Implementation of DenseNet Architecture With Transfer Learning to Classify Mango Leaf Diseases

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ABSTRACT Mango plants (Mangifera indica) are a significant export commodity in the horticultural industry, offering numerous nutritional and economic benefits. They are rich in essential micronutrients, vitamins, and phytochemicals, contributing to their high demand globally. However, mango plants are susceptible to various diseases that can severely impact their yield and quality. These diseases pose a challenge to mango farmers, many of whom struggle to identify and treat them effectively, leading to potential harvest failures. This study aims to address this challenge by implementing a Deep Learning approach to classify diseases in mango leaves. Specifically, the research utilizes a Convolutional Neural Network (CNN) with DenseNet architecture, known for its efficiency in image classification tasks. The study incorporates Contrast Limited Adaptive Histogram Equalization (CLAHE) for image preprocessing to enhance detail and improve the model's performance. Transfer Learning is utilized to optimize the DenseNet model, leveraging a pre-trained model to achieve high accuracy even with a relatively small dataset. The dataset used in this research comprises 4000 labeled images of mango leaves, covering seven disease categories and healthy leaves. These images include common diseases such as Anthracnose, Dieback, Powdery Mildew, Red Rust, Cutting Weevil, Bacterial Canker, and Sooty Mould. The DenseNet model achieved an overall accuracy of 99.5% in classifying mango leaf diseases.

KEYWORDS Convolutional Neural Network, DenseNet Architecture, Mango Leaf Disease, Transfer Learning

I. INTRODUCTION

Mango plants (Mangifera indica) are highly valued for their nutritional and economic benefits. Native to India, mangoes are now widely cultivated in Southeast Asia, including Indonesia and Malaysia [1]. Mangoes are a popular export commodity, especially from tropical regions like Indonesia, which is one of the largest producers globally. The economic value of mangoes is significant and growing, presenting opportunities for international competition [2].

Mangoes are rich in essential vitamins and minerals, making them a crucial part of the diet for many people. They provide energy, dietary fiber, carbohydrates, protein, fat, and phenolic compounds. Mangoes are a source of various micronutrients, vitamins, and phytochemicals, which are essential for human health [3]. Mangoes also contain vitamins such as vitamin C, vitamin A, and vitamin E, which contribute to health benefits [4]. The economic value of mangoes is substantial, with the fruit being a significant export commodity in the horticultural industry [2]. The demand for mangoes continues to grow, driven by their nutritional benefits and popularity as a fresh fruit and ingredient in various food products [5].

Despite their benefits, mango plants are susceptible to various diseases that can significantly impact their yield and quality. These diseases pose a challenge to mango farmers, many of whom struggle to identify and treat them effectively [6]. The presence of diseases in mango plants can lead to harvest failures, affecting both the quantity and quality of the produce.

Some of the common diseases affecting mango plants include Anthracnose, Dieback, Powdery Mildew, Red Rust, Cutting Weevil, Bacterial Canker, Sooty Mould, Gall Midges, and others [7]. Anthracnose is a fruit rot disease caused by the fungus Colleto-trichumspt [8]. Dieback is caused by the fungus Lasiodiplodia theobromae, this disease affects the branches and leaves turning brown, drying out, and falling off [7]. Powdery Mildew is caused by the fungus Oidium mangiferae. This disease affects the leaves, flowers, and young fruits, leading to reduced photosynthesis and fruit quality [9]. Red Rust is a parasitic algae, that causes reddish spots on the leaves and fruits [10]. Cutting Weevil is a destructive insect that attacks mango foliage, particularly when the leaves are newly emerged. Bacterial Canker is caused by Xanthomonas axonopodispv, this disease can cause severe damage to mango yields, with losses ranging from 10% to 100%. Sooty Mould is caused by the fungus Meliola mangiferae. This disease interferes with photosynthesis by preventing sunlight from reaching the chloroplasts in the leaves, stunting the plant's growth. Gall Midges are the larvae of small flies that feed within the plant tissue, causing leaves to develop bulges and affecting the plant's overall health [7].

Traditional methods of identifying and managing these diseases involve manual inspection of the mango leaves, which is time-consuming and inefficient. With the rapid advancement of technology, detecting and overcoming diseases in mango plants can now be done more easily. Farmers can use digital tools to identify the diseases affecting their plants and find suitable treatments. Some of these diseases can be visually identified on the leaves, making image-based classification a viable approach.

