Leaf Sense: AI Powered System for Plant Disease Diagnosis and Personalized Care

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Abstract - The project aims to build an AI-driven plant disease prediction and diagnosis system that not only identifies plant diseases from images but also provides tailored treatment recommendations based on contextual data. The system incorporates convolutional neural networks (CNNs) to take into account other parameters such as plant type, planting history, pesticide applications, and environmental conditions to provide personalized solutions.The backend utilizes Python along with powerful libraries such as TensorFlow and Keras for image classification and predictive analytics. The Flask framework powers the web-based interface, ensuring efficient communication between the user and the system. The frontend designed using HTML, CSS, and JavaScript provides an interactive and user-friendly experience. To support long-term data storage and predictive improvements, the system integrates a reliable MySQL database to store user information and plant records for ongoing monitoring.This comprehensive platform provides real- time disease identification, actionable treatment recommendations and advanced monitoring capabilities, making it an invaluable tool for gardeners, farmers and plant enthusiasts. By simplifying decision-making and enhancing plant care management, the project highlights the transformative role of i in modern agriculture.

Keywords: Image Classification, Machine Learning, Personalized Treatment Recommendations, Plant Health Monitoring, Flask Web Application, Python, TensorFlow, Keras, MySQL Database, HTML, CSS, JavaScript

I. INTRODUCTION

Agriculture plays a pivotal role in sustaining economies and ensuring food security worldwide. However, one of the major challenges faced by farmers is the detection and management of plant diseases. These diseases, when not identified and treated promptly, can cause significant declines in crop yield and quality, leading to financial losses and threatening food availability. This problem is further aggravated by a rapidly increasing population and shifting climatic patterns, which contribute to the spread and complexity of plant diseases.

Conventional methods for diagnosing plant diseases often involve expert visual inspection, which is time-consuming, subjective, and prone to errors. By the time visible signs of disease appear, the damage may already be extensive, making containment and treatment efforts less effective and more expensive. The limitations of traditional approaches call for advanced solutions that can enable early, accurate, and efficient disease detection.

Recent technological advancements have demonstrated that artificial intelligence (AI) can play a transformative role in agricultural practices. Specifically, image processing combined with machine learning (ML) and deep learning techniques, including Convolutional Neural Networks (CNNs), has shown great promise in detecting plant diseases at their earliest stages. These models can analyze leaf patterns and subtle visual cues to accurately identify diseases, helping farmers take timely action to prevent damage.

Despite these advancements, the "black-box" nature of many AI models often hinders adoption. Farmers and agricultural professionals may be reluctant to rely on AI systems when they do not understand the basis for the decisions made by the models. Transparency and interpretability are essential to building trust and promoting the adoption of these advanced technologies.

To overcome these challenges, this project introduces an AI-Powered Plant Disease Diagnosis and Treatment Recommendation System that not only detects plant diseases from images but also provides tailored treatment recommendations. The key components of the system include:EfficientNetB0, a cutting-edge CNN architecture, is utilized for efficient and accurate classification of plant diseases.The model is trained on a comprehensive dataset encompassing 38 plant diseases to ensure robust recognition capabilities.

Local Interpretable Model-Agnostic Explanations (LIME) are employed to provide transparency in model decisions.LIME highlights the specific features that influenced the disease classification, enhancing user trust and understanding.Provides practical treatment suggestions based on contextal factors such as plant species, growth phase, and environmental conditions.A user-friendly app called *PlantCare* allows farmers to capture plant images and receive instant diagnoses along with actionable treatment advice.A MySQL database is utilized to store user data and plant health records, facilitating long-term tracking and model optimization. By integrating cutting-edge technologies, this system empowers agricultural stakeholders to make informed decisions and reduce crop losses. Beyond disease detection, it fosters trust through explainable AI while promoting sustainable agricultural practices. Its user-friendly design ensures accessibility for all, including farmers with minimal technical expertise.This project highlights how the convergence of deep learning, XAI, and mobile technology can revolutionize agricultural disease management, promote sustainable practices, and strengthen global food security.

Keywords:
Plant Disease Detection, Deep Learning, EfficientNetB0, Explainable AI (XAI), LIME, Agricultural Technology, Image Processing, Plant Health Management, Disease Diagnosis, Smart Farming.

