ASHESI UNIVERSITY

COWPEA SORTER:

AN ALTERNATIVE TO THE MANUAL COWPEA SORTING PROCESS

CAPSTONE

B.Sc. Electrical/Electronic Engineering

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Cowpea Sorter:

An alternative to the manual cowpea sorting process

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Applied Project submitted to the Department of Engineering, Ashesi University in partial fulfilment of the requirements for the award of Bachelor of Science degree in Electrical/Electronic Engineering.

Kawusara Nurudeen Salley

2019

DECLARATION

I hereby declare that this capstone is the result of my own original work and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature:

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Candidate's Name:

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Date:

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I hereby declare that preparation and presentation of this capstone were supervised in accordance with the guidelines on supervision of capstone laid down by Ashesi University.

Supervisor's Signature:

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Supervisor's Name:

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Date:

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Acknowledgement

Firstly, I am most grateful to God for bringing me this far. I am also very grateful to my supervisor Dr. Ayorkor Korsah, for agreeing to supervise my project and her constant support throughout the entire journey; her dedication and contribution to this project has been very important to its completion.

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Abstract

Cowpea traders find the manual sorting process of cowpeas laborious and time-consuming. Based on the volume of cowpeas and the proportion of damaged cowpeas, the process can span a time interval of about 6 hours. This project integrates the power of computer vision and convolutional neural networks to develop a solution for the cowpea trader to effectively segregate good cowpeas from the damaged ones.

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Chapter 1 : Introduction

1.1 Background

Cowpea is one of the most popular legumes in Ghana and is used in many staple foods such as waakye, beans with oil and gari, koose and tubaani. There have been research and proposed technologies around the production and storage of cowpea; however, there is little research into the handling of cowpeas by the cowpea trader before reaching the consumer. This paper discusses the cowpea market and the pain points of a cowpea trader during the manual cowpea sorting process and proposes a final product for the cowpea trader that can effectively replace the manual cowpea sorting process, and mitigate the pain points experienced during this process.

1.2 Case Study

To understand the various pain points of a cowpea trader in handling the cowpea sorting process, a case study was conducted using observational shadowing, from the time the cowpea retailer starts the cowpea sorting process to the end of it. To commence the manual sorting process, the cowpea retailer brings out three basins, each containing a different variety of unsorted cowpea (typically the difference in varieties of cowpea is due to their place of origin), a sieve, and empty basins to hold the chaff, damaged cowpea and clean cowpea for the different cowpea varieties.

The first step of the process involves getting rid of foreign material. For a particular type of cowpea, the cowpea retailer mounts the perforated basin on an empty basin and she pours a fraction of the unsorted cowpeas onto the sieve. She constantly spreads the cowpeas on the sieve and as a result, the chaff together with tiny stones, tiny cowpeas and weevils/bruchids fall through the holes. When all is done, she transfers the cowpeas into an empty basin. She repeats the process until all the cowpeas are free of foreign materials for a particular type of cowpea. She repeats this process for the other varieties and places them in separate basins.

The second and final step of the process involves handpicking damaged cowpeas for disposal. For each variety of cowpea, the cowpea trader manually sorts the cowpeas by handpicking damaged cowpeas (discoloured and broken cowpeas and cowpeas with holes) such that only good cowpeas remain. She continually does this until she ends up with three basins of clean and good cowpeas, each containing a different variety of cowpea. Afterwards, she puts the clean and good cowpeas on display and discards the damaged cowpeas.

She spent a total of 5 hours sorting 20 'olonka' of cowpeas with the help of two other ladies; an 'olonka' is the maximum standard of measurement of grains such as cowpeas, maize and millet used by local traders on the market. Based on this, it can be estimated that it takes about 45 minutes to manually sort 1 'olonka' of cowpeas by one person. According to her, the process is time-consuming and laborious. Depending on the number of varieties of cowpea that require sorting, the volume of cowpeas to be sorted, and the level of damage of the cowpeas, she spends from 2 to 6 hours on a daily basis manually sorting cowpeas to prepare them for sale to consumers. The cowpea sorting process is very important to the cowpea trader because it contributes to keeping her customers and attracting new ones.

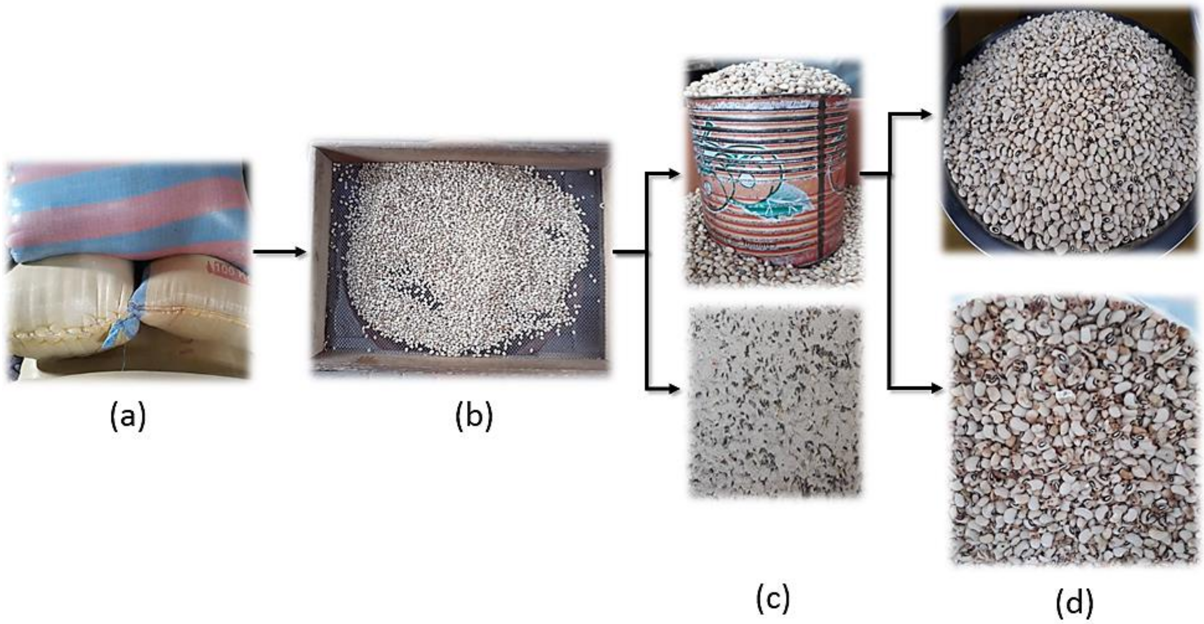


Figure 1.1: The processes carried out by a cowpea retailer for one variety of cowpea: (a) The cowpeas are in sacks when purchased from the wholesaler (b) Foreign materials are discarded from the cowpeas with a sieve mounted on a basin (c) The cowpeas (above) are now cleared of foreign materials (below) (d) The cowpeas are manually sorted to obtain the good cowpeas (above) and the bad/damaged cowpeas (below)

1.3 Justification/Motivation

The manual cowpea sorting process in Ghana by cowpea retailers is very common and has been in action for years. The tediousness and time-consuming nature of this process is underestimated by many, except the cowpea retailers. Some of the common issues encountered by cowpea retailers are:

- The long hours spent in removing chaff and manually segregating the good cowpea from the damaged ones.
- The laborious process of chaff removal and hand-picking of damaged cowpea.

Understanding the issues involved in the manual cowpea sorting process from the cowpea retailer motivated the existence of this project, which is to propose a replacement for the manual cowpea sorting process.

Beyond a typical Ghanaian cowpea retailer, this project has the potential to encourage research in replacing the manual sorting process of other agricultural products. In effect, the concept on which this project is based has the capability of boosting economic activity with regards to quality improvement in the agricultural sector.

1.4 Problem Definition

A middle-aged, hardworking, female cowpea retailer, who is also involved in the trading of other foodstuff, and has a large customer base who require clean and good cowpeas, needs to effectively and efficiently segregate good cowpea from the sacks of cowpeas she purchases from her wholesaler because it is a very time-consuming and laborious process to manually sort the cowpea to sell to her customers.

1.5 Scope of Work

This project targets the cowpea retailer, hence the solution proposed is centered on the requirements of the cowpea retailer.

