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Vision-based Egg Grading System using Support Vector Machine

Way Soong Lim, Kang Lai Desmond Ji, Sin Ting Lim*, Boon Chin Yeo

***Abstract* – Being known as a nutrient-dense food, eggs are high in demand in the marketplace and high-quality eggs are much sought-after. Hence, egg grading is in place to sort eggs into different grades. Experienced graders are required for their knowledge to classify egg grades and as humans are involved, errors when performing manual grading are unavoidable. This study aims to develop a vision-based egg classification system that requires minimal human intervention. The proposed system houses a camera to acquire real-time images of the eggs and these images are served as the input to the algorithm. Based on the 6 geometrical features derived from the geometric parameters of the egg image, the eggs are classified using Support Vector Machine (SVM). The experiment results show the proposed egg grading system with a linear kernel SVM model can yield as high as 92.59% training accuracy.**

Keywords— Egg Geometrical Parameters, Egg Segmentation, Egg Grading, Computer Vision, SVM Classifier

I. INTRODUCTION

There is a growing demand and expectations for high-quality eggs. This is manifested by the fact that several egg production companies are competing to produce eggs that are well-shaped and well-weighted. According to the deputy president of the Federation of Livestock Farmers Associations of Malaysia, Malaysians consume 27 million to 28 million eggs daily, with grades A, B and C accounting for 90% of their consumption [1]. Egg grading is an essential operation in the production of commercial eggs to control egg quality. In Malaysia, the common egg grading parameters used by the industries are based on weights as listed in Table 1 [2].

TABLE 1. Egg grades based on weights.

Grade	Weights (g)
A	65 – 69.9
B	60 – 64.9
C	55 – 59.9
D	50 – 54.9
F	40 – 44.9

To ease the grading process, the egg grading sorting machine that grades eggs by weight is often used in Malaysia. However, these machines entail costly and time-consuming scheduled maintenance and calibration to ensure precision and accuracy in weight measurement. Besides, when manual grading is performed to check for the interior and exterior quality of an egg, the knowledge of an experienced grader is

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required. However, no matter how experienced the grader is, manual grading for thousands of eggs is energy-draining, time-consuming, and error-prone.

To overcome the issues faced in manual egg grading or sorting machines that depend on weight only, vision-based egg classification systems using egg size or shape parameters are getting more attention. This is because the integration of AI tools and methodologies can further enhance manufacturing knowledge, reduce costs, and open new avenues for development [3]. In this project, a vision-based egg classification system that uses SVM model is designed and developed. The parameters derived from the egg images are utilized in the training and testing process of the proposed egg grading classification algorithm.

II. Literature Review

A. Manual Egg Grading System

Traditionally, manual egg grading systems classify the eggs based on the measurement of weights, sizes, and exterior and interior conditions. The standards on how eggs are evaluated and manually graded in the United States can be found in [4]. The graders or workers are tasked to perform the basic operations required to grade and pack the eggs. Each egg is examined for interior and exterior quality before a candling light and the size of each egg is determined. Tools such as the egg scale are created to accurately check whether the weighted egg meets the egg weight standards. The workers must then accurately count the eggs and pack them into cartons according to the graded results [4].

The grade of an egg is subjective to the grader's perspective. Due to the large number of decisions that the grader is forced to make in fast succession on each egg, this technique of grading was time-consuming, costly, exhausting, and prone to error [4]. To determine the weight of eggs, egg scales or weighing devices in egg sorting machines may be utilized. The mass determination productivity with electronic scales is around 715 eggs/h [5]. In measuring the diameter and length of eggs, one common tool used is vernier calipers [6]. The use of a digital density meter to measure the density of eggs is not ideal as eggs will tend to absorb water during the measurement process [7]. Egg provides information on small and large diameters, area, and perimeter of the longitudinal section of the egg, followed by the calculation of the index and egg shape coefficient with high productivity and sufficient accuracy [5].

B. Computer Vision-based Egg Grading System

A computer vision-based egg grading system is equipped with cameras to capture egg images and it often comes with a lighting system to eliminate noise. Figure 1 shows the block diagram of a generic computer vision-based egg grading system.

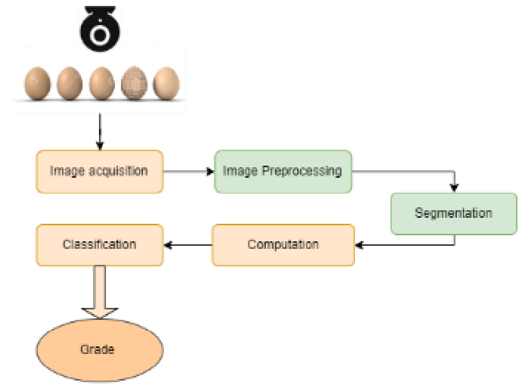

FIGURE 1. A computer vision-based egg grading system.

