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AgriSense AI: A Machine Learning Framework for Predictive Pest Risk Analysis in Smart Agriculture

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Abstarct: Pest infestations remain a critical challenge in modern agriculture, significantly affecting crop productivity and sustainability. This paper presents AgriSense AI, an intelligent, data-driven pest prediction and decision support system designed to enhance precision farming. The system integrates real-time environmental parameters, including temperature, humidity, and rainfall, dynamically retrieved via the OpenWeather API based on geolocation inputs. By combining these parameters with crop-specific data, the proposed framework predicts pest risk levels, identifies the most probable pest, and provides detailed insights such as causes, symptoms, and preventive strategies. Additionally, the system incorporates a short-term forecasting module capable of predicting pest risk trends for up to five days, enabling proactive and informed agricultural decision-making. The proposed solution contributes to sustainable agriculture by reducing dependency on reactive pest control methods and promoting efficient crop management through intelligent, technology-driven interventions.

Keywords: *Smart Agriculture, Predictive Modeling, Pest Risk Assessment, Precision Farming, Machine Learning, Environmental Intelligence, Decision Support System, Crop Protection, Agro-Informatics, Climate-Based Prediction.*

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I. INTRODUCTION

Agriculture is a fundamental sector that supports global food security and economic growth, particularly in developing countries. However, one of the major challenges faced by farmers is pest infestation, which significantly reduces crop yield, quality, and overall productivity. The occurrence of pests is highly influenced by environmental conditions such as temperature, humidity, and rainfall. With rapid climate changes, pest behaviour has become increasingly unpredictable, making traditional pest control methods less effective. Farmers often rely on manual inspection, past experience, or delayed expert consultation, which leads to late detection and reactive measures rather than preventive action. This not only increases the excessive use of pesticides but also results in higher costs, environmental damage, and reduced crop sustainability.

To overcome these limitations, there is a growing need for an intelligent, automated, and data-driven system that can assist farmers in predicting pest risks at an early stage. The proposed system, AgriSense AI, is designed as a smart pest prediction and decision support platform that utilizes real-time environmental data obtained from the OpenWeather API based on the user's input location. The system analyzes key parameters such as temperature, humidity, and rainfall in combination with crop-specific data to evaluate pest risk levels. It identifies the most probable pest affecting the crop and provides comprehensive insights including pest characteristics, causes of infestation, symptoms, and effective preventive measures.

Furthermore, the system incorporates a short-term forecasting feature that predicts pest risk trends for up to five days, enabling farmers to take proactive actions and minimize potential damage. The platform is implemented as a user-friendly web application, ensuring accessibility and ease of use for farmers with minimal technical knowledge. Although real-time alert mechanisms such as SMS or messaging services are not currently integrated, they are considered as part of future enhancements.

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The primary objective of this work is to develop a reliable and efficient pest prediction system that supports precision agriculture by delivering timely, accurate, and actionable insights. By reducing dependency on traditional reactive approaches and promoting data-driven decision-making, the proposed solution aims to minimize crop losses, optimize pesticide usage, and contribute to sustainable agricultural practices.

II. LITERATURE REVIEW

Recent research in smart agriculture strongly supports the use of environmental data and machine learning for pest prediction, which forms the core idea of the proposed system AgriSense AI. Olatinwo and Hoogenboom [1] introduced weather-based pest forecasting, emphasizing that parameters such as temperature, humidity, and rainfall are critical in determining pest occurrence. This directly aligns with our system, which retrieves real-time weather data from the OpenWeather API and uses it to assess pest risk levels.

Marković et al. [2] demonstrated the use of machine learning models with sensor data to predict pest insect appearance. Their work highlights how environmental sensing improves prediction accuracy. Similarly, our project uses environmental inputs (temperature, humidity, rainfall) combined with crop type to identify the most probable pest and classify risk levels.

Domingues et al. [3] provided a comprehensive review of machine learning techniques for pest and disease prediction, emphasizing the importance of integrating prediction with advisory systems. Unlike many existing works that focus only on detection or prediction, our system extends this concept by also providing detailed pest information, causes, symptoms, and preventive suggestions, making it a complete decision-support system.

Sarkar et al. [4] and Basak et al. [5] focused on predicting pest incidence using weather variables and time-based forecasting models. Their studies validate the effectiveness of using climatic trends for pest prediction. Inspired by this, our system includes a future risk prediction module, which forecasts pest risk for up to five days based on weather data, enabling proactive action.