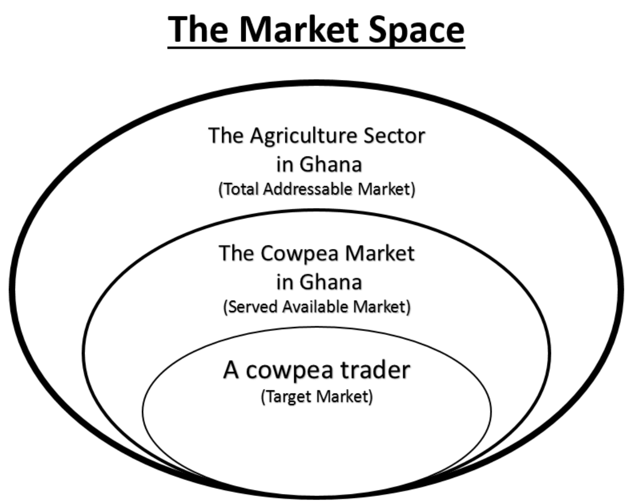


Figure 1.2: This gives an overview of the space within which this project is placed.

In the implementation of this project, the focus is to propose a system for improving the quality of cowpeas sold by the cowpea retailer to her customers by proposing a system to replace the manual cowpea sorting process. This project does not cover crop science or storage technologies for improving the quality of the cowpeas. Further, this solution is such that it is suitable for the cowpea trader/retailer and not for use on a large scale by a cowpea wholesaler.

1.7 Objectives

The objectives of this project is to create a cowpea sorter for the cowpea retailer that is:

- Accurate: This is a major goal that the proposed solution/design should achieve. The accuracy of the proposed solution should be equally as good as the manual sorting process or better in terms of its ability to effectively segregate good cowpeas from foreign materials and damaged cowpeas.

- High-speed: Another aim of the solution/design is that it should have the ability to segregate the good cowpeas from the damaged ones in a shorter period of time as compared to the manual sorting process. The time duration for cowpea sorting 1 'olonka' of cowpeas with the proposed solution should be lower than 45 minutes (the time taken for one person to sort one olonka of cowpeas by the manual sorting process).
- Light-weight: The proposed solution should not be heavy so that it can easily be moved around by the cowpea retailer. Hence, the target weight of the solution/design should be about 2kg or lower.
- Low-power: It is also a necessary factor that the proposed solution runs on low power (achievable by using a rechargeable power bank and/or 9V batteries) while effectively achieving the task. In this case, the cowpea retailer does not have to spend much money to keep the machine operating at all times.

Chapter 2 : Literature Review

2.1 The Cowpea Market

Cowpea (Vigna unguiculata) is one of the most common legumes in Ghana [1] with a large cultivation area, high production and consumption [2]. Cowpea production in West and Central Africa constitute 70% of the world cowpea production [3]. In Ghana, cowpea production takes place in the Northern parts of Ghana (Northern, Savannah, North East, Upper East and Upper West Regions) and also in some parts of the Brong Ahafo Region [1]. Although Ghana is a major producer of cowpea, it is also a net importer of cowpea [4] with an estimated consumption per capita of 5kg in the year 2008 [1]. Cowpeas contribute to the good health of humans due to its high protein content and other vital minerals [1], and it also contributes to the sustainability of the soil by providing it with essential minerals. Some of the popular foods prepared in Ghana using cowpea include waakye, boiled beans with oil and gari, koose and tubaani.

Typically in Ghana and other West African countries (Togo, Benin, Burkina Faso), the cowpea farmers sell their harvest to the rural cowpea traders. The rural traders sell the cowpea either directly to urban wholesalers or via commission agents [1] [5]. Sometimes, the cowpea retailers can also purchase directly from the farmers and sell in small quantities to consumers [1] [5]. There is a significant amount of cowpea that moves from the Northern Regions of Ghana where the cowpea is produced, to the southern parts (more humid areas where cowpeas struggle to thrive), with Accra being the largest consumer of cowpeas [5].

There are several issues that threaten the quality and production levels of cowpeas from the production to consumption phases. One of these issues is the absence of effective and efficient pest and disease control mechanisms to control the production levels and quality of cowpeas [6]. Production and consumption of cowpeas do not occur exactly at the same time and as a result, the surplus cowpeas are stored to sell later to consumers [5]. The storage of cowpeas makes it vulnerable to weevils and bruchids, the common cowpea pests in Africa that are responsible for damage to cowpeas [5] [7]. This affects the major stakeholders (cowpea farmers and retailers) in the cowpea trade because it increases the loss of cowpeas. This is what contributes to high prices of cowpeas because the farmer would have to make up for the money that went into the production of the cowpeas. There is the need to conduct research into effective storage technologies to improve the quality and quantity of cowpeas on the market [2]. Davies et. al [9] also stress the need for the development of suitable machinery to cater for the different stages of cowpea processing to reduce labor requirements, as its food and industrialization uses increase.

As Ghana is a net importer of cowpeas, it is very common to find that the cowpea retailers sell a variety of cowpeas most commonly from Togo, Niger, Burkina Faso and Nigeria, with a significant amount of the cowpeas from Togo [2]. The characteristics of a product are essential in determining its demand and hence, it is necessary to determine the characteristics of the product that consumers deem worthy [10]. Several researchers have investigated consumer preferences on the characteristics of cowpeas and they came up with various cowpea characteristics that consumers value when purchasing cowpeas: colour, size, taste, cooking duration, cleanliness (no stones and foreign materials), dryness, weevil/bruchid damage and origin of the cowpea [1] [2] [4] [8] [5] [10]. From their findings, consumers generally prefer large, white-coated cowpea which is tasty and takes a shorter time to cook and these characteristics are dependent on a specific cowpea type (or place of origin of the cowpea). However, regardless of the variety of cowpeas with all the desired cowpea characteristics, the cowpeas must be clean and free of damage. Otherwise, consumers pay discount prices for dirty and damaged cowpeas [4]. Thus to remove the damaged cowpeas, cowpea retailers manually sort the cowpeas purchased from cowpea wholesalers before they sell to consumers [4] [8] [5].It is common to find them sorting the cowpeas as they serve customers, especially in West African markets [8].

The researchers mentioned in this section, have explored the various issues faced in the cowpea market and suggested areas of research that can contribute significantly in solving these issues. Storage technologies have been highly recommended by most of the researchers because a large number of cowpeas are damaged due to weevil/bruchid attack. This is because the lower the quantity of damaged cowpeas, the less time the cowpea retailer spends manually sorting the cowpeas. Although storage technologies are a good way of improving the quality of cowpeas, they cannot completely eliminate the damaged cowpeas. Hence, it is very important to also explore technologies that will eliminate damaged cowpeas just before they are sold to consumers.

2.2 Quality evaluation using non-destructive techniques

Destructive techniques in quality evaluation damage the specimen (fruit/vegetable) under test. In the past, these were the only techniques available to carry out quality evaluation in the agricultural sector but this means that the products cannot be sold after undergoing destructive tests. This motivated most researchers to start investigating methods to conduct quality evaluation using non-destructive techniques. Non-destructive techniques in quality evaluation successfully test the quality of the product without damaging it, hence rendering it safe for consumption.

Narayan et. al [11] conducted an assessment of various non-destructive approaches for quality evaluation of fruits. The electric nose was one of the non-destructive techniques discussed that has been applied in fruit quality evaluation and it classifies fruits based on the smell it detects from them. The concept of the electronic nose was developed differently by various researchers. One version of the electronic nose achieved 99% accuracy at quality evaluation by classifying fruits based on their maturity level (immature, mature and over-mature). Although the electronic nose is highly accurate, it is not applicable in the cases where there is not enough aromatic substance in the fruit to give off an odor. Cowpeas do not constitute aromatic substances which are responsible for odor in fruits; this makes the electric nose technique inapplicable to cowpeas.

Nuclear Magnetic Resonance/Magnetic Resonance Imaging (NMR/MRI) is another non-destructive technique discussed in the paper by Narayan et. al [11]. This technique detects the state of atoms in a specimen by sending electromagnetic radiation into the specimen. An accuracy of 87.5% was obtained when the NMR approach was used to conduct quality evaluation of apples into three categories. It has also been successful in detecting damage in other fruits including pear and kiwifruit. Although the NMR is highly accurate in determining the internal features of fruits (due to its strong penetration) and is less harmful to the fruit, it is not effective for quality evaluation in cases where the fruit under classification contains water (eg. tomato). Another disadvantage is that it takes a longer time to process the quality of a fruit and this makes it a mechanism that is not commonly used [11]. Although cowpeas do not contain water, this technique will not be suitable in the quality evaluation of cowpeas as there is a large number of cowpeas (in this case, 1 olonka of cowpeas at a time) to be sorted at any given time, and this process will take a long time to process the cowpeas.

Other non-destructive techniques like X-ray, near-infrared spectroscopy, gloss meter and hardness tester have been explored in the past for the classification of fruits and vegetables [11]. However, all these methods mentioned and discussed require well-engineered sensors which require research, engineering, mathematical analysis and in some cases, large computational power to design and build the product. Although they have been successful on a commercial scale, they are not practical for small-scale applications due to the capital that has to be invested in developing the sensors and devices used for testing the fruits and vegetables [11].

