CROP ROTATION INTELLIGENCE SYSTEM (CRIS) USING IOT AND AGENTIC AI

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ABSTRACT:

In order to improve decision-making in contemporary agriculture, this study introduces the Crop Rotation Intelligence System (CRIS), a comprehensive and intelligent framework that combines the Internet of Things (IoT), ensemble machine learning, and Agentic Artificial Intelligence. The system gathers real-time environmental and soil data from the field using Internet of Things (IoT) sensors, such as temperature, soil moisture, pH, and rainfall sensors, connected via an ESP32 microcontroller. To enable precise analysis of changing agricultural circumstances, these data are sent to a cloud-based database for ongoing monitoring, processing, and storage. The solution guarantees timely insights that assist precision agricultural methods by utilizing real-time data capture.

The best crop is predicted using a stacking ensemble machine learning model based on important factors like temperature, humidity, pH, rainfall, NPK levels, and designed soil type characteristics. The model improves prediction accuracy, resilience, and generalization under various scenarios by combining Logistic Regression as a meta-learner with XGBoost, LightGBM, and CatBoost as base learners. Reliable suggestions are produced by this ensemble approach, which successfully captures the

intricate interactions between crop suitability and environmental conditions. The system includes an Agentic AI layer that offers context-aware and explainable agricultural insights in addition to predictive capabilities. In order to preserve long-term soil fertility and sustainability, they include crop suitability analyses, fertilizer recommendations, and crop rotation techniques. With this capability, the system becomes an intelligent decision-support system instead of just a basic prediction tool.

Through the integration of powerful ensemble machine learning, Agentic AI, and real-time IoT-based sensing, the system empowers farmers to make data-driven, educated decisions that are customized to dynamic field conditions. It lessens the need for conventional trial-and-error methods and lowers the dangers of poor crop selection and wasteful resource use.

KEYWORDS: Crop Rotation Intelligence System (CRIS), Internet of Things (IoT), Ensemble Machine Learning, Stacking Classifier, XGBoost, LightGBM, CatBoost, Agentic Artificial Intelligence, Precision Agriculture, Smart Farming, Crop Recommendation, Soil Health Monitoring, Decision Support System, Agentic AI, Sustainable Agriculture.

I.INTRODUCTION:

Even while agriculture plays a significant role in both economic growth and food security, conventional farming methods still mostly rely on human judgment. This frequently leads to ineffective crop rotation, poor crop selection, and slow soil deterioration, all of which have an impact on sustainability and production. Intelligent, data-driven agricultural systems are becoming more and more necessary due to the mounting difficulties of climate change, resource scarcity, and the pressing need for environmentally responsible farming. To overcome these obstacles, researchers have recently investigated the use of optimization methods and artificial intelligence. For example, [1] used Double Deep Q-Learning for regional crop planning, which allowed for the best possible distribution of crops among several farms. In a similar vein, [2] emphasized the integration of real-time soil and environmental data with AI to improve precise crop rotation. AI-based expert systems have also been proposed to support global crop rotation decisions by improving both sustainability and profitability [3]. In addition, optimization models that consider constraints such as water scarcity and uncertain economic returns have been developed to enhance resource efficiency in agriculture [4]. Reinforcement learning and other data-driven approaches have further contributed to crop rotation planning by generating realistic and adaptive strategies based on environmental conditions [6], while machine learning techniques have demonstrated significant improvements in crop yield and sustainability [7].

Despite these advancements, most existing approaches primarily focus on large-scale optimization or lack real-time adaptability and explainable decision-making at the farm level. These limitations reduce their practical applicability for individual farmers who require timely and interpretable insights. To address these gaps, this research proposes a Crop Rotation Intelligence System (CRIS) that integrates Internet of Things (IoT), ensemble machine learning, and Agentic Artificial Intelligence. The system collects real-time data using sensors that measure temperature, soil moisture, pH, and rainfall, connected through an ESP32 microcontroller, enabling continuous monitoring of field conditions [11]. A stacking ensemble model combining XGBoost, LightGBM, and CatBoost is used to predict the most suitable crop based on soil and environmental parameters. Furthermore, an Agentic AI layer provides explainable insights, including crop suitability reasoning, fertilizer recommendations, and crop rotation strategies [15].

