Prediction Model for Chicken Egg Fertility Using Artificial Neural Network

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***Abstract*—Prediction of fertility status of chicken eggs is an important process in the hatchery industry. Currently, the Philippine poultry sector relies on the traditional manual candling procedure which is subjective and laborious. For these reasons, an attempt to improve to the candling procedure, reduce loss and establish a standard platform that classify the fertility status of chicken eggs was conceptualized. The primary objective of this endeavor is to create a predictive model for early detection of the fertility status of chicken eggs. An experimental the imaging system set up was constructed to captures the image of a five (5) day old chicken egg without damaging the eggshell. A total of one hundred fifty (150) images were transferred to a computer. Images were pre-processed and undergone the color segmentation process in order to extract the color space parameters. One hundred (100) out of the one hundred fifty (150) images were fed directly into the classification algorithm. Matlab R2018a neural network toolbox was used, specifically the pattern recognition to train the dataset. Results of the accuracy of the system was shown in the confusion matrices, training is 98.6% accurate while validation accuracy is 93.3 % and testing has an accuracy of 93.3%. The predictive model has an over-all accuracy of 97%. The remaining fifty (50) chicken eggs were used in the final testing. Result of the comparison also revealed that the predictive model has a lower mistake ratio compared to the prediction made through manual candling process.**

Keywords-egg fertility; neural network; image processing; color space; pattern recognition

I. Introduction

Chicken egg is one the most important product in the poultry sector and a major contributor in the Philippines agricultural and economic sector. One of the challenges that concerns the poultry industry is the early fertility detection in chicken eggs. Local poultry owners rely on the traditional candling procedure of determining egg fertility by examining the egg against a light bulb. An opaque egg is a fertilized egg but if the egg seems to have a translucent color it is otherwise. Therefore, if the egg is fertile it should undergo incubation period and is expected to hatch after several days. Hence, this practice requires several years of experience and judgement could sometime be subjective. For these reasons, the need for resolving the prediction technique as explanatory variables would be of great impact in establishing standards for the poultry industry.

Several studies have attempt early detection of fertility status and prediction of embryo development by using near-infrared hyperspectral imaging[1], hyperspectral imaging[2], spectral and imaging information[3], ultrasound[4], dielectric properties[5]visible transmission spectroscopy[6] and machine vision[7],[8]. Different experimental set-ups and analysis were employed using hyperspectral imaging. The study by [1] use the hyperspectral imaging technique in order to detect the developing embryo during the first three (3) days of incubation of hatching eggs. The classification model was developed using the Mahalanobis distance (MD). The model managed to obtain an accuracy of 100% on the second and third day of incubation. However, the study was only limited to a sample size of twenty-four (24) fertile eggs. Likewise, the study by [2] also use the hyperspectral imaging system to collect transmission images days 0 up to the third day of incubation of the eggs. The study collected a total of ninety-six (96) images from 400 to 900 nm to determine the fertility status of the eggs. Results showed that day 0 and day 1 has an accuracy of 91.7% and 95.8% while second and third day obtained a 100% accuracy using the Mahalanobis Distance. Furthermore, related study by [3] explains that hyperspectral imaging technology using wavelength between 400 and 1000 nm could be used to distinguish infertile and fertile eggs. The dimensionality of the image-spectrum fusion of the information was reduce to six (6) principal components using the Principal component analysis (PCA). Data were trained using the Support vector machine (SVM) and yields an accuracy rates 84.00%, 90.00% and 93.00% respectively. Similarly, other methods such as visible transmission spectroscopy [6] using the spectra 500–750 nm was used to develop a non-destructive detection system for egg fertility. It uses 165 broiler hatching eggs samples with light brown-shell. Multivariate analysis ere used to analyzed the dataset. Results obtained using the k-means clustering has a classification accuracy of 100% for infertile eggs and 96% for fertile eggs during the 96 hours of incubation. Meanwhile, LDA and SVM classification models achieved a classification accuracy of 100% for both fertility status of eggs. In the study of [4], a non-destructive imaging system was developed in capture images from six(6) different positions. The fertility status was predicted using the logistic regression method. The regression value was calculated to be 0.8675. Machine vision was also used by [7] and [8] in order to detecting fertility in early incubation. The image captured for the developing eggs during the third and fourth day of incubation was used in this. The histogram shape parameters of the images were fed to the algorithm and was able to obtained accuracies of 88 to 90% on the third day of

