Non-destructive Fertility Detection of Multiple Chicken Eggs Using Image Processing and Convolutional Neural Network

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Abstract. This paper presents a non-destructive fertility detection of multiple chicken eggs in incubation industry based on image processing technique and convolutional neural network (CNN). The aim of this research were to design and implement the system for simultaneously distinguish multi eggs infertilility from fertility one. LED light source setting up for illumining the 48 eggs, consisting of both egg types and randomly placed on a tray in dark box. In addition, a pre-trained CNN is performed to classify fertile and infertile eggs. All eggs is captured and processed to extract a region of interest (ROI) for each egg, generating large ROI egg images dataset which used to train and test the CNN model. A designed system is programmed using Python, operating on Windown7-64bit supported by OpenCV and Keras. Experimental results showed the accuracies for fertile incubated eggs detection between day 7 and day 9 reaches 100%. Meanwhile, eggs location has 100% of accuracy is also observed. Hence, the proposed technique are high reliability, high accuracy system and suitable to use in real application.

1. Introduction

Chicken production is the one of food industries which plays an important role to Thailand’s purpose to be the kitchen of the world, one of crucial government policy. Thailand produced the chicken products over 2.1 million tons in 2016, placing the top five largest countries in the world by exporting the chicken meat [1]. However, the most important factor of chicken production is the number of day-old chicks that supply to all scale of this industry’s operation. Incubation industry is the day-old chicks’ supplier, a significant factor that highly influences the chicken industry. Incubation industry is totally dependent on the fertility and hatchability of eggs. Fertility is a ratio of fertile eggs to incubated eggs, while hatchability refers to a ratio of fertile eggs that hatch to all fertile eggs [2]. Early detection infertile and absence of development eggs cloud allow hatcheries to improve hatching rates, saving incubator spaces, handling cost and preventing the spread of infections from exploder eggs [3]. Candling hatching eggs during incubation are convenient tool for analyzing poor hatches with recognizing the dead embryos or clear eggs. In this method, the light source is illuminated and sharpened to the eggs in dark box, resulting in the inner side of eggs can be visible and one can distinguish infertile eggs and early dead embryos from fertility one. If the inside of an egg is a black spot near the center alongside with some blood vessel, it is considered as a fertile egg, while the inside of an infertile egg is wholly clear without any blot [4]. Nowadays, the candling process is labor employing; the vast number of eggs are randomly candled about 5%. Nevertheless, the thousands of eggs per day
are checked by labors, leading to the loss of capability due to fatigue and sight mistake of employers. In addition, the separation between fertility and non-fertility of eggs must be operated by expert workers [5][6].

Recently, many researchers have been proposed the different methods for nondestructive automatic detection of fertile eggs. Although, the proposed methods using hyper spectral imaging [3][5][7], ultrasound [8], heart rate detection [9], oxygen flux detection [10], visible/near infrared transmittance spectroscopy [11] and thermal imaging [12], which are showed high accuracies and abilities to detect fertility in early, but those techniques are expensive and complicated. Low cost detecting fertility instruments using light-dependent resistor [13] and temperature sensor [14] has also been proposed. Like the methods that mentioned in above, the process for classifying between fertilized and non-fertilized of them are sophisticated. It can be seen that the automated systems using computer vision for detecting fertility have not only been obtained high accuracy, but also achieved low cost implementation [6][15][16]. However, only single egg can be inspected by the methods above. In spite of multi egg inspections simultaneously capability in ref [17], a low accuracy of 91.43% is obtained. Nowadays, the convolutional neural network is becoming more popular method to practically classify objects in image. Many researcher has been applied CNN in different fields, such as agriculture [18], medical [19], robotic [20], traffic enforcement [21] and so on. This paper presents multi fertile egg detection simultaneously based on image processing technique and CNN. The eggs location and sorting can be accomplished by image processing, producing resized images fed into pre-trained CNN model to classify between fertile and infertile eggs. CNN model is constructed by three convolutional layers and two fully connected layers. The following paper is organized as follows: overview of proposed model, eggs location and fertile eggs detection technique, experimental results and conclusion.

2. Overview of the proposed model

A block diagram of a proposed model demonstrates in Figure 1. Multi eggs are placed on a tray inside dark box. LED light source is illuminated and sharpened to all eggs under a tray, enabling the inner side of eggs can be visible. It should be noted that 48 eggs are placed on a tray with 6 rows and 8 columns, resulting the proposed system can be inspected all of eggs simultaneously. A HD webcam is then captured eggs image with resolution of 1280x960 pixels. Captured image can be removed the noises with 5x5 Gaussian average filter and eroded pixels with 7x7 mask, called preprocessing task. The canny technique is applied to find the edges of each egg in the preprocessed image. Then, the locations of each egg are achieved by Hough circle transform. However, the proposed sorting algorithm is taken to rearrange each egg’s location into correct order of rows and columns. It makes the detection system can be known in each location whether egg available or not. Each detected eggs area is cropped and resized corresponding to the size of input of pre-trained CNN model. Finally, the predictor classifies each egg images whether fertility or non-fertility, and label result related to eggs sorted location.

