IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⨳ Peer-reviewed & Refereed journal ⨳ Vol. 13, Issue 4, April 2026

DOI: 10.17148/IARJSET.2026.13438

Crop Disease Detection: AI-Based Crop Disease Detection and Weather Risk Prediction System

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Abstract: Agriculture plays a vital role in the economy, and early detection of crop diseases is essential for improving yield and reducing losses. Traditional methods of disease identification rely heavily on manual inspection by experts, which is time-consuming, costly, and often inaccessible to farmers in rural areas. This paper presents **Crop Disease Detection**, an AI-powered web-based system designed to detect crop diseases from leaf images and predict weatherbased disease risks.

The system utilizes advanced Artificial Intelligence models, including GPT-4o-mini Vision for image-based disease detection and Gemini Flash for real-time weather risk analysis. The proposed solution allows users to upload leaf images, analyze crop health, and receive detailed information such as disease name, severity, symptoms, and treatment recommendations.

In addition, the system integrates weather-based risk prediction using parameters such as temperature, humidity, and rainfall to forecast potential disease outbreaks. The system also provides multilingual support, voice assistance, and a structured database for storing and analyzing historical data.

Experimental results show that the system improves accuracy, reduces manual effort, and provides real-time assistance to farmers. Crop Disease Detection offers a scalable and intelligent solution for modern precision agriculture and can be extended further with IoT integration and advanced predictive analytics.

Keywords: Crop Disease Detection, Artificial Intelligence, Image Processing, Precision Agriculture, Weather Risk Prediction, Machine Learning, Smart Farming, GPT Vision AI, Agricultural Analytics

I. INTRODUCTION

Agriculture is one of the most important sectors contributing to economic growth and food security. However, crop diseases pose a significant threat to agricultural productivity, leading to major losses for farmers. Early detection and proper management of plant diseases are crucial to ensure healthy crop production.

Traditionally, farmers rely on manual inspection or agricultural experts to identify plant diseases. This approach is not only time-consuming but also inefficient, especially in remote areas where expert access is limited. Additionally, environmental factors such as temperature, humidity, and rainfall significantly influence the spread of crop diseases, making prediction equally important.

The advancement of Artificial Intelligence and web technologies, automated systems can now assist in disease detection and prediction. This paper presents Crop Disease Detection, an intelligent system that combines image-based disease detection with weather-based risk prediction.

The system allows users to upload crop leaf images and utilizes AI models to analyze and identify diseases. It also evaluates real-time weather conditions to predict disease risks and provides preventive recommendations. The integration of multilingual support and voice assistance further enhances usability for farmers.

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Overall, Crop Disease Detection aims to improve agricultural decision-making, reduce crop losses, and provide an accessible, efficient, and intelligent farming solution.

II. LITERATURE SURVEY

In recent years, the agricultural sector has witnessed a significant transformation with the adoption of advanced technologies for crop monitoring and disease detection. Traditional methods of identifying plant diseases rely on manual observation by experts, which is time-consuming, less efficient, and prone to human error, especially when dealing with large-scale farming. With the emergence of technologies such as Deep Learning, Machine Learning (ML), Computer Vision, and Image Processing, there has been a shift toward automated plant disease detection systems. These technologies enable accurate analysis of plant leaf images, early disease identification, and improved decision-making, thereby enhancing agricultural productivity and reducing crop losses.

Deep learning-based approaches have shown remarkable performance in plant disease detection tasks. Early research demonstrated that Convolutional Neural Networks (CNNs) can effectively learn complex features from plant leaf images and classify diseases with high accuracy [1]. These models leverage large datasets to achieve reliable predictions and have laid the foundation for modern plant disease detection systems. Further studies have evaluated multiple deep learning architectures and reported accuracy levels exceeding 99% under controlled conditions, highlighting the robustness and efficiency of such models [2].

In addition to model development, several studies have focused on improving classification performance through preprocessing techniques and data augmentation. These methods enhance the quality and diversity of training data, thereby improving model generalization and reducing overfitting [3]. Moreover, the integration of deep learning models into web-based platforms has enabled the development of user-friendly applications that allow farmers and agricultural experts to detect diseases in real time using simple interfaces [4]. Such systems demonstrate the practical applicability of deep learning in real-world agricultural scenarios.

Research has also explored the use of deep neural networks for real-time plant disease recognition, emphasizing their superiority over traditional machine learning methods. These approaches utilize image classification techniques to identify diseases efficiently and accurately, even in complex conditions [5]. Furthermore, comparative studies on finetuning pre-trained models have shown that transfer learning significantly improves performance, particularly when working with limited datasets. This approach reduces training time and computational requirements while maintaining high accuracy [6].

