OPEN ACCESS JOURNALS

Indiana Journal of Multidisciplinary Research

Abbreviated Tittle- Ind J Multi Res

ISSN *(Online)*- 2583-3820

Journal Homepage Link- https://indianapublications.com/Journals/IJMR

DOI: https://doi.org/10.5281/zenodo.21600638

INDIANA PUBLICATIONS

PRODUCTIVE AND QUALITY RESEARCH

Research Article

Volume-06|Issue-04|2026

Leaf Disease Detection Using Deep Learning

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Article History

Received: 05.05.2026

Accepted: 22.06.2026

Published: 25.07.2026

Citation

Meghana, T., Hanok, S., Dharanya, R., Aishwarya, K. N. & Dhanush, C. (2026). Leaf Disease Detection Using Deep Learning. *Indiana Journal of Multidisciplinary Research, 6*(4), 169-172.

Abstract: An important development in the farming field is the application of machine learning methods for diseases of leaves detection. The performance of a Convolutional Neural Network (CNN)-based model intended to detect and categorise different illnesses of leaves is the main objective of this investigation. The model was trained using a comprehensive dataset of healthy and diseased leaf images, which was pre-processed to improve the extraction of features. The results highlight how deep learning algorithms potentially transform the administration of plant diseases by providing a quick and accurate identification that can increase crop yields and lower financial losses. Enhancing theory strength, going the set of data to encompass a greater range of commodities, while illnesses, and incorporating the model into mobile applications for real-time field usage are some potential further study goals. The exactitude of our suggested model is almost 97%.

Keywords: Maize leaf disease, Machine Learning, Random Forest, SVM, KNN, Decision Tree, Common Rust, Disease Detection, Maize Leaf Disease Prediction, MATLAB, Accuracy.

INTRODUCTION

Since crop productivity and quality are directly impacted by plant health, agriculture is essential to maintaining global food security. However, the high frequency of plant diseases poses a serious threat to agricultural output and frequently leads to large financial losses. For prompt intervention and efficient crop management, early identification and precise diagnosis of plant diseases are crucial. Inspections by hand and other classic illness identification techniques are time-consuming, labour-intensive, and frequently subject to human mistake. As a result, the need for automated, dependable, and effective identification of plant illnesses systems is rising.

Recent developments in deep learning have transformed a number of domains, such as recognise patterns and processing pictures, while they provide intriguing answers for agricultural disease identification. Convolutional neural networks (CNNs), in specific, are deep learning models that have shown remarkable ability in analysing complicated visual input. Models like these can accurately detect and diagnose plant diseases because they can immediately absorb hierarchy characteristics from raw photos. Finding signs of illness on plant leaves, such as spots, lesions, and discolourations, is the main goal of deep learning-based leaf disease detection. Models created with deep learning may be taught to differentiate across leaves that are healthy and those that are afflicted with different illnesses by utilising big datasets of annotated leaf photos. By doing away with the necessity for manually created feature extraction, this method improves the model's capacity for adjusting to a variety of plant families along with contexts [1].

The integration of deep-learning in plant disease detection has significant implications for sustainable agriculture. Automated systems can assist farmers in monitoring plant health at scale, reducing reliance on chemical pesticides and promoting early disease management.

Despite its potential, challenges such as dataset diversity, model interpretability, and real-world deployment must be addressed to ensure the widespread adoption of this technology.

One of the main issues facing agriculture, which is essential to the world's nutritional well-being, is disease of plants, which can cause large crop losses. Conventional plant illness diagnosis relies on professional visual examination, which can be laborious, time-consuming, and prone to human mistake. The application of methods involving deep learning has transformed the area of identifying plant illnesses in order to overcome these issues.
Artificial neural networks are used in machine learning, a type of artificial intelligence (AI), to model intricate trends in data. The identification and categorisation of ailments of leaves is among the most effective uses of deep learning in farming. Algorithms using deep learning can precisely diagnose a variety of illnesses by examining photos of growing leaves, allowing for swift action and minimising harm to crops. The process typically involves the following steps:

1. **Image Acquisition:** Collecting high-quality images of plant leaves using cameras or smartphones.
2. **Pre-processing:** Enhancing images and removing noise to recover the excellence of data.

