IJEAST

INTERNATIONAL JOURNAL
OF ENGINEERING APPLIED SCIENCE
AND TECHNOLOGY

VOLUME : 10 ISSUE : 12 Print / Issue Publication Date: April 2026

ISSN : 2455-2143

DOI : 10.33564/IJEAST.2026.v10i12.010

Indexed In

Google Scholar OPEN ACCESS doi Crossref

WWW.IJEAST.COM

editor@ijeast.com

International Journal of Engineering Applied Sciences and Technology, 2026
Vol. 10, Issue 12, ISSN No. 2455-2143, Pages 73-78
Published Online April 2026 in IJEAST (http://www.ijeast.com)

AI-DRIVEN CROP DISEASE DETECTION AND MANAGEMENT IN SMART AGRICULTURE

Nallamilli V K Reddi
Assistant Professor, Department of CSE,
Aditya College of Engineering & Technology (A),
Andhra Pradesh, India

B. Sravya, G. Mythri, B.S S Karthikeya, K. Thanusha
Student, Department of CSE,
Aditya College of Engineering & Technology (A),
Andhra Pradesh, India

Abstract: **Agriculture is a fundamental component of human civilization. It contributes to the economy while also providing sustenance. Plant foliage or crops are susceptible to many illnesses during agricultural agriculture. The illnesses impede the development of their respective species. Timely and accurate identification and categorization of illnesses may mitigate the risk of further harm to the plants. The identification and categorization of these disorders have emerged as significant challenges. The conventional methods used by farmers to anticipate and categorize plant leaf diseases may be tedious and inaccurate. Challenges may occur while endeavouring to manually forecast illness kinds. The failure to promptly identify and categorize plant diseases may lead to the devastation of crops, causing a substantial reduction in yield. Agriculturalists using computerized image processing techniques in their fields may mitigate losses and enhance output. A multitude of strategies has been used in the identification and categorization of plant diseases using photographs of sick leaves or crops. In this research, convolutional neural networks (CNNs) are often used for image recognition and classification because of their intrinsic ability to autonomously extract relevant visual characteristics and comprehend spatial hierarchies. Consequently, in many sophisticated image recognition and classification tasks, deep learning, mostly via convolutional neural networks, is favoured when substantial data and computing resources are accessible, demonstrating effective detection and classification outcomes on their datasets. This methodology seeks to enhance productivity, minimize crop losses, and foster sustainable agricultural practices via the provision of valuable information and the automation of disease identification. The multilingual solution guarantees inclusion for diverse agricultural communities by automating disease detection and providing actionable information.**

Index Terms - **Agriculture Technology, Image Processing, Convolutional Neural Networks (CNNs), Crop Disease Detection, Early Disease Prediction, Pattern Recognition**

I. INTRODUCTION

Agriculture has long played a vital role in human existence by supplying food, means of subsistence, and other necessities for survival. At the core of this system are plants, which provide oxygen, nutrients, and ecological balance. Governments and researchers have consistently strived to enhance farming methods over the years by implementing cutting-edge technologies and creative ideas.

However, agriculture is still seriously threatened by plant diseases. These illnesses can harm many plant parts, including leaves, stems, and branches, and are brought on by bacteria, fungi, and shifting environmental circumstances. Unpredictable weather patterns and climate change frequently exacerbate these effects, resulting in lower crop yields and, eventually, food insecurity in many areas.

Early detection of plant diseases is essential to avoiding significant harm. In order to safeguard soil quality and crop health, pesticides must be used carefully and under supervision. Automated disease detection systems have become effective tools in this setting, assisting farmers in promptly identifying issues and taking appropriate action.

The development of artificial intelligence, particularly deep learning, has improved the efficiency and accuracy of disease diagnosis. The ability of Convolutional Neural Networks (CNNs) to study photos in detail and recognize patterns that differentiate healthy plants from unhealthy ones makes them very useful. These models can help with early detection and improved disease control by only looking at leaf photos, which will ultimately improve crop productivity and quality.

