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Crop Yield Prediction and Disease Detection

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Abstract: Agriculture plays a vital role in ensuring food security and economic sustainability, yet it faces significant challenges such as climate variability, pest infestations, and plant diseases that adversely affect crop productivity. This paper proposes an intelligent agricultural management system that integrates machine learning and deep learning techniques for crop yield prediction, plant disease detection, and crop recommendation. A hybrid approach using SARIMAX and XGBoost models is employed for crop yield prediction by capturing both temporal patterns and nonlinear relationships in environmental and historical data, including rainfall, temperature, and location-specific factors. For disease detection, YOLOv5 is utilized to accurately identify and localize diseases in leaf images, while a Large Language Model (Groq) is used to generate detailed explanations and treatment recommendations.The system incorporates a weather analysis and crop recommendation module that provides short-term weather forecasts and suggests suitable crops based on environmental conditions. A user-friendly chatbot powered by a Large Language Model enables farmers to interact with the system, upload images, and receive real-time guidance. The proposed system offers a scalable and automated solution for precision agriculture, enhancing decision-making, reducing crop losses, and promoting sustainable farming practices.

Index Terms: Crop Yield Prediction, Plant Disease Detection, YOLOv5, SARIMAX, XGBoost, Large Language Model, Precision Agriculture, Crop Recommendation.

I. INTRODUCTION

Agriculture plays a crucial role in ensuring food security, economic stability, and sustainable development, particularly in countries like India where a significant portion of the population depends on farming for their livelihood. However, modern agriculture faces numerous challenges, including climate variability, soil degradation, pest infestations, and plant diseases, all of which significantly impact crop productivity and yield. Traditional farming practices, which rely on manual observation and past experience, are often inefficient, time-consuming, and prone to human error, making them inadequate for addressing the complexities of present-day agricultural systems.

Recent advancements in machine learning and deep learning have enabled the development of intelligent systems capable of analyzing large-scale agricultural data and providing accurate predictions and insights. Crop yield prediction and plant disease detection are two critical areas where artificial intelligence can significantly enhance decision-making. Accurate yield prediction assists farmers in planning resource allocation and market strategies, while early disease detection helps in reducing crop loss and minimizing the excessive use of pesticides.

In this context, the proposed system presents an integrated approach that combines multiple intelligent modules for smart agriculture. A hybrid model using SARIMAX and XGBoost is employed for crop yield prediction by capturing both temporal patterns and nonlinear relationships in environmental and historical data. For disease detection, YOLOv5 is utilized to identify and localize plant diseases from leaf images, and a Large Language Model (LLM) deployed via the Groq platform is used to generate detailed explanations and treatment recommendations.

Additionally, the system includes a weather analysis and crop recommendation module that provides short-term weather forecasts and suggests suitable crops based on environmental conditions. A chatbot interface powered by a Large Language Model enables farmers to interact with the system, ask queries, and receive real-time guidance. By integrating these technologies, the proposed system aims to reduce dependency on manual monitoring, improve agricultural productivity, minimize crop losses, and promote sustainable farming practices.

II. PROBLEM STATEMENT

Agriculture continues to face significant challenges in maintaining crop health and achieving optimal yield due to the limitations of traditional farming practices. Existing methods primarily rely on manual observation and historical knowledge, which are time-consuming, labor-intensive, and prone to human error. As a result, early symptoms of plant diseases often go undetected, leading to severe crop damage, reduced productivity, and increased dependency on excessive pesticide usage.

Crop yield prediction is a complex task influenced by multiple dynamic factors such as temperature, rainfall, soil conditions, and geographical variations. Traditional statistical methods are often insufficient to capture both temporal dependencies and nonlinear relationships among these variables, resulting in inaccurate and unreliable predictions. Furthermore, most existing systems address either disease detection or yield prediction independently, lacking an integrated approach that combines both functionalities.

In addition, farmers often lack access to real-time weather insights and crop recommendations that are essential for effective agricultural planning. The absence of intelligent advisory systems further limits their ability to make timely decisions regarding crop selection, irrigation, and disease management. This gap is more pronounced in rural areas where access to expert guidance is limited.

