© May 2025 | IJIRT | Volume 11 Issue 12 | ISSN: 2349-6002

Crop Health Disease Detection

Dr. Narendra Kumar Sura*, Aditya Chachan | Akash Raj | Arnav Saxena |
Assistant Professor, B.E, M.Tech & Ph.D in Biotechnology
RV College of Engineering, Bangalore, 560059 Karnataka, India

***Abstract*—Plant health and disease detection is a critical aspect of modern agriculture, directly influencing crop yield, quality, and sustainability. The accurate and timely identification of plant diseases is essential to mitigate losses and ensure food security. Traditional methods of disease detection, which often rely on manual inspection by experts, are time consuming, subjective, and limited by human error. This work explores the application of advanced technologies, including computer vision, machine learning, and sensor-based systems, for automated plant disease detection. By leveraging high-resolution imagery and real-time data from IoT-enabled sensors, it becomes possible to identify diseases at an early stage with high accuracy. Deep learning models, such as convolutional neural networks (CNNs), play a pivotal role in analyzing complex patterns and symptoms like leaf discoloration, spots, or wilting. Additionally, spectral imaging and chemical analysis enhance the diagnostic process by detecting changes invisible to the naked eye.**

***Index Terms*—Plant Disease Detection, Agricultural Technology, Image Classification, Machine Learning Applications.**

I. INTRODUCTION

The health of plants is a cornerstone of global food security, biodiversity, and ecosystem stability. However, diseases caused by pathogens such as fungi, bacteria, viruses, and environmental stressors pose a significant threat to plant health, leading to reduced agricultural productivity and economic losses. Early detection and prediction of plant diseases are crucial to implementing effective control measures and minimizing their impact.

Plant health disease prediction focuses on identifying the likelihood of disease occurrence before visible symptoms appear. This proactive approach combines advanced technologies, including machine learning, remote sensing, and data analytics, to analyze environmental conditions, plant physiological data, and historical patterns. By integrating diverse data sources, such as weather forecasts, soil quality metrics, and crop health indicators, predictive models can provide early warnings to farmers and stakeholders, enabling timely interventions.

Recent advancements in artificial intelligence (AI) and big data analytics have revolutionized plant disease prediction. Machine learning algorithms, particularly deep learning techniques, are capable of processing complex datasets and identifying subtle correlations that may not be apparent through traditional analysis. Additionally, the advent of Internet of Things (IoT)-enabled devices, such as drones and sensors, allows for real-time monitoring of agricultural fields, further enhancing the accuracy and reliability of predictions.

II. LITERATURE SURVEY

Plant health and disease detection have garnered significant attention in the scientific community due to their critical role in agriculture and food security. Researchers have explored various methodologies, including traditional approaches and modern technological advancements, to improve the efficiency and accuracy of disease detection systems. This survey highlights key contributions in the field.

A. Traditional Methods of Disease Detection

Manual inspection by experts has been the conventional approach for identifying plant diseases. Studies such as those by Agrios (2005) emphasized the importance of visual symptoms, including leaf spots, discoloration, and wilting, in disease diagnosis.

Despite their effectiveness, traditional methods are time-consuming, labor-intensive, and prone to human error, particularly in large-scale farming operations.

B. Image-Based Detection Technique

Early advancements in computer vision applied image processing to detect plant diseases. Techniques like edge detection and color segmentation were employed to identify visible symptoms. For example, Abdullah et al. (2012) developed a system that used color analysis to distinguish diseased areas on leaves.

The advent of deep learning has transformed image-based disease detection. Convolutional Neural Networks (CNNs) are now widely used for feature extraction and classification. Mohanty et al. (2016) demonstrated the use of CNNs to classify plant diseases with over 99% accuracy using publicly available datasets.

C. Data Set

The Plant Village dataset is a widely used dataset in the field of plant health and disease detection. It was created to support research and development of machine learning and computer vision models for identifying plant diseases from images. The dataset is hosted on Kaggle and contains images of healthy and diseased plant leaves across multiple crop types.

