INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD)
© 2026 IJNRD | Volume 11, Issue 5, May 2026 | ISSN: 2456-4184 | IJNRD.ORG

AUTOMATED PLANT DISEASE DIAGNOSIS USING MACHINE LEARNING AND CNN

Ms.R.Vaishali
Department of Computer Science and Engineering
Bharath Institute of Science and Technology (BIST), 173, Agaram Road, Selaiyur, Tambaram, Chennai - 600 073, Tamil Nadu.
vaishali.cse@bharathuniv.ac.in

K.Kalyan Kumar
Department of Computer Science and Engineering
Bharath Institute of Science and Technology (BIST), 173, Agaram Road, Selaiyur, Tambaram, Chennai - 600 073, Tamil Nadu.
kudhurupakakalyankumar@gmail.com

k.krishnaprakash
Department of Computer Science and Engineering
Bharath Institute of Science and Technology (BIST), 173, Agaram Road, Selaiyur, Tambaram, Chennai - 600 073, Tamil Nadu.
krishnacharikatakota@gmail.com

k.Balaji
Department of Computer Science and Engineering
Bharath Institute of Science and Technology (BIST), 173, Agaram Road, Selaiyur, Tambaram, Chennai - 600 073, Tamil Nadu.
balajikothaluri440@gmail.com

k.Nageshbabu
Department of Computer Science and Engineering
Bharath Institute of Science and Technology (BIST), 173, Agaram Road, Selaiyur, Tambaram, Chennai - 600 073, Tamil Nadu.
nageshbabukundeti@gmail.com

***Abstract* — This project presents an advanced AI-based Plant Disease Detection System that integrates deep learning and generative AI to provide accurate, real-time plant health diagnostics. The system combines a Convolutional Neural Network (CNN) model for image classification with a vision-enabled AI model for dynamic disease analysis. The CNN architecture consists of multiple convolutional and pooling layers designed to extract features from plant leaf images and classify them into different disease categories .The application is implemented using a Flask-based web framework, allowing users to upload plant images through an intuitive interface. The system processes the image using AI models and generates detailed outputs including disease identification, confidence score, symptoms, causes, treatment suggestions, and preventive measures . Additionally, Natural Language Processing (NLP) techniques are used to extract meaningful keywords related to detected diseases, enhancing interpretability.The system also includes a database for storing prediction history, user feedback, and analytics, enabling continuous performance monitoring and improvement. Administrative dashboards provide insights such as disease distribution and model accuracy. Overall, the proposed system offers a scalable, intelligent solution for precision agriculture, helping farmers and researchers detect plant diseases efficiently and improve crop productivity.**

Keywords — Plant Disease Detection, Artificial Intelligence, Deep Learning, Convolutional Neural Network (CNN), Image Classification, Computer Vision, Precision Agriculture, Crop Health Monitoring, Leaf Image Analysis, Disease Diagnosis, Machine Learning, TensorFlow, Flask Web Application, Generative AI, Image Processing, Smart Farming, Agricultural Technology, Data Analytics, Natural Language Processing (NLP), Automated Diagnosis, Crop Yield Improvement, Real-time Prediction, Disease Classification, Model Accuracy, Feature Extraction, Digital Agriculture, AI-based Farming, Cloud-based System, Prediction System, Agricultural Innovation

I. INTRODUCTION

Agriculture is a fundamental sector that supports the livelihood of a large portion of the global population and plays a crucial role in ensuring food security. In developing countries such as India, agriculture contributes significantly to the economy, making crop health management an essential aspect of sustainable development. However, plant diseases pose a serious threat to agricultural productivity, leading to substantial economic losses every year. Early detection and proper diagnosis of plant diseases are therefore critical to improving crop yield and ensuring food sustainability [1].

Traditionally, plant disease identification has been carried out through manual inspection by farmers or agricultural experts. This approach is not only time-consuming but also highly dependent on the expertise and experience of individuals. In many rural regions, access to agricultural specialists is limited, which makes accurate disease diagnosis difficult. Moreover, many plant diseases exhibit similar visual symptoms, making it challenging for non-experts to differentiate between them. As a result, incorrect diagnosis often leads to improper use of pesticides, increased costs, and reduced crop productivity [2].