In image acquisition, egg candling is used as one of the non-destructive selection methods for detecting abnormalities in an egg by shining a bright light on it. Egg candling is done in a dark chamber where the light penetrates the egg's shell, making it transparent and allowing the internal components of the egg to be examined [6]. This enables the egg's interior structure to be visible due to the extreme contrast between foreground and background. Blood stains, spots, fissures, expanded air cells, cracked shells, and fertilized eggs can be detected using the egg candling method. Ab Nasir et al. [3] proposed an egg grading system with an analysis of weight measures and geometrical features. They performed feature extraction using principal component analysis and a k-nearest neighbour classifier in the classification process. Their study concluded that a vision-based egg grading system is better by implementing shape-based features rather than weight parameters.

In image preprocessing, the uniformity of edges and other specific information is to be maintained for further processing [8]. In the next step, the segmentation process segregates the input image into several regions and thresholding, as one segmentation technique, is used to distinguish objects of interest (OOP) from the background based on the grayscale distribution of the image [9]. Thipakorn et al. [10] proposed that six egg geometrical characteristics namely perimeter, area, height, width, shape index and volume can be computed from the segmented egg region.

A classifier is used to perform segregation of the parameters and determine the size of the eggs. Thipakorn et al. [10] and Waranusast et al. [11] proposed implementing egg size classification using machine learning to manage the parameters. The training data is made up of a sequence of training instances, each of which has a pair of input objects and desired output values. This training pair connection is learned by a supervised learning method, resulting in an inferred function. Truth data gives a category label or cost for each pattern in the training set that is used as a classifier in supervised learning. When investigating the link between features, a 'true' category label is not inserted in this scenario [12].

SVM is a supervised machine learning algorithm that can deal with classification and regression problems. It is, however, mostly employed to solve categorization issues. In SVM, each data point is represented as a point in n-dimensional space (where *n* represents the features), with every feature's value being the SVM algorithm's value of a given coordinate. Next, classification is achieved by selecting the hyperplane that clearly distinguishes the classes. SVM is well-suited and robust with a small sample size due to their focus on maximizing the margin [13]. This makes them suitable in this research where the dataset is small. Thipakorn et al. [10] employed SVM to categorize egg size into six classes and found that SVM yields an average accuracy of 87.58% in classifying egg sizes. It is also intriguing to know the performance of SVM in classifying egg grades in this current research.

III. METHODOLOGY

A. System Overview

The goal of the proposed vision-based system is to classify the eggs into three grades A, B, and C according to the egg grade standards set by the Malaysian Ministry of Agriculture and Food Industry. To prepare a dataset for training, data for a total sample of 60 eggs with 20 eggs for each grade are collected. In each egg, the weights, and geometrical parameters such as width, height, area, shape index and volume are collected by manual measurement methods. These collected data are used as ground truth to train the classifier model. A platform is then built with a top-mounted camera to capture real-time images of the eggs. The proposed algorithm will display the video capture footage while extracting the egg's geometrical features. Finally, the classification of egg grades is performed based on geometrical features extracted from the images using SVM. The overview of the proposed vision-based egg grading system is shown in Figure. 2.

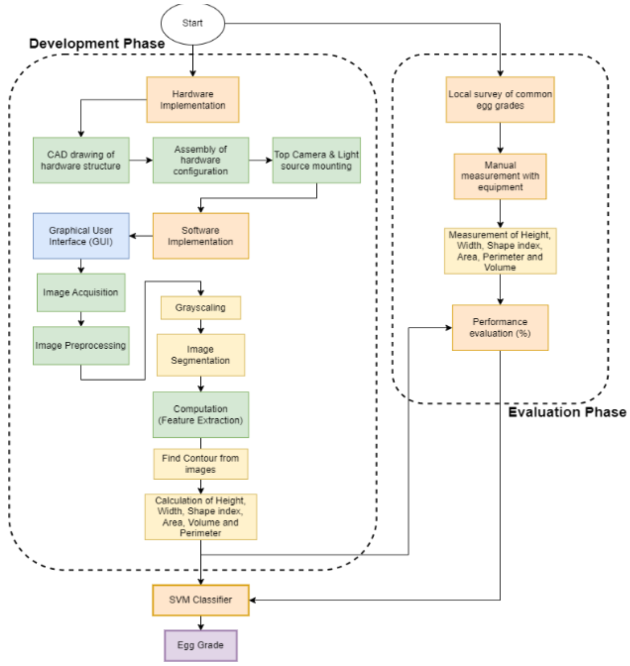

FIGURE 2. The framework of the proposed system.

