Jurnal Teknik Informatika (JUTIF) Vol. 7, No. 3, June 2026, Page. 2480-2490
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2026.7.3.4966

Classification of Banana Leaf and Ornamental Plant Diseases Using Gray Level Co-occurrence Matrix (GLCM) and Hybrid Random Forest–Support Vector Machine (SVM)

Novia Urfiyati*[1], Nova Rijati[2], Pujiono[3], Arief Soeleman[4], Iqbal Firdaus[5], Yeni Agus Nurhuda[6]

[1,2,3,4]Master of Informatics Engineering, Universitas Dian Nuswantoro, Indonesia
[5,6]Information Technology, Faculty of Computer Science, Institut Bisnis dan Teknologi Kalimantan, Banjarmasin, Indonesia

Email: [1]p31202302580@mhs.dinus.ac.id

Received : Jun 28, 2025; Revised : Jul 17, 2025; Accepted : Jan 29, 2026; Published : Jun 15, 2026

Abstract

Leaf diseases in banana plants and ornamental crops can significantly reduce productivity and product quality, **highlighting the need for accurate early detection methods**. This study **proposes an image-based classification approach utilizing texture features extracted from the Gray Level Co-occurrence Matrix (GLCM) combined with a Hybrid Stacking model that integrates Random Forest (RF) and Support Vector Machine (SVM)**. The preprocessing stage **involves image resizing and noise reduction**, followed by feature extraction using energy, contrast, homogeneity, and correlation parameters. The dataset consists of **eight classes of healthy and diseased leaves, collected from both field documentation and secondary sources**. Model performance was evaluated using **accuracy, precision, recall, and F1-score metrics under a cross-validation scheme**. Experimental results show that **SVM achieved 89.2% accuracy, RF 88.5%, while the stacking model yielded the best performance with 91.7% accuracy**, effectively reducing misclassification among visually similar disease classes. **This study demonstrates the effectiveness of combining GLCM features and hybrid stacking models for leaf disease classification, with potential applications in automated plant monitoring systems to support precision agriculture.**

Keywords : *GLCM, Leaf Disease Classification, Plant Leaf Images, Random Forest, Stacking, Support Vector Machine.*

1. INTRODUCTION

Banana plants are one of the world's primary food commodities, playing a crucial role in food security and the economy of tropical producer countries. Indonesia, as one of the largest banana producers, faces serious challenges from leaf diseases such as Sigatoka (Mycosphaerella spp.), Cordana leaf spot (Neocordana musae), and Pestalotiopsis leaf fall disease (PGDP), which can reduce productivity by up to 50% [1], [2]. On the other hand, ornamental plants with high economic value are also highly vulnerable to leaf diseases, which reduce their aesthetic quality and market value [3], [16], [17]. Manual disease detection remains the primary method used by farmers; however, it heavily relies on the experience and subjectivity of the observer [4]. This makes diagnosis systems inconsistent and difficult to implement on a large scale. Therefore, automated image-based classification systems are required to support precision agriculture, improve diagnostic accuracy, and minimize production losses [18], [19].

Image-based leaf disease identification faces several major challenges: (1) the similarity of texture patterns among diseases often leads to misclassification [5], (2) variations in lighting, leaf size, and background affect feature extraction [6], and (3) dataset limitations in both quantity and disease diversity hinder model performance [7]. Recent studies also emphasize that uncertainty in field data further degrades classification accuracy [20], [21]. To address these issues, the Gray Level Co-occurrence Matrix (GLCM) method has been widely used in texture feature extraction, as it effectively represents spatial relationships between pixels [8], [9]. Several studies have demonstrated the effectiveness of GLCM in classifying cucumber leaf diseases [10], medicinal plants [11], rice [12], and various other crops. However, model performance strongly depends on the chosen classification algorithm [22], [23]. The Random Forest (RF) algorithm is known to be robust against noise and capable of handling high-dimensional data [13], while the Support Vector Machine (SVM) is effective at separating classes with an optimal margin in non-linear data [14]. Nancy & Kiran (2024) demonstrated that GLCM + RF can detect cucumber leaf diseases with competitive accuracy [10]. Jamjoom et al. (2023) reported that the GLCM + SVM combination achieved an accuracy of 97.2% [15]. Purnawansyah et al. (2022) further compared GLCM-SVM versus GLCM-CNN, showing that SVM outperformed CNN under limited lighting conditions [11]. Moreover, Andal (2022) highlighted the importance of hybrid CNN–SVM–RF approaches in improving model generalization [23], while Javidan (2024) showed that GLCM-based feature engineering remains highly competitive compared to purely deep learning methods [24].

