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Sheep Face Classification using Convolutional Neural Network

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Abstract

Monitoring sheep species identification and classification in the farming environment can be a tedious task and can be a significant workload for a starting farmer. In this paper, Convolutional Neural Network is proposed to reduce the workload of sheep farmers. This experiment compares which neural architecture model is more useful to classify sheep species based on its face. The experiment was conducted using the training dataset obtained from Kaggle. The dataset contains 420 of each Marino sheep, Suffolk sheep, White Suffolk sheep, and Poll Dorset sheep, totaling 1680 sheep face images. This experiment was run on Google Colab, using the Resnet50 network architecture model and VGG16 network architecture model. The experiment shows good accuracy results on the dataset achieving 86% using the Resnet50 network architecture model. Better accuracy results were achieved using VGG16 network architecture, with an accuracy value of 94%.

Keywords—Sheep breed identification, Convolutional neural network, Image classification, Computer vision

I. INTRODUCTION

Indonesia is a country where sheep are suitable for farmed in lowland areas with rice monoculture and grazing lands. Development programs in Indonesia are more focused on goats than sheep, even though based on its Muslim religious festivities culture, sheep are often used as sacrifices rather than goats [1]. The surveillance system of wild animals as a non-invasive approach in monitoring animals can now classify and recognize animal species using a camera [2]. Sheep are commercially valued based on their meat or carcass weight and their wool [3]. Different breeds of sheep may produce additional meat yield and wool yield, so it is essential to know the difference between them. For a farmer who just started or still low in experience, an automation system that can help them identify each breed will reduce their workload to focus on other tasks efficiently. Machine learning, especially computer vision approaches, may benefit them.

There are many kinds of research with sheep as subjects. The study by Abu Jwade *et al.* implements the automation of sheep breed classification using deep learning. Usually, it is not easy to estimate the sheep's productivity as it is only counted during its slaughter [4]. The sheep's weights are needed to estimate how much meat the sheep farm is producing. As different breeds may have different meat yield, it is essential to know which species produce specific meat yield [4]. Shahinfar *et al.* use Artificial Neural Network, Model Tree, and Bagging to predict wool growth and quality in adult Australian Merino Sheep [5]. The study suggests that Model Tree and Bagging are the most effective for predicting adult sheep wool growth [5]. Machine learning was also used in predicting sheep carcass traits from early-life records [6]. One study uses five machine learning algorithms: Deep Learning, Gradient Boosting Tree, K-Nearest Neighbor, Model Tree, and Random Forest. The analysis was most accurate when utilizing birth, weaning, and pre-slaughter weight to predict intramuscular fat and Greville rule fat depth [6]. The result is most accurate when using weaning, six-monthly weight measures after weaning and pre-slaughter weight to predict hot carcass weight, loin weight, and computer tomography lean meat yield [6]. Prediction of carcass traits is crucial as it led to better management of the sheep farm [7].

Convolutional Neural Network (CNN) is an algorithm that has become a tool for pattern recognition and object detection [8]. In this experiment, sheep species classification using the sheep faces extracting features on the sheep's faces. For this task, the Resnet50 network architecture model and VGG16 network architecture model will be employed to identify sheep species based on features on the sheep's face. The evaluation will be based on the model's precision, recall, F1-score, support, accuracy, macro average, and weighted average.

II. PROPOSED METHODOLOGY

The dataset of this experiment was obtained from Kaggle.com. These images were pre-processed to enable training and testing CNN models. Dataset consists of 1680 photos of sheep face with dimensions of each photo 156x181 pixels, and resolution of both vertical and horizontal are 96 dpi. The dataset is divided into four folders of Marino sheep, Suffolk sheep, White Suffolk sheep, and Poll Dorset sheep. The dataset's images contain a picture of a sheep face with its eyes, mouth, and nose. Fig. 1 includes samples of each species' sheep faces.

