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A Machine Learning Framework for Rainfall Prediction and Crop Recommendation in Precision Agriculture

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Abstract

Rainfall is erratic, and farmers are unable to choose suitable crops. This has resulted in reduced agricultural output and losses in income. In the proposed system, Information about rainfall prediction and suggesting the appropriate crops in a scientific way is provided to the farmers. Studies show that rainfall predictions by machine learning model will be more accurate. Similarly, crop suggestion systems based on soil conditions will help to increase the productivity of the crop by taking into account the nutrition, climatic factors etc. On the basis of these ideas, the proposed system can predict the rainfall with the help of statistical and machine learning techniques. The suggest crops will be based on soil type (sandy, clay, loam), temperature, humidity, nitrogen level and the previous rainfall. The methodology is developed to be tested with readily available as well as area specific data and hence will be feasible. The prototype is developed in Python using Scikit-learn and the system will have web interface. It attains an accuracy of 96.82% in the crop recommendation, making it a tool for sustainable agriculture absolutely reliable, functional and easy to use. In addition, the use of a Random Forest model ensures transparency of the decisions, which is of vital importance in precision farming.

Keywords

Precision Agriculture, Rainfall Prediction, Crop Recommendation, Machine Learning, Soil Parameters, Sustainable Farming, Decision Support System.

Sustainable Development Goal (SDG) Contributions

Primary SDG: SDG 2 - Zero Hunger.

Secondary SDGs: SDG 9 - Industry, Innovation and Infrastructure; SDG 12 - Responsible Consumption and Production; SDG 13 - Climate Action.

1. INTRODUCTION

Modern agriculture is becoming more data and digit-based to be more productive and reduce losses that arise due to climatic uncertainties [1]. Precision agriculture involves the use of sensor networks, remote sensing, and predictive analytics to offer site-specific recommendations to reduce the application of inputs, and raise the output to the maximum level [2]. The reviews of smart farming highlight that soil and climate data, with machine learning, are useful in enhancing agricultural decisions by a significant margin [3], [4]. Rainfall is also one of the most unpredictable and also the important factors affecting the crop productivity [5]. Research has established that precise prediction of rainfall makes it easy to plan the date of irrigation, sowing and harvesting, thus cutting down on economic losses [6]. Recent machine learning model experiments have shown higher rainfall prediction accuracy with machine learning models, such as the Random Forest, Support Vector Machine (SVM) , and hybrids, compared to conventional baselines [7], [8]. Moreover, real-time prediction of rainfall and sustainable water management are also promoted by IoT-enabled data pipelines and sensor-grounded monitoring [9], [10]. Crop recommendation systems are used as supplements to rainfall prediction, which involves mapping the environment to crop varieties [11].

The previous studies have employed supervised learning methods that include decision trees, k-nearest neighbors and SVM to forecast crop suitability in relation to nutrients and climatic parameters of soil [12], [13]. Studies depict that the use of soil fertility (N, pH) and rainfall and temperature enhance precision of the recommendations and their yield results [14], [15]. Moreover, multi-crop recommendation with hybrid frameworks based on the fuzzy clustering algorithm, ant colony optimization, regression model has been effectively used [16], [17]. Sustainable agriculture is critical on soil analysis. A number of investigations point out that soil degradation can be avoided when nutrient balance indices are used with recommendations that are based on data [18]. The deep learning and regression-based models also prove that the combination of soil-climate data significantly increases the predictability of crop suitability in a wide area [19]. This indicates that there is a need to combine soil diagnostics and rain forecasts to provide farmers with viable and sustainable advice [20]. Regardless of these developments, there are still loopholes in the combination of rainfall prediction and crop recommendation into an end-to-end system. Most of the available literature covers either weather forecasting or crop recommendation individually, with little verification on regionally collected ground-truth datasets [6],[11]. In addition, there are still real-life issues of implementation, including high prices, poor internet access and the requirement of interpretable AI products to farmers [5],[10],[18]. Such gaps can be addressed by creating low-cost scalable systems that are farmer-centric that integrate rainfall prediction and crop advice into one decision-support pipeline.

