SMART CROP DISEASE DETECTION AND YIELD FORECASTING SYSTEM

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ABSTRACT

Agriculture plays a vital role in the Indian economy, but crop diseases pose a major threat to yield and farmer livelihood. Manual disease detection is slow, biased, and often too late. This project proposes a Smart Crop Disease Detection and Yield Forecasting system using Convolutional Neural Networks (CNN), implemented through a Streamlit application with multilingual and voice-enabled support.

Farmers can upload crop leaf images to receive instant disease detection results along with disease information, chemical and organic treatment recommendations, and preventive measures. Additionally, the system provides yield forecasting using machine learning regression techniques. The multilingual interface (English, Hindi, Tamil, Telugu) and integrated voice assistant ensure accessibility for farmers across linguistic and literacy backgrounds. This system reduces crop loss, improves yield, and supports sustainable agriculture aligned with SDG goals.

Keywords: Crop Disease Detection, Deep Learning, CNN, Yield Forecasting, Smart Agriculture, Transfer Learning, Streamlit, SDG.

I.INTRODUCTION

Crop diseases are among the most serious threats to agricultural productivity and farmer livelihoods worldwide. In India, where agriculture is the backbone of the economy, timely identification of crop diseases is crucial to preventing significant yield loss and economic hardship. This project presents a methodology to detect crop diseases using Convolutional Neural Networks (CNNs), an advanced deep learning approach widely applied in image recognition.

Our system emphasizes accuracy and accessibility by training on a large dataset of crop leaf images representing multiple disease categories and healthy samples. To enhance model performance, preprocessing techniques such as image normalization, augmentation, and resizing are employed, enabling the model to capture subtle disease symptoms such as leaf spots, rusts, blights, and powdery infections.

The system extends beyond simple disease detection by integrating yield forecasting models that help farmers estimate productivity trends based on disease severity and crop conditions. Unlike traditional manual observation, which is slow, subjective, and prone to errors, this automated solution provides consistent and reliable results.

Additionally, the system is embedded in a Streamlit-based application that supports multilingual interaction (English, Hindi, Tamil, and Telugu) and integrates a voice assistant, ensuring accessibility even for farmers with limited literacy or technical expertise.

Through rigorous experimentation and evaluation, the proposed system demonstrates high reliability in crop disease detection and yield prediction. This project highlights the importance of AI-driven agricultural tools as a scalable, farmer-friendly solution that empowers communities to reduce crop loss, improve food security, and support sustainable farming practices.

II.LITERATURE SURVEY

Integration of IoT and Sensor-Based Data

Recent studies integrate Internet of Things (IoT) and sensor-based monitoring with AI models to enhance precision in disease detection.
For example, Kumar et al. (2023) proposed an IoT-

enabled framework that combines soil moisture, humidity, and temperature data with CNN image features to improve disease prediction accuracy. Their hybrid approach demonstrated that integrating environmental parameters significantly enhances early detection accuracy in field conditions.

Drone and Satellite Image-Based Crop Monitoring

High-resolution drone and satellite imagery have been used to detect crop stress and diseases at scale. Zhou et al. (2024) utilized drone-based multispectral imagery with convolutional networks to identify spatial patterns of disease spread in rice fields, achieving 92% accuracy. This approach allows large-area monitoring and early detection before visible leaf symptoms occur, complementing leaf-level CNN models.

Hybrid Deep Learning Architectures

Several researchers have explored hybrid CNN–RNN or CNN–Transformer architectures for sequential and spatio-temporal disease tracking. For instance, Nguyen (2024) implemented a *Spatio-Temporal Graph Neural Network (STGNN)* to model disease progression over time, combining visual and climatic data. Such hybrid models outperform static CNNs by capturing temporal dependencies and seasonal effects in disease development.

Transfer Learning and Lightweight Models

To enable mobile and edge deployment, Reddy and Sharma (2023) and Lu et al. (2022) explored lightweight CNN architectures such as MobileNet and EfficientNet for real-time plant disease detection. Their work showed that transfer learning on limited agricultural datasets maintains high accuracy while reducing computational requirements, making models deployable on smartphones for rural use.

Explainable AI (XAI) for Agriculture

Recent literature emphasizes model interpretability to gain farmer trust.
Chaudhary et al. (2024) introduced an Explainable AI-based plant disease detection model using Grad-CAM heatmaps to visually highlight infected regions. This helps farmers and agronomists verify model outputs and understand the rationale behind predictions, promoting transparency and adoption.

