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Classification of Sumba Horse Types Using The Convulation Neural Network (CNN) Method

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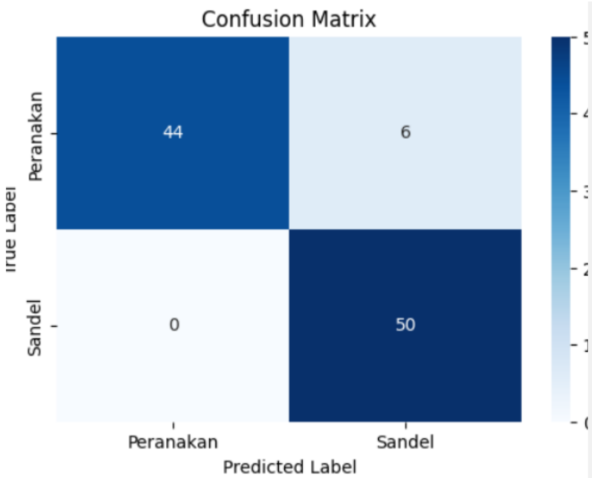

Highlights:

- High Accuracy: The model achieved an overall accuracy of 94% in classifying the two types of Sumba horses (Peranakan and Sandel).
- Excellent Sandel Class Performance: All 50 Sandel class data sets were correctly classified (100% Recall), indicating the model was highly accurate in recognizing this class.
- Errors Occurred in the Peranakan Class: Of the 50 Peranakan data sets, 6 were misclassified as Sandel (88% Recall).
- High Precision: The Peranakan class achieved 100% precision, while the Sandel class achieved 89%, indicating highly accurate Peranakan predictions despite slightly lower recall.

Abstract

This study aims to classify two types of Sumba horses, namely the Sandelwood horse and the Peranakan Luar horse, using the Convolutional Neural Network (CNN) method. The classification process was carried out by implementing two CNN architectures, namely MobileNetV2 and ResNet50, which were tested to compare their performance. The dataset used consisted of 600 images, which went through preprocessing stages including cropping, normalization, and augmentation to improve data quality and model generalization capabilities. The test results showed that MobileNetV2 provided the best performance with 94% accuracy, 100% precision for the Peranakan class, and 100% recall for the Sandelwood class. In contrast, ResNet50 only achieved 65% accuracy, with low training stability. Analysis of accuracy and loss graphs indicated overfitting in MobileNetV2 due to limited data amount. Based on these findings, MobileNetV2 is recommended as a more efficient architecture for limited datasets. For further development, the use of additional data augmentation techniques, regularization, and early stopping is recommended to improve the model's generalization capabilities.

Keywords: CNN, MobileNetV2, ResNet50, Image Classification, Sumba Horse

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1. Introduction

Indonesia boasts a rich and diverse fauna, including the Sumba horse, a unique and renowned native horse. Originating from Sumba Island, East Nusa Tenggara, the Sumba horse comprises numerous breeds with distinct characteristics such as size, color, and body shape. The Sumba horse's uniqueness, aesthetic appeal, and physical strength make it a popular horse for various purposes, including transportation, agriculture, sport, and cultural activities, particularly in traditional ceremonies like the Pasola (Pasola) [1]. Therefore, manually classifying Sumba horse breeds is often difficult. The physical differences between Sumba horse breeds are so subtle that it requires considerable experience and expertise to distinguish them. Furthermore, manually classifying horses by breed is time-consuming and labor-intensive, especially if you have a large number of horses to categorize. This manual process also tends to have a high degree of inaccuracy due to observer subjectivity. Study of color and morphometric diversity of sandalwood horses in Central Sumba Regency[2] .

