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Optimization of Classification of Tea Leaf Disease Images Using LBP–HOG and MobileNetV2

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Abstract

This study was motivated by the need for an accurate and efficient system for detecting tea leaf diseases, given that the current method Manual identification has limitations in terms of consistency, speed, and It also depends on expert labor. To address these challenges, the study It developed a classification model for detecting diseases in tea leaves using a combination of features Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG) integrated with the MobileNetV2 architecture. The research method includes the following stages: importing the dataset, data partitioning, exploratory data analysis (EDA), preprocessing, features, and training four model scenarios: baseline MobileNetV2, LBP-based model, HOG-based model, and hybrid LBP–HOG model. Evaluation is done with the metrics of accuracy, precision, recall, and F1-score. The results show that the baseline model achieved 91.67% accuracy, the LBP model achieved 60.67%, the HOG model achieved 68.67% accuracy, and the hybrid model achieved 66.67% accuracy. These findings indicate that MobileNetV2 is still the most optimal model, but the integration of texture features and gradients provides a deeper understanding of the characteristics of disease patterns. This study emphasizes the importance of exploring classic features to enriching visual representation in lightweight CNN models, as well as providing a contribution to the development of plant disease diagnosis systems that are efficient.

Keywords: *CNN, LBP, HOG, Classification, Tea leaf Disease*

1. Introduction

The classification of tea leaf diseases is an important aspect of plant health monitoring, given its impact on the productivity and quality of agricultural commodities. Manual identification has various limitations, such as subjectivity, instability of results, and the need for large amounts of labor. Deep learning technology offers a more accurate solution, but large models are often not optimal for field applications that require computational efficiency. MobileNetV2 is a lightweight architecture suitable for deployment on devices with limited computing power. However, this lightweight model tends to be less sensitive to fine texture patterns relevant to leaf disease detection. Therefore, the integration of classic features such as LBP and HOG is used to enrich the visual representation of the model. This study evaluates the effect of integrating LBP and HOG on the performance of MobileNetV2 and compares it with the baseline model. The results of this study are expected to contribute to the development of image-based plant diagnosis systems.

2. Research Metodology

Deep learning, particularly CNN, has been widely applied in image classification due to its capability in hierarchical feature learning [1]. Transfer Learning (TL) further enhances this capability by leveraging pretrained ImageNet features [2]. The lightweight MobileNetV2 architecture provides an efficient solution for resource-constrained environments [3]. Complementary to deep features, LBP captures micro-texture through local thresholding [4], while HOG captures gradient orientation structure [5]. Both methods have shown effectiveness in plant disease detection and classification, especially when fused with CNN-based features [6]. Given that tea leaf diseases exhibit characteristic texture perturbations, combining LBP–HOG with MobileNetV2 offers an opportunity to enhance discriminative performance without significantly increasing computational cost.

2.1. Local Binary Patterns (LBP)

LBP is used to extract local textures by thresholding pixels based on the intensity values of their neighbors. The resulting LBP histogram becomes a texture representation that is stable against changes in lighting.

2.2. Histogram of Oriented Gradients (HOG)

HOG calculates the gradient and its orientation on small cells of the image, then forms a normalized histogram. This feature helps distinguish edge patterns and disease structures.

2.3. MobileNetV2

The MobileNetV2 base model is used as the backbone due to its lightweight and efficient nature. The model is fine-tuned on a tea leaf dataset to learn high-level visual representations.

2.4. Model Hibrid LBP–HOG–MobileNetV2

The hybrid model was created by combining texture (LBP) and gradient (HOG) features and integrating them as additional input channels to MobileNetV2. This approach aims to improve the model's sensitivity to disease symptoms that have subtle texture patterns.

2.5. Implementation Stages

The research implementation stages are as follows: Import Dataset The dataset is taken from a public source (Kaggle) and stored in a directory structured based on disease class. Exploratory Data Analysis (EDA) Analysis is performed to understand image size distribution, lighting conditions, class variation, and potential noise. Image Preprocessing Includes resizing, pixel normalization, conversion to grayscale for LBP/HOG, and augmentation to increase data diversity. Feature Extraction LBP and HOG are extracted from each image and stored as additional feature representations. Four Model Scenarios Training MobileNetV baseline model, MobileNetV2 + LBP model, MobileNetV2 + HOG model, MobileNetV2 + LBP–HOG (hybrid) model. Model Performance Evaluation Models are tested using test data and evaluated based on accuracy, precision, recall, and F1-score.

