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Broiler Live Weight Estimation through Image Processing and YOLO-based Deep Learning

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ABSTRACT
This study aims to estimate the live weight of broilers using image processing and deep learning techniques. The proposed method is designed to optimize management processes in broiler production systems, reduce labor requirements and operational costs, minimize animal stress caused by direct human contact, and serve as an effective alternative to traditional manual weighing practices. The study was conducted at a commercial broiler farm located in Kahramanmaraş, in the Mediterranean region of Türkiye. An automatically controlled measurement enclosure was constructed to capture broiler images with minimal human intervention. Digital cameras mounted at the top of the enclosure recorded images of broilers that spontaneously entered the enclosure. By using these images, live weight estimation was carried out in two stages: the first stage involved morphological image processing in the MATLAB environment, while the second stage focused on deep learning-based modeling for prediction. During the image processing stage, multiple regression analysis was performed using the actual weights obtained through manual weighing and the estimated weights derived from image-based measurements. The analysis resulted in an adjusted R^2 value of 0.97 and a standard error of ± 131 g ($P<0.01$). The mean absolute error (MAE) was calculated as 84.4 g, while the mean relative error (MRE) was found to be 7.6%. In the deep learning stage, the YOLOv8 model was trained for 150 and 500 epochs. Notable improvements in both accuracy and generalization capability were observed after 500 epochs. Under these conditions, the model achieved a high mean Average Precision (mAP) of 0.969, with substantial increases in precision, recall, and F1-score across all 17 predefined broiler live weight classes. Furthermore, regression-based performance indicators were approximated from the class-based predictions to enable a quantitative assessment of weight estimation accuracy. Based on this indirect evaluation, the proposed model achieved an estimated MAE of 37.0 g and MRE of 4.43%. Overall, the findings suggest that the proposed framework has strong potential for adaptation to live weight prediction in other livestock species.

Keywords: Broiler, live weight estimation, image processing, YOLO

1. Introduction

In 2010, it was estimated that global agricultural total factor productivity (TFP) would need to increase by at least 1.75% annually to double agricultural production through improvements in efficiency by 2050. However, the current global agricultural productivity (GAP) index falls short of the projected target by 6%, based on 40 years of compound calculations (GHI 2014). Among various livestock sectors, poultry farming plays a crucial role in meeting the demand for animal protein due to its high feed conversion ratio and rapid production cycles. Poultry farming is critical in meeting global demand for meat and eggs. It is projected that global chicken production will increase by 2% in 2023, reaching a total of 102.7 million tons (Shams et al. 2025). To meet the rapidly growing demand for healthy animal-based food, it is necessary to increase flock size. However, the increasing number of animals per farm has raised concerns about animal welfare due to the growing difficulty of individual care (HSUS, 2010). In broiler farming, live weight is an important parameter for assessing flock growth performance, feed conversion efficiency, disease emergence, and market suitability. Additionally, the average live weight must be predicted in advance for accurate slaughter timing. Efficiency in broiler production is determined by evaluating the relationship between the feed consumed and the weight gained during the rearing process. Tracking the difference between the expected weight gain based on the feed consumed and the actual measured weight on a daily basis allows for the early detection of potential diseases, nutritional deficiencies, and welfare issues within the flock (Lott et al. 1982; Turner et al. 1984; Ross & Davis 1990; Flood et al. 1992; Mollah et al. 2010; Wongsriworaphon et al. 2015).

Traditionally, the average weight of the flock is estimated by individually or collectively catching randomly selected broilers and manually weighing them, or through automated weighing systems in well-equipped poultry houses. Careful attention must be paid to the sample size and distribution of broilers to accurately represent the average body weight of the flock. For this

purpose, at least 5% of the flock should be weighed by taking equal samples from each area of the poultry house (Mollah et al. 2010). However, manual weighing is a labor-intensive and time-consuming process that can also cause stress to the animals. This method is not ergonomic and is prone to human error during data recording and analysis (Turner et al. 1983; Feighner et al. 1986; Doyle & Leeson 1989; Amraei et al. 2017a). Furthermore, heavier broilers, which tend to move less, are more easily caught during manual weighing, leading to discrepancies in the average live weight results (Blokhuis et al. 1988). In automated weighing systems, although more costly than manual weighing, daily average live weight measurements are performed with much less stress. However, as broilers grow heavier, they may visit the automatic weighing platform less frequently, leading to discrepancies between the average live weight and the true value (Newberry et al. 1985; Chedad et al. 2003).

In recent years, the development of computer-aided digital imaging systems has provided alternative methods for estimating live weight based on the body measurements of animals. Image processing technology has been successfully used to measure the size and growth rates of various animal species, such as pigs, fish, and cattle, as well as plants. It is believed that this technology can also be used to estimate broiler live weights rapid, cost-effectively and accurately, without causing stress or damage (Mollah et al. 2010; Electra et al. 2022; Li et al. 2023; Campbell et al. 2025).

The use of deep learning models, particularly object detection algorithms such as YOLO (You Only Look Once), has demonstrated broad applicability across diverse fields due to their capability to perform complex image analysis with remarkable accuracy and speed. YOLO-based frameworks have shown significant improvements in detection precision, inference speed, and computational efficiency, making them suitable for a wide range of real-time applications, including automated surveillance, traffic monitoring, medical diagnostics, agricultural monitoring, and industrial quality control (Redmon & Farhadi 2018; Khan et al. 2020; Rohan et al. 2024; Ultralytics 2024).

Today, digital imaging and deep learning-based systems provide alternative, scalable solutions for intelligent visual analysis and decision-making processes. Unlike conventional image processing techniques such as morphological operations, thresholding, or texture analysis-where feature extraction relies heavily on hand-crafted rules and domain expertise-deep learning enables end-to-end feature learning directly from raw image data. This capability allows models to autonomously capture spatial hierarchies, semantic patterns, and contextual features across multiple layers, improving generalization to real-world visual variability (LeCun et al. 2015; Goodfellow et al. 2016).

Among deep learning architectures, convolutional neural networks (CNNs) are particularly effective in object detection and localization tasks, offering robust performance even under challenging conditions such as occlusion, varying illumination, and cluttered backgrounds. These advantages are critical for practical deployments where image variability is often high and unpredictable.

In this study, YOLOv8, a state-of-the-art object detection model developed by Ultralytics, was employed for real-time detection and localization tasks. YOLOv8 introduces several architectural improvements, including a decoupled detection head, anchor-free object localization, and enhanced C2f (Cross-Stage Partial with Feature Fusion) modules, which collectively improve detection accuracy, training stability, and inference efficiency (Jocher et al. 2023; Sohan et al. 2024). Owing to its lightweight structure, dynamic input resolution capability, and balanced trade-off between precision and computational cost, YOLOv8 provides a practical and robust framework for real-time livestock monitoring. At the time of this research, it represented one of the most advanced and widely adopted object detection architectures, outperforming earlier YOLO versions in both stability and generalization performance (Elmessery et al. 2023; Shams et al. 2025).

The aim of this study is to develop an innovative live weight estimation method that integrates both morphological image processing techniques and a deep learning-based object detection model, offering a practical and non-invasive alternative to manual weighing procedures in broiler production. Rather than focusing on a direct comparison, both approaches were independently implemented to estimate live weight based on 2D image data, and their respective outputs were evaluated.

2. Material and Methods

The study was conducted at a commercial broiler farm located in Kahramanmaraş, in the Mediterranean region of Türkiye. Ross 308 broiler chicks are reared at the farm, with each production cycle lasting approximately 40 to 42 days (Figure 1).



