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Hybrid Deep Learning Model with GLCM and CIELAB Feature Fusion for Tea Leaf Disease Classification

Ade Davy Wiranata[1], *Riduan* Syahri[2], *Yessi* Jusman[3*], *Saifuddin* Saifuddin[4], and *Rohmat Indra* Borman[5]

[1]Informatics Engineering Study Program, Faculty of Industrial Technology and Informatics, Universitas Muhammadiyah Prof. Dr. HAMKA, Jakarta Selatan, Indonesia
[2]Informatics Engineering Study Program, Institut Teknologi Pagar Alam, Sumatera Selatan, Indonesia
[3]Department of Electrical Engineering, Faculty of Engineering, Universitas Muhammadiyah Yogyakarta, Yogyakarta, Indonesia
[4]Smart City Information Systems Study Program, Universitas Tunas Pembangunan Surakarta, Surakarta, Indonesia
[5]Faculty of Engineering and Computer Science, Universitas Teknokrat Indonesia, Bandar Lampung, Indonesia

Abstract. Tea leaf diseases significantly affect the quality and productivity of tea plants, leading to economic losses in the agricultural sector. This study proposes a hybrid deep learning classification model that integrates the MobileNetV2 architecture with additional features from the CIELAB color space and Gray Level Co-occurrence Matrix (GLCM) texture descriptors. The Tea Sickness Dataset, comprising eight classes of diseased and healthy leaves with approximately one hundred images per class, was used and preprocessed through color conversion, normalization, and moderate augmentation. GLCM texture features were extracted from the luminance channel at four orientations, resulting in twenty statistical features that were fused with CNN features. Experimental results show that the hybrid model achieved an accuracy of eighty-six percent, compared to eighty percent for the baseline MobileNetV2. While these findings confirm the benefits of combining visual and statistical features, the relatively small dataset size and potential class imbalance remain challenges that may limit generalization. Future work will focus on larger and more balanced datasets, alternative fusion strategies, and advanced architecture such as attention mechanisms and explainable AI to further enhance performance and applicability in real-world precision agriculture systems.

1 Introduction

Tea (Camellia sinensis) is one of the most important agricultural commodities globally, consumed daily by over two billion people in various forms. In 2022, global tea production exceeded 6.5 million tons, making it a high-value commodity in international trade [1].

* Corresponding author: yjusman@umy.ac.id

Beyond its role as a foreign exchange earner through exports, the tea industry also provides livelihoods for millions of farmers and workers in developing countries [2]. However, tea productivity and quality are significantly affected by biotic stresses, particularly leaf diseases such as Anthracnose, Algal Leaf, Bird Eye Spot, Brown Blight, Red Leaf Spot, and White Spot. These diseases cause visual damage, reduce harvest quality, and result in substantial economic losses. Conventional detection and identification methods still rely on manual visual inspection by plant experts, which requires a high level of expertise and is prone to inconsistency, delayed decision-making, and limited scalability in field applications.

In recent years, deep learning-based approaches, especially Convolutional Neural Networks (CNNs), have demonstrated high performance in various image classification tasks, including automated plant disease recognition [3]. However, a major challenge in applying CNNs in the agricultural domain is the limited availability of large and high-quality annotated datasets [4]. Although data augmentation techniques can expand the dataset, excessive use may produce synthetic images that do not realistically represent the visual characteristics of plant diseases. To address this issue, lightweight architectures such as MobileNetV2 have been adopted in this study for their computational efficiency without sacrificing accuracy. MobileNetV2 is also well-suited for deployment on edge devices with limited resources [5]. Nevertheless, classifying leaf diseases often requires an understanding of subtle visual variations, where color and texture patterns across classes frequently overlap [6]. RGB channels alone are often insufficient to support accurate classification.

