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A Robust Framework for Automated Leaf Disease Diagnosis and Predictive Treatment in Smart Agriculture

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Abstract: Monitoring plant health is essential for improving crop productivity and minimising losses due to diseases. Traditional methods rely on manual inspection, which is often time-consuming, inconsistent, and prone to error. Existing automated systems primarily focus on disease detection but lack features such as severity quantification, causal analysis, treatment recommendations, and continuous monitoring, limiting their effectiveness for practical agricultural use. To address these challenges, this study proposes an integrated leaf health monitoring system that combines disease detection, severity assessment, causal diagnosis, treatment guidance, and pesticide evaluation. The system architecture includes image acquisition of leaves, preprocessing, feature extraction, and classification to determine whether a leaf is healthy or unhealthy. It calculates the percentage of affected areas to quantify disease severity and identifies potential causes, such as fungal, bacterial, or environmental stress factors. Upon detection, real-time alerts are generated, and suitable treatments, including recommended pesticides, are suggested. A temporal tracking module provides daily updates over seven days, enabling farmers to monitor the effectiveness of interventions and adjust treatments accordingly. The system was trained and tested using publicly available datasets of healthy and diseased leaf images, achieving high accuracy in disease detection and reliable quantification of infection severity. Experimental results demonstrate that this approach effectively integrates detection, analysis, and actionable guidance, offering a practical, data-driven solution for precision agriculture. By integrating real-time monitoring with treatment recommendations, the proposed system supports sustainable crop management, reduces crop loss, and enhances overall farming efficiency.

Keywords: Plant Disease Detection; Machine Learning; Precision Agriculture; Treatment Recommendation; Support Vector Machine (SVM); Naïve Bayes; Real-Time Monitoring; Sustainable Farming; Crop Health Management.

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1. Introduction

Agriculture underpins global food security and economic development, sustaining billions of people and providing the primary livelihood for a significant portion of the population. However, the health and productivity of crops are continuously challenged by numerous biotic and abiotic stressors, including diseases caused by fungi, bacteria, and viruses, as well as environmental factors such as nutrient deficiencies, poor soil conditions, and unpredictable climate patterns. These challenges often result in substantial yield losses, affecting both small-scale farmers and large agricultural enterprises [1]. Traditional plant disease detection methods rely heavily on manual inspection by experts, which, while effective in certain cases, is time-consuming, inconsistent, and impractical for large-scale monitoring. Human error, limited accessibility to expert pathologists in remote areas, and delayed intervention further exacerbate crop loss. With the rapid advancement of artificial intelligence (AI) and machine learning (ML) technologies, particularly in image recognition and computer vision, there is a tremendous opportunity to revolutionise agricultural disease diagnosis through automation, precision, and data-driven decision-making. The proposed project, Smart Agriculture: Automated Leaf Disease Diagnosis and Predictive Treatment System, addresses these challenges by developing an integrated machine learning-based framework capable of not only detecting plant diseases from leaf images but also quantifying disease severity, identifying causal factors, recommending effective treatments, and providing real-time monitoring and predictive insights. The core innovation of this paper lies in its holistic approach, combining computer vision with intelligent decision support to create a complete agricultural management tool [2].

Unlike conventional models that merely classify leaves as healthy or diseased, this system analyses the percentage of affected leaf area to quantify infection severity and identify potential causes, such as fungal, bacterial, or environmental stress. Once a disease is identified, the system generates actionable insights by recommending appropriate pesticides and preventive measures tailored to the specific infection type. A unique temporal tracking feature monitors the treated crop for 7 days, evaluating recovery progress and dynamically adjusting recommendations [3]. This integration of image processing, disease analysis, and predictive feedback transforms the model from a simple diagnostic application into a comprehensive precision agriculture system. By employing convolutional neural networks (CNNs) for feature extraction and classification, the system achieves high accuracy in recognising intricate visual patterns, including colour variations, lesion shapes, and texture irregularities associated with different plant diseases. Furthermore, through preprocessing techniques like noise reduction, normalisation, and data augmentation, the system is optimised to perform reliably even under varying lighting conditions and environmental backgrounds. Beyond detection accuracy, this paper emphasises usability, scalability, and sustainability. The model is lightweight and optimised to run efficiently on smartphones and other low-resource devices, ensuring accessibility for farmers in rural areas with limited technological infrastructure. The intuitive user interface displays not only the detected disease and severity percentage but also visually highlights infected areas on the leaf and provides a seven-day recovery forecast through graphical visualisations [4].

These features enable farmers to make quick, informed, and confident decisions directly in the field without requiring expert assistance. Additionally, the system's pesticide recommendation module prioritises environmentally sustainable practices by analysing pesticide efficiency and promoting minimal chemical use, aligning with global goals for eco-friendly, responsible farming. By offering precise, data-backed treatment guidance, it minimises waste, reduces costs, and protects soil and water ecosystems from the harmful effects of excessive agrochemical application [5]. The motivation behind developing this research stems from the growing global need to enhance agricultural productivity while maintaining ecological balance. As the world's population continues to grow and arable land becomes increasingly scarce, optimising crop yields through smart, sustainable practices is no longer optional—it is imperative. In this regard, integrating artificial intelligence into agriculture presents a transformative opportunity. The Smart Agriculture system contributes to this shift by providing a scalable, cost-effective, and practical solution that empowers farmers to diagnose and manage plant diseases efficiently. It bridges the gap between traditional agricultural knowledge and modern data analytics, allowing even small-scale farmers to benefit from cutting-edge technology. Moreover, by leveraging publicly available datasets for model training and validation, the system achieves high generalizability across different crop species and disease types, ensuring robust performance under real-world conditions [6].

From a technical standpoint, the project employs advanced ML algorithms, including Support Vector Machines (SVMs) and Naïve Bayes, for comparative analysis, with CNNs serving as the backbone for deep feature extraction. The CNN architecture captures hierarchical patterns within leaf images, progressively identifying fine-grained disease features that distinguish one infection from another. The system's performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score to ensure reliability [7]. In addition, the model's predictive module incorporates a severity reduction equation that simulates disease progression over time, enabling proactive rather than reactive management. By projecting how a leaf's health is expected to improve under recommended treatments, the system supports data-driven decision-making and minimises guesswork in pesticide application. What truly sets this research apart is its ability to translate AI-generated insights into practical agricultural action. Farmers often face the challenge of identifying not just what disease their crops are suffering from but also why it occurred and how it can be effectively treated [8]. The Smart Agriculture system addresses all three aspects by integrating causal diagnosis, real-time monitoring, and treatment forecasting. It provides a clear feedback loop between detection, intervention, and recovery, empowering farmers with a continuous learning system that evolves through usage. For instance, the temporal tracking module evaluates treatment outcomes over a week, helping farmers understand which methods yield the best results and adjust recommendations based on the observed data.

