Broiler Chicken Weight Estimation Model Design Using Image Processing Approach

Jordan Electra[1, a)], Praditya Ajidarma[1, b)], Mohammad M. Isnaini[1, c)]
[1] Faculty of Industrial Technology, Engineering Management Department, Bandung Institute of Technology. Jl. Ganesa No. 10, Bandung, West Java 40132, Indonesia
[a)] jordanelectra9@gmail.com
[b)] ajidarmap@itb.ac.id
[c)] isnaini@itb.ac.id

Abstract

This paper presents a method to estimate broiler weight automatically using computer vision approach and machine learning model. The data used in this paper obtained using a broiler cage video and manual weight calculation on daily basis for 33 days. The broilers image is processed using several image processing methods such as noise removal, adaptive thresholding, morphological operations, and image segmentation to generate morphological data of each broiler. The model development is carried out by utilizing morphological data of each broilers which increased along with the increase in weight. Five features of broilers were used, namely area, perimeter, mean radius, maximum radius, and major axis. The proposed model then was validated using a 10-fold cross validation method. The proposed model performance is calculated using the RMSE metrics, which shows SVR model has the best performance with RMSE value of 144,7 grams.

Keywords
Broiler weight estimation, computer vision.

1. Introduction
Livestock is one of the industrial sectors that make a significant contribution to the Indonesian economy, one of the sub-sectors in the livestock industry is poultry farming. Currently the large number of meat demand encourages broiler breeders to increase the productivity of broiler chicken cages. Nyalala (2021) mentioned productivity in chicken cage is commonly measured using FCR (feed conversion) ratio which is the ratio between the weight of feed consumed by broilers and the weight of broilers. Low FCR ratio is desired because it is indicating high productivity. Farm X strives to achieve a low FCR value by monitoring the weight development of broiler chickens every day during the growing period to allocate the right amount of feed every day. When allocating the amount of feed, farmers need to know how much weight the broilers have grown in the last 3-4 days and how much weight they need to gain for the next 3-4 days (Mollaha et al. 2010). The daily weight of broiler chickens in farm X was measured manually by putting several chickens into sacks and weighing them at once to obtain the average weight of each broiler in the sack.

Manually measuring the weight of broilers has the disadvantage that it requires a lot of time and labor and can also make broilers easily stressed (Mortensen 2016). To increase productivity, farm X requires an automatic method of measuring broiler weight. One alternative method of measuring broiler weight automatically is to use an image/computer vision-based approach (Daud 2020). In simple terms, the image-based approach measures the weight of chickens by using images that are processed using certain machine learning algorithms. Image based approaches can be grouped into two parts, namely image retrieval and image processing, this research focuses on the image processing section. Image processing is carried out to convert image data into feature data that can be used to determine the weight of broilers using certain model. The alternative modek that will be chosen in this study uses a machine learning approach.

The machine learning approach is an approach developed to study patterns from a dataset to perform the inference process independently. The machine learning approach can be used to make classifications or predictions based on previous historical data. Some of the algorithm that are often used in various studies include linear regression, decision trees, support vector machines, random forests, artificial neural networks, naïve bayes, k-naearest neighbors, etc.

2. Methods

2.1 Image and Weight Data Collection

The data requirements in this study were formulated in accordance with the literature study from previous studies. Previous studies used image data of broilers in cages which were further processed to obtain morphological features of the broilers (Kumar 2018). Other data needed in this study is broiler chicken weight data every day. Farm X provides broiler chicken weight data in the form of average broiler chicken weight every day. Broiler image data is not provided directly by farm X, instead broiler image data is provided in the form of daily video of the cage. The data used in this study is a daily video of broiler chickens in the cage for 33 days. The data was taken by the cage manager every day using a cellphone camera. Each video data has a duration of five to ten seconds. Not all broiler chickens in the cage are included in the video recorded, but only broiler chickens in certain parts of the cage are recorded in the video.

Each daily video data is converted into several frames of broiler image data. This research uses the first ten frames of image generated from each video. The use of the first ten frames of data is carried out to accommodate broilers whose positions overlap in one frame; the other frames are expected to present the position of the broilers separately from one another. The image data obtained has a pixel size of 352 x 640 and is of RGB type. The image data is then entered into a data list for later image processing for each frame. Before the image data is processed further the image data type needs to be changed from RGB type to grayscale type, this will make the broiler identification process easier.

2.2 Image Processing

The image processing stage is carried out to prepare each image data frame so that the morphological data of each broiler in the picture can be acquired (Amraei 2017). The image processing stage is done by using EBImage library in R programming language. The image processing stage consists of noise removal, adaptive thresholding, morphological operations, image segmentations, and feature extraction.

