# Cattle weight prediction model using convolutional neural network and artificial neural network

**Yulianingsih[1], Sri Nurdiati[2], Heru Sukoco[1], Cece Sumantri[3]**
[1]Department of Computer Science, Faculty of Mathematics and Natural Science, IPB University, Bogor, Indonesia
[2]Department of Mathematics, Faculty of Mathematics and Natural Science, IPB University, Bogor, Indonesia
[3]Departemen Animal Production and Technology, Faculty of Animal Science, IPB University, Bogor, Indonesia

**Article Info**

***Article history:***

Received Feb 16, 2024
Revised May 20, 2024
Accepted Jun 5, 2024

***Keywords:***

Artificial neural network
Cattle weight
Convolutional neural network
Mean absolute percentage error
Prediction

**ABSTRACT**

The weight of livestock is a crucial metric for evaluating management efficacy, informing policy decisions, and determining the market value of animals. In certain scenarios, conventional methods such as physical weighing and measurement calculations can prove challenging, including the absence of livestock health records or weighing equipment. This research aims to develop a predictive model for estimating the live weight of cattle through visual assessments and metadata, including age and pixel count, utilizing a combination of convolutional neural network (CNN) and artificial neural network (ANN) methodologies. A total of 223 data were obtained from a local farm before augmentation. The model's predictive capability was successfully demonstrated, with its performance quantified by an average mean absolute percentage error (MAPE) of 10% on test data. This study demonstrates that through the combination of CNN and ANN, as well as optimal parameter tuning, efficient prediction of cattle weight can be achieved.



***Corresponding Author:***

Yulianingsih
Department of Computer Science, Faculty of Mathematics and Natural Science, IPB University
Street of Agatis, Campus IPB Darmaga Bogor 16680, Indonesia
Email: ipb_yulianingsih@apps.ipb.ac.id

## 1. INTRODUCTION

The livestock subsector's ability to meet the demand for animal-sourced products is heavily influenced by management practices. In Indonesia, various livestock commodities are produced by Livestock Business Households (RTUP), with a notable increase of 4.56% from 2013 to 2018 [1]. A key indicator of successful livestock rearing is healthy weight gain. Regular weight measurements are essential for monitoring livestock development and assessing the impact of technological or management interventions. Several methods are currently used to estimate cattle weight. These include formulas based on physical dimensions like chest circumference [2] and body length or morphometrics [3], which are believed to correlate with weight. However, studies have shown that these formulas can deviate from actual weights [4]. Efforts to modify these formulas to suit different cattle breeds have not yielded a universal solution, largely due to variations in environmental factors, feeding practices, and the size and shape of the cattle [5], [6] including the lack of sufficiently comprehensive health records. Another method, direct weighing with scales, can yield more accurate results but poses risks of injury or stress to the animals, potentially leading to weight loss, and requires considerable labor to move the livestock to the weighing area.

The problem in this study is that to estimate the body weight of cattle, specifically Bali cattle, using data sourced from the characteristics of the cattle. Recent studies have explored the use of machine learning for measuring cattle weight. Several methods utilizing data sourced from measurements or morphometrics have been extensively conducted. The application of an artificial neural network (ANN) using three algorithms-Levenberg-Marquart, Bayesian regularization, and scaled conjugate-has shown promising results, surpassing both multiple linear regression [7] and random forest (RF) [8], which still rely on morphometric data. On the other hand, research involving weight measurement using segmented visual data with multi-layer perceptron (MLP) and recurrent neural network (R-CNN) approaches has been successful [9], but these studies did not include additional information like age [10]. The capabilities of convolutional neural networks (CNN) [11] and computer vision [12], [13] offer solutions for issues based on visual observations. Digital observation with specific algorithms allows for easier and more accurate object recognition [14], [15]. Object detection, classification, and prediction are common applications of machine learning in computer vision data [16]. Both visual and measurement methods have their respective advantages. This research addresses the challenge of determining cattle weights through visual assessments and metadata, including age and pixel count, utilizing a combination of CNN and ANN. This study also extensively involves testing the fine-tuning of several parameters, including the configuration of dense layers, selection of activation functions, and determination of the best dropout rates which constitutes part of the innovation in this study.

## 2. METHOD

To answer the research objectives, a framework of thought was prepared as an outline of the logical flow of the research as shown in Figure 1. Data collection for this research involved gathering both image and morphometric data from the People's Animal Husbandry School (SPR) Musi Banyuasin and local animal husbandry operations in Depok, West Java. The research focused on collecting images of cows from two perspectives: a side view or lateral covering the area from the head to the base of the tail, and a rear view focusing on the distance between the ischium. These views were chosen to assess potential meat deposition [17]. Additionally, morphometric data such as weight and age were gathered. Weight was used as a label in the study. In total, 223 images of cattle in side view and 223 in rear view were collected simultaneously to ensure accuracy in representing the actual conditions. While CNN architecture generally requires a large dataset, this is not a universal rule. For instance, in image classification, using 100 human brain images yielded an accuracy of 72.82%, whereas the same number of shoulder images resulted in an accuracy of 95.53% [18]. The sample dataset shown in Tables 1 and 2.

