Advancing Poultry Farming Efficiency Through YOLOv5 and Image Regression-Based Broiler Weight Estimation

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***Abstract*—The precise calculation of broiler chicken weight is crucial for the efficient management of the farm and optimization of production. Conventional weighing methods are labor-intensive and can induce stress in the poultry, highlighting the need for non-invasive and precise measurement techniques. The system developed in this paper is a method designed for Cobb500 broilers, whereby an innovative image analysis approach yields weight estimates. The system has used two models: YOLOv5 and image regression. The YOLOv5 model used in this study was trained with 3920 annotated images and 490 test sets, while the image regression model had 2240 labeled data with a 280 test set. Evaluation of the models was done on a separate farm to ensure unbiased results, which yielded a score of 0.00053kg MSE, 0.02303kg RMSE, and an R² of 0.73 on single broiler detections, and 0.00026kg MSE, 0.01625kg RMSE, and 0.77 R² on multiple broiler detections. These results outperformed previous similar studies in terms of MSE and RMSE, demonstrating the system's enhanced accuracy and reliability in broiler weight estimation.**

***Keywords*—Broiler Chicken, Cobb500, Commercial Poultry Farming, Weight Estimation, Computer Vision, YOLOv5, Image Regression, Convolutional Neural Network**

I. Introduction

The poultry industry stands as a cornerstone of global food production and economic sustainability, meeting the ever-growing demand for protein-rich food sources. Chicken production in the Philippines is on an upward trend, with estimates indicating an increase to almost 15.17 thousand metric tons with 455.04 and 470.21 metric tons in 2022 and 2023, respectively [1]. Efforts to meet rising demand, especially with challenges like African Swine Fever outbreaks affecting pork production and increasing demand for chicken due to cases of bird flu in layers, drive this growth [2]. Within this dynamic sector, commercial poultry farming plays a pivotal role, employing advanced management practices to optimize production processes and ensure profitability.

Central to these practices is the accurate estimation of broiler chicken weights, as it serves as a fundamental metric for monitoring growth, managing feed intake, and assessing overall flock health. By periodically checking the weight of broilers, farmers may be able to identify health issues, discover variations from typical growth trends, and apply appropriate interventions to avoid or resolve problems. Additionally, weight monitoring aids in improving feed consumption and lowering feed loss, leading in cost savings for the poultry farm [3].Conventional weighing methods are labor-intensive and can induce stress in the birds, highlighting the need for non-invasive and precise measurement techniques.

Over recent years, machine learning and computer vision techniques have emerged as promising alternatives for automating the weight estimation process. The performance of computer-vision techniques in real-world conditions also speaks for its accuracy. Existing non-invasive methods came across various challenges that hinder the accuracy and efficiency of weight estimation of broilers. These include abnormal weight estimation due to varying postures [4] and poor estimation of broiler weights in complex backgrounds and when chickens overlap [5][6][7]. These issues highlight the need for advanced methods that can handle the variability and complexity of actual farm settings, ensuring accurate and efficient weight estimation.

This study proposed an innovative approach to broiler weight estimation utilizing advanced computer vision techniques and high-resolution full HD cameras. By harnessing the YOLOv5 object detection framework alongside a CNN image regression model, this study achieved accurate and real-time weight estimation, circumventing the need for complex 3D camera systems. To validate the effectiveness of their method, the researchers utilized standardized metrics such as MSE (mean squared error), RMSE (root mean squared error), R^2 (coefficient of determination), and a mAP (mean average precision). Furthermore, the researchers assessed scalability by analyzing processing speed and resource utilization, ensuring practical applicability within commercial poultry farms. Through rigorous experimentation and validation against ground-truth weight measurements, this study endeavored not only to narrow the research gap in poultry farming but also to contribute to evaluating broiler weight estimation methodologies.

II. METHODOLOGY

A. Data Gathering

Due to the lack of dataset for the specific broiler breed online, the researchers opted to manually gather images for Cobb500 broilers, specifically focusing on 23-day-old broilers.

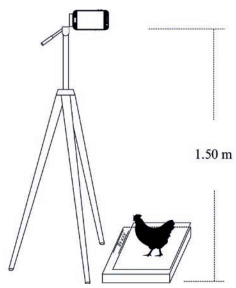


Fig. 1: Schematic diagram of the data acquisition setup.