2.6. Technical Implementation

The implementation was carried out using Google Colab with the Python programming language, using the TensorFlow, Keras, OpenCV, and scikit-image libraries. Training was conducted over several epochs with the Adam optimizer and a learning rate adjusted for fine-tuning MobileNetV2.

3. Research Stages

The research process began with downloading and loading the tea leaf image dataset from Kaggle, followed by dividing the data into training, testing, and validation sets. The next stage was Exploratory Data Analysis (EDA) to assess image quality, class distribution, and potential problems such as noise and imbalance as a basis for data processing strategies. After that, three model scenarios were developed, namely a baseline model without feature extraction, a model with LBP features, and a model with HOG features, each using fine-tuning on MobileNetV2. The three models were then tested using accuracy, precision, recall, and F1-score metrics to ensure objective comparison. The final stage involved performance analysis to determine the best model and evaluate the contribution of LBP and HOG feature integration in improving the classification capabilities of MobileNetV2.

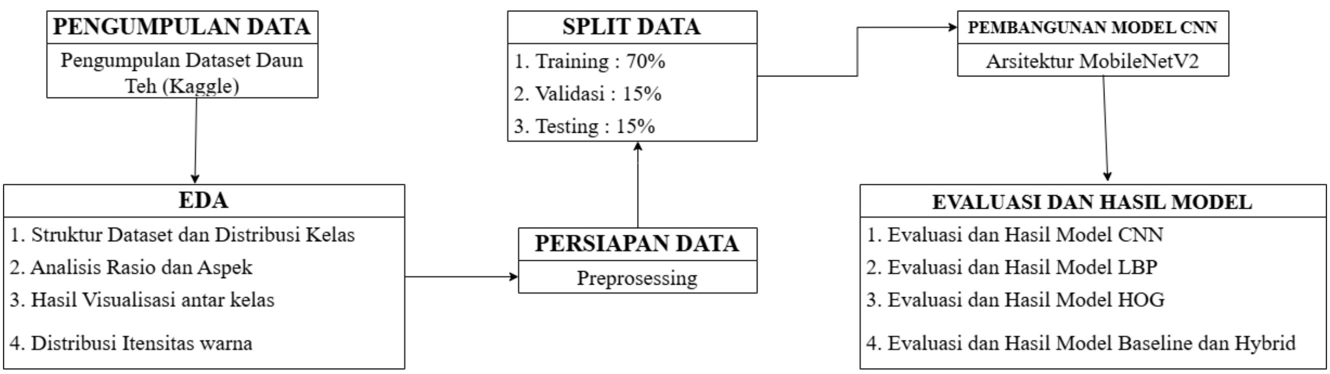

Fig.1: the classification capabilities of MobileNetV2.

3.1. Data collection

The first stage of this research was to import the dataset obtained from the Kaggle platform, namely the TeaLeafNet dataset containing four classes of tea leaf images: Brown Blight (BB), Healthy (GL), Red Rust (RR), and Red Spider Mite (RSM). Each class contains 1,250 images according to the Kaggle dataset structure. The dataset was then downloaded and uploaded to the Google Drive directory to be further processed into the EDA stage.

3.2. Exploratory Data Analysis (EDA)

The Exploratory Data Analysis (EDA) stage is conducted to understand the characteristics and structure of the dataset through several important analyses, including evaluating the number of images in each class to identify potential data imbalances, examining image size and aspect ratio to ensure input dimension uniformity, and visualizing sample images from each class to see variations in leaf shape, texture, and vein patterns. In addition, the distribution of RGB color intensity is also analyzed to determine visual patterns relevant to classification. The results of this EDA form the basis for determining the appropriate preprocessing, normalization, and augmentation strategies prior to the model training stage.

3.3. Split Data

After the dataset has been collected, the next step is to divide it into three subsets, namely 70% training data, 15% testing data, and 15% validation data. This division aims to provide the model with adequate training data, test it using objective data, and validate it to prevent overfitting. The separation process is done randomly (random splitting) to ensure that each subset has a balanced class representation so that the model can learn and be evaluated optimally.