To overcome these limitations, hybrid approaches that combine CNNs with handcrafted color and texture features have become highly relevant. Several prior studies have shown that integrating texture features with CNNs can enhance the classification accuracy of plant diseases. For example, combining Gray Level Co-occurrence Matrix (GLCM)-based texture features with CNNs has been shown to improve rice leaf disease classification accuracy up to 96%, compared to conventional CNNs without additional features [7]. Furthermore, using the CIELAB color space, which separates luminance from chrominance, has been found to provide more informative color representations, contributing to classification accuracy as high as 94.65% [8]. Other studies report that combining color and texture features using GLCM achieved an accuracy of 98.79% with a standard deviation of 0.57 under ten-fold cross-validation [9]. Additionally, integrating YCbCr color histograms with Local Gradient Binary Pattern (LGGP)-based texture descriptors yielded an accuracy of 98.33% [10].

Based on this background, the present study aims to develop a tea leaf disease classification model based on hybrid deep learning by combining the MobileNetV2 architecture with additional color (CIELAB) and texture (GLCM) features. The key contributions of this study are as follows: (1) designing a lightweight MobileNetV2-based model that remains effective under limited data conditions; (2) integrating classical color and texture features as metadata into the CNN architecture; and (3) conducting comprehensive evaluations of the model's accuracy, precision, and generalization performance. Hence, this research offers a synergistic approach that combines feature learning and feature engineering to achieve reliable tea leaf disease classification without relying on large-scale data.

2 Methodology

This study develops a tea leaf disease classification model using a hybrid deep learning approach by combining visual features from a CNN architecture (MobileNetV2) and statistical texture features extracted using the Gray Level Co-occurrence Matrix (GLCM) method. The development process includes dataset preparation, image preprocessing, texture feature extraction, hybrid model architecture design, and model performance evaluation using various metrics. Fig. 1 illustrates the overall workflow of the research.

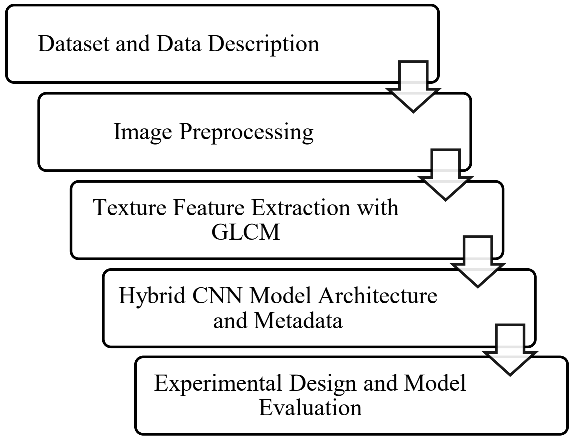


Fig. 1. Research Process Flow.

2.1 Dataset and Data Description

This study uses the publicly available Tea Sickness Dataset from Kaggle [11]. The dataset contains eight classes: Anthracnose (110 images), Algal Leaf (98 images), Bird Eye Spot (112 images), Brown Blight (105 images), Gray Light (108 images), Red Leaf Spot (110 images), White Spot (102 images), and Healthy leaves (140 images), for a total of 885 images. All images were manually annotated by plant experts and resized to 224 × 224 pixels to match the CNN input requirements. The dataset was split into 80% training and 20% testing using stratified sampling to preserve proportional representation across classes. Although the number of images varies slightly among classes, the dataset is considered reasonably balanced, minimizing the risk of severe class imbalance.

2.2 Image Preprocessing

The preprocessing stage aims to enhance the quality of data representation before feeding it into the classification model [12]. All original RGB images were converted into the CIELAB color space, which better approximates human visual perception by separating luminance (L) from chrominance (a and b). The L channel represents light intensity, while channels a and b encode color information from green to red and blue to yellow. This transformation improves the accuracy of color differentiation between diseases, which often appear similar in the RGB space [13]. The images were normalized to a [0, 1] range using min-max scaling. To increase data variation and reduce overfitting, moderate augmentation was applied in the form of horizontal flipping and random rotation (±15°). These techniques were chosen because they preserve the essential characteristics of leaf diseases while introducing sufficient diversity to improve the model's generalization capability.

2.3 Texture Feature Extraction with GLCM

In this study, texture features were extracted from the L channel of the images that had been converted to the CIELAB color space using GLCM. The matrix was computed at four orientations, namely 0 degrees, 45 degrees, 90 degrees, and 135 degrees, with a pixel distance of one. For each orientation, five statistical features were calculated, which include contrast, correlation, homogeneity, energy, and dissimilarity. This process produced a total of 20 texture features for each image. The resulting feature vector was used as metadata and combined with the spatial features extracted by the CNN through a feature fusion mechanism in the proposed hybrid architecture.