Therefore, there is a need for a comprehensive, intelligent, and user-friendly system that integrates plant disease detection, crop yield prediction, weather analysis, and crop recommendation. Such a system should leverage advanced machine learning and deep learning techniques to provide accurate predictions, early disease detection, and actionable insights, thereby enabling farmers to improve productivity, reduce losses, and adopt sustainable farming practices.

III. LITERATURE SURVEY

The rapid advancement of precision agriculture has led to the widespread adoption of Machine Learning (ML) and Deep Learning (DL) techniques to improve agricultural productivity and sustainability. Various research efforts have focused on crop yield prediction, plant disease detection, pest management, and crop classification using data-driven approaches. These studies highlight the effectiveness of models such as Random Forest, XGBoost, and deep neural networks in capturing complex relationships within agricultural data. However, challenges such as data dependency, model complexity, and lack of real-time applicability still persist.

Screpnik et al. [1] conducted a comprehensive review of artificial intelligence techniques for crop yield prediction. Their study identified ensemble models, particularly Random Forest and Gradient Boosting, as highly effective due to their ability to handle nonlinear relationships. The authors emphasized the importance of integrating multiple data sources such as satellite imagery, climate data, and soil parameters. However, they noted a significant gap between high-performing models and their practical deployment in real-world farming environments.

Sharma et al. [2] explored a hybrid approach combining traditional machine learning models and deep learning techniques for yield prediction. Their study evaluated Decision Tree, Random Forest, XGBoost, CNN, and LSTM models, where Random Forest achieved the highest accuracy of 98.96%. Despite achieving high performance, the study highlighted the limitation of requiring large and diverse datasets for effective generalization.

Ashfaq et al. [5] proposed a wheat yield prediction model using a combination of climate data and NDVI indices. Their ensemble approach achieved an RMSE of 2.2982 kg/ha and an R^2 value of 0.9752. Similarly, Kumar et al. [7] applied ensemble learning for sugarcane yield prediction using meteorological data, where Random Forest achieved an R^2 of 0.93.

Badshah et al. [4] developed machine learning models for crop classification and yield prediction, achieving a classification accuracy of 99.53% and a regression R^2 of 0.9973 using CatBoost. Haider et al. [9] further improved prediction accuracy using a Voting Regressor combining Random Forest, XGBoost, and LightGBM, achieving an R^2 of 0.99.

The integration of IoT technologies has also enhanced agricultural monitoring systems. Saleem et al. [13] proposed an IoT-based pest prediction system using deep neural networks, achieving 98.26% accuracy. Hoque et al. [11] incorporated meteorological and pesticide data into a Random Forest model for yield prediction, achieving an R^2 of 0.997.

In the field of plant disease detection, Rani et al. [3] reviewed various AI-based techniques, highlighting the effectiveness of convolutional neural networks. Khalid and Talukder [10] proposed a hybrid deep learning model achieving 99.89% accuracy on the PlantVillage dataset. Mamun et al. [6] explored self-supervised learning approaches to reduce dependency on large labeled datasets. Large-scale agricultural monitoring has also been explored using remote sensing techniques. Shafi et al. [8] applied machine learning with satellite data for wheat yield prediction, achieving an R^2 of 0.87. Mai et al. [12] demonstrated that incorporating high-resolution soil moisture data significantly improves prediction accuracy. Finally, Najjar et al. [14] emphasized the importance of explainable AI using SHAP analysis to improve model transparency, while Iniyan and Jebakumar [15] developed a mobile-based system for crop yield prediction, enhancing accessibility for farmers.

Despite these advancements, most existing systems focus either on yield prediction or disease detection independently. There is a lack of integrated frameworks that combine both functionalities into a single system with real-time user interaction. To address these limitations, the proposed system integrates machine learning and deep learning techniques for both crop yield prediction and plant disease detection within a unified platform.

