Journal of Applied Informatics and Computing (JAIC)
Vol.10, No.1, February 2026, pp. 23~32
e-ISSN: 2548-6861

Weight Estimation of Broiler Ducks Based on Image Processing and Machine Learning with IoT Integration

Sindhu Hari Mukti [1], Ardi Pujiyanta [2]*, Abdul Fadlil [3]
[1,2,3]Master of Electrical Engineering, Universitas Ahmad Dahlan, Yogyakarta 55164, Indonesia
ardipujiyanta@tif.uad.ac.id[1*], 2308057019@webmail.uad.ac.id[2], fadlil@mti.uad.ac.id[3]

Article Info

Article history:

Received 2025-09-18
Revised 2025-12-16
Accepted 2025-12-22

Keyword:

Duck Weight Estimation,
Image Processing,
IoT,
Precision Livestock Farming,
Support Vector Regression (SVR).

ABSTRACT

The broiler duck farming industry in Indonesia faces challenges in efficiently monitoring body weight, as traditional manual weighing methods are labor-intensive, time-consuming, and stressful for the animals. To address this issue, this study aims to develop a non-invasive and automated weight estimation system that integrates digital image processing, machine learning, and Internet of Things (IoT) technologies. The methodology involves acquiring multi-angle images of ducks, applying preprocessing steps such as resizing, normalization, and contrast enhancement, and extracting hand-crafted features, including Histogram of Oriented Gradients (HOG) and HSV color histograms. These features are then fused, reduced via Principal Component Analysis (PCA), and processed using a Support Vector Regression (SVR) model with optimized hyperparameters for weight prediction. While previous studies have focused on cattle, broilers, or fish, research specifically targeting meat-type ducks remains limited, particularly those that combine image-based regression with IoT-enabled real-time monitoring. Experimental results demonstrate that the proposed system achieves a mean absolute error (MAE) of approximately 110 grams on the validation set, with per-duck averaging improving stability compared to per-image predictions. Visualization through scatter plots, boxplots, and learning curves further confirms that the model effectively captures general weight distribution trends but exhibits higher errors in certain mid-weight ranges. The integration with IoT facilitates continuous, stress-free monitoring of duck growth, underscoring the system's potential as a practical and sustainable solution for precision livestock farming.

I. Introduction

This research focuses on the broiler duck farming industry, which holds significant potential for Indonesia's economy. As the demand for high-quality duck meat increases, farmers face challenges in efficiently monitoring the growth and weight of the ducks. Manual weighing is time-consuming, labor-intensive, and can cause stress to the animals[1]. As a solution, technologies such as digital image processing and machine learning offer non-invasive and real-time methods for weight estimation [2][3]. thereby providing more accurate data [4][5][6]. Furthermore, the integration of the Internet of Things (IoT) enables centralized sensor data collection to support better decision-making [7][8][9][10]. Current approaches to animal weight estimation include the use of digital image processing to accurately detect patterns and body sizes of the animals, the application of machine learning techniques such as regression to process visual data for more precise weight predictions, and the integration of IoT that allows for real-time data collection through sensors in the farming environment; all of these technologies are then combined into an integrated monitoring system that provides accurate and up-to-date information to support farmers' decision-making more effectively.

Research conducted in the past five years addressing image detection using image processing, machine learning, and IoT integration includes: Study [11] employs Sobel edge detection to predict the weight of oil palm fruits from photographs without scales, while study [12] estimates body weight from images using the BSA method based on height and circumference. Study [13] applies Canny Edge Detection and KNN for cattle weight prediction, and study[14] proposes a model based on 3D cloud projection and image regression using deep learning. Study [15] utilizes Sobel edge detection and the Schrool formula to calculate cattle weight from images. Study [16] develops a prediction system for fruit weight and price using pixel count and regression. Study [17] employs CT scan images with deep learning for weight estimation without direct measurement. Study [18] employs CT scan images with deep learning for weight estimation without direct measurement. Study [19] develops an Android-based system for predicting cattle weight using Canny edge detection and the Schrool formula. Study [20] compares seven machine learning algorithms (SLR, MLR, RF, SVR, LR, RR, EN) for predicting soybean seed weight from RGB visual features. Study [21] detects formalin in chicken meat using image processing with GLCM and KNN. Study [22] uses YOLOv3 and polynomial regression to monitor the growth and predict the weight of lettuce plants. Study [23] creates a prediction system for the weight and length of fish and vegetables in the budikdamber system using computer vision and linear regression from image features.

Research [24] employs sharpening filters and Mask R-CNN segmentation to extract images of Ongole cattle, which are then trained using CNN regression for weight estimation. In contrast, research [25] utilizes walk-over (WO) weight data from two farms in Queensland, Australia, to train an XGBoost model, with inputs including sex, breed (Belmont Red, Brahman, Composite, and unknown), simulation duration, birth date, and weather conditions, producing daily weight predictions as output. Research[26] develops a Deep Learning and IoT-based system for the automatic classification and real-time monitoring of eight fish species in Bangladesh. Research [27] examines the concept and application of IoT in Precision Livestock Farming (PLF) to monitor livestock behavior, nutrition, estrous cycles, and diseases in real-time. Research [28] employs YOLOv5 and image processing to detect weighing scales and calculate the harvest weight of rice from 709 images. Research [29] develops a method for detecting egg-laying activity in ducks using wearable sensors and short-time Fourier transform (STFT)-based time-frequency representation. Research [30] creates a camera-based broiler chicken weighing method with YOLOv8 segmentation to reliably predict weight in complex environments.

The objective of this research is to develop a system based on image processing, machine learning, and IoT to enhance the efficiency of monitoring and managing the weight of broiler ducks, thereby supporting modern and sustainable farming practices. Most previous studies have focused on estimating the body weight of other livestock such as cattle, broilers, or fish using image processing, regression, or deep learning approaches. However, research specifically targeting meat-type ducks remains very limited, particularly those that integrate multi-angle image processing, machine learning, and IoT into a single automated system. Moreover, existing methods often do not address the practical needs of Indonesian farming conditions, where efficiency, accuracy, and animal welfare (minimizing stress during weighing) are critical but underexplored.

