Classification of Eggshell Translucent Areas for Quality Determination Using Alexnet

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Declaration

This thesis is original research work form me. This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree. All the work is under supervisor by Dr. Yen Kin Sam, at the University Science Malaysia.

Signed: ………………………………………………………… (WONG HSUEH CHUNG)

Date:

In my capacity as supervisor of the candidate's thesis, I certify that the above statements are true to the best of my knowledge.

Signed: ……………………………………………….……… (DR. YEN KIN SAM)

Date:

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Abbreviations

Deep Neural Networks	DNNs
Artificial Neural Network	ANN
Complementary metal–oxide–semiconductor	CMOS
Light Emitting Diode	LED

Abstract

Microbial contaminants are usually the biggest problem faced by egg manufacturer. Bacteria usually penetrate the eggshell through cracks, micro cracks and translucent area are. A fine-tuned Alexnet and a machine vision system were used for inspection of pattern of translucent area. Images 150 cracked egg and 30 intact eggs were taken. To fit into the Alexnet, 1010 images were cropped randomly within the boundary of egg in the size of 227×227×3 in size training and validation data at the ratio of 7:3. The trained network was then evaluated qualitatively using Google Dream Images and quantitatively by visualizing and prioritizing channel with highest activation energy in each convolution layer. Extra 100 cropped images were used as testing images. The trained network was able to detect reject defective egg with accuracy of 91% with false reject rate of 12.5%. The developed system acted as a preliminary study for the development of automated quality determination based on translucent area.

Abstrak

Bahan pencemar mikrob biasanya merupakan masalah terbesar yang dihadapi oleh pengeluar telur. Bakteria biasanya menembusi kulit telur melalui retak, retak mikro dan kawasan lut. Alexnet yang baik dan sistem penglihatan mesin digunakan untuk pemeriksaan corak kawasan lut. Imej 150 telur retak dan 30 telur utuh diambil. Untuk dimuatkan ke dalam Alexnet, 1010 imej telah dipotong secara rawak dalam sempadan telur dengan saiz 227 × 227 × 3 saiz latihan dan data pengesahan pada nisbah 7: 3. Rangkaian terlatih kemudian dinilai secara kualitatif menggunakan Google Dream Images dan secara kuantitatif dengan memvisualisasikan dan memprioritaskan saluran dengan tenaga pengaktifan tertinggi dalam setiap lapisan konvolusi. Imej 100 tambahan yang dipotong digunakan sebagai imej ujian. Rangkaian yang terlatih dapat mengesan telur yang cacat dengan ketepatan 91% dengan kadar menolak palsu sebanyak 12.5%. Sistem yang dibangunkan bertindak sebagai kajian awal untuk pembangunan penentuan kualiti automatik berdasarkan kawasan tembus.

1.0 Introduction

Eggs are an economical source of nutrients for a healthy diet and life [1]. They represent a "complete food" required for well-being and are recognized by consumers as versatile and wholesome with a balance of essential nutrients [2]. Egg proteins, average at 6.5 g per egg, contain a balanced supply of nine amino acids essential to human health: histidine, isoleucine, leucine, lysine, methionine, phenylalanine, threonine, tryptophan, and valine [3]. Amino acids are vital for production of enzymes, some hormones, hormone receptors, DNA components, and other functional components required for growth, tissue maintenance, and regulation of metabolic functions.

Food safety is a major concern throughout the years as people are gradually emphasizing on eating healthy and organic food. Egg manufacturer must reject eggs with defects according to international egg grading manual to ensure processed eggs are within quality specification [69] as distribution of defective eggs violates the international egg distributions law. Defects of egg can be divided into internal and shell defects. Common internal defects are blood spots, meat spots, watery whites, pale yolks and mottled yolk. Eggshell defects on the other hand can be generalized into different types of cracks, abnormal shape, unnecessary stains and lastly translucent areas when observed under candling. [4]

Microbial contaminants of eggs are usually enteric bacteria, with Salmonella enteritidis being the greatest threat. Egg contents are often suitable media for bacterial growth. Hence, risk of egg contamination by pathogenic bacteria, particularly S. enteritidis, is a major concern for egg production and egg product manufacturing industries [5]. Salmonella can cause Salmonellosis which is characterized by nausea, vomiting, abdominal cramps, diarrhea, fever, and headache. The symptoms begin between 6 hours and 72 hours after the consumption of Salmonella contaminated food [6]. U.S. Food and Drug Administration (FDA) estimates that 79,000 cases out of 1 million cases each year are the result of consuming eggs contaminated with Salmonella, of which result in 30 deaths [7].

