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CLASSIFICATION OF COFFEE LEAF SPOT DISEASES USING THE RESIDUAL NEURAL NETWORKS

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Abstract

Coffee is one of the competitive commodities that requires detailed quality control. The common diseases that attack coffee plants are miner, rust, and phoma. Despite their visual similarity, the diseases differ in symptoms and treatments, requiring precise identification aided by computer vision. Miner and phoma have similar image features that are challenging in this study. Avoiding treatment error, several deep learning approach is needed to help classify the diseases. One of the robust methods is the Residual Network. Considering the number of datasets and alignment with the state-of-the-art, this study picked ResNet50 and ResNet101 to be observed. This study employed ResNet50 and ResNet101 in two scenarios. The first scenario was training the models on datasets without preprocessing, while the second scenario trained models on processed datasets. The preprocessing involved converting the color model to HSV and taking the range of leaf spot color from light red to dark brown for color segmentation. This study successfully achieved accuracy, precision, and F1-score at 89,16%, 89,42%, and 89,15% respectively, for the ResNet50 model trained on preprocessed data, slightly higher than the metrics of ResNet101. The ResNet101 achieved 87.95% of accuracy, 88.05% of precision, and 87.98% of F1-Score. These results indicate that ResNet50 is more robust for classifying the leaf spot, and the color segmentation helped the model to optimize the performance.

Keywords: CNN; ResNet; Coffee Leaf Diseases; Transfer Learning; Image Processing

Abstrak

Kopi merupakan salah satu komoditas unggulan yang membutuhkan pengendalian kualitas yang detail. Penyakit yang umum menyerang tanaman kopi adalah miner, rust, dan phoma. Meskipun penampilan tiap penyakit terlihat mirip, penyakit-penyakit tersebut memiliki gejala dan solusi yang berbeda sehingga membutuhkan penanganan yang teliti dan membutuhkan bidang computer vision untuk dapat membedakan gejalanya. Miner dan phoma memiliki fitur gambar yang serupa yang menjadi tantangan dalam penelitian ini. Beberapa pendekatan deep learning digunakan untuk membantu menghindari kesalahan penanganan penyakit akibat kesalahan klasifikasi tradisional. Salah satu model yang paling akurat adalah Residual Network. Penelitian ini menggunakan varian ResNet50 dan ResNet101 setelah mempertimbangkan jumlah dataset yang akan dipelajari dan kesesuaian dengan state-of-the-art ResNet. Sehingga, tujuan dari penelitian ini adalah mengembangkan sebuah model klasifikasi penyakit pada daun kopi yang handal berbasis ResNet. Penelitian ini menggunakan ResNet50 dan ResNet101 dalam dua skenario. Skenario pertama melatih model pada dataset yang belum diproses, sedangkan skenario kedua melatih model pada dataset yang telah diproses. Prapemrosesan melibatkan pengubahan model warna ke HSV dan pengambilan rentang warna bercak daun dari merah muda hingga coklat tua untuk segmentasi warna. Penelitian ini berhasil mencapai akurasi, presisi, dan skor F1 masing-masing sebesar 89,16%, 89,42%, dan 89,15%, untuk model ResNet50 yang dilatih pada data praproses. Sementara itu, ResNet101 menghasilkan akurasi sebesar 87,95%, presisi sebesar 88,05%, dan F1-Score sebesar 87,98%. Hasil ini menunjukkan bahwa ResNet50 lebih andal untuk mengklasifikasikan bercak daun, dan segmentasi warna membantu model untuk mengoptimalkan kinerjanya.

Kata kunci: CNN; ResNet; Penyakit Daun Kopi; Transfer Learning; Pengolahan Citra Digital

INTRODUCTION

Coffee is one of the competitive commodities that requires detailed quality control (Sunarharum et al., 2021). A small mistreatment can lead to infection, decrease the quality of the crops, and ultimately affect their taste and aroma.

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Common diseases of coffee plants are miner, rust, and phoma, which not only infect the leaves and stems but also decay fruits. Miner is a leaf mining pest caused by an insect identified as Leucoptera coffella, which uses leaves as places to lay its larvae and causes spots on the leaves (Purnomo et al., 2025). Rust is caused by a fungus called Hemileia vastatrix, which spreads its uredospores and issues powder-like yellow-to-brown spots. The severe attack of the fungus can cause all the leaves to fall (Harmiansyah et al., 2023). The last common infection is phoma or stem cancer, which is caused by a fungus called Fusarium solani (Wiyono et al., 2019). The fungus attack blocks nutrients from reaching the leaves. These three diseases have slow-growing and small-sized symptoms in common that are often not realized. The traditional approach does not always detect the disease accurately. Thus, inaccurate detection leads to errors in disease handling.