In addition, deep learning models such as CNN and MobileNetV2 have been increasingly applied [16], [17]. Nevertheless, deep learning models require large datasets and high computational resources, making them less optimal for studies with limited resources. Therefore, the hybrid stacking RF–SVM approach is a promising solution, as it can combine the strengths of both algorithms while reducing misclassification among diseases with similar textures [18]. Recent studies also reveal the potential of stacking and ensemble learning in banana disease classification, achieving accuracies above 97% [19], [22], [25]. This study contributes to two main aspects: in agriculture, by providing an automated diagnostic system based on banana and ornamental plant leaf images that can enhance productivity and support precision farming; and in computer science, by enriching the literature on GLCM-based image classification, exploring RF–SVM stacking as an optimization strategy, and opening opportunities for integration with lightweight deep learning architectures such as MobileNetV2 for diverse data processing. Thus, this research is not only practically beneficial but also provides significant contributions to the development of computer vision technology for smart agriculture applications.

2. METHOD

This research begins with a literature study related to banana and ornamental banana leaf diseases, followed by collecting the dataset used to train the machine learning model. Previous studies on leaf disease classification using texture feature extraction with the Gray Level Co-occurrence Matrix (GLCM) have shown promising results [12], [16]. Random Forest (RF), as an ensemble algorithm, has proven capable of handling complex features and noisy data [17]. Support Vector Machine (SVM) is effective in separating classes with optimal margins [18]. Stacking combines the strengths of both models to achieve better performance [16]. Several prior works have applied this hybrid approach for leaf and ornamental plant classification with competitive accuracy [17], [18]. However, the choice of an RF–SVM stacking model in this study is theoretically justified compared to alternatives such as CNN or XGBoost, which typically require larger datasets and higher computational cost [19], [20].

2.1. Data Collection

This study uses a dataset consisting of banana and ornamental banana leaf images, collected from both Kaggle (Dataset Link) and manual data acquisition for ornamental bananas. The dataset includes 8 classes, covering different disease categories and healthy leaves. Images were resized to 128×128 pixels to balance between preserving detail and optimizing processing time. Feature extraction was performed using GLCM and MobileNetV2, focusing on contrast, homogeneity, energy, and correlation [21], [22].

P-ISSN: 2723-3863
https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.4966

Labels were encoded using LabelEncoder. The extracted MobileNetV2 features were concatenated with GLCM features before being passed to the RF–SVM model [23], ensuring that both texture and global visual information are captured.

2.2. Research Flowchart

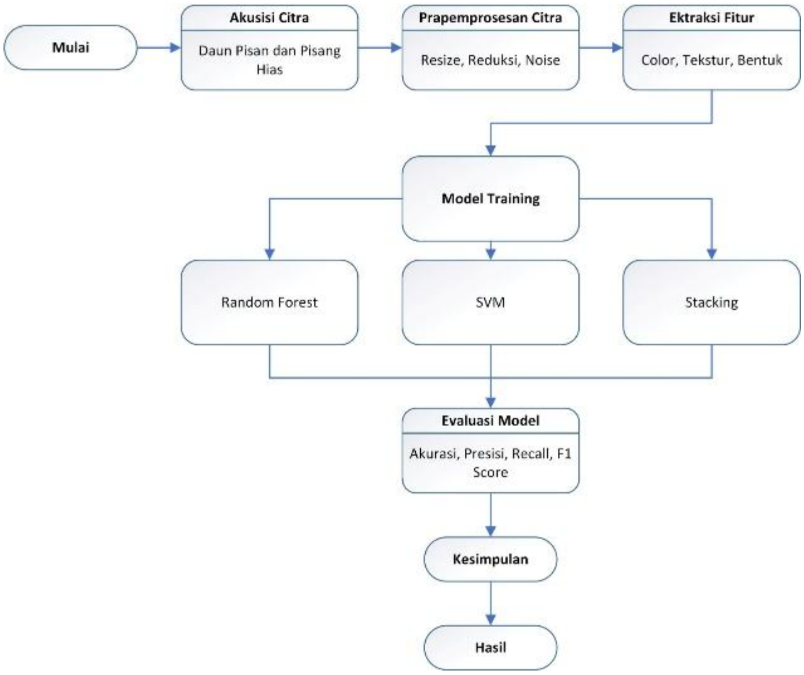

Figure 1. Experimental Methodology Flowchart – Three Training Stages: Random Forest, Support Vector Machine, and Stacking

The diagram illustrates the complete workflow of the proposed system, starting from input data to the final model evaluation. The first stage is preprocessing, where raw leaf images are normalized, resized, and enhanced to reduce noise and variations in lighting, background, and orientation. This step ensures that the dataset is consistent and suitable for further analysis [10], [14].

