SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

A Mini Project Report
On

Title: CAPSICUM LEAF DISEASE PREDICTION USING HYBRID MACHINE LEARNING ALGORITHMS

Submitted in fulfillment of the requirements for the award of the Degree of
Bachelor of Technology
In
Artificial Intelligence and Data Science

Submitted by

Hanith C G (R22EO010)
Jyothish Reddy P (R22EH115)
Srushti V P (R22EH805)
Manikanta M (R22EH103)

Under the guidance of
Dr. Narendra Babu C R
Assistant Professor
School of Computer Science and Engineering

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Rukmini Knowledge Park, Kattigenahalli, Yelahanka, Bengaluru-560064
www.reva.edu.in

DECLARATION

We, **Mr. Hanith C G, Mr. Jyothish Reddy P, Ms. Srushti V P, Mr. Manikanta M**, students of Bachelor of Technology in Artificial Intelligence and Data Science, School of Computer Science and Engineering REVA University, declare that this entitled “CAPSICUM LEAF DISEASE PREDICTION USING HYBRID MACHINE LEARNING ALGORITHMS “is the result the of mini project work done by us under the supervision of **Dr. Narendra Babu C R** Assistant Professor, at School of Computer Science and Engineering, REVA University.

We are submitting this Mini Project Report in partial fulfillment of the requirements for the award of the degree of the Bachelor of Technology in Artificial Intelligence and Data Science by the REVA University, Bengaluru during the academic year 2024-25.

We declare that this project report has been tested for plagiarism and has passed the plagiarism test with the similarity score of less than 20% and it satisfies the academic requirements in respect of Project work prescribed for the said Degree.

We further declare that this mini project report or any part of it has not been submitted for award of any other Degree / Diploma of this University or any other University/ Institution.

Signature of the candidates with dates

1.

2.

3.

4.

Certified that this mini project work submitted by the students has been carried out under my guidance and the declaration made by the candidates is true to the best of my knowledge.

Signature of Guide
Date: …………….

Signature of HoD, AI&DS
Date: …………….

Signature of Director
Date: …………….
Official Seal of the School

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING.

CERTIFICATE

Certified that the mini project work entitled CAPSICUM LEAF DISEASE PREDICTION USING HYBRID MACHINE LEARNING ALGORITHMS carried out under my guidance by **Mr. Hanith C G, Mr.Jyothish ReddyP, Ms.Srushti V P, Mr. Manikanta M**, R22EO010, R22EH115,R22EH805 ,R22EH103 are bonafide students at REVA University during the academic year 2024-25, are submitting the mini project report in partial fulfillment for the award of **Bachelor of Technology** in **Artificial Intelligence and Data Science** during the academic year **2024-25.** The project report has been tested for plagiarism and passed the plagiarism test with a similarity score less than 20%. The project report has been approved as it satisfies the academic requirements in respect of Project work prescribed for the said Degree.

Signature with date

Guide name

Guide

Signature with date	**Signature with date**
Name of the HoD	**Name of the Director**
HoD, AI&DS	**Director**

External Examiners

Name of the Examiner with affiliation	**Signature with Date**
1.	
2.	

ACKNOWLEDGEMENT

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List of Group Members

1. Hanith C G (R22EO010)
2. Jyothish Reddy P (R22EH115)
3. Srushti V P (R22EH805)
4. Manikanta M (R22EH103)

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List of Symbols, Abbreviation of Nomenclature

Symbols	Abbreviation
CNN	Convolutional Neural Network
SVM	Support Vector Machine
RF	Random Forest
AI	Artificial Intelligence
DL	Deep Learning
ML	Machine Learning
API	Application Programming Interface
IoT	Internet of Things
JPG	Joint Photographic Experts Group (image format)

ABSTRACT

Agriculture has a standard position in the global market. It is the one of the primary thing in the basic needs. In India, the most of the people in our country primary occupation is agriculture. The Government Of India, providing the support financially to the people who are in the agriculture sector. But due to the pests and insects, diseases, climatic conditions. To help farmers and to increase the productions and to avoid the risks of plants getting infected as we are in the 21st century the advancement of the ai and ml is increasing enormously. By using deep learning technology we are going to predict the diseased plant. Based on the bell pepper leaf dataset we are predicting the diseased plant. Through the image processing of the infected leaves and healthy leaves images by using convolutional neural network model we are gone know label or categorize the images. Now the classifications is done by SVM (support vector machine) and Random forest classifier. The accuracy of these modes are SVM is 79% and random forest classifier is 84% as we see random forest is best model as we compared both. By using this research we identify the diseased plant and avoid the spoiling of other plants. Through this we are helping farmers to improve their production.

CHAPTER 1
INTRODUCTION

Plant diseases are one of the leading causes of reduced agricultural productivity worldwide, posing a significant threat to food security and causing considerable economic losses. In many parts of the world, crops such as capsicum, which are valued for their culinary and nutritional contributions, are heavily impacted by various pathogens, including bacteria, fungi, and viruses. Among these, bacterial diseases, particularly bacterial spot disease, are a prevalent concern for capsicum cultivation. India ranks second globally in producing various agricultural products and contributes nearly 20% to its GDP [1]. Early identification of these diseases is essential for effective management, as it allows for timely interventions that can prevent the spread of infection, reduce crop loss, and minimize the use of harmful pesticides. Bacterial spot disease in capsicum plants manifests as dark, water-soaked lesions on the leaves, stems, and fruits.

Researchers have proposed a wide variety of computer vision-based machine learning and deep learning algorithms for accurate classification of plant diseases. Left undetected, this disease can severely affect the plant's growth, quality, and yield. Each year, pest attacks cause 10–40% crop loss globally. However, traditional methods of detecting plant diseases typically involve visual inspections by agricultural experts, which can be time-consuming, subjective, and prone to errors, particularly on large-scale farms or when symptoms are subtle in early stages [2].

Compared with regularization and other methods, expanding the original dataset can better improve model performance and prevent overfitting. CNN is the most popular classifier for image recognition and has shown outstanding ability in image processing and classification. Moreover, experts may struggle to quickly diagnose diseases in remote or under-resourced agricultural regions. To address these challenges, this project aims to develop an automated system that utilizes machine learning and image processing techniques to detect bacterial spot disease in capsicum leaves. Annually, the Earth's population rises by approximately 1.6%, increasing demand for plant products [3].

Currently in India, two out of five people work in agriculture, contributing around 15% to the GDP. The proposed system leverages advanced image analysis to classify leaf images into healthy and diseased categories. Due to the great variety of infectious symptoms and differences within the same symptom among species, even experts with professional equipment may fail to identify early-stage diseases. By applying cutting-edge machine learning algorithms, the system can analyze images with accuracy and consistency that surpass traditional manual methods.