Figure 1- Image of broiler house

In this study, image and weight data were collected using a specially designed measurement chamber. The chamber features a top-mounted camera for capturing overhead 2D images and an integrated electronic scale (capacity 5000 g, accuracy 0.01 g) with an LCD display installed on the floor for live weight measurement. Opposing side doors allow controlled entry and exit of animals, while the remaining sides are enclosed to minimize external disturbances and ensure consistent imaging and weighing conditions. A Raspberry Pi single-board computer was utilized to record image data and to control the entrance and exit doors of the measurement chamber. For the automated operation of the chamber doors, a 4-channel 5V relay board was employed. To drive the actuators responsible for opening and closing the entrance and exit doors, a motor direction control circuit was designed using transistors and resistors. The operation of this circuit is based on the activation of one of the input signals, which triggers the conduction of the corresponding transistor and subsequently energizes one of the relay coils (Figure 2).

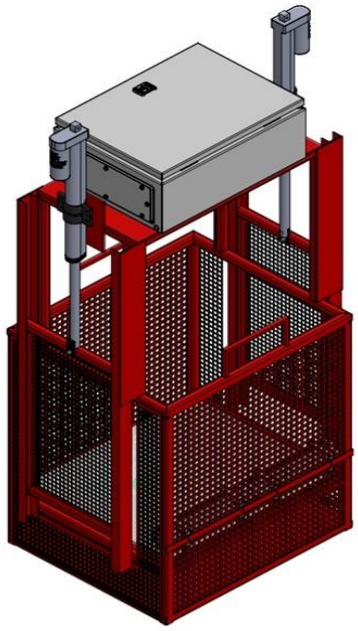

Figure 2- The developed measurement chamber and control panel

Automation of the image capture process was achieved through a Python-based software developed using the OpenCV library. When the camera detects a broiler, the entrance door automatically closes. After image capture is completed via a remote connection, the exit door opens, allowing the broiler to leave the chamber. In cases where more than one broiler enters the chamber, image capture is not performed, and an audio prompt is triggered to guide the broilers out. An example image of a broiler entering the chamber is shown in Figure 3, and the flowchart of the image capture process is presented in Figure 4.



Figure 3- Capturing the image and measuring the weight of a broiler

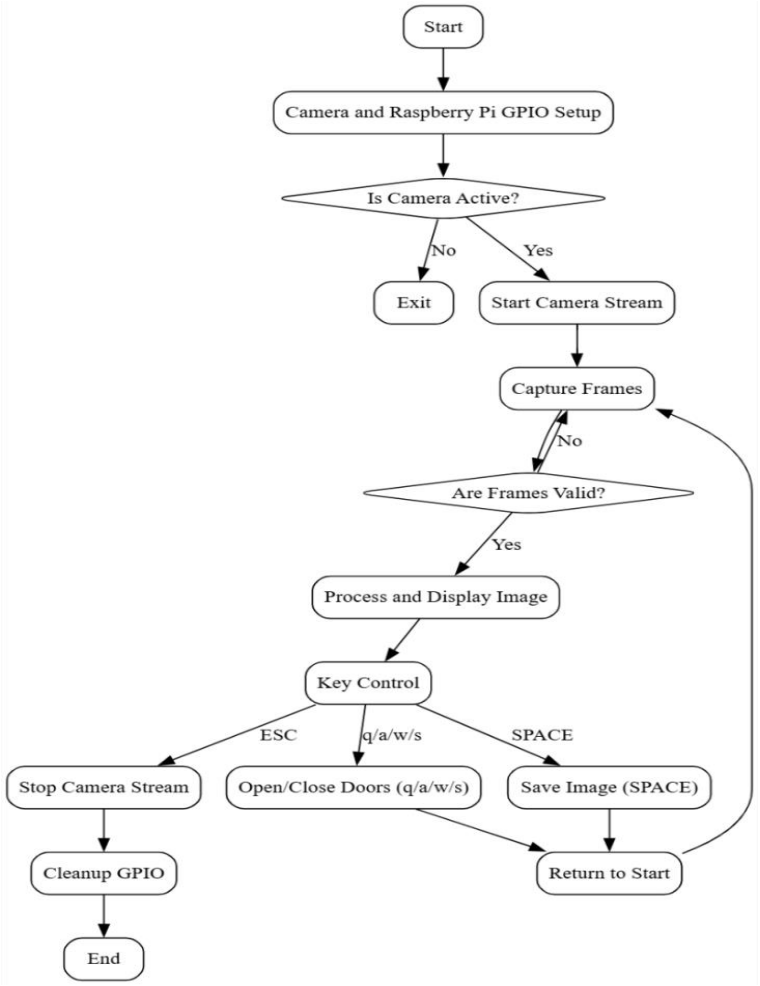

Figure 4- Flowchart of the image acquisition process

The image analysis workflow consisted of several sequential stages, as illustrated in Figure 5. Initially, broiler images were imported into the MATLAB environment and cropped to isolate the region of interest. The RGB images acquired from 151 distinct white-feathered broilers were initially converted to grayscale to streamline the subsequent analysis procedures. In grayscale images, the color information is reduced to a single intensity channel, thereby lowering computational demands. Following this, Otsu's automatic thresholding method (Otsu 1979) was applied to transform the grayscale images into binary format. Otsu's method determines the optimal threshold value by minimizing the intra-class variance between the foreground and background regions. The resulting binary images provided a foundation for further analysis by enabling clear separation between objects and the background.

To extract the morphological features of the objects in the refined binary images, the "regionprops" function was employed. This function processes binary or labeled images by identifying and quantifying properties of each individual object (label). In labeled images, distinct objects are assigned unique label identifiers. The "regionprops" function outputs a structured array containing

key geometric attributes such as shape descriptors, spatial positions, dimensional measurements, and other relevant features (MathWorks 2024).

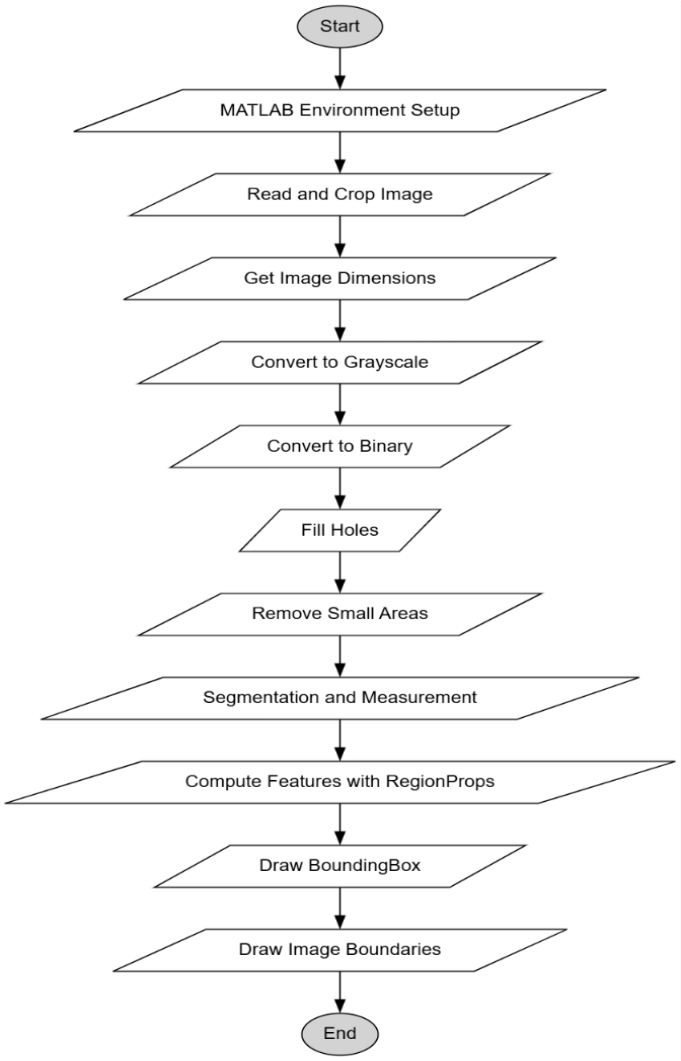

Figure 5- Image processing flowchart

In the process of live weight estimation using the YOLOv8 model, a dataset comprising broiler images was employed for training and testing purposes. To enable the model to generate more generalizable and accurate predictions under varying conditions, data augmentation was performed utilizing the Albumentations library on the Roboflow platform, thereby expanding the dataset to 4.529 images.

