

PRETRAINED CONVOLUTIONAL NEURAL NETWORKS AS FEATURE EXTRATOR OF EGGSHELL MOTTLING PATTERN FOR QUALITY INSPECTION

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(MANUFACTURING ENGINEERING WITH MANAGEMENT)

School of Mechanical Engineering
Engineering Campus
Universiti Sains Malaysia

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Signed (NG ENG YEONG)

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LIST OF ABBREVIATIONS

Artificial Intelligence

AI

Complementary metal–oxide–semiconductor

CMOS

ABSTRAK

Terdapat teknologi yang ada dalam penyelidikan untuk mendapatkan pemeriksaan pada retakan pada kulit telur. Walau bagaimanapun, masih terdapat beberapa kesukaran ketika datang ke pemeriksaan di kawasan tembus di mana sebelum retakan berlaku. Buatan rangkaian neural mempunyai kecekapan yang sangat tinggi dalam mengklasifikasikan telur ke dalam tiga kelas iaitu baik, buruk dan tidak diketahui. Alexnet, Resnet dan Inception yang mempunyai pelbagai seni bina telah dibandingkan dengan mengira ketepatan masing-masing. Hal ini dapat membuktikan bahawa Alexnet memberikan ketepatan ramalan tertinggi iaitu 96.80%, diikuti oleh Resnet, 93.15% dan Inception, 90.16%. Alexnet mempunyai keupayaan untuk melakukan klasifikasi dengan menggunakan kebarangkalian dari lapisan Softmax dari jumlah gambar berlabel yang terhad. Selain itu, ANOVA dan student t-test telah digunakan untuk mengukur hubungan antara cara ketepatan dari set latihan dan pengujian set data imej. Visualisasi pada saluran yang penting membolehkan untuk mengetahui bagaimana buatan rangkaian belajar untuk mengklasifikasikan telur. Imej mimpi telah dijanakan untuk mengetahui ciri-ciri yang dibelajari. Sistem yang dibangunkan ini boleh menjadi langkah pertama pada klasifikasi telur menggunakan kecerdasan buatan.

Abstract

There are technologies available in research in order to have inspection on macro and micro cracks on eggshell. However, there are still some difficulties when coming to inspection on translucent areas where before the micro-cracks happening. Transfer leaning using pre-trianed neural network is used at minimized computational resources while having a very high efficiency in classifying the eggs into three classes which are good, bad and unknown. Alexnet, Resnet and Inception of different architectures are compared to compute respective accuracy. It proved that the Alexnet gives highest predictive accuracy which is 96.80%, followed by Resnet, 93.15% and Inception, 90.16%. Results obtained from Alexnet is used to do statistical analysis such as ANOVA and student-t test to measure statistically significant differences between the means of accuracy from training set and testing set of image data. Visualization on channel along with activation strengths allow to know how a network learn to classify an egg with the help of Pareto chart. The deep dream images are generated by referring to the generation of images that produce desired activations.

CHAPTER 1

INTRODUCTION

Table eggs, otherwise called shell eggs which most natural to consumers, are among the most nutritious nourishments that are being expended day by day [1]. It is an inexpensive but highly nutritious food that provides balanced nutrients that impact human health [2]. Eggs contain ample essential proteins, fats, vitamins, minerals, and bioactive compounds. For a grade-A shell egg, it contains the nutrition such as proteins (6g), vitamins (A, D, E, B12) and minerals which helps to build up a healthy status of people [3]. As a result of its high ubiquity, the volume of eggs and egg yolks delivered by poultry ventures are continually expanding and its mass production has gone up to 600 million worldwide basis [4] [5]. From year 1993 to 2013, the egg production has increased from 20.7 to 39.9 million or by 93.0 % at worldwide [6]. Therefore, the egg safety is a major concern throughout the years which the internal and external egg quality must be in good condition where no blood spot, mottled yolk, cracked, yolk discoloring and others is observed [7].

Consumption of bad egg which has low internal and external quality of eggs would cause food-borne illnesses and this is mainly caused by Salmonella. [8] Salmonellas is a bacteria of organism that causes food poisoning for almost the whole of the 20th century [9]. This type of bacteria can penetrate into eggshell based on some extrinsic and intrinsic factors such as bacterial strain, temperature differential, moisture, number of organisms present and cracks [10]. In order to make sure that the eggs are safe to be consumed, the bacteria on the eggshell must be eliminated.

In early years, egg washing method is used to reduce the presence of bacteria on the eggshell surface which believed to have decreased the penetration of Salmonella across the eggshell [11]. Lately, researchers show that wet washing can damage the cuticle layer which the pores would be leaving exposed and allowing bacteria penetration [12]. Alternatively, pasteurization is another process of heat processing the eggshell surface to kill pathogenic bacteria to make the food safe to eat and this process is commonly implemented in poultry industries. Three most common pasteurization processes are dry pasteurization [13], moist pasteurization [14] and microwave pasteurization [15]. Among these three processes, moist pasteurization of eggs in water

bath appeared suitable as it needs shorter time and left no adverse effect on egg albumen [16]. Additionally, the intrinsic factor from eggshell itself is another important topic.

Before the bacteria such as Salmonella bacteria is able to enter and contaminate the egg, the eggshell which is a primary protective barrier to stop the pathogen to enter [17]. High values of Haugh unit, albumen ratio and albumen percentage content of eggshell indicate that quality of eggs are higher [18]. However, use of the Haugh unit of eggshell has a little bias from calculated data when comes against regression between albumen height and egg weight [19]. Therefore, uniformity of eggshell thickness and ultra-structures are the parameters to evaluate eggshell quality which a more uniform eggshell has higher strength than those with thick but less uniform eggshell [20]. This uniformity of eggshell contributes to mottled pattern where opaque and translucent areas appeared on the same shell. Translucent areas of the eggshell are weaker in terms of strength than opaque areas [21]. The lower the shell strength, the more likely the cracks or micro-cracks would happen on the shell which are extremely prone to bacterial contamination and threaten consumer health. [22]

Traditionally, an expert egg inspector checks for its quality and grade by tapping carefully with an aid of candling backlighting [23]. The candling backlighting method is a nondestructive selection method that consists on applying a bright light against an egg to detect abnormalities [24]. However, there will be micro-cracks on eggshell which are difficult to be observed and being passed to the downstream station.