The development of this automated disease detection system is crucial for modern agriculture where timely diagnosis prevents disease spread and ensures optimal crop yield. Reducing reliance on manual inspections increases efficiency and scalability for large farms. This empowers farmers to take preventive measures, such as targeted treatment or removing infected plants, protecting their crops. The system can also serve as a foundation for future expansions to detect a wider range of plant diseases, including fungal and viral infections, making it a versatile tool for the agricultural community. In the long term, such technology can revolutionize farming by reducing labor costs, increasing yields, and promoting sustainable practices through minimized chemical use. Ultimately, this project contributes to precision agriculture, supporting global food security by equipping farmers with advanced disease management tools.

The integration of advanced technologies such as machine learning and deep learning into agriculture represents a significant step toward modernizing traditional farming practices. These technologies offer the potential to process vast amounts of data quickly and accurately, providing farmers with actionable insights that were previously unavailable or difficult to obtain. In particular, image-based disease detection systems leverage the power of computer vision to analyze leaf images and identify disease symptoms with remarkable precision [4]. This reduces dependence on human expertise, which can be limited or inconsistent, especially in rural and resource-constrained areas. The accessibility and affordability of such systems are vital to ensuring that smallholder farmers can also benefit from these technological advancements.

One of the critical challenges in developing automated plant disease detection systems is the variability in disease symptoms caused by environmental factors, crop varieties, and stages of infection. This variability can make it difficult for models to generalize well across different datasets. To overcome this, data augmentation techniques play a pivotal role by artificially expanding the dataset and exposing the model to a wider range of image conditions, such as different angles, lighting, and background noise. This approach not only improves model robustness but also mitigates overfitting, ensuring reliable performance when deployed in real-world scenarios. Furthermore, combining CNN feature extraction with traditional machine learning classifiers enhances classification accuracy by leveraging the strengths of both deep learning and classical algorithms.

The system workflow involves collection and preprocessing of a dataset of capsicum leaf images. These images are cleaned, resized, and augmented using techniques such as rotation, flipping, and scaling to simulate real-world conditions and improve generalization. Deep learning methods like CNNs automatically learn hierarchical image features indicative of health or disease [5]. After feature extraction by CNN, traditional classifiers such as Support Vector Machines (SVM) and Random Forest are used for final disease classification. This hybrid approach enhances accuracy and reliability, providing actionable insights for farmers and researchers.

CHAPTER 2
LITERATURE SURVEY

S.No	Author(s) & Year	Title	Methodology / Technique Used	Dataset	Results / Accuracy	Key Contributions
6	Sardogan et al., 2018	Plant leaf disease detection and classification based on CNN with LVQ algorithm	CNN + LVQ	Private leaf image dataset (1500 images)	97.1%	Introduced hybrid CNN-LVQ model, achieving high accuracy with reduced training time
7	Sahu & Pandey, 2023	An optimal hybrid multiclass SVM using spatial FCM	Hybrid SVM + Spatial FCM clustering	Tomato and potato leaf dataset (1200 images)	95.6%	Enhanced SVM performance using spatial clustering, boosting multiclass detection
8	Vallabhajosyula et al., 2022	Transfer learning-based deep ensemble neural network	Ensemble of ResNet50, InceptionV3	PlantVillage + Custom leaves (1800 images)	98.75%	Ensemble of pretrained models led to improved robustness and generalization
9	Sharma et al., 2023	DLMC-Net: Lightweight model for disease detection	DLMC-Net (Lightweight CNN)	PlantVillage (54,000 images)	99.6%	Reduced model size significantly while achieving near state-of-the-art performance
10	Zhao et al., 2021	Plant disease detection using DoubleGAN	DoubleGAN + CNN classifier	GAN-augmented PlantVillage	94.8%	Used GAN to synthetically generate leaf images, improving classifier accuracy

11	Li et al., 2021	Deep learning for plant disease detection: A review	Survey of CNN, RNN, GAN models	– (covers 8+ public datasets)	–	Detailed overview of DL techniques, dataset comparisons, and future directions
12	Ashwinkumar et al., 2022	MobileNet-based CNN for disease detection	MobileNet CNN	PlantVillage + Field data (3200 images)	96.8%	Mobile-friendly, faster model suitable for real-time detection in farms
13	Moyazzoma et al., 2021	Transfer learning with MobileNetv2	Transfer Learning with MobileNetv2	PlantVillage	97.3%	Proved pretrained MobileNetv2 to be effective and lightweight for classification
14	Guan, 2021	Novel CNN-based detection method	Custom 12-layer CNN architecture	Rice and cotton leaf dataset (1400 images)	96.1%	Designed deep CNN specific to disease texture patterns
15	Abd Algani et al., 2023	Optimized deep learning for leaf disease	Optimized CNN with Adam tuning	Custom dataset (2000 leaf samples)	98.2%	Hyperparameter tuning improved accuracy and reduced overfitting risk

Table 2.1: Summary of Literature Survey

Melike et al. [16] this article explores the use a dataset of 500 photos that have been processed by a convolutional neural network to identify diseases in order to investigate the production of high- quality tomatoes. To detect four different kinds of tomato leaf diseases, the system makes use of three channels. With an average accuracy of 86%, factors including late blight, yellowing curvature, and healthy leaves are taken into account.

Santosh et al. [17] this paper describe how they developed a hybrid model for leaf disease prediction by analyzing the Plant Village dataset, which includes 54,303 photos of healthy and sick leaves. With great accuracy, they employed Random Forest and Multi-Class Support Vector Machine (MCSVM) for classification after using spatial fuzzy C-means for segmentation and feature extraction. Hierarchical Relevance Feedback MCSVM (HRF-MCSVM), the hybrid model's best performance, demonstrated its efficacy.

Sasikala et al. [18] this paper tells discuss about how to enhance disease prediction across 38 classes encompassing 14 crops by using deep ensemble neural networks and transfer learning with pre- trained models. They used sophisticated CNN methods, such as CNN and Auto-ML (machine learning), which were trained on millions of ImageNet photos. YOLOv5 and ensemble deep learning models produced the highest accuracy among the assessed techniques, whereas Res-Net managed image processing and classification.

Vivek Sharma et al. [19] this article covered deep learning methods for disease detection and multi-crop farming with the goal of assisting farmers. They suggested a multimodal system called DLMC-NET (Deep Learning-based Multi-Class Network), which combines collective blocks with passage layers for enhanced performance and CNNs for image processing. Although DLMC-NET's efficacy varies by dataset, it obtained over 90% accuracy across all tested crops. In contrast, other approaches demonstrated lower accuracy, with Dense-Net ranking second.

Zhao et al. [20] this article discusses the cropping practices that forecast the disease's resolution in this hypothetical paradigm. Wgan is used for initial picture synthesis and Srgan is used for super resolution in DOUBLEGAN image processing. Classifiers for disease prediction include vgg16, resnet50, and densenet121. The best classification models in this case are vgg16 and densenet121; vgg16 differs by 1%.