Machine vision is a non-destructive technique that captures the image of the fruit, processes the image and evaluates the quality of the fruit. This technique is based on the foundation that there is a relationship between the external and internal characteristics of a fruit such that the quality output determined using external characteristics will be the same output obtained from an internal quality evaluation of the fruit. Some of the external features captured by image processing algorithms in machine vision are color, shape and area of surface defect (eg, holes, stains). This technique can be computationally complex and the complexity can vary from fruit to fruit if there are multiple factors to be considered for the quality evaluation for a given fruit.

2.3 Quality evaluation using computer vision and convolutional neural networks

Computer/Machine vision refers to a system that utilizes image processing algorithms to identify objects; it captures the image of an object which serves as an input to the system, and produces a numerical or symbolic output that represents the identity of the object. In the past, computer vision was a complex area of exploration; however, with the discovery of machine learning algorithms such as convolutional neural networks, computer vision algorithms have become much simpler.

A Convolutional Neural Network (CNN) is a deep learning algorithm that is capable of object identification [12] by training it with images of the object to enable it to recognize patterns in the image, hence it is able to make predictions on unseen data. CNNs have become an integral part of computer vision due to their effectiveness in executing object identification and classification using images as input [12]. Unlike other image classification techniques such as K-Nearest Neighbors (K-NN), Support Vector Machines (SVMs) and Naïve Bayes, CNNs do not require feature extraction [12] [13] and have the highest classification accuracy [13]. However to achieve high performance with a CNN, it requires a large dataset of images [13] [14].

Basically, a CNN is made up of an input layer, a hidden layer and an output layer [14]. However, most CNNs are built using multiple hidden layers to enable it to learn useful patterns in complex images and they layers consist of convolutional, pooling and fully connected/dense layers [13][14]. The convolutional layers use a filter (also called a kernel) to extract features from the input image to generate a feature map, and the max pooling layers reduce the dimensions of the feature map whiles maintaining the important features extracted from the input image [13] [14]. The output of the final feature map is flattened and serves as an input to the fully connected layers. Each layer in a fully connected layer are made up of neurons. Each of the neurons in one layer are connected to all the other neurons in the next layer. These layers have their weights adjusted during the training phase so that these weights can be used in the future for classification. The output layer of the CNN which is based on the softmax function [13], is used to assign probabilities to the possible outputs.

Lu et. al [13] developed a 6-layer CNN to classify nine(9) different types of fruits and achieved an accuracy of 91.44%. The architecture of the CNN included 2 convolutional layers, 2 pooling layers, 2 fully connected/hidden layers and an output layer. The image set used for training the CNN were obtained online: a total of 1800 images with 200 images for each type of fruit. The final structure and parameters used for the CNN were obtained through trial-and-error experiments. The 1800 images were divided equally for training and testing sets for the CNN. The training was done over 30 epochs with a batch size of 256. The accuracy of the CNN network surpassed other state-of-the-art approaches such as VB-SVM and GA which achieved accuracies of 86.56% and 82.33% respectively. In the future, Lu et. al propose increasing the images dataset to achieve a much a higher accuracy for the CNN.

Motivated by the need to replace the manual sorting process of green coffee beans and to provide an alternative to expensive optical sorters, Pinto et. al [14] used a CNN algorithm in sorting green coffee beans into categories with different defects and achieved accuracies ranging between 72.4% and 98.7%. The data acquisition process was as follows: the coffee beans were spread on a white sheet of paper with adequate illumination, and the camera was positioned to take a photo of the coffee beans. Pre-processing techniques were applied to the images obtained to isolate each coffee bean and set its size to 256x256 pixels. The CNN architecture used in this application consisted of 4 convolutional layers, 4 pooling layers and 2 fully connected layers.

This capstone will be the first to employ computer vision and convolutional neural networks to the quality evaluation of cowpeas. This approach is suitable for this application due to the high accuracies it has produced in quality evaluation applications. Unlike the other non-destructive quality evaluation techniques discussed in chapter 2.2, this approach is the cheapest and least complex approach. It can also be scoped for quality evaluation on a small scale which makes it suitable for this application as the final solution is being developed for the cowpea trader, and not for use in industrial environments.

Chapter 3 : Design

3.1 Design Objective

This project seeks to develop an affordable, light-weight, low-power, accurate and fast cowpea sorter system for a Ghanaian cowpea trader/retailer that will automatically segregate good cowpea from chaff and bad cowpea.

3.2 Evaluation of Alternatives

There are many alternative designs for implementing the different components of the cowpea sorter system and as a result, it is very important to evaluate the various alternatives based on the desirable attributes of the system to come up with the best alternatives suitable for the cowpea sorter system. To achieve this evaluation for the cowpea sorter system, the Pugh matrix was used.

The chaff removal process

A component of the proposed design removes the chaff (dirt, weevils/bruchids, and stones) from the cowpeas. The chaff removal process popular among cowpea traders in Ghana is the use of a perforated basin. The cowpea traders spread the cowpeas in a flat perforated basin and slowly spread the cowpeas on the flat surface of the basin. This allows the chaff to fall through the holes of the perforated basin. This method will be set as the baseline for comparing other chaff removal alternatives: a vibratory perforated basin and a 12V DC fan. The vibratory perforated basin alternative is made up of a perforated basin and a 7.5V DC motor. As the motor vibrates, the cowpeas spread over the surface of the perforated basin and the chaff is removed through the holes.

As a basin of cowpeas containing chaff is held/placed above an empty basin below and the cowpeas are allowed to fall into the empty basin, a 12V DC fan eliminates chaff from cowpeas when it is placed about midway of the distance between the two basins.

Table 3.1: The Pugh Matrix for evaluating the alternatives of the chaff removal process for the cowpea sorter system

		Baseline (Perforated basin)	**Weight**	**Vibratory Perforated Basin (7.5V DC motor)**	**12 V DC Fan**
Criteria					
Efficiency		0	5	0	-1
Speed		0	4	+1	0
Power consumption		0	3	-1	-1
Total				+1	-8

Efficiency in Table 1 refers to the extent to which each alternative removes the chaff present in the cowpeas. Speed refers to the rate of chaff removal from the cowpeas of each of the alternatives and power consumption refers to the electrical power required to operate each of the alternatives.

The results from the Pugh Matrix in Table 1 show that the vibratory perforated basin is the best alternative, hence this will be used in the implementation of the chaff removal system in the proposed design.

The Processing board

A processing board is required for the cowpea sorter system to run the algorithm that determines the quality of the cowpea, and has GPIO pins that will control an output accordingly. The Arduino (a microcontroller), Raspberry Pi (a microprocessor) and FPGA (Field Programmable Gate Array) are good processor boards with varying characteristics. The Arduino is commonly used for developing electronics project because it is easy to use and the programming language used to control Arduino is based on a simplified version of the C++ programming language which is easy to learn, it also allow for control using the Python and MATLAB programming languages; it will be set as a baseline for evaluating the FPGA and Raspberry Pi as shown in Table 2 below.

Table 3.2: The Pugh Matrix for evaluating the alternatives of the processing boards for the cowpea sorter system

		Baseline (Arduino)	**Weight**	**FPGA**	**Raspberry Pi**
Criteria					
Speed		0	5	+1	+1
Power consumption		0	4	0	0
Camera installation complexity		0	2	-1	+1
Total				+3	+7

Speed refers to the rate at which the boards process instructions and power consumption refers to the amount of power (or voltage supply) required for normal operations of the boards.

As mentioned in chapter 2.3, this project will employ computer vision and computer vision operates with a camera. For the processing board alternatives, camera installation complexity refers to the ease of camera integration with the boards.

The results from the Pugh Matrix in Table 2 show that the Raspberry Pi is the best alternative for the processing board, hence this will be used as the processing board for the cowpea sorter system.

The cowpea rejection process

The solenoid valve method as implemented in [16] for rejecting a bad seed/grain from a moving array of seeds/grains can be very accurate when implemented correctly; however, this method requires complex computations for localization and elimination of the bad seed [15]. This approach is set as a baseline for evaluating the bi-directional conveyor belt and the servo motor deflection system for rejecting bad cowpeas. The bi-directional conveyor belt system has motors that can be controlled to move in one direction when there is a good cowpea and move in the other direction when there is a damaged cowpea. A container that will hold the cowpeas one at a time will be placed atop the servo motor and will rotate at a given angle when there is a good cowpea and rotate at a different angle when there is a bad cowpea.