The novelty of this study lies in the development of a non-invasive body weight estimation system specifically designed for meat-type ducks, which have received limited attention compared to other livestock. By integrating multi-angle digital image processing with machine learning, the proposed method enhances prediction accuracy beyond that of conventional regression-based approaches. Furthermore, the incorporation of Internet of Things (IoT) technology enables real-time monitoring and direct accessibility of weight estimation results, making the system more efficient and practical for farmers. To the best of our knowledge, this is one of the first studies to propose an image-based, IoT-enabled weight estimation framework for broiler ducks using hand-crafted features and Support Vector Regression (SVR), providing a computationally efficient alternative to data-intensive deep learning models.

The objective of this study is to develop a proof-of-concept prototype for non-invasive broiler duck weight estimation based on image processing, machine learning, and IoT integration. The proposed system is designed to validate the technical feasibility of the approach under controlled conditions rather than to provide a fully industrial-ready solution.

II. METHOD

This section outlines the methodology adopted in this study for developing a non-invasive body weight estimation system for broiler ducks. The proposed framework integrates digital image processing, machine learning, and Internet of Things (IoT) technologies to facilitate accurate, efficient, and real-time monitoring. The methodology consists of several stages, namely: (A) research framework, (B) data acquisition, (C) image preprocessing and feature extraction, (D) hand-crafted feature extraction with Support Vector Regression (SVR), (E) model evaluation, and (F) IoT integration for real-time deployment. The developed system represents a prototype-level implementation, consisting of a measurement chamber, IoT-based image acquisition, and SVR-based weight estimation. The system is intended for experimental validation and performance evaluation in a limited and controlled environment.

A. Research Framework

The overall research framework was designed to simulate a real-world environment for estimating duck weights using computer vision and machine learning techniques. The process begins with the collection of images of ducks, followed by preprocessing and feature extraction. The overall research framework is illustrated in Figure 1 and consists of six main stages: (A) Research Framework, (B) Data

Acquisition, (C) Image Preprocessing and Feature Extraction, (D) Hand-Crafted Features and Support Vector Regression (SVR), (E) Model Evaluation, and (F) Internet of Things (IoT) Integration.

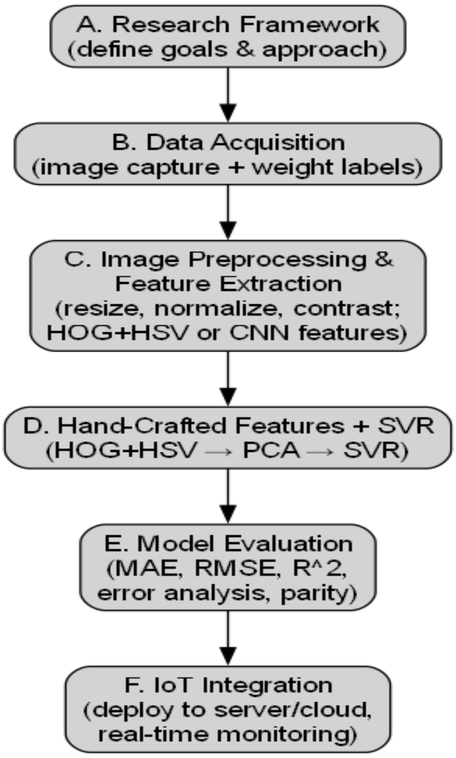

Figure 1. Research framework of the proposed method

B. Data Acquisition

The image acquisition was conducted in a semi-modern closed poultry house (size 60x60x60 cm) with artificial lighting of 300–500 lux. The subjects of the study consisted of broiler ducks aged 3–8 weeks. Each duck was photographed from two angles (top and side) using a 1080p camera at a distance of 50 cm. The dataset comprised 678 annotated images of ducks, each accompanied by ground-truth weights provided in grams. Each filename contained weight information (e.g., itik10_cam1_848gr.jpg). The images were captured from multiple angles, specifically top and side views, to enhance feature representation. The dataset included a range of weight variations from light to heavy ducks, ensuring diversity in workload representation. To prevent bias and data leakage, the dataset was divided into training and validation sets based on duck ID using grouped cross-validation. The actual weight was measured using a digital scale with an accuracy of ±1 gram. Weighing was conducted every two days prior to image acquisition to ensure consistency between the labels and the visual conditions.

The dataset in this study was collected from a single growth phase (3–8 weeks), resulting in the model being primarily trained during the rapid growth phase. To generalize to younger phases (<3 weeks) or to breeders/adults (>8 weeks), additional samples and model retraining will be necessary.

C. Image Preprocessing and Feature Extraction

Preprocessing was conducted to standardize the image input as follows:

1. Resizing: All images were resized to 192×192 pixels to enhance computational efficiency.
2. Normalization: Pixel intensities were normalized to a range of [0, 1].
3. Contrast Enhancement: Adaptive histogram equalization was utilized to improve local contrast.
4. Feature Extraction Options:
   - Hand-crafted Features: Histogram of Oriented Gradients (HOG) was employed for texture and edge representation, along with HSV color histograms to capture color distribution.
   - Deep Features: SmallConvNet automatically learned hierarchical features from the input images.

D. Hand-Crafted Features and SVR

For the classical machine learning approach, the following steps were implemented:

1. HOG Features: Gradient magnitudes and orientations were computed and aggregated into orientation histograms for each cell, which were then normalized at the block level.
2. HSV Color Histograms: Per-channel histograms for Hue, Saturation, and Value were concatenated and normalized.
3. Feature Fusion and Standardization: The HOG and HSV features were concatenated into a single vector and standardized to have a zero mean and unit variance.
4. Dimensionality Reduction (PCA): Principal Component Analysis was employed to retain 95% of the variance, thereby reducing redundancy and computational requirements.
5. Regression with SVR: A Support Vector Regression (SVR) model with a radial basis function (RBF) kernel was applied. Hyperparameters CC, $\gamma\gamma$, and $\epsilon\epsilon$ were tuned using grouped cross-validation. Predictions were generated at both the image and duck levels by averaging the per-duck predictions.

