

International Journal of Multidisciplinary Research in Science, Engineering and Technology

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.206

Volume 9, Issue 3, March 2026



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

A Hybrid CNN and MI Framework for Plant Disease Classification

S.K. Umar Faruq^[1], V. Ramya^[2], S.K. Rabbani^[3]

UG Student, Department of ECE, R.V.R & J.C College of Engineering, Chowdavaram, India^[1]

UG Student, Department of ECE, R.V.R & J.C College of Engineering, Chowdavaram, India^[2]

UG Student, Department of ECE, R.V.R & J.C College of Engineering, Chowdavaram, India^[3]

ABSTRACT: Plant diseases significantly impact agricultural productivity and crop quality, making early detection essential. This paper presents a hybrid classification system that integrates deep learning and machine learning techniques for accurate plant disease identification. Input leaf images are enhanced and segmented to improve feature representation. Deep features are extracted using multiple pre-trained CNN models, while texture characteristics are captured using Local Binary Patterns (LBP). The combined feature set is classified using a Support Vector Machine (SVM) to determine disease categories. The proposed system achieves high accuracy and offers an efficient and reliable solution for automated plant disease detection with reduced human effort.

KEYWORDS: Plant Disease Classification, Multi-CNN, Feature Fusion, SVM, LBP

I. INTRODUCTION

Plant diseases pose a serious threat to agricultural productivity by affecting crop yield and quality. Early identification of such diseases is essential to ensure effective crop management [1]. Traditionally, disease detection has relied on manual observation by experts, which is time-consuming, labor-intensive, and difficult to scale for large agricultural areas [2]. These approaches also lack automation and real-time monitoring capabilities.

With the rapid development of Artificial Intelligence (AI) and computer vision, automated plant disease detection systems have gained significant attention [3]. Conventional machine learning methods based on handcrafted features often struggle with variations in lighting conditions and complex backgrounds [4]. Deep learning models, especially Convolutional Neural Networks (CNNs), have shown improved performance by learning complex patterns directly from images [3][5]. However, relying on a single model may limit the ability to capture diverse feature representations [6].

To address these challenges, this work presents a hybrid classification approach that integrates deep learning with traditional feature extraction techniques [7]. Deep features are obtained from multiple pre-trained CNN models, while texture information is captured using Local Binary Patterns (LBP) [8]. The combined features are classified using a Support Vector Machine (SVM) to enhance accuracy and robustness [9]. The proposed system offers an efficient and automated solution for plant disease detection with reduced dependence on human intervention.

II. LITERATURE REVIEW

Plant disease detection has been widely studied using machine learning and deep learning techniques. Early approaches mainly relied on handcrafted features such as color, texture, and shape descriptors extracted from leaf images. These features were classified using traditional algorithms like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees [10]. Although these methods are computationally efficient, they are highly sensitive to variations in lighting, background, and image quality, which limits their performance in real-world conditions [11].

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become widely used for plant disease classification. Models such as AlexNet and other deep architectures automatically learn hierarchical features from images, leading to improved accuracy [12]. These models eliminate the need for manual feature extraction and perform well on benchmark datasets [13]. However, individual CNN architectures may not capture all relevant feature representations in complex disease patterns [14].



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

To overcome these limitations, hybrid approaches combining deep learning and traditional feature extraction techniques have been explored [15]. These methods integrate deep features with handcrafted descriptors such as Local Binary Patterns (LBP), enabling better representation of both global and local image characteristics [16]. While such approaches improve classification performance, many existing systems rely on limited feature combinations or single CNN models, leaving scope for further improvement [17][18].

III. PROPOSED METHOD

Problem Statement

Plant diseases continue to be a major concern in agriculture as they directly impact crop yield, quality, and overall productivity. With the expansion of large-scale farming, early identification of diseases has become increasingly important. Conventional detection methods depend heavily on manual observation, which is time-consuming, labor-intensive, and often inconsistent when applied across large agricultural areas.

Furthermore, many existing automated approaches rely on single models or limited feature representations, which may not perform well under varying environmental conditions such as changes in lighting, background complexity, and diverse disease patterns. These challenges indicate the need for an efficient and automated system capable of accurately detecting plant diseases while reducing dependency on human intervention.

Objectives

- Design an automated framework for plant disease identification
- Utilize multiple CNN models to obtain diverse feature representations
- Extract texture information using Local Binary Patterns
- Integrate deep and texture features through a fusion strategy
- Apply SVM for effective classification of disease categories
- Improve prediction accuracy while reducing dependency on manual analysis

System Architecture

The overall architecture of the proposed plant disease classification system is shown in Fig. 1. The system follows a hybrid pipeline that integrates preprocessing, feature extraction, feature fusion, and classification for accurate disease detection.