Asides than cracks and micro-cracks, strip marks and eggshell mottling which are caused by pattern of translucent areas are the advanced inspection for egg quality classification. The translucent areas are related to the thickness of eggshell which contributes to the development of micro-cracks [25]. In aspect of health, there was a significant correlation between egg shell translucency and egg shell penetration by Salmonella which would increase the probability of contaminated eggs [26]. For pattern of translucent areas to be analyzed and studied, machine vision can be utilized to classify the eggs into good eggs and bad eggs. When using machine vision, presence of eggshell such as dirt and micro-cracks can be detected at acceptable accuracy and at the same time helps to improve human ergonomics when inspecting the eggs.

Machine vision integrated with artificial intelligence (AI) put a step closer to revolutionize shop-floor productivity in different field of production including poultry

industry. Neural Network is a flexible and powerful artificial intelligence by letting the computer learn to classify at fast response and computational times due to its parallel architecture [27]. In many researches related to AI application, there is one technique which is transfer learning being very popular in item classification. Quantification and identification of cellular phenotypes from high content microscopy images is one of the application that has been researched. As reported, the classification process using this technique is accurate and quick to distinguish between different cell morphologies from a scarce amount of labelled data [28].

In this project, a manual machine vision inspection system on the egg using candling is remodeled. Every image captured is directly transferred into computer for image processing and preparation purpose. Next, technique of transfer learning with few pre-trained models are used. The ultimate goal for this project is to compare the suitability of pre-trained models used in egg classification in terms of accuracy. Then, visualization is used to verify the model by quantitative and qualitative analysis. After the model is verified, a system is built up to classify eggs into three classes.

1.1 OBJECTIVES

- i. To compare the pre-trained neural network models of different architectures to classify the eggs.
- ii. To classify the eggs into 3 categories which are good eggs, bad eggs, and others based on the pattern of translucent areas on eggshell.
- iii. To visualize and analyze the neural network in classification of pattern of translucent area on eggshell from each layer for consistency.

1.2 PROBLEM STATEMENT

Commonly, inspection on eggs is done by doing candling process manually and this method is very inefficient and unproductive. Machine vision has been an alternative to improve the inspection system in terms of time and standardization. However, this method is only best-suit for the macro and some obvious micro-cracks inspection, for the translucent areas or mottling pattern on the eggshell, it could not give a very desirable result. Thus, investigation on the available technique of AI application such as transfer learning integrated with vision is a solution to this problem but also a challenge to look for the best tuned model to implement. The unknown issues such as technique to use the transfer learning, model tuning and computer sources needed to be clearly clarified.

1.3 SCOPE OF RESEARCH

Eggs are to be classified into three classes which are bad, good and unknown. Few distinctive fine-tuned pre-trained models in terms of architecture are selected to undergo transfer learning. The final outcome is to compare the best model and justify what has the model learnt.

CHAPTER 2

LITERATURE REVIEW

The eggshell has a function to act as a barrier to protect egg physically from existing pathogenic challenges in external environment. The properties of eggshell quality is fulfilled by its structure which is an ordered bio-ceramic complex between both mineral and organic matrix constituents [29]. The composition of eggshell structure consists of the shell membranes, mammillary layer, palisade layer and cuticle to compose of about 95.1% inorganic matter and 3.3% protein [30]. The shell membranes has two layers which are inner membrane and outer membrane. These membranes help in forming shell at a very first step by anchoring the inner portion of the shell mineral. Then, the mammillary layer is responsible to enclose the albumen by a keratin-like layer at about 30% of the total shell thickness. The palisade layer makes up about 70% of the shell thickness and contains calcium and hydrogen carbonate crystal known as “calcite”. Under normal conditions and good handling practices, the cuticle offers a natural barrier to the common microbes that colonise the surface of the egg and its removal could increase bacterial penetration from 20% to 60% [31] [32] [33].

There are some direct and indirect methods to evaluate eggshell quality. Quasi-static compression fracture, impact fracture, and puncture force are the direct methods while the egg specific gravity, nondestructive deformation, and beta backscatter are the indirect methods to evaluate eggshell quality. Among these methods, researchers had conducted an experiments to study effects of storage duration on eggshell strength using nondestructive deformation, quasi-static compression strength, impact fracture strength and specific gravity. Researcher observed that all these tend to decrease with time and indicated that material and structural properties of the eggshell were influenced by the length of storage. After all, it is found that the variation pattern of eggshell thickness across the whole eggshell could be considered as an indicator of eggshell strength and thus its quality [34] [35].

Upon the forces being applied on the eggshell, micro-cracks or macro-cracks would happen at a point where the value of force is bigger than eggshell strength. These cracks could allow infiltration of bacteria into the egg which caused food poisoning

issues for those who has consumed it. Two common macro-cracks on the eggshell are hairline crack and star crack. In one of the research, hairline cracks in eggshell could cause egg weight loss up to 24% while the star crack could cause egg weight loss up to 20.7%. It can concludes that the hairline cracked eggs have higher contamination rate and inability of chicks to consume yolk sac [36]. On the other hand, micro-cracks which is difficult to be detected by naked eyes could possibly initiate eggs at loads cause total structural failure. It is happened before cracks is where the shell is broken, but shell membranes are undamaged. [36], [37]. At normal condition, these micro-cracks formed from small applied loads as a result from high stress concentration on the inner surface of eggshell. A study showed that micro-cracks cannot easily be detected especially those using mechanical excitation [38] [39].

