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Hyperparameter tuning of MobileNetV2 on forest and land fire severity classification

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ABSTRACT

Forest and land fires pose significant environmental challenges, causing economic and ecological damage depending on their severity. This study proposes a deep learning-based classification model to assess fire severity using the MobileNetV2 architecture. A dataset of 560 post-fire images was categorized into five severity levels, with dataset preprocessing involving resizing, rescaling, and image augmentation. To enhance model performance, K-means clustering was applied for balanced data distribution across classes. The model was trained using grid search for hyperparameter tuning, with the optimal combination being a batch size of 8, learning rate of 0.0001, and dropout of 0.3. Training was conducted in 50 epochs, and evaluation using the confusion matrix demonstrated an accuracy of 85%, precision of 86%, and recall of 81%. The results indicate that MobileNetV2 effectively classifies post-fire severity levels, offering a reliable tool for post-disaster assessment. This study highlights the significance of dataset preprocessing and hyperparameter tuning in improving model accuracy. Future research should explore alternative architectures and expand the dataset to enhance model generalization. These findings can aid authorities in assessing fire impact, supporting mitigation strategies, and improving post-fire land management.

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1. INTRODUCTION

Forest and land fires are events caused by human or natural activities, characterized by widespread fire and the burning of forests and land. Forest fires is one of the environmental issues that has both economic and ecological detrimental impacts [1]. Forest fires are complex phenomena influenced by the interaction of natural and anthropogenic factors. The main drivers of forest fires generally include climate, vegetation, and varying topography [2]. Peat and mineral soils are two characteristic types of forest fire sites, the variation between the two lies in their organic matter content, with mineral soils having a low content, while peat soils have a high content, forest and land fires that occur in peat soil differ from those in mineral soil because fires in peat soil are dominated by ground fires. Even though the fire that has burned trees and grasses has been extinguished, the fire may still be burning deep beneath the surface of the soil [3]. The increase in the number and intensity of forest fires has occurred worldwide over the past decade, raising public concerns about the potential future impacts [4]. The effects of global warming suggest that the number and area of fires worldwide are expected to continue [5]. Forest and land fire also affects Indonesia, which has vast forests, and the extent of Indonesia's forests continues to decline each year. Between 2012 and 2022, forest fires in Indonesia have reached 442.822,51 km^2 [6], Indonesia is under pressure from various parties to reduce forest fires, and efforts have been made to control it [7]. Control of forest fires in areas that have already burned needs to be observed so that the data obtained can be used to measure the severity of the fire [8].

The severity level of a forest fire is defined as a term that describes the extent to which the fire alters ecosystem components and can be used to explain the impact of the fire [9]. Forest fires will produce severity levels that depend on the interaction between the area burned, fuel load, timing, intensity, duration of burning, soil texture and moisture, topography, vegetation type, fire climate, soil water status, and time since the last fire [10]. The severity level of a forest and land fire describes the ecosystem's response to fire and is used to explain the impact of forest and land fire. The general classification of forest and land fire severity levels is based on soil conditions and their properties in the burned area. Studying and measuring the severity level of forest and land fires is important because it can serve as a basis for information in fire recovery planning, forest conservation, and law enforcement [11]. The severity level of forest and land fires can be measured using image data obtained from field observations [8].

The processing of image data used in the case of forest and land fires aims to provide supporting information about the response to forest and land fire disasters, enabling decision-makers to respond quickly to forest and land fire incidents [12]. Image data processing techniques for pattern recognition have been explored in various domains. For example, Ahmed *et al.* [13] proposed a system to improve feature extraction in image classification tasks. This method highlights the importance of effective feature extraction in image-based classification problems. Image data processing to measure the severity level of forest and land fires can provide valuable information in understanding and effectively addressing the fires. With the continuous advancement of technology, the image data collected can be processed using certain methods to provide insights in analyzing forest and land fire severity levels one such method is deep learning (DL) [14]. DL can be considered a suitable methodology for modelling the complex interactions of variables that frequently occur in Earth system problems, particularly forest fires [15]. DL has transformed computer vision by allowing computers to learn from data, identify patterns, and classify objects with remarkable accuracy. This enables the creation of sophisticated computer vision algorithms and applications that can accurately identify objects in images [16]. The deep learning technique commonly used for image data is the convolutional neural network (CNN).

