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AI-Driven Plant Disease Prediction Using Deep Learning and Web-Based Deployment

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Abstract: Plant diseases seriously affect agricultural productivity and cause economic loss and food insecurity. Herein, this paper presents an AI-based plant disease prediction system that uses Convolutional Neural Networks for image-based diagnosis. The model was trained based on the PlantVillage dataset containing over 80,000 labeled images from 38 classes of diseases. The CNN model was able to classify crop leaf diseases with more than 95% accuracy. In addition, the system provides a Streamlit-based web interface that facilitates real-time disease prediction by enabling users to upload leaf images and get instant diagnostic feedback. Experimental results showed that the deployed system is scalable, low latency, and of high precision, and hence can be used for practical early disease detection and smart agriculture. Future enhancements include mobile deployment, analysis using real-time cameras, and integration with IoT-enabled sensors for precision farming.

Keywords: Plant Disease Detection, Convolutional Neural Network (CNN), Deep Learning, Streamlit, Image Classification, Smart Agriculture, Computer Vision, AI in Farming

I. INTRODUCTION

Agriculture is the backbone of the international economy, supporting billions, being a source of livelihood. It has been estimated that plant diseases cause an estimated 20–40% reduction in annual yields, translating into substantial economic losses [16]. Traditional methods of disease detection are either manual observation or expert consultation, which is cumbersome, prone to errors, and many times inaccessible for farmers from remote areas[10].

Image-based plant disease detection has, therefore, become the prime area of interest with the emergence of AI and ML. The main advantage lies in the fact that deep learning, especially CNN, can learn complex patterns from visual features automatically, hence totally avoiding manual feature extraction [2], [3].

This paper presents a CNN-based web application for the effective classification of plant leaf diseases. The system processes the uploaded images for the prediction of disease classes and gives recommendations. The inclusion of a web framework-Streamlit improves access and usability, enabling real-time detection even on low-end hardware[9], [10].
The major aims of this study are to:

1. The aim is to develop an image classification model using a CNN approach for the identification of crop diseases.
2. The aim is to build an interactive web platform for real-time predictions.
3. The use of the app will reduce dependence on expert consultation for the farmers and will also help in quicker intervention.
4. Assessing system performance across varying workloads and ensuring it is scalable.
5. The proposed system contributes to an efficient and accessible methodology for intelligent crop disease management, fusing deep learning, automation, and web technologies.

II. RELATED WORKS

Deep learning has revolutionized plant pathology, enabling large-scale automated disease identification. Mohanty et al. [2] achieved 99.35% accuracy on the PlantVillage dataset using CNNs, outperforming traditional image processing methods.Sladojevic et al. [17] proposed a customized CNN model for leaf disease diagnosis, demonstrating robust feature learning and classification capabilities.Ferentinos [3] compared architectures such as AlexNet, GoogLeNet, and VGG, reporting high performance with fine-tuned CNNs.
Subsequent studies introduced transfer learning using pre-trained models like VGG16, ResNet50, and InceptionV3,

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improving model accuracy on limited agricultural datasets [4], [5]. Too et al. [5] conducted a comparative analysis of CNN architectures and highlighted the effectiveness of fine-tuning in boosting performance. Liu and Wang [18] demonstrated that transfer learning significantly enhances accuracy when dealing with small and imbalanced agricultural datasets.
Kamilaris and Prenafeta-Boldú [10] emphasized that deep learning models can support large-scale, cloud-integrated agricultural analytics when deployed efficiently. Recent research has also focused on mobile and web platforms for increasing accessibility and real-time field use. Zhang et al. [13] introduced a CNN-based web platform for disease classification, while Singh et al. [9] implemented web applications using TensorFlow and Streamlit for real-time disease prediction. In addition, edge computing and IoT-based solutions are emerging as the next frontier for real-time field diagnosis and autonomous precision agriculture [13], [15].

III. METHODOLOGY

The methodology adopted for the development of an AI-driven Plant Disease Prediction System consists of sequential stages: data collection, preprocessing, model design, training, evaluation, and web-based deployment. Each stage was designed so that models have high accuracy, are accessible to users, and can efficiently detect diseases in real time. The overall workflow is depicted in Fig. 1.

