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Original Article

Classification of Hatchery Eggs Using a Machine Learning Algorithm Based on Image Processing Methods: A Comparative Study

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ABSTRACT

Eggs are a cornerstone of the food industry. They are a versatile ingredient used in a wide variety of products for their rich protein, vitamin and mineral contents. The use of efficient and high-quality eggs is of great importance in hatcheries, as well as in direct food consumption. The use of quality and efficient eggs in hatcheries has a strong impact on chick, egg, and white meat production. Artificial intelligence-based smart systems usage for product quality classification is growing steadily in productive sectors. In many of these systems, product images are used as input data. The use of such smart systems provides both fast and low-error quality control. Smart systems can quickly and accurately classify new products with algorithms trained by product images. In this study, an intelligent classification system using a machine learning algorithm, which is a subfield of artificial intelligence, was designed to classify the quality and efficiency of chick eggs in a chicken hatchery. Eggs are most commonly classified according to their size as either Large (L), Medium (M) or Small (S). In this study, 425 egg images were obtained using the image acquisition system designed on the hatchery belt system, and the data for each egg was recorded in a dataset. In the next stage, image processing methods (Morphological operations and Hough Transform) and the SVM machine learning algorithm were used together in the proposed model. According to our results, the classification of eggs into L, M, and S was successfully achieved at 98.0% using the SVM algorithm on the dataset.

INTRODUCTION

Chicken eggs are one of the most widely consumed foods by humans (Rachmawanto *et al.*, 2020). As the need for egg consumption increases due to the increase in the world population, chicken egg production must follow this trend. Chicken eggs are also one of the basic nutrient sources needed for human life, and so their production must be sustainable and fulfill the demand.

Efficient egg-laying hens produce a higher quantity of eggs of higher quality. Hatcheries serve as chicken production centers. The use of efficient eggs in hatcheries leads to high-quality and efficient chicks (Tekin, 2023), producing efficient egg-laying hens or broilers that will yield more eggs and white meat. Measuring the weight of chicken eggs and evaluating their size have a strong impact on egg classification. Accurate classification helps to increase the efficiency of chicken production and produce eggs of better quality (Rahmat *et al.*, 2023).

Today's high technologies, such as the Internet of Things (IoT), various optical sensors, robotics, artificial intelligence (AI), big data processing, and cloud computing methods have transformed the traditional industry into a smart and sustainable egg industry, now also known as Egg Industry 4.0 (EI 4.0). The EI 4.0 approach offers opportunities that have the potential to improve biosecurity, protect animal welfare, promote smart classification in animal husbandry, increase quality control, and increase efficiency by using smart systems (Ahmed et. al, 2023).

Circle detection is a challenging and important task in computer vision. This method is also used in product counting and product quality control applications (Çelik & Tekin, 2020). The commonly used Circle Hough Transform circle detection algorithm is also used in industrial production and security systems. The Circle Hough Transform algorithm can be successfully used in automatic artificial vision systems and applications (Zhou, 2015).

Today, the process of egg classification and quality determination is generally done manually by laborers by looking at eggs under a lamp. In cases where the number of eggs to be checked is high, the classification error rate increases and the process becomes time consuming (Yuniar *et al.*, 2020).

In this study, an automatic egg L, M and S classification model was designed using the SVM machine learning algorithm. The egg images used for classification were obtained from a camera system installed in a hatchery production facility. A dataset was created by extracting attributes from egg images. In the following stage, comparison of the attributes was evaluated by the classification results in the study. In addition to contributing to the literature, this study will contribute to the increase of high-yielding egg and white meat production through rapid and accurate classification.

MATERIAL AND METHODS

Significant achievements have come from using machine learning-based computer vision applications in product classification (Qadri *et al.,* 2021). Deep learning methods also successfully perform classification tasks (Ahmad *et al.,* 2023). In this study, a machine learning model was used, which is a sub-branch of artificial intelligence.

The proposed system is showed in Figure 1. The system consists of 2 parts: an egg imaging system and the classification model. The images from eggs in the egg tray were obtained by a camera system mounted on the hatchery belt system. Each of the eggs has accurately detected in the images by applying morphological operations and Circle Hough Transform methods. The 5-feature dataset was from the detected egg data. The eggs were classified into Large (L), Medium (M), and Small (S) classes using the dataset with the SVM machine learning algorithm.

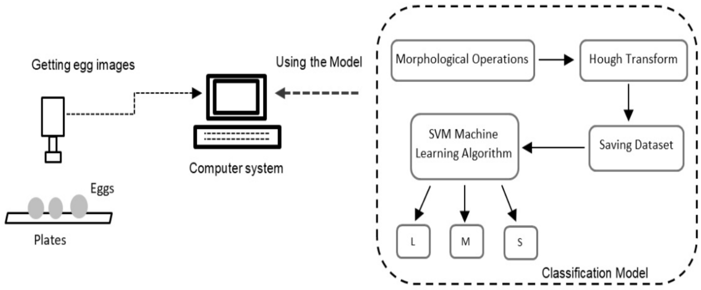


Figure 1 – The block diagram of the proposed model.