By combining real-time data acquisition, advanced machine learning models, and intelligent advisory capabilities, the proposed system offers a scalable and practical solution for precision agriculture. It addresses the limitations identified in existing research while enhancing decision-making, improving crop productivity, and promoting sustainable farming practices to meet the evolving demands of modern agriculture.

II.ALGORITHM:

Input:
Soil parameters $S = \{N, P, K, pH, SM\}$(where SMdenotes soil moisture), Environmental parameters $E = \{T, H, R_f\}$(temperature, humidity, rainfall)

Output:
Recommended Crop C, Crop Rotation Plan R, Advisory Insights A

The proposed Crop Rotation Intelligence System (CRIS) utilizes a hybrid algorithm that combines ensemble machine learning and Agentic Artificial Intelligence to generate accurate, reliable, and interpretable agricultural recommendations. The algorithm begins with the formation of an input dataset $D = \{S, E\}$, representing the combined influence of soil nutrients and environmental conditions on crop growth. To ensure uniformity, each feature is normalized using min-max scaling:

$$X_i' = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

where $X_i$represents the original feature value and $X_i'$is the normalized value. This transformation ensures that all features contribute proportionately during model training.

A key enhancement in the algorithm is feature engineering through the derivation of a soil classification variable. The soil type function is defined as:

$$soil\_type = \begin{cases} 1, & \text{if } pH < 6 \text{(acidic)} \\ 2, & \text{if } 6 \le pH \le 7.5 \text{(neutral/fertile)} \\ 3, & \text{if } pH > 7.5 \text{(alkaline)} \end{cases}$$

Additionally, a fertility index $F$is computed to represent nutrient richness:

$$F = \alpha N + \beta P + \gamma K$$

where α, β, γ are weighting coefficients reflecting the importance of each nutrient. The final feature vector is expressed as:

$$X = \{N, P, K, pH, SM, T, H, R_f, soil\_type, F\}$$

The prediction mechanism is based on a stacking ensemble learning framework. Three base learners—XGBoost (M_1), LightGBM (M_2), and CatBoost (M_3)—are trained independently using the dataset ($X'Y$), where Yrepresents crop labels. Each model generates a probability distribution over possible crops:

$$P_i = M_i(X') = \{p_{i1}, p_{i2}, \dots, p_{in}\}$$

where $n$is the number of crop classes. These outputs are concatenated to form a new feature vector:

$$Z = [P_1, P_2, P_3]$$

A meta-learner M_{meta}, implemented using Logistic Regression, combines these predictions. The final crop probability is computed as:

$$P(C = k) = \sigma\left(\sum_{j=1}^{m} w_j Z_j + b\right)$$

where $\sigma$is the sigmoid function, $w_j$are learned weights, and $b$is the bias term. The recommended crop is:

$$C = \arg\max_k P(C = k)$$

Following prediction, a crop rotation strategy is generated using a rotation function:

$$R = f(C, F, pH)$$

The function ensures nutrient balance by alternating crops with complementary nutrient demands. For instance, nitrogen-depleting crops are followed by nitrogen-fixing crops to restore soil fertility.

To enhance decision transparency, the algorithm incorporates an Agentic AI module. This module generates advisory insights $A$by analyzing input parameters and prediction outputs. The insights include explanations of crop suitability, fertilizer requirements based on nutrient deficiency:

$$FertilizerNeed = Target_{NPK} - Current_{NPK}$$

and precautionary measures for adverse conditions such as low moisture or extreme temperature.

Finally, the algorithm outputs a tuple:

$$Output = \{C, R, A\}$$

where $C$is the predicted crop, $R$is the recommended rotation plan, and Acontains actionable insights. The system can be periodically retrained with new data to update model parameters and improve predictive performance over time. This integrated approach ensures robust, scalable, and intelligent decision-making for precision agriculture, effectively bridging the gap between data-driven analytics and practical farming needs.

