	0.23878	0.24064	0.40905	0.20009	0.2647	0.12742	0.081131	Clinker
0.19261	0.34598	0.038028	0.20518	0.23841	0.063599	0.22742	0.074997	0.058786	Clinker
0.19018	0.33767	0.049969	0.20307	0.23016	0.072356	0.22681	0.071528	0.061069	Clinker
0.18316	0.3439	0.025589	0.1954	0.24506	0.056851	0.22018	0.077636	0.063543	Clinker
0.20799	0.3247	0.036796	0.21864	0.22157	0.063065	0.24614	0.068725	0.063565	Clinker
0.11831	0.45061	0.11148	0.12318	0.35882	0.13321	0.13188	0.13385	0.088213	Clinker
0.10716	0.4451	0.087665	0.10939	0.35204	0.10981	0.11688	0.11166	0.069396	Clinker
0.12356	0.39661	0.069801	0.12565	0.30561	0.095572	0.13157	0.1005	0.065189	Clinker
0.23882	0.32813	0.089964	0.252	0.2179	0.097664	0.28038	0.064996	0.062374	Clinker
0.23285	0.30405	0.073023	0.2462	0.19395	0.082713	0.26858	0.054581	0.054408	Clinker
0.22657	0.23974	0.02175	0.24132	0.13875	0.052954	0.26816	0.045418	0.054786	Clinker
0.20007	0.3903	0.089821	0.21317	0.28439	0.10224	0.24051	0.096279	0.074815	Clinker
0.19517	0.41533	0.10162	0.20758	0.30638	0.10849	0.2374	0.11346	0.086528	Clinker
0.21494	0.35774	0.048548	0.22719	0.24869	0.068726	0.25213	0.071719	0.062579	Clinker
0.2191	0.42363	0.11079	0.23026	0.3038	0.1097	0.25403	0.072334	0.058869	Clinker
0.20392	0.45956	0.15102	0.21685	0.36371	0.15882	0.24637	0.15032	0.10899	Clinker
0.23671	0.32438	0.039165	0.25085	0.21582	0.062265	0.28007	0.061734	0.055779	Clinker
0.22185	0.32286	0.074444	0.23269	0.22042	0.088599	0.25337	0.067477	0.060203	Clinker
0.1359	0.37828	0.13389	0.13792	0.24484	0.11467	0.12929	0.034956	0.022566	Clinker
0.1359	0.37828	0.13389	0.13792	0.24484	0.11467	0.12929	0.034956	0.022566	Clinker
0.10437	0.47473	0.14555	0.10602	0.36782	0.14545	0.11377	0.1104	0.067356	Clinker
0.10714	0.41911	0.085012	0.10914	0.31995	0.10833	0.11485	0.096461	0.059867	Clinker
0.097354	0.33315	0.086978	0.10033	0.2246	0.10603	0.10825	0.058195	0.044706	Clinker
0.087244	0.38986	0.12157	0.090367	0.28014	0.13411	0.093754	0.078202	0.051565	Clinker
0.098215	0.31757	0.095792	0.10238	0.19489	0.09912	0.10352	0.042874	0.034754	Clinker
0.11298	0.43604	0.23885	0.11485	0.30257	0.17845	0.11158	0.064285	0.042837	Clinker
0.11145	0.39578	0.10634	0.11249	0.27469	0.10222	0.11171	0.064409	0.040256	Clinker
0.10412	0.3869	0.077311	0.10458	0.2759	0.088866	0.1111	0.076337	0.048738	Clinker
0.092823	0.41093	0.071175	0.093573	0.3049	0.08946	0.10107	0.091015	0.056047	Clinker
0.092786	0.37483	0.062053	0.094742	0.26835	0.085154	0.09172	0.071165	0.044894	Clinker
0.10195	0.33071	0.083851	0.10381	0.21958	0.097192	0.10931	0.052498	0.042099	Clinker
0.09834	0.34052	0.088139	0.10094	0.22792	0.099797	0.10572	0.057883	0.042961	Clinker
0.086083	0.33786	0.097451	0.089573	0.22125	0.10962	0.097001	0.060111	0.043501	Clinker
0.093772	0.34688	0.098398	0.096404	0.22939	0.10669	0.1008	0.057776	0.041103	Clinker
0.10949	0.36013	0.084206	0.11056	0.2423	0.094075	0.10822	0.058344	0.037994	Clinker
0.11071	0.34095	0.073615	0.10986	0.24758	0.10287	0.11023	0.070872	0.04885	Clinker
0.099264	0.3992	0.12591	0.097963	0.30588	0.14475	0.096315	0.098337	0.063796	Clinker
0.13531	0.29246	0.054779	0.137	0.18134	0.071248	0.13592	0.035249	0.028903	Clinker
0.10991	0.37444	0.092878	0.11133	0.267	0.10628	0.11026	0.071852	0.047243	Clinker
0.10813	0.36718	0.096408	0.10984	0.25821	0.11424	0.10949	0.071307	0.046949	Clinker
0.10001	0.43195	0.094181	0.10225	0.32333	0.10899	0.10912	0.096939	0.061284	Clinker
0.10001	0.43195	0.094181	0.10225	0.32333	0.10899	0.10912	0.096939	0.061284	Clinker
0.11116	0.40349	0.10309	0.11269	0.29523	0.11421	0.11704	0.076615	0.050009	Clinker
0.11116	0.40349	0.10309	0.11269	0.29523	0.11421	0.11704	0.076615	0.050009	Clinker
0.10844	0.46348	0.2349	0.10677	0.38339	0.23907	0.10944	0.12992	0.088534	Clinker
0.15104	0.44978	0.2072	0.15154	0.33614	0.19367	0.14532	0.084474	0.056032	Clinker
0.10693	0.52617	0.19983	0.10656	0.39589	0.16305	0.11007	0.093525	0.053564	Clinker
0.10351	0.5641	0.28444	0.10381	0.40808	0.2024	0.10616	0.098685	0.059691	Clinker
0.10461	0.36739	0.057433	0.10635	0.2603	0.079329	0.11488	0.061986	0.044838	Clinker
0.10117	0.27085	0.0084348	0.10467	0.16189	0.043048	0.10355	0.033363	0.031725	Clinker
0.075949	0.42523	0.12752	0.077199	0.31595	0.13556	0.081475	0.089486	0.05722	Clinker
0.13048	0.35462	0.099488	0.13272	0.2529	0.11881	0.13038	0.073557	0.051728	Clinker
0.13667	0.35327	0.11581	0.13945	0.24018	0.12498	0.13426	0.067748	0.046769	Clinker
0.079955	0.49758	0.19509	0.083251	0.36592	0.16319	0.087628	0.10146	0.061052	Clinker
0.10012	0.40757	0.10833	0.1047	0.2972	0.12326	0.11707	0.087236	0.059682	Clinker
0.099201	0.4024	0.11697	0.10407	0.28462	0.1223	0.11596	0.074557	0.051587	Clinker
0.11183	0.47319	0.24935	0.11682	0.34871	0.21067	0.12908	0.10249	0.074718	Clinker
0.10815	0.43699	0.11572	0.10975	0.32915	0.12574	0.11696	0.086315	0.054515	Clinker
0.099289	0.37644	0.073591	0.10225	0.26814	0.090301	0.10582	0.074401	0.050214	Clinker
0.11253	0.66951	0.84384	0.11573	0.66036	0.97557	0.11963	0.42743	0.6901	Clinker
0.11328	0.40538	0.17907	0.11483	0.28912	0.17252	0.11142	0.077154	0.056154	Clinker
0.030379	0.53185	0.18052	0.025228	0.44005	0.18483	0.026109	0.1363	0.073854	Clinker
0.12525	0.28902	0.052173	0.1281	0.188	0.077258	0.12771	0.042003	0.031263	Clinker
0.11744	0.34475	0.06736	0.12061	0.23754	0.086999	0.12436	0.058327	0.041108	Clinker
0.11442	0.28163	0.02983	0.11891	0.17477	0.060707	0.12502	0.046366	0.04066	Clinker
0.10736	0.39393	0.11287	0.1113	0.28239	0.11873	0.12364	0.084517	0.060042	Clinker

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.098977	0.42186	0.13612	0.10133	0.30482	0.12986	0.10981	0.077287	0.053931	Clinker
0.098128	0.35562	0.073639	0.10129	0.23382	0.084518	0.10154	0.059191	0.042289	Clinker
0.12986	0.32678	0.057125	0.13625	0.22634	0.085871	0.14081	0.063318	0.046391	Clinker
0.13018	0.41036	0.15614	0.13282	0.30275	0.16175	0.12898	0.069698	0.049342	Clinker
0.1354	0.34034	0.091669	0.13706	0.2382	0.10876	0.14345	0.060828	0.047197	Clinker
0.11816	0.37346	0.14517	0.11801	0.2886	0.16075	0.12121	0.098442	0.067952	Clinker
0.12393	0.38013	0.096858	0.12831	0.27249	0.11278	0.1383	0.080669	0.058228	Clinker
0.11801	0.40602	0.13292	0.12258	0.29831	0.14077	0.13283	0.099588	0.068809	Clinker
0.10426	0.39135	0.13311	0.10821	0.28809	0.14406	0.11921	0.1022	0.071059	Clinker
0.10607	0.34453	0.10707	0.10986	0.2409	0.12166	0.119	0.078207	0.057478	Clinker
0.11983	0.33196	0.073118	0.12472	0.22535	0.09387	0.13463	0.07243	0.054883	Clinker
0.1247	0.37032	0.12915	0.12983	0.26709	0.14631	0.14194	0.097842	0.076963	Clinker
0.12692	0.42997	0.23208	0.1313	0.32509	0.22068	0.13922	0.12908	0.10384	Clinker
0.13291	0.4462	0.17997	0.13624	0.33488	0.17422	0.14015	0.092735	0.062072	Clinker
0.13068	0.43371	0.166	0.13249	0.32544	0.16305	0.14073	0.095766	0.066275	Clinker
0.13816	0.29471	0.092665	0.14081	0.18938	0.11596	0.13957	0.047135	0.04038	Clinker
0.12596	0.25794	0.048121	0.13004	0.15454	0.078898	0.12689	0.048437	0.039426	Clinker
0.11145	0.41002	0.14995	0.11527	0.30666	0.15521	0.12085	0.092361	0.063404	Clinker
0.10833	0.37093	0.087026	0.11239	0.26997	0.1096	0.1204	0.085047	0.059304	Clinker
0.10376	0.375	0.090343	0.10694	0.27564	0.11309	0.11638	0.0962	0.054515	Clinker
0.097042	0.3241	0.087807	0.099266	0.22836	0.1103	0.11245	0.069244	0.054812	Clinker
0.12632	0.33164	0.10145	0.13119	0.22948	0.12213	0.14075	0.075806	0.061186	Clinker
0.14001	0.42945	0.1623	0.14437	0.33413	0.17256	0.15253	0.10601	0.075636	Clinker
0.1429	0.42679	0.18317	0.14568	0.33014	0.1844	0.14852	0.11789	0.088744	Clinker
0.098315	0.37081	0.091883	0.10255	0.25792	0.10482	0.11174	0.077329	0.054092	Clinker
0.1051	0.41022	0.10027	0.10927	0.2983	0.11296	0.11736	0.082012	0.053495	Clinker
0.10337	0.44574	0.13569	0.10661	0.33541	0.14108	0.11496	0.1063	0.069228	Clinker
0.10486	0.43599	0.12408	0.1079	0.32647	0.13206	0.11815	0.1012	0.066048	Clinker
0.10338	0.37958	0.0612	0.10622	0.2743	0.084374	0.1171	0.091345	0.062355	Clinker
0.10389	0.38678	0.065654	0.10635	0.28625	0.087471	0.11353	0.10014	0.064958	Clinker
0.10819	0.39331	0.06691	0.11026	0.29573	0.089337	0.12261	0.10181	0.067818	Clinker
0.1019	0.36363	0.075487	0.10443	0.26371	0.097151	0.11345	0.087853	0.061773	Clinker
0.09341	0.43067	0.11773	0.09615	0.33052	0.13224	0.10344	0.10878	0.070411	Clinker
0.097379	0.44918	0.12929	0.10043	0.34025	0.13548	0.10846	0.11499	0.073725	Clinker
0.093709	0.39151	0.082761	0.095925	0.29113	0.10515	0.10339	0.096869	0.065296	Clinker
0.10518	0.42323	0.13209	0.10751	0.32495	0.14217	0.11857	0.10927	0.072441	Clinker
0.1164	0.40011	0.14263	0.11975	0.3022	0.15388	0.12386	0.095645	0.064648	Clinker
0.096593	0.35082	0.12091	0.098712	0.25209	0.13757	0.10006	0.078648	0.055085	Clinker
0.1148	0.34814	0.062408	0.11916	0.24162	0.08542	0.1317	0.070626	0.053011	Clinker
0.12146	0.3474	0.074231	0.12662	0.23889	0.09428	0.13302	0.07457	0.054518	Clinker
0.12707	0.38357	0.096337	0.13252	0.27256	0.11017	0.14252	0.081563	0.058029	Clinker
0.13756	0.32392	0.05068	0.14195	0.21558	0.072787	0.15417	0.053372	0.044777	Clinker
0.13683	0.441	0.14363	0.14124	0.3263	0.14553	0.14873	0.089555	0.061569	Clinker
0.13427	0.46508	0.18241	0.13787	0.34544	0.17691	0.1431	0.099666	0.070406	Clinker
0.12399	0.32181	0.083448	0.12794	0.22162	0.10763	0.13043	0.06497	0.050291	Clinker
0.12044	0.38188	0.10307	0.12339	0.2806	0.11741	0.13003	0.084986	0.058574	Clinker
0.10962	0.35997	0.062527	0.11251	0.26241	0.09147	0.1181	0.084482	0.056965	Clinker
0.10436	0.31405	0.048998	0.10725	0.21969	0.083513	0.1116	0.072006	0.05192	Clinker
0.093759	0.38167	0.065891	0.096779	0.28261	0.091942	0.097635	0.084404	0.054781	Clinker
0.098777	0.35668	0.098161	0.10142	0.25952	0.117	0.10653	0.075198	0.054182	Clinker
0.099363	0.33135	0.094418	0.10091	0.24027	0.11768	0.10741	0.070667	0.053108	Clinker
0.13677	0.3825	0.13121	0.14075	0.27524	0.13649	0.1426	0.083848	0.057958	Clinker
0.10685	0.38929	0.093044	0.11085	0.28561	0.11413	0.11784	0.08046	0.05713	Clinker
0.1179	0.30879	0.041392	0.12276	0.20206	0.070982	0.12887	0.045166	0.038554	Clinker
0.11681	0.3757	0.10295	0.12228	0.26499	0.11772	0.1351	0.073281	0.05452	Clinker
0.11403	0.35626	0.079965	0.11937	0.25379	0.1048	0.12856	0.07454	0.054839	Clinker
0.10481	0.4376	0.15199	0.10968	0.33243	0.15698	0.12034	0.10656	0.072032	Clinker
0.10825	0.43051	0.14093	0.11251	0.32828	0.15109	0.12452	0.10189	0.069965	Clinker
0.11166	0.34805	0.090224	0.11456	0.24183	0.10747	0.12449	0.065496	0.051482	Clinker
0.11395	0.39083	0.14526	0.11604	0.28296	0.14777	0.11865	0.084039	0.063911	Clinker
0.10141	0.41288	0.096408	0.10466	0.31697	0.11985	0.11269	0.10993	0.073705	Clinker
0.11253	0.51394	0.22286	0.1148	0.41897	0.23017	0.1237	0.16683	0.12486	Clinker
0.10453	0.45676	0.14832	0.10181	0.35477	0.14916	0.095919	0.08688	0.047879	Clinker
0.10213	0.45572	0.1474	0.099221	0.3542	0.14863	0.094123	0.087332	0.048198	Clinker
0.10891	0.35714	0.048192	0.10767	0.25828	0.077504	0.10268	0.065357	0.039618	Clinker
0.10849	0.38182	0.099749	0.1092	0.28145	0.11456	0.1124	0.086463	0.05388	Clinker
0.10527	0.36568	0.10015	0.10804	0.26764	0.12373	0.11081	0.077167	0.052607	Clinker
0.094895	0.36005	0.14815	0.097258	0.25827	0.15767	0.10004	0.0793	0.057235	Clinker
0.079056	0.34794	0.10281	0.080434	0.24209	0.11743	0.084617	0.074342	0.051416	Clinker
0.080754	0.34145	0.10842	0.081993	0.23193	0.11481	0.08974	0.075795	0.054479	Clinker
0.078707	0.34748	0.10849	0.08033	0.23693	0.11536	0.084776	0.075833	0.052422	Clinker
0.083263	0.35539	0.11496	0.085303	0.24328	0.11698	0.092671	0.07796	0.055204	Clinker
0.093709	0.39163	0.15671	0.096509	0.28314	0.15899	0.10215	0.083892	0.059097	Clinker
0.10151	0.3922	0.15865	0.10376	0.28454	0.16052	0.10373	0.082799	0.056729	Clinker
0.10543	0.34888	0.12704	0.1065	0.24222	0.13544	0.10344	0.070337	0.04692	Clinker
0.10583	0.27351	0.080605	0.10589	0.16726	0.096167	0.097794	0.042246	0.030381	Clinker
0.1473	0.55184	0.25494	0.14351	0.42048	0.1975	0.12993	0.083909	0.044794	Clinker
0.17077	0.52353	0.21625	0.16589	0.38839	0.16637	0.14688	0.070128	0.035513	Clinker
0.14442	0.51712	0.18455	0.13753	0.39033	0.15384	0.11945	0.077442	0.037515	Clinker
0.15588	0.53057	0.1944	0.14279	0.34763	0.12115	0.11863	0.041441	0.018242	Clinker
0.13365	0.33811	0.13038	0.13345	0.23908	0.13169	0.12111	0.055157	0.033505	Clinker
0.13318	0.33094	0.096692	0.13284	0.23254	0.10929	0.12784	0.059141	0.03796	Clinker
0.11699	0.31418	0.053191	0.11829	0.20326	0.074407	0.11612	0.043677	0.03258	Clinker
0.096443	0.4003	0.12929	0.098876	0.28295	0.1273	0.10165	0.077067	0.050416	Clinker
0.10461	0.39417	0.093162	0.10629	0.27754	0.099941	0.10873	0.075037	0.049634	Clinker
0.1055	0.44924	0.16732	0.10734	0.34513	0.16633	0.10704	0.10674	0.067468	Clinker
0.11886	0.42588	0.13735	0.11946	0.32463	0.13954	0.11662	0.079377	0.047161	Clinker
0.13583	0.41819	0.1034	0.13459	0.31525	0.11245	0.12085	0.069845	0.037967	Clinker
0.15277	0.35121	0.12245	0.15122	0.22996	0.11251	0.13434	0.047269	0.029176	Clinker

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.11965	0.31888	0.045752	0.11993	0.22052	0.071946	0.11419	0.060863	0.040743	Clinker
0.12238	0.27987	0.038051	0.12381	0.17965	0.066347	0.12322	0.043263	0.034802	Clinker
0.10178	0.37712	0.10714	0.10372	0.2638	0.11549	0.10381	0.06484	0.043616	Clinker
0.10644	0.37932	0.10193	0.10794	0.26702	0.11383	0.10999	0.072388	0.048641	Clinker
0.10532	0.34896	0.046889	0.10647	0.24232	0.072151	0.10791	0.057962	0.039258	Clinker
0.10233	0.3849	0.091906	0.10363	0.27725	0.11003	0.10635	0.068027	0.04579	Clinker
0.098602	0.38957	0.12403	0.099041	0.28906	0.14006	0.098718	0.080994	0.052057	Clinker
0.10748	0.39768	0.12197	0.10758	0.28961	0.12851	0.10315	0.081022	0.048918	Clinker
0.14869	0.40548	0.1487	0.14706	0.28665	0.13503	0.13399	0.055796	0.03519	Clinker
0.14056	0.47682	0.19061	0.14093	0.35501	0.16684	0.13893	0.074694	0.042557	Clinker
0.13047	0.34876	0.033739	0.1319	0.24436	0.059046	0.12734	0.05058	0.032068	Clinker
0.13098	0.34003	0.054424	0.13305	0.22978	0.071905	0.12597	0.046017	0.02968	Clinker
0.12158	0.3616	0.092617	0.12334	0.24686	0.10099	0.12454	0.05141	0.034768	Clinker
0.13228	0.37164	0.080676	0.13567	0.25777	0.093767	0.1318	0.062697	0.040745	Clinker
0.13877	0.43253	0.13126	0.1396	0.31343	0.12521	0.13333	0.074828	0.04487	Clinker
0.13778	0.36979	0.050988	0.13849	0.26643	0.072356	0.13244	0.066525	0.041232	Clinker
0.15527	0.33904	0.048216	0.15798	0.22891	0.065772	0.15396	0.051624	0.03611	Clinker
0.142	0.32999	0.094726	0.14469	0.21837	0.10216	0.13938	0.054003	0.035988	Clinker
0.11033	0.35434	0.077927	0.11071	0.24641	0.089501	0.1106	0.06142	0.040614	Clinker
0.10392	0.38037	0.058049	0.10452	0.27066	0.075658	0.10218	0.064526	0.039214	Clinker
0.096842	0.39017	0.065512	0.097169	0.28508	0.086856	0.097714	0.074311	0.045471	Clinker
0.10532	0.39589	0.081173	0.10767	0.2941	0.098464	0.11089	0.087253	0.056804	Clinker
0.10856	0.33273	0.035611	0.11089	0.22956	0.062347	0.1237	0.062591	0.053379	Clinker
0.1081	0.42057	0.11747	0.11034	0.31514	0.12472	0.11747	0.082457	0.055606	Clinker
0.11157	0.40077	0.10174	0.11458	0.29699	0.11534	0.11607	0.078025	0.051983	Clinker
0.11358	0.39659	0.070251	0.11551	0.29515	0.093398	0.11881	0.079351	0.051015	Clinker
0.10587	0.42685	0.097403	0.10796	0.31569	0.10993	0.11258	0.097069	0.061206	Clinker
0.098427	0.39488	0.089371	0.10048	0.28781	0.10207	0.099536	0.088287	0.054742	Clinker
0.1346	0.41236	0.12081	0.13444	0.29829	0.11465	0.12301	0.06026	0.03378	Clinker
0.12803	0.41979	0.13316	0.12772	0.30406	0.12381	0.12024	0.06825	0.040083	Clinker
0.12249	0.41311	0.11939	0.12247	0.29748	0.11292	0.11694	0.064013	0.037135	Clinker
0.11457	0.37248	0.087026	0.11657	0.25891	0.092721	0.11765	0.052446	0.03378	Clinker
0.10131	0.38621	0.12024	0.10403	0.27009	0.12463	0.105	0.067519	0.044008	Clinker
0.11754	0.41112	0.13439	0.12085	0.30701	0.13997	0.12779	0.088713	0.058496	Clinker
0.14096	0.23705	0.0040752	0.14508	0.13247	0.037798	0.14023	0.029572	0.028602	Clinker
0.1364	0.27104	0.045491	0.13924	0.1662	0.070182	0.13777	0.039172	0.033347	Clinker
0.11136	0.31552	0.053405	0.11269	0.21557	0.077934	0.11387	0.058834	0.041958	Clinker
0.12267	0.48165	0.13176	0.12404	0.36878	0.13111	0.12784	0.10237	0.059691	Clinker
0.11988	0.36211	0.069137	0.12186	0.24491	0.077422	0.12399	0.054027	0.037804	Clinker
0.12479	0.368	0.11036	0.12685	0.25716	0.11147	0.12816	0.069147	0.047307	Clinker
0.16928	0.39622	0.076127	0.16983	0.28276	0.085154	0.16117	0.052908	0.031243	Clinker
0.17314	0.37926	0.070298	0.17392	0.26339	0.083349	0.15897	0.053494	0.030367	Clinker
0.18405	0.27855	0.025233	0.18452	0.15827	0.045817	0.16856	0.020357	0.016017	Clinker
0.1587	0.32616	0.09937	0.15912	0.19826	0.096495	0.14812	0.041127	0.027004	Clinker
0.15815	0.32502	0.099322	0.15858	0.19816	0.096803	0.1472	0.041131	0.026919	Clinker
0.13153	0.3677	0.1355	0.13236	0.24805	0.1267	0.1219	0.057132	0.034143	Clinker
0.13969	0.50017	0.1669	0.14069	0.36059	0.13856	0.14239	0.080554	0.047178	Clinker
0.13831	0.28355	0.11823	0.14015	0.17427	0.12549	0.12679	0.044074	0.030457	Clinker
0.12721	0.44849	0.10342	0.12848	0.34874	0.11481	0.1284	0.098007	0.05557	Clinker
0.13942	0.41586	0.090627	0.14093	0.30957	0.10082	0.13954	0.084613	0.050109	Clinker
0.16286	0.28853	0.0038383	0.16436	0.18468	0.032281	0.16093	0.037816	0.029395	Clinker
0.1748	0.32872	0.035824	0.1759	0.21244	0.048565	0.16932	0.038267	0.028322	Clinker
0.15874	0.35511	0.09764	0.15858	0.22323	0.086158	0.15052	0.041935	0.029821	Clinker
0.16845	0.44559	0.24781	0.15765	0.23777	0.12894	0.13904	0.023272	0.013598	Clinker
0.16845	0.44559	0.24781	0.15765	0.23777	0.12894	0.13904	0.023272	0.013598	Clinker
0.12004	0.35892	0.057764	0.12019	0.25106	0.080703	0.11372	0.059627	0.036463	Clinker
0.088305	0.46013	0.10996	0.088045	0.35648	0.12303	0.088789	0.098615	0.055387	Clinker
0.084186	0.402	0.094584	0.08433	0.3061	0.11454	0.092592	0.094654	0.060743	Clinker
0.079044	0.4264	0.11588	0.0803	0.32309	0.12941	0.084327	0.099354	0.060746	Clinker
0.11105	0.29716	0.062621	0.11312	0.1798	0.080457	0.10717	0.031805	0.028531	Clinker
0.12314	0.29711	0.062787	0.12614	0.191	0.090117	0.12119	0.040085	0.032967	Clinker
0.12788	0.62948	0.3709	0.12828	0.46584	0.2483	0.12055	0.10456	0.05919	Clinker
0.12555	0.62246	0.355	0.12565	0.455	0.24229	0.11836	0.10324	0.059901	Clinker
0.13321	0.40795	0.11224	0.13444	0.28503	0.10271	0.1261	0.062405	0.037714	Clinker
0.12869	0.41078	0.093707	0.12996	0.29983	0.10257	0.12597	0.07062	0.044967	Clinker
0.14455	0.35333	0.10406	0.1449	0.23923	0.104	0.14012	0.058578	0.038308	Clinker
0.14549	0.35148	0.10771	0.1452	0.23959	0.10702	0.14334	0.057134	0.038308	Clinker
0.11759	0.42858	0.10297	0.1187	0.31321	0.10581	0.12372	0.080791	0.05284	Clinker
0.11222	0.43785	0.0961	0.11267	0.32951	0.107	0.11659	0.092022	0.056879	Clinker
0.10139	0.45286	0.12591	0.10198	0.34612	0.12947	0.099748	0.099849	0.059044	Clinker
0.090964	0.49817	0.17168	0.091146	0.38993	0.15837	0.09415	0.12512	0.074131	Clinker
0.086008	0.47938	0.16595	0.087296	0.3739	0.16206	0.098982	0.12971	0.081381	Clinker
0.07862	0.47999	0.16427	0.080554	0.37069	0.15923	0.086228	0.14088	0.086567	Clinker
0.092374	0.31596	0.070251	0.095356	0.20829	0.092045	0.10614	0.068043	0.054228	Clinker
0.095082	0.27558	0.054234	0.097258	0.17352	0.081318	0.10484	0.054028	0.047458	Clinker
0.11472	0.29637	0.085983	0.1172	0.17911	0.091265	0.11826	0.038429	0.035944	Clinker
0.10528	0.40044	0.11423	0.10719	0.28267	0.11376	0.1111	0.074594	0.049999	Clinker
0.10487	0.3921	0.11832	0.10858	0.2765	0.12135	0.11089	0.072503	0.048743	Clinker
0.11535	0.39662	0.16761	0.11575	0.27682	0.14808	0.11831	0.066002	0.045714	Clinker
0.13022	0.3771	0.10977	0.13248	0.27597	0.11938	0.13413	0.0604	0.04001	Clinker
0.14532	0.82791	0.66668	0.14163	0.59223	0.40852	0.14215	0.099666	0.057047	Clinker
0.093397	0.46291	0.21921	0.093723	0.31452	0.16145	0.095523	0.072655	0.045286	Clinker
0.08335	0.31439	0.074042	0.085139	0.20042	0.092783	0.087152	0.054679	0.038372	Clinker
0.066962	0.36426	0.11027	0.06833	0.2442	0.1154	0.080604	0.074834	0.055945	Clinker
0.044309	0.34108	0.072715	0.045049	0.23274	0.098648	0.057764	0.075044	0.055626	Clinker
0.04356	0.40468	0.083495	0.043116	0.27835	0.097479	0.048548	0.075204	0.049646	Clinker
0.031578	0.41597	0.11721	0.02812	0.29929	0.128	0.035441	0.084569	0.053973	Clinker
0.026623	0.41192	0.10984	0.02202	0.30104	0.12753	0.029824	0.089095	0.055041	Clinker
0.054169	0.70547	0.47927	0.046487	0.49963	0.31174	0.041525	0.082358	0.045449	Clinker



Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.059486	0.69622	0.44809	0.05167	0.50142	0.29976	0.041952	0.096548	0.050783	Gypsum
0.093959	0.29755	0.03952	0.092419	0.1803	0.063045	0.097873	0.034575	0.033103	Gypsum
0.82591	0.22265	0.07679	0.79477	0.24368	0.057015	0.7224	0.052565	0.022189	Gypsum
0.80519	0.2286	0.057859	0.77447	0.24921	0.053447	0.6979	0.050487	0.021079	Gypsum
0.861	0.22101	0.074823	0.83125	0.25548	0.05037	0.77065	0.051847	0.019791	Gypsum
0.91455	0.13285	0.042221	0.89981	0.19861	0.030989	0.84778	0.061146	0.026179	Gypsum
0.92681	0.11362	0.046415	0.9077	0.1806	0.022519	0.85321	0.04641	0.018364	Gypsum
0.90801	0.14058	0.047434	0.88425	0.19506	0.025964	0.81432	0.037352	0.013121	Gypsum
0.90384	0.15212	0.047576	0.87784	0.20076	0.024652	0.81625	0.037847	0.013495	Gypsum
0.91506	0.13663	0.05883	0.89023	0.18957	0.027605	0.82332	0.03673	0.012535	Gypsum
0.88998	0.14335	0.043667	0.86283	0.1893	0.025144	0.7999	0.037302	0.013901	Gypsum
0.84463	0.19777	0.030091	0.81948	0.24502	0.039152	0.75993	0.062319	0.02698	Gypsum
0.90929	0.14107	0.047884	0.88267	0.19753	0.02137	0.81707	0.03923	0.014033	Gypsum
0.80338	0.2296	0.07461	0.76512	0.23494	0.044997	0.67308	0.030487	0.0079414	Gypsum
0.78655	0.22071	0.07153	0.7462	0.21333	0.038003	0.64559	0.025538	0.0061659	Gypsum
0.73034	0.27024	0.056627	0.68569	0.22568	0.025308	0.59305	0.0266	0.00625	Gypsum
0.731	0.30618	0.10906	0.69145	0.28771	0.083328	0.60889	0.038837	0.011941	Gypsum
0.73692	0.29983	0.10916	0.69919	0.28525	0.083861	0.61121	0.039938	0.012874	Gypsum
0.80142	0.24349	0.061555	0.77101	0.27449	0.063291	0.69972	0.070263	0.031258	Gypsum
0.80373	0.25091	0.030162	0.77604	0.2852	0.051006	0.70791	0.072762	0.03165	Gypsum
0.8195	0.2138	0.027271	0.79327	0.25616	0.045345	0.73006	0.083387	0.040073	Gypsum
0.85627	0.18144	0.030849	0.83005	0.22248	0.03142	0.76513	0.056	0.02392	Gypsum
0.75607	0.18549	0.14114	0.71476	0.14761	0.03866	0.63147	0.012492	0.00091979	Gypsum
0.73845	0.27841	0.16306	0.70166	0.25716	0.097192	0.61483	0.030609	0.0086582	Gypsum
0.77081	0.24136	0.15557	0.73299	0.21805	0.071638	0.64657	0.022273	0.0045313	Gypsum
0.97401	0.060634	0.055419	0.95407	0.13614	0.0082241	0.89501	0.030036	0.010221	Gypsum
0.91696	0.11779	0.042624	0.8981	0.18294	0.025677	0.84326	0.046696	0.01927	Gypsum
0.88425	0.15106	0.047197	0.85945	0.19992	0.031953	0.80151	0.052604	0.02232	Gypsum
0.83369	0.18215	0.038028	0.80488	0.22505	0.039952	0.73281	0.055655	0.023776	Gypsum
0.86725	0.14558	0.030707	0.84189	0.19632	0.026949	0.77643	0.051676	0.022133	Gypsum
0.79984	0.24716	0.062242	0.76828	0.2663	0.056892	0.69441	0.053432	0.021044	Gypsum
0.90749	0.13086	0.058712	0.88613	0.19254	0.035194	0.82034	0.047573	0.018902	Gypsum
0.95296	0.089681	0.067289	0.93216	0.1486	0.015115	0.88131	0.029946	0.01063	Gypsum
0.90479	0.17816	0.049045	0.8849	0.22723	0.032527	0.83463	0.054407	0.021789	Gypsum
0.97164	0.029627	0.038857	0.97143	0.11385	0.0079985	0.96673	0.077294	0.039097	Gypsum
1	0	0.051296	1	0.095792	0.0075473	0.98315	0.062668	0.030323	Gypsum
0.95243	0.068706	0.035469	0.93649	0.13481	0.0041223	0.88957	0.049921	0.022427	Gypsum
0.96103	0.056685	0.040895	0.94807	0.13543	0.007937	0.90439	0.058505	0.026695	Gypsum
0.94549	0.08258	0.038478	0.92755	0.14303	0.0049632	0.88112	0.039283	0.017035	Gypsum
0.96186	0.070133	0.040847	0.94506	0.13896	0.0036506	0.89779	0.050035	0.02205	Gypsum
0.96251	0.070566	0.038099	0.94449	0.14416	0.0038147	0.90336	0.052879	0.023167	Gypsum
0.97066	0.056931	0.040681	0.95781	0.13958	0.0060502	0.92142	0.059418	0.026934	Gypsum
0.9635	0.045689	0.039852	0.95225	0.13002	0.0074243	0.91271	0.063426	0.02941	Gypsum
0.9387	0.056206	0.036654	0.92416	0.13493	0.011136	0.87928	0.061305	0.02876	Gypsum
0.91757	0.066161	0.031536	0.90082	0.1413	0.01249	0.8572	0.060931	0.029366	Gypsum
0.88318	0.11097	0.030209	0.86132	0.16957	0.018848	0.80146	0.064731	0.030525	Gypsum
0.85764	0.15613	0.042458	0.83326	0.20625	0.033081	0.77587	0.06759	0.031075	Gypsum
0.84774	0.16946	0.048879	0.82139	0.2148	0.037142	0.76003	0.064052	0.028662	Gypsum
0.95725	0.047151	0.031512	0.95452	0.12702	0.0074653	0.95189	0.074979	0.038381	Gypsum
0.99006	0.0083762	0.035493	0.99086	0.096206	0.0019894	0.98405	0.065228	0.033653	Gypsum
0.98486	0.037611	0.033905	0.97584	0.12078	0	0.94542	0.053767	0.024614	Gypsum
0.96846	0.062125	0.042411	0.95204	0.13839	0.0039788	0.91075	0.054744	0.024027	Gypsum
0.96937	0.065939	0.048761	0.95434	0.14912	0.0085523	0.91466	0.059963	0.026014	Gypsum
0.92465	0.094963	0.036014	0.90978	0.1703	0.016223	0.86644	0.07761	0.03591	Gypsum
0.91409	0.09704	0.031228	0.89754	0.17058	0.015669	0.86079	0.078079	0.03721	Gypsum
0.87914	0.13793	0.030019	0.85512	0.19139	0.018622	0.79959	0.063425	0.028998	Gypsum
0.9325	0.13981	0.078259	0.91022	0.18222	0.021617	0.84178	0.030277	0.0088569	Gypsum
0.94778	0.12816	0.068095	0.93148	0.186	0.024119	0.86386	0.035755	0.011847	Gypsum
0.96643	0.10457	0.055205	0.95587	0.17062	0.019586	0.89903	0.042007	0.015747	Gypsum
0.96338	0.10019	0.042482	0.9545	0.16596	0.01694	0.89876	0.039372	0.014612	Gypsum
0.92143	0.15674	0.056698	0.9064	0.21615	0.036342	0.84656	0.046783	0.016954	Gypsum
0.87934	0.19747	0.066152	0.85781	0.22976	0.04393	0.78623	0.038359	0.012275	Gypsum
0.82056	0.23893	0.072999	0.79527	0.25989	0.060686	0.72056	0.054585	0.020526	Gypsum
0.83552	0.21747	0.060963	0.81422	0.25417	0.057179	0.75338	0.075043	0.033269	Gypsum
0.84859	0.2187	0.031512	0.83456	0.26778	0.046371	0.79034	0.1051	0.049758	Gypsum
0.87652	0.19592	0.021679	0.86527	0.23921	0.030599	0.81202	0.071032	0.030089	Gypsum
0.90962	0.143	0.025636	0.90277	0.20815	0.027421	0.87104	0.093664	0.044139	Gypsum
0.93259	0.12253	0.020281	0.92956	0.19425	0.018376	0.89985	0.092761	0.043392	Gypsum
0.97079	0.059206	0.027792	0.97248	0.14404	0.0096392	0.95049	0.078327	0.036957	Gypsum
0.98154	0.034347	0.031702	0.98644	0.1219	0.007855	0.97811	0.078361	0.038204	Gypsum
0.99141	0.017092	0.037293	0.99999	0.10785	0.007978	0.99831	0.085898	0.042389	Gypsum
0.91347	0.13784	0.036488	0.90607	0.194	0.026293	0.87038	0.076282	0.035141	Gypsum
0.9743	0.037927	0.031228	0.98121	0.12402	0.010542	0.97513	0.089703	0.044497	Gypsum
0.97073	0.04649	0.084325	0.95131	0.1082	0.014295	0.87933	0.018651	0.0048373	Gypsum
0.94265	0.11241	0.047244	0.93389	0.17867	0.028015	0.88464	0.052144	0.021682	Gypsum
0.96252	0.064775	0.056248	0.94833	0.1287	0.014602	0.8751	0.030409	0.010886	Gypsum
0.92449	0.13383	0.041345	0.91139	0.19115	0.025964	0.8609	0.055604	0.023362	Gypsum
0.96877	0.043794	0.035635	0.97113	0.1297	0.015977	0.95131	0.079581	0.038785	Gypsum
0.9366	0.092413	0.020637	0.93865	0.16548	0.018212	0.92015	0.092917	0.045619	Gypsum
0.90449	0.11889	0.042364	0.89254	0.17364	0.025616	0.84585	0.063795	0.029885	Gypsum
0.9274	0.11091	0.032223	0.92437	0.17628	0.024057	0.89903	0.087583	0.04261	Gypsum
0.96403	0.061552	0.037056	0.95939	0.1401	0.015013	0.91271	0.045603	0.020394	Gypsum
0.94204	0.069724	0.028361	0.93681	0.141	0.016018	0.89892	0.059499	0.029064	Gypsum
0.93411	0.096431	0.027863	0.93071	0.16497	0.020201	0.89026	0.060575	0.02811	Gypsum
0.93992	0.080738	0.025162	0.9369	0.15514	0.016264	0.8961	0.076077	0.036891	Gypsum
0.93632	0.091079	0.024475	0.93193	0.16948	0.017802	0.88532	0.073794	0.03424	Gypsum
0.93234	0.094355	0.024215	0.92812	0.17204	0.019196	0.88107	0.075528	0.035202	Gypsum
0.93692	0.11248	0.016111	0.93004	0.17384	0.010357	0.88704	0.070917	0.032309	Gypsum
0.93602	0.11307	0.016254	0.9289	0.17456	0.01048	0.88466	0.07046	0.032059	Gypsum

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.92883	0.09763	0.022177	0.92226	0.17077	0.017043	0.88297	0.076116	0.035102	Gypsum
0.9384	0.086406	0.015922	0.93814	0.15861	0.012531	0.90555	0.085976	0.041218	Gypsum
0.95292	0.07886	0.017723	0.95619	0.15562	0.011834	0.92269	0.089104	0.04225	Gypsum
0.9472	0.085476	0.019334	0.94867	0.16044	0.013372	0.91957	0.09038	0.043066	Gypsum
0.94518	0.097297	0.016088	0.94509	0.17446	0.01288	0.91804	0.093586	0.044293	Gypsum
0.97505	0.08144	0.033502	0.97122	0.15882	0.012285	0.92218	0.052957	0.02197	Gypsum
0.94633	0.093688	0.028219	0.93984	0.16085	0.016858	0.89121	0.052899	0.022773	Gypsum
0.93366	0.10643	0.025565	0.9277	0.17471	0.020406	0.88041	0.066319	0.030208	Gypsum
0.93173	0.10783	0.025186	0.92592	0.17975	0.021637	0.88358	0.073139	0.033731	Gypsum
0.92198	0.11956	0.01578	0.91943	0.18873	0.021022	0.88347	0.080905	0.038403	Gypsum
0.9613	0.067811	0.034474	0.95973	0.14891	0.016038	0.92427	0.068226	0.031314	Gypsum
0.95457	0.076111	0.032792	0.95203	0.15287	0.016407	0.90938	0.065901	0.030001	Gypsum
0.96916	0.083276	0.030162	0.96667	0.16356	0.012716	0.92839	0.07044	0.031299	Gypsum
0.94415	0.09935	0.029593	0.93252	0.17229	0.014274	0.8792	0.065985	0.028709	Gypsum
0.95225	0.099988	0.019002	0.94619	0.16709	0.0096598	0.88992	0.062363	0.026817	Gypsum
0.95089	0.097496	0.018504	0.94644	0.16453	0.010213	0.90085	0.065514	0.028959	Gypsum
0.94101	0.11332	0.037578	0.93515	0.18464	0.022355	0.89681	0.075143	0.032935	Gypsum
0.9324	0.12698	0.053215	0.92175	0.19447	0.029759	0.87101	0.060836	0.025264	Gypsum
0.93824	0.13282	0.054518	0.92404	0.18874	0.025964	0.85422	0.04358	0.016037	Gypsum
0.88284	0.17556	0.028077	0.86355	0.219	0.028815	0.78963	0.052488	0.020996	Gypsum
0.90011	0.17155	0.023409	0.88358	0.21754	0.02338	0.81152	0.052259	0.020782	Gypsum
0.9083	0.15092	0.026513	0.88944	0.19653	0.018868	0.81683	0.049903	0.019976	Gypsum
0.91525	0.14114	0.028622	0.89915	0.19175	0.02014	0.82813	0.047861	0.0189	Gypsum
0.9319	0.12089	0.037767	0.9196	0.19168	0.025493	0.85562	0.059067	0.024309	Gypsum
0.94757	0.10629	0.036417	0.93912	0.17976	0.020119	0.88332	0.052568	0.021339	Gypsum
0.96648	0.073496	0.03727	0.95817	0.15161	0.011383	0.90117	0.047209	0.018761	Gypsum
0.9673	0.080498	0.045302	0.95942	0.16167	0.017084	0.9037	0.057857	0.023891	Gypsum
0.95543	0.086879	0.036772	0.94676	0.15686	0.016059	0.88714	0.055136	0.023355	Gypsum
0.96078	0.074549	0.040113	0.95643	0.15145	0.02055	0.90666	0.054767	0.02382	Gypsum
0.94715	0.076988	0.04452	0.93966	0.1484	0.023278	0.89137	0.052242	0.023306	Gypsum
0.89955	0.13454	0.033858	0.88463	0.19035	0.026641	0.82435	0.055955	0.024304	Gypsum
0.89632	0.13545	0.030446	0.88237	0.19149	0.025903	0.82694	0.062544	0.028319	Gypsum
0.89356	0.13773	0.030351	0.87978	0.193	0.026518	0.82251	0.064041	0.029161	Gypsum
0.89179	0.14165	0.034663	0.87628	0.196	0.02822	0.82042	0.061194	0.027423	Gypsum
0.8774	0.16159	0.032223	0.86204	0.21356	0.031543	0.81134	0.073295	0.034138	Gypsum
0.85862	0.19313	0.03336	0.84171	0.23723	0.035911	0.78329	0.077474	0.034824	Gypsum
0.8662	0.18285	0.051509	0.85278	0.23284	0.048914	0.78438	0.060994	0.026147	Gypsum
0.91233	0.14547	0.028835	0.9033	0.20232	0.027728	0.83716	0.058098	0.024494	Gypsum
0.89285	0.15432	0.030754	0.8759	0.20982	0.030846	0.80825	0.053606	0.021473	Gypsum
0.93682	0.10787	0.04407	0.92538	0.16736	0.023237	0.86861	0.054576	0.018542	Gypsum
0.96301	0.068992	0.036914	0.95354	0.14723	0.013392	0.89388	0.044256	0.017926	Gypsum
0.9679	0.051889	0.039402	0.96109	0.14014	0.014561	0.90867	0.058981	0.026371	Gypsum
0.89079	0.14191	0.0067289	0.88369	0.18794	0.017453	0.843	0.05814	0.028044	Gypsum
0.82731	0.1889	0.022082	0.81118	0.21913	0.034845	0.75837	0.053538	0.024684	Gypsum
0.86868	0.19852	0.070677	0.84497	0.22264	0.043705	0.7669	0.041483	0.014627	Gypsum
0.88998	0.16313	0.056935	0.87272	0.21506	0.042905	0.80434	0.054244	0.021716	Gypsum
0.93464	0.14512	0.046273	0.92773	0.21227	0.034066	0.87091	0.064069	0.02633	Gypsum
0.96967	0.10084	0.046486	0.96243	0.16862	0.019299	0.89113	0.034269	0.010829	Gypsum
0.9446	0.11179	0.065702	0.93011	0.17137	0.029513	0.85921	0.038139	0.013062	Gypsum
0.92092	0.12007	0.047813	0.90115	0.17293	0.022662	0.82602	0.03709	0.013129	Gypsum
0.92676	0.12711	0.051249	0.91179	0.19021	0.030333	0.84284	0.042967	0.01562	Gypsum
0.89416	0.12461	0.048761	0.8763	0.17911	0.03345	0.80722	0.042203	0.017354	Gypsum
0.91298	0.12536	0.025376	0.89837	0.17936	0.019545	0.83687	0.051817	0.022147	Gypsum
0.92388	0.14812	0.033502	0.91035	0.19831	0.022334	0.83357	0.039737	0.013811	Gypsum
0.94011	0.1318	0.035919	0.92785	0.18618	0.018068	0.86481	0.040858	0.014732	Gypsum
0.92746	0.12541	0.055513	0.91333	0.18361	0.028856	0.85377	0.04637	0.018242	Gypsum
0.91188	0.14262	0.059375	0.89348	0.18739	0.027051	0.83011	0.038621	0.014298	Gypsum
0.88909	0.162	0.063853	0.86716	0.1929	0.029164	0.79457	0.033311	0.011325	Gypsum
0.95373	0.09391	0.037459	0.9459	0.16544	0.015197	0.90573	0.056207	0.024283	Gypsum
0.96443	0.063354	0.056745	0.95477	0.14016	0.017371	0.91915	0.053141	0.02317	Gypsum
0.94488	0.10163	0.04561	0.93345	0.17032	0.018417	0.8915	0.061416	0.026238	Gypsum
0.9352	0.11134	0.045207	0.92452	0.17913	0.022232	0.88004	0.064574	0.02792	Gypsum
0.89678	0.13976	0.032057	0.88533	0.1963	0.025862	0.84294	0.074855	0.034798	Gypsum
0.89955	0.13576	0.030612	0.88915	0.19247	0.024816	0.85213	0.076104	0.035956	Gypsum
0.88191	0.14296	0.032531	0.8701	0.19529	0.028261	0.8252	0.063141	0.029298	Gypsum
0.87622	0.14671	0.03118	0.86316	0.19876	0.029102	0.81664	0.06777	0.03128	Gypsum
0.88449	0.14531	0.032318	0.87275	0.20108	0.028795	0.83056	0.07264	0.033692	Gypsum
0.89717	0.13189	0.028811	0.88563	0.19761	0.024918	0.84556	0.087731	0.041101	Gypsum
0.8806	0.14611	0.029854	0.86279	0.19989	0.025124	0.8135	0.070428	0.032241	Gypsum
0.9349	0.074508	0.035943	0.92866	0.1533	0.01694	0.90811	0.079904	0.038523	Gypsum
0.93819	0.080744	0.039781	0.93166	0.16065	0.017064	0.91006	0.07888	0.037222	Gypsum
0.92821	0.079024	0.048879	0.91482	0.15101	0.017515	0.86908	0.05154	0.022997	Gypsum
0.90763	0.10329	0.044401	0.89324	0.16833	0.021801	0.84379	0.058635	0.026595	Gypsum
0.90031	0.1329	0.040492	0.88532	0.19285	0.026621	0.83265	0.055399	0.023871	Gypsum
0.97534	0.066565	0.057172	0.96535	0.13997	0.014397	0.92403	0.051352	0.021122	Gypsum
0.95263	0.10333	0.038762	0.9456	0.17362	0.0161	0.90999	0.071386	0.031277	Gypsum
0.95336	0.10143	0.035943	0.94722	0.17109	0.014828	0.91173	0.072683	0.032095	Gypsum
0.91478	0.12792	0.029806	0.90523	0.18915	0.020776	0.86533	0.066929	0.030038	Gypsum
0.89808	0.14596	0.025162	0.88911	0.20832	0.02537	0.85696	0.087575	0.041422	Gypsum
0.93196	0.10041	0.018031	0.92888	0.17029	0.011567	0.90185	0.079514	0.037634	Gypsum
0.91458	0.10759	0.017035	0.91002	0.17645	0.015341	0.8853	0.09065	0.044142	Gypsum
0.901	0.11588	0.0213	0.89275	0.17575	0.017433	0.85937	0.083518	0.040964	Gypsum
0.91901	0.10228	0.030019	0.91136	0.17212	0.019258	0.88144	0.07798	0.036921	Gypsum
0.93784	0.088231	0.028479	0.93693	0.15686	0.01409	0.92121	0.08044	0.039117	Gypsum
0.92471	0.11217	0.020945	0.91997	0.1723	0.014192	0.89657	0.07906	0.038094	Gypsum
0.92712	0.10893	0.01713	0.923	0.16942	0.011957	0.89942	0.080048	0.038885	Gypsum
0.92448	0.090161	0.02393	0.91563	0.15234	0.012346	0.874	0.057544	0.027389	Gypsum
0.92507	0.09005	0.024072	0.91634	0.152	0.012223	0.87492	0.057472	0.027326	Gypsum
0.93181	0.090992	0.023599	0.9316	0.15882	0.015484	0.913	0.085672	0.042554	Gypsum



Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.92153	0.09484	0.019144	0.91631	0.15592	0.012264	0.89697	0.081498	0.041059	Gypsum
0.91508	0.10933	0.025518	0.90867	0.17159	0.01895	0.88152	0.082133	0.040129	Gypsum
0.93002	0.10445	0.015353	0.92619	0.17116	0.013639	0.891	0.076144	0.0362	Gypsum
0.89561	0.11609	0.021632	0.88559	0.17562	0.020673	0.83933	0.071083	0.03452	Gypsum
0.9061	0.109	0.022082	0.89705	0.17077	0.018068	0.86005	0.072152	0.034824	Gypsum
0.91333	0.1175	0.056722	0.89485	0.17879	0.027728	0.8318	0.043605	0.016881	Gypsum
0.90121	0.11829	0.03028	0.88755	0.1803	0.020324	0.83529	0.065547	0.029332	Gypsum
0.84401	0.19663	0.048879	0.82295	0.24064	0.046002	0.76341	0.077784	0.035367	Gypsum
0.92179	0.12713	0.059778	0.91068	0.19882	0.036691	0.87035	0.069083	0.030077	Gypsum
0.91709	0.11337	0.01514	0.91172	0.17255	0.013208	0.88017	0.072809	0.034474	Gypsum
0.91438	0.13901	0.016775	0.90739	0.20049	0.017863	0.87304	0.079977	0.03658	Gypsum
0.95909	0.068618	0.028005	0.96037	0.1486	0.013126	0.94054	0.073623	0.034946	Gypsum
0.98874	0.027527	0.037412	0.99231	0.11911	0.0082241	0.9869	0.076221	0.036779	Gypsum
0.91639	0.1063	0.027816	0.9108	0.17394	0.02016	0.88696	0.088226	0.043219	Gypsum
0.90821	0.11477	0.018386	0.90046	0.17597	0.015771	0.86679	0.080146	0.038557	Gypsum
0.86148	0.17203	0.050159	0.84084	0.21435	0.038167	0.78097	0.065381	0.029205	Gypsum
0.98671	0.0090138	0.041321	0.99714	0.096627	0.011485	1	0.078072	0.040115	Gypsum
0.98432	0.021601	0.033479	0.99191	0.10797	0.0075268	0.9925	0.07593	0.038313	Gypsum
0.95488	0.051099	0.024025	0.95916	0.1279	0.0094136	0.94914	0.079136	0.040485	Gypsum
0.9398	0.058791	0.019026	0.94241	0.13028	0.010583	0.93568	0.083431	0.044227	Gypsum
0.9519	0.051292	0.024333	0.95237	0.12415	0.0083882	0.93024	0.066203	0.033522	Gypsum
0.94275	0.069273	0.029332	0.94028	0.14139	0.013618	0.91587	0.068539	0.03358	Gypsum
0.96352	0.058481	0.030683	0.9624	0.13305	0.0088804	0.9394	0.065354	0.03069	Gypsum
0.88672	0.13955	0.012605	0.88157	0.19413	0.020242	0.85596	0.093273	0.046805	Gypsum
0.88073	0.15175	0.032057	0.87131	0.20573	0.031276	0.83906	0.084613	0.040648	Gypsum
0.94772	0.066226	0.022911	0.94813	0.14621	0.010829	0.93832	0.085342	0.043	Gypsum
0.9472	0.072227	0.020258	0.94557	0.14522	0.0089009	0.91939	0.07464	0.036346	Gypsum
0.94358	0.065073	0.015187	0.94686	0.1408	0.010234	0.93753	0.095123	0.048913	Gypsum
0.95202	0.07366	0.015282	0.95266	0.1468	0.0062347	0.93438	0.074719	0.036446	Gypsum
0.94743	0.077158	0.018694	0.94399	0.15155	0.0085318	0.91521	0.069929	0.032947	Gypsum
0.91192	0.11635	0.014074	0.90775	0.18078	0.015587	0.88532	0.090094	0.044349	Gypsum
0.9073	0.12872	0.028906	0.9016	0.1911	0.023483	0.87959	0.089798	0.043457	Gypsum
0.98587	0.027445	0.040279	0.991	0.10975	0.0093316	0.98886	0.073267	0.03666	Gypsum
0.98984	0.021373	0.040587	0.9967	0.10496	0.0090855	0.99063	0.074635	0.037308	Gypsum
0.90529	0.11555	0.01796	0.89718	0.17344	0.017022	0.86679	0.073041	0.035725	Gypsum
0.88114	0.16768	0.015519	0.86607	0.21482	0.020591	0.82232	0.058675	0.025273	Gypsum
0.8949	0.12815	0.00834	0.88849	0.18738	0.016264	0.86758	0.086906	0.043477	Gypsum
0.93718	0.089874	0.026134	0.93503	0.15284	0.013762	0.91593	0.075635	0.036879	Gypsum
0.89547	0.14928	0.039284	0.88548	0.20076	0.029882	0.85366	0.075369	0.035117	Gypsum
0.89079	0.15734	0.042553	0.87618	0.2177	0.03507	0.83346	0.071968	0.032232	Gypsum
0.9103	0.13955	0.04324	0.89822	0.20916	0.032609	0.85517	0.070904	0.031379	Gypsum
0.9732	0.036008	0.033834	0.97871	0.11582	0.010398	0.97542	0.073191	0.037218	Gypsum
0.93756	0.065775	0.03028	0.93324	0.13828	0.016202	0.90618	0.068001	0.033529	Gypsum
0.91066	0.1058	0.029688	0.89456	0.16412	0.017699	0.84226	0.055042	0.024862	Gypsum
0.85036	0.17609	0.020992	0.8316	0.21029	0.027215	0.77255	0.057802	0.025826	Gypsum
0.87665	0.15254	0.012794	0.86527	0.20008	0.02094	0.81997	0.068802	0.032431	Gypsum
0.92157	0.10742	0.025399	0.91747	0.17556	0.018848	0.89214	0.079041	0.038023	Gypsum
0.9175	0.11107	0.024523	0.91345	0.17798	0.019278	0.8895	0.087601	0.042226	Gypsum
0.92379	0.12895	0.045325	0.91428	0.20092	0.029554	0.86417	0.088669	0.040504	Gypsum
0.96296	0.048935	0.030304	0.95945	0.1326	0.010316	0.91722	0.067101	0.031289	Gypsum
0.96591	0.057487	0.028977	0.96529	0.14145	0.011813	0.9235	0.071731	0.032945	Gypsum
0.9646	0.066337	0.033028	0.96237	0.14864	0.014602	0.91257	0.070131	0.031158	Gypsum
0.91721	0.12044	0.024333	0.90524	0.17983	0.018561	0.83946	0.055122	0.023547	Gypsum
0.93563	0.080486	0.032555	0.92828	0.15068	0.017556	0.86174	0.053484	0.02363	Gypsum
0.94255	0.079369	0.039497	0.93753	0.15555	0.020222	0.88862	0.073307	0.034004	Gypsum
0.93113	0.055498	0.039947	0.92532	0.13971	0.017945	0.87637	0.074643	0.035253	Gypsum
0.9161	0.076029	0.039426	0.90574	0.15032	0.020653	0.84685	0.060156	0.027318	Gypsum
0.86462	0.15657	0.021087	0.85234	0.21054	0.02902	0.79399	0.079355	0.037106	Gypsum
0.85806	0.16194	0.014808	0.8468	0.2156	0.027995	0.79079	0.089659	0.043219	Gypsum
0.92433	0.093957	0.025044	0.9181	0.16807	0.018294	0.87518	0.075622	0.035842	Gypsum
0.89321	0.13297	0.020708	0.88028	0.194	0.024406	0.81284	0.061201	0.026875	Gypsum
0.91098	0.11786	0.025778	0.89844	0.1822	0.021576	0.83278	0.053826	0.02278	Gypsum
0.95014	0.075532	0.03618	0.94111	0.15155	0.016428	0.88448	0.047478	0.020012	Gypsum
0.96745	0.057376	0.036914	0.96238	0.14343	0.01368	0.91466	0.054701	0.023676	Gypsum
0.96514	0.068524	0.027129	0.96076	0.15015	0.0095982	0.90349	0.054744	0.023314	Gypsum
0.97078	0.065108	0.02765	0.96653	0.14573	0.0081831	0.91556	0.06467	0.028609	Gypsum
0.96531	0.072046	0.027603	0.96007	0.14992	0.0093931	0.90888	0.063092	0.027776	Gypsum
0.94589	0.062851	0.020092	0.94034	0.14427	0.0092086	0.90473	0.082678	0.040202	Gypsum
0.93779	0.076316	0.022722	0.9301	0.1479	0.01048	0.87896	0.066296	0.031199	Gypsum
0.93823	0.069794	0.024143	0.92914	0.14116	0.0098648	0.87856	0.06623	0.031435	Gypsum
0.94916	0.060862	0.02521	0.94018	0.13724	0.0076499	0.89739	0.068262	0.032378	Gypsum
0.94396	0.066027	0.025281	0.93452	0.14035	0.0090035	0.88384	0.066621	0.031323	Gypsum
0.94078	0.077831	0.02938	0.93013	0.15339	0.012552	0.88593	0.070814	0.033137	Gypsum
0.89202	0.14004	0.07589	0.86168	0.18125	0.024857	0.78163	0.033395	0.011253	Gypsum
0.89099	0.14346	0.069161	0.86488	0.1853	0.027687	0.79293	0.039794	0.014999	Gypsum
0.9401	0.079644	0.040042	0.93491	0.15445	0.020489	0.89068	0.071144	0.032723	Gypsum
0.95892	0.047929	0.055134	0.95074	0.12417	0.019176	0.89752	0.050756	0.022291	Gypsum
0.97225	0.045835	0.046249	0.97118	0.12986	0.017105	0.92715	0.057395	0.025872	Gypsum
0.99564	0.054299	0.065157	0.99151	0.15027	0.018212	0.94502	0.049453	0.019301	Gypsum
0.96212	0.078053	0.030943	0.95622	0.15308	0.012511	0.90756	0.056284	0.024231	Gypsum
0.9254	0.13708	0.024594	0.91408	0.19487	0.018868	0.86214	0.058596	0.024786	Gypsum
0.87172	0.17052	0.030588	0.8557	0.2207	0.035481	0.791	0.061301	0.026815	Gypsum
0.82089	0.22612	0.048026	0.8004	0.26067	0.054657	0.73389	0.059037	0.02569	Gypsum
0.8255	0.22149	0.042719	0.80728	0.26067	0.055272	0.74091	0.065124	0.029322	Gypsum
0.80066	0.2481	0.061816	0.77378	0.26579	0.057159	0.69764	0.044851	0.01561	Gypsum
0.84285	0.22541	0.036156	0.82467	0.27078	0.046063	0.77091	0.073734	0.032168	Gypsum
0.94382	0.13625	0.028242	0.93649	0.21687	0.020632	0.88535	0.071261	0.029933	Gypsum
0.91586	0.16702	0.030185	0.90378	0.23066	0.027995	0.84661	0.07222	0.030435	Gypsum
0.92496	0.089968	0.043548	0.90751	0.15449	0.021329	0.84416	0.042836	0.01777	Gypsum

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.93341	0.11604	0.061058	0.91097	0.17133	0.020776	0.82797	0.028597	0.0082202	Gypsum
0.9425	0.11212	0.051414	0.92745	0.18065	0.023831	0.86594	0.041727	0.01552	Gypsum
0.93942	0.089845	0.048074	0.92307	0.15634	0.015566	0.8596	0.052928	0.022206	Gypsum
0.94315	0.0927	0.055703	0.9197	0.14613	0.0083062	0.8417	0.02662	0.0080082	Gypsum
0.93924	0.086827	0.052883	0.92139	0.15202	0.018909	0.84693	0.033908	0.012545	Gypsum
0.89418	0.13826	0.012629	0.88261	0.20487	0.024037	0.82773	0.081676	0.039146	Gypsum
0.92656	0.10086	0.038194	0.91389	0.1628	0.022498	0.85776	0.047	0.019584	Gypsum
0.9239	0.14928	0.036251	0.91372	0.21614	0.031461	0.85654	0.062044	0.025322	Gypsum
0.90836	0.15656	0.071814	0.88199	0.17935	0.019278	0.79853	0.02042	0.0037269	Gypsum
0.87726	0.19679	0.055561	0.86238	0.2487	0.048524	0.80811	0.075127	0.032855	Gypsum
0.88893	0.13611	0.032981	0.87425	0.19687	0.027892	0.82771	0.087088	0.040926	Gypsum
0.84272	0.20507	0.055253	0.82136	0.25307	0.053795	0.74691	0.074169	0.031871	Gypsum
0.87575	0.17654	0.041321	0.85594	0.22793	0.038844	0.77785	0.051068	0.019362	Gypsum
0.85622	0.21781	0.055466	0.83558	0.24968	0.050555	0.75866	0.04419	0.015691	Gypsum
0.86428	0.22035	0.064185	0.83873	0.24213	0.043459	0.7581	0.034301	0.009393	Gypsum
0.85569	0.25169	0.060134	0.83181	0.27085	0.049324	0.75523	0.050829	0.018654	Gypsum
0.90456	0.14596	0.051699	0.89001	0.19875	0.034681	0.82985	0.038162	0.014228	Gypsum
0.87715	0.19079	0.052907	0.85991	0.23245	0.040751	0.79871	0.045979	0.017071	Gypsum
0.87654	0.19713	0.053381	0.85948	0.23819	0.041285	0.79845	0.048936	0.018181	Gypsum
0.84583	0.21117	0.06755	0.82508	0.24253	0.050124	0.7731	0.05876	0.024402	Gypsum
0.94001	0.099953	0.052149	0.91895	0.14451	0.011095	0.84038	0.022089	0.0058406	Gypsum
0.90353	0.12051	0.072359	0.88334	0.17107	0.037655	0.80714	0.030369	0.010323	Gypsum
0.89509	0.14502	0.058049	0.87459	0.17989	0.029307	0.80547	0.024806	0.007353	Gypsum
0.94446	0.074818	0.057267	0.93236	0.14836	0.025575	0.87811	0.034376	0.013155	Gypsum
0.95629	0.060874	0.044899	0.94397	0.14008	0.016387	0.8811	0.044117	0.01832	Gypsum
0.94674	0.072145	0.051367	0.92721	0.13281	0.013105	0.861	0.029088	0.010364	Gypsum
0.88385	0.18251	0.063853	0.86115	0.22135	0.042331	0.78921	0.046626	0.017303	Gypsum
0.92416	0.13671	0.049329	0.90397	0.19107	0.024057	0.82631	0.034693	0.010683	Gypsum
0.93394	0.12155	0.048003	0.91521	0.18338	0.022683	0.84313	0.037327	0.012363	Gypsum
0.91293	0.099689	0.060347	0.89462	0.13511	0.023052	0.83198	0.023987	0.0084513	Gypsum
0.96618	0.052117	0.09629	0.9516	0.10619	0.024262	0.91006	0.019083	0.006077	Gypsum
0.97036	0.062617	0.064635	0.95841	0.14467	0.022621	0.90819	0.038048	0.014878	Gypsum
0.93978	0.11176	0.039781	0.92965	0.18181	0.02457	0.87584	0.056212	0.024209	Gypsum
0.90839	0.14737	0.041203	0.89288	0.19931	0.029759	0.82742	0.050635	0.020862	Gypsum
0.86434	0.17941	0.03907	0.84219	0.21816	0.033696	0.76764	0.044632	0.01757	Gypsum
0.89101	0.15833	0.038667	0.86562	0.19183	0.020673	0.78496	0.030423	0.0094925	Gypsum
0.88233	0.17728	0.056911	0.86228	0.22539	0.04432	0.7858	0.037474	0.012087	Gypsum
0.92712	0.13534	0.045799	0.91106	0.18789	0.023319	0.85253	0.033286	0.010907	Gypsum
0.88018	0.13725	0.049495	0.85682	0.17528	0.029061	0.78174	0.035531	0.01423	Gypsum
0.88699	0.13215	0.048074	0.86357	0.17328	0.026969	0.79834	0.03668	0.01499	Gypsum
0.85047	0.19261	0.053713	0.82196	0.20524	0.030969	0.74083	0.033266	0.01125	Gypsum
0.78637	0.23506	0.07724	0.7545	0.23517	0.049099	0.67601	0.035588	0.012221	Gypsum
0.88858	0.13921	0.05883	0.86628	0.18179	0.035358	0.79314	0.036618	0.013914	Gypsum
0.76671	0.24288	0.045918	0.75026	0.26157	0.067003	0.72861	0.09832	0.054294	Gypsum
0.76671	0.24288	0.045918	0.75026	0.26157	0.067003	0.72861	0.09832	0.054294	Gypsum
0.79034	0.22396	0.0281	0.77356	0.23778	0.046063	0.74881	0.074549	0.038301	Gypsum
0.79889	0.20302	0.035279	0.77988	0.21265	0.041141	0.75037	0.060028	0.030296	Gypsum
0.79201	0.18925	0.032412	0.77201	0.1907	0.035481	0.74078	0.050232	0.026685	Gypsum
0.79928	0.21359	0.023859	0.78169	0.23738	0.043274	0.76196	0.066634	0.033003	Gypsum
0.80774	0.19373	0.021869	0.78941	0.21672	0.039275	0.76148	0.077371	0.040322	Gypsum
0.81467	0.19411	0.017746	0.79619	0.21387	0.035091	0.76951	0.070102	0.036056	Gypsum
0.81071	0.18533	0.024712	0.79239	0.19414	0.03224	0.76275	0.061777	0.033312	Gypsum
0.81893	0.19308	0.0204	0.80532	0.21351	0.037552	0.79673	0.0925	0.052166	Gypsum
0.81253	0.2078	0.019097	0.80355	0.24139	0.048401	0.80101	0.12766	0.072276	Gypsum
0.81328	0.20707	0.018978	0.80394	0.24053	0.047766	0.80724	0.12834	0.072987	Gypsum
0.82911	0.19403	0.021703	0.81919	0.23118	0.039931	0.79747	0.085994	0.044283	Gypsum
0.82911	0.19403	0.021703	0.81919	0.23118	0.039931	0.79747	0.085994	0.044283	Gypsum
0.82012	0.19145	0.035516	0.80445	0.2234	0.043089	0.77202	0.068384	0.033227	Gypsum
0.7352	0.28535	0.089632	0.71097	0.27842	0.082446	0.66938	0.059251	0.027182	Gypsum
0.85273	0.16177	0.026821	0.84288	0.19961	0.035686	0.82536	0.073181	0.038291	Gypsum
0.81861	0.18225	0.026418	0.80984	0.20684	0.043807	0.79428	0.073248	0.040599	Gypsum
0.7913	0.19178	0.002938	0.7841	0.21222	0.038126	0.79565	0.11999	0.074657	Gypsum
0.7826	0.20174	0.0064209	0.77392	0.23315	0.046207	0.7848	0.14158	0.085418	Gypsum
0.77526	0.23524	0.012344	0.76604	0.24822	0.043254	0.73843	0.096861	0.053702	Gypsum
0.78039	0.22523	0.013505	0.76502	0.24232	0.043089	0.74223	0.097807	0.054442	Gypsum
0.78954	0.22	0.019073	0.77688	0.24576	0.048996	0.75604	0.10711	0.05967	Gypsum
0.77448	0.23233	0.0007108	0.76613	0.25589	0.042925	0.75874	0.12051	0.068797	Gypsum
0.71631	0.29245	0.020305	0.71022	0.29754	0.06647	0.72132	0.12508	0.072639	Gypsum
0.73535	0.25826	0.052267	0.72088	0.26362	0.070715	0.71219	0.093681	0.050377	Gypsum
0.86802	0.16785	0.027366	0.85657	0.22305	0.032876	0.82126	0.078244	0.036434	Gypsum
0.88285	0.13029	0.022461	0.87596	0.189	0.024488	0.84933	0.076225	0.037668	Gypsum
0.8906	0.12571	0.026205	0.88342	0.18111	0.023319	0.86716	0.073384	0.036115	Gypsum
0.92431	0.11718	0.03092	0.91694	0.17954	0.020324	0.88847	0.064359	0.029137	Gypsum
0.87956	0.15603	0.015875	0.86989	0.20791	0.024406	0.84344	0.076205	0.036434	Gypsum
0.87718	0.14472	0.027532	0.86286	0.1922	0.02701	0.82111	0.059594	0.027764	Gypsum
0.85193	0.1451	0.02919	0.83678	0.19247	0.033184	0.79702	0.061506	0.030569	Gypsum
0.81043	0.19121	0.028811	0.7935	0.22141	0.040977	0.75227	0.07131	0.036034	Gypsum
0.76916	0.23974	0.074823	0.74292	0.23158	0.05681	0.68531	0.043956	0.019012	Gypsum
0.74036	0.26738	0.054139	0.71437	0.29579	0.076581	0.66777	0.07554	0.036477	Gypsum
0.89687	0.12816	0.024143	0.88709	0.18674	0.023073	0.85918	0.070489	0.034335	Gypsum
0.87805	0.17044	0.028811	0.8624	0.21195	0.028426	0.81773	0.056586	0.025015	Gypsum
0.87795	0.16593	0.042885	0.85997	0.20607	0.032671	0.81083	0.049912	0.020845	Gypsum
0.807	0.216	0.027247	0.78857	0.2506	0.044566	0.74799	0.085716	0.043197	Gypsum
0.8139	0.1997	0.034569	0.79227	0.23371	0.042454	0.74202	0.062319	0.028874	Gypsum
0.75808	0.2661	0.069303	0.73031	0.2677	0.064973	0.66666	0.053536	0.022741	Gypsum
0.55328	0.49767	0.11745	0.52541	0.5003	0.17308	0.47605	0.13139	0.065578	Gypsum
0.87826	0.1545	0.034474	0.86403	0.20485	0.03222	0.82398	0.060267	0.027888	Gypsum
0.83416	0.20447	0.019784	0.8209	0.24775	0.038721	0.7881	0.077983	0.038196	Gypsum
0.8394	0.21296	0.02258	0.82448	0.24986	0.039049	0.79322	0.06722	0.031652	Gypsum

