Optimization of Machine Learning Models with segmentation to Determine the Pose of Cattle

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ABSTRACT

Image pattern recognition poses numerous challenges, particularly in feature recognition, making it a complex problem for machine learning algorithms. This study focuses on the problem of cow pose detection, involving the classification of cow images into categories like front, right, left, and others. With the increasing popularity of image-based applications, such as object recognition in smartphone technologies, there is a growing need for accurate and efficient classification algorithms based on shape and color. In this paper, we propose a machine learning approach utilizing Support Vector Machine (SVM) and Random Forest (RF) algorithms for cow pose detection. To achieve an optimal model, we employ data augmentation techniques, including Gaussian blur, brightness adjustments, and segmentation. The proposed segmentation methods used are Canny and Kmeans. We compare several machine learning algorithms to identify the optimal approach in terms of accuracy. The success of our method is measured by accuracy and Receiver Operating Characteristic (ROC) analysis. The results indicate that using the Canny segmentation, SVM achieved 74.31% accuracy with a testing ratio of 90:10, while RF achieved 99.60% accuracy with the same testing ratio. Furthermore, testing with SVM and K-means segmentation reached an accuracy of 98.61% with a test ratio of 80:20. The study demonstrates the effectiveness of SVM and Random Forest algorithms in cow pose detection, with Kmeans segmentation yielding highly accurate results. These findings hold promising implications for real-world applications in image-based recognition systems. Based on the results of the model obtained, it is very important in pattern recognition to use segmentation based on color even though shape recognition.

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1. INTRODUCTION

Pose estimation in animal husbandry is a specialized task to detect the predefined positions of humans, cows, pigs in an image. This research started in the 1990s, aimed at animal detection, face pattern estimation and motion tracking. Recently, the cost, time and technical aspects of pose estimation have become much more efficient. Now applications can gradually be integrated into aspects of life, such as gesture-based human-computer interaction [1], gesture assessment by viewing animal and human postures in healthcare applications [2], [3], social security-adversary action detection [4]. Technological advances using machine learning and deep learning models, which have led to an increase in pose estimation work, open up topics into animal pose estimation. For computational analysis of animal behavior, pose estimation is often a critical step and deep learning-based tools have rapidly influenced neuroscience, ethology, and medicine [5], [6]. Tracking animals between frames can be difficult due to similarity in appearance, immobile behavior and possible occlusion. Based on human pose estimation research, several packages for multi-animal pose estimation have emerged [7], [8].

Automatic animal tracking and pose estimation have become crucial tools in various fields, including neuroscience, ethology, and animal welfare research. This study focuses on developing an automatic pose detection system for cows, aiming to improve cow behavior monitoring and welfare assessment. Accurate and efficient pose detection in cows can facilitate the detection of reduced activity, discomfort, or disease, contributing to better overall animal welfare [9], [10]. However, using image analysis for behavior monitoring is preferable in pigs, as only relatively small sensors can be used and sensors are always at risk of being damaged, as in the past, many animals' exploratory behaviors [11].

Previous research has shown promising results in animal pose detection. For instance, studies have compared models for dairy cow classification based on morphology using SVM, artificial neural networks, random forest, and logistic regression with various segmentation techniques [12], [13]. However, the focus of this paper is on developing an automatic pose detection system specifically tailored for cows. The research conducted provides a reference that in object classification using machine learning is very good, where classification is based on shape. If the image preprocessing is maximized, it can provide optimal model results.

Despite advancements in machine vision research, multi-animal pose estimation poses unique challenges, particularly in dealing with interacting animals, similar appearances, and occlusions. The proposed approach involves three main steps: pose estimation (keypoint localization), assembly(grouping keypoints into individual animals), and tracking. To address these challenges, the study integrates machine learning algorithms, including Support Vector Machine (SVM) and Random Forest (RF), with advanced segmentation techniques.

