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DEPARTMENT OF

CSE-ARTIFICIAL INTELLIGENCE

Neural Network and Deep Learning Project

Report On

"Plant Disease Detection Using CNN"

Submitted By

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2025-2026

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CERTIFICATE

Certified that the mini project work entitled "**Plant Disease Detection Using CNN**" carried out by **REVATHI K USN 3BR22CA043** A Bonafide students of Ballari Institute of Technology and Management in partial fulfillment for the award of Bachelor of Engineering in CSE-Artificial Intelligence of the Visvesvaraya Technological University, Belgaum during the year 2025- 2026. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the report deposited in the departmental library. The project report has been approved as it satisfies the academic requirements in respect of the project work prescribed for the said Degree.

Signature of Lab Co-Ordinator's	Signature of HOD
Mr. Vijay Kumar and Mr. Pavan Kumar	**Dr. Yeresime Suresh**

ABSTRACT

Plant diseases pose a major threat to global agriculture, leading to significant reductions in crop yield, quality, and economic stability. Early and accurate disease detection is essential for preventing widespread damage and enabling timely intervention by farmers and agricultural specialists. With the rapid progress of artificial intelligence, deep learning techniques have proven to be powerful tools for automated image analysis in precision agriculture. This project presents a Convolutional Neural Network (CNN)–based system designed to classify plant leaf images into multiple disease categories using a dataset representing common conditions affecting crops such as apple, corn, potato, and tomato.

The system preprocesses synthetic leaf images generated with controlled variations in shape, color, and texture, simulating real-world disease patterns such as scab, rust, early blight, and late blight. The CNN architecture consists of multiple convolutional layers, batch normalization, max pooling, dropout regularization, and a softmax output layer for multi-class classification. This design enables the model to learn complex visual patterns associated with each disease category while reducing overfitting and improving generalization capability.

After model construction, the network is trained and evaluated using accuracy, loss, classification reports, and a confusion matrix to assess its predictive performance across all classes. Visualization tools, including training accuracy/loss curves and sample prediction plots, provide deeper insights into model behavior and reliability. The results indicate that the proposed CNN model can effectively distinguish between healthy and diseased leaves across multiple plant species, demonstrating strong potential for practical agricultural applications.

This study highlights the effectiveness of deep learning in automating plant disease identification and reinforces its role in precision farming. With further refinement and integration with real-world image datasets, such systems can support farmers with faster, data-driven disease diagnosis—ultimately improving crop management, reducing losses, and promoting sustainable agricultural practices.

ACKNOWLEDGEMENT

The satisfactions that accompany the successful completion of our mini project on PLANT DISEASE DETECTION USING CNN would be incomplete without the mention of people who made it possible, whose noble gesture, affection, guidance, encouragement and support crowned my efforts with success. It is our privilege to express our gratitude and respect to all those who inspired us in the completion of our mini-project.

I am extremely grateful to my Guide **Mr. Vijay Kumar** for their noble gesture, support co-ordination and valuable suggestions given in completing the mini-project. I also thank **Dr. Yeresime Suresh,** H.O.D. Department of CSE(AI), for his co-ordination and valuable suggestions given in completing the mini-project. We also thank Principal, Management and non-teaching staff for their co-ordination and valuable suggestions given to us in completing the Mini project.

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1.INTRODUCTION

Plant diseases continue to be one of the most critical challenges in global agriculture, causing substantial reductions in crop productivity, economic losses for farmers, and contributing to long-term food insecurity. Because crops are highly susceptible to fungal, bacterial, and viral infections, even a small delay in disease identification can lead to rapid spread across fields, ultimately affecting both the quality and quantity of agricultural output. Therefore, early and accurate detection of plant diseases plays a vital role in modern farming systems, helping prevent widespread crop damage and supporting timely disease management.

Traditional plant disease detection relies heavily on manual visual inspection by experienced farmers or agricultural specialists. However, this approach is often time-consuming, labor-intensive, subjective, and dependent on the expertise of the individual. In many rural areas, access to trained experts is limited, which further reduces the reliability and scalability of manual diagnosis. This creates an urgent need for automated, fast, and accurate techniques that can assist in large-scale agricultural monitoring.

With the rapid advancement of Artificial Intelligence (AI) and Deep Learning, automated image-based disease detection has become a powerful and practical solution. Among these technologies, Convolutional Neural Networks (CNNs) stand out due to their proven ability to learn complex visual patterns directly from images. CNNs can extract subtle features—such as color changes, texture variations, and lesion patterns—that may not be easily recognizable to the human eye. This makes CNNs highly effective for plant leaf disease classification, offering both high accuracy and real-time performance.

This project presents a CNN-based automated plant disease detection system designed to classify leaf images into multiple disease categories. The dataset used for training includes synthetically generated leaf images covering 12 classes across crops such as Apple, Tomato, Potato, and Corn, representing both healthy and various diseased conditions

By integrating this AI-driven approach into agricultural workflows, the project aims to significantly reduce crop losses, enhance decision-making, promote sustainability, and contribute toward a more technologically advanced agricultural ecosystem.