Table 3.3: The Pugh Matrix for evaluating the rejection method of bad cowpeas for the cowpea sorter system

		Baseline (Solenoid valve method)	**Weight**	**Bi-directional conveyor belt**	**Servo motor deflection**
Criteria					
Accuracy		0	5	0	0
Speed		0	4	-1	+1
Power consumption		0	3	-1	+1
Total				-7	+7

Accuracy refers to how best the alternatives are able to discard a good or bad cowpea without the interference of the incoming cowpea and speed refers to how fast they act when there is a good or bad cowpea. Power consumption refers to the rate of energy consumption by each of the alternatives.

The results from the Pugh Matrix in Table 3.3 show that the servo motor deflection system is the best alternative to effectively segregate good cowpeas from damaged ones for the cowpea sorter system.

3.3 The Finalized Design

This section discusses the various components and functions of the design. Figure 3.1 shows an illustration of the cowpea flow in the finalized design.

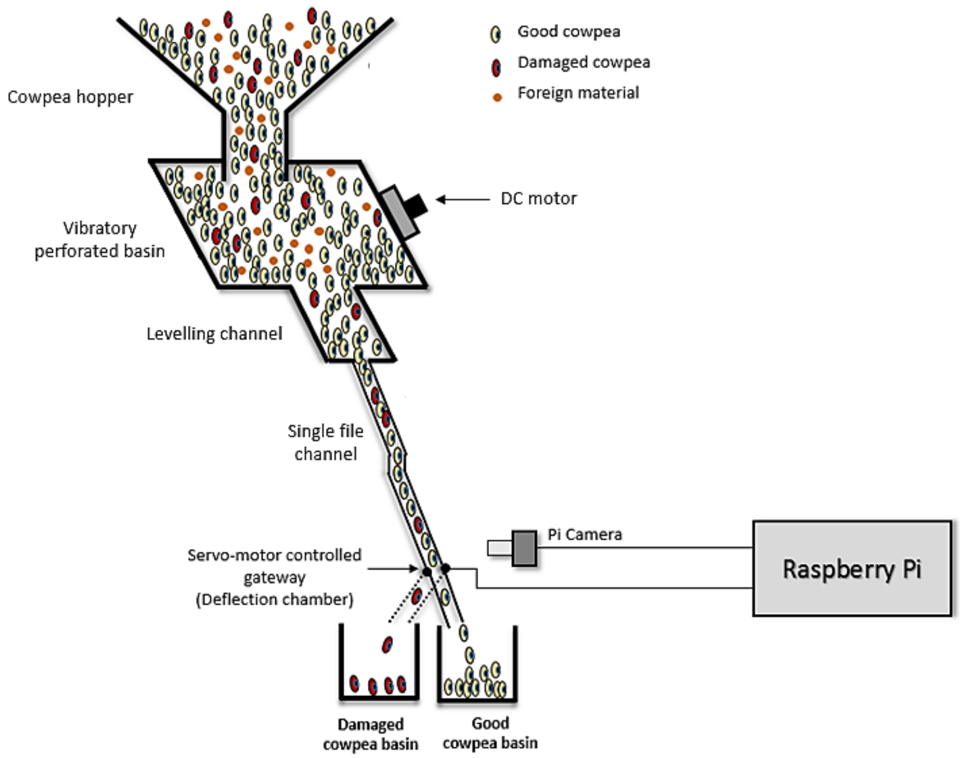


Figure 3.1: An illustration of the cowpea flow in the cowpea sorter system

The design of the cowpea sorter is in three (3) modules:

I. The Mechanical Module

The mechanical module is made up of all the mechanical components that aid in the sorting of the cowpeas. The design of each component is based on the most effective structure to carry out the desired tasks.

a. Cowpea hopper

The cowpea hopper receives the cowpeas at the start of the sorting process. Its internal surface is smooth to reduce friction and enable the cowpeas to smoothly glide on its surface and move downwards to the next chamber. Its dimensions are such that it can receive 1 olonka of cowpeas at a time.

b. Vibratory perforated basin

The cowpeas are transferred to the vibratory perforated basin as they exit the cowpea hopper. The base of this chamber is perforated such that the chaff is eliminated from the cowpeas. The perforated basin vibrates to spread the cowpeas on its surface as it removes the chaff through the holes, and move the cowpeas to the next chamber. The perforated basin used by the cowpea retailers will be obtained and sized to the desired dimensions.

c. Levelling channel

From the vibratory perforated basin, the cowpeas are transferred to a levelling channel in order to spread them in a single layer. This is the next chamber after the cowpeas have been transferred from the vibratory perforated basin. In this channel, the cowpeas are levelled out to reduce overlapping of the cowpeas, and exit to the next chamber one cowpea at a time.

d. Single file channel

The width of the single file channel is 10mm, which is about the width of one cowpea; the width of a cowpea is on average about 6 – 10 mm. This is to ensure that as each cowpea exits the levelling channel, it moves in a single file stream into the deflection chamber.

e. Deflection chamber

The deflection chamber is a rotary chamber controlled by a servo motor. The deflection chamber moves to 2 main positions: the good cowpea basin and damaged cowpea basin. Based on whether the incoming cowpea is good or damaged, the deflection chamber moves to point towards the corresponding basin so the cowpea falls into the right basin.

II. The Electronic Module

The electronic module is made up of the power supply and the components that require power to aid in the sorting of the cowpeas.

a. Power supply

The power supply consists of a rechargeable power bank and a 9V DC source. The power bank powers the raspberry pi, pi camera and servo motor; and the 9V DC source powers the 7.5V DC motor attached to the perforated basin.

b. 7.5V DC motor

The purpose of the 7.5V DC motor is to cause the perforated basin to vibrate. This is achieved by supplying power to the terminals of the motor and attaching a load to the rotary end of the motor.

c. Servo motor

The servo motor is the mechanism that drives the deflection chamber. It is set to move a set angle for good cowpea deflection and a different angle for a damaged cowpea.

III. The Computer/Processing Module

The processing module is made up of the components that identify the good cowpeas from the damaged ones as they fall in the deflection chamber.

a. Pi Camera

The pi camera is placed at a distance above the deflection chamber, close to the cowpea entry point. It acquires the image of a single cowpea in real-time as it falls off the edge of the single file chamber into the deflection chamber. The image obtained is passed to the Raspberry Pi.

b. Raspberry Pi

The raspberry pi takes the input from the pi camera and processes it using a trained cowpea model that distinguishes good cowpeas from damaged cowpeas, and controls the turning of the servo motor based on the output of the trained cowpea model.

c. The trained cowpea model

The trained cowpea model is based on a CNN architecture developed in the Python environment using the Keras library, with Tensorflow as backend. The steps to obtain the trained cowpea model will be discussed in detail in the next section.

Chapter 4 : Implementation

4.1 The Mechanical Module

The 3D model of the different components of the cowpea sorter system is created and put together in an assembly as shown in Figure 4.1 below.

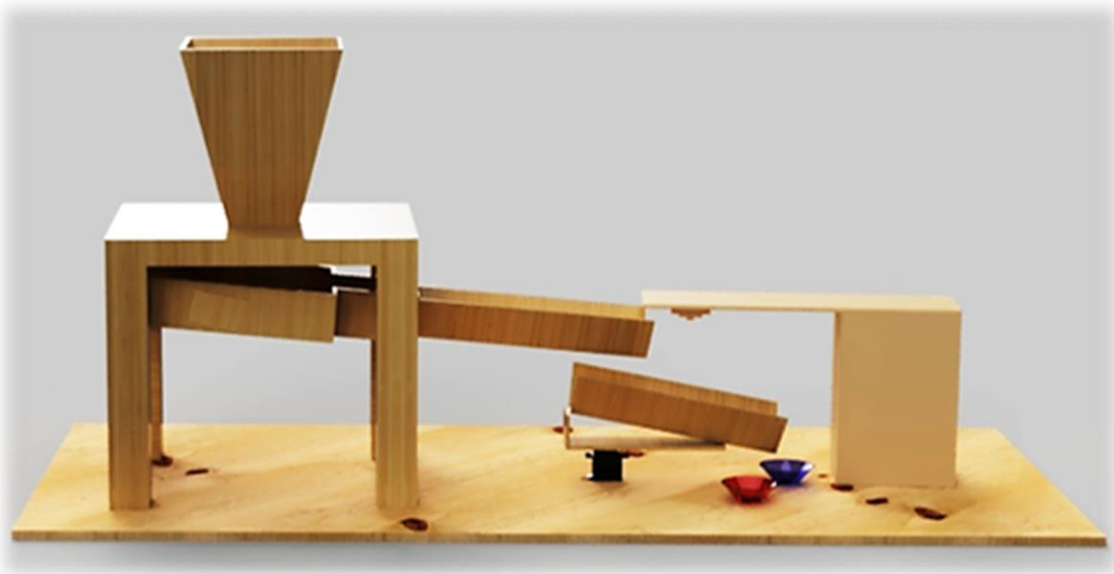


Figure 4.1: The 3D model of the cowpea sorter system implemented using the Fusion 360 software

To ensure that the whole system is light and easy to carry around (about 2kg) by the cowpea trader, majority of the parts including the cowpea hopper, the vibratory perforated basin, levelling and single file channels, and deflection chamber are built using aluminium. For stability, Alucobond (a composite material made of aluminum and polyethylene) is used in fabricating the support for the cowpea hopper and the Raspberry Pi stand. All the components of the cowpea sorter are mounted on a 2mm-thick sheet of wood to make it easier to move the cowpea sorter from one surface to the other. The fabricated cowpea sorter system is shown in Figure 5 below.