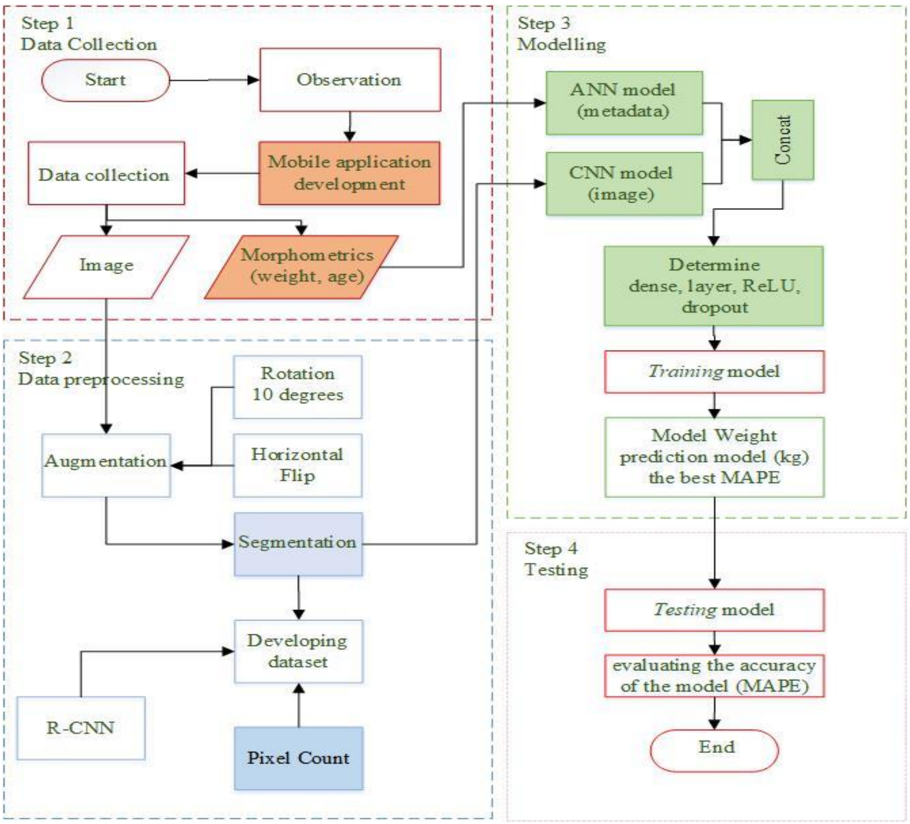



Figure 1. Research stages

Table 1. Dataset of cattle

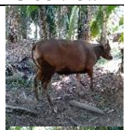
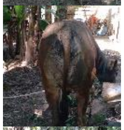
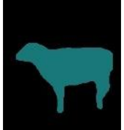
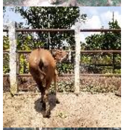
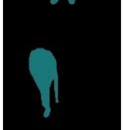
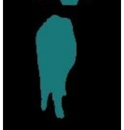
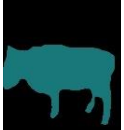
| ID | Weight | Age | Rear pix | Side pix | Rear view | Side view | Rear seg | Side seg |
|---|---|---|---|---|---|---|---|---|
| B4A01 | 196 | 12-24 | 29,394 | 92,349 |  |  |  |  |
| B4A05 | 244 | 25-36 | 188,454 | 110,706 |  |  |  |  |
| B4A20 | 248 | 25-36 | 123,108 | 133,998 |  |  |  |  |
| C1A08 | 168 | 37-48 | 38,160 | 76,212 |  |  |  |  |
| C1A24 | 182 | 12-24 | 168,327 | 206,982 |  |  |  |  |
| D026 | 255 | 37-48 | 91,590 | 156,420 |  |  |  |  |
| D136 | 247 | 49-60 | 51,498 | 113,949 |  |  |  |  |
| D148 | 327 | 49-60 | 113,415 | 167,127 |  |  |  |  |
| D180 | 367 | 37-48 | 65,523 | 131,880 |  |  |  |  |