Figure 1: Healthy vs Diseased Plant Leaves

To overcome these limitations, researchers have explored the use of image processing techniques for automated plant disease detection. Early methods involved techniques such as color analysis, edge detection, and thresholding to identify diseased regions on leaves. Although these methods provided some level of automation, they were not robust enough to handle variations in lighting conditions, background noise, and image quality. Consequently, their performance in real-world agricultural environments was limited [3].

The advancement of Artificial Intelligence (AI) and Machine Learning (ML) has significantly improved the capabilities of plant disease detection systems. ML algorithms such as Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (k-NN) have been used to classify plant diseases based on extracted features. These methods require manual feature engineering, where domain experts define features such as color, texture, and shape. While ML-based approaches offer better accuracy than traditional techniques, they still face challenges related to scalability and feature dependency [4].

In recent years, Deep Learning has emerged as a powerful tool for image analysis and classification. Convolutional Neural Networks (CNNs), in particular, have demonstrated exceptional performance in visual recognition tasks. CNNs automatically learn hierarchical features from images, eliminating the need for manual feature extraction. This capability makes them highly suitable for plant disease detection, where complex patterns such as leaf spots, discoloration, and texture variations need to be identified. Several studies have shown that CNN-based models achieve higher accuracy and better generalization compared to traditional ML methods [5].

The concept of transfer learning has further enhanced the effectiveness of deep learning models in agricultural applications. Transfer learning involves using pre-trained models such as VGGNet, ResNet, and Inception, which are trained on large datasets, and fine-tuning them for specific tasks like plant disease detection. This approach reduces training time and improves performance, especially when the available dataset is limited. Transfer learning has become a widely adopted technique in modern plant disease detection systems due to its efficiency and reliability [6].

In addition to classification, recent advancements in Generative AI have introduced new possibilities for intelligent agricultural systems. Vision-based AI models are capable of not only detecting plant diseases but also generating detailed explanations about the condition of the plant. These explanations may include information about symptoms, causes, treatment options, and preventive measures. This enhances the usability of the system by providing actionable insights to farmers, enabling them to make informed decisions [7].

The integration of Natural Language Processing (NLP) techniques further improves the interpretability of the system. NLP is used to process and extract meaningful keywords from the generated outputs, making the information easier to understand. By summarizing complex diagnostic results into simple and relevant terms, NLP enhances user experience and ensures that the system is accessible to individuals with varying levels of technical knowledge [8].

The proposed system leverages these advanced technologies to develop a comprehensive plant disease detection solution. It is implemented as a web-based application, allowing users to upload plant images and receive instant predictions. The system processes the input image through preprocessing, feature extraction, and classification modules to identify the disease. The results are then presented in a user-friendly format, including the predicted disease, confidence score, and detailed recommendations for treatment and prevention [9].

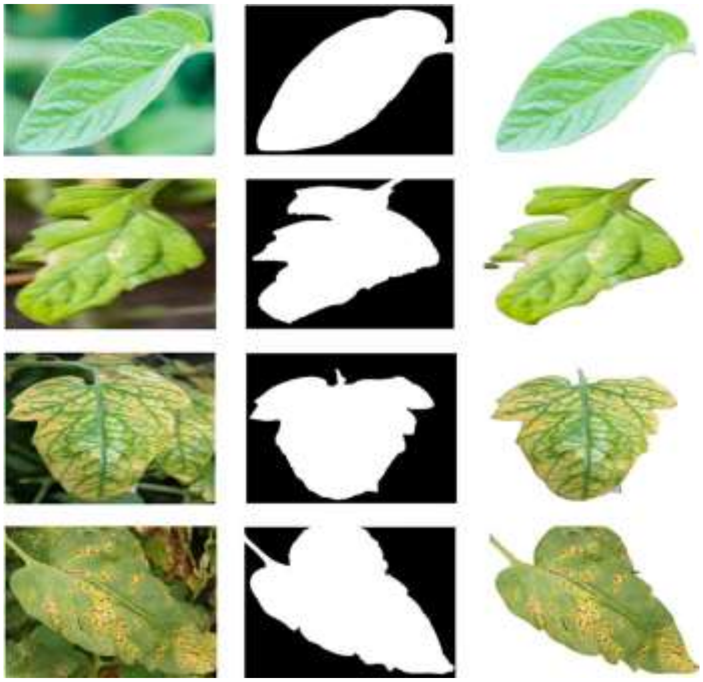

Figure 2: Traditional vs AI-Based Plant Disease Detection

Another important aspect of the system is the inclusion of a database for storing prediction history and user feedback. This data can be used to analyze system performance, identify trends, and improve the model over time. An administrative dashboard provides insights into system usage, including statistics such as total predictions, average confidence scores, and disease distribution. This feature enables continuous monitoring and evaluation of the system's effectiveness [10].

