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Deep Learning-Based CNN for Tea Leaf Disease Classification

Febrian abie pratama[1]*, Miftahus solihin[2], Siti mujilahwati[3]

[1,2,3]Universitas Islam Lamongan
febrianabiepratama@gmail.com[1*], mitahus.solihin@unisla.ac.id[2], Siti.mujilahwati@mail.com[3]

Abstract

Tea leaf diseasve is one of the main factors affecting the quality and quantity of tea plant production. Early detection and accurate classification of leaf disease types are essential to prevent wider damage. This study aimed to develop a digital image-based tea leaf disease classification system using the DenseNet121 architecture with a Transfer Learning approach. The tea leaf image dataset used came from the Kaggle platform, which consisted of eight classes: Algal Leaf, Anthracnose, Bird Eye Spot, Brown Blight, Gray Blight, Red Leaf Spot, White Spot, and Healthy.
The model was developed through four training scenarios with varying numbers of epochs (20, 40, 60, and 80) to evaluate the effect of training duration on classification performance. The macro average approach was used to evaluate each scenario using accuracy, precision, recall, and F1-score metrics. The best results were obtained in scenario 4 (Epoch 80), with an accuracy of 92.57%, macro precision 92.91%, macro recall 92.49%, and macro F1-score 92.47%. These results indicated that DenseNet121 was able to classify tea leaf diseases effectively and accurately.
This study demonstrates the potential of the DenseNet architecture as a Deep Learning-based solution in detecting plant diseases and opens up opportunities for the development of decision support systems in agriculture.

Keywords: *Deep Learning, DenseNet121, Tea Leaves, Image Classification, Plant Diseases, Transfer Learning.*

1. Introduction

Tea (*Camellia sinensis*) is one of Indonesia's leading plantation commodities with high economic value, playing a vital role as a source of income for farmers as well as a raw material for the processing industry. Generally cultivated in highland areas with a cool climate, the main tea-producing regions in Indonesia include West Java, Central Java, and North Sumatra, with West Java contributing more than 70% of the national production. The types of tea derived from *Camellia sinensis* are distinguished based on their level of fermentation, namely green tea (unfermented), white tea and yellow tea (lightly fermented), oolong tea (semi-fermented), black tea (fully fermented), and pu-erh tea (post-fermented). In China, tea is commonly classified into six main categories: white, green, yellow, oolong, black, and post-fermented. In Indonesia, tea production remains dominated by black tea for export markets, while green, white, and oolong teas are produced in smaller quantities for niche markets.

Traditional methods that rely on manual observation, however, have significant limitations, including dependence on worker expertise, potential subjectivity, and time inefficiency. These challenges hinder consistency in quality control and operational efficiency in plantations. Consequently, a technology-driven approach is required to enable more accurate and efficient classification and detection processes.

With the advancement of artificial intelligence, Convolutional Neural Networks (CNNs) have been widely applied in plant image classification. Several studies have shown that CNNs can detect diseases in tea leaves with high accuracy. These findings affirm that CNN-based approaches can support rapid and reliable identification of plant diseases, thereby assisting farmers in improving plantation productivity [1].

Subsequent research has explored the implementation of Convolutional Neural Networks (CNNs) in leaf classification using data mining techniques. These studies demonstrated that CNNs are capable of recognizing complex visual patterns in leaf images and producing highly accurate classifications, confirming CNN as an effective method for agricultural image data processing [2].

The application of CNN is not limited to tea but also extends to other plantation commodities; for instance, studies have shown that CNN combined with transfer learning can classify apple leaf diseases with higher accuracy. Transfer learning has been proven to accelerate the training process while improving model performance in plant disease recognition [3].

In the context of tea quality, research on classifying the maturity levels of tea shoots using CNN revealed that CNN can assist in determining leaf maturity, which directly affects the flavor and overall quality of processed tea, thereby proving its relevance not only for plant health but also for product quality assessment [4].