To overcome the problems, the machine learning approach has been utilized (Harvyanti et al., 2023). Computer vision becomes a favorable approach as it has the flair to detect small features of images so that prevention procedures can be executed as soon as possible. Support Vector Machine (SVM) is one of the popular models employed by computer vision researchers (Al-Shamasneh, 2025; Firdaus et al., 2020; Meghana et al., 2025). An SVM model has been employed to detect potato leaf diseases and successfully classified 98.45% of the test set (Al-Shamasneh, 2025). For classifying pomegranate leaf diseases, SVM achieved 96% (Meghana et al., 2025). SVM has achieved 100% accuracy in the study of Cardamom disease detection (Malayil & Mosleh, 2024). Besides SVM, Convolutional Neural Networks and their derivatives are the most popular deep learning approaches. A study developed a DarkNet-19 model that obtained 98.61% accuracy in classifying cocoa leaf diseases (Harvyanti et al., 2023). A scratch 12-layer CNN achieved 93.6% precision, 93.3% recall, and 93.2% F1-score after classifying four classes of banana leaf, such as healthy leaves and three groups of infectious leaves by Sigatoka, Fusarium, and Xanthomonas (Patil et al., 2024). CNN can be mixed with other models, for instance, the Random Forest. A study used Random Forest as a classifier after the CNN extracted coffee leaf disease image features. As a result, both overall accuracy and F1-score got 77% (Kumari et al., 2024). However, deeper networks are inefficient for a limited dataset, as they might increase the error in both training and testing, and decrease the accuracy instead (Bharti et al., 2024; Nhut et al., 2023; Pakiding & Selao, 2025). The research of Nhut, Khang, and Nhan (2023) showed that a 101 network depth model had only 92.68% accuracy for classifying 984 images of rice leaves, while ResNet50 could hit 98.33% training accuracy on 3737 images with a 0.00001 learning rate. A possible reason is that the gradient becomes uncommonly small when backpropagated to the initial layers makes the model's performance decrease. This phenomenon is called a vanishing gradient problem.

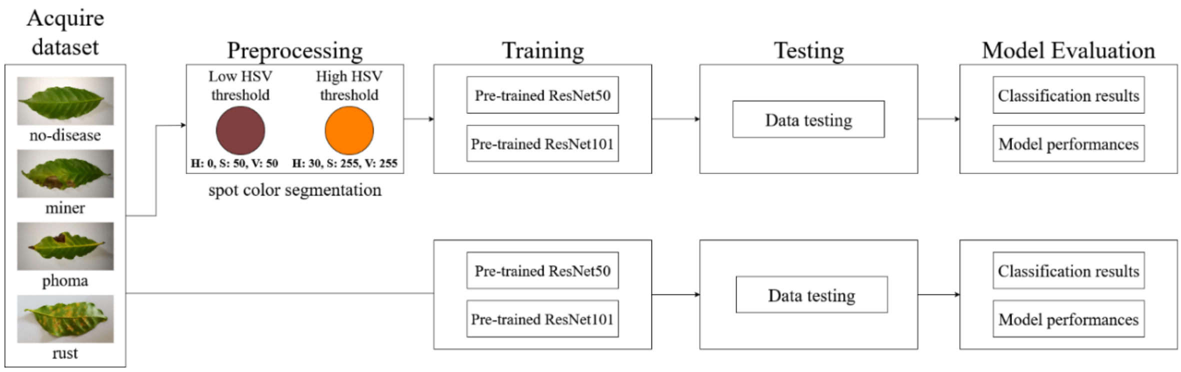

Figure 1. Research flow diagram

The residual network (ResNet) is one of the CNN-based architectures that are employed to overcome the vanishing gradient problem. ResNet allows for skip connections to avoid the vanishing gradient problem and prevent a decrease in accuracy. Using potato leaf disease as the object, a study benchmarked ResNet50 with CNN. As a result, ResNet gained 98.36% accuracy, whereas CNN gained only 94.29% (Bharti et al., 2024). ResNet18 also outperformed VGG16 with 99% and 97% accuracy, respectively (Li & Rai, 2020). ResNet is suitable for handling larger datasets and still maintains an accuracy of more than 94% (Atul et al., 2024; Balavani et al., 2023; Kant, 2024; Mridha Atul et al., 2025; Naga Saranya et al., 2024; Nasra et al., 2025; Nhut et al., 2023; Sirenjeevi et al., 2023). The result indicated that a model, which has a deeper architecture, has an advanced image feature extraction performance (Bharti et al., 2024). Despite having a deeper architecture, ResNet maintains performance in deep architectures using shortcut connections that enhance the extraction of complex image features (Guojian & Peisong, 2021; He et al., 2015).