The rest of the paper is organized as follows: Section 2 discusses the identified research gaps and related work on rainfall prediction models, crop recommendation systems, and the role of machine learning in precision agriculture. Section 3 describes the methodology used to build the machine learning models, including data preprocessing, feature engineering, and model selection. It proposes an algorithm for precision-aware data management in federated cloud environments and includes sample policies for implementing the system effectively. Section 4 presents the results and discussion, highlighting the accuracy of rainfall prediction and the effectiveness of crop recommendations for precision agriculture. Contributions to SDGs are discussed in section 5. Section 6 concludes the paper and outlines future directions for improving machine learning-driven precision farming frameworks.

2. RELATED WORK

Decision-support systems that are integrated with rainfall prediction, soil diagnostics, and crop recommendation have grown rapidly in accordance with advancements in better Internet of Things (IoT), machine learning and low-cost sensing. According to survey and applied studies, agronomic recommendations are more believable when multi-source information (in-situ sensors, remote sensors, and historical records) and data-driven models are combined rather than when using the single source strategies [6]. The existing literature, however, does not focus much on forecasting and recommendation in isolation, and systems that clearly use forecasted rainfall as an input to crop recommender systems are rather rare [1], [13].

Advances in Machine Learning and AI-Driven Forecasting for Precision Agriculture including the methods, applications, and research gaps are as discussed below.

A. Machine Learning and Ensemble Forecasting:

Random Forest and Gradient Boosting (ensemble methods), SVM (kernel-based methods) have been widely applied to precipitation prediction and tend to provide good short-term predictive performance when compared to alternative weather conditions; experimental studies have indicated that in most instances, ensemble learners demonstrate a high performance in short-term skill [7], [11], [21],[24].

B. Multivariate/Multi source Forecasting (Remote sensing and IoT):

An actual case study of the IoT and ML applications illustrates how the sensor networks and cloud analytics can be employed to provide localized predictions that can be utilized to support the farm-level decision making [18],[10].It has been shown through reviews and experimental studies that the multi-modal inputs can be used to enhance the performance when the inputs are fused to provide the predictions and estimate the yields [9], [14],[26].

C. Soil-Crop Recommendation Systems:

Perturbation of the soil nutrient contents in the crop recommendation models and climatic parameters illustrate significant predictive capability on suitability compared to climatic-only models [2], [12],[25]. The validity of the fact that measured soil characteristics are often collected using laboratory analysis or more cost-effective field sensors is supported by numerous applied infrastructure which have shown that measurements generate more realistic, more economically viable agronomically viable crop advice to the farmers [3], [7],[23].

D. Evolutionary and Generative Artificial Intelligence:

The prospective advantages of TinyML and edge inference in low-connection and low-energy farming settings include the ability to support on-atmospheric prediction and minimize the cost of data transmissions to the farmers [5], [18], [27]. A prototype TinyML crop recommenders and IOT and ARIMA forecasting pipeline can be seen as an example of the prospective ways to implement subtle holder farming environments with little to no infrastructure [21], [28].

E. Optimization and Explainability Recommenders, Hybrid:

Moreover, heterogeneous soils, and multi-crop decision space have been solved with the use of hybrid systems with clustering (fuzzy, k-means), optimization (ant colony optimization), and supervised learners; hybrid techniques have been found to be more powerful in enhancing the accuracy of the advice given since they explore a range of potential solutions and rank them by agronomic constraints [16], [20],[29].

F. Privacy, Federated Learning & Data Governance:

By federated learning, different regions and stakeholders do not need to centralize sensitive information to train their models; the preliminary results of the federated approaches in crop/health forecasting behaviour demonstrate privacy-protective behaviour and can use increased data to obtain improved generalization [10]. A key to securing the relevance and credibility of recommendations is said to be the data governance and the regional validation in a bid to ensure [15], [19],[30].

