International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 07 | July - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Plant Disease Detection

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Abstract - Plant diseases significantly impact agricultural productivity and food security, making early and accurate disease detection crucial for effective crop management. Traditional disease identification methods rely on manual inspection, which is time-consuming, labor-intensive, and prone to errors. Recent advancements in artificial intelligence (AI) and computer vision have enabled automated plant disease detection using deep learning techniques. This paper explores various machine learning approaches, including convolutional neural networks (CNNs), to classify and detect plant diseases from leaf images. The PlantVillage dataset of diseased and healthy plant images is used to train and evaluate the model. The proposed system achieves high accuracy in distinguishing different plant diseases, demonstrating its potential for real-time application in precision agriculture. By integrating AI-driven plant disease detection with smartphone applications or IoT-based monitoring systems, farmers can receive instant alerts and take timely corrective actions, ultimately reducing crop losses and improving yield quality.

Key Words: artificial intelligence, convolutional neural networks, computer vision, internet of things(IoT), deep learning, machine learning

1. INTRODUCTION

Traditional methods of plant disease detection have primarily relied on visual inspection by farmers, agricultural extension officers, or plant pathologists. Although this approach has long served as the foundation for diagnosing diseases in crops, it has significant limitations—especially in the era of modern, large-scale farming. Visual inspections are often subjective and depend heavily on the expertise of the individual, environmental factors, and the progression stage of the disease. Moreover, this process is time-consuming and labor-intensive, making it unsuitable for vast farms that require regular and thorough monitoring.

In regions where access to agricultural experts is limited, relying solely on manual inspection leads to delays in disease identification and management. These delays often result in crop damage, reduced yields, and economic loss. To tackle these challenges, technology-driven solutions—particularly those powered by artificial intelligence (AI)—have gained prominence. AI, machine learning (ML), and deep learning algorithms offer innovative and effective ways to monitor plant health, allowing for faster, automated, and more accurate disease detection using image data.

Among the most promising AI techniques in this domain is the Convolutional Neural Network (CNN), a type of deep learning algorithm highly effective for image classification tasks. CNNs can be trained on comprehensive datasets such as PlantVillage, which contains thousands of labeled images showing various plant diseases and healthy conditions. These models learn to recognize patterns like leaf discoloration, lesion shapes, and texture changes that are often invisible to the untrained eye. As a result, CNNs can classify diseases across multiple plant species with remarkable accuracy, even in complex, real-world environments.

Once trained, these AI models can be deployed through accessible interfaces such as smartphone apps, web platforms, or IoT-based devices embedded in smart farming systems. Farmers can simply take a photo of a leaf using a mobile device, and the model can instantly identify the disease and suggest treatment options. This real-time detection capability is especially valuable in rural or remote areas, where expert consultations may not be readily available.

Additionally, these AI tools can be integrated with GPS and geospatial data to create disease heat maps. Such maps help farmers and agricultural planners visualize the spread of disease and take preventive actions in specific zones, improving overall crop management strategies.

Beyond conventional RGB image analysis, the integration of hyperspectral and multispectral imaging technologies has significantly advanced the scope of AI-based plant disease detection. These imaging techniques capture information across various wavelengths, including those invisible to the human eye. Hyperspectral imaging, for instance, analyzes subtle variations in leaf reflectance, chlorophyll content, and moisture levels—allowing detection of plant stress before visible symptoms appear. While hyperspectral imaging is highly detailed but costly, multispectral imaging offers a more cost-effective solution and is increasingly being used in combination with drone technology.

Drones equipped with multispectral cameras and AI algorithms can rapidly scan large areas of farmland, identifying disease hotspots and assessing overall crop health. This aerial surveillance allows for precision agriculture practices such as targeted pesticide application, localized irrigation, and nutrient optimization. These techniques not only improve productivity and reduce input costs but also support sustainability by minimizing chemical overuse that could degrade soil, water, and biodiversity.

AI and ML technologies also contribute significantly to integrated crop management systems. When combined with other smart farming tools like automated irrigation, robotic weeders, and real-time sensors, they create a comprehensive ecosystem for efficient farm operations. Data collected from various sources can be processed using predictive AI models to forecast disease outbreaks, taking into account environmental factors, historical data, and pathogen behavior. These insights enable proactive measures and better preparedness against climate-driven stressors.

From a global perspective, AI-powered plant disease detection contributes to improved food security and agricultural resilience. By minimizing losses and improving yield quality, these technologies ensure a stable food supply while addressing the challenges posed by labor shortages and changing weather patterns. Importantly, several educational and governmental programs are focused on making AI tools more accessible and affordable, especially for smallholder farmers in developing countries. These efforts include training workshops, open-source platforms, and collaborative projects to democratize technology use in agriculture.

