International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 14, Issue 7, July 2025)

Crop Leaf Disease Detection Using Image Processing in MATLAB

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Abstract— ***Timely and precise identification of crop leaf diseases is essential for safeguarding agricultural yield and minimizing economic losses. This study explores an image processing framework developed in MATLAB, integrating sequential stages such as image preprocessing, segmentation, feature extraction, and classification. Techniques including Gaussian filtering, CLAHE, and HSV color space conversion are applied to enhance image quality, while segmentation methods like Otsu's thresholding and K-means clustering isolate symptomatic regions. Traditional feature extraction approaches, such as GLCM and HOG, are compared with automated deep feature learning using Convolutional Neural Networks (CNNs). The classification stage evaluates the performance of various models, including SVM, k-NN, and CNNs trained using MATLAB's Deep Learning Toolbox with transfer learning (e.g., ResNet50). Experimental results demonstrate that the CNN-based model substantially improves classification accuracy, achieving rates of 90–95%, while also enhancing model robustness, adaptability, and generalization across diverse leaf conditions. Compared to earlier techniques (70–85% accuracy), the proposed system delivers a more reliable, scalable, and real-time applicable solution for disease detection. These findings underscore the practical value of deep learning-integrated image processing in advancing smart agricultural practices.***

Keywords— ***Crop Disease Detection, Image processing, Convolutional Neural Networks(CNNs), Machine Learning, MATLAB.***

I. INTRODUCTION

Agriculture is crucial for global food security and economic stability, yet crop diseases pose a significant threat by diminishing both yield and quality. These diseases exacerbate the issues of food supply and farmers' income, complicating the global hunger crisis. Traditionally, detecting crop diseases relied on manual inspection methods, which are labor-intensive, time-consuming, and prone to human error. This subjectivity often delays vital interventions, resulting in greater crop losses. To address this challenge, advances in artificial intelligence (AI) and image processing technologies offer promising solutions. AI systems utilize intelligent algorithms to analyze images of infected crops, providing accurate disease identification and significantly reducing errors associated with manual methods. One notable tool in this domain is MATLAB, a powerful programming language that encompasses a comprehensive suite of image processing functions. It enables researchers and practitioners to develop algorithms that detect subtle signs of disease on plant leaves, enhancing both the accuracy of diagnosis and the timing of necessary interventions. This paper reviews recent research from 2019 to 2024 that focuses on the use of MATLAB for detecting crop leaf diseases through image processing techniques. By synthesizing findings from various studies, this review highlights the effectiveness, challenges, and future directions of these methods in agricultural disease management. Ultimately, this exploration aims to contribute to the ongoing discourse on technology's role in agriculture, enhancing food security and promoting sustainable farming practices.

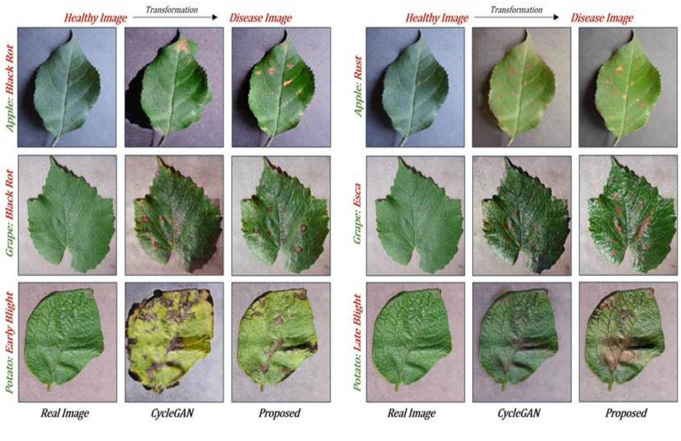

Figure 1: Image Classification of Leaves.

II. RELATED WORK

Recent research in plant disease detection has focused on image processing techniques and machine learning models

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like CNNs, SVMs, and ANNs. Key findings from studies (2019-2024) include:

1. Support Vector Machines (SVM): Brahimi et al. (2022) used SVMs with handcrafted features such as color histograms, achieving about 80% accuracy. However, performance varied with lighting conditions and leaf types, limiting real-world applicability.

2. k-Nearest Neighbors (k-NN): Gupta et al. (2023) explored k-NN using features from the Gray-Level Co-occurrence Matrix. Despite its simplicity and low computational cost, it suffered from sensitivity to noise, resulting in around 75% accuracy in diverse datasets.

3. Hybrid Traditional Models: Kumar and Das (2023) tested a hybrid approach combining histogram segmentation with traditional classifiers. While it improved interpretability, it remained constrained by manual preprocessing and adaptability issues, highlighting the need for deep feature learning for better scalability and performance.