Furthermore, other studies compared several CNN transfer learning architectures for classifying crop diseases, showing that architectural selection significantly influences the accuracy achieved, making model choice a crucial factor in developing CNN-based agricultural systems [5].

This research also provides an in-depth review of the fundamental principles of Convolutional Neural Networks (CNNs) and their applications across various domains, including agricultural image classification. The study emphasizes that CNNs are capable of automatically extracting complex visual features without requiring manual feature engineering, making them highly suitable for tasks such as plant disease and crop quality classification [6].

Furthermore, it highlights the superiority of CNNs over traditional methods in classifying tea leaf diseases, as CNN models can identify disease symptoms more consistently and accurately, resulting in more reliable classification outcomes [7].

Beyond tea or apple classification, CNNs have also been successfully applied to other agricultural commodities, such as oil palm, where CNN-based models have proven effective in assessing seedling quality. Such applications assist farmers in selecting superior seedlings, thereby significantly improving plantation productivity [8].

The present study focuses on the application of the DenseNet121 architecture to classify diseases on tea leaves. The main issues addressed are how DenseNet121 can be applied for leaf disease classification and how accurately the model performs in identifying different types of tea leaf diseases using image-based datasets. To ensure a clear research scope, this study is limited to disease types available in the dataset, with image data collected from open datasets or acquired through specific techniques. Furthermore, the model used in this research is restricted to the DenseNet architecture, particularly DenseNet121, and evaluation of model performance is limited to classification metrics such as accuracy, precision, recall, and F1-score.

The objectives of this research are to implement the DenseNet121 architecture in developing an image-based classification model for tea leaf diseases, to evaluate its accuracy and performance in identifying various types of diseases, and to provide a classification system that can serve as an early detection tool for tea plant health monitoring.

The expected benefits of this research include providing a more accurate and efficient system for detecting tea leaf diseases, supporting farmers and the tea industry in monitoring processes and decision-making for plant disease management in a faster and more precise manner, and contributing scientifically by demonstrating the potential of CNN-based architectures, specifically DenseNet121, for agricultural disease detection task.

2. Research Methodology

The type of research conducted in this study is applied research, which aims to implement existing theories or methods to address real-world problems—in this case, the classification of tea leaf diseases using Deep Learning technology. The focus of this research is to develop an automated image-based classification model by employing the pretrained DenseNet121 architecture through transfer learning and fine-tuning.

A quantitative experimental approach was adopted, as the collected data consisted of tea leaf images analyzed numerically using evaluation metrics. Experiments were carried out by training the Deep Learning model and assessing its performance based on accuracy, precision, recall, and F1-score. The results of this approach were then used to draw conclusions regarding the effectiveness of the model in automatically classifying tea leaf diseases.

2.1 Research Flow

The research workflow consists of six integrated stages: literature review, dataset acquisition, data preprocessing, DenseNet121 implementation, model training, and performance evaluation, as illustrated in Figure 1. Each stage is designed to complement one another, beginning with a theoretical foundation and prior studies, followed by data collection and preparation to ensure readiness for model input. Afterward, the DenseNet121 architecture is implemented, and the model is trained on the dataset to learn patterns of tea leaf diseases. The final stage, performance evaluation, serves as a key step to assess the system's effectiveness in meeting its objectives while also identifying the strengths and limitations of the model. With this structured workflow, the study aims to produce a classification system that is methodologically sound and relevant for further development.