Classification of Sumba horse breeds using a Convolutional Neural Network (CNN) is performed through image processing. Computerized image processing is the study of image quality improvement (contrast enhancement, color changes, image restoration), image transformation (translation, rotation, scaling, geometric transformation), selecting optimal image features (highlight images) for analysis, storing previously reduced and compressed data, transmitting data, and... [3]

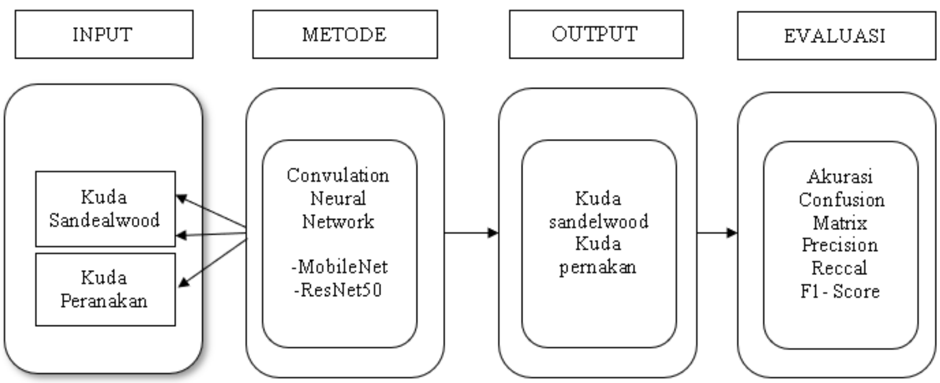
Based on previous research by [4] entitled "Cat Breed Classification Using Images Using a Convolutional Neural Network (CNN)," this study produced a model designed to identify five cat breeds: Angora, Bengal, Domestic, Persian, and Ragdoll, using a CNN optimized with Adam. The results showed a fairly good accuracy of 77.62% and a validation accuracy of 60% with 500 iterations. However, this required a large number of iterations, resulting in a significant training time, with significant fluctuations in the results between each iteration.

A Convolutional Neural Network (CNN) is a type of neural network designed to process spatially structured information, such as images and images [5]. CNNs consist of a series of layers that work in parallel to separate important features from the input data. Each layer in a CNN performs a convolution operation, which combines environmental data to distinguish features such as edges, corners, or more complex features. This design is based on the way organic neural networks process visual data, with interconnected neural units (neurons) working together to effectively handle augmentation. CNNs have proven highly attractive in various applications, particularly in computer vision, such as image recognition, question finding, and image segmentation [6]

Based on the existing problems, this research aims to classify Sumba horse species using an image-based Convolution Neural Network (CNN) method. This research will help the public understand the Sumba horse species.

2. Methods

Fiure 1 Frameword



In figure 1 The image above shows a flowchart of a horse breed classification system consisting of four main stages: input, method, output, and evaluation. In the input stage, the system receives images of two horse breeds: a Sandelwood Horse and a Crossbred Horse. The classification process is then carried out using a Convolutional Neural Network (CNN) with two architectures: MobileNet and ResNet50, which extract features and differentiate the visual characteristics of each horse breed. The classification process produces a predicted class label, identifying whether the image is a Sandelwood Horse or a Crossbred Horse. Finally, the system's performance is evaluated using accuracy metrics, confusion matrix, precision, recall, and F1-score to measure the model's success rate and accuracy in classifying.

2.1 Dataset

DATASET	JUMALAH
	300
	300

Fiure 2 Dataset

In figure 2 The image above is a flowchart of a horse breed classification system consisting of four main stages: input, method, output, and evaluation. In the input stage, the system receives images of two types of horses: the Sandelwood Horse and the Crossbred Horse. Data collection in this study was carried out directly using a smartphone camera. In this study, objects were divided into two classes: the Sandelwood Horse and the Crossbred Horse. The data used was 600 images. Next, the classification process was carried out using the Convolutional Neural Network (CNN) method with two architectures: MobileNet and ResNe50, which function to extract features and differentiate the visual characteristics of each type of horse. The results of this classification process produce an output in the form of a class prediction label, namely whether the image is a Sandelwood Horse or a Crossbred Horse. Finally, the system performance was evaluated using accuracy metrics, confusion matrix, precision, recall, and F1-score to measure the success and accuracy of the model in performing classification.

2.2 Preprocessing

Before training or testing a model, a stage known as preprocessing is performed. In this stage, the images to be used are processed through a series of steps, such as resizing, augmentation, and normalization. This process aims to facilitate the CNN algorithm's ability to recognize features from the input image[7]. Before the image is analyzed by the CNN algorithm, it undergoes three stages of preprocessing to ensure optimal data quality. Preprocessing is a crucial step before model training and testing. The image is preprocessed to allow the CNN algorithm to more effectively train and extract features from the given image. The following explains the three stages of image preprocessing performed before being processed by the CNN algorithm:

1. Cropping

Cropping or cutting out irrelevant or unnecessary parts of the image can improve the accuracy and efficiency of image processing using the Convolution Neural Network (CNN) algorithm[8].