This feedback mechanism fosters adaptive farming strategies and long-term improvements in crop health. In addition to its technical and practical benefits, the project contributes significantly to the broader vision of sustainable agriculture and food security. By reducing dependency on manual labour and expert intervention, it democratizes access to agricultural intelligence. Minimising unnecessary pesticide use protects biodiversity and soil fertility. By enabling precise, timely action, it helps farmers mitigate losses, improve yield quality, and enhance economic resilience [9]. The system also holds potential for future integration with Internet of Things (IoT) devices, drones, and smart irrigation systems to build a fully interconnected agricultural ecosystem. Such integration would enable real-time monitoring of vast farmlands, automatic sensor data collection, and coordinated interventions—paving the way for a new era of autonomous smart farming. Ultimately, this research represents a crucial step toward bridging the gap between technology and agriculture. The Smart Agriculture: Automated Leaf Disease Diagnosis and Predictive Treatment System is not merely a machine learning model—it is a paradigm shift in how farming challenges are addressed. It demonstrates how artificial intelligence can extend beyond industrial or urban applications to empower the most fundamental sector of human existence: food production. By fusing accuracy, accessibility, and environmental responsibility, this paper sets a benchmark for intelligent crop management systems. It stands as a testament to AI's transformative potential in shaping a sustainable agricultural future [10].

2. Literature Review

Ahmed and Sarkar [1] explore the significant evolution of precision farming, specifically evaluating the transition toward highly intelligent systems such as YOLOv7 and SwinRDM. Their research highlights how machine learning applications have matured to a point where they can consistently achieve up to 99% accuracy in disease detection, marking a major milestone in agricultural technology. The authors emphasise the critical role of AI in overcoming traditional inefficiencies, such as manual inspection errors and delayed response times. By integrating data-driven insights into daily operations, this work showcases how intelligent systems can optimise resource management and labour allocation. Ultimately, the study advocates for the widespread adoption of these models to ensure long-term sustainability and resilience in modern food production systems. Qwaid et al. [2] introduce a specialised AI-enabled framework meticulously tailored for date palm cultivation within arid and semi-arid regions. By integrating IoT-based soil and moisture sensors with advanced machine learning algorithms, the study directly addresses the unique environmental stresses and water scarcity challenges of desert agriculture. This research provides a sustainable, data-driven approach to monitoring tree health and optimising vital irrigation schedules to prevent unnecessary water waste. The authors demonstrate that localised AI models can significantly improve the survival rate of high-value crops in harsh climates by predicting disease outbreaks before they become visible. Their findings offer a scalable blueprint for smart farming in regions where environmental factors are the primary barrier to agricultural productivity.

Sudha and Loret [3] present a comprehensive review of the powerful synergy between Internet of Things (IoT) hardware and machine learning software for modern crop monitoring. Their research underscores how integrating real-time data streams from expansive sensor networks enables more precise, agile decision-making in precision agriculture. By analysing large-scale environmental datasets, the authors illustrate how AI can help farmers mitigate the devastating impacts of climate change and unpredictable weather patterns on food security. The paper details various communication protocols and sensor types that form the backbone of a responsive agricultural ecosystem. It concludes that the convergence of these technologies is no longer a luxury but a necessity for feeding a growing global population in a resource-constrained world. Chettri et al. [4] conduct a systematic and rigorous review of deep learning methodologies currently utilised in precision agriculture while identifying critical challenges such as data scarcity and the need for more efficient model architectures. The authors meticulously outline future directions for the field, arguing that deep learning remains the primary driver of the transition toward truly autonomous and intelligent farming systems. They highlight the importance of transfer learning and data augmentation in training robust models when labelled agricultural datasets are limited. The study also explores the computational trade-offs involved in running complex neural networks in rural areas with limited connectivity. By bridging the gap between theoretical AI research and practical field application, this review serves as a roadmap for researchers developing the next generation of ag-tech solutions.

Talaat et al. [5] focus on the critical hardware-software interface and propose an innovative IoT-integrated robotic system for automated plant disease detection and environmental monitoring. Their modular architecture enables mobile, high-resolution monitoring, with autonomous robots traversing uneven field terrain to collect multisensor data from every individual plant. This approach enables much earlier detection of foliar diseases than static sensor setups or infrequent manual scouting. The integration of robotics enables targeted interventions, such as localised spraying, significantly reducing the farm's overall chemical footprint. The study provides detailed insights into robot navigation, battery management, and real-time data transmission protocols. Ultimately, this work demonstrates how mobile automation can transform plant protection from a reactive task into a proactive, precision-guided operation. Anwar et al. [6] review the rapid progression of computer vision techniques in agriculture, tracking the technological journey from simple pixel-level analysis to highly complex diagnostic models. They emphasise the transformative potential of deep learning for non-invasive plant protection, demonstrating how visual data from drones and handheld devices can be converted into actionable management insights. The authors discuss the shift from traditional hand-crafted features to automated feature learning provided by Convolutional Neural Networks (CNNs). Their work highlights the specific challenges of varying lighting conditions and complex backgrounds that models must overcome in real-world field settings. By providing a taxonomy of current vision-based tools, the research clarifies which techniques are most effective for specific crop types and disease symptoms.

Murad et al. [7] propose a forward-looking "Agentic AI" framework that utilises sophisticated multi-agent systems to automate traditional farming workflows fully. In this innovative model, specialised software agents are assigned to specific domains, such as soil health, weather forecasting, and disease detection, all working under the supervision of a chatbot. This shifts the agricultural paradigm from simple automated tasks to a fully autonomous, digital farming ecosystem where agents can "negotiate" resource allocation based on real-time needs. The framework allows for a more natural interaction between the farmer and the technology through conversational AI interfaces. The authors argue that this multi-agent approach increases the system's reliability by preventing a single point of failure in the diagnostic pipeline. Subhan et al. [8] investigate the efficacy and practical benefits of the EfficientNetB0 architecture for high-speed crop disease detection in precision agriculture. Their study demonstrates that by utilising lightweight but powerful deep learning models, diagnostic precision can be maintained without the prohibitive computational costs associated with deeper, more traditional CNN architectures. This makes the model particularly suitable for deployment on mobile devices or edge computing units located directly on the farm. The researchers provide a detailed performance analysis, comparing EfficientNet with heavier models such as ResNet and VGG in terms of both accuracy and inference speed. Their findings suggest that architectural efficiency is just as important as raw accuracy for the practical adoption of AI by small-scale and resource-limited farmers.

