AI Powered Crop Rotation

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Abstract—
This project presents a Crop Rotation Recommen- dation System using the Rule Learning Crop Optimizer (RLCO) approach. The system is designed to suggest suitable crops by applying rule-based logic derived from agricultural knowledge. It uses simple and understandable rules to analyze inputs like soil type, weather conditions, and crop history in order to recommend the next appropriate crop for cultivation.The proposed system helps farmers in making better crop planning decisions by reducing the risk of soil nutrient depletion and improving overall productivity. Since the recommendations are based on clear rules, the system is easy to understand and practical to use. This project aims to support sustainable farming practices and assist farmers with an effective decision-support tool for crop rotation planning.

***Keywords*—Crop Rotation, Rule Learning Crop Optimizer (RLCO), Precision Agriculture, Soil Nutrient Management, Yield Estimation, Feedforward Neural Network, Machine Learning in Agriculture, Soil–Water Balance, Sustainable Agriculture, Agronomic Rules**

I. Introduction

Agriculture is one of the main sources of livelihood for a large population, especially in countries like India. Farmers depend on agriculture not only for income but also for food security. One crucial factor that affects agricultural productiv- ity is crop rotation, which means growing different crops one after another on the same land. Proper crop rotation helps in maintaining soil fertility, controlling pests, and improving crop yield.However, choosing the right crop sequence is not easy. Many factors such as soil type, climate, season, rainfall, and the previously grown crop influence this decision [1][2][4]. In many cases, farmers rely on traditional knowledge or personal experience, which may not always give the best results. Improper crop selection can lead to soil nutrient loss, low productivity, and increased use of fertilizers and pesticides.

The crop rotation systems developed using machine learning techniques till now face several limitations in real-world agri- cultural use. Most ML-based systems require large amounts of accurate and updated data related to soil, weather, and crop yield, which is often not available for many farming [3], [5]. These are usually complex and work as black-box models, making it difficult for farmers to understand how the recommendations are generated. In addition, ML models may not perform well when climatic conditions change or when applied to new regions with different soil characteristics. The need for high computational resources and technical expertise also limits their practical adoption. As a result, many existing ML-based crop rotation systems lack transparency, adaptability, and ease of use for small-scale farmers.

ML models trained on past data may fail to provide accurate recommendations when applied to new regions with different soil types or cropping patterns. The requirement of high computational resources, internet connectivity, and technical expertise also limits their usage at the farmer level. Small and marginal farmers often lack access to such infrastructure and training [3]. Due to these challenges, existing ML-based crop rotation systems lack transparency, flexibility, and user-friendliness, which reduces their practical adoption and effec- tiveness in supporting sustainable farming decisions.

To address these limitations, this project adopts the Rule Learning Crop Optimizer (RLCO) approach, which uses sim- ple, interpretable rule-based logic derived from agricultural knowledge integrated with ML model. RLCO, is easy to under- stand, and can be adapted to different regions and conditions. By providing transparent and practical crop recommendations, the proposed system improves usability, builds farmer trust, and supports sustainable crop rotation practices.

II. Literature Survey

Crop rotation is a fundamental practice in sustainable agri- culture, aimed at improving soil fertility, controlling pests, and optimizing yield.Traditionally, crop rotation decisions have been based on farmer experience, expert knowledge, and fixed seasonal practices.While these are effective to a good extent there is much uncertainity in them due to changing soil,climatic and market conditions.To make crop rotation more effective Artificial Intelligence was introduced to it.

Early research in crop recommendation systems primar- ily focused on rule-based expert systems, where predefined thresholds for soil nutrients , pH, moisture, and rainfall were used to recommend crops.Rule based expert systems were suitable only for very simple crop farmland.They offered simplicity, transparency, and understandability by laymen but were limited by their static character as they could not model complex interactions among multiple paramters or adapt to real time variations in conditions. With the passage of time Machine learning came into the picture due to large datasets being available.

In the recent years Machine learning and Deep learning have come to be used increasingly in Agriculture.Algorithms such as Markov chain,Qlearning,XGBoost among many others have been used to predict crop sequences,yields and water levels. [1]Several studies have applied supervised learning models such as Random Forest, Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Decision Trees for crop yield prediction and crop suitability classification. [1].Random Forest and XGBoost models have been able to perform well due to their ability to handle non linear relationships and feature interactions. [6] [7].

Neural network-based models, including Multilayer Percep- trons (MLP), have also been widely used to predict crop yield based on soil and climatic features. However, many of these approaches focus solely on yield maximization and do not explicitly consider crop rotation effects or resource constraints. Recent literature has explored AI-powered crop ro- tation optimization using advanced techniques such as Markov chains and reinforcement learning. [2]These models treat crop rotation as a sequential decision-making problem, where the choice of the current crop influences future soil health and yield. Reinforcement learning-based approaches aim to learn optimal crop sequences by maximizing long-term rewards such as yield or soil quality. While promising, such models often require large historical datasets and complex training processes, limiting their practical deployment for small and medium-scale farms.