CNN utilizes convolutional layers that can automatically extract features from images, allowing the model to recognize patterns and objects without the need for complex preprocessing [17]. CNN has two important blocks: feature learning and classification [18]. CNN can be used to identify and classify areas affected by fires; by leveraging image data, CNN can evaluate the impact of the fire on the ecosystem [19]. CNN also has several architectures, one of which is MobileNetV2. The MobileNetV2 architecture is designed for computational efficiency through the use of Depthwise separable convolutions (DSC) and is considered state-of-the-art, with several additional layers following it for specific classification tasks [20]. To further optimize its performance, this study implements data set clustering using K-means before training and uses principal component analysis (PCA) to reduce the feature dimensionality, thereby reducing the computational burden, and applies hyperparameter tuning using grid search.

Hyperparameter tuning in MobileNetV2 is the process of adjusting values that are not automatically learned by the model, which plays an important role in model performance and generalization. Hyperparameters are parameters defined outside the model being trained. This includes factors such as the quantity filters in convolutional layer, number of epochs, batch size, various other dimensions, and kernel size [21]. The aim of hyperparameter tuning is to identify the best combination of hyperparameter values, allowing the CNN model to excel in learning the patterns in the training data while preventing overfitting or underfitting [22]. A technique that can be used for hyperparameter tuning is grid search. This technique involves creating a grid of parameters to be tested, and then the model will be trained and validated for each combination. The results of each combination are measured based on the model's performance, such as accuracy or loss, and the best combination is selected to be applied to the data [23].

Several studies have been conducted on image-based fire severity. One of them is a study by Arrafi *et al.* [24] focused on mapping the severity of forest and land fires using the normalized burn ratio (NBR) algorithm on Landsat 8 Imagery. This approach provides broad insights but often has difficulty in capturing details on the ground surface. Previous studies have focused more on general fire detection or severity estimation using satellite imagery, but few have discussed fire severity classification on the ground surface. This study aims to address this gap by developing a MobileNetV2-based model to classify post-fire severity using post-fire area imagery. In addition, this classification model is optimized through hyperparameter tuning and dataset clustering to improve accuracy and generalization in predicting forest and land fire severity classes.

2. METHOD

This research uses a methodological approach that focuses on model building using MobileNetV2. The applied methodology follows a structured and systematic set of stages to create an image-based land and forest fire severity classification model. The research process is divided into several main phases, data collection, dataset identification, pre-processing, model training, and model evaluation. This methodology aims to produce a technological solution for forest and land fire severity classification. The phases can be seen in Figure 1.

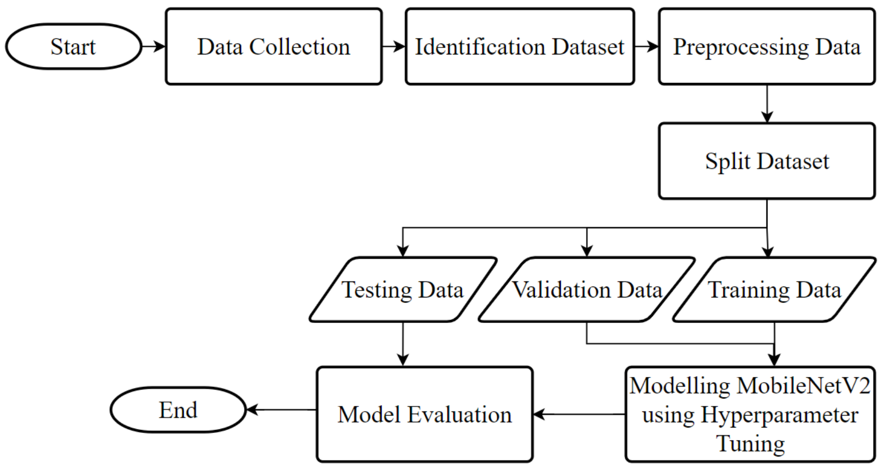

Figure 1. Research steps

2.1. Data collection

The dataset used in this research consists of images of areas after forest and land fire handling obtained from the Ministry of Environment and Forestry and from open-source media such as the shutterstock.com. This dataset encompasses a variety of conditions in post-fire areas, totaling 560 images from various forest fire events in Indonesia. No sensitive information was contained within the dataset. Expert validation was conducted with informed consent from participating forest and land fire specialists. Ethical approval was not required, as the study did not involve human subjects or personal data. Although the size of this dataset is relatively small for deep learning applications, extensive data augmentation can overcome this limitation by artificially expanding the dataset. The augmentation includes horizontal flipping, zooming, rotation, and contrast adjustment to introduce variation and improve generalization ability. An overview of the dataset is presented in Figure 2, where Figure 2(a) shows images categorized as light severity, Figure 2(b) represents moderate severity, and Figure 2(c) illustrates severe severity.