Table 2. Attribute dataset of cattle

| No | Attribute | Description |
|---|---|---|
| 1 | ID | Id number, A-D indication of data location site |
| 2 | WEIGHT | Weight of the cattle is measured in kilograms. |
| 3 | AGE | Age data is obtained based on tooth growth |
| 4 | REAR_PIX | Pixel count from rear segmentation |
| 5 | SIDE_PIX | Pixel count from side segmentation |
| 6 | REAR_VIEW | Focusing on the distance between the ischium |
| 7 | SIDE_VIEW | Covering the area from the head to the base of the tail |
| 8 | REAR_SEG | Segmentation results from rear |
| 9 | SIDE_SEG | Segmentation results from side |

The data collection process is detailed in Figure 2. The morphometric measurements were conducted using a digital scale, while age determination was based on tooth growth. Cattle specimens were captured from a distance of 220 cm with a camera height of 150 cm. The image capture employed 1:1 aspect ratio to facilitate the augmentation process.

Preprocessing phase, augmentation was conducted by rotating each image by 10 degrees and applying horizontal flipping to enhance model performance and prevent overfitting [19]. Subsequently, segmentation was performed, followed by pixel counting of the segmented areas [20]. The obtained results served as new inputs for the ANN algorithm as independent variables alongside age.


Figure 2. Data collection stage

It is noteworthy that there is no universally applicable segmentation approach, as certain methods have shown greater efficacy [21]. This study utilized R-Mask CNN for segmentation [22], which has proven to be effective in detection and layer generation [23], [24], compared to other methods such as multi-task network cascades (MNC) [25] and fully convolutional instance-aware semantic (FCIS) [26]. Algorithm 1 is the pseudocode used to perform pixel counting. In this pseudocode, the function CountPixels takes two parameters: mask_template, which is the mask template, and target_color, which is the color whose pixels we want to count. This function iterates through each pixel in mask_template and counts the pixels that have the same color as target_color. The result is then returned as pixel_count. In the code, we call this function with mask_template as the first argument and [122, 120, 24] as the second argument to count pixels with the color [122, 120, 24]. The result is then printed.

Algorithm 1. Pseudocode used to perform pixel counting
```
CountPixels(mask_template, target_color):
    pixel_count = 0
    for each pixel in mask_template:
        if pixel is equal to target_color:
            pixel_count = pixel_count + 1
    return pixel_count
# Calling the function to count pixels with a specific color
n_pixel = CountPixels(mask_template, [122, 120, 24])
print(n_pixel)
```

Modeling stage, an integration of two algorithms was implemented. The CNN was designated for the critical task of feature extraction from images, whereas the ANN was utilized to assimilate supplementary information such as the age and pixel count for each cow object. Concurrently, fine-tuning of several parameters, including the configuration of dense layers and selection of activation functions and determination of the best dropout rates. The model is implemented on both side and rearview image data to predict weight separately, and then the average value of both predictions is determined. This approach for constructing a weight prediction regression model was adapted and modified from the experimental model used in the International Skin Imaging Collaboration (ISIC) 2019 skin lesion classification challenge [27]. Testing and measuring the accuracy of the model based on the best mean absolute percentage error (MAPE) to examine the extent to which the model generalizes the prediction results and indicate how much error in predicting when compared to real or actual values. The optimal MAPE obtained from various parameter combinations will be recommended for the prediction of cattle weight.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Ai-Fi}{Ai}\right| x\ 100\% \tag{1}$$

Where: n is sample size, Ai is the actual data value, and Fi is predicted value.

## 3. RESULTS AND DISCUSSION

Preprocessing phase involved augmentation to expand the dataset to 892 instances. For training model data divided into75:25. Subsequently, segmentation was conducted to calculate the pixel count of segmented objects. The number of pixels in each object represents the weight of the cattle. Table 3 illustrates the pixel counting results for each object. Furthermore, the results of pixel counting for each object serve as new inputs for the ANN algorithm to accompany the independent variable of age.

Modelling phase, an integration of two algorithms was implemented. the CNN was designated for the critical task of feature extraction from images, whereas the ANN was utilized to assimilate supplementary information such as the age and pixel count for each cattle object. This approach is particularly innovative in its use of the number of pixels from the images as a representation of a certain weight. This methodology leverages the visual data for a more accurate and comprehensive analysis, while the tabular data provides contextual and specific details, enhancing the overall predictive capability of the model. An illustration of the conceptual framework underpinning this research is provided in Figure 3, offering a visual representation of how these different data types are combined and utilized within the study.

