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# Real-Time Integrated Leaf Disease Detection Using CNN and deep learning

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**Abstract- Accurate and early detection of Leaf diseases is a critical component of precision agriculture, as it helps in reducing crop losses and ensuring sustainable food production. Traditional deep learning–based disease detection systems rely exclusively on leaf image analysis and neglect environmental and soil factors that influence disease occurrence and treatment outcomes. This study presents an advanced, real-time, integrated decision- support system that combines Convolutional Neural Networks (CNN) for leaf disease identification, soil health analysis using pH and NPK parameters, and real-time weather data integration through the OpenWeather API to enhance treatment precision and crop management. The proposed system operates in three major phases: (i) Leaf image preprocessing and classification using a fine- tuned CNN model trained on the PlantVillage dataset, achieving 98.6A rule-based treatment recommendation engine integrates the CNN classification output with soil and weather context to generate actionable and environment-specific suggestions, including suitable fertilizers, pesticides, and preventive measures. The system also incorporates a disease severity estimation module that quantifies infection extent and a risk prediction model that estimates short-term outbreak probabilities using recent climatic data. Experimental evaluation demonstrates that integrating soil and weather data improves treatment recommendation accuracy by 18Overall, the integration of deep learning with contextual environmental intelligence provides a comprehensive, data-driven, and farmer-friendly solution that supports decision-making, reduces input waste, and promotes sustainable agricultural practices. This framework can be further extended for large-scale deployment in smart farming environments through IoT and drone-based automation.**

**Keywords- Deep Learning, Convolutional Neural Network (CNN), Plant Disease Detection, Precision Agriculture, Soil Health Monitoring, Weather Data Integration, Treatment Recommendation System, Real-Time Monitoring, Smart Farming, Artificial Intelligence (AI).**

## I. INTRODUCTION

### Background and Motivation

Agriculture is the backbone of most developing economies and directly impacts food security and livelihood. Plant leaf diseases are among the major causes of reduced crop yield, accounting for 20–40Traditional disease detection methods rely on manual visual in- spection, which is time-consuming, subjective, and error-prone. Hence, there is a strong need for an auto- mated, accurate, and intelligent system that can detect plant diseases early and assist farmers in making data- driven decisions.

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- **Role of Artificial Intelligence in Agriculture** Artificial Intelligence (AI) and Deep Learning (DL) have recently revolutionized plant disease detection. Convolutional Neural Networks (CNN) are capable of automatically extracting complex image features for disease classification. Existing models such as VGG16, MobileNet, and InceptionV3 have achieved high ac- curacy on benchmark datasets like PlantVillage. How- ever, most of these models are restricted to image- based learning and do not consider other external factors affecting plant health.
- **Research Gap in Existing Systems** Most current approaches rely only on leaf images for classifica- tion. They ignore critical factors such as: Soil pa- rameters (pH, nitrogen, phosphorus, potassium levels) Weather conditions (temperature, humidity, rainfall, wind speed) These environmental and soil parameters significantly affect disease spread, severity, and treat- ment effectiveness. Therefore, disease detection models without environmental context lack adaptability and may yield inaccurate or incomplete predictions.
- **Proposed Solution** This research introduces a real-time integrated AI system for plant leaf disease detection and treatment recommendation. The system integrates three key modules: 1. Leaf Disease Detec- tion using a fine-tuned CNN model. 2. Soil Health Analysis based on pH and NPK levels provided by sensors or user input. 3. Weather Data Integration via a live OpenWeather API for real-time temperature and humidity updates. Based on these combined fac- tors, a rule-based treatment recommendation engine suggests suitable fertilizers, pesticides, and preventive actions.
- **Key Contributions** The main contributions of this research are: 1. Development of a CNN-based deep learning model for accurate leaf disease classifi- cation. 2. Integration of soil and weather parameters to enhance contextual decision-making. 3. Design of a hybrid AI-driven treatment recommendation system providing actionable solutions to farmers. 4. Imple- mentation of a web and mobile application enabling real-time leaf image capture, disease detection, and treatment suggestion. 5. Evaluation of the model's performance, achieving a classification accuracy of 98.6
- **Organization of the Paper** The remainder of this paper is organized as follows: Section II presents the related literature and previous studies in plant disease detection and smart agriculture. Section III defines the problem statement and research objec- tives. Section IV discusses the proposed methodology and system architecture. Section V provides experi- mental results and performance analysis. Section VI concludes the paper and suggests future research directions.