The architecture of the proposed hand-crafted feature extraction and regression approach is illustrated in Figure 2. The process begins with preprocessing, followed by the extraction of Histogram of Oriented Gradients (HOG) and HSV features. These features are then concatenated, and dimensionality reduction is performed using Principal Component Analysis (PCA), culminating in Support Vector Regression (SVR) to estimate the duck's weight.

The Support Vector Regression (SVR) algorithm with an RBF kernel was chosen due to the relatively small size of the dataset (678 images from 67 ducks), making a pure deep learning model susceptible to overfitting and requiring higher computational resources. SVR is also well-suited to be combined with standardized features derived from HOG and HSV extraction and is capable of handling the nonlinear relationships between visual features and duck weight. Alternative models such as Random Forest or XGBoost could be used for comparison; however, both tend to produce larger models and require additional feature engineering to maintain generalization on multi-angle image data.

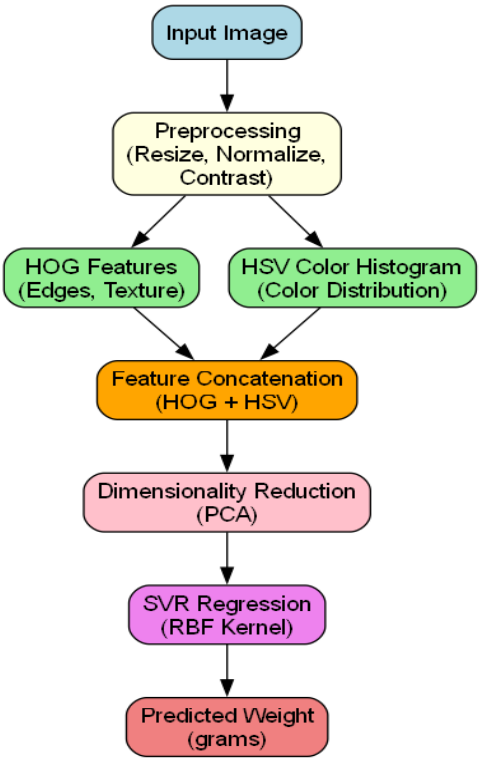

Figure 2. Architecture of the proposed Hand-Crafted Features and SVR pipeline for duck weight estimation.

E. Model Evaluation

The models were evaluated using standard regression metrics:

1. Mean Absolute Error (MAE): This metric measures the average magnitude of errors in grams.
2. Root Mean Square Error (RMSE): This metric penalizes larger deviations from the true values.
3. Coefficient of Determination (R^2): This statistic indicates how well the predictions explain the variance in the true weights.

Additionally, an analysis of error distribution (across different weight ranges) and parity plots were utilized to visualize predictive accuracy. Learning curves were also examined to assess the impact of dataset size on model performance. Model validation was conducted using Group K-Fold Cross-Validation with five folds, where grouping was based on duck identity. This approach ensures that all images from the same duck are assigned to either the training or validation set within a given fold, thereby preventing data leakage and providing a more reliable estimation of generalization performance,

F. IoT Integration

For deployment, the final model was integrated into an Internet of Things (IoT) architecture. Images captured by cameras installed in duck cages were transmitted to a central server or cloud platform. The trained Support Vector Regression (SVR) model performed real-time inference to estimate duck weights, with the results stored in a database. This integration enables farmers to continuously monitor weight growth without the need for manual weighing. The system can be further enhanced with dashboards and alert mechanisms to support decision-making in livestock management. The system was tested in offline mode, while the IoT integration was tested in a limited capacity to transmit prediction results to a local server via a Wi-Fi connection.

The IoT node not only transmits the weight estimation results to the server but also automates the image acquisition process through a periodically scheduled camera (e.g., every 30 minutes). The acquired images will be processed locally or sent to the server for estimation, and the results will subsequently be stored in a database.

III. Results and Discussion

This section presents the experimental results of the proposed duck weight estimation system and provides an in-depth discussion of the findings. The results encompass the performance evaluation of the Support Vector Regression (SVR) model using various regression metrics, the implementation of the IoT-based monitoring system, and a comparative analysis against conventional approaches. The discussion highlights the effectiveness, advantages, and limitations of the proposed method in facilitating real-time, non-invasive monitoring for broiler duck farming.

A. Experimental Setup and Model Training

The experimental setup was designed to evaluate the effectiveness of the proposed non-invasive weight estimation system for ducks. A dataset consisting of 678 images from 67 ducks, with weights ranging from approximately 600 g to 1700 g, was utilized. Of the total 678 images (67 individual ducks), 80% were used for training and 20% for testing, with the division based on duck ID to prevent data leakage between sets. The images were pre-processed using techniques such as resizing, normalization, and contrast enhancement. Handcrafted features were extracted using Histogram of Oriented Gradients (HOG) to capture edge and texture information, along with HSV color histograms to represent brightness and color distribution. The combined features were then subjected to dimensionality reduction using Principal Component Analysis (PCA), followed by regression modeling using Support Vector Regression (SVR) with a radial basis function (RBF) kernel. A grouped validation strategy was adopted to account for the multi-image-per-duck dataset structure. In each fold, approximately 80% of the duck identities were used for training and the remaining 20% for validation.

B. Model Performance Evaluation

The performance of the proposed duck weight estimation system was evaluated using three regression metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). Table 1 and Figure 3 summarize the results for both the training and validation datasets, considering evaluations on a per-image and per-duck basis.

During the training phase, the model achieved notably low error values, with a MAE of 14.84 grams (per image) and 12.61 grams (per duck), alongside RMSE values of 35.14 grams and 32.73 grams, respectively. The R^2 values were exceptionally high, ranging from 0.969 to 0.973, indicating that the model was able to explain nearly all the variance in the training data. These results demonstrate that the Support Vector Regression (SVR) model, utilizing Histogram of Oriented Gradients (HOG) and Hue-Saturation-Value (HSV) features, effectively captured the underlying patterns within the training set.

