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An Automated Egg Incubator with Raspberry Pi-Based Camera Assisted Candling and R-CNN-based Maturity Detection

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Abstract: This study focuses on developing an automated egg incubator with a camera-assisted candler for egg maturity detection of balut and penoy commercial duck eggs. The incubator is a four-layer chamber installed with a heater, fan, and DHT11 sensors. DHT11 sensors are interfaced with a Raspberry Pi 4 to observe and maintain the optimal parameters inside the incubator. Trays with built-in candlers made from fluorescent bulbs are placed per layer with a capacity of 20 eggs positioned on rollers. These rollers are programmed to drive every 8 hours for 5 minutes for the egg turning which is essential in incubating eggs. Cameras are installed to capture the images of the candled eggs on their 1st, 10th, and 18th day. The result will be shown on a monitor with a user-friendly GUI which will help the vendor to determine the condition and maturity of the eggs inside the incubator. A region-based convolutional neural network (R-CNN/RCNN) was used as the classifier algorithm for balut, penoy, and fresh eggs. The classification accuracy of the proposed system is 80.5%.

Keywords: Balut, Candling, Duck Egg, Egg Incubator, Penoy, Region Based Convolutional Neural Network (R-CNN)

1. Introduction

Balut is a famous delicacy which came from the Asian countries like China, Vietnam and the Philippines. It is a famous street food which is made of chicken or duck egg. It is a boiled fertilized developing egg embryo that is at least 18 days old and is commonly sold by many street vendors in the country [1]. Traditionally, eggs are incubated with the optimal parameters for it to develop properly but as the modern technology grows, artificial incubators are made to sustain more efficient environment for eggs. The eggs are incubated with the use of artificial incubator made for mass production. The status and classification of the eggs were known by candling the eggs. During this process, the eggs were exposed in a bright light to see the shadow casted by the embryo inside the egg. The eggs were candled one by one to classify the eggs properly. The only problem in the balutan industry is that candling process of eggs takes too long, and incubators often produces "abnoy" which is not profitable.

Incubation stimulates embryonic development which is essential in the process of hatching an egg. For eggs to be hatched smoothly and prevent it from dying, there are many factors to consider along the process. Several studies exhibited that the factors affecting the incubation process are namely the following: temperature, humidity, ventilation and egg turning [2], [3], [4], [5]. An artificial incubator should be able to stimulate and meet the optimum environmental conditions. One reason why egg do not hatch is because of overheating and underheating, since temperature is critical for the speed of their metabolic rate. Lack of moisture and turning is necessary because it can lead the chick to stick to the shell [6].

The advised parameters for incubating duck and chicken eggs are both 100^{o}F in temperature while 85-86 and 85-87 percent humidity, respectively. One more recommendation is to stop the turning process and open the vent after the 25th day for duck eggs and after 18th day for chicken eggs [2]. The demand of artificial incubator is for increasing the quality of eggs for the improvement of production for human consumption and economic market. In today's technology, control and automation of devices are accomplished using various techniques in electronics [7].

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Candling is a way to sight the yolk, white, and the air cell of an egg. It is also a way to observe the germ development, blood spots, bloody white and the meat spots. Another purpose of this is to determine whether an egg is fertile or infertile depending on the development of the embryo [8], [9], [10]. Egg candling is performed by making a box with a single hole, where the egg to be candled is placed. Inside the box is a high-powered light so that the light can penetrate properly into the eggshell. the egg candler will be placed in a dark room and it where the candling will be done [11].

In balut production, egg candling was done to monitor the growth of the eggs and also to classify which among the incubated eggs were balut or penoy. Through egg candling the producers can determine where are the "abnoy" eggs or these are the non-viable eggs, in which they can immediately separate it from those eggs that are incubated [12], [13], [14], [15], [16].

Previous work was made in the classifying of duck eggs. A neural network model in [17] was proposed which aims to classify the balut and reject eggs. It has an accuracy of 76%.

Another previous work [18] was conducted where its aim is to create a module for classifying the fertility of duck egg by using light received by the LDR on the eggs' candling process and then labelling the raw value, if the raw value is less than 399, then it is said to be balut and if its greater than 400 then it is penoy.