In this study, a camera-based image acquisition system was designed on a hatchery belt system, and eggs on trays were recognized with the help of this system (Figure 2). Figure 2 shows the camera placement (for image taking) and the egg tray mounted on a metal structure.

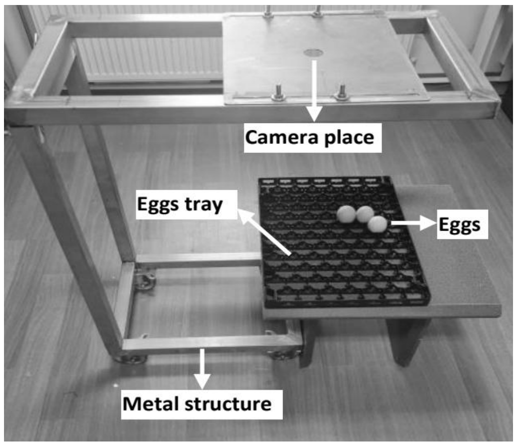


Figure 2 – Hatchery image acquisition system (Tekin, 2023).

In order to accurately detect the eggs on the trays, morphological image processing methods were applied to the obtained images in the beginning. For this purpose, the widely used erosion and dilation morphological operations were applied to the egg tray images (4 times erosion, 1 time dilation). After this step, each egg was detected on the tray images using the Circle Hough Transform algorithm, and the features of each egg (5 items) were extracted and stored in the dataset. In the final stage, L, M and S egg classification was performed using the SVM machine learning algorithm, and the classification success was tested.

Dataset

When creating the dataset of object images, their features are extracted using digital image processing methods (Qadri *et al.,* 2021). When necessary, the data set can be improved by applying optimization methods on these attributes (Aslam *et al.,* 2022). The dataset used in this study consists of data from 425 eggs. In the dataset, 88 of these eggs belong to the Large (L) class, 209 to the Medium (M) class, and 128 to the Small (S) class. Image of each tray was obtained by the image acquisition system and the features of the detected eggs were recorded in the dataset after the image processing steps were applied. The dataset contains 5 real features for each egg, as well as the L, M, and S class information for each egg (Table 1). Minor, Major, Box Perimeter, Area, and Contour Perimeter data were used as egg features (Tekin, 2023). In this study, for the accuracy of classification, sample eggs from the L, M, and S classes were selected and their weights were measured and verified.

Table 1 – Eggs dataset details.

Dataset	Dataset feature	Attributes	Categories	Sample Counts by Category	Total Sample Count
		- Minor axis	Large(L)	88	
		- Major axis			
Eggs dataset	Real	- Box perimeter	Medium(M)	209	425
		- Area			
		- Contour perimeter	Small(S)	128	

Major and minor axes are significant size detecting attributes for the model. Area supplies sensitive information about egg size to determine categorization. The sum of the tangent quadrilateral constitutes Box perimeter, and the egg boundaries constitutes the Contour Perimeter values. The attributes of an egg used in this study, are shown in Figure 3.

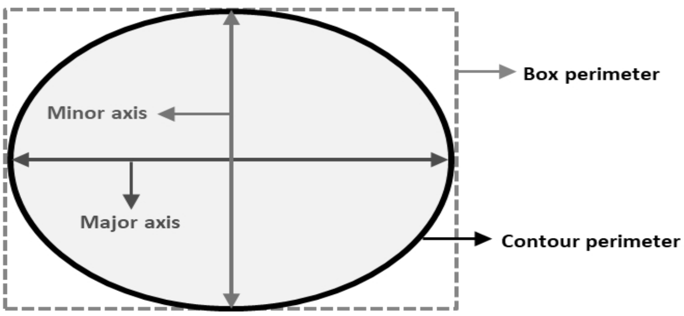


Figure 3 – The attributes of an egg.

The attribute values of 12 eggs randomly selected from the dataset used in this study are shown in Table 2. In the table, it can be seen that the Minor axis attribute values of the eggs are between 36.93 and 43.65, the Major axis values are between 37.27 and 45.84, the Box perimeter values are between 232.14 and 282.13, the Area values are between 4,288.27 and 6,333.45, and the Contour perimeter values are between 248.35 and 302.05.

Chicken egg sizing classes vary depending on the chicken breed, feeding methods, and countries (Orville *et al.,* 2021). In this study, the average values for the L, M, and S classes were based on an European Union report (European Union, 2023). In this report, eggs are divide in 4 categories according to their weight: XL (Very Large), L (Large), M (Medium) and S (Small). XL eggs have weights of 73 g or more, L eggs have

Table 2 – Examples of actual records and attribute values within the dataset (Tekin, 2023).