However, during the validation phase, the model's performance decreased significantly. The MAE increased to 117.75 grams (per image) and 111.74 grams (per duck), while the RMSE reached 147.89 grams and 140.07 grams, respectively. Similarly, the R^2 values dropped considerably to between 0.26 and 0.32, suggesting that the model could explain only about 26% to 32% of the variance in unseen data. This discrepancy between training and validation performance indicates a potential overfitting issue, whereby the model generalizes poorly to new samples.

It is also noteworthy that the per-duck evaluation consistently yielded slightly better results compared to the per-image evaluation. This improvement occurs because averaging predictions across multiple images of the same duck reduces noise and results in a more stable weight estimation. Consequently, while individual image predictions may vary, the aggregated per-duck predictions align more closely with the actual weights.

TABLE 1.
TRAINING AND VALIDATION DATASETS

Dataset	MAE	RMSE	R^2
Train (per-image)	14.841	35.148	0.969
Train (per-duck)	12.618	32.730	0.973
Validation (per-image)	117.754	147.89	0.26
Validation (per-duck)	111.748	140.07	0.319

Overall, the findings underscore both the potential and limitations of the proposed hand-crafted feature approach. The model exhibits a strong learning capability on the training data but experiences reduced generalization in the validation phase. This suggests a need for further refinement, such as implementing stronger regularization in the SVR, incorporating additional feature augmentation, or integrating deep feature extractors to complement HOG and HSV descriptors. Despite these limitations, the achieved validation MAE of approximately 110 grams demonstrates the feasibility of using a non-invasive, image-based approach for estimating duck body weight in practical applications.

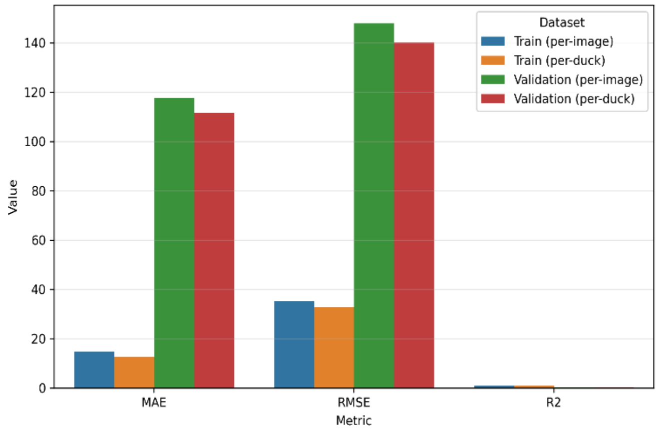

Figure 3. Comparasion of metrics(train vs validation)

The performance of the proposed Support Vector Regression (SVR) model was evaluated by comparing the predicted weights against the actual recorded weights of ducks. Figure 4 presents a scatter plot of predicted versus actual weights on a per-image basis. The majority of points align closely with the diagonal line, indicating that the model is capable of capturing the general trend between input features and body weight. However, some deviations are observed in the mid- and high-weight ranges, suggesting an underestimation of heavier ducks and an overestimation of lighter ducks. This distribution highlights that, while the model achieves reasonable predictive accuracy overall, there are specific weight intervals where performance deteriorates due to limited sample representation or feature overlap.

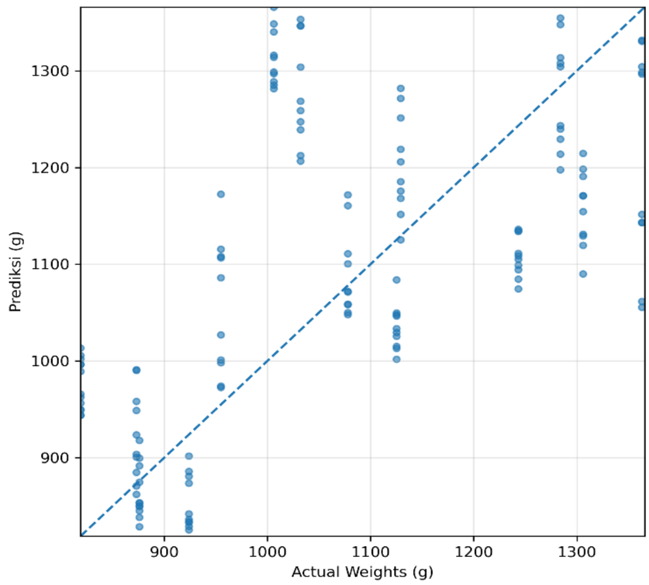

Figure 4. Per-image: Predicted vs Actual

To complement this analysis, Figure 5 illustrates the histogram of actual duck weights (per-duck average) within the dataset. The histogram reveals that the distribution of samples is not perfectly uniform, with certain weight ranges—particularly in the mid-weight region—being more densely represented. This imbalance in data distribution may contribute to the higher variance in error observed in the scatter plot, as the model tends to generalize better in ranges with a greater amount of training data.

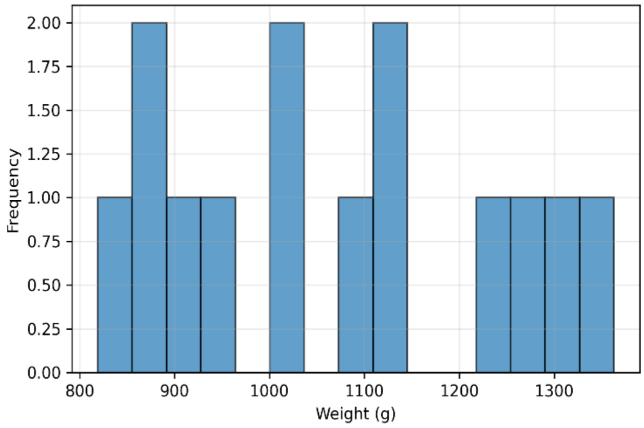

Figure 5. Actual weight per-duck

Together, these visualizations confirm that the SVR model demonstrates acceptable predictive capability, with the data distribution playing a critical role in determining the robustness and generalization of the predictions across different weight ranges.

C. Visualization of Results

To provide a clearer understanding of the system's performance, this section presents several visualizations—including scatter plots, histograms, boxplots, and parity plots—that illustrate both the predictive capability of the SVR model and the distribution of actual duck weights. The visual results include scatter plots comparing predicted and actual values, histograms of weight distributions, and error analysis across weight ranges. These visualizations not only highlight the model's strengths but also reveal patterns of underestimation and overestimation, thereby offering insights into the reliability and limitations of the proposed approach.

