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Two-stages of segmentation to improve accuracy of deep learning models based on dairy cow morphology

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ABSTRACT

Computer vision deals with image-based problems, such as deep learning, classification, and object detection. This study classifies the quality of dairy parents into three, namely high, medium, and low based on morphology by focusing on Bogor Indonesia farms. The morphological images used are the side and back of dairy cows and the challenge is to determine the optimal accuracy of the model for it to be implemented into an automated system. The 2-step mask region-based convolutional neural network (mask R-CNN) and Canny segmentation algorithm were continuously used to classify the convolutional neural network (CNN) in order to obtain optimal accuracy. When testing the model using training and testing ratios of 90:10 and 80:20, it was evaluated in terms of accuracy, precision, recall, and F1-score. The results showed that the highest model produced an accuracy of 85.44%, 87.12% precision, 83.79% recall, and 84.94% F1-score. Therefore, it was concluded that the test result with 2-stages of segmentation was the best.

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1. INTRODUCTION

The Indonesian economy has excellent potential, particularly in the aspect of livestock sector. It has been observed that the public consumption of livestock products, such as meat, eggs, milk, cheese, and other products is quite high in this country. One of the products from the livestock sector is cow milk, but its production is still low. This is revealed from the statistics of domestic fresh milk (SSDN), presenting that 78% *Badan Pusat Statistik (BPS)* 2020 of the production is still dominated by those imported, while the remaining 22% were domestically produced. Furthermore, cow milk still dominates the production compared to goat and buffalo which are not yet optimal. It is necessary to increase the population and quality of livestock raised by dairy farmers in order to increase their strategic value. This is achievable through the physical assessment of dairy cows, which serves as a good parameter for determining their sizes, body shapes, muscles, and legs, as well as their characteristics [1]. There are three ways of estimating the weight and changes in the body of livestock, which include direct weighing, observing the physical images and videos, and measuring the parameters of the cow's body. It has been discovered that Indonesians are still using the traditional way of measuring livestock dimensions through measuring sticks, periods, and bands.

This study was conducted to reduce errors in measuring cows using digital imaging techniques. An image is a visual representation of an object captured with cameras, drones, and satellites that are used for its transfer. The image data obtained is further processed into more accurate information using computer vision techniques. According to [2], morphometric measurements through computers provide more accurate results compared to traditional or manual. This means that machine learning methods are expected to be a solution to make selection tools smart, precise, and easy for users to utilize. Furthermore, the methods are popularly used for detecting problems with both quantitative and qualitative data. The examples of studies that utilized this technique include; i) the determination of nitrogen content excretion [3], ii) the prediction of individual insemination of cows based on phenotype and genotype [4], [5], iii) prepartum behavior characterization and prediction of the calving process in dairy cows [6], iv) the determination of conception's outcome for future mating and its benefits to the producer [7], and v) diary cows' identification based on tailheads [8].

Determining the position of this spatial point helps to provide relatively accurate information about the livestock's location, but does not give higher semantics. The recent advances in deep learning have helped to address these challenges. For example, the potential of deep neural networks in feature learning [9], [10] has supported advancements in computer vision, object detection, and segmentation. Regarding object detection, the methods of faster region-based convolutional neural network (R-CNN) [11] and mask R-CNN [12] have contributed significantly to powerful object detection. Also, in object segmentation, the mask R-CNN method has good image object detection and segmentation tactics [13] but has not been able to fully distinguish between foreground and background images.

The previous studies that have predicted body conditions with cow side view using deep learning include [14]: i) the detection of cows using a deep learning framework [15], ii) cow's detection with video cementation mask R-CNN and faster R-CNN [16], iii) identification of dairy cow classification using CNN-long short-term memory (LSTM) with a top view [17], and iv) CORF3D contour map with the application of Holstein cow recognition for red, green, blue (RGB) and cow top view thermal image [18].