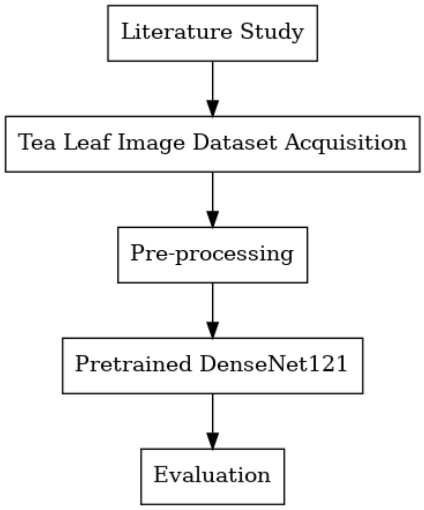

Fig. 1: Research Flow

2.2 Tea Leaf Image Dataset Acquisition

At this stage, the dataset of tea leaf images is collected as the primary input for the study. The dataset can be obtained from open-access image repositories or through direct image acquisition using digital cameras in the field. The collected images represent various conditions of tea leaves, including healthy leaves and those affected by different diseases.

2.3 Pre-processing

In this phase, the raw tea leaf images are preprocessed to improve data quality and ensure consistency before training. Pre-processing includes resizing images, normalization, noise reduction, and data augmentation techniques such as rotation, flipping, and contrast adjustment. These steps are essential to prepare the dataset and reduce the risk of overfitting in the model.

2.4 Pretrained DenseNet121

At this stage, the DenseNet121 architecture is applied as the core model for classification. The model is pretrained on large-scale datasets such as ImageNet, which provides a strong feature extraction capability. The pretrained model is then fine-tuned using the tea leaf dataset to classify different types of leaf diseases with higher accuracy.

2.5 Evaluation

In the final stage, the trained model is evaluated to measure its performance. Evaluation is conducted using classification metrics such as accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of the model's effectiveness in identifying tea leaf diseases, and the results are analyzed to determine the reliability of the system in practical applications.

3. Result and Discussion

3.1 Data Collection

Dataset is a crucial component in machine learning and deep learning research. In this study, the dataset consists of tea leaf images downloaded from Kaggle, a widely used and reliable platform for data sharing and science competitions. The dataset contains labeled images of tea leaves, including both healthy samples and those affected by diseases such as Algal Leaf, Bird Eye Spot, Anthracnose, Brown Blight, Gray Blight, Red Leaf Spot, and White Spot.

The images are organized into class-based folders to ensure compatibility with deep learning frameworks such as TensorFlow/Keras. To reduce bias, the number of samples per class is balanced, and augmentation techniques are applied when necessary. Low-quality or irrelevant images are removed to maintain dataset reliability, In total, 882 tea leaf images are used in this research, divided into 70% training data, 10% validation data, and 20% testing data, as shown in Table 1.

Table. 1: The dataset for this research

Class Name	Data Training	Data Testing	Total
Algal Leaf Spot	91	22	103
Bird Eye Spot	80	20	100
Anthracnose	79	20	99
Brown Blight	91	22	103
Gray Blight	80	20	100
Healthy	60	13	73
Red Leaf *Spot*	114	29	143
White *Spot*	113	28	141
Total	708	174	882

The division of the dataset is intended to ensure that the training process achieves a balance between the model's learning ability and its capacity to generalize to new data. With this composition, the training data is used to build the model's knowledge, the validation data serves to monitor performance and prevent overfitting, while the testing data is employed to evaluate the final performance of the model on previously unseen conditions.

3.2 Pre-processing

Pre-processing is a crucial step in the machine learning pipeline, especially in digital image processing. Its main goal is to ensure that input data is uniform, properly formatted for the deep learning architecture, and free from unnecessary noise that may disrupt training.

In this study, the pre-processing of tea leaf images consists of three main steps: (1) Resizing all images to 224 × 224 pixels to match the standard input of pretrained models such as DenseNet121; (2) Pixel normalization by scaling values from 0–255 to the [0,1] range to stabilize training and improve convergence; and (3) Data augmentation, including random rotations, flips, zooming, shearing, and shifting, to increase dataset diversity and reduce overfitting.

Through these steps, the tea leaf dataset is properly prepared for fine-tuning with DenseNet121, ensuring that input quality supports optimal classification performance.