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.82994	0.20555	0.04433	0.80944	0.23893	0.047458	0.76882	0.058913	0.026912	Gypsum
0.70746	0.34819	0.05703	0.68259	0.35897	0.087738	0.63867	0.097981	0.047168	Gypsum
0.82866	0.1927	0.062195	0.80781	0.23067	0.05439	0.75887	0.058863	0.027452	Gypsum
0.82299	0.17874	0.032957	0.80568	0.2056	0.036014	0.76909	0.06596	0.033692	Gypsum
0.80064	0.22801	0.037625	0.78075	0.25646	0.052524	0.7407	0.071548	0.034712	Gypsum
0.84197	0.17931	0.031654	0.82494	0.22083	0.039459	0.78398	0.070201	0.034026	Gypsum
0.86816	0.17927	0.027176	0.84926	0.21636	0.028487	0.80075	0.052595	0.022627	Gypsum
0.86722	0.16426	0.023291	0.84938	0.20276	0.023914	0.79885	0.05333	0.023822	Gypsum
0.85559	0.1866	0.032957	0.83477	0.21793	0.032138	0.78506	0.051531	0.021738	Gypsum
0.82355	0.20721	0.039047	0.80381	0.23691	0.046412	0.74593	0.052442	0.022654	Gypsum
0.83414	0.18645	0.045728	0.81104	0.21275	0.039788	0.76117	0.053876	0.024039	Gypsum
0.74025	0.30598	0.071293	0.71279	0.30565	0.073874	0.65064	0.058801	0.024188	Gypsum
0.86298	0.1584	0.029309	0.85056	0.20064	0.032261	0.81427	0.060438	0.029084	Gypsum
0.82791	0.20612	0.035042	0.81037	0.23671	0.045838	0.76494	0.07273	0.035487	Gypsum
0.85079	0.17881	0.022224	0.837	0.22058	0.033409	0.80157	0.072672	0.035136	Gypsum
0.87062	0.15243	0.015922	0.85901	0.198	0.025021	0.8253	0.065099	0.032081	Gypsum
0.89664	0.13106	0.024404	0.88578	0.18722	0.02377	0.85596	0.058106	0.027224	Gypsum
0.87675	0.16342	0.041629	0.86226	0.21569	0.038967	0.81567	0.057782	0.025743	Gypsum
0.83982	0.19345	0.033668	0.8243	0.23535	0.044094	0.7824	0.072465	0.034936	Gypsum
0.80272	0.23347	0.045799	0.78204	0.2524	0.051416	0.74033	0.056043	0.025164	Gypsum
0.83801	0.19201	0.032294	0.82325	0.23192	0.042392	0.78314	0.065615	0.031233	Gypsum
0.82896	0.19058	0.030635	0.80992	0.21782	0.037778	0.77321	0.070854	0.034905	Gypsum
0.86656	0.17951	0.034355	0.8521	0.22489	0.039644	0.81524	0.068003	0.031443	Gypsum
0.8469	0.20164	0.03862	0.82584	0.22881	0.038208	0.76951	0.055868	0.024024	Gypsum
0.78582	0.23633	0.058854	0.75825	0.23735	0.048217	0.70601	0.046073	0.019659	Gypsum
0.8902	0.14791	0.030493	0.87765	0.18552	0.022991	0.84001	0.045789	0.021037	Gypsum
0.87529	0.1459	0.024309	0.86241	0.19311	0.026518	0.83803	0.06307	0.031141	Gypsum
0.84252	0.1918	0.028811	0.82718	0.22617	0.036178	0.78887	0.060846	0.02821	Gypsum
0.79929	0.27513	0.037886	0.7806	0.28182	0.049939	0.74635	0.073241	0.034493	Gypsum
0.81745	0.22353	0.030635	0.80028	0.25878	0.047991	0.77257	0.081404	0.039779	Gypsum
0.8651	0.15233	0.023172	0.84641	0.17913	0.019607	0.8026	0.04281	0.01964	Gypsum
0.85539	0.13904	0.033384	0.84262	0.18271	0.034066	0.81355	0.067829	0.034486	Gypsum
0.8561	0.1794	0.033692	0.84331	0.23041	0.03948	0.80941	0.07825	0.03712	Gypsum
0.80994	0.23938	0.051509	0.78816	0.25754	0.053057	0.73714	0.060055	0.026612	Gypsum
0.83663	0.16514	0.03118	0.81778	0.18248	0.029964	0.77572	0.036479	0.017719	Gypsum
0.84613	0.15023	0.033194	0.82253	0.17149	0.023873	0.78393	0.040469	0.019026	Gypsum
0.84336	0.1917	0.049069	0.82178	0.21175	0.039726	0.7755	0.039327	0.015929	Gypsum
0.82411	0.19323	0.028527	0.80875	0.22915	0.043725	0.77049	0.069383	0.034128	Gypsum
0.82322	0.19859	0.017438	0.80821	0.24054	0.039357	0.76523	0.083354	0.040921	Gypsum
0.82455	0.19594	0.015969	0.80631	0.23227	0.034722	0.75715	0.073833	0.035793	Gypsum
0.83309	0.21414	0.059257	0.81185	0.23816	0.052134	0.76914	0.058298	0.026522	Gypsum
0.81665	0.20188	0.03509	0.79318	0.21877	0.036301	0.74881	0.054912	0.026067	Gypsum
0.8005	0.21007	0.041629	0.77275	0.20357	0.028774	0.7219	0.035343	0.013836	Gypsum
0.79548	0.20302	0.047671	0.77052	0.21187	0.041059	0.721	0.043575	0.018425	Gypsum
0.83497	0.17853	0.015495	0.8157	0.19929	0.025493	0.76531	0.043662	0.019908	Gypsum
0.83943	0.16297	0.030872	0.8219	0.20306	0.03466	0.78108	0.054879	0.026549	Gypsum
0.83097	0.17079	0.033123	0.81242	0.20734	0.036896	0.76626	0.052765	0.025157	Gypsum
0.82144	0.21655	0.041274	0.80081	0.24186	0.044935	0.74913	0.053507	0.022812	Gypsum
0.89362	0.14375	0.022935	0.88166	0.19798	0.022806	0.83336	0.074327	0.034656	Gypsum
0.89284	0.14556	0.02303	0.88037	0.19876	0.022888	0.83518	0.074335	0.034732	Gypsum
0.89005	0.16021	0.016775	0.87891	0.21492	0.022847	0.83386	0.086836	0.040215	Gypsum
0.91162	0.12171	0.022603	0.89906	0.17664	0.014767	0.85097	0.062348	0.028558	Gypsum
0.92649	0.090097	0.022106	0.92045	0.15984	0.015218	0.88157	0.071271	0.033746	Gypsum
0.92204	0.10539	0.0195	0.92019	0.17117	0.016448	0.89401	0.083848	0.040877	Gypsum
0.91729	0.11912	0.014548	0.91342	0.1812	0.014438	0.88553	0.082803	0.039545	Gypsum
0.90744	0.14457	0.014098	0.90069	0.20281	0.018376	0.86768	0.083727	0.039036	Gypsum
0.90896	0.12971	0.020566	0.90267	0.18532	0.018356	0.86409	0.075864	0.035806	Gypsum
0.93641	0.090097	0.020424	0.93573	0.15401	0.012305	0.91696	0.077403	0.037858	Gypsum
0.93748	0.09043	0.019073	0.93724	0.15647	0.01288	0.91933	0.080864	0.039647	Gypsum
0.94009	0.084715	0.016206	0.93655	0.1524	0.0096392	0.89995	0.074242	0.035708	Gypsum
0.91365	0.12041	0.011704	0.90641	0.18186	0.013577	0.85673	0.083926	0.039735	Gypsum
0.82856	0.23833	0.022675	0.81215	0.28653	0.04594	0.76051	0.10122	0.047338	Gypsum
0.92514	0.12359	0.029877	0.91351	0.18997	0.018171	0.86911	0.076058	0.034053	Gypsum
0.9165	0.13231	0.023433	0.9053	0.19718	0.017781	0.86016	0.077552	0.03481	Gypsum
0.93842	0.091261	0.024262	0.93267	0.15832	0.011341	0.89752	0.071907	0.033595	Gypsum
0.9161	0.11235	0.028645	0.90515	0.17504	0.018356	0.8633	0.069135	0.031859	Gypsum
0.93163	0.090208	0.031346	0.92238	0.15608	0.014356	0.8778	0.057286	0.025899	Gypsum
0.94416	0.066167	0.028598	0.94118	0.13424	0.01087	0.91894	0.069538	0.034284	Gypsum
0.96545	0.039161	0.024854	0.96867	0.11404	0.0057015	0.95596	0.073289	0.037339	Gypsum
0.96234	0.045221	0.032128	0.96265	0.12031	0.0098443	0.94249	0.070295	0.035138	Gypsum
0.95436	0.05107	0.033408	0.95449	0.125	0.01208	0.93692	0.072687	0.036789	Gypsum
0.85166	0.20206	0.053902	0.82788	0.23164	0.039644	0.76603	0.052829	0.021393	Gypsum
0.92574	0.11162	0.032033	0.91368	0.17046	0.015013	0.87104	0.064404	0.029432	Gypsum
0.92963	0.10325	0.029759	0.91874	0.16757	0.013926	0.87701	0.070595	0.03283	Gypsum
0.89626	0.14098	0.027697	0.88455	0.20006	0.025001	0.83497	0.081866	0.037972	Gypsum
0.91331	0.11766	0.038833	0.90007	0.17976	0.022293	0.84139	0.055108	0.023642	Gypsum
0.92843	0.097712	0.029711	0.92195	0.16967	0.01733	0.89023	0.083857	0.039616	Gypsum
0.94135	0.081855	0.022627	0.94027	0.1534	0.01167	0.91392	0.078152	0.037712	Gypsum
0.94257	0.087377	0.018244	0.93945	0.15561	0.0094752	0.91236	0.080414	0.038333	Gypsum
0.93898	0.094934	0.033289	0.93068	0.16067	0.015484	0.88807	0.058854	0.026308	Gypsum
0.96438	0.052971	0.022769	0.96866	0.12633	0.0075473	0.95844	0.080624	0.040263	Gypsum
0.83525	0.20739	0.052196	0.8123	0.23606	0.043787	0.73986	0.054066	0.022617	Gypsum
0.78586	0.25261	0.083353	0.75258	0.24899	0.055231	0.66891	0.036726	0.011903	Gypsum
0.84541	0.18931	0.046605	0.81913	0.22082	0.035152	0.74884	0.039914	0.014639	Gypsum
0.82862	0.2059	0.05241	0.80201	0.22901	0.044976	0.7172	0.036051	0.012387	Gypsum
0.80321	0.2245	0.057741	0.77221	0.23094	0.044546	0.69323	0.036402	0.012852	Gypsum
0.77693	0.23431	0.059352	0.74593	0.24121	0.052011	0.66967	0.040138	0.0149	Gypsum
0.78381	0.253	0.042103	0.75832	0.26652	0.051478	0.69241	0.057557	0.023258	Gypsum
0.80925	0.23278	0.031749	0.79216	0.27215	0.053426	0.72961	0.089399	0.041933	Gypsum

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.81394	0.23018	0.032199	0.796	0.27164	0.052339	0.73603	0.080037	0.036088	Gypsum
0.76509	0.27275	0.07743	0.73536	0.27761	0.069444	0.66212	0.051063	0.020107	Gypsum
0.70619	0.3744	0.068829	0.6852	0.40749	0.11276	0.63194	0.13387	0.067227	Gypsum
0.79577	0.25483	0.04606	0.77112	0.27763	0.055764	0.70453	0.063338	0.027046	Gypsum
0.80572	0.22518	0.040989	0.7827	0.25051	0.049693	0.71192	0.060324	0.026357	Gypsum
0.79597	0.23368	0.041913	0.77175	0.26075	0.054267	0.70046	0.059888	0.025785	Gypsum
0.84841	0.21349	0.023054	0.83055	0.25684	0.038188	0.774	0.070019	0.030306	Gypsum
0.84737	0.20042	0.022864	0.82981	0.24588	0.036588	0.77397	0.072748	0.032689	Gypsum
0.82873	0.20824	0.027674	0.80831	0.24332	0.039747	0.74868	0.06685	0.030028	Gypsum
0.81958	0.21311	0.03246	0.79835	0.24706	0.043397	0.73244	0.062666	0.027304	Gypsum
0.7426	0.31884	0.082145	0.71422	0.31929	0.084661	0.63688	0.062078	0.025084	Gypsum
0.82941	0.20202	0.048524	0.80271	0.23492	0.043048	0.72401	0.050674	0.020779	Gypsum
0.86555	0.16914	0.029522	0.8449	0.21942	0.030292	0.78189	0.057363	0.024504	Gypsum
0.89548	0.14221	0.03092	0.88216	0.19771	0.027051	0.82359	0.05658	0.024212	Gypsum
0.86751	0.19108	0.068876	0.84538	0.22818	0.049857	0.78335	0.05283	0.021373	Gypsum
0.83577	0.21249	0.072762	0.80794	0.21847	0.04391	0.73574	0.027763	0.0078056	Gypsum
0.83562	0.21902	0.04189	0.80866	0.23483	0.035768	0.73748	0.039558	0.01346	Gypsum
0.85625	0.18782	0.047529	0.832	0.22343	0.03829	0.76415	0.046098	0.017819	Gypsum
0.84396	0.20016	0.029925	0.8267	0.25298	0.043951	0.7735	0.077688	0.03537	Gypsum
0.77499	0.28701	0.073212	0.74719	0.3094	0.079944	0.67786	0.072078	0.030958	Gypsum
0.79221	0.24899	0.045586	0.76787	0.28125	0.05921	0.6955	0.083113	0.037975	Gypsum
0.86133	0.18925	0.059423	0.8369	0.21821	0.039541	0.76613	0.042353	0.01543	Gypsum
0.84079	0.19883	0.053902	0.81596	0.22174	0.043459	0.74559	0.039724	0.01506	Gypsum
0.8596	0.16315	0.040089	0.83645	0.1968	0.031399	0.76037	0.034227	0.012455	Gypsum
0.78289	0.21857	0.043548	0.75419	0.21745	0.036404	0.67973	0.033745	0.012094	Gypsum
0.80287	0.20292	0.053191	0.77924	0.22519	0.050657	0.71013	0.045379	0.019289	Gypsum
0.80187	0.21662	0.044946	0.77799	0.24273	0.049673	0.7153	0.053179	0.022909	Gypsum
0.80049	0.24185	0.037578	0.78129	0.27731	0.056072	0.72341	0.085629	0.040215	Gypsum
0.8483	0.1807	0.06582	0.82046	0.19981	0.036978	0.74226	0.035645	0.012987	Gypsum
0.8783	0.17075	0.044472	0.86121	0.21527	0.036916	0.79357	0.044747	0.01692	Gypsum
0.82696	0.22749	0.083543	0.80165	0.24647	0.06286	0.73376	0.040129	0.014106	Gypsum
0.82378	0.2431	0.052528	0.79377	0.24181	0.037265	0.71733	0.033642	0.0096542	Gypsum
0.88399	0.16977	0.040231	0.86601	0.21947	0.034599	0.80698	0.052809	0.021271	Gypsum
0.88209	0.14889	0.04061	0.86503	0.19836	0.033204	0.79869	0.044467	0.018072	Gypsum
0.82042	0.23565	0.059873	0.79392	0.24759	0.048176	0.7195	0.038642	0.013531	Gypsum
0.79735	0.24234	0.081434	0.76506	0.24021	0.050575	0.69101	0.034119	0.010723	Gypsum
0.81796	0.22665	0.071222	0.79059	0.2483	0.0556	0.7134	0.04479	0.016772	Gypsum
0.85388	0.14488	0.055087	0.83101	0.18396	0.039049	0.76235	0.03992	0.016129	Gypsum
0.82252	0.17993	0.072904	0.79477	0.19934	0.049468	0.72338	0.04202	0.017841	Gypsum
0.80862	0.20449	0.07326	0.77762	0.20343	0.041797	0.69309	0.030178	0.009763	Gypsum
0.7837	0.23307	0.061863	0.75068	0.21706	0.036506	0.66611	0.026313	0.0070538	Gypsum
0.84396	0.21616	0.062645	0.82421	0.23741	0.05236	0.75618	0.042608	0.015766	Gypsum
0.88208	0.13476	0.04144	0.8668	0.19078	0.035378	0.81395	0.051417	0.023004	Gypsum
0.75989	0.28016	0.086078	0.72658	0.2646	0.060276	0.64607	0.036323	0.011969	Gypsum
0.85892	0.1768	0.040184	0.83371	0.21	0.031892	0.76341	0.037229	0.013545	Gypsum
0.86734	0.15812	0.050017	0.84397	0.1947	0.033901	0.7758	0.038342	0.014749	Gypsum
0.84353	0.16346	0.065109	0.81234	0.16112	0.022252	0.73748	0.01623	0.0033722	Gypsum
0.92483	0.12393	0.074468	0.90446	0.16296	0.025575	0.835	0.02112	0.0054097	Gypsum
0.88688	0.11494	0.063285	0.86778	0.14722	0.031666	0.8116	0.0236	0.0089284	Gypsum
0.89164	0.088646	0.053902	0.87392	0.13287	0.02943	0.81617	0.028037	0.012485	Gypsum
0.88275	0.1363	0.045112	0.86553	0.17716	0.033184	0.80479	0.038582	0.016407	Gypsum
0.76907	0.30606	0.075984	0.74102	0.30849	0.074038	0.66901	0.055158	0.02095	Gypsum
0.84023	0.21513	0.023409	0.80683	0.25452	0.030251	0.74709	0.057782	0.023345	Gypsum
0.85276	0.20287	0.036464	0.81988	0.24827	0.033717	0.76235	0.069158	0.030586	Gypsum
0.8591	0.20456	0.02983	0.82881	0.25588	0.032425	0.77323	0.078467	0.035146	Gypsum
0.85929	0.21065	0.02085	0.8327	0.2672	0.033614	0.77611	0.086298	0.038493	Gypsum
0.87723	0.17419	0.016633	0.85197	0.23834	0.024447	0.79924	0.076452	0.033924	Gypsum
0.88164	0.17419	0.01341	0.85733	0.23973	0.021904	0.80429	0.080444	0.035947	Gypsum
0.87994	0.17808	0.01841	0.85306	0.24142	0.023606	0.7937	0.074021	0.03199	Gypsum
0.87305	0.19178	0.022319	0.84458	0.25243	0.028959	0.78123	0.07285	0.030995	Gypsum
0.87695	0.19111	0.025091	0.8479	0.24988	0.028487	0.77862	0.069187	0.028808	Gypsum
0.89958	0.1282	0.030778	0.86779	0.19062	0.015771	0.80217	0.046698	0.01906	Gypsum
0.91742	0.1143	0.044615	0.8824	0.16502	0.0074653	0.82195	0.02949	0.00982	Gypsum
0.94641	0.065038	0.052552	0.91916	0.13012	0.0086958	0.87439	0.034004	0.014425	Gypsum
0.96188	0.052375	0.053334	0.93946	0.1215	0.0058451	0.91004	0.028353	0.012093	Gypsum
0.93658	0.11235	0.054518	0.91288	0.16836	0.015156	0.87574	0.027416	0.0097228	Gypsum
0.89053	0.15	0.032602	0.85853	0.19547	0.015669	0.79945	0.036542	0.013477	Gypsum
0.88699	0.14515	0.031725	0.85507	0.19247	0.016428	0.79283	0.039493	0.015309	Gypsum
0.85793	0.17058	0.034024	0.82325	0.21571	0.025165	0.75108	0.047021	0.018534	Gypsum
0.81695	0.22687	0.03618	0.78007	0.26569	0.040177	0.70595	0.058743	0.023464	Gypsum
0.79991	0.24414	0.042719	0.76399	0.28681	0.052995	0.69001	0.076282	0.033356	Gypsum
0.76845	0.28308	0.061768	0.7287	0.30977	0.066449	0.65901	0.080299	0.03554	Gypsum
0.88024	0.16613	0.034853	0.84939	0.22208	0.024467	0.78166	0.053767	0.021639	Gypsum
0.90544	0.14222	0.030375	0.87786	0.20363	0.018581	0.81627	0.049688	0.019533	Gypsum
0.90005	0.13303	0.040018	0.87398	0.19943	0.028754	0.81712	0.052912	0.022435	Gypsum
0.90317	0.12488	0.041605	0.87808	0.19614	0.029574	0.82861	0.055247	0.024188	Gypsum
0.94397	0.091652	0.049756	0.92012	0.15592	0.012469	0.8741	0.035164	0.013782	Gypsum
0.90768	0.10689	0.051012	0.87591	0.15792	0.016305	0.8144	0.030584	0.011818	Gypsum
0.88502	0.11919	0.053476	0.84992	0.15578	0.016141	0.77925	0.025714	0.0096074	Gypsum
0.8826	0.12421	0.054708	0.84667	0.15907	0.016612	0.78171	0.025625	0.0095125	Gypsum
0.79969	0.22982	0.051367	0.76202	0.24885	0.042802	0.68993	0.045562	0.017509	Gypsum
0.87318	0.18465	0.027958	0.84778	0.23874	0.029533	0.79832	0.073179	0.032862	Gypsum
0.88726	0.15933	0.036985	0.8585	0.21145	0.024672	0.79784	0.044101	0.017312	Gypsum
0.93763	0.092629	0.064967	0.91393	0.15611	0.019689	0.87315	0.027314	0.010021	Gypsum
0.91556	0.13287	0.062929	0.89092	0.18432	0.024508	0.84656	0.02777	0.0092096	Gypsum
0.91991	0.12425	0.062977	0.89065	0.17267	0.017453	0.83798	0.025344	0.0075083	Gypsum
0.91267	0.14621	0.035848	0.88529	0.20538	0.017699	0.83069	0.044903	0.017071	Gypsum
0.87493	0.17207	0.045396	0.84199	0.21842	0.026846	0.77416	0.043777	0.016105	Gypsum
0.83701	0.2106	0.040681	0.80117	0.25505	0.037819	0.7307	0.061785	0.025344	Gypsum

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.80629	0.24441	0.043217	0.76909	0.27936	0.046638	0.70157	0.073435	0.031745	Gypsum
0.90967	0.10676	0.025281	0.88704	0.16666	0.011013	0.84358	0.052475	0.024141	Gypsum
0.93265	0.094279	0.025304	0.91368	0.16355	0.0096187	0.87645	0.059299	0.027657	Gypsum
0.91855	0.10889	0.026845	0.89639	0.17186	0.011895	0.85047	0.054426	0.024974	Gypsum
0.90951	0.10657	0.029309	0.8846	0.16823	0.013946	0.83771	0.052514	0.024295	Gypsum
0.90296	0.10873	0.038123	0.87637	0.17397	0.019525	0.8337	0.05227	0.023686	Gypsum
0.89337	0.11261	0.03445	0.86454	0.1678	0.017207	0.8064	0.042944	0.018583	Gypsum
0.88997	0.12342	0.02765	0.8604	0.17458	0.014151	0.80767	0.045495	0.019866	Gypsum
0.88164	0.13093	0.026442	0.85196	0.17777	0.014931	0.79145	0.04567	0.019929	Gypsum
0.91026	0.11359	0.020661	0.88775	0.17095	0.011177	0.83518	0.050639	0.022824	Gypsum
0.90815	0.10948	0.022959	0.88578	0.1731	0.013905	0.8403	0.058819	0.027469	Gypsum
0.89677	0.13286	0.022153	0.87471	0.19569	0.019094	0.82599	0.062157	0.028246	Gypsum
0.89849	0.13101	0.027129	0.87417	0.19675	0.019914	0.81963	0.057278	0.025349	Gypsum
0.87159	0.15801	0.022722	0.84375	0.21442	0.023647	0.78794	0.058009	0.025366	Gypsum
0.85237	0.17089	0.017817	0.82211	0.20976	0.019689	0.76035	0.046453	0.019345	Gypsum
0.85582	0.16903	0.020589	0.82256	0.20603	0.017289	0.75713	0.042153	0.01638	Gypsum
0.85333	0.17192	0.027318	0.82292	0.21593	0.025636	0.76291	0.055358	0.024343	Gypsum
0.84629	0.19063	0.026228	0.81596	0.23048	0.028754	0.75161	0.05847	0.025315	Gypsum
0.84465	0.20346	0.02258	0.81474	0.24208	0.027995	0.75235	0.0639	0.027306	Gypsum
0.91249	0.11194	0.022793	0.8924	0.17488	0.012387	0.85168	0.057267	0.026649	Gypsum
0.9138	0.10863	0.02258	0.89396	0.17122	0.011629	0.85559	0.057312	0.027063	Gypsum
0.93293	0.1056	0.030991	0.9086	0.1598	0.0053323	0.86032	0.035617	0.014481	Gypsum
0.91374	0.12176	0.028124	0.88751	0.17058	0.0084087	0.83156	0.033731	0.012688	Gypsum
0.89621	0.13676	0.038431	0.86664	0.18795	0.016899	0.80701	0.037424	0.014118	Gypsum
0.88667	0.14758	0.040681	0.85721	0.20254	0.023196	0.79864	0.043531	0.017052	Gypsum
0.88283	0.14286	0.040231	0.85488	0.2007	0.02658	0.79969	0.053413	0.023077	Gypsum
0.885	0.13881	0.024025	0.85996	0.18796	0.017535	0.8031	0.046514	0.019985	Gypsum
0.86564	0.16622	0.02021	0.83789	0.215	0.022662	0.78543	0.058636	0.026135	Gypsum
0.86752	0.16614	0.025115	0.83922	0.21584	0.02379	0.77479	0.052792	0.022349	Gypsum
0.86992	0.18162	0.019831	0.83945	0.22136	0.01694	0.77305	0.040835	0.014887	Gypsum
0.8644	0.19	0.019997	0.83414	0.22781	0.019114	0.76985	0.043987	0.01648	Gypsum
0.86911	0.17849	0.022272	0.83948	0.21758	0.019402	0.77854	0.048768	0.019808	Gypsum
0.8598	0.1828	0.021395	0.8298	0.21704	0.019812	0.77051	0.051292	0.021561	Gypsum
0.85408	0.18598	0.022698	0.82321	0.22229	0.022191	0.7609	0.049463	0.020633	Gypsum
0.85587	0.1837	0.020187	0.82295	0.21355	0.016018	0.75916	0.048219	0.020046	Gypsum
0.84734	0.20992	0.025162	0.816	0.24926	0.029061	0.7509	0.055953	0.022318	Gypsum
0.82338	0.21762	0.033526	0.79004	0.25007	0.034291	0.72095	0.064715	0.028034	Gypsum
0.88298	0.20364	0.058973	0.84984	0.24177	0.031727	0.78588	0.035468	0.010484	Gypsum
0.81927	0.22808	0.035777	0.78133	0.24296	0.030005	0.70355	0.044443	0.016229	Gypsum
0.81244	0.22824	0.027081	0.77625	0.24674	0.031502	0.7077	0.056452	0.023598	Gypsum
0.78822	0.24689	0.037435	0.75536	0.25586	0.042966	0.68826	0.050103	0.020808	Gypsum
0.78103	0.24199	0.029309	0.74692	0.24084	0.033881	0.68084	0.047167	0.019796	Gypsum
0.78404	0.25323	0.03971	0.75266	0.26935	0.050657	0.68631	0.053952	0.022542	Gypsum
0.79709	0.2543	0.046415	0.76604	0.28154	0.057138	0.69402	0.058206	0.023822	Gypsum
0.8065	0.24762	0.042529	0.77166	0.27126	0.04754	0.70722	0.055326	0.022052	Gypsum
0.8363	0.22401	0.022295	0.80457	0.25392	0.031461	0.7341	0.050499	0.019674	Gypsum
0.84809	0.22247	0.022414	0.8139	0.24447	0.023421	0.75029	0.04663	0.017609	Gypsum
0.86619	0.1552	0.026039	0.83296	0.19442	0.016797	0.76779	0.040596	0.016234	Gypsum
0.85821	0.16902	0.035611	0.82521	0.20972	0.027051	0.75929	0.044076	0.017643	Gypsum
0.83214	0.19602	0.054803	0.79407	0.20767	0.027667	0.71527	0.031552	0.010402	Gypsum
0.81082	0.20855	0.078141	0.77041	0.19676	0.029471	0.68832	0.021749	0.0049099	Gypsum
0.79015	0.23779	0.079491	0.74923	0.22345	0.036998	0.67664	0.026344	0.0064225	Gypsum
0.85746	0.17871	0.037957	0.82736	0.21078	0.026969	0.76505	0.039318	0.014583	Gypsum
0.8525	0.18221	0.036962	0.82226	0.21524	0.028364	0.76391	0.039338	0.014885	Gypsum
0.81303	0.22129	0.036464	0.78166	0.23703	0.036875	0.71501	0.045478	0.018571	Gypsum
0.78937	0.23507	0.039023	0.75762	0.24663	0.045592	0.69391	0.061381	0.028258	Gypsum
0.77006	0.25636	0.024238	0.73314	0.25924	0.035952	0.67023	0.054086	0.023121	Gypsum
0.79886	0.24022	0.03663	0.77095	0.27058	0.052852	0.70733	0.056829	0.023482	Gypsum
0.86048	0.16956	0.036701	0.83169	0.20206	0.026477	0.76956	0.036283	0.014016	Gypsum
0.89996	0.13261	0.036654	0.87486	0.18573	0.020078	0.80569	0.035948	0.013757	Gypsum
0.88904	0.13558	0.037696	0.85895	0.18689	0.022745	0.79483	0.043875	0.017712	Gypsum
0.86624	0.16142	0.04824	0.82664	0.17566	0.01288	0.74641	0.022675	0.0056191	Gypsum
0.79629	0.23582	0.079467	0.75345	0.22838	0.041285	0.6701	0.027396	0.0072315	Gypsum
0.89951	0.15659	0.027484	0.87976	0.22111	0.025165	0.82641	0.065417	0.028828	Gypsum
0.88602	0.16143	0.029546	0.86506	0.22511	0.031071	0.81165	0.069685	0.031187	Gypsum
0.84642	0.19233	0.024594	0.81978	0.23855	0.033778	0.75398	0.059416	0.025342	Gypsum
0.82841	0.23784	0.038028	0.79464	0.25808	0.037388	0.71327	0.041987	0.014335	Gypsum
0.82656	0.22249	0.029024	0.79146	0.24298	0.029943	0.70928	0.040014	0.013867	Gypsum
0.83612	0.22426	0.03073	0.80003	0.24691	0.027913	0.7257	0.045964	0.017256	Gypsum
0.83421	0.23784	0.026205	0.80025	0.26287	0.032117	0.71823	0.049305	0.018084	Gypsum
0.8424	0.24038	0.045207	0.81098	0.26939	0.044053	0.73223	0.048076	0.017171	Gypsum
0.8467	0.22603	0.046842	0.8138	0.25275	0.038598	0.73682	0.044282	0.015944	Gypsum
0.87198	0.20528	0.037933	0.84099	0.23953	0.028426	0.76893	0.042902	0.01478	Gypsum
0.89506	0.17553	0.039118	0.8686	0.22424	0.026662	0.79438	0.043738	0.015545	Gypsum
0.90735	0.15977	0.03201	0.88307	0.21787	0.022765	0.81538	0.052837	0.020343	Gypsum
0.90207	0.15542	0.033621	0.87729	0.2166	0.024836	0.81377	0.058365	0.024158	Gypsum
0.87953	0.17312	0.037649	0.85383	0.23101	0.034332	0.79074	0.057764	0.024171	Gypsum
0.88832	0.1516	0.051059	0.86184	0.21169	0.033635	0.79684	0.052334	0.021122	Gypsum
0.90197	0.11609	0.033147	0.88246	0.18246	0.024201	0.83241	0.050885	0.022717	Gypsum
0.88803	0.17141	0.040681	0.86307	0.2182	0.028713	0.79314	0.038792	0.013589	Gypsum
0.85956	0.24837	0.044733	0.82977	0.27942	0.040977	0.74612	0.045496	0.014413	Gypsum
0.82772	0.2382	0.057504	0.79381	0.24789	0.041428	0.7224	0.041999	0.015296	Gypsum
0.83088	0.22847	0.051462	0.79751	0.24822	0.041264	0.72597	0.037618	0.012811	Gypsum
0.80699	0.2542	0.050088	0.76875	0.25841	0.037511	0.67762	0.034735	0.009606	Gypsum
0.79888	0.23247	0.0417	0.76036	0.24506	0.038926	0.66793	0.042567	0.015413	Gypsum
0.84534	0.186	0.048785	0.81321	0.22121	0.037573	0.73371	0.04702	0.018834	Gypsum
0.80198	0.25567	0.065654	0.76903	0.27549	0.059435	0.69183	0.053563	0.020679	Gypsum
0.65773	0.40165	0.11157	0.61994	0.39292	0.12695	0.53976	0.085438	0.038798	Gypsum
0.87139	0.19129	0.037246	0.84725	0.24713	0.038106	0.78599	0.06806	0.029497	Gypsum

