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Real-time Chicken Counting System using YOLO for FCR Optimization in Small and Medium Poultry Farms

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Abstract

Feed Conversion Ratio (FCR) is a widely recognized technique in the animal farming industry, especially for optimizing feed efficiency and reducing the operational costs. A key aspect of managing FCR involves achieving efficiency in the correlation between the number of animals and the required feed quantity. However, to achieve accurately counting large populations of animals, such as chickens, presents a significant challenge especially in large-scale farming. Computer vision technology offers a promising solution to automate this counting process, helping the FCR management. This research specifically evaluates the capability of the YOLOv11 model for real-time chicken detection. Evaluation of the model's performance indicates high efficacy, achieving accuracy, precision, and recall values of 93%, 94%, and 98%, respectively. The implementation of the technology for precise chicken detection facilitates the accurate adjustment and optimization of feed allocation, which can substantially enhance the overall FCR process.

Keywords: *Deep Learning, Detection, FCR, Segmentation, YOLO*

Introduction

FCR (Feed Conversion Ratio) is a crucial measure in poultry farming, such as for broiler and layer chickens. This indicator shows how efficiently the livestock utilize the feed provided. Specifically, FCR measures the amount of feed required to produce one kilogram of product, whether it is meat from broiler chickens or eggs from layer chickens (Li et al., 2024). A lower FCR value indicates that feed utilization in the farming process is more efficient. Calculating FCR itself requires sufficient detailed data, such as the number of chickens, and the others. The number of chickens is one of the main crucial factors for the FCR calculation; however, manual calculation performed by medium-scale farms is difficult regarding the movement and the amount of the chickens. There are severals ways to implementing FCR. One of the approaches taken to implement FCR is by using a tools called *efficient feeder*, which is a special tool for feeding chickens that utilizes several parameters. One of the most importants parameters is that the machine needs to know whether chickens are present or not at a given time. In fact, this is very difficult if done manually without technological intervention.

This research proposes a solution to detect the presence of chickens by utilizing image processing methods or computer vision. Our research was conducted by utilizing one of the most popular deep learning models, called YOLO (You Only Look Once). There are several considerations for using YOLO in this study, one is the YOLO model's known robustness, which makes it reliable in various scenarios. Our research aims to prove YOLO's capability in detecting chickens in real time. We used several evaluation metrics, including the model's accuracy and precision. In this research, we performed a training technique called transfer learning by utilizing a pre-trained YOLO model (Apostolopoulos & Mpesiana, 2020;

Febriantono et al., 2021; Ma et al., 2024; Nayak et al., 2024; Terven & Cordova-Esparza, 2023). The results obtained from this training process show that the YOLO model which utilizing the transfer learning process achieved highly accurate results in detecting chickens in the real time.

Methods

In this research, we conduct several steps that illustrated in the Flow Diagram Research, shown in Figure 1.

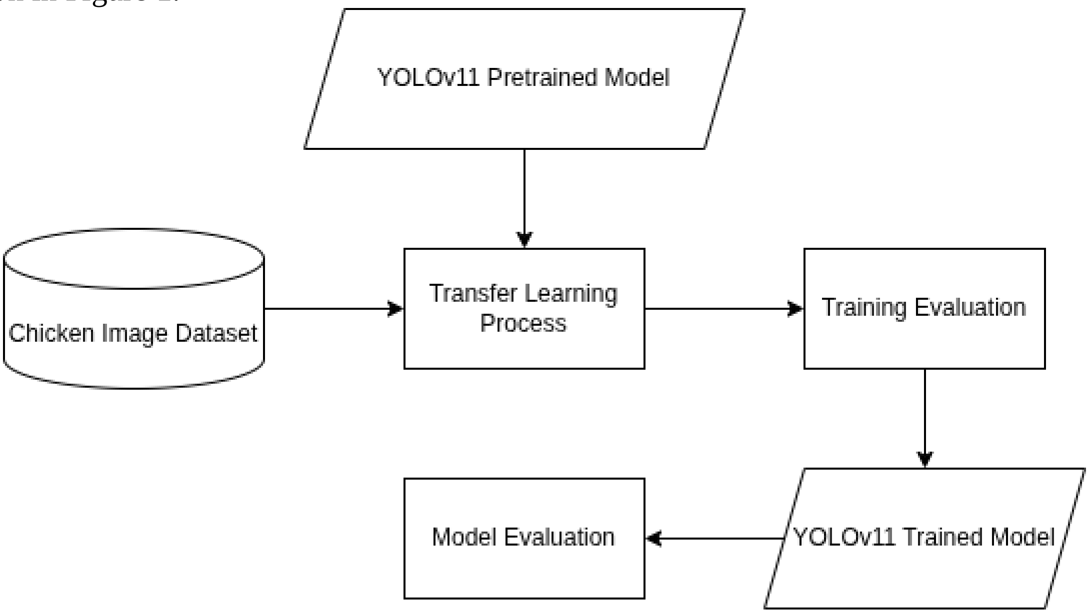

Figure 1. Experiment flow diagram, chicken image dataset was utilized to trains the YOLOv11 pre-trained model