2.4 Hybrid CNN Model Architecture and Metadata

The classification model employs MobileNetV2 as the backbone to extract spatial features from tea leaf images. MobileNetV2 is a lightweight convolutional network that utilizes depth wise separable convolutions and inverted residual blocks, making it efficient in parameter usage and suitable for limited datasets [4]. The architecture can generate rich feature representations while maintaining low computational cost. Additionally, MobileNetV2 has proven effective in preserving classification accuracy despite its compact architecture, making it ideal for deployment on resource-constrained devices [5]. Although deeper architectures such as ResNet and EfficientNet achieve high accuracy, they are computationally expensive and require larger datasets. MobileNetV2 provides a better balance between accuracy and efficiency, making it more suitable for agricultural applications where deployment of mobile and edge devices is essential. The hybrid architecture integrating visual features from MobileNetV2 with CIELAB and GLCM is shown in Fig. 2.

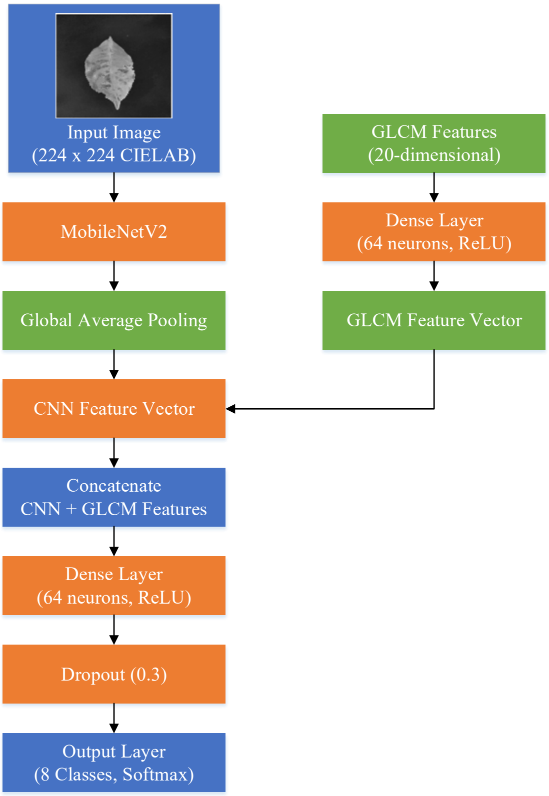


Fig. 2. Hybrid Architecture Integrating MobileNetV2 with CIELAB–GLCM Features.

Fig. 2 illustrates the architecture and workflow of the proposed hybrid CNN–GLCM model. Tea leaf images sized 224×224 pixels are converted to CIELAB and passed through MobileNetV2 for feature extraction via depthwise separable convolution, followed by Global Average Pooling. In parallel, 20 texture features are extracted using GLCM, based on five statistical metrics (contrast, dissimilarity, homogeneity, energy, and correlation) from four directional angles (0°, 45°, 90°, and 135°). The GLCM vector is passed through a dense layer with 64 neurons and ReLU activation. CNN and GLCM features are concatenated and passed through another dense layer with 64 ReLU-activated neurons, followed by a 0.3 dropout rate to reduce overfitting. The final softmax layer contains eight neurons representing the tea leaf disease class. This integrated architecture enables complementary learning from visual and texture cues, enhancing classification accuracy, especially for diseases with overlapping visual patterns.

2.5 Experimental Design and Model Evaluation

Four model configurations were evaluated to measure classification effectiveness: MobileNetV2 with RGB images, MobileNetV2 with CIELAB images, and the combination of MobileNetV2 with CIELAB and GLCM features. All models were trained using categorical cross-entropy loss and the Adam optimizer (learning rate 0.0001) for 30 epochs with a batch size of 32. The training and testing datasets were split 80:20 with stratified sampling. Light augmentation (rotation, flipping) improved generalization. A custom generator combined images and texture features for the hybrid model. Evaluation used accuracy, precision, recall, F1-score, confusion matrix, and Grad-CAM to assess feature contribution and model performance.