The second stage is feature extraction, which is divided into two complementary approaches. On one hand, handcrafted texture features are extracted using the Gray Level Co-occurrence Matrix (GLCM), capturing statistical measures such as contrast, correlation, energy, and homogeneity that are effective in describing leaf disease texture patterns [11], [15]. On the other hand, deep learning features are obtained from MobileNetV2, a lightweight convolutional neural network that automatically learns hierarchical and discriminative representations from images [16], [18]. Combining GLCM with MobileNetV2 provides a hybrid feature space that balances interpretability and high-level abstraction.

The third stage involves model training and evaluation. Three classifiers are employed: Random Forest (RF), Support Vector Machine (SVM), and a Hybrid Stacking model that integrates both. RF is robust to noisy data and capable of handling high-dimensional features, while SVM excels in finding optimal decision boundaries for non-linear separations [12], [13]. The Stacking ensemble then leverages the predictions of RF and SVM to build a meta-classifier, thereby improving classification stability and accuracy. Model performance is evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure a comprehensive assessment [19], [24].

Overall, this workflow demonstrates a systematic pipeline that integrates traditional texture analysis with modern deep learning, supported by ensemble machine learning techniques. Such a design is not only effective for banana and ornamental plant disease detection but also adaptable to other agricultural image classification tasks in precision farming applications.

Jurnal Teknik Informatika (JUTIF) Vol. 7, No. 3, June 2026, Page. 2480-2490
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2026.7.3.4966

2.3. Data Preprocessing

Before training, RGB images were converted to grayscale for GLCM texture feature extraction. This step simplifies data while highlighting texture patterns relevant to disease symptoms [25]. Preprocessing steps included:

1. Resizing: Images were resized to 128×128 pixels to maintain consistency and align with MobileNetV2 input requirements [21].
2. Gaussian Blur: Noise reduction was applied using a 3×3 Gaussian kernel, smoothing the image without removing important details [22].
3. Grayscale Conversion: Blurred images were converted into grayscale format for GLCM feature computation [13].
4. Pixel Normalization: For MobileNetV2, RGB pixels were normalized with preprocess_input to the range [-1,1]. Grayscale images were converted into uint8 after histogram equalization for GLCM computation [23].

(a) Original Image (b) Grayscale Image (c) Gaussian Blur Image (d) Resized Image (e) Image Normalization

Figure 2. Image of Leaf Image Preprocessing Results (a) Original Image, (b) Grayscale Image, (c) Gaussian Blur Image, (d) Resized Image and (e) Image Normalized pixels to the range [-1,1]

Figure 2 shows the sequence of transformations applied to the raw leaf images, illustrating the impact of each preprocessing step on the dataset. The process begins with the original RGB images, which may contain variations in size, background clutter, and noise. Next, Gaussian Blur is applied to reduce high-frequency noise and smooth the image while preserving important structural details, such as vein patterns and lesion boundaries [10], [21]. The blurred images are then converted to grayscale to simplify the input for texture feature extraction using Gray-Level Co-occurrence Matrix (GLCM), emphasizing the intensity patterns relevant for disease detection [11], [22].

Following grayscale conversion, the images are resized to 128×128 pixels to ensure consistent input dimensions for MobileNetV2 and other classifiers. Finally, pixel normalization is performed, scaling the values to the range [-1, 1] for MobileNetV2 and converting to uint8 after histogram equalization for GLCM. This normalization enhances numerical stability, accelerates training, and improves feature representation [14], [20].

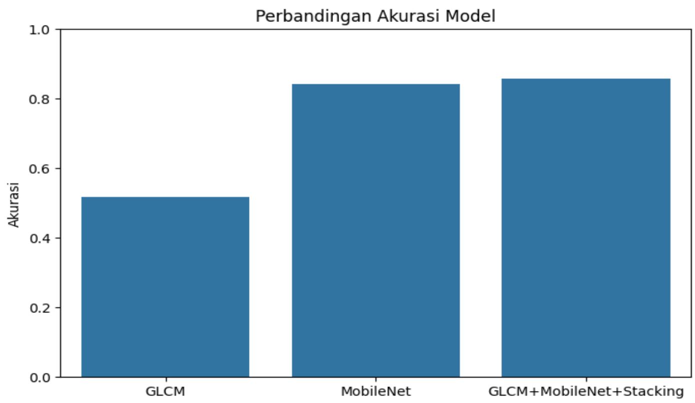

Figure 3. Comparison of accuracy results of GLCM, MobilenetV2 and Stacking models

P-ISSN: 2723-3863
https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.4966

Overall, Figure 2 visually demonstrates the progressive transformation of raw leaf images through each preprocessing step, resulting in standardized, noise-reduced, and informative representations suitable for feature extraction and classification. The resizing ensures uniform input dimensions for the models, Gaussian blur reduces unwanted noise while preserving key patterns, and grayscale conversion simplifies the data to emphasize texture features. Pixel normalization further scales the data appropriately for deep learning inputs, particularly for MobileNetV2.