A. Chicken Image Dataset

The dataset employed in this study is an image collection featuring chicken objects, carefuly annotated through manual segmentation process(Jocher et al., 2022; Mendes Junior et al., 2020). This dataset, contains arround of 375 images, with each image containing multiple manually segmented chicken instances objects (Gupta et al., 2024; Meyer, 1992), which publicy available on the Roboflow sites (URL: https://universe.roboflow.com/hayri-yigit/chicken-counter). In the experiment section, we divides the datasets into 2 parts including training dataset and validation dataset, each of them was 70:30 in probabilities, respectively. Several sample of the dataset was shown in Figure 2.

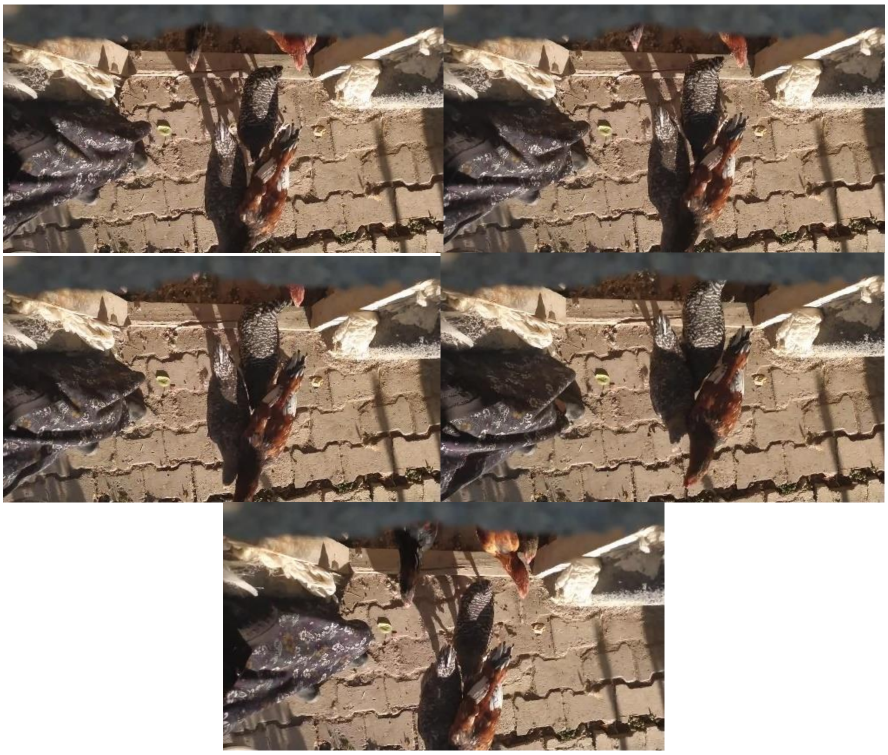

Figure 2. Sample images from the dataset employed in this study are shown, illustrating their capture from an aerial viewpoint.

Figure 3. Segmentation result image, used for training using YOLO format. Each image contains more than 1 objects.

Since we utilize YOLO model, we also use the YOLOv11 format TXT dataset to ensure the model and framework can recognize the dataset. The YOLOv11 format TXT contain the train and validation dataset added with txt information regarding the dataset including the number of comparison dataset, location, etc. There is also a TXT file that contains segmentation keypoint for each image, this keypoint represents the manual segmentation result provided by the dataset publisher. Several image that contains segmentation result was shown in Figure 3.

B. YOLOv11 Pre-trained Model

The latest iteration of the YOLO architecture developed by Ultralytics is the YOLOv11 pre-trained model, which obviously demonstrates state-of-the-art performance compared to older versions, benefiting from advancements in feature extraction, speed, efficiency, and accuracy (Nayak et al., 2024; Terven & Cordova-Esparza, 2023). The YOLOv11 framework offers several specialized models (e.g., YOLOv11, YOLOv11-seg, YOLOv11-pose, YOLOv11-obb, YOLOv11-cis). To achieve the objective of accurately counting chicken instances within image frames, the YOLOv11-seg variant was selected for its specific instance segmentation capabilities.