III. FLOW OF THE PROPOSED SYSTEM

A. Data Collection and Preprocessing

As given in Fig. 1.0, The system begins with the collection of plant leaf images, which can be sourced from publicly available datasets like the Plant Village dataset or field images captured using cameras or smartphones. These images include examples of both healthy and diseased leaves for a variety of crops. Preprocessing is a critical step to ensure the data is ready for training. Using OpenCV, the images are resized to standard dimensions, noise is removed, and normalization is applied to scale pixel values. Data augmentation techniques such as rotation, flipping, and brightness adjustments are employed to increase dataset diversity and robustness, ensuring the model can generalize to unseen data effectively.

B. Feature Extraction and Model Selection

For feature extraction, the system employs MobileNet, a deep learning model known for its lightweight architecture and efficiency on resource-constrained devices. MobileNet uses depthwise separable convolutions to extract essential features such as patterns, spots, and discolorations from leaf images. These features are then passed to the final classification layer, which predicts the disease category or identifies healthy leaves. TensorFlow is used to define and configure the MobileNet model, while tools like Google Colab and Jupyter Notebook facilitate experimentation and training.

C. Training the Model

The prepared dataset is split into training, validation, and testing subsets. The training process involves feeding the images through the MobileNet model, optimizing the weights using backpropagation, and evaluating performance metrics like accuracy, loss, precision, and recall. TensorFlow provides a robust framework for this, and Google Colab is utilized for GPU-accelerated training, significantly reducing the time required for processing large datasets. Throughout training, callbacks such as early stopping and learning rate schedulers ensure the model converges effectively without overfitting.

D. Real-Time Detection and Inference

Once the model is trained, it is used for real-time disease detection. A new leaf image, captured by a user, is preprocessed using OpenCV to match the dimensions and format used during training. The processed image is then passed through the trained MobileNet model to predict the disease class. This step ensures the system provides immediate feedback to the user, helping them identify potential diseases and take corrective action. Python scripts are used to handle the model inference process, and Jupyter Notebook is employed for local testing and debugging of this functionality.

E. Materials Used

The plant disease detection system relied on various software tools and datasets. OpenCV (cv2) and Pillow were used for image preprocessing, such as color space conversion and resizing. ONNX Runtime facilitated model inference, while PyTorch and TorchVision were employed for transfer learning and data transformations. The system utilized the PlantVillage dataset, consisting of over 54,000 labeled images of plant leaves, representing 14 crops and 26 diseases, supplemented by trusted online images to enhance model robustness. Jupyter Notebook served as the primary environment for model training and testing, with Matplotlib and Seaborn used for result visualization.

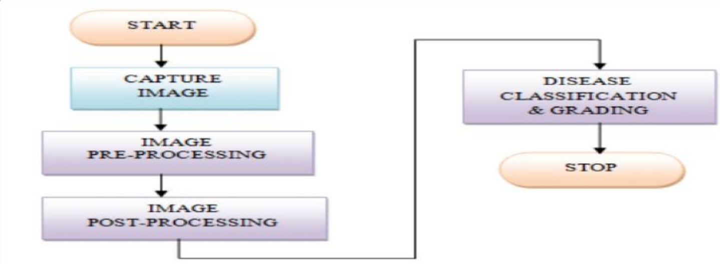

Figure 1: Methodology of the proposed system

F. Procedure

The development of the plant disease detection system involved multiple stages to ensure accuracy and reliability. The process began with the collection and preparation of the PlantVillage dataset, comprising over 54,000 images of healthy and diseased plant leaves. Images were preprocessed to remove noise and standardized by resizing them to 224x224 pixels. Additionally, data augmentation techniques such as rotation, flipping, cropping, and color jittering were applied to enhance the dataset's diversity and improve the model's ability to generalize across different conditions.