Balanageshwara et al. [9] address the controversial "black box" nature of artificial intelligence by conducting a deep comparative study of Explainable AI (XAI) techniques, including Grad-CAM++ and LIME. Their research strongly highlights that for AI to be successfully adopted by the farming community, the systems must not only be accurate but also provide interpretable visual explanations of their diagnostic logic. By highlighting the specific regions of a leaf that led to a "diseased" classification, these tools build trust and allow farmers to verify the AI's findings against their own expertise. The study evaluates the trade-offs between model complexity and interpretability, suggesting that XAI is essential for high-stakes agricultural decisions. This work bridges the gap between data science and human-centric design in the context of smart farming. Goluguri and Baik [10] provide a highly targeted review of imaging and AI innovations specifically focused on detecting and managing wheat plant diseases. They analyse how various modalities, including hyperspectral imaging and high-resolution RGB data, can be combined with AI to protect one of the world's most critical staple crops. The paper discusses the biological markers of common wheat infections and how they manifest in digital imagery at different growth stages. By focusing on a single, vital crop, the authors provide deep technical insights into the spectral signatures of wheat pathogens. Their work emphasises the need for global, collaborative datasets to train AI models that can withstand the diverse varieties and environmental conditions of wheat-producing regions worldwide.

Parganiha and Verma [11] develop a highly systematic model for smart agriculture that utilises advanced deep learning methods specifically to improve crop productivity and diagnostic speed. Their approach introduces the Modified Residual U-Net (MRU-Net) for high-precision segmentation, which allows the system to isolate diseased leaf areas from complex environmental backgrounds with extreme accuracy. This is followed by a stacking ensemble of boosting algorithms, including XGBoost and AdaBoost, which synthesises the strengths of multiple classifiers to achieve results exceeding 99.5% accuracy. The research demonstrates remarkable robustness across diverse datasets, proving that their multi-stage pipeline is generalizable to various plant species. By combining segmentation with ensemble learning, the authors provide a comprehensive solution that addresses both the "where" and the "what" of plant pathology. Ibrahim et al. [12] present a novel and highly practical AI-IoT "smart pivot" system that leverages existing central pivot irrigation machinery as a mobile platform for disease detection. By mounting ResNet50-based vision models directly onto the moving irrigation infrastructure, they achieve a 99.8% detection rate without the need for additional drones or expensive standalone robots. This ingenious use of existing farming equipment enables continuous, high-frequency surveillance of vast fields throughout the normal watering cycle. The paper details the integration of edge computing devices that process images locally to save bandwidth and provide immediate feedback. This research offers one of the most cost-effective and scalable solutions for large-scale agricultural monitoring currently available in the literature.

Goyal et al. [13] introduce an intelligent deep learning recommendation system for fruit plant monitoring, optimised specifically using the Henry Gas Solubility Optimisation (HGSO) algorithm. Their work focuses on the "Optimal Mobile Network-based CNN" (OMNCNN), enabling the generation of disease prevention and treatment recommendations with minimal latency on standard mobile devices. The system goes beyond mere diagnosis by providing actionable treatment advice based on the severity and type of disease detected. This holistic approach helps farmers move immediately from identification to intervention, potentially saving entire harvests from rapid-onset infections. The authors demonstrate that meta-heuristic optimisation can significantly refine neural network training, leading to more reliable and faster agricultural AI. Islam et al.

[14] focus on cotton disease prediction using fine-tuned deep learning models that are seamlessly integrated into a user-friendly smart web application. This research emphasises the practical accessibility of AI by demonstrating how complex backend models can be made available to farmers through simple, cloud-based interfaces. The study details the process of fine-tuning pre-trained models on specialised cotton datasets to ensure high performance even with limited local data. By providing a complete end-to-end pipeline from image upload to diagnosis, the authors show how technology can be democratised for users with varying levels of technical expertise. Their work serves as a case study for the successful deployment of AI tools in developing agricultural economies. Sivaraman et al. [15] apply the VGG16 deep learning architecture to the specialised and high-value domain of tea leaf disease recognition and management. Their study demonstrates that established convolutional neural networks can be successfully adapted to identify unique pathological markers in tea plants, such as blister blight and red rust. By focusing on sustainable crop management, the researchers demonstrate how AI-driven diagnostics can reduce reliance on broad-spectrum fungicides in tea plantations (Figure 1).