2. Image Argumentation

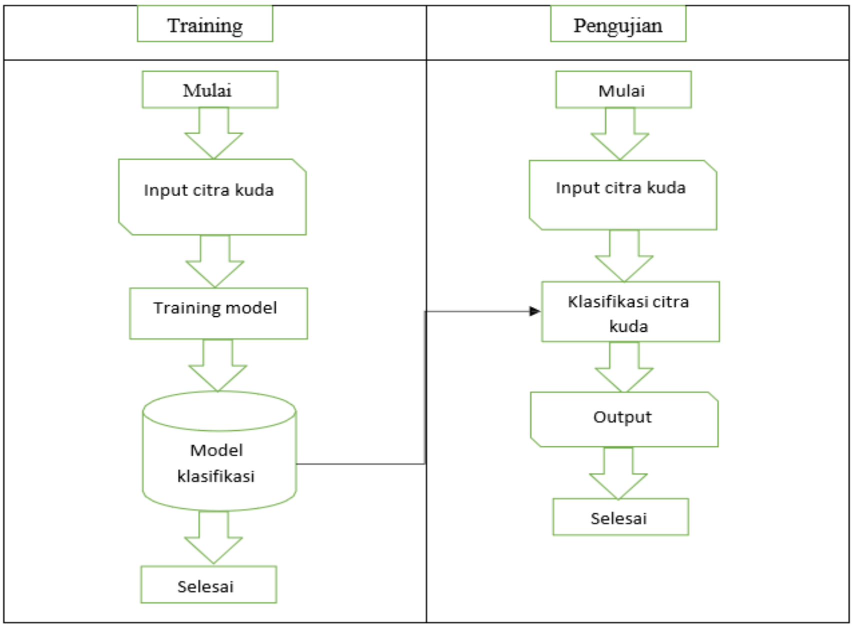
To improve model accuracy and reduce overfitting, image augmentation in a Convolution Neural

Network (CNN) involves applying image adjustments to the original image, such as rotation, shifting, zooming, and so on[9].

2.3 Training and Testing

The training process in a Convolutional Neural Network (CNN) is an iterative process carried out repeatedly with the main goal of minimizing the prediction error produced by the model. In each iteration, the system calculates the loss value, or error, between the model's prediction results and the actual labels from the training data. After that, the weights and biases in each CNN layer are updated using a backpropagation algorithm in collaboration with an optimization function, such as Adam or SGD, to adjust the model parameters for greater accuracy[10]. During this process, the model gradually learns to recognize important patterns in the image data used. The ultimate goal of this CNN training process is to optimize the model's performance so that it can classify new or previously unseen data with a high level of accuracy.

Fiure 3
Training and
Testing Model



In Figure 3The image above shows a flowchart of the training and testing process in a horse image classification system. In the training phase, horse images are input to train the model using a CNN algorithm to produce a classification model. This model is then used in the testing phase, where nxew horse images are input and classified by the model, producing an output of the detected horse species.

2.3 Model Evaluation

2.3.1Accuracy

Accuracy measures how often a show is correct in classification, namely the number of correct add ups to predictions (both correctly detected edges and correctly classified non-edges) divided by the number of add ups to predictions [11].

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

2.3.2 Precision

Precision in the context of CNNs (Convolutional Neural Networks), particularly in classification tasks, is an evaluation metric that measures how many of the model's positive predictions turn out to be correct (relevant). Precision is especially important when false positives must be avoided, such as in disease diagnosis, face detection, or the classification of visually similar horse images[12]..

$$Precision \frac{TP}{TP + FP}$$

2.3.3 F1-Score

The F1-score is an evaluation metric that combines precision and recall into a single harmonic value. This metric is particularly useful when there is an imbalance between the amount of data in each class, or when we want to maintain a balance between false positives and false negatives. In the context of classification using CNNs (Convolutional Neural Networks), the F1-score provides a comprehensive overview of model performance, especially when used on imbalanced real-world data[13].