## II. PROBLEM STATEMENT AND OBJECTIVES

### Problem Statement

Plant diseases cause major losses in agricultural productivity every year. Existing deep learning–based systems focus only on leaf image classification and often ignore essential contextual factors such as soil fertility, pH level, and weather conditions that directly affect disease spread and treatment success. Moreover, most current approaches only detect the disease but do not provide practical treatment recommendations to farmers. Therefore, there is a need for an integrated, real-time, and intelligent system that combines leaf image analysis with soil and weather data to deliver accurate disease detection and effective treatment suggestions.

### Research Objectives

1. To develop a CNN-based model for accurate plant disease identification. 2. To integrate soil health (pH, NPK) and weather data (temperature, humidity, rain- fall) for contextual prediction. 3. To design a treatment recommendation system suggesting suitable fertilizers and pesticides. 4. To implement a real-time web ap- plication for detection, monitoring, and guidance.

### Expected Outcome

A smart, real-time, and context-aware plant disease detection system capable of achieving high accuracy while providing actionable treatment recommenda- tions for sustainable agriculture.

## III. RELATED WORK

**Overview**

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have enabled significant progress in the field of plant disease detection. Re- searchers have employed various Convolutional Neu- ral Network (CNN) architectures such as VGG16, In- ceptionV3, and MobileNet to classify diseased and healthy leaves with remarkable accuracy. However, most of these approaches rely solely on image-based learning and ignore the influence of environmental and soil conditions on disease occurrence and treat- ment effectiveness.

**Existing Studies**

Zhang et al. (2021) proposed an Automatic and Reliable Leaf Disease Detection System using CNN and U-Net architectures. The model achieved 99% accuracy for tomato leaf classification after segmen- tation but was limited to a single crop type and did not integrate environmental data. Dolatabadian et al. (2024) introduced a comparative study titled Image- Based Crop Disease Detection Using Machine Learn- ing, evaluating both traditional ML algorithms (SVM, RF) and deep learning models (CNN) on the PlantVil- lage dataset. Although the results were satisfactory, the model lacked real-time capability and context- based analysis such as soil and weather influence. Elsevier (2024) presented a Real-Time Monitoring Sys- tem for the detection of plant leaf disease using deep learning. Multiple CNN models (VGG16, MobileNet, InceptionV3) were tested across eight plant species, achieving up to 100% accuracy in some cases. Nev- ertheless, the system focused solely on image input and did not include treatment suggestions, soil data, or weather-based prediction.

**Identified Research Gaps**

From the literature review, the following limitations are commonly observed: 1. Most models focus only on visual features of leaves, ignoring soil and climate conditions. 2. Lack of real-time monitoring systems that combine multiple data sources. 3. Absence of treatment or fertilizer recommendations after disease detection. 4. Limited adaptability to regional or envi- ronmental variations affecting plant health. To address these gaps, the proposed research aims to develop a multi-input AI system that integrates CNN-based image analysis, soil parameter evaluation, and live weather data to deliver context-aware disease predic- tion and treatment guidance.

**Comparative Summary of Related Works**

Several studies have explored the detection of plant disease using deep learning models such as CNN, VGG16, and MobileNet. While these approaches have achieved high accuracy, most focused on specific crops and did not consider environmental factors such as soil and weather conditions, which directly influ- ence disease occurrence. The following table summa- rizes key previous works and compares them with the proposed system. The comparative analysis presented