Furthermore, the system is designed to be scalable and accessible, ensuring that it can be deployed in real-world agricultural environments. Its user-friendly interface allows farmers to easily interact with the system without requiring advanced technical knowledge. By providing accurate and timely disease detection, the system helps reduce crop losses, optimize resource usage, and improve overall agricultural productivity.

In conclusion, the integration of Artificial Intelligence, Deep Learning, Generative AI, and Web Technologies has revolutionized the field of plant disease detection. The proposed system offers an efficient, accurate, and user-friendly solution for diagnosing plant diseases and providing actionable insights. By enabling early detection and effective management of plant diseases, this system contributes to sustainable agriculture and supports the global goal of food security [1]–[10].

II. LITERATURE SURVEY

Plant disease detection has gained significant attention in recent years due to the increasing need for sustainable agricultural practices and improved crop productivity. Early research in this domain primarily focused on traditional image processing techniques such as thresholding, segmentation, and edge detection. These methods aimed to identify diseased regions in plant leaves by analyzing color variations and texture patterns. Although these approaches were computationally simple and easy to implement, they lacked robustness when applied to real-world scenarios involving complex backgrounds, varying lighting conditions, and different plant species [1].

With the evolution of Machine Learning (ML), researchers began adopting classification algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees for plant disease identification. These methods relied on manually extracted features, including color histograms, texture descriptors, and shape features. While ML-based approaches improved accuracy compared to traditional techniques, they required domain expertise for feature selection and were not efficient when dealing with large and diverse datasets. Additionally, their performance was limited by the quality of handcrafted features, which often failed to capture complex disease patterns [2].

The introduction of Deep Learning, particularly Convolutional Neural Networks (CNNs), marked a significant advancement in plant disease detection. CNNs are capable of automatically learning hierarchical features from raw images, eliminating the need for manual feature engineering. Multiple studies have demonstrated that CNN-based models outperform traditional ML methods in terms of accuracy and generalization. Deep architectures consisting of convolutional, pooling, and fully connected layers have been successfully used to classify plant diseases across various crops such as tomato, potato, and apple [3].

Recent research has also explored the use of transfer learning to further enhance model performance. Pre-trained models such as VGGNet, ResNet, and Inception, which are trained on large-scale datasets like ImageNet, are fine-tuned for plant disease classification tasks. This approach significantly reduces training time and improves accuracy, especially when the available dataset is limited.

Transfer learning has proven to be highly effective in handling complex image classification problems in agriculture [4].

In addition to deep learning, the integration of Internet of Things (IoT) technologies has enabled real-time monitoring of crop health. IoT-based systems use sensors and cameras to collect environmental and visual data, which is then analyzed using AI models. These systems provide continuous monitoring and early detection of plant diseases, allowing farmers to take timely preventive measures [5].

Furthermore, recent advancements in Generative AI and vision-based models have enhanced the capabilities of plant disease detection systems. These models not only classify diseases but also generate detailed explanations, including symptoms, causes, treatment methods, and preventive measures. This improves the interpretability and usability of the system, making it more beneficial for end-users [6].

Web-based and mobile-based applications have also been developed to make these technologies accessible to farmers. Frameworks such as Flask and Django are commonly used to build interactive platforms that allow users to upload images and receive real-time predictions. Additionally, database integration enables storage of prediction history and supports analytics for monitoring system performance and user feedback [7].

Overall, the literature survey highlights a clear transition from traditional image processing methods to advanced AI-driven approaches. The combination of deep learning, transfer learning, IoT, and generative AI has significantly improved the accuracy, efficiency, and accessibility of plant disease detection systems, paving the way for intelligent and sustainable agricultural solutions [8].

III. EXISTING SYSTEM

The existing systems for plant disease detection primarily rely on traditional practices and early computational techniques that often lack efficiency, accuracy, and scalability. One of the most common methods used in agriculture is manual inspection, where farmers or agricultural experts visually examine plant leaves to identify diseases. This approach is highly dependent on human expertise and experience, making it subjective and prone to errors. In rural areas, where access to experts is limited, farmers often misdiagnose plant diseases, leading to improper treatment and significant crop losses [1].