Albumentations is a flexible and efficient Python library widely employed for image processing and data augmentation tasks. It is frequently utilized in deep learning applications for the pre-processing and augmentation of image datasets. The library offers a wide range of transformations and augmentation techniques aimed at enhancing dataset diversity and subsequently optimizing model performance. These techniques include horizontal and vertical rotation, flipping, scaling, cropping, and adjustments to brightness and contrast. By increasing the variability within the dataset, such augmentation strategies contribute to reducing the risk of overfitting and improving the overall robustness and accuracy of the model. Figure 6 illustrates the statistical distribution of broiler weights.

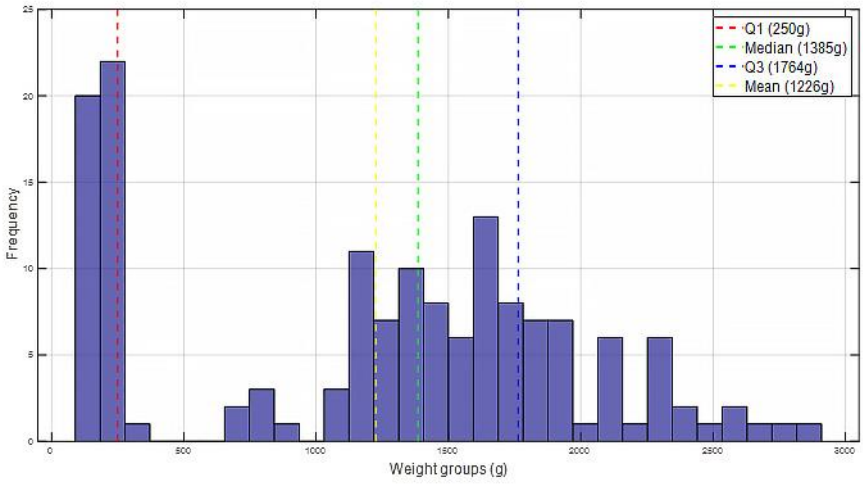

Figure 6- Statistical distribution of broiler weights

In this study, the performance of the YOLOv8 deep learning model was analyzed using key evaluation metrics such as Accuracy, Precision, Recall, and F1 Score (Erdoğan 2023; Alkan 2024). Unlike the morphological image processing method, which employed a regression-based estimation approach, a classification-based framework was adopted in this stage to enhance the robustness of predictions under limited and imbalanced training data. Direct regression models are typically more sensitive to outliers and labeling noise, which can lead to unstable learning when estimating continuous weights from images. By grouping live weights into discrete intervals, the YOLOv8 classifier was able to generalize morphological patterns more effectively and reduce overfitting caused by minor variations in broiler posture, illumination, or camera angle. The dataset was therefore labeled and classified into 17 weight-based categories: Chicken-101-150 g, Chicken-201-250 g, Chicken-651-700 g, Chicken-751-800 g, Chicken-1101-1150 g, Chicken-1201-1250 g, Chicken-1351-1400 g, Chicken-1451-1500 g, Chicken-1601-1650 g, Chicken-1651-1700 g, Chicken-1801-1850 g, Chicken-1851-1900 g, Chicken-1901-1950 g, Chicken-2251-2300 g, Chicken-2351-2400 g, Chicken-2501-2550 g, and Chicken-2701-2750 g.

3. Results

3.1. Live weight estimation of broilers using morphological image processing

In this study, morphological image processing was used to determine various features of a broiler represented by an object in the binary image, such as pixel area (Area), pixel perimeter (Perimeter), major axis length (MajorAxisLength), and minor axis length (MinorAxisLength). The extracted features were subsequently utilized to model and analyze the correlation between the morphological attributes of the broiler and its live weight.

In the next step, bounding boxes were drawn around the segmented objects to facilitate clearer visualization and validation of the extracted morphological features. An example of the Broiler segmentation and bounding box detection in MATLAB is shown in Figure 7.



Figure 7- Broiler segmentation and bounding box detection in MATLAB

Multiple Linear Regression (MLR) analysis was conducted using pixel area, pixel perimeter, major axis length, and minor axis length as predictor variables. The results of the analysis are presented in Tables 1-3, and the corresponding prediction equation is provided in Equation 1.

The analysis yielded an adjusted R-squared (R^2) value of 0.97, and the standard error was found to be 131 g. Based on the p-value, the model was considered highly significant ($P<0.01$).

The live weight estimation equation is as follows:

$$y = b_0 + 0.05 \times b_1 + 0.22 \times b_2 - 2.84 \times b_3 + 5.74 \times b_4 \quad (1)$$

Where: y is the estimated live weight (g), b_0 is the intercept constant (-241.85), b_1 is the pixel area (pixel), b_2 is the pixel perimeter (pixel), b_3 is the major axis length (pixel), and b_4 is the minor axis length (pixel).

Table 1- Regression analysis parameters of morphological measurement values

Regression Statistics	
R	0.986
R^2	0.972
Adjusted R^2	0.971
$S_{\bar{x}}$	131
n	151

Table 2- Regression analysis of variance for morphological measurement values

Sources of Variation	*df*	*MS*	*F*-Value	*P*-Value
Regression	4	21457633	1258	$5.154x10^{-112}$
Residual	146	17052		

Table 3- Coefficients of morphological measurement values

Predictor Variables	*Coefficients*	*Standard Error*	*t Stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Intercept	-241.85	99.80	-2.42	0.02	-439.08	-44.61
Pixel Area	0.05	0.01	8.37	0.00	0.04	0.06
Pixel Perimeter	0.22	0.09	2.50	0.01	0.05	0.39
Major Axis Length	-2.84	0.74	-3.84	0.00	-4.29	-1.37
Minor Axis Length	5.74	1.26	4.54	0.00	3.24	8.24

The distribution graph between the measured and predicted live weight values is shown in Figure 8. Additionally, the minimum, maximum, and averages of these morphological measurement values are provided in Table 4.

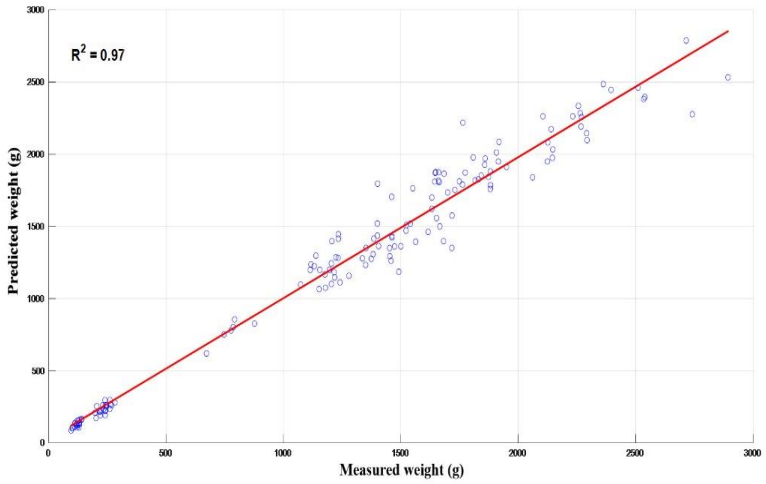

Figure 8- Distribution graph of measured and predicted live weight values

Table 4- Minimum, maximum, and averages of morphological measurement values

Parameters	*Minimum*	*Maximum*	*Mean*	*MAE*	*MRE*
Measured weight (g)	96	2893	1226	84.4	7.6
Predicted weight (g)	86	2788	1224		
Pixel Area (pixel)	3908	49325	24114		
Pixel Perimeter (pixel)	281	1810	939		
Major Axis Length (pixel)	85	359	225		
Minor Axis Length (pixel)	57	214	131		

MAE: Mean Absolute Error (g), MRE: Mean Relative Error (%)

3.2. Live weight estimation of broilers using YOLOv8-based deep learning model

During the testing phase, the model was assessed using previously unseen broiler chicken images, each labeled according to predetermined weight categories. As presented in Figure 9, YOLOv8 accurately detected the broilers and extracted key morphological features required for weight estimation. The results confirmed that the model maintained a strong generalization capability, evidenced by the close agreement between predicted and actual weights. Overall, these outcomes validate the reliability and robustness of the YOLOv8 model for practical applications.

