# Classification of Hybrid and Peking Duck DOD Varieties Based on Feather Images Using CNN

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**Abstract**

Hybrid meat duck is a fast-growing variety with superior meat structure, the result of crossbreeding between Peking duck and laying duck to increase egg productivity. Day Old Duck (DOD) hybrid duck is highly sought after in the rearing industry, and this crossbreeding process produces hybrid and Peking varieties with different feather color patterns. Sorting DOD is important to maintain the consistency of hybrid varieties, but the process requires high expertise and a long time. The feather color of DOD meat duck can be used to distinguish between hybrid and Peking varieties. In this study, a deep learning approach with the Convolutional Neural Network (CNN) algorithm was applied to classify DOD varieties based on feather images. The study used 1702 images including hybrid and Peking ducklings. The model was tested with test data and evaluated using a confusion matrix to measure the performance of the developed model in identifying DOD varieties.

**Keywords:** DOD, Fur Image, Classification, Deep Learning, CNN.

## I. INTRODUCTION

Hybrid meat ducks are duck varieties that have rapid growth with a maintenance period of 35 days with a weight of up to 1.8 kilograms, hybrid duck varieties have good meat structure so that they are in great demand by the public [1]. Hybrid meat duck varieties are formed from the cross-breeding process between Peking meat duck varieties and Mojosari laying ducks which are specifically carried out to produce new meat duck varieties to meet the needs of a shorter egg-laying cycle so that the need for hatching meat ducklings can be obtained faster with the existence of hybrid duck varieties [2]. Peking meat ducks are one of the meat duck varieties that have become a favorite as a consumption duck. This is based on their large body posture and rapid weight growth, making their maintenance period relatively shorter when compared to other types of meat ducks [2]. The increase in demand for Peking meat ducks is not in line with the relatively long egg-laying cycle. In contrast to egg-laying duck varieties which have a shorter egg-laying cycle. To overcome this, cross-breeding was carried out between Peking meat duck varieties and Mojosari egg-laying duck varieties. The goal is to create a hybrid meat duck variety that weighs up to 1.8 kilograms in 35 days of rearing, but also has a fast egg-laying cycle and is resistant to disease. Although crossing between Peking meat ducks and laying ducks can produce hybrid meat duck varieties, not all incubated eggs will produce hybrid varieties. Therefore, a careful sorting process is needed to group hybrid varieties, which will then be selected for market demand and parent enlargement needs.

Separating hybrid and Peking duck varieties is important for meat duck breeders and cultivators. By separating Peking and hybrid meat duck varieties early, it can increase the ratio of meat duck egg production. Currently, the process of separating hybrid and Peking meat duck varieties is still done manually by breeders, so the fatigue factor and the level of expertise of breeders in seeing the differences in duck varieties are the main problems. These factors result in the possibility of mixing duck varieties into the rearing process being quite large. As a result, duck varieties that have been mixed in the rearing process can reduce egg productivity in the rearing cage. The separation process is carried out by distinguishing the color of the feathers, the color of the duck feathers can be used to distinguish meat duck varieties, to distinguish between hybrid and Peking meat duck varieties, we can identify the difference through the image of the feathers. Image is an alternative term for picture, which is often used in everyday contexts to refer to the representation of objects [3].

Based on these problems, the Deep Learning approach can be utilized for the sorting process [4]. Deep learning is an algorithm in artificial neural networks that utilizes data as input and processes it through various hidden layers to obtain a deep understanding [4]. Then a non-linear transformation of the input data will be carried out to calculate the desired output [5]. One of the algorithms in deep learning that can classify duckling varieties based on feather images is the Convolutional Neural Network (CNN) which is able to process information in the form of images [6]. This method is very good at carrying out image classification tasks and can provide accurate prediction results in recognizing images [7].

This method tries to imitate the human image detection sense by processing image information and identifying the input image that is read [8]. Convolutional Neural Network (CNN) has three dimensions of neurons, namely width and height determine the size of the layer, while depth refers to the number of layers present [9]. The image data used in this study were DOD images of hybrid and Peking ducks obtained from 2 boxes of hatching cages consisting of 1 box of DOD hybrid ducks totaling 102, and 1 box of DOD Peking ducks totaling 102, then images were taken using a DSLR camera and produced 1702 images consisting of 834 hybrid duck images and 869 Peking duck images. From the total DOD image dataset totaling 1702, it was then divided into 75% training data and the remaining 25% test data. The experiment was carried out by predicting test data using the designed model.