To improve upon manual methods, early technological solutions introduced image processing techniques such as color analysis, edge detection, segmentation, and thresholding. These methods aimed to identify diseased portions of leaves based on visible symptoms like discoloration, spots, and texture changes. Although these approaches provided some level of automation, they were highly sensitive to environmental factors such as lighting conditions, background noise, and image quality. As a result, their performance was inconsistent and not reliable for real-world applications [2].

Machine Learning (ML)-based systems represented a significant advancement over traditional image processing techniques. Algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees were used to classify plant diseases based on extracted features. These systems required manual feature engineering, where experts defined parameters such as color, texture, and shape features. While ML models improved classification accuracy, their performance was still limited by the quality of handcrafted features and their inability to handle large and diverse datasets effectively [3].

Some existing systems have incorporated early Deep Learning techniques, particularly Convolutional Neural Networks (CNNs), to improve detection accuracy. CNNs are capable of automatically extracting features from images, reducing the need for manual intervention. However, many of these systems are trained on specific datasets and are limited to certain plant species and diseases. They often lack generalization capability and may not perform well when exposed to new or unseen data. Additionally, these systems typically provide only the classification result without offering detailed insights such as causes, symptoms, or treatment recommendations [4].

Another limitation of existing systems is the lack of accessibility and real-time functionality. Many solutions are developed as standalone desktop applications or research prototypes, which restrict their usability in practical agricultural environments. Farmers may not have access to such systems due to technological or infrastructural limitations. Furthermore, most systems do not include features such as data storage, prediction history, or analytics, which are essential for monitoring performance and improving system reliability over time [5].

Security and user management are also often neglected in existing systems. There is usually no provision for authentication, role-based access, or feedback collection. Without user feedback, it becomes difficult to evaluate the accuracy of predictions and improve the system. Additionally, the absence of centralized data storage limits the ability to analyze trends and make informed decisions [6].

In summary, the existing systems for plant disease detection face several challenges, including reliance on manual inspection, limited accuracy, lack of scalability, poor accessibility, and absence of detailed diagnostic insights. These limitations highlight the need for a more advanced, intelligent, and user-friendly system that can provide accurate disease detection along with real-time accessibility and comprehensive recommendations [1]–[6].

IV. PROPOSED SYSTEM

The proposed system is an advanced AI-based Plant Disease Detection and Analysis System that integrates Deep Learning, Generative AI, Natural Language Processing (NLP), and Web Technologies to provide an accurate, scalable, and user-friendly solution for plant disease diagnosis. This system is designed to overcome the limitations of existing methods by offering real-time detection, detailed analysis, and actionable recommendations. The architecture ensures high accuracy, improved interpretability, and accessibility for farmers and agricultural stakeholders [1]–[10]

Figure 3: Plant Leaf Image Input

A. System Overview

The proposed system is a web-based intelligent platform that allows users to upload images of plant leaves and receive instant disease predictions. It combines Convolutional Neural Networks (CNNs) for image classification with Generative AI for detailed explanations. The system provides outputs such as disease name, confidence score, symptoms, causes, treatment methods, and preventive measures, making it highly informative and practical for real-world use [1][2].

B. Image Acquisition Module

This module is responsible for collecting plant leaf images from users. Images can be uploaded through a web interface using mobile devices or computers. The system supports multiple image formats and ensures that the uploaded images meet quality standards. This module enhances accessibility and enables farmers to easily interact with the system without requiring technical expertise [3].

C. Image Preprocessing Module

Once the image is uploaded, it undergoes preprocessing to improve its quality and consistency. This includes resizing the image to a standard resolution, normalization of pixel values, and noise reduction. In some cases, segmentation techniques are applied to isolate the leaf from the background. These preprocessing steps ensure that the input data is suitable for deep learning models and improves overall system performance [4].