Previous research by Saragih et al. [11] used Convolutional Neural Networks (CNNs) to classify mango leaf diseases but was limited to three categories: anthracnose, black sooty mold, and healthy leaves. This study achieved an accuracy of 98%, which is quite high. However, the method could only classify three diseases, highlighting the need for a more advanced system capable of identifying a broader range of diseases.

Rizvee et al. [12], conducted a classification of 7 common disease conditions on mango leaves, these diseases include Anthracnose, Powdery Mildew, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, and Sooty Mold. Using LeafNet Architecture which compared to other architectures such as AlexNet and VGG 16 resulted in better performance on evaluation parameters such as average accuracy, precision, recall, F1-score, and specificity with accuracy results of 98.55%, precision of 99.508%, recall of 99.45%, F1-score of 99.47%, and specificity of 99.878%. LeafNet has lower computational complexity compared to other model architectures such as AlexNet and VGG 16 [12]. This study compares 3 architectural models but, has not tested the performance comparison when compared with DenseNet and the use of Transfer Learning methods on 7 types of mango leaf diseases namely Anthracnose, Powdery Mildew, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, and Sooty Mold.

Kulkarni et al. [13] conducted classification research using a custom CNN model on 3 types of diseases in mango plants Anthracnose, Red rust, and Powdery mildew and Normal (healthy), with a total dataset of 980 images. For evaluation, confusion matrix, accuracy, precision, recall, and F1-score are used. The result of the research using this custom CNN is an accuracy of 90.36%.

Rajbongshi et al. [14] conducted research using the CNN DenseNet201 model with transfer learning to classify anthracnose, gall machi, powdery mildew, red rust, and healthy with an accuracy of 98%. This DenseNet model obtained the best results compared with other models, namely InceptionResNetV2, InceptionV3, ResNet50, ResNet152V2, and Xception with transfer learning which compared performance in classifying mango leaf diseases. The results of this study show satisfactory results for classification models using transfer learning methods.

Computer Vision, a field of artificial intelligence (AI), refers to the ability of computers and systems to interpret and make decisions based on visual inputs such as photos and videos [15]. It is developing rapidly and is often used in various fields for image processing [16]. The CNN method is one of the most widely used Deep Learning methods, in Computer Vision systems for image classification, due to its ability to provide good results with low computational complexity [12]. Deep Learning, a subset of machine learning, involves algorithms that learn from data through multiple layers of processing [17]. CNNs, inspired by biological neural networks, connect multiple processing layers using convolution operations, making them effective for image classification tasks [18]. In classifying images, CNN architecture namely DenseNet can be used, which is a collection of layers that are tightly netted between CNNs for classification [19].

Transfer Learning, a method where a pre-trained model on one problem is used for another problem, allows for deep learning training that achieves high accuracy even with a small number of samples [20]. Previous studies have shown that DenseNet, combined with Transfer Learning, can achieve high accuracy in classifying mango leaf diseases.

In maximizing the performance of the model, the Transfer Learning method, image preprocessing techniques, and optimizer can be used to maximize the accuracy performance of the DenseNet model. Image processing techniques are applied at the initial stage (pre-processing) and data augmentation, namely using the digital image processing method Contrast Limited Adaptive Histogram Equalization (CLAHE) before training to improve model performance for better accuracy results.

CLAHE (Contrast Limited Adaptive Histogram Equalization) is a technique to improve the quality of digital images by increasing the contrast of small tiles, and then recombining them by removing artificial boundaries between tiles. With CLAHE, image details become clearer and image noise is reduced, making the image easier to analyze [21].

The Stochastic Gradient Descent (SGD) optimizer is used in this research to optimize model performance. Stochastic Gradient Descent (SGD) is an optimizer whose algorithm is based on gradients. SGD is recognized as a fast algorithm for optimization because SGD does not perform calculations on all given data but rather SGD takes one piece of data and performs calculations for that data, then the gradient value will be updated using a learning rate, and the value update process lasts until the value reaches the lowest point [22].

This research aims to improve the performance of the CNN model for mango leaf disease classification by integrating these methods into the DenseNet architecture.

II. RESEARCH METHODS

The research methodology is structured into several key stages: data collection, data preprocessing, model selection, model training, and model evaluation. Each stage is crucial for ensuring the accuracy and reliability of the model in classifying mango leaf diseases. Figure 1 shows the research stages.