Under FDA regulation, all eggs products need to be pasteurized before reaching end consumers. It is also advised not to eat shell eggs that are raw or undercooked to minimize the risk as Salmonella can still travel into human body through digestive system. [8] Pasteurization is the immersion of eggs into precise controlled temperature water bath for a certain period to destruct Salmonella bacteria and avian flu viruses [9]. The most common pasteurization egg method is thermal pasteurization. Along years of development of this method. Numerous techniques have been proposed, namely water immersion pasteurization [10] [11], hot-air pasteurization humid air pasteurization [12], microwave egg pasteurization [13] and radiofrequency egg pasteurization [14] [15]. Among these techniques, water immersion pasteurization is most popular and being used commercially. However, bacteria can still infect the egg after pasteurization process.

Superior shell quality is an important characteristic of an egg that will resist physical aggression as well as bacterial penetration. The absence of microcracks is essential for food safety. The mineralized shell is about 96% calcium carbonate while the remainder is mainly an organic matrix that exhibits extensive intermingling with the inorganic phases. The precursors of the eggshell matrix are present in the cellular uterine fluid, from which they become incorporated into the calcifying shell during its formation. Shell mineralization can be separated into three distinct phases: initiation (5 hours), rapid mineralization (12 hour), and termination (1.5 hours) [16].

Cracked egg shells are proven to be more vulnerable to Salmonella and other infection leading to health hazards [17]. Conventionally, egg crack inspection is done by trained human graders. Human graders inspect the moving candled pasteurized eggs and pick up the cracked eggs. The presence of microcracks can be confirmed by careful squeezing or tapping. Human graders working at egg candling station is exposed to high intensity candling light. Exposure time of human grader is controlled to avoid retina damage [18] [19]. Sometimes, cracks especially microcracks can go undetected by human graders which is would further distributed down to the end customer through supply chain.

There are already mechanical excitation based automatic egg crack inspection systems in the commercial market now. However, these crack inspection machines are unable to detect microcracks which could potentially compromise egg safety. On the other side, automatic egg inspection machine that are based on machine vision are mainly focusing on detecting abnormalities like blood in albumen, egg with no yolk and dirt. [20] [21] [22]

The eggs are also checked for eggshell mottling and strip mark at the candling station. Mottling is the presence areas with greater translucency ranging from pin points to areas covering the entire shell while strip marks are usually in elongated line shape. They become prominent when the shells candled which lead to mottled appearance. Shell mottling might be due to various factors ranging from genetic to the food intake of the hens. Strips mark on the other hand is basically translucent line instead of discrete translucent area and are mostly caused by external environmental factors.

Translucent areas do not highly influence the microbial quality such as Haugh unit and thick albumen ratio while cracks do. [23] However, there was a significant correlation between eggshell translucency and eggshell penetration by Salmonella [24]. Besides, Eggshell of translucent areas are comparatively thinner which will result in a lower eggshell strength which contribute to a higher probability of crack development. There were instances where salmonella infection outburst happened even after pasteurization. [25]

Penetration of bacteria into the eggshell is a serious issue faced by egg manufacturers around the world. The automated quality inspection system's emphasis should not only be put only on the cracks but also the translucent areas which allow high penetration of Salmonella. An early rejection of egg with high contamination risk based on the amount and pattern of translucent areas can minimize the risk of Salmonella infection.

For translucent areas to analyzed and classified, the classification system need to be robust as there are too many irregularities in the translucent pattern, it is believed that pretrained networks can provide the robustness to classify and identify eggs with high potential crack development and cracked egg before pasteurization process.

