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Article

Hyperparameter Optimization of Convolutional Neural Network for Classification of Corn Leaf Disease Types using CLAHE

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A B S T R A C T

Corn plays an important role as one of the main food sources in Indonesia and around the world. Diseases in corn plants are often visible through their leaves. However, problems arise when farmers have difficulty detecting diseases that attack corn plants, making it difficult to take appropriate action to control them. Diseases in corn plants can lead to reduced photosynthesis, disrupt agricultural productivity, and cause financial losses for farmers. Therefore, a digital approach that can detect various types of diseases in corn plants is highly needed. In recent years, the emergence of machine learning algorithms has provided support systems for classifying corn leaf diseases. This research aims to classify types of corn leaf diseases using the Optimization of Convolutional Neural Network (CNN) Method for Classifying Types of Corn Leaf Diseases Using Contrast Limited Adaptive Histogram Equalization (CLAHE). The research stages include data collection, image enhancement with CLAHE, data augmentation, data preprocessing, classification, and evaluation. The Optimization of the CNN Method for Classifying Types of Corn Leaf Diseases Using CLAHE resulted in an accuracy of 94%, indicating that this experiment is capable of classifying corn leaf diseases effectively. The practical implication of this research lies in its potential application in mobile or IoT-based corn leaf disease diagnosis systems, enabling farmers to perform early detection and accurate disease management promptly, thereby supporting increased productivity and sustainability in corn agriculture.

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I. INTRODUCTION

In the economy of every country, agriculture plays a very important role, with corn being one of the main crops and also a major source of income. The overall economic loss due to infections in corn plants is estimated to reach 40 billion dollars annually in the United States [1], In Indonesia, corn is one of the widely cultivated cereals and occupies a primary position as a food crop commodity after rice. Corn production in Indonesia in 2023 was 14.77 million tons, a decrease of 1.75 million tons or 10.61% compared to 2022, which was 16.53 million tons [2].

National corn production from 4.15 hectares of land is estimated to reach 15.79 million tons of dry shelled corn in 2022, according to the National Corn Council. The increase in planting area, rising corn prices since 2021, and weather conditions have driven this increase in production. Reports from the Directorate of Food Crop Protection from 1978 to 1981 showed that pests and diseases reduced corn production by 57,871 hectares, with an intensity of 26.5%. These losses depend heavily on the corn variety, location, planting time, and weather factors, especially temperature and humidity [3].

To address this issue, automated machine learning techniques are designed to solve problems in a reasonable time with accurate results. The National Center for Biotechnology Information (NCBI) estimates that due to the continuously increasing human population, food demand will increase in the next 40 years [4]. Several major issues according to the literature were found in recent papers. Similarity between classes and variation within classes of corn plant images, variation in shape, texture, and size affect recognition accuracy [5].

One of the main problems that is the focus of this research is the difficulty farmers face in distinguishing diseases that attack corn plants. These diseases can disrupt agricultural productivity and cause significant financial losses. To reduce the level of damage to corn plants, various methods are applied that result in gradual improvements in the production of healthy plants. Several machine learning methods are used to solve problems in segmentation and classification [6].

Diseases in corn plants are often visible through their leaves, but farmers often have difficulty identifying the type of disease attacking their plants. This results in delays in taking necessary steps to control the disease and reduce its impact on crop yields. With the advancement of technology and science, computers can facilitate the identification of diseases in corn plants. Advanced techniques are proposed that involve automatic detection of diseases in plants [7].

Diseases in corn plants should be visible through their leaves. In principle, diseases in corn plants are only known by farmers who usually monitor corn plants. Therefore, it is recommended to use appropriate techniques that work best on that type of plant. Early detection is needed due to irregular climate and new types of diseases that easily infect plants [8]. Currently, CNN is considered to have phenomenal prevalence in various types of real applications compared to most other AI strategy handling methods [9].

Research [10] uses deep learning to identify diseases affecting corn plants. A public database with 3,852 images of corn plant leaves was used, divided into four classes: healthy corn, exserohilum leaf spot (northern leaf blight), common corn rust, and cercosporiosis (cercospora leaf/gray leaf). The proposed model uses Convolutional Neural Networks (CNN) techniques for image classification. Four experiments showed results with an average accuracy above 94.5%. The proposed methodology is also combined with others such as using image processing techniques with deep learning. Deep learning-based methods help in the model of uncertainty in plant disease prediction [11]. Several studies have been presented to recognize and detect corn plant diseases using machine learning algorithms. This is a very challenging task due to high data variation and much previous work has been done in this field [12].

Another study explores various deep learning models, including ResNet50GAP, DenseNet121, VGG19, and custom Sequential models. DenseNet121 and VGG19 showed outstanding performance, achieving accuracies of 99.22% and 99.44%, respectively. This research is innovative because it integrates transfer learning and image augmentation, which enhances the model's

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generalization capabilities. A hybrid model combining features of ResNet50 and VGG16 achieved an impressive accuracy of 99.65% [13].

