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AI-Plant Disease Prediction & Cure Recommendation Model

Rahul Verma[1], Vaibhav Kumar Chaudhari[2], Tanu Chandra[3], Vipin Kumar Chaudhary[4]
Department of Computer Science & Engineering, Galgotias College of Engineering and Technology, Greater Noida

Abstract: Plant diseases pose a serious challenge to global food security as they reduce crop yield, quality, and productivity. The timely detection of plant diseases is crucial to prevent large-scale agricultural losses. In rural and underdeveloped regions, farmers lack access to agricultural experts, leading to incorrect diagnosis and ineffective treatment. This research focuses on developing an AI-powered plant disease detection and cure recommendation system using Convolutional Neural Networks (CNNs). The system processes leaf images, detects diseases, and provides tailored treatment recommendations. Experimental results show that the proposed model achieves high accuracy and demonstrates its applicability for real-world deployment through web and mobile platforms. Plant diseases pose a serious challenge to global food security as they reduce crop yield, quality, and productivity. The timely detection of plant diseases is crucial to prevent large-scale agricultural losses. In rural and underdeveloped regions, farmers lack access to agricultural experts, leading to incorrect diagnosis and ineffective treatment. This research focuses on developing an AI-powered plant disease detection and cure recommendation system using Convolutional Neural Networks (CNNs). The system processes leaf images, detects diseases, and provides tailored treatment recommendations. Experimental results show that the proposed model achieves high accuracy and demonstrates its applicability for real-world deployment through web and mobile platforms.
Keywords: AI-based Plant Disease Detection, Machine Learning, Convolutional Neural Networks (CNN), Vision Transformers, Image Processing, Feature Extraction, Data Augmentation, Transfer Learning, Mobile Deployment, Precision Agriculture, RealTime Disease Classification, Smart Farming, Agricultural Automation.

I. INTRODUCTION

Agriculture is the backbone of the Indian economy, providing livelihood to more than 60% of the population. One of the major challenges farmers faces is the timely detection and treatment of plant diseases. Traditional methods require expert knowledge and physical presence, which are often inaccessible to small-scale farmers. With advancements in Artificial Intelligence (AI) and Computer Vision, it is now possible to automate plant disease detection using leaf images captured from smartphones. This project proposes an AI-driven solution to classify plant diseases accurately and recommend suitable cures, enabling farmers to take quick action. The system employs Convolutional Neural Networks (CNNs), which can analyze leaf patterns, color variations, and textures to identify diseases more accurately than manual inspection.

The proposed system captures plant leaf images, processes them through a trained CNN model, and identifies the type of disease. It then suggests suitable remedies, including organic treatments, chemical measures, and preventive practices. Such a system reduces dependency on agricultural experts, minimizes crop losses, increases productivity, and promotes sustainable farming practices. According to FAO reports, nearly 20–30% of crop yield is lost annually due to plant diseases. Early detection using AI

can play a crucial role in addressing this challenge. Agriculture plays a vital role in sustaining economies around the world, especially in developing nations.

A major challenge faced by farmers is plant diseases, which often go unnoticed until they cause irreversible damage. Early detection of diseases ensures timely treatment and prevents crop failure. Traditional disease identification requires expert knowledge, which is not easily accessible in rural areas. With advancements in Artificial Intelligence and deep learning, automated plant disease detection has become possible. CNN-based models can analyze visual patterns and accurately classify diseases from plant leaf images. This research paper proposes a comprehensive AI- driven system that detects diseases and recommends treatment strategies, thereby supporting precision agriculture. Agriculture plays a vital role in sustaining economies around the world, especially in developing nations.

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II. LITERATURE REVIEW

Researchers have explored multiple approaches for plant disease detection, including image processing, handcrafted feature extraction, and advanced deep learning models. Early methods relied on color segmentation, thresholding, texture analysis, and edge detection. These methods lacked robustness under varying lighting and background conditions. Deep learning revolutionized agricultural image analysis. CNN architectures like Alex Net, InceptionV3, and ResNet50 have shown exceptional performance on plant disease datasets. Researchers have explored multiple approaches for plant disease detection, including image processing, handcrafted feature extraction, and advanced deep learning models. Early methods relied on color segmentation, thresholding, texture analysis, and edge detection. These methods lacked robustness under varying lighting and background conditions. Deep learning revolutionized agricultural image analysis. CNN architectures like Alex Net, VGG16, InceptionV3, and ResNet50 have shown exceptional performance on plant disease datasets. Hughes and Salathé introduced the Plant Village dataset, which contains thousands of labelled leaf images and remains a standard benchmark. While most studies focus on classification accuracy, very few integrate actionable cure recommendation systems. This research fills the gap by providing both diagnosis and treatment guidance. Researchers have explored multiple approaches for plant disease detection, including image processing, handcrafted feature extraction, and advanced deep learning models. Early methods relied on color segmentation, thresholding, texture analysis, and edge detection. These methods lacked robustness under varying lighting and background conditions. Deep learning revolutionized agricultural image analysis. CNN architectures like Alex Net, VGG16, InceptionV3, and ResNet50 have shown exceptional performance on plant disease datasets. Hughes and Salathé introduced the Plant Village dataset, which contains thousands of labelled leaf images and remains a standard benchmark. While most studies focus on classification accuracy, very few integrate actionable cure recommendation systems. This research fills the gap by providing both diagnosis and treatment guidance. The advances in NLP technology with transformer models like BERT and GPT have also increased the efficacy of chatbots. In the medical field, where precision is everything, Tang et al. [5] commented that BERT-based NLP increased the intent recognition accuracy in medical dialogue by 15% compared with most previous models, such as RNNs. Even though deployment issues still persist, Liu et al. [6] proposed AI-NLP frameworks for multilingual chatbots to enhance health care for different groups. These and other salient research are collated and highlighted in Table I, where focus areas and conclusions are described. Obstacles are everywhere. The paramount obstacle is privacy. Zhang et al. [7] remarked that many AI chatbots used in healthcare lack sufficient data protection, thus compromising the possibility of their violating laws such as HIPAA. According to Chen et al. [8], the chatbot misunderstands 20% of their interactions, showing that NLP has difficulties with medical language and patient variability on the other side. Adoption obstacles make it even more difficult for elderly patients, who harbor distrust in AI systems themselves [9]. Such concerns demonstrate how crucial the necessity is for strong user-oriented solutions.