1.1 Objectives

1. To classify the good and bad eggs based on the translucent areas.
2. To develop a machine vision system to acquire images of eggshell with high contrast between opaque and translucent areas.
3. To perform transfer learning on a pretrained network for egg quality classification.
4. To validate the trained network through qualitative and quantitative visualization.

1.2 Problem statement

Microcracks and translucent areas of eggshell can allow enteric bacteria such as salmonella to contaminate the egg which can lead to infection for consumer. Pasteurization process is common and effective technique used to kill the bacteria inside the egg. However, there are still cases of Salmonella infection even the eggs are pasteurized. The existing automated inspection system are all focusing on detection of microcracks without considering the risk of bacteria penetration through translucent area.

1.3 Scope of work

The machine vision system emphasizes on the capturing of translucent areas instead of microcracks. Also, pretrained network was limited by the computing resources. A simple model will be selected to perform the transfer learning.

2.0 Literature Review

Chicken eggshell represents about 11% of the egg weight and is composed of 94% calcium carbonate in the form of calcite, 1% magnesium carbonate, 1% calcium phosphate, and 4% organic material. In an egg weighing 60 g, about 2.3 g of calcium is found deposited in the eggshell [26]. The interior of the shell is lined with two shell membranes with the inner one in intimate contact with the albumen. The shell membranes are essentially organic forming into a mesh of protein fibers. Above this mesh and interconnected is the mineral portion of the eggshell, which is further divided into three distinct layers [27]. The more inner portion of the shell consists of knobs that form calcified cores known as the mammillary layer. A thicker palisade layer emerges from the mammillary cores. Next, a thin outer layer of the shell is deposited consisting of crystallites arranged in vertical position relative to the eggshell surface. Finally, a protective cuticle is placed around the shell. The cuticle consists of an inner layer composed mainly of mineral with the external layer being organic, uncalcified, and insoluble in water. Pigment of the shell, if expressed, is deposited on the outer layer of the cuticle [27] [28] [29].

Several laboratories have developed equipment for testing the strength of eggshells when subjected to various standard loads [30] [31]. The rationale for such measurements is understandable on the basis that, if mechanical forces lead to cracking of shells, then response to a standardized mechanical insult should be an indication of resistance to breakage under commercial conditions. The measurement of breaking strength when the egg is subjected to increasing load until the shell fractures has also been used to evaluate egg shells. General purpose equipment such as the Instron apparatus, and purpose-built machines such as the Ottawa egg tester [32] can be used to measure breaking strength under quasi-static compression. In this procedure the loading rate is strictly controlled, and the deformation rate of the shell precisely measured.

Cracks are one of the shell defects as it brings significance effects on the nutritional value. Khabisi et al [33] included major eggshell damages as complete eggshell breakage, hairline cracks, and star cracks. Arivazhagan et al [34] defined gross cracks as large cracks, holes that is the result broken shell membrane while hairline and star cracks are defined as extremely fine cracks running lengthwise along the shell. Lastly, slightly indented cracks radiating outward from a central point of impact, respectively. King'ori [35] investigated the complexity of the eggshell structure leads to different breakages, such as cracks of various severities, shapes, and lengths, in eggs.

Microcracks are only visible under candling and can be caused by rough handling during egg processing or transport. Microcracks form because of very high stress concentrations on the inner surface of the shell under the point of contact in both static and dynamic loading conditions. Microcracks will initiate at the inner surface of the eggshell at the load as small as 5N. [36]

All the current commercial egg crack detection systems in the market are based on vibration analysis that utilize either the light mechanical impact [37] [38] or applying acoustic signals to detect crack on the eggshell [39] [40] with crack detection accuracy up to 98%. A machine vision eggshell crack detection system with pressure chamber was proposed in 2008. The cracks are intensified by high pressure gradient, then the atmospheric image and negative pressure image is compared to identify the cracks. The system had accuracy of 98.8% accuracy [41] [42] which is a breakthrough in machine vision-based egg crack detection system. Since then, numerous of algorithms had been proposed based on the pressure system proposed by Lawrence et. al for different application such as industrial application that can be used on eggs with dirt and unwashed eggs [43] [44]. Patel et. al incorporated artificial intelligence in machine vision system to grade and identify proposed to grade eggs also based on sizes and defects such as internal blood spot, cracks and breakage. [45]