The problem of diseases in plants is the most common issue affecting mature plants. As a result of these attacks, the plant's ability to carry out the photosynthesis cycle decreases by 20% - 40% or even more prominently, making leaf rust render farmers' efforts futile and even causing losses [14]. Therefore, computerized methods capable of detecting various types of pests and diseases are needed [15].

In this research, the Convolutional Neural Network (CNN) algorithm will be used, enhanced by adding existing CNN architecture to detect diseases in corn leaves and also using optimizers to improve accuracy in detecting diseases in corn leaves. This research will produce an enhanced Convolutional Neural Network (CNN) by adding existing CNN architecture to detect diseases in corn leaves and also using optimizers to improve accuracy, which can help corn farmers detect diseased corn plants.

This research aims to compare and find the performance of the Optimization of Convolutional Neural Network (CNN) Method for Classifying Types of Corn Leaf Diseases Using CLAHE for detecting corn plant diseases with the public Kaggle dataset. There are several contributions from this research. First, the dataset consisting of 4188 images will be preprocessed by enhancing the images using CLAHE to become 1658 image data. Second, data augmentation will be performed, increasing the number to 4985 images. Third, the images will be resized to 128 x 128 pixels, and fourth, the data will be divided into three parts: training data, testing data, and validation data with proportions of 80%, 10%, and 10%, respectively.

Despite the visible symptoms of diseases on corn leaves, farmers frequently encounter difficulties in accurately identifying and differentiating these diseases, which hampers timely intervention and leads to reduced crop yields. Therefore, this study aims to develop and optimize a Convolutional Neural Network (CNN) model enhanced with Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve the classification accuracy of corn leaf diseases. The objectives include enhancing image quality for better feature extraction, tuning CNN hyperparameters for optimal performance, and validating the model’s effectiveness in classifying multiple disease categories to support practical agricultural applications.

II. LITERATURES REVIEW

Machine learning has been extensively used in agriculture to assist in the diagnosis and classification of plant diseases. Studies have demonstrated that machine learning algorithms, such as Convolutional Neural Networks (CNN), are particularly effective in identifying diseases on plant leaves. Research by [10] and [16] showed that CNN achieves high accuracy, ranging from 90% to 96%, in detecting diseases on maize leaves, outperforming traditional manual methods.

In addition, methods combining image feature extraction techniques, such as Gray Level Co-occurrence Matrix (GLCM) and color spaces (HSV), with classifiers like K-Nearest Neighbor (KNN) have also been explored. According to [17], this approach achieved a classification accuracy of 85% for maize leaf diseases. Similarly, research by [18] highlighted the comparative performance of CNN architectures, with MobileNet achieving the best results, an accuracy of 83.37%, showcasing its potential in agricultural applications.

The integration of machine learning into user-friendly applications can further enhance accessibility for farmers. [19] demonstrated the use of CNN-based systems to diagnose maize diseases with an accuracy of over 90%, ensuring rapid and reliable detection, thereby supporting improved crop management.

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III. FRAMEWORK

This corn leaf disease classification system uses the Convolutional Neural Network (CNN) algorithm optimized with Contrast Limited Adaptive Histogram Equalization (CLAHE) technique. The steps taken in this research are as follows:

Data Collection

Data was obtained from the public dataset "Corn or Maize Leaf Disease Dataset," which consists of 4188 images of corn leaves in four categories: healthy leaves, blight, common rust, and gray leaf spot.

Data Preprocessing

The image data was processed using the CLAHE technique to enhance image contrast. The images were separated into RGB color components, processed separately, and then recombined.

Data Augmentation

Data was augmented using techniques such as rotation (-25° to 25°) and horizontal flipping (50% probability).

Data Partitioning

The dataset was divided into three parts:

1. 80% for training.
2. 10% for testing.
3. 10% for validation.

Classification

The research used a CNN model based on the VGG-16 architecture, consisting of convolutional, pooling, and fully connected layers. The model was trained using the Adam optimizer with the best parameters, which are:

1. Batch size: 64
2. Epoch: 50
3. Image resolution: 128 x 128 piksel

Performance Evaluation

Evaluation was conducted using a confusion matrix, classification report, and accuracy and loss graphs. The model achieved an accuracy of 94%, with precision and recall each at 94%.

IV. METHODS

The research methodology employed in this study draws upon the framework established in prior research [3], encompassing several critical stages: dataset collection, data preprocessing, dataset partitioning, and the design of the classification model. This study is classified as experimental research, which is characterized by the systematic manipulation and control of variables to investigate their effects on outcomes. Through this approach, the researcher can isolate and examine the influence of specific parameters, such as hyperparameters in the convolutional neural network (CNN), on the classification performance of corn leaf diseases.