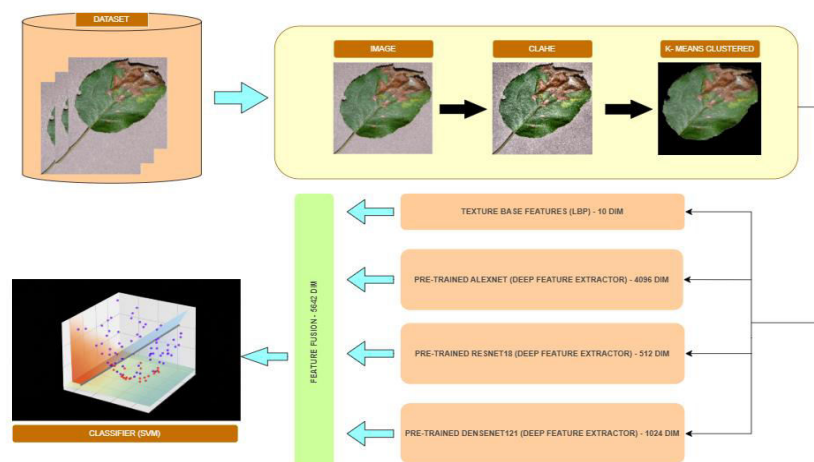


Fig. 1: System Architecture Diagram.



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

- 1. Image Acquisition:** The system takes leaf images as input from the dataset for disease classification.
- 2. Image Preprocessing and Leaf Segmentation:** The input images are resized and enhanced using CLAHE to improve contrast and highlight disease-affected regions. K-means clustering is applied to separate the leaf region from the background, ensuring that only relevant information is processed.
- 3. Deep Feature Extraction:** Multiple pre-trained CNN models, including AlexNet, ResNet18, and DenseNet121, are used to extract deep features from the input images.
- 4. Texture Feature Extraction:** Local Binary Patterns (LBP) are used to extract texture features such as spots and lesions from leaf images.
- 5. Feature Fusion:** The extracted deep and texture features are combined into a single feature vector representing both global and local characteristics.
- 6. Classification:** The fused features are classified using a Support Vector Machine (SVM) with an RBF kernel to identify disease categories.
- 7. Output Generation:** The system outputs the predicted plant disease class based on the classification result.

IV. IMPLEMENTATION

Dataset Description

The experiments are conducted using the PlantVillage dataset, a widely used benchmark dataset for plant disease classification [13], which contains images of plant leaves collected under controlled environmental conditions. In this work, the Apple Leaf Disease subset is considered, consisting of four classes: Healthy, Apple Scab, Black Rot, and Cedar Apple Rust. Sample images from the dataset are shown in Fig. 2.

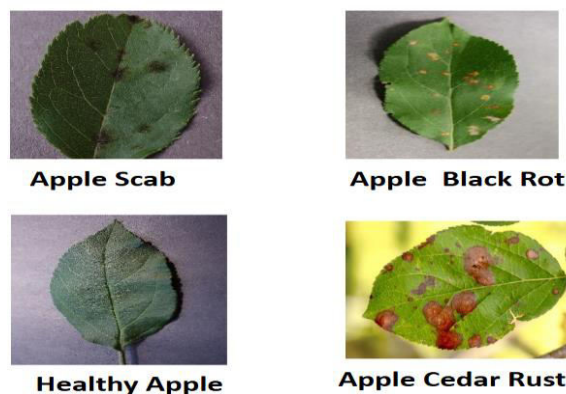


Fig. 2: Sample images from the PlantVillage apple leaf disease dataset.

The dataset contains a total of 3171 images. The detailed distribution of images across different classes is presented in Table 1. The dataset exhibits class imbalance, with the Healthy class having the highest number of samples and Cedar Apple Rust having the least.