B. Image Acquisition

The installed camera is a webcam that produces 720p resolution to capture fine details of egg images. The captured video images will be processed to compute the geometrical parameters of the eggs. An LED light ring is used to help eliminate part of the shadow formed on the platform by projecting uniform light onto the eggs and platform. Figure 3 shows the image acquisition hardware configuration designed in this study.

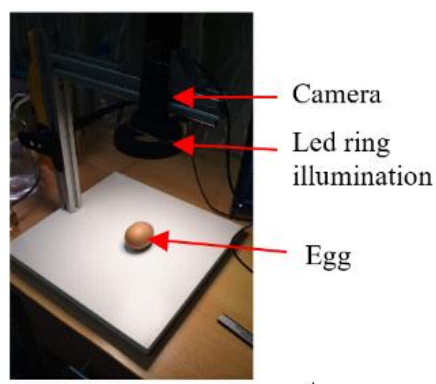

FIGURE 3. Hardware configuration.

The RGB and real-time images captured by the camera are fed and displayed on the Graphical User Interface (GUI) designed as seen in Figure 4.

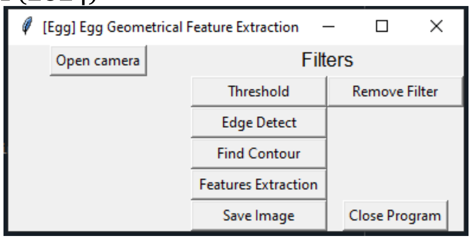

FIGURE 4. Egg images will be displayed on the GUI.

C. Image Preprocessing

Prior to image segmentation, the captured images will undergo a series of image preprocessing that includes grayscaling and noise reduction process. Grayscaling can improve the processing speed of egg feature extraction [14]. This is because grayscaling reduces every form of colour information while maintaining different shades of gray. It helps in simplifying and enabling further algorithms to function with the elimination of image complexities. It simply reduces the 3-channel RGB 8-bit image to a single 8-bits channel image and the example of the grayscale image is shown in Figure 5(b).

To prepare the images for geometrical feature extraction, the noises of an image must be reduced, Bilateral filtering is a straightforward, non-iterative that performs edge-preserving smoothing [14].

D. Image Segmentation

In segmenting the egg from the background, thresholding is one of the most effective techniques [9] to convert colour image to binary image (black and white) which only consists of 1 and 0 pixels. Adaptive thresholding is used to calculate the threshold for a pixel based on a tiny region around it. As a result, distinct thresholds for various sections of the same image can be obtained, even though images are under changing lighting environments.

Canny edge filtering technique is then applied in detecting the egg edges. Canny edge technique uses Sobel operator to locate the edges. Sobel operator computes gradients in both the horizontal, G_x and vertical, G_y directions. These gradients will then be used to compute the edge gradient and direction for each pixel since edges are perpendicular to the gradient direction using equation (1) and equation (2):

$$G = \sqrt{{G_x}^2 + {G_y}^2} \qquad (1)$$

$$\theta = \tan^{-1}\frac{G_y}{G_x} \qquad (2)$$

The edges are made thinner by using non-max suppression. In this method, a pixel is determined whether it is a local maximum in its neighbourhood in the gradient direction for each pixel. It is preserved as an edge pixel if it is a local maximum; otherwise, it is suppressed. Subsequently, each pixel value will be compared to the two adjacent pixels in the gradient direction. To differentiate which pixels are edges hysteresis thresholding is applied. High and low thresholds are to be set according to the rules below:

- Any edges with intensities higher than 'High' are surely edges.
- Edges with intensities less than 'Low' are always non-edges.
- Edges between the 'High' and 'Low' criteria are only considered edges if they are connected to another edge; otherwise, they are eliminated.

The contour detection method is then applied to extract the image's largest foreground object i.e., the egg. The largest contour will be drawn and updated on the video frame as shown in Figure. 5(d). After detecting the contour, the algorithm calculates the area or number of pixels inside the contour boundary. If the contour area is less than the preset value, it will be neglected. This is to prevent unwanted foreground objects to be detected by the system.

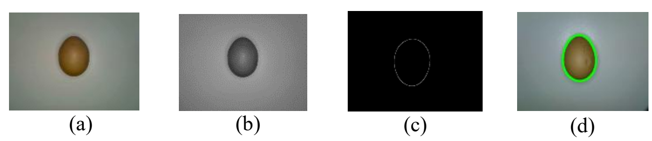

FIGURE 5. Image processing is applied to an egg image.
a) Original egg image; b) Grayscale egg image;
c) Edge detection; d) Contour detection.

