AI Driven Crop Disease Detection and Management System

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Abstract: Crop diseases cause large yield losses worldwide and represent a serious threat to food security. Traditional detection methods rely on manual inspection, which is time-consuming and error-prone. The AI-driven Crop Disease Detection and Management System presented in this paper combines environmental data analytics utilizing Random Forest regression for disease risk predictions with Convolutional Neural Networks (CNNs) for image-based disease identification. A carefully selected portion of the PlantVillage dataset, with an emphasis on the crops maize, tomato, and potato, is used to train the model. The hybrid approach leverages temperature, humidity, and rainfall data to increase prediction reliability. When compared to traditional CNN-only methods, experimental evaluation shows an accuracy of 94.33% and enhanced early disease prediction skills. The system, which offers real-time disease monitoring, is implemented as a mobile application and web platform. detection, forecasting, and treatment suggestions. This hybrid approach promotes sustainable agriculture through proactive disease management and optimized resource use.

Keywords: *Crop Disease Prediction, Convolutional Neural Network (CNN), Deep Learning, Plant Village Dataset, Disease Risk Assessment, Precision Agriculture, AI in Agriculture, Sustainable Farming, Real-Time Disease Detection.*

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I. INTRODUCTION

Agriculture is the cornerstone of global food security. However, the growing incidence of agricultural diseases threatens farmers' livelihoods around the world by reducing production by 20–40% every year. Traditional identification techniques mostly rely on agricultural specialists' visual inspections, which are time-consuming, arbitrary, and out of reach for small farmers.

Traditional agriculture is changing as a result of data-driven solutions brought about by the quick developments in artificial intelligence (AI) and machine learning (ML). In leaf image-based disease classification, deep learning—in particular, Convolutional Neural Networks, or CNNs—has demonstrated impressive performance, providing precise and scalable early detection systems.

However, environmental variables like rainfall, humidity, and temperature can affect the occurrence of disease. Therefore, combining image-based algorithms with environmental data can improve prediction accuracy and offer early disease outbreak alerts.

➢ *Problem Statement*

Current methods for detecting plant diseases mostly use image data and frequently overlook environmental factors that can affect the spread of the disease. Moreover, farmers lack real-time and field-level diagnostic support technologies that integrate predictive analytics and management recommendations.

➢ *Objectives*

This study aims to:

- Create a hybrid AI system that combines environmental modeling and CNN-based image classification.
- Make mobile and web apps usable in real time for field use.
- Analyze how the incorporation of environmental data affects the accuracy of predictions.
- Provide a decision-support tool delivering treatment suggestions and risk forecasts.

➢ *Contributions*

- CNN and Random Forest regression are used in this innovative hybrid deep learning architecture.
- disease risk modeling that incorporates environmental variables (temperature, humidity, and rainfall).
- creation of a web platform for real-time detection and management using Flask and ReactJS.
- Better performance is shown in comparison to the most advanced CNN models.

II. LITERATURE REVIEW

Early studies by Mohanty et al. (2016) shown the promise of deep learning for crop disease identification by employing CNNs to reach 99.35% accuracy on the PlantVillage dataset. This dataset was increased in later studies, such as Ferentinos (2018), which attained 99.53% accuracy.

In order to improve feature extraction, Brahimi et al. (2017) and Too et al. (2019) incorporated deeper architectures (VGG, DenseNet). Transfer learning was used for field adaptability in recent studies such as Singh et al. (2023) and Selvaraj et al. (2020).

However, these models ignore environmental relationships and only concentrate on image-based diagnosis. By combining environmental data modeling and CNN classification, the suggested approach overcomes this drawback.

III. PROPOSED METHODOLOGY

➤ *System Overview*

Two modules comprise the suggested AI-driven framework:

- Using pictures of leaves, the Image Classification Module (CNN) can identify crop diseases.
- Using meteorological data, the Random Forest Environmental Prediction Module predicts the likelihood of disease.
- The ensemble model merges both predictions for improved accuracy and real-time decision support.