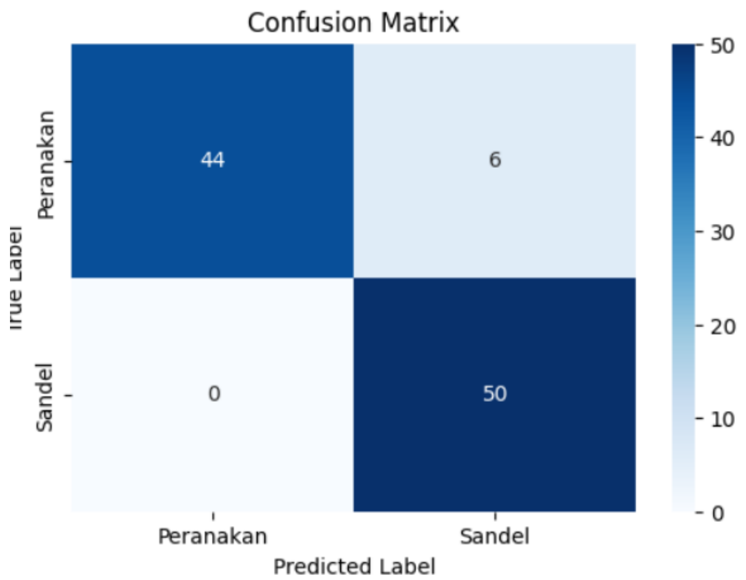
$$F1 = 2X \frac{PrecisionXRecall}{PrecisionXRecall}$$

3. Results and Discussion

Results and discussion can be made as a whole that contains research findings and explanations.

3.1. Results of Training and Testing Stages

3.2.1. Performance Evaluation of the 80-20 Model (MobileNet)



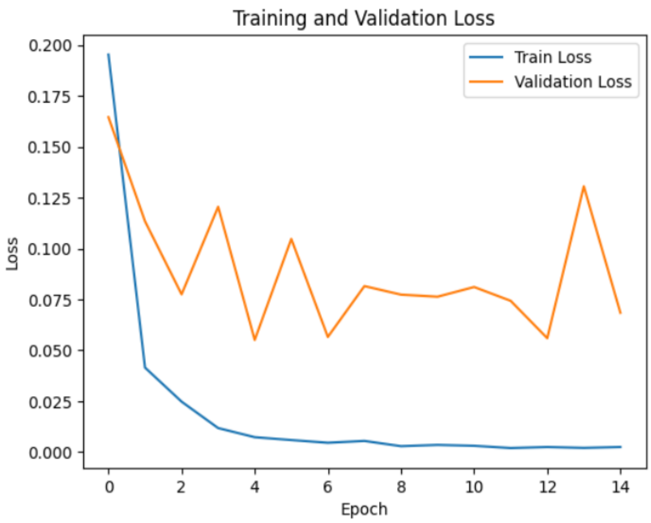
Fiure 4
Confusion Matrix (MobileNet)

In Figure 4 The confusion matrix image shows the performance of the classification model in distinguishing two types of horses, namely Peranakan and Sandel. From a total of 100 test data, the model successfully classified 94 images correctly, resulting in an accuracy of 94%. A total of 44 Peranakan horse images were correctly classified, while the other 6 were incorrectly recognized as Sandel. In contrast, all 50 Sandel horse images were successfully predicted correctly without error. These results indicate that the model is very good at recognizing Sandel horses (100% recall), and quite accurate in detecting Peranakan horses with 100% precision and 88% recall. Overall, the model shows strong performance in the classification of these two classes.

Fiure 4
Grafik Training and Validation

In Figure 4 The graph above displays the development of model accuracy during the training and validation processes versus the number of epochs. The blue line represents training accuracy, while the orange line shows validation accuracy. The graph shows a rapid increase in training accuracy early in the process, reaching nearly 100% in just the first few epochs. After that, the training accuracy tends to stabilize without significant improvement. Conversely, validation accuracy exhibits a more fluctuating pattern, although it remains in a relatively high range (around 94%–98%). The striking difference between training accuracy approaching 100% and unstable validation accuracy indicates an overfitting problem. Overfitting occurs when a model focuses too much on specific patterns in the training data and loses the ability to generalize those patterns to new data. As a result, despite excellent performance on the training data, results on the validation or test data are suboptimal. This condition indicates that steps are needed to reduce overfitting, such as using regularization techniques (e.g., dropout or L2 regularization), adding training data (data augmentation), or implementing an early stopping strategy so that training is stopped before the model overfits to the training data.