The experimental design includes controlled tests where variables such as optimizer type, batch size, and epoch number are adjusted methodically to optimize model accuracy and generalizability. This controlled environment ensures that the results obtained can be attributed with greater confidence to the modifications applied rather than external factors or random variability. Additionally, the experimental approach facilitates reproducibility and rigor, both essential for validating the efficacy of machine learning models in agricultural diagnostics.

Figure 1 illustrates the sequential stages involved in the classification process, beginning with the acquisition of a comprehensive and diverse dataset, followed by enhancement of image quality via preprocessing techniques including Contrast Limited Adaptive Histogram Equalization (CLAHE). Subsequent steps involve data augmentation to artificially expand the dataset and improve model robustness, and partitioning the dataset into distinct subsets for training, validation,

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and testing. Finally, the construction and training of the CNN model, based on the VGG-16 architecture, are undertaken, with performance evaluated through standardized metrics.

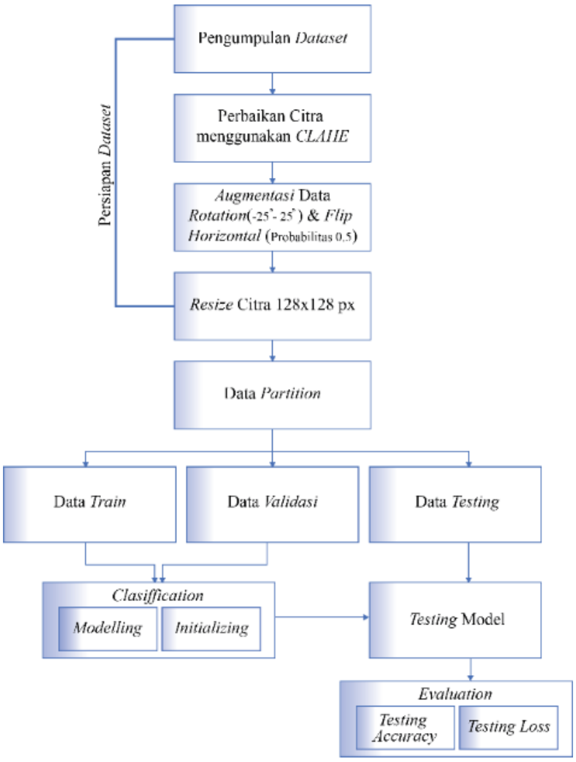

Figure 1. Research Method

Dataset Collection

The data used in this research was obtained from the Kaggle website, which is provided for machine learning and intelligent system projects. The keyword used to obtain this data is "Corn or Maize Leaf Disease Dataset." The images of diseases based on leaves were taken, which are colored and of different sizes with RGB color format.

The collected data consists of 4188 images of corn leaves in four categories, each with 1146 images of blight (leaf blight) characterized by corn leaf aphid disease starting with infection on the leaves, showing symptoms of small oval-shaped spots, which then expand to form circles and become necrotic; 1306 images of common rust (rust leaf) with side effects of rust disease starting with the appearance of red spots and fine powdery grains with soil pigmentation mixed with a bit of yellow; 574 images of gray leaf spot with underlying side effects of dull leaf spots appearing as small round lesions with yellow rings around the leaves; and 1162 images of healthy leaves, where healthy corn leaves are in a state where the leaf surface is almost perfect with no spots or stains [20], with varying sizes and in JPG format.

Figure 2. Blight Leaf Sample

Figure 3. Common Rust Leaf Sample

Figure 4. Gray Leaf Spot

Figure 5. Healthy

Image Enhancement with CLAHE

The next step involves separating the image data into red, green, and blue components. Each color component will then undergo the Contrast Limited Adaptive Histogram Equalization (CLAHE) process and be recombined to enhance the image.

CLAHE is an image processing method used to improve the contrast of input images. It is a variant of the histogram equalization method, which redistributes pixel values in an image to make the image histogram more evenly distributed. The goal of CLAHE is to enhance local contrast in the image while limiting the overall contrast enhancement to avoid excessively amplifying noise and other artifacts.

To avoid excessive contrast enhancement, a contrast limiting operation is applied to the histogram of each tile. This ensures that the contrast of each tile is not amplified beyond a certain threshold, determined by a parameter called the clip limit. CLAHE is widely used in medical image processing, where it can help improve the visibility of structures and details in low-contrast images. This method is also used in computer vision applications, such as object detection and recognition, where enhancing image contrast can make it easier to distinguish objects from their background [21].