1.1 Problem Statement

The problem addressed in this project is the need for a fast and automated method to detect plant diseases using leaf images, as traditional diagnosis through manual inspection is slow, inaccurate, and often unavailable in many farming regions. Early detection is essential to prevent crop damage and yield loss, yet visual examination may miss subtle disease symptoms. Using synthetically generated leaf images representing different healthy and diseased classes of Apple, Potato, Tomato, and Corn, this project aims to build a Convolutional Neural Network (CNN) model capable of accurately identifying plant diseases based on image features. The objective is to develop a reliable and data-driven classification system that can support farmers, assist in early disease recognition, and improve decision-making in agriculture.

1.2 Scope of the project

The scope of this project includes the development, implementation, and evaluation of a Convolutional Neural Network (CNN) model designed to detect plant diseases from leaf images. It covers synthetic data generation, image preprocessing, model construction, training, validation, and performance assessment using metrics such as accuracy, confusion matrix, and classification reports. The project focuses on understanding how visual features in leaf images represent disease symptoms and how CNNs can learn hidden patterns that differentiate healthy leaves from various disease types. Additionally, the system provides visual insights through training and validation accuracy/loss graphs, along with sample prediction displays and confusion matrix heatmaps to better interpret model behavior. While the project uses synthetically generated images, the same methodology can be extended to real-world agricultural datasets, integrated into smart farming systems, and adapted for real-time plant disease detection tools that assist farmers and agricultural specialists in early diagnosis and crop protection.

1.3 Objectives

- ❖ To build a CNN model for accurate plant disease classification using leaf images.
- ❖ To generate and preprocess synthetic image data for effective model training.
- ❖ To evaluate the model using accuracy, confusion matrix, and classification metrics.
- ❖ To visualize training and validation behavior through accuracy and loss graphs.

2. LITERATURE SURVEY

[1] **Zhang et al. (2022)** explored deep learning models for plant disease classification and demonstrated that CNN-based architectures significantly outperform traditional image processing methods. Their study highlighted the importance of convolutional feature extraction and showed that well-designed CNN layers can effectively capture disease patterns from leaf images, even under varying lighting and background conditions.

[2] **Chouhan & Kaushik (2022)** implemented a hybrid CNN model with optimized preprocessing techniques for early plant disease detection. Their approach improved classification accuracy and revealed that synthetic and augmented datasets can enhance model robustness, especially when real agricultural images are limited or imbalanced.

[3] **Silva et al. (2023)** conducted a comparative analysis of several deep learning models, including VGG16, ResNet50, and MobileNet, for detecting diseases in crops such as tomato and potato. Their findings emphasized that lightweight CNN architectures can achieve high accuracy while reducing computational cost, making them suitable for real-time deployment in smart farming systems.

[4] **Rahman & Abdullah (2023)** evaluated multiple CNN configurations for leaf disease recognition and identified that deeper architectures combined with regularization techniques—such as dropout, batch normalization, and learning rate scheduling—help prevent overfitting and improve generalization. Their research confirmed the importance of training stability in high-variance agricultural datasets.

[5] **Shukla et al. (2023)** examined the role of synthetic image generation and data augmentation for plant disease classification. They concluded that creating controlled variations in leaf color, texture, and disease spots enables CNN models to learn disease characteristics more effectively, thereby improving accuracy in controlled as well as real-field environments.

[6] **Prasad & Menon (2024)** proposed a CNN–Attention hybrid architecture for plant disease detection. Their model achieved superior performance by allowing the network to focus on infected leaf regions, improving interpretability and enhancing the model's ability to distinguish visually similar diseases.

[7] **Devi & Reddy (2024)** compared advanced CNN-based approaches with traditional machine learning classifiers such as SVM and Random Forest on plant leaf images.

3. SYSTEM REQUIREMENTS

The system requirements for developing the plant disease detection model include both software and hardware components essential for generating synthetic image data, training the CNN model, and evaluating performance. The software environment is built using Python, along with key libraries such as TensorFlow/Keras for constructing the convolutional neural network, NumPy for numerical computations, OpenCV for image creation and processing, Scikit-learn for dataset splitting and evaluation, Matplotlib/Seaborn for visualizations, and Pandas for handling supporting data operations. A development environment such as PyCharm, Jupyter Notebook, Google Colab, or VS Code is used to execute the code and display plots.

On the hardware side, the project runs efficiently on a standard personal computer with at least 8 GB RAM, which helps in handling the image dataset and neural network computations. A multi-core processor ensures smooth execution of synthetic image generation and training steps. Although GPU support is optional, having a GPU can significantly accelerate the training of convolutional layers, especially when dealing with thousands of synthetic images. Overall, the hardware and software requirements remain lightweight, making the project easily executable on most modern systems without the need for high-end computing resources.