Considering ResNet's performance and adaptability to various types of datasets, this study employs pre-trained ResNet50 and ResNet101 architectures to recognize and classify the spots across four variables: no disease, rust, miner, and phoma. We chose ResNet50 and ResNet101 as aligned with the original ResNet state-of-the-art baseline. The deeper variant of ResNet (50/101/152) had higher accuracy than ResNet34 and ResNet18. Moreover, the deeper network can reduce the top-1 training error. Considering the number of datasets, we excluded ResNet152 from our experiment. In this experiment, simple spot color segmentation was the only preprocessing step, as the datasets had clear foregrounds, backgrounds, and adequate lighting.

RESEARCH METHODS

This research was conducted using an experimental research method, which is descriptive, quantitative, and evaluative. This study was designed under two experimental scenarios using a pre-trained ResNet, with datasets partitioned into training, validation, and testing subsets. In the first scenario, the model was trained on the raw images without preprocessing, whereas in the second scenario, spot color segmentation was applied as a preprocessing step. The outcomes of both scenarios were evaluated in terms of classification accuracy and overall model performance. The flow diagram of the research is shown in Figure 1.

Types of research

As mentioned above, the type of study is experimental, which is descriptive, quantitative, and evaluative. The purpose of the experimental approach was to test ResNet performance through a controlled experimental environment and draw a conclusion. A description is needed to explain the features of the images and the evaluation model results. The quantitative approach is applied to analyze model performance through predefined metrics. The objective of this study is to provide a comprehensive explanation of ResNet performance in classifying spot diseases on coffee leaves.

Data Acquisition

In this study, we utilize the Coffee Leaf Diseases dataset provided by Gaurav Dutta on Kaggle. There are four classes, such as no disease, miner, phoma, and rust. Miner and phoma have slight differences in color and texture. By human vision, Phoma's spot looks darker and drier than the miner, and it causes the leaf to crumble. Rust disease gives small yellow spots to the coffee leaf. However, the color and size of spots on the coffee leaf pose a challenge to the model (Figure 2).

a

b

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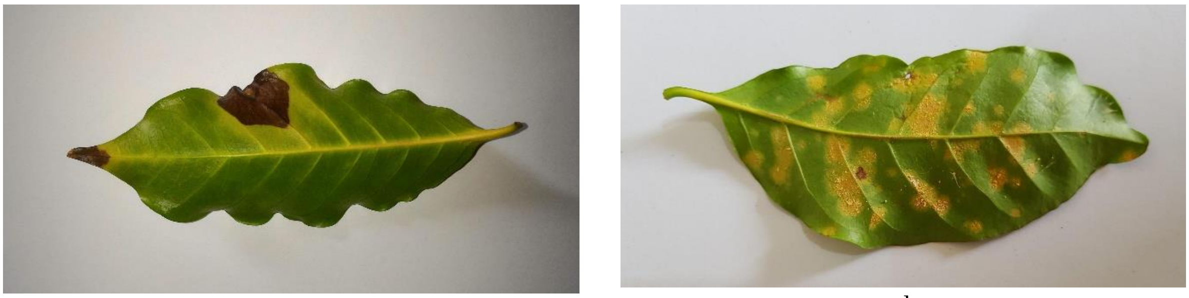


c d

Figure 2. Coffee leaf diseases dataset, (a) no disease, (b) miner, (c) phoma, (d) rust

Originally, the dataset had no validation set. A validation set is important to tune the hyperparameters to avoid errors. Using Roboflow, we rearranged the dataset with a ratio of 70:15:15 for train, validation, and test sets. The balance of the class distribution for each set must be ensured to avoid biased models. The distribution of data is depicted in Table 1.

Data Preparation

Data preparation is crucial for maintaining training quality. It usually includes data preprocessing and data augmentation. The preprocessing procedure helps to reduce learning time, whereas data augmentation helps prevent overfitting due to a limited amount of data. Thus, this study does not need an augmentation process, as the dataset is distributed equally. Observing both the effect of preprocessing and the performance of pre-trained ResNet at once is the reason why this training set was trained both with and without preprocessing in different scenarios.