E. Feature Extraction

In the case when spectral information such as the egg's area, length and position are extracted, in which their measurements are required in mathematical units, rather than in pixels, image calibration is to be conducted [15]. Calibration is the process of finding the relationship between pixel units and physical units. This enables any measurements taken in pixel units to be scaled to physical units.

Taking an egg sample as a reference as seen in Figure. 6, where the known values are height, *h*, width, *w*, pixel value height (a) and pixel width (b), the pixel per millimetre (*PPM*) calibration parameters can be calculated as stated in equation (3).

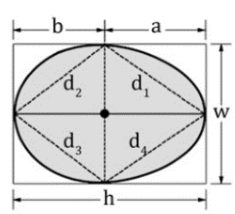

FIGURE 6. Geometrical parameter of an egg.

$$PPMa = \frac{a}{h}\,;\ PPMb = \frac{b}{w} \qquad (3)$$

A boundary box with 4 extreme points (red solid dot) is drawn on the contour as shown in Figure. 7. The extreme points are the pixel coordinates found on the outermost boundary of the contour.

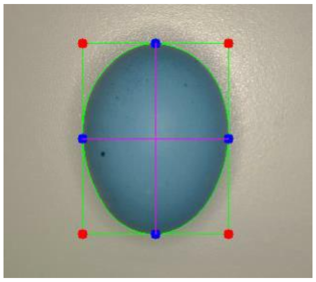

FIGURE 7. Boundary box with midpoints.

With the 4 extreme points coordinates found, the 4 midpoints (*x*,*y*) coordinates (blue solid dot) are obtained as follows:

$$\frac{(x_1 + x_2)}{2}, \frac{(y_1 + y_2)}{2} \qquad (4)$$

With the 4 midpoint coordinates computed, lines are drawn across the midpoints as shown in Figure. 7. The Euclidean distance is computed as in equation (5). where a, b is the distance (line) between the midpoints.

$$d(a,b) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \qquad (5)$$

With the boundary box drawn, and with the calibrated parameters PPM obtained, the 6 geometrical parameters can be extracted according to the computational described below:

- The length and width of the object can be extracted by substituting the calibrated parameters PPM, *a* and *b* values into equation (3).
- Egg shape index (SI). Computation of egg shape index by substituting eggs height, *h* and width, *w* into equation (6).

$$SI = \left(\frac{W}{h}\right) \times 100 \qquad (6)$$

- Area of the egg (A). Mathematical computation of area of an ellipse.
- Perimeter of the egg (P). A perimeter is a collection of adjoining pixels. Perimeter length is calculated by adding 1s for each horizontal and vertical neighbour, as well as $\sqrt{2}$ for diagonal neighbours [16].
- Egg volume of the ellipsoid shape can be computed using equation (7).

$$V = \frac{2}{3}\pi\,(w * h) \qquad (7)$$

F. Classification

To classify the grades of the eggs, the 6 geometrical parameters derived in the earlier processes are used with a Support Vector Machine (SVM) classifier. SVM is particularly esteemed for its ability to manage high-dimensional feature spaces and its effectiveness in binary classification tasks [17].

IV. Results and Discussion

A total of 60 eggs with 20 Grade A eggs, 20 Grade B eggs and 20 Grade C eggs are prepared for this experiment. For each egg, the weight is measured with a digital scale in grams; the height and width are measured in millimetres with a digital vernier caliper and the volume is measured with the water displacement method.

Grade A, B and C are labelled as 0, 1 and 2 respectively and box plots for 6 geometrical features are drawn in Figure. 8. The plotted graphs suggest that area and perimeter parameters are the most ideal features to classify the egg grade classes.

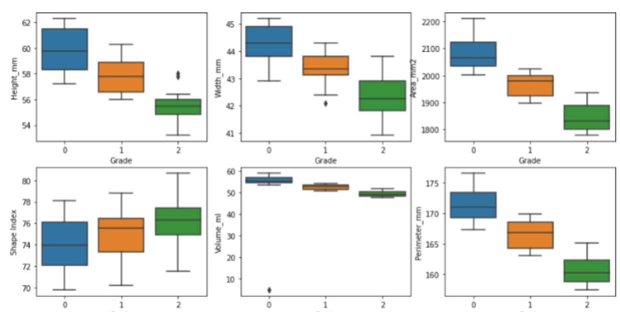

FIGURE 8. Box plots of geometrical features for three egg grades.