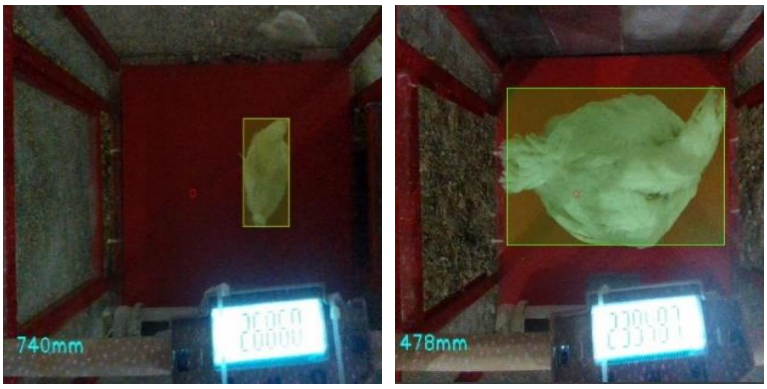

Figure 9- Two labeled example images

3.3. Performance metrics for 150 epochs

The model's performance after 150 training epochs was analyzed through a series of quantitative visualizations, including Precision-Recall, Recall-Confidence, F1-Confidence, and Precision-Confidence curves. These metrics collectively provide an in-depth perspective on detection accuracy, recall sensitivity, and classification balance.

The Precision-Recall curve (Figure 10), illustrating the trade-off between precision and recall, yielded an average precision (AP) of 0.353 across all classes. While the Chicken-101-150 class reached a notably high AP of 0.849, several other categories exhibited lower AP scores, likely due to limited training data or inconsistencies in annotation quality. This finding highlights the need for additional data augmentation and improved labeling to achieve uniform model performance.

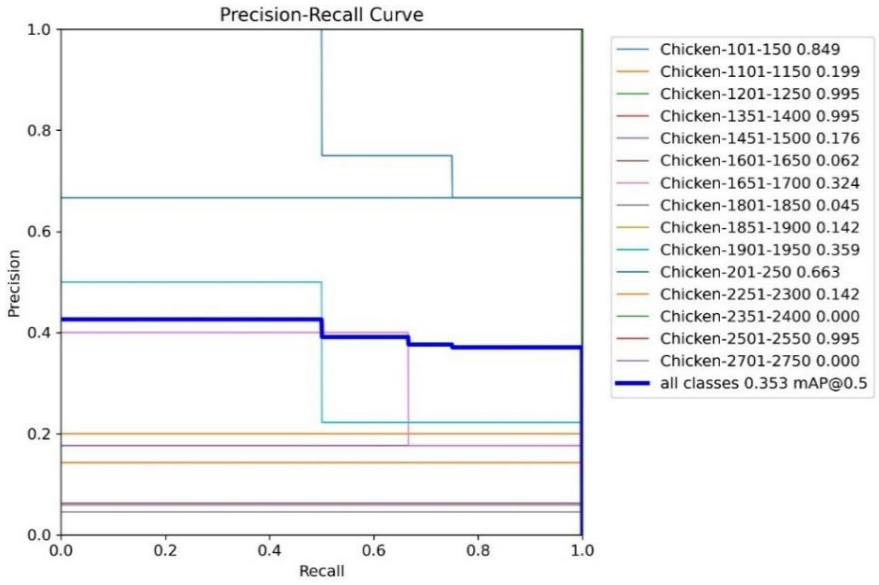

Figure 10- Precision-Recall curve

The Recall-Confidence curve (Figure 11) reveals how recall changes with different confidence thresholds. An overall average recall of 0.79 was achieved, demonstrating that the model sustains satisfactory sensitivity even at lower confidence levels. The consistent recall performance, particularly for the Chicken-101-150 class, underscores the model's ability to detect this class reliably across varying thresholds.

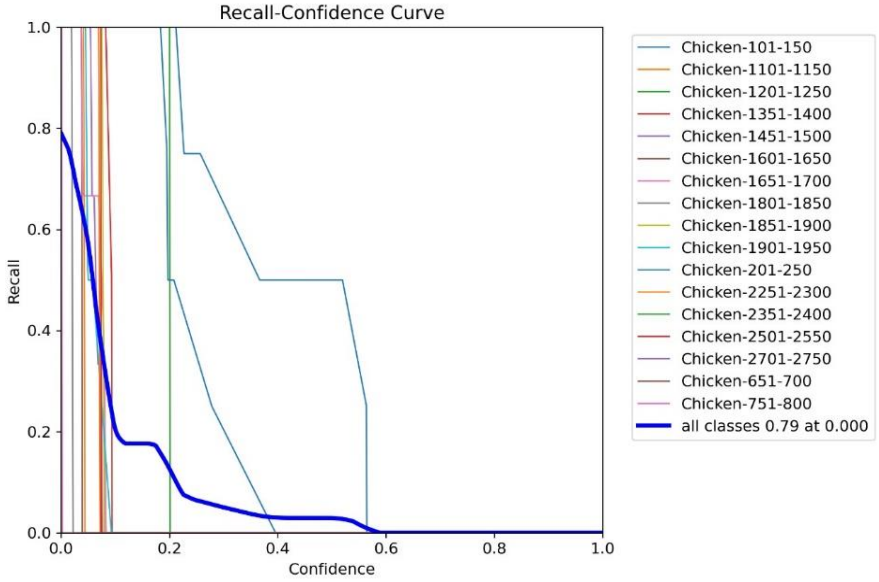

Figure 11- Recall-Confidence curve

Figure 12 presents the F1-Confidence curve, which illustrates how the model's F1 score varies across different confidence thresholds. The F1 score, as a harmonic mean of precision and recall, serves as a comprehensive indicator of the model's overall classification performance. This curve is particularly valuable for assessing the balance between sensitivity and precision under varying levels of confidence. Notably, the presence of high F1 scores even at lower confidence levels suggests that the model is capable of generating consistent and reliable predictions, regardless of the confidence threshold applied.

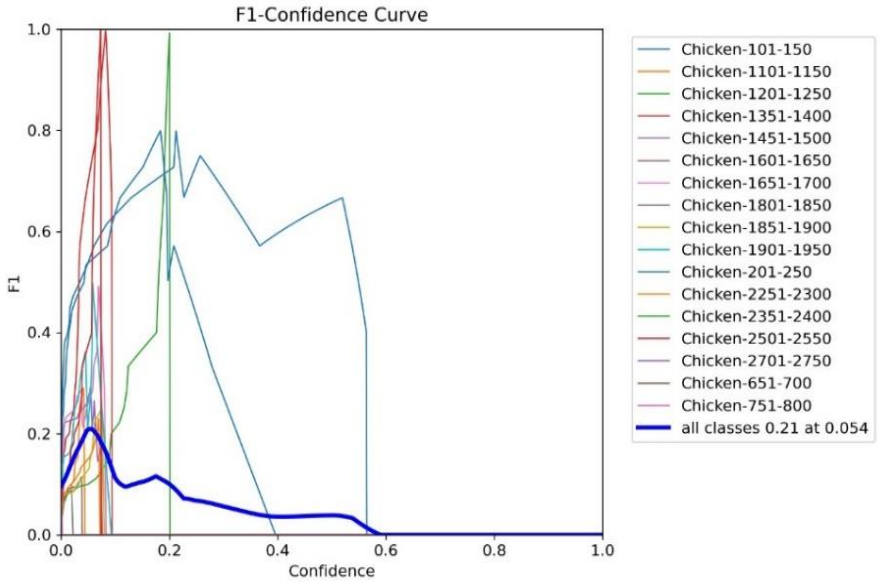

Figure 12- F1-Confidence curve

Figure 13 presents the Precision-Confidence curve, depicting how precision varies with confidence. A noticeable trend of increasing precision with higher confidence levels demonstrates that the model remains accurate even as prediction certainty grows. For example, the high precision achieved for the Chicken-1201-1250 class confirms the model's ability to generate highly accurate predictions within specific weight ranges.