A similar study was also conducted which aims to classify whether the egg is fertile or infertile. The previous work [19] was conducted by having 5 days of trials that garnered them the accuracies of 47.13%, 81.41%, 93.08%, 97.37% and 98.25%. The researchers developed an algorithm called Dynamic Threshold funding which aims to find the suitable size for the indicators of fertility of an egg. For example, not all nerves of eggs are same in size, they may differ in sizes due to its age. But using this algorithm, they can find the proper value of its size and help in classifying eggs.

Users' established business rule is considered as a traditional data quality control method, but it limits the performance of the system since it is very time consuming and produces lower than desirable accuracy. A way to overcome these problems and provide greater products to the users, utilizing deep learning, advanced techniques and computing resources is implemented [20]. Image processing with the use of Convolutional Neural Network (CNN) has been the new trend for different types of image recognition [21]. With its system having the presence of human-like neurons, it was able to produce accurate results in testing subjects [22]. But with that being said, a CNN remains a challenging task with the lack of training database [21]. Deep learning algorithms' accuracy can be improved with the method of feeding high quality images in it [23]. Data accuracy is necessary because people tend to verify and review the quality of data to ensure that a device is effective and efficient [20], [23], [24]. As an example, a study in [25] used CNN for image classifying. They used 2000 egg images to train the CNN, resulting to the project's accuracy of 92.3% for the 89,000 test subjects. Even though image quality impacts the accuracy of CNNs, selected CNNs still improve the classification accuracy of eggs.

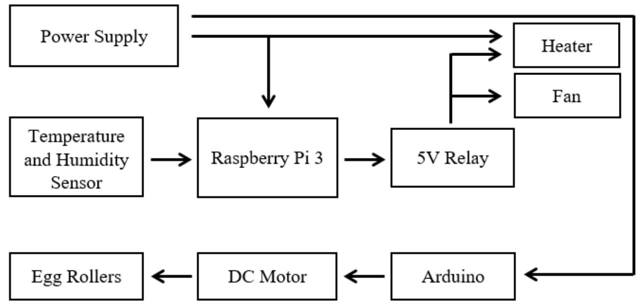


Figure 1. Incubator System's Block Diagram

This study aims to develop an automated artificial incubator that controls the parameters inside the chamber and the camera-assisted candling process for maturity detection to produce high quality eggs for the economic market of balut and penoy production. Moreover, it aims to construct a four-layer automatic artificial incubator that controls the temperature and humidity regulation, egg turning, ventilation and candling process using Arduino and to develop the camera – assisted candling apparatus for the identification of fertility and maturity of the eggs.

2. Methodology

A. Block Diagram

Figure 1 shows the block diagram of the incubation system. Here, the Raspberry Pi 4's objective is to automatically detect and regulate the temperature along with the humidity inside the incubator. By feeding the inputs in the microcomputer, the Raspberry Pi 4 will then analyze the given data and will trigger the relay that will make the heater and fan regulate the parameters depending on the readings. An Arduino powered by the 12V power supply is connected to a DC motor which drives the egg rollers for the egg turning.

Figure 2 shows the block diagram of the Candling System. Here, the power supply then carries power to both LED light bulbs and for the camera. A program would then be set to automatically let the Camera capture photos and it would be sent to the Raspberry Pi 4 for image processing.

B. Hardware Development

Figure 3 shows the hardware design of the incubator. The machine will have a height of 6ft, length of 4ft, and width of 3ft. Each layer consists of a fan visible on the left side and heater on the right side. It also consists of four DHT11 which serves as the temperature and humidity