This current study employed 2-stages of segmentation to improve the model's accuracy. Stage 1 segmentation uses the mask region-based convolutional neural network (mask R-CNN) and stage 2 deals with the edge detection using the Canny algorithm. After the segmentation, the CNN was classified using the side and back of Holstein dairy cows. The objects with two kinds of morphological positions were used to obtain optimal results when selecting expected dairy cows.

2. METHOD

This section describes the steps applied in processing the captured image, which include segmentation consisting of the mask R-CNN and edge detection using the Canny algorithm, followed by the utilization of a CNN as transformation and normalization classifiers. Figure 1 shows the implementation of the selected learning model for classifying the quality of the parent dairy cow. All morphological images used show the diary cow's right and back side views. The total number of cows consists of 102 which are categorized into three classes, such as high, medium, and low quality. The image data with a high proportion was 49%, while the medium and small were 27% and 24%, respectively.

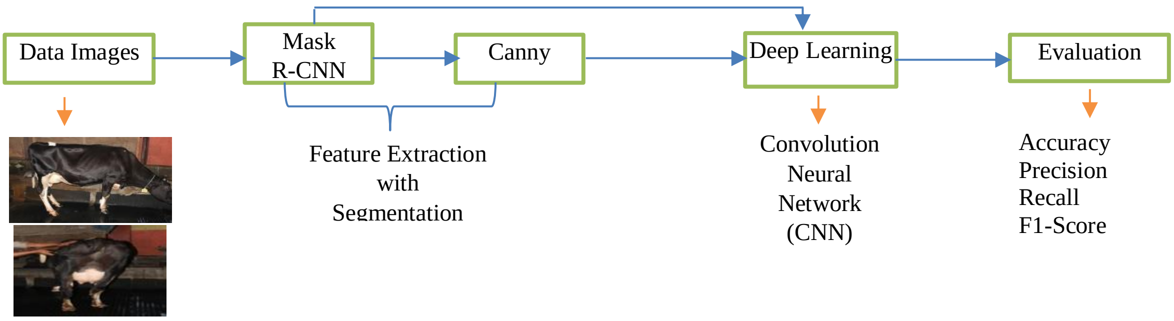

Figure 1. Proposed method

2.1. Data acquisition

The images of cows in this study were captured in two positions, such as side and back views with a complex background, and were used for individual classification in the original cattle farm. Furthermore, the object was Friesian Holstein cattle at Kunak Bogor Farm Indonesia in November 2021 with Canon 1200D camera, having a maximum resolution of 3456×5184 pixels. A total of 1,020 original images from 102 cows were collected and some examples were shown in Figure 1. It was observed that the dataset scale has a huge impact on the performance of the training network such that when the feature dimensions of the space sample are greater than the training sample's number, the model tends to overfit [19]. Therefore, the training and validation are set at ratios of 90:10 [20], 80:20 [21], and 67:33 [22], using python script algorithm in order to determine the optimal model accuracy. It is important to note that this training requires a sufficient sample size to avoid an overfitted model, which was the reason the training set was expanded [23]. After the images are collected, the pixel size was continually reduced to 256x256 for the feature extraction and model testing stages. Consequently, the cow morphological images were converted into RGB in order to reduce the data dimensions [24]. Figure 2 shows the examples of dairy cow morphology, Figure 2(a) shows the side of the cow and Figure 2(b) the back of the cow.