C. Transfer Learning

Transfer learning has gathered significant attention in this recent years, which, produce better solution especially in field of natural language processing (NLP) and computer vision (Apostolopoulos & Mpesiana, 2020; Febriantono et al., 2021). Transfer learning is commonly performed through two principal methods. One method entails freezing the weights of the early layers of a pre-trained network while allowing the weights of the later layers to be fine-tuned on the new dataset. The alternative approach utilizes the pre-trained model purely as a feature extractor, with the resulting feature maps subsequently used as input for training a separate classifier layer.

D. Training Evaluation

The training evaluation utilized in this research was box loss training, class loss, and DFL loss (Lei et al., 2024). Box loss training means how the model could learn well on box location accurately, the higher values means more focus on minimizing location error. Another loss function was Cross entropy loss, or, several says cls loss(Georgescu et al., 2022; Lei et al., 2024). This loss means calcluating the degree of randomness or disorder with the system, shown in (1) below:

$$H = -\sum p(x) \log p(x) \tag{1}$$

Denotes, x is the data and p is the probability. The last loss function utilised in the training section was *Distributed Focal Loss* (DFL loss). Means that how model could handle the class imbalance, which could made the model accuiring better focus the data. Since we are using YOLO pre-trained model and YOLO training scenarios. Those of three loss function are well presented.

E. Model Evaluation

The model evaluation consist of several loss, including precission, recall and mAP50. Precision means that how well the model increase its ability to maintain its accuracy, shwon in (2) below:

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Where, TP is True Positive, means how much model could detect the real class, and FP is False Positive, means, how model determine the result is true while the actual result is false.

Another matrix used in this research is *recall*, means how model accurately detect all relevant cases within the dataset, shown in (3).

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

Where, *FN* is the False Negative, meaning that how model determine the result is false while the actual result is true. In this evaluation stage, a comparison was made between the performance of YOLOv11 and that of the previous version of YOLO, YOLOv10. Both models were tested using equal hyperparameter tuning to ensure a fair comparison between the two models.

Results and Discussions

In the experiment scenario, there are several parameters used including *epoch* number, *learning rate,* and activation. This session will explain each result and its comparison of training evaluation and model evaluation.

A. Box Loss Training Result

Figure 4. Box Training Loss, loss value are constantly decreased following the epoch values

According to the Figure 4, the loss value was constantly decreased following the epoch values, this mean that the model are not overfitting and gained its optimal performance and robustness.

B. Segmentation Loss Result

Referring to the Figure 5, the rapidly decrease loss values indicates that model is learning rapidly and reduce its error significanlyat the begining of the learning process.

Figure 5 Segmentation Training Loss, loss value reached its best values in epoch 100

C. Class Entropy Loss

The class entropy loss indicates the randomness of the model, shown in Fig. 6.

Figure 6. Class Entropy Loss, YOLOv11 model drastically decrese its class entropy loss in 100 epoch

Referring to the Figure 6, YOLOv11 model drastically decrease its cross entropy loss. This indicate that model learning better using the chicken dataset provided. After training process was completed, it will provides the trained model. Furthermore, the next process is to evaluate the model using such matrix like precision, recall and mAP. Nevertheless, the precision result was shown in Fig. 7.