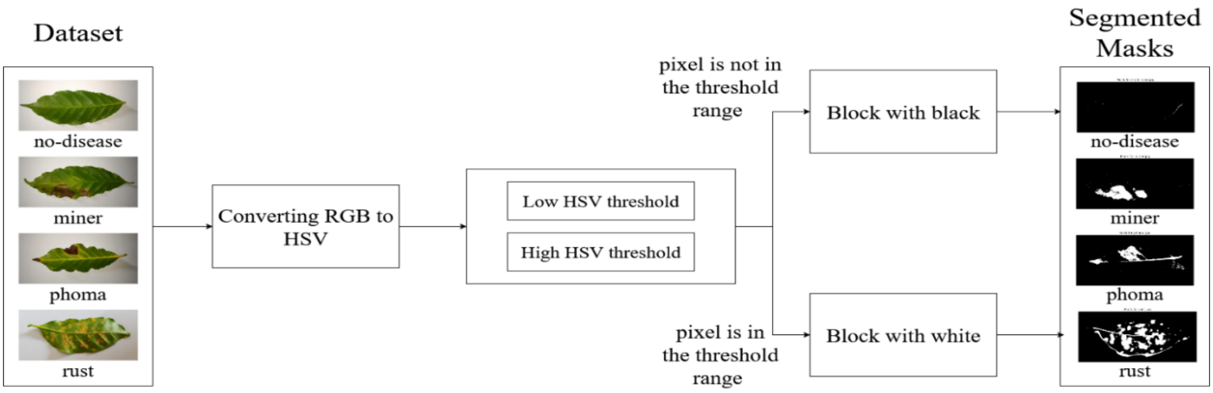


Figure 3. HSV segmentation

Table 1. Dataset Distribution

	Train set (80%)	Validation set (10%)	Test set (10%)	Total
Miner	330 (28.3%)	56 (22.5%)	74 (29.6%)	430
Health	267 (22.9%)	70 (28.1%)	63 (25.2%)	400
Phoma	337 (28.9%)	79 (31.7%)	68 (27.2%)	484
Rust	231 (19.8%)	44 (17.6%)	45 (18.0%)	320
Total	1,165	249	250	1,664

As preprocessing steps, each input for both research scenarios will be resized to 255 x 255, and the whole dataset will be rescaled into the 0 to 1 range. Rescaling is a kind of effort to reduce learning time and standardize the input. For the second scenario, we segmented the spots in every image by their reddish-brown color, based on the hue, saturation, and value (HSV) color model. In the first scenario, we did not preprocess the dataset, as the objective was to measure the accuracy of the ResNet model in identifying features without any assistance from image preprocessing steps, and to evaluate the effectiveness of image color segmentation in enhancing model performance.

Before segmentation, all images were converted from the RGB color space to the Hue, saturation, and value (HSV) model, where hue represents color type, saturation indicates color intensity, and value corresponds to brightness. HSV is projecting the RGB color model to a non-linear chroma angle, a radial saturation percentage, and the value of the lightness (Szeliski, 2021). Before converting, the range of the R, G, and B values must be changed from 0 to 255 to 0 to 1 (R`, G`, B`). The Cmax is the maximum value of R', G', and B', while Cmin is the minimum value of the normalized three channels. The delta (Δ) is the aggregate between Cmax and Cmin. Then the color model can be converted to the HSV model using the three functions below:

$$H = \begin{cases} 0^\circ, \Delta = 0 \\ 60^\circ \times \left(\frac{G' - B'}{\Delta} mod\ 6\right), C_{max} = R' \\ 60^\circ \times \left(\frac{B' - R'}{\Delta} + 2\right), C_{max} = G', \\ 60^\circ \times \left(\frac{R' - G'}{\Delta} + 4\right), C_{max} = B', \end{cases} \quad (1)$$

$$S = \begin{cases} 0, C_{max} = 0 \\ \frac{\Delta}{C_{max}}, C_{max} \neq 0 \end{cases} \quad (2)$$

$$V = C_{max} \quad (3)$$

To segment the leaf spot regions, the lower threshold was set to dark brown (0% hue, 50% saturation, 50% value) and the upper threshold to light red (30% hue, 100% saturation, 100% value). Pixels that have color outside the threshold range will be blocked with black, letting the model focus on the spot. This simple segmentation approach, capable of isolating even the smallest spots, was expected to enhance the ResNet model's ability to classify diseases (Figure 3).

Residual Network (ResNet)

The residual network (ResNet) is a deep learning architecture released by researchers at Microsoft Research [23]. ResNet introduced skip connections or shortcut connections to overcome vanishing gradient problems, which makes learning deeper networks harder. Developing a convolutional neural network was quite complicated; the shorter network might be robust to a few datasets, but it cannot simply add more layers to train the network on larger datasets, as the accuracy declines. This phenomenon is called the gradient explosion effect. Hoping that each few stacked layers fit perfectly to the desired underlying mapping is impossible, so letting these layers fit to a residual mapping is easier. Common neural networks denote the underlying mapping as H(x) = F(x) + x, so the residual learning unit recasts the stacked nonlinear layers to fit another mapping F(x):= H(x) – x. The shortcut connection performed identity mapping, which does not add extra complexity, and added the output to the output of stacked layers (Figure 4).