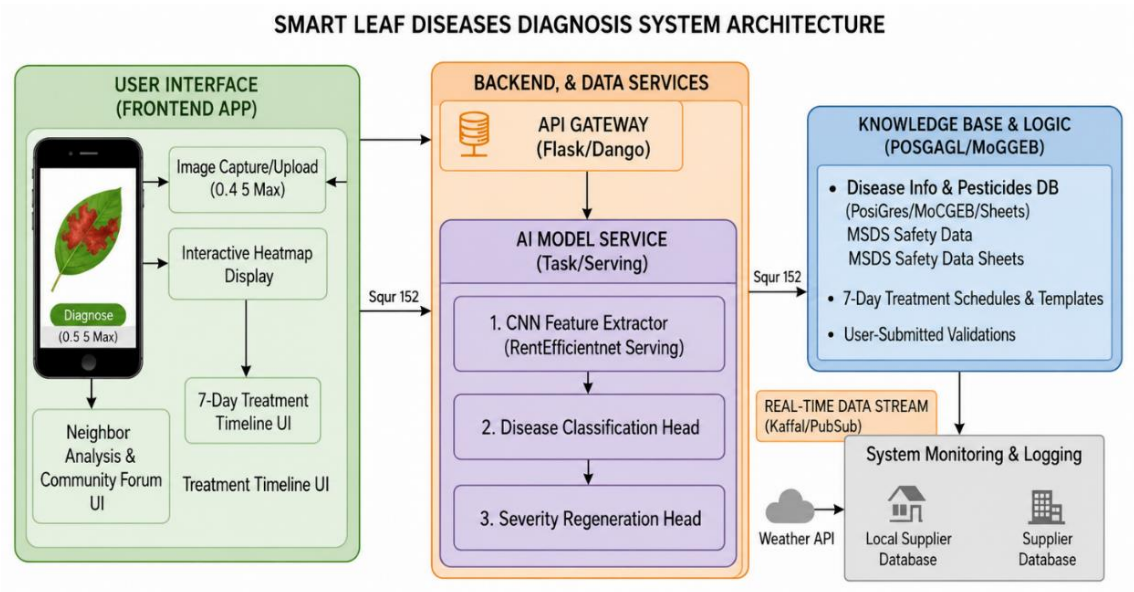

Figure 1: Functional block diagram

The paper provides a detailed analysis of the feature maps generated by the VGG16 model, offering insights into what the network "sees" when evaluating leaf health. This work contributes to the long-term economic and environmental sustainability of the global tea industry by ensuring consistent quality through automated health monitoring. The recent literature in smart agriculture emphasises a significant shift toward autonomous, data-driven systems that integrate IoT sensors, robotics, and advanced deep learning to enhance crop productivity. Key research highlights the transition to "Agriculture 5.0," where complex architectures like YOLOv7, EfficientNet, and Vision Transformers are utilised to achieve diagnostic accuracies often exceeding 99%. These advancements are not limited to general crop monitoring but also extend to specialised frameworks for staple crops such as wheat [10], high-value tea plantations, and sustainable date palm cultivation in arid regions. Furthermore, integrating hardware, such as central pivot irrigation systems and autonomous mobile robots, demonstrates a move toward continuous, real-time surveillance that identifies plant pathologies long before they are visible to the human eye. Beyond raw accuracy, current trends prioritise interpretability and practical accessibility to ensure these technologies are adoptable by the global farming community. The emergence of Explainable AI (XAI) techniques, such as Grad-CAM and LIME, addresses the "black box" nature of deep learning by providing visual justifications for diagnoses, thereby building trust between farmers and AI systems. Additionally, the development of Agentic AI frameworks and mobile-optimised recommendation systems shows a clear trajectory toward fully autonomous decision-making and immediate therapeutic interventions. By combining high-precision segmentation tools such as MRU-Net with user-friendly web applications, this body of research establishes a robust foundation for a proactive, sustainable agricultural ecosystem that minimises chemical use while maximising global food security.

3. Methodology

The proposed Smart Leaf Disease Diagnosis system is designed to detect plant leaf diseases and automatically provide actionable treatment recommendations. Figure 1. Illustrates the Functional Block Diagram. The system integrates image processing, deep learning, and decision-support mechanisms to ensure accurate, real-time diagnosis. Leaf images were collected from the PlantVillage dataset and additional verified agricultural sources. Each image was labelled as either its disease type or healthy. The dataset was split into training, validation, and test sets at 80:10:10, ensuring balanced class representation. To enhance the model's robustness, data augmentation techniques such as rotation, flipping, zooming, and brightness adjustments were applied to simulate real-world variations in lighting and leaf orientation. Before model training, each image underwent preprocessing to ensure consistency. All images were resized to 224×224 pixels, and pixel values were normalised to a range between 0 and 1 using the equation:

$$I(norm)(x,y) = \frac{I(x,y) - I_{min}}{I_{max} - I_{min}} \tag{1}$$

where $I_{norm}(x,y)$ represents the pixel intensity at location (x, y), and I_{max} and I_{min} are the minimum and maximum pixel intensities of the image. Noise reduction was performed using Gaussian and median filters to remove unwanted background artefacts. Feature extraction and classification were performed using a Convolutional Neural Network (CNN). The CNN comprised multiple convolutional layers to detect patterns in leaf lesion colour, texture, and shape, followed by pooling layers to reduce spatial dimensions while retaining significant features. The convolution operation can be mathematically expressed as:

$$S(i,j) = (I * K)(i,j) = \sum_{m} \sum_{n} I\,(i-m,\ j-n)\,K(m,n) \tag{2}$$

where K is the convolution kernel and $S(i,j)$ represents the resulting feature map. Fully connected layers were then processed extracted features, and a Softmax activation function provided a probability distribution over all possible classes

$$P(y = c|x) = \frac{e^{z_c}}{\sum_{k=1}^{N} e^{z_k}} \tag{3}$$

where y_i denotes the logit score for class i, and N represents the total number of classes. The model was trained using categorical cross-entropy loss, defined as:

$$L = -\sum_{(i=1)}^{N} y_i log(\hat{y}_i) \tag{4}$$

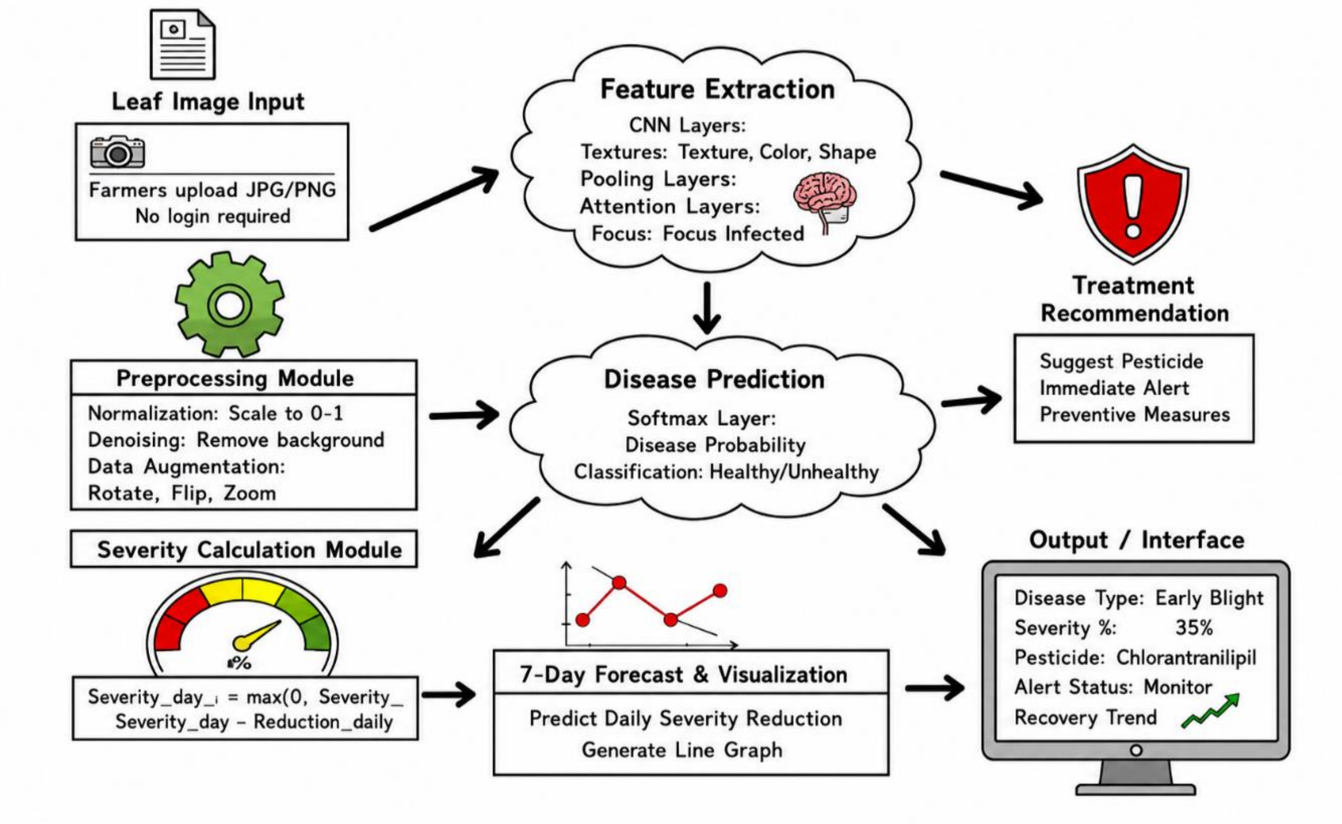

Figure 2: Working flow of the CNN diagram

The Adam optimiser is employed for efficient weight adjustment. To further improve performance, an attention mechanism was integrated, allowing the model to focus on infected areas while ignoring healthy regions of the leaf. After training, the system predicts whether a leaf is healthy or unhealthy. If classified as unhealthy, it identifies the disease type and calculates a severity percentage based on the prediction confidence. A 7-day treatment projection is also generated to forecast how the leaf's health is expected to improve under the suggested pesticide treatment. The system then recommends the appropriate pesticide, preventive measures, and indicates whether immediate intervention is required. A visual representation of the 7-day severity reduction is generated as line graphs, allowing users to track the expected recovery easily. Figure 2 shows the workflow of CNN. The system's workflow can be summarised as follows: upon receiving a leaf image, preprocessing is performed, followed by feature extraction using a CNN with attention. The model predicts the health status and disease type. For unhealthy leaves, severity is calculated, and pesticide recommendations are provided alongside a 7-day projected recovery graph. This approach not only detects diseases accurately but also simulates treatment effects, offering practical guidance for farmers. Model performance was evaluated using accuracy, precision, recall, and F1-score. Additionally, Mean Absolute Error (MAE) was calculated to measure the accuracy of severity predictions:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (5)$$

where y_i is the actual severity and $\hat{y}_i$ is the predicted severity for each leaf image. This methodology ensures that the system provides accurate disease detection, severity estimation, and treatment recommendations in a practical, farmer-friendly interface. The integration of predictive modelling, forecasting, and visualisation makes it a novel tool for real-time crop health management. Despite advances in agriculture, manual disease detection remains time-consuming, labour-intensive, and prone to errors. Early-stage infections are often missed, leading to significant crop loss and increased pesticide use. The proposed system addresses this challenge by providing instant, precise diagnosis, reducing human effort, and enabling targeted treatment, thereby supporting both economic efficiency and sustainable farming practices. The system is designed to work on low-resource devices, such as smartphones, ensuring accessibility for farmers even in rural areas. With an optimised model size and fast inference speed, predictions can be generated in real time, enabling immediate decision-making in the field. Furthermore, it can integrate with farm management platforms to track disease history and treatment outcomes, providing long-term insights into crop health trends. A key feature of the system is its interpretability.

Beyond simply identifying the disease, it highlights the affected areas on the leaf, helping farmers visually understand the infection. Combined with a severity percentage and a 7-day recovery forecast, the system guides farmers not only in treatment but also in preventive measures, such as adjusting irrigation or applying protective sprays. This human-centred approach ensures that the technology is practical and actionable, not just predictive. While the current model focuses on a limited set of common diseases, the framework is easily scalable. It can incorporate additional crops and disease types as new datasets become available. Using transfer learning, the model can quickly adapt to new environments or plant species, making it a versatile tool for global agriculture. The system's 7-day severity projection simulates the expected response to pesticide application, enabling farmers to plan interventions. This approach not only improves treatment efficiency but also reduces unnecessary chemical use, minimising environmental impact. This predictive capability sets the system apart from standard disease detection tools. The system can integrate with IoT sensors, drones, and automated irrigation systems, forming a fully automated smart-farming ecosystem. Early detection, combined with automated interventions, can maximise crop yield while minimising losses due to infections, making it a truly innovative tool for modern agriculture.

Algorithm 1

Input: Leaf_Image
Output: Disease_Type, Severity_Percentage, Recommended_Pesticide, Alert_Status, 7-Day_Recovery
Begin
 # Step 1: Preprocessing
Preprocessed_Image ← Resize(Leaf_Image, 224, 224)
Preprocessed_Image ← Normalize(Preprocessed_Image)
Preprocessed_Image ← Denoise(Preprocessed_Image)
Augmented_Images
Data_Augmentation(Preprocessed_Image)
 # Step 2: Feature Extraction
Features
CNN_Feature_Extraction(Augmented_Images)
Features ← Attention_Layer(Features)
 # Step 3: Disease Prediction Probabilities ← Softmax(Features)
Max_Prob_Class ← argmax(Probabilities)

```
  If Max_Prob_Class = "Healthy" Then
     Output "Leaf is Healthy"
     Exit
 End If
  # Step 4: Severity Estimation
  Disease_Type ← Max_Prob_Class
           Severity_Percentage     ←
Calculate_Severity(Preprocessed_Image, Disease_Type)
  # Step 5: Treatment Recommendation
  Recommended_Pesticide ← Get_Pesticide(Disease_Type)
           Alert_Status    ←
Check_Immediate_Treatment(Disease_Type,
Severity_Percentage)
  # Step 6: 7-Day Recovery Forecast    For day ← 1 to 7 do
             Severity_Percentage[day+1]  ←        max(0,
Severity_Percentage[day] - Daily_Reduction(Disease_Type))
  End For
  # Step 7: Output Results
           Display(Disease_Type,            Severity_Percentage[1],
Recommended_Pesticide, Alert_Status)
  Plot_7_Day_Recovery(Severity_Percentage[1..7])
 End
```