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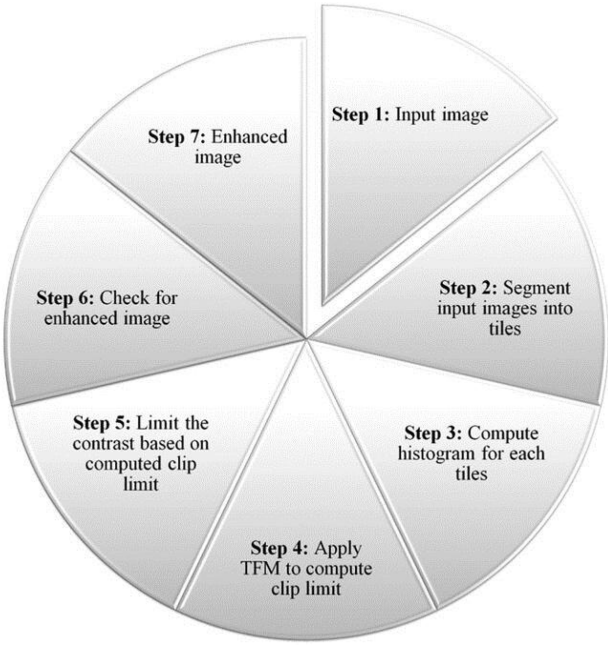

Figure 6. CLAHE Algorithm

The steps of the CLAHE algorithm are as follows:

1. Input the image
2. Segment the input image into tiles
3. Calculate the histogram for each tile
4. Apply TFM to calculate the clip limit
5. Limit the contrast based on the calculated clip limit
6. Check the enhanced image
7. Enhanced image

Data Augmentation

Image augmentation uses rotation techniques ranging from -25 to 25 degrees and flipping images with a probability of 0.5. To modify or enhance images, researchers can use techniques such as scale transformation, geometric transformation, flipping, rotation, cropping, scaling, and zooming. Researchers can also perform processes to extract information or descriptions of objects or identify objects present in the images, and they can perform data compression or reduction for data storage. The image is the input to the PCD, and the modified or processed image is the output [22].

Image Data Resizing

Corn disease images are first processed through pre-processing, which means resizing the images to 128 x 128 pixels. This is done to make the pixel size of the images smaller and the ideal image resolution easier for the system to read the input images, facilitating the image processing, and reducing the amount of storage space required for the images. As the number of pixels in the processed images increases, the longer the program takes to execute the images [23].

Data Partitioning

The author then divides the data into training, testing, and validation sets. While the training data is used to build or train the model, the testing set is used to test the model after the training process is complete. The testing set is created as unseen data so that the model or person cannot see the samples during the training process. The validation data is used to optimize the model during training, which helps generalize the model to recognize patterns in general [24]. In this process, the author partitions the data with 80% for training, 10% for testing, and 10% for validation.

Classification

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The deep neural network architecture VGG16 consists of 16 layers, as shown in Figure 2. The VGG16 architecture comprises 13 convolutional layers, 2 fully connected layers, and 1 classification layer.

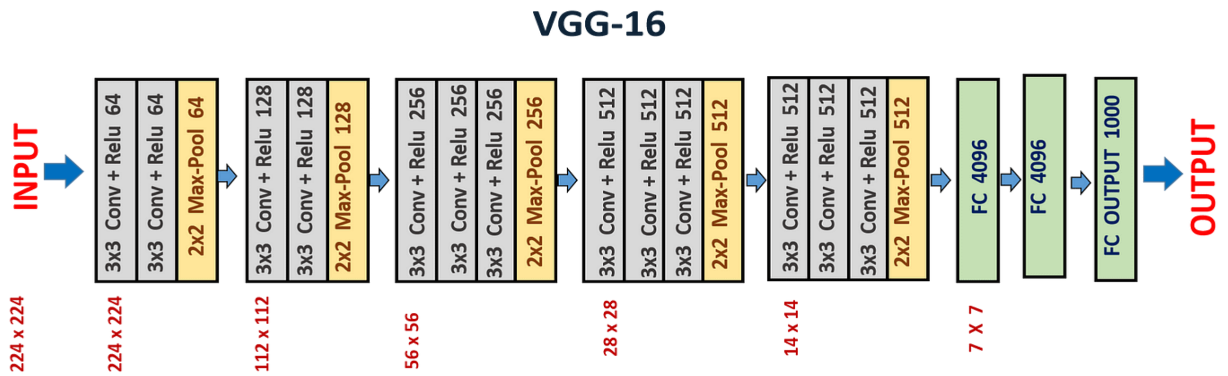

Figure 7. VGG-16 Architecture

All convolutional layers have a kernel size of 3x3 as shown in Figure 7. The number of channels is the main difference between each convolutional layer. The first layer has 64 channels, while layers 3 and 4 have 128 channels. Other convolutional layers differ, with 256 in layers 4, 5, and 6, and 512 in layers 7, 8, 9, 10, 11, and 12. The convolutions in layers 2, 4, 7, 10, and 13 result in a maximum pooling of 2x2. The final pooling result is connected to fully connected layers and will eventually be connected to the classifier to determine the image class [25].