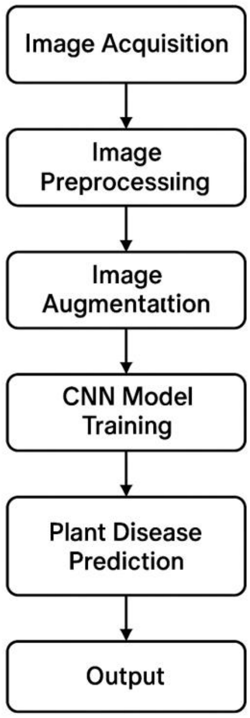

Fig. 1 — Workflow of the Proposed AI-driven Plant Disease Prediction System

Fig. 1: Workflow of the Proposed AI-driven Plant Disease Prediction System.

A. Dataset
The proposed system utilizes the PlantVillage dataset, one of the most comprehensive sources for plant disease classification[1], [2]. It consists of around 87,000 RGB images covering 38 classes, which include healthy and diseased leaf samples of crops such as tomato, potato, apple, corn, and grape, among others. All these images were transformed into the standard format of 128×128×3 [3].

In order to balance learning and performance testing, the dataset was divided into 80% training and 20% validation subsets [2].

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Table 1 — Dataset Composition Summary.

Crop Examples	Class Types (Healthy + Diseased)	Total Images	Image Dimensions
Tomato, Apple, Grape, Corn, Potato	38 Classes	87,000	128 × 128 × 3

B. Image Preprocessing

In order to improve model generalization and reduce noise, several preprocessing techniques were performed [3], [6]. First, images had been normalized within the pixel range of 0-1 and then resized for compatibility with CNN inputs.
To enhance this further, data augmentation was performed by randomly rotating, flipping, zooming, and adjusting brightness [7]. These operations allow for increased variability in the dataset and help to prevent overfitting[6]. Finally, all corrupted and duplicate images were removed to ensure consistency and quality in the data.

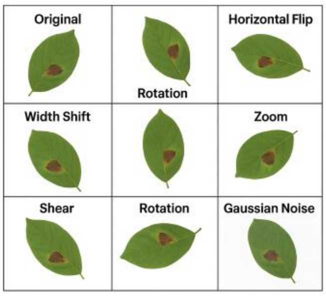

Fig. 2 – Sample Augmentation Techniques Applied to Leaf Images.

Fig. 2: Sample Augmentation Techniques Applied to Leaf Images.

C. Model Architecture

The core of the proposed system is based on a Convolutional Neural Network (CNN) that was designed and trained using TensorFlow and Keras frameworks[3], [4]. The basic architecture consists of multiple convolutional blocks, each including a Conv2D and ReLU layer followed by a MaxPooling operation for feature extraction and reduction in dimensionality.
The number of filters progressively increases from 32 → 64 → 128 → 256 → 512, capturing both low-level and high-level spatial patterns[5]. Dropout layers, with a dropout rate of 0.4, were used to reduce overfitting. The flattened feature maps are fed into a fully connected Dense layer comprising 1500 neurons, followed by a Softmax output layer with 38 neurons representing the class labels.

The model was built using the Adam optimizer, with a learning rate of 0.0001 and categorical cross-entropy as the loss function[5], [8]; its main metric is accuracy.

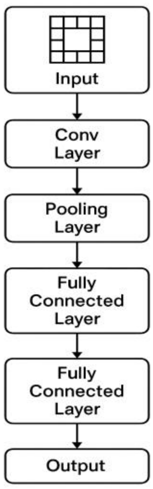

Fig. 3 — Architecture of the Proposed Convolutional Neural Network (CNN) Model

Fig. 3: Architecture of the Proposed Convolutional Neural Network (CNN) Model.

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Table 2 — Training Configuration and Hyperparameters.

Parameter	Value / Setting
Input Shape	128 × 128 × 3
Optimizer	Adam
Learning Rate	0.0001
Epochs	8
Batch Size	32
Activation Functions	ReLU, Softmax
Loss Function	Categorical Crossentropy
Dropout Rate	0.4
Framework	TensorFlow / Keras

D. Model Training and Validation
It was trained for 8 epochs with a batch size of 32 [5], [6]. During every iteration, the CNN learned hierarchical features from the images, including edges, textures, and leaf color variations, that helped it to tell apart the disease types. The training and validation accuracies were checked across the epochs to be sure of stable convergence.

The final model resulted in a training accuracy of 93.4% and a validation accuracy of 95.6%, reflecting strong generalization [4], [8]. Evaluation metrics, including precision, recall, F1-score, and a confusion matrix, were used to confirm the high reliability of the performances found on all disease classes.