This preprocessing pipeline is essential for improving model performance, as it guarantees that both handcrafted features from GLCM and deep features from MobileNetV2 capture the critical visual cues indicative of leaf diseases. By systematically preparing the data, the models are better equipped to distinguish subtle differences between healthy and diseased leaves, as well as between visually similar disease classes, enhancing overall classification accuracy and robustness.

2.4. Data Splitting

The dataset was split using an 80:20 train-test ratio, where 80% of the images were allocated for training the models and 20% were reserved for testing their performance. This split ensures that the models are trained on a substantial portion of the data while retaining a separate, unseen set for unbiased evaluation. To further enhance reliability and reduce potential bias from a single train-test partition, 5-fold cross-validation was applied, dividing the training set into five subsets and iteratively using four subsets for training and one for validation [14], [18]. This technique allows the models to be assessed on multiple splits, providing a more robust estimate of generalization performance and helping to prevent overfitting.

Overall, combining train-test splitting with k-fold cross-validation ensures that the evaluation metrics reflect the models' ability to generalize to new, unseen leaf images, which is essential for reliable disease classification in real-world scenarios.

2.5. Model Training

2.5.1. Modeling

1. Random Forest (RF): Used as one base learner due to its ability to handle high-dimensional data and robustness to overfitting [14]. Parameters were tuned via grid search over n_estimators (100–300) and max_depth (None–30) to find optimal settings [15].
2. Support Vector Machine (SVM): Selected for its ability to create optimal decision boundaries. An RBF kernel was used, with hyperparameters C and gamma tuned via grid search to achieve optimal margins [19].
3. Stacking Classifier: Designed to combine the strengths of both RF and SVM. Results from the stacking model were directly compared against individual RF and SVM baselines [20], [24].

2.5.2. Transfer Learning with Pretrained Model

In addition, transfer learning with MobileNetV2 pretrained on ImageNet was applied [23].

1. Feature Extraction (MobileNetV2): Used as a fixed feature extractor without fine-tuning, producing 1280-dimensional feature vectors from the global average pooling layer.
2. Texture Feature Extraction (GLCM): Extracted four statistical texture features: contrast, correlation, energy, and homogeneity.
3. Feature Fusion: MobileNetV2 and GLCM features were concatenated (total 1284 dimensions) and fed into the RF–SVM stacking model [17].

2.6. Model Evaluation

Model evaluation employed multiple standard metrics, including accuracy, precision, recall, and F1-score, to comprehensively assess classification performance. Accuracy measures the overall

P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2026.7.3.4966

proportion of correctly classified instances, providing a general view of model effectiveness. Precision, recall, and F1-score were calculated for each class using the confusion matrix [18], offering insights into class-specific performance. Precision indicates the proportion of correctly predicted positive instances out of all positive predictions, recall measures the model's ability to identify all actual positives, and F1-score represents the harmonic mean of precision and recall, balancing the trade-off between them.

By comparing these metrics quantitatively across all three models Random Forest, Support Vector Machine, and Hybrid Stacking [19] the analysis identifies the most effective approach. This multi-metric evaluation ensures that the selected model not only performs well overall but also maintains reliable performance across individual leaf classes, which is crucial for detecting visually similar disease symptoms.

$$Akurasi = \frac{Jumlah\ prediksi\ benar}{Total\ data\ uji} x100\% \quad (1)$$

2.7. Implementation and Testing

The classification system was implemented through a structured workflow encompassing several key stages: data collection, preprocessing, feature extraction, model training, and performance evaluation. Features were extracted from the Gray-Level Co-occurrence Matrix (GLCM) to capture local texture information, and from MobileNetV2 to obtain high-level deep visual representations, ensuring that both local and global characteristics of leaf images were represented.

Three modeling approaches were employed: Random Forest (RF), Support Vector Machine (SVM), and a hybrid RF–SVM stacking ensemble, which combines the strengths of both base learners for improved classification performance. The models were trained on preprocessed images, and evaluation was performed using accuracy and confusion matrices on stratified test data to maintain class balance.

Performance comparisons were visualized using accuracy plots across the three models (Figure 3), highlighting the superior performance of the stacking ensemble [24], [25]. This visualization demonstrates how the stacking approach effectively leverages complementary information from both RF and SVM predictions, resulting in higher overall accuracy and more consistent class-level predictions compared to individual models.