To ensure that the CNN model built has optimal performance, an evaluation of training parameters such as batch size and epoch is carried out to obtain the best combination [10]. The evaluation process uses a confusion matrix and classification report that includes Accuracy, Precision, Recall, and F1-Score metrics. This study contributes to filling the gap in studies that are still limited regarding the classification of Day-Old Duck (DOD) varieties based on feather images, especially between Hybrid and Peking types. The novelty of this study lies in the focus of specific study objects and the CNN parameter optimization approach that can improve the performance of image classification models [10].

## II. RESEARCH METHODS

Classification of meat duck varieties based on feather images is carried out through a series of systematic and structured stages. The first stage begins with collecting data in the form of duckling images in their original condition, namely without any modification or digital manipulation, in order to maintain the authenticity and validity of the data that will be used in the model training process. After the image data is collected, the next stage is to carry out preprocessing which aims to remove the background from the image, so that the main focus in the image is only on the main object, namely the duck's body itself. After the background is removed, the image resizing process is also carried out to match the pixel resolution, which will be used as a standard in further processing of the characteristics of duck feathers [11]. The next step is to build and design a Convolutional Neural Network (CNN) model that is adjusted to the characteristics of the duck object that will be trained and tested in the classification process. After the model is completed, the testing process is carried out by classifying duck images using the CNN algorithm to determine the model's ability to recognize and distinguish duck varieties based on their feather patterns. The final stage of this entire process is the evaluation of model performance, which is carried out using the Confusion Matrix method to assess how accurate and effective the model is in classifying images according to the expected target. Figure 1 is the flow of this research activity.

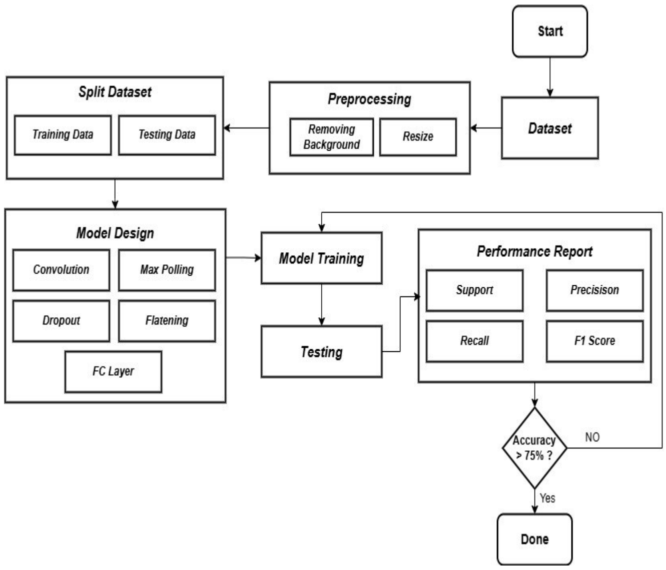


Figure 1. Research Flow

### A. Dataset

The dataset produced from the data collection process stages originating from the process of taking direct photos from 9 angles of 102 hybrid duckling varieties and 102 Peking duckling varieties, produced 1,702 duckling image data consisting of 834 hybrid ducklings and 869 Peking ducklings (Figure 2).

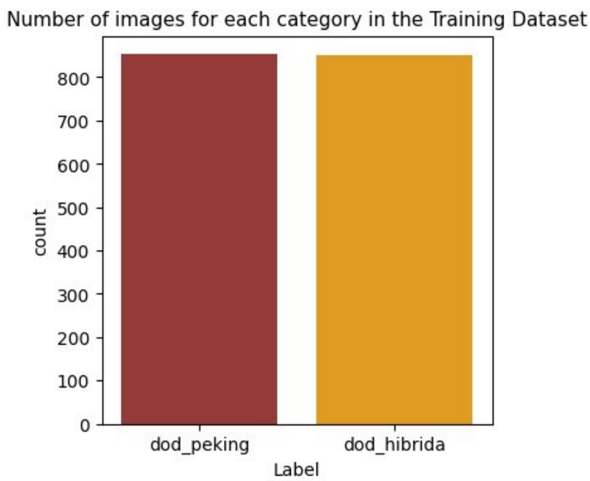


Figure 2. Visualization of Dataset Quantity

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### B. Preprocessing

Before the stage of separating the dataset into training data and testing data, a total of 1,702 datasets consisting of 869 varieties of Peking ducks and 834 hybrid ducks were first carried out the background removal process to focus on the object of the duckling image used (Figure 3) [12]. After the DOD image was removed from the background, the next step was Resize. This is done to change the size of an image to be smaller or larger [13]. Preprocessing by focusing on the object can provide more optimal results on the model built in making predictions [14].