Fiure 5
Grafik Training and Validation Los



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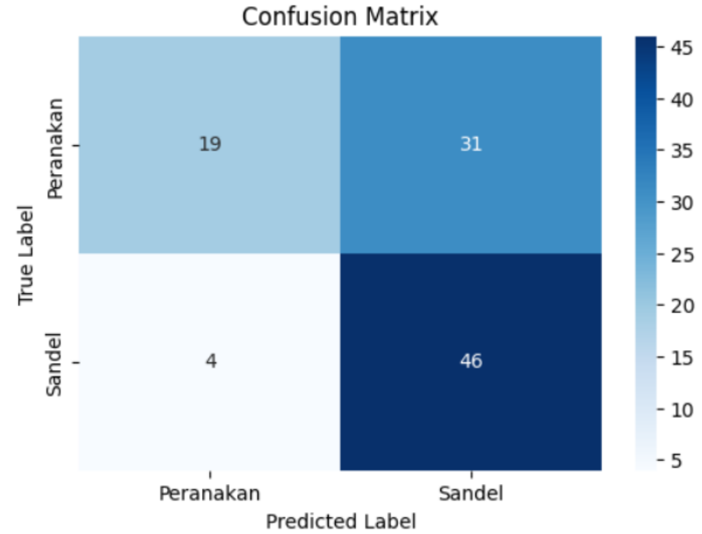
In figure 5 This graph shows the development of the loss value during the training and validation processes versus the number of epochs. The blue line shows the training loss, while the orange line represents the validation loss. The graph shows that the loss value on the training data drops significantly in the early epochs and approaches zero after a few epochs, indicating that the model has learned very well on the training data.

In contrast, the loss on the validation data exhibits a fluctuating pattern and does not decrease steadily. Although there is a decrease at the beginning of training, the graph shows that the validation loss value tends to fluctuate around a certain number without following the downward trend that the training loss does. The significant difference between the training loss, which approaches zero, and the unstable validation loss, indicates overfitting. This condition aligns with the findings in the previous accuracy graph, where the model is highly optimized on the training data but less able to generalize on the validation data.

Performance Evaluation of the 80-20 Model (ResNet50)

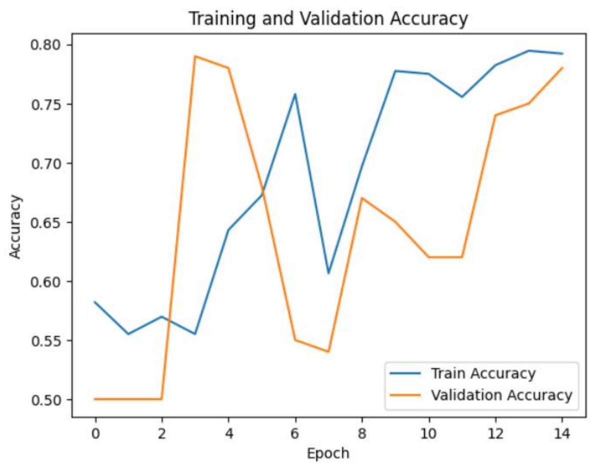
ResNet50 is a variation of the ResNet architecture, with 50 layers trained on at least 1 million images from the InageNet database. ResNet50 consists of five stages, each with a convolution and identity block. Each convolution block consists of two convolution layers, and each identity block also has three convolution layers. ResNet50 has over 23 million trainable parameters.