Egg Code	Minor axis	Major axis	Box perimeter	Area	Contour perimeter	Class
egg-373	40.81	41.25	257.11	5,260.28	274.25	M
egg-2	43.06	45.84	276.57	6,086.84	295.81	M
egg-30	36.93	37.27	232.14	4,288.27	248.35	S
egg-31	39.64	39.70	247.69	4,882.03	264.84	S
egg-383	41.35	41.81	259.91	5,375.26	277.91	M
egg-6	45.04	45.62	282.13	6,333.45	302.05	L
egg-325	37.27	37.79	234.63	4,380.79	250.94	S
egg-8	41.45	41.55	258.80	5,329.71	277.32	M
egg-206	41.49	42.02	261.02	5,421.60	279.32	M
egg-10	43.85	44.53	276.78	6,095.95	295.56	L
egg-83	39.25	39.75	244.36	4,751.66	262.25	S
egg-424	43.65	45.39	278.89	6,189.25	297.56	L

weights from 63 g up to 73 g, M eggs have weights from 53 g up to 63 g, and S eggs have weights under 53 g (Table 3).

Table 3 – Grading of eggs (European Union, 2023).

Categories	Egg Weights Gram(g)
XL (Very Large)	73 g and more
L (Large)	From 63 g up to 73 g
M (Medium)	From 53 g up to 63 g
S (Small)	Under 53 g

Morphological Operations

Mathematical morphology is used in image processing for tasks such as image filtering, edge detection, object shape extraction and determination of the boundaries of moving objects, proportional resizing of objects within images, merging and separating objects, and reducing noise in images. Dilation and erosion are fundamental operators in mathematical morphology (Cheng, 2009). Dilation and erosion image processing operators have been successfully employed in various fields, such as healthcare, agriculture (Çelik & Tekin, 2020), health (Saturi *et al.,* 2023), industry, security, and automatic detection systems for image processing (cleaning and correction). They are particularly widespread for correction and cleaning operations on videos or images to obtain high-quality visuals (Guo *et al.,* 2021).

Dilation and erosion operations limit unnecessary calculations by confining pixels that have actual effects on the objects in the image. In most applications, morphological operations like dilation and erosion are performed sequentially (Bao *et al.,* 2009).

In this study, operations conducted on egg tray images and egg images are shown in Figure 4. In the initial step, the colored image is converted to a binary (black and white) image format using a threshold value (Figure 4a and Figure 4b) (Tekin, 2023). In the second step, the erosion process is applied to remove unwanted pixels and contact points between eggs on the image (Figure 4c). In the third step, dilation is applied to adjust egg boundaries (Figure 4d).

Erosion process

When the erosion operation is applied to an image, the white-colored area of the object in the image decreases, and the edges of the object become thinner. In erosion, redundant white-colored small pixels on the image are removed.

In the erosion process, a kernel matrix, often in the form of a 3x3 matrix, is applied over the source image. While scanning this kernel matrix over the image, the minimum pixel values at positions overlapping with the kernel matrix are calculated, and the pixel in the source image is replaced with the minimum value obtained. The application of the erosion operation on an image is illustrated in Equation 1 (OpenCV, 2023).

$$dst(x,y) = \min_{(x',y'):\text{element}(x',y')\neq 0} src(x + x', y + y') \quad (1)$$

When erosion is applied to a binary image, it reduces the white areas and increases the black areas.

Dilation process

The process of edge dilation on an image is commonly used in morphological operations aimed at enhancing the image quality within objects (Singh *et al.*, 2017). The dilation operation is employed on binary images to expand the boundaries of the foreground or white pixels (Mukherjee *et al.*, 2017). This process thickens the edge area of the image and is frequently utilized to optimize image performance and sharpen the edges of lines (Moses, 2019; Liyin Z. & Chen, 2011).

In the dilation operation, a predefined kernel matrix (often in the form of a 3x3 matrix) is applied to the source image. While applying this kernel matrix over the image, the maximum pixel values at positions overlapping with the kernel matrix are calculated, and the pixel in the source image is replaced with the maximum value obtained. The application of the

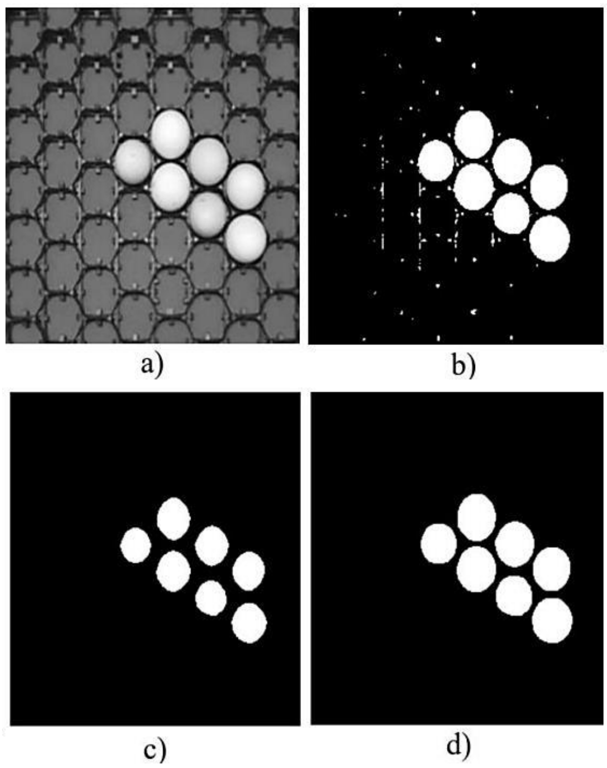


Figure 4 – Application of erosion and dilation processing on the egg tray image. a) Egg tray image b) Binary image c) Results of erosion processing d) Results of dilation processing (Tekin, 2023).

erosion operation on an image is illustrated in Equation 2 (OpenCV, 2023).

$$dst(x,y) = max_{(x',y'):\text{element }(x',y')\neq 0} src(x + x', y + y') \quad (2)$$

When the erosion operation is applied to a binary image, it results in a decrease in the white (bright) regions and an increase in the black regions.