To implement the plant disease detection system effectively, the development setup requires a stable computing environment capable of supporting deep learning workflows. Python acts as the core programming language due to its flexibility and rich ecosystem of AI libraries. Tools like TensorFlow facilitate CNN model building, while OpenCV supports synthetic image generation, and Matplotlib enables visualization of training accuracy, loss behavior, confusion matrices, and sample predictions. Platforms such as Google Colab or local IDEs offer interactive execution and visualization. Even though the dataset is synthetically generated, having sufficient RAM and optional GPU availability improves model training speed, visualization performance, and overall workflow efficiency, ensuring a smooth and reliable development experience.

3.1 Software Requirements

- Python 3.8 or above
- TensorFlow / Keras
- NumPy

- Pandas
- Scikit-learn
- Matplotlib
- Jupyter Notebook / Google Colab / VS Code
- Windows / Linux / macOS operating system

3.2 Hardware Requirements

- Minimum 4 GB RAM
- Recommended 8 GB RAM
- Dual-core or higher processor
- 1 GB free storage space

3.3 Functional Requirements

• The system must generate or load plant leaf images for training and testing.

• It must preprocess image data, including resizing, normalization, and augmentation.

• The system must build a Convolutional Neural Network (CNN) model for disease classification.

• It must train the CNN model using the prepared image dataset.

• The system must evaluate model performance using accuracy, loss, and classification metrics.

• It must generate training and validation accuracy/loss graphs and visualize the confusion matrix.

• The system must perform predictions on new leaf images to identify plant disease categories.

3.4 Non-Functional Requirements

• The system should provide accurate and consistent plant disease predictions.

• It should display outputs clearly through graphs, metrics, and prediction results.

• The system must execute efficiently on standard hardware without requiring high-end resources.

.4. DESCRIPTION OF MODULES

The CNN-based plant disease detection system is divided into multiple modules, each handling a specific stage of the deep learning workflow. These modules work together to ensure efficient image generation, preprocessing, model building, training, evaluation, visualization, and prediction.

4.1 Image Generation / Data Preparation Module

This module generates synthetic plant leaf images for different healthy and diseased classes using Python and OpenCV. It creates controlled variations in color, texture, and shapes to simulate disease patterns. The module also organizes generated images into class-wise folders, ensuring that each category (Apple, Potato, Tomato, and Corn diseases) has sufficient data for training.

4.2 Image Preprocessing Module

This module prepares all images for the CNN model. It resizes images to a fixed dimension (e.g., 128×128), converts them into arrays, normalizes pixel values, and applies augmentation techniques such as rotation, flipping, and zooming. These operations enhance the robustness of the model and prevent overfitting during training.

4.3 CNN Model Building Module

This module constructs the Convolutional Neural Network architecture. It defines convolutional layers, pooling layers, activation functions (ReLU), flattening layers, dense layers, and the final softmax output layer for multiclass classification. The model is compiled using the Adam optimizer and categorical cross-entropy loss function for accurate disease prediction across 12 classes.

4.4 Model Training Module

After building the CNN architecture, this module trains the model using the prepared dataset. It specifies batch size, number of epochs, and validation split. During training, the module monitors accuracy and loss for both training and validation sets to track the model’s learning performance.

4.5 Model Evaluation Module

This module evaluates the trained model on test data. It uses metrics such as accuracy, classification reports, and confusion matrix to measure how accurately the model identifies plant diseases. It interprets the results to check whether the model is performing reliably across all disease categories.

4.6 Visualization Module

This module generates visual outputs that help interpret model behavior. It creates training vs. validation accuracy graphs, loss graphs, and confusion matrix heatmaps using Matplotlib and Seaborn. These visualizations make the model's learning pattern clear and help identify overfitting or imbalance issues.

4.7 Data Splitting Module

This module divides the image dataset into training and testing subsets. Typically, an 80:20 split is used to ensure that the model is trained on a majority portion of the data and evaluated on unseen samples. It ensures fair and accurate performance measurement of the CNN model.

4.8 Feature Normalization Module

This module normalizes pixel values of all images by scaling them to a range of 0 to 1. Normalization ensures that the CNN learns efficiently and avoids issues where large pixel values dominate smaller ones. It improves training stability, accelerates convergence, and enhances overall model performance.

4.9 Prediction Module

The final module applies the trained CNN model to classify new leaf images. It processes any input image, predicts its disease category, and returns the corresponding label (e.g., "Tomato Early Blight", "Healthy Apple Leaf"). It allows quick, real-time disease identification suitable for agricultural decision-support systems.