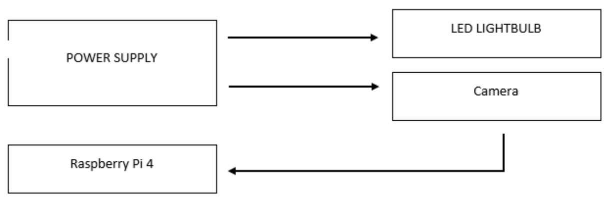


Figure 2. Candling System's Block Diagram

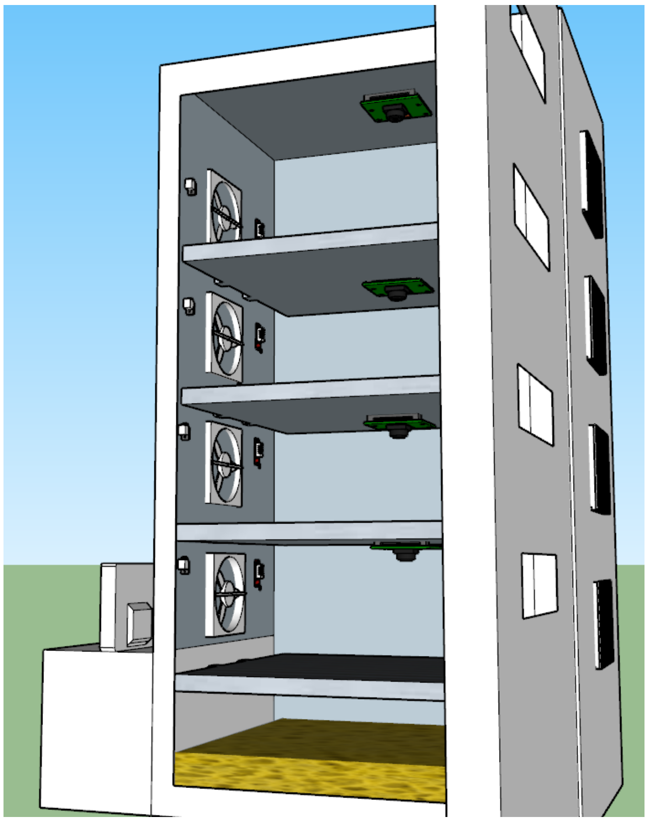


Figure 3. Incubator Prototype Design

sensors that were located on the left and right side. Two at the front, and the other two is at the back side of every layer which signifies the temperature and humidity regulation on the four quadrants of each layer. The camera is located on top of every layer at exactly 19 inches distant from the tray. The four fluorescent lamps beneath the tray is for candling. A layer made up of cardboard was placed on top of the light bulbs to serve as a tray for the eggs which can hold 20 eggs. The box behind the incubator is where the power supply and other wirings located.

C. Software Development

Python was used in implementing the convolutional neural network which is needed to perform the maturity detection of the egg. The candling process was done in the Raspberry Pi 4 where the maturity detection was depicted through a user-friendly GUI for an easy implementation of

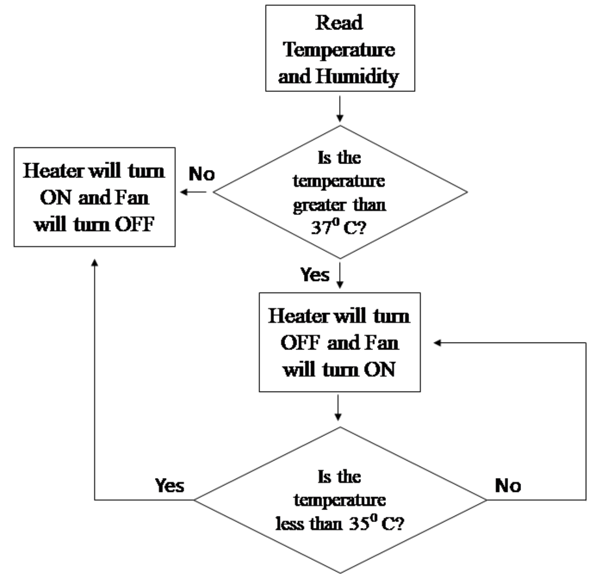


Figure 4. Temperature and Humidity Control Flowchart

the program. Raspberry Pi 4 was also used to automatically regulate the temperature and humidity inside the incubator. The egg rollers were programmed in an Arduino Uno to perform egg turning for every 8 hours.

1) Temperature and Humidity Control

Figure 4 shows the process of automatically controlling the temperature and humidity. From the start of the incubation, heaters are turned on until it reaches 35°C and then the temperature will be regulated between 35-37 degrees Celsius. In regulating the temperature, the temperature will be read by the sensors. If the temperature reading is higher than 37°C meaning it is too hot for the eggs, the heater will be turned off and the exhaust fan will be turn on to remove the excess heat. But, if the temperature is reading is below 35°C, the heater will be turned on and the exhaust fan will be turned off. Every reading will be displayed GUI so that the user will monitor if the incubator is properly maintaining the ideal temperature and humidity.

