An Explainable Artificial Intelligence Framework for Multi-Sensor Crop Risk Prediction and Intelligent Decision Support

[1]Gifta Stuthi K, [2]Jaisree J B, [3]Ashmitha A K , [4] Akshaya Princy P S, [5]Athira V S

Department Of Artificial Intelligence And Data Science,
Arunachala College Of Engineering For Women, Manavilai , Nagercoil-629203, Tamil Nadu, India

Abstract : Agriculture plays a crucial role in ensuring global food security; however, crop productivity is increasingly threatened by climate change, unpredictable weather conditions, soil degradation, pest infestations, nutrient deficiencies, and water scarcity. Traditional crop monitoring and risk assessment methods often depend on manual field inspections or single-source data, which are time-consuming, less accurate, and incapable of providing timely decision support. Although recent Artificial Intelligence (AI) models have significantly improved prediction accuracy, most existing approaches operate as "black-box" systems, making it difficult for farmers and agricultural experts to understand the reasoning behind their predictions. This lack of transparency limits user confidence and practical adoption in real-world agricultural environments

.This paper proposes an Explainable Artificial Intelligence (XAI) Framework for Multi-Sensor Crop Risk Prediction and Intelligent Decision Support that integrates heterogeneous data from multiple sensing sources, including soil moisture sensors, temperature and humidity sensors, weather stations, IoT devices, remote sensing imagery, and historical agricultural datasets. The proposed framework consists of five major stages: data acquisition, data preprocessing, multi-sensor data fusion, machine learning-based crop risk prediction, and explainable decision support. Advanced machine learning algorithms are employed to identify potential crop risks such as disease outbreaks, drought stress, nutrient deficiencies, irrigation imbalance, and expected yield reduction. To improve transparency and interpretability, Explainable AI techniques, including SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations), are incorporated to explain prediction outcomes by identifying the most influential environmental and agronomic factors affecting crop health.

Based on these explainable insights, the proposed framework generates intelligent recommendations for irrigation scheduling, fertilizer application, pest management, and preventive crop protection strategies. The integration of explainable AI with multi-sensor data fusion not only enhances prediction accuracy but also increases user trust, enabling farmers, agronomists, and policymakers to make informed and evidence-based decisions. The proposed framework contributes to sustainable agriculture by minimizing crop losses, optimizing resource utilization, improving productivity, and supporting climate-resilient farming practices. Furthermore, the framework provides a scalable and adaptable solution that can be deployed across diverse agricultural regions and crop varieties, bridging the gap between high-performance AI models and practical, transparent decision-making in modern agriculture.

***Keywords**:* Explainable Artificial Intelligence (XAI), Multi-Sensor Data Fusion, Crop Risk Prediction, Intelligent Decision Support System, Machine Learning, SHAP, LIME, Internet of Things (IoT), Precision Crop Monitoring, Sustainable Agriculture, Climate-Smart Farming, Agricultural Analytics.

1.INTRODUCTION

Agriculture plays a vital role in global food security and economic development. However, crop production is increasingly affected by climate change, irregular rainfall, soil degradation, water scarcity, pest infestations, and nutrient deficiencies. Traditional farming practices rely heavily on manual field inspections and farmers' experience, making early detection of crop stress difficult and often resulting in reduced yield and economic losses. Therefore, intelligent crop monitoring and timely decision-making have become essential for sustainable agriculture.

Recent advancements in Artificial Intelligence (AI), the Internet of Things (IoT), remote sensing, and wireless sensor technologies have significantly improved agricultural monitoring. Multiple sensors can continuously collect real-time information such as soil moisture, temperature, humidity, weather conditions, crop images, and crop growth stages. Machine learning models analyze these data to predict crop diseases, water stress, nutrient deficiencies, and yield performance. However, many existing AI models operate as black-box systems, providing accurate predictions without explaining the factors behind their decisions, which reduces user trust and practical adoption.