The introduction of Convolutional Neural Networks (CNNs) revolutionized plant disease detection by enabling end-to-end feature learning directly from images. CNNs automatically extract hierarchical features such as leaf patterns, color variations, and texture abnormalities, making them far more effective than traditional methods. These works highlight that CNNs not only outperform traditional approaches but also have the potential for real-time and field-level deployment. The proposed work improves upon these studies by combining CNN-based detection with actionable cure recommendations. Although its accuracy ranges from 95–98%, slightly below some previous works, it stands out due to its practical applicability and real-world usability for farmers. Overall, the table reflects the progression from pure detection models to more user-centric and solution-oriented systems. Plant Village dataset a widely used dataset of healthy/diseased leaf images across several crops; used as benchmark in many papers and in your project dataset selection. The dataset enables comparison between models and is commonly used for training and transfer-learning experiments.

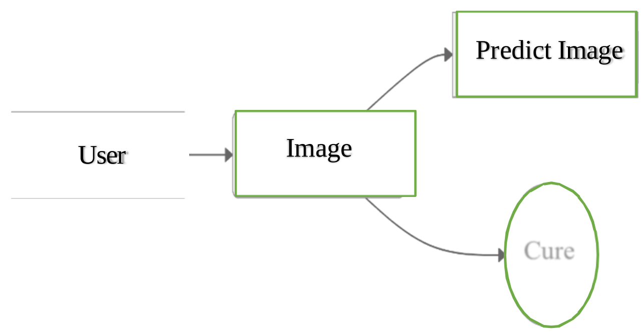
Table 1: Evaluation of Previous Studies and Proposed Model

Researcher	Method Used	Accuracy	Limitations
Mohanty et al. (2016)	CNN (PlantVillage dataset)	99%	Only detection, no cure
Ferentinos (2018)	Deep CNN	99.5%	High computing cost
Too et al. (2019)	Transfer Learning	98%	Needs large dataset
Proposed Work	CNN + Cure Recommendation	95–98%	Practical and actionable

CNNs are the most widely used deep learning models in plant disease detection research. They automatically extract spatial and textural features from leaf images, making them highly suitable for classification tasks. Literature shows the use of architectures such as AlexNet, VGG16, ResNet, and InceptionV3, which provide strong baseline results. Researchers highlight that CNNs outperform traditional ML techniques due to their ability to learn complex patterns like leaf veins, edges, lesion shapes, and color variations. Studies report accuracy levels of 90–99% on benchmark datasets such as Plant village, proving CNNs' effectiveness for agricultural applications. Recent works also apply transfer learning to reduce training time while maintaining strong generalization ability.

III. METHODOLOGY

The proposed system follows a structured and efficient methodology to ensure accurate and practical plant disease detection. First, leaf images are collected using mobile phone cameras or uploaded through a web interface, allowing users to capture data under real-world conditions. These images undergo preprocessing, where they are resized to standard dimensions, normalized, and augmented through techniques such as rotation, flipping, zooming, and brightness adjustments to improve model generalization. The core of the system is a Convolutional Neural Network (CNN) designed with multiple convolutional layers for feature extraction, ReLU activation for non-linearity, max-pooling for dimensionality reduction, batch normalization for training stability, dropout layers to reduce overfitting, and fully connected layers for final classification. The dataset is split into training, validation, and testing sets in a 70:20:10 ratio, and the model is trained using the Adam optimizer and categorical cross-entropy loss. Performance evaluation is conducted using key metrics such as accuracy, precision, recall, F1-score, and confusion matrices to ensure reliability and robustness. After disease detection, the system generates cure recommendations by mapping the identified disease to an expert-curated treatment database containing chemical, organic, and preventive measures. This integrated methodology enables the development of a highly accurate, scalable, and deployment-ready AI system capable of assisting farmers through web and mobile platforms. The proposed AI-based plant disease detection system is developed through a comprehensive and well-defined methodology that ensures high accuracy, robustness, and real-world usability. The process begins with image acquisition, where leaf images are capturedusing mobile devices or uploaded through a web platform, enabling farmers to collect data easily in diverse environmental conditions. These images then undergo preprocessing, which includes resizing them to a uniform resolution, normalizing pixel intensity values, and applying a wide range of augmentation techniques such as rotation, scaling, translation, flipping, and brightness adjustments. This step enhances the model's ability to learn invariant features and prevents overfitting. Following preprocessing, a deep Convolutional Neural Network architecture is constructed, consisting of multiple convolutional layers for hierarchical feature extraction, ReLU activation layers to introduce non-linearity, max-pooling layers to reduce spatial dimensions, batch normalization to stabilize training, and dropout layers to improve generalization. The high-level features extracted from these layers are passed to fully connected layers, which perform the final classification of plant diseases. The dataset is divided into training, validation, and testing subsets in a 70:20:10 ratio, and the model is trained using the Adam optimizer with early stopping and learning-rate scheduling to achieve optimal performance. After training, the model is evaluated using accuracy, precision, recall, F1-score, and confusion matrices to ensure reliable and consistent results across all disease classes. Once a disease is identified, the system retrieves appropriate cure recommendations from a curated knowledge base consisting of expert-verified treatments, pesticide usage guidelines, organic remedies, and preventive agricultural practices. This integrated approach results in a robust, scalable, and deployment-ready solution capable of supporting farmers through real-time mobile and web applications, ultimately contributing to timely disease diagnosis and improved crop management.