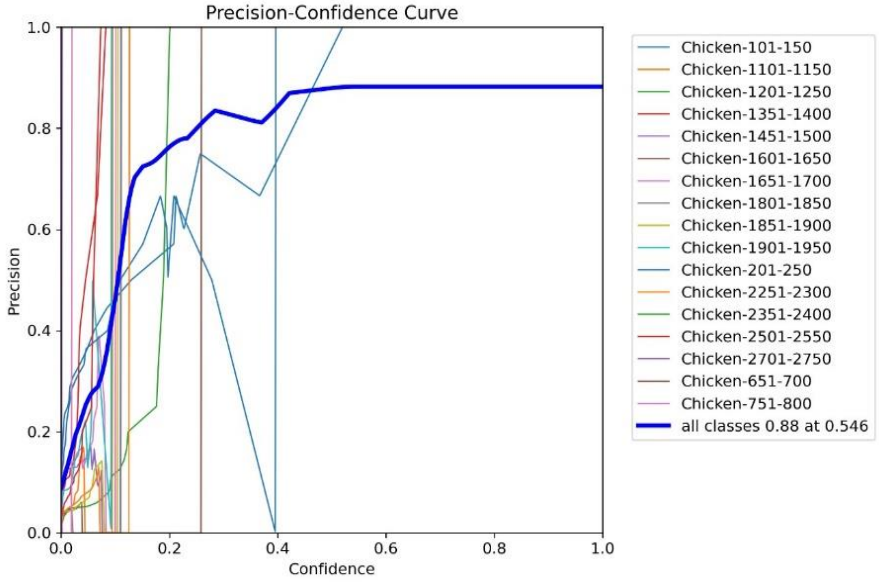

Figure 13- Precision-Confidence curve

The Precision-Confidence curve demonstrates that the model is able to achieve high precision values even at high confidence levels. This indicates that the model can maintain precision while adjusting the confidence level to increase the true positive rate. For example, the high precision value observed for the Chicken-1201-1250 class highlights the model's ability to make accurate predictions in this class.

3.4. Training and test losses for 150 epochs

The losses obtained during the training process of the model are crucial metrics for evaluating its performance over time. Training and validation losses are used to detect overfitting or underfitting conditions and to develop improvement strategies. The graphs illustrating the training and validation losses are presented in Figure 14.

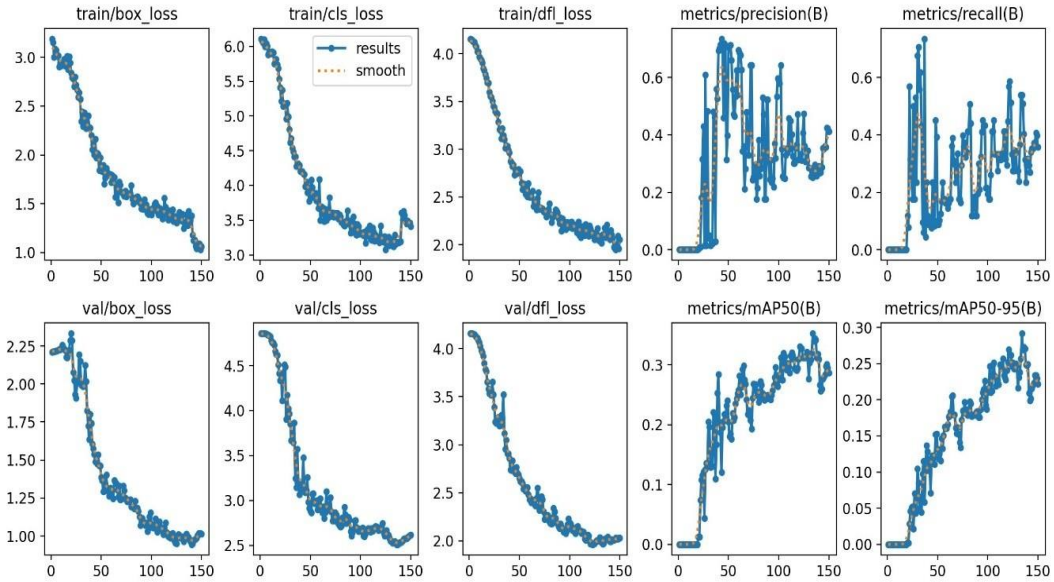

Figure 14- Training and validation losses

An analysis of the training process revealed a steady and substantial decrease in train/box_loss, indicating the model's increasing accuracy in localizing bounding boxes over time. Similarly, the train/cls_loss showed a consistent downward trajectory, reflecting improvements in the model's classification performance. The reduction in train/dfl_loss (Distribution Focal Loss) further confirmed the progressive refinement of the model's predictions as training advanced.

Although the values of metrics/precision(B) and metrics/recall(B) exhibited notable fluctuations, including some abrupt changes, the overall trend demonstrated a consistent upward trajectory. This suggests that the model became more proficient in identifying true positive instances and minimizing false positives over time, although the observed volatility across epochs may indicate occasional instability in the learning dynamics.

On the validation dataset, both val/box_loss and val/cls_loss showed clear and sustained declines, which confirms that the model generalized well to unseen data. Toward the later epochs, the decrease in these losses became more gradual, indicating a stabilization in the model's learning behavior. The continued reduction in val/dfl_loss reinforced the model's growing precision in validation tasks.

The performance metrics mAP50(B) and mAP50-95(B) increased consistently throughout the training process. These improvements across varying IoU thresholds reflect the model's enhanced detection accuracy. Despite minor fluctuations, the clear upward trend, particularly after epoch 50, demonstrates the model's effective learning and robust generalization capability.

3.5. Predicted labels for 150 epochs

The predicted labels generated by the model are analyzed to visualize and evaluate its performance on real-world data. Some examples of the model's predictions during the training process are presented in Figure 15.

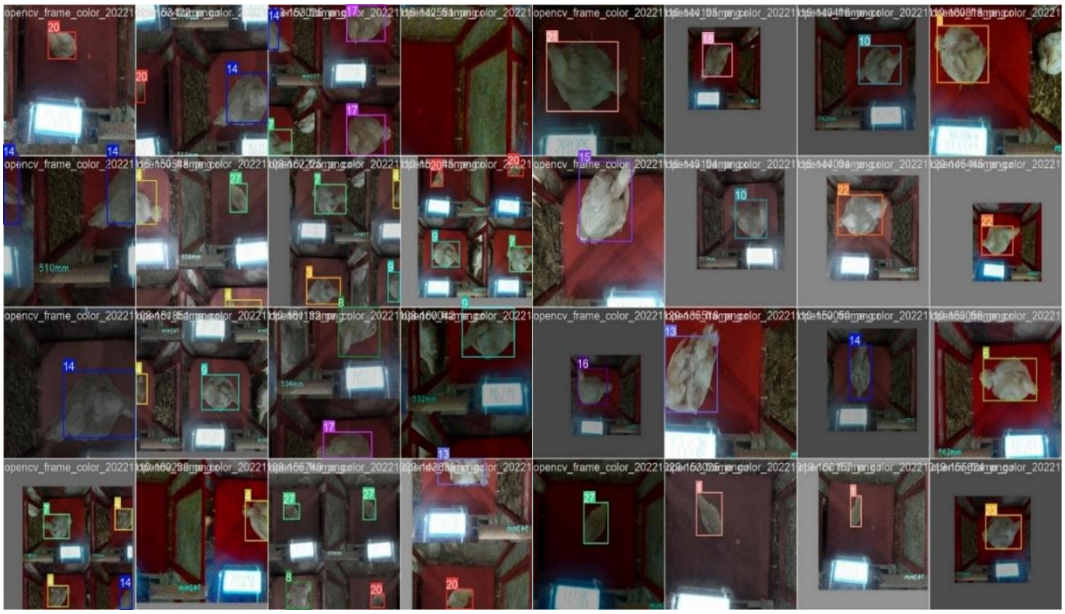

Figure 15- Predicted labels by the model

These visualizations illustrate how the model classifies objects throughout the learning process, highlighting the classes it distinguishes with high accuracy and those where it struggles. It has been observed that while the model performs well in certain classes, it exhibits lower discriminative ability in others.