Although several smart agriculture systems have been developed, most focus on a single agricultural problem or individual data source. Limited research has integrated heterogeneous sensor data with explainable AI to provide transparent crop risk prediction and intelligent decision support within a unified framework. Moreover, existing systems rarely offer adaptive recommendations that continuously improve using newly collected agricultural data, creating a need for a more comprehensive and interpretable solution.

To address these challenges, this paper proposes An Explainable Artificial Intelligence Framework for Multi-Sensor Crop Risk Prediction and Intelligent Decision Support. The proposed framework integrates multi-sensor data, applies advanced AI techniques for crop risk prediction, and incorporates Explainable AI to provide transparent and interpretable predictions. It also introduces a Dynamic Crop Risk Score and a self-learning recommendation module to support irrigation, nutrient management, disease prevention, and sustainable agricultural decision-making. The proposed system aims to improve prediction accuracy, enhance user confidence, optimize resource utilization, and support climate-resilient farming practices.

2.LITERATURE REVIEW:

Recent advancements in Artificial Intelligence (AI), the Internet of Things (IoT), and remote sensing have significantly improved smart agriculture by enabling real-time crop monitoring and intelligent decision-making. Various studies have used soil moisture, temperature, humidity, weather, and crop image data with machine learning algorithms such as Random Forest, Support Vector Machine (SVM), Decision Tree, and Artificial Neural Networks (ANN) to predict crop diseases, irrigation requirements, nutrient deficiencies, and yield. Deep learning models, particularly Convolutional Neural Networks (CNNs), have also demonstrated high accuracy in crop disease detection using plant images. These technologies have improved agricultural productivity by reducing manual monitoring and supporting data-driven farming practices.

In recent years, Explainable Artificial Intelligence (XAI) has emerged as an effective approach for improving the transparency of AI models. Techniques such as SHAP and LIME help explain prediction outcomes by identifying the most influential features, enabling users to better understand AI-based decisions. However, most existing agricultural systems either focus on a single data source or prioritize prediction accuracy without providing explainable insights. As a result, farmers often find it difficult to trust and interpret the recommendations generated by AI models.

Based on the reviewed studies, a significant research gap exists in integrating multi-sensor data fusion, explainable AI, dynamic crop risk assessment, and intelligent recommendation generation within a single framework. To address these limitations, this research proposes An Explainable Artificial Intelligence Framework for Multi-Sensor Crop Risk Prediction and Intelligent Decision Support, which combines heterogeneous sensor data, AI-based prediction, Explainable AI, Dynamic Crop Risk Score, and a self-learning recommendation module to provide accurate, transparent, and reliable decision support for sustainable agriculture.

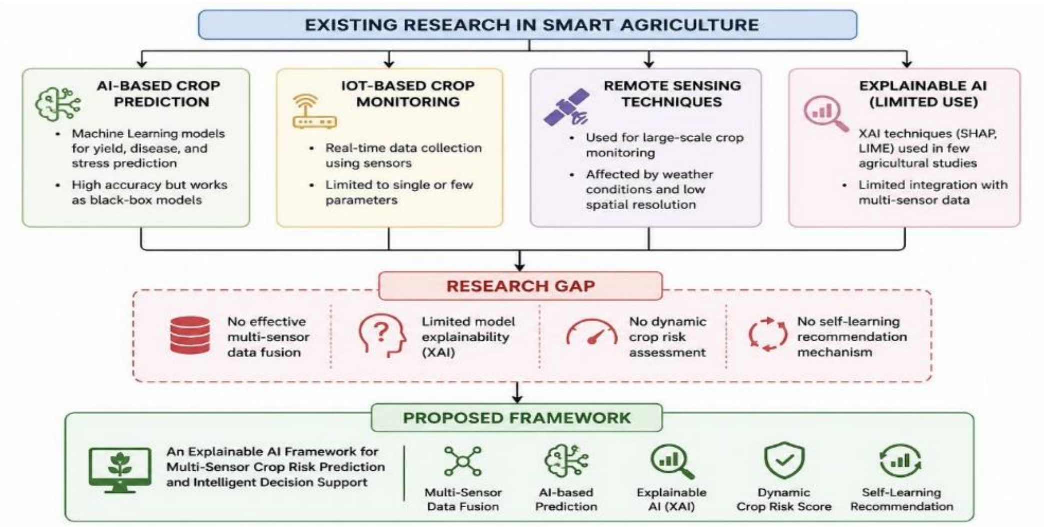

Figure 1. Research Gap Analysis and Motivation for the Proposed Framework

3.PROPOSED METHODOLOGY:

This research proposes an Explainable Artificial Intelligence (XAI) Framework for Multi-Sensor Crop Risk Prediction and Intelligent Decision Support to provide accurate, transparent, and reliable crop risk assessment. The framework integrates heterogeneous data collected from multiple agricultural sensors, preprocesses the data, extracts relevant features, performs multi-sensor data fusion, and applies Artificial Intelligence algorithms to predict crop risks. To improve user trust and model transparency, Explainable AI techniques are incorporated to interpret prediction results. Based on the predicted risk level, the framework calculates a Dynamic Crop Risk Score (DCRS) and generates intelligent recommendations for irrigation, nutrient management, disease prevention, and crop protection. The overall workflow of the proposed framework is illustrated in Figure 2.

3.1 System Architecture:

The proposed framework consists of six major modules: Data Collection, Data Preprocessing, Multi-Sensor Data Fusion, AI-Based Crop Risk Prediction, Explainable AI, and Decision Support System. Data from multiple sources are integrated to create a comprehensive representation of crop health. The AI prediction module evaluates crop risks, while the Explainable AI module interprets the prediction results. Finally, the Decision Support System provides actionable recommendations to farmers.

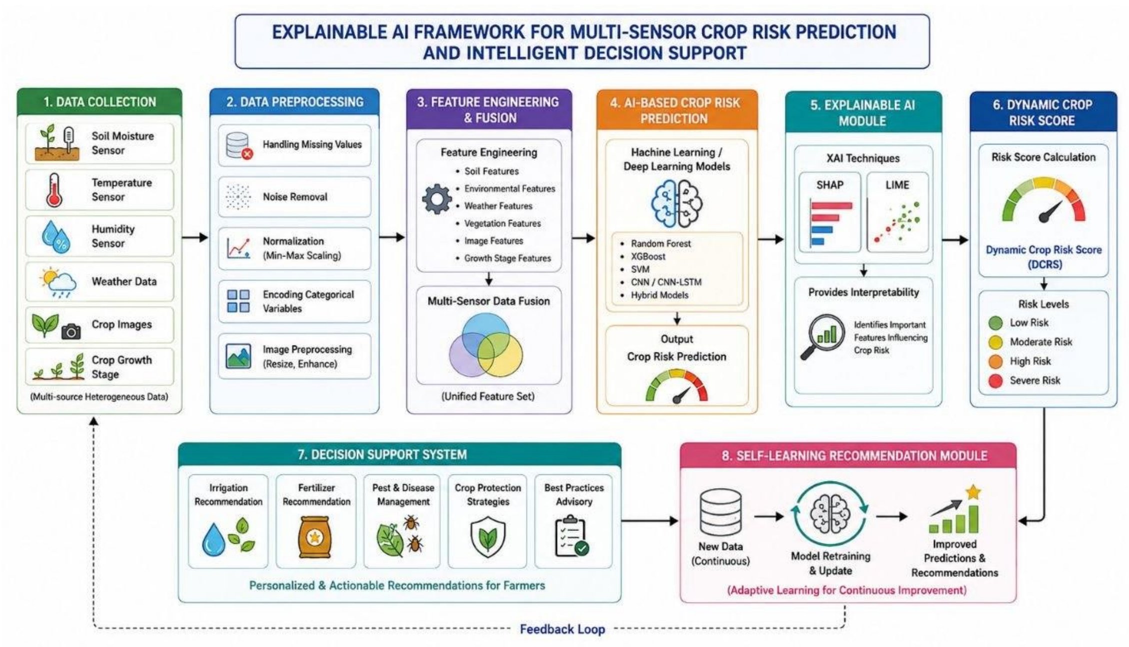

Figure 2. Overall Architecture of the Proposed Explainable AI Framework

3.2 Data Collection:

The proposed framework collects heterogeneous agricultural data from multiple sensing sources to improve prediction accuracy.