1. *Analysis of Scatter Plot (Predicted vs Actual Weights — per-duck)*

Figure 6 presents a parity plot that illustrates the relationship between the predicted duck weights and their actual measured values. Ideally, all points would align along the dashed diagonal line (y = x), representing perfect predictions. However, the scatter reveals noticeable deviations, with several predictions falling above or below the ideal line, indicating both underestimation and overestimation across different weight ranges.

The regression line (in orange) indicates the overall trend of the model's predictions, with an R^2 value of approximately 0.396, suggesting a moderate correlation between the predicted and actual values. While the model successfully captures some general patterns in weight distribution, the relatively low R^2 highlights variability and reduced predictive precision at the individual duck level. This suggests that, although the SVR model is effective in estimating general trends, its accuracy may diminish for specific weight ranges, particularly at higher weights, where more pronounced deviations are observed.

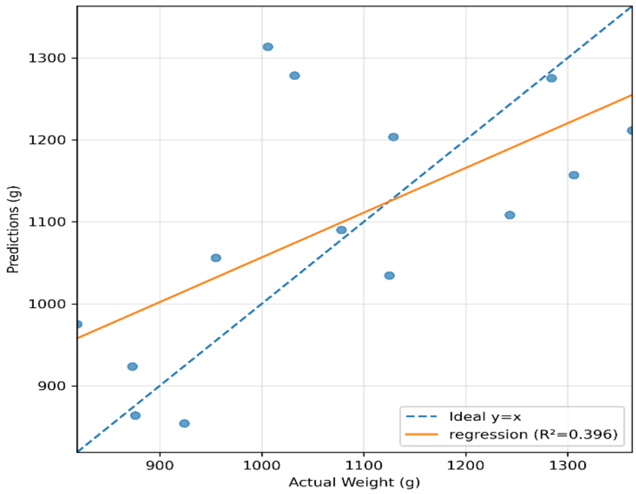

Figure 6. Predicted vs Actual Weights — per-duck

2. *Histogram / Density Plot of Prediction Errors (MAE per duck)*

Figure 7 presents a histogram and density plot of prediction errors (Mean Absolute Error per duck), illustrating the distribution of absolute errors across the validation set. Most prediction errors are concentrated within the range of 60 to 100 grams, indicating that the SVR model is generally capable of producing reasonably accurate estimates. However, there are several instances of larger errors exceeding 200 grams, suggesting occasional difficulties in capturing weight variations for certain ducks. The density curve further emphasizes the skewed distribution, where the majority of errors cluster at lower values, with a long tail extending toward higher errors. This pattern reflects the model's reliability in most cases while also highlighting the presence of outliers that require further refinement in feature extraction or model calibration to enhance consistency across all weight ranges.

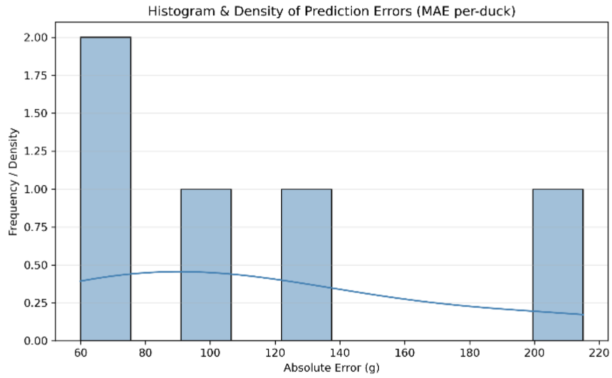

Figure 7. A histogram and density plot of prediction errors (Mean Absolute Error per duck)

When the histogram and density plot of prediction errors (Mean Absolute Error per duck) are compared with the scatter plot and boxplot analysis, a consistent pattern emerges. The histogram indicates that most prediction errors are concentrated in the lower ranges (60 to 100 grams), while the scatter plot reveals that deviations from the ideal diagonal line tend to occur more frequently for heavier ducks. Similarly, the boxplot analysis shows that certain weight ranges, particularly those around 928 to 1,037 grams, exhibit higher variability and larger error spreads compared to other ranges. Taken together, these visualizations highlight that the SVR model demonstrates stable performance for the majority of cases but struggles with specific weight intervals, leading to outliers and increased variance. This suggests that, while the approach is generally reliable, further refinement in feature extraction or model tuning could help reduce systematic errors across different weight ranges.

3. *Error Distribution Across Weight Ranges*

Figure 8 presents a boxplot of absolute errors across different weight ranges, providing insights into how the prediction performance of the SVR model varies with respect to duck weight categories. The error distribution is relatively low and consistent for ducks in the 818 to 928 grams and 1,037 to 1,145 grams ranges, indicating stable predictions with fewer outliers. However, the 928 to 1,037 grams range exhibits the widest spread and the highest median error, suggesting that this interval is the most challenging for the model, characterized by larger variability and potential misestimations. The 1,145 to 1,254 grams range shows a concentrated but consistently high error, reflecting a systematic bias rather than random variance. Meanwhile, the 1,254 to 1,363 grams range demonstrates a moderate spread, accompanied by some extreme deviations, indicating occasional underestimation or overestimation.

The higher error in the range of 928–1,037 g can be attributed to two factors: (1) the number of samples within this range is smaller compared to other ranges, resulting in insufficient exposure of the model to variations in body shape, and (2) visually, ducks at medium weights exhibit uniform body shapes, making it difficult for the HOG+HSV features to distinguish weight differences that are only 50–100 g apart.