II. Literature Review

The integration of artificial intelligence (AI) into agriculture has transformed plant disease detection and management, offering solutions that are faster, more accurate, and more accessible than traditional methods. Conventional approaches rely on manual inspection, expert assessment, and laboratory testing, which are often time-consuming, costly, and impractical for small-scale farmers. AI-driven technologies, particularly deep learning-based image classification and predictive analytics, have significantly enhanced disease identification and treatment efficiency.

Deep Learning for Image-Based Disease Detection

Machine learning, especially deep learning, has revolutionized plant disease diagnosis through automated image-based classification. Convolutional Neural Networks (CNNs) have demonstrated superior performance in identifying plant diseases compared to traditional machine learning models. Architectures such as ResNet, VGG16, and Inception are widely used due to their ability to extract intricate patterns from plant images, enabling high classification accuracy. Unlike conventional models that require handcrafted feature extraction, CNNs process raw images through multiple layers of convolutions, pooling, and activation functions to distinguish diseased from healthy plants. Research indicates that deeper networks tend to achieve higher accuracy but demand extensive computational resources. To address this, techniques like transfer learning—where pre-trained models are fine-tuned on agricultural datasets—enhance performance while reducing training time.

Context-Aware AI for Disease Management

Recent studies emphasize the importance of integrating contextual data to refine disease diagnosis and treatment recommendations. Factors such as plant species, growth stages, soil conditions, weather patterns, and pesticide history
significantly influence disease progression and treatment effectiveness. Multimodal AI models that combine image analysis with structured agricultural data offer a more comprehensive assessment of plant health. This personalized approach allows for precise disease management strategies 0tailored to specific crops and environmental conditions, improving treatment outcomes.

Scalability Through Web-Based AI Platforms

The growing adoption of AI-powered plant disease detection has led to the development of web-based diagnostic platforms that enhance accessibility and scalability. Research highlights the effectiveness of frameworks like Flask in building interactive applications where farmers can upload plant images, receive real-time disease analysis, and obtain treatment recommendations remotely. Additionally, cloud-based databases, such as MySQL, facilitate data storage and continuous model updates, ensuring the accuracy and relevance of AI-driven disease detection systems.

Challenges and Future Directions

A major challenge in AI-based plant disease diagnosis is the availability and diversity of training datasets. Many models are trained on limited datasets, making them less effective across different plant species and geographic regions. Researchers propose collaborative data-sharing initiatives and open-source repositories to mitigate this limitation. Another critical consideration is the ethical and environmental impact of AI-generated pesticide recommendations, emphasizing the need for sustainable and ecologically responsible agricultural practices. Future research explores the integration of AI with precision agriculture technologies, such as drone-assisted disease monitoring and IoT-based soil sensors, to enhance plant health assessments and disease prevention strategies.

III. PROBLEM STATEMENT

Plant diseases are a major challenge for global agriculture, leading to significant losses in harvest and economic production. Traditional methods for identifying diseases are based on manual observation, expert diagnosis, and clinical testing. This is often time-consuming, expensive and often inaccessible to smallholder farmers. A lack of timely and accurate recognition of disease leads to delayed treatment, and even inefficient characteristic extraction and lack of integration into real-world agricultural states. Many models do not include context-related factors such as soil health, weather conditions, and pesticide history. These are extremely important for accurate assessment of the disease and recommendations for treatment. Furthermore, scalability of diagnostic tools with AI-based diagnostic tools remains a challenge. This is because many solutions don't have a user-friendly interface that allows for seamless acceptance by farmers. Deep learning techniques, especially the folding network (CNN), integrate agricultural data to achieve high classification accuracy while simultaneously improving context-related agricultural data. The web-based interactive platform further improves accessibility and allows farmers to receive real-time recommendations for analyzing diseases and treatments Addressing these challenges will enable more efficient, scalable and accurate solutions for disease management, ultimately increasing agricultural sustainability and nutritional certainty.
computational time. Figures 2 and 3 show examples of images before and after pre-processing, respectively.

IV. PROPOSED SYSTEM

This section presents the proposed methodology, as illustrated in the approach consists of multiple stages, including data preprocessing, feature extraction, model training and validation, and prediction explainability. These steps ensure the efficient and accurate classification of plant diseases while maintaining transparency in decision-making.

A. Data Pre-processing

Initially, we remove the background from the plant images to isolate the region of interest (ROI). This crucial step eliminates noise that could lead to inaccurate diagnoses. For example, shadows or surrounding elements might be mistaken for disease symptoms. Additionally, images are categorized into distinct crop classes to enhance the efficiency of model training.