III.PROPOSED SYSTEM:

This paper proposes a Crop Rotation Intelligence System (CRIS) that combines Internet of Things (IoT), ensemble machine learning, and Agentic Artificial Intelligence to provide real-time, data-driven, and explainable agricultural decision support in order to overcome the drawbacks of conventional farming and current crop planning techniques. The suggested system is intended to function at the field level with continuous monitoring and intelligent advisory capabilities, in contrast to current methods that concentrate on large-scale optimization or lack farm-level adaptability.

Real-time data collection using IoT sensors forms the basis of the suggested solution. Sensor modules linked to an ESP32 microcontroller are used to gather environmental and soil characteristics, including temperature, soil moisture, pH, and rainfall [11]. This real-time sensing strategy is consistent with precision agriculture techniques covered in [2], where the incorporation of real-time environmental data greatly enhances crop planning precision. A cloud-based platform receives the gathered data, allowing for ongoing storage, monitoring, and accessibility for additional processing.

The system uses sophisticated feature engineering techniques to improve prediction accuracy. Based on domain information, a derived characteristic termed soil type is produced in addition to primary factors including NPK levels, temperature, humidity, pH, and rainfall. This strategy enhances previous research like [7], which highlights the significance of data-driven feature representation in raising agricultural output. Better crop adaptability discrimination across varied field conditions is made possible by the incorporation of soil intelligence.

An ensemble machine learning model built on a stacking architecture forms the basis of the suggested solution. Logistic Regression serves as a meta-learner in this model, which incorporates three potent algorithms as base learners: XGBoost, LightGBM, and CatBoost. Large-scale or sequential decision optimization is the main goal of reinforcement learning techniques like Double Deep Q-Networks, which have been used to regional crop planning in [1] and DQN-based rotation schemes in [6]. By utilizing the advantages of several models, the suggested stacking ensemble model, on the other hand, focuses on precise, real-time crop prediction at the farm level, increasing robustness and decreasing overfitting.

The approach adds an Agentic AI layer in addition to prediction to offer context-aware and explicable agricultural insights. This element tackles a significant shortcoming noted in earlier research like [3] and [4], where decision-making systems frequently lack interpretability and user-level advice. The Agentic AI module delivers optimal crop rotation plans, assesses soil health, makes fertilizer recommendations based on nutrient deficits, and produces thorough explanations for crop suggestions. These suggestions are in line with resource-conscious planning and sustainable practices that are emphasized in [4] and [8].

Additionally, the system includes a crop rotation planning mechanism that takes long-term sustainability and soil nutrient balance into account. The suggested method combines real-time data and AI-driven reasoning to produce adaptive rotation strategies [14], in contrast to conventional optimization models that concentrate on restrictions like water shortage and economic rewards [4]. This guarantees increased agricultural yield, decreased insect cycles, and higher soil fertility.

The system's output is presented via an intuitive web-based dashboard that shows AI-generated insights, anticipated crop suggestions, and real-time sensor data [12]. This closes the gap between sophisticated computational models and useful field applications by guaranteeing farmers' accessibility and use.

All things considered, the suggested CRIS framework offers a clever and scalable precision agriculture solution. The system addresses the shortcomings of previous research [1]–[10] and provides a useful, farm-level decision-support system that boosts productivity, maximizes resource utilization, and encourages sustainable agricultural practices by fusing explainable Agentic AI, ensemble machine learning, and real-time IoT data acquisition.

