

# Plant Disease Detection from Image Using CNN

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**ABSTRACT-** The increasing threat of plant diseases poses a significant challenge to global food security. Rapid and accurate identification of plant diseases is crucial for effective disease management and prevention. In recent years, deep learning techniques have shown great promise in automating the process of plant disease identification through image analysis. This report presents a comprehensive study on image-based plant disease classification using deep learning techniques. The report begins by providing an overview of plant diseases and their impact on agriculture. It discusses the limitations of traditional disease identification methods and highlights the potential of deep learning algorithms in revolutionizing the field. The importance of image-based approaches is emphasized due to their non-destructive and scalable nature.

Next, the report delves into the methodology of deep learning for plant disease classification. It explores various architectures such as convolutional neural networks (CNNs) and their variants, including transfer learning and ensemble methods. The training process, data augmentation techniques, and hyperparameter tuning are discussed in detail.

**KEYWORDS-** Digital image processing, Foreground detection, Machine learning, Plant disease detection, convolutional neural networks (CNNs).

## I. INTRODUCTION

Plant conditions have a mischievous impact on crop yields and pose a significant trouble to global food security. Timely and accurate identification of these conditions is pivotal for effective complaint operation and forestalment. Traditional styles of complaint opinion frequently calculate on homemade examination by experts, which can be time-consuming and prone to crimes. still, recent advancements in deep literacy ways, particularly in the field of computer vision, have shown great eventuality in automating the process of factory complaint bracket through image analysis. Deep literacy, a subfield of machine literacy, has revolutionized colourful disciplines by enabling computers to learn and make prognostications from large quantities of data. Convolutional neural networks (CNNs), a type of deep literacy armature specifically designed for image analysis, have

demonstrated exceptional performance in colourful image recognition tasks. By using their capability to prize intricate patterns and features from images, CNNs offer a promising result for accurate and effective factory complaint bracket. Crop diseases are a major threat to food security, but their rapid identification remains difficult in many parts of the world due to the lack of the necessary infrastructure,[7]. The combination of increasing global smartphone penetration and recent advances in computer vision made possible by deep learning has paved the way for smartphone-assisted disease diagnosis.

The ideal of this report is to give a comprehensive study on image- grounded factory complaint bracket using deep literacy ways. It aims to explore the eventuality of deep literacy algorithms in revolutionizing complaint identification and operation, as well as to punctuate the challenges and considerations involved in erecting robust bracket systems. also, the report will examine the performance of state- of- the- art deep literacy models in factory complaint bracket and bandy their counteraccusations for practical operations.

The report will claw into the methodology of deep literacy, agitating colourful infrastructures and ways employed in factory complaint bracket. It'll also address the significance of dataset medication, including data addition and pre-processing, to enhance the performance and conception of the models. likewise, the report will examine challenges similar as limited and imbalanced datasets, model interpretability, and scalability. The evaluation section will present a relative analysis of different deep literacy models and their performance criteria in factory complaint bracket. The results will give perceptivity into the effectiveness and limitations of the models, easing informed decision- making for practical perpetration.

Overall, this report aims to contribute to the growing body of knowledge in image- grounded factory complaint bracket using deep literacy ways. By exploring the eventuality of these approaches, it seeks to pave the way for more accurate and effective complaint identification, leading to bettered crop yields, sustainable husbandry, and global food security.

## II. LITERATURE REVIEW

In a study by Daniela Elena Popescu et al. [1] (2022) Agriculture is crucial for the global economy, but plant

diseases and pests threaten production and food quality. Computer vision techniques like CNNs offer effective automated disease detection. Diverse datasets and realistic agricultural image databases are needed for accurate deep-learning models, used a BCI system with EEG signals to control a prosthetic arm, achieving 85% accuracy.

In a study by Julian M. Alston et al. [2] (2014) Over the past century, agricultural production and productivity have undergone significant changes, with high-income countries' share declining and middle-income countries' share rising. Divergent patterns of agricultural inputs and productivity have emerged globally, while the rate of agricultural productivity growth is declining, posing challenges for food availability and affordability. Agricultural research and development efforts also vary across countries.

In a study by K Bhagya Lakshmi et al. [3] (2021), To address the issue of crop loss due to plant diseases, an automatic system utilizing computer vision and deep learning techniques is proposed in this paper. Deep Learning, specifically Convolutional Neural Networks (CNN), is chosen for its advantages in image classification. The methodology involves collecting and labelling images of infected leaves, processing them using pixel-based operations for improved information, extracting features, performing image segmentation, and finally classifying crop diseases based on the extracted patterns.