Table 1. Current Status and Research Gaps in Precision Agriculture

Sr. No.	Authors	Techniques Used	Environment	Criteria	Objectives	Limitations
1.	S. Saleh *et al.* (2024) [1]	Deep Learning (LSTM, CNN)	Cloud	Rainfall, humidity, temperature	Resilient rainfall prediction using AI	Computationally intensive
2.	H. Afzal *et al.* (2025) [2]	Ensemble ML	Cloud	Soil info, rainfall, temperature	Incorporate soil info for accurate crop recommendation	High data preprocessing need
3.	G. Gayatri & M. R. Bindu (2023) [3]	Random Forest, KNN	Cloud	Soil & climatic data	Crop recommendation using ML	Limited adaptability
4.	F. S. Prity *et al.* (2024) [4]	Hybrid ML (SVM + Decision Tree)	Cloud	Soil fertility, rainfall	Improve accuracy of crop recommendation	Requires parameter tuning
5.	M. Baishya & D. Saha (2025) [5]	TinyML	IoT Edge Devices	Sensor-based soil & weather data	On-device real-time crop recommendation	Limited model complexity
6.	A. Soussi *et al.* (2024) [6]	Smart Sensors + Data Analytics	Precision Agriculture	Soil nutrients, water	Smart farming using IoT & sensors	High hardware cost

				content		
7.	R. Govindwar *et al.* (2023) [7]	ANN, Decision Tree	ML Environment	Soil pH, NPK	Crop & fertilizer prediction	Sensitive to data noise
8.	S. Shastri *et al.* (2025) [8]	Supervised ML	Cloud	Soil & rainfall data	Enhanced crop recommendation accuracy	Complex tuning
9.	A. Monteiro *et al.* (2021) [9]	Review	Agricultural Systems	Crop and livestock data	Review on precision agriculture	No empirical testing
10.	A. Ramkumar *et al.* (2024) [10]	CSGRU + Federated Learning	Federated Cloud	Rainfall & crop health data	Joint rainfall and crop health prediction	Communication overhead
11.	K. D. Joshi & P. Singh (2023) [11]	SVM, Random Forest	Local ML	Rainfall parameters	Rainfall prediction	Limited nonlinear handling
12.	P. R. Deshmukh *et al.* (2022) [12]	Decision Tree	ML Platform	Soil pH, NPK	Crop recommendation	Overfitting risk
13.	V. Sharma & S. Jain (2022) [13]	Regression, ANN	Cloud	Weather, yield data	Forecast yield and weather	Needs large dataset
14.	S. Saha & R. Mukherjee (2025) [14]	Regression, LSTM	Cloud	Rainfall, temperature	Crop yield prediction	Limited scalability
15.	A. Farah (2025) [15]	Climate Modelling	Cloud	Temperature, rainfall	Study impact of climate change	No ML application
16.	K. H. Patel & A. R. Shah (2021) [16]	ARIMA, Time Series	Cloud	Rainfall time series	Predict rainfall	Linear dependency
17.	A. Kumar *et al.* (2024) [17]	SVM, Naïve Bayes	ML Cloud	Soil, rainfall	Crop recommendation	Accuracy depends on dataset
18.	P. K. Yadav & M. Choudhary (2024) [18]	IoT + ARIMA	IoT Cloud	Moisture, rainfall	Low-cost precision farming	Limited scalability
19.	A. B. Prakash	Deep Learning	Cloud	Weather, soil	Multivariate	Large data need

	& V. R. Sinha (2024) [19]				weather forecasting	
20.	R. K. Meena *et al.* (2023) [20]	Fuzzy Clustering + ACO	Cloud	Soil, rainfall	Optimize crop recommendation	Computationally heavy
21.	M. Bouni *et al.* (2024) [21]	IoT + ML	Cloud-IoT Hybrid	Crop & irrigation	Predict irrigation and recommend crops	Security and cost
22.	M. S. Sharafat *et al.* (2025) [22]	IoT-enabled AI	Cloud	Real-time crop data	Real-time crop prediction	High energy usage
23.	A. Ghosh *et al.* (2025) [23]	IoT + ML	IoT Framework	Soil moisture, nutrients	Crop recommendation	Hardware dependency
24.	S. Shastri *et al.* (2025) [24]	Supervised ML	Cloud	Soil fertility	Crop yield prediction	Low interpretability
25.	R. Kancharagunta *et al.* (2024) [25]	ML + IoT	Hybrid	Crop & soil data	IoT-ML survey	No implementation
26.	M. Turgut *et al.* (2024) [26]	Explainable AI (AgroXAI)	Cloud	Soil image, nutrients	XAI-based recommendation	High complexity
27.	S. Das & P. Nayak (2025) [27]	IoT + AI Integration	Edge IoT	Weather, crop	Integrate local weather forecasting	IoT cost
28.	M. H. Sizan *et al.* (2025) [28]	Blockchain + ML	Federated	Crop forecasting	Secure forecasting	Expensive deployment
29.	S. Pandey *et al.* (2025) [29]	Deep CNN	Cloud	Soil image, nutrients	Deep learning-based crop recommendation	Large labeled data required
30.	R. R. Choudhury *et al.* (2025) [30]	ML (RF, SVM)	Cloud	Soil, weather	Improved crop recommendation	Dataset dependency