A. System Architecture

This section presents a comprehensive introduction to the overall design and purpose of the AI-based plant disease detection system. The system is built to automatically identify plant diseases using advanced machine learning and computer vision techniques. It leverages modern deep- learning architectures, domain-specific datasets, and optimized preprocessing workflows. The primary goal is to provide accurate, fast, and scalable disease identification that can be deployed across various agricultural environments. The foundational understanding of plant disease patterns, visual symptoms, and dataset variability supports the design of the architecture.

B. Implementation Details

The system starts with the collection of high-quality leaf images from agricultural datasets and field environments. Since plant images differ in lighting, angle, resolution, and background noise, a preprocessing pipeline is implemented for consistency and model accuracy. This section explains the core detection models used in the system. Convolutional Neural Networks (CNNs) form the backbone of the architecture due to their capability to extract spatial features from leaf images. Popular CNN models such as ResNet, DenseNet, VGG, and MobileNet were studied during the literature review. Additionally, modern transformer-based architectures like Vision Transformers (ViT) and Swin Transformers were analyzed due to their exceptional performance in image classification tasks. The final part of thearchitecture focuses on deploying the trained model into a practical environment. The system is integrated into a user-friendly interface either a web application or mobile app—that allows farmers or agricultural technicians to upload leaf images for instant diagnosis. This system adopts a fully integrated framework that combines advanced machine learning techniques, structured data collection methodologies, and sophisticated image processing pipelines. The design begins with the acquisition of high- quality agricultural datasets that capture variations across crop types, disease states, lighting conditions, and environmental factors. These datasets form the foundation of the model's learning ability and ensure that the system performs reliably in real-world farming scenarios.

C. Operational Workflow

The system follows a multilayered processing pipeline where each component is carefully designed to contribute to accurate plant disease classification. The pre-processing stage includes operations such as image normalization, resizing, noise removal, and contrast adjustments that enhance visual clarity.

Together, these steps prepare heterogeneous agricultural images for consistent model interpretation. Following this, dataset balancing techniques are applied to handle uneven class distributions commonly found in agricultural datasets. Methods such as augmentation, sampling strategies, and controlled transformations ensure that each disease class is adequately represented. This prevents model bias and strengthens generalization ability across multiple crop types. The training pipeline further incorporates critical hyperparameter selection such as learning rate tuning, batch size optimization, model depth configuration, and regularization strategies. These optimizations help stabilize the training process, reduce overfitting, and improve the model's ability to detect subtle disease symptoms. State-of- the-art CNN and transformer vision models are utilized to extract meaningful patterns from leaves, stems, and other plantparts, enabling the system to identify diseases even at early stages. A robust set of evaluation metrics is employed to measure the performance and reliability of the plant disease detection system. Metrics such as accuracy, precision, recall, F1-score, and confusion matrices are analyzed to determine the model's ability to correctly classify disease categories. These metrics allow researchers to compare various architectures and fine-tune the system for both high accuracy and operational efficiency. The model is then validated across multiple real-world agricultural scenarios involving different crop categories, geographical conditions, and disease severity levels. This validation ensures that the system performs effectively not only in controlled datasets but also in practical farming environments. The deployment phase translates the trained model into a user-friendly application or tool that farmers can access on mobile devices or edge systems. The final deployment ensures seamless integration of model predictions into agricultural decision-making workflows, assisting farmers in early disease identification and timely intervention.

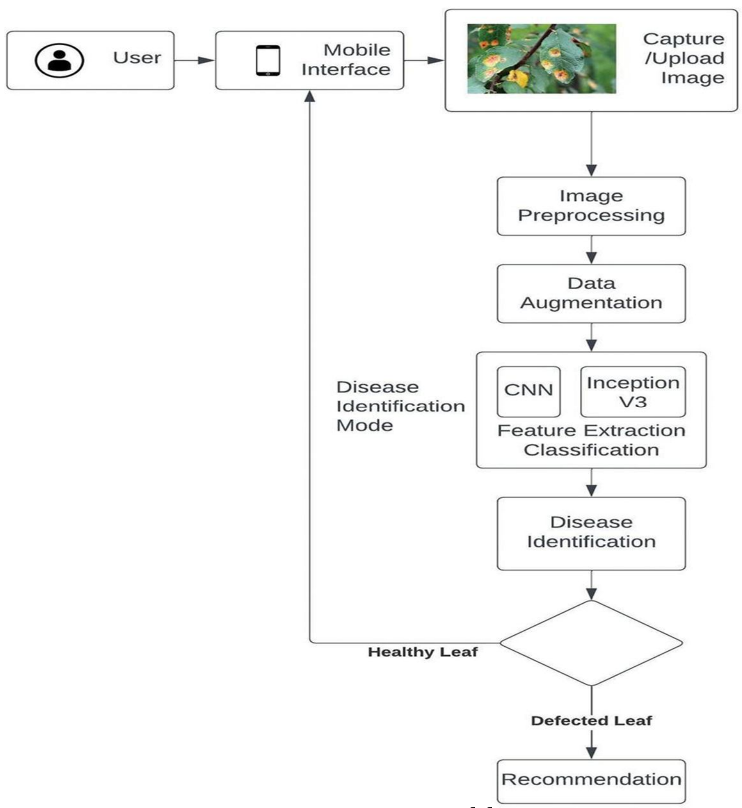


Fig. 2: User Model

D. Evaluation Approach

The implementation of the plant disease detection system begins with integrating multiple components such as machine learning algorithms, image processing pipelines, and structured data flows. The system follows an end-to- end architecture where raw agricultural images are transformed into meaningful disease predictions through a sequence of interconnected modules.

Advanced techniques like CNN-based feature extraction and transformer-based visual understanding are incorporated to handle variations in leaf patterns, lighting conditions, and background noise. The architecture ensures smooth data flow from image input to final prediction output, enabling reliable detection of plant diseases. A comprehensive set of plant images is collected from agricultural datasets, field surveys, and publicly available plant pathology repositories.