3.4. Data Preparation

During the data preparation stage, images undergo preprocessing in the form of resizing according to MobileNetV2 input, pixel value normalization, format conversion if necessary, and noise cleaning so that all images have consistent quality and format. This step ensures that the dataset is ready to use and easy for the model to learn.

3.5. Application of Convolutional Neural Network (CNN) Model

The core stage of this research is the development of a Convolutional Neural Network (CNN) model using the lightweight and efficient MobileNetV2 architecture for image classification tasks. At this stage, the model is configured with transfer learning parameters (include_top=False), then a classification layer is added according to the number of classes. After that, the model is compiled using the appropriate loss function and optimizer, then trained using training data with performance monitoring through validation data to ensure that the learning process runs optimally.

3.6. Evaluation of Experimental Results

The final stage of the research is to evaluate the performance of all methods by comparing the results using accuracy, precision, recall, F1-score, confusion matrix, and learning curve metrics. The evaluation was conducted on four approaches, namely the MobileNetV2 baseline trained using original RGB images, the LBP-based model that extracts texture patterns, the HOG-based model that highlights gradient and contour information, and the hybrid method that combines three feature channels, CNN, LBP, and HOG, in a single input tensor as a form of input-level fusion. Through this evaluation, the performance of each method can be compared to assess the effectiveness of texture and gradient features in improving the classification capabilities of MobileNetV2, as well as to determine whether the integration of features from LBP and HOG provides significant benefits compared to the baseline method.

4. Results and Discussion

4.1. Data Collection Results

The data collection process was carried out by downloading the TeaLeafNet dataset from the Kaggle platform, which consists of four main folders representing four classes of diseases and conditions affecting tea leaves. Each folder contains 1,250 images, namely Brown_Blight (BB), Healthy (GL), Red_Rust (RR), and Red_Spider_Mite (RSM), so that the total dataset is balanced and does not show any imbalance in the number of classes. This consistent folder structure facilitates the labeling process and ensures that each class has the same representation in the training, testing, and validation stages, so that the model can be trained without bias due to differences in the amount of data between categories.

Table 1: Data Collection

No	Class Name	Total
1	Brown_Blight (BB)	1250
2	Healthy (GL)	1250
3	Red_Rust (RR)	1250
4	Red_Spider_Mite (RSM).	1250

4.2. Hasil Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was conducted to understand the characteristics of the tea leaf image dataset through analysis of class distribution, image dimensions, visual patterns, and color intensity. The data distribution showed that all classes had a balanced number of samples, so class imbalance handling was not necessary. Analysis of size and aspect ratio reveals that the images have diverse dimensions and varying ratios, making the resize process an important step in preprocessing. Inter-class visualization shows high variation in background, lighting, and leaf orientation, but still retains visual characteristics relevant to classification, so augmentation is needed to improve model generalization. Color histogram analysis shows that the green channel dominates, with variations in color patterns between classes that can aid the class separation process. Meanwhile, the mean image shows a dominant green pattern in the central area despite the high variation in the images, indicating that the leaves as the main object remain consistent and allow the model to learn patterns well.

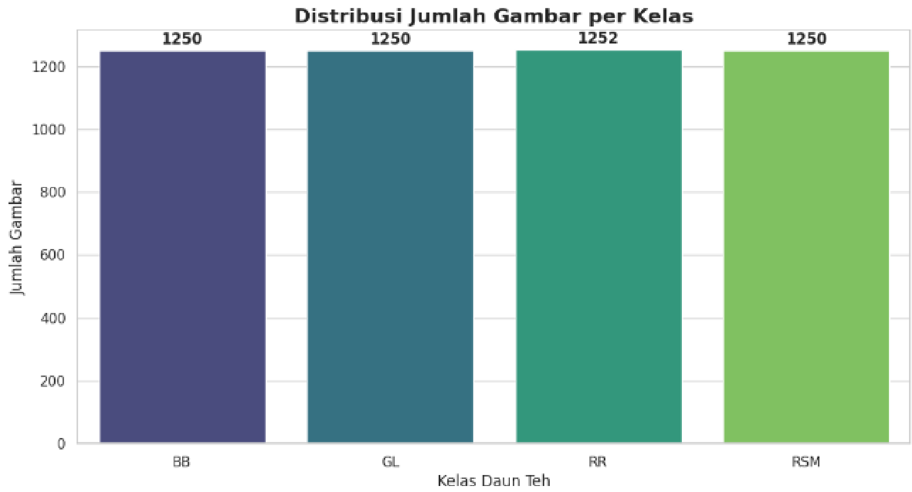

Fig.2: EDA

4.3. Data Distribution Results

The results of dividing the data into 70% train, 15% test, and 15% validation can be seen in Table 4.1 below. It can be seen that the data division was successful, and the four classes were evenly distributed in each subset.

