

# PLANT DISEASE DETECTION USING DEEP LEARNING

Mrs. Y. Swathi<sup>1</sup>, Bijinepalli Hari Chandana<sup>2</sup>,

Doppalapudi Leela Sowjanya<sup>3</sup>, Shaik Nagur Sharif<sup>4</sup>, Bhavanam Abhilash Reddy<sup>5</sup>

<sup>1</sup>Associate Professor, Department of Computer Science and Engineering, Tirumala Engineering College

<sup>2,3,4,5</sup>Student, Department of Computer Science and Engineering, Tirumala Engineering College

\*\*\*

**Abstract** - Crop diseases pose a significant threat to food security, but their timely detection is challenging in many regions due to a lack of necessary infrastructure. Recent advancements in leaf-based image classification have yielded promising outcomes. This study leverages Random Forest to differentiate between healthy and diseased leaves using newly created datasets. The proposed methodology includes dataset generation, feature extraction, classifier training, and image classification. Diseased and healthy leaf datasets are collectively trained using Random Forest for accurate classification. Feature extraction techniques are utilized for this purpose to enhance the accuracy of identification.

**Key Words:** Leaf Based Classification, Disease Prediction, Feature Extraction, Random Forest, Diseased Leaves

## 1. INTRODUCTION

Farmers in rural areas may struggle to identify diseases affecting their crops, making it difficult for them to seek help from agricultural authorities. Our main goal is to use image processing and machine learning to identify plant diseases based on their morphology. Pests and plant diseases can cause significant damage to crops, leading to reduced food production and food insecurity. Unfortunately, many farmers in less developed countries lack knowledge about how to manage or control these pests and diseases. Harmful bacteria, a lack of effective disease management, and extreme weather conditions are some of the main reasons for decreased food production. New technologies have been developed to reduce the time it takes to process crops after they are harvested, to make agriculture more sustainable, and to increase productivity. Laboratory methods like polymerase chain reaction, gas chromatography, mass spectrometry, thermography, and hyperspectral techniques have been used to identify diseases. However, these methods are expensive and take a lot of time. In recent times, server-based and mobile-based approaches for disease identification have been employed for disease identification. Several factors of these technologies being high resolution camera, high-performance processing, and extensive built-in accessories are the added advantages resulting in automatic disease recognition.

Recent methodologies, like machine learning and deep learning algorithms, have been implemented to improve the accuracy and rate of plant disease recognition. Various research projects have delved into the realm of machine learning for the

purpose of detecting and diagnosing plant ailments. Some commonly used traditional machine learning techniques encompass random forest, artificial neural networks, support vector machines (SVM), fuzzy logic, the K-means method, and convolutional neural networks. Random forests stand out as a versatile machine learning approach that can handle classification, regression, and a range of other tasks.

## 2. LITERATURE SURVEY

Researchers S. S. Sannakki and V. S. Rajpurohit proposed a method for the classification of pomegranate diseases based on neural networks. This method involves dividing negative space into sections and using color and texture as features. They use a neural network classifier for classification and convert it to  $L^*a^*b$  to extract the chromaticity process of the image. The accuracy of this classification is as high as 97.30%, but its main disadvantage is that it can only be used for some crops. P.R. Rothe and R. V. Kshirsagar focused on the identification of cotton diseases using pattern recognition techniques. This method includes the snake part and uses the call duration as a special character. and assessing the area of damage, researchers use GLCM to extract data content and fuzzy logic to rank diseases. an artificial neural network (ANN) was then used as a classifier to evaluate the severity of infected leaves. Color features are expressed as HIS in RGB form, GLCM is used to extract the negative image, and 7 discrete moments are obtained. They used an SVM classifier with MCS for offline detection of diseases in wheat.

In their research, Godliver Owomugisha, John A. Quinn, Ernest Mwebaze, and James Lwasa discussed the "Automated Vision-Based Diagnosis of Banana Bacterial Wilt Disease and Black Sigatoka Disease." They utilized color histograms that were extracted and transformed from RGB to HSV, as well as from RGB to  $L^*a^*b$ . Peak components were used to create a max tree, five shape attributes were considered, and the area under the curve analysis was employed for classification. The researchers tested various classifiers including nearest neighbors, Decision tree, random forest, extremely randomized tree, Naïve bayes, and SV classifier. Among these classifiers, the extremely randomized trees stood out with a high score, providing real-time information and flexibility to the application.