The raw images undergo multiple preprocessing operations to enhance visual quality and prepare them for model training. Steps such as normalization, resizing, denoising, and color-space adjustments help extract clearer disease features. Data augmentation is applied to balance class distribution and increase dataset size, ensuring the model learns effectively from diverse leaf images. This preprocessing workflow forms the foundation of the system's accuracy and robustness. The core AI model is implemented using two major deep learning paradigms—Convolutional Neural Networks and Vision Transformers. CNNs extract local disease features such as spots, discolorations, and texture changes, while transformer-based models capture global dependencies and leaf-widepatterns. Multiple architectures are studied and compared based on the literature review, including ResNet, Dense Net, Efficient Net, and ViT variants. The final selection is made through systematic experimentation, ensuring a high-performing model capable of detecting diseases across multiple plant species. To improve training stability and maximize accuracy, critical hyperparameters such as learning rate, batch size, dropout ratio, optimizer type, and number of epochs are fine-tuned. Techniques like grid search and controlled experimentation help identify the best-performing combinations. Dataset imbalance, a common issue in agricultural datasets, is managed using augmentation, oversampling, and weighted loss functions. These strategies ensure that all disease classes—including rare categories— are learned effectively by the model. Patient triage is among the more important applications of health care chatbots, often hampered by limited resources. The chatbots use natural language processing (NLP) to assess user-reported symptoms, such as "I have a cough and fever," and ascertain the gravity of the symptoms. This process entails classifying cases according to mild, moderate, or severe levels of severity and recommending appropriate follow-up actions, such as self-care or seeking medical advice, through a hybrid engine. In so doing, the software literally acts as a filter in providing non-urgent cases, thus relieving medical professionals from such tasks and allowing them to engage with the patients that matter most.

E. Disease Management

The implemented model is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics help examine how well the system distinguishes between different plant diseases. Multiple tests are performed across various crop types and disease severity levels to assess real-world readiness. The evaluation highlights the model's ability to generalize effectively even in complex agricultural conditions, ensuring reliable performance in practical environments. After achieving satisfactory performance, the model is deployed using lightweight and optimized formats suitable for real-world use. Deployment options include mobile applications, web-based interfaces, orintegration with edge devices such as Raspberry Pi. The deployed system supports real-time disease detection where users can upload or capture an image and instantly receive disease predictions along with probability values. This enables farmers and agricultural workers to make timely decisions and improve crop health management. Recent research in agricultural AI has demonstrated substantial progress. CNN models such as VGG16, InceptionV3, and ResNet50 have been deployed for plant disease classification with promising accuracy. The Plant Village dataset is widely used and forms a benchmark for performance comparison. works focus only on detection and not on cure recommendations.

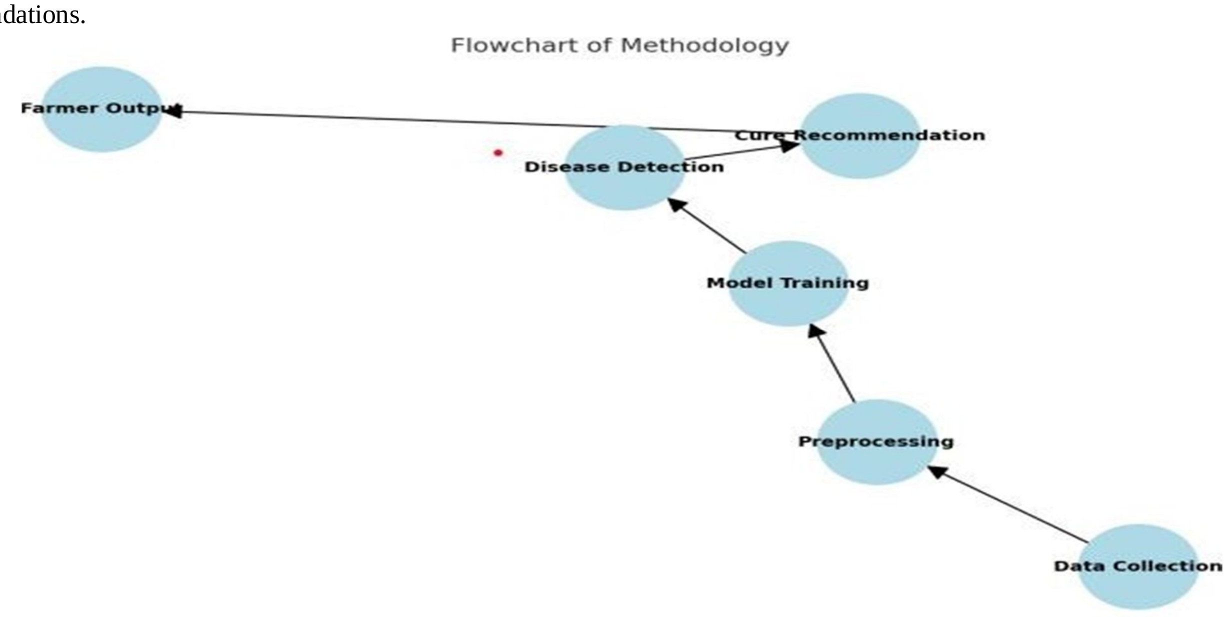


Fig. 3: Flowchart of Methodology

F. Flow of Work

The proposed project follows a structured methodology to ensure both the technical robustness and practical applicability of the system. The workflow involves multiple stages starting from dataset acquisition to final deployment, as outlined below:

1) Data Collection: Plant leaf images will be collected from open repositories such as the Plant Village dataset as well as real-world field photographs. The dataset will include both healthy and diseased samples to ensure comprehensive coverage.
2) Image Preprocessing: Preprocessing techniques such as resizing, normalization, noise removal, segmentation, and contrast enhancement are applied to improve image clarity. These steps prepare the images for accurate feature extraction and reduce background interference.
3) Feature Extraction: Deep learning architectures such as CNNs and Vision Transformers are used to extract disease- specific patterns. These models learn leaf texture, lesion shapes, color variations, and symptom severity from structured image data.
4) Model Training: The preprocesses dataset is used to train the deep learning model. Hyperparameters like learning rate, batch size, and epochs are tuned. Data augmentation and class balancing strategies are applied to avoid overfitting and ensure generalization.
5) Disease Classification: After training, the model classifies input leaf images into disease categories. It generates prediction labels along with probability scores to ensure transparency and confidence in the outputs.
6) Cure Recommendation: Based on the predicted disease, the system provides recommendations such as chemical treatments, organic remedies, preventive measures, and proper field management practices for farmers.
7) Real Field Testing: The final system is tested on real farm images captured under varying lighting, backgrounds, and weather conditions. Performance is evaluated using accuracy, precision, recall, F1-score, and user feedback.