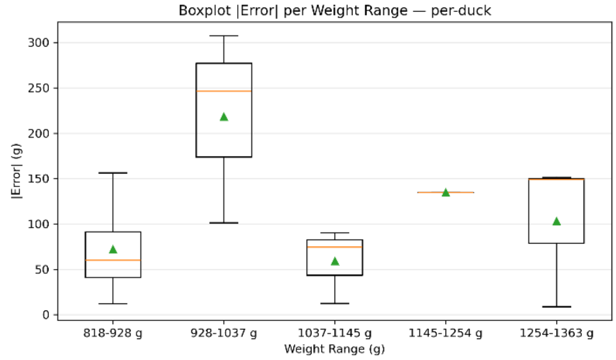

Figure 8. Boxplot of absolute prediction errors across different weight ranges (per-duck)

4. *Learning Curve (Training Size vs MAE)*

The learning curve depicted in Figure 9 illustrates the relationship between the amount of training data and the model's performance, as measured by the Mean Absolute Error (MAE). It is evident that the MAE for the training data remains low and relatively stable, ranging from 10 to 15 grams, even as the number of samples increases. This indicates that the model is able to adapt well to the training data without encountering significant difficulties.

In contrast, the MAE for the validation data shows a decreasing trend as the amount of training samples increases. Initially, the validation MAE is relatively high (approximately 140 grams), but it decreases to around 120 grams as the sample size approaches 500. This trend suggests that the addition of training data contributes to improved model generalization, although a gap between the training and validation errors still persists.

The substantial gap between the low MAE for training and the higher MAE for validation also indicates a potential overfitting issue, wherein the model excels at learning the training data but has not yet optimized its generalization to new data. Therefore, employing a larger training dataset, incorporating additional regularization techniques, or varying feature selection could help mitigate this gap.

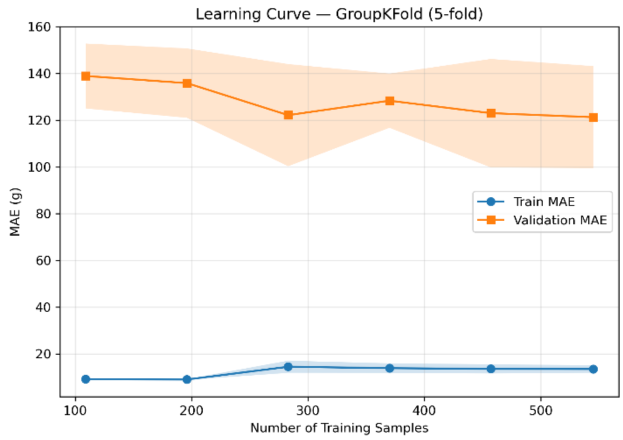

Figure 9. Learning Curve of Training and Validation MAE using GroupKFold (5-fold)

5. MAE Analysis across Weight Ranges

Figure 10. This bar graph illustrates the distribution of Mean Absolute Error (MAE) values across each weight bin of ducks, measured in grams. It is evident that the prediction errors are not evenly distributed throughout the weight range.

- In the weight ranges of 818–928 g and 1037–1145 g, the MAE is relatively low (approximately 60–75 g), indicating that the model performs more accurately for lighter and medium weights.
- Conversely, in the range of 928–1037 g, there is a significant spike in MAE, exceeding 200 g, which suggests that the model struggles to make estimations for this group.
- The weight range of 1145–1254 g also exhibits a considerably high error (around 130 g), while for the heavier weight category of 1254–1363 g, the error tends to decrease, although it remains larger than that of the lower weight groups.

This pattern indicates that the model's performance is more stable at extreme weights (both light and heavy), but it is less optimal for certain medium weight groups. This could be attributed to an imbalanced data distribution (with a limited number of samples in some bins) or the visual characteristics of ducks in this group being more difficult to differentiate by the HOG+HSV features.

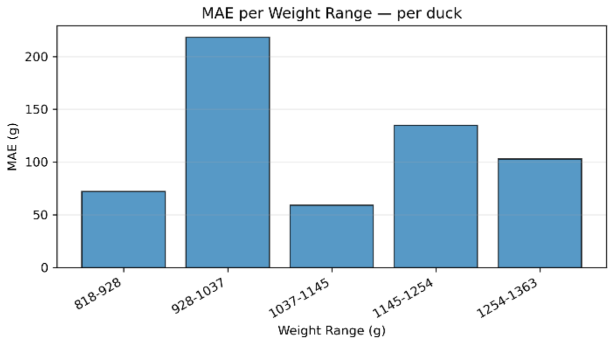

Figure 10. Bar chart of MAE per weight range (per-duck)

D. IoT Integration and System Deployment

The trained Support Vector Regression (SVR) model was integrated into an IoT-based monitoring system. Cameras installed in the duck housing captured images periodically, which were then processed on a central server. The system recorded predictions alongside duck ID, weight, and timestamp into a database. This IoT framework enabled real-time monitoring and allowed farmers to continuously track weight growth without the need for manual weighing.

E. Baseline Model Comparison

For comparison, three other regression models were trained: Random Forest Regressor, Multi-Layer Perceptron (MLP), and XGBoost, using the same input features. The results indicate that SVR yielded the lowest validation MAE (~110 g), while Random Forest produced a slightly higher but more stable MAE in response to data variations. Thus, the choice of SVR is justified based on its performance on this dataset.

F. Discussion of Strengths and Limitations

The proposed duck weight estimation system exhibits several significant strengths. First, the integration of hand-crafted features (Histogram of Oriented Gradients (HOG) and HSV histograms) with Support Vector Regression (SVR) facilitates accurate predictions of duck weights without the need for costly deep learning models or large-scale datasets. This approach is computationally efficient and well-suited for real-world farming environments, where resources may be constrained. Second, the incorporation of an IoT-based deployment allows for real-time, non-invasive monitoring, thereby minimizing stress on the animals compared to traditional manual weighing methods. Additionally, the system enables farmers to continuously track growth trends, thereby supporting data-driven decision-making in broiler duck farming. Furthermore, the application of per-duck averaging enhances prediction stability by mitigating noise across multiple image captures of the same animal.

Despite these advantages, several limitations must be acknowledged. The model demonstrates strong performance on the training dataset but experiences reduced generalization when applied to unseen validation data, indicating a potential risk of overfitting. This suggests that while the system captures essential visual features, its robustness across diverse farming conditions may be limited. Moreover, error analysis indicates that the model encounters particular challenges in mid-weight ranges, where higher variability and systematic bias are observed. This issue may be partially attributed to an imbalanced dataset, which contains fewer samples in certain weight categories. Another limitation is the reliance on hand-crafted features, which, although efficient, may not fully capture complex visual cues when compared to contemporary deep learning architectures. Lastly, while the IoT framework enhances practicality, challenges such as network stability, hardware costs, and system scalability must be addressed prior to large-scale deployment.