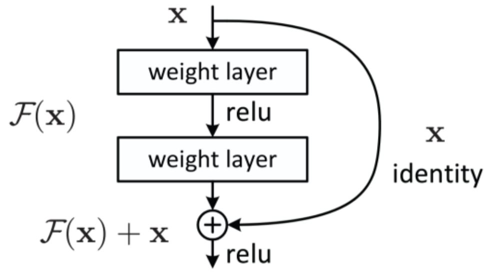


Figure 4. Residual learning unit of ResNet.

In this study, we employed pre-trained ResNet50 and ResNet101 with ImageNet-trained weights. The transfer learning reduced training time and improved models to adapt to new data. Each architecture includes convolutional layers, batch normalization, ReLU activation, max-pooling layers, and features several residual learning units with escalated filter sizes of 64, 128, 256, and 512.

Model Evaluation

Model evaluation is an important part to know whether the classification model is decent or mediocre. This study used the confusion matrix to check whether an object was classified correctly or not. For reporting classification performance, we also used classic matrices such as accuracy, precision, and F1-score. Accuracy is an uncomplicated matrix that shows the amount of correct classification compared with the total classified data. Precision and recall were used to compare the number of true positives for each class. Precision measures the percentage of true positives over the sum of true positives and false positives in that class, while recall gives a ratio between correct class predictions over all instances belonging to the observed class. The harmonic mean of precision and recall is the F1-score, which is useful to evaluate a machine learning model for imbalanced data.

RESULTS AND DISCUSSION

Considering the performance and alignment with the ResNet state-of-the-art, we employed two ResNet architectures with different layer depths, namely ResNet50 and ResNet101, for coffee leaf spot classification. To check the performance, we have two scenarios. Both models were trained on coffee leaf disease images without segmentation for the first scenario, and color segmentation was employed to segment the color of leaf spots before we trained for the second scenario. Before the segmentation, we converted all RGB datasets into HSV color mode. After that, we took a small random sample of the datasets and observed the distribution of hue, saturation, and value before getting dark brown (0% hue, 50% saturation, 50% value) as the lower threshold and light red (30% hue, 100% saturation, 100% value) as the higher threshold.

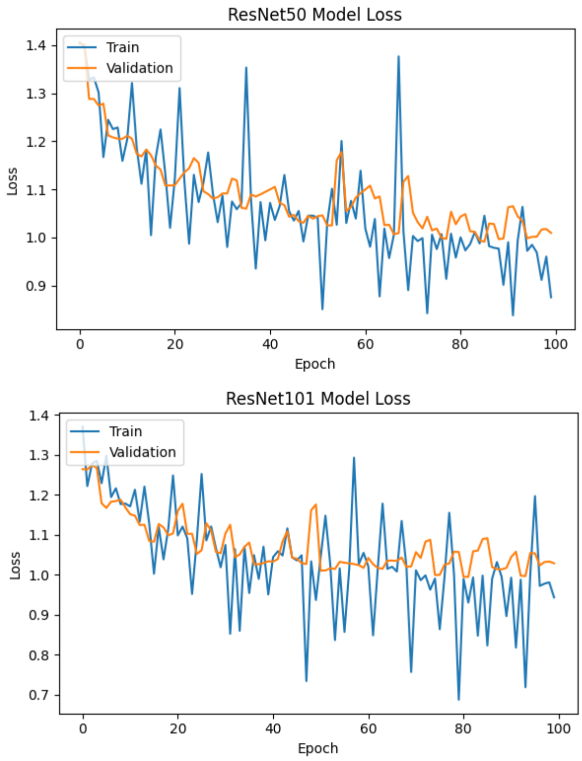


Figure 5. Model loss before image preprocessing. Top: ResNet50, bottom: ResNet101