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IV. PROPOSED METHODOLOGY

A. System Architecture

The proposed system is designed as an integrated framework that combines crop yield prediction, plant disease detection, weather analysis, and crop recommendation within a unified platform. The workflow begins when a user interacts with the system through a web-based interface. The backend processes the request and routes it to the appropriate module. The system architecture consists of the following components:

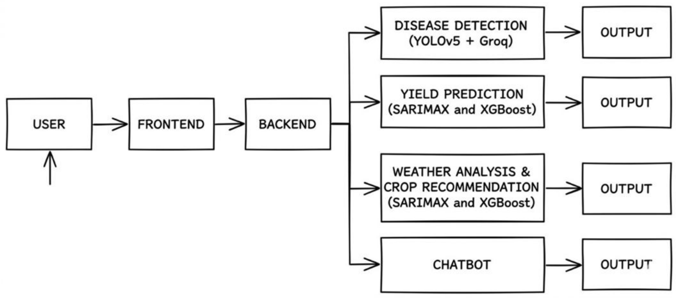

Figure 1. System Architecture

1. User Interface: A web-based interface enables farmers to upload leaf images, enter crop details, and access prediction results.
2. Chatbot Interface: The chatbot is powered by a Large Language Model (LLM) deployed via the Groq platform. It allows users to interact with the system in a conversational manner and receive intelligent responses and guidance.
3. Plant Disease Detection Module: This module performs disease identification using deep learning:
   - Image Input and Preprocessing: Leaf images are resized, normalized, and cleaned.
   - YOLOv5 Detection: The preprocessed image is analyzed using YOLOv5 to detect and localize diseased regions.
   - Disease Identification: Based on detected patterns, the system identifies the disease.
   - LLM-based Recommendation: The detected disease is passed to an LLM (via Groq) to generate explanations, causes, and treatment suggestions.
4. Crop Yield Prediction Module: This module predicts crop yield using a hybrid approach:
   - Input: Crop name provided by the user.
   - Location Fetching: The system automatically retrieves the user’s location.
   - SARIMAX Model: Captures temporal patterns and seasonal trends.
   - XGBoost Model: Used as an alternative when SARIMAX performance is insufficient, capturing nonlinear relationships.
     - Yield Prediction: The system outputs estimated yield per hectare.
5. Weather Analysis and Crop Recommendation Module:
   - Location Input: User provides or system fetches location.
   - Weather Data Retrieval: Short-term weather data (e.g., 5-day forecast) is collected.
   - Prediction Models: SARIMAX and XGBoost analyze environmental conditions.
     - Output: Suitable crop recommendations and weather insights.
6. Output and Visualization: The system presents:
   - Disease detection results
   - Yield prediction values
   - Weather forecasts
   - Crop recommendations
   - Chatbot responses

B. Crop Yield Prediction Module

The crop yield prediction module estimates agricultural output using time-series and machine learning models. The user provides the crop name, and the system automatically fetches the geographical location.

The SARIMAX model captures seasonal patterns and temporal dependencies in historical yield data. When SARIMAX does not provide satisfactory accuracy, the XGBoost model is used as an alternative to capture nonlinear relationships between environmental variables. The final output is expressed as yield per hectare, enabling region-specific agricultural planning.

C. Crop Recommendation and Weather Analysis

This module provides weather forecasting and crop recommendations based on location. The system retrieves environmental parameters such as temperature, rainfall, and humidity.

Using SARIMAX and XGBoost models, the system analyzes climatic conditions and recommends suitable crops. Weather forecasts help farmers plan irrigation, harvesting, and other activities effectively.

D. Disease Detection Module

The disease detection module identifies plant diseases from leaf images using deep learning techniques. Input images are preprocessed to ensure uniformity and quality.

YOLOv5 is used to detect and localize diseased regions in the leaf image. Based on these detections, the system identifies the disease type.

A Large Language Model (LLM) integrated via the Groq platform is used to generate detailed explanations, symptoms, and treatment recommendations, enabling early diagnosis and effective disease management.

E. Dataset Description

The system utilizes two types of datasets: image datasets for disease detection and tabular datasets for yield prediction. The image dataset consists of labeled leaf images for disease detection.

The yield prediction dataset includes historical agricultural records such as temperature, rainfall, humidity, soil conditions, and past yield values. These datasets were obtained from Kaggle and other publicly available sources.

F. Data Preprocessing

Data preprocessing is performed to improve model performance. Image data is resized, normalized, and augmented using techniques such as rotation and flipping.

Tabular data preprocessing includes handling missing values, removing outliers, feature scaling, and feature engineering such as seasonal trend extraction.

G. Training Details

All models were trained using Google Colab to leverage GPU acceleration. The datasets used for training were obtained from Kaggle.