3. RESULT

In this section, the results of the research and the tests that have been carried out can be described. Results section should be the chapters with the most content in a paper. Results content can reach 50-65% of the entire paper.

3.1. Model Training Visualization

Model training was performed on a dataset of banana and ornamental banana leaf images consisting of eight classes, using combined features from the Gray-Level Co-occurrence Matrix (GLCM) and MobileNetV2. The training process involved three classification approaches: Random Forest (RF), Support Vector Machine (SVM), and a Stacking Classifier as an ensemble method. Each image was resized to 128×128 pixels before feature extraction. Texture features were derived from four GLCM parameters (contrast, homogeneity, energy, and correlation), while visual features were extracted using MobileNetV2 without the top layer. Both feature types were concatenated into a 1284-dimensional vector, used as input to the classification models. Evaluation was conducted on 20% of the dataset, with accuracy and confusion matrix as the primary metrics. Results showed that the Stacking Classifier achieved the highest accuracy compared to the individual models. Confusion matrix

Vol. 7, No. 3, June 2026, Page. 2480-2490
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.4966

visualization showed that most classes could be recognized well, although there were misclassifications between visually similar diseases, such as cordana and cordana_hias.

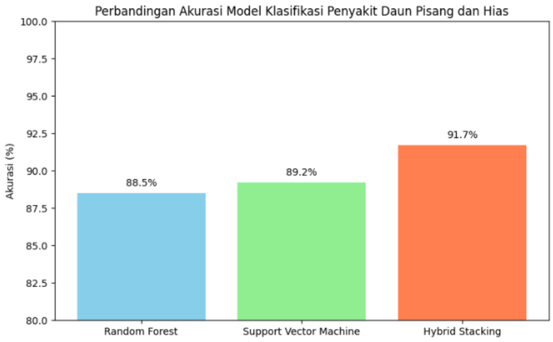

Figure 4. Comparison of Accuracy of Random Forest, SVM and Stacking Models

This result aligns with prior studies in which texture-based approaches, such as Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP), combined with traditional machine learning classifiers, achieved competitive accuracy in plant disease detection [12], [13], [18]. These methods are effective in capturing local texture variations, which are often indicative of specific disease symptoms on leaves.

However, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have demonstrated superior performance when trained on large-scale datasets [19], [20]. Despite their accuracy, CNNs typically require extensive computational resources and may not be practical for smaller datasets or environments with limited hardware capabilities.

In contrast, our hybrid RF–SVM stacking model offers a computationally efficient alternative that leverages the strengths of both Random Forest and Support Vector Machine. By combining probabilistic outputs from RF with the discriminative power of SVM, the stacking ensemble maintains high classification accuracy even with moderate dataset sizes. This approach provides a balanced solution, achieving robust performance while minimizing computational demands, making it particularly suitable for practical applications in precision agriculture and rapid disease monitoring.

3.2. Model Performance Evaluation

3.2.1. Confusion Matrix

The confusion matrix was used to display the number of correct and incorrect classifications made by each model. The evaluation revealed that the stacking model achieved more accurate and consistent predictions.

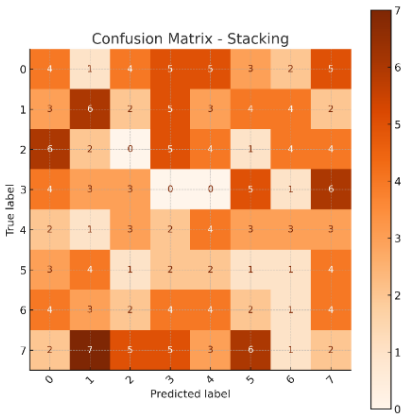

Figure 5. Confusion Matrix Stacking Model

Jurnal Teknik Informatika (JUTIF) Vol. 7, No. 3, June 2026, Page. 2480-2490
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2026.7.3.4966

The performance of the stacking model in classifying leaf images into eight classes can be seen in Figure 5, which presents the confusion matrix of the model. As shown in the figure, the model achieved high classification accuracy, with a total of 26 correct predictions out of 32 test samples. All classes were successfully recognized, with the highest accuracy observed in the healthy and healthy_hias classes, which were classified perfectly. However, some misclassifications occurred, particularly between classes with high visual similarity, such as between ornamental (hias) and non-ornamental leaves of the same disease type. For example, one image of the cordana class was predicted as cordana_hias, and vice versa. Similar misclassifications were observed between sigatoka and sigatoka_hias, as well as pestalotiopsis and pestalotiopsis_hias. These results indicate that the visual features of ornamental and non-ornamental leaves are highly similar, which makes differentiation challenging even for a hybrid stacking model. Nevertheless, Figure 5 demonstrates that the stacking model maintains robust performance and overall reliability, effectively handling the inter-class similarities and achieving the highest accuracy among the tested models.