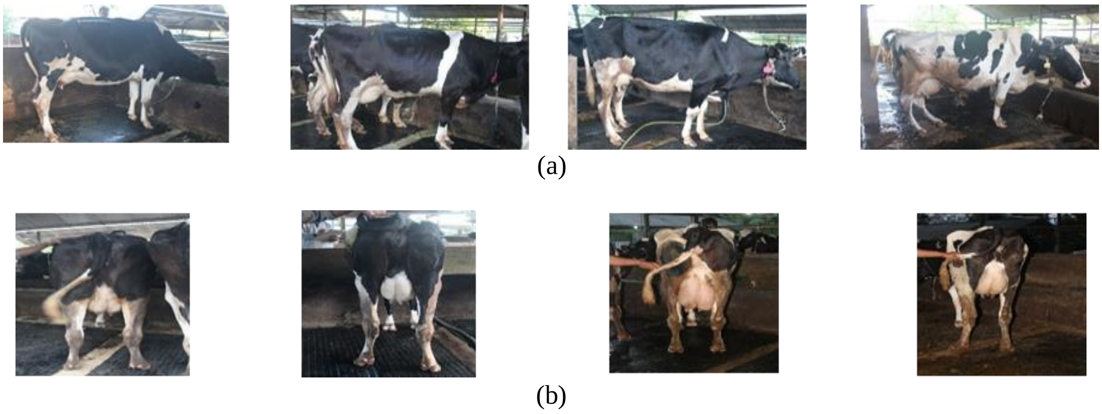

Figure 2. Examples of dairy cow morphology: (a) the side of the cow and (b) the back of the cow

2.2. Feature extraction with segmentation
2.2.1. Mask R-CNN
This stage describes the mask R-CNN architecture used for cow segmentation by applying the same network architecture defined in [12], [25]. Figure 3 shows the 2-stages mask R-CNN framework, the first entails scanning the image and generating a region of interest (ROI) where possible objects are located. The second stage is to classify the region and produces a mask box and a box. At the high level, the mask R-CNN consists of a pyramid network feature+Backbone layer, followed by a region network proposal that produces a positive region or object and bounding box improvement. The masked convolution network takes the positive ROI and predicts based on the pixels already obtained.

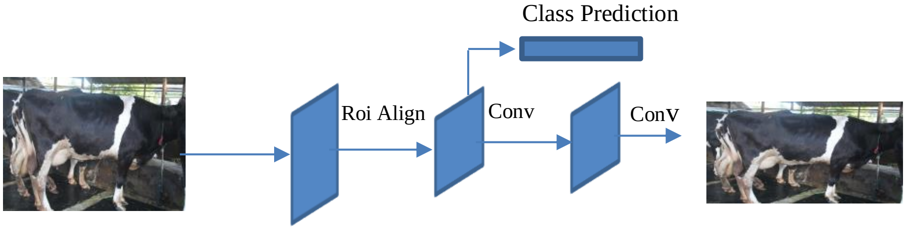

Figure 3. Mask R-CNN architecture

2.2.2. Canny edge detection
The steps in Canny edge detection are very important in digital image processing [26] and it is the first step in pattern recognition [27] as well as segmentation. This edge detection consists of taking the dairy cow image edges in order to retrieve useful information from the image [28]. The steps for edge detection include: i) noise reduction, which deals with smoothing the image using a Gaussian blur filter; ii) gradient calculation for producing two pieces of information from the image, such as the edge strength or its magnitude and the edge direction or orientation [29]; iii) non-maximum suppression, which is the stage of producing a slimmer thin-line using the orientation value in order to determine the pixel's direction; and iv) thresholding is the final step of the Canny algorithm, which is to perform hysteresis thresholds. When the pixel value from the previous process is greater than the upper threshold, the pixel is accepted as the edge of the image [30]. Figure 4 shows the performance flow of the Canny algorithm.

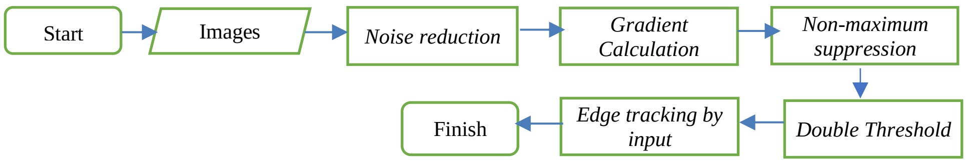

Figure 4. Canny algorithm performance flow

2.3. Convolutional neural network classifier

Convolution is a property extracted from the input image, while the fully connected layer is a classifier for the input image using the extracted properties. As a deep learning method, the CNN architecture is often used in the literature for image classification, object recognition, and detection [31], [32]. Furthermore, CNN consists of one or more convolution layers and is followed by a standard fully connected multilayer neural network. In the CNN deep learning model with a layered structure, data is transferred to the next layer by performing separate operations and each of them performs this function. The four main layers in the CNN architecture are highlighted below, while its inner layers and operations are shown in Figure 5.