Another key development is the rise of explainable AI (XAI), which ensures that model decisions are transparent and understandable. This fosters trust and confidence among users, encouraging the widespread adoption of AI systems in everyday farming practices.

The transition from traditional manual inspection to AI-powered plant disease detection marks a revolutionary step in agricultural practices. The use of AI, ML, and advanced imaging technologies offers fast, accurate, and scalable solutions for identifying and managing plant diseases. When combined with drones, IoT devices, and cloud computing, these systems provide a robust framework for precision farming. As research continues to improve their performance and accessibility, AI tools will play an increasingly vital role in helping farmers around the world make smarter decisions, reduce crop loss, and cultivate more sustainable and productive farms. Ultimately, AI-based plant disease detection stands as a cornerstone of smart agriculture and a key solution to meeting the global demand for food in a changing world.

2. LITERATURE SURVEY

Nithin Lokhande et al. [1] conducted a comparative study titled "Comparative Analysis of Different Plant Leaf Disease Classification and Detection using CNN", evaluating various CNN architectures—VGG16, VGG19, InceptionV3, ResNet50, and MobileNetV2—for plant disease classification using the PlantVillage dataset. The study applied transfer learning and standardized training configurations to ensure fair performance comparison across models. Results indicated that InceptionV3 and ResNet50 achieved the highest accuracy, while MobileNetV2 offered a good trade-off between accuracy and computational efficiency, making it suitable for deployment on resource-constrained devices. The study highlights CNNs as effective tools for automated plant disease detection and emphasizes the importance of balancing accuracy with computational cost for practical agricultural applications.

Parmar and Rai et al. [2] proposed a web-based plant disease detection system using CNN models to address the limitations of manual diagnosis in large-scale agriculture. The study compared a custom-built CNN and a pretrained ResNet50 model using a diverse leaf image dataset. While ResNet50 achieved a validation accuracy of 93.96%, the custom CNN outperformed it with 95.58%, demonstrating the effectiveness of lightweight, task-specific architectures. The trained models were deployed in a scalable web application, enabling real-time, accessible disease detection, particularly beneficial for farmers in remote or resource-constrained regions.

Shivaprasad and Wadhawan et al. [3] proposed a deep learning-based pipeline for plant leaf disease detection using CNNs, addressing limitations of traditional diagnosis methods. Using the PlantVillage dataset and data augmentation techniques, they developed a custom CNN model that achieved a classification accuracy of 98.2%, outperforming pretrained models like VGG16, ResNet50, and InceptionV3 in terms of both accuracy and computational efficiency. The study emphasizes real-time deployment feasibility on mobile devices and suggests integration with IoT platforms for smart farming applications, making it highly practical for use in rural and resource-limited areas.

Hassan and Maji et al. [4] proposed a custom Convolutional Neural Network (CNN) for plant disease detection using the PlantVillage dataset comprising over 54,000 leaf images across 38 classes. Their lightweight CNN architecture, optimized through data augmentation techniques, achieved a classification accuracy of 98.49%, outperforming deeper models while maintaining computational efficiency. Designed for real-world deployment on mobile and edge devices, the model offers quick and accurate diagnosis, making it particularly suitable for precision agriculture and resource-constrained environments. The authors also highlight future directions, including real-time integration and decision support systems for smart farming.

Pachori, Kant, Surya, and Kumar et al. [5] presented a comprehensive study on plant disease detection using a combination of image processing techniques and machine learning algorithms. The workflow includes image acquisition, preprocessing, segmentation, feature extraction, and classification using models like SVM, KNN, Decision Trees, and CNNs. CNNs were noted for their superior accuracy in handling image-based diagnosis. The study emphasizes the importance of diverse datasets like PlantVillage, highlights challenges such as lighting variability and symptom overlap, and suggests future integration with mobile and IoT systems for real-time, scalable plant disease detection.

3. SYSTEM ANALYSIS

The Existing system discusses the detection of diseases on Plants, focusing on the Convolutional Neural Network. Plant diseases significantly impact agricultural productivity and crop quality. Early identification is crucial for effective disease management. However, farmers often rely on manual inspection methods, which are time-consuming and error-prone, subjective and dependent on expert availability, costly due to labor and expert consultation fees. To address these challenges, an automated system using Convolutional Neural Networks (CNNs) can be developed to accurately detect plant diseases from images. This innovation improves agricultural productivity by minimizing crop losses and enhancing early disease detection using deep learning models. This system ensures scalability to support multiple plant species and disease types.