Table 2: Data Sharing

No	Class Name	Presentase	Ammount of data
1	Training	70%	1200
2	Validasi	15%	300
3	Testing	15%	300

4.4. Data Preparation Results

The results of data preparation cover the main processes in this experiment. In the data preparation stage, only the dataset is prepared for processing without changing the original image or resizing it. The following are the results of image normalization processing without augmentation.

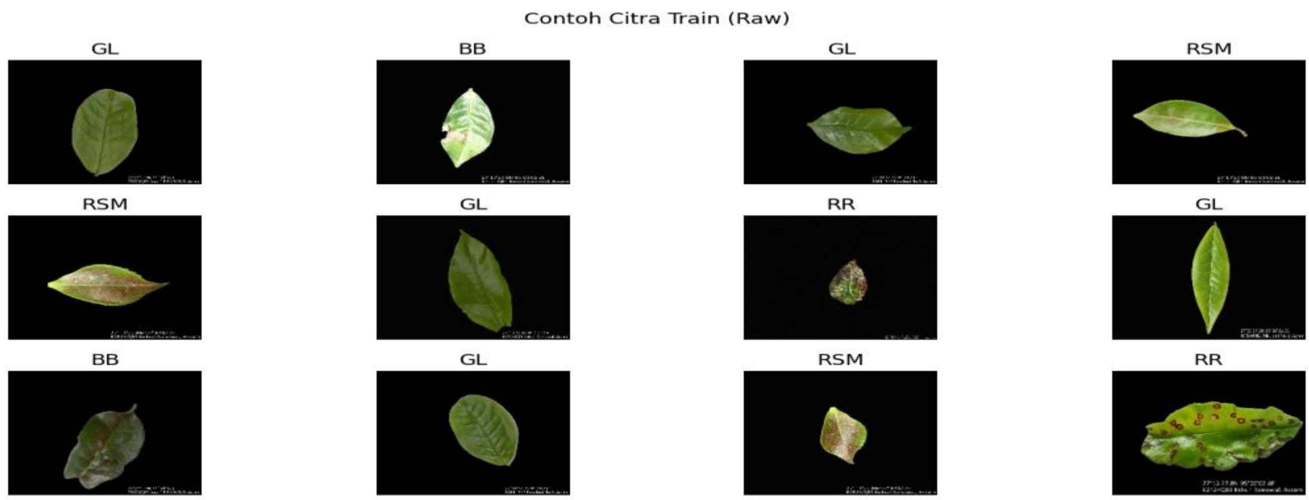

Fig. 2: Data Preparation Results

4.5. Results of Convolutional Neural Network Model CNN Application

The first method is the baseline or the main benchmark for this study. In this scenario, the input image is the original color image (RGB) that only goes through the resize and standard normalization processes. The following is a description of the evaluation results for the four scenarios.

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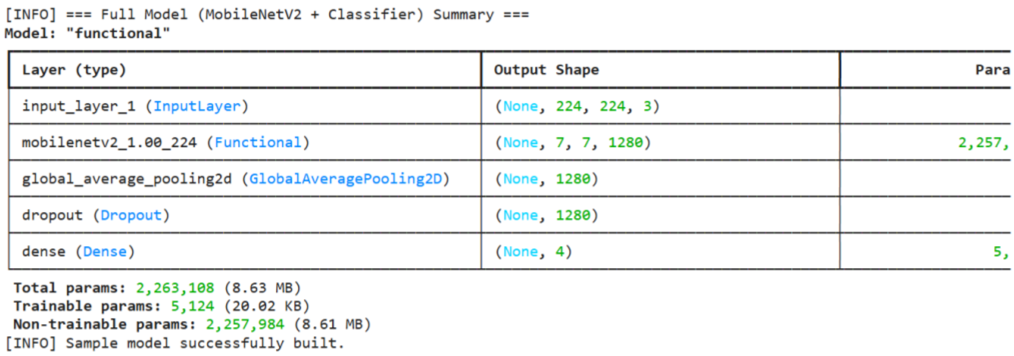
[INFO] === Full Model (MobileNetV2 + Classifier) Summary ===
Model: "functional"