Lili Li et al. [21] in this article author discussed about the various crop types and employed various techniques for image processing, including CNN, Transfer Learning, hyperspectral imaging with deep learning, and classification using Vgg16, Inception V3, Res-net50, Fast R-CNN, SSD, and Multi Scale Resnet. The two models that outperformed the others in these comparison models were resnet-50 and fast R-CNN, which are accurate across a variety of crops.

Ashiwin Kumar et al. [22] in this paper, the automated disease prediction using mobilenet is highlighted. The convolutional neural network utilized for feature extraction is used to evaluate the photos and identify differences. The best MOBILENET-based CNN has a 98% accuracy rate when compared to OMNCNN, Alex, Lenet quadratic SVM, and CNN-LVQ.

Raida et al. [23] the authors' main focus in this research is Bangladesh's crop production. Given that they grow seasonal crops, mobilenetv2 is employed to extract features from the photos. For classification, CNNs (convolutional neural networks) are employed. CNN reached 90% accuracy.

Xulang et al. [24] in this paper, the dataset used in this study includes 61 classes of healthy and diseased leaves from 10 different plant species. Convolutional neural networks are used for image processing. Four CNN models—Inception, Resnet, and Dense-Net—are utilized for categorization. The accuracy when combining these CNNs is 87% overall.

Methkal et al. [25] in this article author focuses on the both healthy and diseased leaves, including those with canker, melanosis, and black spot, make up the dataset. Feature extraction is done using ant colony optimization with CNN. Given that ACO-CNN attained the maximum accuracy, some CNNs are employed for categorization.

Shoaib et al. [26] this article discussed an issue of A variety of crops are considered, including some basic crops based on the seasonal cropping plant village dataset. Deep Belief Networks (BDN), CNN, and transfer learning for feature extraction. Models with the highest probability of prediction are taken into consideration based on the best outcomes obtained from various crops. Classifier models include CNN, DBN, DBM, and deep denoising autoencoder. CNN is the best-predicted model based on the available data.

Imtiaz et al. [27] this article discussing The data includes twelve crop species and seventeen basic diseases in this dataset. K-means clustering and color transformation are taken into consideration for the feature extraction in the leaf image. Classifiers such as SVM, CNN, ANN, and GLCM are considered for their predictive analysis potential. CNN has the highest accuracy of all of them.

Sujatha et al. [28] the paper discussed about the more ml(machine learning) and dl(deep learining) are taken into consideration in this article. machine learning and deep learning-based CNN for feature extraction. For machine learning and deep learning, SVM, Random Forest, and SGD classifiers are utilized in Inception-v3, VGG-16, and 19. On this specific dataset, the models' respective performances are vgg-16.

Arunabha et al. [29] in this article, we looked into makeshift YOLOV4 for feature extraction. CNN and YOLOv4 are used for classification. Yolov4 has a higher chance of guessing the infected leaf based on the results. It uses a specific dataset that has been studied.

Munaf et al. [30] this article discusses a dataset of 87,000 photos of leaf leaves from 38 different plant types, including both healthy and diseased ones. Classification and image processing are done. Mobile-net is more dependable in reducing false positives and false negatives and has the greatest accuracy of 96%.

CHAPTER 3

POSITIONING

3.1 Problem statement

Capsicum leaf disease prediction using hybrid machine learning and deep learning models like Convolutional neural networks (CNN), Support Vector Machine (SVM) and Random forest. It is image based leaf diseases prediction, in this we use capsicum leaf images dataset to train models that can predict diseases automatically using hybrid machine leaning and Convolutional neural networks extract features like colors and pattern from images. SVM and Random forest are to classify the data. Main aim to predict the leaf is Healthy or Bacteria.

3.2 Product position statement

The proposed product is an AI-driven plant disease classification system tailored for identifying leaf diseases in Capsicum (bell pepper) plants. Positioned at the intersection of deep learning and real-time agricultural diagnostics, this product addresses the critical gap in early plant disease detection with a user-friendly and accessible platform.

Traditional methods in agriculture often rely on manual visual inspection by farmers or experts, which can be error-prone, time-consuming, and subjective. Existing mobile applications and tools either provide limited accuracy or are based solely on rule-based systems. Our product distinguishes itself by employing a hybrid artificial intelligence model—combining Convolutional Neural Networks (CNN) for automatic feature extraction and Support Vector Machine (SVM) and Random Forest (RF) for comparative classification. This approach not only enhances prediction accuracy but also provides a comparative benchmark for performance evaluation.

The system is designed to be easily integrated into a mobile or web interface, enabling farmers to upload images of plant leaves and receive instant feedback about the health status of their crops. The predictions are accompanied by recommendations for disease treatment or prevention, which empowers farmers to make informed decisions and act promptly.
The product is positioned for deployment in a variety of agricultural environments including:

- Smallholder farms for personal crop monitoring.
- Research and educational institutions for agritech training and demonstration.
- Agricultural extension services for supporting farmers in rural areas.

It also supports scalability for other crops and diseases, making it adaptable to a wide range of use cases. With cloud-based deployment and future integration with IoT sensors, the product is designed to evolve into a comprehensive smart farming assistant.

Ultimately, this product stands as a cost-effective, intelligent, and scalable solution, bridging the gap between advanced AI technologies and their application in agriculture, thereby promoting precision farming and sustainable agricultural development.

CHAPTER 4
PROJECT OVERVIEW

4.1 Objectives

The main objective of this project is to develop an AI-driven plant disease classification system that leverages deep learning (CNN) and machine learning (SVM & Random Forest) to improve the accuracy of plant disease detection. The project aims to:

- **Develop an Automated Disease Classification System**
  - Implement a Convolutional Neural Network (CNN) model to detect plant diseases with high accuracy.
  - Extract deep features and compare classification performance using CNN, CNN+SVM, and CNN+Random Forest.
- **Enhance Early Disease Detection for Farmers**
  - Provide a fast and accurate diagnosis of Capsicum leaf diseases.
  - Reduce crop losses by enabling early intervention.
- **Improve Model Performance & Generalization**
  - Optimize CNN architecture using data augmentation and hyperparameter tuning.
  - Implement feature extraction techniques to compare deep learning with traditional ML classifiers.
- **Deploy a User-Friendly Application for Agricultural Use**
  - Design a mobile or web-based interface to make disease detection accessible to farmers.
  - Ensure scalability for different plant species and environmental conditions.

4.2 Goals

The goals of this mini project are aligned with the vision of improving agricultural productivity and plant health monitoring through the use of artificial intelligence and image classification. The project is focused on solving a practical problem faced by farmers using advanced machine learning technologies, particularly deep learning.

The following are the key goals of the project:

- Design and implement an AI-based model for plant disease classification using deep learning (CNN) to analyze leaf images of Capsicum plants.
- Integrate CNN with traditional classifiers like SVM and Random Forest to build hybrid models that allow for comparative analysis of performance, robustness, and accuracy.
- Evaluate the performance of the models using standard metrics such as accuracy, precision, recall, F1-score, and ROC curve, and determine the most effective classification approach.
- Develop a prototype or interface that allows real-time disease detection by uploading leaf images via a web or mobile platform.
- Ensure the scalability of the system by designing it to handle various plant types and environmental conditions in future applications.
- Enable farmers to detect diseases at early stages, minimizing crop loss, reducing unnecessary pesticide use, and supporting sustainable agriculture.