Table 3. Pixel counting results

| ID | Weight | Age | Rear pix | Side pix |
|---|---|---|---|---|
| B4A01 | 196 | 12-24 | 29,394 | 92,349 |
| B4A05 | 244 | 25-36 | 188,454 | 110,706 |
| B4A20 | 248 | 25-36 | 123,108 | 133,998 |
| C1A08 | 168 | 37-48 | 38,160 | 76,212 |
| C1A24 | 182 | 12-24 | 168,327 | 206,982 |
| D026 | 255 | 37-48 | 91,590 | 156,420 |
| D136 | 247 | 49-60 | 51,498 | 113,949 |
| D148 | 327 | 49-60 | 113,415 | 167,127 |
| … | … | … | … | … |
| D180 | 367 | 37-48 | 65,523 | 131,880 |

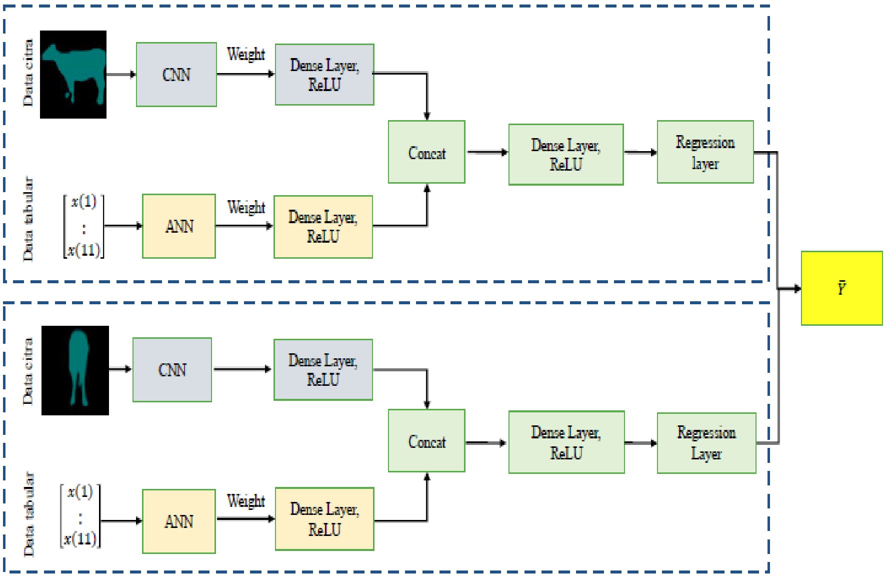



Figure 3. Cattle weight prediction model

There are two separate inputs to this model, the first input layer is for image data, while the second input layer is for additional data. The model demonstrates that the outputs from multiple pathways are processed independently before being combined, enabling the model to learn from both image data and additional data simultaneously. The output layer generates the model's final prediction utilizing a single neuron for regression tasks. For the output layer that performs regression, a linear operation is applied as follows:

$$Y_{pred} = W_{final} X_{concat} + b_{final} \quad (1)$$

where:
$Y_{pred}$ is the predicted weight outcomes for each input.
Y^ is The average value of the two prediction outcomes.
$X$concat is the output from the concatenation layer.
$W_{final}$ is the weight of the output layer.
$b_{final}$ is the bias of the output layer.

Concurrently, fine-tuning of several parameters. Before the integration, CNN consisting of filters 64, 8, 16 with a 2:2 pooling layer and rectified linear unit (ReLU) activation, while in ANN, they consist of nodes 8, 16 with ReLU activation. Subsequent to integration, the model's parameters were adjusted to incorporate 4 units in total, comprising a single output layer unit with linear activation. Additionally, a dropout function with a rate of 0.5 was incorporated, and the Adam optimizer was employed. We conducted iterations over 200 epochs, beginning with a combination of 1 layer in the CNN and 2 layers in the ANN. This process continued until reaching a combination of 3 layers in both with grid search to find the best combination. To identify the most effective model, we recorded the MAPE values. The exhaustive grid search process demands a considerable amount of time. Therefore, we constrain our search combinations to a maximum of 64, given the limitations in time and resources. Based on our observations, we have noted that as the complexity of MAPE calculations increases, there is no corresponding improvement in MAPE values. Tables 4 and 5 present the training results for both side-view and rear-view inputs. Based on our testing results, we found that the best model for the rear-view data achieved an MAPE of 11.259 with 3:2 combination using CNN filters of 64, 8, 16, and ANN nodes 8, 16. Meanwhile, the best model for the side-view data attained an MAPE of 12.432 with 2:2 combination using CNN filters of 64, 64, and ANN nodes of 64, 64.