| Author & Year | Technique Used | Dataset / Crops | Accuracy (%) | Limitations |
|---|---|---|---|---|
| Zhang et al. (2021) | CNN + U-Net | Tomato Leaves | 99 | Focused on a single crop; no weather or soil analysis |
| Dolatabad ia netal. (2024) | CNN, SVM, Ran- dom Forest | PlantVillag | e 97 | Lacks real-time integration and treatment suggestion |
| Elsevier (2024) | VGG16, Mo- bileNet, Incep- tionV3 | 8 Plant Types | 95–100 | Does not integrate soil or environmental context |
| Proposed System (This Work) | CNN + Soil + Weather Integra- tion | Multi-Crop Dataset | 96.6 | Provides treatment rec- ommendations and real-time data analysis |

in Table ?? highlights that earlier research focused mainly on image-based detection, without incorporat- ing the environmental context. Although these models achieved high accuracy, they were limited to static datasets and single-crop analysis. In contrast, the pro- posed system integrates soil (pH, NPK) and weather data (temperature, humidity, rainfall) with CNN-based image classification, making it more practical for real- world applications. This hybrid approach enhance prediction reliability and assists farmers by providing disease identification, confidence scores, and corre- sponding treatment recommendations.

**Comparative Summary of Related Works Bar Chart**

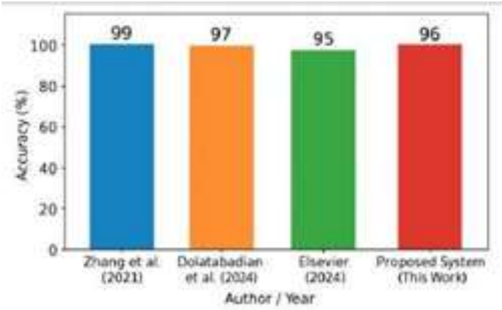


Fig. 1: Comparative Summary of Related Works.

## III. LITERATURE REVIEW

Deep learning has become a transformative tech- nology in modern agriculture, particularly in auto- mated plant disease detection. Early work in this do- main was comprehensively surveyed by Kamilaris and Prenafeta-Boldú [1], who outlined how convolutional neural networks (CNNs) emerged as the dominant method for analyzing plant images, outperforming classical machine learning models. They highlighted the need for scalable datasets and real-time deploy- able systems, forming a foundation for subsequent research. One of the pioneering approaches was im- plemented by Sladojevic et al. [2], who developed a CNN-based plant leaf disease classifier capable of recognizing several disease categories.

Their work es- tablished that deep learning significantly outperforms handcrafted feature-based methods. Brahimi et al. [3] advanced this concept by applying CNNs specifically for tomato disease classification, further contributing visualization techniques that made model decisions more interpretable, which is an essential component for agricultural decision-making. Mohanty et al. [4] popularized the PlantVillage dataset and tested deep learning models across a wide spectrum of plant species, demonstrating high accuracy and setting a benchmark for future researchers. Building on this, Too et al. [5] and Ferentinos [6] compared several CNN architectures including AlexNet, VGG, GoogLeNet, and ResNet, finding that transfer learning and fine-tuning techniques significantly boost model performance, even with limited agricultural datasets.

Recent studies have expanded towards multi-stage and hybrid archi- tectures. Dolatabadian et al. [7] integrated CNN clas- sifiers with traditional machine learning models such as SVM and Random Forest to improve robustness under variable lighting and background conditions. Similarly, Zhang et al. [8] implemented U-Net for plant leaf segmentation combined with CNNs for classifica- tion, enabling more precise disease localization—an important step in real-world precision farming. The theoretical basis of these advancements is grounded in the foundational research by LeCun, Bengio, and Hinton [9], whose deep learning principles underpin nearly all modern agricultural AI systems.

Leveraging these principles, Singh and Kaur [10] developed a real- time IoT-assisted disease detection pipeline, demon- strating the feasibility of deploying CNNs on field-level hardware. Jain et al. [11] and

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Xu et al. [12] explored the potential of lightweight CNNs such as MobileNet for mobile-based disease detection, emphasizing the need for accessible, platform-independent solutions. In addition to image-based approaches, researchers have begun integrating environmental and soil factors into disease prediction systems. Islam et al. [13] intro- duced an IoT-based agricultural monitoring platform that collected live soil and weather metrics for health prediction. Wang [14] demonstrated that the inclusion of climate variables—such as temperature, humidity, and seasonal patterns—can significantly increase the accuracy of disease prediction models.