(a) (b) (c)

Figure 2. Overview of research datasets (a) light, (b) moderate, and (c) severe

2.2. Identification dataset

The initial dataset collected included various images of the post-fire management area and had not been segregated by class. This unsegregated dataset was carefully selected using a technique to ensure that the model could be effectively trained to classify different severities of forest fires. Each of these categories or classes describes the impact of the fire on the environment and the level of damage caused. The flow of dataset creation can be seen in Figure 3.

Figure 3 is a process part of the methodology in Figure 1, namely dataset identification. The process starts by initializing the dataset using the MobileNetV2 model pre-trained with weights from ImageNet. The images are loaded from a folder, resized to 224×224, and converted to an array. The features of the images were extracted using the MobileNetV2 model, which provides a vector representation of the features. Clustering is performed using PCA to reduce the dimensionality of the features, thus facilitating clustering and reducing the computational burden. This process is followed by the K-means algorithm that groups the images into five clusters. However, visualization of the cluster results showed overlap between clusters, indicating that the separation was not entirely clear. The cluster results were evaluated using three metrics: the Davies-Bouldin index, the Silhouette score, and the Calinski-Harabasz index. The Davies-Bouldin index yields a value of 1,113, indicating a lack of separation between clusters and suggesting that the clusters overlap somewhat. The Silhouette score yielded a value of 0,281, indicating that the clustering was less than optimal and many points were between clusters, indicating overlap. The Calinski-Harabasz index gave a value of 268,602, indicating that there is fairly good cluster separation, although it does not guarantee excellent clustering.

These three metrics emphasize that the clustering performed still needs improvement to achieve clearer separation. As a corrective step, validation is conducted by forest and land fire experts to ensure the accuracy and minimize noise due to overlapping classes, resulting in some photos being moved to more appropriate classes. After the validation process, the distribution of images in each class becomes more balanced, with the number of images ranging from 100 to 123 data points. The final stage involves storing the images in separate folders based on the established cluster classifications.

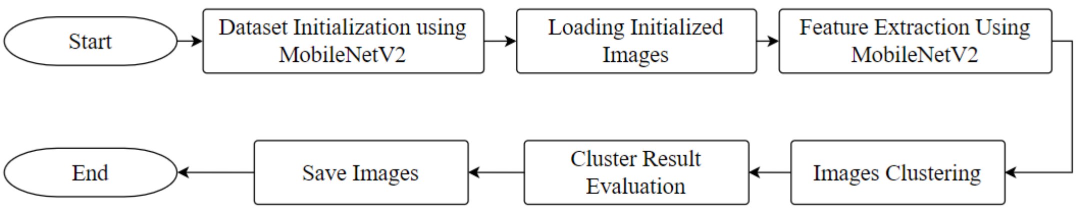

Figure 3. Dataset identification flow

2.3. Data preprocessing

The data pre-processing stage is performed to ensure that the image has a consistent size and format [25]. Resize aims to resize the image to be consistent with the input size accepted by the MobileNetV2 model which is 224×224. Rescale aims to normalize the image pixel values to be in the same range, changing the image pixel values from a range of 0-255. Zoom range is used to enlarge or reduce the image in the dataset, the value used is 0.5. Horizontal flip which aims to add variety by flipping the image horizontally which is activated using the True function. Fill mode aims to handle empty areas that appear after transformations such as rotation or cropping, in this process using nearest to fill with the nearest pixel value.

2.4. Split dataset

The images were divided into 70% training data, namely 392 images, and 30% validation data, namely 168 images, while the test data is tested with new data, as much as 10% of the total data collected. The data is also separated based on the severity of the forest and land fires, namely very mild, mild, moderate, severe and very severe. Each subset has a specific purpose in training and evaluating the model, which helps to ensure that the resulting model performs well and generalizes effectively to previously unseen data. The number of data subsets is presented in Table 1.