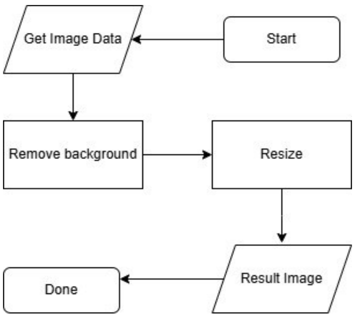


Figure 3. Visualization of Dataset Preprocessing Flow

### C. Split Dataset

At this stage, the dataset that has gone through a series of preprocessing processes, such as resizing, normalization, and data augmentation, is then divided into two main parts, namely training data and testing data [15]. This division is done to ensure that the developed model can be trained properly and tested objectively using data that has never been seen before. The training data in this study serves to train the Convolutional Neural Network (CNN) model to be able to recognize important patterns and features of DOD images, so that it can produce an optimal classification model and has a high level of accuracy [16].

The proportion of training data used at this stage is 0.75 or 75% of the total available dataset as shown in Figure 4. This ratio was chosen because it can avoid overfitting and ensure that the model's generalization ability can be tested adequately and provide high accuracy in image classification [17]. This means that most of the data is used for the learning process by the model, while the rest, namely 25%, is allocated as testing data to test the model's ability to predict new data that is not included in the training data [18]. If too much data is used for training, the testing data becomes too little so that the evaluation results are less reliable. Conversely, if too little data is trained, the model is at risk of failing to capture the pattern as a whole [17].

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Training Dataset:
Number of images: 1277
Number of images with peking: 648
Number of images with hibrida : 629

Test Dataset:
Number of images: 426
Number of images with peking : 221
Number of images with hibrida : 205
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Figure 4. Distribution of Training Data and Testing Data

### D. Model Design

After the process of separating the dataset into two main parts, namely training data and testing data that has been carried out in the previous stage, the first step in the model training process is to apply the convolution operation. This operation aims to extract important features from the image, such as shape, pattern, and texture, while also helping to smooth the appearance of the image, sharpen important details, and detect the edges of objects in the image [3]. After this initial convolution stage, the process is continued with a second convolution using different kernels and parameters, in order to extract more complex and in-depth features from the image. Furthermore, the model goes through several additional layers such as pooling, dropout, and flattening. The pooling layer functions to reduce the spatial dimension of the feature, while dropout is used as a regularization technique to reduce the risk of overfitting, and flatten is used to convert multidimensional data into one dimension so that it can be processed by the next layer. After that, two fully connected or Dense layers are used to process the extracted feature information and formulate the final result in the form of predictions. In this final stage, an optimization process is carried out on the architecture of the Convolutional Neural Network (CNN) model so that it can work effectively in recognizing visual patterns found in the images of Peking and hybrid meat ducks. The results of the CNN model that has been built and trained are then visualized and shown in Figure 5 as a representation of the performance of the developed system.

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d (Conv2D) | (None, 75, 75, 32) | 2,432 |
| max_pooling2d (MaxPooling2D) | (None, 37, 37, 32) | 0 |
| dropout (Dropout) | (None, 37, 37, 32) | 0 |
| conv2d_1 (Conv2D) | (None, 37, 37, 64) | 18,496 |
| max_pooling2d_1 (MaxPooling2D) | (None, 18, 18, 64) | 0 |
| dropout_1 (Dropout) | (None, 18, 18, 64) | 0 |
| conv2d_2 (Conv2D) | (None, 18, 18, 96) | 55,392 |
| max_pooling2d_2 (MaxPooling2D) | (None, 9, 9, 96) | 0 |
| dropout_2 (Dropout) | (None, 9, 9, 96) | 0 |
| conv2d_3 (Conv2D) | (None, 9, 9, 96) | 83,040 |
| max_pooling2d_3 (MaxPooling2D) | (None, 4, 4, 96) | 0 |
| dropout_3 (Dropout) | (None, 4, 4, 96) | 0 |
| flatten (Flatten) | (None, 1536) | 0 |
| dense (Dense) | (None, 512) | 786,944 |
| dropout_4 (Dropout) | (None, 512) | 0 |
| dense_1 (Dense) | (None, 1) | 513 |