There is a variation in the design of the 3D model designed in Fusion 360 (Figure 4.1) and the fabricated system shown in Figure 4.2. Due to the base size of the hopper, the cowpeas moved too fast from the hopper to the perforated basin and as a result, the cowpeas did not drop one at a time into the deflection chamber. This is a problem as the PiCamera needs to capture the image of a single cowpea at a time to enable it make accurate predictions of the state (good or bad) of the cowpea.

Figure 4.2: The fabricated cowpea sorter system

This major observation led to a slightly different fabrication design: the base area of the cowpea hopper was reduced using two aluminium sheets to cover approximately 3/4 of the cowpea hopper base area. The rectangular levelling channel in Figure 4 was replaced with a triangular levelling channel. This is because as the cowpeas were transferred from the perforated basin to the rectangular levelling channel, about half or more of the cowpeas were stuck at the corners of the levelling channel and did not proceed to the next chamber. The triangular levelling channel is used because it does not allow a single cowpea to get stuck.

Since the flow of cowpea has been restricted at the cowpea hopper and the exit point of the levelling channel spits out one cowpea at a time, the single file channel in Figure 4 is eliminated from the fabricated cowpea sorter in Figure 4.2. This elimination also decreases the overall length of the wooden base on top of which the cowpea sorter is mounted.

4.2 The Electronic Module

The DC motor is connected to a 9V DC Supply in series with a switch that will allow the vibratory basin to be turned on or off. The connection is shown in Figure 4.3 below.

The pi camera serves the photos of the cowpeas as input to the raspberry pi. The raspberry pi hosts the CNN model responsible for the prediction of the type of cowpea (good or bad) and the servo motor operates based on the output of the CNN model. The connection of the raspberry pi, pi camera and servo motor is shown in Figure 4.3 below.

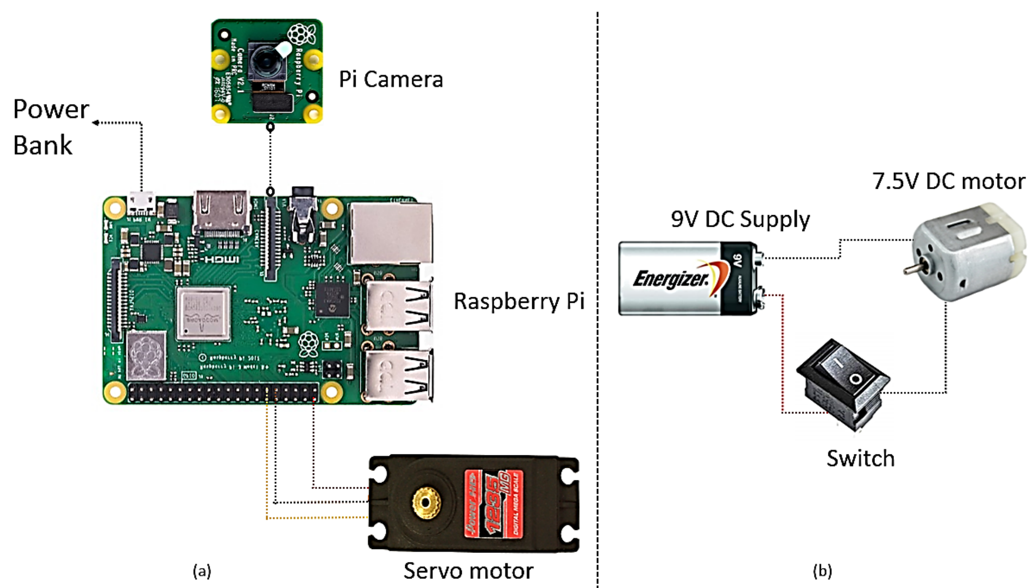


Figure 4.3: The circuit in the system (a) This circuit operates at the deflection chamber for cowpea segregation (b) This circuit operates at the perforated basin for the vibratory effect

4.3 The Computer/Processing Module

The implementation of this module is achieved under 2 main sections: the first section deals with obtaining the trained cowpea model, capable of differentiating a good cowpea from a bad cowpea (binary classification) and the second section deals with the real-time capture and classification of the cowpeas using the trained cowpea model that was obtained.

4.3.1 Obtaining the trained cowpea model

Data Acquisition & Pre-processing

The first step to obtaining the trained cowpea model is to gather images of cowpeas. To gather images of the cowpeas for training, a sample of good and bad cowpeas were collected from a cowpea trader. A total of 1600 images of both the good and damaged cowpeas were captured in ambient lighting on a white surface using a 24MP camera; the resolution of the images obtained were 5664x4248 pixels. The images were pre-processed by cropping and re-sizing to 200x200 pixels using a python script (Appendix I). For training, the images were split into training, validation and test sets in the ratio 7:2:1. Each of these sets contained two subsets of images labelled “Good Cowpea” and “Bad Cowpea”. The training and validation sets were used during the training process and the test set is used to evaluate the model obtained after the training process.

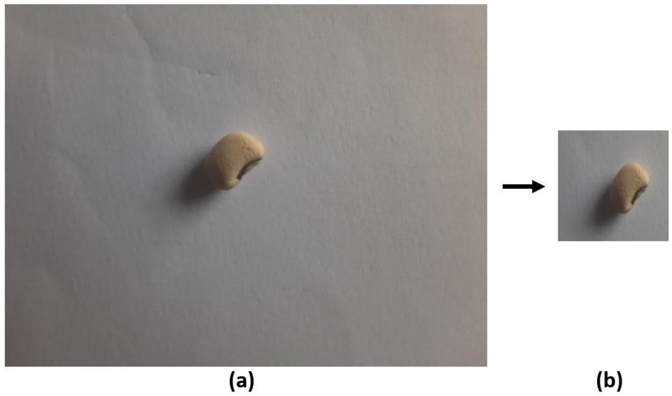


Figure 4.4: (a) Image (5664x4248 pixels) captured by the 24 MP camera (b) Image obtained after cropping and re-sizing to 200x200 pixels

Figure 4.5: A sample of the re-sized cowpea images used for training (a) Good cowpea samples (b) Damaged cowpea samples

Software Implementation

The CNN was built using these packages in Python: Keras and Tensorflow. Keras is a high-level Application Programming Interface (API) developed by Google to run on top of Tensorflow for building neural networks.

Data Augmentation

As stated in Section 2.3, CNNs perform better with large datasets. Data Augmentation is a technique that is used to increase the number of images through transformation functions whiles ensuring a balance of the different sets of images used during training [14]. This technique was implemented on the training set of the cowpea images using the 'ImageDataGenerator' function provided by Keras. Augmentation on the cowpea images was accomplished using the following transformations:

1. Horizontal flip: This produces new cowpea images of the existing cowpea images by flipping them along the horizontal axis.
2. Zoom: This produces new cowpea images of the existing cowpea images by randomly zooming into them.
3. Shear: This produces new cowpea images of the existing cowpea images by randomly applying shearing transformations.

The Architecture of the Convolutional Neural Network (CNN)

The CNN model consists of 2 convolutional and max pooling layers (convolution block) for feature extraction; pooling layers can be implemented in many ways however the max pooling approach is mostly common in CNN implementation [14]. In addition to the max pooling layers, dropout layers are also used to aid the architecture in generalization and reduce over-fitting; over-fitting occurs when the model performs so well during training and poorly on unseen images. A flatten layer is used for obtaining a 1-dimensional array of the extracted features to serve as an input to the fully connected layers. Asides convolutional layers, activation functions are also used in the creation of a CNN to aid in identifying useful features; they achieve this by introducing non-linearity in each neuron of the hidden layers (convolutional, pooling and dense layers) to decide which neuron should be activated or not [14]. The Rectified Linear Unit (ReLu) activation function is used for the neurons in the hidden layer and the Sigmoid activation function is used for the neurons in the output layer. ReLu is suitable because it is faster but it is unsuitable for the output layer because the output neurons need to provide probability values for a given input data; the sigmoid function achieves this by compressing its output value in the range from 0 to 1, a very useful characteristic for binary classification [14], as in this case with differentiating between a good cowpea and a bad one. The implemented architecture is shown in Figure 9 below.