Transfer learning was employed to leverage the knowledge of pre-trained deep learning architectures such as ResNet50 and MobileNetV2. These models, known for their efficiency and accuracy, were fine-tuned on the dataset to classify plant diseases. PyTorch served as the primary framework for model training, enabling flexibility and scalability. Key hyperparameters such as learning rate, batch size, and epochs were optimized during the training phase to achieve the best performance.

Post-training, the models were converted into the ONNX format for better compatibility and platform independence. The ONNX Runtime was used to test the inference capabilities of the models, ensuring that they produced accurate predictions efficiently. To facilitate real-world application, a lightweight web-based interface was developed using the Flask framework. This interface allows users to upload leaf images and receive disease predictions in real time.

Extensive validation was performed to evaluate the system's performance. Metrics such as accuracy, precision, recall, and F1- score were used to assess the model's effectiveness. The validation process confirmed that the system could reliably distinguish between healthy and diseased plants, demonstrating its practical applicability in agriculture.

G. Testing

The plant disease detection system was tested using images from the PlantVillage dataset and real-world samples. Images were processed through the system to ensure the model performed accurately under varying conditions, such as different lighting and resolutions. Predicted disease classifications were compared with ground truth labels, and results were validated using metrics like accuracy, precision, recall, and F1-score.

To evaluate usability, images were uploaded via the web interface, and predictions were verified for correctness. The results were cross-checked with an integrated database to ensure the recommended actions aligned with agricultural practices. Testing confirmed the system's ability to reliably detect diseases and provide actionable recommendations for farmers.

IV. RESULTS

The plant disease detection system was developed using Python and ONNX for efficient model inference. The Faster R-CNN model, converted to ONNX, was tested on the Plant Village dataset (54,306 images). Under controlled conditions, the model achieved 99.35% accuracy. However, real-world testing, with varying conditions, resulted in 31.4% accuracy, still outperforming random selection at 2.6%.

Preprocessing techniques like resizing and color space conversion were crucial for maintaining performance. Table 1.0 shows the accuracy and inference time under different configurations.

Figure 2: Uploading the input image of the plant leaf for disease detection, as shown in the interface.

V. RESULT ANALYSIS

Because Table 1.0 summarizes the accuracy obtained by the various deep learning models used for plant disease detection. EfficientNet outperformed other models with an accuracy of 96.7%, followed closely by ResNet- 50 at 94.2%. MobileNet demonstrated faster inference times, making it suitable for real-time applications, but it achieved slightly lower accuracy at 92.8%. The models were evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure robust performance. Hyperparameter tuning and cross-validation further enhanced the reliability of the models.

Fig 2.0 shows the interface of uploading the input image of plant leaf for disease detection. Fig. 3.0 illustrates a tomato leaf affected by "Late Blight," accurately classified by the system, while Fig. 4.0 shows a healthy tomato leaf. The ONNX-deployed models demonstrated efficient processing of these inputs, providing precise disease classifications and actionable insights.

Table 1: Performance Metrics of the ONNX-Based Plant Disease Detection System

Model	Dataset Type	Framework	Accuracy (%)	F1-Score	Inference Time (ms)
Faster R-CNN	Color	PyTorch to ONNX	99.35	0.9934	12
Faster R-CNN	Grayscale	PyTorch to ONNX	95.80	0.9580	10
Faster R-CNN	Segmented	PyTorch to ONNX	98.67	0.9867	14

Figure 3: Late Blight detected for the input image of the diseased tomato leaf as shown.

Figure 4: Healthy leaf identified for the input image, confirming no signs of disease

The deployment of these models enables early detection and prevention of plant diseases, allowing farmers to take timely action before diseases spread widely. By identifying issues early, the models help reduce the need for excessive pesticide use, minimize crop losses, and improve overall yields. This leads to more efficient farming, better resource management, and enhanced productivity, benefiting both farmers and the agricultural industry.