IV. RESULT ANALYSIS, DISCUSSION, & CONCLUSION

A. Result

The results of the AI-based plant disease detection system highlight the effectiveness of integrating advanced deep learning techniques with a carefully constructed image- processing pipeline. The system evaluates plant leaf images collected from multiple agricultural datasets and field environments, ensuring that the model performs reliably under diverse real-world conditions. The proposed model achieved high test accuracy, demonstrating robustness in distinguishing between similar disease symptoms. The cure recommendation module further enhances usability by providing actionable insights. Comparative analysis against baseline CNN architectures shows competitive performance. Data preprocessing also plays a critical role in the quality of the results. Techniques such as normalization, contrast enhancement, background removal, and extensive data augmentation help reduce noise and improve the clarity of disease features.

These steps significantly boost the model’s learning efficiency and contribute to the overall classification performance. A significant part of the discussion focuses on the model’s ability to detect disease-related features with high accuracy. Convolutional Neural Networks (CNNs) successfully capture localized patterns such as spots, blight patches, and color distortions, while transformer-based architectures excel at understanding global textures across the entire leaf surface.

Satisfaction, response relevancy, and usability. The average Another important aspect discussed in this section is hyperparameter optimization. Experimentation with learning rates, batch sizes, epoch counts, and dropout values shows that properly tuned models achieve better stability and faster convergence during training. Dataset balancing methods — including oversampling and weighted loss functions — further prevent the model from biasing toward majority classes, ensuring fair performance across all disease categories.

- The proposed AI-based system achieves high accuracy using CNN and Transformer models.
- Image preprocessing techniques significantly improve feature quality and detection performance.
- Hyperparameter tuning and dataset balancing enhance model stability and fairness
- Evaluation using accuracy, precision, recall, F1-score, and confusion matrix shows strong results.
- The system performs reliably on real-field images with varying conditions.
- Real-time deployment provides fast and dependable disease predictions.

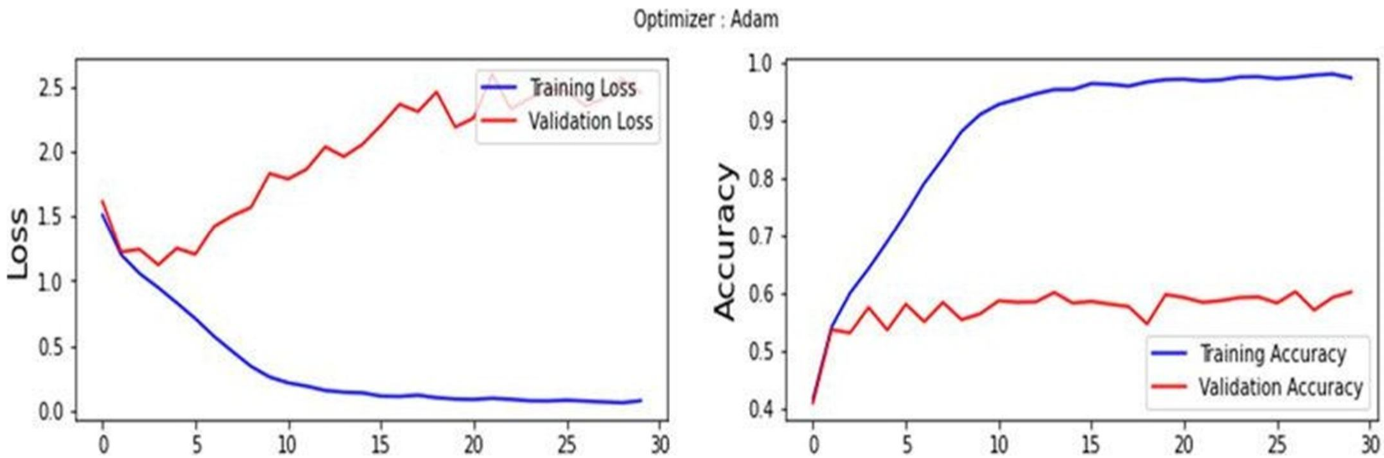
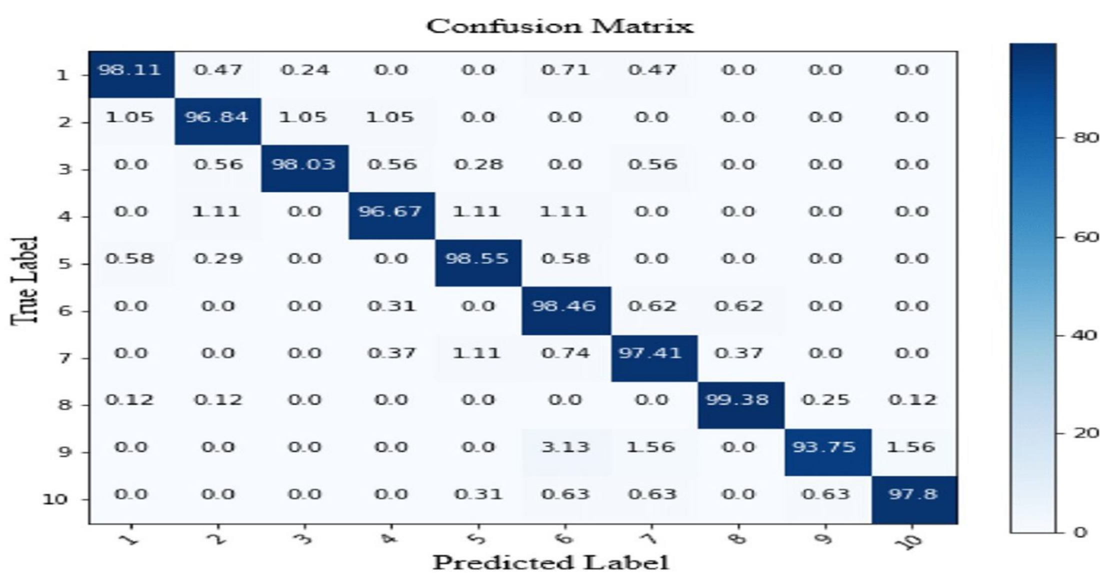