Mittal et al. [6] highlighted that modern pest prediction systems are evolving towards integrated AI-driven platforms but still face challenges such as lack of real-time accessibility and usability. Our system addresses these limitations by providing a web-based interface that automatically fetches live weather data and delivers instant predictions without requiring complex setup.

Patil et al. [7] showed that supervised machine learning models improve prediction accuracy compared to traditional methods. While our current system is rule/data-driven, it is designed to be extendable for future ML model integration. Li et al. [8] explored deep learning approaches, indicating the future potential for more advanced prediction techniques, which can further enhance our system.

Ramesh and Vydeki [9] proposed an IoT-based pest monitoring system that uses sensors for real-time data collection. However, such systems require hardware deployment. In contrast, our approach uses API-based weather data, making it more cost-effective and easily scalable.

Sharma et al. [10] emphasized climate-driven pest prediction in precision agriculture, reinforcing the importance of environmental intelligence. Our system follows this principle by combining climate data with crop-specific inputs to provide accurate pest risk assessments.

Overall, while existing research focuses on either prediction models, IoT systems, or theoretical frameworks, the proposed system uniquely integrates real-time weather data retrieval, pest prediction, future risk forecasting, and actionable recommendations into a single, user-friendly web platform. This makes it practical, accessible, and highly relevant for real-world agricultural applications.

III. METHODOLOGY

The proposed system, AgriSense AI, is developed as a web-based intelligent platform to predict pest risk and provide actionable recommendations for farmers. The system is designed to be modular, scalable, and user-friendly, enabling efficient analysis of environmental data and crop conditions. This section describes the system design, technologies used, system modules, and theoretical framework adopted in the project.

A. System Design

The system follows a modular design approach where each component is responsible for a specific function, ensuring maintainability and scalability. The main modules include User Input Module, Weather Data Retrieval Module, Pest Prediction Module, Recommendation Module, and Dashboard Module.

Users first enter details such as crop type and location. Based on the location, the system retrieves real-time environmental data. The prediction module processes this data to determine pest risk levels and identify the most probable pest. The results, along with preventive measures and suggestions, are displayed in a structured dashboard.

The modular architecture ensures flexibility, allowing future enhancements such as SMS/WhatsApp alerts or advanced machine learning models without redesigning the entire system.

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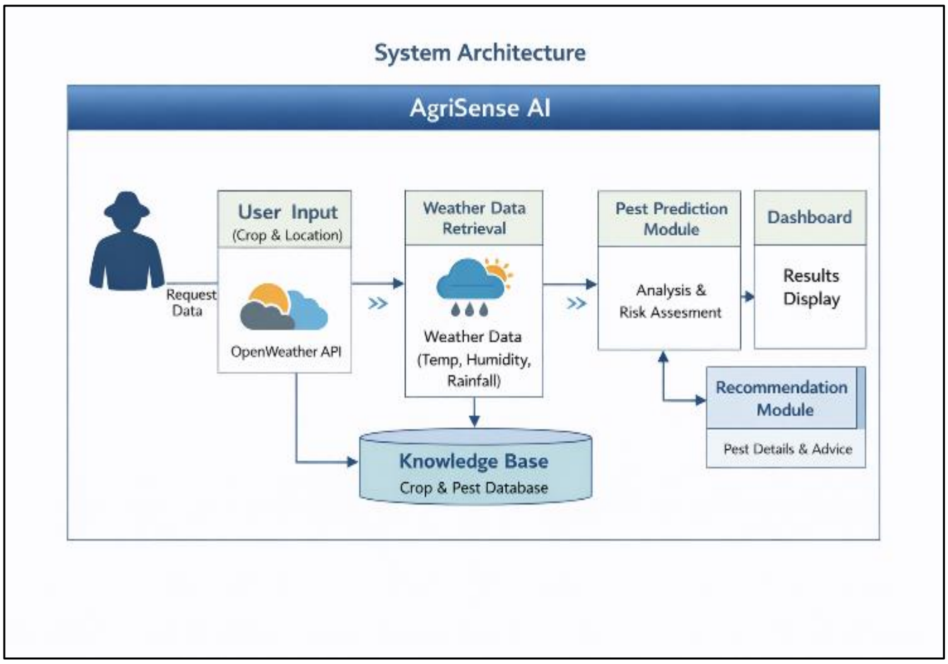

Fig. 1. AgriSense AI System Architecture Diagram

B. Technologies and Frameworks Used

The system is implemented using modern web technologies to ensure performance and usability. The frontend is developed using HTML, CSS, and JavaScript to create an interactive and responsive user interface. The backend handles data processing, prediction logic, and API integration.