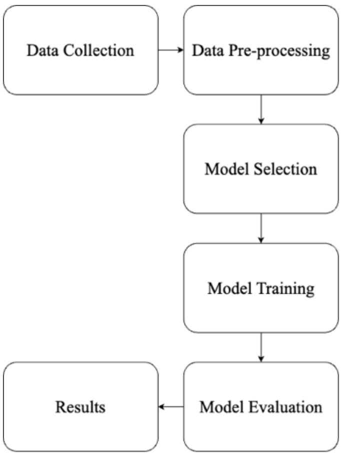

Figure 1. Research Stages

The following is an explanation of the research stages shown in Figure 1:

1. Data Collection

The dataset used in this research consists of a collection of mango leaf images that have been labeled for the classification of seven mango leaf diseases and one healthy leaf category. The labeled datasets were obtained from secondary sources, specifically from a previous study conducted by Ahmed et al. [7] with the title MangoLeafBD: A Comprehensive Image Dataset to Classify Diseased and Healthy Mango Leaves.

This study includes a dataset of 4000 images of mango leaves, each labeled according to the type of disease or health condition. The dataset is balanced, with an equal number of images—500 for each category. The categories include Anthracnose, Powdery Mildew, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Sooty Mold, and Healthy. These images were obtained from 4 mango plantations in Bangladesh. Although the leaf images were obtained from mango leaf diseases in Bangladesh, these diseases are common to mango leaves in many countries.

The dataset from this previous study can be retrieved from Mendeley Data [23] from the 4000 images, 1800 of these images are whole leaf photos while the rest are the result of zooming and rotating. The image size is 240x320 pixels with RGB color and is in PNG image format. Images are taken using a mobile device camera and individually each leaf is taken on a white background. The dataset size for these images is 103 MB. This dataset is used for training the model of the DenseNet architecture. Figure 2 shows some of the dataset images of each class.

Figure 2. Images of Anthracnose, Powdery Mildew, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Sooty Mould and Healthy

2. Data Pre-processing

Dataset augmentation is a strategy that allows a significant increase of diversity of existing data in training the developed model, without having to collect new data [26].

In the dataset provided by Mendeley Data [23], image augmentation has already been applied to 1,800 whole leaf images, which resulted in an additional 2,200 images through zooming and rotating. Thus, the final total number of images after the augmentation process is 4,000.

Then, the stage of pre-processing the dataset is to perform image enhancement in the form of Contrast Limited Adaptive Histogram Equalization (CLAHE), which is done at the beginning for all images to increase the detail in damaged or low-quality images because it can disguise existing information [24].

The Contrast Limited Adaptive Histogram Equalization (CLAHE) method will improve the local contrast of the image by giving a boundary value to the histogram. This limit value is called the clip limit which states the maximum height limit of a histogram. The clip limit of a histogram can be defined by (1) [25]:

$$\beta = \frac{M}{N}\left(1 + \frac{\alpha}{100}(s - 1)\right) \times 100\% \qquad (1)$$

Where M denotes the region size, N the grayscale value (256), and α the clip factor (the addition of a histogram limit that is between 0-100) [25]. The next pre-processing stage is to change the entire dataset size to 227x227.

To improve the accuracy and robustness, augmentation will be undertaken. The techniques of augmentation that are implemented is geometric transformation such as random rotation and flipping both vertically and horizontally. This transformation is implemented using the Keras layers library. The Random Rotation layer randomly rotates the input image, while the Random Flip Horizontal and Vertical layer randomly flips the input images horizontally and vertically. During this augmentation process no images is added to the dataset. Augmentations are applied to images when drawing from a batch, creating stacked variations. Each batch will feature slightly different augmented images due to the randomness involved in their application. The image augmentation creates random variations of images processed during training in each epoch, without adding any images to the dataset.

Then, image normalization is applied to the dataset. Normalizing the image so that the image pixel value is in the range of 0 - 1. Before the normalization, the input image pixel range of values is 0 to 255. To change the pixel value to the range of 0 – 1, the input image is multiplied by 1/255. In data normalization, the pixel value from a range of 0 - 255 is changed to a range of 0 – 1. By standardizing the values in the images to a range between 0 and 1, the CNN model can more effectively identify important features. This is essential because it ensures that the model can process images consistently [11]. Pre-processing is done on the model to improve the accuracy of the Deep Learning model.

3. Model Selection

In this Deep Learning classification model, the architecture used in classifying diseases in mango leaf is DenseNet121.