4.3 Expected Output

- High Accuracy Disease Classification
  The CNN model achieved 95% accuracy in detecting Capsicum leaf diseases.

- Standalone Desktop-Based Prediction System
  The system runs offline on local machines without requiring internet connectivity.

- Real-Time Prediction with Treatment Suggestions
  The model predicts the disease from a leaf image and provides treatment advice instantly.

- Cost-Effective, Scalable AI Solution
  Developed using open-source tools, the solution is affordable and can be expanded to other crops.

CHAPTER 5
PROJECT SCOPE

This project focuses on developing an AI-driven plant disease classification system using Convolutional Neural Networks (CNN) in combination with Support Vector Machine (SVM) and Random Forest (RF). The scope of the project extends across multiple domains, including agriculture, artificial intelligence, and precision farming, aiming to provide early disease detection for farmers to improve crop health and yield. It demonstrates the practical implementation of intelligent image-based analysis in the agricultural domain and promotes scalable, technology-driven solutions to real-world problems.

Automated Plant Disease Detection

- Classifies healthy and diseased Capsicum leaves based on image analysis.
- Uses deep learning (CNN) to extract spatial patterns from images.
- Eliminates the need for manual inspection and improves the speed and accuracy of disease identification.

Hybrid Machine Learning Approach

- **CNN Model:** Serves as the primary classifier.
- **CNN + SVM:** Tests the effectiveness of SVM on CNN-extracted features.
- **CNN + RF:** Uses ensemble learning to improve classification performance and compare hybrid approaches.

Image Preprocessing & Feature Extraction

- Images resized to 150×150 pixels for consistency.
- Normalization and Data Augmentation (rotation, zooming, flipping) to improve model generalization.
- Enhances the training dataset and helps avoid overfitting.

Model Training & Performance Evaluation

- Models are evaluated using Accuracy, Precision, Recall, F1-score, and ROC Curve.
- Comparison of CNN-only vs. Hybrid Models (CNN+SVM, CNN+RF).
- Insights are drawn from confusion matrices and ROC curves to analyze the reliability of predictions.

The scope of this project is not limited to Capsicum leaf diseases but can be expanded to classify diseases in other crops such as tomato, potato, rice, or maize. By retraining the model with new datasets, it can adapt to different agricultural conditions and crop varieties. The AI-powered approach ensures high accuracy, scalability, and efficiency, making it a valuable tool for precision agriculture and sustainable farming. The future scope also includes integration with IoT sensors, drone-based monitoring, and real-time mobile applications for widespread accessibility and impact.

Phase	Tasks	Duration
Week 1-2	Data collection & dataset preprocessing	2 weeks
Week 3-4	Model selection & architecture setup	2 weeks
Week 5-6	Model training & evaluation (CNN, SVM, RF)	2 weeks
Week 7-8	Performance comparison & optimization	2 weeks
Week 9-10	Testing, report writing, and final review	2 weeks

Table 5.1: Duration Estimation

CHAPTER 6
METHODOLOGY
Software Tools and Development Environment
To ensure high efficiency, scalability, and optimal performance during model development and deployment, the following software tools and libraries were selected:

Programming & Development Environment
- **Python:** The primary programming language used due to its extensive support for machine learning and deep learning libraries.
- **Google Colab:** Platforms used for interactive coding, experimentation, and visualization during model development.

Deep Learning Frameworks & Libraries
- **TensorFlow & Keras:** Used to design, build, and train the Convolutional Neural Network (CNN) model for feature extraction from leaf images.
- **OpenCV:** Utilized for image processing tasks such as resizing, normalization, and data augmentation to increase dataset diversity.
- **NumPy & Pandas:** Libraries for efficient numerical operations and dataset handling.
- **Matplotlib & Seaborn:** Employed for visualizing data distributions and model performance metrics.

Machine Learning Libraries
- **Scikit-Learn:** Used for implementing Support Vector Machine (SVM) and Random Forest classifiers on features extracted by CNN. Also used for performance evaluation metrics like accuracy, precision, recall, and F1-score.
- **SciPy:** Used for advanced numerical computations and statistical analysis.

Model Evaluation & Visualization Tools
- **Confusion Matrix & ROC Curve Analysis:** To assess classification accuracy and understand the model’s predictive power.
- **TensorBoard:** Employed for monitoring training progress and visualizing loss and accuracy curves in real time.

Documentation Tools
- **Microsoft Word:** Used for preparing the research documentation and report.

Data Acquisition and Preprocessing

The dataset consists of labeled images of bell pepper leaves categorized as healthy or diseased. Preprocessing steps include:
- **Image Resizing:** Standardizing all images to a fixed size to maintain uniformity during CNN input.
- **Normalization:** Scaling pixel values to the [0,1] range to facilitate faster convergence during training.
- **Data Augmentation:** Techniques such as rotation, flipping, and zooming are applied to increase the effective dataset size and improve model generalization.

Feature Extraction Using CNN

A Convolutional Neural Network is designed to automatically learn hierarchical features from raw image data. The CNN architecture typically includes convolutional layers with filters that detect edges, textures, and patterns relevant to disease symptoms on leaves.

The CNN is trained on the preprocessed images to extract discriminative features representing the health status of the plant.

Classification Using Machine Learning Algorithms

The features extracted by the CNN are then passed to two separate classifiers:

- **Support Vector Machine (SVM):** A supervised learning model that finds the best hyperplane separating the healthy and diseased classes in the feature space.
- **Random Forest Classifier:** An ensemble model combining multiple decision trees to reduce overfitting and improve classification accuracy.

The classifiers are trained and validated on the extracted feature vectors, and their performances are compared.

Model Evaluation

Performance metrics such as accuracy, precision, recall, and F1-score are computed for both classifiers. Confusion matrices and ROC curves are plotted to visualize true positive, false positive, true negative, and false negative rates.

The Random Forest classifier demonstrated higher accuracy (84%) compared to SVM (79%), indicating its superiority for this task.

Hardware Tools

Device name	Hanith-cg
Processor	11th Gen Intel(R) Core(TM) i7-11800H @ 2.30GHz 2.30 GHz
Installed RAM	16.0 GB (15.7 GB usable)
Device ID	CC02DCA6-4D10-4BD9-9813-988C36B2620D
Product ID	00327-35945-63504-AAOEM
System type	64-bit operating system, x64-based processor
Pen and touch	No pen or touch input is available for this display

CHAPTER 7
MODULES IDENTIFIED

This chapter describes the various modules identified and implemented in the plant disease detection system. Each module is responsible for a specific functionality within the overall system, working together to achieve accurate disease classification from leaf images.