![Figure 1. Block diagram of the proposed model.](image-url)
3. Eggs location and fertile eggs detection

There are two main procedures of the proposed system for classifying between fertile and infertile eggs, each eggs location and fertile eggs detections. Image processing technique is applied to remove noise in acquired image and used Hough circle transform to locate each egg’s position. The sorting algorithm is also used in this step. To detect fertile eggs, the state of the art machine learning called convolution neural network, the one method of deep learning (DL) is utilized, in order to predict the eggs whether fertility or non-fertility. The deep details for both processes will be explained in sequence.

3.1. Each eggs location

Figure 2 illustrates pseudo code of the proposed technique to locate each egg in captured image. In each loop, RGB image showed in Figure 3(a) is captured and converted into gray color to remove its dimensions. Both 5x5 Gaussian average filter and 7x7 erosion mask are used to reduce the noises in gray image. Then, the filtered image shows in Figure 3(b) can be detected the edges using canny technique, demonstrating result showed in Figure 3(c). All circles in edged image can be extracted by Hough circle transform, producing difference center positions and radiuses for each circle. To remove the detected circle that might be the noises, hence the detected circles must have radiuses greater than expected values. The filtered circles can be numbered by compute Euclidean distant between detected center and expected center, expressing as

\[ DE_i = \sqrt{(cX_i - dX_i)^2 + (cY_i - dY_i)^2} \quad \text{when} \quad i = 1, 2, 3, ..., 47, 48 \]  

(1)

where \( DE_i \) presents Euclidean distant of circle index \( i \), \((cX_i, cY_i)\) and \((dX_i, dY_i)\) are the center position of expected and detected circle index \( i \), respectively. It should be noted that the expected centers had defined before compute \( DE_i \). Detected circle can be numbered with \( i \) number at which \( DE_i \) is minimized, indicating as

\[ \arg \min\limits_i (DE_i) = \left\{ i \mid DE_i = \min\limits_i (DE_i) \right\} \quad \text{when} \quad i = 1, 2, 3, ..., 47, 48 \]

(2)

The result of circle detection and sorting is illustrated in Figure 3(d). Next, region of interest (ROI) for each egg are cropped corresponded to rectangles’ position in previous step. Some example egg ROI image is demonstrated in Figure 3(e). Finally, each ROI images are resized related to the input size of CNN classifier, showed in Figure 3(f).

```
01: while true
02:   if exit then break end if
03:   Acquire RGB image
04:   Convert RGB image to gray
05:   Filtering gray with 5x5 Gaussian average filter
06:   Erode filtered image with 7x7 mask
07:   Detect edges in eroded image using canny
08:   Find all circles in edged image using Hough circle transform
09:   for cX, cY, radius in circles
10:     if radius > expected radius
11:       Sorting circle by comparing detected \((cX, cY)\) and expected center
12:       Crop gray image as rectangle ROI
13:       Resize cropped image
14:     end if
15:   end for
16: end while
```

Figure 2. Pseudo code of the proposed technique to positioned each egg.
3.2. Fertile eggs detection

The classification between fertilized and non-fertilized of eggs uses CNN classifier model, constructing by three convolutional layers and two fully connected layers showed in Figure 4. It can be seen that three convolutional layers are supported by rectifier linear units (ReLU) and max-pooling like sandwich, it can be enhanced learning process. The input image constitutes segmented eggs of 64x64x3 pixel resolution. The first and second convolutional layers use 5x5 filters and they has 64 filter, while the third layer uses 3x3 filter with 128 filters. The third convolutional layer generates pooled output and feeds into the first fully connected layers. The dropout ratio of 0.5 is added to the inputs of the second fully connected layer, preventing over-fitting during training process. The output from dropout is then sends into Softmax classifier to classify the input image is whether fertile or infertile egg. Softmax activation function provides statistic that shows the probability of both categories. More details of training process will be described in section 3.3.

![Figure 4. Architecture of the proposed classifier model.](image-url)
3.3. Training the classifier model
The model for classifying the eggs is trained by optimizing the multinomial logistic regression objective using stochastic gradient descent (SGD). By initializing both learning rate and decay to be $1 \times 10^{-1}$, while the number of epochs is defined to 30 and initialized the batch size equal to 32. The model is trained on Windows7-64bit with Intel CPU core i-7 2.0GHz processor, 8GB RAM, Python 3.7.3 and Keras 2.2.4 with Tensorflow 1.14.0 backend. The datasets to train the model consist of 313 and 603 images of fertile and infertile eggs, respectively. Meanwhile, the validation images have fertile eggs images of 75 and infertile eggs images of 95. Some fertile eggs images shows in Figure 5(a) and infertile eggs images are demonstrated in Figure 5(b). The best performances of both training and validation accuracies are 100%. It has training and validation loss of 0.1025 and 0.1147, respectively.