B. Feature Extraction

Next, we extract the most relevant features from the pre-processed data to develop our machine learning model. This is a critical stage, as the model's performance heavily relies on the quality and quantity of these features. We employ transfer learning using the EfficientNetB0 model as our default feature extraction technique. The base model's layers are frozen to prevent retraining, and we extend it with global average pooling and a dense layer for multi-class classification. This process generates a rich set of features, enhancing the model's disease detection capabilities.

C. Model Training and Validation

To ensure the model's robustness, the dataset is divided into an 80:20 split: 80% of the images are used for training, and the remaining 20% are used for validation. provides a description of the dataset. Here's a paraphrased version of that training description, focusing on clarity and conciseness. The model is trained iteratively to optimize its ability to distinguish between different plant diseases. To guide this learning process, we use categorical cross-entropy, a measure of how well the model's predictions match the actual disease labels. The Adam optimizer is employed to efficiently adjust the model's internal parameters (weights), leading to faster and more stable learning.

D. Prediction Explainability

Finally, we utilize the LIME framework to explain individual model predictions. LIME approximates any black-box machine learning model by creating a local interpretable model. This involves perturbing the original data points, feeding them into the black-box model, and observing the results. Weights are assigned to the perturbed data points based on their proximity to the original point. These weights are then used to train a surrogate model, such as linear regression, on the perturbed dataset. The resulting interpretable model can then be used to explain the predictions for each original data point.

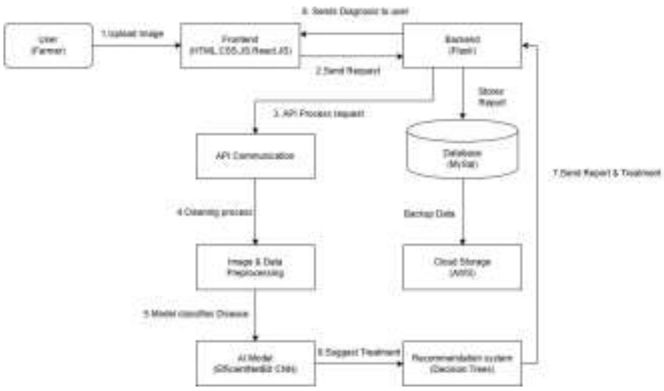

Fig. 1. Workflow Diagram

V. METHODOLOGY

The methodology of the proposed AI-Powered Plant Disease Diagnosis and Treatment Recommendation System is structured into several key stages: data acquisition and preprocessing, model selection and training, metadata integration, care routine generation, and system deployment.

Data Acquisition and Preprocessing

The system begins with the collection of a comprehensive dataset comprising grayscale images of various plants affected by multiple diseases. The choice of grayscale images was made to reduce the computational complexity and focus the model on structural and texture features critical for disease identification. Each image undergoes preprocessing steps that include resizing to a standardized resolution, normalization of pixel values, and augmentation techniques such as rotation, flipping, and zooming to enhance model generalization. This preprocessing pipeline ensures that the input data is consistent and robust against variations in lighting and orientation.

Model Selection and Training

EfficientNetB0, a state-of-the-art convolutional neural network, was selected as the backbone for disease classification. This model is known for its compound scaling method that balances network depth, width, and resolution, delivering high accuracy with fewer parameters compared to traditional architectures. Transfer learning is employed by initializing EfficientNetB0 with weights pretrained on the ImageNet dataset, enabling the model to leverage learned low-level features. The final layers are fine-tuned on the plant disease dataset with categorical cross-entropy loss and the Adam optimizer, using a learning rate scheduler to optimize training efficiency. The model training includes early stopping criteria based on validation loss to prevent overfitting.

Integration of Plantation Metadata

To improve diagnostic accuracy beyond image data alone, the system incorporates user-provided metadata, specifically plantation time and cultivation duration. These temporal parameters are critical as the manifestation and severity of plant diseases can vary depending on the growth stage. The system processes this metadata through rule-based logic that adjusts the interpretation of the model's predictions. For example, if plantation time and cultivation duration are less than six months, the system applies a specific diagnostic threshold and treatment set (Diagnosis A), whereas if the period exceeds six months, an alternative diagnosis and treatment plan (Diagnosis B) is applied. This integration ensures that the system accounts for the biological context of disease development.