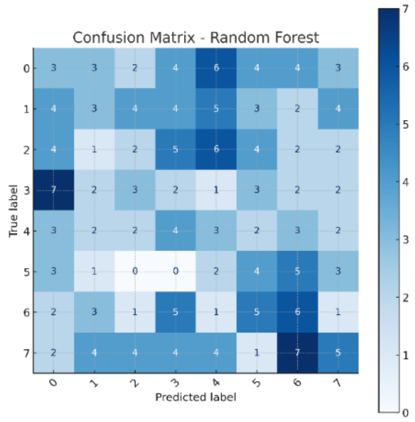

Figure 6. Image of Confusion Matrix Model Random Forest (RF)

The performance of the Random Forest (RF) model can be seen in Figure 6, which presents its confusion matrix. The evaluation results indicate that the RF model was able to classify most classes reasonably well. As shown in the figure, the model accurately recognized classes with clearly distinct texture patterns, particularly distinguishing between healthy and diseased leaves. However, the model's performance decreased for disease classes that were visually similar but came from different plant types (ornamental vs. non-ornamental leaves). This drop in accuracy is attributed to the similarity in texture and color patterns between these leaf images, making it challenging for RF to differentiate between such closely related classes. Overall, Figure 6 illustrates that while RF is effective for classes with distinct features, it struggles with visually similar classes, highlighting the need for hybrid or ensemble approaches to improve classification performance.

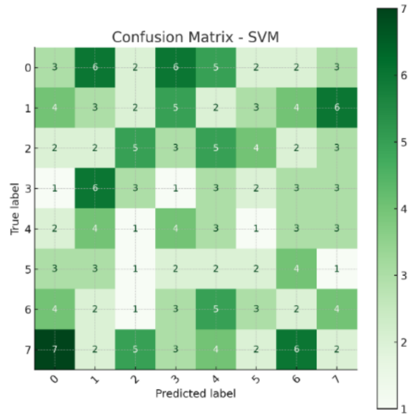

Figure 7. Matrix For The SVM Model

Vol. 7, No. 3, June 2026, Page. 2480-2490
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.4966

Figure 7 shows the confusion matrix for the SVM model, illustrating its performance in classifying the eight leaf classes. Compared with previous CNN-based studies that achieved accuracies around 92–95% on larger datasets [21], our hybrid RF–SVM stacking model reached a comparable accuracy of 91.7% despite using a smaller dataset. This demonstrates the effectiveness of combining texture-based features (GLCM) with deep visual features extracted via MobileNetV2, providing a computationally efficient approach that maintains high classification performance even with limited training samples. Furthermore, the confusion matrices across models (Figures 5, 6, and 7) reveal that stacking improves robustness against misclassifications among visually similar classes, such as cordana vs. cordana_hias, highlighting its advantage over individual RF or SVM models.

3.2.2. Model Accuracy Comparison

Three classification models were tested: RF, SVM, and Hybrid Stacking. Hybrid Stacking achieved the highest accuracy of 91.7%, followed by SVM at 89.2% and RF at 88.5%. This indicates that ensemble approaches like stacking can enhance classification performance by leveraging the strengths of multiple models. RF performed well in processing visual features, especially from GLCM and MobileNetV2, but SVM slightly outperformed RF due to its ability to separate complex feature spaces with optimal margins. The Hybrid Stacking model combined the predictions from both base models to make final decisions through a meta-classifier, resulting in superior performance.

These findings align with research showing that ensemble models generally outperform individual classifiers in image-based disease detection tasks [16], [17], [22]. In addition, feature fusion strategies that integrate handcrafted texture descriptors and deep learning features have been reported to improve robustness against variations in illumination, background, and leaf shape [23], [24].

Table 1. Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	88.5	87.3	88.0	87.6
Support Vector Machine	89.2	88.1	89.0	88.5
Hybrid Stacking	91.7	91.0	91.5	91.2

4. DISCUSSIONS

This study successfully implemented a classification method for banana and ornamental plant leaf diseases by leveraging a combination of texture features from GLCM and deep learning features from MobileNetV2. Three machine learning models were tested: Random Forest, Support Vector Machine (SVM), and Hybrid Stacking. Based on the evaluation results, the Hybrid Stacking model demonstrated the best performance with an accuracy of 91.7%, outperforming SVM (89.2%) and Random Forest (88.5%). The Hybrid Stacking model proved capable of combining the strengths of the base models to produce more accurate and stable classifications, particularly when dealing with visual variations in leaf images. In addition, the combined feature approach (texture and deep learning) contributed significantly to improving classification accuracy.