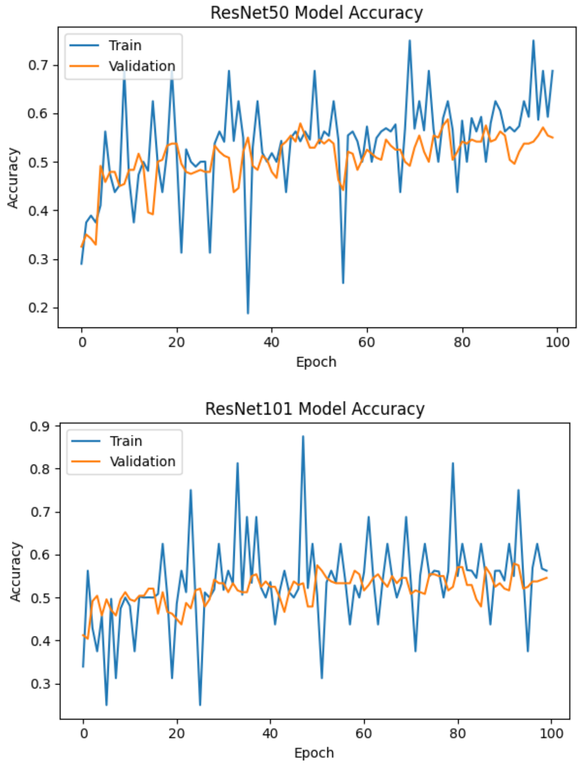
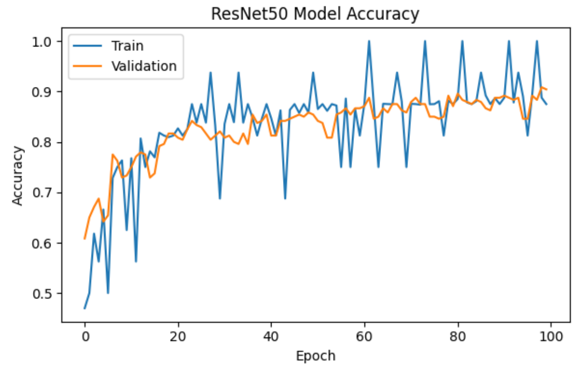


Figure 6. Model accuracy before image preprocessing. Top: ResNet50, bottom: ResNet101

Overall, without image preprocessing, neither model has decent performance, although both accuracies increased at the last epoch, and the losses decreased. Both validation accuracies cannot exceed 0.6, and their loss ended at over 1.0. However, a shorter network means better training performance, as shown in Figures 5 and 6. ResNet50 reduces the loss slope lower than ResNet101. Moreover, both performances were unstable, as shown in severely fluctuating graphs.



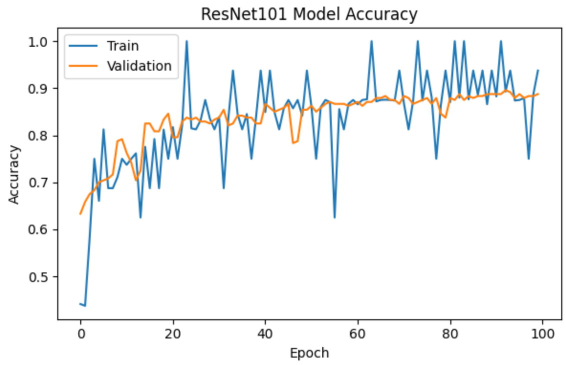
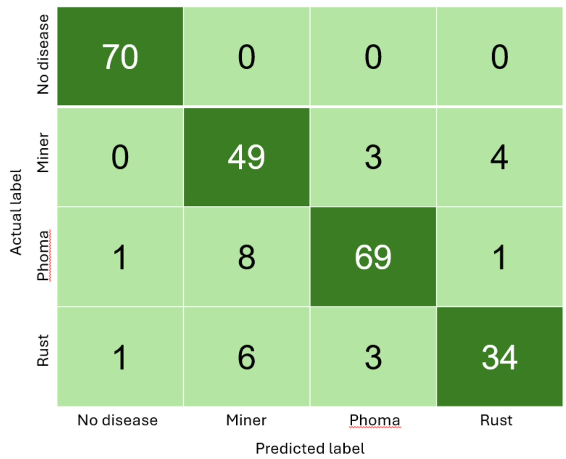
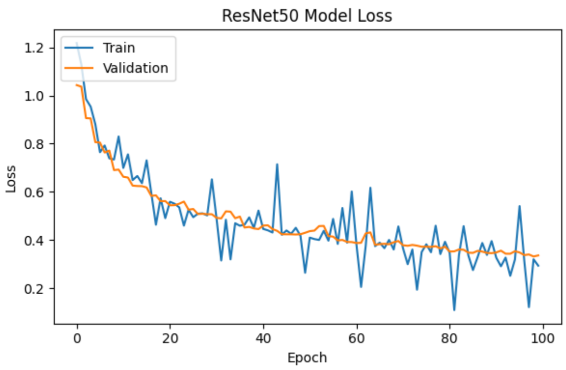