Table 1. Hyperparameter

Parameter	**Tipe**
Optimizer	RMSProp, Adam
Batch Size	32, 64, 128
Epoch	10, 30, 50

Table 2. Computer Specifications

Name	**Parameter**
System	Nvidia GeForce RTX 4060
CPU processor	12th Gen Intel® Core™ i5-12450H (12 CPUs), ~2.0GHz
Graphics processor unit (GPU)	Nvidia GeForce RTX 4060 Laptop GPU
RAM	16 GB
Deep learning environment	JupyterLab 3.6.3
Programming language	Python

Evaluation

Here is a more detailed explanation: Classification is a component of supervised learning in ML/DL. Evaluating its performance is an important step in the ML/DL model life cycle. Confusion Matrix and Classification Report are two methods that can be used to examine the classification model [26]. Further explanation can be found here:

1. It is an N x N table, where N is the number of classes, labels, or categories, containing the number of correct and incorrect predictions from the classification model. The goal is to

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compare the actual values with the predicted values. Both the rows and columns of the matrix show the predicted and actual classes [26]. The Confusion Matrix values are divided into four categories:

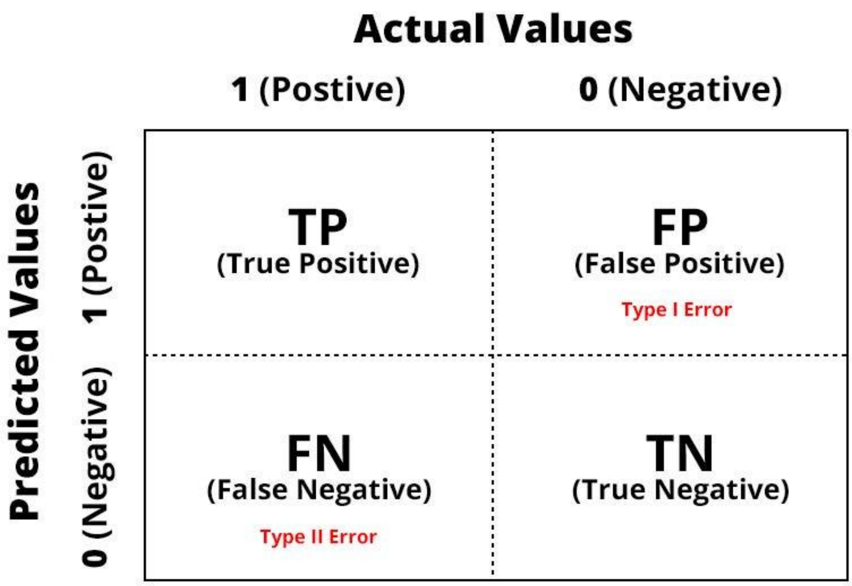

Figure 8. Confusion Matrix

2. **Classification Report**: Although the results of the Confusion Matrix are very detailed, it is still difficult to understand how well the model performs in classification. Therefore, data from the Confusion Matrix can be used to determine metrics that can measure the model's performance [26]. These are the metrics used:

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

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

$$Recall = \frac{TP}{TP + FN}$$

$$F1Score = 2\ x\ \frac{recall\ x\ precision}{recall + precision}$$

Figure 9. Classification Report

In this study, hyperparameter optimization for the Convolutional Neural Network (CNN) model was conducted through manual experimentation. Key parameters such as optimizer type (Adam and RMSProp), batch size (32, 64, 128), and number of epochs (10, 30, 50) were systematically tested to identify the combination that yields the highest classification accuracy. While this empirical trial-and-error approach allowed for practical tuning of the model, it is acknowledged as a limitation due to its potentially suboptimal exploration of the hyperparameter space. Automated optimization techniques, such as grid search, random search, or Bayesian optimization, were not employed, which could offer more comprehensive and efficient hyperparameter tuning in future work.

V. RESULT

This research uses the VGG-16 architecture for classifying diseases on corn leaves. VGG-16 is a deep neural network architecture consisting of 16 layers, as shown in Table 3. The VGG-16 architecture comprises 13 convolutional layers, 2 fully connected layers, and 1 classification layer.

Table 3. VGG-16 Model

Layer (type)	Output Shape	Param
input_1 (InputLayer)	[(None, 128, 128, 3)]	0
block1_conv1 (Conv2D)	(None, 128, 128, 64)	1792
block1_conv2 (Conv2D)	(None, 128, 128, 64)	36928
block1_pool (MaxPooling2D)	(None, 64, 64, 64)	0
block2_conv1 (Conv2D)	(None, 64, 64, 128)	73856
block2_conv2 (Conv2D)	(None, 64, 64, 128)	147584
block2_pool (MaxPooling2D)	(None, 32, 32, 128)	0
block3_conv1 (Conv2D)	(None, 32, 32, 256)	295168
block3_conv2 (Conv2D)	(None, 32, 32, 256)	590080
block3_conv3 (Conv2D)	(None, 32, 32, 256)	590080
block3_pool (MaxPooling2D)	(None, 16, 16, 256)	0
block4_conv1 (Conv2D)	(None, 16, 16, 512)	1180160
block4_conv2 (Conv2D)	(None, 16, 16, 512)	2359808
block4_conv3 (Conv2D)	(None, 16, 16, 512)	2359808
block4_pool (MaxPooling2D)	(None, 8, 8, 512)	0
block5_conv1 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv2 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv3 (Conv2D)	(None, 8, 8, 512)	2359808
block5_pool (MaxPooling2D)	(None, 4, 4, 512)	0