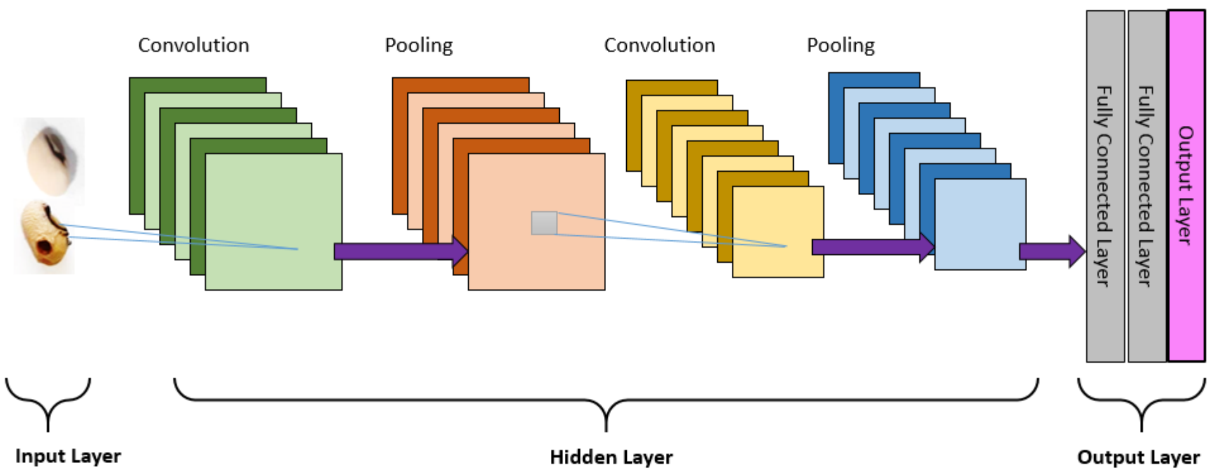


Figure 4.6: The proposed CNN architecture for the cowpea classification

The model is finally compiled using ‘binary cross-entropy’ as the loss function and ‘adam’ as the optimizing function. The loss function computes the average error between the actual labels and the model’s predicted label; cross-entropy is the best loss function for classification problems [14] and since this is a binary classification problem, the binary crossentropy function was used. The optimizing function sets the parameters of the CNN to minimize the loss at the output, it achieves this by continually updating the parameters of the neurons based on the output of the loss function [14]. The adam optimization function is commonly used due to its efficiency and minimal memory requirements [14]. The python script developed to train the CNN is in Appendix II.

Training the CNN model

During training, an epoch refers to one iteration over all the images in the training and validation sets. The training sets are used for training the model and the validation sets are used for evaluating the performance of the model during training. For the training dataset, there were 560 images each for the good and bad cowpeas datasets and for the validation dataset, there were 160 images each for the good and bad cowpeas datasets.

The batch size refers to the number of cowpea images that will be retrieved from the datasets at a time to train the CNN model. The images were taken in batches of 32 for each step in an epoch. For each epoch, the number of steps specified for the training dataset was 100 and the number of steps specified for the validation dataset was 50. The model was trained over 10 epochs.

Fine-tuning the parameters of the CNN model

After building the CNN architecture, the training of the CNN model is commenced to obtain a trained cowpea model. In training the model, different parameters of the architecture are experimented with to obtain a model with the lowest loss and highest accuracy values. As described earlier, the loss value represents the average error between the actual label of the images and model's predicted labels; the lower the loss, the better the model. The accuracy computes the number of correctly classified images out of the total number of images. Hence, while the accuracy value is as a percentage, the loss is not.

The number of layers, kernel size and number of kernels are varied in the convolutional layer. The number of dense layers and the neurons in each dense layer are also varied. For better generalization of the model, dropout layers are used in creating the model. The number of dropout layers are held constant and the value associated with the dropout layers are varied. A summary of the different parameters that are altered are shown in Table 4.1 below.

Table 4.1: A summary of the training results after each fine-tuning process of the CNN model

	Convolution			Fully connected/Dense layers		Dropout	Accuracy	Loss
	No. of layers	Kernel (Filter) size	No. of kernels	No. of layers	No. of neurons			
Model 1	2	3x3	64	2	512, 54	0.50	0.49	0.30
Model 2	1	3x3	32	2	512, 54	0.50	0.92	0.50
Model 3	2	3x3	32	2	512, 54	0.25	0.96	0.50
Model 4	2	3x3	32	2	64,10	0.50	0.95	0.10
Model 5	2	3x3	32	3	512, 128, 54	0.50	0.92	0.30
Model 6	2	3x3	32	2	512, 54	0.50	0.98	0.05

Model 6 is chosen as the final trained cowpea model because it has the lowest loss and the highest accuracy amongst the rest of the models. The accuracy and loss curves obtained after the training process of Model 6 is shown in Figure 4.7. This trained model is saved after the training process into an hdf5 file.

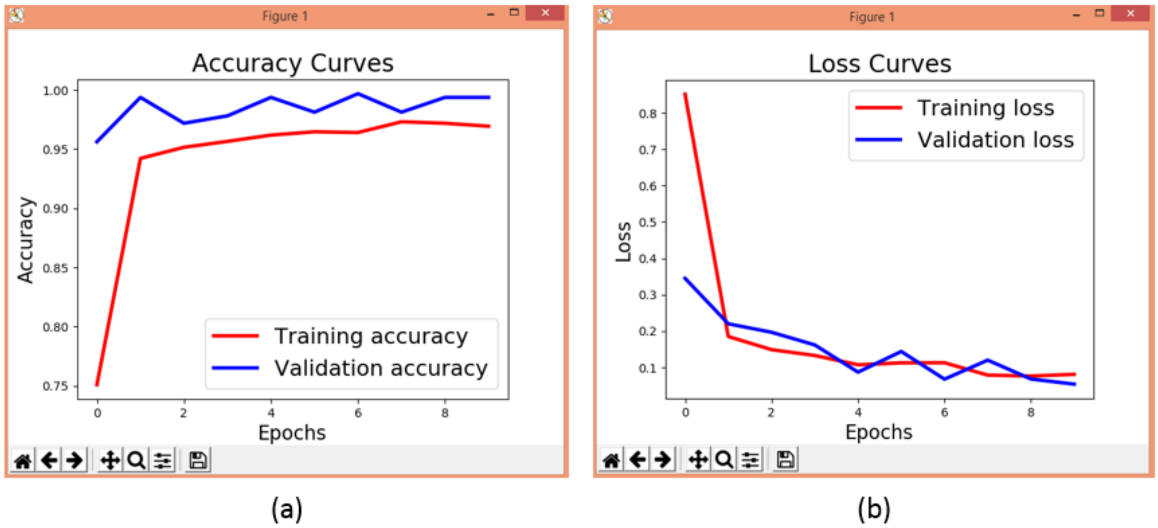
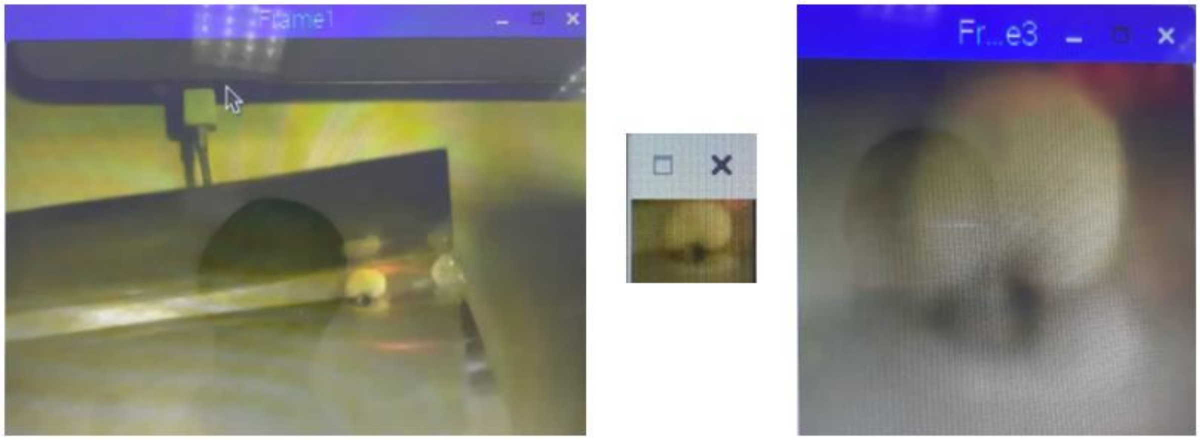


Figure 4.7: (a) The accuracy curves obtained from the training process of Model 6 (b) The loss curves obtained from the training process of Model 6

4.3.2 Real-time Capture and Classification

The trained cowpea model, which is in the form of the hdf5 file obtained after training is transferred onto the Raspberry Pi. A python script (Appendix III) is run on the Raspberry Pi to capture the images of the cowpeas as they fall into the deflection chamber. The frame obtained from the PiCamera is cropped to remove unwanted regions, and re-sized to 200x200 pixels to be fed into the model, which only accepts images of the size 200x200 pixels.



