Implementation of YOLOv8 for Classifying Fertile and Infertile Eggs in the Chicken Hatching Process

Michael Arihta[1], Maribeth Adventina Manullang[2], Zikri Hanafi[3], Reni Rahmawati[4]
[1,2,3,4] Electrical Engineering, University of Singaperbangsa Karawang, Karawang, Indonesia
[1] email: 2110631160050@student.unsika.ac.id

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ABSTRACT: *This study aims to develop an embryo detection system in chicken eggs using the YOLOv8 algorithm based on computer vision. This approach is proposed as a solution to the manual candling method which is often inaccurate and time consuming. The dataset used amounted to 4,396 chicken egg images, consisting of fertile and infertile categories. The model was trained using Google Collaboratory with GPU support, where the model was trained for 100 epochs to maximize accuracy. The evaluation results show that the YOLOv8 model is able to detect embryos with a high level of accuracy, indicated by a precision value of 93.2%, mean average precision (mAP) of 98.5%, and recall of 87.2%. The fertile category was successfully detected with a precision of 100% and a recall of 94.2%, while the infertile category had a precision percentage of 86.4% and a recall of 100%. These findings prove that the YOLOv8 algorithm can be effectively implemented to automate the selection process of fertile and infertile eggs, thereby improving efficiency and accuracy in the livestock production process.*

KEYWORDS: *Computer vision, embryo detection, chicken eggs, YOLOv8.*

I. INTRODUCTION

Native chickens (*Gallus Domesticus*) are a type of local livestock that are widely raised by the community. In addition to being consumed for their meat, native chicken eggs can also be processed. Native chickens are commonly found in residential areas, both on the streets and in coops. It must be acknowledged that with the growth of the human population, the demand for animal protein has increased significantly[1] . According to the Central Statistics Agency, the consumption of animal protein by Indonesians reached 61.70 grams/day/capita in 2024[2].

Village chicken farming greatly supports the Indonesian economy, especially through the sale of village chicken eggs. Village chicken eggs can provide a supply of animal protein to the Indonesian people, who can be said to have low protein intake. Meeting this protein need can be a business opportunity for village chicken farmers[3] . Village chicken eggs fall into two categories: *fertile* eggs and *infertile* eggs. *Fertile* eggs are eggs that can hatch because they contain an embryo, which appears as a blood spot. Infertile eggs, on the other hand, cannot be hatched because there is no embryonic development inside the egg. These *infertile* eggs have actually been fertilized by a rooster, but when attempted to be hatched, they fail to do so[4] .

Free-range chicken egg farmers usually sort *fertile* and *infertile* eggs using a conventional method, namely by using a flashlight to examine the eggshell (*candling*). This method is not very effective in sorting eggs because not all farmers can see the results of egg *candling* clearly, resulting in errors in sorting *fertile* and *infertile* eggs[4] .

With the development of computer vision technology in various fields, such as digital image processing, deep learning, and object detection, this technology is related to various disciplines such as artificial intelligence, robotics, industrial automation, and signal processing. Now, computer vision is used to detect objects, recognize facial expressions, and even detect chicken egg embryos. These applications often use artificial neural network methods[5] . Object detection applications can be used as an alternative solution to automatically sort fertile and non-fertile eggs so that free-range chicken farmers do not need to manually examine eggshells. This detection system aims to perform effective candling to hatch free-range chicken eggs.

YOLO (*You Look Only Once*) is an algorithm that fundamentally changes object detection in digital image analysis. This algorithm focuses on real-time object detection with fast detection times. YOLO has evolved into several versions, with developments aimed at increasing the speed of detecting objects such as objects in images and videos, as well as improving prediction accuracy. The version of YOLO used by researchers is YOLOv8, released in 2023, which provides high accuracy and efficiency through various features and the latest optimizations, making it the right choice for various object detection tasks. YOLOv8 has several sizes, such as YOLOv8n, which means nano, YOLOv8s, which means *small,* and YOLOv8m, which means medium. These three sizes can be used depending on the amount of data processed and the number of objects detected[6] . "State of the Art" is a key feature of YOLOv8, created as a flexible framework to support all previous versions of YOLO, enabling improved performance and accuracy in various object detection scenarios[7].