The researchers utilized the 12-megapixel back camera of the Pocophone F1 to capture and store the data gathered for the dataset of the image regression and YOLOv5 models. To ensure consistent image capture, they fixed a mobile phone on a tripod that is approximately 1.5 meters above perpendicular to the subject. Simultaneously, an electronic weighing scale was employed to measure the actual weight of the broilers as a reference point (Figure 1). All sampling images were acquired during daytime in a commercial poultry farm in Barangay Calunasan (M'lang, Cotabato). A total of 700 raw images of single and multiple broilers were collected from 100 randomly selected broilers. With 400 images being single broilers. An 80:10:10 data split for train-valid-test was used for both models and distributed as follows:

TABLE I: Dataset Splitting Summary

Model	Raw	Augmented	Train	Valid	Test
YOLOv5	700	4900	3920	490	490
Image Regression	400	2800	2240	280	280

B. Data Preprocessing

To enhance the performance and accuracy for the weight estimation of Cobb500 broilers, several preprocessing techniques were employed for the YOLOv5 object detection model and the CNN image regression model. The process was conducted in Roboflow and as follows: data cleaning, data labeling and annotation, and data augmentation. These transformations aimed to simulate real-world scenarios, ultimately enhancing model performance.

C. Object Detection Model Training

To achieve precise object detection, the YOLOv5 model by Ultralytics was utilized. The training process was facilitated using several machine learning services, including Roboflow for data preprocessing and augmentation, GitHub for accessing the Ultralytics YOLOv5 repository, and Google Colaboratory for computational resources. Initially, the YOLOv5 repository was cloned from GitHub, followed by the installation of its dependencies. Images were preprocessed using Roboflow, ensuring they were properly prepared for training. A script was executed to download the preprocessed images, although direct downloads were considered for better data management. With the YOLOv5 model architecture already established, training commenced with iterative adjustments to training parameters and hyperparameters to optimize model performance [8].

D. Weight Estimation Model Training

For the weight estimation model, specific preprocessing methods were necessary due to the requirement for uniform image ratios. The dataset augmentation involved resizing images for uniformity; and applying horizontal and vertical flips to the sample images. The model, based on a modified image regression template from a public library by the user hugohadfield on GitHub [9], was adapted to suit the specific needs of the study. Modifications were made to enhance the model's efficiency and applicability. The training process was conducted on Google Colaboratory, with parameters finely tuned to achieve the best possible outcomes for weight estimation.

E. System Architecture

The Raspberry Pi 4 Model B is the central computing unit, handling processes such as data processing, communication with the machine learning models, and overall operation of the program. It works alongside a microcontroller, which facilitates communication between the camera, sensors, and the Raspberry Pi itself. YOLOv5, responsible for object detection, and the CNN image regression model, which estimates the weight of detected broilers, both run on the Raspberry Pi. These models process the collected data and provide outputs (individual and average weight) then displayed on the LCD. Data acquisition was achieved through an HD webcam, which measures the real-time weight of individual broilers.

F. Evaluation Metrics

To ensure the effectiveness and seamless integration of the YOLOv5 object detection model and the image regression model for broiler weight estimation, the researchers evaluated the system using a range of metrics: mAP, MAE, RMSE, and R^2.

III. RESULTS AND DISCUSSION

A. Performance of Broiler Weight Estimation System

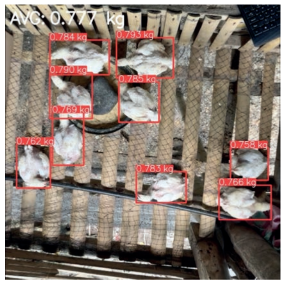
Precision and recall were important metrics in object detection models as they evaluated the model's performance and provided perspective on how the models perform in different conditions [10]. Precision measured how accurate the model was in predicting objects as true positives. Recall, on the other hand, measured the ability of the model to detect all relevant objects.

The YOLOv5 model used for object detection demonstrates strong performance, consistent with existing research. For

(a)

(b)

(c)



(d)

Fig. 2: The figure shows weight estimation results of (a) single and (b) multiple broilers from the test set and (c) single and (d) multiple broilers in actual deployment. The models detected and estimated the weights of multiple broilers, each highlighted with bounding boxes and labeled with their corresponding predicted weights.