(a) (b) (c)

Figure 4.8: The frames captured from the Pi Camera (a) The original photo capture by PiCamera (b) The cropped frame (c) The frame is resized to 200x200 pixels

Chapter 5 : Tests and Results

This chapter discusses the tests conducted on the different components of the cowpea sorter to ensure that they function as expected. After these components have been brought together into an assembly, a system test is conducted to ensure that the cowpea sorter functioned as expected.

5.1 Component Testing

Component testing covers all the tests that were conducted on the different components of the cowpea sorter. As mentioned previously, the component tester can be divided into the electronic, mechanical and computer/processing modules. Tests were conducted on each of these modules.

5.1.1 Mechanical module tests

The vibratory perforated basin

This section of the cowpea sorter is made of the perforated basin and the 7.5V DC motor; collectively, these components remove chaff from the cowpeas. This test was conducted by comparing the cowpeas before they were placed in the sorter and after they came out of the sorter. The following results were expected:

- There will be no chaff in the cowpeas that come out of the sorter.
- The cowpeas that come out of the sorter will not contain foreign materials: stones, broken cowpeas, and weevils/bruchids.

Results

After conducting the test, the expected results as listed above were exhibited by the components of the vibratory perforated basin.

The deflection chamber

This section of the cowpea sorter consists of components that deflect the cowpeas into the right basin based on whether the cowpea in the chamber has been detected to be good or bad. This test was conducted by running the capture and classification code on the raspberry pi. The deflection chamber was expected to:

- Detect the cowpeas as they move one at a time into the deflection chamber.
- Turn to the right basin depending on whether the cowpea has been labelled good or bad.

Results

After conducting the test, the results showed that the cowpeas were moving too fast in the deflection chamber and could not be detected. The cowpeas were detected only when they got stuck in the deflection chamber and the servo motor turns accordingly.

5.1.2 Electronic module tests

This test was conducted to verify that all the electronic components used functioned properly, there was good contact at the points that required wire connections to the terminals of the electronic components and that the implementation of the circuit connections in the cowpea sorter was as described in section 4.2

The DC motor test

For this test, the components and circuit connections of the DC motor as described in section 4.2 was tested, with a load attached at the rotary end to cause vibrations when attached to the perforated basin. The following results were expected:

- The DC motor starts functioning when the switch is turned on and stops operating when the switch is turned off.
- The DC motor, together with the load causes the perforated basin to vibrate.

Results

After conducting the test, the expected results as listed above were exhibited by the DC motor connection attached to the cowpea sorter.

The computer/processing module test

For this test, the components and circuit connections of the raspberry pi, pi camera and servo motor (the computer/processing module of the cowpea sorter) as shown in section 4.2 were tested. The following results were expected:

- The red and green lights on the Raspberry pi were blinking.
- The red light on the pi camera turned on when it is about to capture a image and the image captured is stored, when a simple capture command was run on the raspberry pi.
- The servo motor turns and executes simple servo commands that was run on the Raspberry pi.

Results

After conducting the test, the expected results as listed above were exhibited by the different components of the computer/processing module of the cowpea sorter.

5.1.3 Computer/Processing module tests

The trained cowpea model

This test was conducted after the training phase (with the training and validation datasets) and the weights of the final model were saved to an hdf5 file for future classification. The hdf5 file was tested on the testing set of the cowpea images which is made up 160 cowpea images, which is 10% of the total cowpea images. The results were expected to show:

- 156 of the cowpea images classified correctly.

Results

From the 160 images that were fed into the model, 140 of the cowpea images were classified correctly.

The real-time cowpea detection and classification process

This test was conducted after transferring the hdf5 model obtained after training to the Raspberry Pi. A live video stream was run on the raspberry pi and the frames were obtained, cropped and re-sized to 200x200 pixels and fed into the model. The following results were expected:

- Out of 10 cowpea images captured by the pi camera, 9 images should be classified or labelled correctly by the model.

Results

Out of the 10 cowpea images, 5 were classified correctly; the pi camera classified all the cowpeas to be good cowpea images. The low resolution of the pi camera is a major contribution to this because, the details like the colour and tiny holes in the cowpeas that make it damaged is not captured by the pi camera.

5.2 System Testing

System testing is conducted on all the components of the cowpea sorter as a whole. This is to ensure that the various components of the cowpea sorter were working together seamlessly. To conduct this test, all the components of the cowpea sorter were put together; the switch of the vibratory perforated basin is turned on, the Raspberry pi, pi camera and servo motor are powered (to run the real-time capture and classification of cowpeas) via the connection of the Raspberry pi to the power bank, and finally, 1 olonka of unclean cowpeas are placed as input to the cowpea sorter via the cowpea hopper. The desktop of the Raspberry pi is monitored via an SSH connection using a remote computer during the testing. The following results are expected at the output of the cowpea sorter:

- The chaff and foreign materials are discarded via the vibratory perforated basin from the cowpeas.
- There will be two separate of heaps of cowpeas; one heap of good cowpeas and one heap of damaged cowpeas.

Results and Observations

During the testing, the chaff and foreign materials were eliminated through the perforated basin with some of the cowpeas that got stuck in the basin. Although the cowpea sorter was able to group the cowpeas into 2 heaps of cowpeas, the cowpea sorter was unable to effectively separate all the good cowpeas into one heap and the damaged cowpeas into the other heap; majority of the cowpeas were classified as good cowpeas. The factors that contributed to this output are:

- There was no code that detected if there was a new object in the frame, so images captured from the frames during the video stream that did not contain cowpeas were fed into the trained cowpea model. These images were all labelled as 'good cowpea' by the model.
- The cowpeas moved very fast in the deflection chamber and as a result, most of the images captured from the frames contained no cowpea but were moved to the 'good cowpea' position since the empty images were labelled as 'good cowpea' by the trained cowpea model.
- The cowpeas that were stuck in the deflection chamber were captured in the images obtained from the video stream; it took 4 seconds for the stuck cowpea to be detected by the pi camera.

Possible resolutions to these problems will be discussed in detail in section 6.2.

5.3 Statistical Analysis of Results

The Chi-square test will be used to evaluate the output of the cowpea sorter. The data used for the cowpea test will be gathered from the first 50 cowpeas (25 good cowpeas and 25 damaged cowpeas) that were able to pass through the cowpea sorter and were categorized into one of the two labels: 'good cowpea' and 'damaged cowpea'. The expected values in Table 5.1 refer to the number of cowpeas that are expected to be in the good cowpea or damaged section and the observed values refer to the number of cowpeas that were recorded to be in the good cowpea section and bad cowpea section after the system testing of the cowpea sorter.

The null hypothesis statement signifies that there is no difference between the desired and expected results whiles the alternative hypothesis signifies otherwise.

Null hypothesis (H_O):

$$\mu_o = \mu_1$$

Alternative hypothesis (H_A):

$$\mu_o \neq \mu_1$$

Table 5.1: The data gathered from the first 50 cowpeas that passed through the cowpea sorter.

	Observed	**Expected**
Good cowpea	**25**	**25**
Damaged cowpea	**0**	**25**

The p-value, which is obtained using the 'chitest' function in Excel obtained for the data for Table 5.1 is 5.733×10^{-7}, which is below 0.05, hence the null hypotheses is rejected. This means that the cowpea sorter is not operating as desired.

Chapter 6 : Conclusion

6.1 Discussion

This capstone was aimed at the development of a cowpea sorter to replace the manual cowpea sorting process for cowpea traders. The design should be accurate, operate at a high speed, light and run on low power. The components of the design can be broken down into three (3) main components: the electronic, mechanical and computer/processing parts. The electronic components consist of the power supply components and the parts that require power, the mechanical components of the structures that enable the flow of the cowpeas in the cowpea sorter and the computer/processing module consists of the components that differentiate a good cowpea from a damaged one. For the computer/processing module, a CNN model was developed from scratch and an accuracy of about 98% was achieved however, model performed poorly during real-time capture and classification because a camera with a lower resolution was used.

The results from the testing phase show that although the different components of the cowpea sorter may operate well independently, they do not work well together as a whole. Hence, a different mechanism for the cowpea sorter should be explored or mechanisms can be put in place to ensure the effective operation of the entire system as a whole.