Figure 7. Model accuracy after image preprocessing. Top: ResNet50, bottom: ResNet101





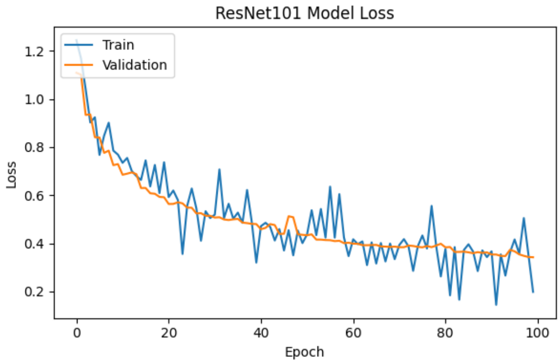


Figure 8. Model loss after image preprocessing. Top: ResNet50, bottom: ResNet101

Color segmentation for leaf spots improved performance compared to previous results. As shown in Figures 7 and 8, both accuracies exceed 0.8, and losses decline below 1.0. Color segmentation made masks on the spots that helped the ResNet model to recognize image features. Although both models have shown similar performance, ResNet50 outperforms ResNet101. Its accuracy and loss graph appear more stable than all ResNet101 training attributes. Furthermore, the ResNet101 model dropped to near 0.6 after 50 epochs.

Both models, which were trained on unpreprocessed data, performed inefficiently—models considered to classify spotted leaves as healthy leaves, and vice versa for clear leaves. 'No disease' was a common class to be assigned by ResNet50. It indicates that before preprocessing, the architecture was difficult to find spots and leisurely, considering there were no spots on the leaves. ResNet101 also had a similar problem. However, it tended to misclassify images into the 'miner' and 'phoma' classes due to their similar visual features, even though the dataset has been distributed relatively equal (Table 1).

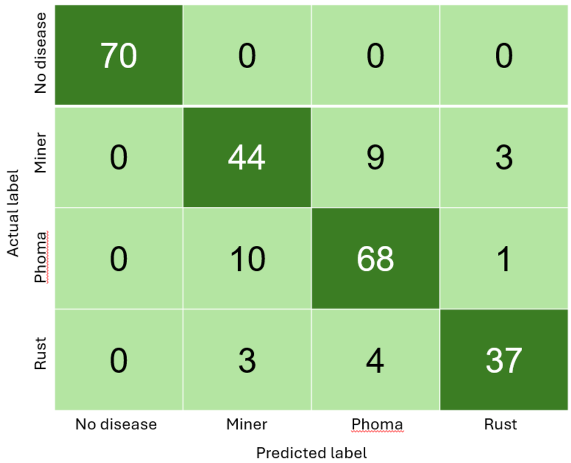


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Figure 9. Confusion matrix after image processing. Top: ResNet50, bottom: ResNet101

Spot color segmentation reduced those tendencies. The segmentation marks the spots and helps the models focus only on those spots. In Figure 9, the number of true positives was more than the previous true positives. In this study, the ResNet50 slightly outperformed its competitor. In other words, the 101-network-length ResNet is too long for classifying 1,664 coffee leaf spot images into four classes.

Table 2. ResNet50 classification performance on no-preprocessed data

Classification Reports:				
Accuracy	0.5502			
Precision	0.5675			
F1-Score	0.5302			
	Precision	Recall	F1-score	Support
No disease	0.44	0.61	0.51	70
Miner	0.50	0.14	0.22	56
Phoma	0.81	0.77	0.79	79
Rust	0.41	0.57	0.48	44
Accuracy			0.55	249
Macro avg	0.54	0.52	0.50	249
Weighted avg	0.57	0.55	0.53	249

Table 3. ResNet50 classification performance on preprocessed data

Classification Reports:				
Accuracy	0.8916			
Precision	0.8942			
F1-Score	0.8915			
	Precision	Recall	F1-score	Support
No disease	0.97	1.00	0.99	70
Miner	0.78	0.88	0.82	56
Phoma	0.92	0.87	0.90	79
Rust	0.87	0.77	0.82	44
Accuracy			0.89	249
Macro avg	0.89	0.88	0.88	249
Weighted avg	0.89	0.89	0.89	249

According to the classification reports, overall performance was supported by spot's color segmentation. Without preprocessing, the results did not meet our expectation that the 'no disease' class is always at the top of all metrics, as there is no spot to be detected. As seen in Table 2, the accuracy reached was only 0.55 before pre-processing. However, the 'phoma' class outperformed in precision, recall, and F1-score as it has the highest support. Not only in the test set, the number of 'phoma' set members was a slightly bigger portion in the train and validation sets (Table 1). It indicated that the ResNet model will show a decent performance after being trained on a proper number of datasets or well-defined features. Moreover, the segmentation strategy needs to be evaluated.