4. Model Training

The dataset is divided as follows: 80% for training, 10% for validation, and 10% for testing. This means that 3200 images are used for training, 400 images for testing, and 400 images for validation out of a total of 4000 images. Each class has a balanced class of images, with 400 for training, 50 for validation, and 50 for testing. The image size is 227x277 and the batch size is 32. In addition, a learning rate scheduler is also used to organize learning on the deep learning model at a certain learning rate value. The optimizer used for the model is Stochastic Gradient Descent (SGD) with a learning rate value of 0.001, Sparse categorical cross-entropy is applied because of the imbalance datasets, as it considers the true probability distribution of the classes. This ensures that the model is penalized for misclassifying minority classes, which can improve its performance. An epoch value of 250 is applied during the training process.

The model will employ transfer learning during its deep learning training process. This process consists of five stages: first, a pre-trained network from the DenseNet architecture is imported. Next, several convolutional layers are frozen to preserve essential information. The classification layer, which was trained on 1,000 ImageNet datasets, is then removed. Following this, a new classification layer is added to identify diseases in mango plant leaves. Finally, data augmentation and optimization techniques are applied to enhance the accuracy of the model's training results. Figure 3 shows the stages of the transfer learning process.

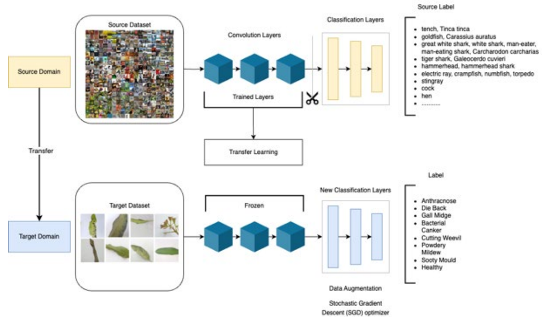

Figure 3. **Stages of the transfer learning process**

5. Model Evaluation

Model evaluation in the form of performance metrics namely accuracy, precision, recall, F1-score, and loss are used to measure model performance in this research.

Accuracy, precision, recall, and F1-score are calculated for each class in the DenseNet model. Equations (2), (3), (4), and (5) represent Accuracy, Precision, Recall and F1-score respectively [27].

$$\text{Accuracy} = \left(\frac{TP+TN}{TP+FN+FP+TN}\right) \times 100\% \tag{2}$$

$$\text{Precision} = \left(\frac{TP}{TP+FP}\right) \times 100\% \tag{3}$$

$$\text{Recall} = \left(\frac{TP}{TP+FN}\right) \times 100\% \tag{4}$$

$$\text{F1-score} = 2 \times \left(\frac{Precision \times Recall}{Precision+Recall}\right) \times 100\% \tag{5}$$

Confusion Matrix was created to visualize the classification result of the DenseNet model. Confusion matrix is a table that states the classification of the number of correct test data and the number of incorrect test data. It is a useful tool for evaluating the performance of a classification algorithm. As an example, the concept of confusion matrix for binary classification is depicted in Table 1 [28].

The model loss and accuracy graphs are displayed to visualize how the model performance changes during training. The final epoch accuracy and loss, including the final epoch accuracy, final epoch val_accuracy, final epoch loss, and final epoch val_loss, are presented in Table 4 and Table 5.

TABLE 1
CONFUSION MATRIX

		Prediction Class	
		1	0
Actual Class	1	TP	FN
	0	FP	TN

III. RESULTS AND DISCUSSION

A. RESULTS

The DenseNet model using CLAHE demonstrated exceptional performance in classifying mango leaf diseases, achieving an overall accuracy of 99.5%. This high level of accuracy indicates the model's effectiveness in distinguishing between different disease categories and healthy leaves. The performance metrics for each class, including accuracy, precision, recall, and F1-score, are detailed in Table 2.

TABLE 2
PERFORMANCE EVALUATION METRICS FOR EACH CLASS USING DENSENET MODEL WITH CLAHE

Leaf Disease	Accuracy	Precision	Recall	F1-score
Anthracnose	99.5 %	100 %	100 %	100 %
Bacterial Canker	99.5 %	100 %	98 %	99 %
Cutting Weevil	99.5 %	100 %	100 %	100 %
Die Back	99.5 %	100 %	100 %	100 %
Gall Midge	99.5 %	100 %	100 %	100 %
Healthy	99.5 %	98 %	100 %	99 %
Powdery Mildew	99.5 %	100 %	100 %	100 %
Sooty Mould	99.5 %	98 %	98 %	98 %

Table 2 shows the performance evaluation metrics of the DenseNet model with CLAHE for the Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, Sooty Mould classes. The model achieved an accuracy of 99.5% across all classes. Precision values for the classes ranged from 98% to 100%. Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, and Powdery Mildew achieve the highest precision results at 100%. Recall values ranged from 98% to 100%. Anthracnose, Cutting Weevil, Die Back, Gall Midge, Healthy, and Powdery Mildew obtain the highest recall values at 100%. The F1-score, which is the harmonic mean of precision and recall, ranged from 98% to 100%. Anthracnose, Cutting Weevil, Die Back, Gall Midge, and Powdery Mildew demonstrate the highest F1-score results at 100%. To compare the improvement using CLAHE, the results before using CLAHE can be seen in Table 3.