3 Results and Discussion

To develop a hybrid deep learning model using feature fusion from GLCM and CIELAB, the initial step involved preparing the dataset for training and testing. This study employed the Tea Sickness Dataset obtained from the Kaggle platform [11]. The dataset consists of eight classes of tea leaf diseases: Anthracnose, Algal Leaf, Bird Eye Spot, Brown Blight, Gray Light, Red Leaf Spot, White Spot, and Healthy leaves. Each class comprises 100 high-resolution images, which were resized to 224 × 224 pixels to match the input standard of the CNN architecture Fig. 3 illustrates visual differences across classes.

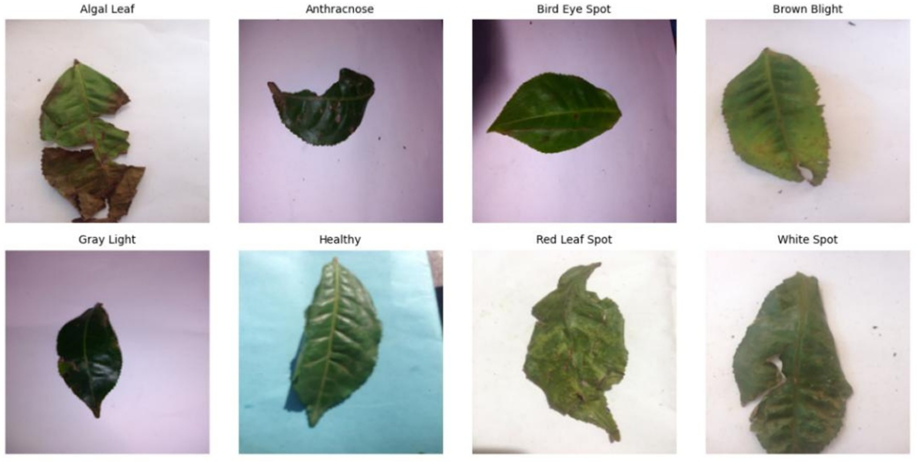
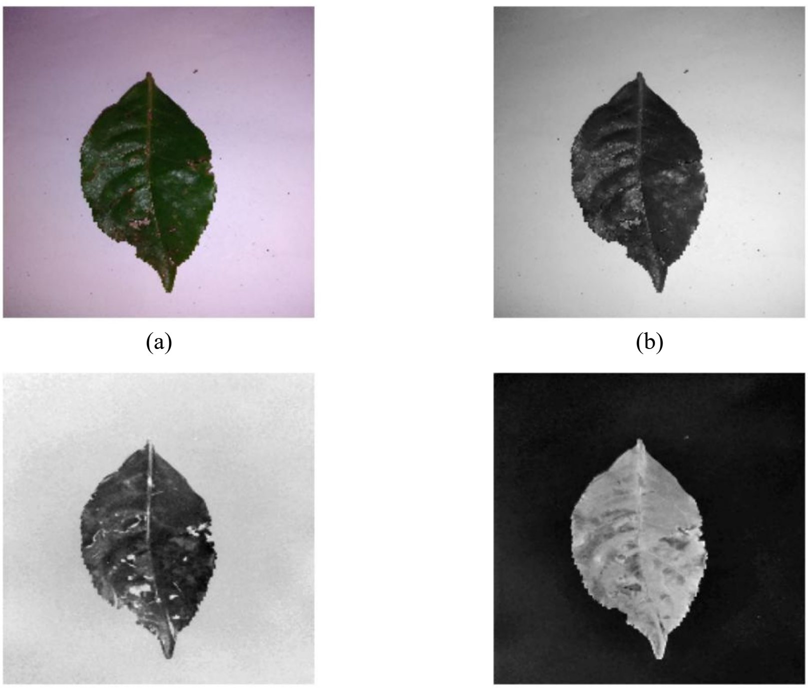


Fig. 3. Samples of Each Class in the Dataset Used.