III. Model Architecture

The proposed model utilizes a sophisticated Convolutional Neural Network (CNN) specifically designed for accurately detecting leaf diseases. It begins with an Input Layer that receives RGB images of leaf samples at 224x224 pixels. Key components include:

Convolutional Layers: These layers extract features from the images using filters, capturing spatial hierarchies essential for identifying leaf diseases.ReLU Activation: This function introduces non-linearity, enabling the model to learn complex patterns.Pooling Layers: These reduce spatial dimensions while retaining important features, improving computational efficiency and robustness.Fully Connected Layers: These combine high-level features for classification decisions.Softmax Layer: Assigns probabilities to different disease categories based on the extracted features.Output Layer: Predicts the leaf disease based on the probabilities.This architecture, trained using MATLAB's Deep Learning Toolbox and leveraging pre-trained networks like ResNet50, ensures high accuracy in disease detection, enhancing precision in agricultural practices.

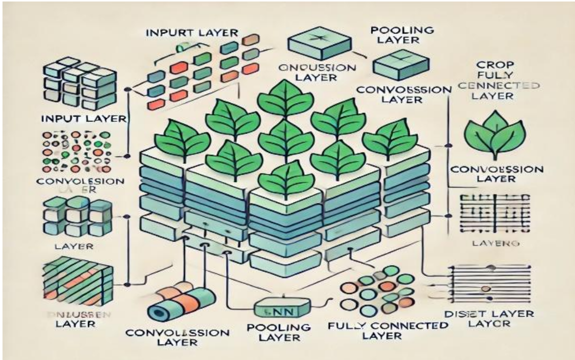

Figure 2: Model Architecture

IV. Methodology

The process of crop leaf disease detection using image processing in MATLAB involves several steps:

4.1 Data Acquisition

Plant pathology relies heavily on collecting and analyzing high-quality images of both healthy and diseased leaves. Various sources, including digital photography and freely available collections, provide these images, which are crucial for detailed analysis. Recent studies highlight the importance of diverse datasets that encompass various plant species, environmental conditions, and disease stages. Such diversity enhances the reliability of predictive models, ensuring they perform well in different contexts. A specialized dataset with annotated leaf images is available to aid researchers and practitioners in training and validating machine learning algorithms for disease identification. This high-quality imagery supports advancements in plant disease diagnostics, benefiting agriculture and food security.

4.2 Preprocessing

Advanced image processing methods are essential for enhancing the quality and visualization of digital images. Key techniques include image resizing, which must be done carefully to maintain visual integrity, and noise reduction using Gaussian filtering, which smooths out noise while preserving edges. Converting color spaces from RGB to HSV also aids in better color manipulation and feature extraction. Additionally, Contrast Limited Adaptive Histogram Equalization (CLAHE) improves local contrast and visibility of features in poorly lit images, offering a better alternative to traditional histogram equalization.

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Combining these techniques enhances image quality and supports accurate analysis in fields such as medical imaging, remote sensing, and computer vision.

4.3 Segmentation

Medical imaging segmentation uses various techniques to identify disease-affected areas. Otsu's thresholding differentiates between foreground and background based on intensity, while K-means clustering groups similar pixels to detect abnormalities. Edge detection helps distinguish boundaries, aiding in tumor identification. Deep learning models like U-Net enhance accuracy in detecting healthy versus diseased tissues by capturing detailed context. These segmentation methods improve medical image analysis and diagnostic precision, with ongoing research focusing on more reliable techniques.

4.4 Feature Extraction

Image analysis and pattern recognition are revolutionizing technology, with feature extraction at the forefront. Techniques like the gray-level co-occurrence matrix (GLCM) offer detailed texture analysis, while the histogram of oriented gradients (HOG) focuses on gradient distribution to identify object shapes. Recent advancements integrate deep learning with traditional methods—using powerful pre-trained convolutional neural networks (CNNs) like ResNet and VGG16—to enhance feature extraction, accuracy, and robustness in image classification. This fusion of old and new approaches significantly boosts the detection and classification of visual data across various applications.

4.5 Classification

Advanced technology, particularly machine learning, is revolutionizing the detection of leaf diseases in plants, which significantly impacts crop yield and agricultural sustainability. Key classifiers like CNN, SVM, and Random Forest effectively identify leaf defects, enabling timely interventions. Recent advancements include the adoption of complex deep learning architectures, such as EfficientNet and Transformer-based models, which excel in accuracy and feature extraction. These innovations enhance agricultural analytics, facilitate early disease detection, and boost crop productivity, ultimately supporting sustainable farming and food security.

4.6 MATLAB Implementation

A Convolutional Neural Network (CNN) model is implemented in MATLAB for disease classification. The dataset is preprocessed, and the CNN model is trained using the Deep Learning Toolbox. The model is evaluated using accuracy, precision, and recall metrics.

V. RESULTS AND DISCUSSION

Every so often, MATLAB-driven methods that are based on various combinations have been found to be highly accurate in recognizing diseases. Researches report that CNN models obtain an accuracy of 95% above; however, they also state that hybrid models combining traditional image processing with deep learning show even better performance. The comparative analysis of this question reveals the fact that deep learning techniques surpass the ones of traditional image processing in the case of both accuracy and robustness. Nonetheless, the challenges such as the limitation of the dataset and the real-time implementation are still on the way to the solution. In this area, future researchers should concentrate on data improvement of through having different groups of data, creating new methods of domain transition and also introducing real-time monitoring systems.