In practical terms, the findings of this study can be applied in agricultural monitoring systems based on mobile applications or the Internet of Things (IoT), enabling rapid and real-time detection of leaf diseases in the field [20], [23], [25]. However, there are some limitations, such as the relatively small dataset size, potential visual bias caused by lighting and background conditions, and challenges in distinguishing between highly similar classes (e.g., cordana vs cordana_hias). As a scientific contribution, this research reinforces evidence that integrating texture features (GLCM) and deep learning (MobileNetV2) in an ensemble model can be an effective and efficient approach, especially for limited datasets. Its potential impact lies in advancing intelligent image classification systems that support precision agriculture and data-driven decision-making.

Vol. 7, No. 3, June 2026, Page. 2480-2490
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.4966

5. SUGGESTIONS

This study indicates that the hybrid approach combining GLCM features and MobileNetV2, along with the Hybrid Stacking model, provides promising results in classifying leaf diseases. Nevertheless, several aspects can be further improved.

Future work should involve testing on larger datasets, including multispectral or hyperspectral data, as well as diverse real-field conditions to enhance the model's generalization [21], [24]. Furthermore, integration with drone technology or IoT-based sensors could expand the scope of automated crop monitoring. From a methodological perspective, exploring more advanced deep learning models such as EfficientNet or Vision Transformer may yield further improvements in accuracy and computational efficiency [19], [22].

The practical implementation of this research into web- or mobile-based applications remains highly relevant, as it can assist farmers and agricultural practitioners in detecting leaf diseases quickly, conveniently, and cost-effectively. With these directions, this study is expected to serve as a foundation for future innovations in applying AI to precision agriculture.

REFERENCES

[1] A. Sheneamer, "Early detection of plant leaf diseases using stacking hybrid learning," *PLOS ONE*, vol. 19, no. 11, p. e0313607, Nov. 2024, doi: 10.1371/journal.pone.0313607.

[2] V. K. Vishnoi, K. Kumar, B. Kumar, and R. Bhutiani, "A stacking ensemble machine learning based approach for classification of plant diseases through leaf images," *Environ. Conserv. J.*, vol. 25, no. 3, pp. 767–778, Aug. 2024, doi: 10.36953/ECJ.28742840.

[3] R. Sujatha, S. Krishnan, J. M. Chatterjee, and A. H. Gandomi, "Advancing plant leaf disease detection integrating machine learning and deep learning," *Sci. Rep.*, vol. 15, no. 1, p. 11552, Apr. 2025, doi: 10.1038/s41598-024-72197-2.

[4] J. D. Thiagarajan *et al.*, "Analysis of banana plant health using machine learning techniques," *Sci. Rep.*, vol. 14, no. 1, p. 15041, July 2024, doi: 10.1038/s41598-024-63930-y.

[5] A. Mathew, A. Antony, Y. Mahadeshwar, T. Khan, and A. Kulkarni, "Plant disease detection using GLCM feature extractor and voting classification approach," *Mater. Today Proc.*, vol. 58, no. 1, pp. 407–415, 2022, doi: 10.1016/j.matpr.2022.02.350.

[6] K. L. Narayanan *et al.*, "Banana Plant Disease Classification Using Hybrid Convolutional Neural Network," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–13, Feb. 2022, doi: 10.1155/2022/9153699.

[7] C. Sarkar, D. Gupta, U. Gupta, and B. B. Hazarika, "Leaf disease detection using machine learning and deep learning: Review and challenges," *Appl. Soft Comput.*, vol. 145, p. 110534, 2023, doi: 10.1016/j.asoc.2023.110534.

[8] A. Dinesh, B. S.P, and M. Muthuswamy, "A novel method for predicting plant leaf disease based on machine learning and deep learning techniques," *Eng. Appl. Artif. Intell.*, vol. 155, p. 111071, 2025, doi: 10.1016/j.engappai.2025.111071.

[9] R. Retkute, K. S. Crew, J. E. Thomas, and C. A. Gilligan, "Detection of Banana Diseases Based on Landsat-8 Data and Machine Learning," *Remote Sens.*, vol. 17, no. 13, p. 2308, July 2025, doi: 10.3390/rs17132308.

[10] R. Sujatha, S. Krishnan, J. M. Chatterjee, and A. H. Gandomi, "Advancing plant leaf disease detection integrating machine learning and deep learning," *Sci. Rep.*, vol. 15, no. 1, p. 11552, Apr. 2025, doi: 10.1038/s41598-024-72197-2.