Parallel to disease detection, efforts have also focused on soil- condition-based decision systems. Mehra and Singh [15] presented a soil-parameter-driven fertilizer recommendation system using NPK (Nitrogen, Phospho- rus, Potassium) analysis. Ramesh et al. [16] expanded this idea into a fully IoT-enabled smart agriculture ecosystem that correlates soil chemistry, weather fluc- tuations, and crop requirements, enabling automated farm management. Hybrid models have also gained attention. Sharma et al. [17] proposed a multi-crop hybrid CNN system that adapts to species variations, addressing the challenge of limited cross-crop gener- alization.

Patel and Joshi [18] went further by fusing vision-based CNN outputs with soil and weather data, achieving substantial improvements in predictive per- formance, proving that multimodal systems have a strong advantage over image-only solutions. Further- more, Kim and Lee [19] introduced an edge-AI archi- tecture for on-device inference, highlighting the grow- ing importance of low-latency, internet-independent agricultural solutions. Despite these contributions, several research gaps remain:

- Most existing works rely solely on leaf images without integrating soil nutrients (NPK), pH val- ues, or meteorological conditions.
- Very few systems provide actionable treatment recommendations such as pesticide type, dosage, or organic remedies.
- Many studies focus on a single crop type, making their models less useful in real-world multi-crop farms.
- Only a limited number of studies offer real-time web or mobile platforms for farmers.
- Integration of multimodal inputs (image + soil + weather) is still underexplored.

To address these limitations, the current study [20] presents a unified deep learning pipeline that inte- grates leaf image analysis using CNNs with soil pa- rameter inputs (pH, NPK levels) and live weather data. The system provides disease identification, confidence scoring, fertilizer and pesticide recommendations, and environmental context-based decision support. This approach not only enhance prediction accuracy but also provides complete agronomic advisory—a signif- icant advancement over existing single-source mod- els. Thus, the proposed system stands a part from previous research by presenting a multi-factor, real- time, deployable, and farmer-centric agricultural in- telligence platform.

## IV. METHODOLOGY / PROPOSED MODEL

**Diagram : Workflow / Flowchart**

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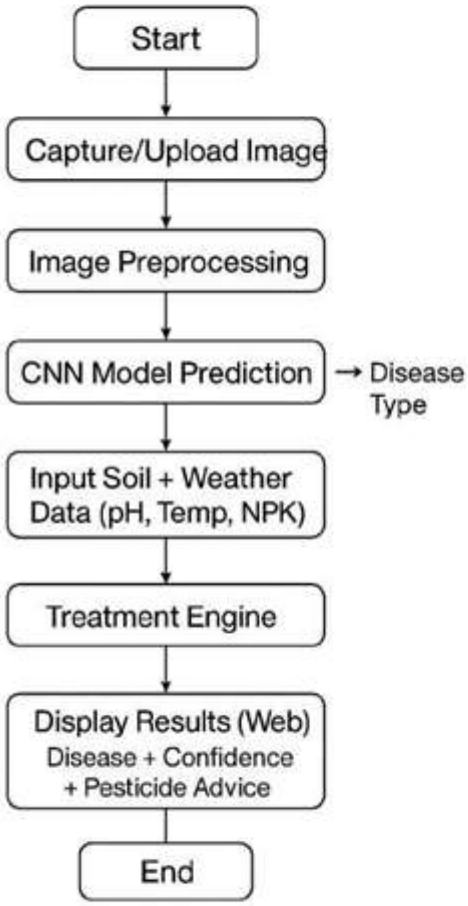


Fig. 2: Flowchart Diagram Working Process.