The proposed system follows a step-by-step algorithm to diagnose leaf diseases and provide treatment recommendations. First, the system receives a leaf image, which undergoes preprocessing to ensure consistency. Next, the preprocessed image is passed through a Convolutional Neural Network (CNN). The CNN applies multiple convolutional layers to detect important patterns, such as colour variations, textures, and shapes of leaf lesions. Pooling layers then reduce the spatial dimensions while retaining significant features. Once the disease is identified, the system calculates the infection's severity based on the model’s confidence scores. Using a predictive model, a 7-day severity projection is generated to simulate the expected improvement in leaf health following the recommended pesticide treatment. Finally, the system presents the results through a farmer-friendly interface, highlighting infected areas on the leaf, providing the severity percentage, suggesting appropriate pesticides, and indicating preventive measures or urgent interventions. By integrating image processing, deep learning, attention mechanisms, and predictive analytics, this algorithm not only detects leaf diseases with high accuracy but also provides actionable guidance for farmers, enabling efficient and sustainable crop management.

4. Experimental Setup

4.1. Training

The training process starts by dividing the dataset into three parts — training, validation, and testing — to ensure the model is evaluated fairly and performs well on unseen data. Convolutional Neural Networks (CNNs) were developed using Python frameworks such as TensorFlow and PyTorch. To improve both efficiency and accuracy, transfer learning was applied using pre-trained models like ResNet and VGG16. To make the model more adaptable to real-world conditions, such as changes in lighting, background, or leaf orientation, data augmentation techniques were used. These included rotating, flipping, and adjusting image brightness to increase dataset diversity. The model was trained by minimising a loss function (categorical cross-entropy) with optimisers such as Adam or SGD, and learning rate scheduling helped stabilise training. Performance was continuously monitored using accuracy, precision, recall, and F1-score, ensuring the system correctly classified plant diseases and effectively handled dataset imbalance.

4.2. Evaluation

After training, the model was tested on unseen images to evaluate its real-world performance. Metrics such as accuracy, precision, recall, and F1-score were calculated, and confusion matrices were used to analyse misclassifications. The segmentation algorithm was also tested by comparing the predicted infection areas against manually annotated ground truths. To test real-time performance, the system was deployed on a mobile device and evaluated for image capture, preprocessing, and recognition speeds. Each test was repeated ten times to ensure reliability. The model performed strongly even under varying lighting conditions, angles, and distances. Most disease types, such as corn blight, apple scab, and grape black rot, achieved accuracies of 96–98%. However, classes like tomato target spot showed slightly lower confidence due to fewer training samples or noisy backgrounds. Interestingly, fungal diseases were detected more easily than bacterial and viral ones, likely because their visual symptoms were more distinct. Overall, the system proved accurate, efficient, and well-suited for real-time disease diagnosis in practical farming scenarios.

4.3. Implementation

The CNN model was implemented using Keras with TensorFlow as the backend, making it easier to design, train, and fine-tune deep learning models in Python. To avoid overfitting and improve generalisation, data augmentation was performed using Keras' Image Data Generator, which slightly altered the images through rotation, flipping, and scaling. All input images were resized to 200 × 200 pixels in RGB format before being fed into the network. Training was conducted with a batch size of 150 over 10 epochs on a system equipped with an Intel Core i7 CPU, 16 GB RAM, and an RTX 3060 GPU. For this multi-class classification task involving 38 plant disease categories, the model used a softmax activation function in the output layer.

4.4. Hardware Requirements

The hardware setup of the proposed system is designed to support both image and sound data acquisition, processing, and real-time inference. The major components include. The system utilises a high-performance computing unit equipped with an Intel Core i7 processor and 16 GB RAM to handle the computational load of training and testing deep learning models. A dedicated NVIDIA GPU (RTX 3060, 6GB) is employed to accelerate image and audio feature extraction using convolutional operations. A high-resolution digital camera captures clear leaf images under controlled lighting conditions, ensuring accurate visual feature detection. Additionally, a high-frequency ultrasonic microphone is integrated to record acoustic signals emitted by plants under stress conditions such as disease or pest attacks. These sounds, often inaudible to humans, are converted into spectrograms for analysis. All data are stored on a 512 GB SSD to ensure high-speed read/write operations during training and evaluation. The system operates on a 220V AC power supply with stable connectivity to support continuous data collection and real-time monitoring.

4.5. Software Requirements

The software environment is configured to support deep learning model development, training, and evaluation using both image and sound modalities. The system is implemented in Python 3.10 due to its broad support for scientific libraries and frameworks. The models are developed using TensorFlow and Keras for neural network implementation, while OpenCV is used for image preprocessing tasks such as resizing, normalisation, and augmentation. For sound data, Librosa is used for feature extraction, particularly for generating Mel-Frequency Cepstral Coefficients (MFCCs) and spectrograms from recorded plant sounds. The Jupyter Notebook environment provides an interactive interface for code development, visualisation, and model evaluation. Scikit-learn is used to analyse model performance using metrics such as accuracy, precision, recall, and the confusion matrix. Visualisation libraries like Matplotlib and Seaborn are used to plot accuracy graphs, spectrograms, and heatmaps.

5. Results and Discussions

The Smart Leaf Disease Diagnosis System was trained and tested using a large dataset containing both healthy and diseased plant leaves (Figure 3).