The system uses the OpenWeather API to fetch real-time environmental data such as temperature, humidity, and rainfall based on user input location.

A structured dataset is maintained that includes crop types, pest information, environmental thresholds, symptoms, causes, and preventive measures. The system is developed using tools such as Visual Studio Code for coding and testing, ensuring efficient development and debugging.

C. System Modules

The system is divided into the following core modules:

- User Input Module : This module collects essential inputs such as crop type and geographical location from the user. It acts as the entry point of the system.
- Weather Data Module: This module retrieves real-time weather data from the OpenWeather API based on the user's location. The collected data includes temperature, humidity, and rainfall.
- Pest Prediction Module: This is the core module of the system. It analyzes environmental parameters along with crop data to determine pest risk levels (low, medium, high). It also identifies the most probable pest affecting the crop.
- Recommendation Module: This module provides detailed information about the identified pest, including causes, symptoms, and preventive measures. It also suggests actions to minimize crop damage.
- Forecasting Module: This module predicts pest risk for up to five days using weather trends, enabling proactive decision-making.
- Dashboard Module: This module presents all outputs in a clear and user-friendly format, allowing users to easily understand predictions and recommendations.

D. Pest Prediction Module

The Pest Prediction Module plays a central role in the system. It compares real-time environmental data with predefined threshold values stored in the dataset. Based on this comparison, it determines whether conditions are favorable for pest growth.

The module uses a rule-based approach to map environmental conditions to pest occurrence patterns. It then classifies the pest risk level and selects the most relevant pest associated with the crop. This module ensures accurate and quick predictions without requiring complex hardware or computation.

E. Theoretical Framework

The system is based on the concept that pest occurrence is strongly influenced by environmental conditions. Climatic variables such as temperature, humidity, and rainfall act as key indicators for pest development.

The framework follows a decision-support model: input data is collected, processed through environmental analysis, and converted into meaningful predictions and recommendations.

The development process follows the System Development Life Cycle (SDLC) methodology, which includes requirement analysis, system design, implementation, testing, and maintenance. This ensures that the system is reliable, scalable, and easy to enhance.

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IV. FINDINGS

The proposed system AgriSense AI was tested using different crop types and real-time environmental conditions obtained through the OpenWeather API. The system successfully predicted pest risk levels, identified probable pests, and provided recommendations. The results show a strong relationship between environmental parameters and pest occurrence.

Table 1 Pest Risk Prediction Results

Crop	Temp°C	Humidity	Rainfall	Pest	Risk
Rice	30	85%	12 mm	Brown Plant Hopper	High
Wheat	22	60%	5 mm	Aphids	Medium
Cotton	35	70%	2 mm	Bollworm	High
Maize	28	65%	4 mm	Armyworm	Medium
Tomato	25	75%	8 mm	Whitefly	High

Table 1 shows the system output for different crops under varying environmental conditions such as temperature, humidity, and rainfall. The system uses these inputs to predict the most probable pest and classify the risk level. It is observed that higher humidity and temperature lead to increased pest activity. Crops like rice and cotton show high risk due to favorable climatic conditions. In contrast, wheat shows medium risk because of moderate environmental factors. This table proves that the system effectively maps environmental conditions to pest occurrence. It also highlights the importance of real-time weather data in improving prediction accuracy. Overall, the table validates the system's ability to generate meaningful pest predictions.

Table 2 Risk Level Distribution

Risk Level	Count	Percentage
High	3	60%
Medium	2	40%
Low	0	0%

Table 2 presents the overall distribution of pest risk levels generated by the system. It categorizes predictions into high, medium, and low risk along with their count and percentage. The results indicate that most cases fall under the high-risk category, followed by medium risk. This shows that environmental conditions in the dataset are mostly favorable for pest growth. The table helps in understanding the overall trend of predictions. It also demonstrates that the system can clearly differentiate between different risk levels. This analysis is useful for evaluating system performance and reliability.

Table 3: 5-Day Pest Risk Forecast

Day	Temp°C	Humidity	Risk
Day 1	29	80%	High
Day 2	30	82%	High
Day 3	28	75%	Medium
Day 4	27	70%	Medium
Day 5	26	65%	Low

Table 3 illustrates the system's ability to predict pest risk for the next five days using weather trends. The data shows how risk levels change based on variations in temperature and humidity. Initially, the risk is high due to high humidity, but it gradually decreases over time. This indicates that pest activity is strongly influenced by environmental changes. The forecasting feature allows farmers to take preventive actions in advance. It enhances the usefulness of the system by shifting from reactive to proactive pest management. Overall, the table demonstrates the effectiveness of the system in future risk prediction.