The YOLOv5 model was trained using labeled image datasets. Data augmentation techniques were applied to improve generalization.

The SARIMAX model was optimized to capture seasonal patterns, while XGBoost was trained to model nonlinear relationships in the data.

Model performance was evaluated using appropriate metrics, and hyperparameters were tuned to achieve optimal accuracy.

V. IMPLEMENTATION DETAILS

The proposed system is implemented using Python-based frameworks and modern machine learning libraries. The disease detection module is developed using YOLOv5, which is implemented in PyTorch for object detection tasks. The crop yield prediction and recommendation modules are implemented using SARIMAX from the Statsmodels library and XGBoost for machine learning-based prediction.

The Large Language Model (LLM) functionalities, including the chatbot and disease recommendation system, are integrated using the Groq platform, which provides fast inference for generating explanations, treatment suggestions, and user responses.

The system is developed using a web-based architecture. The frontend allows users to upload leaf images, enter crop details, and interact with the chatbot. The backend is implemented using a Python-based framework such as Flask, which handles request processing, model inference, and data flow between modules.

The models are trained using Google Colab with GPU support to improve training efficiency. The datasets used for training are obtained from Kaggle, including image datasets for disease detection and tabular datasets for yield prediction.

During execution, the backend processes user inputs and routes them to the appropriate module. YOLOv5 performs disease detection and localization, SARIMAX or XGBoost generates yield predictions, and the LLM provides recommendations and chatbot responses. The final results are displayed to the user through the interface in real time.

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VI. EXPERIMENTAL RESULTS

The proposed system was evaluated using standard datasets to measure its effectiveness in disease detection and yield prediction. The results demonstrate high accuracy, efficiency, and reliability across different tasks. The disease detection module achieved an overall accuracy of 97.66%, while the yield prediction model demonstrated strong performance with high R^2(0.93) values and low error metrics.

A. Evaluation Metrics

The performance of the disease detection model was evaluated using metrics such as accuracy, precision, recall, and F1-score. For yield prediction, evaluation metrics such as R^2 score, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) were used to measure prediction accuracy and model performance.

B. Performance Analysis

The experimental results indicate that the proposed system performs effectively in both disease detection and yield prediction tasks. The YOLOv5 model provides high accuracy in detecting and localizing plant diseases, while the integration of a Large Language Model (LLM) via the Groq platform enhances the system by generating explanations and treatment recommendations.

The SARIMAX model effectively captures temporal patterns, and XGBoost improves prediction performance by modeling nonlinear relationships when required. The system demonstrates robustness across different datasets and conditions, with fast response time and reliable predictions.

VII. DASHBOARD / OUTPUT VISUALIZATION

The proposed system provides clear and interactive visualization of outputs generated from disease detection, crop yield prediction, crop recommendation, weather analysis, and chatbot modules. The outputs are presented in an intuitive format to assist farmers in making informed decisions. The disease detection output is shown in Fig. 2. The system processes the input leaf image and uses YOLOv5 to detect and localize diseased regions. The identified disease is then passed to a Large Language Model (LLM) via the Groq platform to generate detailed explanations and treatment recommendations.

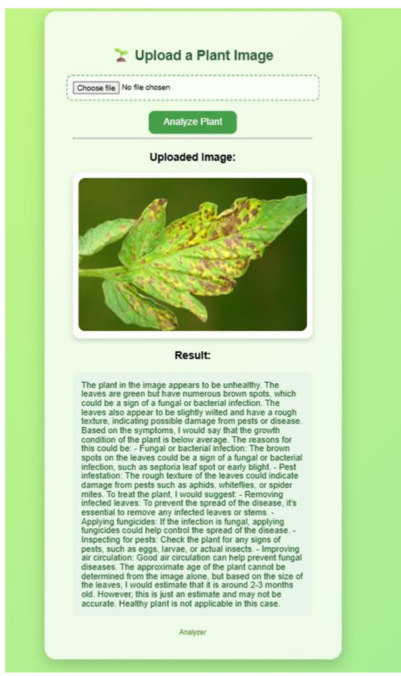

Figure 2. Disease Detection Output

The crop-based yield prediction output is illustrated in Fig. 3. The user provides the crop type, and the system automatically fetches location-based environmental parameters such as temperature, rainfall, and humidity. Based on this data, SARIMAX or XGBoost models generate accurate yield predictions.