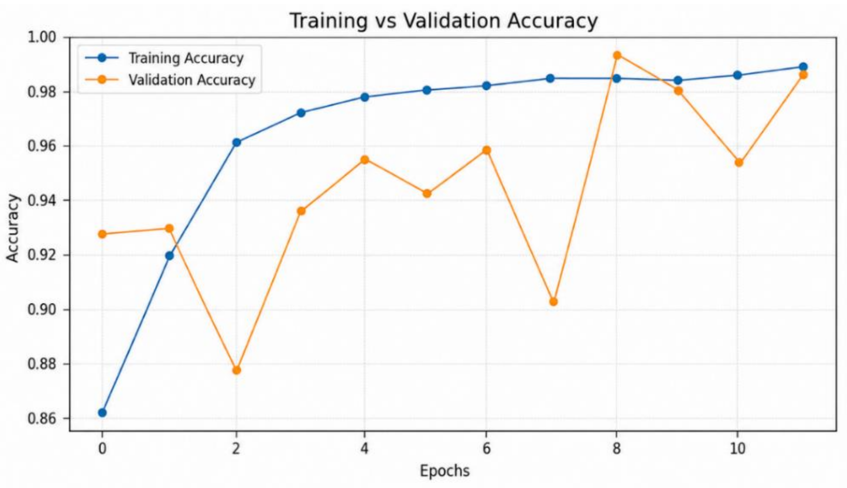

Figure 3: Validation accuracy

The results clearly show that the proposed approach is highly effective at detecting plant diseases, estimating infection severity, and suggesting suitable treatments. During training, the model's accuracy and loss were closely monitored across multiple epochs. It was observed that both training and validation accuracy quickly reached nearly 100% within just two epochs, while the loss values dropped almost to zero. This rapid convergence indicates that the model efficiently learned the key visual patterns necessary for accurate disease classification. When tested with real-world images, the system demonstrated strong robustness and consistency. It not only identified diseases accurately but also segmented the infected regions on the leaf, providing an estimate of the affected area. For example, when a farmer uploads a leaf image showing symptoms, the system automatically detects the disease type and calculates the infection percentage, providing valuable insights into the condition's severity. Compared to existing approaches, the proposed system offers several distinct advantages. Traditional methods depend on expert inspections or laboratory testing, which are accurate but slow, expensive, and impractical for large-scale farming. Mobile applications have attempted to address this challenge, yet many struggle with low accuracy and cannot measure infection severity (Figure 4).

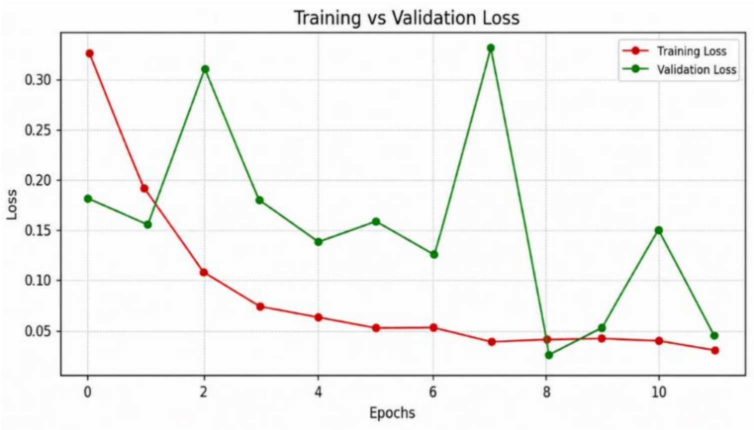

Figure 4: Validation loss

Older machine learning methods, such as SVMs and Random Forests, provided moderate accuracy but required manual feature extraction and lacked flexibility. In contrast, the Smart Leaf Disease Diagnosis System combines deep learning–based detection with severity estimation and treatment guidance, giving farmers an all-in-one decision-support tool that is both accurate and practical (Figure 5).

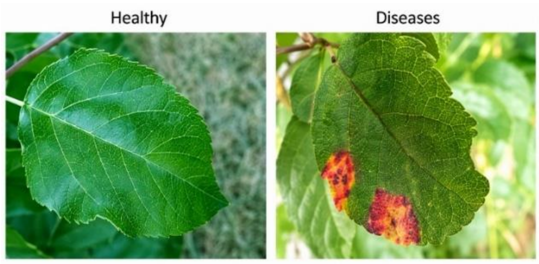

Figure 5: Sample predicted output

A key strength of this research lies in its ability to connect diagnosis directly with treatment advice. Many existing systems stop after identifying the disease, leaving farmers uncertain about what to do next. By linking each diagnosis to a structured treatment knowledge base, the system provides clear, actionable steps for managing infections effectively. The inclusion of infection percentage analysis further empowers farmers to prioritise interventions based on disease severity, ensuring timely and efficient crop protection. Another notable achievement is the system's efficiency and suitability for real-time use. Because the model converges quickly, it can run on mobile and web platforms without requiring heavy computational resources. Farmers can capture a leaf image directly in the field and receive instant feedback, minimising delays in diagnosis and treatment. This real-time capability is crucial in agriculture, where even a short delay can lead to rapid disease spread. The user-friendly interface also ensures that farmers with limited technical experience can easily adopt the system. However, some limitations need to be addressed. The very high training and validation accuracy may suggest possible overfitting if the dataset is not diverse enough. Although the system performed well on test data, future work should include a wider variety of leaf samples captured under different lighting conditions, backgrounds, and angles. Additionally, class imbalance in the dataset might cause the model to favour more common diseases.

Table 1: Predicted health condition

Parameter	Details
Leaf Condition	Unhealthy
Disease	Leaf Blight
Reason	Fungal infection due to high humidity
Pesticide to Use	Fungicide A
Alert Treatment Needed	Yes
Current severity	34.32%

Expanding the dataset, applying advanced augmentation, and exploring explainable AI techniques could help improve transparency, trust, and generalisation in future versions. Table 1 lists the Predicted Health Condition. Overall, the experimental results confirm that the Smart Leaf Disease.

Figure 6: Plant health analysis

Diagnosis System is a reliable and comprehensive solution for plant health monitoring. By combining high-accuracy detection, infection quantification, and treatment recommendations into a single integrated platform, it provides farmers with practical, data-driven insights for sustainable crop management.

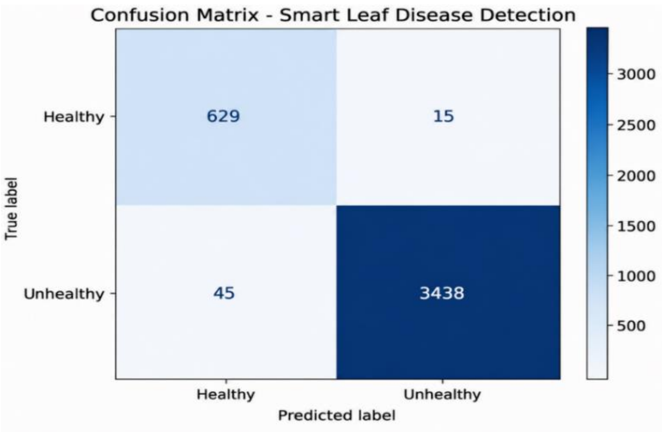

Figure 7: Confusion matrix

Its scalability and adaptability for mobile deployment make it a promising tool for precision agriculture, where quick and informed decisions can make all the difference. Figure 6 shows the Plant Health Analysis. Figure 7 shows the confusion matrix, which illustrates the performance of the Smart Leaf Disease Detection model.