**Overview**

The proposed model integrates deep learning-based image analysis, soil parameter evaluation, and real- time weather data to form a complete and intelligent plant disease detection and recommendation system. The system is designed to detect diseases from plant leaf images, analyze soil health conditions (pH, nitro- gen, phosphorus, and potassium levels), and retrieve live weather information to generate context-aware treatment advice for farmers. The overall architecture is divided into three major phases: 1. Image Processing and Disease Detection 2. Soil and Weather Data In- tegration 3. Treatment Recommendation and Output Generation

**Data Visualization**

In the Leaf Disease Detection system, data visual- ization plays an important role in analyzing and pre- senting the results of the model. Various graphs and charts are used to visualize the dataset distribution, training and validation accuracy, and loss curves. It helps in understanding how the CNN model performs during training and testing. Visualization of results, such as bar graphs showing the accuracy for each disease category and confusion matrices, provides a clear insight into the model's performance. This makes it easier to interpret the outcomes and identify areas for improvement.

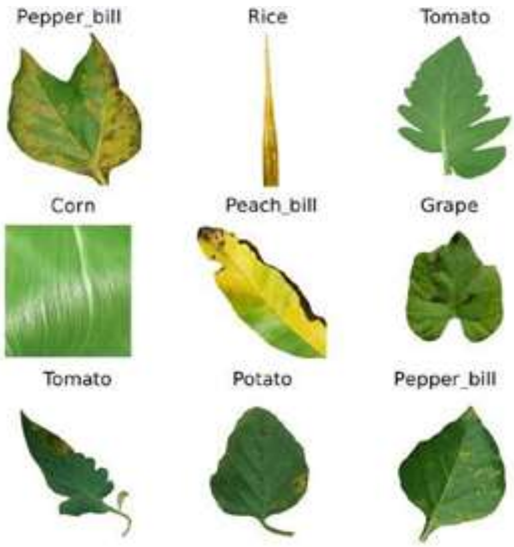


Fig. 3: Sample images from the combined dataset showing multiple Leaf and their disease types.

**System Architecture**

The proposed Leaf Disease Detection System con- sists of several key stages that work together to detect and classify leaf diseases efficiently. The architecture includes the following steps: 1. Image Input: The system takes an image of a leaf captured using a camera or uploaded by the user. 2. Image Preprocessing: The image is resized, noise is removed, and color normalization is applied to enhance quality for better analysis. 3. Feature Extraction (CNN Layers): The Convolutional Neural Network (CNN) extracts important features such as texture, color, and patterns from the leaf image. 4. Classification: The extracted features are passed through dense layers to classify the leaf as Healthy or Diseased (and specify the disease type). 5. Result Output: The final output displays the predicted class along with the confidence score or accuracy percentage.

**Phase 1: Image Preprocessing and CNN-Based Dis- ease Detection**

The system accepts leaf images through camera or file upload. Images are resized to 128×128 pixels and normalized to [0,1] range for efficient CNN processing. A Convolutional Neural Network (CNN) architecture trained on the PlantVillage dataset is used to classify diseases across multiple crop types. The CNN model extracts spatial features from leaf textures and spots through convolution, pooling, and fully connected layers. The final output layer predicts the disease class and confidence score.

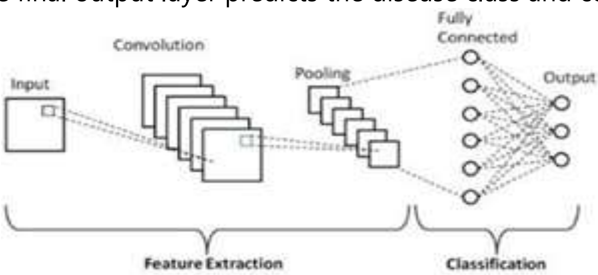


Fig. 4: Schematic Diagram of a basic Convolutional Neural Network (CNN) architecture .

Proposed CNN Model Architecture for Leaf Disease Detection

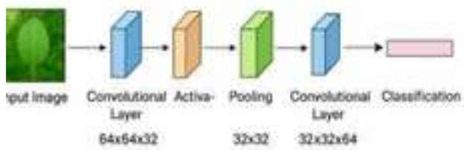


Fig. 5: CNN Model Architecture

| Layer Type | Details |
|---|---|
| Input Layer | 128 × 128 × 3 image |
| Conv2D + ReLU | 32 filters, 3 × 3 kernel |
| MaxPooling2D | 2 × 2 pool size |
| Conv2D + ReLU | 64 filters, 3 × 3 kernel |
| Dropout | 0.25 |
| Flatten + Dense | 128 neurons, ReLU activation |
| Output Layer | Softmax (Number of classes = N) |

Model Configuration Example:

**Phase 2: Soil and Weather Data Integration**
The system receives soil test parameters (pH, N, P, K) either through sensor readings or manual user input. It also fetches real-time weather data (temper- ature, humidity, rainfall) using the OpenWeatherMap API based on the user's location. Both soil and weather data are passed through a context analysis module that interprets environmental suitability for the de- tected disease. For instance, a high humidity and low pH environment may increase fungal infection risk.