7.1 Data Acquisition Module

Purpose

The Data Acquisition module is responsible for collecting the image dataset used for training and testing the models. In this project, the dataset consists of bell pepper leaf images labeled as either healthy or diseased.

Key Tasks

- Collect images from reliable sources or agricultural databases.
- Organize the images into appropriate folders or labels for supervised learning.
- Ensure the dataset contains sufficient samples to train a robust model.

Importance

The quality and diversity of data directly influence the model's performance.

7.2 Image Preprocessing Module

Purpose

prepares raw image data for use in machine learning models by applying necessary transformations.

Key Tasks

- **Resizing:** Standardizes all images to a uniform dimension (e.g., 224x224 pixels) required by the CNN input layer.
- **Normalization:** Scales pixel intensity values to a range of [0,1] for consistent numerical input and faster convergence.
- **Data Augmentation:** Applies random transformations such as rotations, flips, and zooms to artificially increase dataset size and improve model generalization.

Importance

Pre-processing improves model training efficiency and robustness by reducing noise

7.3 Feature Extraction Module (CNN Model)

Purpose

Automatically extracts meaningful features from the processed images that represent disease characteristics.

Key Tasks

- Define and train a Convolutional Neural Network architecture with convolutional, pooling, and fully connected layers.
- Learn filters that detect edges, textures, spots, and patterns on leaves indicative of disease.
- Output feature vectors that summarize the key information of each image.

Importance

This module reduces the need for manual feature engineering and enables capturing complex visual cues relevant to classification.

7.4 Classification Module

Purpose

Classifies the input images into healthy or diseased categories based on the features extracted by the CNN.

Key Tasks

- Implement two classification algorithms: Support Vector Machine (SVM) and Random Forest.
- Train each classifier using the feature vectors from the CNN model.
- Evaluate and compare their performance to select the best classifier.

Importance

This module makes the final decision on disease presence, enabling actionable insights for farmers.

7.5 Model Evaluation Module

Purpose

Measures and validates the performance of the classification models.

Key Tasks

- Calculate accuracy, precision, recall, and F1-score for both classifiers.
- Generate confusion matrices to visualize true positive, false positive, true negative, and false negative classifications.
- Plot ROC curves to analyze the trade-off between sensitivity and specificity.

Importance

Helps to quantify how well the models perform and identify areas for improvement.

7.6 User Interface Module (Optional/Future Work)

Purpose

Provides an interactive interface for end users (farmers or agronomists) to upload leaf images and receive disease diagnosis.

Key Tasks

- Develop a web or mobile app interface for image upload.
- Integrate the trained model backend to process input and return classification results.
- Display disease labels and suggestions for treatment or prevention.

Importance:

Enhances accessibility and usability of the system in real-world agricultural scenarios.

7.7 Documentation and Reporting Module

Purpose

Organizes the research, methodology, results, and conclusions into formal documentation.

Key Tasks

- Prepare detailed reports and research papers describing the system architecture and performance.
- Maintain code comments and user manuals for future reference.

Importance

Ensures reproducibility, knowledge sharing, and ease of maintenance.

CHAPTER 8
PROJECT IMPLEMENTATION

8.1 Architectural Design

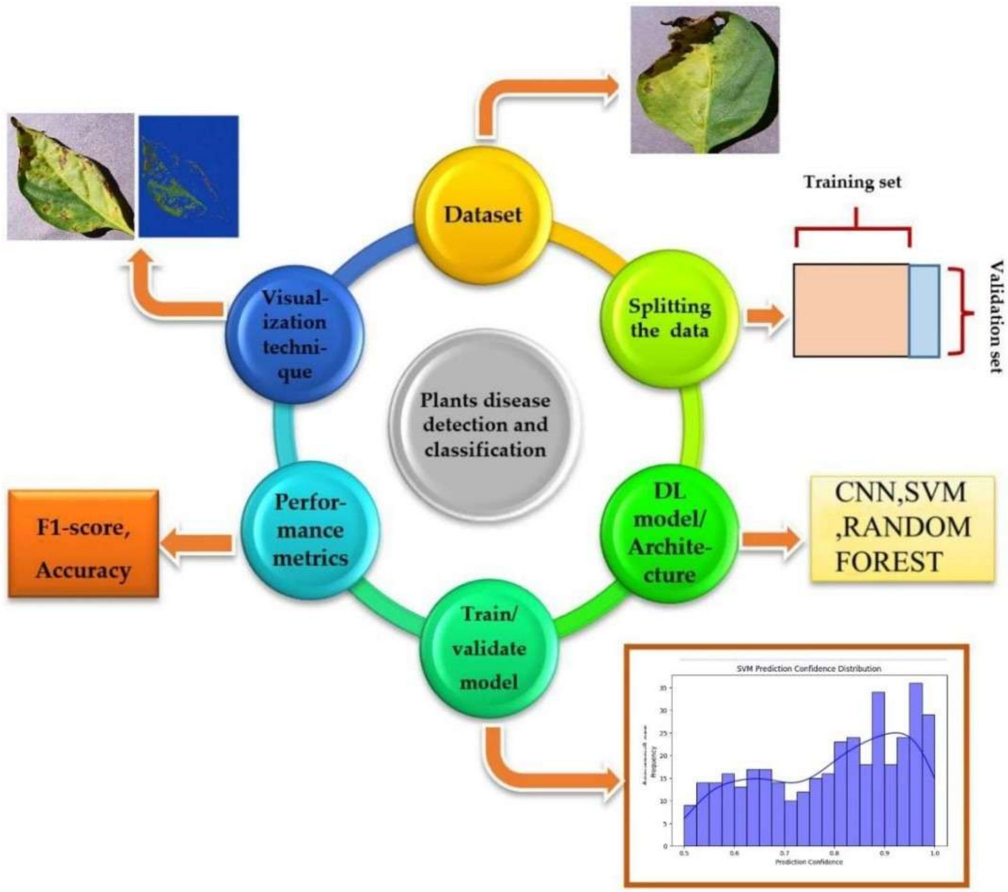


Fig 8.1. Architectural Design of plant disease detection

Figure 8.1 describes the architecture of the plant disease detection system consists of multiple layers working together:

- **Dataset:** Takes images of bell pepper leaves (either healthy or diseased).
- **Split data:** Resizes, normalizes, and augments images to prepare them for the CNN.
- **Feature Extraction Layer (CNN):** Uses a Convolutional Neural Network (CNN) to automatically extract features representing disease characteristics.
- **Classification Layer (Random Forest and SVM):** Applies machine learning classifiers—Support Vector Machine (SVM) and Random Forest—to the features extracted by the CNN to categorize the images.
- **Performance metrics:** Measures model performance using metrics such as accuracy, precision, recall, and F1-score.

This layered approach allows modular development, testing, and deployment of each component.