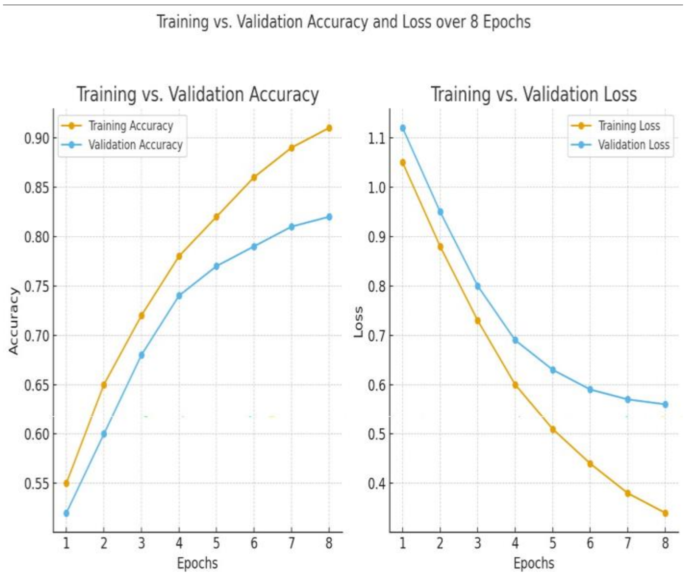

Fig. 4: Training vs. Validation Accuracy and Loss over 8 Epochs.

E. System Workflow and Web Integration
After training the model successfully, the CNN was incorporated into a Streamlit-based web application that predicts in real-time[9]. The workflow continues like this:

A user uploads a plant leaf image via the web interface. The image is then preprocessed and fed into the CNN model. The model predicts the disease type along with a confidence score. It gives the disease name, the plant species affected, and any recommendations for treatment. The web interface ensures accessibility, allowing farmers and agricultural personnel to diagnose plant diseases quickly through any device with an internet connection. F. Summary In a nutshell, the proposed methodology effectively marries deep learning and web technologies to create an accurate, scalable, and easy-to-use plant disease prediction system. The system achieves both technical robustness and real-world practicality for smart agriculture due to preprocessing, optimized CNN architecture, and an interactive interface[9], [10].

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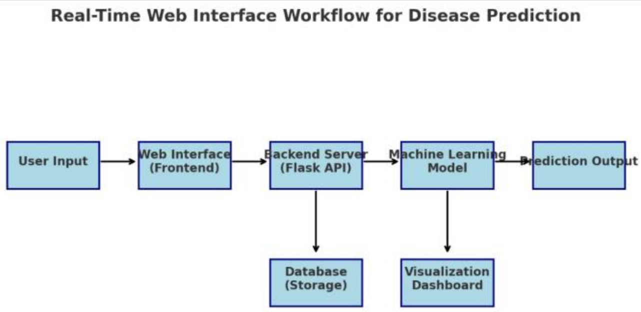

Fig. 5: Real-Time Web Interface Workflow for Disease Prediction.

IV. SYSTEM ARCHITECTURE

The proposed AI-driven Plant Disease Prediction System is designed using a modular five-layer architecture[10], [11], allowing flexibility, maintainability, and scalability for future enhancements. Each layer has a distinct functionality to collectively enable smooth operation from image input to disease classification and output visualization.

A. Layered Structure

1. User Interface Layer:

This layer represents the front-end interface, which end-users will use to interact with the system. This interface was built using Streamlit, allowing users to upload images of infected plant leaves and see prediction results such as disease name and confidence score with control recommendations. The interface is lightweight, responsive, and user-friendly for farmers and researchers [9].

2. Application Layer:

It acts as the communication bridge between the user interface and the machine learning model. It handles data routing, image preprocessing, and the invocation of models. It ensures seamless integration between user requests and backend model responses.