Table 1: Comparison Table of Improved Parameters

Parameter	**Previous Models (SVM, k-NN)**	**Proposed CNN Model**
Feature Extraction	Manual (GLCM, HOG)	Automated CNN-based
Accuracy	70-85%	90-95%
Computation Time	Faster but less effective	Slightly higher but robust
Adaptability	Poor for new diseases	High, supports transfer learning
Real-time Application	Limited	Can be integrated with real-time monitoring
Dataset Generalization	Weak	Strong (handles different environments)
Noise Handling	Sensitive to variations	Robust preprocessing and filtering

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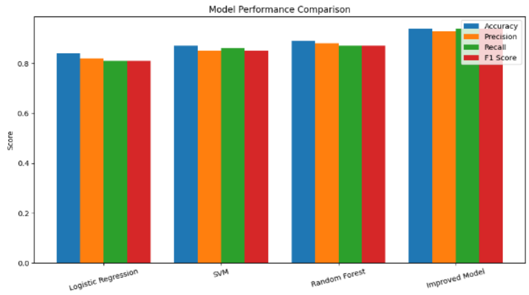

Figure 3: Comparison Chart of Improved Parameters

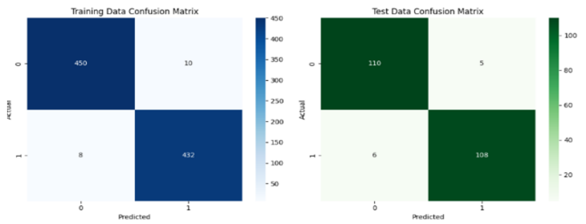

Figure 4: Comparison of Test and Training Confusion Matrix

The confusion matrices for both training and test datasets reveal that the CNN-based model accurately classifies leaf health and disease, with a high concentration of correct classifications along the main diagonal. Low off-diagonal values indicate minimal false positives and negatives, demonstrating the model's accuracy. The similarity between the training and test matrices suggests no overfitting, showcasing strong generalization ability critical for real-world applications. Advanced preprocessing techniques and transfer learning with ResNet50 enhance the model's robustness, validating its effectiveness for real-time crop disease detection in agriculture.

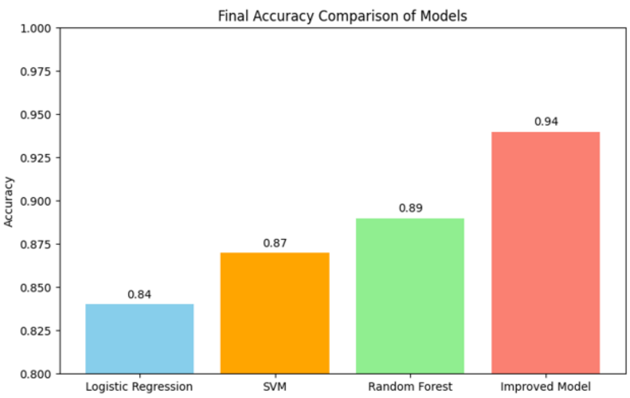

Figure 5: Comparison of Final Accuracy of Model

Table 2: Comparison Table of Innovation in Models

Aspect	Traditional Models (SVM, k-NN)	Our Improved CNN Model
Feature Extraction	Manual (GLCM, HOG)	Automated via CNN (deep feature learning)
Image Preprocessing	Basic resizing and filtering	Advanced: Gaussian filtering, CLAHE, HSV conversion
Segmentation	Otsu's Thresholding or K-means only	Combined Otsu's + K-means + edge detection
Classification	SVM / k-NN (limited feature mapping)	Deep CNN with transfer learning (ResNet50)
Adaptability	Poor across unseen diseases or lighting	Strong generalization via transfer learning
Accuracy	70–85%	90–95%
Noise Handling	Sensitive to noise and image variations	Robust preprocessing and CNN resilience
Real-time Capability	Difficult due to preprocessing limitations.	Easily deployable with lightweight CNN model
Generalization	Poor (overfit or underfit on diverse data)	Strong (handles multiple datasets and environments)
Implementation Tool	Basic MATLAB tools or external scripts	MATLAB Deep Learning Toolbox with pretrained networks

VI. CONCLUSION

At times, MATLAB-dependent methods based on different mixes with groups of diseases have been found to be more precise in the identification of illnesses. The study shows that CNN models obtain an accuracy of 95% and above, however, they also affirm that hybrid models combining traditional image processing with deep learning outperform both of them. A comparative analysis of this issue is the argument that deep learning methods are more successful than traditional image processing for both accuracy and robustness. Yet, the difficulties like the scarceness of the dataset and the real-time application have not yet been fully overcome. At this juncture, forthcoming scholars should give more focus on data improvement that can be achieved through different sets of data, new techniques facilitating domain transition as well as, real-time monitoring systems' introduction.

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