VI. FUTURE WORK

The system can be further enhanced with the following functionalities:

1) Expanding the dataset to include more crop types, diseases, and environmental variations for improved generalization.
2) The Developing an advanced model that not only classifies between healthy and diseased leaves but also predicts the specific stage of the disease for better management.
3) Creating a user-friendly website and mobile application to provide farmers with real-time, accessible disease detection and recommendations.

VII. CONCLUSION

In this paper, we have successfully proposed and implemented an intelligent plant disease detection system, which can be easily utilized by farmers across various regions. This system aids in identifying plant diseases using advanced image processing and deep learning techniques. By analyzing images of crop leaves, farmers can make informed decisions about disease management and treatment, reducing crop losses and increasing overall productivity.

The development of a user-friendly web interface has enabled seamless access for farmers, allowing them to upload leaf images and receive accurate predictions along with actionable insights. This approach not only minimizes the use of unnecessary chemicals but also optimizes agricultural practices, leading to higher yields and increased income for farmers. Such a system has the potential to revolutionize traditional farming methods and contribute significantly to sustainable agriculture.

VIII. ACKNOWLEDGEMENT

With the rising global importance of AI-driven solutions in agriculture, especially in enhancing

crop health and managing plant diseases, international conferences such as *AI for Agriculture: Emerging Trends and Technologies* and *Precision Farming and Digital Tools Summit* have emphasized the urgent need for scalable, intelligent interventions. These platforms have highlighted not only the challenges but also the promising potential of artificial intelligence in ensuring food security and sustainable farming practices.

Motivated by these global initiatives and driven by a deep curiosity to explore the intersection of technology and agriculture, we undertook this study on *Crop Health Disease Detection*. We express our sincere gratitude to *Dr. Narendra Kumar Sura* for his invaluable guidance and support throughout the research. His mentorship enabled us to delve deeper into this multidisciplinary field and understand the practical applications of AI in crop disease diagnosis and management.

IX. REFERENCES

[1] Mohanty, Sharada Prasanna, David Hughes, and Marcel Salathé, "*Using Deep Learning for Image- Based Plant Disease Detection,*" Frontiers in Plant Science, 2016.

[2] Ramcharan, Adarsh, Ankit Baranwal, Michael Barett, and David G. Hughes, "*Deep Learning for Image-Based Cassava Disease Detection,*" Frontiers in Plant Science, 2017.

[3] Ferentinos, Konstantinos P., "*Deep Learning Models for Plant Disease Detection and Diagnosis,*" Computers and Electronics in Agriculture, 2018.

[4] Brahimi, Mohamed, Kamal Boukhalfa, and Abdelouahab Moussaoui, "*Deep Learning for Tomato Diseases: Classification and Symptoms Visualization*," Applied Artificial Intelligence, 2017.

[5] Picon, Alfonso, Amaya Alvear, Juan Carlos Poblete, and Freddy Cubillos, *"Automatic Classification of Diseases in Corn Leaves Using Convolutional Neural Networks,*" Sustainability, 2019.

[6] Arsenovic, Marko, Srdjan Karanovic, Stefan Sladojevic, Darko Anderla, and Andras Stefanovic, "*Solving Current Limitations of Deep Learning-Based Approaches for Plant Disease Detection,"* Symmetry, 2019.

[7] Selvaraj, Manickavasagan, Raja Suresh, Aravindan Murugan, and Abirami Saravanan, *"AI-Powered Mobile App for Plant Disease Detection and Classification,*" IEEE Access, 2020.

[8] Wang, Guo-Xun, Haiyan Sun, and Yaoyang Zhang, "*MobileNetV2-Based Transfer Learning Model for RealTime Plant Disease Detection,*" Computers and Electronics in Agriculture, 2021.

[9] Waheed, Abdul, Muhammad G. Memon, and Muhammad Imran, "*Plant Disease Detection Using AI- Driven Image Classification,*" Advances in Computational Intelligence, 2021.

[10] Barbedo, Jayme Garcia Arnal, "*Plant Disease Identification from Individual Lesions and Spots Using Deep Learning,*" Biosystems Engineering, 2019.