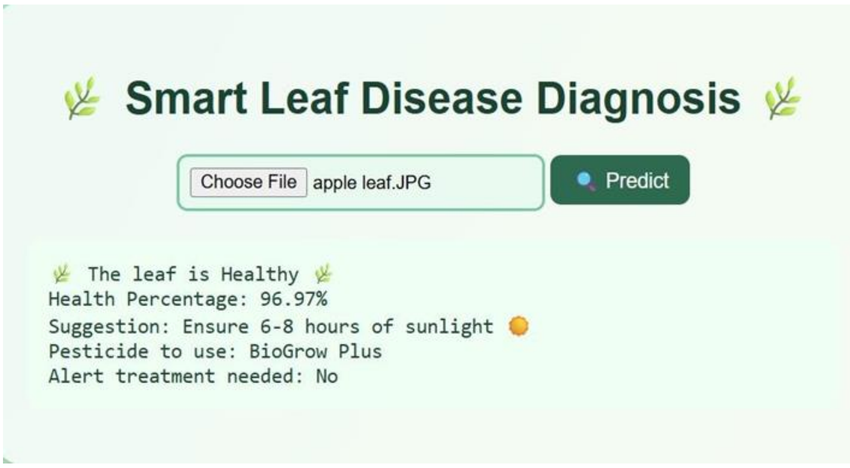

Figure 8: Healthy percentage

It shows high accuracy, correctly predicting 3438 unhealthy leaves and 629 healthy leaves, indicating the model's strong ability to distinguish between diseased and healthy plants. Figure 8 shows the Smart Leaf Disease Diagnosis interface, which displays the prediction result indicating the leaf's health status (96.97% healthy), along with personalised suggestions, such as sunlight requirements and recommended pesticides for optimal plant care.

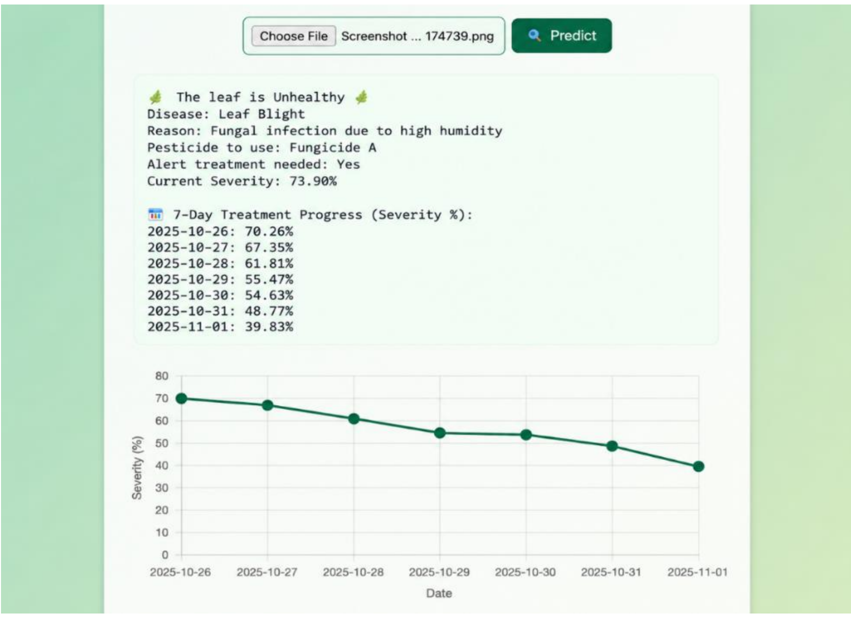

Figure 9: Unhealthy percentage

Figure 9 shows that the system output indicates the leaf is unhealthy, affected by Leaf Blight, a fungal infection caused by high humidity. It recommends using Fungicide A and provides a 7-day treatment progress chart showing a steady reduction in disease severity from 73.9% to 39.8%, confirming the treatment's effectiveness.

6. Conclusion

The Smart Leaf Disease Diagnosis System highlights how artificial intelligence and image processing can revolutionise traditional farming practices. Conventional disease detection methods are often slow, rely heavily on expert judgment, and are not easily accessible to farmers in rural or resource- limited areas. In contrast, the developed system provides an automated, accurate, and easy-to-use solution that allows farmers to upload a photo of a plant leaf and receive instant information on the disease type, the percentage of the affected area, and suitable treatment recommendations. The experimental results demonstrate that the model performs exceptionally well, achieving high accuracy in both training and validation with minimal error. By using convolutional neural networks (CNNs) for disease classification and image segmentation to measure infection, the system delivers consistent, precise diagnoses. What makes this approach even more valuable is the integration of a treatment recommendation module, which goes beyond identification to offer practical, science- based solutions. This turns the system into a comprehensive decision-support tool for plant health management. From an agricultural perspective, the system plays a key role in advancing precision farming. It helps reduce crop losses, improve yield quality, and promote environmentally sustainable practices. By providing real-time insights, farmers can act quickly to control diseases, saving both time and resources. The inclusion of a disease-treatment database ensures that the tool remains practical and relevant, bridging the gap between detection and effective management. Looking ahead, this system can be further developed into a mobile application that supports real-time field monitoring, GPS-based disease mapping, and multilingual accessibility, enabling it to reach farmers across diverse regions. Expanding the dataset to include more plant species and region-specific diseases will also enhance its adaptability. Overall, this research demonstrates how AI-driven innovation can make agriculture smarter, more sustainable, and more farmer-friendly— empowering communities to protect their crops and improve productivity with confidence.

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Data Availability Statement: The research utilises the Automated Leaf Disease Diagnosis dataset, which contains features and characteristics used for the detection, classification, and identification of plant leaf diseases.

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Ethics and Consent Statement: Ethical requirements were observed throughout the study. Permission was obtained from the relevant organisation and participating individuals during data collection, and the necessary ethical approval and informed consent were secured.

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