Fiure 6
Confusion Matrix
(ResNet50)

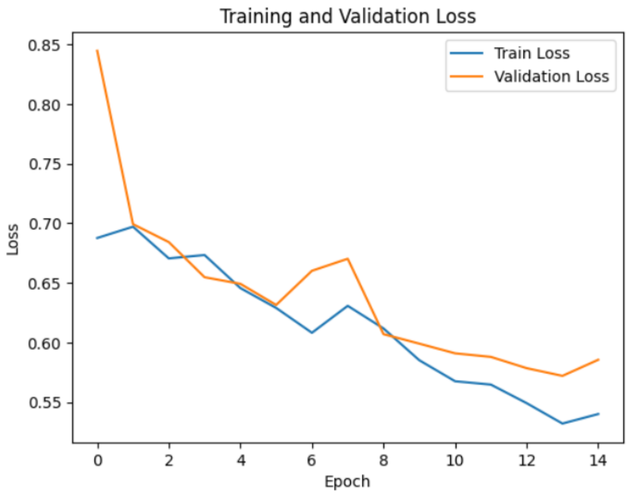


In Figure 6 The confusion matrix image above shows the classification results of two classes, namely Peranakan and Sandel, by the model. From the total test data, the model successfully classified 19 Peranakan images correctly, but incorrectly classified 31 Peranakan images as Sandel. In contrast, the model showed better performance in the Sandel class with 46 images correctly classified and only 4 incorrectly recognized as Peranakan. This indicates that the model has a better tendency to recognize the Sandel class than Peranakan, and also indicates a potential imbalance in performance between classes that needs to be addressed to improve overall accuracy.

Fiure 7
Grafik Training and validation Accuracy



In figure 7 This graph shows the progression of training and validation accuracy over 15 epochs. Training accuracy (blue line) tends to increase gradually, although there are some sharp fluctuations, especially around epoch 7. Validation accuracy (orange line) experiences a sudden spike in epochs 3 and 4, but then drops sharply until around epoch 7 before gradually increasing again. These sharp fluctuations indicate that the model is still unstable in the learning process and may require more epochs, more representative training data, or parameter tuning to improve training and validation consistency.

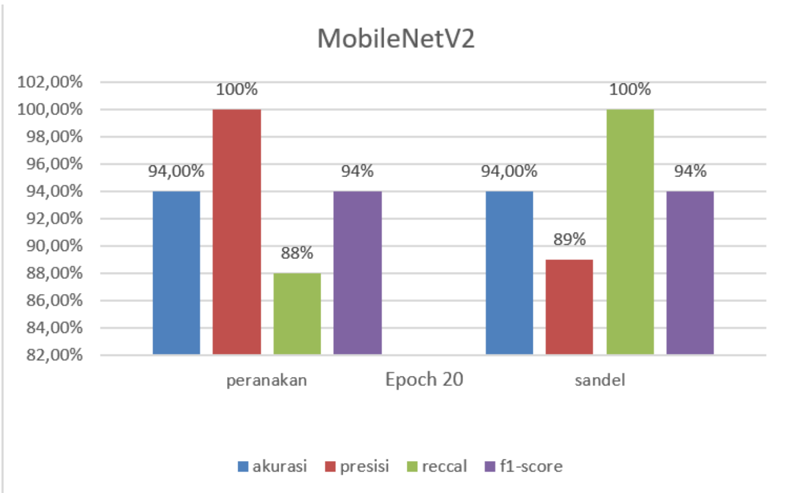


Fiure 8
Grafik Training and validation Accuracy

In Figure 8 This loss graph shows that the loss values on the training and validation data generally decrease with increasing epochs. The training loss (blue line) and validation loss (orange line) are initially quite high, but gradually decrease, although the validation loss experiences some small increases at some points. This pattern indicates that the model is learning and improving its predictions, but small fluctuations in the validation loss indicate there is still room for improvement, for example through regularization or improving the quality of the validation data to reduce instability.