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incubation and increased to 96 to 100% during the fourth day of incubation [7]. Likewise, same methodology but different algorithm was used in [8]. Captured images of fertile and infertile eggs were fed to the neural network to train the data of different in gray level histograms at early incubation stage. A machine vision system with a suitable backlighting was used to take pictures of eggs at second, third and fourth day were. Results attained the following classification accuracies for the testing sets: 67.6% at the second day of incubation, 93.5% at third day and 93.9% at the fourth. Meanwhile, the study of [9], reveals that neural network using the backpropagation algorithm is an effective tool in object recognition and identification coupled with image processing techniques such as image segmentation. Images were-preprocessed to obtain the information to be used as inputs in the learning process.

Accurate prediction of the fertility status of the egg before the incubation can yield a huge advantage in the production process. As stated earlier, there were different techniques and methods in determining the fertility status of chicken eggs, yet it is still necessary to establish a scientific approach that detect the egg fertility prior to the incubation. Since, technology offers a wide range of image processing tools and machine learning techniques that could pave the way in establishing a standard platform in identifying egg fertility prior to incubation.

The primary objective of this paper is to create an egg fertility status prediction model for the chicken egg using color space parameters and supervised machine learning tools. Specifically, it aims to use the color segmentation in image processing to extract the color information of different color spaces. Secondly, to use Artificial Neural Network (ANN) in and developing the predictive model. Lastly, it aims to assess the accuracy of the models in predicting the fertility of chicken eggs before the incubation process.

This study could improve the manual method which is time consuming, labor extensive, and it is subjective due to sight mistakes and exhaustion of workers during the detection process which affects the productivity. Likewise, attempts in automating the candling system [10] was also done, hence, no predictive model was used to determine the fertility status of egg. This study could provide initial step in developing concrete predictive models for several platforms in automating the candling system. Moreover, the presence of dead embryos during the incubation period could contaminate other eggs and yields greater loss to the poultry owner. Hence, it will be beneficial a develop a predictive model that could accurately determine egg fertility at an early stage to minimize energy loss, improved time efficiency of the incubator use and maximize handling cost.

The study was focused on developing a predictive model that could actually detect the fertility status of the chicken eggs. A total of one hundred fifty (150) chicken egg was used in this study. The samples were placed one by one inside a box with sides painted black to reduce the effect of ambient illumination. A bright LED bulb was used as light source and a 25-megapixel camera was used to capture the image. Image were processed using a licensed Matlab R2018a. The predictive model used the neural network toolbox in the learning process and development of the egg fertility detection classification system.

II. Materials and Methods

The experimental methodology employed in this paper was illustrated in Figure 1. The initial procedure begins by gathering one hundred fifty (150) chicken eggs that are consist of randomly selected fertile and infertile chicken eggs. The next stage was divided into two (2) major process which is image acquisition and manual candling process. After the image was acquired, it was pre-processed before the color space parameter were extracted. Next, the data gathered is fed to the neural network for the learning process. Lastly, after the training has reached an acceptable accuracy percentage, the training stops, and the model is developed. An evaluation procedure was also done in order to further validate the model accuracy.