TABLE II: mAP Summary

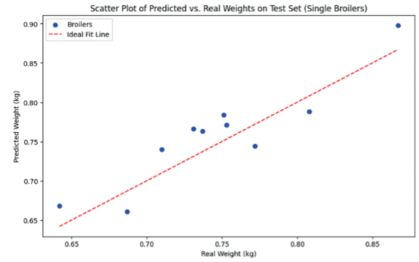
Data Set	Test/Actual	Precision	Recall	mAP[a]
Single Broilers	Test	0.9	1	0.98
	Actual	0.9	0.5	0.92
Multiple Broilers	Test	0.7	0.8	0.89
	Actual	0.9	0.5	0.90

[a] mAP: Mean Average Precision

example, other studies employing YOLO models for animal detection reported high precision with mAP values around 0.90 or higher [11][12]. The model in this study achieved mAP scores of 0.98 (test set) and 0.92 (real-world deployment) for single broilers, and 0.89 (test set) and 0.90 (real-world deployment) for multiple broilers. These results reflected a high level of accuracy and reliability in detecting and predicting broiler weights, aligning well with or exceeding established benchmarks.

B. Integration of Models on Raspberry Pi 4B

The integration of the CNN image regression and YOLOv5 models on the Raspberry Pi 4B was successfully executed, demonstrating effective deployment on a resource-constrained device. The process involved optimizing the models through pruning and quantization, techniques commonly used for deploying models on edge devices [13]. Despite the high CPU usage (100%) and RAM usage (90%), typical for such



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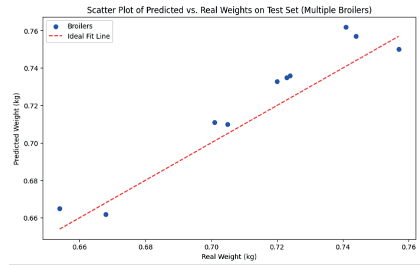
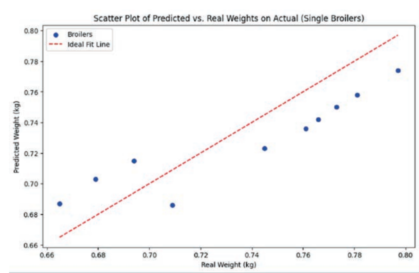
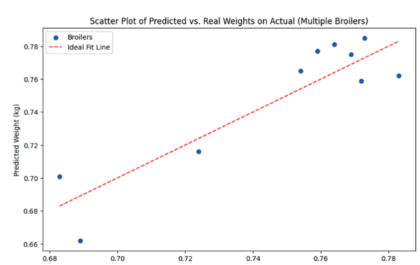


(b)

Fig. 3: The figure shows the scatter plots of the predicted weights versus the real weights of (a) single broilers and (b) multiple broiler groups from the test set. The plot indicates a good correlation between the predicted and real weights, as most points were close to the ideal fit line.



(a)



(b)

Fig. 4: The figure shows the scatter plots of the predicted weights versus the real weights of (a) single broilers and (b) multiple broiler groups in actual deployment. Each blue dot represents an (a) individual broiler and (b) broiler group, and the red dashed line is the ideal fit line where predicted weights perfectly match the real weights. Most points were closely clustered around this line, indicating that the model provides a prominent level of accuracy in predicting the total weights of multiple broiler groups.

computational tasks, the Raspberry Pi 4B efficiently managed both models.

A streamlined workflow was developed for capturing images, running inferences, and displaying results. The process began with the webcam capturing live video footage of the broilers, which was then fed into the YOLOv5 model for object detection. A frame from the footage was subsequently passed to the CNN image regression model to estimate their weight. The individual weights and average weight were displayed on the 7-inch LCD, providing real-time feedback to the user. To enhance usability, a shortcut was created on the Raspberry Pi 4B to quickly open the main script and start the system, allowing for easy operation with minimal user intervention.

TABLE III: Real-Time Performance and Resource Utilization on Raspberry Pi 4B

Metric	Value
Average Inference Time	3000ms
Latency	3010ms
CPU Usage	100%
RAM Usage	90%

The integrated system was evaluated based on real-time performance, latency, frame rate, and resource utilization. The average inference time in detecting multiple broilers was approximately 3000ms, with a total latency of around 3010ms. While this results in a low frame rate, the stationary nature of the broilers mitigated the impact of this limitation [14]. The system's latency and inference times were acceptable for the intended application, as the broilers did not move rapidly, allowing sufficient time for accurate weight estimation.