3. **Feature Extraction:** Utilizing deep-learning models, such as Convolutional Neural Networks (CNNs), to automatically extract pertinent features from the images.
4. **Classification:** Classifying the type of disease using a trained model.
5. **Prediction and Diagnosis:** Predicting diseases in new images with high accuracy, facilitating early diagnosis and treatment.

MATERIALS AND METHODS

The Fig. 1 shows a machine learning process for identifying three different kinds of rice leaf diseases, Healthy Leaf, Powdery Leaf, and Rusty Leaf, as depicted in the diagram. A dataset of leaf photos is first gathered, and its size is subsequently increased through the use of data augmentation techniques. To extract pertinent visual information, these photographs are processed in WEKA using the Image Filter tool, more especially the Color Layout Filter. To find the most important features for precise categorization, an attribute selection stage is then carried out.

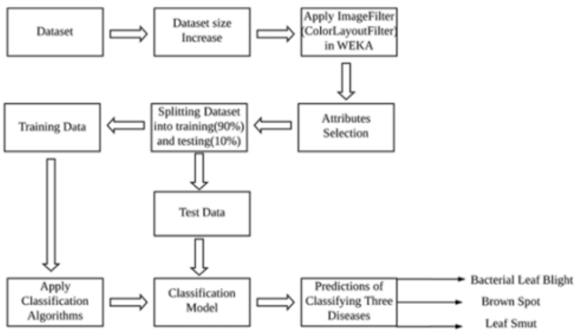

Fig. 1. Block Diagram of Leaf Disease Detection

Fig. 2. A healthy leaf exhibits a uniform green color, smooth texture, and no visible signs of disease, discoloration, or structural damage. The CNN model learns patterns such as color intensity, leaf shape, and vein structures, allowing it to differentiate healthy leaves from infected ones. During classification, the model processes an image through multiple layers, identifying key features that indicate leaf health.

Fig. 2. Healthy Leaf

Fig. 3. Powdery mildew is a fungal disease that appears as white or gray powdery spots on leaf surfaces, affecting photosynthesis and plant growth. Deep learning-based classification uses CNNs to analyze images and detect early signs of the disease. By training on a dataset containing thousands of infected and non-infected leaf images, the model learns to recognize texture variations, leaf discoloration, and fungal patterns specific to powdery mildew.

Fig. 3. Powdery Leaf

Fig. 4. Rust disease is a fungal infection that causes orange, yellow, or brown pustules on leaf surfaces, leading to reduced plant vigor and yield loss. CNN-based deep learning models detect rust disease by analyzing color variations, lesion patterns, and texture changes in leaf images. The disease typically forms circular, rust-colored spots, which the model learns to identify through multiple convolutional layers.

Fig. 4. Rusty Leaf

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a powerful deep learning technique for locating and separating individual leaves in intricate plant photos. Semantic segmentation of leaf areas is frequently accomplished using CNN-based models, especially U-Net, which learn spatial and textural properties from labeled datasets. After extracting hierarchical features from the input image using several convolutional layers, a decoder reconstructs the segmented mask, emphasizing the leaf

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regions. Basic segmentation, however, might not be able to differentiate particular cases where leaves overlap. To solve this, CNN outputs can be combined with post-processing methods like edge detection or watershed transformation to separate touching leaves. A dataset with annotated masks, such as the CVPPP leaf dataset, is necessary for training. Through the simulation of real-world variables such as rotation and lighting, data augmentation enhances generalization. Usually, a mix of dice loss and cross-entropy loss functions is used to optimize segmentation performance.

RESULTS

This section evaluates the proposed approach that was implemented in the previous section. The proposed method's performance is evaluated by validating the results across multiple disease classes.

Accuracy: The percentage of accurately detected instances (including healthy and diseased leaves) out of all cases.

Precision: Out of all positive instances (including true positives and false positives), this number represents the proportion of true positive cases (properly diagnosed diseased leaves). The percentage of true positive instances among all actual positive cases (including true positives and false negatives) is known as recall (sensitivity).