Table 4. Result training model rear-view image data

| Rear-view image data | | | |
|---|---|---|---|
| Combination | CNN | ANN | MAPE |
| 1:2 (8 - 64) | 32 | 16:32 | 11.402 |
| 2:1 (8 - 64) | 32:32 | 16 | 12.03 |
| 2:2 (8 – 64) | 64:16 | 3:32 | 11.495 |
| 2:3 (8 - 64) | 32:8 | 64:8:64 | 11.858 |
| 3:2 (8 - 64) | 64:8:16 | 8:16 | 11.259 |
| 3:3 (8 - 64) | 64:64:32 | 32:64:16 | 11.532 |

Table 5. Result training model side-view image data

| Side-view data | | | |
|---|---|---|---|
| Combination | CNN | ANN | MAPE |
| 1:2 (8 - 64) | 16 | 32:8 | 13.193 |
| 2:1 (8 - 64) | 16:64 | 64 | 12.719 |
| 2:2 (8 - 64) | 64:64 | 64:64 | 12.432 |
| 2:3 (8 - 64) | 8:8 | 64:8:64 | 12.656 |
| 3:2 (8 - 64) | 32:32:64 | 32:64 | 12.721 |
| 3:3 (8 - 64) | 8:32:8 | 64:32:16 | 12.488 |

After identifying the best model from both inputs, the average prediction values using the test data were determined, as shown in Table 6. To measure the error value between the predicted and actual values, the MAPE measurement method is used. The same procedure is applied during the modeling process.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Ai-Fi}{Ai}\right| x\ 100\% \qquad (2)$$

Where: n is sample size, Ai is the actual data value, Fi is predicted value.

The average MAPE obtained was 10. In the analysis of prediction outcomes utilizing the test dataset, as delineated in Table 6, which encompasses 15 paired bovine image datasets, it was observed that the side view aspect images of cows yielded predictions more closely aligned with their actual weight relative to the rear-view aspect images. Nonetheless, both sets of image data significantly contributed to the overall predictive accuracy. This is evidenced by an average MAPE of 10%, underscoring the efficacy of the employed predictive model in estimating bovine weight with a reasonable degree of precision.

The residual distribution of our model, as illustrated in Figure 4, is relatively symmetrical around the zero value, suggesting that the model does not possess a significant systematic bias meaning it neither consistently overpredicts nor underpredicts. This symmetry indicates that the model generally avoids making large errors in comparison to the true values, reflecting a commendable level of accuracy. Variations in the residual values suggest that while the model does incur prediction errors, these errors are contained within a certain range, and the absence of very large errors points to the model's consistency. Moreover, the balance observed between positive and negative residuals further implies that the model maintains a neutral approach in its predictive accuracy, without a tendency to skew in one direction. The residual histogram shows a mixture of positive and negative residuals, with no dominant trend to either side. This indicates that the proposed model in this study does not systematically overestimate or underestimate the predicted values. Test data was collected using the digital weight artificial intelligence (DiWAI) interface while inference was done on a server preinstalled with a prediction model, as illustrated in Figure 5. The information that can be provided consists of predictive outcomes, age, and data collection locations.

Table 6. Result of implementation model

| No | ID | Actual weight (kg) | Age | Prediction for rear (kg) | Prediction for side (kg) | Average prediction (kg) | MAPE |
|---|---|---|---|---|---|---|---|
| 1 | B4A03.jpg | 243 | 2 | 251 | 254 | 252 | 3.9095 |
| 2 | B4A11.jpg | 212 | 2 | 192 | 223 | 207 | 2.1226 |
| 3 | C1A07.jpg | 270 | 5 | 204 | 238 | 221 | 18.148 |
| 4 | C1A21.jpg | 230 | 2 | 186 | 215 | 205 | 12.826 |
| 5 | D019.jpg | 177 | 3 | 193 | 289 | 241 | 36.158 |
| 6 | D058.jpg | 147 | 2 | 149 | 159 | 154 | 4.7619 |
| 7 | D066.jpg | 297 | 3 | 331 | 291 | 311 | 4.7138 |
| 8 | D069.jpg | 277 | 2 | 314 | 265 | 289 | 4.5126 |
| 9 | D075.jpg | 291 | 3 | 239 | 254 | 246 | 15.292 |
| 10 | D0125.jpg | 252 | 3 | 241 | 264 | 242 | 0.1984 |
| 11 | D134.jpg | 305 | 3 | 250 | 238 | 244 | 20 |
| 12 | D146.jpg | 280 | 3 | 253 | 301 | 277 | 1.0714 |
| 13 | D147.jpg | 247 | 4 | 214 | 247 | 230 | 06.6802 |
| 14 | S11.jpg | 257 | 2 | 229 | 224 | 226 | 11.868 |
| Average MAPE | | | | | | 10.162 | |