Layer (type)	Output Shape	Para
input_layer_1 (InputLayer)	(None, 224, 224, 3)	
mobilenetv2_1.00_224 (Functional)	(None, 7, 7, 1280)	2,257,
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1280)	
dropout (Dropout)	(None, 1280)	
dense (Dense)	(None, 4)	5,

Total params: 2,263,108 (8.63 MB)
Trainable params: 5,124 (20.02 KB)
Non-trainable params: 2,257,984 (8.61 MB)
[INFO] Sample model successfully built.

Fig.3: Results of CNN Model Application

4.6. Experiment Evaluation Results

An evaluation of the four methods—Baseline CNN, LBP, HOG, and Hybrid—was conducted through training history analysis and confusion matrix to assess learning stability and the model's ability to distinguish between the four classes of tea leaves. The Baseline MobileNetV2 model, which uses RGB images, showed the most stable accuracy because it directly utilizes color, texture, and shape information. In the LBP method, images are converted into microtexture representations so that the model focuses more on surface patterns, although the loss of color information causes accuracy to tend to decrease compared to Baseline. The HOG method highlights the edges and shapes of disease spots, but loses texture and color details, resulting in lower performance in classes with similar morphological variations. The Hybrid method (LBP+HOG+CNN) combines all three features in a single input to provide texture, shape, and structure information simultaneously; this approach aims to reduce classification errors in visually similar classes and improve model robustness. Overall, Baseline remains superior in efficiency and accuracy, while Hybrid offers better resilience to inconsistent lighting or color conditions.