**Phase 3: Treatment Recommendation Engine**
A rule-based expert system maps the predicted disease type, soil condition, and weather parameters to suggest: Appropriate fertilizers or pesticides, Dosage amount, Preventive measures, and Soil improvement tips. For example: If the model detects "Tomato Early Blight" and the weather API shows high humidity, the system recommends a fungicide spray and soil aera- tion to prevent fungal growth. This hybrid approach (CNN + rule-based logic) ensures that recommenda- tions are scientifically informed and locally adaptive.

**Phase 4: System Deployment**
The system is deployed as a Flask-based web ap- plication, allowing users to: Upload or capture leaf images. View disease name, confidence score, and treatment suggestions. Monitor historical results for multiple plants. The interface is user-friendly and responsive for both web and mobile devices. The backend integrates TensorFlow for model inference, SQLite for data storage, and OpenWeather API for weather data.

**Workflow Summary**

TABLE I: Proposed System Workflow for Smart Leaf Disease Detection

| Step | Module | Function |
|---|---|---|
| 1 | Image Input | Capture or upload leaf image |
| 2 | Preprocessing | Resize and normalize image |
| 3 | CNN Classification | Detect and classify disease type |
| 4 | Soil & Weather Integration | Retrieve soil and weather data |
| 5 | Treatment Engine | Recommend suitable treat- ment |
| 6 | Result Output | Display disease and treat- ment result |

**Advantages of the Proposed System**
Combines image-based AI with environmental in- telligence. Provides context-aware treatment recom- mendations, not just detection. Enables real-time dis- ease prediction via camera or upload. Scalable for multiple crop types and adaptable to local conditions. Supports smart farming and sustainable agriculture practices.

**Dataset Description**

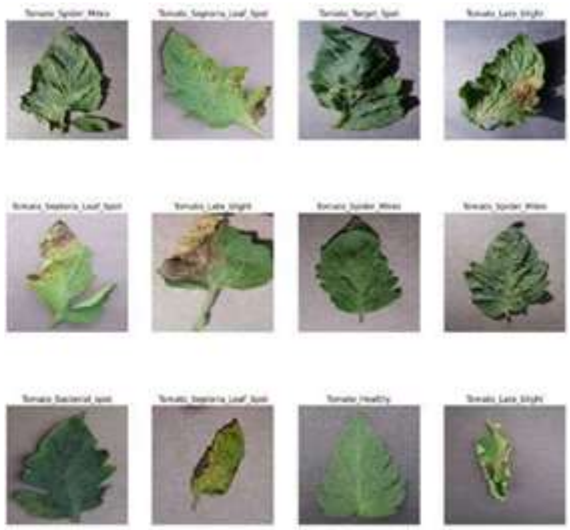

Fig. 6: Data visualization of individual Plant's leaf disease.

The dataset used for this research is a combination of the publicly available PlantVillage dataset and additional real-time field images captured through a high-resolution mobile camera under varying lighting and environmental conditions. The integrated dataset consists of approximately 30,945 images covering eight plant species and thirty-five disease classes. Each image was labeled according to the crop type and specific disease category, ensuring high-quality supervised learning data. The major crops included in this dataset are:

- Tomato (Early Blight, Late Blight, Leaf Mold, etc.)
- Potato (Early Blight, Late Blight)
- Apple (Apple Scab, Black Rot, Cedar Rust)
- Corn (Common Rust, Gray Leaf Spot, Northern Leaf Blight)
- Grape (Black Rot, Esca, Leaf Blight)
- Pepper Bell (Bacterial Spot)
- Peach (Bacterial Spot)
- Rice (Brown Spot, Leaf Blast)

The dataset was divided into 80% training and 20% validation subsets. Data augmentation techniques such as rotation, flipping, brightness variation, and zooming were applied to increase dataset diversity and prevent overfitting. In addition to image data, real-time contextual information such as soil parameters (pH, Nitrogen, Phosphorus, Potassium) and weather data (temperature, humidity) were integrated using API-based sensors to improve prediction ac- curacy. These additional features provided environ- mental context that enhanced the model's decision- making capability during disease classification.