2) Egg Turning Control Program

Figure 5 shows the egg turning control flowchart, wherein it shows how the egg turning for both chicken and duck eggs is automatically controlled. Since this study only focuses on producing balut and penoy, the rollers will start and the egg turning will continue for 5 minutes straight. After 5 minutes, the turning will stop, and the system will wait for 8 hours before doing another cycle. This will make the eggs to be turned once in the morning, afternoon and evening. The process will continue until the eggs are mature enough and ready to be harvested

3) Egg Classification Program

Figure 6 shows the flowchart on how the program determines the maturity of the eggs by classifying it as balut,

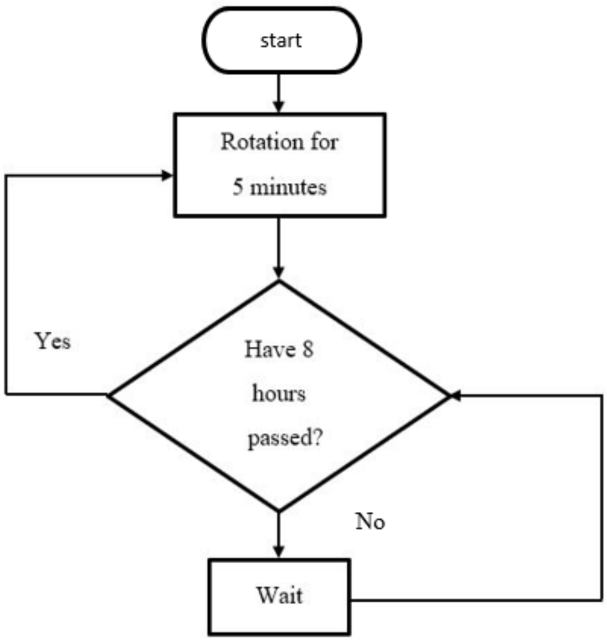


Figure 5. Egg Turning Control Program Flowchart

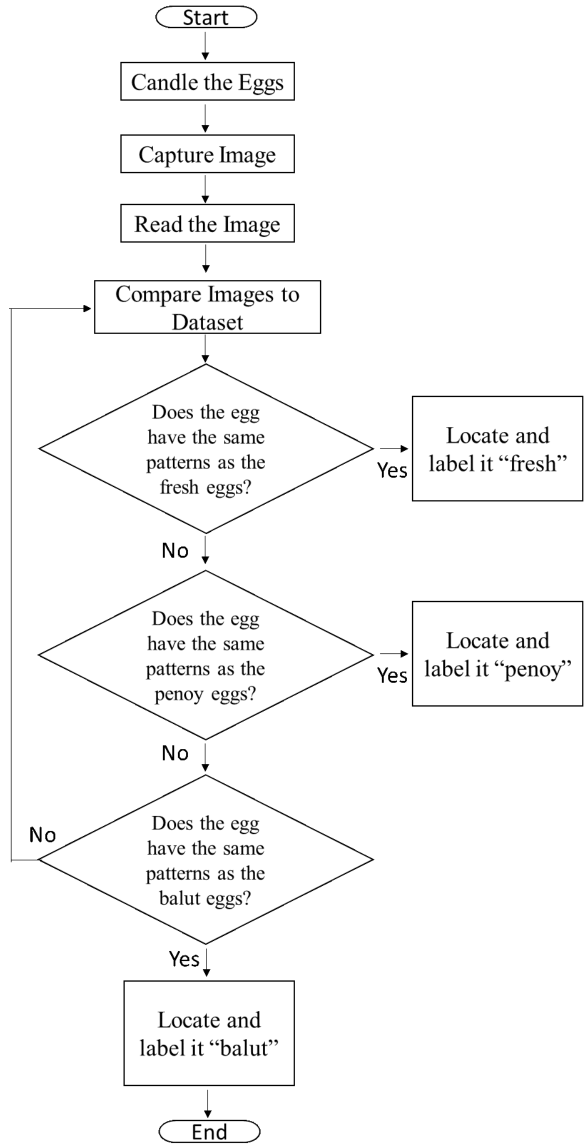


Figure 6. Egg Classification Flowchart

penoy or fresh egg. The program will start by reading the captured images when the eggs were candled and comparing it to the dataset learned by the program. With the use of Convolutional Neural Network, the patterns of balut, penoy and fresh eggs gathered in the datasets are the one being compared with the test images captured by the camera. Using R-CNN, the eggs that has the same pattern will be located and labelled as fresh, penoy or balut. In this case, the patterns on how dark the shadow of the egg determines its maturity. If the egg is very dark, it means that it has a developed chick/duckling inside, so it will give a sign that the egg is still growing so it will be classified as Balut. The lighter the color will mean that the egg is not developing thus it can be concluded that the egg with the lightest color will be determined as Fresh and the egg with a yellowish color will be classified as Penoy. The classification of the candled eggs will be displayed in the GUI so that the user can monitor the growth of the eggs and to verify whether the classifications are accurate.