For the learning framework, several studies have been conducted using the SOLO architecture based on Deep Learning for Location-based Object Identification [14]. Leukocyte Classification Using Color-based Meta-Learning, where meta-learning can be applied to other medical images [15]. Canny edge detection is a method applied to digital image processing as a result of the quality of the oyster mushroom harvest which is influenced by the diameter size. Canny edge detection is used to determine the boundaries of oyster mushroom objects by the acquisition process [16].

Therefore, an automatic Pose detection system for pigs is important for continuous monitoring without manual work. Such a system requires automatic object detection in video images, which is the algorithmic task of localizing, and classifying objects in images. Most current approaches binarize the image into black and white pixels, removing pixels that are too small.

In this paper, we propose a methodology that maximizes the segmentation stage to improve image quality and reduce noise in cow images. The subsequent steps involve training SVM and Random Forest algorithms to accurately detect and track cow poses. The proposed system aims to automate cow behavior monitoring, providing continuous and non-intrusive surveillance without manual intervention. The success of the proposed approach will be evaluated based on accuracy and Receiver Operating Characteristic (ROC) metrics. By achieving an optimal model, this research endeavors to offer a valuable reference for automating cow pose detection, contributing to advancements in animal welfare research and practical applications in the livestock industry.

2. METHODS

The proposed approach consists of several steps to achieve automatic pose detection for cows. The overall research flow is illustrated in Fig. 1.

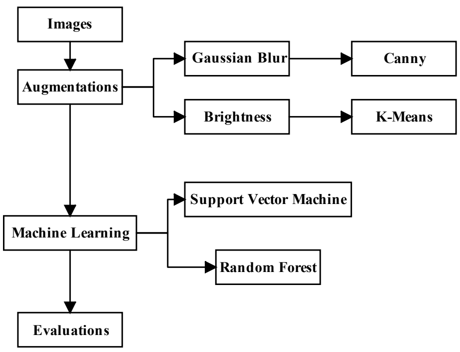

Fig. 1. Proposed method

2.1. Data Acquisition

The dataset used for this study is obtained from https://www.kaggle.com/datasets/afnanamin/cow-images, comprising four categories: front, left, right, and others. Each category contains a specific number of images (front: 89 images, left: 60 images, right: 50 images, others: 72 images). The original dataset is augmented to increase its diversity using Gaussian blur, brightness adjustments, and two segmentation techniques: Canny Edge Detection and K-Means. The dataset image is 2D [17], [18].

2.2. Augmentations

Data augmentation techniques are employed to generate transformed versions of the original images, enhancing the diversity of the dataset. Gaussian blur is applied with various kernel configurations to create different levels of blur. Image sharpness adjustments are made to produce varying focus levels and image clarity. Brightness adjustments increase contrast for improved image quality. These augmented images serve to enhance the generalization capabilities of machine learning algorithms [19]-[23]. For the segmentation results can be seen in Fig. 2.