3.3 Pretrained DenseNet121

Several After the pre-processing stage, the input images are ready to be processed by a deep learning model. This study employs DenseNet121 as the base model, which was pretrained on the ImageNet dataset Figure 2. The implementation uses a fine-tuning approach, allowing the model weights to adapt to the specific characteristics of tea leaf images. The training process is conducted using the preprocessed dataset divided into training, validation, and testing sets. Key parameters such as batch size, learning rate, and number of epochs are adjusted to optimize learning. Performance metrics are monitored during training to prevent overfitting and ensure good generalization to new data. Finally, the model is evaluated using metrics such as accuracy, precision, recall, F1-score, and a confusion matrix. These evaluations measure the model's ability to correctly classify tea leaf diseases and provide insights into its potential application for automated plant disease detection in real-world scenarios.

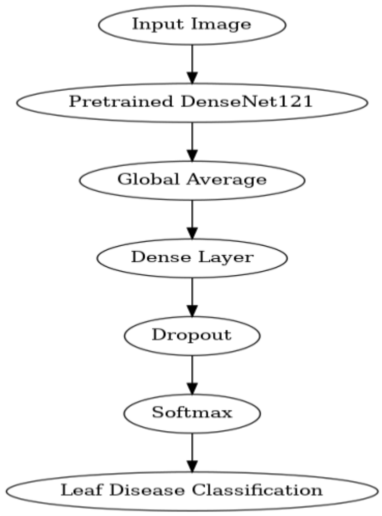

Fig. 2: The Architecture of the DenseNet121 Model

The implementation flow of the model can be summarized as follows. Preprocessed tea leaf images with a resolution of 224×224 pixels and normalized values are used as input, representing visual features such as texture, color, and patterns. These images are processed using the pretrained DenseNet121 architecture, where most early layers are frozen and only the final layers are fine-tuned for the tea leaf disease classification task. The output feature maps are reduced using Global Average Pooling to produce compact feature vectors, which are then passed through a Dense layer for classification. A Dropout layer with a rate of 0.5 is applied to prevent overfitting. Finally, the Softmax activation function generates probability distributions across disease classes, enabling the model to classify the input image into categories such as Red Rust, Brown Blight, or Gray Blight.

This implementation leverages transfer learning from DenseNet121, ensuring efficient computation and high accuracy while adapting to the specific characteristics of tea leaf disease detection.

3.4 Evaluation

After training the DenseNet121 model with the tea leaf image dataset, the next step is evaluation to measure its performance in accurately and reliably classifying tea leaf diseases. The evaluation is conducted using the testing set, which consists of unseen data, thereby reflecting the model's effectiveness in real-world scenarios.

The evaluation employs several metrics:

1. Accuracy

Measures the proportion of correct predictions compared to the total number of samples, commonly used when class distribution is balanced..

2. Precision

Indicates how many of the samples predicted as positive are truly positive.

3. Recall

Reflects the model's ability to detect all actual positive samples.

4. F1-score

The harmonic mean of Precision and Recall, useful for balancing both metrics, especially in imbalanced datasets.

3.5 Experimental Results

The experimental results were obtained through four training scenarios with different epoch settings: 20, 40, 60, and 80. Each scenario was analyzed to evaluate the model's performance in classifying tea leaf diseases and to assess its stability and generalization on validation data.

The evaluation included accuracy and loss graphs as well as classification metrics such as accuracy, precision, recall, and F1-score for each class. These metrics are important since some disease categories share similar visual features, which may affect classification performance.

By comparing the four scenarios, the study aimed to identify the impact of epoch variation on model performance and to determine the optimal balance between underfitting and overfitting. The results were also compared with previous studies using other deep learning architectures to highlight the advantages of DenseNet121 in agricultural disease classification.

1. Scenario 1 Using 20 Epochs

In the first scenario, the DenseNet121 model was trained on tea leaf disease images for 20 epochs. The aim was to observe the model's ability to recognize and classify images with a minimal number of epochs. Training was conducted using the Adam optimizer and categorical crossentropy loss, with a consistent training–validation split across all scenarios.