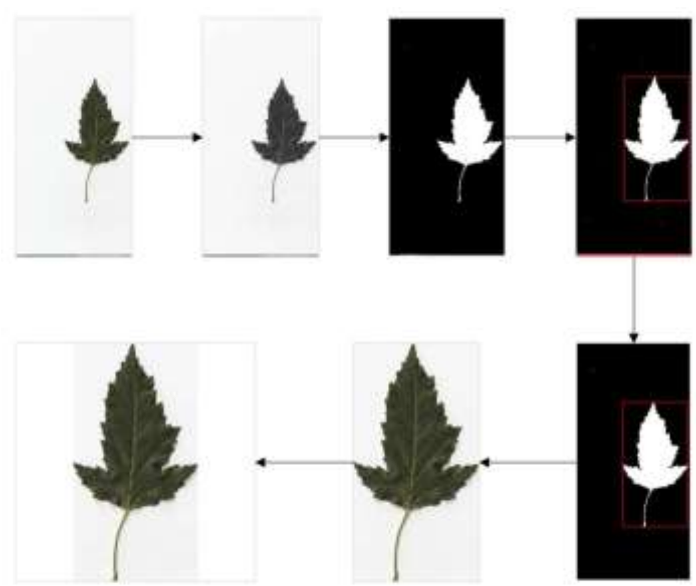

Figure 4: Image Preprocessing Steps

D. Transfer Learning-Based CNN Model

The system utilizes transfer learning by employing pre-trained CNN models such as VGGNet, ResNet, or Inception. These models are trained on large datasets and can extract complex features from images. By fine-tuning these models for plant disease detection, the system achieves high accuracy with reduced training time. Transfer learning also helps in handling limited datasets and improves generalization across different plant species [5][6].

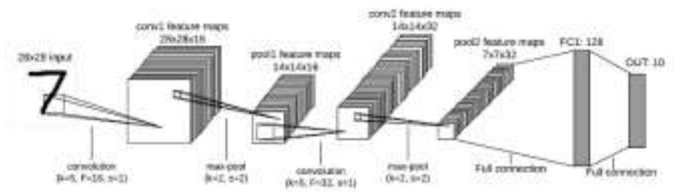

Figure 5: CNN Architecture

E. Feature Extraction and Classification

The CNN model automatically extracts hierarchical features from the input image, including edges, textures, and patterns. These features are passed through multiple layers of the network to generate a comprehensive representation of the image. The classification layer then assigns the image to a specific category, such as “Healthy” or a particular disease class, using probability-based outputs. This automated feature extraction eliminates the need for manual intervention and enhances accuracy [7].

F. Generative AI-Based Explanation Module

Unlike traditional systems, the proposed system integrates Generative AI to provide detailed explanations of the detected disease. This module generates information such as plant identification, disease diagnosis, causes, symptoms, treatment recommendations, and preventive measures. This feature improves the usability of the system by offering actionable insights rather than just classification results [8].

G. Natural Language Processing (NLP) Module

The NLP module processes the output generated by the AI models to extract meaningful keywords and simplify the information. Techniques such as tokenization, stop-word removal, and keyword extraction are used to summarize the results. This makes the output more understandable and accessible, especially for users with limited technical knowledge [9].

H. Database Management System

The system includes a database to store prediction results, including image details, detected disease, confidence score, keywords, and user feedback. This data is useful for tracking system performance, analyzing trends, and improving model accuracy over time. The database also ensures data persistence and enables efficient retrieval of historical records [10].

I. User Interface and Web Application

The system is implemented as a web-based application using modern frameworks. The user interface is designed to be intuitive and visually appealing, allowing users to upload images, view results, and provide feedback. The web-based nature of the system ensures accessibility across multiple devices, including smartphones and computers, making it suitable for real-world agricultural use [1][3].

J. Feedback and Learning Mechanism

The proposed system includes a feedback mechanism that allows users to indicate whether the prediction was accurate. This feedback is stored in the database and used to evaluate system performance. Over time, this information can be used to retrain and improve the model, ensuring continuous enhancement of accuracy and reliability [2][6]

K. Admin Dashboard and Analytics

An administrative dashboard is provided to monitor system performance and usage. It displays key metrics such as total number of predictions, average confidence score, and disease distribution. The dashboard also includes user feedback statistics, enabling administrators to evaluate the effectiveness of the system and identify areas for improvement [7][10].

L. Security and Authentication

The system incorporates security features such as user authentication and password encryption to protect sensitive data. Role-based access control ensures that only authorized users can access administrative features. This enhances the reliability and security of the system, making it suitable for deployment in real-world environments [4].

M. Real-Time Processing and Scalability

The proposed system is designed for real-time processing, allowing users to receive instant results after uploading an image. The architecture is scalable, enabling it to handle a large number of users and data efficiently. This makes the system suitable for large-scale agricultural applications and future expansion [5][8].