![Figure 5](image)

Figure 5. Some images dataset; (a) Fertile eggs; (b) Infertile eggs.

4. Experimental results
To verify performances of the proposed model in Figure 1, experimental has been setup illustrated in Figure 6(a). The 240 eggs comprise 45 fertile (7-9 days) and 195 infertile eggs that the CNN pre-trained model never seen before, are used to verify the model. The 48 eggs mixed with both types of eggs which are placed randomly positions on a tray. The detection process use the sources as training process explained in section 3.3. However, OpenCV 4.1.0 is applied to find each egg positions in location process. The proposed model shows 100% accuracies of both location and fertile eggs classification for 240 samples, separating to 5 times classification. It should be noted that fertile eggs detection accuracy is compared with the result that achieved by expert of fertile eggs classification. Some detected result image is shown in Figure 6(b).

![Figure 6](image)

Figure 6. Experimental; (a) Experimental setup; (b) Experimental result.

5. Conclusion
The classification between fertility and non-fertility of multi eggs is proposed in this paper. There are two main process, eggs location and fertile eggs detection. In location process, image processing technique is used to preprocessing image and cropped eggs ROI. The CNN pre-trained model is implemented for distinguish eggs non-fertility from fertility one. The experimental results show 100% accuracies of both location and fertile detection for 240 mixed sample eggs. In this paper, the fertile
eggs of day 7-9 are inspected and compared the results with expert. Experimental results showed that the proposed technique can be suitably applied to incubation industry. However, early classification between fertile and infertile eggs of day 1-6 will develop in the future.

6. References

[1] Chetchuda C 2018 Thailand industry outlook vol 20 (Bangkok: Krungsri research)
[2] King’ori A.M 2011 Kenya. J.Poul.Sci. 10 483
[3] Lui L and Ngadi M.O 2012 Canada. J.Food.Bio.Tech. 6 2053
[4] Ernst R.A, Bradley F.A, Abbott U.K and Craig R.M 2004 pub 8134 (California: University of California)
[5] Smith D.P, Mauldin J.M, Lawrence K.C, Park B and Heitschmidt G.W 2005 Proc. 11th Euro. Symp. On Quality of Eggs and Egg Products (Doorworth: Netherlands) p 176
[6] Mahdi H and Nacer F 2016 Iran. J.Comp.Intl.Syst. 9 850
[7] Zhu Z, Liu T, Xie D, Wang Q and Ma M 2015 Chaina. J.Agric & Biol.Eng. 8 69
[8] Eray O, Ilker H, Timur G and Banur B 2017 Turkey. Indian.J.Anim.Res. 51 322
[9] Lei G, Yuzhou H, Zhitao X and Jiangtao X 2019 Chaina. J.Appl.Sci. 9 1408
[10] Wang Q, Fu D, Ma M and Zhang T 2017 Chaina. J.Agric & Biol.Eng. 10 243
[11] Jun D, Xiaoguang D, Yanlei L, Yankun P, Kuanglin C, Cuiying V and Xiuying T 2019 (USAand Chaina). J.Coptr.Elttn.Argic. 157 471
[12] Chern-Sheng L, Po T.Y, Der-Chin C, Yih-Chih C and Chi-Hung L 2013 Taiwan. J.Coptr.Elttn.Argic. 91 94
[13] Said E.A, Wael M.E and Ahmed A.E 2018 Egypt. Misr.J.Ag.Eng. 35 199
[14] Tong Q, Romanini C.E.B, Exadaktylos V, McGonnell I.M, Berckmans D, Bahr C, Bergoug H, Roulston N, Guinebretière M, Eterradossi N, Verhelst R and Demmers T.G.M 2016 (UK, Belgium and Frence).J.Livst.Sci. 183 19
[15] Dehrouyeh M.H, Omid D, Ahmadi H, Mohtasebi S.S and Jamzad M 2010 Iran. J.Adv. Sci & Tech. 16 43
[16] Bhuvaneshwari M and Palanivelu L 2015 India. J.Eng.Tech & Sci. 2 64
[17] Lean S.T, Emmanuel J.G.E and Ralph L.L 2018 Proc. Int. TENCON (Jeju: Korea) p 701
[18] Koodtalang W and Sangsuwan T 2019 Proc. 1st Int. Symp. ICA-SYMP. (Bangkok: Thailand) p 183
[19] Sivaramakrishnan R, Sameer K.A, Mahdieh P, Kamolrat S, Hossain M.A, Richard J.M, Stefan J and George R.T 2018 (USA, Thailand, Bangladesh and UK). peerj.458
[20] Jinwang W, Wei G, Ting P, Huai Y, Lin D and Wen Y 2018 Proc. 21st Int. Conf. On Information Fusion (Cambridge) p 439
[21] Yogameena B, Menaka K and Saravana P.S 2019 India. J.IET.Intlg.Transp.Syst. 13 1190