IV.FLOWCHART:

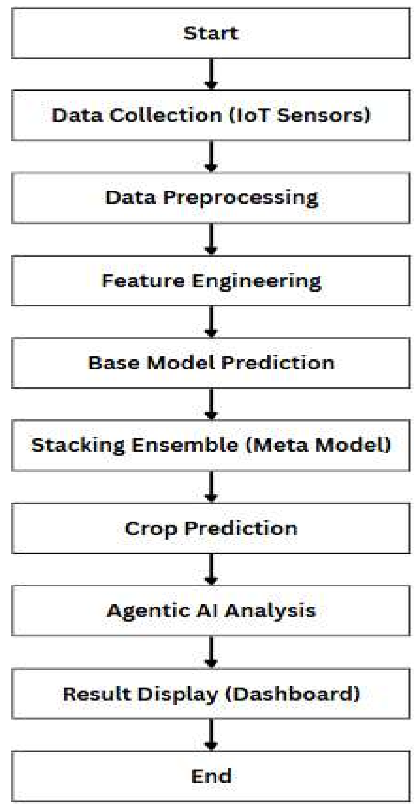

Fig. 1 shows the flow of data from IoT-based data collection to crop prediction and AI-based advisory generation.

V. EXPERIMENTAL RESULT:

The purpose of this experimental study is to assess how well the proposed Crop Rotation Intelligence System (CRIS) integrates Agentic Artificial Intelligence, ensemble machine learning, and the Internet of Things (IoT) to improve agricultural decision-making. The tests are intended to validate the system in a number of ways, such as data acquisition dependability, prediction accuracy, real-time adaptability, and result interpretability. The goal is to show that the suggested system offers scalable and useful precision agriculture solutions in addition to achieving high performance.

Methodology

There are both hardware and software components in the experimental setup. IoT sensors linked to an ESP32 microcontroller are used to gather real-time ambient and soil characteristics, including temperature, soil moisture, pH, and rainfall. These characteristics are constantly observed and are important markers of crop growth conditions. To improve predictive power, NPK values are also added from a typical crop recommendation dataset.

Preprocessing of the acquired data includes feature engineering, which generates an additional soil type attribute based on pH and nutrient composition, and normalization, which ensures uniform feature scaling. The three foundation learners in the machine learning framework—XGBoost, LightGBM, and CatBoost—are integrated using a stacking ensemble technique, with Logistic Regression serving as the meta-learner. Accuracy, resilience, and the system's capacity to deliver timely and comprehensible recommendations are the criteria used to evaluate it.

Experiment 1: System Implementation and Data Acquisition

The purpose of this experiment is to verify the IoT-based data acquisition system's dependability and efficiency. Since machine learning models rely primarily on the integrity of the input data, accurate and ongoing data gathering is crucial to guaranteeing the quality of predictions.

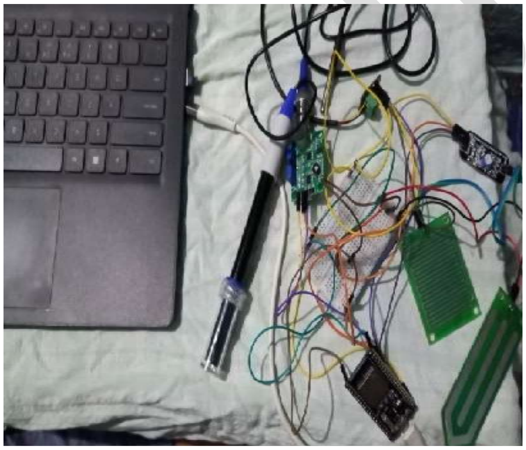

Fig. 1: IoT Sensor Setup and ESP32-Based Data Acquisition System

Results:
With no latency, the IoT system was able to properly record soil and ambient characteristics in real time. The ESP32 microcontroller efficiently handled data transmission to the cloud platform, ensuring uninterrupted data flow [11]. Theoretically, dynamic modeling of agricultural circumstances is made possible by real-time monitoring, which enables the system to adjust to temporal variables such changes in soil moisture and temperature. Precision agriculture is built on this ongoing data collection, which lowers uncertainty and increases downstream prediction accuracy. The experiment verifies that the suggested system's hardware layer is reliable, scalable, and appropriate for practical implementation.

Experiment 2: Crop Prediction Performance

The predictive power of the system's machine learning models is assessed in this experiment. Finding out how well the models can map input features to the best crop suggestions is the goal.