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.86132	0.17789	0.036511	0.83456	0.2217	0.034045	0.76365	0.045494	0.017565	Limestone
0.84254	0.21625	0.038288	0.81023	0.23709	0.032507	0.73117	0.041546	0.015126	Limestone
0.88575	0.17768	0.053713	0.85579	0.21981	0.030312	0.78261	0.043246	0.016032	Limestone
0.87136	0.19579	0.04715	0.84337	0.24421	0.040321	0.77347	0.053953	0.021237	Limestone
0.39496	0.23902	0.028858	0.43452	0.14505	0.06526	0.60107	0.081386	0.16141	Limestone
0.38481	0.26701	0.031773	0.42304	0.1791	0.070982	0.58571	0.10897	0.17364	Limestone
0.37398	0.2704	0.030493	0.41169	0.18251	0.070695	0.56553	0.11357	0.17298	Limestone
0.38538	0.24851	0.038194	0.42343	0.16067	0.076786	0.58534	0.10106	0.17382	Limestone
0.36531	0.3061	0.09283	0.40274	0.22103	0.12539	0.54961	0.1562	0.20114	Limestone
0.34755	0.37872	0.13209	0.38211	0.29454	0.15706	0.52994	0.21733	0.23682	Limestone
0.3322	0.42596	0.14692	0.36538	0.34057	0.16715	0.50807	0.2597	0.25701	Limestone
0.35343	0.38616	0.10387	0.3896	0.30128	0.13058	0.53517	0.22045	0.22681	Limestone
0.32322	0.45872	0.116	0.35542	0.37343	0.13792	0.49107	0.26302	0.23505	Limestone
0.33175	0.43042	0.12318	0.36512	0.34164	0.14192	0.50102	0.2216	0.20807	Limestone
0.32944	0.40742	0.11316	0.36217	0.32146	0.13669	0.49548	0.20349	0.19669	Limestone
0.35152	0.26701	0.10728	0.38479	0.18114	0.13298	0.52196	0.11297	0.164	Limestone
0.32872	0.2825	0.11927	0.35897	0.19735	0.14379	0.48325	0.12111	0.15876	Limestone
0.32274	0.29477	0.090011	0.3492	0.20613	0.11489	0.47193	0.11734	0.14427	Limestone
0.29372	0.38964	0.18417	0.317	0.31111	0.21569	0.41819	0.19109	0.21539	Limestone
0.28762	0.39601	0.19251	0.31026	0.31943	0.22384	0.41249	0.19844	0.22578	Limestone
0.28608	0.45706	0.21919	0.31053	0.40219	0.25273	0.42606	0.28308	0.28479	Limestone
0.29274	0.53654	0.23075	0.31939	0.49076	0.26079	0.44024	0.36467	0.30726	Limestone
0.29983	0.62536	0.28065	0.32725	0.57752	0.2972	0.45981	0.45204	0.34979	Limestone
0.30178	0.67671	0.31822	0.32999	0.62293	0.32224	0.4653	0.50725	0.37918	Limestone
0.30178	0.67671	0.31822	0.32999	0.62293	0.32224	0.4653	0.50725	0.37918	Limestone
0.29593	0.69043	0.32363	0.32413	0.63406	0.32367	0.45505	0.51946	0.38275	Limestone
0.30724	0.57964	0.22272	0.33649	0.51102	0.23173	0.47784	0.41983	0.32483	Limestone
0.31353	0.49881	0.16573	0.34416	0.42499	0.18349	0.48267	0.33189	0.27186	Limestone
0.31442	0.52063	0.17853	0.3453	0.44788	0.19397	0.48352	0.35368	0.28225	Limestone
0.28804	0.40454	0.1006	0.31654	0.32175	0.12543	0.43765	0.21633	0.20313	Limestone
0.27585	0.41767	0.12595	0.30117	0.32844	0.14381	0.42001	0.21376	0.20719	Limestone
0.29549	0.3811	0.12155	0.32301	0.29011	0.14412	0.44898	0.18796	0.20165	Limestone
0.29584	0.37472	0.11671	0.32422	0.28402	0.141	0.44571	0.18438	0.19791	Limestone
0.3747	0.39754	0.047434	0.41599	0.31638	0.088271	0.58726	0.22345	0.22235	Limestone
0.37581	0.40293	0.05132	0.41718	0.32214	0.091696	0.59048	0.23057	0.22801	Limestone
0.37839	0.40283	0.051083	0.41918	0.32172	0.091368	0.5988	0.2308	0.23009	Limestone
0.34958	0.33615	0.062384	0.39061	0.24547	0.098361	0.55782	0.16591	0.21782	Limestone
0.3239	0.34377	0.066247	0.36283	0.25325	0.10277	0.51784	0.16914	0.21932	Limestone
0.30949	0.44454	0.16495	0.34562	0.35182	0.18458	0.49463	0.25127	0.26246	Limestone
0.33633	0.56615	0.31583	0.37446	0.51391	0.35263	0.53224	0.44221	0.4593	Limestone
0.32459	0.60719	0.38786	0.36235	0.56483	0.42402	0.50741	0.52651	0.56472	Limestone
0.36103	0.55807	0.37452	0.40331	0.49903	0.3918	0.55848	0.42457	0.45516	Limestone
0.37841	0.53412	0.34332	0.42204	0.47064	0.36088	0.5885	0.37989	0.40756	Limestone
0.3565	0.52983	0.28903	0.39907	0.44581	0.29094	0.55188	0.26328	0.24778	Limestone
0.34363	0.48942	0.2852	0.38404	0.39627	0.2772	0.53712	0.22267	0.22321	Limestone
0.28648	0.47673	0.26518	0.32076	0.38586	0.26553	0.44571	0.23585	0.22706	Limestone
0.28176	0.40759	0.21452	0.31071	0.34006	0.25187	0.43464	0.28695	0.35028	Limestone
0.28356	0.38725	0.20905	0.31383	0.31603	0.24611	0.42976	0.26465	0.33099	Limestone
0.3057	0.36778	0.11742	0.33612	0.2915	0.15669	0.46385	0.20139	0.23317	Limestone
0.31106	0.32913	0.08532	0.34111	0.24921	0.1202	0.46944	0.15275	0.18538	Limestone
0.32666	0.30647	0.11548	0.35934	0.21825	0.14014	0.49033	0.1294	0.17559	Limestone
0.3143	0.33781	0.10264	0.34632	0.25192	0.12855	0.47388	0.15601	0.18524	Limestone
0.30574	0.42681	0.10243	0.33724	0.34237	0.12785	0.46894	0.22924	0.21188	Limestone
0.29216	0.47079	0.13744	0.32241	0.38465	0.15624	0.45672	0.26475	0.23785	Limestone
0.29236	0.42087	0.12292	0.32334	0.32998	0.142	0.45526	0.22065	0.21946	Limestone
0.32217	0.42221	0.10082	0.35691	0.33662	0.12718	0.50227	0.2189	0.21239	Limestone
0.33895	0.33688	0.055087	0.37619	0.25026	0.094136	0.52466	0.15675	0.19117	Limestone
0.39769	0.37154	0.10863	0.43891	0.29594	0.15279	0.60258	0.21702	0.24671	Limestone
0.40437	0.37885	0.13351	0.44539	0.30663	0.18128	0.61665	0.24739	0.29226	Limestone
0.38027	0.35241	0.11612	0.41891	0.27988	0.16473	0.58206	0.22702	0.2889	Limestone
0.37451	0.41168	0.12162	0.41341	0.33907	0.16112	0.56611	0.23893	0.24398	Limestone
0.34895	0.51659	0.2552	0.38399	0.43203	0.26295	0.53276	0.31482	0.29404	Limestone
0.31727	0.29126	0.13913	0.34842	0.19042	0.15228	0.4766	0.10086	0.15651	Limestone
0.29819	0.26146	0.066602	0.32578	0.16503	0.094239	0.45049	0.085933	0.14374	Limestone
0.30835	0.30236	0.10726	0.33542	0.2201	0.14578	0.45553	0.13592	0.19137	Limestone
0.29266	0.37478	0.14503	0.31712	0.29154	0.17777	0.43319	0.19221	0.23658	Limestone
0.28793	0.38291	0.12477	0.31252	0.29981	0.15788	0.42329	0.19833	0.23038	Limestone
0.27368	0.42571	0.13069	0.29723	0.3473	0.16354	0.40391	0.22478	0.23131	Limestone
0.29264	0.42094	0.10897	0.31852	0.34489	0.14418	0.43311	0.2216	0.21145	Limestone
0.29121	0.4483	0.12522	0.31754	0.37121	0.15423	0.43242	0.23723	0.21068	Limestone
0.29121	0.4483	0.12522	0.31754	0.37121	0.15423	0.43242	0.23723	0.21068	Limestone
0.30956	0.42345	0.12844	0.3384	0.33031	0.14038	0.46654	0.21743	0.20739	Limestone
0.32391	0.36972	0.07089	0.35342	0.2817	0.10117	0.48906	0.17115	0.17842	Limestone
0.32587	0.35792	0.074136	0.35516	0.26664	0.10244	0.49429	0.15807	0.17545	Limestone
0.32826	0.48148	0.23926	0.36121	0.4084	0.24724	0.49239	0.29056	0.26209	Limestone
0.33767	0.46809	0.22741	0.36938	0.39333	0.2361	0.50591	0.27218	0.247	Limestone
0.32391	0.45141	0.20289	0.35323	0.36775	0.20638	0.4766	0.2339	0.20742	Limestone
0.30881	0.36751	0.11468	0.33796	0.28666	0.13464	0.45503	0.17054	0.16063	Limestone
0.28311	0.30568	0.082666	0.31014	0.23223	0.11145	0.41801	0.13985	0.1513	Limestone
0.29658	0.28386	0.10316	0.31996	0.2171	0.13011	0.43018	0.12275	0.14749	Limestone
0.28904	0.4103	0.15782	0.31233	0.34	0.17281	0.4239	0.21435	0.19158	Limestone
0.31897	0.40081	0.11778	0.34614	0.32415	0.14127	0.47277	0.20814	0.19017	Limestone
0.36138	0.43395	0.10406	0.39539	0.35655	0.12904	0.53781	0.24684	0.20316	Limestone
0.38728	0.50428	0.22305	0.42277	0.42557	0.22689	0.57274	0.3082	0.24836	Limestone
0.34879	0.3922	0.21878	0.3796	0.30921	0.2198	0.5081	0.17062	0.16424	Limestone
0.34819	0.38881	0.21791	0.379	0.30445	0.21713	0.50472	0.16585	0.16012	Limestone
0.34482	0.31853	0.16962	0.3757	0.22732	0.17168	0.50525	0.1186	0.13957	Limestone
0.34482	0.31853	0.16962	0.3757	0.22732	0.17168	0.50525	0.1186	0.13957	Limestone
0.3356	0.37633	0.14882	0.36497	0.28351	0.15644	0.49358	0.15392	0.15677	Limestone



Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.38687	0.25558	0.1078	0.42634	0.16685	0.12759	0.57551	0.10111	0.15567	Limestone
0.3611	0.41525	0.099559	0.39506	0.34035	0.12822	0.54652	0.23084	0.21111	Limestone
0.37606	0.40758	0.11915	0.4136	0.32697	0.15021	0.56846	0.24392	0.24768	Limestone
0.40049	0.37721	0.10586	0.44009	0.29667	0.1339	0.60247	0.20301	0.2141	Limestone
0.39059	0.29025	0.03092	0.42936	0.20865	0.073668	0.58689	0.14223	0.18298	Limestone
0.39059	0.29025	0.03092	0.42936	0.20865	0.073668	0.58689	0.14223	0.18298	Limestone
0.39064	0.27702	0.043051	0.42998	0.19283	0.082713	0.58692	0.13443	0.18234	Limestone
0.32049	0.48088	0.15128	0.35413	0.40823	0.17472	0.49545	0.33375	0.28447	Limestone
0.32836	0.46684	0.13136	0.3613	0.39528	0.1587	0.50913	0.30444	0.25759	Limestone
0.31309	0.42713	0.19485	0.34109	0.34948	0.20294	0.45519	0.20132	0.18093	Limestone
0.31938	0.45871	0.23158	0.34578	0.37742	0.22804	0.46852	0.21888	0.19231	Limestone
0.32511	0.45697	0.25984	0.35191	0.37202	0.24765	0.47618	0.2149	0.19286	Limestone
0.31644	0.46261	0.2121	0.34204	0.38542	0.21053	0.46076	0.23395	0.19664	Limestone
0.31967	0.45477	0.19817	0.34592	0.37956	0.20015	0.46411	0.22775	0.18935	Limestone
0.30985	0.53806	0.27802	0.33569	0.46048	0.26332	0.4564	0.31594	0.25574	Limestone
0.31799	0.41392	0.14901	0.34364	0.32952	0.15899	0.46472	0.19468	0.18004	Limestone
0.31799	0.41392	0.14901	0.34364	0.32952	0.15899	0.46472	0.19468	0.18004	Limestone
0.32954	0.37958	0.13079	0.35558	0.28931	0.14036	0.47998	0.16801	0.16698	Limestone
0.35401	0.28238	0.080012	0.38393	0.19146	0.09912	0.51116	0.10934	0.13818	Limestone
0.44477	0.38621	0.10987	0.48851	0.31647	0.13932	0.66402	0.23597	0.21911	Limestone
0.45622	0.34242	0.091883	0.50034	0.26878	0.12225	0.67942	0.19508	0.19726	Limestone
0.44596	0.15112	0.072478	0.48601	0.078005	0.1006	0.65021	0.053329	0.13619	Limestone
0.40468	0.21372	0.15223	0.44001	0.13719	0.17199	0.58631	0.091214	0.16015	Limestone
0.39145	0.2457	0.1854	0.42749	0.17155	0.19869	0.57805	0.11171	0.17874	Limestone
0.36779	0.29714	0.081339	0.40855	0.21656	0.11397	0.57081	0.14641	0.19304	Limestone
0.37668	0.3251	0.10212	0.41936	0.24628	0.13419	0.58544	0.17277	0.20958	Limestone
0.3669	0.41365	0.16834	0.40977	0.33112	0.18614	0.57498	0.23697	0.2461	Limestone
0.34242	0.41646	0.18407	0.3809	0.33174	0.19781	0.53704	0.2268	0.23563	Limestone
0.29089	0.55679	0.37476	0.32375	0.51658	0.40017	0.45711	0.40152	0.44377	Limestone
0.34744	0.36386	0.20973	0.3886	0.30593	0.24195	0.53556	0.24294	0.30843	Limestone
0.35341	0.40848	0.15093	0.39341	0.3421	0.17976	0.55114	0.23808	0.25499	Limestone
0.391	0.28955	0.071269	0.43357	0.18525	0.097233	0.59804	0.10111	0.16614	Limestone
0.35638	0.39221	0.092593	0.39573	0.30382	0.11709	0.56252	0.21892	0.23229	Limestone
0.3533	0.39953	0.069421	0.39345	0.31613	0.099838	0.55967	0.226	0.22641	Limestone
0.39624	0.2995	0.091954	0.44178	0.21575	0.11682	0.61523	0.14382	0.19858	Limestone
0.4262	0.4185	0.11572	0.47213	0.33183	0.13903	0.65697	0.22973	0.22404	Limestone
0.42285	0.43931	0.15922	0.46647	0.3513	0.17324	0.64599	0.24386	0.22862	Limestone
0.3441	0.33304	0.10991	0.37894	0.23893	0.13109	0.51935	0.13846	0.17242	Limestone
0.42833	0.34783	0.079373	0.47636	0.25923	0.10753	0.66088	0.1705	0.19996	Limestone
0.37388	0.31552	0.094821	0.41426	0.22143	0.12033	0.57681	0.14133	0.19079	Limestone
0.41772	0.24547	0.084182	0.46451	0.14323	0.10777	0.63807	0.074122	0.15429	Limestone
0.30907	0.48442	0.3114	0.34469	0.43184	0.34127	0.48251	0.33208	0.39113	Limestone
0.31933	0.4101	0.23182	0.35726	0.32003	0.237	0.50229	0.19635	0.21828	Limestone
0.31933	0.4101	0.23182	0.35726	0.32003	0.237	0.50229	0.19635	0.21828	Limestone
0.38612	0.39056	0.17417	0.43002	0.31012	0.19385	0.60184	0.22074	0.23415	Limestone
0.39556	0.31889	0.17303	0.43446	0.23467	0.18339	0.59278	0.15613	0.1968	Limestone
0.12174	0.80668	0.74494	0.1388	0.73685	0.68037	0.21839	0.56826	0.57192	Limestone
0.16244	0.8044	0.47474	0.18485	0.768	0.46912	0.28722	0.65071	0.51878	Limestone
0.2166	0.67753	0.28221	0.24541	0.61537	0.29383	0.37021	0.52141	0.41302	Limestone
0.1053	0.53574	0.30119	0.12231	0.46181	0.31088	0.19528	0.2886	0.26149	Limestone
0.098527	0.57588	0.3544	0.1135	0.49948	0.34925	0.18435	0.31684	0.28591	Limestone
0.088143	0.55929	0.36627	0.10262	0.48222	0.36627	0.17067	0.32145	0.30015	Limestone
0.060759	0.44186	0.26475	0.071551	0.3581	0.28401	0.13323	0.23558	0.24622	Limestone
0.054006	0.41609	0.19433	0.064434	0.32654	0.22248	0.12156	0.19608	0.19616	Limestone
0.050836	0.4926	0.22101	0.060794	0.39713	0.23144	0.11245	0.24231	0.20821	Limestone
0.056053	0.48569	0.21769	0.065663	0.39368	0.23116	0.12378	0.23817	0.21224	Limestone
0.058138	0.60184	0.34038	0.067625	0.50981	0.32646	0.12945	0.3382	0.28703	Limestone
0.052921	0.60356	0.35808	0.062622	0.51062	0.34223	0.12077	0.36222	0.31809	Limestone
0.040926	0.5055	0.23509	0.049049	0.41189	0.2433	0.105	0.26584	0.23804	Limestone
0.040926	0.5055	0.23509	0.049049	0.41189	0.2433	0.105	0.26584	0.23804	Limestone
0.042237	0.49122	0.22504	0.049993	0.3948	0.22925	0.10928	0.24181	0.22239	Limestone
0.10222	0.39728	0.18642	0.11691	0.29295	0.19697	0.18601	0.16972	0.16974	Limestone
0.10704	0.3742	0.17403	0.12144	0.27263	0.18778	0.198	0.16063	0.1737	Limestone
0.11586	0.34071	0.14711	0.13134	0.25393	0.17714	0.20991	0.14684	0.16689	Limestone
0.11364	0.36674	0.15626	0.12867	0.28474	0.18868	0.20698	0.17324	0.18262	Limestone
0.11443	0.61911	0.63638	0.1301	0.58002	0.66419	0.20972	0.53451	0.78395	Limestone
0.13129	0.56044	0.53535	0.14891	0.50437	0.54997	0.22565	0.39429	0.51561	Limestone
0.13164	0.4468	0.30628	0.14779	0.37015	0.31467	0.22784	0.23526	0.26173	Limestone
0.11926	0.42044	0.2485	0.1348	0.33665	0.26397	0.20576	0.21543	0.22876	Limestone
0.1056	0.42254	0.27501	0.11897	0.34693	0.30068	0.19061	0.22412	0.24376	Limestone
0.11271	0.59803	0.36582	0.12719	0.53345	0.37692	0.20043	0.32369	0.28454	Limestone
0.14274	0.77761	0.48439	0.15921	0.69284	0.43715	0.23592	0.45371	0.35286	Limestone
0.13354	0.72477	0.42537	0.15013	0.63692	0.39265	0.21997	0.38345	0.2943	Limestone
0.10759	0.44777	0.17798	0.12169	0.36564	0.20503	0.19092	0.19255	0.17768	Limestone
0.089903	0.72397	0.68339	0.1041	0.67166	0.69042	0.16666	0.49998	0.59736	Limestone
0.1198	0.8588	0.88727	0.13705	0.82039	0.86302	0.21569	0.6982	0.8447	Limestone
0.11824	0.89343	0.89769	0.13578	0.8542	0.87366	0.2126	0.78932	0.9561	Limestone
0.11176	0.72523	0.87291	0.12833	0.68016	0.84715	0.20624	0.58217	0.78086	Limestone
0.11766	0.5709	0.26551	0.13393	0.48896	0.27829	0.2074	0.31	0.25338	Limestone
0.12418	0.4257	0.13818	0.14156	0.33773	0.1668	0.22023	0.19997	0.18573	Limestone
0.12793	0.54402	0.23968	0.14578	0.47611	0.27049	0.23019	0.32543	0.274	Limestone
0.12315	0.6974	0.41124	0.14003	0.65792	0.43336	0.23095	0.51491	0.44654	Limestone
0.10414	0.78346	0.59304	0.11832	0.72806	0.55803	0.20027	0.60421	0.56077	Limestone
0.095981	0.68878	0.51559	0.10924	0.61424	0.48354	0.18567	0.44705	0.42336	Limestone
0.094358	0.49964	0.39404	0.10822	0.41604	0.39439	0.17553	0.25603	0.27678	Limestone
0.096842	0.47153	0.34464	0.11073	0.37833	0.33707	0.17896	0.23655	0.25956	Limestone
0.11536	0.55946	0.3015	0.1302	0.46147	0.28678	0.19533	0.2522	0.22445	Limestone
0.10107	0.61525	0.38667	0.11453	0.51569	0.35565	0.17714	0.29063	0.26219	Limestone
0.092836	0.49625	0.24167	0.10467	0.40589	0.2483	0.17004	0.22509	0.20901	Limestone