The two main approaches of automatic cracks detection with detection rate up to 99% are vibration analysis through light mechanical impact or acoustic signal and machine vision with negative pressure system under normal egg candling. Vibration analysis was already integrated into existing egg production system by machine manufacturer with high output rate. However, vibration analysis was proven cannot effectively detect microcracks. [36] Machine vision approach on the other hand is able detect microcracks with the help of negative pressure system. [41] It is still under development stage and no egg crack detection machine based on machine vision are on the market. One of the biggest challenges of this approach is that the eggs must stay inside the vacuum chamber to undergo a short while of high gradient negative pressure for image acquisition. This solution does not seem to be feasible at this moment as the required gradient pressure gradient might be too high to achieve in a large container.

Strip marks and egg mottling are both characterized by translucent areas when observe under candling. [46] [47] Translucent areas can be artificially induced by disturbing or partially removing the cuticle that when in a liquid or sticky state. Cuticle has the function of excludes bacteria and dust. [48] Thickness is one of the important factors influencing the strength of the eggshell. [49] Although there is no correlation between translucent appearance regardless of severity and interior quality [46], translucent areas are proven to be weaker than opaque areas mainly because of thinner eggshell. [47] A weaker eggshell will contribute to higher crack probability during egg processing which would compromise egg safety. [50]Also, translucency of eggshell increase the penetration of Salmonella which can cause contamination. According to experienced egg graders, cracks usually developed along the translucent areas of the egg. It is theorized that as the strength of eggshell decline with the increase severity of appearance of translucency, cracks will develop easily.

Early rejection on egg with high risk crack development and bacteria penetration based on the pattern and severity of the translucent areas can be done before going through any egg processes. Pasteurization is predicted to be one of the contributors for microcracks as eggs are immersed in elevated temperature medium. Water can weaken the eggshell if given the chance to wet thoroughly. [50] It is also proven that at elevated temperature more than room temperature, the eggshell will become weaker and the probability for cracks to develop will also rise. A much less force can cause microcracks in egg than in room condition [51] However, there are other areas in the egg processing line that can also lead to microcracks in eggs [52]. To this date, no researcher had proposed classification system based on pattern of the translucent areas.

Deep neural networks (DNNs) is an artificial neural network (ANN) with multiple hidden layers between the input and output layers. DNNs archive remarkable performance in vision tasks such as object recognition [59] [60] [61], segmentation [62] and detection [63]. However, the explanation on how the DNNs work exactly is still limited. The most common technique used to understand how DNNs work is visualization which is helpful to understand what a specific neuron represents. Generally, there are two type of visualization: data based on input images [63] [64] [65] and model based on the neural network only [66]. Different constraints have been proposed to avoid the high frequency noise problem. The constraints include weight decay [64] [65] [67], total variance norm [65], gradient clip [67], image blurring [67], image blurring and deblurring and patch prior [68].

3.0 Methodology

In this works, images are taken on the egg with the and pretrained network model, Alexnet is chosen In order to fit in Alexnet, the full images were then cropped into size of 224×224×3 pixels in size randomly within the boundary of the egg. Then, transfer learning was done by replacing the last 3 layers of the original with new one and trained it. Validation of the trained network are done quantitatively and qualitatively using Deep Dream Images and finding channels using with highest activation energy for respective classes. Lastly, the trained network tested on images that was completely strange for accuracy.

3.1 Image acquisition

A 13-megapixels of CMOS (Complementary metal–oxide–semiconductor) sensor camera with f-number of 2.6 was set up to take egg candling photo with 2304×1728 resolution. The camera is positioned perpendicular to the top of the equator of the egg with distance of 15cm. The distance between the lens and the eggs curvature was fixed by hit and trial basis. Opaque boxes were used to create enclosed space to limit light disturbance from the surroundings. Multiple images were taken from one egg.