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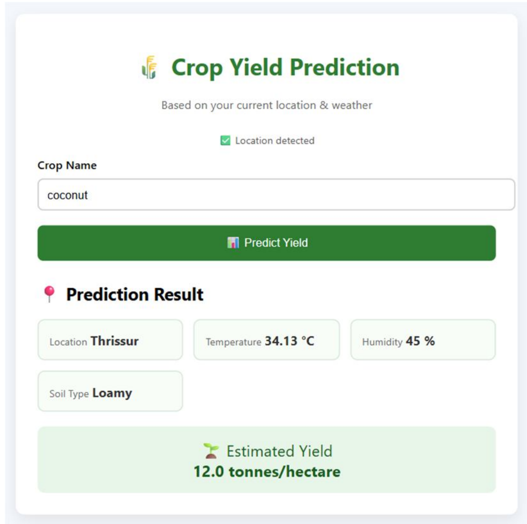

Figure 3. Crop-Based Yield Prediction Output

The crop recommendation and weather analysis output is shown in Fig. 4. The system retrieves location-based weather data and analyzes environmental conditions using machine learning models to recommend suitable crops and provide weather insights.

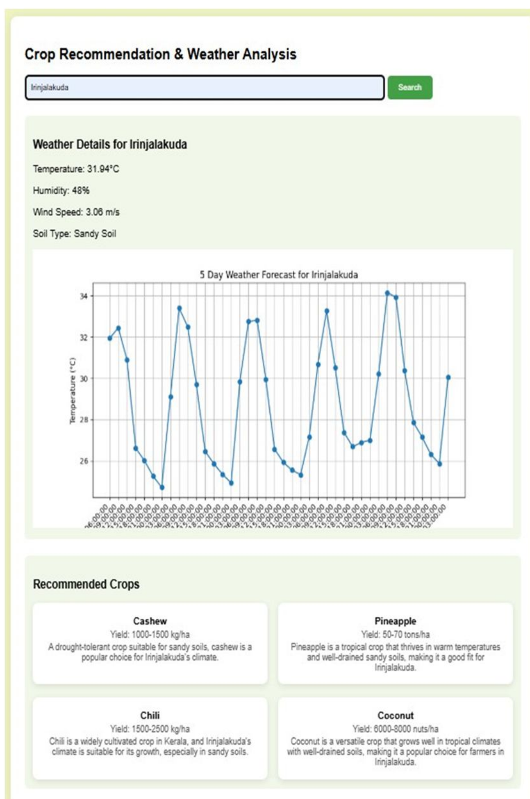

Figure 4. Crop Recommendation and Weather Analysis Output

The chatbot interaction is illustrated in Fig. 5. The chatbot is powered by a Large Language Model (LLM) integrated through the Groq platform, allowing users to ask queries related to disease detection, yield prediction, and farming practices, and receive responses in a conversational format.

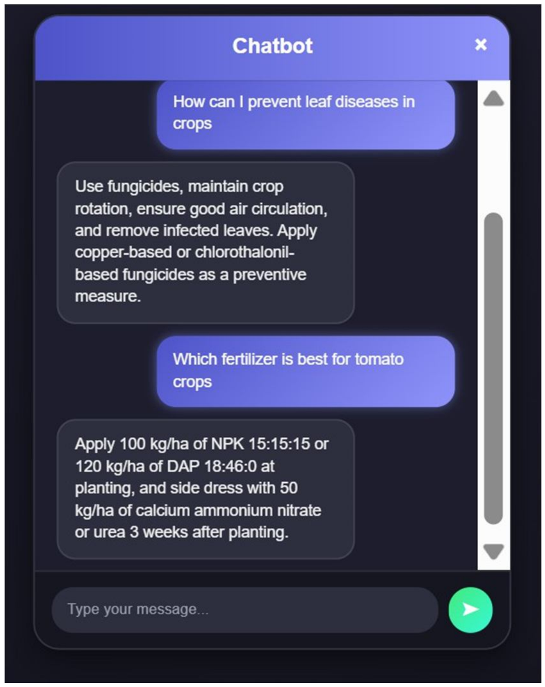

Figure 5. Chatbot-Based Query and Response

VIII. ADVANTAGES

The proposed Crop Yield Prediction and Disease Detection System provides an integrated and intelligent solution to address key challenges in modern agriculture. By combining machine learning, deep learning, and natural language processing techniques, the system enhances decision-making, improves productivity, and reduces crop losses. The inclusion of a chatbot interface further increases accessibility by enabling farmers to interact with the system and obtain real-time insights.