TABLE 3
PERFORMANCE EVALUATION METRICS FOR EACH CLASS USING DENSENET MODEL WITHOUT CLAHE

Leaf Disease	Accuracy	Precision	Recall	F1-score
Anthracnose	99.25 %	100 %	100 %	100 %
Bacterial Canker	99.25 %	100 %	100 %	100 %
Cutting Weevil	99.25 %	100 %	100 %	100 %
Die Back	99.25 %	100 %	100 %	100 %
Gall Midge	99.25 %	100 %	96 %	98 %
Healthy	99.25 %	98 %	100 %	99 %
Powdery Mildew	99.25 %	98 %	100 %	99 %
Sooty Mould	99.25 %	98 %	98 %	98 %

Table 3 shows the performance evaluation metrics for the DenseNet model without CLAHE for the same class. The model achieved lower accuracy of 99.25% for all classes. Precision, Recall, and F1-score values are different for some classes. Precision values ranged from 98% to 100%. The highest precision result of 100% was achieved by Anthracnose, Bacterial Canker, Cutting Weevil, Die back and Gall Midge. Recall values for the classes ranged from 96% to 100% with the highest recall results achieved by Anthracnose, Bacterial Canker, Cutting Weevil, Die back, Healthy and Powdery Mildew. F1-score is ranged between 98% to 100% with the highest results achieved by Anthracnose, Bacterial Canker, Cutting Weevil, and Die back.

The results show better accuracy when using CLAHE as shown in the Table 2 with the accuracy of 99.5 % which is higher compared to not using CLAHE with the accuracy of 99.25 %. The model that is implemented using CLAHE in the preprocessing stage achieves higher metrics. The performance metrics that are measured in the experiment are Precision, Recall, and F1-score. The higher scores are achieved especially for Anthracnose, Cutting Weevil, Die Back, Gall Midge, and Powdery Mildew.

The confusion matrix provides a detailed breakdown of the model's performance for each class for the DenseNet Model with CLAHE in Figure 4 and without CLAHE in Figure 5. It shows the number of correct and incorrect predictions, allowing for a deeper understanding of the model's strengths and weaknesses.

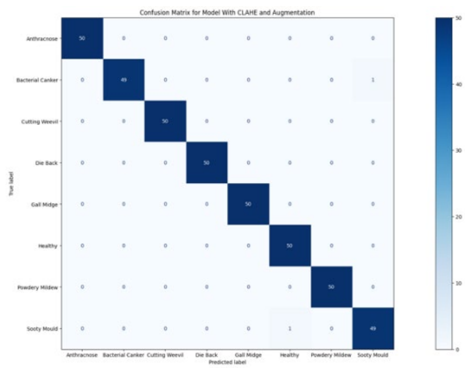

Figure 4. **Confusion Matrix of DenseNet Model with CLAHE**

Figure 4 displays the confusion matrix results for each class classified using the DenseNet architecture with CLAHE. The confusion matrix indicates the model's prediction accuracy, showing the number of classes predicted correctly or incorrectly. Figure 5 presents the evaluation results for each class for the model without CLAHE. The confusion matrix for Figure 5 illustrates the number of classes predicted correctly or incorrectly. In comparison to Figure 4, the results in Figure 5 show lower correctly predicted classes in especially in Gall Midge.

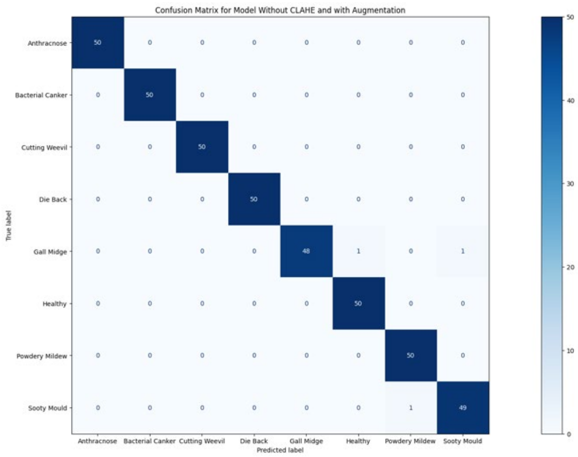

Figure 5. Confusion Matrix of DenseNet Model without CLAHE

The training and validation accuracy and loss graphs illustrate the model's learning process over the epochs for Densenet with CLAHE in Figure 6 and Densenet without CLAHE in Figure 7. The graphs show that the model's accuracy increased steadily while the loss decreased, indicating effective learning and convergence.