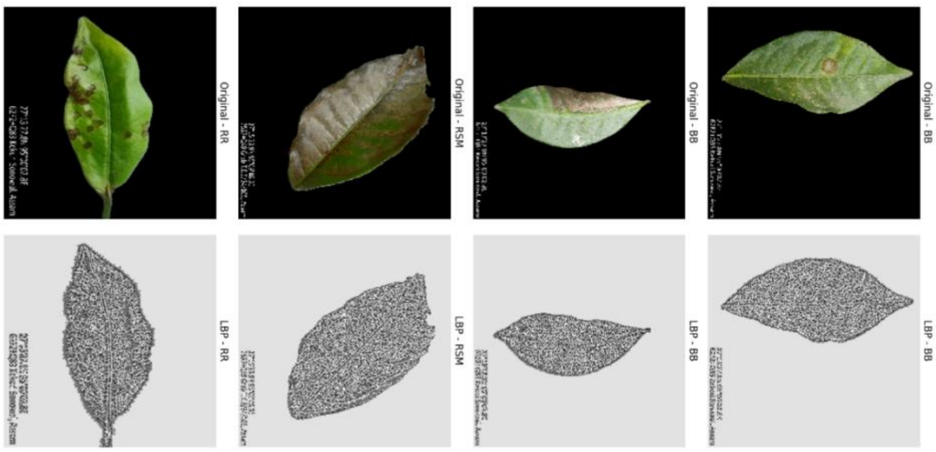

Fig. 4: LBP Result

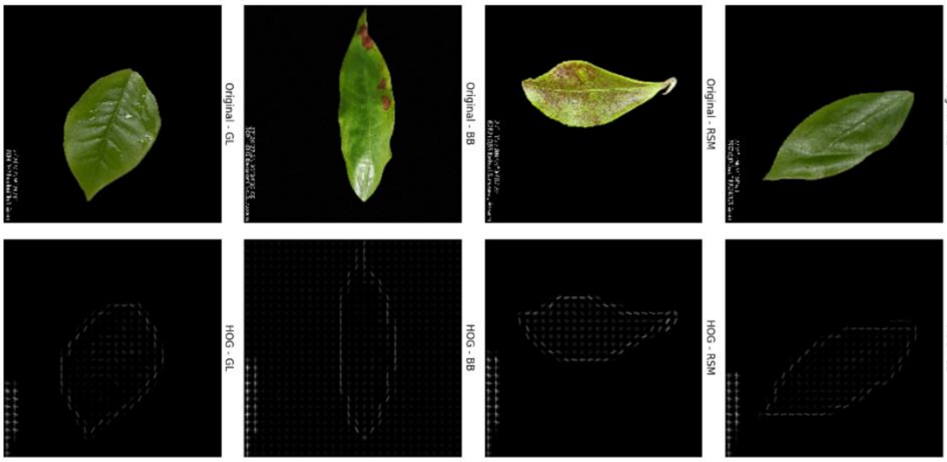

Fig. 1: HOG Result

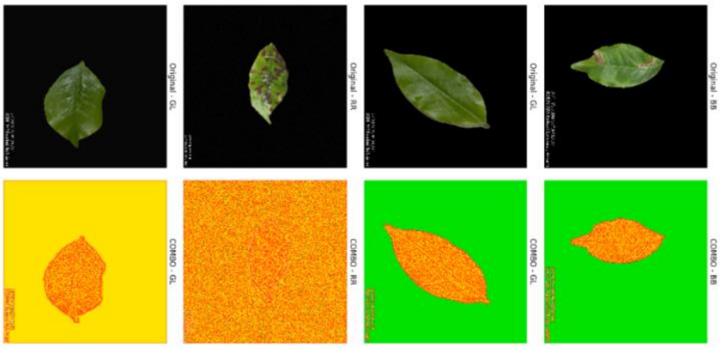

Fig.6: Baseline Results with Hybrid

The development of a tea leaf disease classification model was carried out using the MobileNetV2 architecture, which is known to be efficient for devices with limited computing power, through the stages of data preparation, feature transformation, and model training on Google Colab. The results of the experiment show that the MobileNetV2 baseline model provides stable performance with good validation accuracy, supported by strong feature extractor capabilities even in frozen conditions. The use of mixed precision, small batch sizes, and a data pipeline using tf.data helped speed up processing and reduce memory requirements without compromising training quality. Overall, MobileNetV2 proved to be an efficient and competitive foundation for detecting four classes of tea leaf diseases—Brown Blight (BB), Healthy (GL), Red Rust (RR), and Red Spider Mite (RSM). The evaluation results show that the MobileNetV2 baseline model is capable of providing good initial performance as a feature extractor, but its accuracy is still limited in some classes because it does not utilize additional texture information. In contrast, LBP- and HOG-based models show improved performance on specific characteristics, with HOG excelling on classes with clear edges and contours, while LBP is effective on smooth surface patterns. The combination of the twoin a hybrid model results in higher accuracy, precision, recall, and F1-score than the baseline, as well as reducing classification errors, especially in classes that are difficult to distinguish.

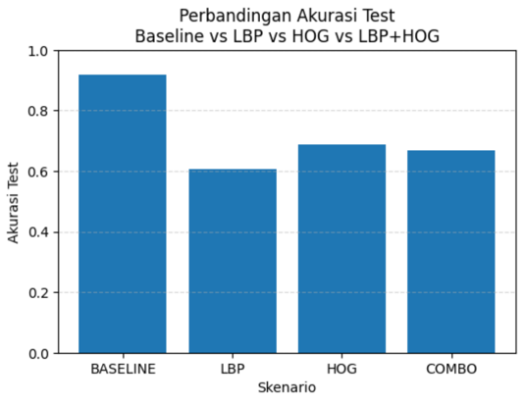

Fig.7: Accuracy Comparison Results

Table 3: Accuracy Summary

No	Skenario	Acuracy Test
1	Baseline 0.916667	0.916667
2	Local Binary pattern (LBP)	0.606667

3	Histogram og Gradients	0.686667
4	Combo	0.666667

5. Conclusion

The evaluation results show that the MobileNetV2 baseline model is capable of providing good initial performance as a feature extractor, but its accuracy is still limited in some classes because it does not utilize additional texture information. In contrast, LBP- and HOG-based models show improved performance in certain characteristics, where HOG excels in classes with clear edges and contours, while LBP is effective in smooth surface patterns. The combination of the two in a hybrid model resulted in higher accuracy, precision, recall, and F1-score than the baseline, and reduced classification errors, especially in classes that were previously often confused, such as GL and RR. More stable training and validation curves also indicated a more consistent learning process. Overall, the integration of LBP–HOG texture features proved to significantly improve the performance of MobileNetV2 in identifying tea leaf diseases.

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