Class	Total Images	Training Images (80%)	Validation Images (20%)
Healthy	1645	1316	329
Apple Scab	630	504	126
Black Rot	621	497	124
Cedar Apple Rust	275	220	55
Total	3171	2537	634

Table 1: Distribution of Apple Leaf Disease Dataset



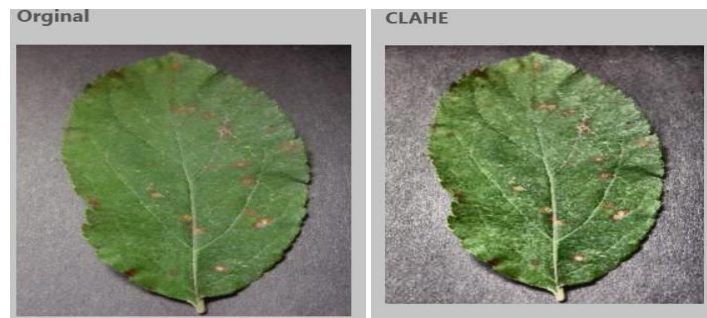
International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Image Preprocessing and Segmentation

Input images are preprocessed to improve feature quality and ensure consistent input for the model. All images are resized to a fixed resolution of 224×224 pixels to match the input requirements of pre-trained CNN models. To enhance image contrast and highlight disease-affected regions, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied [16]. CLAHE improves local contrast by operating on small regions of the image while limiting noise amplification. The parameters used include a clip limit of 2.0 and a tile grid size of 8×8 .

Fig. 3: Effect of CLAHE on leaf image contrast enhancement.



For segmentation, K-means clustering is applied in the LAB color space to separate the leaf region from the background. The number of clusters is set to $k = 2$, and the cluster corresponding to the leaf region is selected to isolate the region of interest. This step reduces background noise and improves the quality of feature extraction. Leaf segmentation using K-means clustering is illustrated in Fig. 4 [16].

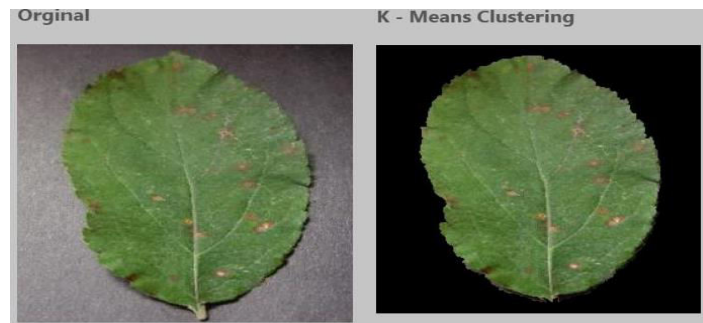


Fig. 4: Leaf segmentation using K-means clustering.

Feature Extraction

Feature extraction is performed using both deep learning models and handcrafted techniques to capture comprehensive information from leaf images. Deep features are extracted using multiple pre-trained convolutional neural network (CNN) models, including AlexNet, ResNet18, and DenseNet121, which are widely used for image representation learning [6][12][15]. These models operate in feature extraction mode by removing the final classification layers, allowing them to generate discriminative feature vectors. Each model captures different levels of feature representations, including global structures, hierarchical patterns, and dense feature relationships.

In addition to deep features, texture-based features are extracted using Local Binary Patterns (LBP), a widely adopted descriptor for texture analysis [8]. LBP captures local intensity variations and texture details such as spots, lesions, and irregular patterns present in diseased leaves. The parameters used include a radius of 1, 8 neighboring points, and the uniform pattern method.

The combination of deep and texture features provides a rich and complementary representation of plant disease characteristics, enhancing the discriminative capability of the proposed classification framework [15].



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Feature Fusion and Classification

The extracted features from multiple CNN models and LBP are concatenated to form a high-dimensional feature vector. This fusion process integrates both global and local information, improving the discriminative capability of the system.

The fused feature vector is then classified using a Support Vector Machine (SVM) with a radial basis function (RBF) kernel to identify disease categories [9].

Training Configuration

The dataset is divided into training and validation sets in an 80:20 ratio while preserving class distribution. Input images are normalized using ImageNet statistics to ensure compatibility with pre-trained CNN models.

The CNN models are used in inference mode without updating weights, ensuring efficient feature extraction. The SVM classifier is trained on the fused feature vectors to perform accurate classification across all disease classes.

Software and Tools

The proposed system is implemented using Python with multiple libraries. PyTorch is used for deep feature extraction from CNN models, OpenCV is used for preprocessing and segmentation, and Scikit-learn is used for implementing the SVM classifier. NumPy is used for data handling and feature operations.

V. RESULTS

Performance Evaluation

The performance of the proposed system is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. The model achieves an overall classification accuracy of **99.69%** on the validation dataset, demonstrating its effectiveness in plant disease classification.

The high accuracy indicates that the proposed hybrid feature fusion approach successfully captures both global and local features, enabling accurate disease identification.

Feature Extraction and Model Performance

The performance of different feature extraction techniques and their combinations is evaluated using Support Vector Machine (SVM) classifiers. The results are summarized in Table 2.