Figure 5. CNN Model Visualization

### E. Model Training

The designed model is then continued to the training stage to evaluate its performance and ability to classify data accurately. This training process is an important stage in model development, because this is where the model learns to recognize patterns and relationships in the data provided.


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During training, a batch size of 16 is used, which means that in each training iteration, 16 data samples are processed simultaneously by the Neural Network [19]. The use of this batch size was chosen because it is able to provide efficiency in the computational process while maintaining stability in updating model parameters. Training is carried out for 40 epochs, which is 40 times the model performs a full iteration of the entire training dataset.

This number of epochs provides sufficient time for the deep learning algorithm to optimally adjust the weights and biases, so that it is able to learn the data representation thoroughly and in depth.

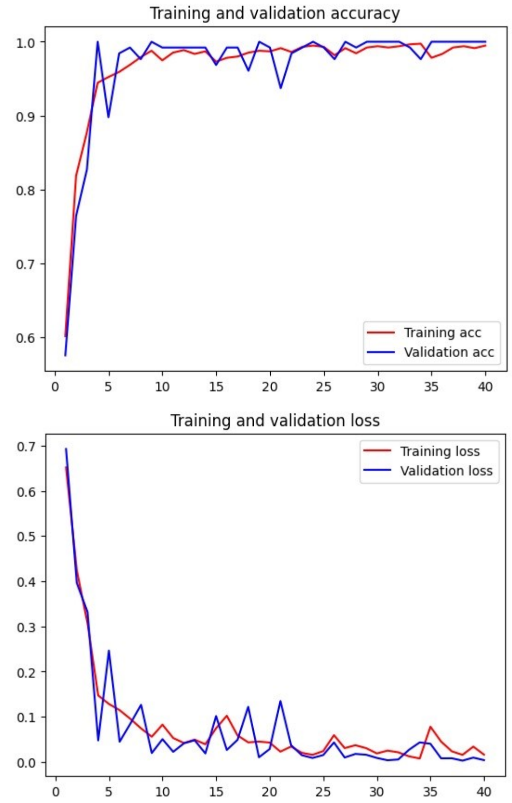


Figure 6. Visualization of Model Training Results

The designed model then goes through a training stage to evaluate its ability to classify data accurately. During this training process, a batch size of 16 is applied, which means that in each iteration, 16 data samples will be processed simultaneously by the Neural Network [19].

The selection of this batch size aims to achieve a balance between computational efficiency and stability of the learning process. The training process is run for 40 epochs, which is 40 times the model accesses the entire dataset in full to fix the weights and biases in the network (Figure 6). With this number of epochs, the deep learning algorithm has enough opportunity to understand the patterns in the data thoroughly. After the training process is complete, the model evaluation results are obtained in the form of a loss value of 0.011, which indicates a very low level of prediction error, and an accuracy value of 0.989, which indicates that the model is able to classify data with a very high level of accuracy.

### F. Confusion Matrix Evaluation

The results of the confusion matrix test for the Convolutional Neural Network (CNN) model were carried out using 426 test data, which are part of the entire available dataset (Figure 7). This model is designed to group data into two classes, namely Dod Hibrida (0) and Dod Peking (1). Based on the confusion matrix obtained, the model successfully classified 221 data from the Dod Hibrida class correctly. Meanwhile, all 205 data from the Dod Peking class were successfully classified correctly without any misclassification. Thus, there were no False Negative errors in this test. Overall, the model produced an accuracy of 98.53%, with a precision for the Dod Peking class of 96.34% and a recall of 100%, which reflects that the model has a very high level of accuracy and sensitivity to the test data.