Another important area of research is the development of decision support systems (DSS) for agriculture. These systems integrate predictive models with visualization tools to present information related to soil nutrients, water bal- ance, and crop performance. [8], [10], [11].Studies show that graphical representations of water availability, nutrient status, and yield predictions improve farmer understanding and decision-making. However, many existing DSS platforms lack economic interpretation, such as projected crop value, which is a crucial factor for real-world adoption..

Several studies rely on large-scale agricultural datasets derived from remote sensing, such as the USDA Cropland Data Layer, to analyze land-use and cropping patterns. [3].They used satellite imagery,land cover classes,annual cropland clas-sification maps and crop type labels. Their work focused on evaluating classification accuracy and temporal consistency of cropland data rather than crop recommendation or yield optimization. Their dataset was derived from USDA Cropland layer.While valuable for understanding land-use dynamics and crop distribution patterns, such approaches do not incorporate soil properties, water availability, or economic considerations required for farm-level decision support.Lark et al. highlighted the strengths and limitations of such datasets and empha- sized cautious interpretation when using them for agricultural decision-making.

Hafiyya et al. (2024) proposed an AI-enhanced precision crop rotation management system that integrates supervised machine learning with real-time weather forecasts and histor- ical crop performance data to generate optimized crop rota- tion plans for sustainable agriculture. The system emphasizes systematic data collection, analysis of soil and environmen- tal conditions, and AI-driven recommendations. [4]. These were gradually superseded by machine learning and, more recently, deep learning models capable of semantic feature extraction [4].

Zhang et al divided the crop planting phase into three categories:in-season mapping,pre-season mapping and post season mapping [5]. Historical crop planting data has been taken into account for prediction of the next crop. [5].

Some studies used drones to gather data rather than using condensed datasets. [9]. More recent studies have highlighted the use of hybrid approaches, combining machine learning with rule-based penalization. Such systems leverage the pre- dictive power of AI while maintaining agronomic realism by penalizing recommendations that violate soil nutrient or water availability constraints. [8]Additionally, several works have employed synthetic data generation to address the scarcity of real agricultural datasets, improving model robustness and generalization.

Despite these advancements, existing crop rotation and recommendation systems often suffer from one or more limita- tions: lack of integrated soil–water–yield modeling, absence of economic indicators, insufficient interpretability, or impractical deployment complexity.

III. METHODOLOGY

The proposed system involves an intelligent AI based Crop Recommendation model that combines soil, weather and Agroclimatic conditions using a hybrid data driven approach. The model implements FeedForward Neural Network (FFN) trained on a multi feature agricultural dataset that include Agroclimatic Region Nitrogen, Phosphorous, Potassium levels, Average rainfall,Soil Moisture,Season,Soil Type.

A. *Requirements Analysis*

Initial requirements were gathered through surveys with job seekers and discussions with career advisors to identify common challenges faced in resume creation and ATS compat- ibility. Essential features such as template flexibility, real-time feedback, and AI-powered content suggestions were mapped out.

B. Data Preprocessing

The dataset used in this study was obtained as a structured CSV file containing agroclimatic conditions. Since the dataset did not contain missing or inconsistent values, no cleaning techniques were required. Categorical variables such as Region, Season, Soil Type, and Crop Planted were transformed into numerical format using One-Hot Encoding. This allowed the neural network to process discrete categories without introducing ordinal bias. All numerical attributes, were standardized using the StandardScaler transformation:

$$X_{Scaled} = \frac{X - U}{\sigma} \quad (1)$$

This ensures that all features contribute equally and numerically larger values do not dominate the learning process.The dataset was divided into training and testing subsets using a 70:30 split. The training data was used to optimize model parameters, whereas the test set was used for evaluating model generalization.

C. User Interface and Experience

The proposed system includes a visualized and intuitive user interface designed to simplify access to crop-rotation recommendations for farmers and agricultural practitioners. The interface minimizes confusion by presenting only the essential input fields such as soil nutrient levels, moisture status, rainfall, season,soil type,and the region in a structured and easily navigable form. Clear labels, dropdown menus, validation checks, and responsive design principles ensure that users can provide accurate data with minimal effort.

D. Crop Prediction

The backend employs a hybrid learning approach combining machine learning-based yield estimation with rule-guided optimization logic, referred to as the Rule Learning Crop Optimizer (RLCO). The model learned during training phase.Each crop is assigned weights based on the suitability of the features for the crop.If a crop grows well in certain conditions the weights are more.For less influential conditions the weights are less.