Table 1: Accuracy Comparison of Machine Learning Models

Model	Accuracy (%)
XGBoost	98.63
LightGBM	98.63
CatBoost	98.86
Stacking Model (Proposed)	98.86

Results:
Table 1 illustrates that the stacking ensemble model outperforms individual models, achieving the greatest accuracy of 98.86%. Theoretically, by merging several weak or strong learners to lower bias and variance, ensemble learning enhances prediction ability. While CatBoost efficiently handles categorical features and minimizes overfitting, XGBoost and LightGBM are excellent at managing structured data and feature interactions. Through the use of a meta-learner, the stacking approach combines these advantages to provide a more resilient and generalized model. This experiment confirms that the suggested ensemble structure guarantees accurate crop prediction under a variety of circumstances and is very successful for complicated agricultural datasets.

Experiment 3: System Output and Visualization

This experiment assesses how well the system presents outputs using an intuitive user interface. In order to connect intricate computational models with real-world user engagement, visualization is essential.

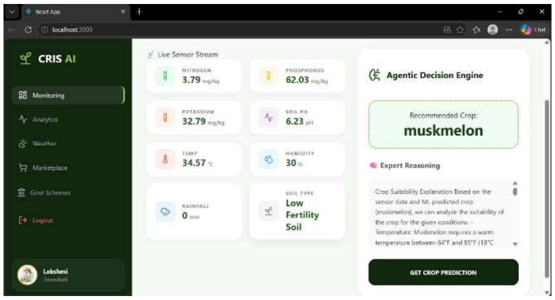

Fig. 2: Dashboard Displaying Real-Time Sensor Data and Predicted Crop Output

Results:
The dashboard effectively presents forecasted crop suggestions in an easy-to-understand style coupled with real-time sensor data [12]. Theoretically, by converting unprocessed data into meaningful information, visualization improves cognitive understanding. The incorporation of real-time updates guarantees that users can quickly monitor changes in environmental conditions and the predictions that go along with them. This dynamic feedback system lessens reliance on human interpretation and facilitates prompt decision-making. The experiment shows how well the system converts complicated model outputs into understandable and useful insights for end users.

Experiment 4: Agentic AI-Based Advisory Analysis

The Agentic AI module, which offers recommendations that are understandable and context-aware, is the main focus of this investigation. Explainable AI improves transparency and trust, in contrast to conventional machine learning systems that function as black boxes.

Results:
By examining input factors and forecast outcomes, the Agentic AI module produces thorough justifications for crop recommendations [15]. In order to preserve soil fertility, it suggests crop rotation techniques and fertilizer recommendations depending on nutrient deficits. In theory, explainable AI enhances decision-making by providing interpretability, which enables consumers to comprehend the logic underlying forecasts. Furthermore, the incorporation of contextual reasoning allows the system to modify recommendations according to different circumstances. This experiment emphasizes how crucial it is to combine interpretability and predictive accuracy to make the system more dependable and user-focused.

The experimental findings verify that the suggested CRIS system successfully combines ensemble machine learning, Agentic AI, and IoT-based sensing to provide a complete agricultural decision-support solution. The system addresses major shortcomings of current methods by achieving high prediction accuracy, real-time adaptability, and explainable insights. Scalability and usefulness are guaranteed by the combination of clever software components and dependable hardware. All things considered, the suggested methodology shows great promise for raising crop yields, maximizing resource use, and encouraging sustainable agricultural methods in contemporary agriculture.

VI. Contributions to Precision Agriculture

By combining IoT, ensemble machine learning, and Agentic Artificial Intelligence into a single decision-support framework, the proposed Crop Rotation Intelligence System (CRIS) significantly advances the field of precision agriculture. The following is a summary of the major contributions:

1. Real-Time Data-Driven Decision Support

The capacity of the suggested system to facilitate real-time agricultural decision-making through IoT-based data collecting is one of its main contributions. The method makes sure that crop recommendations are based on actual field circumstances rather than static or previous data by continuously gathering soil and environmental characteristics like temperature, soil moisture, pH, and rainfall. This dynamic technique enhances agricultural planning's dependability and lowers uncertainty [13].