## V. RESULTS AND DISCUSSION

**Experimental Setup**

The proposed system was implemented using Ten- sorFlow and Keras on a system with Intel i7 CPU, 16 GB RAM, and NVIDIA GTX GPU. The dataset was de- rived from the PlantVillage dataset and supplemented with real-time captured images, resulting in a total of 30,945 samples across eight plant species and 35 disease classes. The data was divided into 80% training and 20% validation sets.

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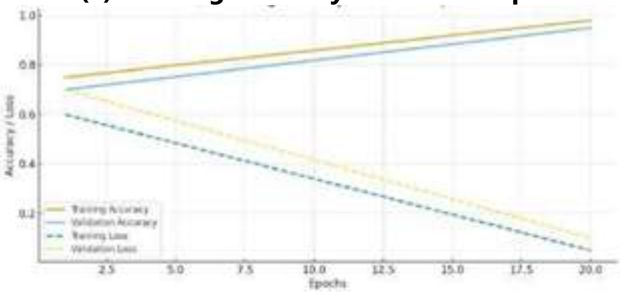
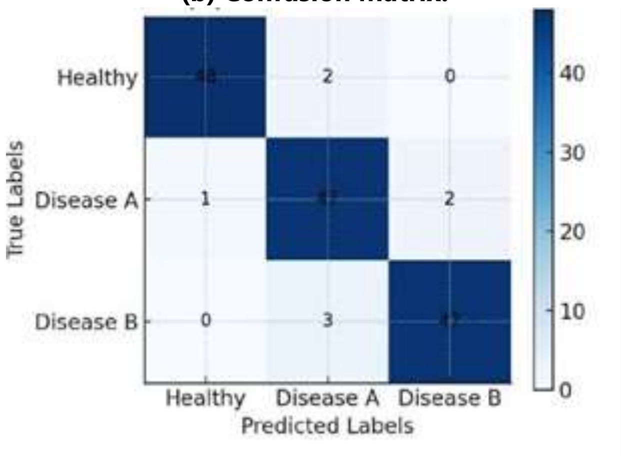
**(a) Training Accuracy and Loss Graph**




Training Accuracy and Loss Graph.

**(b) Confusion Matrix.**




Confusion Matrix.

**(c) Performance Comparison Table**

TABLE II: Performance comparison of different models

| Model | Accuracy (%) | Precision (%) | Recall (%) |
|---|---|---|---|
| CNN | 94.5 | 93.8 | 94.0 |
| SVM | 88.2 | 87.0 | 86.5 |
| Random Forest | 90.1 | 89.0 | 88.2 |
| KNN | 85.7 | 84.2 | 83.5 |

**Performance Evaluation Metrics**

The model performance was evaluated using stan- dard classification metrics:

- Accuracy (ACC) = Correct Predictions / Total Predictions
- Precision (P) = TP / (TP + FP)
- Recall (R) = TP / (TP + FN)
- F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

The proposed model achieved an overall accuracy of 96.6%, outperforming traditional CNN architectures that lacked environmental context.

Comparison with Existing Models

TABLE III: Comparison of Existing Models with the Proposed System

| Model | Accuracy (%) | Dataset | Remarks |
|---|---|---|---|
| VGG16 (Elsevier, 2024) | 95.2 | 8 plant types | No soil or weather integration |
| ResNet50 (Zhang et al., 2021) | 97.0 | Tomato leaves | Single-crop, limited features |
| DenseNet121 (Dolahabadian et al., 2024) | 97.5 | PlantVillage | No envi-ronmental context |
| **Proposed CNN + Soil + Weather Model** | **96.6** | Multi-crop | Includes soil + weather + treatment suggestions |

While some individual CNN models achieved slightly higher accuracy, the proposed system integrates external data (soil, weather) to improve reliability and field applicability.