Fig. 3 illustrates sample images from each class in the dataset, showing variations in color, texture, and leaf damage patterns. Each image reflects the specific condition of a tea leaf, whether healthy or affected by a particular disease. These visual variations form a critical foundation for training a deep learning classification model enhanced with additional features from GLCM and CIELAB.

As an initial preprocessing step, all images were converted from RGB to CIELAB color space. This transformation enhances visual representation by separating luminance (L) from chromatic components (A and B channels), enabling more precise distinction of subtle color variations, which are often early indicators of infection in tea leaves. Unlike RGB, which mixes brightness and color in a single scale, CIELAB provides a perceptually uniform space that aligns more closely with human vision. This makes it especially effective in distinguishing disease symptoms that appear with minor color shifts. Fig. 4 presents examples of CIELAB conversion results, illustrating the visual effects of this transformation.



(a) (b)

(a) (b)

Fig. 4. (a) RGB Image, (b) CIELAB L Channel, (c) CIELAB A Channel, and (d) CIELAB B Channel.

Fig. 4 displays the color space transformation of tea leaf images. Figure 4(a) shows the original RGB image, 4(b) represents the L channel indicating brightness intensity, 4(c) shows the A channel capturing the red-green spectrum, and 4(d) represents the B channel, which spans from blue to yellow.

Next, texture features were extracted from each image using the Gray Level Co-occurrence Matrix (GLCM) method. Five key texture metrics including contrast, correlation, homogeneity, energy, and dissimilarity were calculated at four angles (0°, 45°, 90°, and 135°), resulting in a total of 20 features per image. The use of GLCM aims to capture fine-grained texture patterns and local intensity variations that are often characteristic of specific tea leaf diseases, offering complementary information to color-based features. Table 1 presents an example of GLCM feature extraction results from a tea leaf image.

Table 1. Texture Feature Extraction Results Using GLCM from a Tea Leaf Image Sample

Image Sample	Feature	0°	45°	90°	135°

	Contrast	171.4798	198.5850	131.5580	211.81390
	Correlation	0.9752	0.9714	0.9810	0.9695
	Homogeneity	0.3858	0.3575	0.3731	0.3651
	Energy	0.0302	0.0289	0.0296	0.0292
	Dissimilarity	4.0571	4.5130	3.8535	4.5116

Table 1 indicates that texture feature values vary across orientations, reflecting the complexity of surface patterns on the leaf. High contrast and dissimilarity values suggest significant intensity differences, while correlation values close to one indicate strong pixel relationships. This information is important for distinguishing leaf disease types based on texture.

The proposed classification model is a hybrid model that combines feature learning from the MobileNetV2 architecture with feature engineering based on color (CIELAB) and texture (GLCM). The 224×224 image is processed by MobileNetV2 to produce a feature vector through global average pooling. Simultaneously, the 20-dimensional GLCM features are processed through a dense layer (64 neurons, ReLU activation). Both feature vectors are then concatenated and passed through another dense layer (64 neurons, ReLU), followed by a dropout of 0.3. The final output layer uses softmax with eight neurons for multi-class classification. To evaluate performance, the dataset was split into 80 percent training and 20 percent testing. During training, accuracy and loss metrics were recorded per epoch. The training and validation accuracy and loss curves are presented in Fig. 5 to illustrate model stability and potential overfitting.

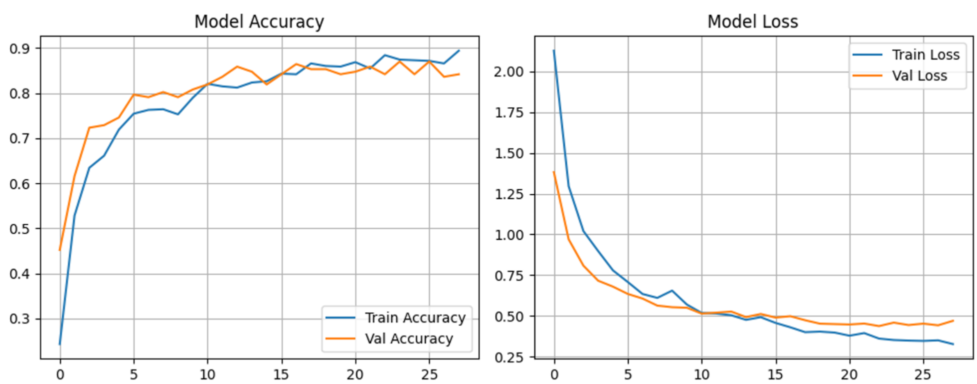


Fig. 5. Model Accuracy and Loss Graph During Training and Validation.