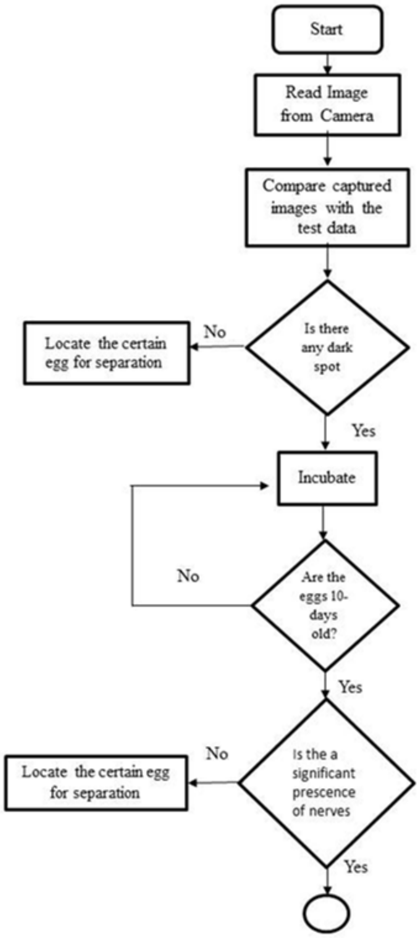
4) Fertility and Maturity Detection Program

Figure 7 shows a flowchart regarding how the program in the fertility and maturity detection will be executed using the camera-assisted candling apparatus. In the beginning, the images taken by the camera will be compared in the data set gathered. Fertility detection will start by detecting whether the egg has dark spot or shadows are visible on the egg while it is incubated which is an indication of fertility. Infertile eggs will be located for harvesting while the fertile eggs will be incubated for 10 days more days. The indication for the next detection is the development of the embryo. A presence of nerves is an evidence that the embryo is growing. As it grows, the shadow casted by the embryo becomes darker. If the egg is almost dark and fully covered by the shadows this means that the egg is matured enough to be harvested. Usually this occurs in the 18th day of incubation.

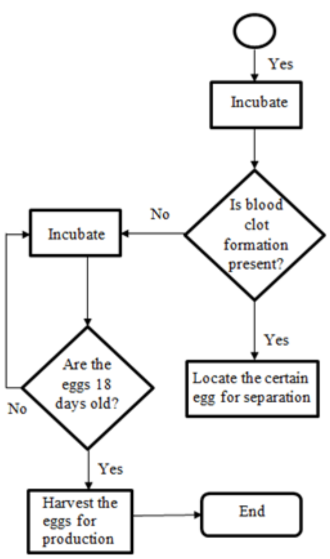
D. Design Implementation

Figure 8 shows the front view of the incubator. The incubator is 6ft high, 4ft long, and 3ft wide. The skeleton of the incubator was made of metal and covered with Hardiflex. It has four layers, and each layer is 18 inches high.

Figure 9 shows the setup in every layer of the incubator. The fan was placed in the right side and the heater was



(a)



(b)

Figure 7. (a) Fertility Detection and (b) Maturity Detection Program Flowchart.

Figure 8. Incubator Prototype

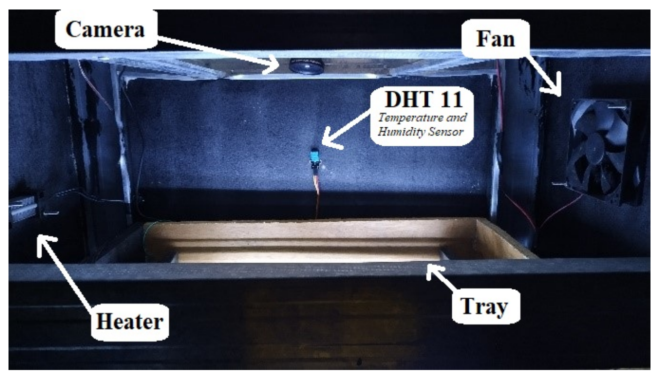


Figure 9. Incubator Interior Per Layer

placed in the left. The temperature and humidity sensors were placed in the four corners. The tray where the eggs will be placed is made of wood and it has a fluorescent lamp installed inside it.