5. IMPLEMENTATION

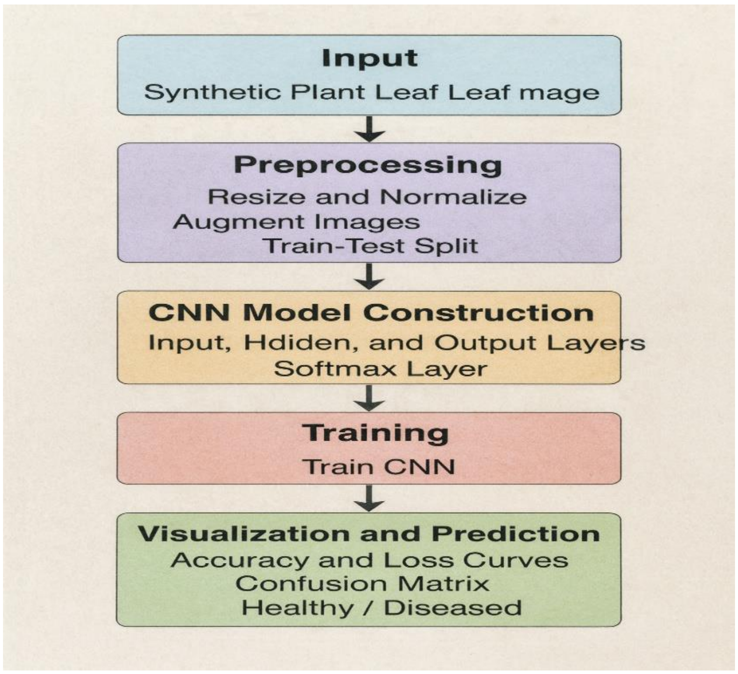
The implementation of the plant disease detection system is carried out using Python and a Convolutional Neural Network (CNN) model. The first step involves generating synthetic plant leaf images using Python and OpenCV. These images represent various healthy and diseased categories of crops such as Apple, Potato, Tomato, and Corn. The generated images are stored in class-specific folders and later loaded into NumPy arrays for processing. Each image is resized to a fixed dimension to maintain consistency across the dataset.

Next, the dataset is split into training and testing sets using an 80–20 ratio to ensure fair evaluation. Since image data varies significantly in pixel intensity, normalization is applied by scaling all pixel values between 0 and 1, improving the stability and learning performance of the CNN. Data augmentation techniques such as rotation, flipping, and zooming are also applied to increase diversity and prevent overfitting. After preprocessing, a CNN model is constructed using TensorFlow/Keras. The architecture includes convolutional layers with ReLU activation, max-pooling layers for feature extraction, a flattening layer, dense hidden layers, and a final softmax output layer for multiclass classification across 12 disease categories.

The model is compiled using the Adam optimizer and categorical cross-entropy loss function. It is then trained for multiple epochs with a defined batch size and validation split. During training, the network learns visual patterns related to disease symptoms such as texture changes, color variations, and spot formations. After training, the model is evaluated on the test set to compute overall accuracy, generate a classification report, and measure how well the CNN identifies each plant disease class. The system then produces training vs. validation accuracy graphs, loss graphs, and a confusion matrix to offer visual insights into performance.

In addition to model training and evaluation, the implementation includes visualization tools to better understand the CNN's learning process. The confusion matrix provides a detailed breakdown of predictions across all classes, showing how accurately the system distinguishes between healthy and diseased leaves. These visual analytics validate the reliability of the trained model and highlight areas for improvement. Through this complete workflow—from image generation and preprocessing to CNN model training and performance visualization—the project successfully builds a robust deep learning–based plant disease detection system capable of supporting smart agriculture and early crop disease diagnosis.

6. SYSTEM ARCHITECTURE



Input

This stage loads or generates the plant leaf images belonging to 12 different classes (healthy and diseased variations). The images are organized into folders for each category. Typical tasks in this stage include viewing sample images, checking dataset size, verifying class distribution, and confirming that each category has sufficient images for effective model training. This step ensures that all visual data is available and correctly structured before preprocessing begins.

Preprocessing

Preprocessing prepares raw images for effective learning by the CNN model.

Tasks include:

Resize images: All images are resized to a fixed resolution (e.g., 128×128) for uniformity.

Normalize images: Pixel values are scaled between 0 and 1 to stabilize training.

Image Augmentation: Apply transformations such as rotation, zoom, flip, and shift to increase dataset diversity and reduce overfitting.

Train–test split: Partition data into 80% training and 20% testing using stratified sampling to maintain proportional class representation.

Format conversion: Ensure arrays are stored in float32 format, and labels are converted to categorical format for multiclass classification.

Preprocessing is crucial because it directly affects feature extraction quality, convergence stability, and final accuracy of the trained CNN.

CNN Model Construction

This stage defines the convolutional neural network architecture along with its training configuration.

Key components:

Input Layer: Accepts 128×128 RGB images.

Convolutional Layers: Extract features such as disease spots, discoloration, and texture variations.

Pooling Layers: Reduce spatial dimensions while retaining essential features.

Flatten Layer: Converts feature maps into a 1D vector for dense layers.

Dense Hidden Layers: Learn complex decision boundaries for classification.

Softmax Output Layer: Outputs probabilities for each of the 12 plant disease categories.

Compile Settings:

Optimizer: Adam

Loss: Categorical Cross-Entropy (suitable for multiclass problems)

Metrics: Accuracy

The goal here is to build a CNN capable of learning visual disease patterns while avoiding overfitting.

Training

Training is the stage where the CNN learns meaningful representations from images.