3.6. Performance metrics for 500 epochs

In this section, the performance metrics and visualizations obtained after training the model for 500 epochs are presented. Compared to training with 150 epochs, the 500-epoch training duration has led to higher accuracy and improved generalization capacity of the model.

The precision and recall curves for the model trained over 500 epochs illustrate its performance across various classes. These curves are crucial for evaluating the model's detection capabilities and overall performance. Figure 16 presents the precision-recall curve for all classes.

The Precision-Recall curve indicates the model's accuracy in detecting objects and how many objects were correctly classified. At the end of 500 epochs, the model achieved a mean Average Precision (mAP) of 0.969, demonstrating its strong object detection capabilities.

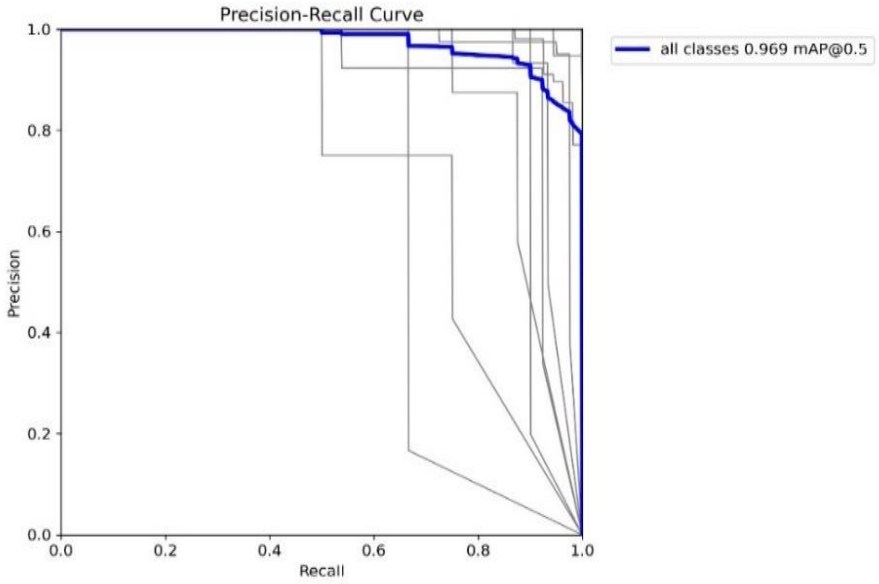

Figure 16- Precision-Recall curve

The Recall-Confidence curve represents the relationship between recall and confidence scores. This curve reflects how well the model classifies objects at different confidence thresholds. As shown in Figure 17, the model maintains high recall values as confidence scores increase, indicating its ability to make highly reliable predictions.

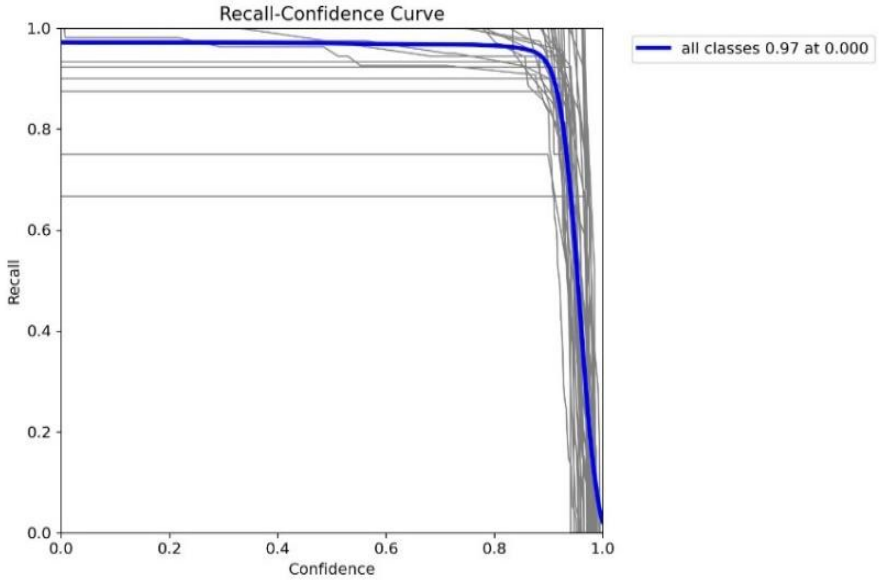

Figure 17- Recall-Confidence curve

The F1-Confidence curve (Figure 18) visualizes the model's F1 score as a function of confidence. The F1 score, which balances precision and recall, is an essential measure of overall detection performance. The graph indicates that the model achieves a high F1 score across all classes, with a peak F1 score of 0.96 at a confidence threshold of 0.838. This suggests that the model maintains a strong balance between correctly identifying objects (recall) and minimizing false positives (precision).

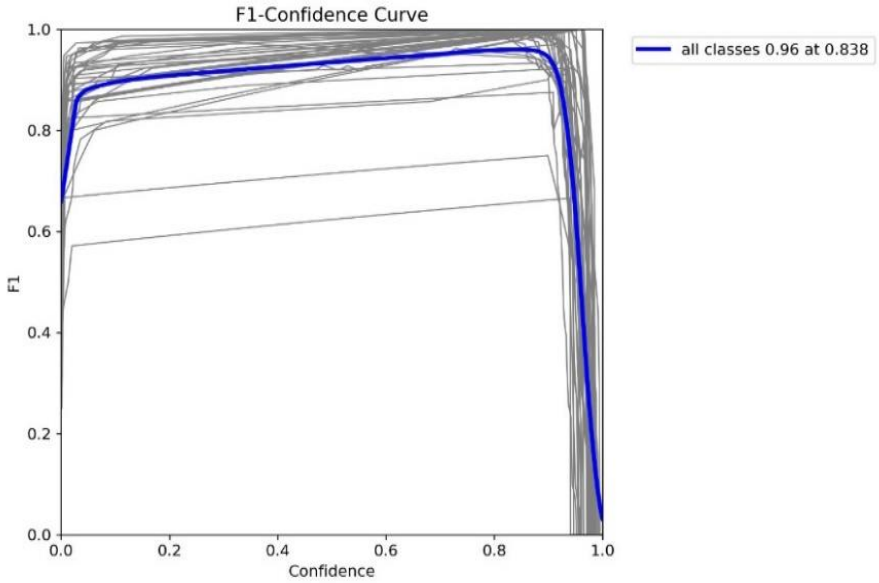

Figure 18- F1-Confidence curve

The Precision-Confidence curve (Figure 19) illustrates the model's precision with respect to confidence scores. A high precision value at higher confidence levels indicates that the model makes accurate predictions when it is certain. The graph demonstrates that the model achieves a precision of 1.00 at a confidence threshold of 0.993, signifying that, at high confidence, the model's predictions are nearly error-free. This further validates the model's reliability in detecting objects correctly when confidence scores are high. In addition to classification-based metrics, regression performance evaluation revealed that the YOLOv8 model achieved a MAE of 37.0 g and a MRE of 4.43%, indicating its strong capability for accurate weight estimation alongside precise object detection.