E. Nutrient Ideal Dictionary Logic

The Rule-Based Learning Crop Optimizer (RLCO) incorporates a crop-specific nutrient recommendation system to adjust predicted yields according to soil fertility. This is implemented using a dictionary of ideal NPK (Nitrogen, Phosphorus, Potassium) values for each crop.The ideal nutrient dictionary provides a reference for optimal soil nutrient levels for each crop. By comparing the actual soil nutrient levels with these ideal values, the system can penalize crops when nutrients are insufficient, reward crops when soil nutrient amounts are favorable.During crop recommendation, the RLCO logic retrieves nutrient values.

$$\text{npk} = ideal_n pk.get(crop.lower(), ideal_n pk[''default''']) \quad (2)$$

The retrieved NPK values are then compared against the actual soil nutrients. In case of deficiency a penalty factor is applied to the adjusted yield calculation.

F. Water Balance Calculation

The water balance calculation is an important component of the proposed RLCO system, as it provides insights into the adequacy of available water with respect to the crop's requirements. For each recommended crop, the available water is estimated based on the measured soil moisture and the average rainfall in the target region:

$$\text{Water Available (mm)} = (SoilMoisture((AverageRainfall(mm)0.8) \quad (3)$$

The water balance is visualized using a line graph, where available water and required water are plotted for each recommended crop, allowing farmers to quickly identify potential deficits and make informed irrigation or crop selection decisions.

G. Testing, Evaluation, and Iterative Improvement

Comprehensive functional and usability tests were conducted. The platform was benchmarked against commercial ATS simulators (Resumeworded, TopResume, VMock). Quantitative metrics such as ATS score increase, keyword matching rate, export fidelity, and user satisfaction scores were recorded. Feedback from real users guided iterative enhancements to optimize both technical performance and user experience.

IV. System Architechture

The proposed system is designed as an AI Powered Crop Rotation tool.It has several layers to it.The architecture consists of the following main layers:

A. Backend

The backend is implemented in Python.It handles all the computations.The backend of the RLCO system is responsible for processing input data, predicting crop yields, calculating water and nutrient requirements, and generating recommendations.It recieves the input parameters from the frontend through API's.After computation the backend sends the result to the frontend in the form of JSON objects.

B. frontend

The front end of the Crop Rotation Recommendation System is designed to provide a simple and user-friendly interface for farmers and users.The system begins with a login and registration page, where users can create an account or log in using valid credentials. This ensures secure access and helps maintain user-specific data such as previous inputs and recommendations. After successful login, users are directed to

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the main dashboard, which is designed in a simple and clear manner to avoid complexity. The layout focuses on ease of navigation so that users with minimal technical knowledge can operate the system comfortably.The dashboard allows users to enter required details.

V. Results

The proposed RLCO system was evaluated using the collected soil dataset and the trained Feedforward Neural Network model. The system produces crop recommendations along with associated yield prediction, water balance estimation, and soil–nutrient suitability analysis. The results demonstrate the effectiveness of the model in capturing the relationship between soil parameters and crop suitability.

A. Accuracy vs. Efficiency

Various machine learning algorithms were tested to know their efficiency and suitability for the task.These were supervised algorithms.The algorithms used were Feedfor- ward neural network,XGBoost,Random Forest,Naive Bayes,K-NN.Their accuracy and other metrics were calculated and the model was chosen based on the evaluation criteria.Their results are given in the table below

TABLE I
Algorithm evaluation Results

Algorithm name	Accuracy	Micro AUC
FFN	90	0.983
SVM	80	0.945
KNN	62.7	0.829

B. Crop Recommendation Ranking

The RLCO model ranks crops based on Predicted yield.The yield is calculated using the soil and climatic conditions as well the previous crop planted.The crops with the top five yields are displayed to the user

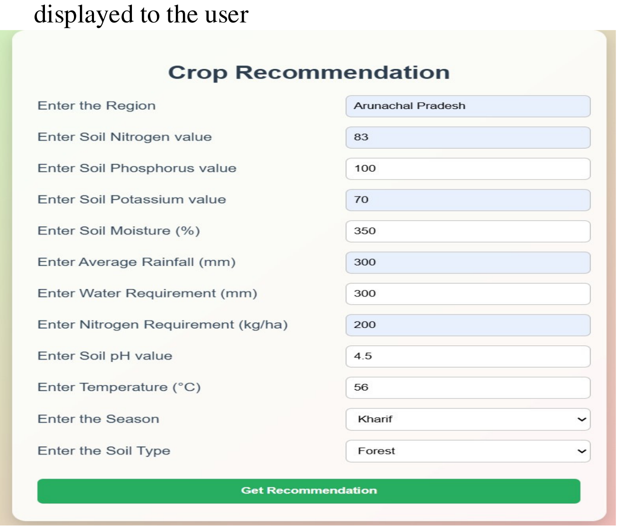

Fig. 1. System Architecture

C. Soil–Nutrient Suitability Analysis

The system visualizes the comparison between the user's current soil nutrient levels (N, P, K) and the ideal nutrient requirements of the recommended crop. The bar chart displays both sets of values side by side, enabling users to easily identify nutrient deficiencies or surpluses.