### 3. EXISTING SYSTEM

Detecting plant diseases has always been a crucial part of agriculture, dating back centuries. Initially, farmers relied on manual observation and visual inspection techniques. While these methods were important, they had their limitations such as being subjective, requiring expert knowledge, and not being able to spot diseases early on. Despite these shortcomings, traditional methods are still used for disease monitoring, particularly in areas where advanced technologies are not readily available. This section gives a summary of the traditional approaches to detecting plant diseases.

- **Visual Inspection:**

When farmers and agricultural workers check plants for signs of disease, they do so by visually examining each plant for symptoms like leaf discoloration, wilting, necrosis, lesions, and unusual growth patterns. This method, known as visual inspection, is low-cost and straightforward. However, it relies heavily on the observer's expertise and can be subjective. In addition, visual inspection may not always catch diseases in their early stages or uncover hidden infections.

- **Symptom Observation:**

When monitoring plant health, it's important to look for specific symptoms that could indicate different diseases, like yellowing leaves for nutrient deficiencies or mosaic patterns for viral infections. This knowledge of plant pathology is crucial for farmers and researchers to accurately identify and interpret these symptoms. However, symptom observation can be subjective and may not always result in a precise diagnosis, especially when conditions change or symptoms are similar.

### 4. PROPOSED SYSTEM

The new system for detecting plant diseases combines cutting-edge technologies to improve upon old methods and make disease diagnosis in farming more precise and effective. It centers around sensors and data collection tools, like multispectral or hyperspectral cameras attached to drones or land-based equipment. These sensors take detailed pictures of crops in fields or plantations, giving essential information on the condition of the plants.

The new system not only uses visual images but also gathers data from IoT devices to constantly monitor environmental conditions like temperature, humidity, and soil moisture. These factors are important for understanding disease progression and can help interpret plant health data. By gathering information from various sources, the system is able to give a complete picture of the factors affecting disease patterns.

After the data is collected, the system uses image processing and analysis methods to gather important data from the images taken. Preprocessing algorithms in the system enhance image quality by eliminating noise and improving

feature extraction. Computer vision techniques are employed to automate the identification and separation of plant areas and disease symptoms. Feature extraction processes measure disease-related details like size, color, texture, and shape, which aids in further analysis.

In the proposed system, machine learning models are key in categorizing diseases. Techniques like Supervised learning with Support Vector Machines (SVM), Random Forest, and Gradient Boosting Machines (GBM) are utilized to train on labeled datasets and classify plants as diseased or healthy by analyzing their features. Additionally, Unsupervised learning methods like clustering algorithms are investigated to detect patterns and abnormalities in plant images that may indicate the presence of a disease.

The new system involves a decision support tool that combines the results of machine learning and deep learning models with up-to-date environmental data to give practical advice to farmers and others in agriculture. Easy-to-use interfaces, like web or mobile apps, make it easy to see disease detection results, view maps showing where diseases are spreading, and get suggestions for specific actions. Ongoing learning and updates to the models, using feedback, help the system stay flexible and successful in dealing with changing disease problems in farming. The success of the new system relies heavily on testing it in real conditions alongside farmers, agricultural experts, and research organizations. This collaboration will help ensure that the system is both practical and useful for real-world agricultural needs. With the use of cutting-edge technology, the goal of the system is to identify plant diseases quickly and accurately, allowing for prompt actions to be taken in order to enhance the health and productivity of crops.

### 5. CHALLENGES AND LIMITATIONS

- Ensuring data quality and availability is essential for developing accurate plant detection models. Obtaining diverse datasets with labeled images of healthy and diseased plants is crucial for training these models. However, inconsistencies in labeling and data annotation can lead to biases that impact the performance of the models.
- Data scarcity is a significant challenge in remote or rural areas where access to technology and internet connectivity is limited. This lack of access makes it difficult to collect and transmit data effectively. In addition, limited infrastructure and expertise can further impede the deployment of sensor networks or IoT devices for monitoring purposes.
- Plant diseases can present a variety of symptoms that are influenced by the type of crop and the surrounding environment. Identifying these

symptoms and distinguishing them from other issues can be difficult, even for experts.

- It is important for detection models to be able to work effectively across different regions, seasons, and crop types. However, they may face challenges when trying to adapt to new environments or unknown diseases, which can affect their overall practical usefulness.
- When detection systems are implemented, it brings up ethical concerns related to data privacy, ownership, and consent. Farmers might be reluctant to disclose confidential information about their crops because of worries about privacy and competition.
- Adding detection systems to current agricultural procedures can pose challenges. Farmers may be hesitant to embrace new technologies that interrupt their routines or necessitate major changes in how they manage their operations. It is crucial to effectively communicate and demonstrate the advantages of detection systems in order to encourage their adoption and approval.