Plant Care Routine Generation

Beyond disease identification, the system offers a plant care routine feature that generates personalized maintenance advice based on plant type and age (number of days since planting). This module uses predefined agronomic guidelines and dynamically adjusts care instructions such as watering frequency, fertilization, pruning, and pest control measures. The care routine is tailored to the specific needs of the plant at its current growth stage, providing users with actionable steps to promote plant health and prevent future disease outbreaks.

System Deployment and User Interface

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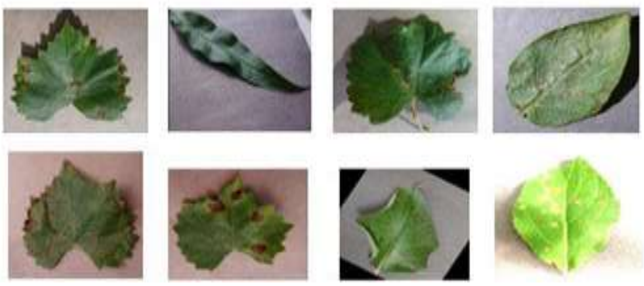
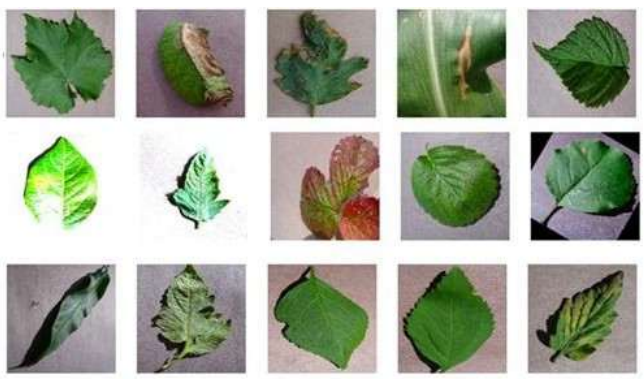
The entire system is implemented in Python, utilizing TensorFlow and Keras for the deep learning components. For serving the model predictions and managing user inputs, a RESTful API is developed using Flask or FastAPI frameworks, ensuring efficient communication between the frontend and backend. The user interface is developed with HTML, CSS, and JavaScript, providing an intuitive web-based platform where users can upload plant images, enter metadata, and receive comprehensive diagnostic reports. These reports include the disease classification, treatment recommendations, and the customized plant care routine.

Evaluation and Validation

The system's performance is evaluated through metrics such as accuracy, precision, recall, and F1-score on a held-out validation set. Additionally, the impact of integrating plantation metadata is quantified by comparing the diagnostic performance of the image-only model versus the combined approach. User feedback is collected to assess the usability and usefulness of the plant care routine feature.





VI. Results and Discussion

This study explores the effectiveness of four advanced deep learning models—CNN, MobileNetV2, EfficientNetB0, and ResNet-50—in detecting plant diseases. The performance analysis summarized in Table 4 reveals that EfficientNetB0 outperforms the other models, achieving superior accuracy, precision, and recall. MobileNetV2 follows as the second-best performer with a classification accuracy of 96.89%, while ResNet-50 delivers the lowest accuracy of 79.83%, making it the least effective among the models tested. These findings confirm that EfficientNetB0 provides the most reliable disease detection results.

A confusion matrix, presented visualizes the classification accuracy across different disease categories, while illustrates how accuracy changes over multiple training epochs. The graph suggests noticeable fluctuations in training and validation accuracy as the number of epochs increases.

To improve transparency in the model's predictions, this study employs explainable AI (XAI) techniques, specifically the Lime (Local Interpretable Model-Agnostic Explanations) framework. Lime enhances interpretability by explaining how the model arrives at its predictions. provides a Lime-based explanation for classifying Pepper Bell with Bacterial Spot disease, showing that the model predicts this disease with a 100% confidence level, ensuring high reliability.

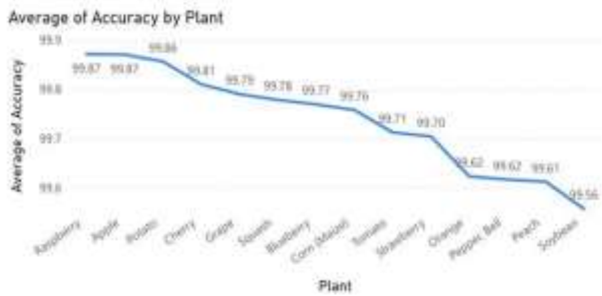
TABLE 4. Performance metrics of CNN models.