Additionally, to increase farming efficiency, precision agriculture integrates technology like image processing, data analytics, and sensor-based monitoring. It focuses on controlling important elements including fertilizer, pesticide use, soil health, and water utilization. Farmers may promote sustainable agricultural practices, cut waste, and make better decisions by utilizing data-driven insights.

II. LITRETAURE SURVEY

Food security, agricultural output, and farmers' livelihoods are all significantly impacted by plant diseases. Impacted crops not only lower yield but also put individuals who rely on farming in financial distress. Since it can stop extensive damage, early detection of plant diseases is crucial. Historically, farmers have used hand observation to detect illnesses, but this method is labor-intensive, skill-intensive, and occasionally results in an incorrect diagnosis.

Rapid developments in deep learning and artificial intelligence (AI) have led to the development of more automated and effective methods for identifying plant diseases. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in evaluating leaf images and determining the health or illness of a plant. These technologies employ enormous plant image collections to identify trends and precisely categorize various illnesses.

For a variety of crops, researchers have been trying to increase the precision and dependability of these models. Even with scarce or complex data, models can perform better because to methods like anomaly detection, data augmentation, and transfer learning. For instance, certain CNN-based algorithms have detected tomato plant illnesses with an accuracy of more than 95%. High classification performance has also been demonstrated by research using popular datasets.

In this work, sophisticated deep learning methods have taken the place of conventional machine learning techniques. The suggested system makes use of Transfer Learning with pre-trained weights from the ImageNet dataset in conjunction with the MobileNetV2 architecture. These techniques facilitate effective learning even with little data, improve the process of feature extraction, and increase classification accuracy.

Even in difficult situations like complicated backgrounds or low-quality photos, more sophisticated algorithms can now identify plant illnesses in real time. For practical agricultural applications, these technologies are quicker, more accurate, and more advantageous.

AI is generally improving the speed, accuracy, and ease of identifying illnesses in agriculture. It is assisting farmers in moving swiftly, lowering crop losses, and transitioning to more productive and sustainable farming methods.

III. METHODOLOGY

A. Integrated Analysis and Synthesis

Diseases can drastically lower the productivity and quality of several major crops, including potatoes, tomatoes, corn, apples, and grapes. Early detection of these illnesses is essential to avoiding significant losses and guaranteeing increased productivity. Convolutional Neural Networks (CNNs) are employed in this work as an efficient and automated method for detecting plant illnesses.

The proposed method uses a Convolutional Neural Network (CNN) to categorize tomato leaf diseases such Early Blight, Late Blight, Septoria Leaf Spot, Tomato Mosaic Virus, and Fusarium Wilt.

The model's primary base is the MobileNetV2 architecture, a lightweight and efficient deep learning model suitable for real-time applications. A pre-trained MobileNetV2 model is refined using Transfer Learning on the tomato leaf dataset to increase performance. This technique improves the accuracy while reducing training times.

Image rotation and flipping are examples of data augmentation techniques used to increase dataset diversity and improve generalization. The CNN algorithm uses multiple layers to learn important visual properties that allow it to distinguish between healthy and unhealthy leaves. With a validation accuracy of 94.8%, the suggested model performs well in identifying and categorizing tomato leaf diseases.

B. Simulation and Implementation

The model is trained using a collection of pictures of plant leaves; each image is scaled to a standard size of 224 × 224 pixels for uniformity. Before training, the images go through preprocessing steps including normalization and augmentation to improve data quality and variance.

During training, some factors are carefully modified to achieve optimal performance. The model is evaluated using common measures including accuracy, precision, and recall to ensure consistent performance. The results show how well the proposed system recognizes and classifies plant diseases.

C. General Steps for Tomato Leaf Disease Detection

The overall working process of the system can be summarized in simple steps:

1. Gathering and labeling photos of both healthy and sick leaves.
2. Using augmented and improved data to train the CNN model.
3. Assessing the model with accuracy and other performance indicators.
4. Using the trained model in real-world situations to detect diseases in real time.