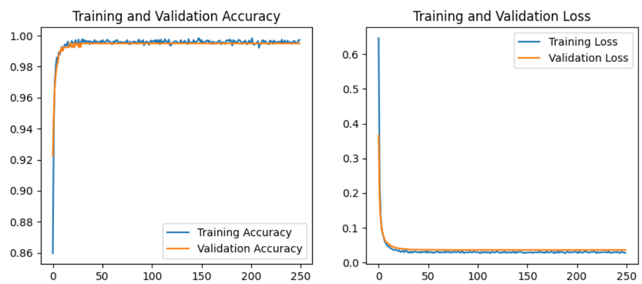

Figure 6. Accuracy and Loss Progress Chart of DenseNet Model With CLAHE

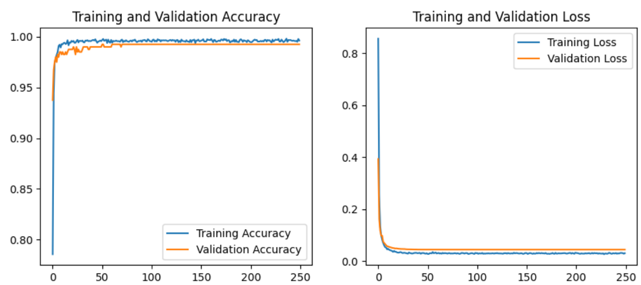

Figure 7. Accuracy and Loss Progress Chart of DenseNet Model Without CLAHE

Figures 6 and 7 display the training process and accuracy and loss of the results of training and validation of datasets. The DenseNet architecture model is slowly changing accuracy and loss values. The accuracy obtained is increasing and the loss obtained is getting smaller. The changes that occur are quite stable for the accuracy and loss values obtained. In comparison, the results in Figure 7 have wider gap in the graph than in Figure 6 for both the training and validation accuracy and the training and validation loss.

Tables 4 and 5 present the final values of accuracy and loss when training is completed at the last epoch. Table 4 displays the results with CLAHE and Table 5 shows results without CLAHE.

TABLE 4
ACCURACY AND LOSS OF THE MODEL WITH CLAHE

Architecture	Final epoch accuracy	Final epoch val_accuracy	Final epoch loss	Final epoch val_loss
DenseNet121	99.72 %	99.50 %	0.0276	0.0360

TABLE 5
ACCURACY AND LOSS OF THE MODEL WITHOUT CLAHE

Architecture	Final epoch accuracy	Final epoch val_accuracy	Final epoch loss	Final epoch val_loss
DenseNet121	99.62 %	99.25 %	0.0298	0.0438

Table 4 outlines the results of the DenseNet model for accuracy and loss at the end of the epoch. The final epoch training accuracy was 99.72%, demonstrating that the model learned effectively from the training data. The final epoch validation accuracy was 99.50%, indicating that the model performed well on unseen data. The final epoch training loss was 0.0276, showing that the model minimized errors during training. The final epoch validation loss was 0.0360, indicating that the model maintained low error rates on validation data. In comparison, Table 5 shows the final epoch accuracy of 99.62%, final epoch validation accuracy of 99.25%, final epoch loss of 0.0298, and final epoch validation loss of 0.0438. Indicating the Densenet model with CLAHE achieved higher performance results.

In addition to using CLAHE, this research also utilizes Augmentation to enhance the robustness and accuracy of the model. Data Augmentation is employed to increase data variation, involving random horizontal and vertical flipping, as well as random rotation. Table 6 presents the performance evaluation metrics, highlighting the model's results when using CLAHE without Data Augmentation.