Model	Accuracy (%)	Precision (%)	Recall (%)
CNN	96.44	94.22	94.22
MobileNetV2	96.89	96.12	96.14
EfficientNetB0	**99.69**	**98.27**	**98.26**
ResNet-50	79.83	75.21	75.21

TABLE 5. ANOVA test results for model accuracy.

Statistical Measure	Value
F-statistic	20.8237
p-value	0.0002

FIGURE 8. Number of samples per plant.



Statistical Evaluation

To validate the statistical significance of variations in model performance, an analysis of variance (ANOVA) test was conducted. The results, including the F-statistic and p-value, are summarized ,Since the p-value falls below the predefined significance threshold ($\alpha = 0.05$), the null hypothesis is rejected, indicating that the variations in model accuracy are statistically meaningful. This confirms that the observed differences in disease classification accuracy stem from differences in the model architectures rather than random fluctuations.

Data Visualization and Insights

To extract deeper insights from the dataset, Power BI was used to generate various data visualizations. Fig. 8 illustrates the number of samples available for each plant species, while displays the classification accuracy for different plants. These results indicate that the quality and diversity of images in the dataset play a crucial role in model performance. Furthermore, highlights the distribution of images based on disease categories, providing an overview of dataset composition.

Challenges and Limitations

Despite its potential benefits for early plant disease detection, this study has certain limitations. Firstly, the dataset used does not encompass a wide range of environmental conditions, which could affect the model's ability to generalize across different real-world scenarios. Expanding the dataset with more diverse samples could enhance model robustness. Secondly, the study relies on four pre-trained deep learning models for evaluation. Incorporating additional state-of-the-art architectures could potentially yield better classification performance. Lastly, increasing the size of the training dataset would likely improve the model's accuracy and reliability, making it more effective in real-world agricultural applications. Addressing these limitations could further strengthen the system's ability to diagnose plant diseases with greater precision.

VII. CONCLUSION AND FUTURE SCOPE

Plant diseases severely impact agricultural productivity and economic stability. This research demonstrates the effectiveness of a deep learning system for plant disease detection, enhanced by explainable artificial intelligence (XAI). Using advanced deep learning models, we achieved high accuracy in disease identification and provided interpretable results through XAI. Specifically, we developed a machine learning model using EfficientNetB0, trained on 87,000 images, which accurately classified 38 different plant diseases. The model achieved impressive performance metrics, including 99.69% accuracy, 98.27% precision, and 98.26% recall. The LIME framework provided clear explanations for the model's predictions, revealing both its effective generalization and potential biases from outlier images. This transparency allows researchers and experts to better understand the model's decision-making process. Statistical analysis, including ANOVA, further validated the model's significant performance.

While the current system demonstrates promising results in diagnosing plant diseases and offering tailored care recommendations, several directions remain for future improvement and expansion. One of the primary goals is to enhance the scalability and generalizability of the model by incorporating a more diverse and extensive dataset that includes a wider variety of plant species, disease types, and environmental conditions. This will allow the system to be adapted for use across different agricultural regions and crop varieties, making it a more universal solution for plant disease diagnosis.

Another important aspect of future development involves creating comprehensive and customizable disease diagnosis reports. These reports will be structured to serve both technical and non-technical users. For agricultural scientists and agronomists, the reports will include detailed analysis such as disease progression patterns, image-based evidence, and model confidence scores. For farmers and general users, the same information will be presented in simplified, actionable formats using visuals and easy-to-understand language. This dual-level reporting system is aimed at encouraging broader adoption of the technology by addressing the varying levels of technical expertise in the user base.

Furthermore, we plan to integrate Internet of Things (IoT) technology into the system, enabling automated and real-time monitoring of plant health in agricultural fields. Sensors installed in farms can collect data on temperature, humidity, soil moisture, and other relevant environmental parameters. These inputs, when combined with periodic image captures from in-field cameras, can provide a holistic view of plant conditions. The system will continuously analyze this data to detect early symptoms of disease, trigger alerts, and automatically update the diagnosis and treatment strategies. Such real-time, end-to-end monitoring will help reduce the time lag between disease occurrence and intervention, leading to improved crop yields and reduced losses.

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