As shown in Figure 3, training accuracy steadily increased from around 15% to 82%, while validation accuracy also improved to about 80%. However, the validation curve was more fluctuating than the training curve, indicating that the model was not yet fully stable in generalizing to new data. This suggests that after 20 epochs, the model began to capture distinguishing visual patterns of tea leaf diseases, but had not yet reached optimal convergence.

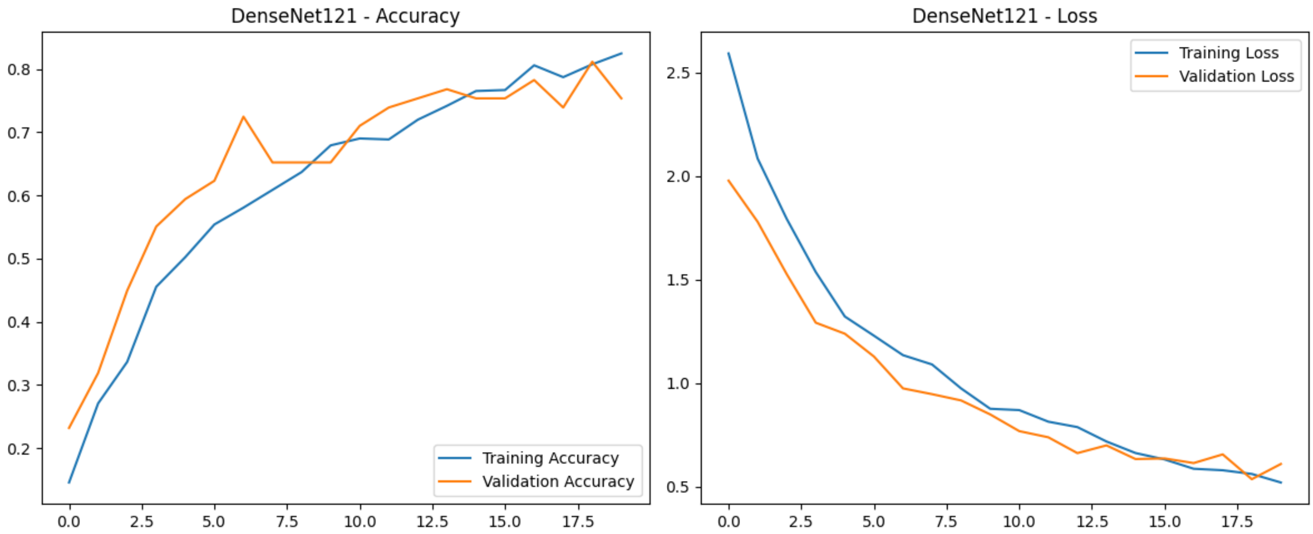

Fig. 3: Training, Validation Accuracy, Training Loss, and Validation with Epoch 20

The loss curve in Figure 3 shows a steady decrease for both training and validation data, with training loss dropping from about 2.5 to 0.5 and validation loss from around 2.0 to a similar value. No signs of overfitting are observed, as the validation curve declines in parallel with training. This indicates that the model is still learning and further epochs could improve performance.

Meanwhile, training accuracy rises consistently from roughly 15% to 82%, while validation accuracy increases to about 80%, though with more fluctuations. This suggests the model can identify key visual patterns but has not yet reached optimal convergence within 20 epochs. Additional epochs or regularization strategies may enhance its stability and overall performance.