In proposing a design for a cowpea sorter to replace the manual sorting process, this capstone/research became the first in the field of applying computer vision ad convolutional neural networks for sorting cowpeas. It also became the first in proposing a solution for replacing the manual cowpea sorting process.

6.2 Limitations

This section discusses the various features that could have affected the proposed design of the cowpea sorter. The following points highlight the constraints that affected the performance of the cowpea sorter.

1. The base of the cowpea hopper was big such that once the cowpeas were placed in the cowpea hopper, they started to rush down in volumes to the different chambers and as a result, they ended up clogging the deflection chamber. By reducing the size of the base of the cowpea hopper such that the amount of cowpeas that can flow down at a time will not end up impeding cowpea flow in the deflection chamber.

2. As the motor vibrated, some of the cowpeas got stuck in the corners of the vibratory perforated basin, which was rectangular in nature. Hence, not all the cowpeas moved into the deflection chamber to be sorted. This limitation might be solved by replacing the rectangular design of the vibratory perforated basin to a triangular one to prevent some of the cowpeas from staying in the vibratory perforated basin.

3. There were discrepancies between the training cowpea images which were captured using a 36MP camera and the images that were captured in real time for the cowpea sorter which was achieved using an 8MP pi camera. To reduce these discrepancies, the pi camera in the cowpea sorter should be replaced with a low-cost camera with a high resolution close enough to the ones captured using the 36MP camera.

4. The pi camera operates at 36 frames per second (fps) during a video stream from which the cowpea images are captured. This frame rate is too slow for the pi camera as the cowpeas moved fast in the deflection chamber. Each cowpea needed to stay in position for about 4 seconds before it could be captured by the pi camera. This limitation could be solved by either replacing the pi camera with a camera that has a higher frame rate or a mechanism that is configured such that single cowpea flows into the pi camera position for a minimum time duration of 4 seconds before it can be released into the deflection chamber.

6.3 Future Work

This section discusses the different areas that could be explored to improve the proposed design of the cowpea sorter. In addition to addressing the limitations discussed in section 6.2, this research can be implemented in different fields.

1. A mechanism that allows multiple single file streams of cowpeas for real-time capture and classification. A pi camera takes a minimum of 4 seconds to classify a single cowpea, this makes the cowpea sorter slower than desired. To increase the speed of the cowpea sorter, multiple single file streams that will be enough to be captured by the field of view of the camera can be implemented to increase the speed of the sorting process.
2. For the multiple single file streams to be implemented, there has to be an algorithm capable of capturing the multiple cowpeas in an image, segmenting the individual cowpea images, feeding them into the model for prediction and controlling the multiple deflection chambers for each of the single file streams.

Appendix

Appendix I (Resize.py)

```
# This python script is used for pre-processing (cropping and re-
sizing) the cowpea
# images to prepare it for training using the CNN.

# Importing the necessary libraries
import os
from PIL import Image
import numpy as np
from scipy.ndimage import zoom
import cv2


# The resize_image function takes each image from an input
directory, re-sizes, and saves it to
# an output directory
def resize_image(input_dir, infile, output_dir='BCI_resized'):
    # Splitting the image file name such that they can be re-named
with '_resized' attached to it
    outfile = os.path.splitext(infile)[0] + '_resized'
    extension = os.path.splitext(infile)[1]


    try:
        # Opening the image file and saving it to the 'img'
container
        img = Image.open(input_dir + '/' + infile)
        # Obtaining the width(w) and height(h) of the image
        w, h = img.size
        left = w/2.5
        top = h/2.5
        right = 3 * w/4
        bottom = 3 * h/4
        # Cropping the image such that the cowpea occupies most
parts of the image
        img = img.crop((left,top,right,bottom))
        # Re-sizing the image to 200x200 pixels; which is a
requirement if the images
        # are to be fed in the CNN.
        img = img.resize((200,200), Image.LANCZOS)

        # Saving and re-naming the new re-sized image
        new_file = output_dir + '/' + outfile + extension
        img.save(new_file)

    except IOError:
        # Print an error message when there is no image file found
        print('unable to resize image {}'.format(infile))
```

```
# Running the main thread
if __name__ == '__main__':
    output_dir = 'BCI_resized'
    dir = os.getcwd()
    input_dir = 'BCI'
    full_input_dir = dir + '/' + input_dir

    # Creating the output directory if it does not exist
    if not os.path.exists(os.path.join(dir, output_dir)):
        os.mkdir(output_dir)

    try:
        # Running the loop that iterates over each image and re-
sizes it
        # by calling the 'resize_image' function
        for file in os.listdir(full_input_dir):
            print('file: {}'.format(file))
            resize_image(input_dir, file, output_dir)
    except OSError:
        # Print an error message when the file is not found
        print('file not found')
```

Appendix II (Cowpea_Classification.py)

```
# This python script builds a CNN architecture and trains it with
single cowpea images (Good
# and Bad) to obtain a .h5 file (trained cowpea model) which can be
used in the future for
# cowpea classification.

# Importing the necesary libraaries
from keras.models import Sequential
from keras.layers import Dense, Conv2D, MaxPooling2D, Dropout,
Flatten
from keras.preprocessing import image
from keras.preprocessing.image import ImageDataGenerator
from IPython.display import display
from PIL import Image
from keras import regularizers
import numpy as np
import matplotlib.pyplot as plt

# Creating the CNN architecture
def createModel():
    # Initialising the architecture
    model = Sequential()

    # 1st phase of feature extraction
    model.add(Conv2D(32, (3, 3), padding='same', activation='relu',
input_shape=(200,200,3)))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.50))

    # 2nd phase of feature extraction
    model.add(Conv2D(32, (3, 3), padding='same', activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.50))

    # Flatten the input images such that they can serve as an input
to the
    # Dense/fully connected layerss
    model.add(Flatten())
    # 1st dense layer with 512 neurons
    model.add(Dense(512, activation='relu'))
    # 2nd dense layer with 54 neurons
    model.add(Dense(54, activation='relu'))
    model.add(Dropout(0.50))
    # Output layer
    model.add(Dense(units=1, activation='sigmoid'))

    # Compiiling the model using 'adam' as the optimizer and
'binary_crossentropy' as the
    # loss function
```

```
    model1.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])

    return model

model1 = createModel()

# This specifies the various alterations to the training set of the
cowpea images
# to generate a larger set of cowpea images
train_datagen = ImageDataGenerator(rescale = 1./255,
                                   shear_range = 0.2,
                                   zoom_range = 0.2,
                                   horizontal_flip = True)

# The alterations are not applied to the validation set of the
cowpea images;
# the images are only re-scaled
val_datagen = ImageDataGenerator(rescale = 1./255)

# The train_datagen is applied to the training images by specifying
the directory containing
# the training set of cowpea images
training_set =
train_datagen.flow_from_directory('CowpeasData/training_set',
                                                 target_size = (200,
200),
                                                 batch_size = 32,#32
                                                 class_mode =
'binary')

# The val_datagen is applied to the validation images by specifying
the directory containing
# the validation set of images
val_set = val_datagen.flow_from_directory('CowpeasData/val_set',
                                          target_size = (200, 200),
                                          batch_size = 32, #32
                                          class_mode = 'binary')

# This section starts the training proces by fitting the cowpea
images to the CNN architecture
# The training is done over 10 epcochs, with 100 cowpea image
samples per epoch (training) and
# 50 cowpea image samples per epoch (validation)
history = model1.fit_generator(training_set,
                               steps_per_epoch = 100,#100
                               epochs =10,#10
                               validation_data = val_set,
                               validation_steps = 50)#50

# Plotting the Loss Curves (for bot training and validation sets)
plt.plot(history.history['loss'],'r', linewidth=3.0)
```

```
plt.plot(history.history['val_loss'],'b', linewidth=3.0)
plt.legend(['Training loss','Validation loss'], fontsize=18)
plt.xlabel('Epochs', fontsize=16)
plt.ylabel('Loss', fontsize=16)
plt.title('Loss Curves', fontsize=20)
plt.show()

# PLotting the Accuracy Curves (for both training and validation
sets)
plt.plot(history.history['acc'],'r', linewidth=3.0)
plt.plot(history.history['val_acc'],'b', linewidth=3.0)
plt.legend(['Training accuracy','Validation accuracy'], fontsize=18)
plt.xlabel('Epochs', fontsize=16)
plt.ylabel('Accuracy', fontsize=16)
plt.title('Accuracy Curves', fontsize=20)
plt.show()

# Saving the weights of the cowpea trained model into an h5 file
which can
# be used for future classification
model1.save_weights('Cowpea_Classification_Test5.h5')
```

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