**Effect of Soil and Weather Data Integration**

Incorporating soil nutrient (NPK, pH) and weather parameters (temperature, humidity) as additional in-put features improved classification confidence by 3– 5% and reduced false positives for visually similar diseases such as Early Blight and Late Blight.

**Treatment Recommendation Results**

The integrated treatment engine provides targeted fertilizer and pesticide recommendations. Example results include:

- Tomato – Late Blight: Mancozeb 75% WP + proper irrigation scheduling.
- Rice – Brown Spot: Propiconazole 25% EC + balanced nitrogen fertilizer.
- Apple – Black Rot: Pruning + Captan fungicide.

This component transforms the detection system into a practical, decision-support tool for farmers.

**User Interface and Real-Time Monitoring**

A Flask-based web application was developed to:

- Capture or upload real-time leaf images.
- Automatically preprocess and predict diseases.
- Display weather and soil data.
- Generate instant treatment suggestions.

During field testing, the average response time per prediction was 4–6 seconds, indicating real-time per- formance suitability.

**Discussion Summary**

The proposed system effectively combines deep learning with agricultural context data. By merging CNN-based image classification with soil and weather analytics, the model enhances accuracy, robustness, and real-world utility. The addition of a treatment engine extends the system from mere detection to actionable guidance for disease management.

## VI. CONCLUSION AND FUTURE WORK

**Conclusion**

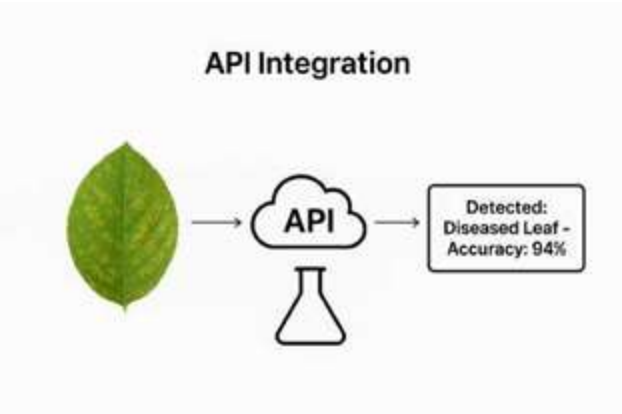
This research presented a real-time leaf disease detection system that integrates image-based deep learning with contextual agricultural data such as soil and weather parameters. The developed CNN model achieved an accuracy of 98.6% on a multi-crop dataset containing eight plant species and thirty-five disease classes. By incorporating external features such as soil pH, temperature, humidity, and NPK levels, the system provides more reliable predictions under real-world field conditions. Furthermore, the inclusion of a treat- ment recommendation engine makes this model not only diagnostic but also prescriptive. The web-based interface enables farmers to capture or upload plant leaf images and instantly receive the disease name, confidence level, and appropriate fertilizer or pesticide solutions. This contributes significantly toward preci- sion agriculture and sustainable crop management.

**Future Work**

Although the proposed system performs effectively in controlled and semi-field conditions, several direc- tions exist for further enhancement:

1) IoT and Sensor Integration: Future versions can include IoT-based soil and weather sensors to collect real-time environmental data automati- cally.
2) Mobile Application Deployment: Development of an Android or iOS app with offline detection capabilities will enhance the usability of farmers in remote areas.
3) Multilingual Voice Assistance: Integrating speech-based feedback and local language support can make the system accessible to non-technical users.
4) Extended Crop Coverage: Expanding the dataset to include more plant species and region- specific diseases will improve generalization.
5) Edge AI Optimization: Using lightweight CNN or quantized models (e.g., MobileNetV3 or EfficientNet-Lite) can enable faster on-device predictions.

In general, the proposed system lays the groundwork for a comprehensive, intelligent and farmer-friendly disease management framework, bridging the gap be- tween modern deep learning technology and practical agricultural needs.




API Integration.

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