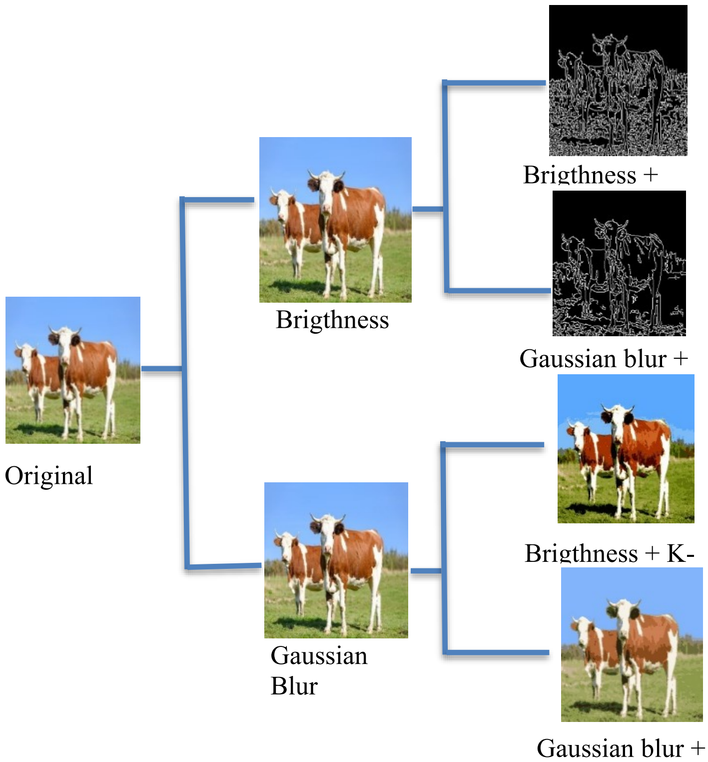

Fig. 2. Illustration of image augmentation result

2.3. Canny Edge Detection

Canny Edge Detection, introduced by John F. Canny in 1986, is applied to dairy cow images to extract useful information. Edge detection helps in distinguishing object boundaries from the background. This study employs the Canny algorithm to retrieve the edges of cow images, a crucial step in pose detection [24]-[27] Fig. 3.

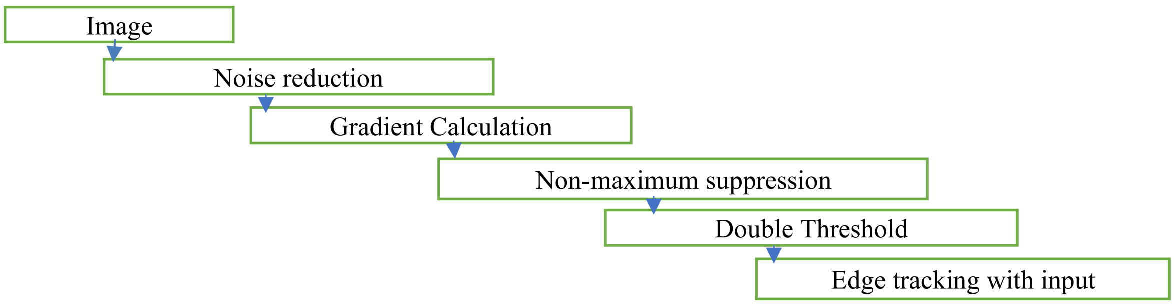

Fig. 3. Canny Algorithm Method

2.4. K-Means Algorithm

The K-Means algorithm is employed for color clustering and image segmentation. By grouping pixels into K clusters, this algorithm reduces the color palette of the images and aids in identifying object structures. K-Means clustering plays an essential role in the pose detection process. Color clustering implementations are often used for image segmentation. Uses for vector quantization include non-random sampling as the K-Means algorithm can work to select K different objects but large data sets for further analysis [28]. The first approach represents k-means clustering, using input training data which need not be labeled. Then, to project any input datum to the new feature space, an "encoding" function, such as a threshold matrix product of the datum with the centroid locations, calculating the distance from the datum to each centroid, or simply an indicator function for the nearest centroid [29]-[31], or a smooth distance transformation Alternatively, transforming the sample-cluster distance via a Gaussian RBF, obtaining the hidden layer of a radial basis function network, or a smooth distance transformation.

2.5. Support Vector Machine (SVM) Algorithm

The SVM algorithm is implemented by using kernel selection which transforms the input data space into the required shape. SVM uses a technique called kernel trick where the kernel takes a low-dimensional input space and transforms it into a higher dimensional space [32]. In simple words, the kernel transforms an inseparable problem into a separate problem that can be separated by adding more dimensions to it. The SVM algorithm is utilized for classification, specifically for cow pose detection. The data is transformed into a higher-dimensional space using kernel selection, making SVM more powerful and flexible. The Radial Base Function Kernel (RBF) is chosen for this study due to its effectiveness in SVM classification [33]-[35].

2.6. Random Forest Algorithm

Random forest is a supervised learning algorithm used for classification and regression, it is mainly used for image classification problems [36]-[38] As we know that a forest consists of trees and more trees means a stronger forest. Similarly, the random forest algorithm creates decision trees on data samples and then gets predictions from each of them and finally chooses the best solution through voting. Random Forest, an ensemble learning algorithm, is utilized for cow pose detection. By creating decision trees on data samples and combining their predictions through voting, Random Forest reduces overfitting and improves accuracy. Forest algorithm works with the help of the following steps.