Macro-cracks in egg shell are one of the most prominent external and can be identified as the places with low luminance. For these cracks detection, the YIQ color model which Y represents luminance and I and Q represent hue is designed in a machine vision inspection system. From the result of analysis, the clean eggs and eggs with dirt and cracks were easily detected. This method is more relying on the image acquisition where scene constraints are the key factor to improve the robustness of system [40]. Besides, there is a research which a machine vision uses CCD camera, halogen candling lamp and thus Matlab to do image processing algorithms are used to do grading and quality inspection of defected eggs. The accuracy to classify between defected eggs and intact eggs is at 85.66% averagely [41].

Furthermore, a study proposed that a system based on acoustic resonance was developed for eggshell crack detection. It was achieved by the analysis of the measured frequency response of eggshell excited with a light mechanism. The response signal was processed by recursive least squares adaptive filter, which resulted in the signal-to-noise ratio of the acoustic impulse response being remarkably enhanced. After that, three pattern recognition algorithms which are K-nearest neighbors, artificial neural network, and support vector machine were examined to develop a robust discrimination model [42]. A more advanced inspection system is utilizing acoustic response system (ARS) including back-propagation artificial neural network model with a structure of 6 input nodes, 15 hidden nodes, and one output node and computer vision system (CVS) for eggshell crack detection. The detection accuracy for eggshell crack reached 98% and it is proved that it is an effective technique to detect eggshell cracks. [43]

For the micro-cracks inspection, one egg system vacuum pressure chamber was fabricated to force open the micro-crack in egg shell and machine vision system was developed to acquire the image. The developed system was able to detect the micro-crack with 100% accuracy without being influenced by the presence of dirt in the egg shell [28].

Before the development of cracks or micro-cracks, eggshell translucency could be one of the factor for bacterial penetration. Eggshell translucency is the appearance of lighter colored regions of the shell that can be seen when an egg is candled over a light source [26]. Translucent eggshell have membranes that are significantly thinner than those of opaque eggs. The thinner the egg shell membrane with non-uniformity, the weaker the eggshell which the shell is more likely to break [44].

In order to assure a high and consistent egg quality, researchers investigated the use of modern sensor technologies to replace the candling operation. 3 classes of techniques which are based on mechanical techniques, spectroscopic principles and software platform are proposed to replace visual inspection of eggs by humans [39]. However, sooner the researchers figured out that vision is applicable on wide fields to solve the difficulties [45]. Firstly, vision system comes along with the camera and computer to inspect on the existence of micro-cracks on eggshell. At that time, a mechanical system equipped with machine vision system was developed to force open the micro-crack present in egg shell and acquire the image [46]. This method was working with only forces to emphasize the existence of cracks. In order to make it non-destructive, deeper image pre-processing techniques are used to segment the features of defects on the eggshell. As a result it successfully identify between defect and non-defect eggs at averagely 97% of validation sets [47]. With the presented way of inspecting eggs, automation was the next step to make the whole production line even more productive and efficiently. A device is then merged automated and manual egg candling analysis that goes to the design and describes valid solutions regarding occupational safety and malnutrition. It shows that it is essential to see for construction of the egg candling device in order to enumerate and describe real-life solutions at 95% of effectiveness [24]. Automation and robotics provide the muscle for Industry 4.0, AR/VR, cameras and other sensors provide the senses, and data and connectivity are its central nervous system. But the real brains behind this industrial revolution is AI. Few researchers came across with grading the egg freshness using a dielectric technique and

artificial neural network method. Using egg dimensional characteristics and dielectric parameters as input variables, test validations show that eggs are graded with a mean performance close to 90% [48].

Nevertheless, application of AI which is using Convolutional Neural network to extract features or visual pattern mining. A specially designed neural network model, PatternNet is developed to leverage the capability of the convolution layers in CNN, where each filter has a consistent response to certain high level visual patterns. The PatternNet on object is to discover discriminative and representative visual patterns by using a specially designed fully connected layer and a lost function to find a sparse combinations of filters, which have strong responses to the patterns in images from the target category and weak responses to images from the rest of the categories. [49]

CHAPTER 3

RESEARCH METHODOLOGY

A machine vision set up consists of camera with lens, fixture and lighting was set up to make a scene constraint for the eggs. The images of eggs were captured and processed into content with high contrast in features of mottled pattern and background before feeding into input of neural network models. As to study the accessibility of machine vision integrated with AI, three different pre-trained deep convolutional neural networks Alexnet, Resnet-101 and Inceptionv3 to predict potential of macro-crack in response to egg mottled pattern and thus classified into bad and good eggs. The dataset of image has to be enough by considering the number of features, statistical characteristic of data and at the same avoid the problem of neural network model over-fitting and under-fitting [50]. There are techniques which is data augmentation to solve the problem of small number of dataset. In this study, hyper-parameters are values that must be initialized to the neural network model and these values are not able to be learnt by model itself. Dropout rate and epoch number are chosen to be tuned for the model training [51]. Lastly, statistical analysis and visualization techniques were used to justify the result qualitatively and quantitatively. The figure 3.1.1.1 below shows algorithm of classifying status of eggs.

Besides that, the traceability and consistency of model trained in egg classification is very important. Beside than training the neural network model for whole egg images, another model for small patches of images within an egg image also need to be done. Initially, the best fine-tuned model for whole egg images is trained. By using the visualization techniques along with activation strength, expectedly there will be some parts of a whole egg image are activated. Within that image, inactivated and activated parts are cropped and save in few patches which will be fed into the model trained for patch images previously. The testing accuracy obtained will be used to determine whether the classification is consistent for whole egg images and patch images.

