# AI-Based Plant Disease Detection System

Using Convolutional Neural Networks (CNNs)

# Introduction

- Plant diseases affect agricultural productivity, causing food shortages and financial losses. Traditional detection relies on expert inspection, which is slow and error-prone. This project introduces an AI-based solution using CNNs to detect plant diseases from leaf images.

# Objectives

- To develop an automated system for plant disease identification
- • To reduce dependency on human experts
- • To provide early detection and prevent large-scale crop damage
- • To make disease detection accessible and cost-effective for farmers

# Problem Statement

- Plant diseases cause major losses in agriculture
- • Traditional inspection is slow and dependent on experts
- • Experts are not always available in rural areas
- • Manual inspection is error-prone and costly
- • Delays in detection cause extensive damage

# Project Solution

- The system uses a CNN to analyze leaf images and identify plant diseases. Users upload an image, and the system quickly returns the predicted disease class. No expert intervention is required.

# Benefits

Fast detection (seconds vs. days)

- Cost-effective (no expert needed)
- Accessible via smartphones and computers
- High accuracy with AI
- Early disease prevention
- Scalable to global usage

# Dataset Description

- Source: Kaggle - 'New Plant Diseases Dataset' by vaporous
- • 87,000 images across 38 classes
- • Includes healthy and diseased leaves
- • Structured in folders per class
- • Format: JPEG

# Reason for Dataset Selection

Large size supports deep learning

- Rich diversity of plant species and diseases

- Publicly available and widely used

- Supports reproducibility and benchmarking

# Methodology: Algorithm Used

- A Convolutional Neural Network (CNN) is used for image classification. CNNs are effective for extracting visual features and identifying disease patterns automatically.

# CNN Architecture Overview

- Multiple Convolutional Layers with ReLU activation
- • Pooling Layers for dimensionality reduction
- • Dropout Layers to prevent overfitting
- • Final Dense Layer with SoftMax for classification

# Why CNN?

Automatically learns features from images

- Ideal for large image datasets
- Regularization techniques reduce overfitting
- Proven success in various detection tasks

# Model Evaluation Metrics

| tric | Precision | Recall | F1-Score |
|---|---|---|---|
| | – | – | 0.98 |
| e | 0.98 | 0.98 | 0.98 |
| rage | 0.98 | 0.98 | 0.98 |

- Precision: 0.98
- • Recall: 0.98
- • F1-Score: 0.98
- • Total Samples Tested: 1401
- • High reliability across classes

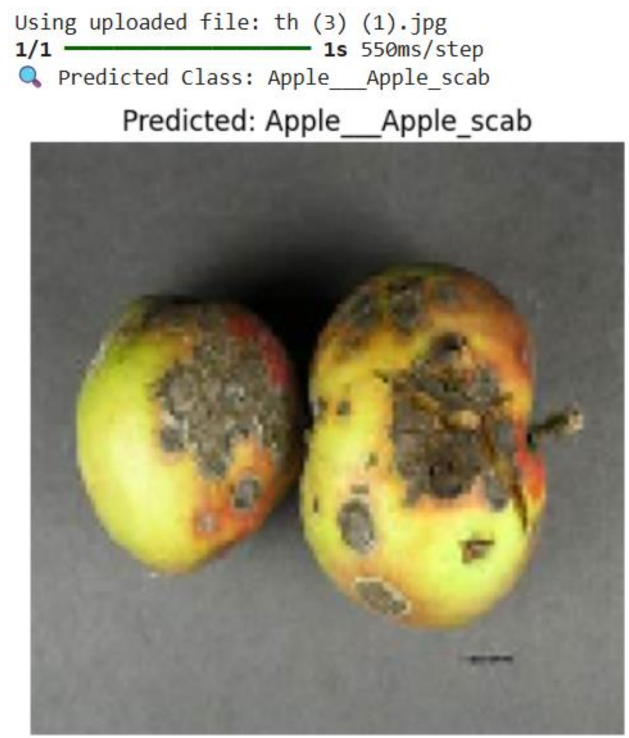
# Class-wise Performance

- Apple Scab: Precision 0.99, Recall 0.96
- • Corn Healthy: Precision 0.99, Recall 1.00
- • Peach Healthy: Precision 0.97, Recall 0.99

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Apple – Apple Scab | 0.99 | 0.96 | 0.98 | 504 |
| Corn (Maize) Healthy | 0.99 | 1.00 | 0.99 | 465 |
| Peach – Healthy | 0.97 | 0.99 | 0.98 | 432 |

# Training Graphs Summary

- Training Accuracy: Increased to 98%
- • Training Loss: Decreased smoothly
- • Indicates effective and stable learning



# Visual Testing

- Model tested on unseen leaf images and successfully identified diseases. Demonstrates generalization and real-world applicability.

# Simulation Results

- Software: Python, TensorFlow, Keras
- • Optimized using Adam optimizer
- • Learning Rate: 0.001, Epochs: 20, Batch Size: 32
- • Input Image Size: 224x224

# Conclusion

- CNN-based plant disease detection system provides accurate, fast, and accessible diagnosis. It reduces dependency on experts, prevents large-scale damage, and fits well in smart farming frameworks.

# Future Scope

- Expand dataset to include more plant types
- • Add environmental data for better prediction
- • Integrate with IoT and real-time monitoring
- • Multilingual support for wider accessibility