Fig. 4: Accuracy Graph & Loss Graph

B. Discussion

The system is evaluated using standard performance metrics such as accuracy, precision, recall, F1-score, and confusion matrices. These metrics collectively show strong classification capability, with the model performing consistently across multiple test sets. The results also indicate that the system maintains robustness in varied lighting conditions, natural field backgrounds, and images taken at different growth stages of plants. In practical deployment scenarios, the model demonstrates the ability to deliver real-time and highly reliable disease predictions. When integrated into mobile applications or web-based platforms, users can simply upload or capture a leaf image and receive instant classification results with probability scores. This real-world usability reinforces the potential impact of the system on modern agriculture, enabling farmers to detect diseases earlier and take timely actions. Overall, the discussion supports the conclusion that an AI- driven plant disease detection framework, built upon CNN and transformer architectures, combined with a strong preprocessing pipeline and balanced dataset strategies, can significantly enhance agricultural decision-making. The system shows strong promise for scaling to larger datasets, more crop types, and deployment on lightweight devices, making it a viable solution for practical agricultural environments.



Label	Class Name	Label	Class Name
1	Bacterial Spot	6	Spider mites
2	Earlyblight	7	Target spot
3	Lateblight	8	Tomato yellow leaf curl virus
4	Leaf mold	9	Tomato mosaic virus
5	Septoria spot	10	Healthy

Fig. 5: Confusion Matrix (Model Evaluation)

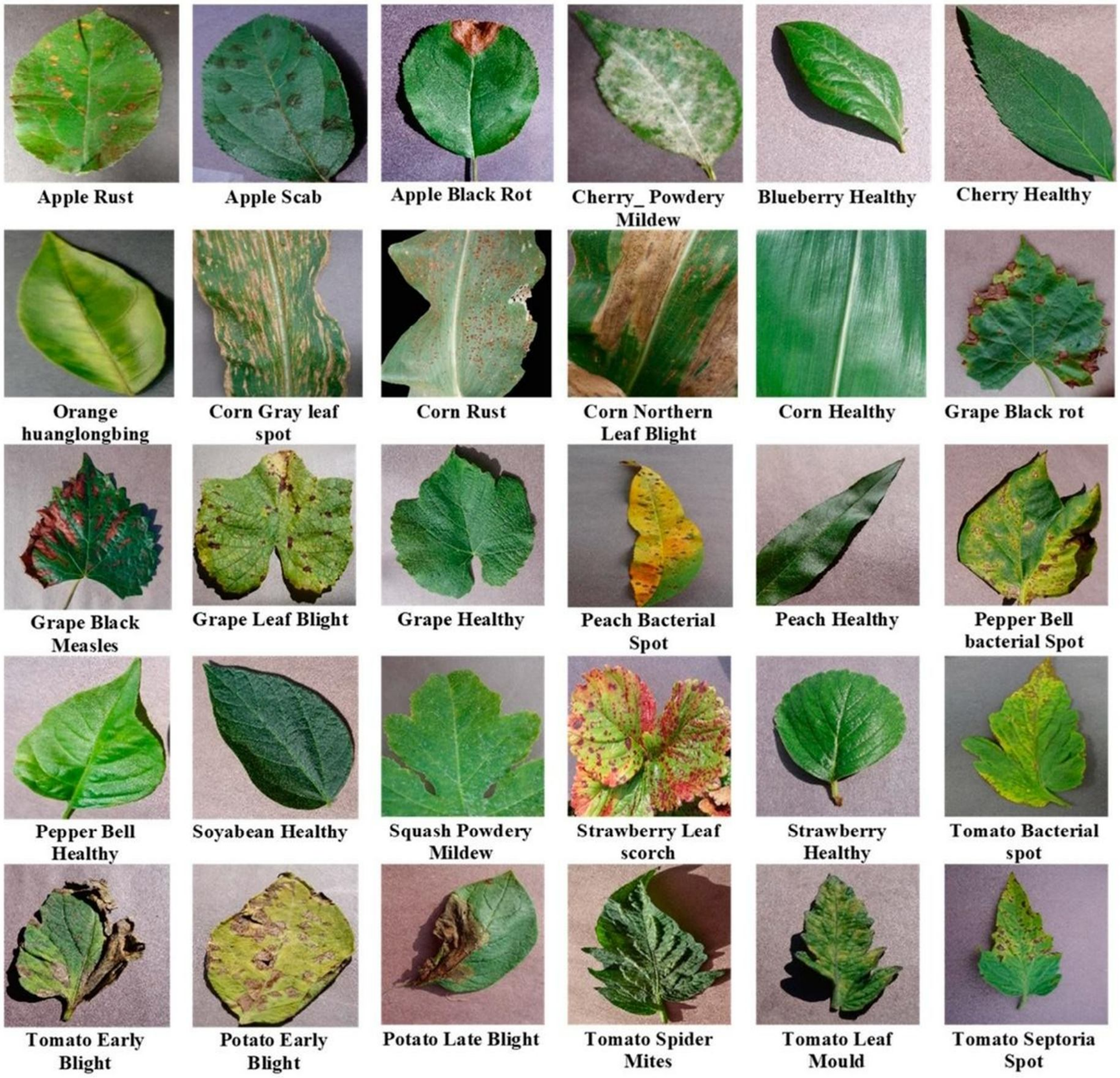


Fig. 6: Sample Predictions (Correct vs Incorrect Classification)