– The convolutional layer is where the matrix dimensions in an image are used.
– Pooling is a merging layer placed after the convolutional and it is where the number of parameters is reduced. This process is accelerated because the number of parameters and pixels that need to be processed have been reduced.
– The rectified linear unit (ReLU) layer is where a non-linearity activation function is applied. Furthermore, the ReLU has a negative value set to zero, while maintaining a positive value. This layer is applied to place the tissue in a nonlinear structure which helps the network to learn faster.
– A fully connected Layer is a standard neural network layer used for classification purposes. The amount of output in the layer depends on the number of classifications used.

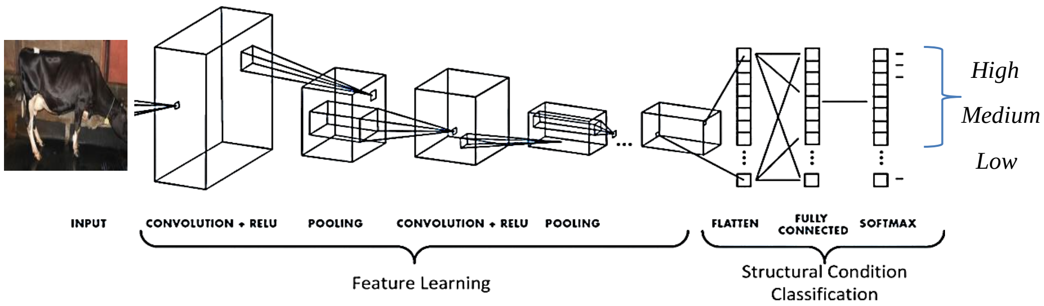

Figure 5. Convolution neural network architecture [33]

2.4. The proposed 2-stages of segmentation

This architecture was proposed by combining two feature extraction stages, which include mask R-CNN segmentation [25] and edge detection using the Canny algorithm. Figure 6 shows the flow and the segmentation results of the mask R-CNN as well as the edge detection [27]. Furthermore, the flow is expected to maximize the segmentation process by obtaining an optimal classification model using CNN.

2.5. Evaluation method

The confusion matrix was employed to evaluate deep learning models for classification [4], and it is described as follows. The confusion matrix can be used to measure performance in binary and multiclass classification problems. Following is some of the benefits of the confusion matrix, namely showing the model when making predictions, it not only provides information about the errors made by the model but also the types of errors made, each column of the confusion matrix represents an instance of the prediction class and Each row of the confusion matrix represents an instance of an actual class.

– True positive (TP) denoting a positive and predicted object class in a positive position.
– False positive (FP) representing a positive object class and negative image position prediction.
– False negative (FN) is a class of negative and predicted objects at the position of a positive image.
– True negative (TN) is a negative object class and negative image position prediction.