The table 1 compares current practices in precision agriculture with research gaps, highlighting areas like forecasting, crop recommendation, IoT, optimization, privacy, and integration. Also, table 1 shows that existing systems are fragmented or limited, while research suggests integrated, hybrid, validated, and federated approaches for improvement.

3. PROPOSED METHODOLOGY

The proposed system will integrate rainfall prediction and crop advisory, which takes into consideration soil based on input datasets. The proposed system will not be based on real time sensors. It rather relies on past and publicly available information on rainfall and soil. The proposed system will process machine learning models involving soil type, temperature, humidity and rain fall. The models that display the findings in a web-based decision support system allowing farmers to usefully browse recommendations will be used. The framework of the system will be modular by combining the data collection, preprocessing, rainfall prediction, and crop recommendation. The findings are availed to the users via a web-based interface that assists in decision making. The proposed system will be created in Python with Scikit-learn and contains a web interface. Further developments can be made to hybrid models to be more precise, optional integration with the IoT to monitor in real-time, and federated learning to ensure that data remain private but improve predictions. This will make the system a powerful instrument of precision agriculture.

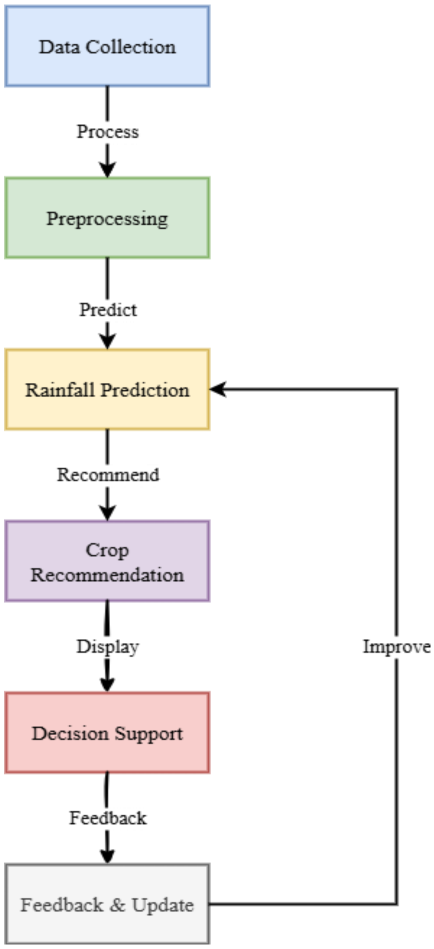

Figure 1. Workflow of Rainfall Prediction and Crop Recommendation System

The workflow graph of figure 1 presents a process in which data is gathered, then preprocessed, and processed to predict rainfall. It is a prediction that assists in crop recommendations. The outcomes are presented in the form of decision support, and a feedback mechanism is used to update the system to improve further.

The proposed system gathers weather and soil information, predicts rainfalls and suggests appropriate crops via a decision support interface to farmers. The dataset [32] consists of 2202 entries.