1. Start with the selection of a random sample from a given data set.
2. Next, the algorithm will build a decision tree for each sample. Then you will get the prediction results from each decision tree.
3. In this step, a vote will be taken for each predicted result.
4. Finally, select the most voted prediction result as the final prediction result.

2.7. Evaluation model

The proposed approach is evaluated using various metrics, including accuracy and the Receiver Operating Characteristic (ROC) curve. Accuracy is computed based on the confusion matrix, which includes True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) predictions. The ROC curve illustrates the classifier's performance at different threshold levels, displaying the True Positive Rate (Sensitivity) and False Positive Rate [39]-[41]. True Positive (TP): a positive prediction and a true positive. False Positive (FP): positive prediction and it’s false. False Negative (FN): negative prediction and it’s false. True Negative (TN): A true negative prediction and a true negative.
Using the confusion matrix, the following accuracy is used (1).

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

The True Positive Rate is often known as Sensitivity and is defined as (2).

$$TPR = \frac{TP}{TP + FN} \tag{2}$$

While the False Positive Rate is defined as (3).

$$FPR = \frac{FP}{TN+FP} = (1 - Specifity) \tag{3}$$

3. RESULTS AND DISCUSSION

The results showed after testing the segmentation method and machine learning method, first testing the canny algorithm model with SVM, RF algorithm, secondly doing some tests with augmentation consisting of brightness, gaussian blur, Canny, K-Means with SVM, RF algorithm. Both machine learning algorithms were tested by dividing training data and testing data with a ratio of 90:10, 80:20 and 67:33. Algorithm performance using accuracy and ROC.

This section is to display the research results obtained and explain the similarities and differences in results from data, methods and results of previous research. However, whether the research conducted is in accordance between the objectives and the proposed method. The explanation also includes a description of the resulting analysis, causes and benchmarks of failure or success, and unfinished parts of this research and steps to be taken as a follow-up process. The results of the experiments are presented in Table 1 and Table 2, showing the accuracy achieved by SVM and Random Forest models with different augmentation and segmentation approaches. The results of using canny segmentation with SVM and Random forest algorithms got the highest accuracy of 74.31% for SVM and 72.35% generated Random forest results. The results using K-means segmentation with SVM and Random forest algorithms got the highest accuracy of 99.60% for Random forest and 72.35% generated by SVM results. so the segmentation stage can have a very big impact on the accuracy of the model and the ROC.

Table 1. Accuracy results using Canny

Ratio Testing	Augmentations	Support Vector Machine	Random Forest
67:33	Brightness + Canny Gaussian blur + Canny	70.39%	69.27%
80:20	Brightness + Canny Gaussian blur + Canny	74.19%	72.35%
90:10	Brightness + Canny Gaussian blur + Canny	74.31%	70.64%

Table 2. Accuracy results using K-Means

Ratio Testing	Augmentations	Support Vector Machine	Random Forest
67:33	Brightness + K-Means Gaussian blur + K-Means	92.73%	96.92%
80:20	Brightness + K-Means Gaussian blur + K-Means	98.61%	99.53%
90:10	Brightness + K-Means Gaussian blur + K-Means	98.16%	99.60%

3.1. Canny Segmentation

When using Canny segmentation, the SVM algorithm achieved the highest accuracy of 74.31% with a testing ratio of 90:10. On the other hand, the Random Forest algorithm achieved a maximum accuracy of 72.35% with a testing ratio of 80:20. The ROC curves for both SVM and Random Forest with Canny segmentation are shown in Fig. 4. Although the accuracy results for both algorithms are relatively lower with Canny segmentation, the SVM model outperformed the Random Forest model.