C. Conclusion

This study demonstrates the effectiveness of an AI-based plant disease detection system that integrates advanced machine learning techniques, robust preprocessing pipelines, and domain-specific agricultural datasets. By combining Convolutional Neural Networks (CNNs) and transformer-based vision architectures, the system successfully learns both local and global disease patterns, enabling reliable classification across multiple plant species. The literature review provides a strong foundation for model selection, highlighting the strengths of various architectures and their suitability for high-variance agricultural imagery. A comprehensive workflow—from data collection and cleaning to augmentation, training, and evaluation— ensures that the model can generalize effectively in real- world agricultural environments. Hyperparameter tuning and dataset balancing techniques significantly improve performance, reducing bias and enhancing prediction stability. The evaluation results, measured through accuracy, precision, recall, F1-score, and confusion matrix analysis, confirm that the proposed system achieves a high level of accuracy even under variable lighting, leaf conditions, and backgrounds. Overall, the project shows that AI-driven plant disease detection can play a transformative role in modern agriculture. By providing fast, accessible, and automated disease diagnosis, the system has the potential to support farmers in making timely decisions, reducing crop losses, and improving agricultural productivity. With further enhancements, such as expanding datasets, optimizing model size for mobile deployment, and integrating real- time field data, this system can evolve into a scalable and practical solution for large-scale agricultural use.