Another important aspect of plant disease detection is the role of dataset size and variability. Studies have shown that larger and more diverse datasets contribute to better model performance and robustness. Variations in lighting conditions, backgrounds, and leaf orientations can significantly impact model accuracy, making dataset diversity a crucial factor in system design [7]. Additionally, comprehensive reviews of plant disease detection techniques have highlighted the evolution from classical machine learning methods to advanced deep learning approaches, emphasizing the growing importance of AI-driven solutions in agriculture [8].

Despite these advancements, several challenges remain in the development of effective plant disease detection systems. Many existing models perform well in controlled environments but struggle under real-world conditions due to variations in environmental factors. Additionally, high computational requirements and dependency on large datasets limit the accessibility of these systems for small-scale farmers. Most current solutions focus primarily on disease classification and lack integration with real-time monitoring, mobile applications, or decision-support systems.

To overcome these limitations, modern research is moving toward the development of integrated and scalable solutions that combine deep learning with practical deployment platforms. Such systems aim to provide real-time disease detection, improved accuracy, and user-friendly interfaces that can be easily used by farmers. The focus is also on reducing computational complexity and enhancing model adaptability to diverse environmental conditions.

Overall, the literature indicates a clear transition from traditional manual disease detection methods to intelligent automated systems based on deep learning and image processing. While significant progress has been made in improving accuracy and efficiency, challenges related to scalability, real-world applicability, and system integration still persist. Future systems aim to address these gaps by developing comprehensive, efficient, and accessible solutions for plant disease detection and management.

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III. PROBLEM STATEMENT

Farmers face significant challenges in identifying crop diseases accurately and at an early stage. Traditional methods rely on manual inspection, which is time-consuming, requires expertise, and may lead to incorrect diagnosis.Additionally, environmental conditions such as temperature and humidity contribute to disease spread, but farmers often lack tools to predict these risks effectively.Existing systems are either limited to disease detection or weather analysis and do not provide an integrated solution. Therefore, there is a need for an intelligent system that can automatically detect crop diseases and predict weather-based risks efficiently with minimal user effort.

IV. SCOPE OF PROJECT

The scope of Crop Disease Detection includes the development of an AI-based system capable of detecting crop diseases from leaf images and predicting disease risks based on weather conditions.The system provides treatment recommendations, prevention tips, and supports multiple languages for better accessibility. It also includes features such as scan history, voice assistance, and data storage.The project is implemented as a web-based application and can be extended in the future with mobile applications, IoT integration, and advanced predictive analytics.

V. PROPOSED METHODOLOGY

The Crop Disease Detection system follows a structured workflow consisting of image processing, AI analysis, and weather-based prediction.Initially, the user uploads a crop leaf image through the web interface.

The image is then processed and sent to the GPT-4o-mini Vision model, which analyzes the image and returns diseaserelated information such as disease name, severity, symptoms, and treatment suggestions.

For weather risk prediction, the system collects user location data and uses the Gemini Flash model to fetch real-time weather information. Based on parameters such as temperature, humidity, and rainfall, the system applies predefined rules to determine the disease risk level.

The processed data is then displayed to the user in a structured format, and the results can be stored in the database for future reference. The system follows a modular architecture to ensure efficiency and scalability.

VI. SYSTEM DESIGN

The system design of Crop Disease Detection plays a crucial role in defining the architecture, workflow, and interaction between various components of the system. It acts as a blueprint that translates system requirements into a structured and efficient implementation. The design focuses on modularity, scalability, and ease of use to ensure that the system can handle real-time data processing and provide accurate results.

The overall architecture of the system is divided into three primary modules: Input Module, Processing Module, and Output Module**.**The Input Module is responsible for collecting data from the user. It allows users to upload crop leaf images and enter their location manually or automatically using GPS. This module ensures proper validation of inputs before sending them for processing. The image is uploaded to cloud storage, and its URL is generated, which is then passed to the AI model for analysis.

The Output Module presents the processed information to the user in a clear and structured format. It displays disease details, risk levels, recommendations, and preventive measures. The results are also stored in the database for future reference and analysis. The system provides additional features such as scan history, filtering options, and statistical summaries.

