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Deep Learning-Based Web Application for Crop Disease Detection Using CNN and Streamlet

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Abstract - Crop diseases can cause significant yield losses and threaten food security if not diagnosed and treated in time. In this paper, we present a real-time web application for crop disease detection using deep learning techniques, primarily Convolutional Neural Networks (CNNs). The application allows farmers to upload leaf images through a Streamlet interface, which are then analyzed by a trained CNN model to detect diseases. The system provides fast, accurate predictions along with suggestions for treatments, promoting smart and sustainable farming. For scalability and maintainability, it makes use of a modular backend, picture preprocessing methods, and the Plant Village dataset. Performance is evaluated using accuracy, precision, recall, and user feedback.

***Key Words*:** Crop Disease Detection, Convolutional Neural Network, Deep Learning, Streamlit, Smart Farming, Plant Village, AI in Agriculture

I. Introduction

In recent years, agriculture has adopted digital transformation to improve productivity and sustainability. Among the various challenges, crop diseases remain one of the most devastating factors for yield loss. Manual inspection is time-consuming, subjective, and inaccessible in remote areas. The development of machine learning and artificial intelligence has made automated crop disease diagnosis a practical remedy. This paper presents a CNN powered crop disease detection system deployed as a web application using Streamlit, which aims to empower farmers with accurate and real-time diagnostic tools.

II. System Objectives

The primary objectives of the project are:

- To develop a CNN-based image classification model for detecting crop diseases.
- To provide an easy-to-use web interface for farmers to upload leaf images.
- To display the predicted disease, confidence score, and treatment suggestions.
- To facilitate early intervention and reduce dependency on agricultural experts.

III. Dataset and Preprocessing

A. Dataset Used

We used the Plant Village dataset, an open-source repository of over 50,000 images of crop leaves, annotated with healthy and diseased classes. It includes crops like tomato, potato, apple, grape, and corn.

B. Preprocessing Steps

- Resizing of Images: Every image was scaled to 128 by 128 pixels.
- Normalization: The values of the pixels were scaled from 0 to 1.
- Augmentation: Rotation, flipping, and zoom were applied to improve generalization.

Split dataset: 10% for testing, 10% for validation, and 80% for training.

IV. Model Architecture and Training

A. CNN Model Structure

• Input Layer: 128x128x3 image tensor

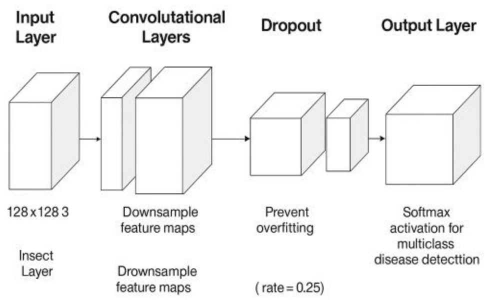
• Convolutional Layers: Extract image features (filters = 32, 64)

• Max Pooling Layers: Down sample feature maps

• Dropout: Prevent overfitting (rate = 0.25)

• Dense Layers: Fully connected layers for classification

• Output Layer: SoftMax activation for multiclass disease detection



B. Training Parameters

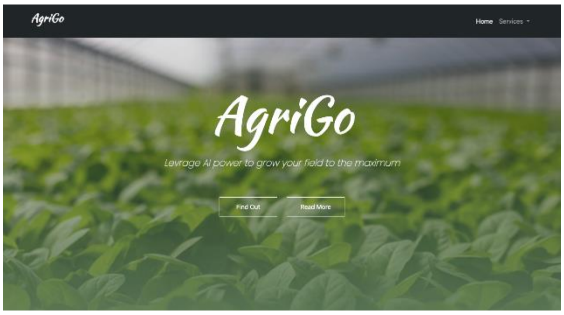
• Loss Function: Categorical Cross-Entropy

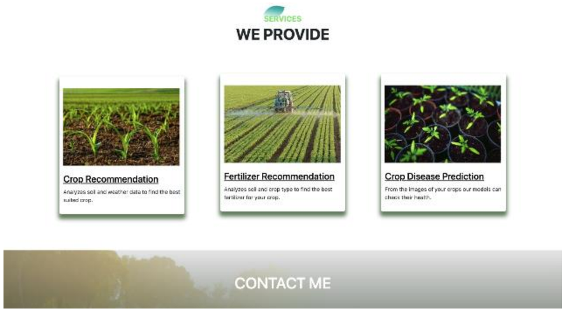
• Optimizer: Adam

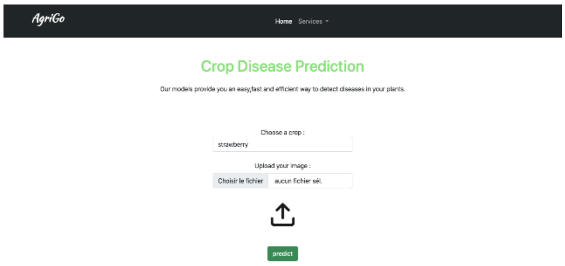
• Epochs: 50

• Batch Size: 32

• Accuracy Achieved: ~92% on validation set







V. Web Application using Streamlit

A. Frontend Features

• File Upload: Drag-and-drop or browse for leaf image upload

• Real-Time Prediction: Result displayed within seconds

• Multilingual Option (Future Scope)

• Mobile and Desktop Compatible

B. Backend Features

• Model Inference: Loads saved .h5 Keras model

• Disease Classification: Predicts disease name and probability

• Treatment Suggestions: Lists symptoms and solutions

• Database Support (optional): Firebase or MongoDB for storing user history

VI. System Architecture

1. User Input: Uploads image via UI

2. Preprocessing Layer: Resizes, normalizes image

3. Model Layer: CNN analyzes and classifies image

4. Output Layer: Displays disease name and remedies

5. Storage (Optional): Saves prediction to a database

VII. Results and Evaluation

A. Performance Metrics

• Accuracy: 92.3%

• Precision: 91.4%

• Recall: 90.8%

• F1-Score: 91.1%

• Inference Time: 1–2 seconds per prediction

B. User Feedback

Collected from local farmers and agricultural students:

• Pros: Easy UI, fast results, relevant suggestions

• Cons: Needs offline version, supports limited crop types

VIII. Challenges and Limitations

A. Dataset Limitations

Limited to PlantVillage crops; real-world images have more variability.

B. Internet Dependency

Relies on stable connectivity for real-time use.

C. Hardware Requirements

High-resolution image processing may not run smoothly on low-end devices.

D. Model Generalization

Struggles with new or rare diseases not included in training data.

IX. Future Enhancements

• Edge AI: Deploy lightweight models for offline mobile use

• Multilingual Support: Add regional languages for accessibility

• Voice Assistance: Help illiterate users interact via speech

• Real-Time Monitoring: Add time-series tracking for disease progression

• Drone Integration: Use drones for wide-field scanning and detection

• Expand Dataset: Include more crops and real-world images

X. Conclusion

This paper presents an effective and scalable approach for real-time crop disease detection using CNN and Streamlit. The web-based application is user-friendly and delivers accurate results to aid early disease management. While it shows promising accuracy, future work will focus on improving generalization, adding offline functionality, and expanding crop support to make the system more robust and farmer-centric.

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