➤ *Flowchart of Proposed System*

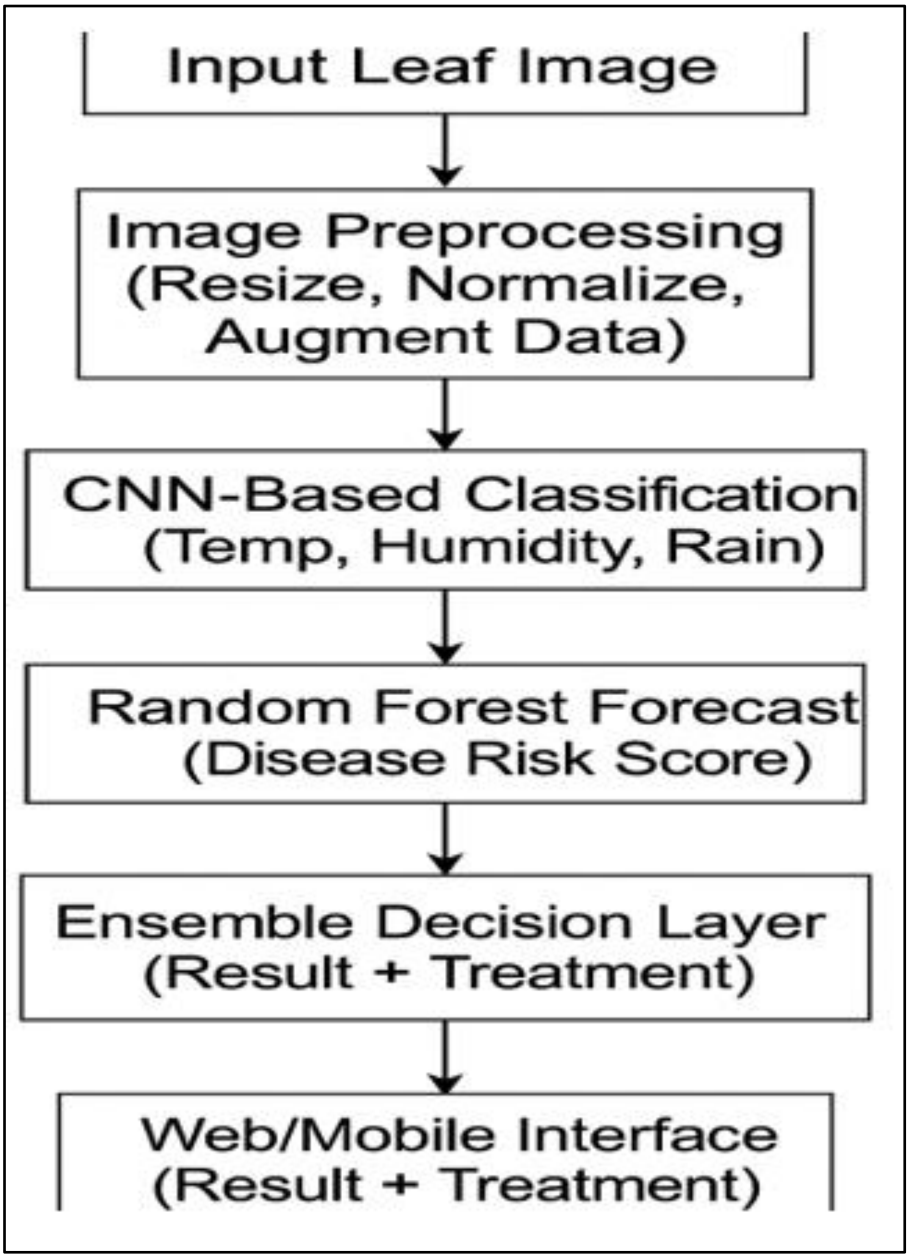

Fig 1 Proposed System Flowchart

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- *Dataset*

- Image Data: PlantVillage collection, which includes 54,000 photos of 17 different potato, tomato, and maize disease classes.
- Environmental Data: Weekly averages of temperature, humidity, and precipitation from the OpenWeatherMap API.

- *Model Design*

- CNN: 4 Conv2D layers (32–512 filters), MaxPooling2D, Flatten, Dense (128, ReLU), Softmax output (17 classes).
- Optimizer: Adam (learning rate = 0.0001), Batch size = 32, Epochs = 50.
- Environmental Model: Random Forest regression for disease risk estimation.
- Ensemble: Weighted averaging of CNN probability and RF forecast.

- *Algorithm (Proposed Hybrid Model)*

- Algorithm 1: AI-driven Crop Disease Detection and Forecasting

- Input: Leaf image I[t], Environmental parameters E[t]
- Output: Disease class D[t], Risk score R[t+h]

- ✓ Preprocess image I[t] (resize, normalize, augment)
- ✓ CNN_Model ← Train CNN on PlantVillage dataset
- ✓ Pred_CNN ← CNN_Model.predict(I[t])
- ✓ Train RandomForest on (Temperature, Humidity, Rainfall)
- ✓ Pred_RF ← RandomForest.predict(E[t])
- ✓ Ensemble_Score ← w1 * Pred_CNN + w2 * Pred_RF
- ✓ Display (Disease Type, Risk Level, Recommended Treatment)

IV. EXPERIMENTAL RESULTS

- *Setup*

- Hardware: NVIDIA Tesla T4 GPU (16 GB RAM)
- Frameworks: TensorFlow/Keras, Flask (backend), ReactJS (frontend)
- OS: Ubuntu 22.04 LTS

- *Performance Metrics*

Table 1 Performance Metrics

Metric	**Value**
Classification Accuracy	94.33%
Precision	93.87%
Recall	94.10%
F1-score	94.01%