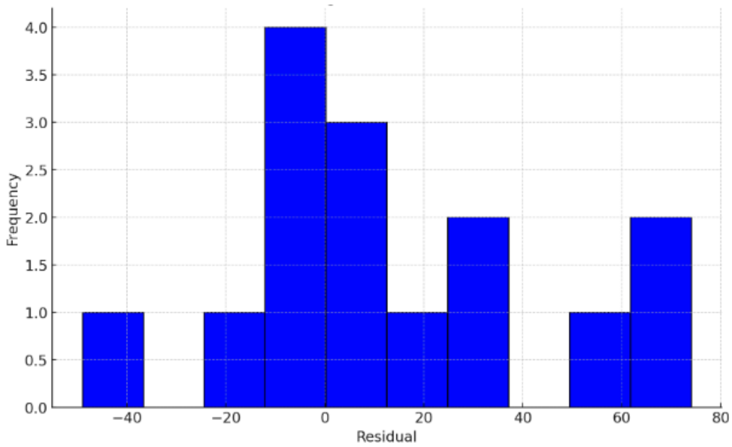



Figure 4. Residual histogram from testing

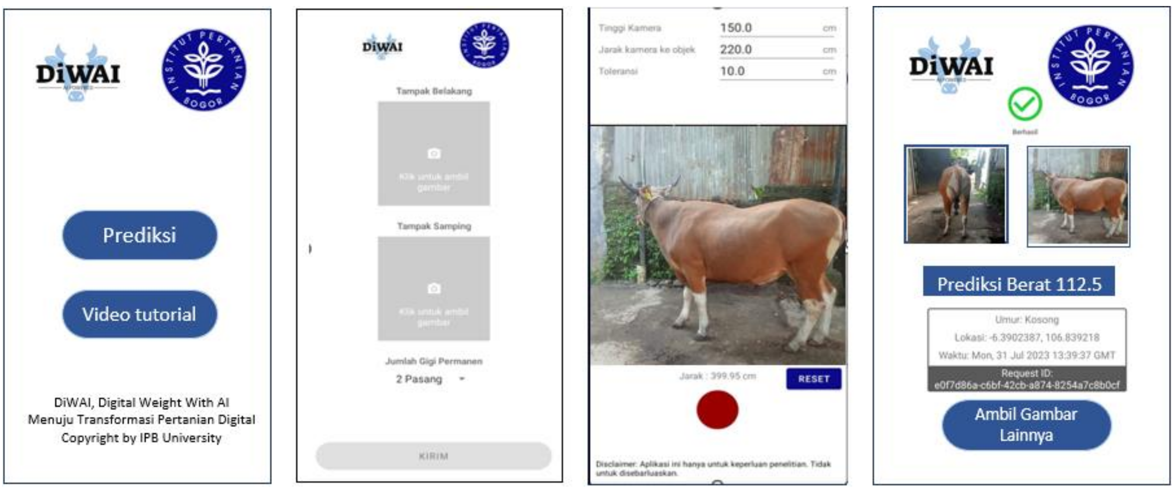



Figure 5. DiWAI interface

## 4. CONCLUSION

In this study, to obtain a predictive model for cattle weight, we combined CNN and ANN algorithms with various parameter combinations using the grid search function. Our findings provide conclusive evidence that the best model for rear-view data achieved an MAPE of 11.259% with a 3:2 combination, utilizing CNN filters of 64, 8, 16, and ANN nodes of 8, 16. Meanwhile, the optimal model for side-view data obtained an MAPE of 12.432% with a 2:2 combination, employing CNN filters of 64, 64, and ANN nodes of 64, 64. The average prediction of both models yielded an MAPE of 10%. Therefore, these predictive models on these parameters can be recommended for predicting cattle weight. Further development prospects involve adding independent variables such as breed, body condition score (BCS), climate or others.

## ACKNOWLEDGEMENT

Gratitude is expressed to the Department of Computer Science IPB University, Department of Mathematics IPB University, Department of Production Science and Technology IPB University, Indraprasta PGRI University, Banyuasin People's Livestock School (SPR), Sapibagus farm, all academic staff and coworkers that have positively contributed to the completion of this research.