Fig.1 Sample images from the dataset of sheep faces of each species

CNN Architecture used in this experiment is Resnet50 and VGG16. Dataset then was reuploaded to Google Drive, then mounted to Google Colab and arranged into dataset fit for training and testing for machine learning. The dataset is then divided into a training dataset and a testing dataset. The dataset is then trained and tested using Resnet50 CNN Architecture and then VGG16 CNN Architecture. The accuracy result from each CNN architecture is then compared for the best results. The experiment was run on a laptop computer with Intel Core i7-7700HQ (2.80 GHz), a GPU of Nvidia GeForce GTX 1050, and 8 GB of memory, running on a Windows 10 64-bit system. The experiment was implemented in Google Colab.

1. Resnet50

The Resnet50 was put forward by Kaiming [9]. Resnet has successfully trained 152 deep neural networks to win the ILSVRC 2015 championship and achieving 3,57% in error rate classification for the top 5 classes [9]. Resnet50 is a convolutional neural network that contains 50 layers deep. The pre-trained network can classify images into 1000 object categories [10]. Resnet50 network was utilized as CNN in wildlife detection and provided satisfactory results. It provided 96% accuracy in animal detection and 90% accuracy in identifying the most common animals such as birds, rats, and bandicoot [2]. The study by Weber *et al.* experiment of recognition of Pantaneira cattle breed also uses Resnet50 and achieves accuracy training of 99.20% and an accuracy test of 99.78%. [11]. Whereas the study by Deeba and Amutha experiment in developing a deep learning-based system for prediction and classification of vegetable leaf compares different neural network types [12]. Among these results, Resnet50 achieved a higher prediction accuracy of 98% compared to LeNet, AlexNet, VGG16, and VGG19 [12].

2. VGG16

VGG16 is a convolutional neural network proposed by Simonyan and Zisserman [13]. The model achieves 92.7% accuracy in ImageNet, a dataset of over 14 million images belonging to 1000 images [14]. The VGG16 network has achieved favorable results in detecting objects. Song *et al.* have constructed a kiwifruit detection system resulting precision of 87.61% using the VGG16 network model. The system can detect several categories of fruits in the field, providing firm support for automatic harvest system using robots that can work all day during the busiest season [15]. In Lian *et al.* experiment with diabetic retinopathy detection, the VGG16 network model was used to classify eye images to detect illnesses caused by complications of diabetes, resulting in an accuracy of 48.13% using randomly initialized parameters. Still, after classified using hyperparameter tuning, VGG16 achieved an accuracy of 93.17% [9].

III. Experimental Result

The metric to evaluate machine learning performance to assess the classifier algorithm's performance in this experiment is accuracy. In this section, the accuracy between CNN Architecture of Resnet50 and VGG16 will be compared.

1.1 Resnet50

The results obtained using Resnet50: 86% accuracy during training with a processing time of 11 minutes and 32 seconds. The training had stabilization from one epoch to another, from 0.8698 to 0.9970, by increasing and decreasing its validation accuracy. Fig. 2 and Table 1 show the results described. The performance of the Resnet50 can be seen in Fig. 4

1.2 VGG16

The results obtained using VGG16 shows 94% accuracy during training with a processing time of 12 minutes and 23 seconds and having improvisation of validation accuracy from one epoch to another, from 0.79762 to 0.94345. Fig. 3 and Table 2 shows the results described. The performance of the VGG16 can be seen in Fig. 5.

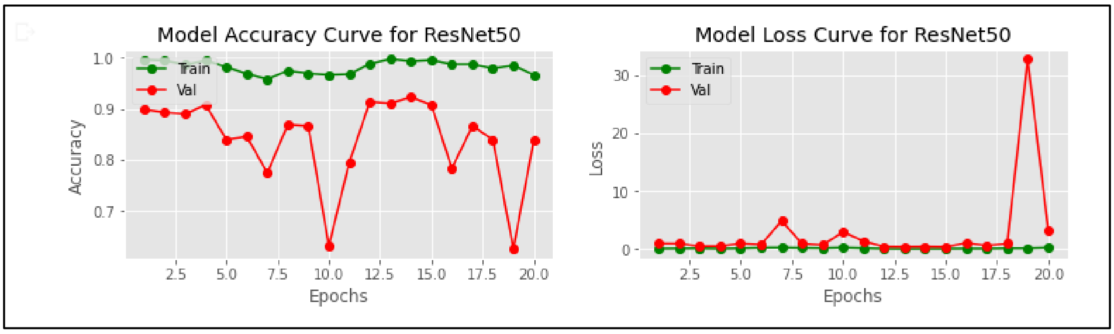

Fig.2 Training accuracy and testing accuracy and loss results for Resnet50

Table 1 Accuracy results in training for Resnet50

Precision	Recall	F1-Score	Support
0.90	0.55	0.68	82
0.85	0.85	0.85	95
0.96	0.96	0.96	74
0.73	1.00	0.84	85