Table 1. Subset of split data

Class	Training data	Validation data
Very mild	70 Images	30 Images
Mild	84 Images	36 Images
Moderate	74 Images	31 Images
Severe	79 Images	33 Images
Very Severe	86 Images	37 Images

2.5. MobileNetV2 modelling

This research uses CNN architecture MobileNetV2 to create a severity classification model on photos of post-fire area. MobileNetV2 is the architecture with the smallest capacity among other models. It ranks highly as a lightweight model, with a small model size and fast inference time, which is crucial for its application in mobile-based systems. MobileNetV2 has the advantage of requiring less storage space and needing lower computational power [26]. In the model training process, the MobileNetV2 architecture is used as the base model, with the final layers of MobileNetV2 frozen to allow the addition of new layers tailored to the needs of forest and land fire image classification. Next, the hyperparameters of this model are tuned using the grid search technique, where several combinations of hyperparameters are tested to find the most optimal combination. The list of hyperparameters used in this study is presented in Table 2.

Table 2. List of hyperparameters in the model

Hyperparameter	Value
Batch size	[8, 16, 32]
Learning rate	[0.0001, 0.00001]
Dropout	[0.3, 0.4, 0.5]

2.6. Prediction and evaluation model

The classification results are analyzed using confusion matrix to check the accuracy value of the modeling process. Confusion matrix for 5 class labels provides more comprehensive information regarding the model's performance in categorizing data into each class, with confusion matrix, results can be calculated using various evaluation metrics such as accuracy presented in (1), precision presented in (2), and recall presented in (3) [27].

$$Accuracy_n = \frac{TP_n+TN_n}{TP_n+FP_n+FN_n+TN_n} \times 100\% \quad (1)$$

$$Precision_n = \frac{TP_n}{TP_n+FP_n} \times 100\% \quad (2)$$

$$Recall_n = \frac{TP_n}{TP_n+FN_n} \times 100\% \quad (3)$$

3. RESULTS

The hyperparameters that have been determined using grid search are processed in the model training using 50 epochs and a dense layer of 512. The most optimal hyperparameter combination is then used to produce the final model that has the best performance. The results of the hyperparameter combination are presented in Table 3.

Table 3. The result of the combination of hyperparameters

Batch Size	Learning Rate	Dropout	Accuracy	Precision	Recall
8	0.0001	0.3	0.852	0.861	0.814
8	0.0001	0.4	0.754	0.786	0.746
8	0.0001	0.5	0.746	0.772	0.746
8	0.00001	0.3	0.797	0.835	0.686
8	0.00001	0.4	0.746	0.843	0.636
8	0.00001	0.5	0.746	0.813	0.627
16	0.0001	0.3	0.763	0.766	0.720
16	0.0001	0.4	0.824	0.833	0.805
16	0.0001	0.5	0.797	0.805	0.771
16	0.00001	0.3	0.729	0.810	0.542
16	0.00001	0.4	0.797	0.866	0.602
16	0.00001	0.5	0.746	0.824	0.593
32	0.0001	0.3	0.788	0.824	0.754
32	0.0001	0.4	0.814	0.832	0.797
32	0.0001	0.5	0.797	0.807	0.780
32	0.00001	0.3	0.686	0.800	0.508
32	0.00001	0.4	0.669	0.797	0.466
32	0.00001	0.5	0.729	0.859	0.466

The most optimal parameter results in this study are using *batch_size* = 8, *learning_rate* = 0.0001, and *dropout* = 0.3. This parameter combination produces an accuracy of 85%, with a precision of 86%, and a recall of 81%. These results show that the MobileNetV2 model that has been tuned with this combination of hyperparameters performs quite well. A graph of the model training process illustrating the development of accuracy and loss is presented in Figure 4. The optimal model training process was evaluated using confusion matrix to analyze its performance in classifying the five categories of forest and land fire severity. Visualization of the confusion matrix of the evaluation results and model predictions can be seen in Figure 5.