Egg candling with backlighting are the established method to check for cracks and internal quality. Different configurations had been tested for best configuration. Examples of images taken with different configurations were shown in Table 1. Configuration of Light Emitting Diode(LED) as backlighting with enclosed space are best configuration as it provides the best contrast between translucent and opaque areas. Circular focus block of diameter 2cm and distance of 2cm from the backlighting light source were used.

Table 1: The images taken using different configuration

			
Front lighting	YES 15cm distance	YES 15cm distance	NO
Back lighting	NO	YES 2cm wide and 2cm distance	YES 2cm wide and 2cm distance

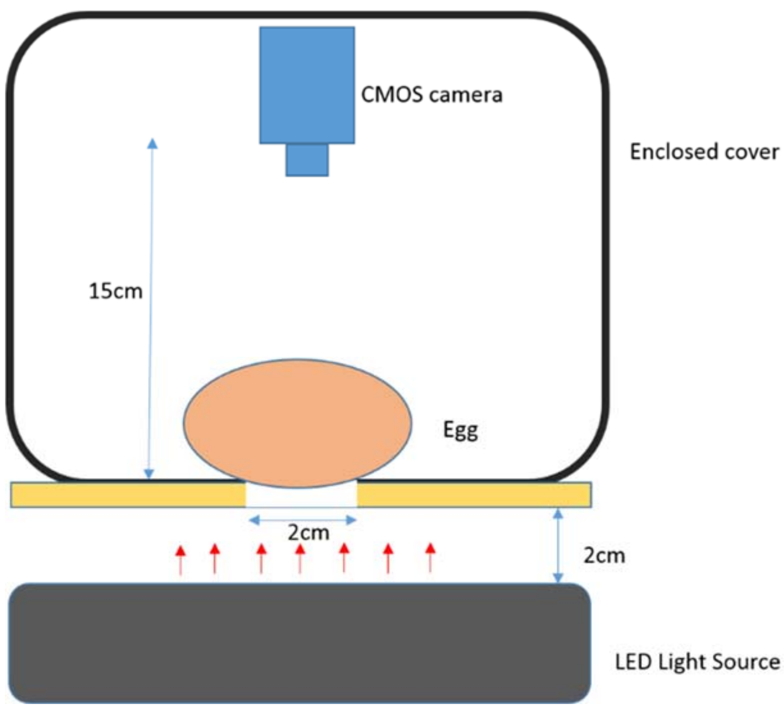


Figure 1: The configuration of the image acquisition set up

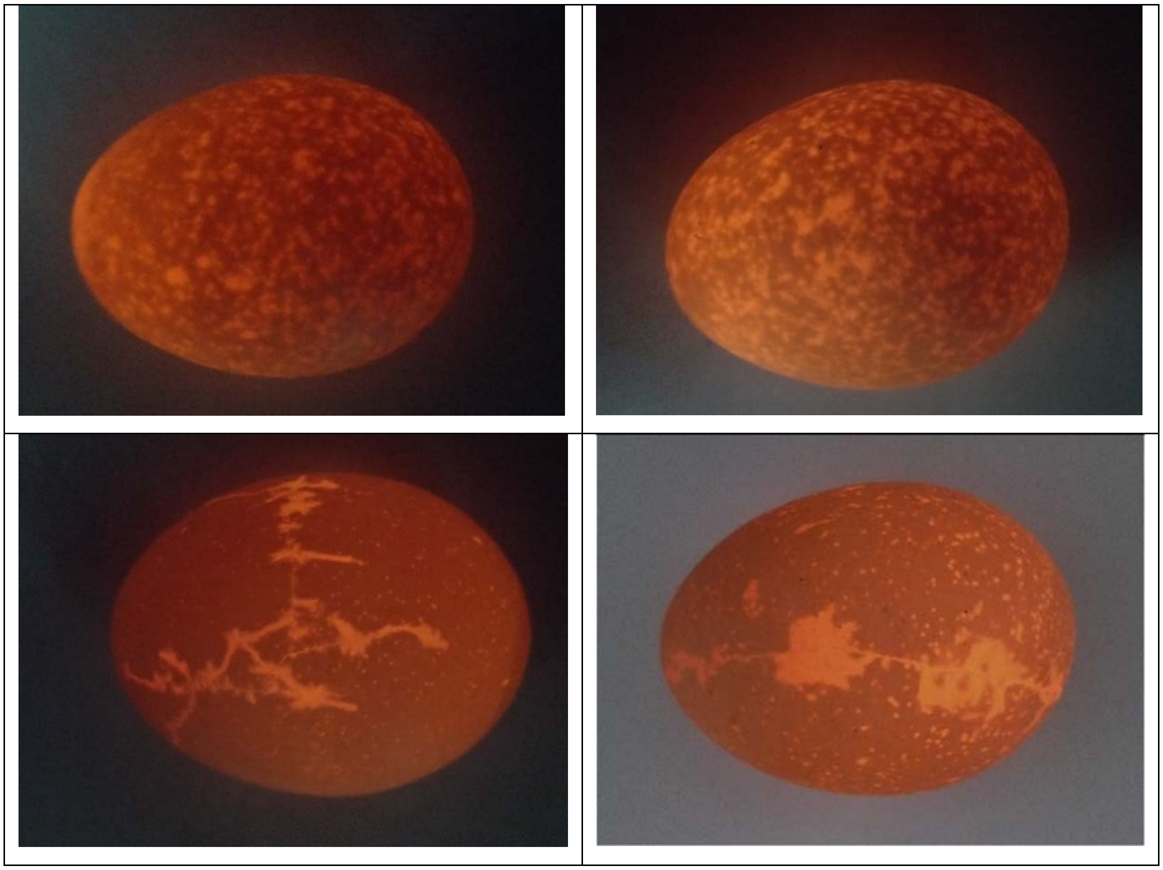


Figure 2: Samples of images taken from image acquisition set up.

The images taken from different eggs are not consistent. The brightness of images fluctuates from one egg to another. This is because some eggs have a better translucency which allow more light from candling to be captured and travel to the background. The classification system must be robust enough to allow eggs with different translucency and brightness to be classified correctly.

3.2 Network Selection

Pretrained network was used to minimize the resources needed to train the network. For this preliminary study, Alexnet was chosen for its lowest computation cost, considerably high accuracy, relatively simple layouts among the modern pretrained network. Besides, Alexnet usually served as the default CNN architecture for various evaluation and analysis for comparison.

Architecturally, the net contains eight layers with weights: the first five are convolutional layers and the remaining three are fully connected as shown in Figure 2. The output of the last fully-connected layer is fed to a 1000-way softmax which produces a distribution over the 1000 class labels. Alexnet maximizes the multinomial logistic regression objective, which is equivalent to maximizing the average across training cases of the log-probability of the correct label under the prediction distribution.