- Soil Moisture
- Temperature
- Humidity
- Weather Data
- Crop Images
- Crop Growth Stage

These data provide comprehensive information about soil condition, environmental changes, and crop health.

3.3 Data Preprocessing:

The collected data are cleaned to remove missing values, duplicate records, and noise. Numerical features are normalized, while categorical variables are encoded. Crop images are resized and enhanced before feature extraction to ensure consistency and improve model performance.

3.4 Feature Engineering:

Relevant features are extracted from the processed data, including soil moisture level, temperature variation, humidity index, rainfall, vegetation characteristics, crop growth stage, and disease-related image features. Feature engineering reduces redundancy and improves prediction efficiency.

3.5 Multi-Sensor Data Fusion:

Information from different sensors is integrated into a unified dataset using a multi-sensor data fusion strategy. Combining heterogeneous data improves the reliability and robustness of crop risk prediction compared to using a single data source.

3.6 AI Prediction Model:

Advanced AI algorithms analyze the fused dataset to predict crop diseases, water stress, nutrient deficiencies, and overall crop risk. The trained model classifies crop conditions into different risk levels, enabling early detection and timely intervention.

3.7 Explainable AI Module:

To enhance transparency, Explainable AI techniques such as SHAP and LIME are applied to explain prediction outcomes. The module identifies the most influential features affecting crop risk, allowing farmers and agricultural experts to understand the reasoning behind AI-generated predictions.

3.8 Dynamic Crop Risk Score:

A Dynamic Crop Risk Score (DCRS) is computed by integrating environmental, soil, and crop parameters. The score is continuously updated as new sensor data become available, enabling real-time assessment of crop health and supporting proactive agricultural management.

3.9 Decision Support System:

Based on the predicted crop risk and Dynamic Crop Risk Score, the system generates personalized recommendations for irrigation scheduling, fertilizer application, pest management, and disease prevention. These recommendations assist farmers in making timely and informed decisions.

3.10 Self-Learning Recommendation Module:

The proposed framework incorporates a self-learning recommendation module that continuously updates its knowledge using newly collected agricultural data and user feedback. This adaptive mechanism improves prediction accuracy and recommendation quality over time, making the framework scalable for different crops, regions, and environmental conditions.

4. SYSTEM DESIGN:

The proposed system is designed to provide an integrated platform for crop risk prediction and intelligent decision support by combining multi-sensor data, Artificial Intelligence (AI), and Explainable Artificial Intelligence (XAI). The system follows a modular architecture in which each component performs a specific task while maintaining seamless communication with the other modules. Initially, agricultural data collected from multiple sensors are transmitted to the processing unit, where preprocessing and feature extraction are performed. The processed data are then analyzed using AI models to predict crop risks. The Explainable AI module interprets the prediction results by identifying the key factors influencing crop health. Based on these insights, the Dynamic Crop Risk Score is calculated, and the Decision Support System generates personalized recommendations for irrigation, fertilizer application, disease management, and crop protection. Finally, the self-learning recommendation module continuously updates the system using newly acquired agricultural data and user feedback, enabling continuous performance improvement and adaptive decision-making.