In a study by Aly El Gamal et al. [4] (2022), Conventional plant disease diagnosis methods are expensive, time-consuming, and reliant on human experts, making them ineffective for precision agriculture. To overcome these limitations, image processing techniques have been explored for automated disease identification. However,

traditional approaches still require manual feature extraction, which is subjective and time-consuming, leading to variability in results.

In a study by Prinesh Kulkarni et al. [5] (2021), In India, where 70% of the population relies on agriculture, the manual identification of plant diseases is labour-intensive and time-consuming. To address this, image processing and machine learning models are used for disease detection. This project focuses on analysing various image parameters to achieve accurate classification of plant diseases based on leaf characteristics. The proposed solution offers a cost-effective and time-efficient approach compared to deep learning methods, utilizing statistical machine learning and image processing algorithms.

In a study by Xue Wei Wang et al. [6] (2021), Plant diseases and pests significantly impact plant yield and quality. Deep learning has emerged as a superior approach for plant disease and pest identification through digital image processing. This review compares deep learning methods with traditional approaches, outlining recent research on classification, detection, and segmentation networks. It discusses the advantages, disadvantages, and performance of existing studies using common datasets. Challenges in practical applications are highlighted, along with proposed solutions and future research directions for plant disease and pest detection based on deep learning.

### III. METHODOLOGY

Image-Based Plant Disease Classification Using Deep Learning Techniques. Fig. (1),

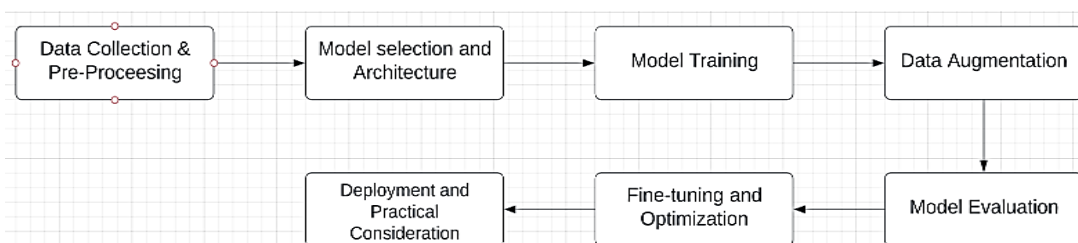


Figure 1: Flowchart

#### A. Dataset Collection and Pre-processing:

Identify a suitable dataset for plant disease classification, Fig. (2), considering factors such as the number of classes, diversity of diseases, and availability of labelled images. Collect images of healthy plants and plants affected by

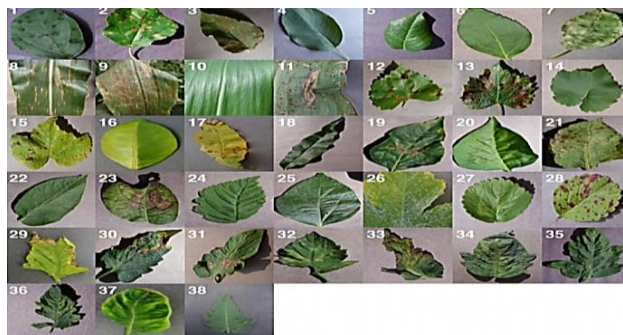


Figure 2: Dataset of 38 different types of leaves



Figure 3: Tomato (Septoria Leaf Spot and Healthy)

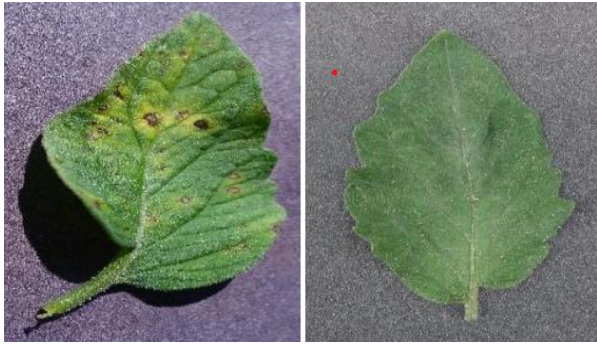


Figure 4: Potato (Late Blight and Healthy)