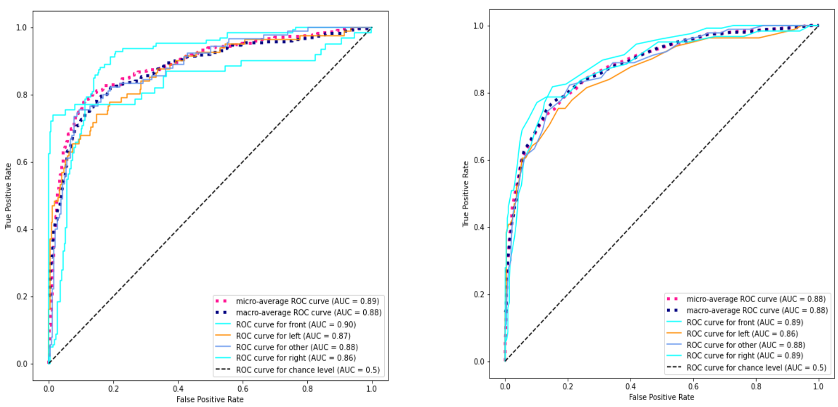

Fig. 4. ROC results of SVM and RF algorithms with Canny segmentation with ratio of 67:33

3.2. K-Means Segmentation

In contrast, when employing K-Means segmentation, the results were significantly improved. The Random Forest algorithm achieved an impressive accuracy of 99.60% with a testing ratio of 90:10, while the SVM algorithm reached an accuracy of 98.61% with a testing ratio of 80:20. The ROC curves for SVM and Random Forest with K-Means segmentation are depicted in Fig. 5. The K-Means approach demonstrated superior performance for both algorithms.

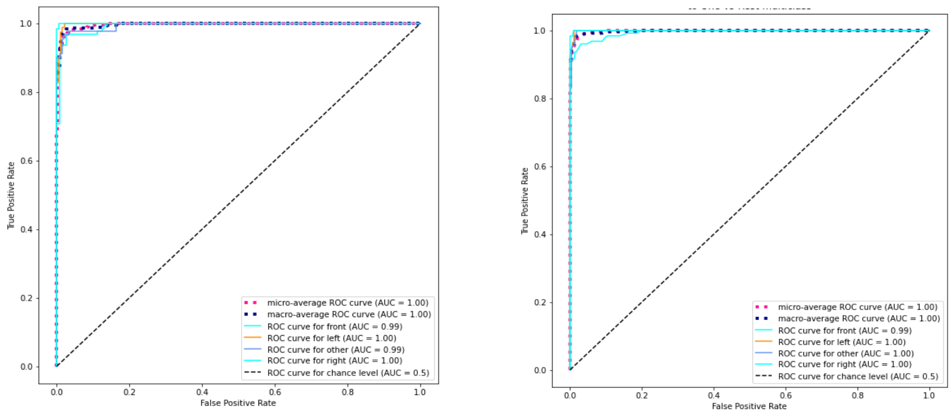

Fig. 5. ROC results of SVM and RF algorithms with K-Means segmentation with ratio of 67:33

On the ROC curve, it can be seen for the front, left, right and other classification curves, the resulting Canny augmentation with SVM Algorithm with a Ratio of 67:33 is better than the Random forest algorithm. The ROC curves using SVM and random forest algorithms with Canny segmentation can be seen in Fig. 4. On the ROC curve, it can be seen that the front, left, right and other classification curves, the resulting K-means augmentation with SVM and random forest algorithms with a ratio of 67:33 is equally good. The ROC curve using SVM and random forest algorithms with K-means segmentation can be seen in Fig. 5. Evaluation using ROC with Canny and K-means segmentation has a different way of working, for canny detects the edges of objects while K-means groups colors into 16 kinds. In this case, the K-means approach is better, so this research object is more suitable for using color clusters.