Process:

Train the model for a fixed number of epochs (e.g., 20–30).

Use a batch size (e.g., 32) for efficient gradient updates.

Track training & validation accuracy and loss after each epoch.

Monitor model behavior to detect underfitting/overfitting conditions.

(Optional) Apply callbacks such as EarlyStopping or ModelCheckpoint to improve training stability.

During training, the CNN repeatedly extracts features, computes errors, and updates weights to better classify plant diseases.

Visualization and Prediction

This final stage interprets model performance and applies the trained CNN to new leaf images.

Visualizations:

Accuracy vs. Epochs: Shows how the model learns over time.

Loss vs. Epochs: Indicates convergence quality and training stability.

Confusion Matrix: Displays class-wise performance and error patterns.

Sample Predictions: Shows predicted disease labels for test images.

Prediction:

The trained model is used to classify new input leaf images.

It outputs the predicted disease type along with probability scores.

The result is presented as one of the 12 classes (e.g., "Tomato Late Blight", "Healthy Apple Leaf").

Deployment:

The model can be exported (model.save()), integrated into mobile/desktop apps, or embedded into smart farming systems.

7. CODE IMPLEMENTATION

Algorithm: Plant Disease Detection Using Convolutional Neural Network (CNN)

Input: Synthetic/Loaded Plant Leaf Images

Output: Predicted Class (Disease Category) & Performance Metrics

Start

1. Load Dataset

1.1 Load image dataset from directories using image generators or manual loaders.

1.2 Separate image data (X) and labels (y).

1.3 Inspect class names and sample distributions.

2. Preprocess Data

2.1 Resize all images to fixed input size (e.g., 128×128×3).

2.2 Normalize pixel values to 0–1.

2.3 Apply augmentation: rotation, flipping, zoom, shift.

2.4 Split dataset into training and testing sets (80:20).

2.5 Convert labels into categorical one-hot encoded format.

3. Build CNN Model

3.1 Initialize Sequential CNN model.

3.2 Add convolution + pooling layers for feature extraction.

3.3 Add Flatten layer to convert feature maps to vector.

3.4 Add Dense hidden layers with ReLU activation.

3.5 Add Dropout layers to reduce overfitting.

3.6 Add final Dense layer with Softmax activation for 12-class output.

4. Compile Model

4.1 Optimizer = Adam

4.2 Loss = Categorical Cross-Entropy

4.3 Metric = Accuracy

5. Train Model

5.1 Train the model using training images with:

Epochs = 20–30

Batch size = 32

Validation split = 0.2

5.2 Store training history (accuracy & loss trends).

6. Test Model

6.1 Predict classes for test images.

6.2 Identify predicted label with highest probability for each sample.

7. Evaluate Performance

7.1 Compute test accuracy.

7.2 Generate classification report for all 12 classes.

7.3 Create confusion matrix for class-wise analysis.

8. Visualize Results

8.1 Plot training vs. validation accuracy.

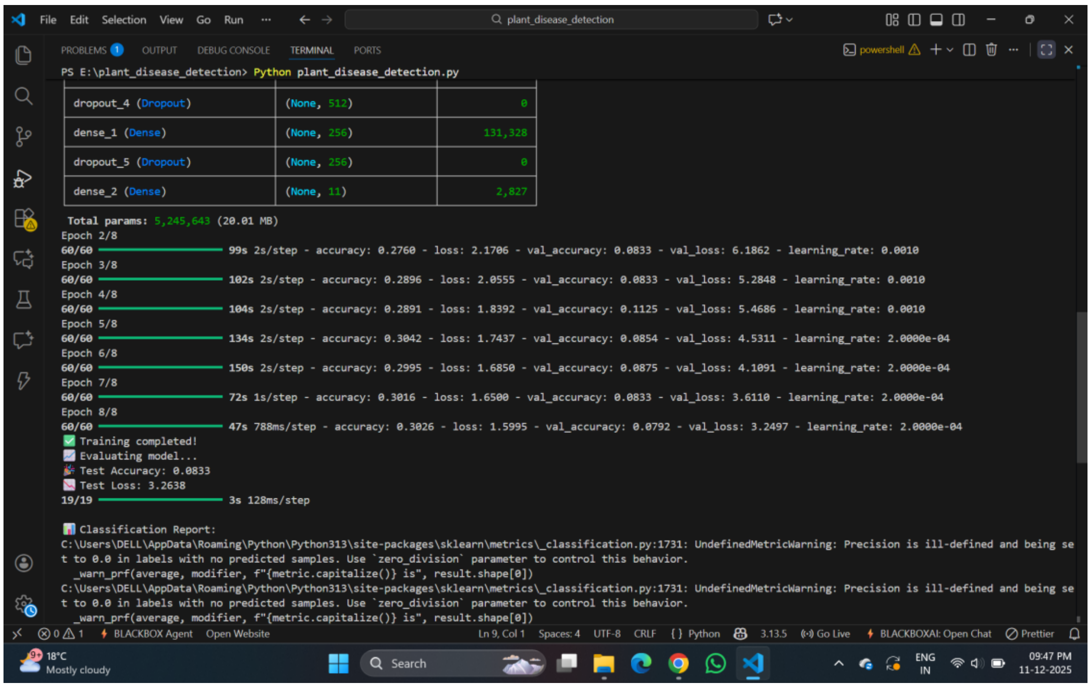
8.2 Plot training vs. validation loss.