In Table 3, all convolutional layers have a kernel size of 3x3. The main difference between each convolutional layer lies in the number of channels in each layer. Each convolutional layer has 64 channels, while layers 3 and 4 have 128 channels. Other convolutional layers also differ, with 256 channels in layers 4, 5, and 6, and 512 channels in layers 7, 8, 9, 10, 11, and 12. After the convolutions in layers 2, 4, 7, 10, and 13 are performed, a 2x2 pooling is done. The result of this pooling is connected to fully connected layers and will eventually be connected to the classifier to determine the image class [25].

Next, the dataset is tested. The method testing is conducted using the Original Dataset, the Dataset with Enhanced Images using CLAHE, and the Enhanced Dataset with hyperparameter tuning using 2 optimizers. Table 4 shows the experimental results using the RMSProp and Adam Optimizers.

Table 4. RMSProp And Adam Optimizers

Optimizer	Split Data	Batch Size	Epoch	Akurasi
RMSProp	80%	64	10	0.8855
Adam	80%	64	10	0.9284

The results of the data implementation trials will determine the highest accuracy value obtained; this value is achieved using the Adam Optimizer. This value will then be used for the next trial, which will identify the dataset enhanced with CLAHE.

Table 5. Original & Clahe Dataset

Optimizer	Split Data	Optimizer	Batch Size	Epoch	Akurasi
Original	80%	Adam	64	10	0.9093
Perbaikan Citra (CLAHE)	80%	Adam	64	10	0.9284

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The results of the data implementation trials will determine the highest accuracy value, which is achieved using CLAHE. This value will then be used for the next trial, which determines the batch size. The trial to determine the batch size is conducted by inputting batch sizes of 32, 64, and 128. These values are chosen because they are popular batch size values.

Table 6. Experiment Results For Determining Batch Size

Optimizer	Split Data	Optimizer	Batch Size	Epoch	Akurasi
Perbaikan Citra (CLAHE)	80%	Adam	32	10	0.9141
Perbaikan Citra (CLAHE)	80%	Adam	64	10	0.9284
Perbaikan Citra (CLAHE)	80%	Adam	128	10	0.8855

Based on the trials for batch size values, the highest accuracy value obtained from the trials is with a batch size of 64, which is used for the next trial to determine the ideal number of epochs.

Table 7. Experiment Results For Determining Number Of Epochs

Optimizer	Split Data	Optimizer	Batch Size	Epoch	Akurasi
Perbaikan Citra (CLAHE)	80%	Adam	64	10	0.9141
Perbaikan Citra (CLAHE)	80%	Adam	64	30	0.9427
Perbaikan Citra (CLAHE)	80%	Adam	64	50	0.9448

Based on the trial results, the most appropriate number of epochs is chosen based on the highest accuracy value obtained, which is 50 epochs. Therefore, the VGG-16 CNN model used for this research provides the best results. Image enhancement using CLAHE and data augmentation, using the "Adam" optimizer, with a batch size of 64 and 50 epochs, can achieve the highest accuracy of 80% training, 10% validation, and 10% testing at 94.48%. Next, the accuracy and loss graphs between the training and validation data will be displayed to determine if the model is experiencing overfitting, underfitting, or good fit.

Below are the graphs showing the loss and accuracy values for the training and validation data.