The first convolutional layer filters the 224×224×3 input image with 96 kernels or channels of size 11×11×3 with a stride of 4 pixels. The second convolutional layer takes response-normalized and pooled output of the first convolutional layer and filters it with 256 kernels of size 5×5×48. The third convolutional layer has 384 kernels of size 3×3×256 connected to the normalized and pooled outputs of the second convolutional layer. The third, fourth, and fifth convolutional layers are connected to one another without any intervening pooling or normalization layers. The fourth convolutional layer has 384 kernels of size 3×3 ×192, and the fifth convolutional layer has 256 kernels of size 3×3×192. The fully-connected layers have 4096 neurons each.

There were pooling, RELUs, normalization layers positioned between some convolution layer. Pooling layers were placed in between early convolution layers. It progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network, at the same time control over fitting. Rectified Linear Units (ReLUs) layers train several times faster than their equivalents with sigmoid function. Batch normalization layer reduced the amount of the hidden unit values shift around, allowing each of a network to learn by itself a little bit more independently of other layers

The last three layers were softmax, fully connected and classification layers. Fully connected layer can learn the non-linear combinations of features for classification purposes. Softmax layer on the other hand worked like max pooling and at the same time be able to be trained by gradient descent. Exponential function of Softmax layer will increase the probability of maximum value of the previous layer compare to other value.