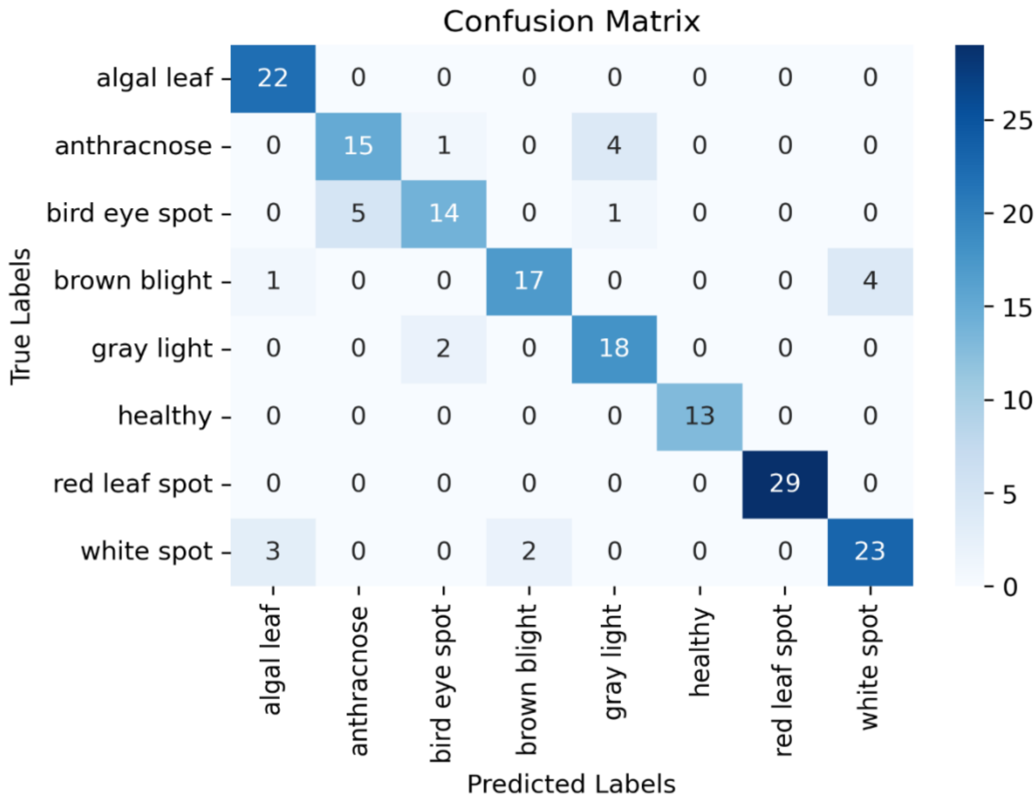

Fig. 4: Confusion Matrix with Epoch 20

After the training process, the model was evaluated using a Confusion Matrix, as shown in Figure 4. The results indicate that the model classified *Algal Leaf, Healthy,* and *Red Leaf Spot* with perfect accuracy, without any misclassification. For *Anthracnose*, 15 samples were correctly classified, while 5 were misclassified (1 as *Bird Eye Spot* and 4 as *Gray Blight*). The *Bird Eye Spot* class achieved 14 correct predictions, with 5 misclassified as *Anthracnose* and 1 as *Gray Blight*. For *Brown Blight*, 17 samples were correctly identified, but 1 was misclassified as *Algal Leaf* and 4 as *White Spot*. The *Gray Blight* class had 18 correct predictions, with 2 misclassified as *Bird Eye Spot*. Finally, *White Spot* had 23 correct predictions, with 3 misclassified as *Algal Leaf* and 2 as *Bird Eye Spot*.

Following this classification, the model's performance was quantitatively evaluated by calculating True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) values for each class, based on the Confusion Matrix distribution. These metrics provide insight into how well the model recognizes each tea leaf disease category.