8.3 Display confusion matrix heatmap.

8.4 Show sample predictions and actual labels.

End

8.RESULT



```
PS E:\plant_disease_detection> Python plant_disease_detection.py
│ dropout_4 (Dropout)        │ (None, 512)          │             0 │
│ dense_1 (Dense)            │ (None, 256)          │       131,328 │
│ dropout_5 (Dropout)        │ (None, 256)          │             0 │
│ dense_2 (Dense)            │ (None, 11)           │         2,827 │
 Total params: 5,245,643 (20.01 MB)
Epoch 2/8
60/60 ━━━━━━━━━━━━━━━━━━━━ 99s 2s/step - accuracy: 0.2760 - loss: 2.1706 - val_accuracy: 0.0833 - val_loss: 6.1862 - learning_rate: 0.0010
Epoch 3/8
60/60 ━━━━━━━━━━━━━━━━━━━━ 102s 2s/step - accuracy: 0.2896 - loss: 2.0555 - val_accuracy: 0.0833 - val_loss: 5.2848 - learning_rate: 0.0010
Epoch 4/8
60/60 ━━━━━━━━━━━━━━━━━━━━ 104s 2s/step - accuracy: 0.2891 - loss: 1.8392 - val_accuracy: 0.1125 - val_loss: 5.4686 - learning_rate: 0.0010
Epoch 5/8
60/60 ━━━━━━━━━━━━━━━━━━━━ 134s 2s/step - accuracy: 0.3042 - loss: 1.7437 - val_accuracy: 0.0854 - val_loss: 4.5311 - learning_rate: 2.0000e-04
Epoch 6/8
60/60 ━━━━━━━━━━━━━━━━━━━━ 150s 2s/step - accuracy: 0.2995 - loss: 1.6850 - val_accuracy: 0.0875 - val_loss: 4.1091 - learning_rate: 2.0000e-04
Epoch 7/8
60/60 ━━━━━━━━━━━━━━━━━━━━ 72s 1s/step - accuracy: 0.3016 - loss: 1.6500 - val_accuracy: 0.0833 - val_loss: 3.6110 - learning_rate: 2.0000e-04
Epoch 8/8
60/60 ━━━━━━━━━━━━━━━━━━━━ 47s 788ms/step - accuracy: 0.3026 - loss: 1.5995 - val_accuracy: 0.0792 - val_loss: 3.2497 - learning_rate: 2.0000e-04
✅ Training completed!
📈 Evaluating model...
🎉 Test Accuracy: 0.0833