Accuracy	0.84
Macro Avg	0.83
Weighted Avg	0.83

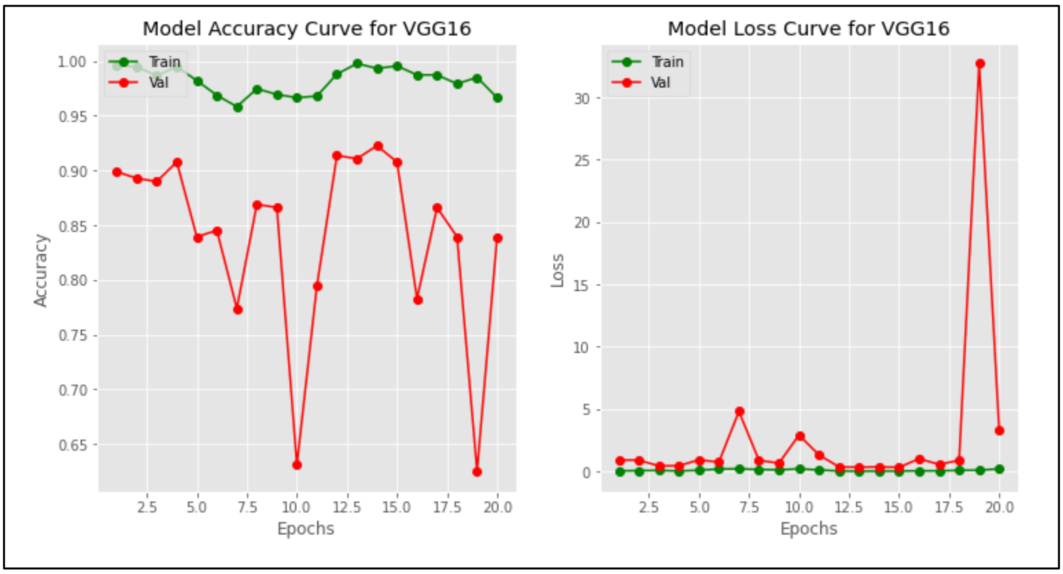

Fig. 3 Training accuracy and testing accuracy and loss results for VGG16

Table 2 Accuracy results in training for VGG16

Precision	Recall	F1-Score	Support
0.96	0.90	0.93	82
0.93	0.93	0.93	95
0.97	0.96	0.97	74
0.92	0.99	0.95	85
Accuracy			0.94
Macro Avg			0.94
Weighted Avg			0.94