International Journal of Engineering Applied Sciences and Technology, 2026
Vol. 10, Issue 12, ISSN No. 2455-2143, Pages 73-78
Published Online April 2026 in IJEAST (http://www.ijeast.com)

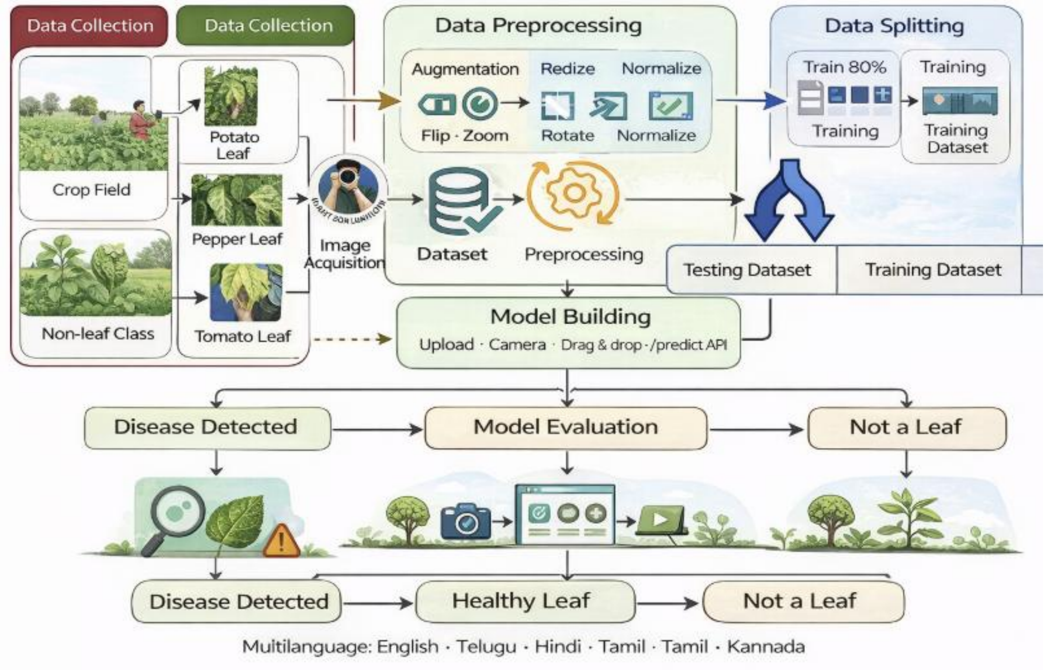


Fig. 1. Graphical Abstract:

IV. DETAILED DESCRIPTION

The proposed system for tomato leaf disease detection using Convolutional Neural Networks (CNNs) follows a systematic workflow consisting of multiple stages, from data acquisition to deployment.

A. Data Collection

Gathering a good collection of photos of tomato leaves, including both healthy and sick examples, is the first stage in this procedure. Every picture is meticulously annotated according to the disease kind it depicts. Because it aids in the model's proper learning during training, this labeling is crucial. In addition to leaf images, a separate class for non-leaf images is included to improve model robustness. This enables the system to distinguish between valid leaf inputs and irrelevant images.

B. Data Preprocessing

To guarantee consistency, the photos are prepped and cleaned before the model is trained. For improved speed, all photos are downsized to a standard size and pixel values are standardized. Techniques like rotation and flipping are used to produce many versions of the same image in order to strengthen the model. This helps lessen overfitting in addition to expanding the dataset.

C. Dataset Splitting

After that, the dataset is separated into three sections: testing, validation, and training. The testing set is used to assess the model's performance on fresh, untested data, the training set is used to educate the model, and the validation set aids in its improvement and tuning.

D. Model Architecture Selection

The MobileNetV2 model is selected for its lightweight design and high efficiency in image classification. Transfer Learning is applied to improve accuracy and reduce training time. This combination makes the model suitable for real-time tomato leaf disease detection.

E. Model Training

The CNN model gains the ability to recognize patterns that distinguish between healthy and diseased leaves during training. It accomplishes this by gradually extracting crucial elements that aid in classification by running photos through a number of layers.