Fig. 5 shows that the model reached stable convergence around the 20th epoch, with validation accuracy between 84 to 87 percent and no signs of significant overfitting. Further performance analysis was conducted using a confusion matrix to assess the distribution of correct and incorrect predictions across classes. This matrix provides a detailed view of the model's classification behavior, highlighting specific class-wise errors and helping to identify patterns of misclassification. The results are visualized as a heatmap in Fig. 6.

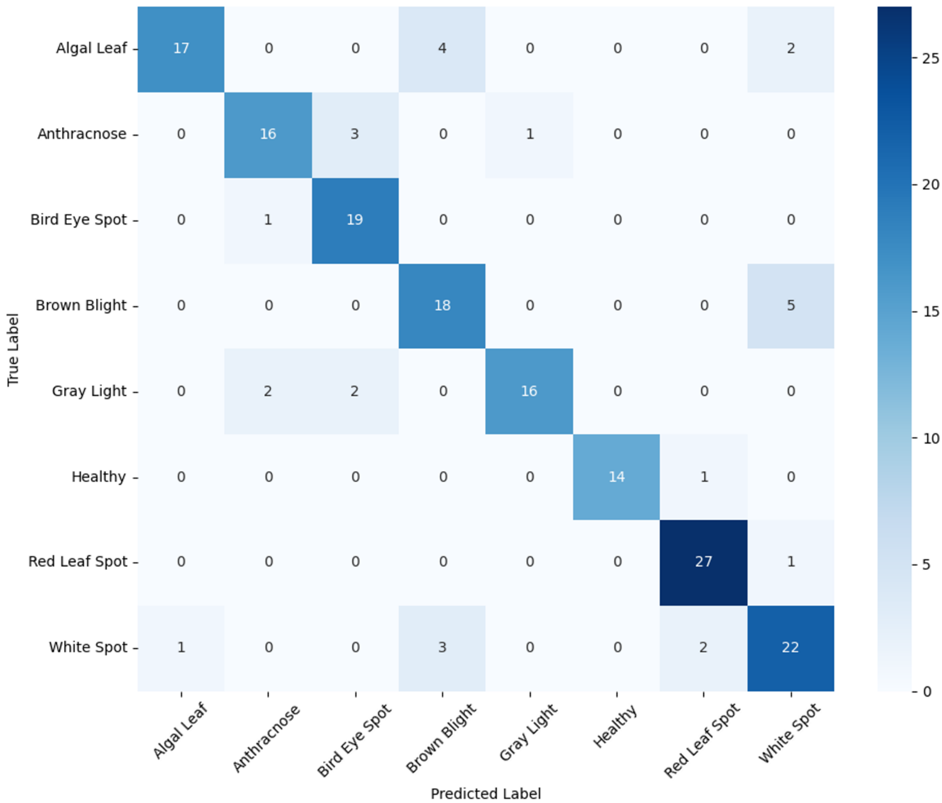
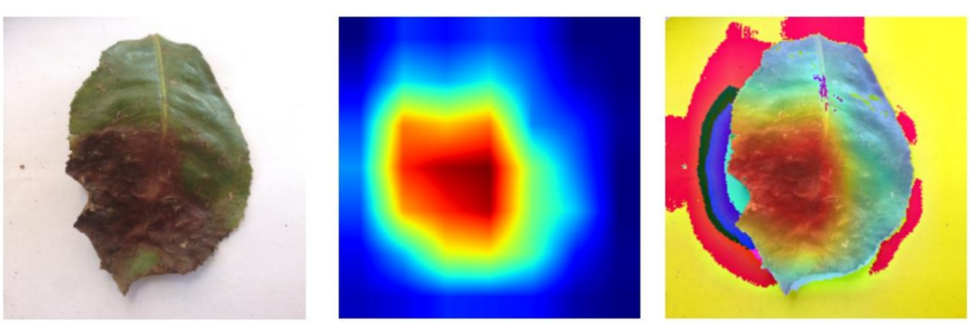


Fig. 6. Confusion Matrix of Model Prediction Results.