E. Prototype Testing and Data Gathering

Figure 10 shows the process of labelling the data gathered from using the automated-candling machine. In the image, it is visible that the eggs were classified into three classes namely fresh, balut, and penoy. The process of data gathering involves many pictures taken while the eggs were being rotated to ensure no bias when it comes to the other side of the egg. The eggs used in data gathering are the eggs classified in the farm and its classification were used in labelling the eggs.

Table I shows the number of images that were used as a dataset. The classification was pre-known and were

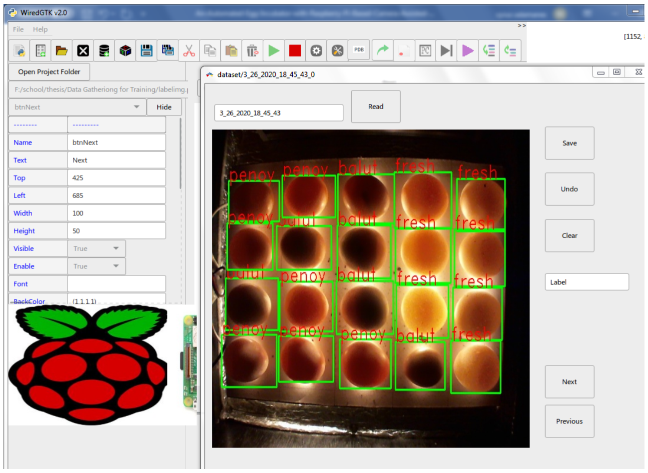


Figure 10. Data Annotation for Machine Learning

classified as to how they look when candled. Logitech model C525 with features such as enabling 720p video record, having 30 fps and having a field of view of 69º for a wider range.

Figure 11 shows how the images were processed to be trained. The captured image would then first undergo Image Annotation, or each image will be labeled on each feature which makes it different from each other. For example, the black spot on the first day is one sign which is labeled. Hyperparameter tuning was executed to find an optimal or balanced combination of parameters. Feature Extraction for Region-based Convolutional Neural Network (R-CNN) which is done by Raspberry Pi was utilized for getting features instead of numbers and using them as the dataset and training. 90% of the images were implemented for training and the remaining 10% were used for testing and validating.

3. Results and Discussion

A. *Efficiency of the Incubator*

During the incubation process, the temperature regulation was monitored from day 1 to 18. Figure 12 shows the regulation of the temperature in one incubation of eggs. Data shows that the incubator was able to maintain the temperature within 35 to 37 degrees Celsius daily which is the optimal level.

B. *Traditional Candling versus Automated Candling*

Figure 13 shows the development of the embryo from day 1 to 18. Based on the figure, the indicator that there is a growth, is the darkening of the egg. The egg which has the darkest color is classified as balut, the darker shade is the penoy, and the lightest shade of the egg is the infertile egg or fresh egg. It can also be seen that the 20 eggs are arranged in 5 rows and 4 columns so that it is easier to arrange, classify and locate the eggs.

Figure 14 shows the User Interface used in automatic candling of eggs. In the GUI, the temperature inside the in-