8.2 class diagram

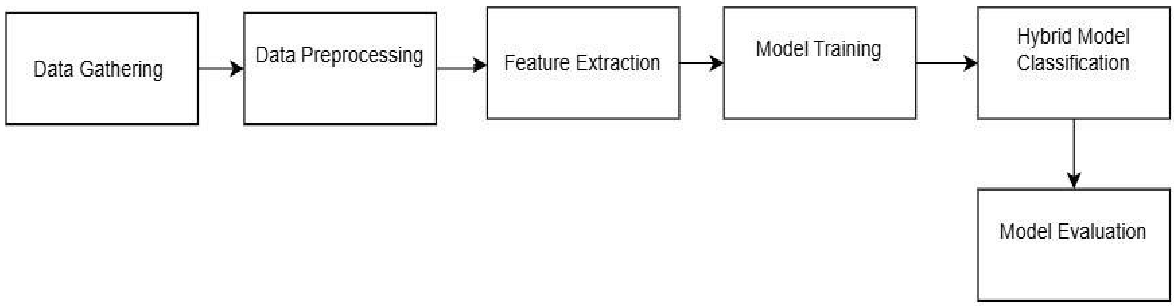


Fig 8.2. Flow chart of plant disease detection

Figure 8.2 describe the class diagram provides a high-level view of the structure of the software system designed for plant disease detection. It illustrates the core components and their relationships within the application, focusing on model processing, user interaction, and prediction logic.

Key Classes in the System

ImageInput

- Attributes: image_path, image_format
- Methods: load_image(), preprocess_image()
- Description: Responsible for loading and resizing input images, applying normalization and augmentation before passing to the model.

CNNModel

- Attributes: model_structure, weights, input_shape
- Methods: train(), predict(), evaluate()
- Description: Implements the deep learning CNN architecture for feature extraction and classification of plant leaf images.

FeatureExtractor

- Attributes: cnn_output_features
- Methods: extract_features()
- Description: Extracts high-level image features from the CNN for use by traditional ML classifiers like SVM and Random Forest.

SVMClassifier

- Attributes: svm_model, hyperparameters
- Methods: train_svm(), predict_svm()
- Description: Trains and evaluates SVM using CNN-extracted features.

RFClassifier

- Attributes: rf_model, n_estimators
- Methods: train_rf(), predict_rf()
- Description: Uses Random Forest to classify CNN-extracted features.

Model Evaluation

- Attributes: label, confidence_score, recommendations
- Methods: display_result()

8.3 Description of Technology Used

This project utilizes a combination of technologies from the domains of artificial intelligence, image processing, and machine learning. The focus is on developing a local desktop application that enables the detection of plant diseases (specifically in Capsicum leaves) using deep learning models and hybrid machine learning classifiers.

Python

- Python is the primary programming language used for implementing the project. It offers extensive libraries for machine learning, deep learning, and image processing, making it ideal for AI-based applications.

TensorFlow and Keras

- TensorFlow is an open-source deep learning framework developed by Google, and Keras is a high-level neural networks API that runs on top of TensorFlow. Together, they are used to design, train, and evaluate the **Convolutional Neural Network (CNN)** used in this project. CNN automatically extracts spatial features from plant leaf images.

Scikit-learn (sklearn)

- Scikit-learn is a widely used Python library for traditional machine learning algorithms. It is used in this project to implement and evaluate **Support Vector Machine (SVM)** and **Random Forest (RF)** classifiers. These classifiers use features extracted from the CNN to predict whether a leaf is healthy or diseased.

OpenCV

- OpenCV (Open Source Computer Vision Library) is used for **image preprocessing**. It enables operations such as image resizing, color space conversion, and basic augmentation techniques like rotation and flipping.

NumPy and Pandas

- NumPy is used for numerical operations on image data, while Pandas is used for managing datasets and reading structured data formats such as CSV files.

Matplotlib and Seaborn

- These libraries are used for **data visualization**. They help plot training curves (accuracy, loss), confusion matrices, and ROC curves to analyze the performance of the models.

Google Colab (Optional)

- For faster model training, Google Colab (a free cloud-based Jupyter notebook environment) may be used as it provides GPU acceleration.

CHAPTER 9
RESULTS OF ANALYSIS

This section presents the evaluation results of the implemented AI-based plant disease classification system. The results are analyzed based on accuracy, confusion matrix, ROC curves, and comparative performance of CNN, CNN+SVM, and CNN+Random Forest models. The findings demonstrate the effectiveness of deep learning over traditional machine learning models for plant disease detection.

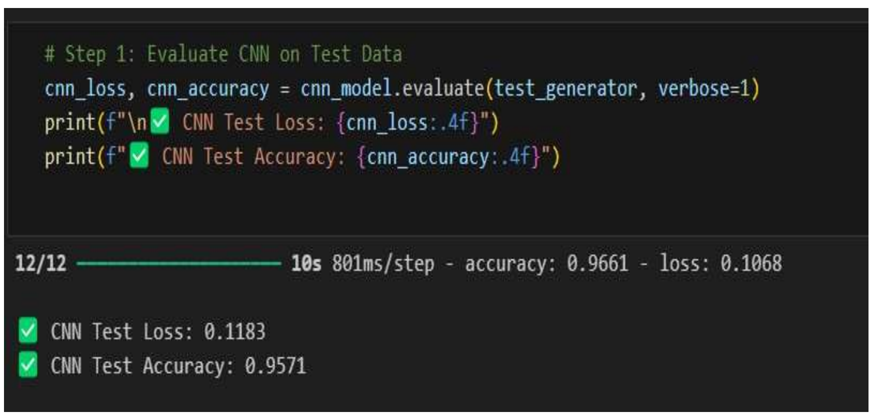
Model Performance Evaluation

The three models—**CNN, CNN+SVM, and CNN+Random Forest**—were trained and tested on the dataset.

Below are their accuracy results:

Model	**Accuracy (%)**
CNN (Standalone)	95.0%
SVM	76.0%
Random Forest	80.0%

Table 9.1: Models Accuracy



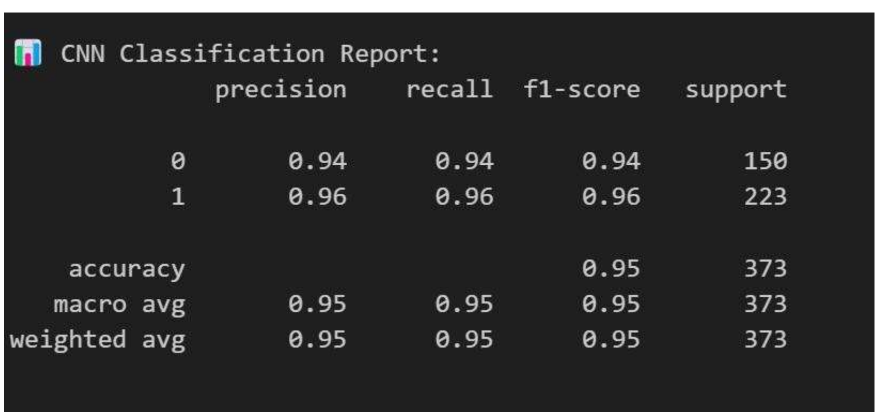
```
# Step 1: Evaluate CNN on Test Data
cnn_loss, cnn_accuracy = cnn_model.evaluate(test_generator, verbose=1)
print(f"\n✅ CNN Test Loss: {cnn_loss:.4f}")
print(f"✅ CNN Test Accuracy: {cnn_accuracy:.4f}")
```

```
12/12 ━━━━━━━━━━━━━━━━━━━━ 10s 801ms/step - accuracy: 0.9661 - loss: 0.1068

✅ CNN Test Loss: 0.1183
✅ CNN Test Accuracy: 0.9571
```