F. Model Evaluation

The validation dataset is used to assess the model after it has been trained. Metrics including accuracy, precision, recall, and F1-score are used to gauge its performance. These indicators aid in assessing the model's disease detection performance.

G. Hyperparameter Tuning

Various parameters, including learning rate, batch size, and number of layers, are changed to further enhance performance. To determine which combination produces the greatest outcomes, several trials are carried out.

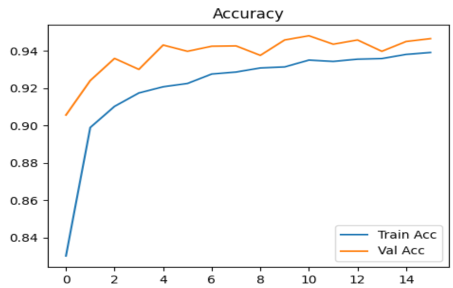
H. Testing

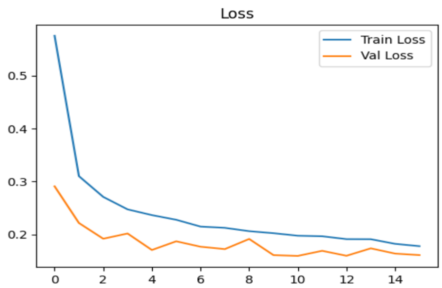
The final model is evaluated using entirely new data after it has been refined. This stage guarantees that the model is not merely memorizing the training data and can function adequately in real-world scenarios.