3.1 SYSTEM REQUIREMENTS

System requirements define the necessary capabilities and constraints of the system. This includes both functional and non-functional requirements.

Functional requirements specify what the system should do, such as user registration or search functionality whereas **Non-**

functional requirements define qualities like performance, security, and scalability.

Functional Requirement : Accept image inputs of plant leaves. Process and classify images into predefined disease categories (e.g., healthy, bacterial spot, leaf mold). Store and manage disease-related data for future reference. Support real-time analysis and quick response times.

Non-functional Requirement : Achieve moderate accuracy in disease detection . Ensure low response time for real-time usability (<1 second per image). Design a scalable system to support multiple plant species and disease types. Ensure security and privacy of user data. Optimize for deployment on mobile and edge devices.

3.2 DEVELOPMENT ENVIRONMENT

- IDE used: PyCharm
- Programming Language used: Python
- Frameworks used:
    - TensorFlow with Keras for deep learning
    - OpenCV for image processing
    - NumPy for dataset handling
    - A Pre-trained CNN Model was used
- Dataset used: PlantVillage Dataset

3.3 SYSTEM DESIGN

A **Plant Disease Detection System** using a **CNN model** involves multiple components, from data collection to disease classification and user notification. Below is a structured **system architecture** with different layers.

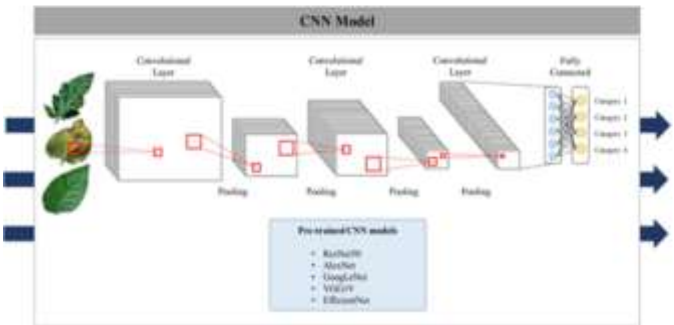

Figure 1; Basic CNN Architecture

The input(Input Layer) is the images of plant leaves. These images are captured by a camera or collected from an agricultural dataset. Here, in this project, we used the PlantVillage Dataset which is a widely used benchmark dataset for plant disease classification and detection. It contains thousands of labeled images(~54,305) of healthy and diseased plant leaves, making it ideal for training deep learning models like CNNs. Other important steps include Pre-processing and Normalization of input images is also done.

Next, the feature extraction(Convolutional Layer) and dimensionality reduction(Pooling Layer) tasks are done by the model automatically with the help of activation functions(ReLu is used). Now, the reduced feature map are flattened to create a 1D vector space, then these can be used for classification(Fully Connected Layer). The flattened outputs from the previous layers are taken and mapped to a specific class or category. Softmax activation function is used for probabilistic predictions.

Finally, the output layer produces the final predictions or classification by mapping the high level extracted features to the desired output class of labels.
Now, the predicted output is checked for errors. One of the common ways to rectify error is Backpropagation. Backpropagation is the learning algorithm that updates the weights of a CNN model by minimizing the error using gradient descent. It enables the network to adjust its filters and weights based on the error between predicted and actual values.

3.4 IMPLEMENTATION

The Model Part is where the training and testing of the CNN Model takes place. Here, we used the deep-learning frameworks “tensorflow” and “keras”. Within the keras and tensorflow, the Sequential class helps to build a model layer-by-layer. This class helps to access each layer of the CNN model by using modules like Conv2D, MaxPooling2D, Flatten etc. and carry out the procedures on the input data. The model is trained on the PlantVillage dataset, where the data is split as 70-30 for training and testing respectively. The Categorical Cross-entropy loss function is used and it calculates how well the predicted class probabilities match the actual class labels.
An optimizer named Adam Optimizer(short for Adaptive Moment Estimation) is used in this system. It handles the sparse gradients and noisy data while offering fast convergence with minimal parameter tuning.

The Main Part calls the model and evaluates an unseen input as “Healthy” or “Diseased” and identifies the disease based on the class labels (diseases) given to the model. This Python script is a graphical user interface (GUI) application developed using the Tkinter library that allows users to classify plant leaf diseases using a pre-trained deep learning model built with TensorFlow or Keras. The application supports image selection through a file dialog, preprocesses the selected image to the required input format (224x224 pixels and normalized pixel values), and then feeds it into the model to make a prediction. The predicted class label and confidence score are displayed in a message box.