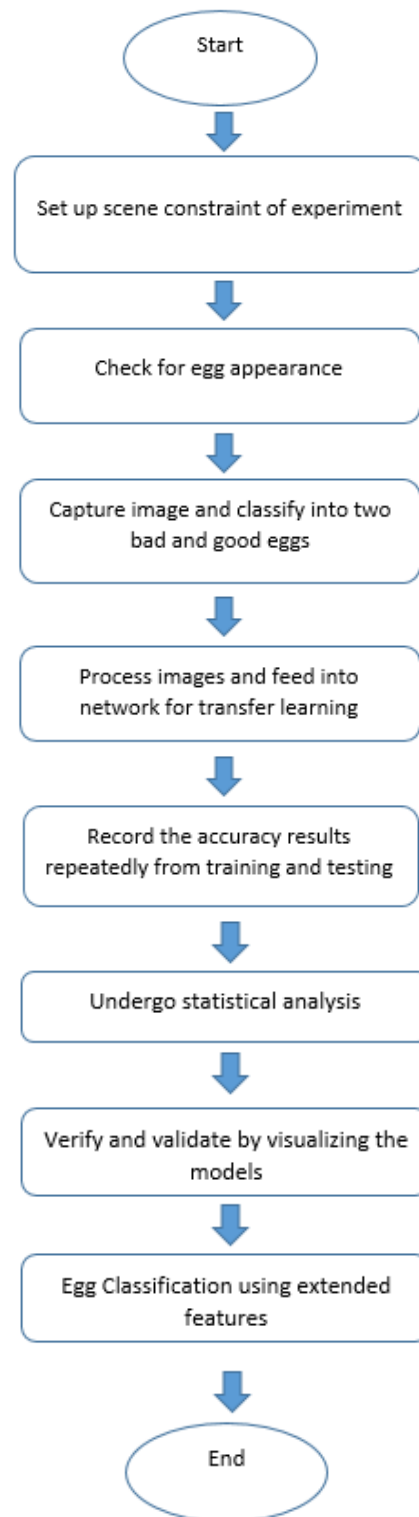


Figure 3.1.1.1: Flow chart for classification of eggs

3.1 IMAGE ACQUISITION WITH SCENE CONSTRAINTS

Before building the neural network model, images have to be collected from the eggs as many as possible to increase the image data size. Usually, batches of egg of classified good and bad eggs are delivered from industry and these eggs needed to be handle softly and keep them in a suitable environment for not more than a week. The images of these samples are captured by a CMOS sensor camera. Subsequently, the images are pre-processed by using Matlab algorithm.

3.1.1 Experiment Setup

The experiment setup is to capture the images required for the crack, hairlines or other abnormalities under diffusing backlighting into the egg.

3.1.2 Material and Apparatus

The images of these samples are captured by using 2 different cameras which are DFK 22BUC03 USB 2.0 colour industrial camera and monochrome CMOS sensor camera with different filters. The colour Micron CMOS has 744×480 (0.4 MP), up to 76 fps. It is mounted with lens of 25mm focal length and f-number ranged from 1.4 to 22. Its working distance is ranged from 0.15 meters without extension tube. Subsequently, the images are observed and compared to choose the best-suit lighting type and camera.

The f-number of the camera is adjusted to its lowest which is 1.4. It provides the biggest aperture opening which allows more light to reach camera sensor especially in a disclosure environment. The formula 1 below is used to calculate the estimated lens-to-object distance when setting up the fixture.

$$\frac{1}{f} = \frac{1}{u} + \frac{1}{v} \quad \text{----- 1}$$

$$\frac{1}{25} = \frac{1}{u} + \frac{1}{26} \quad \text{----- 2}$$

$$V = 650 \text{ mm} \quad \text{----- 3}$$

The lighting used in this project is HBF-08 spot lighting, UV and IR lighting. For the spot lighting, it has input power of 5V and output power of 5V of light intensity. The different channel of light (Red, Green, Blue, White) and respective intensity can be adjusted according to situation. For the UV and IR lightings, the input and output power is 24V and the lighting intensity is adjustable from 0 to 255.

The sample of eggs are received and classified into bad and good categories.

3.1.3 Physical Setup

In order to simplify and standardize the subsequent stages of work on the images, the scene constraint is used to enable known distances, measured on set, to scale a scene more accurately. The position of the egg is constrained at a position perpendicular to the camera as shown in the Figure 2. This position is to imitate the actual happening in production line. The environment must be dark to eliminate ambient noises and a LED light as a light source at the bottom of the egg. This technique is known as backlighting to diffuse light from bottom of eggshell into the egg body and diffuse out from the top of eggshell.

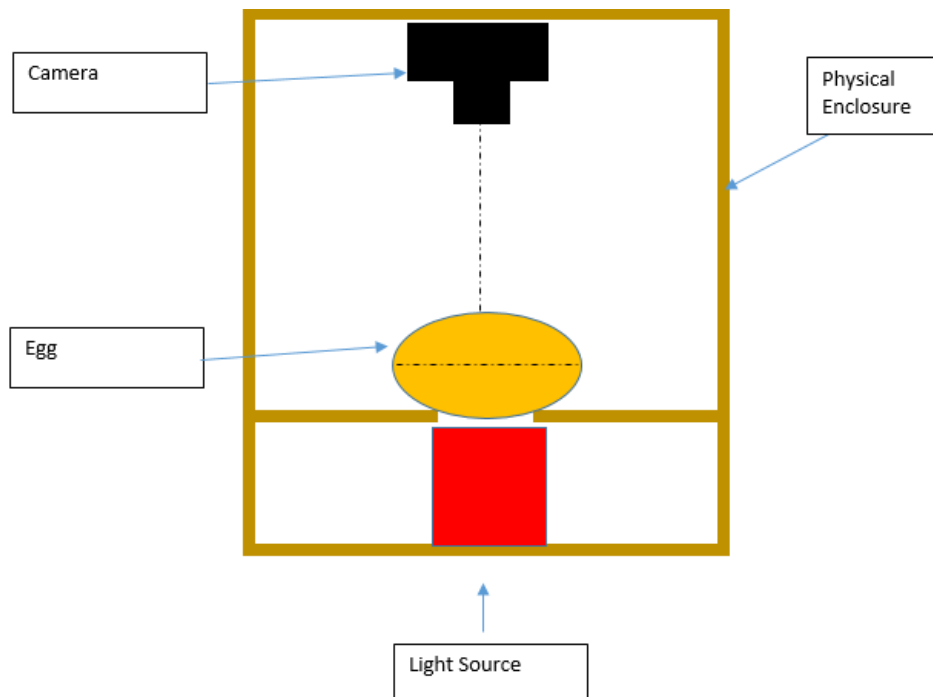


Figure 3.1.3.1: Schematic set-up for image acquisition.