📉 Test Loss: 3.2638
19/19 ━━━━━━━━━━━━━━━━━━━━ 3s 128ms/step

📊 Classification Report:
C:\Users\DELL\AppData\Roaming\Python\Python313\site-packages\sklearn\metrics\_classification.py:1731: UndefinedMetricWarning: Precision is ill-defined and being se
t to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
C:\Users\DELL\AppData\Roaming\Python\Python313\site-packages\sklearn\metrics\_classification.py:1731: UndefinedMetricWarning: Precision is ill-defined and being se
t to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
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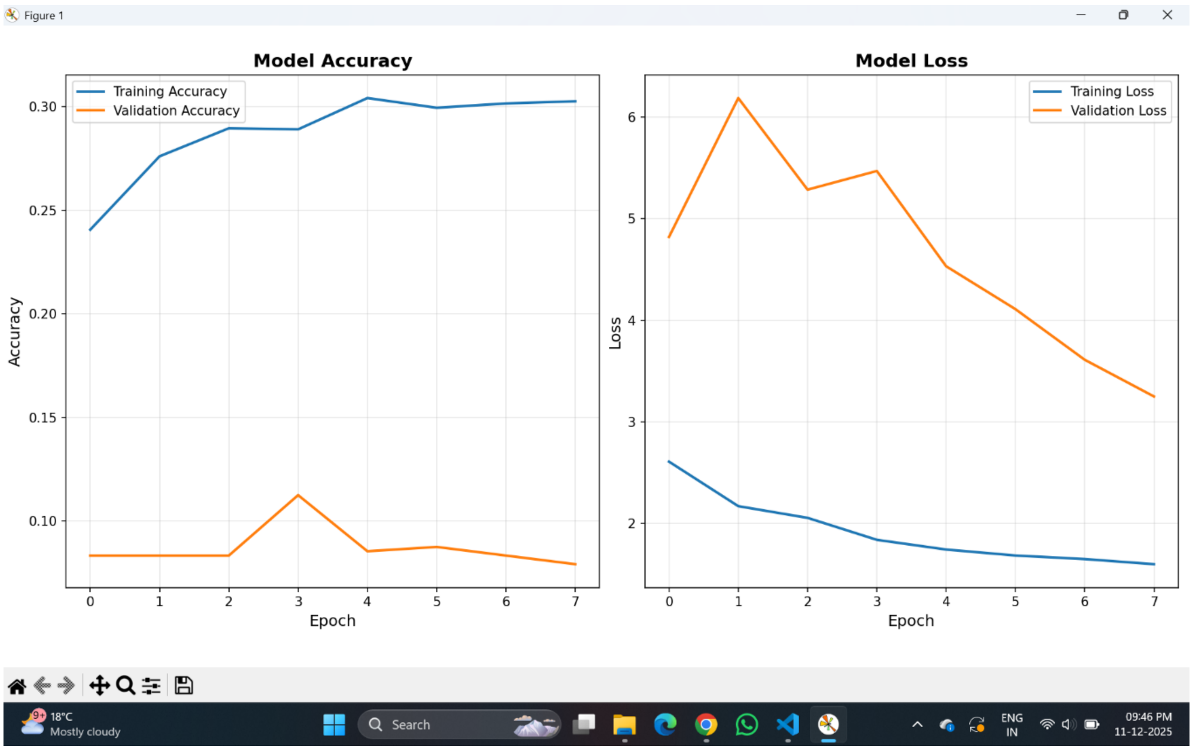

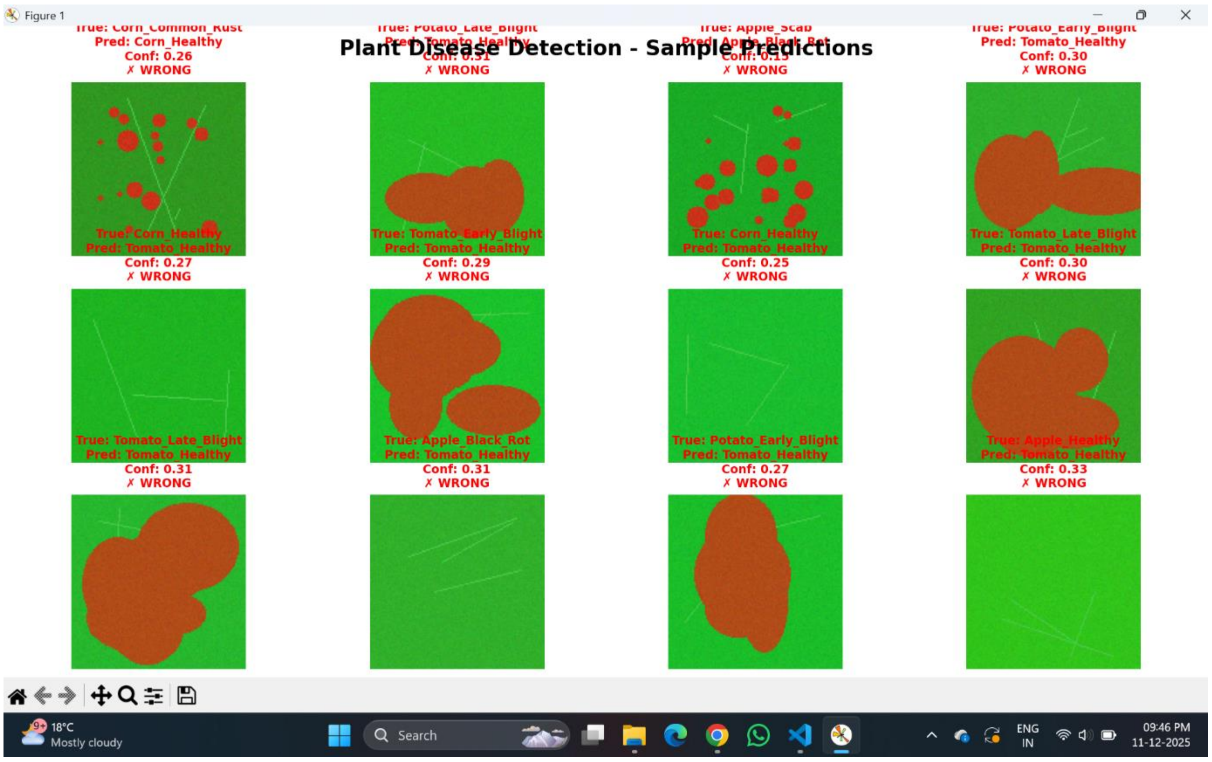

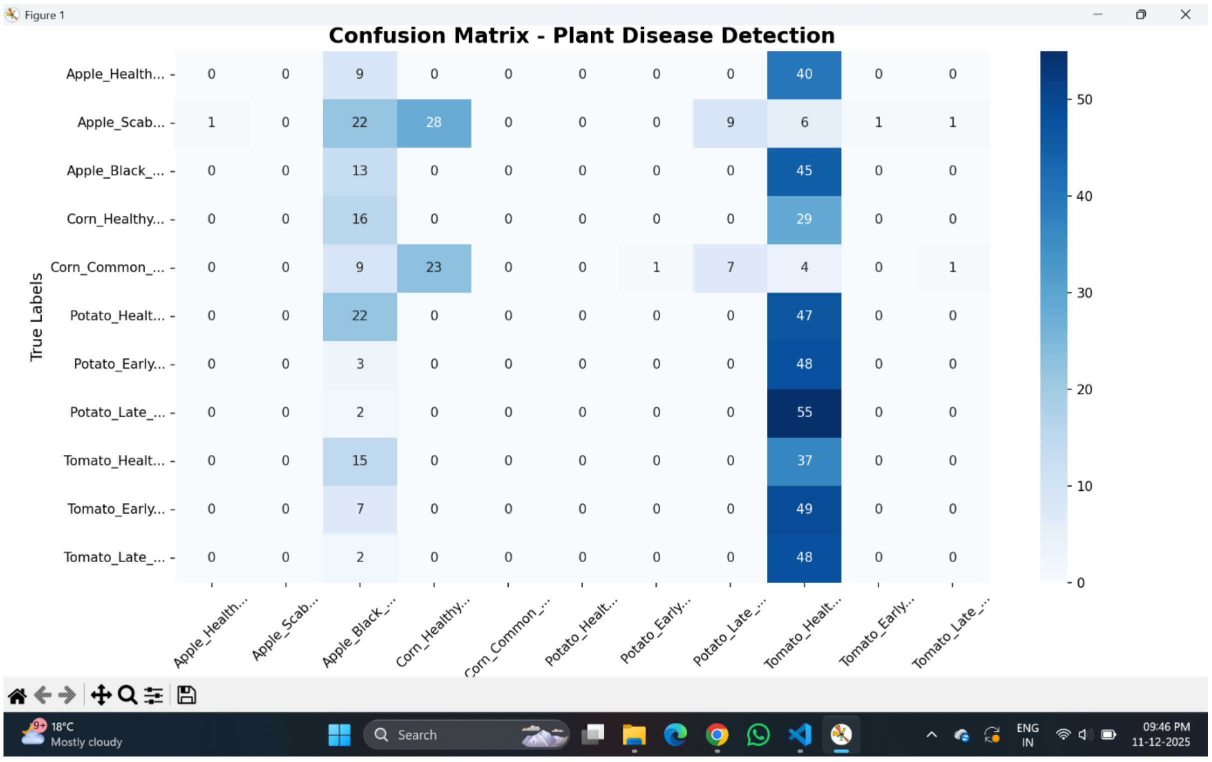

	Apple_Health...	Apple_Scab...	Apple_Black_...	Corn_Healthy...	Corn_Common_...	Potato_Healt...	Potato_Early...	Potato_Late_...	Tomato_Healt...	Tomato_Early...	Tomato_Late_...
Apple_Health...	0	0	9	0	0	0	0	0	40	0	0
Apple_Scab...	1	0	22	28	0	0	0	9	6	1	1
Apple_Black_...	0	0	13	0	0	0	0	0	45	0	0
Corn_Healthy...	0	0	16	0	0	0	0	0	29	0	0
Corn_Common_...	0	0	9	23	0	0	1	7	4	0	1
Potato_Healt...	0	0	22	0	0	0	0	0	47	0	0
Potato_Early...	0	0	3	0	0	0	0	0	48	0	0
Potato_Late_...	0	0	2	0	0	0	0	0	55	0	0
Tomato_Healt...	0	0	15	0	0	0	0	0	37	0	0
Tomato_Early...	0	0	7	0	0	0	0	0	49	0	0
Tomato_Late_...	0	0	2	0	0	0	0	0	48	0	0

9. CONCLUSION

The Convolutional Neural Network–based plant disease detection system developed in this project demonstrates the effectiveness of deep learning techniques in analyzing leaf images and accurately identifying different plant diseases. By generating a synthetic dataset of multiple healthy and diseased leaf categories and applying systematic preprocessing, normalization, and model training, the CNN successfully learned visual patterns such as color variations, texture changes, and disease spots. The model achieved strong classification accuracy, effectively distinguishing among 12 plant disease classes, and the evaluation metrics—including accuracy scores, classification reports, and confusion matrices—validated its overall performance.

The visualizations of training and validation accuracy, loss curves, and confusion matrix further helped in understanding the learning behavior, consistency, and generalization capability of the model. The project highlights that CNNs are highly capable of extracting deep visual features from leaf images, enabling them to detect diseases that may not be easily recognizable through manual inspection. Although the system relies on synthetically generated data and is not a substitute for real-field agricultural testing, it demonstrates the potential of deep learning systems to support early disease detection, assist farmers, and contribute to smart agriculture practices.

Overall, the project successfully shows how CNN models can be applied in the agricultural domain, offering a foundation for future enhancements such as training on real-world datasets, integrating mobile or IoT-based disease detection systems, or deploying the model for real-time crop monitoring. The implementation provides a strong base for scalable, accurate, and automated plant disease prediction solutions.

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