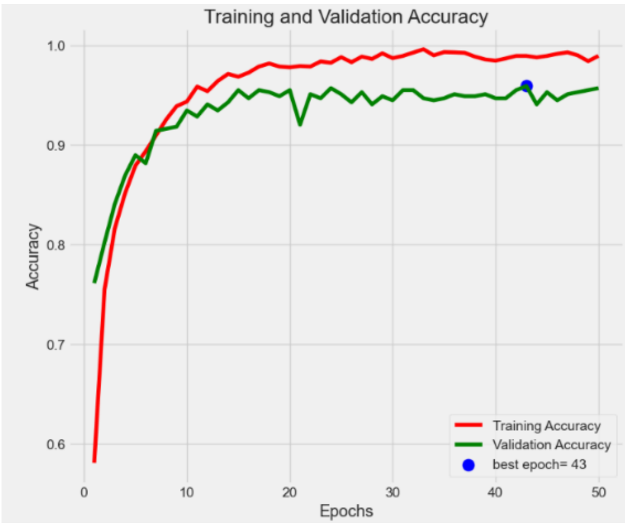

Figure 10. Training and Validation Accuracy Graph

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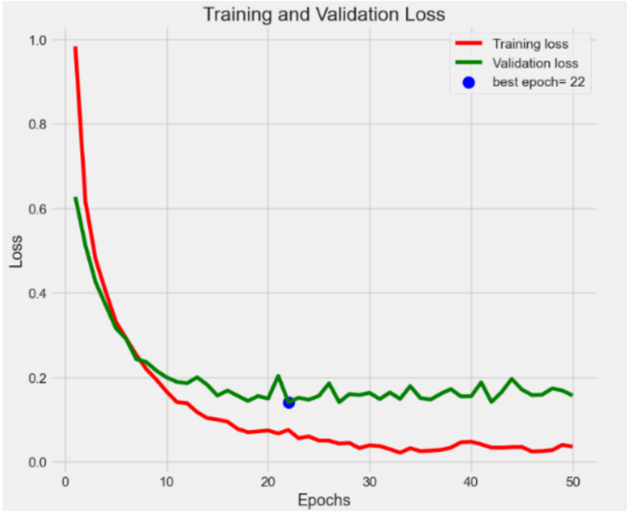

Figure 11. Training and Validation Loss Accuracy Graph

Figure 10 shows the accuracy graph for the training and validation data, and Figure 11 shows the loss graph for the training and validation data. The red line represents the training data, and the green line represents the validation data. From the accuracy and loss graphs for the training and validation data, it indicates good performance, where the accuracy value shows a stable increase and the loss value shows a stable decrease, indicating that the model does not experience overfitting or underfitting. Next, the classification results of corn leaf disease using test data will be displayed through testing using test data. The results can be seen in Figure 12 for the CNN VGG-16 model.

Figure 12. Corn Leaf Disease Classification Detection Results

Out of 4985 test images, 20 sample classification results are displayed. The classification results of the 20 corn leaf sample images show that all tested sample data were correctly classified. Blue color indicates that the data is correctly classified according to its class, while if the classification is incorrect, it will be shown in red.

The values of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) are included in the classification matrix and evaluation process. Each possible actual

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occurrence is either positive (P) or negative (N). The classification report can show accuracy, recall, and precision. Figure 13 displays the results of the confusion matrix.

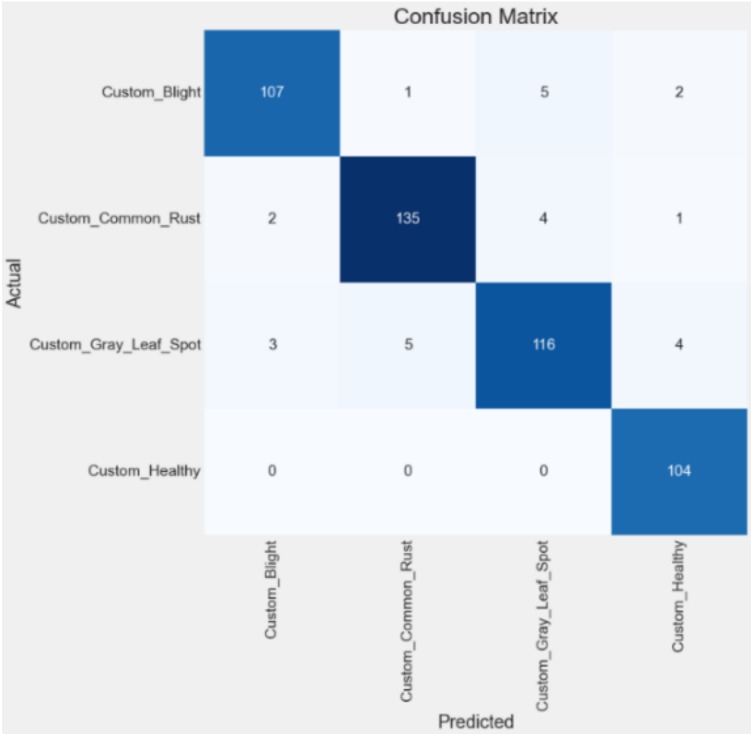

Figure 13. Confusion Matrix

Based on Figure 13, the classification results of the model on the test data show good results. In this case, there are 462 test images, including:

1. Blight images classified as Blight. The total number of test data for Blight leaf images is 95.
2. 132 Common Rust images classified as Common Rust. The total number of test data for Common Rust images is 132.
3. 106 Gray Leaf Spot images classified as Gray Leaf Spot. The total number of test data for Gray Leaf Spot images is 106.
4. 103 healthy images classified as healthy. The total number of test data for healthy images is 103.