- *Comparative Analysis with Prior Works*

Table 2 Comparative Analysis with Prior Works

Model / Method	**Author**	**Key Feature / Finding**
CNN	Mohanty, Hughes & Salathé	99.35% accuracy in classifying 14 crop species & 26 diseases
CNN	Ferentinos	99.53% accuracy across 25 plants, 58 classes
CNN	Sladojevic et al.	91–98% precision, avg. 96.3%
CNN	Brahimi et al.	99.18% accuracy, automatic feature extraction
VGG16, Inception V4, Res Net, Dense Net	Too et al.	Dense Net achieved 99.75% accuracy
Faster R-CNN, R-FCN, SSD VGG/Res Net	Fuentes et al.	Accurate detection in complex environment
Res Net (adapted)	Picon et al.	Balanced accuracy up to 0.96 in field tests
ResNet50, InceptionV2, MobileNetV1	Selvaraj et al.	>90% accuracy in most models tested

- *Visualization*

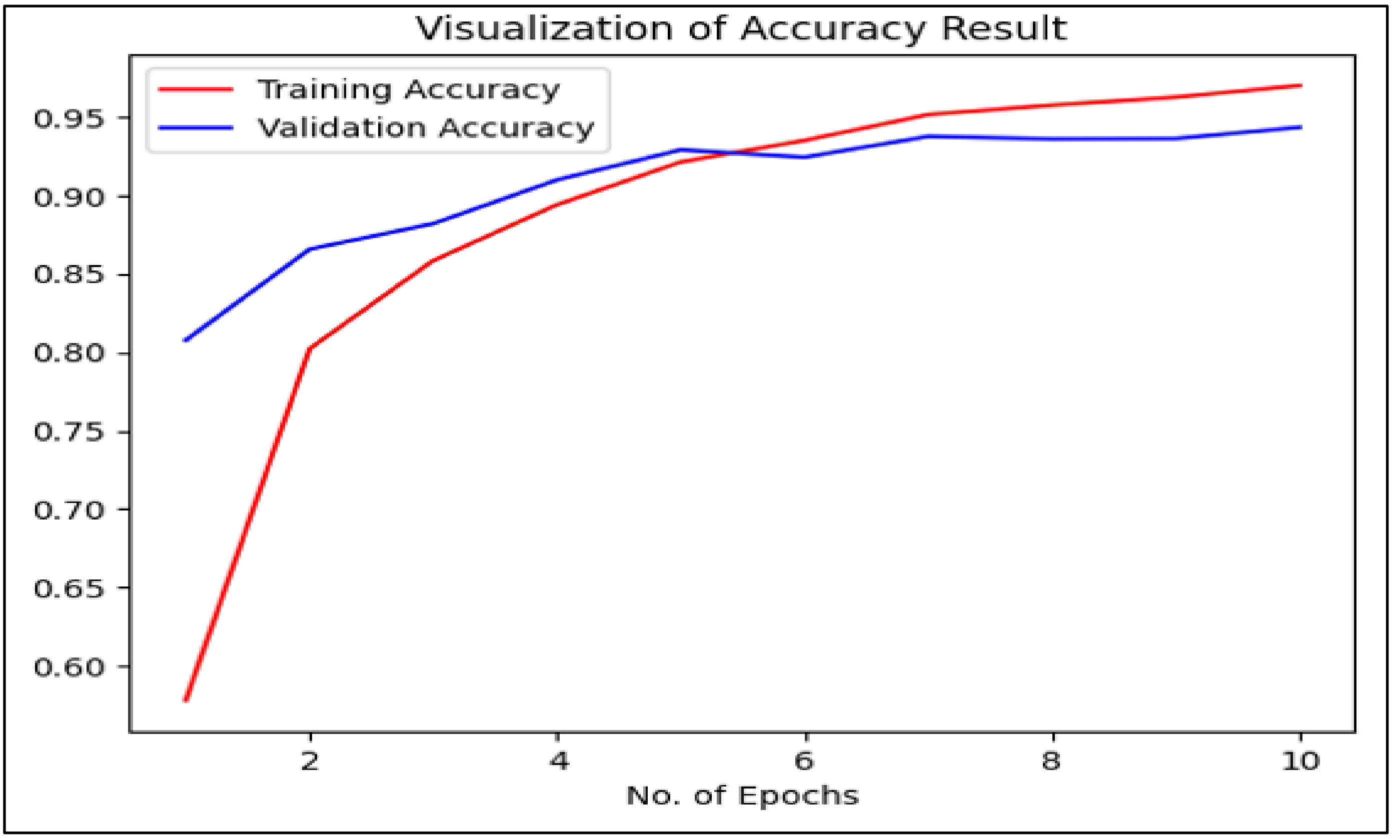

Fig 2 Accuracy Graph

Fig 3 Confusion Matrix

The confusion matrix showed strong prediction consistency across all 17 disease classes.

V. CONCLUSION AND FUTURE WORK

This work introduces a hybrid AI-driven system that combines environmental predictions and CNN-based classification for crop disease diagnosis and control. The method's accuracy of 94.33% shows how crucial environmental data fusion is for increased dependability and early illness detection.

➢ *Future Enhancements:*

- Extend to additional crops and datasets.
- Develop a mobile real-time camera-based app for farmers.
- Integrate IoT sensors (soil moisture, humidity) for continuous monitoring.
- Implement Explainable AI (XAI) to enhance model transparency.

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