Table. 2: TP, FP, TN and FN values with Epoch 20

Kelas	TP	FP	FN	TN
Algal Leaf	22	4	0	148
Anthracnose	15	5	5	149
Bird Eye Spot	14	3	6	151
Brown Blight	17	2	5	150
Gray Blight	18	5	2	149
Healthy	13	0	0	161
Red Leaf *Spot*	29	0	0	145
White *Spot*	23	4	5	142

True Positive (TP) represents the number of correct predictions when the model successfully classifies an image into the right class. False Positive (FP) refers to incorrect predictions where the model misclassifies images from other classes into a certain class. False Negative (FN) indicates instances where data from a class is misclassified into another, while True Negative (TN) shows the number of predictions correctly excluded from the analyzed class. The TP, FP, FN, and TN values are presented in Table 2.

Based on these values, key evaluation metrics are calculated: accuracy, precision, recall, and F1-score. Accuracy measures the overall proportion of correct predictions, precision reflects the correctness of predictions for a specific class, recall evaluates the model's ability to identify all instances of a class, and F1-score provides a balanced measure by combining precision and recall. The confusion matrix results for Epoch 20 are shown in Table 3.

Table. 3 : Accuracy, precision, recall, and f1-score values with Epoch 20

Kelas	Akurasi(%)	*Precision*(%)	*Recall*(%)	F1-Score(%)
Algal Leaf	97.7	84.6	100	91.6
Anthracnose	94.25	75	75	75
Bird Eye Spot	94.82	82.35	70	75.67
Brown Blight	95.97	89.47	77.27	82.92
Gray Blight	95.97	78.26	90	83.72
Healthy	100	100	100	100
Red Leaf *Spot*	100	100	100	100
White *Spot*	94.82	85.18	82.14	83.63

Based on the evaluation metrics in Table 3, the DenseNet121 model demonstrated strong performance in several classes, particularly Healthy and Red Leaf Spot, where precision, recall, and F1-score reached 100, indicating flawless predictions. However, the performance was weaker in certain classes. For example, Bird Eye Spot achieved a recall of only 70, suggesting many instances were misclassified, while Anthracnose showed lower precision and recall (both at 75), reflecting prediction inconsistencies. Overall, most classes obtained F1-scores above 0.8, with per-class accuracy ranging from 0.93 to 1.00. These results indicate that by the 20th epoch, the model effectively recognized most tea leaf disease patterns, though further improvements are needed for visually overlapping classes such as Anthracnose and Bird Eye Spot

2. Discussion of Experimental Results

Based on the evaluation of four training scenarios using DenseNet121, the model's performance varied with changes in the number of epochs. The evaluation was carried out using four main metrics—accuracy, macro precision, macro recall, and macro F1-score—as summarized in Table 4. In the first scenario with 20 epochs, the model achieved an accuracy of 86.78%, macro precision of 86.86%, macro recall of 86.80%, and macro F1-score of 86.58%. These results indicate that even at an early stage, the model was able to perform classification fairly well, although its performance remained moderate as the F1-score had not yet reached 90%.

Table. 4 : Comparison of Accuracy, Macro Precision, Recall, and F1-Score in Each Scenario

Skenario	*Epoch*	Akurasi (%)	Macro *Precision* (%)	Macro *Recall* (%)	Macro F1 Score (%)
1	20	86.78	86.86	86.80	86.58
2	40	91.38	91.88	91.51	91.41
3	60	87.36	87.77	87.61	87.31
4	80	92.57	92.91	92.49	92.47

In the second scenario with 40 epochs, the model's performance improved significantly, achieving 91.38% accuracy, with macro precision, recall, and F1-score reaching 91.88%, 91.51%, and 91.41% respectively. These results indicate a near-optimal condition with good balance across classes. However, in the third scenario (60 epochs), performance slightly declined to 87.36% accuracy, suggesting mild overfitting where the model adapted too closely to the training data and lost generalization ability. In contrast, the fourth scenario (80 epochs) produced the best results, with accuracy of 92.57%, macro precision of 92.91%, recall of 92.49%, and F1-score of 92.47%. Overall, the findings show that increasing epochs improves performance up to a certain point, with 80 epochs emerging as the most effective configuration for achieving high accuracy and balanced classification.