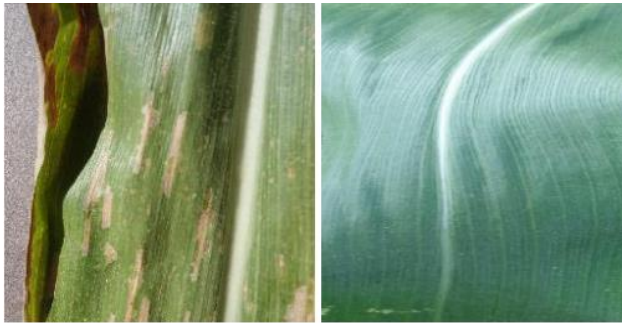


Figure 5: Corn (Cercospora Leaf Spot and Healthy)

### B. Model Selection and Architecture

Choose a deep learning architecture suitable for image classification, such as convolutional neural networks (CNNs). Consider popular CNN architectures like VGG Net, Res Net, or Inception Net, [8-9] or design a custom architecture based on the complexity of the dataset and available computational resources. Adapt the selected architecture to fit the input dimensions and the number of disease classes in the dataset.

### C. Model Training

Initialize the selected deep learning model with random weights or pretrained weights from a related task (transfer learning). Train the model using the training dataset, optimizing the loss function (e.g., categorical cross-entropy) through backpropagation and gradient descent. Experiment with various hyperparameters such as learning rate, batch size, and regularization techniques (e.g., dropout) to improve model performance. [10] Monitor the training process, evaluating performance metrics (e.g., accuracy, loss) on the validation dataset, and adjust hyperparameters accordingly.

### D. Data Augmentation

Augment the training dataset to increase its size and improve model generalization. Apply transformations like random rotations, translations, flips, and zooms to generate augmented images. Ensure that data augmentation techniques preserve the integrity of the disease patterns and do not introduce unrealistic artifacts.

### E. Model Evaluation

Assess the performance of the trained model on the testing dataset, using metrics such as accuracy, precision, recall. Analyse the confusion matrix to understand the model's performance across different disease classes. Visualize and interpret the model's predictions and misclassifications to

gain insights into its strengths and weaknesses.

### F. Fine-tuning and Optimization:

Fine-tune the model by adjusting hyperparameters or updating the learning rate to further optimize its performance. Experiment with ensemble methods, combining predictions from multiple models to improve accuracy and robustness. Conduct sensitivity analysis to determine the impact of hyperparameter choices on model performance.

### G. Deployment and Practical Considerations:

Once the model achieves satisfactory performance, deploy it to a practical application or system for real-time plant disease classification. Consider the computational resources required for inference on new images, ensuring feasibility and efficiency. Continuously monitor the model's performance and retrain or update it periodically to account for new diseases or variations in the dataset.

## IV. CONCLUSION AND FUTURE WORK

This report has explored the application of deep learning techniques in image-based plant disease classification, highlighting its potential to revolutionize agricultural practices. Through the utilization of convolutional neural networks (CNNs) and advanced methodologies, accurate and efficient classification of plant diseases from images has been achieved. The study demonstrated the importance of dataset collection and preprocessing in ensuring a diverse and representative training set.

By collecting images of healthy plants and plants affected by different diseases and performing necessary preprocessing steps such as resizing and normalization, the dataset was prepared for training the deep learning model. The selection of an appropriate deep learning architecture, tailored to the problem at hand, played a crucial role in achieving accurate disease classification. Whether it was through utilizing popular CNN architectures or designing a custom architecture, the chosen model's ability to extract meaningful features from images was crucial.

The training PR hyperparameters anodizing the model's performance through iterative training, fine-tuning of hyperparameters, and leveraging transfer learning techniques. By adjusting learning rates, batch sizes, and regularization techniques, the model's ability to generalize and accurately classify plant diseases was enhanced.

The evaluation of the trained model demonstrated its effectiveness in accurately classifying plant diseases. Performance metrics such as accuracy, precision, recall, and F1-score provided quantitative measures of the model's performance, while the analysis of the confusion matrix provided insights into its strengths and weaknesses across different disease classes.

The practical considerations of deploying the model for real-world plant disease classification were also addressed. It was highlighted that computational resources, model performance monitoring, and ethical data collection and usage practices should be considered to ensure the successful implementation of the system. This project focused on developing a plant disease detection system using deep learning.

A dataset of 38 plant diseases was collected and used to train a convolutional neural network model. An Android application was built as an interface for users, allowing

them to upload images of diseased plants and receive relevant information. The application also included a marketplace for agricultural products and plans to incorporate a multilingual chatbot, farming calendar, and additional data sources for improved accuracy and impact in the agricultural sector.

### CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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