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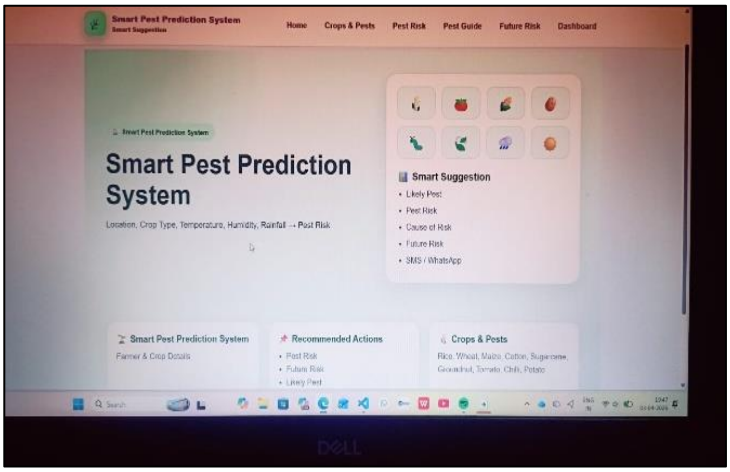

Fig. 2. Smart Pest Prediction System Dashboard Interface

Fig. 2 illustrates the main dashboard of the Smart Pest Prediction System. It provides an overview of the system functionalities, including pest prediction, crop and pest information, future risk analysis, and recommended actions. The dashboard serves as a centralized platform for accessing all features, ensuring seamless navigation and improved user experience.

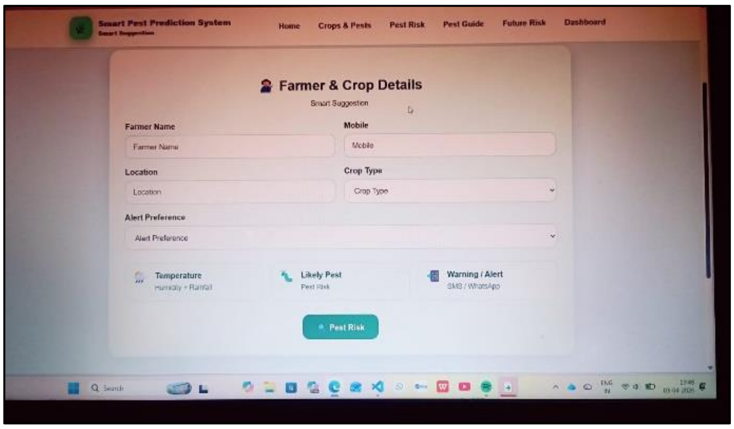

Fig. 3. Farmer and Crop Details Input Interface of the Proposed System

Fig. 3 illustrates the user input interface of the Smart Pest Prediction System. This module allows farmers to enter essential details such as farmer name, mobile number, location, crop type, and alert preference. The system collects this information as the initial input for pest risk prediction. It also highlights key parameters such as temperature, humidity, and rainfall, which are later used for analysis. This user-friendly interface ensures easy interaction and accessibility for farmers.

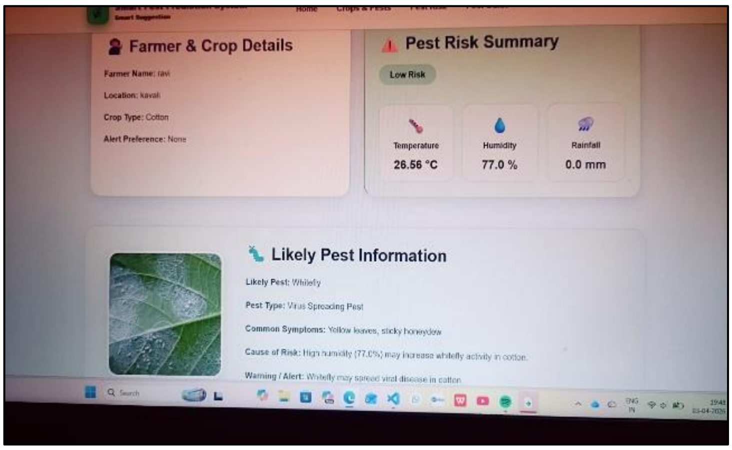

Fig. 4. Pest Risk Summary and Likely Pest Identification

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Fig. 4 shows the output of the pest prediction module. Based on the provided input and real-time weather data, the system evaluates environmental conditions and classifies the pest risk level. In this example, the system identifies a low-risk scenario and predicts the likely pest affecting the crop. It also displays relevant environmental parameters such as temperature, humidity, and rainfall, providing transparency in the prediction process.