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.088742	0.47935	0.21393	0.10046	0.39236	0.2289	0.1647	0.22181	0.20265	Limestone
0.068722	0.59144	0.33192	0.079446	0.51594	0.33395	0.14073	0.33859	0.29163	Limestone
0.092199	0.53289	0.26605	0.10496	0.44918	0.2733	0.17257	0.28865	0.25289	Limestone
0.11349	0.48601	0.14934	0.12821	0.39998	0.17701	0.19755	0.23186	0.19034	Limestone
0.089478	0.49715	0.20793	0.10007	0.4075	0.21994	0.16959	0.23376	0.20364	Limestone
0.075986	0.41997	0.16164	0.084719	0.33638	0.18448	0.14384	0.19773	0.17581	Limestone
0.071006	0.453	0.18478	0.079056	0.37204	0.20275	0.1459	0.22376	0.20211	Limestone
0.13449	0.29666	0.24707	0.1523	0.20642	0.26395	0.22797	0.088895	0.13586	Limestone
0.13665	0.48389	0.42494	0.15482	0.42447	0.43863	0.23766	0.24247	0.26555	Limestone
0.13802	0.76081	0.48422	0.15751	0.70884	0.47296	0.24466	0.55811	0.46363	Limestone
0.26895	0.40854	0.16434	0.29715	0.33384	0.19547	0.40987	0.24292	0.24817	Limestone
0.24554	0.29536	0.16974	0.27308	0.21909	0.20259	0.37206	0.14155	0.19744	Limestone
0.18078	0.45214	0.32621	0.20355	0.41176	0.36844	0.29953	0.30596	0.35145	Limestone
0.16588	0.57609	0.4007	0.18813	0.53166	0.42066	0.28165	0.40846	0.40807	Limestone
0.18794	0.55521	0.27081	0.21416	0.49068	0.28309	0.31484	0.35621	0.31833	Limestone
0.21704	0.58978	0.25136	0.24704	0.49319	0.24492	0.35941	0.33887	0.28379	Limestone
0.21704	0.58978	0.25136	0.24704	0.49319	0.24492	0.35941	0.33887	0.28379	Limestone
0.19227	0.50798	0.28268	0.21969	0.39345	0.26354	0.31938	0.24252	0.24466	Limestone
0.19044	0.6599	0.52962	0.21712	0.60381	0.52864	0.31672	0.45381	0.52138	Limestone
0.18542	0.74682	0.63083	0.21166	0.69311	0.61478	0.30724	0.53991	0.60457	Limestone
0.13229	0.80142	0.73708	0.15029	0.75789	0.72901	0.23354	0.65836	0.81142	Limestone
0.08692	0.42224	0.16038	0.098772	0.34024	0.19543	0.16932	0.21169	0.21101	Limestone
0.093934	0.36204	0.098967	0.10644	0.26847	0.13095	0.17566	0.15066	0.15764	Limestone
0.16916	0.63852	0.38234	0.19026	0.58779	0.39648	0.29013	0.47987	0.43244	Limestone
0.16379	0.62961	0.35907	0.18419	0.57723	0.37454	0.28368	0.47241	0.42195	Limestone
0.10388	0.72755	0.49597	0.11987	0.67348	0.48204	0.19874	0.54669	0.49947	Limestone
0.1052	0.72349	0.52177	0.12193	0.66843	0.50901	0.20468	0.58048	0.59001	Limestone
0.1052	0.72349	0.52177	0.12193	0.66843	0.50901	0.20468	0.58048	0.59001	Limestone
0.18724	0.81932	0.52566	0.21201	0.76775	0.4906	0.32305	0.71489	0.60087	Limestone
0.20876	0.77586	0.41011	0.23353	0.71729	0.39431	0.35691	0.64762	0.51615	Limestone
0.20879	0.70666	0.34585	0.23468	0.64154	0.33936	0.35247	0.54259	0.43386	Limestone
0.17858	0.62101	0.34422	0.20205	0.55303	0.33979	0.30711	0.44097	0.39201	Limestone
0.1086	0.58272	0.26833	0.12294	0.51898	0.2869	0.20281	0.37407	0.3132	Limestone
0.090015	0.74287	0.52284	0.10505	0.72496	0.54849	0.17783	0.57893	0.51045	Limestone
0.12536	0.94771	0.75174	0.14529	0.92359	0.71525	0.22876	0.78767	0.67836	Limestone
0.15429	0.97467	0.75006	0.17618	0.93156	0.68353	0.27545	0.80679	0.67924	Limestone
0.17443	1	0.77631	0.19604	0.94458	0.69829	0.30053	0.85414	0.73806	Limestone
0.16601	0.92443	0.6102	0.1846	0.86608	0.56123	0.2858	0.76306	0.62198	Limestone
0.12906	0.55218	0.27908	0.14428	0.46585	0.27509	0.22509	0.29436	0.25693	Limestone
0.12336	0.58281	0.19149	0.1399	0.52037	0.22211	0.22351	0.38872	0.30029	Limestone
0.24197	0.61646	0.33616	0.27377	0.55891	0.3359	0.40467	0.47047	0.40591	Limestone
0.36313	0.31209	0.13636	0.40815	0.2201	0.16752	0.56675	0.15525	0.21034	Limestone
0.29114	0.39732	0.12825	0.32433	0.30763	0.1557	0.45989	0.22128	0.24415	Limestone
0.1428	0.5103	0.203	0.16154	0.45306	0.24363	0.25274	0.32305	0.29956	Limestone
0.14371	0.61123	0.25485	0.16404	0.56591	0.28709	0.26282	0.45627	0.37956	Limestone
0.13536	0.52277	0.1596	0.15203	0.45009	0.18663	0.23682	0.27681	0.23146	Limestone
0.079006	0.89945	0.66822	0.090861	0.858	0.64152	0.15316	0.65917	0.55116	Limestone
0.049825	0.77972	0.45465	0.057184	0.72156	0.43537	0.12531	0.58302	0.46833	Limestone
0.17737	0.65937	0.34388	0.20121	0.61162	0.35349	0.30428	0.49033	0.41175	Limestone
0.17933	0.66132	0.34493	0.20369	0.61187	0.35292	0.30534	0.49523	0.41328	Limestone
0.17868	0.67478	0.30735	0.20271	0.62519	0.32088	0.30309	0.50376	0.39846	Limestone
0.20026	0.49596	0.1075	0.2204	0.41746	0.1401	0.31944	0.29444	0.24461	Limestone
0.18761	0.48949	0.099938	0.2052	0.41646	0.14104	0.29998	0.30769	0.26042	Limestone
0.11888	0.70201	0.54239	0.13733	0.65693	0.54882	0.22369	0.59326	0.64674	Limestone
0.12883	0.61407	0.3686	0.14884	0.55949	0.37999	0.23877	0.43744	0.40523	Limestone
0.2759	0.5489	0.14792	0.31219	0.47225	0.16795	0.46432	0.38791	0.31695	Limestone
0.32153	0.483	0.091172	0.36231	0.39659	0.11828	0.53556	0.29862	0.26312	Limestone
0.32882	0.47211	0.12368	0.36978	0.37729	0.13725	0.54068	0.27101	0.2488	Limestone
0.2093	0.64175	0.20964	0.23569	0.57196	0.22714	0.34888	0.41359	0.28622	Limestone
0.11815	0.7594	0.52175	0.13383	0.71345	0.51894	0.21395	0.47089	0.39008	Limestone
0.099825	0.86348	0.74707	0.11378	0.81907	0.6891	0.18976	0.59497	0.54295	Limestone
0.2504	0.58057	0.22203	0.27826	0.50942	0.23362	0.39878	0.38681	0.31958	Limestone
0.27019	0.53346	0.15775	0.29817	0.46167	0.18173	0.42553	0.35275	0.28875	Limestone
0.25293	0.46257	0.10461	0.28009	0.38369	0.13552	0.3934	0.26466	0.23274	Limestone
0.18157	0.47735	0.25447	0.20484	0.40209	0.28278	0.29422	0.27277	0.27432	Limestone
0.17755	0.48457	0.30534	0.19949	0.41854	0.33996	0.29081	0.30834	0.33394	Limestone
0.16162	0.54022	0.41757	0.18219	0.48248	0.4343	0.26898	0.37202	0.40082	Limestone
0.13797	0.74289	0.63844	0.15488	0.68305	0.59956	0.24128	0.56242	0.5541	Limestone
0.13702	0.78726	0.55369	0.15637	0.74715	0.53738	0.24569	0.62805	0.54397	Limestone
0.15695	0.86283	0.67997	0.17894	0.82772	0.64698	0.27463	0.69429	0.60255	Limestone
0.15529	0.8664	0.69616	0.17774	0.83234	0.66355	0.26805	0.69925	0.6111	Limestone
0.15533	0.72609	0.54405	0.17676	0.68379	0.53533	0.26803	0.53948	0.48189	Limestone
0.12826	0.6235	0.34232	0.14562	0.57425	0.3611	0.23568	0.42949	0.37372	Limestone
0.12278	0.77445	0.5	0.13898	0.72964	0.49152	0.23051	0.60668	0.52123	Limestone
0.12278	0.77445	0.5	0.13898	0.72964	0.49152	0.23051	0.60668	0.52123	Limestone
0.12539	0.90869	0.69886	0.14076	0.84889	0.62928	0.23135	0.73573	0.64922	Limestone
0.10894	0.93864	0.68917	0.12106	0.88921	0.63529	0.20434	0.74978	0.62626	Limestone
0.10413	0.92595	0.66502	0.11651	0.87525	0.61369	0.19393	0.73194	0.60253	Limestone
0.21163	0.76578	0.52665	0.23658	0.72926	0.53871	0.34943	0.64621	0.62792	Limestone
0.14435	0.79258	0.81614	0.16457	0.75726	0.83275	0.2549	0.72729	1	Limestone
0.14417	0.79153	0.81356	0.16484	0.75505	0.82936	0.25266	0.72435	0.9916	Limestone
0.13271	0.74137	0.84749	0.15164	0.69106	0.83966	0.23394	0.58286	0.79603	Limestone
0.12889	0.65349	0.47607	0.14709	0.5854	0.46207	0.22926	0.44632	0.42426	Limestone
0.1361	0.72963	0.49773	0.15423	0.68514	0.5037	0.24204	0.55349	0.51116	Limestone
0.12202	0.75024	0.48789	0.13862	0.70044	0.48775	0.22089	0.61229	0.57441	Limestone
0.12202	0.75024	0.48789	0.13862	0.70044	0.48775	0.22089	0.61229	0.57441	Limestone
0.1277	0.72163	0.44949	0.1434	0.67032	0.45372	0.23336	0.58194	0.54896	Limestone
0.12982	0.58465	0.27539	0.14514	0.52513	0.30216	0.23048	0.42208	0.39729	Limestone
0.12781	0.52816	0.1587	0.14232	0.46352	0.20099	0.222	0.32203	0.27512	Limestone



Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.12137	0.67118	0.36907	0.13422	0.60302	0.37934	0.21239	0.42645	0.37606	Limestone
0.12507	0.68794	0.45074	0.13888	0.61111	0.44283	0.21767	0.415	0.38991	Limestone
0.12702	0.68319	0.43086	0.14186	0.61113	0.42874	0.21984	0.43011	0.40705	Limestone
0.11671	0.65897	0.41985	0.13206	0.59818	0.41888	0.21107	0.42008	0.37229	Limestone
0.11281	0.61489	0.39423	0.12894	0.55014	0.38516	0.20637	0.38558	0.35047	Limestone
0.13248	0.51987	0.24745	0.15044	0.45617	0.26241	0.23946	0.31424	0.28934	Limestone
0.13366	0.52666	0.25833	0.15193	0.46208	0.27017	0.24064	0.32093	0.29494	Limestone
0.15272	0.55727	0.21423	0.17264	0.49898	0.23741	0.27199	0.36249	0.30497	Limestone
0.17594	0.53741	0.21968	0.19879	0.47091	0.2386	0.29977	0.33462	0.29065	Limestone
0.20753	0.48889	0.20194	0.23371	0.41623	0.22154	0.34151	0.29551	0.27587	Limestone
0.22203	0.42639	0.13152	0.2495	0.35128	0.16282	0.36089	0.23724	0.23544	Limestone
0.22923	0.28022	0.08994	0.25849	0.20835	0.13645	0.37143	0.099953	0.1646	Limestone
0.22923	0.28022	0.08994	0.25849	0.20835	0.13645	0.37143	0.099953	0.1646	Limestone
0.23199	0.29526	0.13638	0.26198	0.23292	0.18103	0.37444	0.11383	0.17581	Limestone
0.16556	0.66353	0.627	0.18861	0.61515	0.64195	0.28347	0.50269	0.62595	Limestone
0.15165	0.728	0.68007	0.17179	0.68277	0.68502	0.26349	0.54528	0.63622	Limestone
0.13515	0.72497	0.50993	0.15318	0.67526	0.50938	0.24289	0.55145	0.51595	Limestone
0.13119	0.80779	0.56982	0.14819	0.76863	0.56338	0.24178	0.68609	0.62439	Limestone
0.14366	0.81902	0.52068	0.16253	0.78974	0.53012	0.25839	0.70304	0.60625	Limestone
0.19119	0.78896	0.47202	0.21278	0.7589	0.49749	0.32031	0.68884	0.65748	Limestone
0.22395	0.65291	0.29993	0.24822	0.60346	0.33614	0.35308	0.48954	0.45114	Limestone
0.21177	0.66408	0.30415	0.23495	0.6159	0.33996	0.33716	0.48333	0.42731	Limestone
0.176	0.79375	0.42989	0.19772	0.74696	0.43633	0.29602	0.62556	0.51873	Limestone
0.17019	0.80001	0.49486	0.19327	0.73198	0.45782	0.29678	0.60082	0.49122	Limestone
0.17534	0.65774	0.35253	0.20066	0.5828	0.34455	0.30146	0.43626	0.36296	Limestone
0.17556	0.65912	0.3631	0.2009	0.5881	0.35784	0.30011	0.45099	0.37939	Limestone
0.16781	0.70288	0.43762	0.1908	0.63615	0.41738	0.29628	0.52478	0.45511	Limestone
0.18279	0.79943	0.56037	0.20828	0.73425	0.51176	0.31862	0.62016	0.53833	Limestone
0.19129	0.79036	0.50303	0.21813	0.7261	0.46873	0.3324	0.61281	0.51293	Limestone
0.21301	0.75666	0.43224	0.24186	0.70053	0.42269	0.36742	0.61037	0.50945	Limestone
0.26594	0.70165	0.3795	0.30145	0.64491	0.38426	0.43966	0.56534	0.4769	Limestone
0.29383	0.67352	0.31536	0.33092	0.61219	0.32974	0.47853	0.5367	0.44479	Limestone
0.33323	0.57314	0.26392	0.37389	0.50868	0.28899	0.53897	0.44242	0.40576	Limestone
0.24402	0.65266	0.33505	0.27249	0.58802	0.33686	0.39348	0.43469	0.36953	Limestone
0.24176	0.67519	0.35123	0.27002	0.61067	0.35025	0.39012	0.46506	0.39283	Limestone
0.19458	0.72502	0.4161	0.21739	0.65221	0.39794	0.3201	0.48235	0.40267	Limestone
0.13905	0.44907	0.2842	0.15796	0.35423	0.28795	0.23531	0.20924	0.21662	Limestone
0.17208	0.92723	1	0.19362	0.91721	1	0.28437	0.75844	0.88587	Limestone
0.20857	0.9962	0.7503	0.23294	1	0.77982	0.34421	1	0.99946	Limestone
0.21457	0.90928	0.63647	0.23931	0.88814	0.65252	0.35466	0.85679	0.82271	Limestone
0.2004	0.6313	0.35542	0.22599	0.58711	0.3844	0.33296	0.46382	0.45185	Limestone
0.20548	0.67838	0.33995	0.23276	0.60467	0.32109	0.34096	0.46944	0.37121	Limestone
0.20216	0.70286	0.37191	0.22827	0.62916	0.34808	0.34038	0.51197	0.40968	Limestone
0.19319	0.59431	0.27347	0.21849	0.51804	0.27361	0.32709	0.39434	0.33112	Limestone
0.17132	0.53288	0.27404	0.19315	0.45807	0.28106	0.28926	0.31299	0.28364	Limestone
0.17313	0.51632	0.26738	0.19563	0.44094	0.2757	0.28765	0.29898	0.2723	Limestone
0.22111	0.57885	0.4474	0.24553	0.54504	0.46016	0.35735	0.409	0.39826	Limestone
0.22161	0.61732	0.49948	0.24613	0.58016	0.49765	0.3572	0.44221	0.42775	Limestone
0.22161	0.61732	0.49948	0.24613	0.58016	0.49765	0.3572	0.44221	0.42775	Limestone
0.22726	0.67487	0.57087	0.25362	0.63008	0.55052	0.36245	0.48598	0.45944	Limestone
0.2636	0.47504	0.3237	0.29486	0.40655	0.31816	0.42276	0.28449	0.28997	Limestone
0.25771	0.47569	0.3232	0.28923	0.40592	0.31705	0.41141	0.28501	0.28815	Limestone
0.26382	0.41046	0.21457	0.29601	0.3399	0.22845	0.42419	0.22238	0.23619	Limestone
0.26369	0.40844	0.19855	0.29612	0.33816	0.21655	0.42316	0.21734	0.22958	Limestone
0.26516	0.36714	0.15972	0.29768	0.28873	0.17931	0.42271	0.17701	0.19711	Limestone
0.295	0.31199	0.088187	0.33139	0.2415	0.13259	0.4781	0.15273	0.22698	Limestone
0.29649	0.31114	0.087665	0.33261	0.24072	0.13167	0.48093	0.15327	0.22773	Limestone
0.32645	0.31882	0.088495	0.36445	0.23896	0.12638	0.51573	0.13981	0.20873	Limestone
0.30851	0.39687	0.12325	0.34246	0.30391	0.14787	0.48125	0.19979	0.22345	Limestone
0.30789	0.39639	0.12268	0.34175	0.304	0.1476	0.48022	0.19895	0.22242	Limestone
0.19843	0.58536	0.31304	0.22111	0.52023	0.3231	0.32371	0.40681	0.36586	Limestone
0.17726	0.67071	0.45373	0.19688	0.60775	0.43643	0.29887	0.50624	0.47797	Limestone
0.1678	0.70976	0.52912	0.18734	0.64321	0.49458	0.28112	0.55616	0.53424	Limestone
0.24336	0.3907	0.099014	0.27196	0.31731	0.13536	0.38653	0.21008	0.22533	Limestone
0.24511	0.38871	0.098469	0.27413	0.31598	0.1361	0.3874	0.21006	0.22579	Limestone
0.28706	0.46901	0.17365	0.31802	0.39249	0.19707	0.45041	0.28743	0.28381	Limestone
0.2886	0.4719	0.17798	0.31985	0.3962	0.20193	0.45183	0.2912	0.28707	Limestone
0.25932	0.43475	0.23883	0.28731	0.35623	0.25987	0.401	0.26221	0.30446	Limestone
0.24643	0.42403	0.23632	0.27303	0.34799	0.26051	0.38144	0.2584	0.30723	Limestone
0.22708	0.40141	0.21338	0.25121	0.32706	0.24332	0.35374	0.22599	0.27809	Limestone
0.20884	0.4126	0.14327	0.23029	0.32789	0.17523	0.32733	0.19008	0.19076	Limestone
0.20826	0.41394	0.14398	0.22977	0.32815	0.1755	0.32617	0.19121	0.19154	Limestone
0.2397	0.65678	0.4179	0.26512	0.583	0.39154	0.37386	0.41494	0.35244	Limestone
0.23767	0.67629	0.42276	0.26307	0.601	0.39304	0.37058	0.43418	0.36213	Limestone
0.26682	0.56418	0.22741	0.29447	0.48382	0.23112	0.42104	0.34769	0.28564	Limestone
0.26786	0.55675	0.22471	0.2956	0.47754	0.23056	0.42316	0.3447	0.28707	Limestone
0.316	0.38684	0.14543	0.35004	0.30595	0.16711	0.48267	0.1982	0.20684	Limestone
0.31523	0.39606	0.13996	0.34836	0.31664	0.16337	0.485	0.21146	0.21608	Limestone
0.21001	0.67531	0.39603	0.23981	0.61573	0.39355	0.35627	0.48286	0.42363	Limestone
0.22599	0.58319	0.27233	0.25772	0.51538	0.28206	0.38265	0.3943	0.34385	Limestone
0.18562	0.67152	0.33377	0.21019	0.62033	0.35269	0.31461	0.4732	0.39356	Limestone
0.17131	0.5697	0.36789	0.19243	0.52147	0.39968	0.29219	0.42035	0.45625	Limestone
0.141	0.74599	0.50884	0.15996	0.70117	0.51057	0.25266	0.60825	0.5756	Limestone
0.17121	0.63324	0.34225	0.19369	0.5645	0.33739	0.29134	0.43434	0.38017	Limestone
0.24732	0.35332	0.06409	0.2751	0.27379	0.10862	0.39612	0.16309	0.18889	Limestone
0.24976	0.31559	0.058902	0.27861	0.23714	0.1049	0.39569	0.14198	0.18459	Limestone
0.20085	0.6131	0.29309	0.22695	0.54636	0.30312	0.34133	0.40818	0.34124	Limestone
0.20007	0.58729	0.30477	0.2276	0.52196	0.31287	0.32662	0.34741	0.28678	Limestone
0.20358	0.57424	0.29595	0.23098	0.50904	0.30476	0.3315	0.33538	0.28009	Limestone