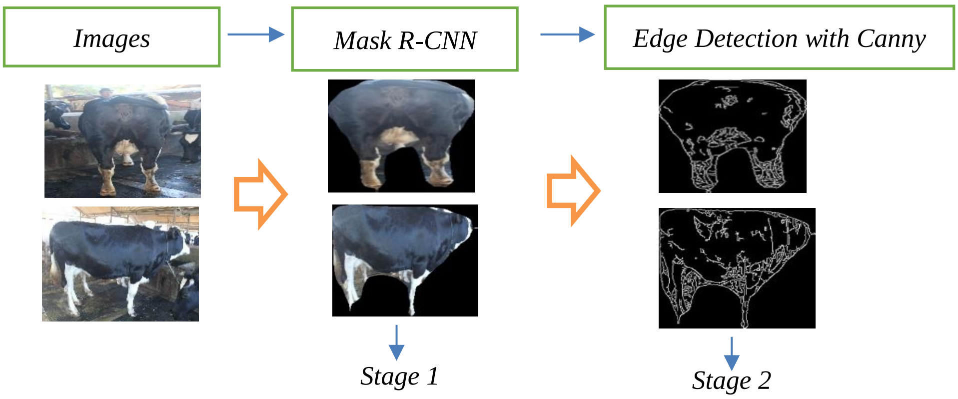

Figure 6. Illustration of the proposed segmentation results

Furthermore, the following metrics are calculated using the confusion matrix terminology below [4], [34].

$$Accuracy = \frac{(TP+TN)}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1 - Score = 2 \times \frac{2Precision*Recall}{Precision+Recall} \tag{4}$$

3. RESULTS AND DISCUSSION

After testing the CNN model with mask R-CNN segmentation and edge detection, several results obtained need to be rejected due to the size of the method used. This study concentrated on the comparison of the classification model results with the mask R-CNN using 2 stages of segmentation. A total of 3 training test ratios, such as 90:10, 80:20, and 67:33 was utilized to determine the optimal model that continues to have application in dairy cow selection. The model results are shown in the form of images and graphs.

Figure 7 shows a CNN with mask R-CNN and 2-stage segmentation using Canny with a test ratio of 90:10. The test results obtained by mask R-CNN+Canny in the aspect of accuracy, precision, recall, and F1-score was 85.44%, 87.12%, 83.79%, and 84.94%, respectively. Meanwhile, the use of only mask R-CNN achieved 84.47%, 84.70%, 83.51%, and 83.92%, respectively. It was observed that the results of the 2-stages models were better by approximately 1%.

Figure 8 shows a CNN with mask R-CNN and 2-stage segmentation using Canny with a test ratio of 80:20. The test results obtained by mask R-CNN+Canny reached an accuracy, precision, recall, and F1-score of 83.90%, 83.34%, 82.17%, and 82.59%, respectively. Meanwhile, using only mask R-CNN yielded 86.83%, 87.96%, 84.58%, and 85.91%, respectively. This simply means that the models with one stage are better by approximately 3%.

Figure 9 shows a CNN with Mask R-CNN and 2-stage segmentation using Canny with a test ratio of 67:33. The results obtained by mask R-CNN+Canny in the aspect of accuracy, precision, recall, and F1-score was 84.62%, 84.51%, 81.85%, and 82.96%, respectively. Meanwhile, using only mask R-CNN achieved respective values of 77.22%, 77.55%, 73.01%, and 74.59%. Therefore, the results of the 2-stages models are better by approximately 7%.

The mask R-CNN segmentation by producing three outputs, namely bounding box, class, and mask has helped in extracting the features created as information from the image of the cow used. For example, the model classification results reached the highest accuracy of 86.83%, 87.96% precision, 84.58% recall, and 85.91% F1-score when the masks were employed. It was observed that among the three kinds of test ratios used, the most optimal performance ratio was 80:20 compared to 90:10 and 67:33. This makes the use of mask R-CNN segmentation to be very good.

It is important to reiterate that 2-stages of segmentation were proposed in this study in which the output from mask R-CNN is followed by the edge detection using the Canny algorithm to extract dairy features. The three ratios used for testing include 90:10, 80:20, and 67:33, of which the most optimal model results were recorded in 90:10 with an accuracy of 85.44%, 87.12% precision, 83.79% recall, and 84.94% F1-score. The utilization of these 2-stages helped to reduce the image size produced after a mask was performed against the background image. It is safe to conclude that the results of the 2-stages of segmentation are much better when compared to just using only the mask R-CNN segmentation

Table 1 shows the comparison of all tests performed and those submitted in this study. It was observed that the test ratios 67:33 and 80:20 showed segmentation with an average increase of 3%, respectively. Meanwhile, that of 90:10 showed the best performance segmentation with an increase in the average for all evaluation models.