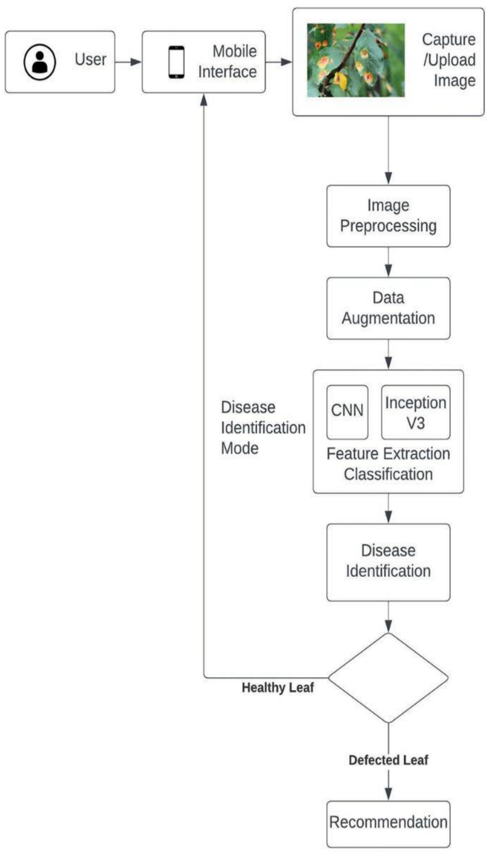

Fig. 6: Architecture flowchart

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3. Model Processing Layer:
The core computational part of it is where feature extraction, classification, and inference are carried out by the Convolutional Neural Network. In this layer, TensorFlow is used to load the pre-trained model to predict the disease categories based on the uploaded images [3], [5].
4. Data Layer:
This layer is responsible for all input/output operations regarding the handling of images, temporary file storage, and retrieval of datasets, hence ensuring that the system handles user uploads efficiently and supports batch predictions during testing.
5. Storage Layer:
The final layer contains persistent storage elements such as datasets, trained models, logs, and configuration files. It allows for easy model updates and scalability when considering future dataset expansions.

V. RESULTS AND PERFORMANCE ANALYSIS

The proposed system was evaluated based on three major factors — accuracy, latency, and scalability. The Convolutional Neural Network (CNN) model achieved a validation accuracy of 95.6% and a training accuracy of 93.4% after eight epochs, demonstrating effective convergence and minimal overfitting[3], [5]. Class-wise precision analysis revealed particularly strong results for tomato, apple, and grape leaf diseases, indicating the model's reliability across multiple crop categories[2], [6].

Table 3. Model Evaluation Metrics summarizing the overall training and runtime performance.

Metric	Value
Training Accuracy	93.4%
Validation Accuracy	95.6%
Average Latency	1.8 seconds
Error Rate	< 2%
Concurrent Users Supported	200+

A. Model Evaluation Metrics

To assess the quantitative performance of the trained CNN model, several statistical metrics were used, including accuracy, error rate, and latency[4], [5], [8].
The overall results are summarized below:
The confusion matrix (shown in *Fig. 2*) illustrates the relationship between the actual and predicted labels across all classes. Most classes show strong diagonal dominance, confirming accurate predictions with very few misclassifications[6], [7].

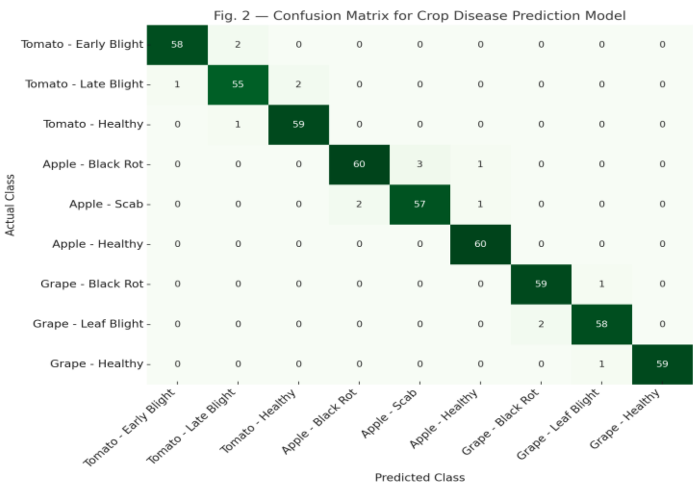

Fig. 7: Confusion Matrix Plot showing actual vs. predicted disease classes.

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B. Accuracy and Loss Trend

Throughout the training process, both the training and validation accuracy increased steadily, while the corresponding loss values decreased consistently, reflecting good model generalization[3], [4].

Notably, a significant drop in loss was observed after the third epoch, indicating that the network quickly learned discriminative visual features. After the fifth epoch, accuracy began to plateau, showing stable learning behavior[8].