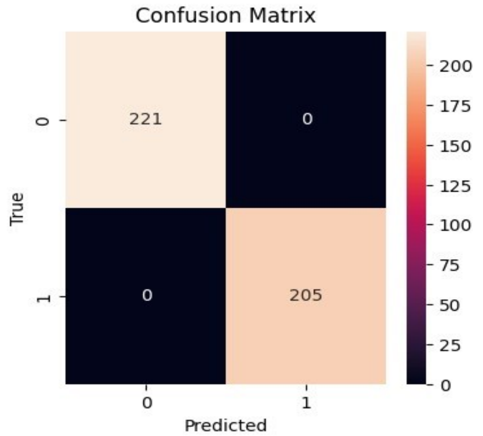


Figure 7. Confusion Matrix Evaluation Visualization

### G. Classification Testing

The test was conducted by implementing the classification process on a number of hybrid DOD and Peking DOD images using a Convolutional Neural Network (CNN) model that had been completed and trained previously. The main objective of this testing phase was to evaluate the model's ability to predict DOD varieties, whether they belong to the hybrid or Peking class, accurately based on the visual characteristics recorded in the image, especially the appearance of the feather pattern and texture.

In the testing process, 25 DOD images were entered into the model as test data to see how accurate the model was in classifying each image according to its original class label. The results of the test showed that the model was able to predict with a high level of success, where 25 DOD images were successfully classified correctly.

An illustration of the results of this test, including correctly predicted and incorrectly predicted images, is shown in more detail in Figure 8, which serves as visual documentation of the model's performance at this stage of testing.

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Figure 8. Prediction Testing Visualization.

## III. RESULTS AND DISCUSSION

The model performance evaluation is carried out comprehensively by testing, analyzing, and comparing the results of the combination of model parameters using batch size and epoch which are then searched for the most optimal accuracy value with the smallest loss as shown in Table 1. In addition, this evaluation is also intended to determine the extent to which the model has succeeded in making accurate predictions, as well as identifying the level of error that may occur during the classification process [10].

Table 1. Evaluation Based on a Combination of Parameters

| No | Batch Size, Epoch | Accuracy | Loss |
|---|---|---|---|
| 1 | 32, 40 | 0.978 | 0.022 |
| **2** | **16, 40** | **0.989** | **0.011** |
| 3 | 64, 40 | 0.987 | 0.013 |
| 4 | 32, 20 | 0.985 | 0.015 |
| 5 | 32, 60 | 0.976 | 0.024 |
| 6 | 16, 60 | 0.967 | 0.033 |
| 7 | 64, 60 | 0.978 | 0.022 |
| 8 | 32, 100 | 0.981 | 0.019 |
| 9 | 16, 100 | 0.982 | 0.018 |
| 10 | 128, 40 | 0.896 | 0.104 |

The results of the parameter optimization experiment where the batch size of 16 and epoch 40 were the most optimal combination were then evaluated using a confusion matrix. The results of the evaluation were then compared between the evaluation results before optimization as shown in Figure 9 and after optimization as shown in Figure 10.

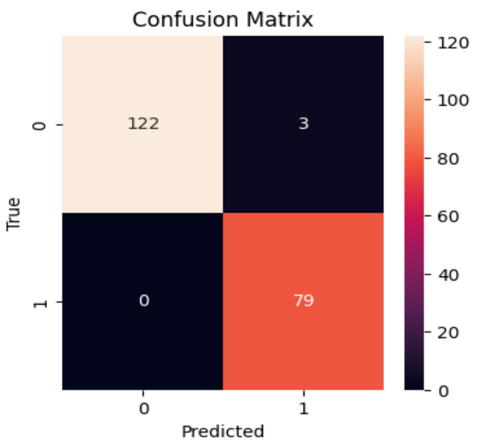


Figure 9. Confusion Matrix Evaluation Before Optimation.

In addition to optimizing parameters, efforts were also made to resample the data, because unbalanced data is prone to overfitting which affects accuracy, for example in the evaluation shown in Figure 10 is the result after optimization and data balancing using the augmentation technique.