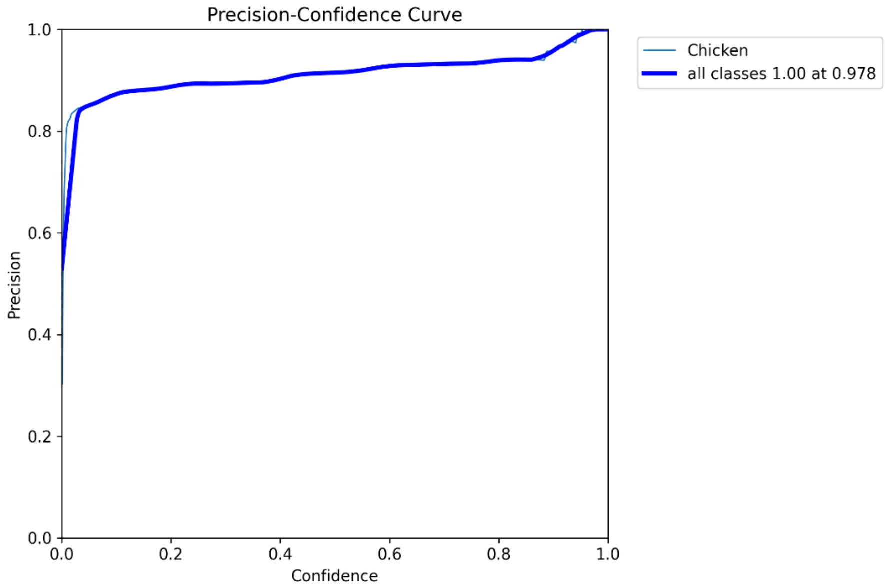

Figure 7. Precision confidence curve

According to the Figure 7, the precision value of the trained YOLOv11 model was achieved 0.99, which means that our model could struggle with any condition by maintaining its accuracy as shown in the confusion matrix in Fig 8.

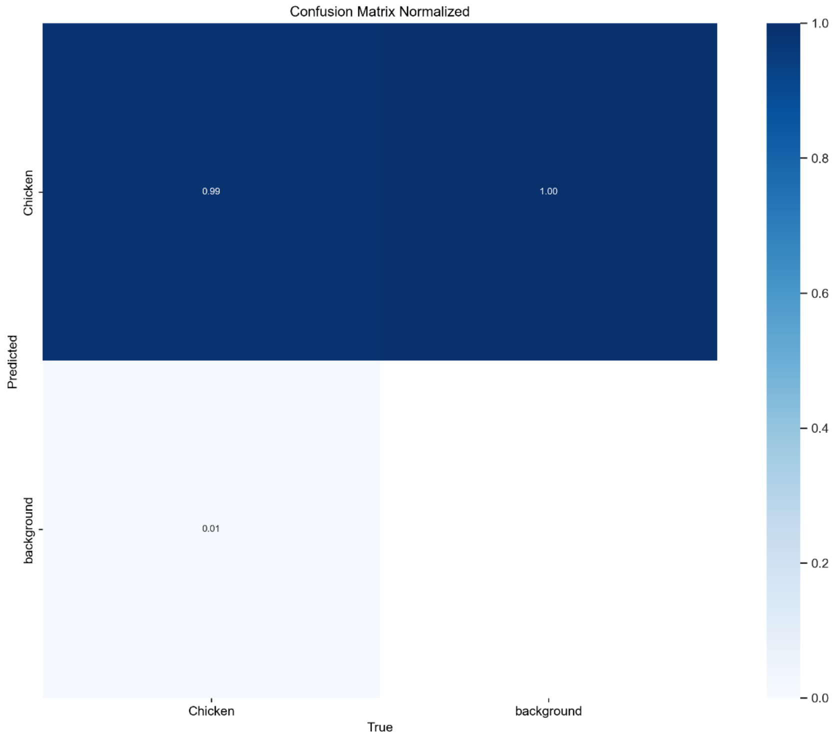

Figure 8. Confusion Matrix Normalized

Since our resaerch only use 1 class (chicken), therefore, the confusion matrix consist of 2 parameters including chicken and background. In this experiment, we also compares our proposed model with another pre-trained model that presented in Table 1.

Table 1. YOLOv11 obtained higher accuracy, precision, recall, until mAP50 compared to the YOLOv10

Model Name	**YOLOv11**	**YOLOv10**
Acc.	0.9379	0.92791
Precision	0.93573	0.93624
Recall	0.98113	0.94573
mAP50	0.97825	0.97754

According to the Table 1, YOLOv11 obtained higher accuracy, precision, recall, until mAP50 compared to the YOLOv10, however, for the precision, YOLOv10 is slightly better compared to the YOLOv11. In summary, the YOLO model demonstrates notable proficiency in both segmentation and detection. This facilitates the operation of the FCR system, as it enables the rapid, precise, and real-time calculation of the number of chickens. Several image sample result for chicken detection and segmentation are also presented in Fig. 9.

Figure 9. Chicken detection result using YOLOv11 trained model

Conclusions

The Feed Conversion Ratio (FCR) is a key performance metric in animal husbandry. Improving the FCR is crucial for reducing feed costs and increasing the economic efficiency of livestock operations. However, enhancing FCR traditionally requires significant investments in labor and technology. This study investigates the application of Computer Vision and Artificial Intelligence (AI) to address this challenge. Results indicate that the YOLOv11 model is highly effective for poultry detection. When compared to the previous YOLOv10 model, YOLOv11 demonstrates superior accuracy and computational efficiency. The improved precision in chicken detection leads to a more efficient feeding process by minimizing the waste between the amount of feed provided and the amount consumed.

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