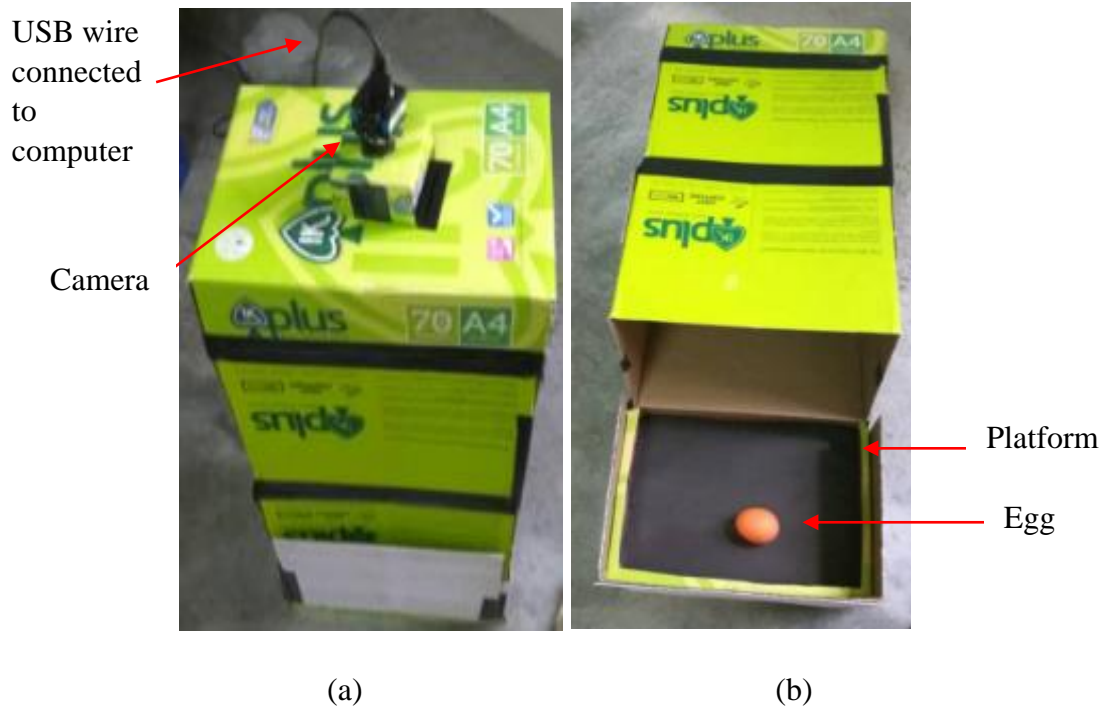


Figure 3.1.3.2: Physical set-up where (a) consists of camera and disclosure, (b) fixture platform to hold the egg at position of focal point of camera lens.

The apparatus are set up as shown in the figure and the distance between the lens and egg is fixed as calculated previously to capture the sharpest images. However, there are some constraints are important when designing the disclosure and doing the experiment.

Table 3.1.3.1: Constraints for image acquisition.

No	Constraints
1	Position of camera is fixed
2	Egg is located at the focal point
3	Disclosure must be totally free of environmental lights
4	Surface for fixture is flat

3.1.4 Image Acquisition Result

The result below shows the different lightings and filters used while taking the images using monochrome camera.

Table 3.1.4.1: Matrix of images of different lighting and filters used.


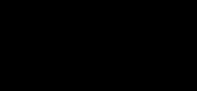
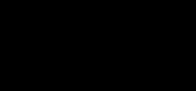
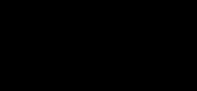
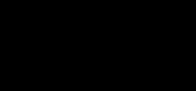
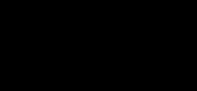
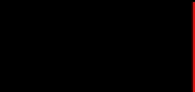

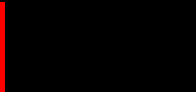
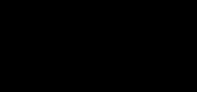
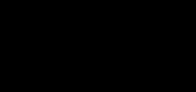
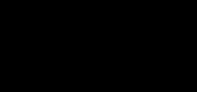
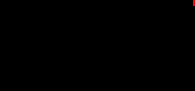
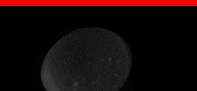
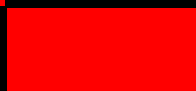
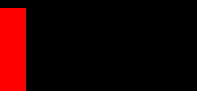
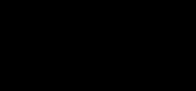
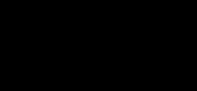
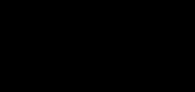



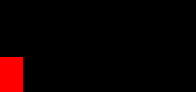
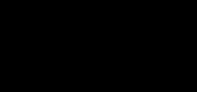
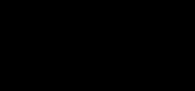
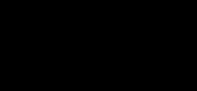

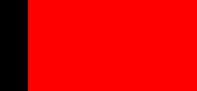
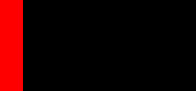
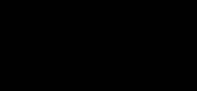
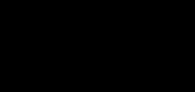
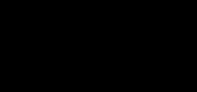
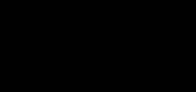