The noise removal stage is carried out to reduce the detail contained in the image so that the broiler chicken object is easier to detect at a later stage (Boyat et al. 2015). The image needs to be changed to blurry so that the identification process of broiler chickens in the image can be carried out more accurately (Hambal 2017). An image that looks blurry has a pixel value that does not change drastically between adjacent pixels, so that identification errors due to outlier pixel values can be avoided.

The adaptive thresholding stage is done to separate the background from the broiler chicken object (Li et al. 2009). Thresholding is a method used to classify each pixel into two groups, namely the black color group and the white color group (Mandyartha et al. 2020). Thresholding changes the value of each pixel in a pixel to black or white by comparing the pixel value with a certain threshold (Guruprasad 2020). The threshold value can be determined the same for each pixel, but for the adaptive thresholding method the threshold value applied is different for each pixel in the image. Determining the threshold value for a pixel depends on the average value of the pixels around the pixel. The image produced at this stage is black and white where the black color shows the background, and the white color shows the broiler chicken object.

Furthermore, morphological operations are carried out to remove small objects or artifacts in the image (Priya et al. 2018). This research uses the morphological opening method, namely the erosion process followed by dilation. The erosion process removes the pixel value in the boundary of the object, so the size of the object will be reduced (Sreedhar 2012). On the other hand, the dilation process adds a pixel value to the boundary of the object so that the size of the object getting bigger. The value of a pixel in the erosion process is changed to the minimum value of the pixels around the pixel. In the case of this research using a black and white image, the value of a pixel in the erosion process will change to zero (black) if there are zero-value pixels around the pixel. On the other hand, the pixel value in the dilation process will be converted to the maximum value of the pixels around the pixel. The combination of erosion and dilation will make object with small pixel size removed from the image.

The image segmentation stage aims to distinguish between one broiler and other broilers. This study uses the watershed () function in EBImage library which applies the watershed segmentation algorithm in the object segmentation process in the image. The watershed algorithm considers the image as a topographic surface, where the part of the image that has a high pixel intensity will represent the peaks and the part of the image with a low intensity will represent the valley (Roerdink et al. 2001). To separate the broiler chicken objects contained in the image using the watershed algorithm, the valleys will be filled with water so that at a point different valley will start to merge. To prevent this, a barrier or watershed line will be built which will then become a boundary that separates one object from another (Mandyartha et al. 2020). The resulting image after this stage is divided into several parts based on the number of broilers in the image. Figure 1 show the example result of image processing stage; different broilers is marked with different color label.