D. Water Balance Results

The system performs a simplified water balance check tailored for smallholder decision-making. Available water is estimated using the farmer's soil moisture and rainfall inputs, while crop water requirement values are calculated using the normalised yield. A comparative bar chart visually highlights potential water surplus or deficit for each recommended crop, enabling intuitive irrigation planning without complex hydrological models.

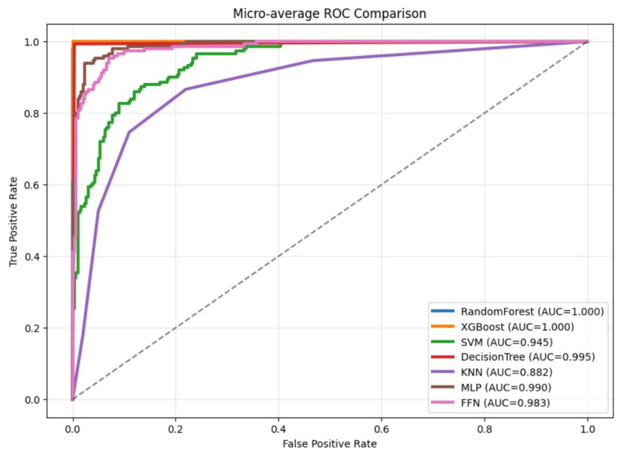

Fig. 2. Accuracy vs. model efficiency comparison

The above figure compares the Receiver Operating Characteristic (ROC) curves of various machine learning algorithms. The ROC curve plots the True Positive Rate against the False Positive Rate across different classification thresholds. This analysis evaluates the models' ability to correctly distinguish between suitable and unsuitable crops under varying decision boundaries.The Area Under the Curve (AUC) serves as a quantitative measure of overall classification performance. Models achieving higher AUC values demonstrate stronger discriminatory capability and robustness.The Feed-Forward Neural Network serves as the learning algorithm in the proposed RLCO system. Its prediction scores are evaluated using the ROC AUC metric to assess the model's discriminative capability. A higher AUC indicates that the FFN effectively distinguishes between optimal and sub-optimal crop choices under varying soil and climatic conditions.

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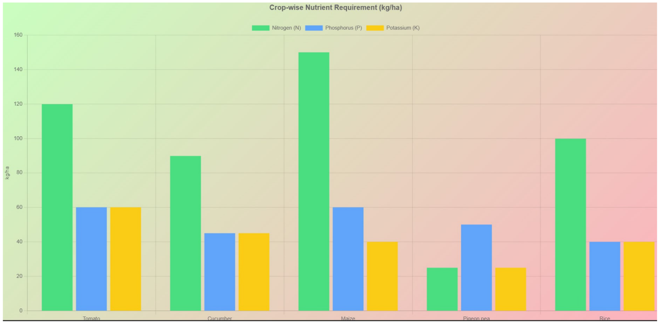

Fig. 3. Output

VI. Conclusion and Future Considerations

Conclusion: This project presented an AI-powered crop recommendation and rotation system based on the proposed Rule Learning Crop Optimizer (RLCO) framework. The system integrates soil nutrient parameters (N, P, K), pH, moisture, rainfall, seasonal conditions, and historical crop patterns to generate informed and adaptive crop recommendations. By combining expert agricultural rules with data-driven machine learning models, the proposed approach addresses the limitations of traditional static rule-based systems.

Multiple machine learning algorithms were evaluated to predict crop suitability and yield performance. Experimental results demonstrated that ensemble-based models achieved higher predictive accuracy and superior ROC-AUC values, indicating strong classification capability and robustness. The FFN further contributed by learning non-linear relationships among soil and climatic parameters, enhancing overall system intelligence.

The system also incorporated water balance analysis and nutrient demand visualization, enabling farmers to understand not only which crop to grow, but also why it is recommended,amount,nutrient composition and water requirement. Graphical outputs such as per-crop water balance and nutrient requirement charts improve interpretability and support practical decision-making. Unlike black-box recommendations, this transparency increases trust and usability for end users.

The proposed RLCO-based decision support system offers practical value by helping farmers optimize crop selection, and manage available resources efficiently. While the current implementation relies on structured datasets, future work can integrate real-time sensor data, market price forecasting, and region-specific policies to further enhance system relevance and scalability. Overall, the project demonstrates the effectiveness of AI-driven decision support systems in advancing sustainable and intelligent agriculture.

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