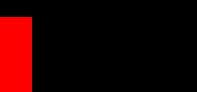
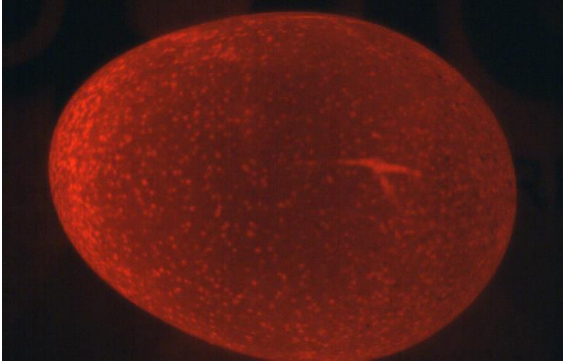
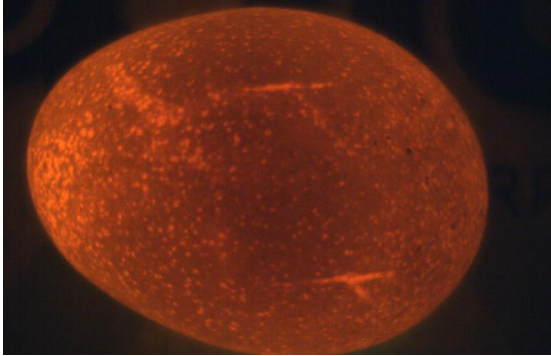
Filters Lighting	IR	UV	Red	Blue	Green	Linear
IR						
UV						
Red						
Blue						
Green						
White						

Table 3.1.4.2: Image captured using red and white lightings.



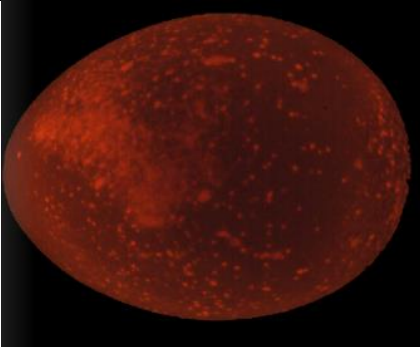
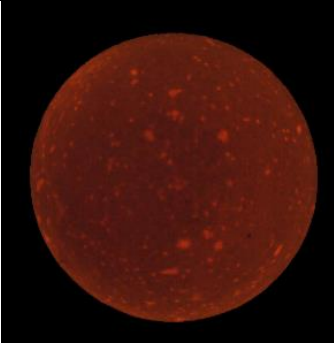
Lighting Distance	Red	White
10 mm	 A photograph of a spherical object, possibly a planet or moon, captured under red lighting. The object is illuminated from the left, showing a dark, textured surface with some lighter patches. The background is black.	 A photograph of the same spherical object, captured under white lighting. The object is illuminated from the left, showing a dark, textured surface with some lighter patches. The background is black.

For the table 3.1.4.1, the red shaded regions show the inappropriate combination of filter and lighting to take images while the black regions show that nothing can be captured from the camera. Out of the combination, only red lighting with UV filter and blue lighting with red filter allow image to be captured. However, the images captured are not desired which the translucent areas on eggshell cannot be shown clearly.

For the table 3.1.4.2, it shows that one using white lighting can give better contrast of mottled pattern on eggshell compared the one using red lighting. Therefore, it is concluded that the white lighting with color camera is used to prepare image data store for neural network training.

The table below shows the image samples from different classes.

Table 3.1.4.3: Egg classes and respective images.

Class	Sample 1	Sample 2
Bad		
Good		

3.2 IMAGE PROCESSING

The captured images of size $468 \times 744 \times 3$ were binarized at certain threshold for each colour channel to make sure that a complete image of egg is reserved and at the same time unimportant noises are removed as well. The ratio of pixels of row by column is made into 1:1 into by adding zero-padding around the boundary as shown in figure below. The final image is now size of 744×744 . This is to make sure that the original features of mottling patterns can be reserved and standardized for all neural network models. Then, the images were then classified manually into two classes which are accept and reject. The images of eggs are classified as rejected whenever there are appearances of cracks or abnormalities on the eggshells as shown in table, otherwise, they are classified as accepted.