3. Tea Leaf Disease System Interface

In the final stage of this research, a web-based interface was designed and implemented to test and visualize the classification results of tea leaf diseases. The interface was developed using the Gradio framework, which enables lightweight and interactive deployment of machine learning models. Gradio was chosen due to its seamless integration with TensorFlow/Keras and its accessibility through a standard web browser without additional software installation.

The system allows users to upload tea leaf images, run classification with a single click using the DenseNet121 model, view predicted disease classes with confidence scores, and receive handling suggestions based on the results. The interface is designed to be simple and user-friendly, making the system not only a research tool but also a potential practical application to support farmers, agricultural extension workers, and researchers in detecting tea leaf diseases quickly and accurately.

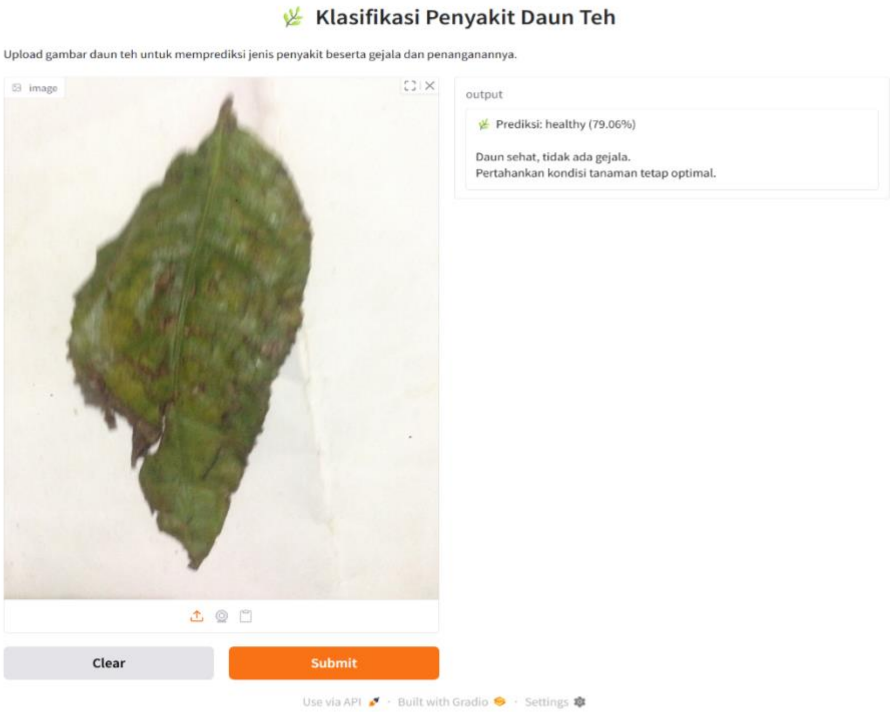

Fig. 5: Tea Leaf Disease System Interface

Figure 5 shows the interface of the implemented tea leaf disease classification system. In the displayed test case, the system predicts the image as *Healthy* with a confidence level of 79.06%. The prediction is accompanied by a brief diagnosis and a recommendation to maintain optimal plant conditions. The interface is designed to be simple and user-friendly, showing only the input image, prediction result, confidence score, and suggested action. This design not only facilitates model testing but also highlights the system's potential application in the field to assist farmers in early detection of tea leaf diseases.

4. Conclusion

This study demonstrated that the DenseNet121 architecture, combined with transfer learning, fine-tuning, and data preprocessing techniques, effectively classified eight categories of tea leaves with a maximum accuracy of 92.57%. The model achieved balanced precision, recall, and F1-scores, confirming its reliability in recognizing both healthy and diseased leaves without bias. These findings highlight DenseNet121's potential as a robust deep learning solution for early detection of tea plant diseases, offering practical benefits for farmers and agricultural stakeholders in improving monitoring, decision-making, and overall tea cultivation productivity.

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