2. High-Accuracy Crop Prediction Using Ensemble Learning

To achieve high prediction accuracy, the system presents a stacking ensemble model that integrates LightGBM, CatBoost, and XGBoost. In contrast to conventional single-model methods, the ensemble framework reduces bias and variance by utilizing the advantages of several algorithms. This enhances agricultural production by producing more reliable and consistent crop forecasts under a range of environmental circumstances.

3. Integration of Feature Engineering for Soil Intelligence

The integration of domain-driven feature engineering through the creation of a soil type characteristic based on pH and nutrient levels is a noteworthy addition of this work. This improves prediction performance and increases the model's capacity to capture intricate soil features. The incorporation of these derived traits highlights the significance of integrating data-driven methodologies with domain expertise.

4. Explainable Decision-Making Through Agentic AI

The suggested approach incorporates an Agentic AI layer to produce recommendations that are understandable and context-aware, in contrast to traditional machine learning systems that function as black boxes. This module produces insights such crop rotation plans, fertilizer suggestions, and crop appropriateness reasoning. The approach increases user trust and promotes improved decision-making by increasing transparency and interpretability.

5. Intelligent Crop Rotation Planning for Sustainability

By using crop rotation techniques that preserve soil fertility and lessen nutrient depletion, the system supports sustainable agriculture. The method suggests ideal crop sequences that enhance long-term soil health and productivity by examining soil parameters and past crop patterns. This tackles a significant issue with soil degradation in contemporary agriculture.

6. Scalable and Practical System Architecture

The suggested CRIS framework is scalable and accessible for practical applications by combining inexpensive IoT devices with cloud-based processing and an intuitive GUI. The gap between research and real-world application is closed by combining machine learning prediction, real-time data monitoring, and AI-driven insights into a single platform.

7. Enhanced User Interaction and Visualization

Effective presentation of sensor data, prediction outcomes, and AI-generated insights is made possible by the creation of a web-based dashboard. This enhances the system's usability and guarantees that intricate analytical results are displayed in an understandable way, making it appropriate for farmers and other agricultural stakeholders[12].

VII. CONCLUSION:

In order to improve agricultural decision-making, this article introduced the Crop Rotation Intelligence System (CRIS), an integrated framework that blends ensemble machine learning, IoT-based sensing, and Agentic Artificial Intelligence. The solution overcomes the main drawbacks of current crop planning techniques and conventional farming methods, which frequently rely on static data, are not flexible in real time, and offer little interpretability. The suggested approach allows for dynamic and data-driven crop recommendations by utilizing real-time environmental and soil data.

The experimental findings show that the stacking ensemble model, which combines LightGBM, CatBoost, and XGBoost, achieves excellent prediction accuracy (98.86%), demonstrating the efficacy of ensemble learning in managing complicated agricultural datasets. In contrast to sequential optimization techniques in [6] and reinforcement learning-based regional planning systems like [1], the suggested system concentrates on farm-level decision support with real-time responsiveness. Additionally, the incorporation of IoT-based data collecting is consistent with the developments in precision agriculture described in [2], guaranteeing ongoing observation and flexibility in response to shifting field circumstances.

The integration of an Agentic AI module, which offers explainable insights such crop suitability reasoning, fertilizer recommendations, and crop rotation techniques, is a significant contribution of this work. This supports sustainable resource management as stressed in optimization-based techniques [4] and data-driven agricultural research [7], while also addressing the lack of interpretability shown in previous AI-based systems [3]. The system is a useful and user-focused solution since it can combine explainability and forecast accuracy.

All things considered, the suggested CRIS framework provides a scalable and clever solution for precision agriculture, enhancing crop yield, maximizing resource use, and encouraging sustainable farming methods. The system is positioned as a major step toward intelligent and resilient agricultural ecosystems thanks to the integration of real-time data, sophisticated machine learning, and explainable AI.

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