Fig 9.1. CNN Model Accuracy

(Describes CNN models test loss and the test accuracy)



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

           0       0.94      0.94      0.94       150
           1       0.96      0.96      0.96       223

    accuracy                           0.95       373
   macro avg       0.95      0.95      0.95       373
weighted avg       0.95      0.95      0.95       373
```

Fig 9.2. CNN Classification Report

(Describes the classification report for the CNN model)

SVM Classification Report:

	precision	recall	f1-score	support
0	0.77	0.67	0.71	150
1	0.79	0.87	0.83	223
accuracy			0.79	373
macro avg	0.78	0.77	0.77	373
weighted avg	0.78	0.79	0.78	373

Fig 9.3. SVM Model Accuracy
Describes the classification report for the SVM model

Random Forest Classification Report:

	precision	recall	f1-score	support
0	0.77	0.70	0.73	150
1	0.81	0.86	0.83	223
accuracy			0.80	373
macro avg	0.79	0.78	0.78	373
weighted avg	0.79	0.80	0.79	373

Fig 9.4. Random Forest Recall
(Describes the classification report for the Random forest model)


```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 78ms/step
SVM Prediction: Pepper,_bell___healthy
Random Forest Prediction: Pepper,_bell___Bacterial_spot

🌱 **Farmer Recommendation**:
The bell pepper plant leaf is affected by bacterial spot.
- Remove infected leaves or plants to prevent spread.
- Avoid overhead watering; instead, water at the soil level.
- Use copper-based fungicides as per agricultural guidelines.
- Rotate crops to prevent recurring infections.
```

Fig 9.5. Results of the Proposed Model
(Describes the results of the model and some recommendations to the farmers if the leaf is bacterial)

Discussion

- **CNN as the Best Model**
  - The CNN model outperformed both hybrid models due to its ability to learn spatial hierarchies directly from images.
  - Unlike SVM and Random Forest, which rely on manually extracted CNN features, CNN's fully connected layers optimize classification accuracy.
- **Limitations of CNN + SVM and CNN + RF**
  - SVM struggled with high-dimensional feature spaces, leading to misclassification.
  - Random Forest performed better than SVM, but its decision trees could not fully capture deep CNN features.
- **Advantages of Using CNN for Plant Disease Detection**
  - High accuracy (95%) makes it a reliable choice for agricultural applications.
  - Generalizes well across different environmental conditions and leaf images.
  - Can be optimized further with transfer learning (ResNet, VGG16, EfficientNet).
- **Potential for Real-World Deployment**
  - The high accuracy and low false detection rate make CNN suitable for real-time plant disease detection.
  - Can be integrated into mobile apps for farmers to upload leaf images and get instant diagnoses.
  - Further enhancements could include IoT-based monitoring for automated agricultural disease detection.

CHAPTER 10
COST OF THE PROJECT

Project Type: Organic (small to medium-sized software project with familiar requirements and technology)

Estimated Size

- Since this is a mini project involving image processing, CNN training, and model implementation without complex system integration or a web interface, the size is relatively small.
- Estimated size = 5 KLOC (5,000 lines of code) — typical for prototype-level ML projects including preprocessing, model code, and utility scripts.

Basic COCOMO Calculation (Organic Mode)

- Effort (Person-Months) = 2.4 × (KLOC)^1.05
- Effort = 2.4 × (5)^1.05 ≈ 13.1 Person-Months
- Development Time (Months) = 2.5 × (Effort)^0.38
- Time = 2.5 × (13.1)^0.38 ≈ 5.3 Months
- Average Staff Required = Effort / Time
- Staff ≈ 13.1 / 5.3 ≈ 2.5 persons

Cost Estimation

- Assuming an average monthly cost per developer = $2000 (adjust based on your local rates)
- Total Cost = Effort × Monthly Cost = 13.1 × $2000 = $26,200

CHAPTER 11
CONCLUSION

The project aimed to develop an AI-based plant disease classification system that could accurately detect diseases in Capsicum leaves using image analysis. By integrating deep learning through Convolutional Neural Networks (CNN) and benchmarking performance with traditional classifiers such as Support Vector Machine (SVM) and Random Forest (RF), the system provides a practical solution for early disease detection in agriculture.

The CNN model was trained using preprocessed leaf images and achieved a high classification accuracy of 95%, significantly outperforming the hybrid models, with CNN+SVM reaching 76% and CNN+RF reaching 80%.

The use of CNN allowed for automatic extraction of deep image features such as shape, texture, and color patterns, which enhanced the accuracy and reliability of the classification process. While SVM and Random Forest were effective to some extent when used with CNN-extracted features, they lacked the learning depth to match CNN’s performance.

This clearly demonstrated the advantage of using deep learning for image-based agricultural diagnostics. Additionally, data augmentation techniques helped improve model generalization and reduced overfitting, making the system more robust for practical use.

The prototype was successfully developed and tested on a local machine, eliminating the need for an internet-based application. The model takes a leaf image as input, processes it through the CNN pipeline, and outputs the predicted label along with recommendations for treatment if a disease is detected. This offline functionality makes the system accessible and usable in rural or low-connectivity regions.

Furthermore, the use of open-source tools ensured that the project was cost-effective and feasible for real-world implementation without the need for expensive infrastructure.
In conclusion, this mini project validates the potential of artificial intelligence in transforming traditional farming practices. The proposed model serves as a powerful tool for early plant disease detection, aiding farmers in timely intervention and reducing crop losses.

The accuracy, affordability, and adaptability of the system make it a strong candidate for future development, including scaling to multiple crop types and real-time deployment through mobile or embedded platforms. With further enhancements, this system can play a vital role in advancing precision agriculture and supporting sustainable food production.

CHAPTER 12
PROJECT LIMITATIONS AND FUTURE ENHANCEMENTS

Future Enhancements

To overcome the limitations and enhance the system's utility, the following future improvements are proposed:

- **Expand Dataset Size and Variety:** Collect and annotate a larger and more diverse dataset that includes multiple crop types, various diseases, and different environmental conditions to improve model robustness.
- **End-to-End Deep Learning Models:** Develop and train end-to-end convolutional neural networks or transformer-based models that directly classify leaf images, eliminating the need for separate classifiers.