The applied threshold produced notable segmentation errors. Yellow leaf veins were frequently misclassified as leaf spots, and shadows on rusted leaves further degraded the accuracy of the masks (Figure 10). Future work should apply adaptive thresholding to minimize the error. These inaccuracies demonstrate that the resulting mask shapes, while partially usable, require more flexible handling to exclude non-spot objects.

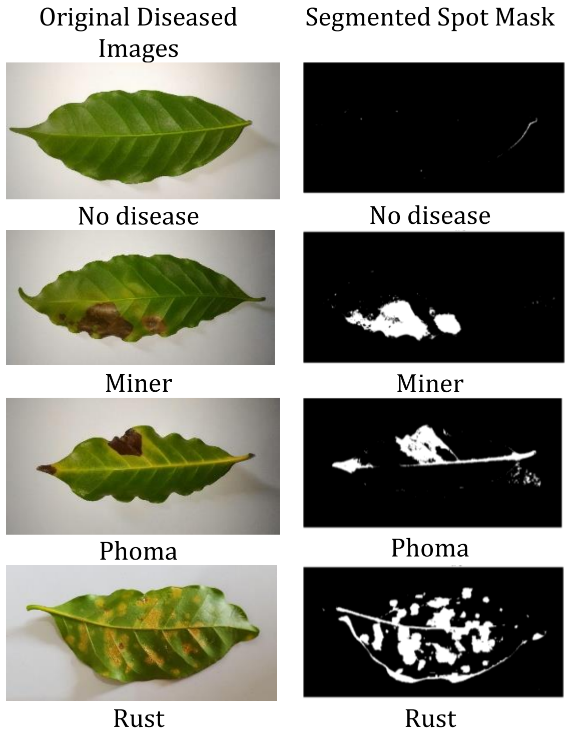

Figure 10. Leaf spot color segmentation

In Table 3, all metrics showed better performance than those written in Table 2. The ResNet50 recorded 89% of accuracy. The 'no-disease' class recorded the highest recall and the F1-score, meaning all healthy leaf images were classified correctly. The F1-score of miner and phoma in ResNet50 was higher than in ResNet101.

Table 4. Performance of models that have a lower network than ResNet

Model	Train Acc	Train Loss	Val Acc	Val Loss
AlexNet	1	3.54E-06	0.940	0.816
LeNet	1	2.52E-06	0.759	2.147
EfficientNetB0	0.994	0.018	0.281	5.842
ResNet50	0.875	0.294	0.904	0.336
ResNet101	0.938	0.198	0.888	0.342

It concluded that image preprocessing assisted ResNet in recognizing the features between similar classes. To optimize the performance, the future work need to apply other segmentation approaches and consider employing a lower network model. As shown in Table 4, AlexNet, LeNet, and EfficientNetB0 have decent training performance, but a decrease in validation. It indicates that having fewer network models is not effective if the model was unresponsive.

CONCLUSIONS AND SUGGESTIONS

Conclusion

This paper aimed to train ResNet50 and ResNet101 models to recognize common coffee leaf diseases, such as miner, phoma, and rust. Thus, every infection requires the right treatment to overcome, as each disease has distinct causes. Therefore, to differentiate between the infections, a machine learning-based tool is needed. One of the most robust ML models is the residual network, or ResNet. Compared with AlexNet, LeNet, and EfficientNetB0, all observed variants of ResNet outperform as their residual blocks skip some layers to connect activations to further layers. The technique overcomes the gradient vanishing problem and reduces error on the validation set.

The results indicated that the ResNets are effective in classifying coffee leaf diseases. The ResNet50 performance was prominent than the ResNet101 in overall aspects. The decent performances were supported by spot color segmentation, which took the color range of the leaf spot from yellow to brown. However, the confusion matrix analysis showed that several false positives and false negatives occurred in this case, especially in the 'miner' and the 'phoma' classes.

The proposed color threshold helped to increase the classification model's performance significantly. However, several non-spot objects were included in the resulting masks, caused by the inflexible threshold range. This finding becomes the next challenge for the following study. The further study requires a more responsive thresholding method and shorter layers of neural networks.

Suggestion

Despite resulting in decent performance, the base model and segmentation method need to be improved. There are several suggestions for further research, such as:

1. Exploring light CNN-architecture models such as DenseNet, MobileNet, EfficientNet, or the latest CNN-based model to increase the performance.
2. Using a more adaptive thresholding method to reduce the masked area to only the spot disease. Combining it with morphological operations is also recommended.

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