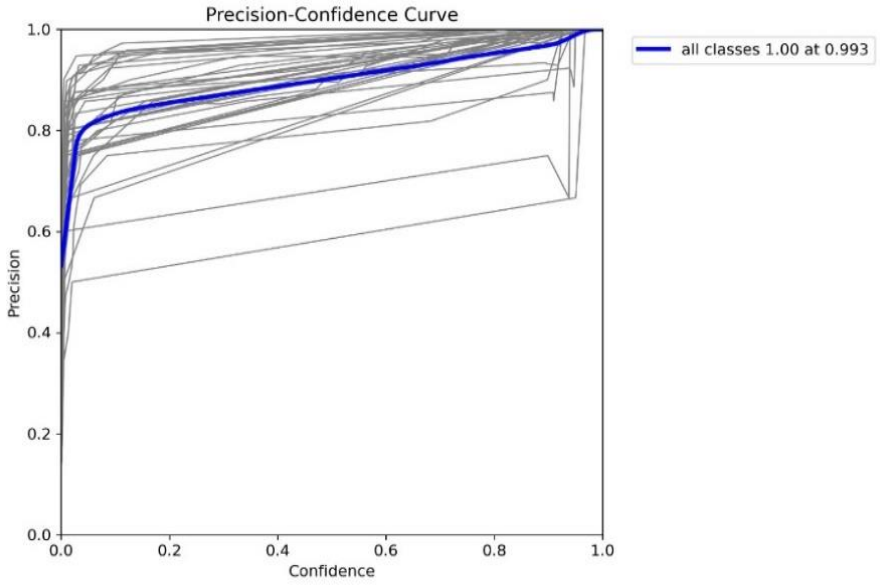

Figure 19- Precision-Confidence curve

3.7. Training and validation losses for 500 epochs

The progression of training and validation losses throughout the learning process offers meaningful insight into the model's capacity for adaptation and generalization. Figure 20 presents the temporal variation of these losses, demonstrating the gradual convergence of the model as it effectively learns the underlying data patterns while minimizing prediction errors.

In Figure 21, the evolution of key performance indicators Precision-Recall, mAP_{50}, and mAP_{50-95} clearly illustrates the continuous improvement in detection accuracy and localization performance across epochs. The steady upward trajectory of Precision and Recall signifies the model's enhanced ability to correctly identify and classify objects, while the consistent growth of mAP metrics indicates improved detection consistency across various object sizes and categories. Overall, these visualizations highlight the model's stable learning dynamics and its capacity to generalize beyond the training dataset. After 500 training epochs, the YOLOv8 network demonstrates not only high accuracy but also reliable generalization, confirming its robustness and suitability for real-world object detection and weight estimation tasks.

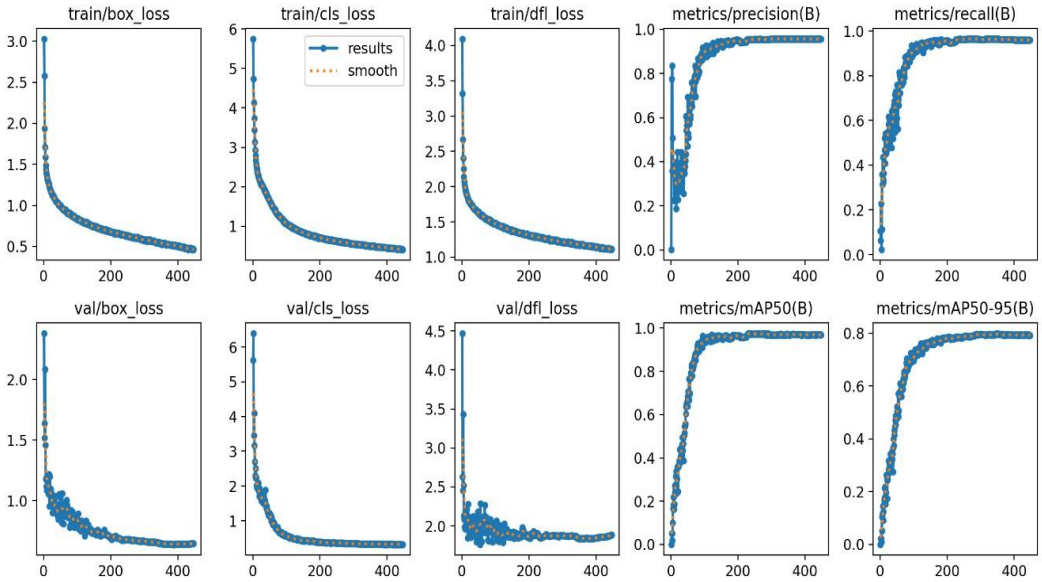

Figure 20- Training and validation losses

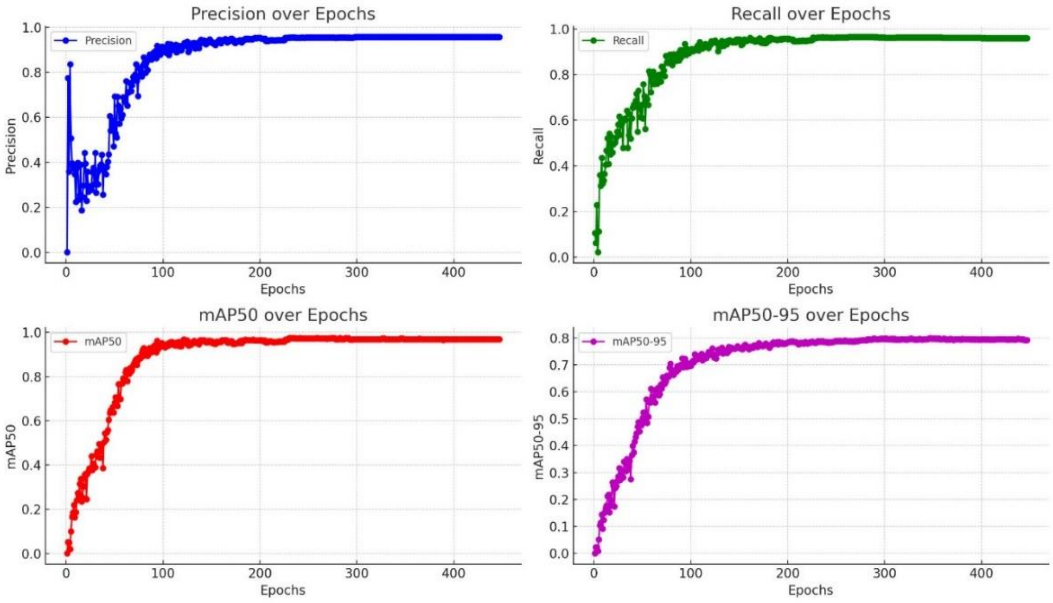

Figure 21- Training performance metrics

3.8. Predicted labels for 500 epochs

The visual results obtained after 500 epochs of training demonstrate the model's effectiveness in object detection and weight estimation. Figure 22 presents the model's performance at different epoch stages, highlighting its progressive improvement over time. These images provide insights into the accuracy of object detection and the model's performance across different classes. Each detected object in the images is correctly identified and labeled, and the weight estimations are successfully performed. This showcases the model's strong ability to recognize objects with high precision and reliability.

As a result, the model trained for 500 epochs has achieved high precision, recall, and F1-score, demonstrating strong performance in the given task. The low training and validation losses indicate that the model has effectively learned the data and exhibits excellent generalization capability. These findings suggest that the model is highly reliable and suitable for practical applications. Given its high performance over 500 epochs, this model can be considered a robust and dependable system for estimating broiler weights.