On the ROC curve, it can be seen for the front, left, right and other classification curves, the resulting Canny augmentation with SVM Algorithm with a Ratio of 80:20 is better than the Random forest algorithm. The ROC curves using SVM and random forest algorithms with Canny segmentation can be seen in Fig. 6. On the ROC curve, it can be seen that the front, left, right and other classification curves, the resulting K-means augmentation with SVM and random forest algorithms with a ratio of 80:20 is equally good. The ROC curve using SVM and random forest algorithms with K-means segmentation can be seen in Fig. 7. Evaluation using ROC with Canny and K-means segmentation has a different way of working, for canny detects the edges of objects while K-means groups colors into 16 kinds. In this case, the K-means approach is better, so this research object is more suitable for using color clusters.

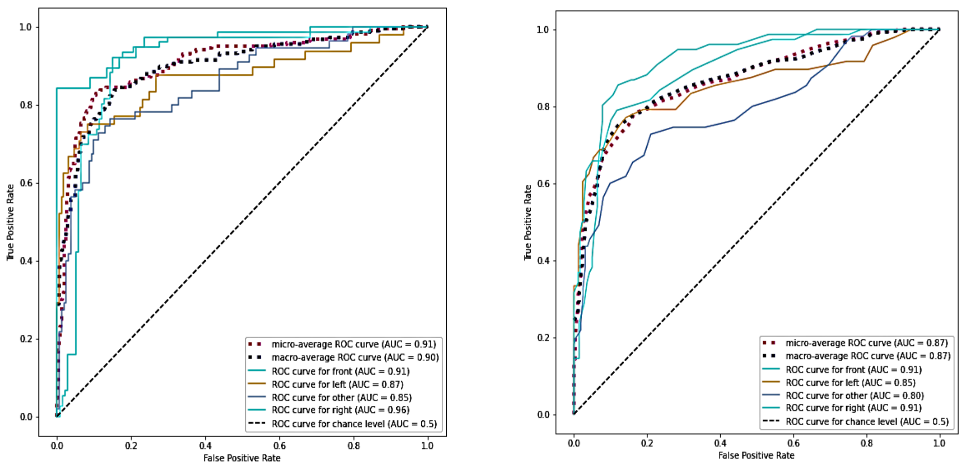

Fig. 6. ROC results of SVM and RF algorithms with Canny segmentation with ratio of 80:20

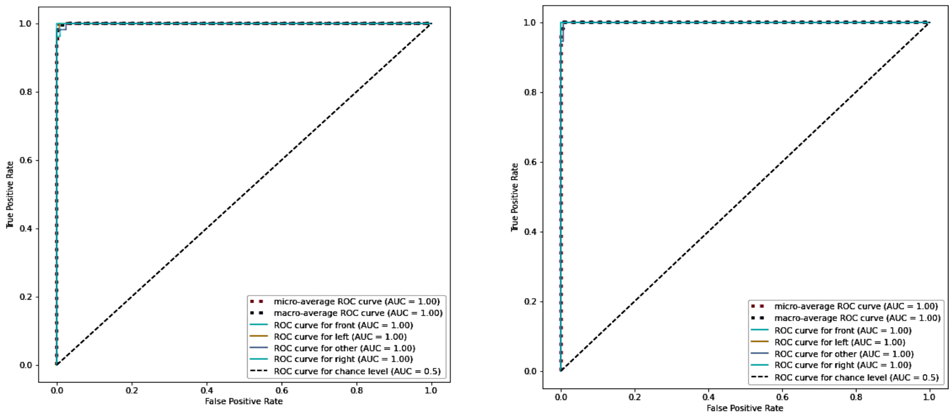

Fig. 7. ROC results of SVM and RF algorithms with K-Means segmentation with ratio of 80:20

On the ROC curve, it can be seen for the front, left, right and other classification curves, the resulting Canny augmentation with SVM Algorithm with a 90:10 Ratio is better than the Random forest algorithm. The ROC curve using SVM and random forest algorithms with Canny segmentation can be seen in Fig. 8. In the ROC curve, it can be seen the front, left, right and other classification curves, produced by K-means augmentation with SVM and random forest algorithms with a ratio of 90:10 are equally good. The ROC curve using SVM and random forest algorithms with K-means segmentation can be seen in Fig. 9. Evaluation using ROC with Canny and K-means segmentation has a different way of working, for canny detects the edges of objects while K-means groups colors into 16 kinds. In this case, the K-means approach is better, so this research object is more suitable for using color clusters.