The dataset is imported into the SVM model. Due to the small size of the dataset, the dataset is separated into 90% training data and 10% testing data. The features (geometrical parameters) are set as *x*, and the labels (egg grades) are set as *y*. For this classification model, the 4-fold cross technique is used to train and evaluate the performance of the model and evaluate the result with different regularization parameters, *C*. Kernel functions are implemented to perform non-linear classification of the data. Three types of kernel functions which are sigmoid, RBF and linear in considered in generating the SVM model and their performance are shown in Figure. 9, 10 and 11, and Table 2.

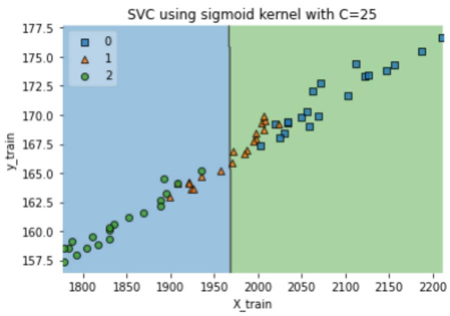

FIGURE 9. Decision boundary of sigmoid kernel with *C* = 25.

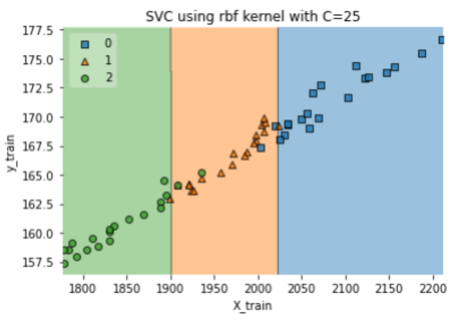

FIGURE 10. Decision boundary of RBF kernel with *C* = 25.

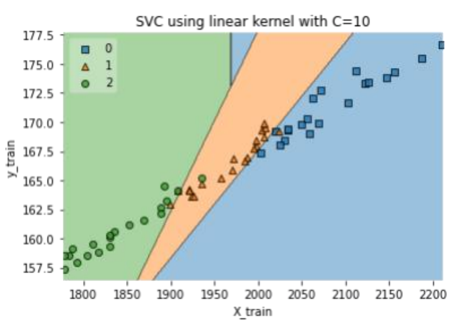

FIGURE 11. Decision boundary of linear kernel with *C* = 10.

TABLE 2. Accuracy of SVM for different kernels

Kernel function	*C*	Accuracy (%)			
		Mean	Std Dev	Train	Test
Sigmoid	25	0	0	35.18	16.67
RBF	25	93.33	4.714	88.88	83.34
Linear	10	91.67	8.66	92.59	100

The boxplots show that the eggs' geometrical parameters do reflect the weights and grading of the eggs. Table 2 shows that the sigmoid kernel has the poorest classification performance with the lowest mean score and lowest standard deviation score of 0%. The linear kernel outperforms the sigmoid and RBF kernel in terms of egg classification with a mean score of 93.33%, standard deviation of 4.714%, training accuracy of 92.59% and testing accuracy of 100%. To further evaluate the consistency performance of the linear kernel SVM model, different training-to-testing dataset compositions are used in the performance evaluation as shown in Table 3.

TABLE 3. Performance of SVM model on different training-to-testing ratio

Training: Testing	Accuracy (%)			
	Mean	Std Dev	Train	Test
90:10	91.67	8.66	92.59	100
80:20	91.67	8.66	91.67	75
50:50	91.67	8.66	93.33	86.67
70:30	91.67	8.66	90.48	83.34

Table 3 shows that changes in the testing-to-training dataset ratio do not cause the SVM performance to reduce drastically.

V. CONCLUSION

A visual-based egg grading system with a training accuracy of 92.59% and a testing accuracy of 100% is successfully developed in this study. The classification model using SVM shows consistent performance under different training-to-testing dataset ratios. A more advanced and efficient algorithm with an increased number of training and testing datasets shall be applied to improve and optimize the classifier accuracy. The grade of eggs is not limited to their geometrical parameters alone; other physical parameters such as impurities on the eggshell, shape pattern, and eggshell thickness can be considered in classifying the grades. The classification accuracy of SVM can also be compared with other classifiers such as the Neural Network (NN) and Random Forest (RF).

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AUTHOR CONTRIBUTIONS

Way Soong Lim: Writing – Original Draft Preparation;

Kang Lai Desmond Ji: Writing – Review & Editing;

Sin Ting Lim: Writing – Review & Editing;

Boon Chin Yeo: Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflict of interests were disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

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