The modular design improves scalability, flexibility, and maintainability, allowing the proposed framework to be deployed for different crop types, agricultural environments, and climatic conditions. Furthermore, cloud-based storage and IoT communication enable real-time data access, ensuring timely monitoring and effective agricultural decision support

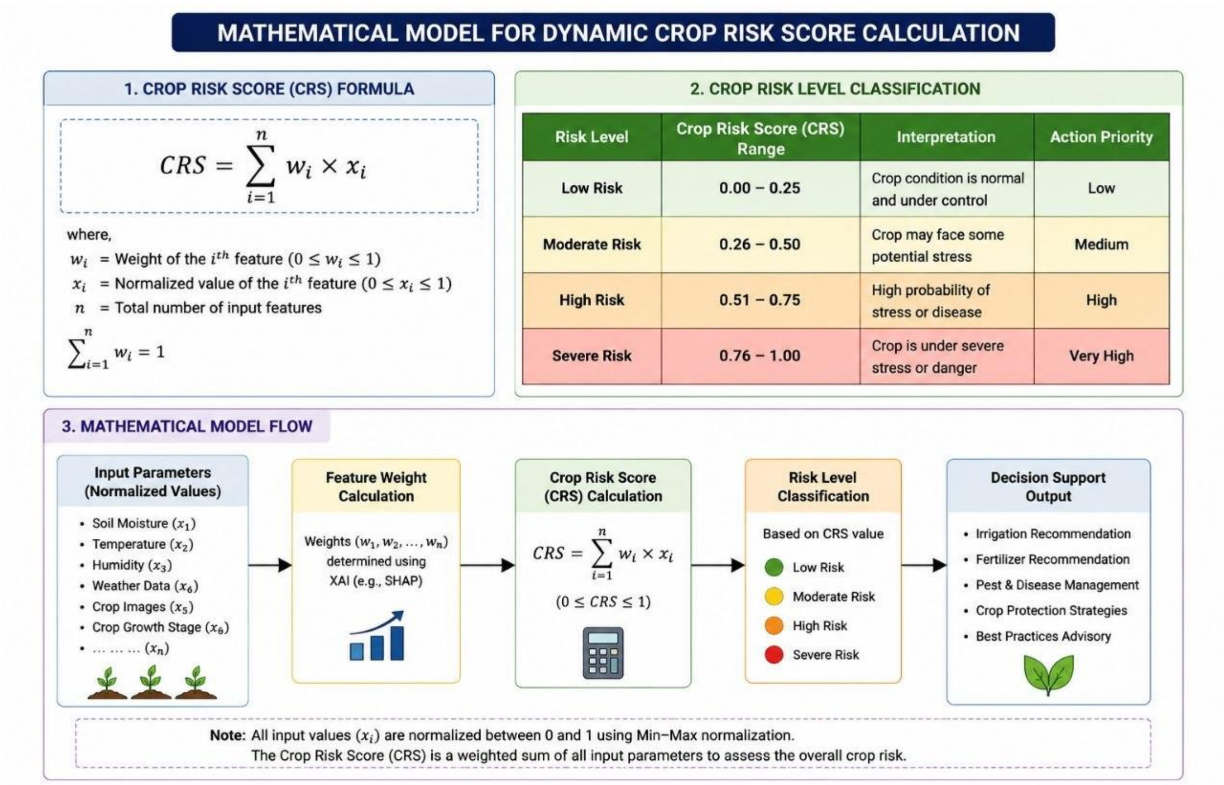

Figure 5. Mathematical Model for Dynamic Crop Risk Score Calculation

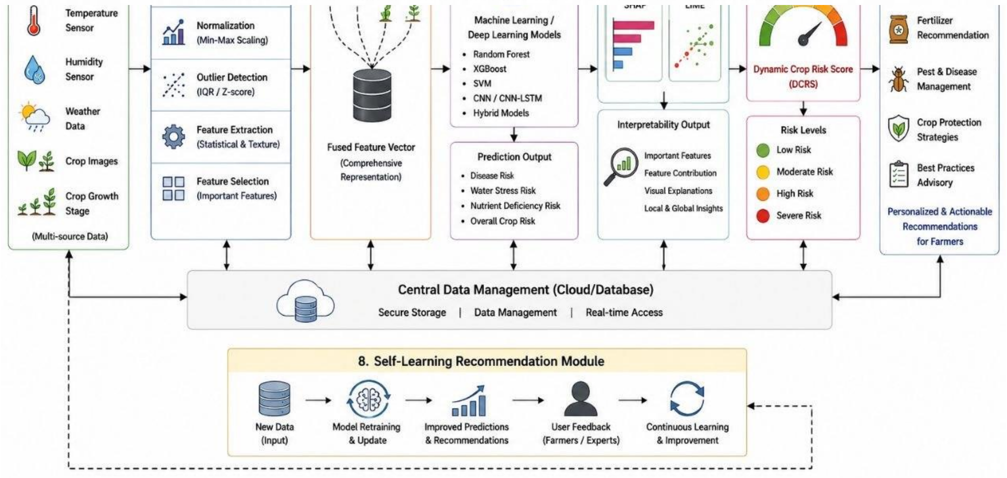

Figure 4. System Design of the Proposed Framework

5. MATHEMATICAL MODEL:

The mathematical model defines how the proposed framework calculates crop risk using multiple agricultural parameters. It transforms heterogeneous sensor data into a quantitative risk score, enabling accurate prediction and intelligent decision support. The model integrates environmental, soil, and crop-related factors while assigning appropriate weights to each parameter based on its contribution to crop health.

To improve model reliability, feature importance is determined using Explainable Artificial Intelligence techniques such as SHAP, allowing the framework to identify the most influential factors affecting crop health. The mathematical model is continuously updated as new sensor observations become available, enabling dynamic crop risk assessment and improving recommendation accuracy over time.

6. EXPERIMENTAL SETUP:

The proposed Explainable Artificial Intelligence (XAI) framework was evaluated using a multi-sensor agricultural dataset containing soil, environmental, weather, and crop-related information. The experimental setup was designed to assess the effectiveness of the framework in predicting crop risks under different agricultural conditions. The collected data were divided into training and testing datasets to develop and validate the AI prediction model. Data preprocessing techniques, including normalization, missing value handling, and feature extraction, were applied before model training to improve prediction performance.