Features Used	Linear SVM Accuracy (%)	Non-Linear SVM Accuracy (%)
AlexNet	97.4	97.9
ResNet18	98.8	98.9
LBP	51.2	51.8
DenseNet121	99.1	99.2
AlexNet + LBP	97.4	97.9
ResNet18 + LBP	98.8	98.9
AlexNet + ResNet18 + LBP	98.9	99.21
Proposed (All Features)	99.5	99.69

Table 2: Feature Extraction Performance

Analysis

From Table 2, it is observed that individual models provide good performance, with DenseNet121 achieving the highest accuracy among single models. However, combining multiple feature extraction methods significantly improves classification performance.



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

The integration of deep features from multiple CNN models with texture-based LBP features results in the highest accuracy of **99.69%**, demonstrating the effectiveness of the hybrid feature fusion approach.

Comparison with Existing Methods

The proposed model is compared with existing approaches, and the results are summarized in Table 3. The performance of the proposed model is compared with several state-of-the-art deep learning models reported in the literature [14]–[18].

Model	Accuracy (%)
EfficientNet-B4 [16]	93.08
Deep CNN [17]	98.00
MobileNetV2 [18]	97.00
Proposed Model	99.69

Table 3: Comparison with Existing Models

Class-wise Performance Analysis

The performance of the proposed model across different classes is evaluated using precision, recall, and F1-score. The results are summarized in Table 4 and Fig. 5.

Class	Precision	Recall	F1-score
Apple Scab	0.98	1.00	0.99
Black Rot	1.00	0.99	1.00
Cedar Apple Rust	1.00	1.00	1.00
Healthy	1.00	1.00	1.00

Table 4: Classification Report

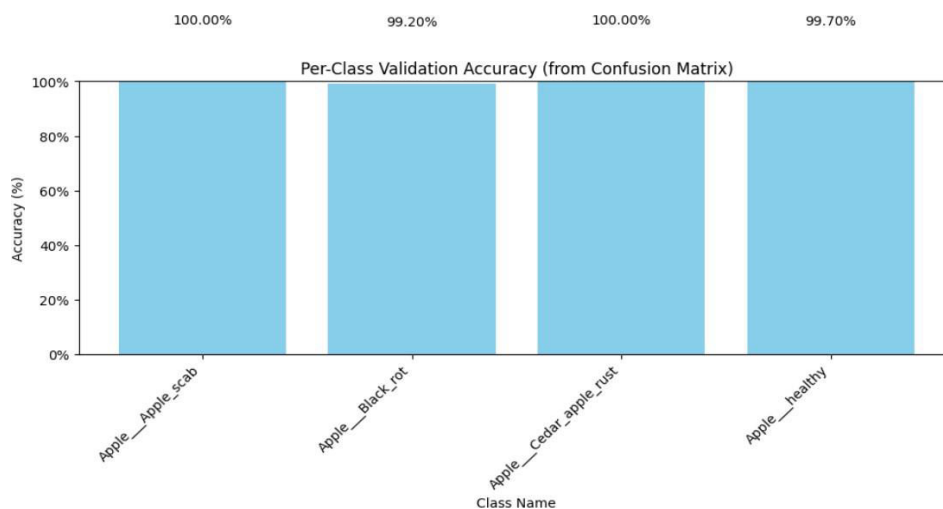


Fig. 5: Class-wise Performance



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Confusion Matrix Analysis

The confusion matrix of the proposed model is shown in Fig. 6. It illustrates the classification performance across all classes.