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.21711	0.58531	0.31405	0.24385	0.50715	0.30448	0.34603	0.34744	0.29384	Limestone
0.27335	0.50042	0.16618	0.30126	0.41716	0.18505	0.42252	0.29155	0.25036	Limestone
0.27384	0.49214	0.15619	0.3019	0.40821	0.17755	0.42199	0.28565	0.24552	Limestone
0.29689	0.45847	0.13005	0.32592	0.3702	0.15493	0.44967	0.25084	0.22223	Limestone
0.30427	0.42555	0.11719	0.33345	0.3297	0.13889	0.45812	0.21207	0.2003	Limestone
0.083849	0.71327	0.52703	0.097708	0.6565	0.52827	0.16877	0.48936	0.47649	Limestone
0.044109	0.80738	0.56184	0.052989	0.75738	0.54743	0.12665	0.62767	0.56384	Limestone
0.17715	0.50051	0.12249	0.19966	0.42661	0.15261	0.29789	0.30072	0.25669	Limestone
0.1575	0.55408	0.17393	0.17717	0.49012	0.20409	0.26805	0.36625	0.30387	Limestone
0.19048	0.38991	0.28901	0.21306	0.30316	0.28721	0.30214	0.19068	0.22568	Limestone
0.20305	0.43992	0.095413	0.22923	0.35574	0.12508	0.33589	0.23119	0.21267	Limestone
0.20305	0.43992	0.095413	0.22923	0.35574	0.12508	0.33589	0.23119	0.21267	Limestone
0.20997	0.445	0.1056	0.23675	0.36935	0.14038	0.34679	0.24379	0.22587	Limestone
0.19592	0.58851	0.42646	0.22202	0.50339	0.39316	0.32728	0.37532	0.36369	Limestone
0.18074	0.4708	0.24712	0.20331	0.4087	0.26832	0.30143	0.26566	0.25391	Limestone
0.18244	0.46344	0.24091	0.20523	0.40282	0.26469	0.30235	0.26028	0.2499	Limestone
0.18472	0.478	0.3169	0.20658	0.42347	0.34299	0.2967	0.2539	0.26343	Limestone
0.20699	0.63586	0.40949	0.22978	0.58939	0.42275	0.33214	0.41605	0.37779	Limestone
0.23479	0.62388	0.35668	0.2599	0.56776	0.36276	0.37417	0.40749	0.35697	Limestone
0.26628	0.48909	0.18834	0.29497	0.41298	0.20562	0.41888	0.29544	0.27239	Limestone
0.26628	0.48909	0.18834	0.29497	0.41298	0.20562	0.41888	0.29544	0.27239	Limestone
0.26447	0.49287	0.17597	0.29287	0.41678	0.19644	0.41674	0.29676	0.2675	Limestone
0.26187	0.49755	0.16379	0.28987	0.41199	0.18563	0.41159	0.29305	0.2555	Limestone
0.25481	0.49846	0.17144	0.28205	0.41105	0.1885	0.40087	0.27341	0.23804	Limestone
0.24758	0.50103	0.17507	0.27519	0.41388	0.19215	0.38587	0.27577	0.23741	Limestone
0.23382	0.47161	0.16225	0.25882	0.38367	0.17904	0.36728	0.24702	0.22301	Limestone
0.20801	0.42531	0.25961	0.23522	0.36428	0.29104	0.33966	0.24331	0.2768	Limestone
0.22053	0.49891	0.26833	0.24977	0.42167	0.27956	0.3638	0.29706	0.29467	Limestone
0.22844	0.49574	0.2557	0.25928	0.42567	0.27298	0.37687	0.32216	0.31519	Limestone
0.21378	0.52546	0.24302	0.24318	0.45885	0.26371	0.35611	0.34008	0.31076	Limestone
0.18586	0.63532	0.29979	0.21372	0.5662	0.31143	0.3196	0.40951	0.34202	Limestone
0.19599	0.62855	0.28209	0.22539	0.55965	0.29428	0.33776	0.39305	0.32162	Limestone
0.24792	0.63934	0.37867	0.28322	0.57097	0.37128	0.41545	0.40523	0.36617	Limestone
0.32364	0.48973	0.16637	0.36767	0.41773	0.19553	0.53237	0.32478	0.32053	Limestone
0.35052	0.37111	0.057338	0.39801	0.28534	0.098587	0.57205	0.21399	0.25426	Limestone
0.35052	0.37111	0.057338	0.39801	0.28534	0.098587	0.57205	0.21399	0.25426	Limestone
0.24684	0.51079	0.09783	0.28022	0.42675	0.12141	0.41075	0.33357	0.27405	Limestone
0.24128	0.54026	0.1228	0.27299	0.45888	0.14274	0.40528	0.36576	0.29689	Limestone
0.20885	0.69259	0.238	0.23368	0.63524	0.25653	0.34962	0.54675	0.40683	Limestone
0.20897	0.68285	0.23459	0.23438	0.62432	0.25474	0.34603	0.52601	0.39113	Limestone
0.20548	0.57237	0.21878	0.23314	0.50653	0.2417	0.34141	0.39961	0.33304	Limestone
0.22203	0.72349	0.34647	0.25387	0.67199	0.35243	0.3789	0.55003	0.42083	Limestone
0.23674	0.80972	0.4782	0.27077	0.75821	0.46205	0.40589	0.62252	0.48761	Limestone
0.23637	0.79709	0.47991	0.27088	0.745	0.46416	0.40158	0.60561	0.48211	Limestone
0.1601	0.72635	0.44522	0.18437	0.66838	0.43571	0.28102	0.46576	0.37489	Limestone
0.2052	0.54042	0.27991	0.23032	0.47061	0.29072	0.34508	0.34767	0.32936	Limestone
0.20407	0.54287	0.26392	0.22977	0.46353	0.26939	0.34632	0.342	0.32113	Limestone
0.19648	0.60306	0.27463	0.22175	0.52225	0.279	0.33193	0.42555	0.3707	Limestone
0.27356	0.44466	0.14441	0.30679	0.36089	0.17238	0.44198	0.26504	0.25966	Limestone
0.25298	0.54643	0.24954	0.28509	0.45907	0.2546	0.41075	0.35572	0.32763	Limestone
0.20246	0.6867	0.37386	0.22947	0.60479	0.35774	0.34228	0.48551	0.41513	Limestone
0.15818	0.72648	0.38175	0.18228	0.66509	0.37653	0.28287	0.50413	0.39967	Limestone
0.18265	0.78451	0.36305	0.20674	0.73805	0.36166	0.32276	0.63975	0.46762	Limestone
0.23683	0.66532	0.26018	0.26758	0.6086	0.27123	0.40156	0.52203	0.39612	Limestone
0.25974	0.61365	0.28681	0.29495	0.54704	0.29199	0.43132	0.45942	0.38799	Limestone
0.30728	0.39595	0.20587	0.34845	0.30579	0.21848	0.48867	0.22296	0.26811	Limestone
0.31445	0.31045	0.097474	0.35396	0.21467	0.12404	0.49989	0.13144	0.19672	Limestone
0.14835	0.81154	0.54217	0.17059	0.75031	0.51242	0.2662	0.64264	0.55364	Limestone
0.13829	0.78486	0.53488	0.15952	0.72617	0.51143	0.25131	0.61822	0.5568	Limestone
0.15679	0.66567	0.34682	0.18048	0.6095	0.35967	0.27819	0.49373	0.43252	Limestone
0.17205	0.63908	0.30363	0.19753	0.58237	0.32531	0.30721	0.46527	0.40221	Limestone
0.16011	0.66764	0.29913	0.18475	0.6124	0.32017	0.29235	0.51237	0.42935	Limestone
0.16011	0.66764	0.29913	0.18475	0.6124	0.32017	0.29235	0.51237	0.42935	Limestone
0.20649	0.24251	0.049306	0.22902	0.15153	0.092537	0.32504	0.081253	0.14549	Limestone
0.21605	0.39464	0.16687	0.24117	0.33119	0.20702	0.33972	0.22728	0.2341	Limestone
0.22313	0.55154	0.27605	0.24834	0.4925	0.29414	0.36203	0.35464	0.31303	Limestone
0.18823	0.43989	0.1936	0.20959	0.38498	0.23157	0.30344	0.27306	0.25674	Limestone
0.10813	0.40787	0.18175	0.11885	0.33196	0.21504	0.19243	0.21237	0.22669	Limestone
0.089191	0.6459	0.4978	0.099491	0.57531	0.48563	0.17157	0.40641	0.43768	Limestone
0.10015	0.62784	0.36568	0.11389	0.56965	0.37177	0.19111	0.42482	0.38468	Limestone
0.10317	0.62532	0.35758	0.11747	0.5693	0.36674	0.19597	0.43078	0.39062	Limestone
0.11971	0.52198	0.24312	0.13769	0.47252	0.27669	0.222	0.35186	0.2999	Limestone
0.10598	0.5478	0.32811	0.12217	0.49861	0.35809	0.20267	0.36798	0.33628	Limestone
0.07304	0.42897	0.21874	0.086936	0.34004	0.2498	0.1449	0.19855	0.19075	Limestone
0.055954	0.54769	0.33438	0.065498	0.46467	0.33959	0.12848	0.29332	0.28031	Limestone
0.042923	0.61963	0.39537	0.052449	0.53244	0.38155	0.11292	0.36783	0.33314	Limestone
0.040914	0.58918	0.34306	0.050322	0.50291	0.33629	0.11493	0.35446	0.32053	Limestone
0.055617	0.5213	0.25001	0.068779	0.42792	0.25733	0.13576	0.30813	0.28225	Limestone
0.052496	0.63405	0.36173	0.064824	0.56013	0.36847	0.1323	0.42095	0.37414	Limestone
0.0031578	0.74708	0.45321	0.0072809	0.67952	0.4384	0.066081	0.54407	0.47593	Limestone
0	0.7508	0.45823	0.00403	0.68135	0.44236	0.058793	0.54749	0.47524	Limestone
0.30724	0.43595	0.25712	0.3458	0.36214	0.27433	0.49078	0.2619	0.29243	Limestone
0.35344	0.43351	0.27198	0.39807	0.35958	0.28514	0.55695	0.28301	0.31037	Limestone
0.35439	0.49183	0.29619	0.39852	0.42431	0.3109	0.5659	0.35839	0.36807	Limestone
0.3333	0.59267	0.34481	0.37639	0.53572	0.36518	0.54179	0.48998	0.4687	Limestone
0.24025	0.52305	0.32216	0.27249	0.47205	0.34915	0.39786	0.36845	0.38923	Limestone
0.22244	0.69913	0.35587	0.24806	0.62737	0.34223	0.35574	0.42447	0.34344	Limestone
0.23218	0.6454	0.2801	0.25855	0.57899	0.28616	0.36768	0.42586	0.34095	Limestone
0.23088	0.50968	0.20916	0.26076	0.44532	0.23038	0.37557	0.31496	0.28406	Limestone

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.23352	0.5121	0.20466	0.26518	0.44574	0.22433	0.37877	0.31107	0.27368	Limestone
0.21616	0.60504	0.24947	0.24286	0.53095	0.2578	0.35997	0.4068	0.34207	Limestone
0.16616	0.53942	0.20559	0.187	0.47292	0.23378	0.28923	0.34474	0.30877	Limestone
0.15402	0.51896	0.18114	0.1733	0.44533	0.20513	0.27149	0.33092	0.29822	Limestone
0.16786	0.52931	0.19485	0.18833	0.46282	0.22205	0.29219	0.35767	0.31992	Limestone
0.16981	0.56292	0.21307	0.19079	0.49554	0.23688	0.29377	0.39006	0.33781	Limestone
0.18057	0.55383	0.21734	0.20297	0.47793	0.23672	0.30539	0.36723	0.3269	Limestone
0.17365	0.64136	0.31308	0.19374	0.54847	0.30261	0.29179	0.37574	0.32914	Limestone
0.32436	0.41744	0.17322	0.36271	0.33457	0.19289	0.51127	0.26214	0.2729	Limestone
0.32717	0.42822	0.1767	0.36556	0.34721	0.19728	0.51652	0.27431	0.28162	Limestone
0.33088	0.25544	0.08513	0.37152	0.16903	0.12568	0.51642	0.10683	0.19294	Limestone
0.2975	0.37585	0.090793	0.33449	0.30043	0.12888	0.47024	0.20405	0.21733	Limestone
0.29312	0.53212	0.175	0.32611	0.46166	0.19666	0.46488	0.34821	0.28727	Limestone
0.24026	0.48653	0.18348	0.26899	0.42591	0.21508	0.38556	0.30146	0.26979	Limestone
0.18104	0.63667	0.37362	0.2053	0.57385	0.37981	0.30713	0.42539	0.37767	Limestone
0.080642	0.47702	0.42316	0.094861	0.39433	0.41121	0.16631	0.25614	0.31096	Limestone
0.065215	0.50744	0.39772	0.077483	0.42595	0.39605	0.14635	0.28776	0.32162	Limestone
0.067536	0.45509	0.27747	0.079251	0.36023	0.2764	0.14891	0.21951	0.24174	Limestone
0.07017	0.58641	0.51317	0.084419	0.49298	0.47304	0.14675	0.28115	0.29007	Limestone
0.07017	0.58641	0.51317	0.084419	0.49298	0.47304	0.14675	0.28115	0.29007	Limestone
0.060297	0.77568	0.69765	0.072794	0.70388	0.63646	0.13806	0.47962	0.45886	Limestone
0.12916	0.64734	0.4642	0.14562	0.61209	0.48555	0.22866	0.44107	0.41586	Limestone
0.16734	0.65003	0.38885	0.18942	0.60332	0.40071	0.28857	0.47232	0.42003	Limestone
0.2261	0.72503	0.40428	0.25531	0.67124	0.40432	0.377	0.56857	0.48014	Limestone
0.25964	0.6724	0.31891	0.29213	0.60834	0.32419	0.42728	0.54344	0.45891	Limestone
0.23399	0.73338	0.39186	0.26289	0.69956	0.40928	0.39282	0.63437	0.52223	Limestone
0.22053	0.76078	0.42039	0.24827	0.72408	0.43007	0.36665	0.65227	0.52759	Limestone
0.13979	0.55115	0.24684	0.15844	0.49258	0.27855	0.2431	0.35241	0.29311	Limestone
0.097816	0.51669	0.32346	0.11276	0.42794	0.32595	0.18451	0.2817	0.26986	Limestone
0.10605	0.4813	0.21286	0.123	0.39356	0.22068	0.20238	0.25867	0.25301	Limestone
0.099039	0.65186	0.34417	0.11446	0.55992	0.32753	0.1937	0.42013	0.3669	Limestone
0.086495	0.50165	0.25226	0.10094	0.39854	0.26377	0.17265	0.24647	0.24632	Limestone
0.046805	0.61619	0.43998	0.056434	0.53018	0.42975	0.12644	0.37653	0.37754	Limestone
0.039541	0.66286	0.56971	0.049154	0.57083	0.52913	0.10851	0.39716	0.40803	Limestone
0.26986	0.80054	0.39892	0.29979	0.75214	0.39829	0.44655	0.65779	0.49859	Limestone
0.26986	0.80054	0.39892	0.29979	0.75214	0.39829	0.44655	0.65779	0.49859	Limestone
0.27139	0.79504	0.38997	0.30223	0.745	0.38945	0.44734	0.65419	0.49428	Limestone
0.30595	0.58065	0.18414	0.34258	0.50315	0.20638	0.4926	0.42569	0.34777	Limestone
0.26313	0.45443	0.18234	0.29486	0.36636	0.19888	0.42289	0.26738	0.27047	Limestone
0.26284	0.3362	0.13455	0.29434	0.24907	0.1604	0.41502	0.15559	0.20044	Limestone
0.2699	0.25702	0.13723	0.30198	0.17586	0.17055	0.41431	0.11654	0.18305	Limestone
0.27429	0.35541	0.24098	0.30442	0.27282	0.25558	0.42155	0.20197	0.24924	Limestone
0.27722	0.3713	0.17216	0.30494	0.29658	0.19557	0.416	0.1915	0.1993	Limestone
0.22354	0.47625	0.27558	0.24529	0.39212	0.26947	0.34288	0.25425	0.25406	Limestone
0.19566	0.50704	0.28939	0.21473	0.42439	0.27841	0.30956	0.28707	0.28552	Limestone
0.26685	0.61452	0.18384	0.29661	0.55727	0.20517	0.42899	0.46937	0.34468	Limestone
0.29871	0.60912	0.083116	0.33273	0.54132	0.11817	0.48376	0.44526	0.29581	Limestone
0.22681	0.70196	0.18398	0.25554	0.64005	0.20591	0.37919	0.52003	0.34239	Limestone
0.16136	0.79656	0.373	0.18416	0.74159	0.36957	0.28197	0.58286	0.42066	Limestone
0.091875	0.65265	0.48299	0.10773	0.59385	0.47253	0.1768	0.37367	0.33465	Limestone
0.13104	0.65862	0.55009	0.14748	0.59432	0.51927	0.23159	0.38571	0.37017	Limestone
0.21457	0.51216	0.27046	0.24105	0.43963	0.28729	0.34653	0.2848	0.26657	Limestone
0.2151	0.51283	0.27124	0.24108	0.44078	0.28791	0.35102	0.28327	0.26779	Limestone
0.35519	0.51193	0.20722	0.39616	0.44742	0.23694	0.56199	0.40001	0.36754	Limestone
0.38761	0.37504	0.18578	0.43225	0.30339	0.2094	0.6048	0.23344	0.25713	Limestone
0.35555	0.37193	0.1995	0.39495	0.29985	0.21742	0.54375	0.21816	0.22746	Limestone
0.30331	0.4884	0.18962	0.33566	0.41427	0.20833	0.45907	0.27461	0.22827	Limestone
0.27659	0.60155	0.38314	0.30742	0.53162	0.37287	0.43322	0.41848	0.36484	Limestone
0.2433	0.49209	0.34789	0.27207	0.43955	0.3805	0.38344	0.39813	0.49307	Limestone
0.22968	0.67924	0.42684	0.25762	0.65116	0.46205	0.37388	0.62105	0.61838	Limestone
0.28975	0.50304	0.15481	0.31997	0.43122	0.1814	0.45347	0.31567	0.27325	Limestone
0.36172	0.35803	0.05023	0.39753	0.26576	0.083533	0.55265	0.16048	0.17452	Limestone
0.3721	0.42623	0.13612	0.4052	0.33322	0.1538	0.55349	0.20311	0.18546	Limestone
0.18167	0.73099	0.41814	0.20421	0.68551	0.42308	0.31756	0.62944	0.54972	Limestone
0.18485	0.72904	0.41421	0.20778	0.68424	0.42027	0.32218	0.62969	0.55052	Limestone
0.17294	0.72043	0.39021	0.19398	0.67444	0.39783	0.30196	0.59825	0.50351	Limestone
0.18475	0.51432	0.17926	0.20502	0.45567	0.21543	0.30362	0.32222	0.27159	Limestone
0.19199	0.50939	0.16659	0.21234	0.44572	0.19968	0.31072	0.30363	0.25226	Limestone
0.25471	0.48742	0.20156	0.27769	0.41516	0.22423	0.37824	0.27825	0.24649	Limestone
0.27683	0.40655	0.13491	0.30219	0.33656	0.17117	0.40937	0.21844	0.21095	Limestone
0.27525	0.4252	0.15465	0.30066	0.35617	0.18331	0.40818	0.23635	0.2223	Limestone
0.31088	0.44011	0.095081	0.34205	0.35824	0.12336	0.48006	0.2301	0.20955	Limestone
0.33062	0.47499	0.18365	0.36352	0.38952	0.19783	0.50303	0.27018	0.25206	Limestone
0.34151	0.43349	0.14098	0.37552	0.34821	0.16216	0.51938	0.24449	0.23536	Limestone
0.37091	0.36634	0.097735	0.407	0.27938	0.125	0.56379	0.18922	0.20873	Limestone
0.37091	0.36634	0.097735	0.407	0.27938	0.125	0.56379	0.18922	0.20873	Limestone
0.39488	0.29469	0.072194	0.43456	0.20698	0.10468	0.59273	0.13638	0.18484	Limestone
0.39961	0.29444	0.074776	0.43862	0.21056	0.10923	0.59999	0.13692	0.18282	Limestone
0.42361	0.21149	0.074966	0.46497	0.11966	0.1062	0.62811	0.075893	0.15643	Limestone
0.39648	0.25087	0.04561	0.43524	0.15837	0.082856	0.58745	0.082133	0.13763	Limestone
0.32896	0.40223	0.12998	0.36154	0.32465	0.16411	0.49757	0.20961	0.21447	Limestone
0.2518	0.50778	0.38814	0.28187	0.45892	0.3916	0.40665	0.34063	0.35989	Limestone
0.22011	0.50372	0.35028	0.24845	0.4444	0.35589	0.35651	0.31616	0.32133	Limestone
0.22099	0.49055	0.33299	0.24924	0.43007	0.33961	0.35651	0.299	0.30448	Limestone
0.18446	0.41758	0.21532	0.2041	0.34296	0.24041	0.29649	0.20803	0.22865	Limestone
0.2063	0.47721	0.2312	0.22752	0.40075	0.24416	0.3192	0.24669	0.23259	Limestone
0.21917	0.50524	0.2026	0.24096	0.43292	0.21799	0.34112	0.287	0.24795	Limestone
0.24301	0.55248	0.16841	0.26858	0.47703	0.18464	0.37922	0.33333	0.25618	Limestone
0.31539	0.41705	0.10309	0.34917	0.33768	0.13089	0.48663	0.24486	0.22859	Limestone

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.32836	0.42063	0.10444	0.36325	0.33691	0.12892	0.50248	0.24848	0.23037	Limestone
0.36188	0.26501	0.069635	0.40121	0.16982	0.098464	0.55156	0.10931	0.17686	Limestone
0.3804	0.23192	0.073378	0.42096	0.15134	0.11071	0.57337	0.10146	0.1728	Limestone
0.38763	0.34309	0.12041	0.42773	0.25948	0.15023	0.58301	0.17655	0.20506	Limestone
0.34833	0.28728	0.11235	0.38623	0.2096	0.14315	0.52688	0.12255	0.17275	Limestone
0.34061	0.39009	0.15365	0.37542	0.32267	0.18331	0.5268	0.21565	0.22973	Limestone
0.14916	0.45744	0.31003	0.16942	0.40129	0.32702	0.25482	0.27407	0.27717	Limestone
0.14637	0.46841	0.29726	0.16625	0.41373	0.31666	0.25504	0.28541	0.2841	Limestone
0.17651	0.52945	0.277	0.20061	0.46659	0.29551	0.29834	0.32702	0.2927	Limestone
0.18095	0.52993	0.30339	0.20413	0.4544	0.30563	0.29353	0.32565	0.29496	Limestone
0.17949	0.53182	0.32112	0.201	0.45423	0.32101	0.29324	0.32907	0.3064	Limestone
0.17723	0.46886	0.26811	0.19849	0.39907	0.28602	0.28899	0.28732	0.29771	Limestone
0.18863	0.53931	0.29925	0.21118	0.48102	0.31609	0.30938	0.35007	0.32508	Limestone
0.17385	0.57852	0.28894	0.1961	0.50478	0.2836	0.29345	0.35953	0.30826	Limestone
0.22275	0.65762	0.44271	0.25034	0.58549	0.40138	0.36023	0.42949	0.3811	Limestone
0.28072	0.54789	0.37412	0.31083	0.45608	0.33151	0.4244	0.30284	0.28262	Limestone
0.30882	0.39521	0.1932	0.34138	0.315	0.2039	0.46812	0.20928	0.21809	Limestone
0.36715	0.2501	0.11866	0.40446	0.18108	0.14961	0.5579	0.12964	0.18864	Limestone
0.35643	0.3958	0.12974	0.39272	0.32266	0.15587	0.55349	0.25473	0.2526	Limestone
0.34717	0.36435	0.047813	0.38382	0.27947	0.085133	0.54948	0.21296	0.23444	Limestone
0.23924	0.755	0.54191	0.27071	0.72831	0.55668	0.39583	0.65936	0.65721	Limestone
0.2302	0.7586	0.53521	0.26145	0.73027	0.54747	0.38006	0.66601	0.64813	Limestone
0.2218	0.75073	0.50507	0.25212	0.71827	0.51	0.36723	0.63527	0.57307	Limestone
0.28097	0.58158	0.22191	0.31613	0.50932	0.24455	0.4607	0.38934	0.33881	Limestone
0.2675	0.46102	0.17879	0.30001	0.37256	0.19603	0.43	0.25401	0.25686	Limestone
0.21516	0.5085	0.19737	0.2421	0.43284	0.21828	0.35331	0.31754	0.29654	Limestone
0.21543	0.55117	0.21748	0.2415	0.47667	0.23343	0.35168	0.34686	0.30175	Limestone
0.3595	0.52219	0.074279	0.39726	0.44963	0.11071	0.57168	0.3636	0.28023	Limestone
0.4312	0.36391	0	0.47561	0.27272	0.04713	0.68063	0.20002	0.21896	Limestone
0.37952	0.40896	0.079538	0.42154	0.31822	0.11362	0.59397	0.2398	0.24306	Limestone
0.36047	0.43167	0.12607	0.40043	0.34567	0.15507	0.56318	0.25131	0.24965	Limestone
0.33727	0.32231	0.13567	0.37684	0.225	0.15712	0.52392	0.12143	0.17244	Limestone
0.32566	0.39916	0.1727	0.36294	0.31666	0.1981	0.50422	0.18484	0.20203	Limestone
0.35223	0.4212	0.141	0.39052	0.34319	0.16791	0.54356	0.23933	0.23371	Limestone
0.3652	0.36179	0.095342	0.40509	0.27168	0.11914	0.55954	0.18069	0.19788	Limestone
0.2276	0.81586	0.49671	0.25729	0.75138	0.4754	0.38637	0.68126	0.59576	Limestone
0.24734	0.72515	0.41245	0.27939	0.66321	0.41203	0.41444	0.61149	0.56408	Limestone
0.32506	0.43737	0.20848	0.36584	0.37028	0.24699	0.50747	0.29173	0.33469	Limestone
0.39408	0.30759	0.080273	0.43823	0.22711	0.12351	0.59545	0.13874	0.19601	Limestone
0.28476	0.56291	0.16218	0.31658	0.48733	0.1863	0.45376	0.36681	0.30441	Limestone
0.18913	0.75392	0.38158	0.21321	0.69608	0.37911	0.3211	0.59688	0.48157	Limestone
0.16599	0.70067	0.29884	0.18706	0.63761	0.30236	0.28802	0.53167	0.41151	Limestone
0.14542	0.68848	0.24504	0.16439	0.64654	0.27585	0.26428	0.55978	0.41901	Limestone
0.22395	0.71162	0.33137	0.25073	0.6522	0.33409	0.37241	0.5708	0.43904	Limestone
0.24866	0.65214	0.34571	0.27703	0.59816	0.35515	0.40325	0.49142	0.4004	Limestone
0.24513	0.58379	0.49775	0.27392	0.54136	0.50065	0.39028	0.37857	0.38894	Limestone
0.23886	0.67723	0.68891	0.26142	0.65021	0.67965	0.37349	0.49304	0.54604	Limestone
0.21115	0.86459	0.816	0.23461	0.84226	0.80071	0.34328	0.73947	0.81122	Limestone
0.28341	0.52314	0.23793	0.31459	0.4484	0.25952	0.4441	0.34212	0.33197	Limestone
0.30349	0.60133	0.30368	0.33882	0.53864	0.30396	0.47882	0.40751	0.33121	Limestone
0.39782	0.42609	0.17694	0.44021	0.33651	0.19291	0.59447	0.20043	0.2177	Limestone
0.39782	0.42609	0.17694	0.44021	0.33651	0.19291	0.59447	0.20043	0.2177	Limestone
0.16155	0.73444	0.38096	0.18297	0.68745	0.38721	0.27658	0.53307	0.43524	Limestone
0.08476	0.90507	0.69066	0.097004	0.84504	0.62157	0.16882	0.66044	0.55086	Limestone
0.13211	0.75187	0.43432	0.15218	0.69574	0.42417	0.23716	0.54781	0.42887	Limestone
0.16671	0.66489	0.39343	0.19187	0.61183	0.39638	0.28619	0.46546	0.3894	Limestone
0.15934	0.45657	0.27674	0.18093	0.38053	0.29543	0.27246	0.24435	0.24982	Limestone
0.14521	0.36202	0.17725	0.16244	0.27154	0.20263	0.24453	0.1489	0.18186	Limestone
0.14415	0.446	0.17839	0.16132	0.36992	0.21046	0.23975	0.21505	0.20284	Limestone
0.15533	0.51078	0.25148	0.1729	0.43951	0.2682	0.25607	0.26323	0.23361	Limestone
0.19803	0.52307	0.25136	0.21798	0.4552	0.27012	0.31057	0.29482	0.27181	Limestone
0.39874	0.3861	0.0544	0.44288	0.30635	0.096003	0.62167	0.20068	0.21168	Limestone
0.36737	0.47797	0.1455	0.40746	0.40094	0.17465	0.5762	0.29403	0.27062	Limestone
0.35257	0.48817	0.17858	0.39348	0.40682	0.19933	0.54884	0.29532	0.27196	Limestone
0.34436	0.42864	0.14389	0.38416	0.34912	0.16932	0.5316	0.23059	0.23183	Limestone
0.32022	0.5598	0.19784	0.35461	0.48292	0.21163	0.49263	0.3381	0.28004	Limestone
0.35473	0.5311	0.16337	0.39222	0.4546	0.19026	0.55304	0.35247	0.31069	Limestone
0.39405	0.42531	0.11821	0.43868	0.3665	0.1726	0.61792	0.33294	0.34641	Limestone
0.43777	0.4076	0.11207	0.49166	0.36735	0.1765	0.69576	0.38283	0.39743	Limestone
0.43547	0.47052	0.12842	0.48995	0.42725	0.19299	0.70537	0.43746	0.42933	Limestone
0.4247	0.48575	0.17301	0.47792	0.44013	0.22939	0.69037	0.45764	0.45937	Limestone
0.27831	0.48154	0.26826	0.31455	0.42124	0.29322	0.44771	0.32169	0.34253	Limestone
0.25356	0.48643	0.25833	0.28261	0.42821	0.2822	0.39665	0.28366	0.26757	Limestone
0.24108	0.46174	0.28266	0.26912	0.4052	0.3078	0.37684	0.25673	0.25065	Limestone
0.21339	0.42886	0.30209	0.23775	0.37103	0.32316	0.33388	0.21262	0.22677	Limestone
0.21402	0.52266	0.5005	0.23846	0.47258	0.50356	0.33628	0.30863	0.35997	Limestone
0.24381	0.73926	0.60299	0.27128	0.69516	0.5892	0.38534	0.54641	0.54388	Limestone
0.31692	0.40618	0.12828	0.3517	0.32004	0.15406	0.49865	0.22574	0.2367	Limestone
0.4365	0.2208	0.22205	0.49058	0.14559	0.25337	0.66611	0.14782	0.27037	Limestone
0.42585	0.27847	0.18711	0.47748	0.20467	0.22351	0.65592	0.17415	0.27035	Limestone
0.35805	0.39451	0.19725	0.40078	0.30783	0.21584	0.55589	0.21638	0.25389	Limestone
0.31816	0.38969	0.11048	0.35813	0.31414	0.14377	0.50139	0.21592	0.23167	Limestone
0.31523	0.50364	0.11162	0.35197	0.42878	0.1444	0.49308	0.32474	0.27417	Limestone
0.35686	0.46307	0.18713	0.40211	0.40096	0.22909	0.56479	0.37361	0.38945	Limestone
0.35131	0.54063	0.23831	0.3993	0.47628	0.26988	0.56086	0.40959	0.39731	Limestone
0.23737	0.67425	0.33185	0.26793	0.61271	0.34068	0.3954	0.51585	0.44644	Limestone
0.2076	0.61444	0.28292	0.23518	0.54422	0.29037	0.3483	0.42465	0.36508	Limestone
0.19728	0.50585	0.22895	0.22437	0.44714	0.25466	0.33024	0.29686	0.27181	Limestone
0.24983	0.5041	0.24577	0.28211	0.44613	0.26717	0.40111	0.28385	0.2636	Limestone