Hough Transform Algorithm

The Hough Transform method was developed by Paul Hough in 1962 (Hough, 1962). Hough Transform is used for detecting objects expressed mathematically on digital images (Çelik & Tekin, 2020). This algorithm effectively works to detect lines, circles, and irregularly shaped objects in images.

Computerized automatic circle detection systems designed to fulfill human needs use the Circle Hough Transform algorithm. They can also handle learning materials in educational processes for individuals with special requirements (Fachruddin & Buliali, 2022). Furthermore, this technique is applied in tasks such as traffic sign detection, robot vision, iris localization, points of hand-drawn sketches, and automatic inspection of manufactured products and components (Le & Duan 2016). It is also utilized in agriculture for applications like crop and seed counting (Çelik & Tekin, 2020).

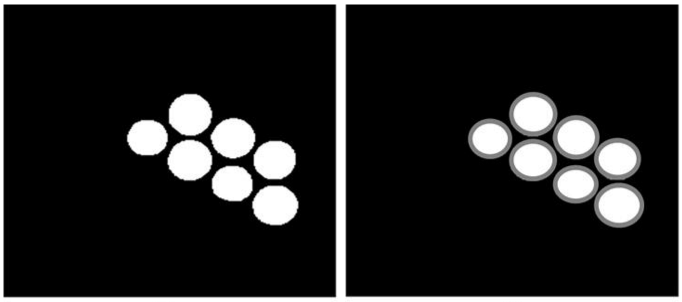
Circle Hough Transform algorithm evaluates three parameters: the center coordinates (a, b) of the object within the image and the radius "r" (Li & Wu 2020). In the initial stage of algorithm application, the image should be converted into a binary (black and white) format using a threshold value.

Initially, an edge map of the image is created, and an expected circle radius is determined to detect circular shapes. Circle Hough Transform is used to compare edge pixels by defining a parameter space (Hough space) representing the center of the circle, and circles are then detected by finding the local maximum of the parameter space (Le & Duan, 2016; Zhou, 2015; Ballard, 1981). Circle calculation using the Circle Hough Transform algorithm is shown in equation 3 (Le & Duan, 2016).

$$r^2 = (x_i - a)^2 + (y_i - b)^2 \quad (3)$$

The center coordinates of the circle are represented as (a, b), and the radius of the circle is denoted as "r". Each edge point on the circumference of the circle has coordinates ($x_i x_i, y_i y_i$). Assuming n points are selected on the circle, in the parameter space, by iteratively testing radius values, a three-dimensional matrix can be obtained by incrementing values corresponding to the dimensions of center coordinates and radius length (a, b, r). This process allows us to explore and populate the parameter space (Ballard, 1981; Çelik & Tekin, 2020).

In this study, the image processing methods applied to the images are shown in Figure 5. When the erosion and dilation morphological operations were applied to the egg tray image (Figure 5a), Circle Hough Transform algorithm was subsequently used, resulting in the successful detection of each egg, as shown in Figure 5b. For each detected egg, five attributes were extracted and recorded to the dataset.



a) b)

Figure 5 – Applying image processing methods to images a) Morphological operations on images b) Hough Transform algorithm on images.

SVM (Support Vector Machine)

Supervised machine learning methods use a number of features to predict outcomes when labeling outcome variables (Yu & Maruejols, 2023). In this study, SVM (Support Vector Machine) was used for the classification operation. SVM is a machine learning algorithm capable of performing both linear and non-linear classification tasks. It calculates the most suitable hyper plane for classification using the support vector method (Vijayaragavan, 2020; Demirel, 2022). In SVM calculations, classification is achieved by finding the maximum margin between decision planes that separate the classes. SVM can handle multi-class problems in addition to binary classification problems, often using the one-versus-all method (Asrol, 2021).

The SVM machine learning algorithm uses n training data points represented as x_i for training. The decision planes resulting from the classification of a training set using SVM algorithm are shown in Equation 4.

$$\begin{aligned} &y_i\,(x_i\,.w + b) - 1 \geq 0 \\ &y_i\,(x_i\,.w + b) + 1 \leq 0 \end{aligned} \quad (4)$$

In this context, N represents the number of examples in the training set, while x_i represents the feature vector of the i-th example, and y_i indicates the class of the i-th example. Moreover, w represents the weight vector of the data, and b is the bias coefficient. The class value, y_i, is in the range of $y_i \in \{-1, +1\}$.