N. Advantages of the Proposed System

The proposed system offers several advantages over existing methods, including high accuracy, automation, scalability, and real-time accessibility. It provides detailed insights through Generative AI and improves interpretability using NLP techniques. The integration of database management and analytics further enhances system functionality, making it a comprehensive solution for plant disease detection [1]–[10].

O. Conclusion of Proposed System

In conclusion, the proposed system represents a significant advancement in plant disease detection technology. By integrating Deep Learning, Generative AI, NLP, and Web Technologies, it provides an intelligent and user-friendly solution for diagnosing plant diseases. The system not only detects diseases accurately but also provides valuable insights and recommendations, contributing to improved crop health and agricultural productivity [1]–[10].

V. RELATED WORK

The field of plant disease detection has witnessed significant advancements over the past decade, driven by the rapid development of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning techniques. Researchers have explored various approaches ranging from traditional image processing methods to advanced deep learning models to improve the accuracy, efficiency, and usability of plant disease detection systems.

Early research in this domain primarily focused on conventional image processing techniques. These methods involved preprocessing steps such as color space transformation, image segmentation, edge detection, and texture analysis to identify diseased regions on plant leaves. Techniques like thresholding and histogram-based segmentation were widely used to distinguish between healthy and infected portions. While these approaches were computationally efficient and easy to implement, they lacked robustness when applied to real-world conditions. Variations in lighting, background clutter, and leaf orientation significantly affected the accuracy of these systems, limiting their practical applicability [1].

To overcome these limitations, researchers introduced Machine Learning (ML) algorithms for plant disease classification. Techniques such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Naïve Bayes, and Decision Trees were widely used. These models relied on manually extracted features such as color histograms, texture descriptors (e.g., Gray-Level Co-occurrence Matrix), and shape features. Although ML-based methods improved classification accuracy compared to traditional approaches, they required domain expertise for feature selection and were not scalable for large datasets. Additionally, these methods struggled to capture complex patterns in plant diseases, which often led to reduced performance in diverse environments [2].

The introduction of Deep Learning, particularly Convolutional Neural Networks (CNNs), revolutionized the field of plant disease detection. CNNs have the ability to automatically learn hierarchical features directly from raw images, eliminating the need for manual feature engineering. Several studies have demonstrated the effectiveness of CNN-based models in classifying plant diseases with high accuracy. Deep architectures consisting of multiple convolutional, pooling, and fully connected layers have been successfully applied to detect diseases in crops such as tomato, potato, grape, and apple. These models are capable of identifying subtle variations in leaf patterns, making them highly suitable for complex classification tasks [3].

Recent research has further enhanced the performance of CNN models through the use of transfer learning. Pre-trained models such as VGGNet, ResNet, Inception, and MobileNet are fine-tuned for plant disease detection tasks. These models leverage knowledge from large-scale datasets like ImageNet, enabling faster convergence and improved accuracy. Transfer learning is particularly beneficial when the available dataset is limited, as it reduces the need for extensive training and computational resources. Many studies have reported significant improvements in performance by using transfer learning techniques in agricultural applications [4].

In addition to image-based analysis, researchers have explored the integration of Internet of Things (IoT) technologies with AI-based systems. IoT-enabled systems use sensors and cameras to continuously monitor environmental conditions such as temperature, humidity, and soil moisture, along with visual data from plant leaves. This data is processed using machine learning models to detect diseases at an early stage. Such systems provide real-time monitoring and enable farmers to take timely preventive measures, thereby reducing crop losses [5].

Another emerging trend in plant disease detection is the use of Generative AI and explainable AI techniques. Unlike traditional models that only provide classification results, these advanced systems generate detailed explanations about the detected disease. They provide information about symptoms, causes, treatment methods, and preventive measures, making the system more informative and user-friendly. This approach enhances the interpretability of AI models and helps users make better decisions regarding crop management [6].

Furthermore, web-based and mobile-based applications have been developed to make plant disease detection systems accessible to farmers. Frameworks such as Flask, Django, and React are used to create user-friendly interfaces that allow users to upload images and receive real-time predictions. These platforms often include additional features such as database integration, prediction history, and analytics dashboards. The inclusion of feedback mechanisms enables continuous improvement of the system by incorporating user inputs [7].