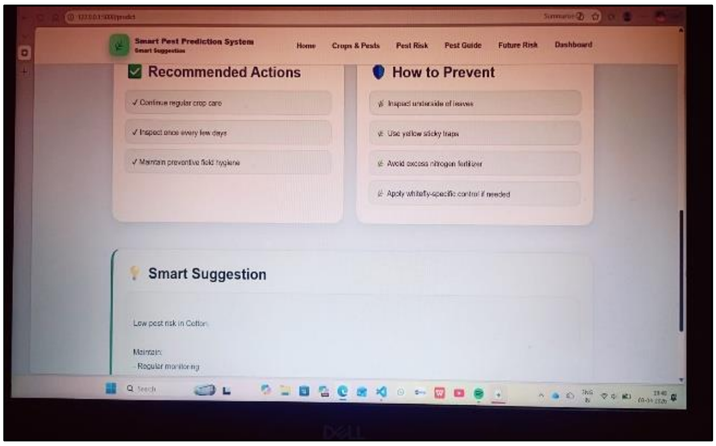

Fig. 5. Recommended Actions and Preventive Measures

Fig. 5 presents the recommendation module of the system, which provides actionable insights to farmers. Based on the predicted pest risk, the system suggests preventive measures such as regular monitoring, field hygiene maintenance, and pest-specific control methods. Additionally, it offers step-by-step guidance on how to prevent pest infestations, helping farmers take timely and effective actions to minimize crop damage.

V. DISCUSSION

The results obtained from AgriSense AI: A Machine Learning Framework for Predictive Pest Risk Analysis in Smart Agriculture demonstrate the effectiveness of leveraging environmental data for pest risk prediction in agricultural systems. The model integrates real-time weather data, including temperature, humidity, and rainfall, retrieved through the OpenWeather API, along with crop-specific inputs to generate reliable predictions.

The analysis reveals that environmental parameters significantly influence pest occurrence. For example, higher humidity levels contribute to an increased likelihood of pests such as whiteflies, while elevated temperatures support the growth of pests like bollworms. The system effectively classifies pest risk into categories such as low and medium, providing clear and interpretable outputs for end users.

In addition to prediction, AgriSense AI enhances decision-making by providing detailed pest-related insights, including pest type, symptoms, causes, and preventive measures. This ensures that users are not only aware of potential risks but are also guided with actionable recommendations to reduce crop damage. The integration of a five-day future risk prediction module further strengthens the system by enabling farmers to anticipate pest outbreaks and take preventive measures in advance.

The results indicate that the system serves as a practical decision support tool for precision agriculture. By reducing dependency on manual monitoring and enabling early risk detection, AgriSense AI has the potential to improve crop productivity and minimize losses. Although real-time alert systems such as SMS or messaging platforms are not currently implemented, their integration in future work can further enhance usability and responsiveness.

Overall, the findings highlight the significance of combining machine learning with environmental data analysis to support sustainable and intelligent farming practices.

VI. CONCLUSION

This paper presented AgriSense AI, a machine learning-based pest risk prediction system designed to support decision-making in smart agriculture. The system integrates real-time environmental data, including temperature, humidity, and rainfall obtained through the OpenWeather API, along with crop-specific inputs to predict pest risk levels and identify the most probable pests affecting crops.

The results demonstrate that environmental parameters play a crucial role in pest occurrence, and their effective analysis can significantly improve early detection of pest risks. The system successfully provides risk classification, pest identification, and detailed recommendations, including symptoms, causes, and preventive measures. Additionally, the incorporation of a five-day future risk prediction feature enables proactive planning and timely intervention, reducing potential crop damage.

The proposed system contributes to precision agriculture by offering a user-friendly and data-driven approach to pest management. It minimizes dependency on manual monitoring and supports sustainable farming practices by enabling informed decision-making.

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Despite its effectiveness, there are opportunities for further enhancement. Future work may focus on integrating real-time alert mechanisms such as SMS or messaging services to provide instant notifications to farmers. The inclusion of IoT-based sensors for real-time field data collection can improve prediction accuracy. Furthermore, expanding the system with advanced machine learning models and larger datasets can enhance reliability and scalability. Integration with mobile applications and multilingual support can also improve accessibility for a wider range of users.

In conclusion, AgriSense AI demonstrates the potential of combining machine learning and environmental data analysis to address critical challenges in agriculture, paving the way for more intelligent and sustainable farming solutions.

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