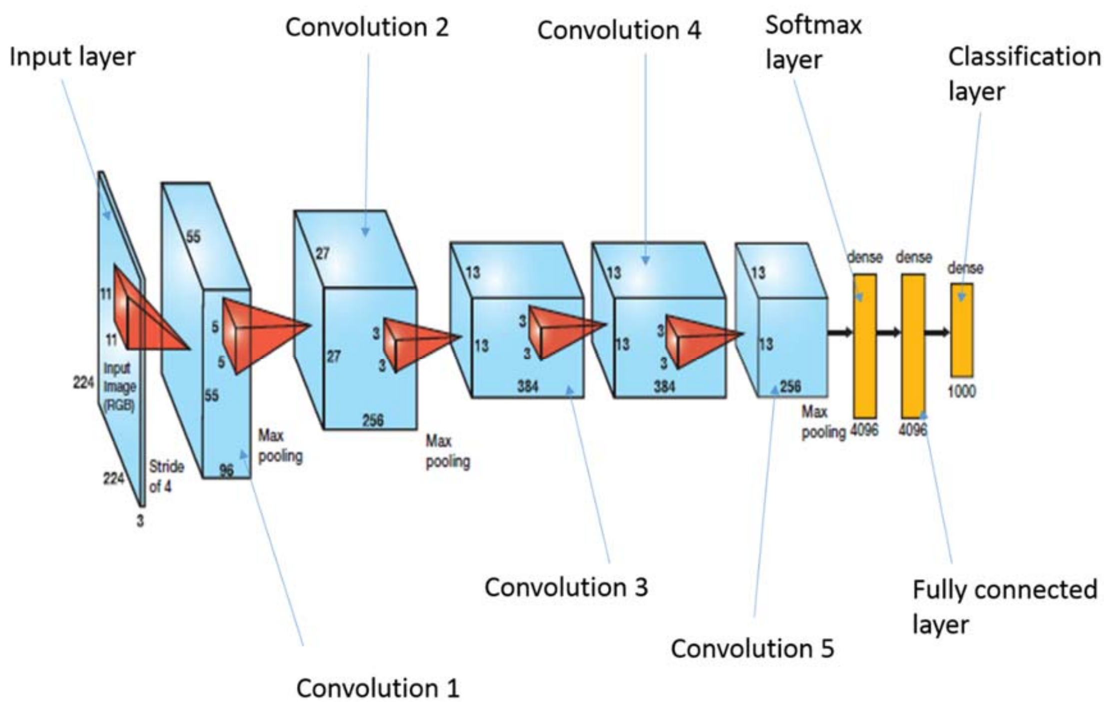


Figure 3: Architecture of Alexnet with its labels.

3.3 Image Prepossessing

The captured images were then randomly cropped into images of size 227×227×3 pixels within the boundary of the egg to fit into the selected pretrained network. Cropping ensured no important information are lost while minimizing computation cost. The images were then classified manually into two classes: accept and reject. The classes were classified into reject classes if the images meet any of the listed criteria in Table 3. The rest of the images were classified into the class accept. The illustration of different features stated in criteria are shown in Figure 1.