Fig. 6 demonstrates that the model accurately classified most images, especially for the Red Leaf Spot, Bird Eye Spot, and Healthy classes. However, some misclassifications still occurred, such as Algal Leaf being predicted as Bird Eye Spot, and White Spot being confused with Brown Blight. Overall, the model showed robust and consistent performance across the eight tea leaf conditions.

To identify which parts of the image contributed most to the model's decisions, Grad-CAM (Gradient-weighted Class Activation Mapping) visualization was performed. This technique enables interpretation of important image areas focused on by the model during classification, especially in visually similar disease cases. Grad-CAM results are shown in Fig. 7.



(a) (b) (c)

Fig. 7. (a) Original Image, (b) Grad-CAM Heatmap, (c) Superimposed Image.

Fig. 7 displays Grad-CAM interpretations. Figure 7(a) shows the original image, 7(b) is the heatmap highlighting high-contribution areas, and 7(c) is the superimposed image showing the model's focus on infected leaf regions. This confirms that the model recognizes relevant disease patterns rather than making random classifications. The visualization also demonstrates that the proposed hybrid model pays attention to disease-specific regions of the leaf, which strengthens the reliability and transparency of the classification process. Such interpretability is important for practical agricultural applications, as it allows farmers and agronomists to trust the model's decisions by understanding which areas of the leaf influenced the prediction.

Final evaluation compared four model configurations: MobileNetV2 (baseline), MobileNetV2 + CIELAB, MobileNetV2 + GLCM, and MobileNetV2 + CIELAB + GLCM. The performance comparison is presented in Table 2.

Table 2. Performance Comparison of Classification Models.

Model	Accuracy	Macro Precision	Macro Recall	Macro F1-Score
MobileNetV2	0.80	0.82	0.80	0.80
MobileNetV2 + CIELAB	0.81	0.83	0.82	0.82
MobileNetV2 + GLCM	0.83	0.84	0.83	0.83
MobileNetV2 + CIELAB + GLCM	0.86	0.87	0.86	0.86

The results show consistent improvements with the addition of features. CIELAB increased accuracy from 0.80 to 0.81, while GLCM provided a more significant boost to 0.83. The combination of both features achieved the best performance, with 0.86 accuracy and balanced macro scores. This proves that integrating color and texture features enhances data representation and classification accuracy. The model's main advantage lies in its multimodal approach, combining visual features from MobileNetV2 with statistical features from CIELAB and GLCM. This enables more comprehensive recognition of disease patterns, including color, shape, and texture.

However, the model still has limitations. GLCM extraction requires grayscale conversion, which may reduce color information even though CIELAB was used to compensate for this. In addition, the dataset, although relatively balanced across classes, remains limited in size, which could restrict generalization to real-world conditions. Addressing these challenges will require richer datasets with more balanced class distributions and more flexible feature integration strategies to preserve both color and texture information.

4 Conclusion

This study successfully developed a tea leaf disease classification model using a hybrid deep learning approach that integrates MobileNetV2 with color features from CIELAB and texture features from GLCM. The experimental results showed that the hybrid model achieved an accuracy of eighty-six percent, improving from eighty percent with the baseline MobileNetV2. This demonstrates that combining handcrafted color and texture descriptors with CNN-based visual features enhances representation and significantly improves classification accuracy. The proposed multimodal approach proved effective in distinguishing complex and overlapping disease patterns, while Grad-CAM visualization further confirmed that the model consistently focused on relevant infected regions, providing interpretability for practical agricultural use. Nonetheless, the study is limited by the relatively small dataset size and moderate class imbalance, which may restrict its generalization to broader real-world scenarios. Future work will involve expanding the dataset with larger and more balanced samples, exploring alternative feature fusion strategies, and adopting advanced architectures such as attention mechanisms and visual transformers. Furthermore, incorporating Explainable AI (XAI) techniques will be important to improve interpretability and foster greater trust in deploying the model for precision agriculture.

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