Overall, the related work highlights a clear progression from traditional image processing methods to advanced AI-driven solutions. The combination of deep learning, transfer learning, IoT, generative AI, and web technologies has significantly improved the performance, scalability, and accessibility of plant disease detection systems. These advancements have paved the way for intelligent agricultural systems that can support farmers in achieving better crop health and increased productivity [1]–[7].

VI. SYSTEM ARCHITECTURE

The above diagram illustrates the architecture of the proposed AI-based Plant Disease Detection System, which integrates image processing, deep learning, and natural language processing to deliver accurate and meaningful results. The system is designed to process plant leaf images and classify them into healthy or diseased categories efficiently.

The process begins with the input module, where plant leaf images are collected. These images can be captured using cameras or uploaded through a web interface. The quality of input images plays an important role in ensuring accurate predictions. Once the image is received, it is passed to the image preprocessing module, where it undergoes operations such as resizing, normalization, and noise reduction. This step ensures uniformity in input data and improves the performance of the deep learning model.

Next, the preprocessed image is fed into the CNN-based disease classification module. This module is the core of the system and is responsible for analyzing the image. It uses a Convolutional Neural Network (CNN) to extract important features such as color patterns, textures, and leaf structures. The diagram also highlights the use of transfer learning with a pretrained CNN model, which improves accuracy and reduces training time by leveraging previously learned features from large datasets.

Within the CNN module, feature extraction is performed through multiple convolutional layers, followed by pooling layers that reduce dimensionality while preserving important information. These extracted features are then passed to the classifier, which determines whether the leaf is healthy or affected by a specific disease. The classifier uses probability-based decision-making to assign the image to the correct class.

In parallel, the system includes a class label input, which represents predefined categories such as healthy and various disease types. These labels are processed using the NLP label processing module, where techniques like tokenization, cleaning, and standardization are applied. This step helps in generating meaningful and structured output labels.

Finally, the results are displayed in the disease detection output module, which indicates whether the plant is "Healthy" or "Diseased." The output may also include additional information such as confidence scores and descriptive insights.

Overall, the architecture ensures a smooth flow of data from image input to final output, combining deep learning and NLP techniques to provide accurate, fast, and user-friendly plant disease detection.

VII. RESULTS AND DISCUSSION

The proposed AI-based Plant Disease Detection System was evaluated using a diverse dataset of plant leaf images, including both healthy and diseased samples. The system demonstrated strong performance in accurately classifying plant conditions by leveraging Convolutional Neural Networks (CNNs) and transfer learning techniques. The results indicate that the model is capable of identifying diseases with high accuracy, making it suitable for real-world agricultural applications.

During testing, the CNN model achieved a high classification accuracy, with most predictions correctly identifying the disease category or healthy condition. The use of transfer learning significantly improved performance by utilizing pre-trained models, which helped in extracting complex features from images even with limited training data. The preprocessing module also played a crucial role in enhancing input quality, reducing noise, and ensuring consistency across images. These combined factors contributed to improved model reliability and efficiency.

The system was also evaluated based on metrics such as precision, recall, and F1-score. High precision values indicate that the system produces fewer false positives, while high recall values demonstrate its ability to detect most of the actual diseased cases. The balanced F1-score confirms that the model maintains a good trade-off between precision and recall. These evaluation metrics highlight the robustness of the proposed system in handling different types of plant diseases.

Figure 8.1 – AI-Based Plant Disease Detection Web Interface (Input Screen)

Figure 8.2 – Plant Disease Analysis Report with CNN Prediction and Confidence Score