The purpose of this research is to develop a chicken egg detection system using YOLOv8 as a reliable automation solution in the egg sorting process. By using a chicken egg image dataset and training the YOLOv8 detection model, it is hoped that this model will be able to detect two categories of chicken egg embryos, namely fertile and infertile, quickly and accurately. After the model has been trained and tested, evaluations such as *mean average precision* (mAP), *accuracy, precision, recall,* and *F-1 Score* will be carried out.

The chicken egg detection process is an important step in sorting fertile and infertile eggs before the incubation process. A popular conventional method used is *candling*. *Candling* is the process of shining a bright light on eggs to observe the embryo, which can be seen directly with the naked eye. This *candling* method is effective in some conditions, but sometimes farmers must be careful in observing the presence of embryos in eggs and are prone to inconsistencies due to their observation abilities, such as eye fatigue or eye diseases.

In the field of artificial intelligence, there is another subfield called *deep learning*, which is widely used to detect objects due to its reliability in automatically recognizing patterns. In detecting the presence of embryos in native chicken eggs, researchers use the YOLO (*You Look Only Once)* approach. The use of YOLO for fast and accurate detection has been proven in various applications, from traffic monitoring to object identification in agriculture. The latest version of YOLO is YOLOv8, which provides greater speed and efficiency in detecting objects than the previous version. The anchor-free approach used by YOLOv8 can improve the accuracy of object detection with various sizes and orientations because it allows bounding box predictions to be made directly at the center of the object.

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The introduction should include the background, problem statement, problem-solving plan, and research objectives.

Articles should be typed on A4 paper (width 21 cm, height 29.7 cm) with a header and footer size of 1 cm.

II. ARTICLE FORMAT (THIS SECTION EXPLAINS THE THEORY SUPPORTING THE RESEARCH)

A. *GOOGLE COLABORATORY*

Google Colaboratory, or Google Colab, is a cloud platform developed by Google LLC to operate and develop Python programming language code through a browser without additional configuration, which will be used by writers when training the YOLOv8 detection model. Google Colab utilizes Google's cloud infrastructure and provides free access to GPUs (*Graphic Processing Units*) and TPUs (*Tensor Processing Units*), but access is limited. The collaboration feature in Colab allows users to work together by sharing notebooks in *real time.* Google Colab can be accessed via the website (colab.research.google.com), making it easy for researchers, students, and the general public to access it. Users do not need high-end computer hardware or laptops to operate Google Colab[8] .

Fig. 1. Google Colaboratory

III. METHOD (REQUIRED)

A. *RESEARCH FLOW*

The figure below shows the research flowchart for detecting the presence of embryos in chicken eggs. The flowchart was designed by the researcher in a structured manner to ensure optimal detection results.

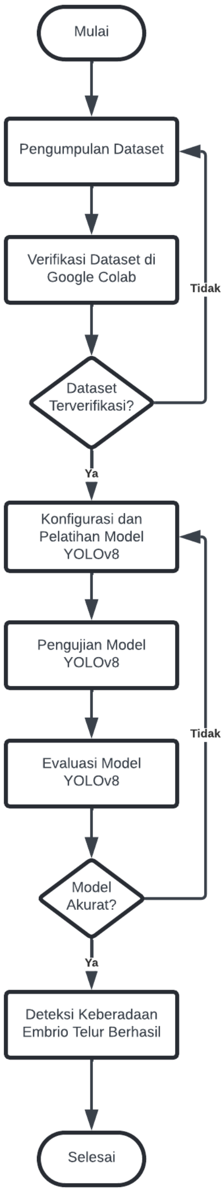

Fig. 2 Diagram Alir Penelitian

The flowchart shown in the image above is the research flow for detecting the presence of embryos in chicken eggs using YOLOv8. First, the dataset is downloaded from the Roboflow website, which contains images of chicken eggs with and without embryos. After that, the dataset is uploaded and verified by Google Colab. The purpose of dataset verification is to ensure that the contents of the dataset folder read in the File Explorer application on the laptop after downloading match the dataset detected by Google Colab. Once the dataset has been verified, the YOLOv8 model is configured and trained, where the YOLOv8 model will learn the dataset that the researcher uploaded to Google Colab. After configuring and training the model to detect the presence of embryos in chicken eggs, the model will be tested and evaluated to measure the extent to which the model detects the presence of embryos in an egg.