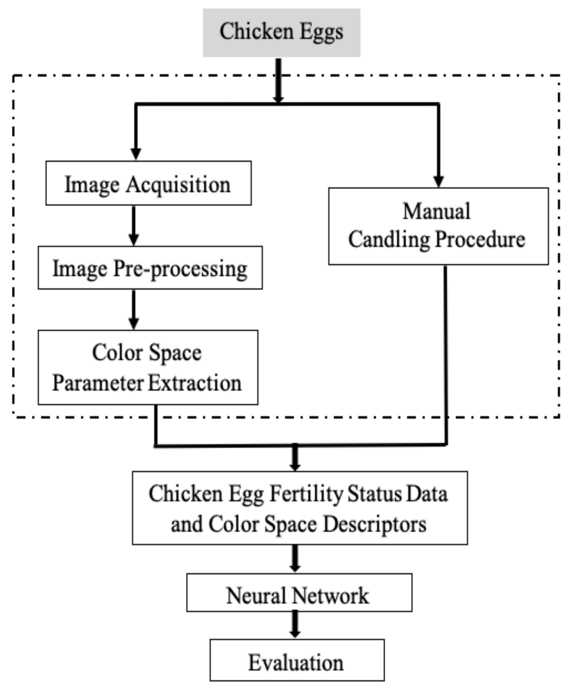

Figure 1. Experimental methodology.

A. Egg Samples

One hundred fifty (150) five-day old eggs were collected from a farm of free range chickens in Laguna. The samples were randomly selected and consist of ninety-three (93) fertile eggs and fifty-seven (57) infertile eggs as shown in Table I.

TABLE I. Distribution of Egg Eamples

Item	Fertile	Infertile	Total
Training	65	35	100
Evaluation	28	22	50
Total	93	57	150

After the eggs were candled manually and data were recorded, it was imaged and labelled, the eggs were placed into the incubator until the hatching period. A total of one hundred (100) randomly selected eggs was used for the learning process. A 70/30 ratio was used for the ANN with the following distribution: 70% training data set and the remaining 30% was allocated for testing and validation set. The remaining fifty (50) eggs were used for the final evaluation from which the new data is fed to the predictive model and results was compared to the manual candling procedure.

B. *Image Acquisition*

The experimental set-up used to acquire the image of the eggs was shown in Figure 2. A nine (9) watts bright LED bulb with a luminosity of 750 lumens was used of illuminating the eggs. The egg was placed inside a customized box made out of cardboard with the black surface inside. Holes were made on opposite side were the bulb and the camera lens were placed. A 25-megapixel camera with n aperture size of F 1.7, a focal length of 27 mm, a pixel size of 9µm and with phase detection autofocus. The camera is interfaced with a computer with a licensed Matlab R2018a.

Figure 2. Egg fertility classification system experimental set-up

C. *Image Processing*

The captured images were loaded to the Matlab software for image pre-processing and feature extraction. The initial step in processing a digital image is segmentation. Image segmentation is a process wherein an image is divided into different portions such that each portions is uniform but combining any two adjacent portions is not possible [11]. The segmented image could affect the image analysis as well as its quality. The color thresholding app was used to separate the background to the egg image. The different color spaces as well as the range for each channel of the color space were set, then the segmentation mask is returned in binary. The original RGB images is returned in the masked RGB and a composite of the masked image.. After the image is segmented, the mean of red, green, and blue color component were extracted by pixel using Matlab. The values of each color descriptor were taken as feature descriptor to be fed to the machine learning algorithm. The color segmentation algorithm used in the digital image is shown in Figure 3.

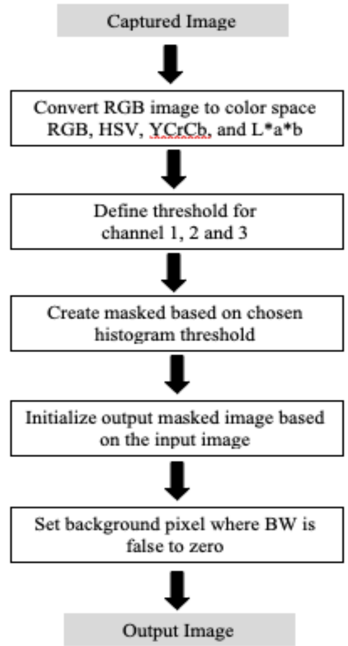

Figure 3. Color segmentation algorithm.