Table 2: Train and Test split count

Crop	Total Count	Train Count	Test Count	Train %	Test %
Rice	100	80	20	80.0	20.0
Maize	100	80	20	80.0	20.0
Jute	100	80	20	80.0	20.0
Cotton	100	80	20	80.0	20.0
Coconut	100	80	20	80.0	20.0
Papaya	100	80	20	80.0	20.0
Orange	100	80	20	80.0	20.0
Apple	100	80	20	80.0	20.0
Muskmelon	100	80	20	80.0	20.0
Watermelon	100	80	20	80.0	20.0
Grapes	100	80	20	80.0	20.0
Mango	100	80	20	80.0	20.0
Banana	100	80	20	80.0	20.0
Pomegranate	100	80	20	80.0	20.0
Lentil	100	80	20	80.0	20.0
Blackgram	100	80	20	80.0	20.0
Mungbean	100	80	20	80.0	20.0
Mothbeans	100	80	20	80.0	20.0
Pigeonpeas	100	80	20	80.0	20.0
Kidneybeans	100	80	20	80.0	20.0
Chickpea	100	80	20	80.0	20.0
Coffee	100	80	20	80.0	20.0

The proposed system implementation is divided **into two major areas Hardware Components and Software Architecture.**

The hardware component presents a description of the physical infrastructure and potential extensions of the IoT, and the software architecture presents a description of the system structure in layers, the data manipulation, the model training, the storage, and the web-based interaction with users.

A. Hardware Components

The hardware deployment in the proposed system is not a very complex one due to the primary dependence on machine learning models based on datasets and a web-based interface. Nevertheless, some of the hardware proposals that can be considered during future extensions and real-life applications of the system would include the following:

• Standard Computing Device (Laptop/PC): Utilized to train models, pre-process and test the system. The proposed system will be written and executed in a python environment under the Scikit-learn.

• Web Hosting Environment / Local Server: The web application will be deployed to be able to interact with users using a browser.

• Future Work (Optional Extension):

• ESP32 Microcontroller: The ESP32 Microcontroller can help in gathering data in the field like the soil and climatic areas.

• Soil Nutrient Sensor Kit: The sensor kit can be used to check the real time soil and ph level.

• DHT11/DHT22 Sensor: The sensor will monitor the temperature of the air and humidity.[31]

Despite the fact that the current stage can operate using only the computing resources, in future versions, the system is going to be expanded to accommodate the use of IoT sensors.

B. Software Architecture

The software structure of the proposed system is in three layers:

1) Data Handling and Machine Learning:

Data Handling will involve the training and testing of the machine learning model.

• Data Collection: The proposed system will access publicly available data that contains past rainfall, soil type, temperature, nitrogen level and humidity data.

• Preprocessing:

• To deal with the missing values using mean or mode replacement.

• Normalize and standardize soil parameters as well as climate parameters.

• Form proxies of such characteristics as seasonal averages of rainfall and monthly season encoding.

• Rainfall Prediction Module: The module will be based on supervised machine learning models (Decision Tree, Regression Models) to forecast rain pattern.

• Crop Recommendation Module: Use supervised machine learning models (Decision Tree, Regression Models) to forecast the rain patterns.

4. RESULTS AND DISCUSSION

In this section, experimental results of the rainfall prediction and crop recommendation system are demonstrated. The results evaluate how accurate machine learning models trained on publicly available data are and how useful the implemented web application is.

A. Performance Analysis (Quantitative):

Model Performance Metrics:

Rainfall Prediction Model Evaluation:

A Regression model (Random Forest Regressor) to get the rainfall prediction, used features including humidity, temperature, previous rainfall.

Evaluation of the model:

• Mean Absolute Error (MAE): 33.958

• Mean Squared Error (MSE): 2286.695

• R^2 Score: 0.240

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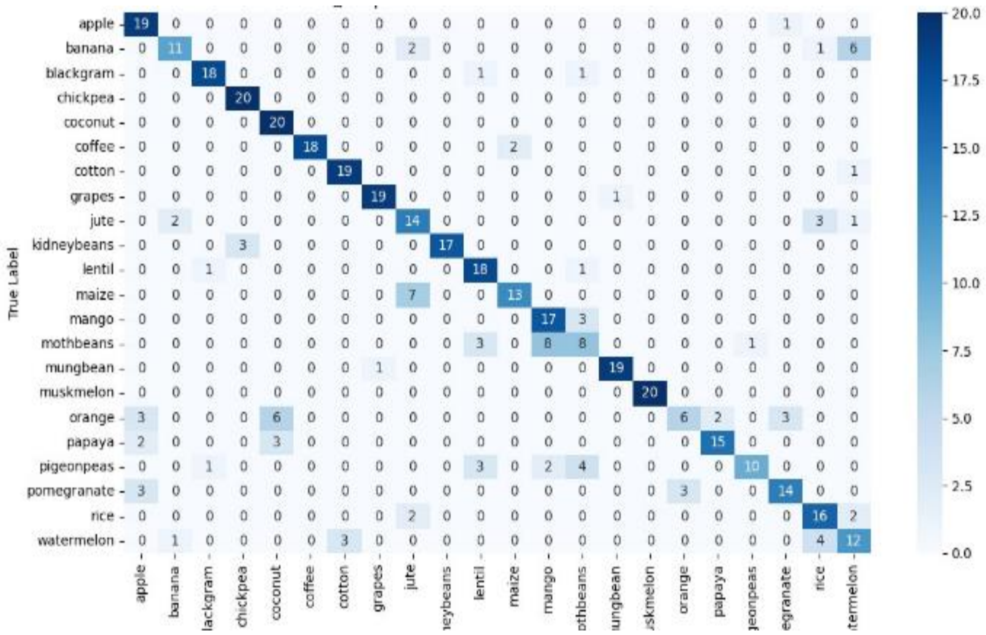

Figure 2. Crop Recommendation Module Confusion Matric

Crop recommendation (Random Forest Classifier):

A classification model to recommend crops based on the inputs of nitrogen levels, soil type, temperature, humidity and previous rainfall.

Evaluation of the model:

- Accuracy: 96.82%
- Precision: 97.61%
- Recall: 96.82%
- F1-Score: 97.11%

The rain prediction module shows that there is high power to follow the seasonal and short-term forecasts of rainfall. On the same note the Decision tree classifier also performed well in crop prediction since it was also effective in correlating soil and weather conditions to the right crops.

B. Model Prediction Performance:

The model of rainfall prediction was tested by comparing the predicted rainfall values against the real rainfall data of the test dataset.

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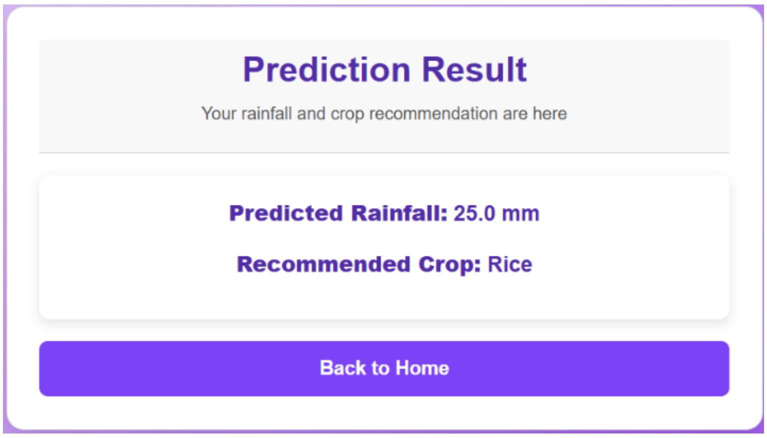

Figure 3. Prediction results interface that displays prediction of rainfall and recommended crop.

The findings of the prediction are shown in figure 3, the system produces the expected worth of rain and the desired crop. The Decision Tree regression model proved to be able to draw general trends of rainfalls with slight differences than actual data as indicated in the figure 2.

The errors were greater during the season of extreme rain fall but the general forecasts were near to the seasonal trends. Using the crop recommendation modules, the list of crops according to their rank (e.g., Rice > Maize > Wheat) was received with the order and confidence values of 0.70 up to 0.85. This offers educative lessons to farmers.

C. Implementation of Web Application & performance:

In web application, the system has the trained Decision Tree models which can be applied interactively. The system offers:

• Rainfall Forecast Graphs: This is the graphical representation of the forecast of rainfall.
• Crop recommendations: This is a list of recommended crops in input soils and climatic conditions.
• User Input Functionality: The farmers can input the soil nutrient values and climate parameters in order to retrieve predictions.