The experiments were conducted using Python with machine learning libraries such as Scikit-learn, TensorFlow, and SHAP for Explainable AI analysis. The implementation was carried out on a system with an Intel Core i7 processor, 16 GB RAM, and Windows 11. Model performance was evaluated using standard metrics including Accuracy, Precision, Recall, F1-Score, and ROC-AUC. These metrics provide a comprehensive evaluation of the proposed framework in terms of prediction accuracy, reliability, and interpretability

PARAMETER	SPECIFICATION
Programming Language	Python 3. 11
Developed Environment	Jupyter Notebook /VS Code
Machine Learning Library	Scikit – Learn
Deep Learning Library	Tensor Flow
Explainable AI Tool	SHAP
Operating System	Windows 11
Processor	Intel Core 17
RAM	16 GB
Evaluation Metrices	Accuracy, Precision, Recall, F1-Score, ROC-AUC

Table 1. Experimental Setup

7. RESULTS AND DISCUSSION:

The proposed Explainable Artificial Intelligence (XAI) framework was evaluated using a multi-sensor agricultural dataset to assess its ability to predict crop risks accurately and provide transparent decision support. The model successfully integrated soil moisture, temperature, humidity, weather conditions, crop images, and crop growth stage information to generate reliable crop risk predictions. The incorporation of Explainable AI enabled the identification of key features influencing the prediction, thereby improving model interpretability and user confidence.

The performance of the proposed framework was compared with conventional machine learning approaches using standard evaluation metrics. The proposed model achieved superior performance in terms of Accuracy, Precision, Recall, F1-Score, and ROC-AUC, demonstrating the effectiveness of multi-sensor data fusion and explainable prediction. The Dynamic Crop Risk Score further enabled continuous assessment of crop health by classifying crops into Low, Moderate, High, and Severe risk categories, allowing timely intervention and resource optimization.