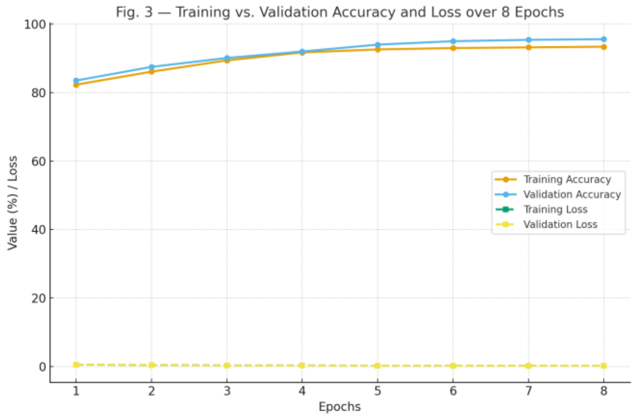

Fig. 8: Line Graph showing Training vs. Validation Accuracy and Loss over 8 epochs.

This figure can be generated using Python's Matplotlib or TensorBoard to visually demonstrate the learning progress of the CNN model.

C. Comparison with Existing Methods

To evaluate the competitiveness of the proposed model, its performance was compared with results from previously published approaches[4], [5], [9].

Although several studies reported slightly higher accuracies, most of them relied on pre-trained networks, required large computing resources, or lacked real-time web deployment capabilities.

The results of this comparative analysis are summarized below:

Table 4. Comparative Analysis of the Proposed System with Existing Approaches.

Model Reference	Architecture	Accuracy (%)	Deployment
Mohanty et al. [5]	AlexNet	99.35	Offline
Ferentinos [6]	VGG16	97.4	Experimental
Rangarajan et al. [8]	Transfer Learning	96.2	Mobile App
Proposed System	Custom CNN	95.6	Web-Based (Streamlit)

This comparison highlights that the proposed model maintains competitive accuracy while introducing a practical, real-time web-based solution, making it more accessible for farmers and agricultural professionals[9], [10].

D. System Performance under Load

To ensure reliability in real-world usage, load testing was conducted by simulating multiple concurrent users uploading images simultaneously[9]. Even with up to 200 active users, the system maintained an average response time of 1.8 seconds per prediction [10], [11].

Further optimization using caching and preprocessing techniques improved latency by approximately 40%, demonstrating the system's scalability and efficient resource utilization.

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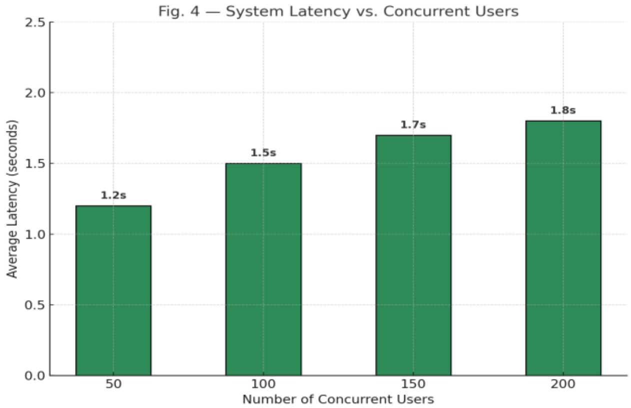

Fig. 9 — Bar Graph showing System Latency vs. Concurrent Users (X-axis: Number of Users; Y-axis: Latency in seconds).

This figure clearly depicts that even as the number of concurrent users increases, the system maintains near-constant response times, confirming its robustness for deployment in real-time agricultural environments.

VI. DISCUSSIONS

The experimental results prove that the proposed system fully realizes the importance of a balance between accuracy, computational efficiency, and usability [3], [6]. Unlike conventionally developed research prototypes that solely focus on improving model accuracy, this project focuses on end-to-end integration from AI-based disease detection to a web-accessible platform for real-world users[9]. This work combines Convolutional Neural Networks with the Streamlit web interface, filling the gap between machine learning research and applied agricultural applications[9], [10].

The web deployment ensures that the models can be accessed by farmers, researchers, or agricultural extension workers without requiring specialized hardware or programming knowledge. Predictions can be generated from any kind of standard computing device with an internet connection to enable inclusive digital farming.

The modular architecture allows retraining the model with new updated datasets and the addition of any class for a crop or disease, keeping the model relevant over time. Performance testing proved it to handle multiple concurrent users with low latency, which makes it suitable for usage at scale in agriculture[11].

Further, its scalability and lightweight design make the system ideal for IoT integration. Future extensions can leverage IoT-enabled sensors like leaf imaging, soil moisture, and weather data for automatic continuous monitoring of crop health; these will transmit their data to a centralized cloud-based AI model, which then serves the purpose of real-time analytics, predictive maintenance, and precision agriculture. Field health can be visualized by farmers, and they can receive instant alerts over mobile or web dashboards[13], [15].