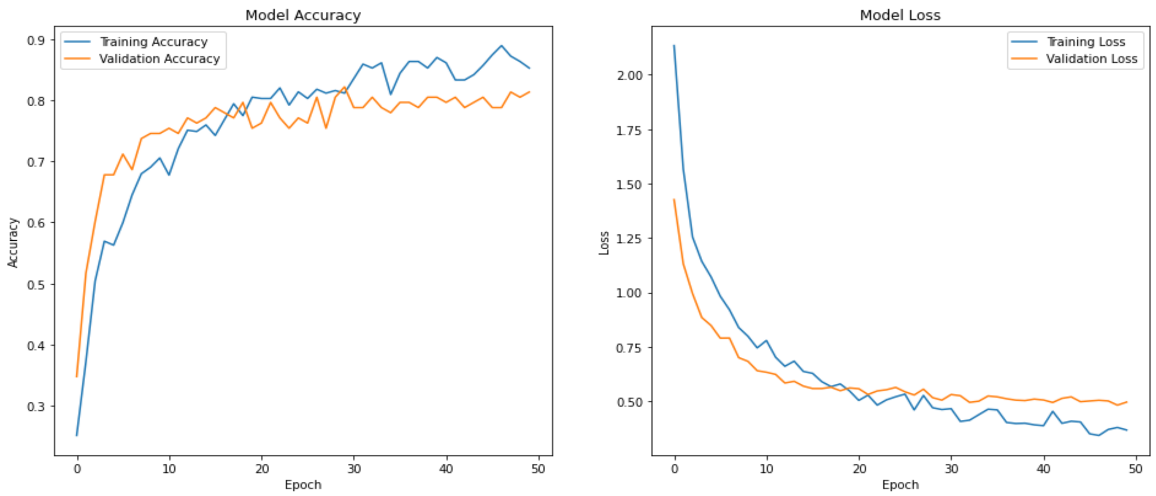

Figure 4. Model training process chart

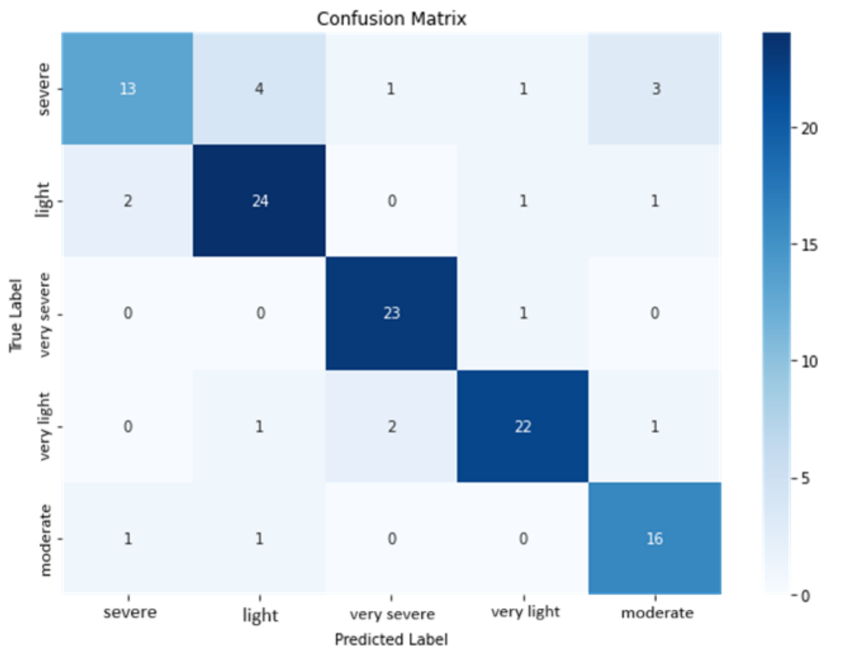

Figure 5. Visualization of confusion matrix of model evaluation and prediction results

Based on the results of the confusion matrix visualization in Figure 5, the model shows a fairly high level of accuracy in distinguishing each class of photos of post-fire handling areas. For the severe class, the model correctly identified 13 out of 22 photos, while 4 photos were misclassified as mild, 1 as very severe, 1 as very mild and 4 as moderate. In the mild class, the model correctly predicted 24 out of 28 photos, but misclassified 2 photos as severe, 1 as very mild and 1 as moderate. For the very severe class, the model correctly classified 23 out of 24 photos, while 1 photo was incorrectly identified as very mild. In the very mild class, the model predicted 22 out of 26 photos correctly, but misclassified 1 photo as mild, 2 as very mild and 1 as moderate. Finally, for the moderate class, the model correctly classified 16 out of 18 photos, while 1 photo was misidentified as severe, 1 as mild. Evaluation of the model's performance shows that MobileNetV2 has a fairly good ability to classify images into the five severity classes. The trained model was then saved in *.h5* format and converted into TensorFlow Lite (TFLite) format so that it can be implemented into a system in the future.