1) Provides accurate crop yield prediction using SARIMAX and XGBoost models.
2) Enables early and precise detection of plant diseases using YOLOv5.
3) Generates detailed explanations and treatment recommendations using a Large Language Model (LLM) via the Groq platform.
4) Reduces dependency on manual monitoring and minimizes human error.
5) Supports data-driven decision making for better agricultural planning.
6) Provides weather-based crop recommendations for improved crop selection.
7) Improves productivity and helps reduce crop losses.
8) Offers a user-friendly interface and chatbot for easy interaction.
9) Promotes sustainable farming practices through optimized resource usage.

IX. LIMITATIONS

Despite the effectiveness of the proposed Crop Yield Prediction and Disease Detection System, certain limitations may impact its performance and real-world deployment. These limitations are mainly associated with data dependency, environmental variability, and computational constraints.

1) The accuracy of both disease detection and yield prediction is highly dependent on the quality, quantity, and diversity of the training datasets.
2) Limited availability of region-specific agricultural datasets may affect model generalization across different crops, soil types, and climatic conditions.
3) The performance of the YOLOv5-based disease detection module may degrade when images are captured under poor lighting conditions, low resolution, or complex backgrounds.
4) The system may not accurately detect rare or newly emerging plant diseases that are not present in the training dataset.
5) Crop yield prediction using SARIMAX and XGBoost may be affected by unpredictable factors such as extreme weather events, pest outbreaks, and sudden environmental changes.

6) The system requires continuous internet connectivity for accessing weather data and utilizing the Groq-based LLM for chatbot interaction and recommendations.
7) High computational requirements for model training and inference may limit deployment on low-resource or edge devices.

X. FUTURE WORK

The proposed crop yield prediction and disease detection system can be further enhanced to improve its accuracy, scalability, and real-world applicability. Future work may focus on improving the disease detection module by adopting advanced architectures such as Vision Transformers and ensemble-based object detection models, which can enhance performance in detecting rare and early-stage diseases. Expanding the dataset to include a wider variety of crops, diseases, and geographic conditions will further improve model generalization.

For yield prediction, the integration of real-time data from IoT sensors, including soil moisture, temperature, and weather conditions, can significantly improve prediction accuracy. Incorporating advanced time-series and deep learning models, such as LSTM or hybrid architectures, may further enhance the capability to capture complex temporal and nonlinear relationships.

Additionally, the system can be extended by enhancing the user interface with voice-based interaction and multilingual chatbot support using advanced Large Language Models deployed via the Groq platform. This will improve accessibility for farmers with limited technical knowledge.

Future developments may also include integration of market price prediction, satellite imagery analysis, and real-time monitoring systems to provide a more comprehensive agricultural decision support platform. Deployment on edge devices for offline functionality and reduced latency can further increase usability in rural areas.

Overall, these improvements can transform the proposed system into a fully autonomous, intelligent, and real-time agricultural decision support system, contributing to sustainable and efficient farming practices.

XI. CONCLUSION

This paper presents an intelligent agricultural management system that integrates machine learning, deep learning, and natural language processing techniques to address key challenges in modern farming. The proposed system combines crop yield prediction, plant disease detection, weather analysis, and crop recommendation within a unified framework, providing a comprehensive solution for precision agriculture. The yield prediction module, based on SARIMAX and XGBoost, effectively captures both temporal trends and nonlinear relationships in environmental and historical data, resulting in accurate and reliable forecasts. “The yield prediction model achieved an R^2 score of 0.93, indicating 93% variance explanation in crop yield prediction.” The disease detection module, utilizing YOLOv5, demonstrates high accuracy in identifying and localizing plant diseases, enabling early diagnosis and timely intervention. In addition, the integration of a Large Language Model (LLM) via the Groq platform enhances the system by generating detailed explanations, treatment recommendations, and enabling chatbot-based interaction. The system achieved a disease detection accuracy of 97.66%, indicating strong performance and practical applicability. Overall, the proposed framework highlights the effectiveness of combining computer vision, time-series analysis, and machine learning techniques for intelligent agriculture. By reducing dependency on manual monitoring and supporting data-driven decision-making, the system contributes to improved crop productivity, efficient resource utilization, and sustainable farming practices.