Weighted Mean Red	Skewness Red	Kurtosis Red	Weighted Mean Green	Skewness Green	Kurtosis Green	Weighted Mean Blue	Skewness Blue	Kurtosis Blue	Material
0.26908	0.39927	0.26212	0.30192	0.33323	0.27697	0.41795	0.18849	0.2054	Limestone
0.23963	0.39365	0.19402	0.26727	0.33873	0.23144	0.37486	0.20582	0.21155	Limestone
0.33475	0.4034	0.10323	0.36767	0.33303	0.13499	0.51674	0.2374	0.22321	Limestone
0.33475	0.4034	0.10323	0.36767	0.33303	0.13499	0.51674	0.2374	0.22321	Limestone
0.34577	0.3482	0.065086	0.38315	0.26116	0.094136	0.53979	0.17197	0.19758	Limestone
0.37828	0.30399	0.037151	0.41685	0.22091	0.077586	0.57937	0.14121	0.1904	Limestone

## Appendix P – Limestone Sampling Procedure



Representative Sampling of Clinker Stock  
May to October 2016

Prepared by Lindsay Notley (0050104515)

Submitted to the Faculty of Health, Engineering & Sciences

University of Southern Queensland

As a supporting document for

Bachelor of Engineering Research Project

Identification of Cement Manufacturing Raw Materials Using Machine  
Vision

Prepared By	Lindsay Notley Part Time Student University of Southern Queensland	Date	11/05/2016
Submitted To	Dr Andrew Maxwell	Date	
Status	Draft - Uncontrolled	Revision	1

## 1. Introduction

This document has been prepared to manage the quality sampling of Clinker as it is being produced to ensure a true representative sample will be extracted for the Identification of Cement Manufacturing Raw Materials Using Machine Vision research project. Since the Clinker which will be used for the project has not been manufactured yet we will use Stratified Random Sampling to acquire the sample increments via stratification of the total tonnes produced during this period.

The chosen method will be sampling directly from the cooler pan conveyor which will be sampled using sample extraction hand tools in AS 1141.3.1-2012 Clause 8.1. Due to project timing, safety considerations and cost constraints this procedure has been carefully designed to minimise sources of error.

The procedure outlined in this document fulfils the requirements outlined in AS 1141.3.1-2012. This standard outlines the technique, sample size, sample quantity and design considerations for developing a sampling plan. Also AS 1289.1.4.2 R2013 will be used to ensure a representative sample locations have been selected using Stratified Random Sampling procedures.

This document will have an associated Cement Australia approved risk assessment CAS-F-5.1B prepared addressing the risk associated with the sampling of Clinker particularly addressing the risk of handling hot clinker, pedestrian/vehicle movements and working alone. Additionally site personnel will be notified of the task prior to commencement of the sampling.

## 2. Scope

The scope of this testing will be limited to the stock pile which currently has been built but will be consumed during the entire timeline of the above mentioned research project.

## 3. Referenced Documents

- AS 1141.3.1 -2012: Methods for sampling and testing aggregates – Sample Less than 63mm,
- AS 1141.3.2 -2012: Methods for sampling and testing aggregates – Sample Greater than 63mm,
- AS 1289.1.4.2 R2013: Method 1.4.2: Sampling and preparation of soils—Selection of sampling or test sites—Stratified random number method
- AS 1141.3.1 -2012: Methods for sampling and testing aggregates
- CAS-F-5.1B: – Job Planning Tool Forms & Interface Job Planning Tool Forms
- Cement Australia – Communications Database – Operations Notification Template
- RA-SF-425 – Cement Australia - Railton Materials Bulk Density Summary
- RA-LP-515 – Cement Australia - Bulk Density Determination - Laboratory Procedure

## 4. Clinker Specifications

**Material Size Distribution:** 93.31% less than 38.1mm (Obtained from Cement Australia – Railton: Laboratory Information Database from 2005 to 2016)



**Material Bulk Density:** 1628kg/m<sup>3</sup> Obtained from CA (RA-SF-425) using RA-LP-515 Method 2  
**Clinker Consumption Period:** May to October 2016  
**Expected Tonnes to be produced per day:** 3615t/d  
**Expected Tonnes total:** 3615 x 184 = 665,160 tonnes

## 5. Definitions

**Sample Increment** – Consists of 10kg of raw material extracted from a specific location in the stockpile.

**Sample** – Consists of 5 Sample Increments.

## 6. Required Equipment

- Stock Pile Face Sampling-Shielding similar to AS 114.3.1 Figure 3
- Farmers Friend Shovel
- 30kg Hand Scale
- Cable Ties
- 15kg steel Sample Bucket
- 10kg Sample bags
- Ute to carry sample bags to storage location
- Sample identification tags containing data listed in section
- Survey Spray Paint
- Measuring Wheel

## 7. Assumptions:

## 8. Australian Standard Considerations and Sampling Scheme

Number of required samples: 5

Number of sample increments per sample: 5

Minimum weight of sample Increment: 10kg,

Purpose of sampling is to collect a representative sample of the stockpile.

Total sample increments to be collected from the stock pile will be 25 x 10kg.

Sample locations will be identified using the Stratified Random Sampling procedure from AS 1141.3.1 and, AS 1289.1.4.2.

## 9. Procedure

### 9.1. Sample Location Identification

Step 1) Using a Sharp EL-531WH generate a random Row Number by pressing the following keys in order

“2ndF” → “7” → “0” → “=”

Step 2) Record this Random Number in table 1 below

Step 3) Determine the total tonnage of each stratum use the equation shown below

$$\text{Length of each stratum } (S) = \frac{\text{Tonnes Produced}}{\text{Number of Increments}} = \frac{665160}{25} = 26,606 \text{ tonnes}$$

Step 4) Determine the sample increment location from start point using equation below

$$\text{Increment Location} = S \times (I - 1 + R)$$

**Table 1: Sample Increment Location Point**

Sample Increment (I)	Random Number (R)	Sample Increment Location in metres from Start Point (SP)
1	0.609	16196
2	0.332	35444
3	0.572	68437
4	0.743	99583
5	0.700	125052
6	0.753	153029
7	0.577	174987
8	0.551	200897
9	0.263	219838
10	0.240	245840
11	0.728	285435
12	0.336	301609
13	0.399	329884
14	0.549	360475
15	0.493	385606
16	0.254	405855
17	0.014	425855
18	0.557	467119
19	0.361	488526
20	0.435	517093
21	0.298	540039
22	0.799	579976
23	0.415	596382
24	0.372	621848
25	0.708	657369

## 9.2. Sample Collection

Step 1) Notify Central Control of sample collection will be taking place,

Step 2) Take the required sampling equipment to the pan conveyor sample station,

Step 3) Since the material is in excess of 300°C use the clinker extraction tool and place 10kg of sample into the metal sample bucket,

Step 4) Weigh the sample bucket to ensure at least 10kg has been sampled

Step 5) Allow the clinker 48 hours to cool and place sample in the sample bag

Step 8) Close the bag using a cable tie

Step 9) Place an identification tag stating the following details

- i. Sample Increment Number
- ii. Date of sampling
- iii. Material Type
- iv. Stockpile Name
- v. Nominal size (40mm)
- vi. Location of material represented (in meters from start point)
- vii. Amount of material represented (in kg)
- viii. List Sampling Procedure AS 11141.1 -2012 Clause 8.1
- ix. Name of sampling operator
- x. Any other relevant information, as required.

## 9.3. Sample Storage

The sample will need to be transported the sample storage location for further processing.

## Appendix O – Gypsum Sampling Procedure



Representative Sampling of Natural Gypsum Stockpile  
May to October 2016

Prepared by Lindsay Notley (0050104515)

Submitted to the Faculty of Health, Engineering & Sciences

University of Southern Queensland

As a supporting document for

Bachelor of Engineering Research Project

Identification of Cement Manufacturing Raw Materials Using Machine  
Vision

Prepared By	Lindsay Notley Part Time Student University of Southern Queensland	Date	11/05/2016
Submitted To	Dr Andrew Maxwell	Date	
Status	Draft - Uncontrolled	Revision	1

## 1. Introduction

This document has been prepared to manage the quality sampling of the Natural Gypsum stock pile to ensure a true representative sample will be extracted for the Identification of Cement Manufacturing Raw Materials Using Machine Vision research project. Different sampling methods of the Gypsum Stockpile can be achieved better representative samples through mechanical means or when the product is being delivered to site. The chosen method for sample extraction will be hand sampled from the sides of a stockpile outlined in AS 1141.3.1-2012 Clause 8.4.3. Due to project timing, safety considerations and cost constraints this procedure has been carefully designed to minimise sources of error.

The procedure outlined in this document fulfils the requirements outlined in AS 1141.3.1-2012. This standard outlines the technique, sample size, sample quantity and design considerations for developing a sampling plan. Also AS 1289.1.4.2 R2013 will be used to ensure a representative sample locations have been selected using Stratified Random Sampling procedures.

This document will have an associated Cement Australia approved risk assessment CAS-F-5.1B prepared addressing the risk associated with the sampling of Gypsum particularly addressing the risk of engulfment, pedestrian/vehicle movements and working alone. Additionally, site personnel will be notified of the task prior to commencement of the sampling.

## 2. Scope

The scope of this testing will be limited to the stock pile which currently has been built but will be consumed during the entire timeline of the above mentioned research project.

## 3. Referenced Documents

- AS 1141.3.1 -2012: Methods for sampling and testing aggregates – Sample Less than 63mm,
- AS 1141.3.2 -2012: Methods for sampling and testing aggregates – Sample Greater than 63mm,
- AS 1289.1.4.2 R2013: Method 1.4.2: Sampling and preparation of soils—Selection of sampling or test sites—Stratified random number method
- AS 1141.3.1 -2012: Methods for sampling and testing aggregates
- CAS-F-5.1B: – Job Planning Tool Forms & Interface Job Planning Tool Forms
- Cement Australia – Communications Database – Operations Notification Template
- RA-SF-425 – Cement Australia - Railton Materials Bulk Density Summary
- RA-LP-515 – Cement Australia - Bulk Density Determination - Laboratory Procedure

## 4. Natural Gypsum Pile Specifications

**Material Size Distribution:** 99.79% less than 38.1mm (Obtained from Cement Australia – Railton: Laboratory Information Database from 2005 to 2016)

**Material Bulk Density:** 1424kg/m<sup>3</sup> Obtained from RA-LP-515 (Using Method 2 – Materials >30mm)

**Stockpile Length:** 114.5m (Direction West to east)

**Stockpile Height:** West 8.7 to East 6.7m

**Stockpile Width:** West 34.8m to East 21.7m

**Stockpile Angle:** 38°

**Stock Pile Construction Method:** Stockpile produced by stacking to full height along a line

**Stockpile Consumption Period:** May to October 2016

**Stockpile Volume:** 23,418 m<sup>3</sup>

**Stockpile Tonnes:** 23,418m<sup>3</sup> x 1.424 = 33,347t

**Stockpile Condition:** Rain and Weather affected with erosion depths up to 350mm  
Maximum in depth

## 5. Definitions

**Sample Increment** – Consists of 10kg of raw material extracted from a specific location in the stockpile.

**Sample** – Consists of 5 Sample Increments.

## 6. Required Equipment

- Stock Pile Face Sampling-Shielding similar to AS 114.3.1 Figure 3
- Farmers Friend Shovel
- 30kg Hand Scale
- Cable Ties
- 10kg Sample bags
- Ute to carry sample bags to storage location
- Sample identification tags containing data listed in section
- Survey Spray Paint
- Measuring Wheel

## 7. Assumptions:

Since the stockpile width cannot be measured in its entirety we will assume the pile with will remain constant similar to the volume model devolved using AutoCAD™. This model will be back checked against a LIDAR survey conducted by Lester Franks Surveying which will be conducted in June.

## 8. Australian Standard Considerations and Sampling Scheme

Number of required samples: 5

Number of sample increments per sample: 5

Minimum weight of sample Increment: 10kg,

Purpose of sampling is to collect a representative sample of the stockpile.

Total sample increments to be collected from the stock pile will be 25 x 10kg.

Sample locations will be identified using the Stratified Random Sampling procedure from AS 1141.3.1 and, AS 1289.1.4.2.

## 9. Procedure

### 9.1. Sample Location Identification

Step 1) Using a Sharp EL-531WH generate a random Row Number by pressing the following keys in order

“2ndF” → “7” → “0” → “=”

Step 2) Record this Random Number in table 1 below

Step 3) Determine the length of each stratum use the equation shown below

$$\text{Length of each stratum } (S) = \frac{\text{Stockpile length}}{\text{Number of Increments}} = \frac{114.5}{25} = 4.58 \text{ meters}$$

Step 4) Determine the sample increment location from start point using equation below

$$\text{Increment Location} = S \times (I - 1 + R)$$

**Table 1: Sample Increment Location Point**

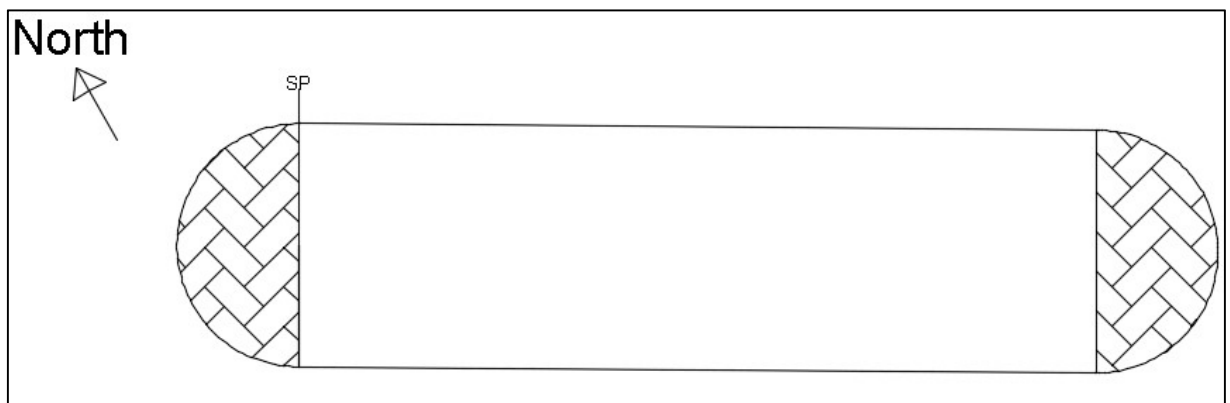
Sample Increment (I)	Random Number (R)	Sample Increment Location in metres from Start Point (SP)
1	0.601	2.8
2	0.164	5.3
3	0.579	11.8
4	0.032	13.9
5	0.058	18.6
6	0.445	24.9
7	0.73	30.8
8	0.47	34.2
9	0.916	40.8
10	0.71	44.5
11	0.552	48.3
12	0.071	50.7
13	0.607	57.7
14	0.154	60.2
15	0.383	65.9
16	0.623	71.6
17	0.584	76
18	0.285	79.2
19	0.616	85.3
20	0.643	90



21	0.766	95.1
22	0.641	99.1
23	0.06	101.1
24	0.056	105.6
25	0.376	111.6

## 9.2. Sample Collection

Step 1) On the day of the sample collection mark the start point which will be the most northern position of the pile and located in line with the first highest point of the pile shown in figure 1. Mark this position with a line and the letters "SP",



**Figure 1: Stockpile Layout showing start point and areas not to be sampled**

Step 2) Using table 1 measure from the starting point each sample increment collection point. Mark this point with the sample increment number e.g. Gypsum- Stock pile sample 1 – sample increment 1 of 5.

Step 3) Carry all the sampling equipment to the required locations

Step 4) Install the Stock Pile Face Sampling-Shield approximately 1.5 meters up from the base of the pile.

Step 5) Remove the first 500mm from the pile below the shield

Step 6) Remove the material taking care not to spill the sample and place approximately 10kg into the sample bag

Step 7) Weigh the sample bag to ensure there is at least 10kg worth

Step 8) Close the bag using a cable tie

Step 9) Place an identification tag stating the following details

- i. Sample Increment Number

- ii. Date of sampling
- iii. Material Type
- iv. Stockpile Name
- v. Nominal size (40mm)
- vi. Location of material represented (in meters from start point)
- vii. Amount of material represented (in kg)
- viii. List Sampling Procedure AS 11141.1 -2012 Clause 8.4.3
- ix. Name of sampling operator
- x. Any other relevant information, as required.

### 9.3. Sample Storage

The sample will need to be transported the sample storage location for further processing.

## Appendix P – Limestone Sampling Procedure



Representative Sampling of Limestone Stock  
May to October 2016

Prepared by Lindsay Notley (0050104515)

Submitted to the Faculty of Health, Engineering & Sciences

University of Southern Queensland

As a supporting document for

Bachelor of Engineering Research Project

Identification of Cement Manufacturing Raw Materials Using Machine  
Vision

Prepared By	Lindsay Notley Part Time Student University of Southern Queensland	Date	11/05/2016
Submitted To	Dr Andrew Maxwell	Date	
Status	Draft - Uncontrolled	Revision	1

## 1. Introduction

This document has been prepared to manage the quality sampling of Limestone as it is being produced to ensure a true representative sample will be extracted for the Identification of Cement Manufacturing Raw Materials Using Machine Vision research project. Since the Clinker which will be used for the project has not been manufactured yet we will use Stratified Random Sampling to acquire the sample increments via stratification of the total tonnes produced during this period.

The chosen method will be sampling directly from the cooler pan conveyor which will be sampled using sample extraction hand tools in AS 1141.3.1-2012 Clause 8.1. Due to project timing, safety considerations and cost constraints this procedure has been carefully designed to minimise sources of error.

The procedure outlined in this document fulfils the requirements outlined in AS 1141.3.1-2012. This standard outlines the technique, sample size, sample quantity and design considerations for developing a sampling plan. Also AS 1289.1.4.2 R2013 will be used to ensure a representative sample locations have been selected using Stratified Random Sampling procedures.

This document will have an associated Cement Australia approved risk assessment CAS-F-5.1B prepared addressing the risk associated with the sampling of Clinker particularly addressing the risk with pedestrian/vehicle movements and working alone. Additionally site personnel will be notified of the task prior to commencement of the sampling.

## 2. Scope

The scope of this testing will be limited to the stock pile which currently has been built but will be consumed during the entire timeline of the above mentioned research project.

## 3. Referenced Documents

- AS 1141.3.1 -2012: Methods for sampling and testing aggregates – Sample Less than 63mm,
- AS 1141.3.2 -2012: Methods for sampling and testing aggregates – Sample Greater than 63mm,
- AS 1289.1.4.2 R2013: Method 1.4.2: Sampling and preparation of soils—Selection of sampling or test sites—Stratified random number method
- AS 1141.3.1 -2012: Methods for sampling and testing aggregates
- CAS-F-5.1B: – Job Planning Tool Forms & Interface Job Planning Tool Forms
- Cement Australia – Communications Database – Operations Notification Template
- RA-SF-425 – Cement Australia - Railton Materials Bulk Density Summary
- RA-LP-515 – Cement Australia - Bulk Density Determination - Laboratory Procedure

## 4. Limestone Specifications

**Material Size Distribution:** 91.5% less than 90mm (Obtained from Cement Australia – Railton: Laboratory Information Database from 2005 to 2016)

**Material Bulk Density:** 1644kg/m<sup>3</sup> Obtained from CA (RA-SF-425) using RA-LP-515 Method 2

**Clinker Consumption Period:** May to October 2016

**Expected Tonnes to be produced per day:** 315t/d

**Expected Tonnes total:** 315 x 184 = 57,960 tonnes

## 5. Definitions

**Sample Increment** – Consists of 12kg of raw material extracted from a specific location in the stockpile.

**Sample** – Consists of 5 Sample Increments.

## 6. Required Equipment

- Stock Pile Face Sampling-Shielding similar to AS 114.3.1 Figure 3
- Farmers Friend Shovel
- 30kg Hand Scale
- Cable Ties
- 15kg Sample bags
- Ute to carry sample bags to storage location
- Sample identification tags containing data listed in section
- Survey Spray Paint
- Measuring Wheel

## 7. Assumptions:

## 8. Australian Standard Considerations and Sampling Scheme

Number of required samples: 5

Number of sample increments per sample: 5

Minimum weight of sample Increment: 12kg,

Purpose of sampling is to collect a representative sample of the stockpile.

Total sample increments to be collected from the stock pile will be 25 x 12kg.

Sample locations will be identified using the Stratified Random Sampling procedure from AS 1141.3.1 and, AS 1289.1.4.2.

## 9. Procedure

### 9.1. Sample Location Identification

Step 1) Using a Sharp EL-531WH generate a random Row Number by pressing the following keys in order

“2ndF” → “7” → “0” → “=”

Step 2) Record this Random Number in table 1 below

Step 3) Determine the total tonnage of each stratum use the equation shown below

$$\text{Length of each stratum } (S) = \frac{\text{Tonnes Produced}}{\text{Number of Increments}} = \frac{57,960}{25} = 2,318 \text{ tonnes}$$

Step 4) Determine the sample increment location from start point using equation below

$$\text{Increment Location} = S \times (I - 1 + R)$$

**Table 1: Sample Increment Location Point**

Sample Increment (I)	Random Number (R)	Sample Increment Location in metres from Start Point (SP)
1	0.069	160
2	0.579	3660
3	0.530	5864
4	0.408	7900
5	0.984	11553
6	0.005	11601
7	0.932	16096
8	0.011	16252
9	0.139	18866
10	0.550	22137
11	0.306	23889
12	0.556	26787
13	0.750	29554
14	0.958	32356
15	0.164	32833
16	0.676	26337
17	0.746	38818
18	0.207	39886
19	0.016	41762
20	0.207	44672
21	0.838	48303
22	0.387	49574
23	0.361	51833
24	0.456	54371
25	0.529	56859

## 9.2. Sample Collection

Step 1) Notify Central Control of sample collection will be taking place,

Step 2) Take the required sampling equipment to the analyser conveyor sample station,

Step 3) Isolate the transfer conveyor and collect the required sample from the analyser conveyor

Step 4) Weigh the sample bucket to ensure at least 12kg has been sampled

Step 5) Place the sample in the plastic sample bag,

Step 8) Close the bag using a cable tie

Step 9) Place an identification tag stating the following details

- i. Sample Increment Number
- ii. Date of sampling
- iii. Material Type
- iv. Stockpile Name
- v. Nominal size (40mm)
- vi. Location of material represented (in meters from start point)
- vii. Amount of material represented (in kg)
- viii. List Sampling Procedure AS 11141.1 -2012 Clause 8.1
- ix. Name of sampling operator
- x. Any other relevant information, as required.

## 9.3. Sample Storage

The sample will need to be transported the sample storage location for further processing.