The One-Versus-Rest (OvR) method is commonly used when dealing with more than two classes in SVM. In this approach, one class is considered as y_i = +1, while the other classes are considered as y_i = -1, and linear classification is performed. This process is applied to all classes, allowing the classification of test data. Figure 6 illustrates the schematic representation of egg classification using the SVM algorithm for the L, M and S egg classes.

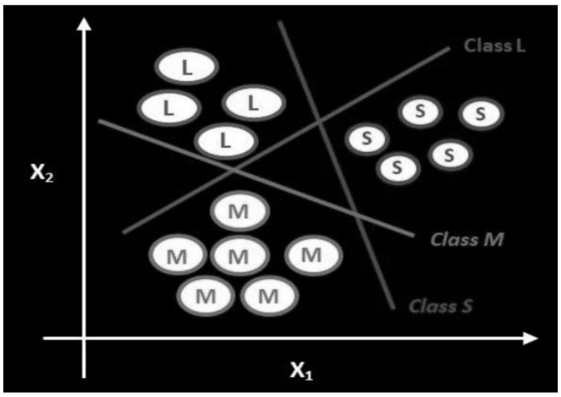


Figure 6 – Multi-egg classification by SVM algorithm.

RESULTS

In this study, out of a dataset containing 425 egg data, 318 data were randomly selected for training and 107 data were randomly selected for testing, and the classification performance was measured. In fact, 22 eggs of class L, 53 of class M and 22 of eggs of class S were used to test the classification success of the SVM machine learning algorithm.

The L, M and S classification success achieved according to the AUC (Area Under the Curve) success metric with the SVM algorithm is shown in Table 4. Using the SVM algorithm, L, M and S classifications were performed with success rates of 0.981, 0.967 and 0.993, respectively. The best result was achieved when classifying S, and the worst result was achieved when classifying M. The average classification success rate was found to be 0.980.

Table 4 – Classification success of the SVM algorithm according to the AUC metric value.

Class	AUC	Average of Classification Success
L	0.981	
M	0.967	0.980
S	0.993	

AUC classification success metric is derived from the ROC (Receiver Operating Characteristics) curve. In the ROC curve of a dataset, there is higher success if the vertical plane data is close to 1.00, the horizontal plane data is close to 0.00, and the area under the curve is large. Figure 7 shows the ROC success graphs of the L, M, and S classifications. The figures show a value of 0.15 when classifying L (Figure 7a), a value of 0.33 when classifying M (Figure 7b), and a value of 0.13 when classifying S (Figure 7c) in the horizontal plane. According to the result, it is seen that the SVM algorithm is fully stable. When the areas under the ROC curve plots are compared, it is seen that the S classification success with the SVM algorithm is higher and M classification success is lower. These results are in line with the ranking of results according to the AUC success metric.

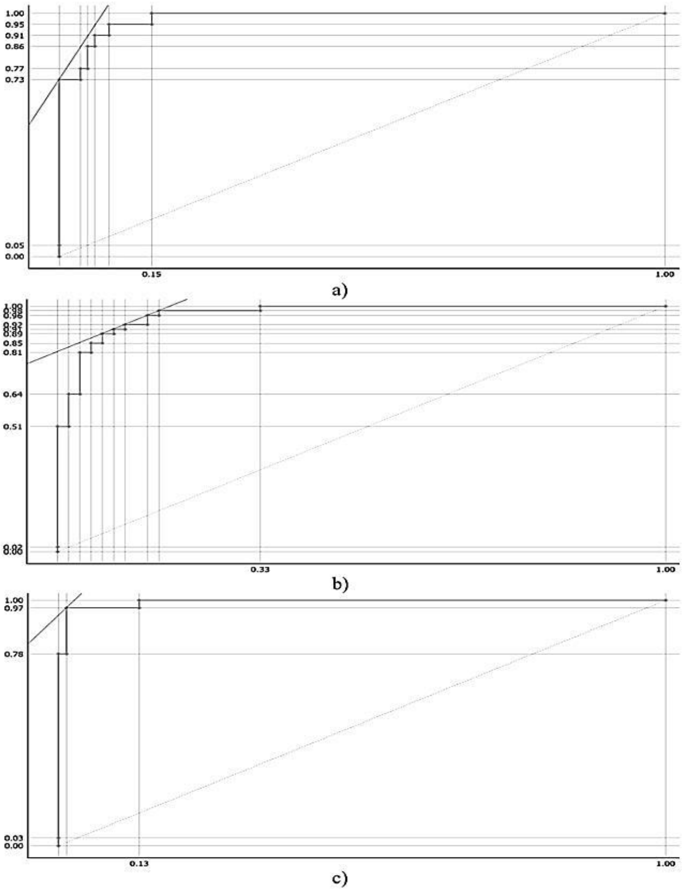


Figure 7 – ROC curves of L, M and S classification achievements obtained by SVM algorithm. a) ROC curve of classification L b) ROC curve of classification M c) ROC curve of S classification.