The CPU usage at 100% indicated that the models fully utilized the processor, meaning all four cores of the Broadcom BCM2711 quad-core Cortex-A72 are engaged in handling the inferencing tasks. This high CPU usage suggested that the current computational load was at the upper limit of what the Raspberry Pi 4B can handle. During the testing, the maximum number of broiler chickens that the researchers encountered in a single frame reached 19 and had an inference time of around 4500ms. Although the maximum number that the model can infer was unknown, the inference times increased as the number of detected broiler chickens increased and may be limited to the computing power of the processing unit.

C. Evaluation of the Models' Accuracy

The accuracy of the two models was defined using several key evaluation metrics. For the YOLOv5 model, these were MSE, RMSE, and R^2, while a mAP was for the image regression model. These metrics provide a comprehensive understanding of the model's predictive accuracy and reliability, both in controlled test conditions and real-world deployment.

In the test set, the models displayed strong performance with low MSE and RMSE values, indicating that predictions were close to actual weights. The RMSE values of 0.02858 kg (single broilers) and 0.01125 kg (multiple broilers) reflect high precision. The R^2 values of 0.86 (single broilers) and 0.87 (multiple broilers) suggested a robust correlation between predicted and actual weights, while high mAP values (0.98 for single and 0.89 for multiple broilers) confirmed the models' precision and reliability in detection and prediction [4]. Compared to the study that reported RMSE values of 80.68g (training), 82.37g (testing), and 82.30g (total data set) with an R^2 value of 0.98 [7], the current model showed lower RMSE values indicating improved accuracy. Additionally, a study reported an RMSE of 67.88g and an R^2 of 0.98 [6], which further supported the superior performance of the current model.

TABLE IV: Evaluation Metrics (Test Set)

Class	MSE ↓	RMSE ↓	R^2 ↑	mAP ↑
Single	0.00082 kg	0.02858 kg	0.86	0.98
Multiple	0.00013 kg	0.01125 kg	0.87	0.89

TABLE V: Evaluation Metrics (Actual Deployment)

Class	MSE ↓	RMSE ↓	R^2 ↑	mAP ↑
Single	0.00053 kg	0.02303 kg	0.73	0.92
Multiple	0.00026 kg	0.01625 kg	0.77	0.90

In real-world conditions, the models maintained high accuracy, with RMSE values of 0.02303 kg (single broilers) and 0.01625 kg (multiple broilers), showcasing their robustness in practical applications. The R^2 values of 0.73 (single broilers) and 0.77 (multiple broilers) suggested a reliable correlation between predictions and actual weights under actual farm conditions. The mAP values (0.92 for single and 0.90 for multiple broilers) indicated the model's high precision and reliability in detecting and predicting weights in a real-world setting [4]. A study reported an RMSE of 102.97g, MAPE of 21.465%, SRE of 0.240, and an R^2 of 0.9842 [15], which demonstrated the practical effectiveness of the model with significantly lower RMSE values. Another study achieved an R^2 value of 0.999 and percentage errors between 0.04% to 16.47% [16], further emphasizing the model's consistent accuracy.

D. Practical Implications and Applications

The system in this study involved placing the device near one of the feeding areas where the broilers congregated (Figure 5). This setup ensured that multiple broilers can be detected simultaneously. Once the user executed the program, the proposed system took less than 5 seconds to estimate the average weight of the detected broilers. Additionally, it can estimate the weights of individual broilers, which the conventional system cannot do.

It was evident that the proposed system offered a significant advantage over conventional methods of weighing broilers.

TABLE VI: Comparison of studies on broiler weight estimation using computer vision methods

Study	Methods		Results			
	Object Detection	**Weight Estimation Model**	**MSE**	**RMSE**	**R^2**	**mAP**
Amraei, 2017 [6]	Image Processing	Support Vector Regression	-	0.06788 kg	0.98	-
Amraei, 2018 [15]	Image Processing	Transfer Function Model	-	0.10297 kg	0.98	-
Li, 2023 [4]	Mask R-CNN	GBDT	0.019608 kg	0.140027 kg	0.71	-
This Study, 2024	YOLOv5	Image Regression	0.00013 kg	0.01125 kg	0.87	0.89

Fig. 5: Actual device setup in a broiler farm located in Barangay La Suerte (M'lang, Cotabato)

The automated nature of the proposed system reduced human error and labor costs, making it a more reliable and cost-effective solution for commercial poultry farms. Although the researchers did not measure broiler weights in their initial stages due to the critical need for controlled temperature and lighting, the researchers conducted the study a week before the broilers' scheduled harvest. They chose this timing because the broilers were already well-adjusted to their environment, and it was crucial for the owners to know the weights at this stage to make informed decisions and meet their quotas.