TABLE 6
PERFORMANCE EVALUATION METRICS FOR EACH CLASS USING DENSENET MODEL WITH CLAHE AND WITHOUT AUGMENTATION

Leaf Disease	Accuracy	Precision	Recall	F1-score
Anthracnose	99 %	100 %	98 %	99 %
Bacterial Canker	99 %	100 %	100 %	100 %
Cutting Weevil	99 %	100 %	100 %	100 %
Die Back	99 %	100 %	100 %	99 %
Gall Midge	99 %	98 %	100 %	99 %
Healthy	99 %	98 %	100 %	99 %
Powdery Mildew	99 %	98 %	98 %	98 %
Sooty Mould	99 %	98 %	96 %	97 %

Table 6 model using CLAHE and without Augmentation shows lower results compared to Table 2 model with CLAHE and Augmentation. Table 6 shows the performance evaluation metrics of the DenseNet model with CLAHE without Augmentation. The model achieved an accuracy of 99% across all classes which is lower than using CLAHE with Augmentation in Table 2 which achieved 99.5% accuracy. Table 6 achieved results of precision values for the classes ranged from 98% to 100%. Anthracnose, Bacterial Canker, Cutting Weevil, and Die Back achieve the highest precision results at 100%. Recall values ranged from 96% to 100%. Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, and Healthy obtain the highest recall values at 100%. The F1-score, which is the harmonic mean of precision and recall, ranged from 97% to 100%. Bacterial Canker and Cutting Weevil demonstrate the highest F1-score results at 100%. This result shows that data augmentation improves the model performance. The augmentation techniques enhance the model ability to learn more and generalize new data, due to the variation images.

Figure 8 illustrates the results of training and validation accuracy and loss graphs, showcasing when the model is using CLAHE and without Augmentation.

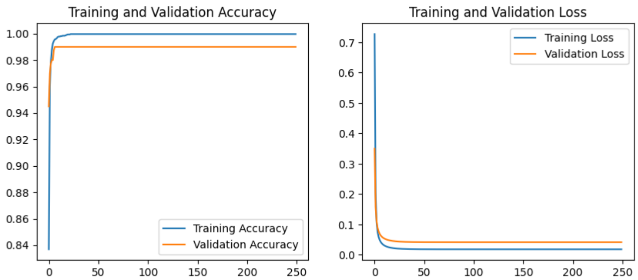

Figure 8. **Accuracy and Loss Progress Chart of DenseNet Model with CLAHE and Without Augmentation**

The results in Figure 8 indicate a difference in model performance when using CLAHE and without Augmentation, compared to using CLAHE and Augmentation in Figure 6. In Figure 8, there is a noticeable gap between the graphs, whereas in Figure 6, the gap is much smaller. This suggests that using Augmentation improves the model, with a smaller gap indicating better performance in terms of robustness and accuracy. Figure 9 shows the confusion matrix for the model with CLAHE and without Augmentation.

The DenseNet model presented in Figure 9, which utilizes CLAHE without augmentation, shows noticeable differences when compared to Figure 4, which employs augmentation. This comparison indicates that the use of augmentation enhances the model's prediction accuracy, particularly in the number of correctly predicted classes. When compared to Figure 4, the results in Figure 9 reveal a lower number of accurately predicted classes, particularly for Anthracnose, Powdery Mildew, and Sooty Mould. This highlights that the use of augmentation significantly improves the model's robustness and accuracy.

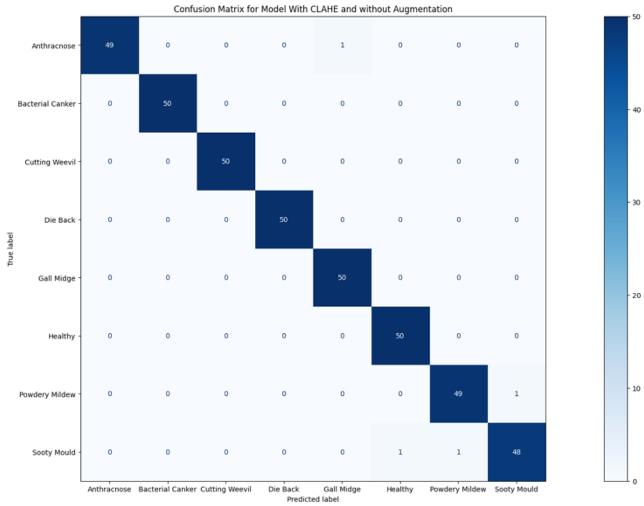

Figure 9. **Confusion Matrix of DenseNet Model Testing Result with CLAHE and without Augmentation**

Based on research conducted on the classification of diseases in mango leaves using deep learning CNN architecture models, the DenseNet model demonstrated exceptional performance. With the implementation of CLAHE (Contrast Limited Adaptive Histogram Equalization) and data augmentation, the DenseNet model achieved an impressive accuracy of 99.5%.

The performance evaluation metrics for the DenseNet model across each class showed precision values ranging from 98% to 100%, recall values also between 98% and 100%, and F1-scores in the same range. Additionally, the confusion matrix indicated satisfactory results, with a high number of correct predictions for each class.