The correlation values and coefficient distribution degrees of the egg attributes in the dataset obtained as a result of the classification process are shown on Table 5. According to the results, it is demonstrated that the degree of correlation of L and S classifications is high. In the M classification, the degree of correlation is medium. In the L classification, the highest correlation was obtained by using the "Area" attribute with a value of +0.810, and the lowest correlation was obtained by using the "Minor" attribute with a value of +0.768. In M classification, the highest correlation was obtained by using the attribute "Minor" with a value of +0.351, and the lowest correlation was obtained by using the attribute "Contour Perimeter" with a value of +0.768. In the S classification, the highest correlation was obtained by using the "Minor" attribute with a value of -0.878, and the lowest correlation was obtained by using the "Box Perimeter" attribute with a value of +0.768.

Table 5 – The correlation values and coefficient distribution degrees of the egg attributes.

Class	Minor	Major	Box Perimeter	Area	Contour Perimeter	Degree of Correlation
L	+0.768	+0.789	+0.790	+0.810	+0.785	High Degree
M	+0.351	+0.336	+0.329	+0.314	+0.313	Medium Degree
S	-0.878	-0.861	-0.875	-0.876	-0.877	High Degree

The Violin Plot graphic showing the distributions of the attribute data used in the study is shown in Figure 8. In the figure, blue violin plots show the distributions of L, red violin plots show the distributions of M, and green violin plots show the distributions of the S class. The distributions of all attribute data of L and M class eggs are close to each other, and the density is high in the regions close to the median (middle) value. However, the results indicate the discrete data are more and are out of boundary data in the distribution of attribute data for S class eggs. It is also seen that there is more discrete data in the "Minor" attribute data in the data distribution of the S class.

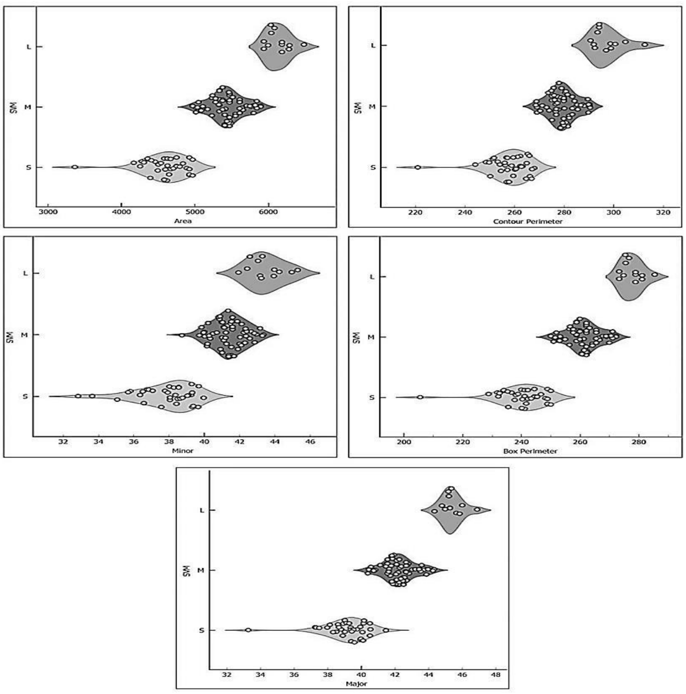


Figure 8 – Violin Plot distribution plots of Attributes in L, M and S Classification.

The figures shows that if the Median and Mean values are close to each other, the distribution of the data is not very discrete, and if these values are remote, the distribution of the data is very discrete. The box plot distributions of the median (middle value) and mean (mean value) values of the 5 attributes used in the study are shown in Figure 9. The figure shows the median and mean values of the attributes for each class. In addition, it is seen that the median and mean values of the attribute data of the L and M classes are very close to each other. Attribute results indicate that the median and mean values of the attribute data of the S class are very far from each other (discrete).