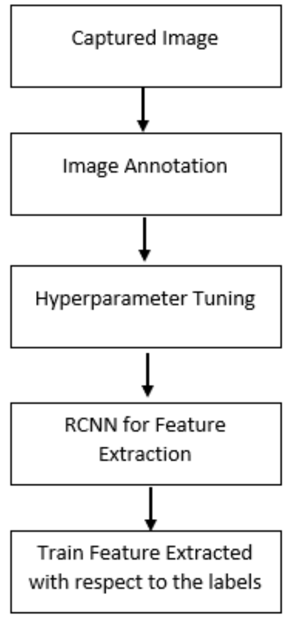


Figure 11. Image Training

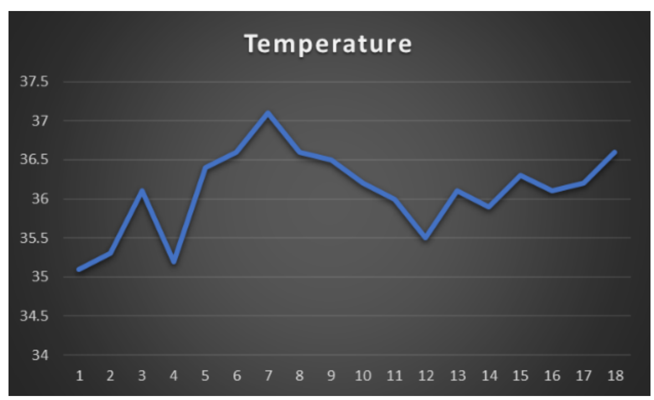


Figure 12. Temperature Readings from day 1 to 18

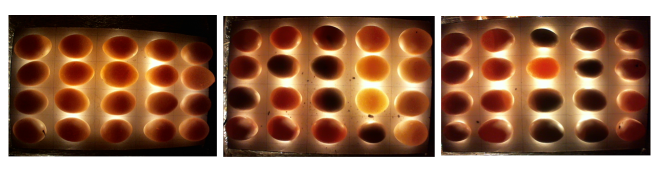


Figure 13. Growth of the embryo from day 1 to 18

TABLE I. Number of Images Used as Datasets

	Datasets Gathered			
	6 Balut, 7 Penoy, 7 Fresh Eggs	5 Penoy, 15 Fresh Eggs	5 Balut, 15 Fresh Eggs	Total
Number of images	13	60	363	436

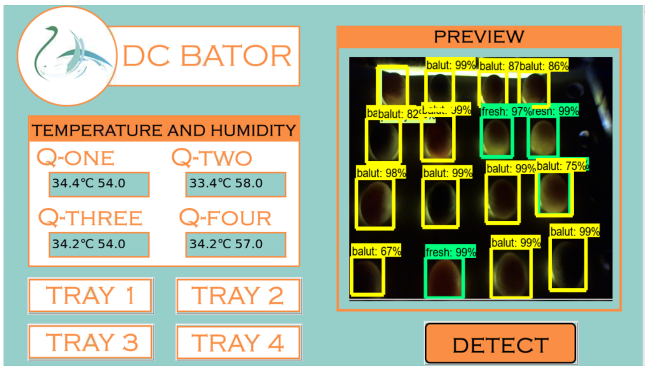


Figure 14. User Interface for Automated Candling

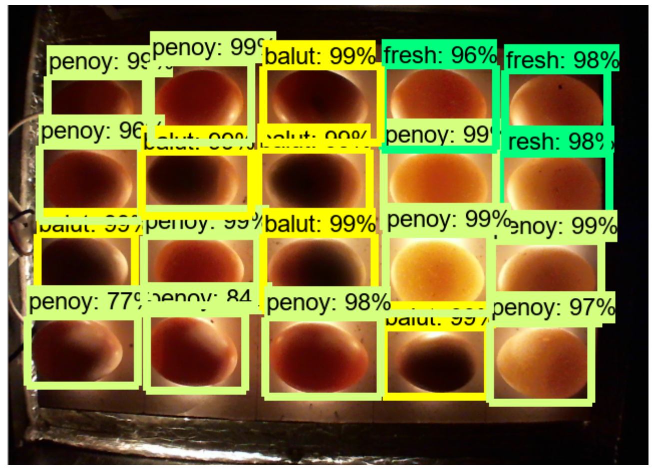


Figure 15. Automated Candling

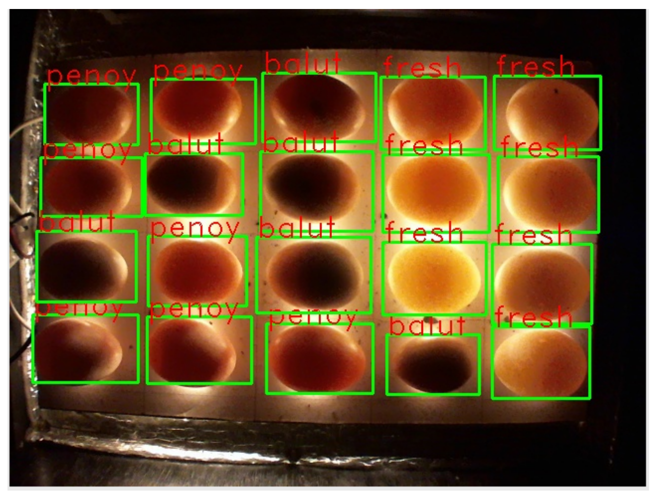


Figure 16. Manual Candling

cubator is displayed. The buttons named with tray numbers will be clicked and the corresponding temperature and real-time preview will appear. By clicking the detect button, it will capture the image and show the classification of each egg.