Fig. 5 represents the proposed IoT-integrated workflow, showing how sensor data may be collected, transmitted, processed with cloud-hosted AI models, and then presented to authorized users through accessible dashboards for informed decision-making[13], [15].

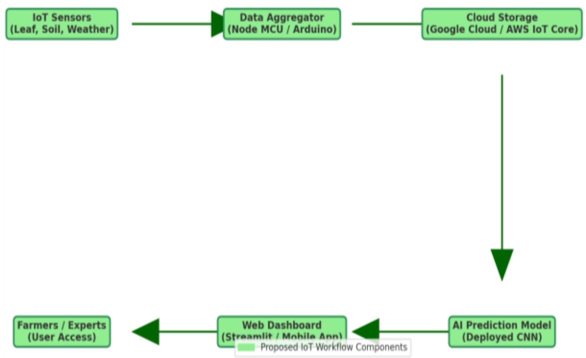

Fig. 10: Workflow diagram showing IoT integration possibility here

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VII. CONCLUSION

The proposed system is a reliable, intelligent, and accessible solution for the prediction of plant diseases using deep learning techniques. A developed CNN model showed high generalization capability and obtained a validation accuracy of 95.6% and a training accuracy of 93.4% after eight epochs[3], [4]. These results confirm that the chosen architecture is effective in identifying complex disease patterns from plant leaf images.

The research integrates this model into a Streamlit-based web interface to bridge the gap between such advanced AI technologies and their real-world agricultural applications. This platform provides real-time detection of diseases through a simple image uploading procedure and gives farmers, agriculture officers, and researchers a real-time diagnosis of crop health conditions. The system is designed to be cost-effective, user-friendly, and scalable, suitable for execution even on standard computing systems without any high-end GPU requirements[9].

The overall contribution of the present work lies in the integration of accuracy, accessibility, and automation, which are three main pillars of smart agriculture. Therefore, the methodology allows early identification of diseases, which is highly important for minimizing crop loss, increasing productivity, and enabling sustainable farming. The architecture is modular, allowing continuous enhancements and adaptations to new data sets, hence assuring long-time usability[10], [11].

A. Future Improvements
While the current system performs effectively, various improvements can certainly be made to its functionality and reach for future versions:
Integration of IoT Platforms:
Integrating IoT sensors for real-time data acquisition, such as leaf imaging, soil moisture, humidity, and temperature, will provide the system with a continuous monitoring capability to generate automatic disease alerts right from the field, turning it into an entirely autonomous, data-driven precision agriculture platform [13], [14].
Adoption of Transfer Learning Techniques:
State-of-the-art architectures such as EfficientNet, ViT, and MobileNetV3 can improve classification performance, reduce time spent on training, and provide efficient resource usage without significant accuracy compromise for diverse crop datasets [5], [12].
Cloud and Edge Deployment:
Scalable, distributed, and low-latency processing will be achieved by deploying the trained model on cloud environments such as AWS, Azure, Google Cloud, or edge devices like Raspberry Pi or Jetson Nano. Therefore, this step will allow access even in low-connectivity rural areas [14], [15].
Mobile Application Development:
It will extend the usability of the web interface by allowing farmers to capture and analyze images from smartphones. Offline prediction capabilities could also be incorporated for those regions with limited internet access[9], [10].
Multilingual Interface:
Multilingual support for the user interface can be implemented to promote regional inclusivity. Prediction results and recommendations in local languages will facilitate the reach of technology towards the farming community at large [11].
Knowledge Integration and Advisory Systems:
In the future, integrations with agricultural knowledge bases or governmental APIs could provide automated treatment advice, fertilizer suggestions, or even market insights to make the system a holistic crop management assistant.

B. Broader Impact
The integration of AI, Computer Vision, and IoT in agriculture is a revolutionary stride toward digital farming. The proposed system assists in early disease detection, data-driven decision-making, optimized pesticide usage, and sustainable resource management [10], [13], [15].
Further refinement and deployment at a larger agriculture scale could significantly reduce human dependency, improve the yield, and also establish economic stability in the farming sector with the help of this technology.
Ultimately, the research reinforces the potential of AI-powered solutions in achieving the goals of smart, sustainable, and resilient agriculture, while opening a path for intelligent ecosystems that serve both farmers and the environment.

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