D. *Classification using Neural Network*

Pattern recognition is a common type of classification algorithm in neural network. It uses features or descriptors of labelled classes or categories to classify new samples by acquiring similar characteristics. According to [12], there were four (4) major steps in building an ANN model. First, inputs and outputs data of known class is organized and later on pre-processed. Next, this labelled dataset was divided into different portions for the training, testing and validation. Then the appropriate network architecture was selected and training process was applied on the datasets. Lastly, the trained network was evaluated in terms of performance. In this study the training of the neural network was done by using the nntool in Matlab R2018a. More specifically, the pattern recognition and classification function was used to create the predictive model, while the *sim* function was used for the actual simulation. Pattern recognition networks can be trained to classify inputs according to target outputs. The scaled conjugate gradient backpropagation algorithm was used to trained the network.

The neural network learning process uses the two-layer feedforward network architecture. It contain ten (10) hidden neurons. Dataset was composed of a 100 x 12 input matrix which contains the twelve (12) color descriptors for each sample, meanwhile the target matrix is a 100 x 2 matrix which indicates fertility status. The transcg function was used to train the dataset using the scaled-conjugate gradient algorithm. In the classification mode, the network and calculates the outputs for each existing input pattern.

E. Evaluation

The remaining fifty (50) egg samples were incubated and was used to verify the result of the classification model. Manual candling was done prior to the incubation as well as the image capturing. The eggs were labelled and was incubated until the hatching period.

Final evaluation was done by comparing the result of prediction made by the neural network classification model and the recorded data of the manual candling.

III. Results and Discussion

A. Characterization of Fertile and Infertile Eggs

A total of one hundred (100) chicken eggs images was used in this study for the learning process and the remaining fifty (50) images was used in the actual testing process. The eggs were of various shades of color and approximately the same sizes. The image of the eggs was segmented using the Matlab image processing toolbox using the color thresholding function to remove unnecessary region in the image.

This study uses color thresholding using the histogram of the four (4) color spaces: RGB, HSV, YCbCr and L*a*b*. Figure 4 shows the RGB color space image segmentation. The threshold values of the three (3) channels which stands for the red, green and blue component of the image where set. From the RGB representations, other color spaces can be derived by using linear or non-linear transformation.

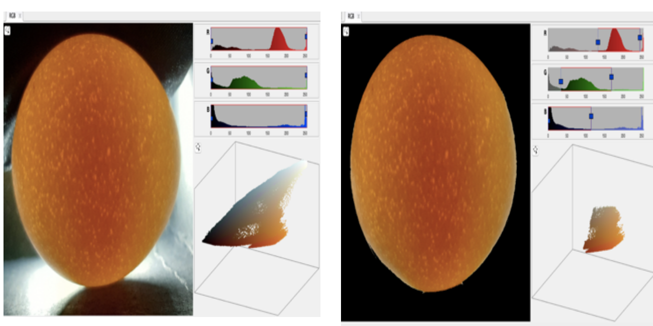
(a) (b)

Figure 4. RGB color space image thresholding (a) original image, (b) threshold image.

Result of the color image segmentation algorithm is shown in Figure 5. The color space for the RGB values of the color descriptors were extracted. Results illustrates that distinctive characteristics were observed in the color histograms of fertile and infertile eggs due to the manifestation of developing embryo for fertile eggs.

B. Color Space Parameter Extraction

Humans identifies colors as a combination of the three primary colors R (red), G (green), and B (blue). From the R, G, B, linear and non-linear transformation can be performed in order to generate other color spaces [11]. The mean RGB values in each segmented image using the four (4) color spaces were extracteed and tabulated in Table II.