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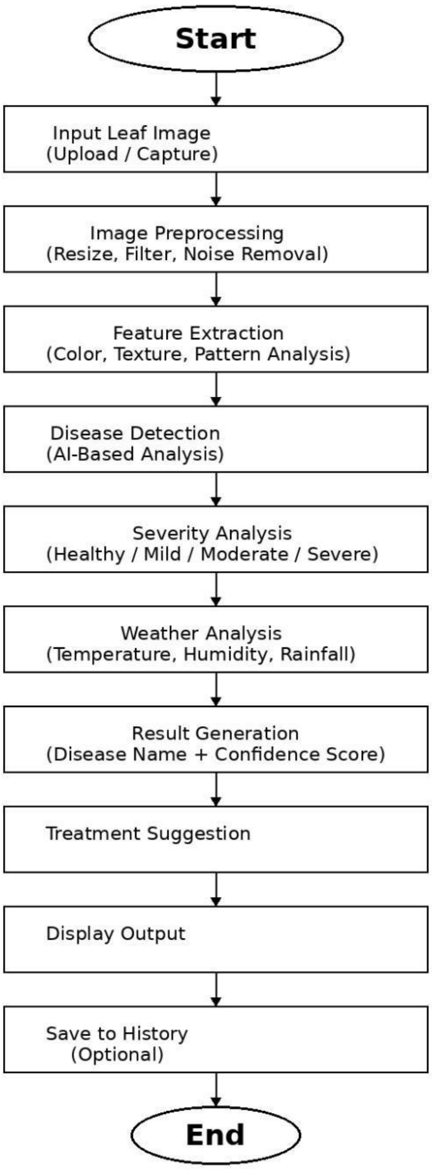

Fig. 1 Flow Diagram

The system follows a modular architecture, where each component performs a specific function. This approach improves maintainability and allows easy integration of new features in the future. The data flow within the system follows a simple pipeline: User Input → AI Processing → Data Analysis → Result Generation → Storage

The system also includes a user-friendly interface designed using modern web technologies. It supports multilingual interaction and voice commands, making it accessible to a wide range of users, including farmers with limited technical knowledge.

Overall, the system design ensures efficient data handling, real-time processing, high accuracy, and scalability. It provides a strong foundation for future enhancements such as mobile integration, IoT-based monitoring, and advanced predictive analytics.

VII. RESULTS AND DISCUSSION

The Crop Disease Detection system was successfully implemented and tested using various crop images and weather conditions. The system accurately identified diseases and provided detailed analysis, including severity and treatment recommendations.

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The weather prediction module effectively analyzed environmental conditions and predicted disease risks with reasonable accuracy. The integration of both modules provided a comprehensive solution for farmers.

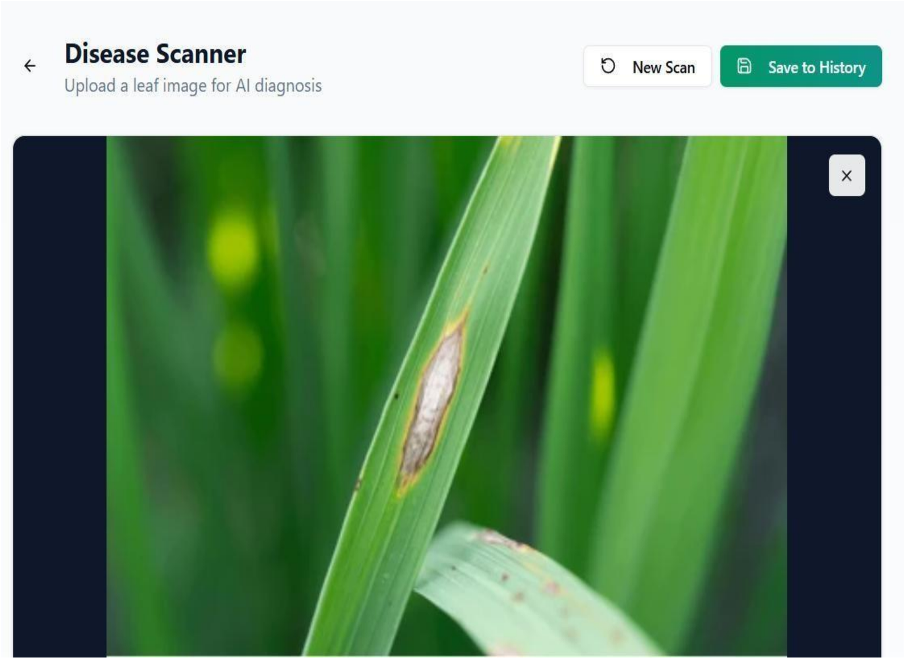

Fig. 2 Disease Image

The system also showed strong performance in weather-based disease risk prediction. By analyzing real-time environmental parameters such as temperature, humidity, and rainfall, the system successfully categorized risk levels into low, moderate, high, and critical. The implementation of fuzzy logic rules allowed the system to simulate real-world agricultural conditions and provide meaningful predictions regarding potential disease outbreaks.