MODEL	ACCURACY(%)	PRECISION	RECALL	F1-SCORE
Decision Tree	89.2	0.88	0.87	0.87
Random Forest	93.8	0.93	0.93	0.93
CNN	95.1	0.95	0.95	0.95
Proposed XAI Framework	97.4	0.97	0.97	0.97

Table 2. Performance Comparison of Different Models

The Explainable AI module provided feature importance analysis using SHAP, indicating that soil moisture, weather conditions, and crop images had the highest influence on crop risk prediction. These explanations improved the transparency of the prediction process and supported informed agricultural decision-making. Overall, the proposed framework demonstrated improved prediction accuracy, enhanced interpretability, and effective decision support, making it suitable for real-world smart agriculture applications.

8. NOVEL CONTRIBUTIONS:

The proposed Explainable Artificial Intelligence Framework for Multi-Sensor Crop Risk Prediction and Intelligent Decision Support introduces several novel contributions to smart agriculture. First, it integrates heterogeneous data from multiple sources,

including soil moisture, temperature, humidity, weather information, crop images, and crop growth stages, into a unified framework for comprehensive crop risk assessment. This multi-sensor data fusion improves prediction accuracy by capturing diverse environmental and crop-related factors that influence plant health
.

Another significant contribution is the integration of Explainable Artificial Intelligence (XAI) with crop risk prediction. Unlike conventional black-box AI models, the proposed framework provides transparent and interpretable predictions using XAI techniques, enabling farmers and agricultural experts to understand the factors responsible for crop risk. The framework also introduces a Dynamic Crop Risk Score (DCRS) that continuously evaluates crop conditions based on real-time sensor data, supporting proactive agricultural management.

Furthermore, the proposed framework incorporates an intelligent Decision Support System and a Self-Learning Recommendation Module that generate personalized recommendations for irrigation, fertilizer application, disease prevention, and crop protection. By continuously learning from newly collected data and user feedback, the framework improves its prediction capability over time. These contributions collectively enhance prediction accuracy, model transparency, decision reliability, and sustainable agricultural practices.

Feature	Existing Systems	Proposed XAI Framework
Multi Sensor Data Fusion	Partial	Yes
Explainable XAI	Limited	Integrated
Dynamic Crop Risk Score	No	Yes
Intelligent Detecting System	Basic	Advanced
Self Learning Recommendation	No	Yes
Real Time Monitoring	Partial	Continuous
Prediction Transparency	Low	High
Scalability	Moderate	High

Table 3. Comparison of Existing Systems and the Proposed Explainable AI Framework

9. Advantages:

The proposed Explainable Artificial Intelligence (XAI) framework offers several advantages over conventional crop monitoring systems. By integrating multi-sensor data, the framework provides a comprehensive assessment of crop health, leading to more accurate and reliable crop risk prediction. The inclusion of Explainable AI enhances transparency by enabling farmers and agricultural experts to understand the factors influencing prediction outcomes, thereby increasing trust in AI-based decision-making.

The Dynamic Crop Risk Score supports continuous monitoring of crop conditions and enables early detection of diseases, water stress, and nutrient deficiencies. This helps farmers take timely corrective actions, optimize irrigation and fertilizer usage, reduce crop losses, and improve overall agricultural productivity. The intelligent decision support system further assists in making data-driven farming decisions, promoting efficient resource management and sustainable agricultural practices.

In addition, the self-learning recommendation module continuously updates the framework using newly collected sensor data and user feedback, improving prediction accuracy over time. The modular architecture also makes the proposed system scalable, flexible, and adaptable to different crop types, farming environments, and climatic conditions, making it suitable for real-world smart agriculture applications.