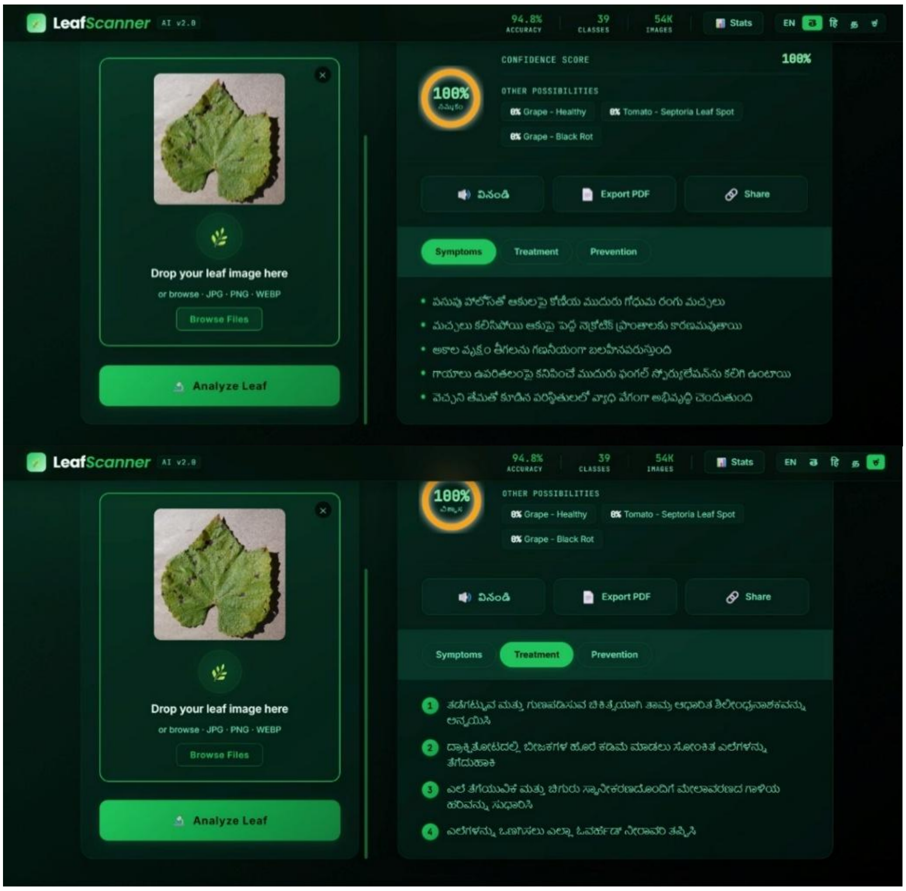
I. Model Deployment

Ultimately, a real-world application is implemented using the learned model. The model classifies inputs into three categories: **Diseased Leaf, Healthy Leaf, and Non-Leaf**. When a user uploads a photograph of a tomato leaf, the system can instantly determine if the leaf is healthy or diseased. Because of this, farmers and agricultural specialists can use the solution to make fast judgments. To further enhance accessibility, the system includes a **voice output feature**, which allows users to listen to the prediction results. This is especially useful for uneducated users, although the feature is currently available only for selected languages. The system also provides **multilingual output support**, allowing users to view the prediction results in different languages. Additionally, the output can be **exported as a PDF report**, enabling users to easily save and share the diagnosis for future reference.

V. RESULTS







This output shows how the Leaf Disease Detection System uses deep learning and an easy-to-use web interface to operate practically. The technology estimates which illness is most likely to be present in Multiple Languages after a user submits an image of a plant leaf. In this case, the uploaded image has been identified as a tomato leaf with "Septoria Leaf Spot." Incorporating non-leaf photos enhances the model's real-world reliability by preventing inaccurate predictions on irrelevant inputs. The prediction is made using a trained Convolutional Neural Network (CNN) model, which analyzes the image and accurately classifies the ailment based on patterns it has learned.With clear options for uploading an image and receiving the result instantaneously, the user interface is kept straightforward and user-friendly.

Over epochs, the model shows steady convergence with rising accuracy and falling loss. Strong generalization performance and efficient learning with little overfitting are indicated by the good agreement between the training and validation curves. The addition of voice output capabilities, PDF export, and multilingual support enhances the system's usability and makes it more accessible and useful for practical agricultural applications.

Overall, this system highlights how artificial intelligence can be effectively used in agriculture. By enabling early detection of plant diseases, it helps farmers take timely action, reduce crop damage, and improve overall yield.

VI. CONCLUSION

This work uses a combination of deep learning and image processing techniques to create an automated system for plant leaf disease detection. First, conventional techniques such feature extraction, segmentation, preprocessing, picture acquisition, and classification were investigated. However, a Convolutional Neural Network (CNN)-based model was proposed to improve efficiency and accuracy.

The suggested method is intended to evaluate photos of leaves and categorize them as either healthy or unhealthy. It not only detects ailments but also offers helpful information about potential treatments. The CNN model's layered structure allows it to recognize patterns in images, which aids in the precise identification of various medical disorders. The entire process entails gathering the dataset, getting the photos ready, training the model, and maximizing its effectiveness.

The system handles both real-time and existing images efficiently. The MobileNetV2 model with Transfer Learning achieves 94.8% accuracy, providing fast and reliable predictions. It helps in early disease detection, improving crop management and supporting sustainable agriculture. The system’s ability to detect non-leaf images makes it more practical and user-friendly for real-time applications.

All things considered, this research shows how deep learning may streamline and enhance plant disease detection. The method fosters improved crop management and advances more effective and sustainable agriculture by assisting farmers in recognizing issues early and taking prompt action.

VII. ACKNOWLEDGMENT

The AI-Driven Crop Disease Prediction and Management System utilizes advanced deep learning techniques, specifically Convolutional Neural Networks (CNNs), to analyze crop leaf images and accurately detect diseases. The system provides realtime insights through a user-friendly mobile and web application, offering disease detection, treatment recommendations, and best farming practices. This innovative solution empowers farmers to manage crop health efficiently, reducing losses and enhancing yield quality, representing a significant advancement in sustainable agriculture.

VIII. REFERENCES

[1]. Ruchi Rani; Jayakrushna Sahoo; Sivaiah Bellamkonda; Sumit Kumar; Sanjeev Kumar Pippal “Role of Artificial Intelligence in Agriculture: An Analysis and Advancements With Focus on Plant Diseases” IEEE 2023.

[2]. Robert G. de Luna, Elmer P. Dadios, Argel A. Bandala, “Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition,” International Conference on Advances in Big Data, Computing and Data Communication Systems (icABCD) 2019.