## 6. FUTURE ENHANCEMENTS

Improvements in plant disease detection using deep learning show great potential for enhancing the precision and effectiveness of detection systems. One way to enhance this is through the incorporation of multi-scale and multi-modal fusion techniques. These techniques combine data from different sources like visual imagery, spectral data (e.g., hyperspectral imaging), and environmental factors. By merging information from various resolutions and modalities, the accuracy of disease detection is improved. Furthermore, weakly supervised learning methods have been developed to train deep learning models with minimal annotations, such as image-level labels or bounding boxes, rather than pixel-level annotations.

The methods mentioned can utilize vast amounts of unlabeled data to enhance the model's ability to generalize and lessen the need for time-consuming manual labeling. Additionally, semi-supervised and self-supervised learning methods have the potential to improve model performance by utilizing unlabeled data. Another important area for improvement involves active learning algorithms that can selectively choose informative samples for annotation, thereby decreasing the labeling workload needed for deep learning model training. Human-in-the-loop systems allow for collaboration between the model and human experts, promoting ongoing refinement and enhancement of detection accuracy.

## 7. CONCLUSION

To summarize, integrating deep learning techniques can greatly improve plant disease detection systems. The progress in multi-scale and multi-modal fusion, weakly supervised learning, active learning, and domain adaptation offers exciting opportunities to enhance the accuracy, efficiency, and scalability of these systems. By using various data sources and new learning approaches, deep learning models can make more reliable predictions for the early and precise identification of plant diseases.

Moreover, the advancement of interpretation and decision support systems helps farmers and agricultural workers make informed choices regarding managing diseases. These systems provide useful insights and improve the transparency and credibility of detection results. Working together with researchers, workers, and stakeholders and sharing data openly are vital for fostering innovation and speeding up advancements in agriculture.

In the end, using deep learning technology for detecting plant diseases could greatly enhance crop health, resource efficiency, and sustainability in agriculture. It is crucial to focus on implementing these systems in real farming practices to make them accessible and user-friendly for farmers worldwide. By working together, we can use deep learning for plant disease detection to tackle the issues in global agriculture and create a stronger and more efficient food system.

## 8. ACKNOWLEDGEMENT

We are very grateful to Mrs. Y. Swathi for her outstanding guidance and support throughout our project. Her expertise and encouragement were crucial to our success, and we are truly thankful for her commitment and mentorship. We also want to thank the faculty in the Computer Science and Engineering Department at Tirumala Engineering College for enabling us to be part of this research project, which has been a valuable learning opportunity for us.

## 9. REFERENCES

1. S. S. Sannakki and V. S. Rajpurohit, "Classification of Pomegranate Diseases Based on Back Propagation Neural Network," International Research Journal of Engineering and Technology (IRJET), Vol2 Issue: 02 | May-2015
2. P. R. Rothe and R. V. Kshirsagar, "Cotton Leaf Disease Identification using Pattern Recognition Techniques", International Conference on Pervasive Computing (ICPC), 2015.
3. Aakanksha Rastogi, Ritika Arora and Shanu Sharma, "Leaf Disease Detection and Grading using Computer Vision Technology & Fuzzy Logic" 2nd International Conference on Signal Processing and Integrated Networks (SPIN) 2015.

4. Gaurav Verma, Charu Taluja, Abhishek Kumar Saxena "Vision Based Detection and Classification of Disease on Rice Crops Using Convolutional Neural Network", 2019
5. Nikhil Shah<sup>1</sup>, Sarika Jain<sup>2</sup> "Detection of Disease in Cotton Leaf using Artificial Neural Network", 2019
6. Ch. Usha Kumari "Leaf Disease Detection: Feature Extraction with K-means clustering and Classification with ANN", 2019
7. Francis, J., Anto Sahaya Dhas D, & Anoop B K., "Identification of leaf diseases in pepper plants using soft computing techniques.", 2016
8. Ganesan, P., Sajiv, G., & Leo, L. M. "CIE Luv color space for identification and segmentation of disease affected plant leaves using fuzzy based approach.", 2017.
9. Plant disease identification using Deep Learning: A review
10. The Indian Journal of Agricultural Sciences 90(2):249-57 DOI:10.56093/ijas.v90i2.98996 February 2020
11. <http://www.apeda.gov.in/apedawebsite/index.html>: Agricultural and processed food products export development authority (2017)
12. Nalawade R, Nagap A, Jindam L, Ugale M (2020) Agriculture field monitoring and plant leaf disease detection, pp 226–231