4. DISCUSSION

This study focuses on developing a forest and land fire severity classification model using CNN architecture MobileNetV2, and has shown significant improvement compared to previous research that also uses the same architecture. Previous research conducted by Hidayat *et al.* [8], where the MobileNetV2 model was used to classify the severity of forest fires with a total of 90 data and two image sizes, namely 224×224 and 112×112, resulted in the best accuracy reaching 77.7%. Meanwhile, in this study, the model trained with hyperparameter optimization, namely *batch_size* = 8, *learning_rate* = 0.0001, and *dropout* = 0.3 resulted in higher accuracy, which is 85%, with precision 86% and recall 81%.

The main difference between these two studies lies in the data processing approach and the use of hyperparameter tuning techniques. The previous study used limited data, which resulted in the model only being able to capture a limited variation in severity. As a result, although MobileNetV2 provides adequate performance, there is still room for improvement, especially in terms of increasing the variety of field data to make the model more robust. In contrast, this study utilizes a more diverse dataset, covering a wide range of forest and land fire events in Indonesia, which gives the model access to a greater variety of severity levels. The application of hyperparameter tuning in this study significantly improved the model's performance. The applied grid search helps to find the most optimal combination of parameters, while in previous studies, the hyperparameter tuning process has not been optimized. The model in this study is more accurate, stable, and can generalize to new data. To further evaluate the contribution of different model components, an ablation study focused on dropout, learning rate, and using a pre-trained MobileNetV2 model. This study aims to analyze the impact of each element on the overall classification performance. Dropout is a regularization technique that reduces overfitting by randomly deactivating neurons during training. Various dropout rates (0.1, 0.3, and 0.5) were tested, and the results showed that a dropout rate of 0.3 provided the best balance between generalization and performance. The learning rate determines the step size when updating model parameters during training. Experiments with three different learning rates (0.01, 0.001, and 0.0001) indicated that 0.0001 was the optimal choice. A higher learning rate (0.01) caused unstable convergence, leading to suboptimal results, while a lower learning rate (0.001) prolonged the training process without significant performance gains.

This study went through a process of clustering the dataset before starting the model training, an approach that was not taken in previous studies. The clustering process, validated by Forest and Land Fire Experts, ensured that the images used in the model training were more evenly distributed in each class. The results obtained in this study show that a more comprehensive approach to data collection, hyperparameter optimization, and dataset clustering has significantly improved model performance. Developing this classification model inevitably introduces potential biases in the dataset, especially regarding image quality and geographic coverage. Variations in image quality, such as differences in resolution, lighting conditions, and sensor types, can cause interference in the training process, leading to inconsistent model performance. To address these biases, applying advanced data augmentation techniques can help mitigate the impact of image diversity limitations by artificially increasing the diversity of training samples. Future work should also expand the dataset to include images from different sources and geographic locations so that the model will be more robust.

5. CONCLUSION

This study successfully created a forest and land fire severity classification model using MobileNetV2 architecture. By applying hyperparameter tuning techniques through grid search, an optimal parameter combination of *batch_size* = 8, *learning_rate* = 0.0001, and *dropout* = 0.3 was obtained. The resulting model shows good performance with accuracy reaching 85%, precision of 86%, and recall of 81%. Hyperparameter tuning using grid search, as well as a dataset clustering approach using K-means prior to model training proved effective in improving the model's performance in classifying the five severity classes of forest and land fires: very mild, mild, moderate, severe, and very severe. Evaluation using confusion matrix shows that the model has a good ability to distinguish the five severity classes.

A suggestion for future research is to expand the dataset with more images from different locations and different forest fire conditions. This aims to improve the model's ability to generalize new data and handle more complex variations. Exploration of other model architectures such as EfficientNet can be done to compare model performance on the same classification task. The addition of more varied data augmentation methods can also help the model improve.

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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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