[3]. Suma VR Amog Shetty, Rishab F Tated, Sunku Rohan, Triveni S Pujar, “CNN based Leaf Disease Identification and Remedy Recommendation System,” IEEE conference paper 2019.

[4]. Peng Jiang, Yuehan Chen, Bin Liu, Dongjian He, Chunquan Liang, “Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolution Neural Networks,” IEEE ACCESS 2019.

[5]. Geetharamani, Arun Pandian, “Identification of plant leaf diseases using a nine- layer deep convolution neural network,” Computers and Electrical Engineering 76 (2019).

[6]. Omkar Kulkarni, “Crop Disease Detection Using Deep Learning,” IEEE access 2018.

[7]. Abirami Devaraj, Karunya Rathan, Sarvepalli Jaahnavi and K Indira, “Identification of Plant Disease using Image Processing Technique,” International Conference on Communication and Signal Processing, IEEE 2019.

[8]. Velamakanni Sahithya, Brahmadevara Saivihari, Vellanki Krishna Vamsi, Parvathreddy Sandeep Reddy and Karthigha Balamurugan, “GUI based

Detection of Unhealthy Leaves using Image Processing Techniques," International Conference on Communication and Signal Processing 2019.

[9]. Balakrishna K Mahesh Rao, "Tomato Plant Leaves Disease Classification Using KNN and PNN," International Journal of Computer Vision and Image Processing 2019.

[10]. Prajwala TM, Alla Pranathi, Kandiraju Sai Ashritha, Nagaratna B. Chittaragi, Shashidhar G. Koolagudi, "Tomato Leaf Disease Detection using Convolutional Neural Networks," Proceedings of 2018 Eleventh International Conference on Contemporary Computing (IC3), 2018.

[11]. Suja Radha, "Leaf Disease Detection using Image Processing," Article in Journal of Chemical and Pharmaceutical Sciences, March 2017.

[12]. Sneha Patel, U.K Jaliya, Pranay Patel, "A Survey on Plant Leaf Disease Detection," International Journal for Modern Trends in Science and Technology, April 2020.

[13]. Priyanka Soni ,RekhaChahar, "A Segmentation Improved Robust PNN Model for Disease Identification in Different Leaf Images," 1st IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES-2016).

[14]. S. Arivazhagan, R. Newlin Shebiah S. Ananthi, S. Vishnu Varthini, "Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features," CIGR Journal, March 2013.

[15]. Adedamola Adedoja & Pius Adewale Owolawi& Temitope Mapayi, "Deep Learning Based on NAS Net for Plant Disease Recognition Using Leave Images," 2018.

[16]. Prajwala TM, Alla Pranathi, Kandiraju Sai Ashritha, Nagaratna B. Chittaragi, Shashidhar G. Koolagudi, "Tomato Leaf Disease Detection using Convolutional Neural Networks," Proceedings of 2018 Eleventh International Conference on Contemporary Computing (IC3), 2018.

IJEAST

INTERNATIONAL JOURNAL
OF ENGINEERING APPLIED SCIENCE
AND TECHNOLOGY

ABOUT IJEAST

International Journal of Engineering Applied Science and Technology (IJEAST) is a peer-reviewed, open access journal that publishes high-quality research papers in the field of Engineering, Applied Science and Technology.

IJEAST aims to provide a platform for researchers, academicians, and professionals to share their innovative ideas, research findings, and practical experiences with the global scientific community.

FOCUS AREAS

- Engineering
- Applied Science
- Technology
- Innovation & Development
- Interdisciplinary Studies

PEER REVIEWED
All submissions are rigorously peer reviewed to ensure quality.

OPEN ACCESS
Free and unrestricted access to research for all.

GLOBAL REACH
Connecting researchers and professionals worldwide.

TIMELY PUBLICATION
We ensure a swift and efficient publication process.

For more information, visit our website
www.ijeast.com

INTERNATIONAL JOURNAL
OF ENGINEERING APPLIED SCIENCE
AND TECHNOLOGY

editor@ijeast.com
www.ijeast.com
India

2455-2143