## REFERENCES

[1] Ditjen PKH, "Livestock and animal health statistics 2023 (in Indoneisan: statistik peternakan dan kesehatan hewan 2023)," vol. 2. Direktorat Jenderal Peternakan dan Kesehatan Hewan Kementerian Pertanian RI, Indonesia, p. 278, 2023.
[2] J. Jakaria, Sutikno, M. F. Ulum, and R. Priyanto, "Live body weight assessment based on body measurements in Bali cattle (Bos Javanicus) at extensive rearing system," *Pakistan Journal of Life and Social Sciences*, vol. 17, no. 1, pp. 17–23, 2019.
[3] Y. Adinata, R. R. Noor, R. Priyanto, L. Cyrilla, and P. Sudrajad, "Morphometric and physical characteristics of Indonesian beef cattle," *Archives Animal Breeding*, vol. 66, no. 2, pp. 153–161, Jun. 2023, doi: 10.5194/aab-66-153-2023.
[4] S. Ozkaya and Y. Bozkurt, "The accuracy of prediction of body weight from body measurements in beef cattle," *Archives Animal Breeding*, vol. 52, no. 4, pp. 371–377, Oct. 2009, doi: 10.5194/aab-52-371-2009.
[5] J. Harsa, D. Heriyadi, and D. Ramdani, "Weight estimation accuracy of certificated garut ewes by using novel formula, schoorl formula, and winter arjodarmoko formula," *Jurnal Ilmu-Ilmu Peternakan*, vol. 30, no. 2, pp. 109–114, Aug. 2020, doi: 10.21776/ub.jiip.2020.030.02.02.
[6] G. Srinivasan and T. Sathiamoorthy, "Morphometric characteristics of pulikulam cattle breed in a nucleus herd," *Journal of Entomology and Zoology Studies*, vol. 8, no. 3, pp. 1893–1895, 2020, [Online]. Available: http://www.entomoljournal.com.
[7] S. Akkol, A. Akilli, and İ. Cemal, "Comparison of artificial neural network and multiple linear regression for prediction of live weight in hair goats," *Yuzuncu Yil University Journal of Agricultural Sciences*, vol. 27, no. 1, pp. 21–29, 2017, doi: 10.29133/yyutbd.263968.
[8] Z. E. Huma and F. Iqbal, "Predicting the body weight of Balochi sheep using a machine learning approach," *Turkish Journal of Veterinary and Animal Sciences*, vol. 43, no. 4, pp. 500–506, Aug. 2019, doi: 10.3906/vet-1812-23.
[9] O. Rudenko, Y. Megel, O. Bezsonov, and A. Rybalka, "Cattle breed identification and live weight evaluation on the basis of machine learning and computer vision," *Computer Modeling and Intelligent Systems*, vol. 2608, pp. 939–954, 2020, doi: 10.32782/cmis/2608-70.
[10] T. D. Tefera, Y. Y. Mummed, M. Y. Kurtu, M. U. Letta, T. G. O'Quine, and J. L. Vipham, "Effect of age and breeds of cattle on carcass and meat characteristics of Arsi, Boran, and Harar Cattle in Ethiopia," *Open Journal of Animal Sciences*, vol. 09, no. 03, pp. 367–383, 2019, doi: 10.4236/ojas.2019.93030.
[11] S. Katiyar and S. K. Borgohain, "Comparative evaluation of CNN architectures for image caption generation," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 12, pp. 793–801, 2020, doi: 10.14569/IJACSA.2020.0111291.
[12] A. Cominotte *et al.*, "Automated computer vision system to predict body weight and average daily gain in beef cattle during growing and finishing phases," *Livestock Science*, vol. 232, p. 103904, Feb. 2020, doi: 10.1016/j.livsci.2019.103904.
[13] P. Tangwannawit and S. Tangwannawit, "Feature extraction to predict quality of segregating sweet tamarind using image processing," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 25, no. 1, pp. 339–346, Jan. 2022, doi: 10.11591/ijeecs.v25.i1.pp339-346.
[14] Z. H. Pradana, B. Hidayat, and S. Darana, "Beef cattle weight determine by using digital image processing," in *2016 International Conference on Control, Electronics, Renewable Energy and Communications (ICCEREC)*, Sep. 2016, pp. 179–184, doi: 10.1109/ICCEREC.2016.7814955.
[15] C. Bhatt, A. Hassanien, N. A. Shah, and J. Thik, "Barqi breed sheep weight estimation based on neural network with regression," *arXiv preprint*, 2018, [Online]. Available: http://arxiv.org/abs/1807.10568.
[16] A. I. Khan and S. Al-Habsi, "Machine learning in computer vision," *Procedia Computer Science*, vol. 167, pp. 1444–1451, 2020, doi: 10.1016/j.procs.2020.03.355.
[17] B. W. Putra, A. M. Fuah, H. Nuraini, and R. Priyanto, "Application of digital image technique for morphometrics measurement on Bali and Ongole Cattle," *Jurnal Ilmu Pertanian Indonesia*, vol. 21, no. 1, pp. 63–68, Apr. 2016, doi: 10.18343/jipi.21.1.63.
[18] J. Cho, K. Lee, E. Shin, G. Choy, and S. Do, "How much data is needed to train a medical image deep learning system to achieve necessary high accuracy?," *arXiv preprint*, 2015, [Online]. Available: http://arxiv.org/abs/1511.06348.
[19] C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," *Journal of Big Data*, vol. 6, no. 1, p. 60, Dec. 2019, doi: 10.1186/s40537-019-0197-0.
[20] Yulianingsih, S. Nurdiati, H. Sukoco, and C. Sumantri, "Exploring pixel segmentation with mask R-CNN: implications for predicting cattle weight," in *2023 3rd International Conference on Smart Cities, Automation & Intelligent Computing Systems (ICON-SONICS)*, Dec. 2023, pp. 32–37, doi: 10.1109/ICON-SONICS59898.2023.10435120.
[21] S. Abdulateef and M. Salman, "A comprehensive review of image segmentation techniques," *Iraqi Journal for Electrical and Electronic Engineering*, vol. 17, no. 2, pp. 166–175, Dec. 2021, doi: 10.37917/ijeee.17.2.18.