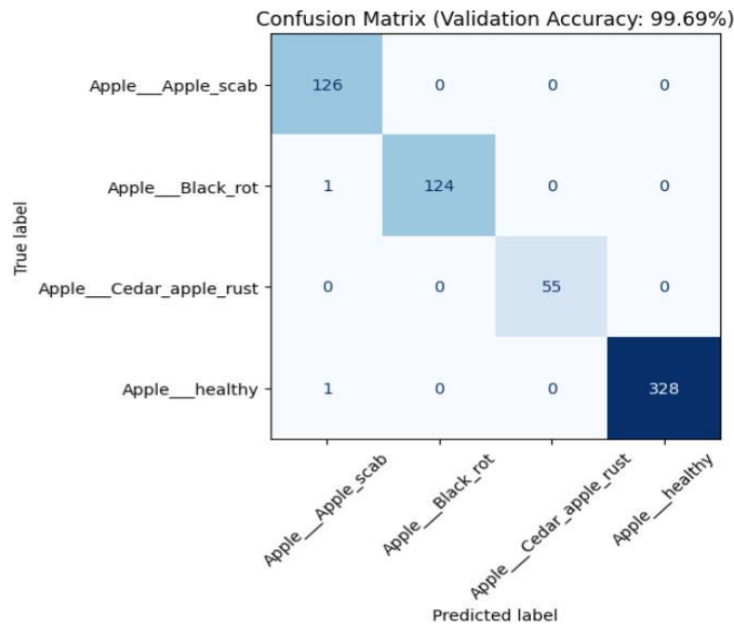


Fig. 6: Confusion Matrix

The confusion matrix shows that most samples are correctly classified with minimal misclassification between similar disease categories, indicating strong feature separability.

Discussion

The proposed model achieves competitive performance compared to existing state-of-the-art models while maintaining lower computational complexity.

The model also demonstrates consistent performance across all classes, indicating strong generalization capability. However, the system requires higher computational time due to multiple feature extraction stages, which may affect real-time deployment.

VI. CONCLUSION

This work presents a hybrid approach for plant disease classification by combining deep learning and traditional feature extraction techniques. The system utilizes multiple pre-trained CNN models along with Local Binary Patterns (LBP) and preprocessing methods such as CLAHE and K-means segmentation to improve feature representation.

The experimental results show that the proposed method achieves a classification accuracy of 99.69%, demonstrating its effectiveness compared to individual models. The combination of deep and texture features enables accurate identification of plant diseases across different classes.

The model also shows consistent performance across all categories, indicating good generalization capability. However, the computational cost increases due to multiple feature extraction stages.

Future work can focus on evaluating the model on real-world datasets, reducing computational complexity, and enabling deployment on edge devices for real-time applications.



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

REFERENCES

- [1] J. G. A. Barbedo, "Factors influencing the use of deep learning for plant disease recognition," *Biosystems Engineering*, vol. 172, pp. 84–91, 2018.
- [2] B. Liu, Y. Zhang, D. He, and Y. Li, "Identification of apple leaf diseases based on deep convolutional neural networks," *Symmetry*, vol. 10, no. 1, p. 11, 2017.
- [3] S. Sladojevic et al., "Deep neural networks based recognition of plant diseases by leaf image classification," *Computational Intelligence and Neuroscience*, 2016.
- [4] S. Singh et al., "Extraction of multiple diseases in apple leaf using machine learning," *International Journal of Image and Graphics*, vol. 22, no. 03, 2022.
- [5] P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018.
- [6] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in *Proc. NIPS*, 2012.
- [7] R. Sujatha et al., "Advancing plant leaf disease detection integrating machine learning and deep learning," *Scientific Reports*, vol. 15, no. 1, 2025.
- [8] T. Ojala, M. Pietikäinen, and D. Harwood, "A comparative study of texture measures with classification based on featured distributions," *Pattern Recognition*, vol. 29, no. 1, pp. 51–59, 1996.
- [9] C.-C. Chang and C.-J. Lin, "LIBSVM: A library for support vector machines," *ACM Transactions on Intelligent Systems and Technology*, vol. 2, no. 3, 2011.
- [10] S. Suthaharan, "Support vector machine," in *Machine Learning Models and Algorithms for Big Data Classification*, Springer, 2016.
- [11] H. Al-Hiary et al., "Fast and accurate detection and classification of plant diseases," *International Journal of Computer Applications*, vol. 17, no. 1, 2011.
- [12] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE CVPR*, 2016.
- [13] D. P. Hughes and M. Salathé, "An open access repository of images on plant health to enable the development of mobile disease diagnostics," *arXiv preprint arXiv:1511.08060*, 2015.
- [14] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv:1409.1556*, 2014.
- [15] G. Huang et al., "Densely connected convolutional networks," in *Proc. IEEE CVPR*, 2017.
- [16] K. P. Sinaga and M.-S. Yang, "Unsupervised K-means clustering algorithm," *IEEE Access*, vol. 8, pp. 80716–80727, 2020.
- [17] A. Too, L. Yujian, S. Njuki, and L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," *Computers and Electronics in Agriculture*, vol. 161, pp. 272–279, 2019.
- [18] M. Sandler et al., "MobileNetV2: Inverted residuals and linear bottlenecks," in *Proc. IEEE CVPR*, 2018.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH IN SCIENCE, ENGINEERING AND TECHNOLOGY

| Mobile No: +91-6381907438 | Whatsapp: +91-6381907438 | ijmrset@gmail.com |

www.ijmrset.com