Therefore, the proposed device was specifically designed to measure the weights of broilers a week before harvesting. It enabled real-time monitoring and ensured that broilers reached the target weight for harvesting. However, if the device detected that a broiler reached the target weight earlier than expected, it was up to the owner to decide on early harvesting, as they were familiar with the reference weight chart. Conversely, if the weight was still below the target, the average weight displayed by the system indicated the need for additional feeding to promote growth. This flexibility allowed for the optimization of feeding schedules, reduction of feed costs, and overall improvement in farm efficiency. In short, the system indirectly aided in deciding the ideal harvest time, ensuring that broilers were harvested when they reached their optimal weight.

E. Comparison to Other Similar Studies

The current study, integrating YOLOv5 object detection and CNN image regression, achieved notable results with an MSE of 0.00013 kg, an RMSE of 0.01125 kg, an R^2 of 0.87, and a mAP of 0.89 in the test set of 23-day-old Cobb500 broilers (Table 6). Although studies in the same field employed different approaches, comparisons can still be made based on similar metrics such as MSE, RMSE, and R^2 to evaluate accuracy. For instance, a study employing image processing and SVR methods, achieved a better RMSE of 0.06788 kg [6] but still higher than that of the current study. Additionally, research involving image processing and TF models reported an RMSE of 0.10297 kg [15], while a study using MF-GBDT methods recorded an MSE of 0.093034 kg and an RMSE of 0.140027 kg [4]. These higher RMSE values indicated less precision compared to the current study. Although the R^2 values in some of these studies were higher than the current study, the R^2 of the current study still was covered within an acceptable range for practical implementation in commercial broiler farms.

Data used in these studies varied: 2,440 individual images (20 1-day-old Ross broilers reared for 42 days), 84 group images, and 420 minutes of video footage (5-minute videos taken twice daily for 42 days) [6]; 2,440 individual images (30 1-day-old Ross broilers reared for 42 days) [15]; and 1,198 pseudo-color images of 200 63-day-old bantam broilers individually, and 105 pseudo-color images of 286 bantam broilers in multiple complex backgrounds [4]. In the current study, a total of 700 raw images of single and multiple broilers were collected from 100 randomly selected Cobb500 broilers, with 400 images being of single broilers. An 80:10:10 data split for train-validation-test was used for both models and distributed as follows: image regression with 2,240 for training, 280 for validation, and 280 for testing; YOLOv5 with 3,920 for training, 490 for validation, and 490 for testing.

Overall, the current study outperformed previous research in terms of MSE and RMSE, demonstrating enhanced accuracy and reliability in broiler weight estimation using computer vision.

IV. Conclusion

In this study, the researchers integrated two CNN models, YOLOv5 object detection and Image Regression, to be an accurate method for broiler weight estimation. They designed a system to capture live video footage, detect broilers using YOLOv5, and estimate their weight using the CNN image regression model, all on a Raspberry Pi 4B. Despite the limited processing power and memory of the Raspberry Pi 4B, the system performed effectively in real-time. They assessed the accuracy of the models' predictions using performance metrics such as R^2, mAP, MSE, and RMSE. In the test set of 23-day-old Cobb500 broilers, it achieved an MSE of 0.00013 kg, an RMSE of 0.01125 kg, an R^2 of 0.87, and a mAP of 0.89. Moreover, similar performance in actual deployment achieved an MSE of 0.00026 kg, an RMSE of 0.01625 kg, an R^2 of 0.77, and a mAP of 0.90. In conclusion, all three objectives in the study were successfully accomplished: accurately measuring the weight of broilers using a CNN image regression model and YOLOv5, developing a system that integrated the two models using a Raspberry Pi 4B, and assessing the accuracy of the models with corresponding evaluation metrics. The promising metric values achieved in this study indicated that the research gap regarding detecting broilers in complex backgrounds and overlapping chickens was addressed. This research can serve as a solid benchmark for future studies involving broiler weight estimation using CNN. The system's implementation can help poultry farms streamline operations, improve weight monitoring accuracy, and ultimately contribute to better poultry farm management and productivity.

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