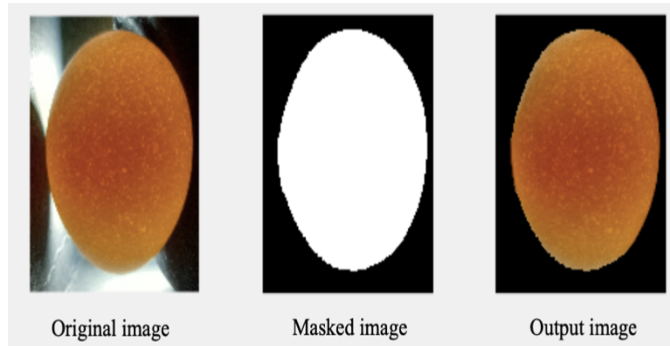

Figure 5. Color iamge segmentation algorithm output.

TABLE II. Mean RGB Values of Selected Samples

Sample No.	Fertility Status	Ave. Red Component	Ave. Green Component	Ave. Blue Component
1	fertile	254.12	136.22	31.02
5	not fertile	180.01	89.55	8.63
10	fertile	235.48	112.24	42.20
18	not fertile	174.67	78.12	10.01
23	fertile	246.15	126.01	21.03
35	not fertile	163.15	76.34	12.15
49	not fertile	146.12	78.20	9.05
57	fertile	251.96	129.11	43.01
62	not fertile	172.16	82.14	11.23
75	fertile	241.07	118.02	35.06
83	fertile	239.76	115.90	27.45
96	fertile	243.19	124.78	29.31

Figure 6. Egg fertility classification confusion matrices.

C. Nueral Network Classifier using Pattern Recognition

Figure 6 shows the classification performance accuracy of the neural network model. This reveals that network outputs are classifying accurately. the green squares and three (3) incorrect responses in the red squares. The training accuracy is 98.6% while the validation accuracy is 93.3% and testing has an accuracy of 93.3 percent. This yields an over-all accuracy of 97%. Results showed that out of the 100 egg samples there were ninety-seven (97) correct predictions of the egg fertility status.

C. Evaluation

The remaining fifty (50) eggs was used in the actual testing process. It was done by comparing the results of the predictive model with the prediction using the manual candling procedure. The summary of predictions was shown in Table III.

TABLE III. COMPARISON OF PREDICTION

Egg Type	**Candling Procedure**		***Actual Egg Hatch***
	Manual	***ANN Model***	
Fertile	34	28	28
Infertile	16	22	22

Results revealed that the prediction model was able to predict the fertility status of a day 5 chicken egg prior to the incubation period. The model was able to have a 100% right ratio. Hence, the manual candling process shows a higher mistake ratio both in judging the fertile and infertile eggs.

IV. CONCLUSION

This study attempts to improve the manual candling procedure by developing a predictive model for determining the fertility status of chicken egg using color descriptors. The experimental methodology has three (3) major procedures which are the image pre-processing, feature extraction and classification. Images were pre-processed through color segmentation to separate the background from the area of interest. The color space parameters were successfully obtained and the mean RGB components of the four (4) color spaces were taken. The work was accomplished by training a set of RGB mean values as input data. A predictive model that was able to classify the fertility status of chicken egg was developed. Results of the ANN shows that the color information extracted from the four (4) color spaces could be used to predict the fertility status of chicken eggs.

The confusion matrix shows an over-all accuracy of 97 % in classifying one hundred (100) chicken eggs consist of fertile and infertile eggs. The evaluation also shows a remarkable result as revealed by a lower mistake ratio of the predictive model versus the manual candling procedure. This study suggest that color thresholding and color information could be used to reveal distinction among different kind of objects that needs to be classified.

V. FUTURE ENHANCEMENT

This paper suggest that color thresholding and color information could reveal distinction among different kind of objects that needs to be classified. Other features or descriptors may be considered on future studies to support the model.

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