The integration of both modules resulted in a unified system capable of providing end-to-end analysis, from disease identification to preventive recommendations. This integration significantly enhances the practical usability of the system for farmers and agricultural stakeholders.

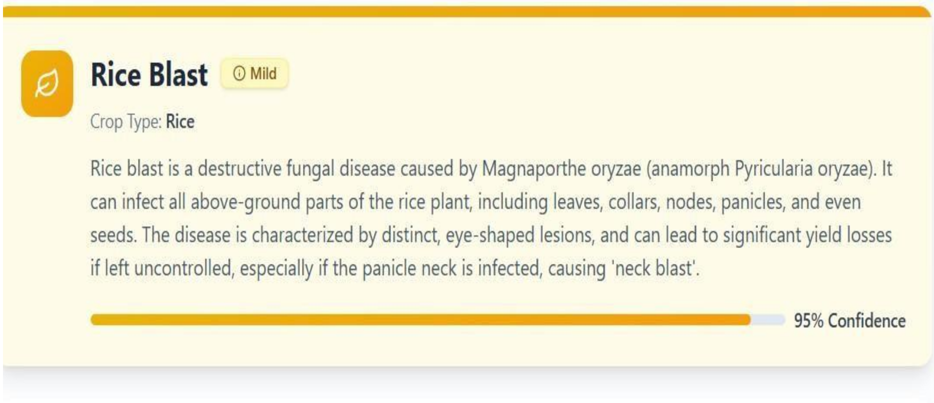

Fig. 3 Disease Detection Result

The system significantly reduces the time required for disease detection compared to manual methods. Features like multilingual support and voice assistance improve usability and accessibility for farmers. However, the system depends on internet connectivity and the accuracy of AI models.

The performance of the system is affected by the quality of input images, as poor lighting or low resolution may reduce accuracy. The weather prediction module also depends on the availability of real-time data from external sources. Additionally, the system currently supports a limited number of crops and diseases.

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Overall, the system provides an efficient and automated solution for crop disease detection and prediction. It improves productivity, reduces manual effort, and supports better decision-making. With future improvements such as offline support, IoT integration, and enhanced prediction models, the system can become more scalable and effective for smart agriculture.

VIII. APPLICATIONS

The Crop Disease Detection system is widely used in agriculture to identify plant diseases at an early stage. It helps farmers take timely action and reduce crop damage, leading to improved productivity and better crop quality. The system reduces dependency on manual inspection methods.

It plays an important role in smart farming by using Artificial Intelligence and modern technologies. Farmers can monitor crop health and receive accurate results quickly, which helps in making informed decisions. This improves efficiency in farming practices.

The system also supports precision agriculture by providing detailed information about diseases, severity, and treatment suggestions. This enables efficient use of resources such as fertilizers and pesticides, reducing unnecessary expenses and environmental impact.

Additionally, the system is useful in agricultural research and education for studying plant diseases. It promotes sustainable farming practices by minimizing losses and encouraging the adoption of advanced technologies in agriculture.

IX. CONCLUSION

The Crop Disease Detection system provides an efficient and reliable solution for identifying plant diseases using Artificial Intelligence and image processing techniques. By analyzing crop leaf images, the system enables early detection of diseases, helping farmers take timely action. This reduces crop damage and improves overall agricultural productivity.

The system also includes weather-based risk prediction by analyzing environmental factors such as temperature, humidity, and rainfall. This feature helps in predicting possible disease outbreaks and allows farmers to take preventive measures in advance. It improves planning and reduces unexpected crop losses.

Additionally, the system provides severity classification, confidence scores, and treatment recommendations, which support better decision-making. The user-friendly interface and multilingual support make the system accessible to farmers from different regions. This ensures ease of use and practical implementation in real-world conditions.

Overall, the proposed system promotes smart farming practices by reducing dependency on manual methods and improving efficiency. It contributes to sustainable agriculture by minimizing losses and optimizing resource usage. The system demonstrates reliable performance and has the potential to be widely used in modern agriculture.

X. ACKNOWLEDGMENT

The authors express their sincere gratitude to their Guide, **Mr. Kanda Kumaran Thevar** for his valuable guidance, Project Co-Ordinator **Mr. Sandeep Shinde** for his valuable support throughout the project. We also thank the Head of Department, **Mr. Ranjeet Pawar,** and the Principal, **Mr. P. N. Tandon**, for their encouragement and support.

We extend our appreciation to **Dr. Anindita Achint Khade, Mr. Madhavan Naikar, and Mr. Gaurav Jadhav** for their assistance during the literature survey. Finally, we thank the Department of Information Technology and all teaching and non-teaching staff for their support in successfully completing this project.

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