Figure 22- Training batch images

4. Discussion

This study aimed to develop an image processing and deep learning-based system as an alternative to conventional manual and automatic weighing methods for broilers. The main innovation of this work lies not merely in the use of advanced algorithms but in the design and implementation of an automated data acquisition and analysis framework that enables real-time, non-invasive, and continuous monitoring of broiler live weight under practical farming conditions. Morphological parameters, specifically pixel area, pixel perimeter, major axis length, and minor axis length, were used as predictors in a regression model, which yielded an adjusted R^2 value of 0.97, a MAE of 84.4 g, and a MRE of 7.6%. These findings demonstrate that the proposed morphological approach is operationally feasible and achieves a prediction accuracy comparable to, or better than, that reported in several previous studies.

Comparable results have been documented in the literature. De Wet et al. (2003) reported a determination coefficient (R^2) of 0.97 and a 10% relative error between body weight and pixel area, while Mollah et al. (2010) observed a strong correlation (r = 0.99) with error rates ranging from 0.04% to 17%. Mortensen et al. (2016) found an average relative error of 7.8%, and Amraei et al. (2017a; 2017b; 2018) achieved R^2 values up to 0.98 in their predictive models. Similarly, Jorgensen et al. (2019) reported an R^2 of 0.96 with an average error of 3.5% for carcass weight prediction. More recently, Electra et al. (2022) reported a mean prediction error of 144.7 g, Li et al. (2023) found an R^2 of 0.71 with an average absolute error of 93 g, and Campbell et al. (2025) achieved a MAE of 60.5 g and a MRE of 7%. Although slightly higher coefficients were reported in some studies, such as those by Amraei et al. (2017a; 2017b; 2018), their exclusion of head and tail regions during feature extraction (Chen-Vase method) may have contributed to improved accuracy by reducing variability.

In the second part of the study, the YOLOv8 deep learning model was implemented for broiler weight estimation through image-based classification. The selection of YOLOv8 in this study is justified by its superior detection accuracy, real-time processing capability, and architectural efficiency compared to earlier versions. Its anchor-free structure, decoupled detection head, and enhanced feature aggregation based on CSPDarknet enable robust performance under variable lighting and partial occlusion conditions. These architectural improvements make YOLOv8 a balanced and scalable model that effectively combines speed, accuracy, and computational efficiency for real-time computer vision applications (Jocher et al. 2023; Wang et al. 2023).

After 500 epochs of training, the model achieved a mean Average Precision (mAP) of 0.969, confirming its robust overall performance across classes. These findings align with previous research demonstrating the effectiveness of CNN and YOLO-based architectures in poultry monitoring and weight prediction (Amraei et al. 2017a; Shams et al. 2025). However, relatively lower Average Precision (AP) scores observed in certain classes during early training stages suggest limited learning caused by class imbalance—a common issue in deep learning models that can reduce generalization capability (Buda et al. 2018; Johnson & Khoshgoftaar 2019).

The integration of regression-based performance metrics (MAE and MRE) into the YOLOv8 analysis allowed for direct comparison with the morphological method and other studies. The proposed model achieved a MAE of 37.0 g and a MRE of 4.43%, alongside an F1-score of 0.96, demonstrating high prediction accuracy and reliability. These results indicate that the YOLOv8 framework not only performs effectively in object detection but also provides accurate mass estimation when calibrated through confidence-weighted regression.

Compared to the morphological approach, which offers simplicity and interpretability, the YOLOv8 based system showed superior robustness under variable lighting and occlusion conditions. The morphological method, relying on 2D geometric descriptors, is better suited for controlled environments, whereas the deep learning model effectively handles real-world variability in broiler positioning, illumination, and perspective. Moreover, the proposed system benefits from an automated measurement chamber, ensuring standardized image acquisition a methodological advantage over prior studies relying on manual capture or inconsistent environmental conditions.

When benchmarked against prior studies, the proposed YOLOv8 based system demonstrates competitive or superior performance in broiler weight estimation. For instance, as shown in Table 5, Zhang et al. (2021) reported a MAE of 45.6 g and MRE of 5% using a CNN based regression model trained on 3D image features, while Mortensen et al. (2016) employed a Bayesian ANN model achieving a MRE of 7.8% with an automated image acquisition platform. Similarly, Amraei et al. (2017a) combined ellipse fitting and Chan-Vese segmentation with artificial neural networks, attaining an R^2 of 0.98, and Mollah et al. (2010) achieved high accuracy through logarithmic regression of surface-area pixels, comparable to manual weighing up to 35 days of age.

More recent work by Shams et al. (2025) utilized YOLOv8 based segmentation integrated with morphological features, achieving a mAP_{50-95} of 0.829 and eliminating the need for direct dimension measurements. Compared to these approaches, the proposed YOLOv8 based detection and regression framework in the current study achieved a MAE of 37.0 g, a MRE of 4.43%, and an F1 score of 0.96, reflecting both accuracy and robustness under real-world imaging conditions (Table 5).

Importantly, the integration of an automatic measurement chamber distinguishes this study from most prior works that relied on manual or semi-automatic image collection, ensuring consistent environmental control and reducing operator-induced variability. This unified data acquisition and prediction framework enhances reproducibility and minimizes handling stress in precision livestock research.

To further enhance performance, future studies should consider transfer learning and retraining with larger, class-balanced datasets, which are crucial for improving model generalization and addressing data imbalance (Pan & Yang 2010; Shorten & Khoshgoftaar 2019). Although extending training duration may improve accuracy, overfitting should be carefully monitored and mitigated through strategies such as early stopping and dropout regularization (Prechelt 1998; Srivastava et al. 2014).

Table 5- Comparative performance of the proposed methods and related weight estimation studies

Study / Approach	*Method Type*	*Performance Metrics*	*Notable Features*
Current study	Traditional image analysis	MAE = 84.4 g; MRE = 7.6%	Utilizes binary image morphology; simple computation; integrated automatic measurement chamber
Current study	YOLOv8 based object detection	MAE = 37.0 g; MRE = 4.43%; mAP = 0.969; F1 = 0.96	YOLOv8 based detection and regression; standardized RGB imaging in an automatic chamber
Mollah et al. (2010)	Traditional image analysis	R^2 = 0.999; MRE = 0.04-16.47%	Logarithmic regression based on surface-area pixels; accuracy comparable to manual weighing up to 35 days of age
Mortensen et al. (2016)	Bayesian ANN based model	MRE = 7.8%	Bayesian Artificial Neural Network trained on 3D depth data; automated image acquisition platform ensuring consistent conditions
Amraei et al. (2017a)	Image analysis + ANN	R^2 = 0.98; most errors < 50 g	Combined ellipse fitting and Chan-Vese segmentation; comparison of multiple ANN training algorithms
Zhang et al. (2021)	CNN regression	MAE = 45.6 g; MRE = 5.0%	CNN-based regression model using 3D image features; manual image acquisition under limited lighting conditions
Shams et al. (2025)	YOLOv8-based segmentation	mAP_{50-95} = 0.829	YOLOv8 segmentation integrating morphological features; removes the need for manual dimension measurements

5. Conclusions

In this study, an automated controlled measurement system was developed for broilers, combining a precision scale and a camera system in an operational environment. Using MATLAB-based software, morphological features such as pixel area, perimeter, and axis lengths were extracted from 151 broiler images. Based on these features, a multiple regression model achieved a high prediction accuracy, with an adjusted R^2 value of 0.97 and an average relative error rate of 7.6%. Additionally, a deep learning model was trained, achieving a mAP of 0.969 after 500 epochs, demonstrating strong performance in object detection tasks. These results indicate that the developed system can serve as an effective alternative to traditional manual and automatic weighing methods, reducing labor, time, costs, and animal stress. Future improvements could involve expanding the dataset and optimizing model training strategies to enhance overall performance.

Author Declarations

Authors' contributions: Concept: H.Ku., A.A., H.Ka., Design: H.Ku., A.A., H.Ka., Data collection: H.Ku., H.Ka., A.T., Analysis: H.Ku., A.A., H.Ka., A.T., Writing: H.Ku., H.Ka.

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