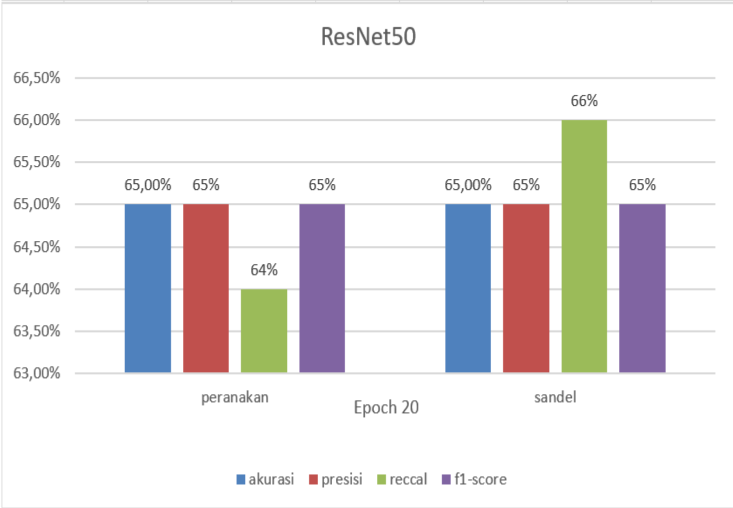
3.2.2. Comparison of 80%-20% graphic results (MobileNet)

In this section, we'll discuss the key results for the 80%-20% data split. We'll examine the model's performance in terms of accuracy, precision, recall, and mAP, then calculate an average value based on these results.



Fiure 9
Bar Chart (MobileNet)

In figure 9 The bar chart above shows the performance of the MobileNetV2 model in the 20th epoch for two classes, peranakan and sandel, based on four evaluation metrics: accuracy, precision, recall, and f1-score. In the peranakan class, the model achieved 94% accuracy, perfect precision (100%), 88% recall, and 94% f1-score. This indicates that the model is very accurate in predicting peranakan (high precision), but there are still some undetected peranakan data (lower recall). Conversely, in the sandel class, recall reached 100%, meaning all sandel data were correctly classified, but the precision was only 89%, indicating that there were some incorrect sandel predictions. Overall, the f1-score for both classes was the same, at 94%, reflecting a balance between precision and recall. This visualization illustrates that although the model's performance is quite high and balanced, there are still imperfections in each metric that can be focused on for model improvement.



Fiure 10
Bar Chart
(ResNet50)

In figure 10 The bar chart above shows the evaluation results of the ResNet50 model in the 20th epoch for two classes, peranakan (crossbreed) and sandel (crossbreed), based on four key metrics: accuracy, precision, recall, and f1-score. For both classes, accuracy and f1-score were consistently at 65%, indicating moderate overall model performance. For the peranakan class, precision was also at 65%, but recall was slightly lower at 64%, indicating that some of the peranakan data was still not recognized by the model. Conversely, for the sandel class, recall reached 66%, which is higher than its precision of 65%, indicating that the model is quite sensitive in detecting sandel but with a higher probability of misprediction. Overall, the ResNet50 model's performance appears balanced between the two classes, but at a moderate level, requiring improvements in accuracy and prediction precision for more reliable use. From the research results, MobileNetV2 proved to be superior to ResNet50 in classifying Sumba horse types, with an accuracy of 94%, precision of 100% for Peranakan horses, and recall of 100% for Sandelwood horses; while ResNet50 only achieved an accuracy of 65%, and showed instability during training and a significant level of misclassification, especially in the Peranakan class, making MobileNetV2 a more reliable and efficient choice for this task.

Penelitian	Objek	Metode	Accuracy
Sistem Informasi Klasifikasi Jenis Hewan Belis Menggunakan CNN (Studi Kasus: Kabupaten Sumba Tengah) Haji, B., Jawa, A. M., & Malo, M. W. (2024)	kuda, sapi, kerbau	Convolutional Neural Network (CNN)	Akurasi training: 80% Validasi akurasi: 100% Loss: 0.2638% Validation loss: 0.0477%
Model Klasifikasi Jenis Hewan Dengan SVM, KNN, Logistic Regression Menggunakan Pre-Trained VGG 16 [13]	Kuda, Kucing,Gajah,Banteng	SVM, KNN VGG 16	CNN menunjukkan akurasi validasi tertinggi (100%) dalam konteks data yang sangat spesifik. Logistic Regression memiliki akurasi training tertinggi (84%)

Table 1
Related research

			di antara tiga algoritma klasik (SVM, k-NN, LR) untuk data hewan umum.
Penelitian ini	Kuda sandelwood dan kuda peranakan	MobileNetV2 ResNet50	Pada fitur mobilenet menghasilkan akurasi 94% Sedangkan Resnet50 menghasilkan akurasi 65%

Table 4.1 compares the accuracy values obtained from this study with those obtained from previous studies that also used various methods. Based on the comparison of the research results above, it is known that the highest accuracy from the study is an average of 80% and above, which is greater than the accuracy obtained from previous studies. However, the accuracy produced by this study is classified as very good, where I compared two architectures to produce the highest and lowest. MobileNet produced the highest accuracy value, reaching 94%. And for ResNet produced the lowest accuracy value, reaching 65%. Therefore, the use of appropriate parameters and architecture greatly affects the performance and results obtained. In this study, the system obtained very good results from the MobileNetV2 architecture for the classification of types of Sumba horses using the Convolution Neural Network (CNN) method.