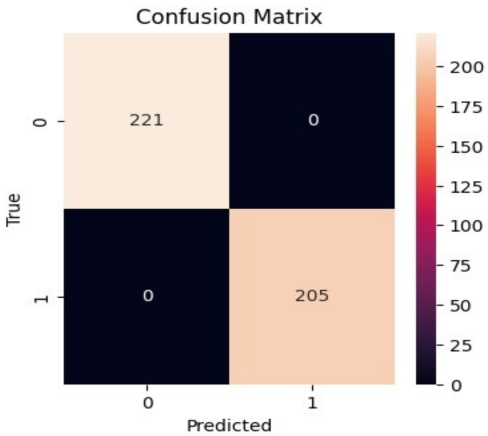


Figure 10. Confusion Matrix Evaluation After Optimation.

In this test, 146 DOD (Day Old Duck) images from two varieties, namely Peking ducks and hybrids, were used to test the performance of the previously developed model. Based on the test results, the CNN model using a batch size of 16 and epoch 40 showed good ability in classifying images, where most of the data was successfully predicted correctly and in accordance with the original class label. The results in Table 2 show that there are a number of images that are not successfully predicted according to their original class, which indicates the limitations of the model before optimization.

Table 2. DOD Images Test Results Before Optimation

| No. | Label | True | False | Total |
|---|---|---|---|---|
| 1 | DOD Hibrida (0) | 57 | 16 | 73 |
| 2 | DOD Peking (1) | 64 | 9 | 73 |

Table 3 presents the results of the model evaluation after the optimization process by adjusting the batch size and epoch parameters, which aims to improve classification accuracy.

Table 3. DOD Images Test Results After Optimation

| No. | Label | True | False | Total |
|---|---|---|---|---|
| 1 | DOD Hibrida (0) | 73 | 0 | 73 |
| 2 | DOD Peking (1) | 73 | 0 | 73 |

Based on the results of the research that has been carried out systematically and in-depth, a number of evaluation values were obtained that showed the high performance of the developed classification model. The Precision value for the hybrid dod class was recorded at 1.00, which indicates that all model predictions for the class are correct without any misclassification as another class. Meanwhile, for the peking dod class, the Precision value obtained was 0.96, indicating that most of the model predictions for this class were accurate, although there were still a few errors. Furthermore, the Recall


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value or sensitivity of the model to the hybrid dod class was at 0.98, which means that the model was able to recognize almost all data from the class very well. For the peking dod class, the Recall value reached 1.00, which means that none of the data from this class failed to be recognized by the model during the testing process. The F1-Score value, which is the harmonic average of Precision and Recall, also shows very high performance, which is 0.99 for the hybrid dod class and 0.98 for the peking dod class, reflecting a good balance between accuracy and completeness in classification. Overall, from the entire training and testing process on the data provided, a global accuracy value of 0.98 or 98% was obtained, which illustrates the level of success of the model in correctly classifying data in almost all cases tested. These results indicate that the designed Convolutional Neural Network (CNN) model has performed very well in completing the task of classifying DOD images based on their type, and has the potential to be applied in real-world scenarios that require automatic and accurate classification.

## IV. CONCLUSION

From all stages of the process that have been passed in this study, starting from model design, training, to evaluation of the results, a very high level of accuracy was obtained on the DOD (Day Old Duck) image dataset of hybrid ducks and Peking ducks. By using the Convolutional Neural Network (CNN) algorithm to classify duck varieties based on the visual characteristics of the feather image, the model managed to achieve an accuracy of 0.98 or 98%, which reflects the success of the model in recognizing and distinguishing between the two types of ducks automatically and efficiently.

The results of testing the CNN model that had been built were then compared with the results of manual sorting carried out by the team of officers in the hatchery as a comparison or ground truth. Of the total 146 DOD images tested, the CNN model managed to identify and predict 121 images correctly and according to their original labels, while there were 25 images that experienced errors in the classification process or were mispredicted. This classification error was mostly caused by the less than ideal image conditions in the dataset, one of which was the position of the DOD object which was not always in the center of the image. This is because DOD is an active animal and tends to move continuously, making it difficult to capture stable and focused images, and producing variations in position and orientation in the images used as training and testing data.

For the development and improvement of model accuracy in the future, it is highly recommended that further research use datasets with a larger and more diverse number of images, and ensure that the images collected are of better and more consistent quality. This is important because both the quantity and quality of images have a significant influence on the performance of the model in classifying, especially in the context of image-based classification as applied in this study. Thus, improvements in the dataset aspect are expected to improve the overall performance and accuracy of the model, as well as expand its application on an industrial scale or wider field practice.

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