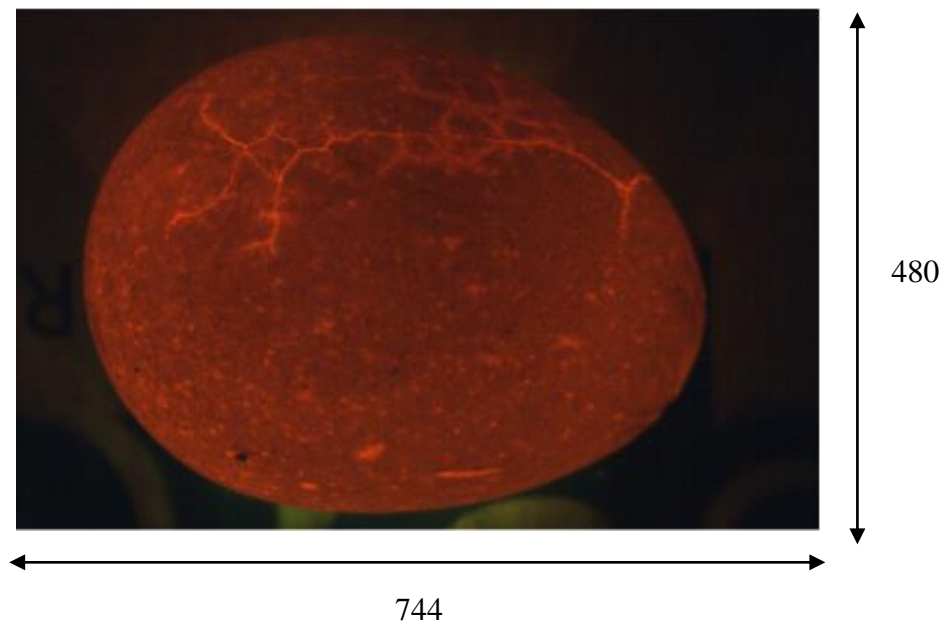


Figure 3.1.4.1: Sample original image captured

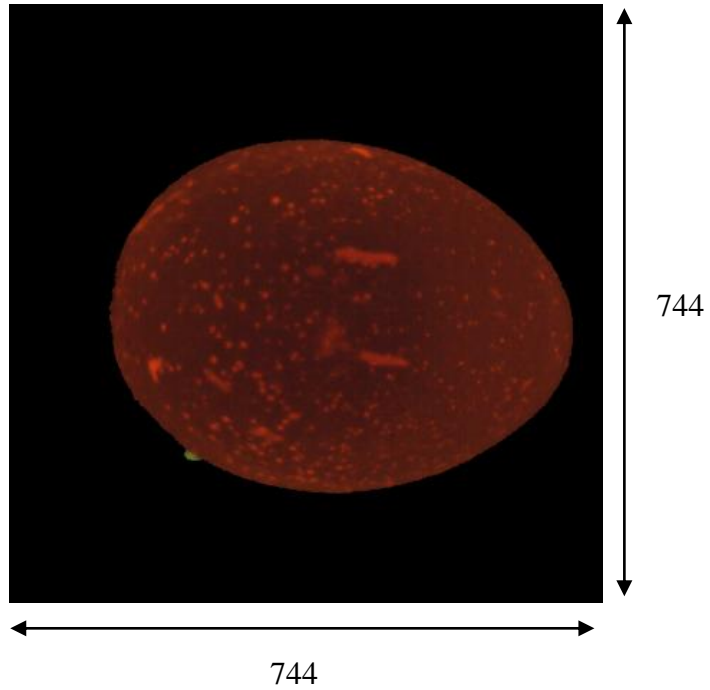
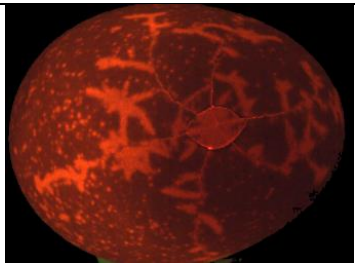
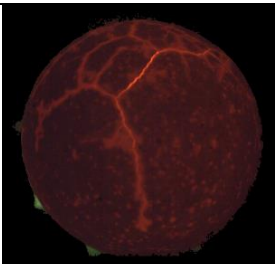
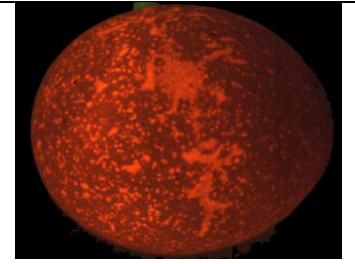





Figure 3.1.4.2: Sample processed image with zero padding

Table 3.1.4.1: Rejected Eggs with their Criterion

No.	Lateral View	Equator View	Criteria
1			Visible cracks or star hairlines
2			Visible connected translucent areas more than 30% of the total area
3			The total translucent areas are more than 50% of the total area

In order to increase the dataset, technique of data augmentation is used. The images of eggs are augmented using image preprocessing techniques such as shearing, zooming, reflection, rotation, translation and brightness adjusting are used to increase augmentation size to improve training performance and generalization capability of the neural network model [52], [53]. This augmentation make use of processing techniques to flip along x and y axis, rotate ranged from 0 to 360 degree, brightness adjustment up to 30, translation along x axis varies from zero to 50 and translation along y axis varies from zero to 400. The figure below shows the examples after the image processing techniques are applied. The image dataset has been increased to 3000 images including for accepted and rejected eggs.

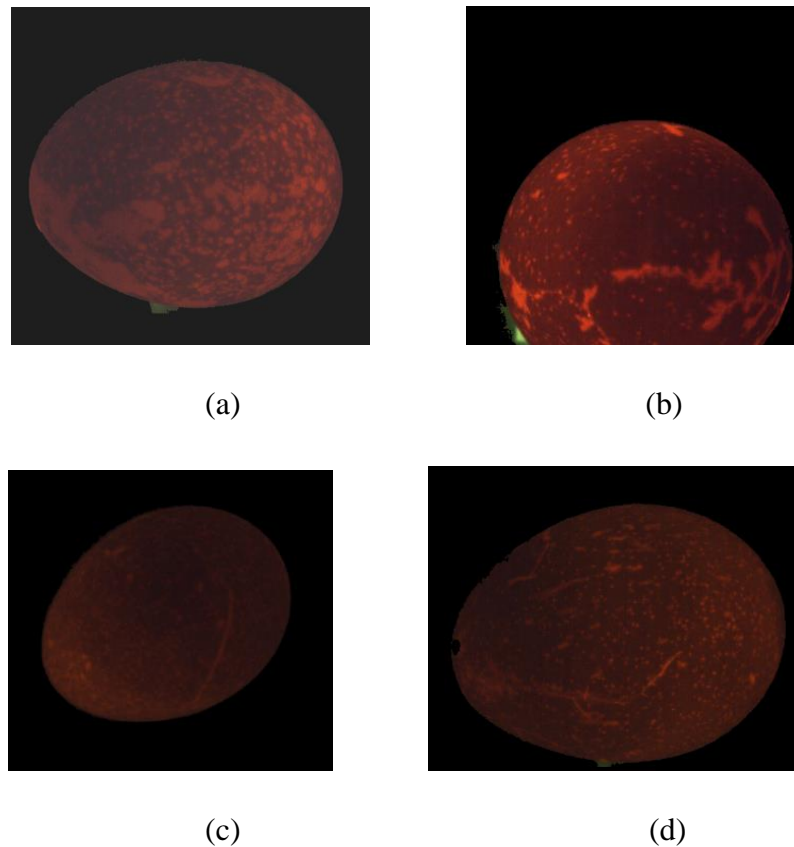


Figure 3.1.4.3: Samples of augmented images with different techniques. (a) Brightness adjustment, (b) translation, (c) rotation (d) reflection.