3.3. Create a Discussion

The results showed that the MobileNetV2 architecture performed better than ResNet50 in classifying Sumba horse breeds. MobileNetV2 achieved 94% accuracy, with perfect precision (100%) in the Peranakan horse class and perfect recall (100%) in the Sandelwood class. In contrast, ResNet50 only achieved 65% accuracy, accompanied by instability during the training process and a significant misclassification rate, particularly in the Peranakan class.

Analysis of the accuracy graph (Figure 4.3) shows that the MobileNetV2 model experienced a rapid increase in training accuracy, reaching nearly 100% in just the first few epochs. However, validation accuracy exhibited a fluctuating pattern that did not align with the training accuracy trend. This striking difference indicates overfitting, where the model adapts well to the data but is less able to generalize to new data. This is confirmed by the loss value graph , which shows a sharp decline in training loss to near zero, while validation loss continues to fluctuate without a significant downward trend. This condition is common in relatively limited datasets, making it difficult for the model to achieve optimal generalization.

In contrast, ResNet50, despite its more complex architecture with a depth of 50 layers, did not demonstrate superior performance. The ResNet50 accuracy graph shows sharp fluctuations in validation accuracy, particularly in early epochs, caused by the model's sensitivity to dataset size and limited data variation. High model complexity requires a significantly larger amount of data to achieve stable convergence. This instability is also evident in the loss graph (Figure 4.7), where validation loss values are inconsistent, although generally showing a downward trend.

The difference in performance between these two models demonstrates that selecting an architecture appropriate to the scale and characteristics of the data significantly determines classification results. MobileNetV2, with its lighter and more efficient design, performs optimally on limited datasets, while ResNet50 requires a larger dataset to effectively utilize its network depth. Therefore, this study recommends the use of additional techniques such as data augmentation, regularization (Dropout, L2 regularization), and early stopping to reduce overfitting and improve model generalization.

These findings align with previous research emphasizing that the combination of architectural efficiency and data sufficiency is a key factor in developing CNN-based image classification models. In this context, MobileNetV2 excels because it provides a balance between high accuracy, training stability, and computational efficiency, making it practical for identifying Sumba horse species to support conservation efforts.

4. Conclusion

This study concludes that the Convolutional Neural Network (CNN) method is able to classify two types of Sumba horses, namely Sandelwood and Peranakan Luar, with varying levels of accuracy depending on the architecture used. Of the two models tested, MobileNetV2 provided the best performance with 94% accuracy, 100% precision for the Peranakan class, and 100% recall for the Sandelwood class, while ResNet50 only achieved 65% accuracy with low training stability. This difference indicates that a lighter and more efficient architecture such as MobileNetV2 is more suitable for limited datasets, while ResNet50 requires larger data to be optimal. The results also indicate overfitting in MobileNetV2, so additional strategies such as data augmentation, regularization, and early stopping are needed to improve the model's generalization ability in the future.

5. Authors' Declaration

Authors' contributions and responsibilities

Write the contribution of each author here, or mark the following column.

√ The authors made substantial contributions to the conception and design of the study.

√ The authors took responsibility for data analysis, interpretation and discussion of results.

√ The authors read and approved the final manuscript.

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Availability of data and materials

√ All data are available from the authors.

Competing interests

√ The authors declare no competing interest.

Additional information

Write additional information related to this research, if any.

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He also thanks his family, friends, and all those who provided moral support, prayers, and assistance in various forms, ensuring the smooth running of this research. He hopes this work will be beneficial to the development of science, particularly in the fields of artificial intelligence and digital image processing, and will serve as a reference for further, more effective research.

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