The accuracy and loss progress graphs for the DenseNet architecture model revealed consistent results, showcasing a final training accuracy of 99.72% and a validation accuracy of 99.50%. The training loss was recorded at 0.0276, while the validation loss was 0.0360.

B. DISCUSSION

The key discussion from the results of this study include:

1. Comparison With Previous Studies

The results of this study surpass those of previous research. For instance, Rajbongshi et al. achieved an accuracy of 98% using the DenseNet architecture with transfer learning. This study implemented additional data preprocessing steps, such as CLAHE and data augmentation, which contributed to the higher accuracy of 99.5%. The inclusion of more disease classes (eight compared to five in previous studies) also demonstrates the model’s enhanced capability to handle a broader range of classifications.

2. Impact Of Data Preprocessing and Augmentation

The use of CLAHE for image preprocessing significantly enhanced the detail in the images, making it easier for the model to identify disease features. Data augmentation techniques, that are used in this study (random rotation, vertical and horizontal flipping), increased the diversity of the dataset, improving the model's robustness and accuracy. These preprocessing steps were crucial in achieving the high performance of the DenseNet model.

3. Transfer Learning Benefits

Transfer learning played a vital role in optimizing the DenseNet model's performance. By leveraging a pre-trained model, the study was able to achieve high accuracy even with a relatively small dataset. Transfer learning allowed the model to benefit from prior knowledge, reducing the need for extensive training from scratch and improving the model's generalization capabilities.

4. Limitations And Future Work

While the DenseNet model achieved high accuracy, there are areas for improvement. Future research could focus on expanding the dataset to include more images and different disease categories to improve the model's robustness and generalizability. Implementing other advanced techniques, such as ensemble learning, could also be explored to boost classification accuracy.

IV. CONCLUSION

This study implemented a Convolutional Neural Network (CNN) using the DenseNet architecture to classify diseases in mango leaves. The research incorporated Contrast Limited Adaptive Histogram Equalization (CLAHE) for image preprocessing, optimizer, and Transfer Learning was utilized to optimize the DenseNet model, resulting in an overall accuracy of 99.5%.

The DenseNet model achieved a remarkable accuracy of 99.5% in classifying mango leaf diseases. This high level of accuracy demonstrates the model's effectiveness in distinguishing between different disease categories and healthy leaves.

The use of CLAHE significantly improved the detail in the images, making it easier for the model to identify disease features. This preprocessing step was crucial in achieving the high performance of the DenseNet model.

Data augmentation techniques, including random rotation and flipping, increased the diversity of the dataset. This improvement in dataset variation contributed to the model's robustness and accuracy.

Leveraging a pre-trained model through Transfer Learning allowed the study to achieve high accuracy even with a relatively small dataset. Transfer Learning enabled the model to benefit from prior knowledge, reducing the need for extensive training from scratch and improving the model's generalization capabilities.

The results of this study surpass those of previous research. For instance, Rajbongshi et al. achieved an accuracy of 98% using the DenseNet architecture with Transfer Learning. However, this study implemented additional data preprocessing steps, such as CLAHE and data augmentation, which contributed to the higher accuracy of 99.5%. The inclusion of more disease classes (eight compared to five in previous studies) also demonstrates the model's enhanced capability to handle a broader range of classifications.

The findings of this study have significant practical implications for the agricultural industry, particularly for mango farmers. The high accuracy of the DenseNet model in classifying mango leaf diseases provides a valuable tool for farmers to identify and manage these diseases more effectively. By leveraging this technology, farmers can improve their crop yield and quality, reducing the economic losses associated with disease outbreaks.

In conclusion, the DenseNet architecture, combined with CLAHE preprocessing, optimizer, and Transfer Learning, effectively classifies mango leaf diseases with high accuracy. The model's performance metrics, confusion matrix, and training and validation graphs all indicate its robustness and reliability. This study demonstrates the potential of deep learning techniques in agricultural applications, providing a valuable tool for farmers to identify and manage mango leaf diseases more effectively.

While the DenseNet model achieved high accuracy, there are areas for improvement. Future research could focus on expanding the dataset to include more images and different disease categories to improve the model's robustness and generalizability. Implementing other advanced techniques, such as ensemble learning, could also be explored to boost classification accuracy.

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AUTHORS CONTRIBUTION

Marsha Alexis Likorawung: writing, experimenting, and testing research.

Daniel Martomanggolo Wonohadidjojo: validating the experiments and revising manuscripts.

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