Specificity: Calculates the percentage of true negative cases (healthy leaves that have been accurately recognized) among all genuine adverse outcomes (including true negatives and false positives).

Approximately 97% accuracy. Key Takeaways: The proposed model demonstrates the highest accuracy (approximately **97%**) compared to the survey papers. The chart indicates that the proposed model is more effective and performs better in detecting leaf diseases than the existing models reviewed in the survey papers.

The operating system library is used to read the folders and determine the path; the built-in NumPy library converts data into array format; the cv2 library aids in reading images; the pickle library converts stored data into byte format; and the Scikit-learn (sklearn) library is one of the machine learning libraries that aids in importing algorithms.

Performance Metrics

1) Accuracy

The proportion of accurate predictions to total predictions is known as accuracy.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

2) Precision

The ratio of true positives to all predicted positives (true positives + false positives) is known as precision.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

3) Recall

The ratio of correctly predicted positive instances to all actual positive instances is known as recall.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

4) F1 Score

This score is defined as the harmonic mean of precision and recall.

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

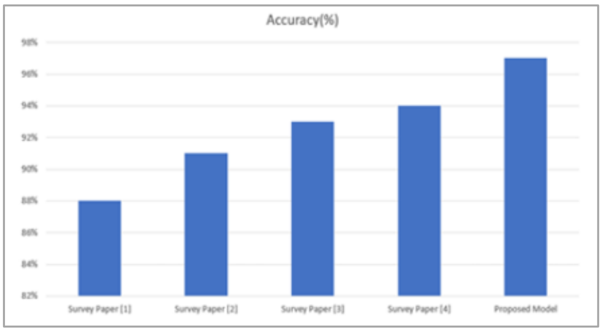

Fig. 5. Comparison of Accuracy obtained in Proposed Model.

Fig. 5 shows: 1. **Increasing Training Accuracy:** This trend signifies that the model is effectively learning and adapting from the training dataset. It becomes progressively better at identifying patterns and features linked with leaf disease. 2. **Fluctuating Validation Accuracy:** The accuracy of the model on unknown data varies, as seen by the oscillations, even if the precision trend of the validation indicates an overall high trend. These discrepancies could result from excessive fitting, a process in which the model retains data from training too thoroughly, impairing its capacity to generalize.

Fig. 6. Comparison of Accuracy obtained in Proposed Model

DISCUSSION

The CNN model successfully differentiates between Healthy, Powdery, and Rusty leaf classes by learning complex visual features such as color, gradient, and pattern variations. Pre-processing significantly enhances performance by normalizing illumination and size inconsistencies. Oscillations in validation accuracy suggest slight overfitting, indicating further optimization potential using regularization or dropout layers.

Deep learning's key strength lies in automation, high recognition speed, and scalability for large-scale agricultural monitoring. However, model generalization depends on dataset diversity and environmental variety in real-world conditions. Future improvements could involve hybrid deep learning architectures and cloud-based or IoT-driven deployment for in-field usability.

CONCLUSION

In conclusion, while deep learning offers significant advantages in the field of leaf disease detection—such as high accuracy, automation, early detection, and real-time analysis—it also comes with limitations, including data dependency, computational resource requirements, and generalization challenges. Despite these limitations, the potential benefits of deep learning in improving agricultural practices, reducing crop losses, and enhancing precision agriculture are substantial. Ongoing research and technological advancements continue to address these challenges, making deep learning an increasingly accessible and effective tool for leaf disease detection. The proposed model achieved around **97% accuracy**.

ACKNOWLEDGEMENTS

We would like to express our sincere gratitude to everyone who contributed to the successful completion of this project.

We are especially thankful to our guide, Dr. Shalini Hanok, for her invaluable guidance, constant support, and encouragement throughout the course of this work. Her expertise and insights played a crucial role in shaping this project.

We also extend our appreciation to our team members Meghana T., Dharanya R., Aishwarya K., and Dhanush C. for their cooperation, dedication, and collaborative efforts.

We are grateful to the faculty members of the Department of Electronics and Communication Engineering, ATME College of Engineering, for providing the necessary resources and academic support.

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