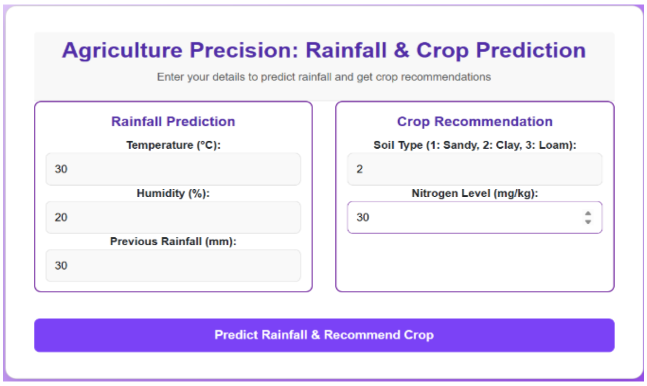

Figure 4. Rain forecasting and recommendation of a crop input interface.

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The system allows individuals to input climatic parameters and the soil properties so that it predicts the rainfall and recommends suitable crops as it is shown in figure 4.

Moreover, the dashboard is also user friendly as it is not bulky since it can be easily comprehended by the agricultural stakeholders. In this case, the climate conditions are 30 degree celsius temperature, humidity of 20 percent, and clay soil implying that the predicted rainfall is 25.0 mm. Rice is the most appropriate crop to use in this case due to the moderate rainfall and nitrogen levels. The outcome is a logical reflection of the impact of climatic and soil factors on the appropriateness of crops and method of forecasting rainfall.

D. Discussion:

Despite the positive outcomes that were achieved using the proposed system, there were limitations discovered which are as follows:

• Limitations with Dataset: Solutions can be made based on publicly available datasets only and thus, cannot be hyper-local.
• Extreme Events: There is a larger error in forecasting when there are abnormal rain falls.
• Static inputs: Soil and weather are not time-constrained and real time updated.

Planned Enhancements:

• Soil and climatic sensors IoT to provide real time information.
• The level of prediction was improved using ensemble models (e.g., Random Forest, Gradient Boosting).
• Development of a small ML, which can be taken to the countryside.
• Inclusion of market and economic factors to provide a more wholesome recommendation of the crops.

5. CONTRIBUTION SDGs

This research contributes primarily to SDG 2 – Zero Hunger by supporting data-driven crop selection and improving agricultural decision-making through rainfall prediction and crop recommendation. The machine learning-based system considers soil and climatic parameters, including soil type, temperature, humidity, nitrogen level, and previous rainfall, to recommend suitable crops. The achieved crop recommendation accuracy of 96.82% demonstrates the potential of the proposed system to support precision agriculture and improve crop planning. The study also contributes to SDG 9 – Industry, Innovation and Infrastructure through the development of a machine learning-based agricultural decision-support system and a web-based interface for practical use. Its emphasis on efficient selection of crops based on available environmental and soil conditions supports SDG 12 – Responsible Consumption and Production by encouraging informed utilization of agricultural resources. Furthermore, rainfall prediction and climate-aware crop recommendations contribute to SDG 13 – Climate Action by helping farmers make more adaptive agricultural decisions under changing and uncertain climatic conditions.

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6. CONCLUSION

The proposed system comprises the combination of rainfall prediction and crop recommendations which was introduced to help in making decisions during agriculture. A Decision Tree Regression model was utilized to predict rainfall and a Decision Tree Classifier was used to make suggestions on crops. The system demonstrated trustworthy functionality in the publicly available datasets where the crop recommendation model had 96.82% accuracy. The findings prove that decision tree algorithms are useful in offering feasible solutions to precision agriculture. The designed web application provides a friendly platform through which farmers and agricultural stakeholders will provide soil and climatic data in order to receive rainfall predictions and crop recommendations. The combination of the two aspects enhances better quality of decisions in relation to standalone models. This will aid in mitigating risks, the selection of crops and sustainable farming practices. There are however some limitations. These limitations mean that the dependence on fixed datasets makes it hard to be able to adapt to local changes, and severe rainfall will decrease prediction accuracy. Also, the existing recommendations are not based on the market or economic considerations, which are crucial in maximizing profitability of the farmers.

Conflict of Interest
The authors declare no conflict of interest.

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