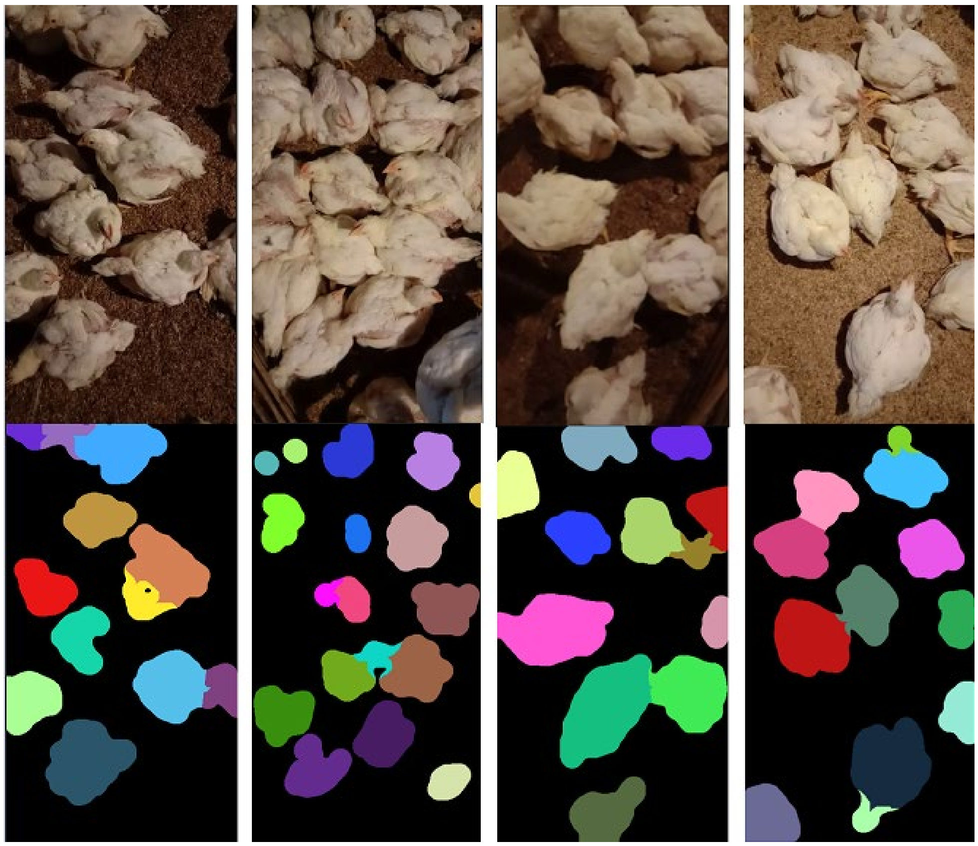

Figure 1. Example of Image Processing Result

After each broiler in the image is identified, feature extraction process is carried out to obtain the morphological data of each broiler. The features that also increase along with the increase in weight of broilers were chosen to predict broiler weight. These features are area, perimeter, mean radius, maximum radius, and major axis. After the tables of features is generated, the column for the average daily weight obtained from the observation data of the breeders is added.

2.3 Weight Estimation Model Development

Before the features data is used to build weight estimation model, the features data is scaled using normalization approach to minimize errors in model development due to differences in the range of feature values (Minaxi 2014). The model validation in this study was carried out using the k-folds cross validation approach. Before building the model, the data set will be randomly divided into ten groups with the same number of members in each group (Ali 2014). One group will be used as a test data set and the other group will be used as a data set for testing build the model at a later stage. This process was repeated ten times so that each group was used as a test data set once.

The weight estimation model in this research was built using three algorithm which is Multiple Linear Regression (MLR), Support Vector Regression (SVR), and Artificial Neural Network (ANN). Each model was built using function in r programming language, MLR model was built using lm() function, SVR model was built using svm() function in library e1071, and ANN model was built using nnet() function in library neuralnet. The performance of each model was measured using Root Mean Squared Error (RMSE) metrics. The RMSE was computed for all ten groups in training data and testing data.

To further increase the performance of SVR and ANN model, hyperparameter tuning was performed (Alonso 2013). Hyperparameter tuning for both SVM, and ANN model was performed using tune () function in library e1071, this function performs hyperparameter tuning using grid search approach (Konig 2008). The parameters to be tuned for the SVR model are cost and epsilon, while the parameters to be tuned for the ANN model are size and decay (Hawkins 2015).

3 Results and Discussion

The estimations model were used to estimate broiler weight on training dataset and testing dataset. Table 1 show the average model performance for all ten groups of datasets. After comparing the performance result for training dataset and testing dataset, there is no indication of overfitting model. Table 1 show that model SVR is the model with best overall performance.

Table 1. Shows the Performance Result of each Model

Dataset	RMSE MLR Training (g)	RMSE MLR Testing (g)	RMSE SVR Training (g)	RMSE SVR Testing (g)	RMSE ANN Training (g)	RMSE ANN Testing (g)
Folds 1	147.5	147.7	143.9	145.0	148.6	148.4
Folds 2	147.3	148.9	143.8	146.1	148.5	149.9
Folds 3	147.9	144.1	144.3	140.8	149.3	145.3
Folds 4	147.4	148.8	143.7	146.2	148.3	150.2
Folds 5	147.7	145.7	144.1	143.5	148.8	147.2
Folds 6	147.6	146.6	144.1	142.7	148.7	146.2
Folds 7	147.6	146.5	144.0	144.7	148.7	148.8
Folds 8	147.1	151.1	143.6	147.5	148.1	153.0
Folds 9	147.4	148.8	143.6	147.4	148.4	149.6
Folds 10	147.5	147.3	144.1	143.0	148.8	147.9
Average	147.5	147.5	143.9	144.7	148.6	148.6

The algorithms used to process image in this research has a few drawbacks that contribute to the errors in model, such as not being able to distinguish between broiler chickens that are attached or overlapping with other broilers. Two or more broilers that stick together will sometimes be designated as one broiler after the image processing is done. This is a limitation of the image-taking process where the recorded body parts of broiler chickens are not evenly distributed due to the overlapping positions of several broilers when shooting. Figure 2 shows the body of the chicken numbered 7 covered by the bodies of other chickens around it, this makes the number of chickens identified to be reduced by one.
Another drawback of the algorithm used in this study is that it cannot work properly at object with high difference in light intensity between its surrounding in the image. Broilers that have too low a light intensity (dark) will fail to be identified as an object and are instead identified as a background. This also makes sometimes only part of the broiler body identified as an object. The size of the object of broiler chickens that are not perfectly identified will lead to greater weight prediction errors. This identification error can be seen in Figure 3 below, broiler chickens marked with a red box are identified with the head only.