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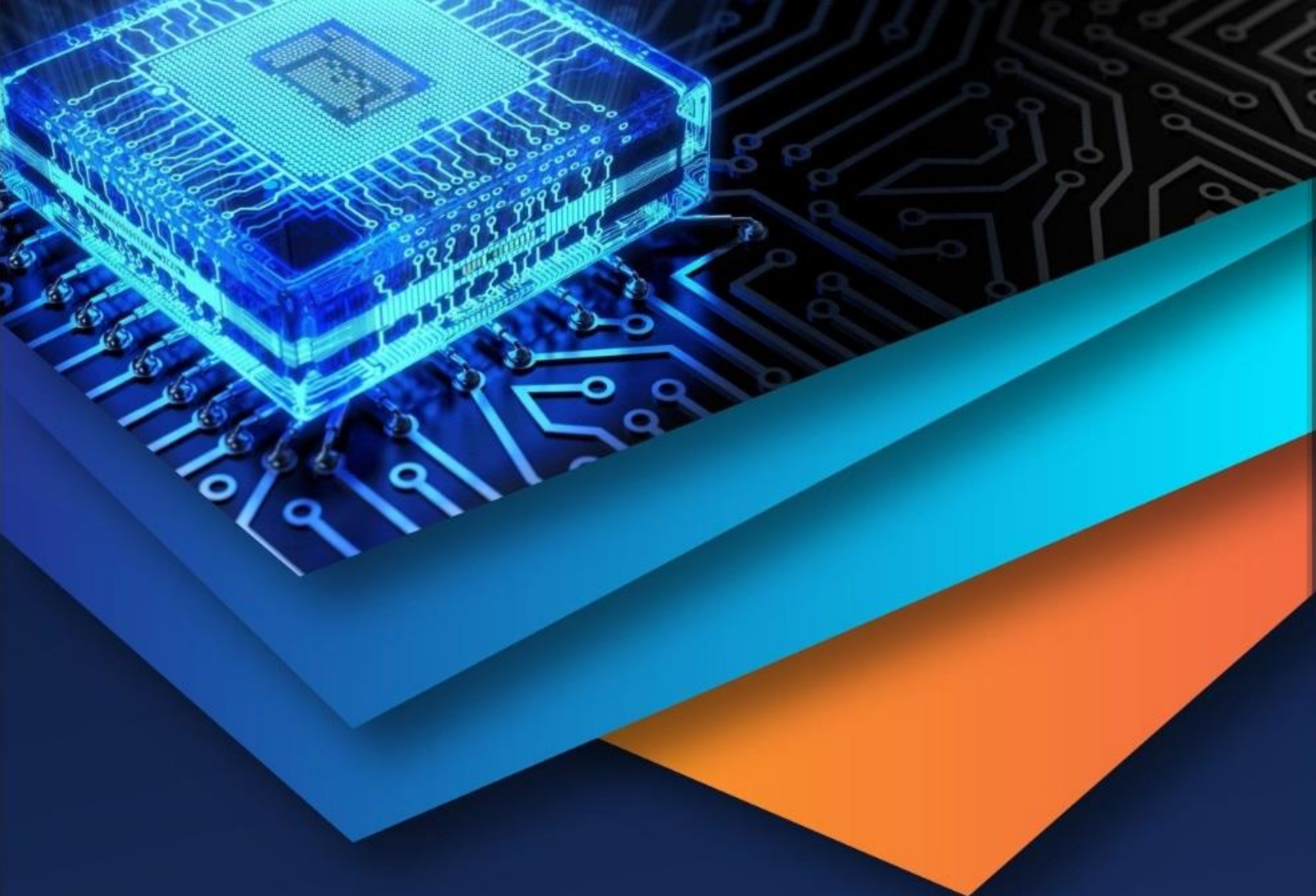

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