Table II shows the difference between the time it takes to candle the eggs manually and automatically. It shows that automatic candling of eggs is 60 times faster than manual candling of eggs since, manual candling was done individually while automatic candling is done per tray.

Figures 15 and 16 show the classified eggs using the manual candling, and automatic candling. In the manual candling, the eggs were classified and labelled manually. In automated candling, with the convolutional neural network, each egg was automatically labelled as fresh, penoy or balut. After the eggs were classified the results were tabulated and being compared with the manual candling.

Table III shows the tabulated format of the candling results using the manual and automated candling, which was compared manually to determine the accuracy of the automatic candling process.

Table IV shows the accuracy of the automatic candling process. The incubated eggs were candled ten times having different setups. Based on the gathered data it shows that the accuracy of the automated candling apparatus is 80.5%.

Lastly, Table V shows the comparison between the previous works, [17], [18], [19] and the proposed system. Given that the system needs to determine three classifications of eggs, it is seen that it has a partially greater accuracy than the previous study. With only 436 data sets, the device already shown a promising performance which can be optimized by adding more images. The classification accuracy for balut and rejects only is 76% while for the proposed system which classifies balut, penoy, and fresh eggs is 80.5%.

4. Conclusion

Based on the tests and data gathered, the automated egg incubator with camera-assisted candling apparatus can be a good alternative or replacement for the traditional egg incubator and usual process of candling eggs in balut production, for it is a four-layered automated artificial incubator that has the capability to incubate the eggs properly since the temperature is properly regulated and eggs are properly

TABLE II. Trial for Patient's Data with Diabetes

Manual Candling		Automatic Candling	
Egg No.	Time (s)	Egg No.	Time (s)
1	3	1	
2	3	2	
3	3	3	
4	3	4	
5	3	5	
6	3	6	
7	3	7	
8	3	8	
9	3	9	
10	3	10	1
11	3	11	
12	3	12	
13	3	13	
14	3	14	
15	3	15	
16	3	16	
17	3	17	
18	3	18	
19	3	19	
20	3	20	
Total	60	Total	1

TABLE III. Automated vs. Manual Candling

Manual Candling					Automatic Candling				
P	P	B	F	F	P	P	B	F	F
P	B	B	F	F	P	B	B	P	F
B	P	B	F	F	B	P	B	P	P
P	P	P	B	F	P	P	P	B	P

TABLE IV. Candling Accuracies Per Trials

Trial No.	Accuracy
1	80%
2	85%
3	80%
4	75%
5	80%
6	80%
7	80%
8	80%
9	85%
11	80%
Average	80.5%

TABLE V. Comparison Between Previous Works and This Work

Parameters	[17]	[18]	[19]	This work
Number of Dataset Images	750	-	4800	436
Classification algorithm	Neural Network Model (NNM)	Light resistance-based Algorithm	Dynamic Threshold Finding	Regional Convolutional Neural Network (R-CNN)
Duck Eggs to be Classified	Balut and Rejects	Balut and Penoy	Fertile and Infertile	Balut, Penoy, Fresh Eggs
Classification accuracy	76% with 7% false positives	-	Average of 83.52% for 5 trials	80.5%

turned. Also, this can reduce the efforts in candling the eggs manually, since the user can monitor the temperature and growth of the incubated eggs in the incubator. It also used R-CNN for the classification of three eggs with an accuracy of 80.5% with only 436 data sets. The proposed work performs better than the prior work [17] having a classification accuracy for balut and rejects only of 76%. Although the classification accuracy of reference [19] is higher, a higher number of dataset images was used to achieve the accuracy of 83.52%.

For future work, this study would have higher accuracy and better performance by increasing the number of dataset images as well as the number of eggs being tested. Furthermore, the use of cameras with higher resolution will contribute to the precision of the image detection process.

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