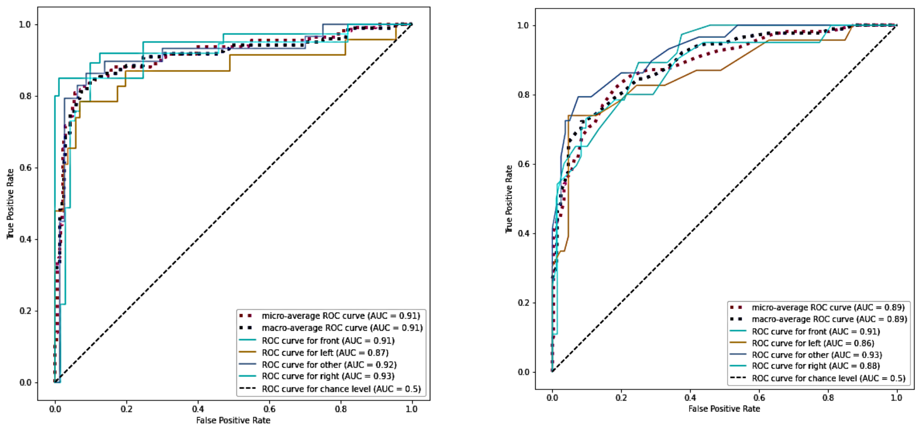

Fig. 8. ROC results of SVM and RF algorithms with Canny segmentation with ratio of 90:10

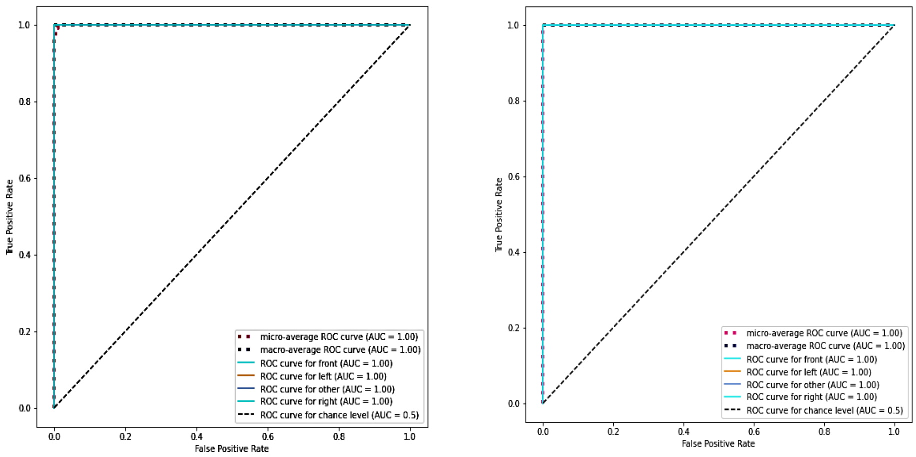

Fig. 9. ROC results of SVM and RF algorithms with K-Means segmentation with ratio of 90:10

This research discusses the comparison of the accuracy of SVM and Random forest models by maximizing the preprocessing stage. The preprocessing stage used with the Gaussian blur, brightness and K-means segmentation approach, Canny, with the problem of classifying the Pose of cows into four criteria, namely front, left, right and others.

Table 1 is the result of comparing the accuracy of Random forest and SVM with canny segmentation approach to improve performance. The results of the two algorithms only the highest accuracy reached 74.31% with the SVM algorithm while the highest Random forest reached 72.35%, from both algorithms it still takes effort to improve performance. based on the accuracy results of the algorithms used are not optimal with the edge detection approach to recognize objects.