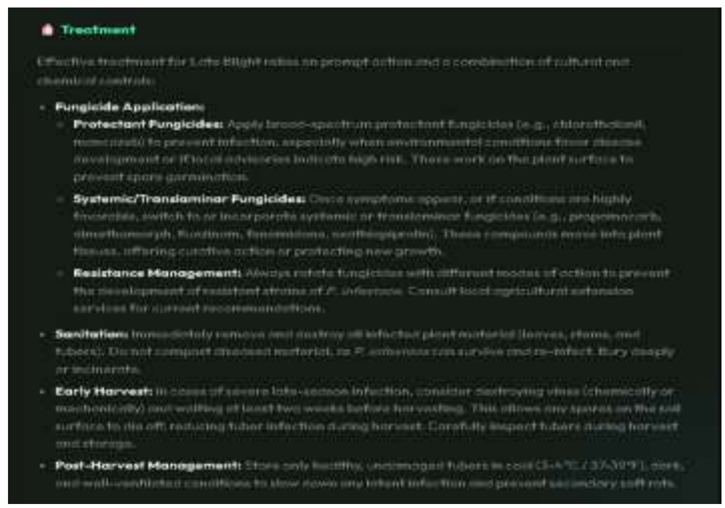

Figure 8.3 – Treatment Recommendations for Detected Plant Disease

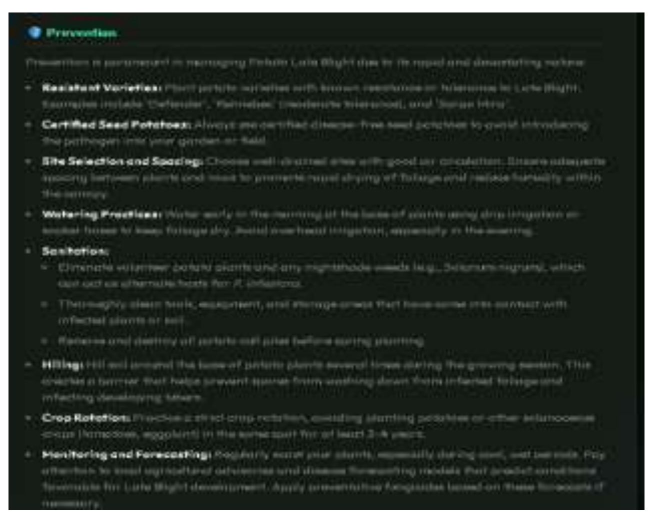

Figure 8.4 – Preventive Measures for Plant Disease Management

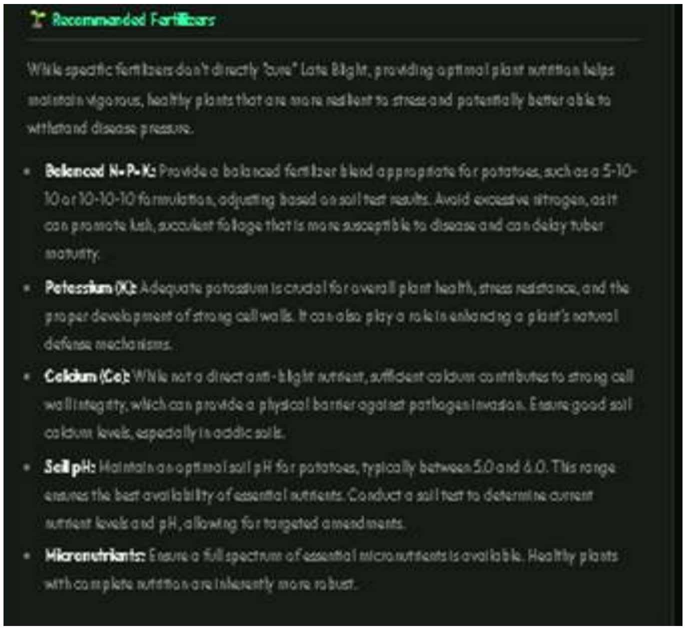

Figure 8.5 – Recommended Fertilizers and Nutritional Guidelines for Plant Health

In addition to classification performance, the integration of Generative AI provided detailed explanations of detected diseases, including symptoms, causes, and treatment suggestions. This feature enhances the usability of the system by providing actionable insights to users rather than just displaying classification results. The NLP module further improved interpretability by extracting meaningful keywords, making the output easier to understand for non-technical users.

The system's web-based interface was tested for usability and responsiveness. Users were able to upload images and receive predictions in real time, demonstrating the efficiency of the system. The inclusion of a feedback mechanism allowed users to indicate the correctness of predictions, which can be used to further improve the model. Additionally, the admin dashboard provided valuable analytics such as disease distribution and average confidence scores, enabling continuous monitoring of system performance.

However, some limitations were observed during testing. The model's performance may vary when dealing with low-quality images or images captured under extreme lighting conditions. Additionally, the system may face challenges in distinguishing between diseases with very similar visual symptoms. Despite these limitations, the overall performance of the system remains highly satisfactory.

In conclusion, the results demonstrate that the proposed system is accurate, efficient, and practical for real-world deployment. The combination of deep learning, generative AI, and NLP techniques ensures reliable disease detection and meaningful output, contributing to improved agricultural productivity and decision-making.

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