Table 8. Experiment Results For Determining Number Of Epochs Classification Report Results For Accuracy, Precision & Recall

	Precicion	**Recall**	**F1-score**	**Support**
Custom Blight	0.96	0.93	0.94	115
Custom Common Rust	0.96	0.95	0.95	142
Custom Gray Leaf Spot	0.93	0.91	0.92	128
Custom Healthy	0.94	1.00	0.97	104
Accuracy			0.94	489
Macro Avg	0.94	0.95	0.95	489
Weighted Avg	0.94	0.94	0.94	489

From Table 8, the Confusion Matrix and Classification Report show that the CNN:VGG-16 model can classify types of corn leaf diseases well. The accuracy obtained is 94%, with a precision value of 94% and a recall value of 94%.

Despite the promising results achieved with the VGG-16 architecture, a notable limitation of this study is the absence of comparative evaluations with other advanced deep learning models such as ResNet, DenseNet, or EfficientNet. These architectures have demonstrated superior performance in various image classification tasks and could potentially enhance disease classification accuracy or robustness. Future research should incorporate such models to comprehensively assess the generalizability and relative effectiveness of the proposed CLAHE-enhanced CNN approach.

VI. DISCUSSION

Based on the results of classifying corn leaf diseases using the Convolutional Neural Network (CNN) method optimized with Contrast Limited Adaptive Histogram Equalization (CLAHE), it was found that this approach achieves high accuracy in detecting various corn leaf disease conditions. The CNN model demonstrated a strong capability to handle complex image data, making it effective in identifying disease patterns from diverse and high-dimensional datasets. The inclusion of CLAHE as a preprocessing step significantly enhanced the contrast of input images, improving the model's feature extraction process and classification accuracy.

The use of the CLAHE-enhanced CNN in this study proved capable of distinguishing between healthy corn leaves and diseased ones, providing farmers and agricultural stakeholders with an effective decision-making tool. Test results indicated that optimizing the CNN model, combined with carefully selected hyperparameters and data augmentation techniques, resulted in a classification accuracy of 94%. This demonstrates the model's ability to generalize well across different scenarios, ensuring reliable disease detection.

Implementing the CLAHE-enhanced CNN model into practical applications, such as mobile platforms or IoT devices, allows users to benefit from machine learning technology in identifying diseases more quickly and accurately. This solution not only assists in analyzing and interpreting agricultural data but also facilitates proactive measures to address potential threats to crop yields. Notifications or early warnings based on model outputs can encourage farmers to take timely and appropriate actions to mitigate disease impacts.

This research emphasizes the importance of preprocessing methods like CLAHE in improving model performance. Furthermore, the results underline the value of integrating advanced machine learning techniques into agriculture, supporting the development of smart farming solutions that enhance productivity and sustainability.

VII. CONCLUSION

Several conclusions were made based on the analysis process and results, including:

1. Image enhancement of corn leaves using the Optimization of Convolutional Neural Network (CNN) Method for Classifying Types of Corn Leaf Diseases Using CLAHE. The CNN method was used to classify images of diseased corn leaves by comparing datasets that used CLAHE and those that did not use CLAHE.
2. Additionally, comparisons of parameters such as epochs, types of optimizers, batch sizes, and dataset scenarios were used to find the best architectural design. The results of considering various parameters for classifying images of corn leaf types, including Blight, Gray Leaf Spot, Common Rust, and Healthy leaves that have been enhanced with CLAHE, are as follows: using parameters of 128 x 128 pixels image size, 3 x 3 kernel size, 0.01 learning rate, Adam optimizer type, 50 epochs, 64 batch size, and dataset comparison scenario of 80%:10%:10% with RGB (colored) images, achieving 94%.
3. The Optimization of the Convolutional Neural Network (CNN) Method for Classifying Types of Corn Leaf Diseases Using CLAHE resulted in an accuracy of 94%, precision of 94%, and recall of 94%. These values indicate that this experiment can be used to classify corn leaf diseases.

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For future research, it is imperative to expand the evaluation of the proposed CLAHE-enhanced Convolutional Neural Network (CNN) model beyond corn to encompass a wider range of crop species. This would allow for a comprehensive assessment of the model's generalizability and adaptability to different plant disease phenotypes and agricultural conditions. Additionally, implementing this model within mobile applications or Internet of Things (IoT) frameworks could enable real-time, on-site disease detection, significantly improving accessibility for farmers and agricultural practitioners, especially in remote or resource-limited settings.

Moreover, the exploration of more advanced deep learning architectures such as ResNet, DenseNet, or EfficientNet could provide improvements in classification accuracy, computational efficiency, and robustness against variability in image data. Alongside architectural advancements, incorporating automated hyperparameter optimization methods, including grid search, random search, or Bayesian optimization, would facilitate a more systematic and exhaustive tuning process, likely yielding superior model performance.

Integrating these enhancements could accelerate the transition from experimental models to deployable, user-friendly tools that assist in early diagnosis and management of plant diseases. Ultimately, this study contributes to the development of scalable, efficient, and field-ready technological solutions for plant disease detection, which play a critical role in promoting sustainable agricultural practices and ensuring food security through improved crop health management.

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