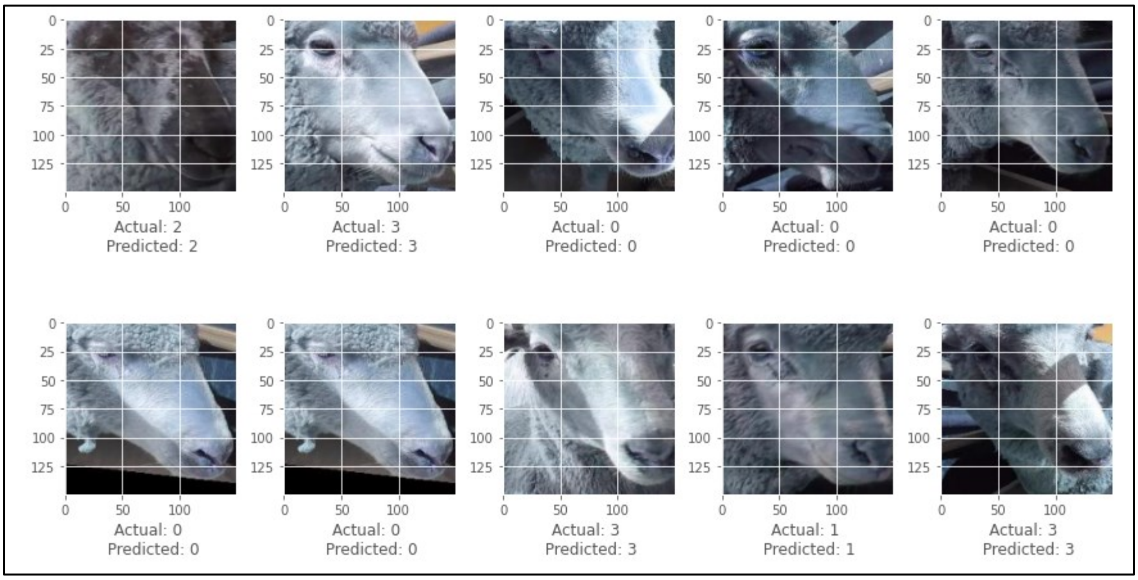

Fig. 4 Performance of Resnet50 Network Architecture Model

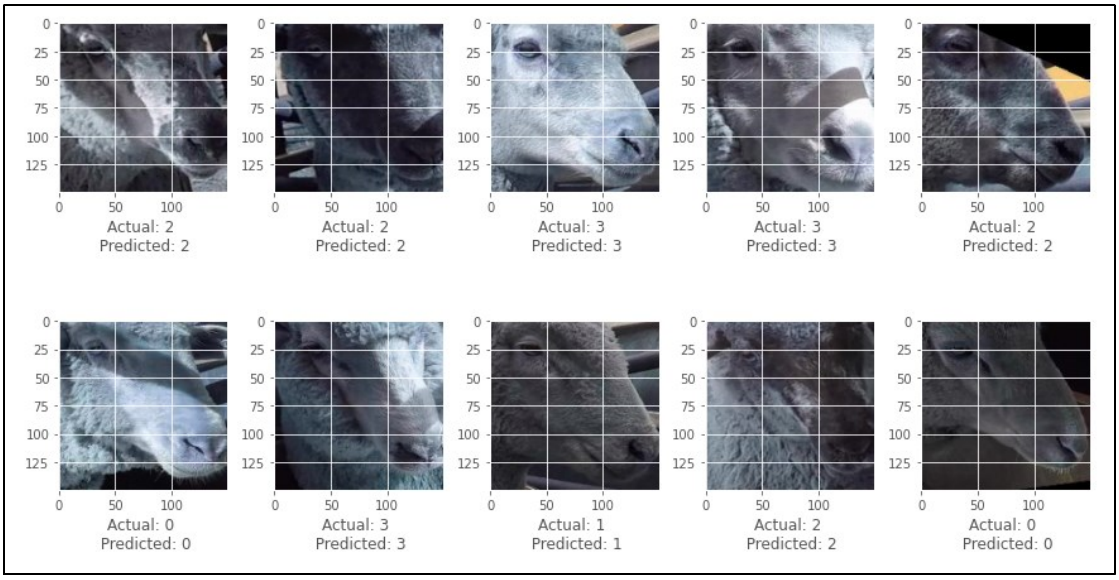

Fig. 5 Performance of VGG16 Network Architecture Model

IV. CONCLUSION

The task of sheep species recognition in the farming environment may pose a tedious challenge caused by repetitive tasks. It may cause a loss in the identifier's focus, causing wrong species classification. This experiment studied the practicality of using computer vision and comparing machine learning techniques to better accuracy. Using the camera and computer vision using the VGG16 network model for sheep face recognition may reduce stress and workload for both sheep and the farmers. The best result was obtained using VGG16, compared to Resnet50, with VGG16 achieving an accuracy result of 94%, compared to Resnet50 achieving an accuracy result of 84% with both Resnet50 and VGG16 uses 20 epochs. This experiment's classifier may help sheep farmers identify and differentiate sheep species without help from experienced people, allowing low-cost and accurate estimation of meat yield, wool yield, and cost management. It is also possible to integrate the technique developed here to predict sheep carcass condition and wool growth prediction developed by others [5], [6] to further efficiently estimate yield from the sheep.

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