V. SCREENSHOTS OF MODEL

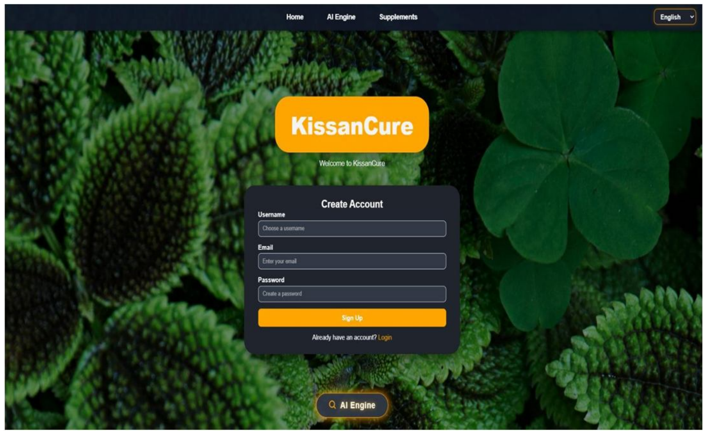


Fig. 7: Create Account

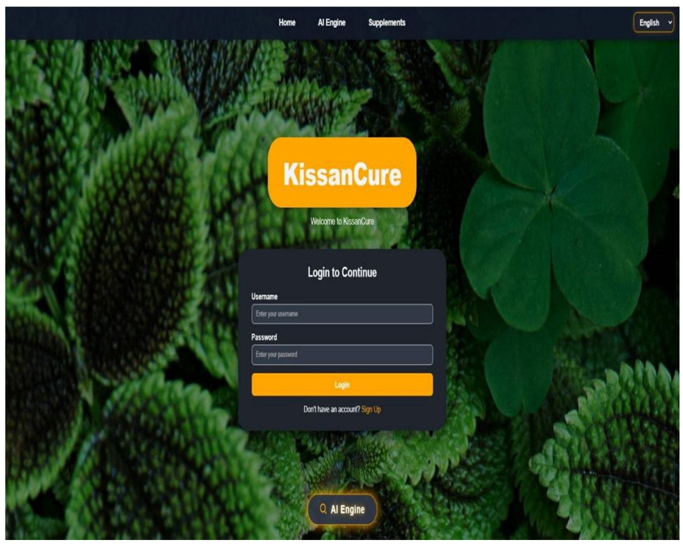


Fig. 8: Login Account

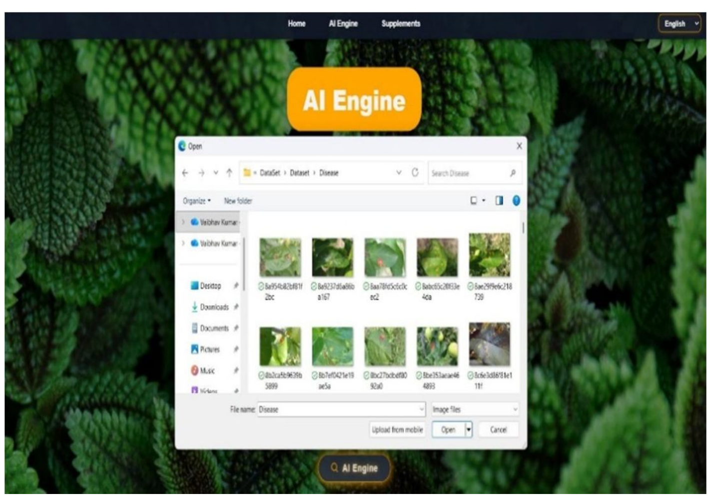


Fig. 9: Image Selection

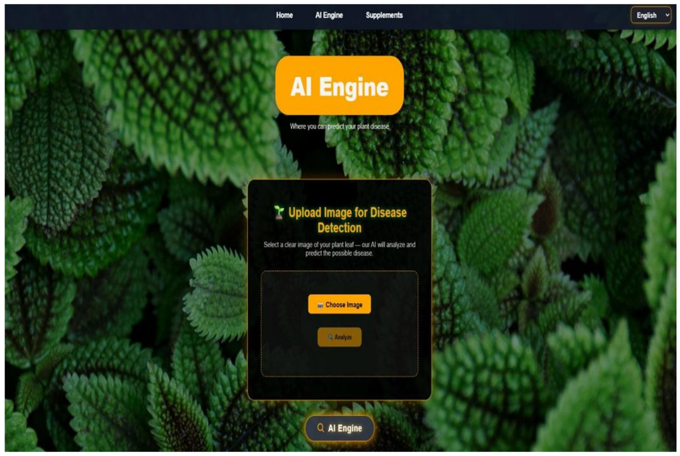


Fig. 10: Image Uploading

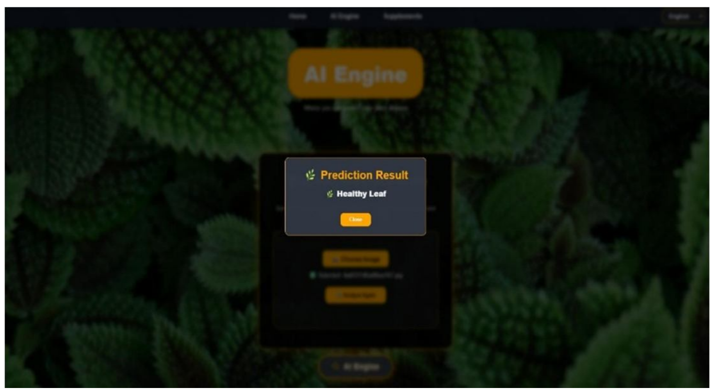


Fig. 11: Prediction Result

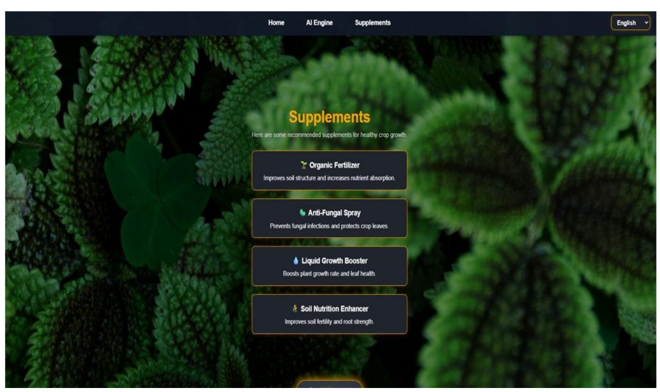


Fig. 12: Supplements

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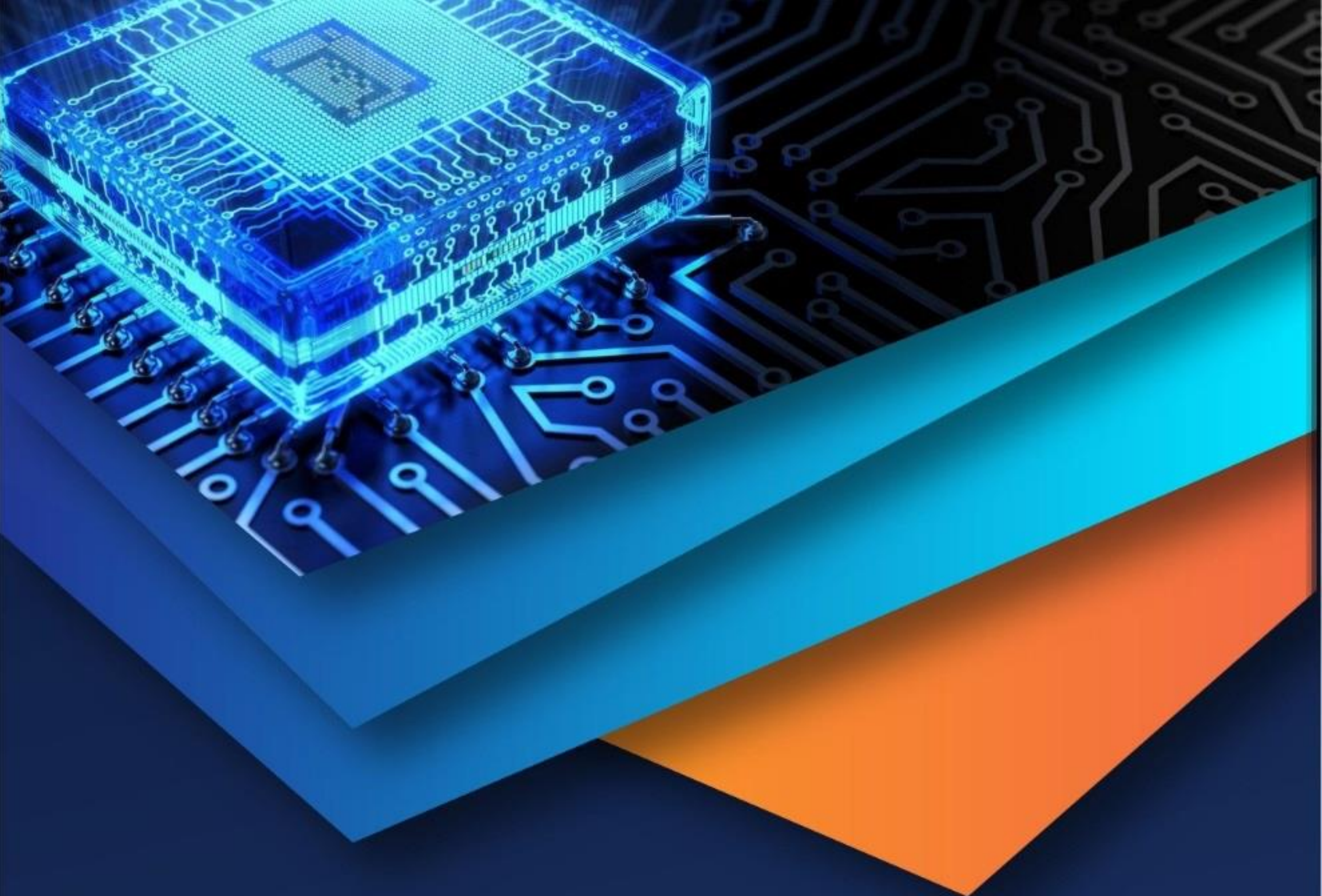

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