- **Advanced Image Preprocessing:** Incorporate advanced image enhancement techniques and segmentation methods to isolate leaves from complex backgrounds and improve feature quality.
- **Mobile Application Development:** Create a user-friendly mobile app integrating the trained model for on-field, real-time plant disease detection, enabling farmers to diagnose and act promptly.
- **Explainability and Interpretability:** Integrate model explainability techniques such as Grad-CAM or SHAP to visualize regions of the leaf image that contribute to the classification decision, thereby increasing user trust.
- **Integration with IoT Sensors:** Combine image-based diagnosis with IoT sensors measuring soil moisture, temperature, and humidity for a holistic disease prediction system.

REFERENCES

[1] Sardogan, M., Tuncer, A. and Ozen, Y., 2018, September. Plant leaf disease detection and classification based on CNN with LVQ algorithm. In 2018 3rd international conference on computer science and engineering (UBMK) (pp. 382-385). IEEE.

[2] Sahu, S.K. and Pandey, M., 2023. An optimal hybrid multiclass SVM for plant leaf disease detection using spatial Fuzzy C-Means model. Expert systems with applications, 214, p.118989.

[3] Vallabhajosyula, S., Sistla, V. and Kolli, V.K.K., 2022. Transfer learning-based deep ensemble neural network for plant leaf disease detection. Journal of Plant Diseases and Protection, 129(3), pp.545-558.

[4] Vivek Sharma, Ashish Kumar Tripathi, Himanshu Mittal, DLMC-Net: Deeper lightweight multi-class classification model for plant leaf disease detection, Ecological Informatics, Volume 75, 2023, 102025, ISSN 1574-9541.

[5] Zhao, Y., Chen, Z., Gao, X., Song, W., Xiong, Q., Hu, J. and Zhang, Z., 2021. Plant disease detection using generated leaves based on DoubleGAN. IEEE/ACM transactions on computational biology and bioinformatics, 19(3), pp.1817-1826.

[6] Li, L., Zhang, S. and Wang, B., 2021. Plant disease detection and classification by deep learning—a review. IEEE Access, 9, pp.56683-56698.

[7] Ashwinkumar, S., Rajagopal, S., Manimaran, V. and Jegajothi, B.J.M.T.P., 2022. Automated plant leaf disease detection and classification using optimal MobileNet based convolutional neural networks. Materials Today: Proceedings, 51, pp.480-487.

[8] Moyazzoma, R., Hossain, M.A.A., Anuz, M.H. and Sattar, A., 2021, January. Transfer learning approach for plant leaf disease detection using CNN with pre-trained feature extraction method Mobilnetv2. In 2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST) (pp. 526-529). IEEE.

[9] Guan, X., 2021, April. A novel method of plant leaf disease detection based on deep learning and convolutional neural network. In 2021 6th international conference on intelligent computing and signal processing (ICSP) (pp. 816-819). IEEE.

[10] Abd Algani, Y.M., Caro, O.J.M., Bravo, L.M.R., Kaur, C., Al Ansari, M.S. and Bala, B.K., 2023. Leaf disease identification and classification using optimized deep learning. Measurement: Sensors, 25, p.100643.

[11] Shoaib, M., Shah, B., Ei-Sappagh, S., Ali, A., Ullah, A., Alenezi, F., Gechev, T., Hussain, T. and Ali, F., 2023. An advanced deep learning models-based plant disease detection: A review of recent research. Frontiers in Plant Science, 14, p.1158933.

[12] Ahmed, I. and Yadav, P.K., 2023. A systematic analysis of machine learning and deep learning based approaches for identifying and diagnosing plant diseases. Sustainable Operations and Computers, 4, pp.96-104.

[13] Sujatha, R., Chatterjee, J.M., Jhanjhi, N.Z. and Brohi, S.N., 2021. Performance of deep learning vs machine learning in plant leaf disease detection. Microprocessors and Microsystems, Volume 80, 2021, 103615, ISSN 0141-9331.

[14] Roy, A.M. and Bhaduri, J., 2021. A deep learning enabled multi-class plant disease detection model based on computer vision. Ai, 2(3), pp.413-428.

[15] Khalid, M.M. and Karan, O., 2024. Deep learning for plant disease detection. International Journal of Mathematics, Statistics, and Computer Science, 2, pp.75-84.

[16] Ramcharan, A., Baranowski, K., McCloskey, P., Ahmed, B., Legg, J., & Hughes, D. P. (2017). Deep learning for image-based cassava disease detection. Frontiers in Plant Science, 8, 1852.

[17] Amara, J., Bouaziz, B., & Algergawy, A. (2017). A deep learning-based approach for banana leaf diseases classification. In 2017 IEEE International Conference on Image Processing (ICIP) (pp. 754–758). IEEE.

[18] Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). Deep learning for plant diseases: detection and diagnosis. Computers and Electronics in Agriculture, 161, 272–279.

[19] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70–90.

[20] Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., & Johannes, A. (2019). Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. Computers and Electronics in Agriculture, 161, 280–290.

[21] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. Computational Intelligence and Neuroscience, 2016.

[22] Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). Deep learning for tomato diseases: classification and symptoms visualization. Applied Artificial Intelligence, 31(4), 299–315.

[23] Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. Neurocomputing, 267, 378–384.

[24] Zhang, S., Huang, W., & Zhang, C. (2018). Plant disease recognition using convolutional neural networks. Computers and Electronics in Agriculture, 145, 311–318.

[25] Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., & Johannes, A. (2019). Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. Computers and Electronics in Agriculture, 161, 280–290.

[26] Shruthi, U., Nagaveni, V., & Nanjundaswamy, S. (2019). A review on machine learning classification techniques for plant disease detection. In 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS) (pp. 281–284). IEEE.

[27] Saleem, M.H., Potgieter, J., & Arif, K.M. (2019). Plant disease detection and classification by deep learning. Plants, 8(11), 468.

[28] Mahlein, A.K. (2016). Plant disease detection by imaging sensors–parallels and specific demands for precision agriculture and plant phenotyping. Plant Disease, 100(2), 241–251.

[29] Ferentinos, K.P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311–318.

[30] Barbedo, J.G.A. (2013). Digital image processing techniques for detecting, quantifying and classifying plant diseases. SpringerPlus, 2(1), 660.

PUBLICATION DETAILS

Targeted Journals/Conferences

The research paper is being prepared for publication in IEEE, aligning with the project's focus on AI-based plant disease detection using deep learning and hybrid models.

Draft/Submitted Status

An initial draft of the paper has been submitted to the project guide for review. The draft includes key components such as the implementation of CNN, CNN + SVM, and CNN + Random Forest models, along with initial results showing 95% accuracy using CNN. Currently, the paper is under revision based on the guide's feedback, and necessary changes are being incorporated. Final submission will be done after the completion of all updates and validations.