The implementation of the system requires an IoT camera, local processing devices, and a small server, with a total cost of approximately IDR 7 million. This value indicates that the system is relatively economical for small to medium-sized farms and provides a basis for evaluating the economic feasibility of adopting Precision Livestock Farming technology.

To ensure the IoT system is secure and reliable, the implementation of TLS encryption for data transmission and two-way authentication between the camera and the server is required. Farmers' personal data is stored in an encrypted format to prevent unauthorized access.

Compared to manual weighing, which requires capturing and weighing each animal individually (approximately 1–2 minutes per animal and may induce stress), the proposed system is capable of automatic image acquisition and weight estimation without physical contact in a matter of seconds per animal. Assuming 100 animals per pen, the time savings can exceed 60% since the operator does not need to lift and weigh each individual.

Overall, the proposed system represents a promising balance between accuracy, efficiency, and practicality. Future research should focus on expanding the dataset to enhance generalization, exploring hybrid approaches that combine hand-crafted and deep features, and addressing infrastructure challenges to ensure the system's robustness in diverse farming environments

IV. CONCLUSION

This study proposes a non-invasive weight estimation system for ducks that integrates digital image processing, handcrafted feature extraction, Support Vector Regression (SVR), and IoT-based applications. Experimental results indicate that the model achieves an acceptable accuracy, with an average prediction error of approximately 110 g on the validation set. Distribution plots, boxplots, and learning curves confirm that while the SVR model captures overall weight distribution trends, prediction performance varies across different weight ranges, with medium-weight ducks exhibiting higher errors. The per-duck averaging strategy effectively reduces noise and enhances stability compared to image-based predictions.

The strengths of the proposed system include computational efficiency, practicality for real-world agricultural conditions, and the ability to provide real-time monitoring without causing stress to the animals. However, limitations such as overfitting on the training data, reduced accuracy at specific weight intervals, and reliance on handcrafted features highlight the need for further refinement.

In conclusion, the developed system demonstrates the feasibility of utilizing image-based regression models for estimating duck weight and offers a valuable tool for precision farming. Future work will focus on expanding the dataset, balancing weight categories, and exploring hybrid approaches that combine handcrafted features and deep learning to improve resilience and prediction accuracy across various farming environments. The proposed system remains in the prototype stage (proof of concept). Although it demonstrates the feasibility of non-contact duck weight estimation with acceptable accuracy, further development is necessary before industrial application, including enhancements in scalability, robustness, and field testing under diverse environmental conditions.

For large-scale farms (≥1000 animals), the system can be developed with a multi-node architecture, where each camera-microcontroller node transmits data to a central server via MQTT.

ACKNOWLEDGMENTS

This research received a research grant from the Ministry of Research, Technology, and Higher Education (Ristekdikti) of the Republic of Indonesia, under contract number NOMOR: 020/PTM/LPPM.UAD/VI/2025.

REFERENCES

[1] Y. Zhao *et al.*, "Review on image-based animals weight weighing," *Comput. Electron. Agric.*, vol. 215, no. July, p. 108456, 2023, doi: 10.1016/j.compag.2023.108456.

[2] G. Gebreyesus, V. Milkevych, J. Lassen, and G. Sahana, "Supervised learning techniques for dairy cattle body weight prediction from 3D digital images," *Front. Genet.*, vol. 13, no. January, pp. 1–15, 2023, doi: 10.3389/fgene.2022.947176.

[3] M. R. H. Hossain, R. Islam, S. R. McGrath, M. Z. Islam, and D. Lamb, "Learning-based estimation of cattle weight gain and its influencing factors," *Comput. Electron. Agric.*, vol. 231, no. January, p. 110033, 2025, doi: 10.1016/j.compag.2025.110033.

[4] R. J. Garro, C. S. Wilson, D. L. Swain, A. J. Pordomingo, and S. Wibowo, "A systematic literature review on the applications of federated learning and enabling technologies for livestock management," *Comput. Electron. Agric.*, vol. 234, no. March, p. 110180, 2025, doi: 10.1016/j.compag.2025.110180.

[5] E. Samperio, I. Lidón, R. Rebollar, M. Castejón-Limas, and C. Álvarez-Aparicio, "Lambs' live weight estimation using 3D images," *Animal*, vol. 15, no. 5, p. 100212, 2021, doi: 10.1016/j.animal.2021.100212.

[6] H. Zhang, Y. Zhang, K. Niu, and Z. He, "Neural network-based method for contactless estimation of carcass weight from live beef images," *Comput. Electron. Agric.*, vol. 229, no. December 2024, p. 109830, 2025, doi: 10.1016/j.compag.2024.109830.

[7] N. Selvamuthukumaran, E. S. J, K. B. Thriambika, and V. B. B, "Intelligent Animal Detection System Using IOT And Deep Learning," no. 04, pp. 2433–2438, 2021.

[8] S. A. Siddiqui, A. Ahmad, and N. Fatima, "IoT-based disease prediction using machine learning," *Comput. Electr. Eng.*, vol. 108, no. March, p. 108675, 2023, doi: 10.1016/j.compeleceng.2023.108675.

[9] T. Kushartadi, M. A. Laagu, and M. Asvial, "Design and Implementation of The Smart Weighing Precision Livestock Monitoring Technology based on the Internet of Things (IoT)," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 13, no. 4, pp. 1438–1448, 2023, doi: 10.18517/ijaseit.13.4.18557.

[10] M. R. Bhuiyan and P. Wree, "Animal Behavior for Chicken Identification and Monitoring the Health Condition Using Computer Vision: A Systematic Review," *IEEE Access*, vol. 11, no. October, pp. 126601–126610, 2023, doi: 10.1109/ACCESS.2023.3331092.