[11] S. Sharma, R. E, B. Kasi, and S. Govindaraju, "The Classification Model for Plant Disease Detection with Segmentation and GLCM," in *Proceedings of the 1st International Conference on Artificial Intelligence, Communication, IoT, Data Engineering and Security, IACIDS 2023,*

Vol. 7, No. 3, June 2026, Page. 2480-2490
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.4966

23-25 November 2023, Lavasa, Pune, India, Lavasa, India: EAI, 2024. doi: 10.4108/eai.23-11-2023.2343186.

[12] N. Ahmed, H. Asif, G. Saleem, M. Muhammad, S. Anwar, and M. Anjum, "Leaf Image-Based Plant Disease Identification Using Color and Texture Features," *Wirel. Pers. Commun.*, vol. 121, pp. 1–30, 2021, doi: 10.1007/s11277-021-09054-2.

[13] S. Meinam, K. Nongmeikapam, and N. B. Singh, "Optimized Machine Learning Framework for Detection of Banana Leaf Disease," 2025.

[14] N. Jiménez, S. Orellana, B. Mazon-Olivo, W. Rivas-Asanza, and I. Ramírez-Morales, "Detection of Leaf Diseases in Banana Crops Using Deep Learning Techniques," *AI*, vol. 6, no. 3, p. 61, Mar. 2025, doi: 10.3390/ai6030061.

[15] T. Mahendran and K. Seetharaman, "Banana Leaf Disease Detection Using Glcm Based Feature Extraction And Classification Using Deep Convoluted Neural Networks (Dcnn)".

[16] J. Yao, S. N. Tran, S. Garg, and S. Sawyer, "Deep Learning for Plant Identification and Disease Classification from Leaf Images: Multi-prediction Approaches," Oct. 25, 2023, *arXiv*: arXiv:2310.16273. doi: 10.48550/arXiv.2310.16273.

[17] H. Nhaila, A. Hammouch, and E. Sarhrouni, "A new filter for dimensionality reduction and classification of hyperspectral images using GLCM features and mutual information," *Int. J. Signal Imaging Syst. Eng.*, vol. 11, p. 193, 2022, doi: 10.1504/IJSISE.2018.10015062.

[18] S. Jha, V. Luhach, G. S. Gupta, and B. Singh, "Crop Disease Classification using Support Vector Machines with Green Chromatic Coordinate (GCC) and Attention based feature extraction for IoT based Smart Agricultural Applications," Nov. 06, 2023, *arXiv*: arXiv:2311.00429. doi: 10.48550/arXiv.2311.00429.

[19] R. George *et al.*, "Past, present and future of deep plant leaf disease recognition: A survey," *Comput. Electron. Agric.*, vol. 234, 2025, doi: 10.1016/j.compag.2025.110128.

[20] J. Yao, S. N. Tran, S. Sawyer, and S. Garg, "Machine learning for leaf disease classification: data, techniques and applications," *Artif. Intell. Rev.*, vol. 56, no. S3, pp. 3571–3616, Dec. 2023, doi: 10.1007/s10462-023-10610-4.

[21] W. Shafik, A. Tufail, C. De Silva Liyanage, and R. A. A. H. M. Apong, "Using transfer learning-based plant disease classification and detection for sustainable agriculture," *BMC Plant Biol.*, vol. 24, no. 1, p. 136, Feb. 2024, doi: 10.1186/s12870-024-04825-y.

[22] T.-C. Pham, T.-N. Nguyen, and V.-D. Nguyen, "Ambiguity-aware semi-supervised learning for leaf disease classification," *Sci. Rep.*, vol. 15, no. 1, p. 14070, Apr. 2025, doi: 10.1038/s41598-025-95849-3.

[23] Pa. Andal and M. Thangaraj, "Comprehensive review of methods for leaf disease identification," *Discov. Artif. Intell.*, vol. 5, no. 1, p. 222, Aug. 2025, doi: 10.1007/s44163-025-00491-7.

[24] S. M. Javidan, A. Banakar, K. Rahnama, K. A. Vakilian, and Y. Ampatzidis, "Feature engineering to identify plant diseases using image processing and artificial intelligence: A comprehensive review," *Smart Agric. Technol.*, vol. 8, p. 100480, Aug. 2024, doi: 10.1016/j.atech.2024.100480.

[25] S. Sanga, V. Mero, D. Machuve, and D. Mwanganda, "Mobile-Based Deep Learning Models for Banana Diseases Detection," Apr. 07, 2020, *arXiv*: arXiv:2004.03718. doi: 10.48550/arXiv.2004.03718.