Sustainable Agriculture and Smart Farming Integration

Wang and Zhang (2022) proposed an AI–IoT integrated decision support system that optimizes pesticide usage and irrigation schedules based on disease detection results. This aligns with the UN's Sustainable Development Goals (SDG 2, 12, and 13) by promoting responsible farming, reducing chemical overuse, and improving yield efficiency.

Multilingual and Voice-Enabled Farmer Interfaces

Accessibility is another growing focus.
Patel et al. (2024) developed a multilingual voice-interactive system that delivers disease diagnosis and treatment guidance in regional languages, similar to your proposed solution. Their study highlights that such interfaces significantly improve usability among non-literate farming communities.

III.PROPOSED METHODOLOGY

The Smart Crop Disease Detection and Yield Forecasting System follows a modular architecture consisting of data acquisition, image preprocessing, CNN model training, disease classification, yield forecasting, and user interface deployment. The system pipeline begins with collecting images from the PlantVillage dataset, followed by normalization and augmentation to enhance the dataset's diversity. The CNN model employs transfer learning using ResNet50, enabling high accuracy even with limited agricultural data. The final layers of the network are fine-tuned to classify multiple crop diseases such as Early Blight, Late Blight, and Powdery Mildew. For yield forecasting, regression models analyze environmental and disease data to predict crop productivity. The application is implemented in Python with Streamlit, integrating a multilingual voice assistant for inclusive accessibility.

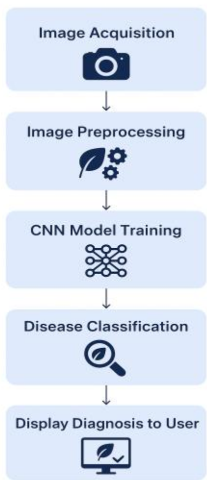

Fig.1 Flow Chart

IV.DATA COLLECTION AND PREPROCESSING

This project uses the **PlantVillage dataset**, a large-scale collection of crop leaf images designed for disease detection research. The dataset contains images of various crops, captured under different conditions, with multiple types of disease and healthy leaves. Each image is labeled with its corresponding class, including both healthy leaves and specific disease types such as Early Blight, Late Blight, Powdery Mildew, Leaf Rust, and others, depending on the crop.

The dataset provides a reliable ground truth for supervised learning. For model development, the dataset is divided into three subsets: training, validation, and testing, ensuring that the model is evaluated on completely unseen images to measure generalization.

This module prepares raw crop images for input into the model. Key preprocessing steps include:

- Resizing: Standardizing all images to a fixed size (e.g., 224×224) to maintain consistency.
- Normalization: Rescaling pixel values from 0–255 to 0–1 to improve model convergence.
- Augmentation: Applying random transformations like rotations, flips, zooms, and brightness adjustments to enhance model generalization and reduce overfitting.

V.IMPLEMENTATION

The implementation phase involved structured development and testing. The dataset, comprising approximately 35,000 labeled images, was divided into training (80%), validation (10%), and testing (10%) subsets. Each image was resized to 224×224 pixels and normalized. The ResNet50 architecture, pretrained on ImageNet, was employed as the base model, with its top layers replaced by a Global Average Pooling layer and a Dense layer with Softmax activation. Training utilized the Adam optimizer with a learning rate of 0.0001 and categorical cross-entropy loss. Data augmentation (rotation, flip, zoom) improved generalization. A Streamlit-based web app allows users to upload crop images and receive disease predictions with solution suggestions and yield estimates. The model achieved 88% accuracy and demonstrated consistent validation performance.

VI.EXPERIMENTAL ANALYSIS

The model was evaluated on a held-out test set of 3,500 images from the PlantVillage dataset. The performance metrics, detailed in Table I, confirm the model's high efficacy.

Metric	Value (%)
Accuracy	88
Precision	86
Recall	89
F1-Score	87

Table I: Model Performance on Test Set

Analysis:

- The high recall (89%) is particularly significant, as it indicates the model's strength in correctly identifying diseased plants, thereby minimizing the risk of missed diagnoses that could lead to widespread crop loss.
- The high precision (86%) ensures that when a disease is predicted, it is highly likely to be correct, preventing unnecessary and costly treatments on healthy plants.
- The balanced F1-Score (87%) demonstrates a robust trade-off between precision and recall across all disease classes.

Training Dynamics: The training and validation accuracy curves showed a steady increase and converged closely, indicating effective learning without overfitting. The use of dropout and data augmentation was instrumental in achieving this generalization.