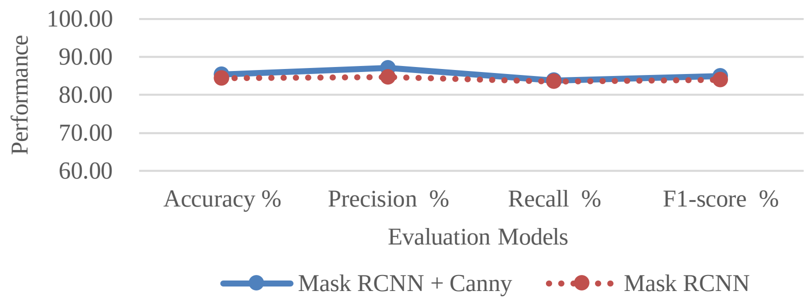

Figure 7. The CNN model results in a ratio of 90:10

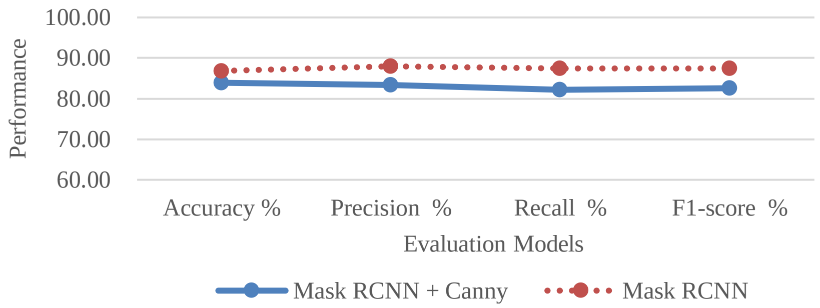

Figure 8. The CNN model results in a ratio of 80:20

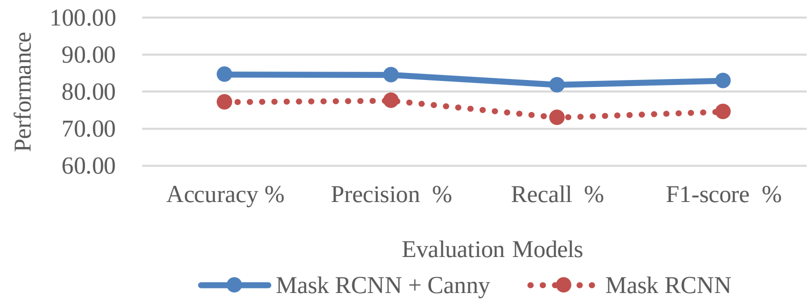

Figure 9. The CNN model results in a ratio of 67:33

Table 1. Comparison of CNN model results

Segmentation + Deep Learning	Test Ratio	Accuracy	Precision	Recall	F1-score
Mask R-CNN + Canny + CNN	67:33	80.62	84.51	81.85	82.96
Mask R-CNN + CNN	67:33	77.22	77.55	73.01	74.59
Mask R-CNN + Canny + CNN	80:20	83.90	83.34	82.17	82.59
Mask R-CNN + CNN	80:20	86.83	87.96	84.58	85.91
Mask R-CNN + Canny + CNN	90:10	85.44	87.12	83.79	84.94
Mask R-CNN + CNN	90:10	84.47	84.70	83.51	83.92

4. CONCLUSION

Based on the test results of the proposed model, several conclusions have been drawn. The most optimal performance with a test ratio of 90:10 for 2-stages of segmentation reached an accuracy of 85.44%, 87.12% precision, 83.79% recall, and 84.94% F1-score. It was observed that as the test ratio reduces, the performance of the resulting model becomes improved. Therefore, the edge detection algorithm is enough to help the model classify the morphology of dairy cows.

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