B. DATASET

The dataset was downloaded from the Roboflow website, with a total of 4,396 images. The images in the dataset were divided into 4,035 for training, 300 for validation, and 60 for testing. The images in the dataset included both fertile and infertile eggs[9] .

Tbl1 . Number of Chicken Egg Embryo Presence Datasets

Training	**4.396 images**
Validation	300 images
Test	60 images

Based on Table 1, if converted into percentages, 92% is for training the YOLOv8 model with the aim of enabling the model to recognize patterns contained in the dataset, 7% is for validating the model with the aim of evaluating the model after pattern recognition during training, and 1% is for testing the model so that the model can measure the accuracy of detecting data that has not been recognized by the model.

C. MODEL CONFIGURATION AND TRAINING

Configuring the YOLOv8 model involves checking the hardware for model acceleration, installing the required libraries, importing the dataset from Drive to Colab, setting hyperparameters, and training the model. In performing the configuration, the researcher used Google Colab as an integrated development environment (IDE). The configuration on Colab includes the availability of a GPU (Graphic Processing Unit) and installing the Ultralytics library for YOLOv8. The model for detecting the presence of embryos in chicken eggs uses the Python programming language on Google Colab to run the source code with a total of 100 epochs in order to understand the patterns of the dataset and reduce the potential for overfitting in the model for detecting the presence of embryos in chicken eggs. The batch size used during model training was 16 to speed up model training with the dataset without sacrificing stability. The image resolution was adjusted to 640 pixels so that the images from the dataset were compatible with the detection model.

D. MODEL MODEL EVALUATION AND TESTING

Once model training was completed on Google Colab and saved in the Google Drive folder for embryo detection models, the trained model was evaluated and tested. This process was carried out to determine the extent to which the model was able to detect the presence of chicken embryos in eggs. The model was evaluated using several metrics, such as *precision*, *recall*, *mean average precision* (mAP), and *F-1 score*.

Precision is used to assess the accuracy of a model in detecting objects accurately, *recall* measures how well a model detects relevant objects, *mean average precision* (mAP) assesses the accuracy of a model in detecting and classifying objects, and *F-1 Score* calculates the harmonic mean between *precision* and *recall*.

1) Precision

Precision is the ratio of *true positives* to *false positives*, as described by equation (1). *Precision* explains how accurate the expected data is compared to the detection results provided by the model[10] .

$$Precision = \frac{TP}{TP + FP} \#(1)$$

2) Recall

Recall is the ratio between *true positive* predictions and the total amount of data that should be predicted as *true positive* and *false negative*, as explained in equation (2). *Recall* represents the model's success rate in recognizing information[10] .

$$Recall = \frac{TP}{TP + FN} \#(2)$$

3) Mean average precision (mAP)

Mean average precision (mAP) is the average value of the average precision of an object in each class. Equation (3) provides the mAP calculation, which can be seen below[10] .

$$mAP = \frac{1}{N} \sum_{k=1}^{k=n} AP_x \times 100\% \#(3)$$

4) F-1 score

The F-1 score is an evaluation metric that measures the balance between *precision* and *recall* in an object detection model[11] .

$$\frac{1}{F1} = \frac{1}{2} \times \left(\frac{1}{precision} + \frac{1}{recall}\right) \#(4)$$

5) Confusion Matrix

The confusion matrix is used to evaluate the performance of an object detection model by comparing the model's prediction results with the actual labels of the objects. The image below shows *the confusion matrix*[11] .

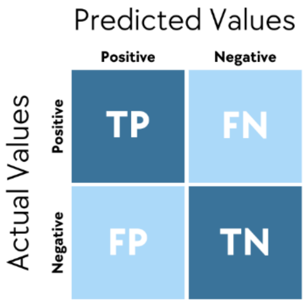

Fig. 3 Confusion matrix

IV. RESULTS AND DISCUSSION

After the model underwent training as described earlier, and parameters such as *epoch*, *image size*, and *batch* were determined, *the confusion matrix* was obtained as a visualization of the results shown in the image.