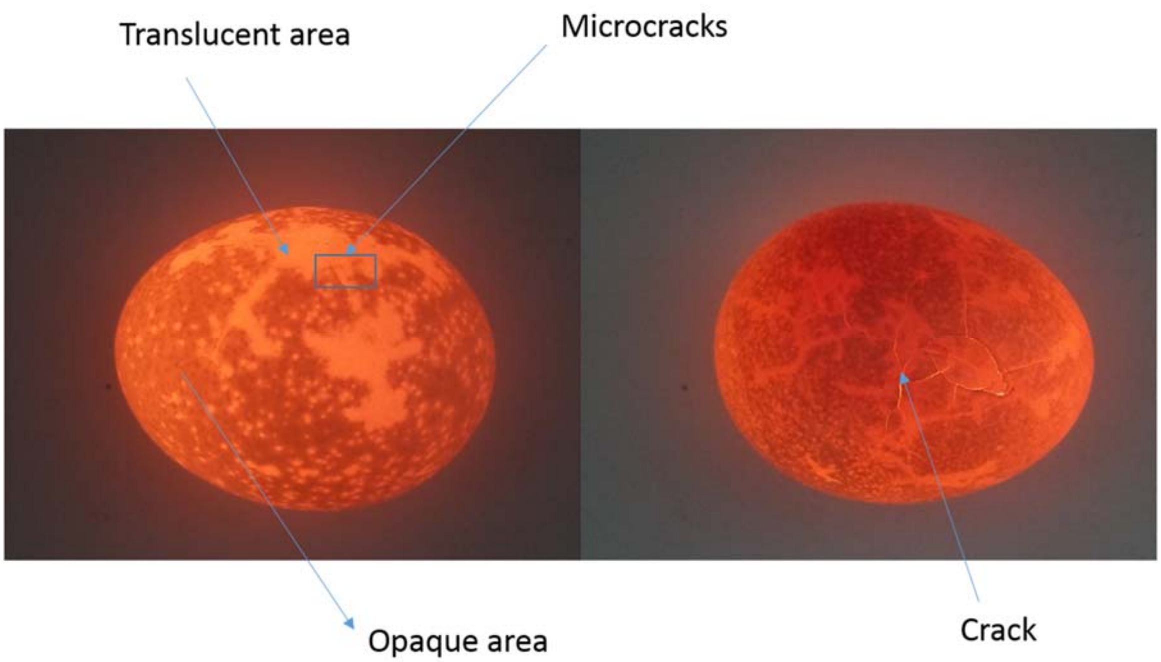
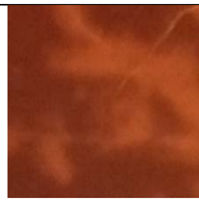
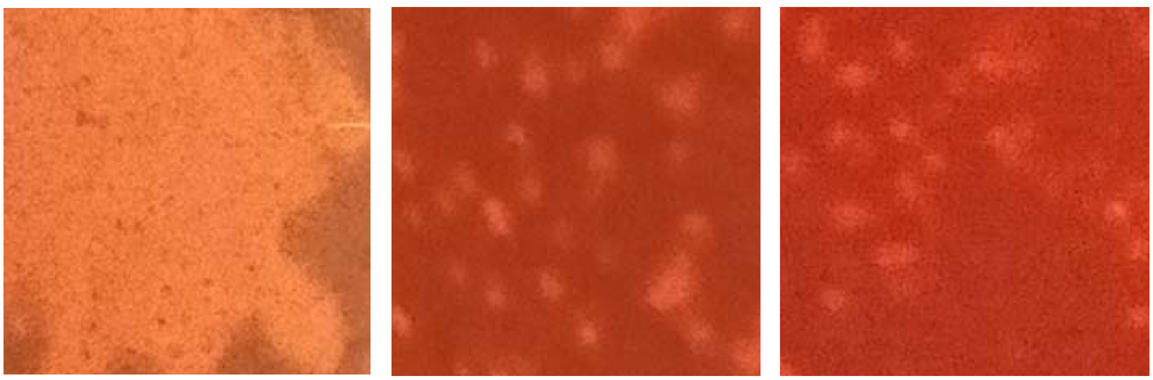


Figure 4: The illustration of different features on eggshell.

Table 2: The criteria for the class accept with example

No.	Criteria for class Reject with example
1	 Visible cracks or micro cracks
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

a) b) c)



d) e) f)

Figure 5: Samples of cropped images with labels of classes. a) reject, b) reject, c) accept, d) reject, e) accept, f) accept.

Table 3: Classes with its total number training and validation samples

Classes	Total number training and validation samples
Accept	620
Reject	390

The cropped images are labelled based on the criteria listed in Table 3 result from constant discussion with experienced egg grader. Images with visible cracks and large translucent area will be labelled as 'Accept' while the rest are classified as 'Reject' as shown in figure 7. There were total of 1010 of total samples with 620 for class 'Accept' and 390 for class 'Reject'. The samples of the labelled cropped images were shown in Figure 4.