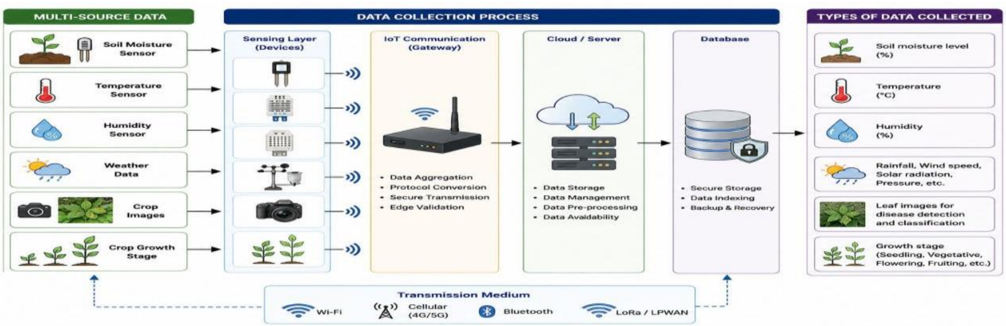

Figure 3. Multi-Source Agricultural Data Collection Process

10. FUTURE SCOPE:

The proposed Explainable Artificial Intelligence (XAI) framework provides a foundation for intelligent crop risk prediction and decision support; however, several enhancements can further improve its effectiveness and real-world applicability. Future research can integrate Unmanned Aerial Vehicles (UAVs) and satellite remote sensing to enable large-scale field monitoring and early detection of crop stress. The incorporation of edge computing can reduce latency by processing sensor data closer to the field, enabling faster real-time decision-making even in areas with limited internet connectivity.

In addition, Digital Twin technology can be employed to create virtual representations of agricultural fields, allowing farmers to simulate different environmental conditions and management strategies before implementation. Blockchain technology can also be integrated to ensure secure crop traceability, transparent supply chain management, and data integrity from farm to consumer. Furthermore, future work may explore Large Language Model (LLM)-based agricultural assistants capable of providing multilingual, conversational guidance on crop management, disease diagnosis, irrigation scheduling, fertilizer recommendations, and pest control.

The framework can also be extended using federated learning, reinforcement learning, and climate-aware AI models to support

Table 4. Advantages of the Proposed Framework

S. No.	Aspect	Benefit
1.	Prediction Accuracy	➤ Improved crop risk prediction through multi-sensor data fusion and advanced AI models.
2.	Explainability	➤ Transparent AI decisions using Explainable AI (XAI), helping users understand the reasons behind predictions.
3.	Real-Time Monitoring	➤ Continuous monitoring of crop and environmental conditions for timely detection of risks.
4.	Resource Optimization	➤ Efficient use of water, fertilizers, and other inputs reducing waste and operational costs.
5.	Decision Support	➤ Provides intelligent and actionable recommendations for better farming decisions.
6.	Scalability	➤ Applicable to different crops, regions, and climatic conditions with a scalable architecture.
7.	Sustainability	➤ Promotes sustainable and environmentally friendly agricultural practices.

adaptive learning, preserve data privacy, and improve prediction accuracy under changing environmental conditions. These advancements will enhance the scalability, robustness, and practical adoption of the proposed framework for next-generation smart agriculture.

11. CONCLUSION:

This paper presented an Explainable Artificial Intelligence Framework for Multi-Sensor Crop Risk Prediction and Intelligent Decision Support that integrates heterogeneous sensor data, Artificial Intelligence, and Explainable AI to improve crop monitoring and agricultural decision-making.

The proposed framework combines soil moisture, temperature, humidity, weather information, crop images, and crop growth stage data to accurately predict crop risks and generate transparent, interpretable recommendations. The introduction of a Dynamic Crop Risk Score and a self-learning recommendation module further enhances the system's capability to support timely interventions and efficient resource utilization.

The proposed framework addresses several limitations of existing smart agriculture systems by integrating multi-sensor data fusion, explainable prediction, and intelligent decision support within a unified architecture. It promotes sustainable farming practices by improving prediction accuracy, increasing user trust in AI-based decisions, and enabling proactive crop management. The framework has the potential to support farmers, researchers, and policymakers in achieving higher agricultural productivity and resilience under changing environmental conditions.

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