4. RESULT

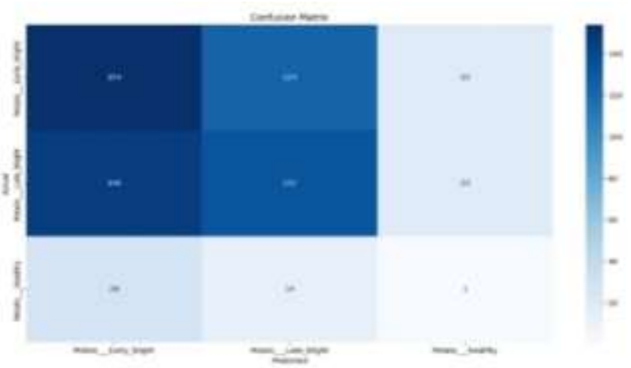

Figure 3; Confusion Matrix

The confusion matrix visualizes the performance of a plant disease detection model trained on the PlantVillage dataset, focusing specifically on classifying potato leaf conditions into three categories: Potato_Early_blight, Potato_Late_blight, and Potato_healthy. The matrix reveals that the model achieves moderate success in identifying diseased leaves but performs poorly in detecting healthy samples.

```
Classification Report:
                       precision    recall  f1-score   support

Potato___Early_blight       0.47      0.48      0.47       298
 Potato___Late_blight       0.46      0.45      0.45       298
     Potato___healthy       0.12      0.12      0.12        43

             accuracy                           0.44       639
            macro avg       0.35      0.35      0.35       639
         weighted avg       0.44      0.44      0.44       639


Process finished with exit code 0
```

Figure 4; Model Report

The classification report presents the precision, recall, and F1-score of a model trained to identify plant diseases in potato leaves using the PlantVillage dataset. The model classifies images into three categories: Potato_Early_blight, Potato_Late_blight, and Potato_healthy. Overall, while the model shows some promise in detecting disease types, its inability to recognize healthy leaves necessitates further refinement through better data balancing, feature engineering, or model enhancement.

5. CONCLUSION

Plant disease detection is crucial in modern agriculture, directly influencing crop yield and global food security. Traditional identification methods, based on manual visual inspection, are often time-consuming, error-prone, and limited in scalability, especially in remote areas. With the increasing demand for sustainable agricultural productivity, artificial intelligence (AI) and computer vision have emerged as transformative tools in plant pathology.

AI techniques, particularly convolutional neural networks (CNNs) and deep learning models, have demonstrated high accuracy in identifying various plant diseases from leaf images. When integrated with high-resolution imaging systems—such as hyperspectral, thermal, or multispectral sensors mounted on drones or smartphones—these models enable early-stage disease detection and timely intervention. Moreover, combining AI with IoT and smart farming infrastructure allows for real-time monitoring, reducing excessive pesticide usage and enhancing precision agriculture practices.

Datasets like PlantVillage have played a vital role in training robust models, improving their adaptability across crops and regions. Cloud-based platforms and mobile apps further democratize access to these tools, supporting farmers and agronomists with limited technical expertise. Despite challenges such as data quality and model interpretability, ongoing research continues to address these limitations. AI-driven plant disease detection is poised to become an integral component of precision agriculture, enhancing efficiency, sustainability, and resilience in food production systems.

6. ACKNOWLEDGEMENT

Our endeavor stands incomplete without dedicating our gratitude to everyone who has contributed a lot towards the successful completion of our Mini Project. First of all, we offer our sincere thanks to our parents for their blessings. We are indebted to God Almighty for blessing us with his grace and taking our endeavor to a successful culmination. We submit this project work at the lotus feet of Late **Dr. P. K. Das**, founder Chairman, Nehru Educational and Charitable Trust. We express our profound gratitude to **Adv. Dr. P. Krishnadas**, Chairman and Managing Trustee and **Dr. P. Krishnakumar**, CEO and Secretary, Nehru Educational and Charitable Trust. We are also grateful to **Dr. K. G. Vishwanadhan**, Principal, for supporting us all along. We also express a heartfelt gratitude to **Dr. Anoop B K,** our Head of Department, Computer Science(AI & ML) for all possible support during this project development. We express our sincere thanks and gratitude to project coordinator **Ms. Sajitha A S**, Assistant Professor, Department of Computer Science, for supporting us all along. We specially thank our project guide **Ms. Rejitha.R**, Assistant Professor, Department of Computer Science for the guidance to us and steering us to the successful completion of this project work. We are really indebted to all the staff and faculty members of our college for all the help they have extended to us. We finally, thank our friends and all our well-wishers who had supported us directly and indirectly during our project work.

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Volume: 09 Issue: 07 | July - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

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