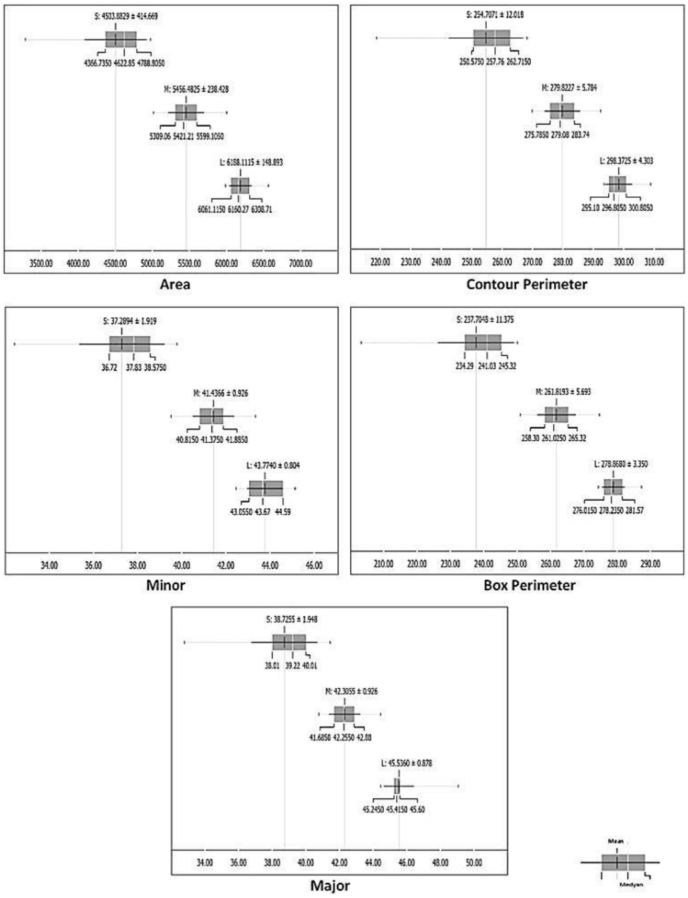


Figure 9 – Mean and Median values of attributes.

DISCUSSION

In recent years, there is an increasing number of studies on different egg classifications using both image processing and machine learning algorithms. In these studies, automatic intelligent systems have been used to perform the following tasks: detection of dirt and cracks on the egg surface, weight estimation, fertile-infertile classification, quality and size classification.

Ozan & Ceylan (2018) detected and classified the defects on egg surfaces using image processing techniques. In the study, images were obtained with a camera system and defect detection and classification operations were performed using an image processing algorithm running on a Raspberry Pi card.

Ab Nasir *et al.* (2018) designed an automatic egg classification system using computer vision methods. In the study, the features of egg images in black and white format, such as perimeter, large radius, small radius, and area, were extracted using the Matlab "regionprops" function. Using these extracted features, egg classification was performed using two methods, namely shape-based and weight-based. According to the results obtained, shape-based classification was found to be better.

Narin *et al.* (2018) obtained egg images using a camera system and processed the obtained egg images using the Matlab software. In the first stage, they detected egg surface cracks using the Canny Edge Detector, an edge detection algorithm, on images converted to Grayscale format. In the final stage, the authenticity of the crack image was verified using the Template Matching method. According to the results obtained, the success rate was determined to be 90%.

Ozan (2019) designed an embedded system that classifies eggs by analyzing egg images obtained from egg conveyor belts in a poultry farm. In the study, cameras were placed on egg conveyor belts to obtain egg images. These images were then measured using the algorithms developed to detect defects and cracks in eggs and to classify them by size.

Okinda *et al.* (2020) obtained images of 1,500 brown-colored eggs of different sizes using the Microsoft Kinect imaging system. In the study, feature extraction and Support Vector Regression (SVR), Gaussian Process Regression (GPR), and Artificial Neural Networks (ANN) algorithms were used to obtain the volume estimate of the eggs.

Ulaszewski *et al.* (2021) performed egg detection on images obtained from a moving egg conveyor belt system using template matching and neural networks algorithms. In the study, the algorithms were tested on CPU (Central Process Unit) and GPU (Graphic Process Unit) based systems, and faster results were obtained when using GPU.

Najem (2022) detected the effects of egg shape index on hatching process and chick quality. According to the results obtained, it was determined that the shape index has a direct effect on both hatching process and chick productivity.

Chiang *et al.* (2022) successfully performed the process of distinguishing between clean and dirty eggs in chicken cages using a real-time artificial intelligence (AI) recognition system.

Indra *et al.* (2018) designed a model to identify fertile and infertile eggs using the Otsu image processing thresholding method. In the study, a model of the egg detection system using image processing was designed to obtain information about fertile and infertile eggs. According to the results obtained, it has been shown that the fertile and infertile eggs of domestic poultry can be distinguished with the algorithm and method used in the study.

Paes *et al.* (2023) used a non-destructive method based on image analysis of egg shape to assess egg quality. In the study, the relationships between egg shape (SI) and quality characteristics were analyzed. For this, different machine learning models were tested to establish a relationship between shape and egg quality characteristics.

Moreover, Bumanis *et al.* (2023) developed a smart poultry management platform with egg production prediction capabilities. Subed *et al.* (2023) also detected eggs on the ground in cage-free chicken coops using the YOLO deep learning model.

When the literature is examined, some studies have been conducted using machine learning algorithms and image processing methods. The proposed study and the previous studies are compared in Table 6. In some of the studies, attribute information was provided, but no comparison or analysis was made in the literature.

Rachmawanto *et al.* (2020) applied an egg classification technique based on eggshell images using the k-nearest neighbor (kNN) algorithm. In the study, two feature extraction methods were used: extraction of Hue Saturation Value (HSV) color features and Gray Level Co-occurrence Matrix (GLCM). According to the results obtained, the highest accuracy of 85.71% classification was achieved when the parameter value was $k = 1$.

Omid *et al.* (2013) designed a fuzzy system to detect egg size and broken or intact eggs on images. After image acquisition, they used pixel elimination techniques to improve results. According to the results obtained, a 95.00% classification success was achieved.