Table 2 is the result of comparing the accuracy of Random forest and SVM with the K-menas segmentation approach to improve performance. The results of the two highest algortime accuracy reached 99.60% with the Random forest algorithm while the highest SVM reached 98.61%, from both algorithms still have very good performance and can be a reference for methods used for classification of cow image objects. Based on the accuracy results of the algorithm used, it has maximum performance with a color grouping approach to recognize objects.

Based on the ROC it can be decided that according to the accuracy results the two algorithms used are almost the same performance. the difference in this work is the approach at the image preprocessing stage. The preprocessing stage used can have a very significant impact. in addition to accuracy, the model evaluation is also carried out using ROC. The evaluation results with ROC are the same as the accuracy that using K-means segmentation can provide excellent can be seen in Fig 4 and Fig. 5 as a test with a ratio of 67:33. The K-Means approach has a better ROC.

Based on the ROC results, the two algorithms used are almost the same performance, both using canny segmentation and K-Means. the difference in this work is the approach at the image preprocessing stage. The preprocessing stage used can have a very significant impact. in addition to accuracy, the model evaluation is also carried out using ROC. The evaluation results with ROC are the same as the accuracy that using K-means segmentation can provide excellent can be seen in Fig. 6 and Fig.7 as a test with a ratio of 80:20. The K-Means approach has a better ROC.

Based on the ROC curves generated, the two algorithms have curves that are almost the same in performance, both using canny segmentation and K-Means. The difference in this work is the approach at the image preprocessing stage. The preprocessing stage used can have a very significant impact. In addition to accuracy, the model evaluation is also carried out using ROC. The evaluation results with ROC are the same as the accuracy that using K-means segmentation provide can be seen in Fig. 8 and Fig. 9 as a test with a ratio of 90:10. K-Means approach has a better ROC.

The observed differences in accuracy between Canny and K-Means segmentation can be attributed to their distinct ways of processing images. Canny edge detection focuses on detecting edges, while K-Means clusters colors into 16 groups. The color grouping nature of K-Means segmentation appears to be more suitable for this specific problem of cow pose detection, leading to superior results.

Moreover, while both SVM and Random Forest models performed well with K-Means segmentation, the Random Forest algorithm exhibited slightly higher accuracy. The differences between the two algorithms' performance might be due to the nature of the problem and the characteristics of the dataset.

4. CONCLUSION

In this study, we explored the performance of several machine learning methods for cow pose detection, with a focus on optimizing the augmentation stage. Through the use of Canny, K-Means, Gaussian blur, and brightness techniques, we compared the effectiveness of edge detection and color grouping approaches. The results clearly demonstrate that K-Means segmentation outperformed the Canny algorithm, leading to significantly higher accuracy and improved ROC scores. The Random Forest algorithm, when combined with K-Means segmentation, achieved the highest accuracy of 99.60% at a test ratio of 90:10. On the other hand, the SVM algorithm, with the highest Canny segmentation, reached an accuracy of 74.31% at a test data ratio of 90:10. This work highlights the superiority of the K-Means algorithm in grouping 16 colors, making it a more optimal approach than edge detection for cow pose detection. The color grouping nature of K-Means segmentation appears to be better suited for the problem, leading to better classification results. The implications of these findings are significant for the field of cow pose detection and related image recognition applications. The use of K-Means segmentation can lead to more accurate and robust models, with potential applications in animal behavior monitoring and welfare assessment. While this study has provided valuable insights, it is essential to acknowledge its limitations. The results were based on a specific dataset, and further research on larger and more diverse datasets is recommended to validate the generalizability of the proposed approach. Additionally, statistical analysis could be incorporated to verify the significance of the observed differences in accuracy. In conclusion, this research demonstrates the importance of image preprocessing and segmentation techniques in machine learning-based cow pose detection. The findings support the superiority of K-Means segmentation and contribute to the advancement of the field. Future research can build upon these results to enhance accuracy and broaden the scope of automated cow behavior monitoring.

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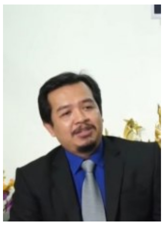

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