The total images including the original images and augmented images are 3000. According to the ratio of training, validating and testing, the images for training is 2250; images for validating is 450; images for testing is 300.

3.3 NETWORK SELECTION

Transfer learning is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned. It is used in this study mainly due to its low computational cost and applicability within shortage of time.

3.3.1 Alexnet

First of all, Alexnet is used due to standard functions used such as ReLU units and dropout layer [54]. Architecturally, the Alexnet contains eight layers with weights where it consists of five convolutional layers with ReLU activation and batch norm and lastly are connected with three fully connected layers as shown in Figure 1. Convolutional layers helps to convolute images to multiple kernels with/without padding while the pooling layers help to pool to down-sample the dimensions while keeping same depth to reduce computation. Among the other layers, ReLU layer helps to reduce the unnecessary processing power on the negative value of convolutional layers and batch normalization layer solves imbalance gradients for back-propagation to increase accuracy.

The first convolutional layer filters $224 \times 224 \times 3$ input images with 96 channels of size $11 \times 11 \times 3$ with a stride of 4 pixels. After that, max pooling layer pool down the pixels with filter 3×3 with a stride of 2 pixels. Then, the same process undergoes as previous layer until last three layers which fully connected all the pixels by having have 4096 neurons each. Next, softmax layer turns the numbers of fully connected layer into probabilities that sum to one.

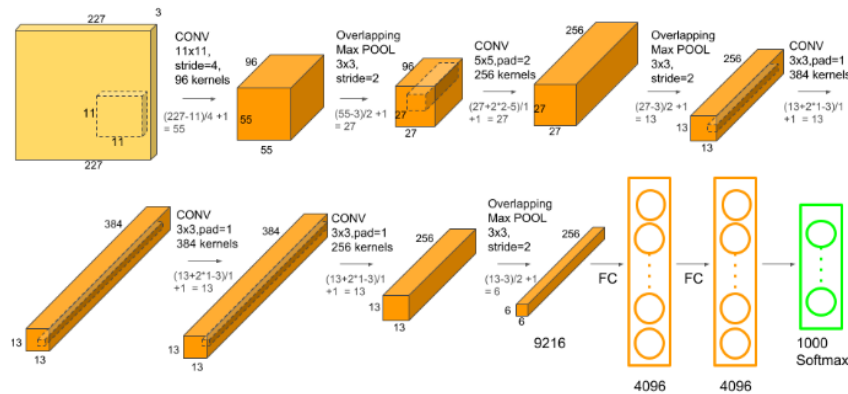


Figure 3.3.1.1: Architecture of Alexnet with its labels.

3.3.2 Resnet

In traditional neural network models, images are passed from layer to layer. Depends on the complexity of problems, layers in the models might need to be increased as to solve the problems. At the same time, increasing the number of hidden layers much more than the sufficient number of layers will make the gradient back-propagated into previous layer to be infinitively small and as a result the performance get saturated. Therefore, Resnet is introduced when adding “identity shortcut connection” that skips one or more layers as shown in figure 2.

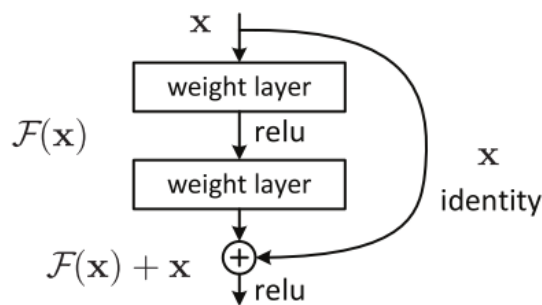


Figure 3.3.2.1: A residue block from Resnet.

In this study, Resnet101 is used. It has 101 layers deep and is able to classify the images of highly complexity and different mottled pattern of translucent areas on the eggshell. On the other hand, choosing this model is a rule-of-thumb method where the guide should be based on practice rather than theory and the decision made can be revealed from the result in following section. Besides that, the result given by deeper layer is that the error decreases significantly. It uses full pre-activation where the convolutional layers, batch normalization layer and activation layer is placed before addition as shown in figure 3.

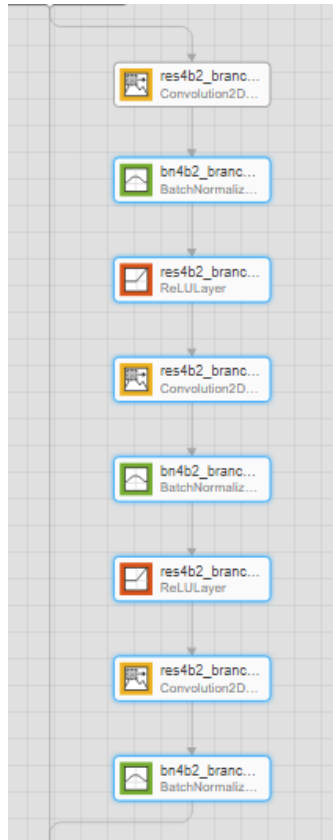


Figure 3.3.2.2: Residue block architecture of Resnet101

The network has an image input size of 224-by-224. The images are then filtered with 64 channels of size 7x7x3 with stride of 2 pixels. Then, it follows by batch normalization, activation layer and max pooling. Then, repeatedly, multiple full pre-activation residue block continues to feed into next layers.

3.3.3 Inception

The problem of over-fitting has become very common when a model is getting deeper with more layers. Besides that, it also causes higher computational resources in order to build the model and train it to solve the problem. Therefore, the idea of building Inception has come out. The Inception architecture was introduced which concatenated the filter outputs from various filter sizes and this is known as inception layer as shown in figure 4. It allows the internal layers to pick and choose which filter size will be relevant to learn the required information. So even if the size of the mottled pattern of translucent areas on eggshell in the image is different, the layer works accordingly to recognize the pattern.