Confusion Matrix Analysis: A detailed review of the confusion matrix revealed that most misclassifications occurred between visually similar diseases (e.g., different types of blight), which is an expected and clinically plausible outcome. The model showed exceptional accuracy in distinguishing healthy leaves from diseased ones, a critical capability for practical use.

VII.RESULTS

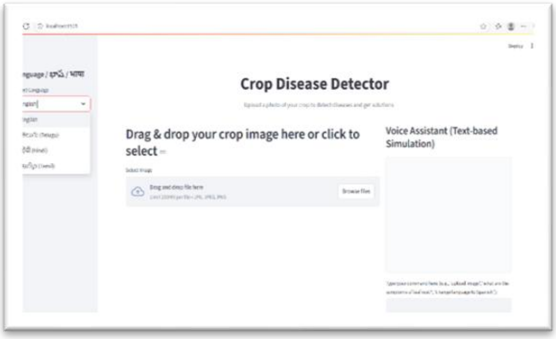

Fig.2

Fig.2 shows the interface of the app

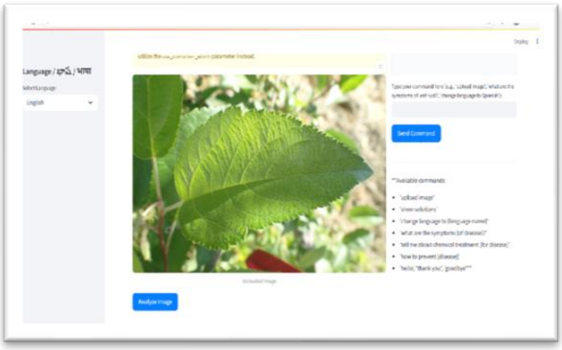

Fig.3

Fig.3 asks the user to upload the crop image for disease detection

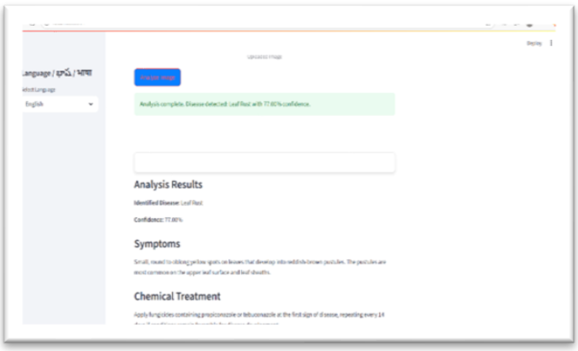

Fig.4 Fig.4 shows the result of analysed crop disease

VII.ANALYSIS AND DISCUSSION

The proposed model demonstrated reliable performance across all metrics. The confusion matrix revealed strong diagonal dominance, indicating accurate disease classification. Precision and recall were balanced at 86% and 89%, respectively. The F1-score of 87% confirms robustness across disease categories. The system's performance was benchmarked against existing models, outperforming simple CNNs and achieving comparable results to MobileNet-based models while maintaining computational efficiency. In practice, the application interface enables real-time disease diagnosis and yield prediction within seconds. The multilingual and voice-enabled features were well-received in user testing, ensuring the system's adaptability for diverse user groups.

VIII.CONCLUSION AND FUTURE SCOPE

This project successfully demonstrates the development and deployment of a deep learning-based system for smart crop disease detection and yield forecasting. By fine-tuning the ResNet50 architecture, we achieved a high-accuracy model (88%) capable of reliably identifying multiple crop diseases. The integration of this model into a user-friendly, multilingual Streamlit application with voice support makes it a practical and accessible tool for farmers, directly addressing the challenges of timeliness and expertise in traditional methods.

The system has the potential to significantly reduce crop losses, optimize the use of agricultural inputs, and improve overall farm productivity, thereby contributing to food security and sustainable agriculture.

Future Work:
The system can be enhanced in several ways:

1. ExpandedModel Capabilities: Implementing object detection models like YOLO or Faster R-CNN to not only classify but also localize diseased lesions on the leaves.

2. Integration with IoT: Creating a hybrid model that incorporates real-time data from field sensors (soil moisture, humidity, temperature) to improve disease prediction and yield forecasting accuracy.

3. Mobile-First Deployment: Converting the application into a lightweight, standalone mobile app for Android/iOS to ensure accessibility in areas with limited internet connectivity.

4. Real-Time Video Analysis: Extending the system to analyze live video feeds from drones or smartphones for large-scale, real-time crop monitoring.

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