[22] K. He, G. Gkioxari, P. Dollar, and R. Girshick, "Mask R-CNN," in *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 2017, pp. 2961–2969.
[23] A. M. Siregar, Y. A. Purwanto, S. H. Wijaya, and N. Nahrowi, "Two-stages of segmentation to improve accuracy of deep learning models based on dairy cow morphology," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 2, pp. 2093–2100, Apr. 2023, doi: 10.11591/ijece.v13i2.pp2093-2100.
[24] C. Lee, H. Lee, and H. Cho, "Cattle weight estimation using fully and weakly supervised segmentation from 2D images," *Applied Sciences*, vol. 13, no. 5, p. 2896, Feb. 2023, doi: 10.3390/app13052896.
[25] J. Dai, K. He, and J. Sun, "Instance-aware semantic segmentation via multi-task network cascades," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2016, pp. 3150–3158, doi: 10.1109/CVPR.2016.343.
[26] Y. Li, H. Qi, J. Dai, X. Ji, and Y. Wei, "Fully convolutional instance-aware semantic segmentation," in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jul. 2017, pp. 4438–4446, doi: 10.1109/CVPR.2017.472.
[27] N. Gessert, M. Nielsen, M. Shaikh, R. Werner, and A. Schlaefer, "Skin lesion classification using ensembles of multi-resolution EfficientNets with meta data," *MethodsX*, vol. 7, p. 100864, 2020, doi: 10.1016/j.mex.2020.100864.


## BIOGRAPHIES OF AUTHORS

**Yulianingsih** is currently pursuing her Ph.D. in Computer Science at Bogor Agricultural University (IPB). She holds a Master of Science degree in Information Systems Management from Sekolah Tinggi Manajemen Informatika dan Komputer (STMIK) Nusa Mandiri, and a Bachelor of Science degree in Information Management from Gunadarma University. Her research interests include machine learning, artificial intelligence, system development, and wireless and mobile technology. She is a faculty member in the Department of Informatics Engineering at Indraprasta University. For academic inquiries or collaborations, she can be contacted at email: ipb_yulianingsih@apps.ipb.ac.id or yuliaunindra@gmail.com.

**Sri Nurdiati** is a Professor in the Department of Mathematics, Faculty of Mathematics and Natural Science, IPB University. She holds a Ph.D. in Applied Mathematics from the University of Twente, Netherlands, a Master's degree in Computer Science from the University of Western Ontario, Canada, and a Bachelor's degree in Statistics from IPB University. Her research focuses on computational mathematical modeling and statistics in various applied fields. A significant part of her work involves analyzing forest and land fires in Indonesia using mathematical modeling based on climate observation data. She has held strategic positions in educational development, including Dean of the Faculty of Mathematics and Natural Sciences (FTMIPA) at IPB University. She can be contacted at email: nurdiati@apps.ipb.ac.id.

**Heru Sukoco** holds a B.Sc. in Computer Science from IPB, an M.Eng. in Electrical Engineering from ITB, and a Dr.Eng. in Advanced IT and Informatics from Kyushu University. He currently works at IPB University's Department of Computer Science, focusing his research on net-centric computing, future internet, IoT, wireless and mobile technology, high performance computing, and agro-maritime 4.0 for modern and smart agriculture. He is a member of APTIKOM, IEEE, and IEICE, receiving research grants from LPDP, Kemendikbudristek, and BRIN. With a strong background in academia and industry collaboration, he has published in reputable national and international publications. He has also held various IT management positions at IPB and is active as a scholarship and journal reviewer. He can be contacted at email: hrskom@apps.ipb.ac.id.

**Cece Sumantri** is a Professor in the Division of Livestock Breeding and Genetics at the Department of Animal Production and Technology, Faculty of Animal Husbandry, IPB University. He holds a Doctorate from Yamaguchi University, Japan, a Master's degree from Nagoya University, and a Bachelor's degree in Animal Production Science from IPB University. His research has been recognized with awards, particularly for his work in developing the IPB-D1 superior local chicken breed, which combines four distinct chicken lines. He is a member of the professorial board at IPB University and serves as a peer reviewer for several journals. He has established collaborations with various entities. He can be contacted at email: ceces@apps.ipb.ac.id.