All objects that are not identified as the background will be designated as broilers by the algorithm used in this research. This gives rise to other shortcomings in the algorithm, namely not being able to distinguish objects that are not broiler chickens such as broiler's places to eat or drink. This shortcoming can be overcome by making sure other object that is not a chicken broiler are not included in the video capture process or additional image processing is carried out to remove objects that are not broilers manually. Figure 4 below shows a broiler feeder that failed to be identified as a background.

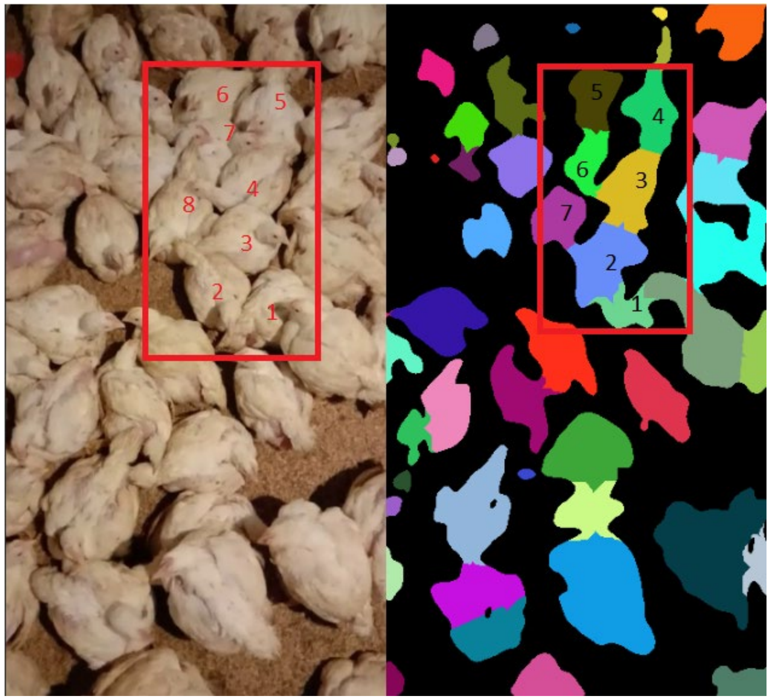

Figure 2. Example of identification error caused by overlapping broilers

Figure 3. Example of error caused by difference in light intensity

Figure 4. Example of error caused by object non broilers present in the image

4. Conclusion

Collecting frequent and accurate weights of broiler is important for breeders to achieve high productivity level. This research provides one alternative way to collect broiler weight automatically on daily basis by using computer vision approach. Image processing method were used to identify morphological data of each broiler inside the image. These broiler's morphological data were used to estimate broiler weight using machine learning model. Based on performance result SVR model is the best model to estimate broiler weight, with RMSE = 144.7 gram. To fully utilize this research for automatic weight estimation, another research is needed to develop the image collection method.

Acknowledgements

This research was funded by the Bottom-up research scheme of LPPM ITB for the fiscal year 2022.

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Biographies

Jordan Electra is an Engineering Management Bachelor from Institut Teknologi Bandung.

Mohammad Mi'raj Isnaini is currently a Senior Lecturer at Faculty of Industrial Technology, Institut Teknologi Bandung. He holds a bachelor's degree in industrial engineering from Institut Teknologi Bandung, Indonesia and a master's degree in industrial engineering and management from Institut Teknologi Bandung, Indonesia. He also holds a doctoral degree in industrial engineering at Kobe University, Japan. He has published numerous publications in various national and international peer-reviewed journals and presented scientific papers across the world. Because of the active association with different societies and academies as well as the contributions, he has been recognized by the subject experts around the world. His clinical and scientific research interests include computer aided design, production process, control and systems engineering.

Praditya Ajidarma is currently a Lecturer at Faculty of Industrial Technology, Institut Teknologi Bandung. He holds a bachelor's degree in industrial engineering from Institut Teknologi Bandung, Indonesia. He also holds a master's degree in industrial engineering from Purdue University, United States. He has published numerous publications in various national and international peer-reviewed journals and presented scientific papers across the world. His clinical and scientific research interests include decision sciences, numerical analysis, control and optimization.