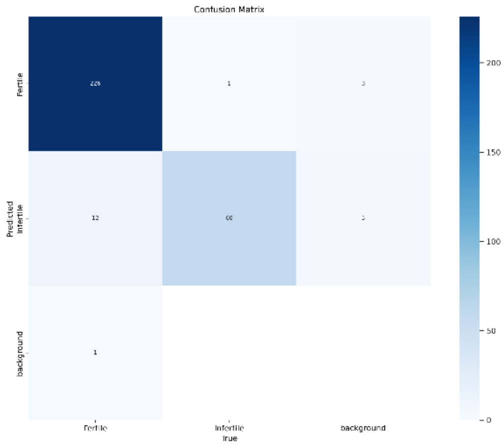

Fig. 4 Confusion matrix of the YOLOv8 model training results

The confusion matrix above shows that the model is able to classify fertile eggs very accurately, marked by 226 correct predictions out of the total predictions in that class. Only 12 fertile eggs were misclassified as *infertile* and 1 egg was detected as background. This creates high accuracy in detecting eggs in the *fertile* class.

In the *infertile* class, the model was able to accurately detect 60 *infertile* eggs, even though there were prediction errors, namely 1 *fertile* egg and 5 eggs categorized as background as infertile. Nevertheless, the model's performance in detecting infertile eggs remained effective, with most infertile eggs being accurately recognized by the detection model. In addition to the *confusion matrix* image as the final visualization, precision, mAP, and recall values were obtained for each class in the model for detecting fertile and infertile chicken embryos in eggs.

Table2 . Evaluation Testing

No	*Class*	*Precision*	*mAP*	*Recall*
1	All	0,932	0,985	0,872
2	Fertile	1	0,994	0,942
3	Infertile	0.864	0,975	1

Based on the evaluation table above, the overall results (*All*) show a *precision* value of 93.2%, mAP of 98.5%, and *recall* of 87.2%. The results of this evaluation show that the model is capable of identifying objects with high accuracy and minimal error. In the *fertile* class, the model has a *precision* value of 100% with an mAP of 99.4% and *a recall* of 94.2%. These values indicate that the model almost never fails to classify fertile eggs as other objects and has high sensitivity in detecting fertile eggs. Meanwhile, infertile eggs had a *precision* value of 86.4%*,* which was slightly lower than the *fertile* class. However, the *recall* value reached 100%, indicating that the model did not miss a single infertile egg. The mAP value of the infertile class was 97.5%, indicating the consistency of the model in making accurate predictions.

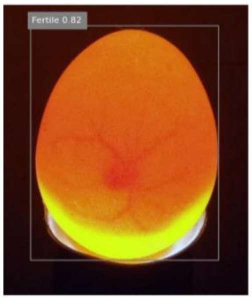

Fig. 5 Detection results of fertile chicken eggs

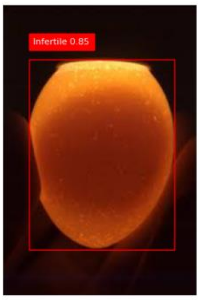

Fig. 6 Detection results for infertile chicken eggs

The detection results from the YOLOv8 model work by dividing the image into several boxes, or *bounding boxes*, to identify an object. In this model, there are two categories of chicken embryo presence that can be classified, namely *fertile* and *infertile*. Figures 5 and 6 show examples of detection results from the model that has undergone training and validation from the given dataset. The classification results shown in Figures 5 and 6 have high *confidence* values of 82% and 85%. It can be concluded that the detection model has a fairly good level of certainty and detects two categories of chicken embryo presence in eggs, namely *fertile* and *infertile.*

V. CONCLUSION

This study developed an embryo detection system in chicken eggs using the YOLOv8 algorithm. This algorithm can accurately identify fertile and infertile egg categories. Using a dataset of 4,396 images covering both categories, the trained model achieved a *precision* value of 93.2%, mAP of 98.5%, and *recall* of 87.2%. These values demonstrate consistency and effectiveness in object detection. YOLOv8 has proven to be an effective solution to manual candling methods, which are often inaccurate and time-consuming. In addition, model training has become easier with its implementation in Google Colaboratory, which allows high-computing access without the need for additional hardware. As a result, this YOLOv8-based method can be relied upon as a contemporary technology in the egg selection process, especially on a larger farm scale.

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AUTHOR BIOGRAPHY AND CONTRIBUTIONS

Michael Arihta, born in Bogor, March 23, 2003. Currently pursuing a bachelor's degree in electrical engineering at Singaperbangsa University, Karawang. He is interested in concentrating in computer engineering.