Thipakorn *et al.* (2017) used image processing and machine learning techniques to predict the weight of a chicken egg and classify the egg size number using a single sample egg image. In the study, a brown chicken egg was candled, and its image was taken as input for the algorithm. The egg image region was separated from the background and 13 features were calculated from the geometric parameters obtained from the egg region. It was shown that the experiment provided

Table 6 – Comparison with previous studies in the literature.

Researcher	Method	Attributes	Success Rate	Classification
Rachmawanto *et al.* (2020)	K-Nearest Neighbor	Contrast Correlation Energy Homogeneity Hue Saturation Value	85.71	Good quality Rotten Defective
Omid *et al.* (2013)	Fuzzy System Classifier	Pixel Based	95.00	Egg size and Broken Intact
Thipakorn *et al.* (2017)	SVM Linear Regression	Egg perimeter Egg region Compactness Major axis Minor axis Egg shape Index length of diagonal lines	87.58	Egg size Weight prediction
Rahmat *et al.* (2023)	Histogram Analysis and ROI		93.7	Fertile Infertile
Waranusast *et al.* (2016)	SVM	Major axis Minor axis Egg Circumference Egg area Axis ratio Compactness	80.4	Egg size
Haoran *et al.* (2020)	SVM	Image processing	98.75	Egg crack No crack
Aragua & Mabayo (2018)	Computer Vision Algorithm	Major axis Minor axis	96.31	Weight estimates
Proposed study	Morphological processes + Circle Hough Transform + SVM	-Minor axis -Major axis -Box perimeter -Egg area -Contour perimeter	98.0	Egg size

an accuracy of 87.58% by using the Support Vector Machine (SVM) technique for egg size classification.

Rahmat *et al.* (2023) designed an egg classification system using thermal camera imaging to distinguish between fertile and infertile eggs. In the study, the image processing methods used were histogram analysis and the ROI method to define the thermal properties of different eggs. According to the results obtained, the method could distinguish between fertile and infertile eggs with an accuracy of 93.7%.

Waranusast *et al.* (2016) performed egg size classification using a reference (coin) with known dimensions. The features of the egg image were extracted, and the size classification was tested on the obtained data using the SVM machine learning algorithm. According to the results obtained; a 80.4% classification accuracy was achieved.

Haoran *et al.* (2020) obtained egg images using a computer vision system with a fixed light source. In the study, 200 egg images were first converted to Grayscale format and then a Median filter was applied. A sharpening operation was subsequently performed on these images to reduce noise. In the final stage, Threshold Segmentation and Closed operations were applied to highlight the crack region on the egg surface. The resulting images were then processed using the SVM algorithm to classify the eggs as cracked or not. The results showed that cracked eggs could be detected with an accuracy of 98.75%.

Aragua & Mabayo (2018) applied image processing methods to 15 egg images obtained from a camera system. In the study, the images were first converted to black and white color format and weight estimates were made by finding the short radius of the eggs. According to the results obtained, a success rate of 96.31% accuracy was achieved.

In this proposed study, it was seen that a 98.00% classification success was achieved, and it had higher success than other studies. More egg samples were used in the study and a dataset including egg attributes was created. In addition, image processing methods (Morphological operations and Hough Transform) and the SVM algorithm were used together. The proposed model achieved a high classification success rate, showing that the correct attribute values describing the eggs have been determined in the study. It could be observed that the image operations performed on the egg images contribute greatly to the calculation of the correct attribute values. According to the method used and the results obtained, it is seen that the developed model is different and more successful than other studies.

In the designed model, the egg images on the tray should be clean, and the eggs should not be dirty or cracked. Moreover, during the image acquisition phase, the ambient light should be constant and the reflection rate from the surface should be low. Otherwise, there is a possibility that the egg detection success will be low.

CONCLUSION

In this study, the classification of eggs into L, M and S in a hatchery production center was carried out by an intelligent automated system. In the study, image acquisition was performed using an image acquisition mechanism placed on the belt system used for the transportation of egg trays. Firstly, erosion and dilation morphological processes were applied to images of egg transport trays with eggs on them. After this process, each of the 425 eggs was detected with the Circle Hough Transform algorithm, their attributes were extracted, and these attributes were recorded in a dataset.

In the study, a correlation comparison of each of the attributes that affected success was made. According to the correlation comparison, the correlation was high in the L and S classification process. In addition, the median and mean values of the attribute data and the data distributions were compared. According to the data distributions, the attribute data in L and M classification were close to each other, but the attribute data in S classification were separated from each other.

In the study, 318 egg data were randomly selected for training, 107 egg data were randomly selected for testing, and a classification success test was performed with the SVM algorithm. As a result of the test process, L classification success was 0.981, M classification success was 0.967 and S classification success was 0.993. The average success rate of the 3 classification processes was 0.980. The results obtained show that this intelligent system designed based on machine learning can perform classification with a high success rate in the egg production sector.

In the future, the goal is to test the designed model on more egg data and prove its success. In the next stage, the product design application will be considered. At the last stage, it is planned to introduce the system to egg and white meat producers.

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CONFLICT OF INTEREST

The authors declare no competing interests.

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