[11] Ardi Wijaya, B. R. Daryono, Rozali Toyib, and Yovi Apridiansyah, "Analisis Pengenalan Pola Pada Citra Digital Untuk Prediksi Berat Buah Sawit," *Decod. J. Pendidik. Teknol. Inf.*, vol. 4, no. 3, pp. 713–724, 2024, doi: 10.51454/decode.v4i3.481.

[12] Sten Dofanky Mooy, Andrew Delfistian Dethan, and Yampi R Kaesmetan, "Identifikasi Berat Badan Berdasarkan Citra Foto Menggunakan Metode Body Surface Area," *SABER J. Tek. Inform. Sains dan Ilmu Komun.*, vol. 2, no. 3, pp. 89–99, 2024, doi: 10.59841/saber.v2i3.1332.

[13] I. Supiyani, J. Haerul, and T. N. Padilah, "Pengolahan Citra Digital Prediksi Bobot Sapi Menggunakan Ekstraksi Fitur Canny Dan Klasifikasi K-Nearest Neighbor," *Nusant. J. Ilmu ...*, vol. 8, no. 7, pp. 2204–2212, 2021.

[14] A. Ruchay, V. Kober, K. Dorofeev, V. Kolpakov, A. Gladkov, and H. Guo, "Live Weight Prediction of Cattle Based on Deep Regression of RGB-D Images," *Agric.*, vol. 12, no. 11, 2022, doi: 10.3390/agriculture12111794.

[15] D. Asahar Johar, "Pengolahan Citra Digital Untuk Penentuan Bobot Sapi Menggunakan Metode Sobel," *J. Sist. Informasi,*

Teknol. Informasi, dan Komput., vol. 12, no. 2, pp. 16–26, 2022.

[16] R. Mahdaliza and B. Sugandi, "Prediksi Berat dan Harga Buah Mengunakan Sensor Visual," *J. Integr.*, vol. 13, no. 1, pp. 10–14, 2021, doi: 10.30871/ji.v13i1.2916.

[17] R. Firmasnyah, "Prototype Alat Pengukur Berat Badan Berbasis Computer Vision Dengan Menggunakan Regresi Linier," 2023.

[18] S. Ichikawa, M. Hamada, and H. Sugimori, "A deep-learning method using computed tomography scout images for estimating patient body weight," *Sci. Rep.*, vol. 11, no. 1, pp. 1–9, 2021, doi: 10.1038/s41598-021-95170-9.

[19] V. Y. Mahendra, A. A. Riadi, and E. Evanita, "Aplikasi Pengolahan Citra Digital Menentukan Bobot Sapi Dengan Metode Titik Berat Berbasis Android," *Jurasik (Jurnal Ris. Sist. Inf. dan Tek. Inform.*, vol. 7, no. 1, p. 88, 2022, doi: 10.30645/jurasik.v7i1.419.

[20] N. T. Duc *et al.*, "Image-based phenotyping of seed architectural traits and prediction of seed weight using machine learning models in soybean," *Front. Plant Sci.*, vol. 14, no. September, pp. 1–15, 2023, doi: 10.3389/fpls.2023.1206357.

[21] L. Nabila, E. Suffa, U. Lestari, and E. Susanti, "Identifikasi Citra Daging Ayam Berformalin Menggunakan Metode Grey Level Co-Occurrence Matrix (Glcm) Dan K-Nearest Neighbor (Knn)," *J. Scr.*, vol. 9, no. 2, pp. 133–141, 2021.

[22] F. Haikal, E. S. J. Atmadji, S. Kautsar, and N. S. Wibowo, "Sistem Monitoring Berat Tanaman Pada Farmbot Dengan Citra Digital Menggunakan Metode YOLO dan Regresi Polinomial," *J. Ilm. Inov.*, vol. 24, no. 2, pp. 122–126, 2024.

[23] H. Fitriyah, "Pengukuran Panjang-Berat Ikan dan Sayuran pada Budikdamber (Budi Daya Ikan dalam Ember) Menggunakan Visi Komputer dan Regresi Linier," *J. SISKOM-KB (Sistem Komput. dan Kecerdasan Buatan)*, vol. 4, no. 1, pp. 8–14, 2020, doi: 10.47970/siskom-kb.v4i1.166.

[24] S. F. Gumelar, "xiv ABSTRACT Cow Weight Estimation Using Convolutional Neural Network and Regression Method," pp. 5–6, 2021.

[25] T. R. Awasthi, A. Morshed, and D. L. Swain, "A machine learning approach to simulate cattle growth at pasture using remotely collected walk-over weights," *Agric. Syst.*, vol. 226, no. March, p. 104332, 2025, doi: 10.1016/j.agsy.2025.104332.

[26] M. A. Ahmed, M. S. Hossain, W. Rahman, A. H. Uddin, and M. T. Islam, "An advanced Bangladeshi local fish classification system based on the combination of deep learning and the internet of things (IoT)," *J. Agric. Food Res.*, vol. 14, no. February, p. 100663, 2023, doi: 10.1016/j.jafr.2023.100663.

[27] Z. B. Ozger, P. Cihan, and E. Gokce, "A systematic review of IoT technology and applications in animals," *Kafkas Univ. Vet. Fak. Derg.*, vol. 30, no. 4, pp. 411–431, 2024, doi: 10.9775/kvfd.2024.31866.

[28] A. C. Tran, T. T. T. Kim, and H. T. Nguyen, "An Image-Based Rice Weighing Estimation Approach on Clock Type Weighing Scale Using Deep Learning and Geometric Transformations," *Adv. Technol. Innov.*, vol. 8, no. 2, pp. 100–110, 2023, doi: 10.46604/aiti.2023.10926.

[29] S. Lv *et al.*, "JTF-SqueezeNet: A SqueezeNet network based on joint time-frequency data representation for egg-laying detection in individually caged ducks," *Poult. Sci.*, vol. 104, no. 2, p. 104782, 2025, doi: 10.1016/j.psj.2025.104782.

[30] M. Y. Shams *et al.*, "Automated on-site broiler live weight estimation through YOLO-based segmentation," *Smart Agric. Technol.*, vol. 10, no. December 2024, p. 100828, 2025, doi: 10.1016/j.atech.2025.100828.