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A Predictive Crop Management System for Precision Agriculture Leveraging Machine Learning

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Abstract: A crop management system for precision agriculture utilizing machine learning aims to develop a farmer-friendly web application that incorporates ensemble learning algorithms. This web application features a crop recommendation system, a fertilizer recommendation system, a yield prediction system, and a crop possibility prediction system, all designed to assist farmers in making informed decisions based on reliable information. The crop and fertilizer recommendation system utilizes fundamental natural and soil properties of various minerals, as well as other factors, to recommend the most suitable crops for a particular region and the type of fertilizer required for that soil. The yield and crop possibility prediction system utilizes authentic data and current conditions, such as region, Season, crop type, and area, to help farmers maximize production and identify possible crops for that Season. The paper compares classification algorithms and chooses the best algorithm based on an analysis of the accuracy using ensemble learning. Based on the accuracy, the best algorithm is identified, and the model is trained accordingly. This improves efficiency, agricultural productivity, asset utilization, and food security. The crop management system serves as a fundamental asset for modern agriculture, enabling more effective strategies and driving economic progress.

Keywords: Crop Recommendation System; Fertilizer Recommendation System; Yield Prediction System; Crop Prediction System; Ensemble Learning; Authentic Data; Crop Possibility Prediction.

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1. Introduction

Agriculture remains the foundation of the global economy, generating billions through the production of essential food supplies. In any case, the segment faces numerous challenges that affect viability, maintainability, and benefit. Unusual climate patterns, unwise crop choices, inefficient asset management, and declining soil health are contributing to a decline in agricultural productivity. Traditionally, farmers have relied on instinct, gathering information, and drawing on past experiences to determine which crops to cultivate. Indeed, even though these strategies have been established or cultivated for a long time, they often

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result in suboptimal crop choices and wasteful resource utilization. To keep pace with the rapid progression in innovation, especially in machine learning and data analysis, agriculture has undergone a significant shift toward precision agriculture. Machine learning calculations are adept at analyzing vast amounts of information to uncover patterns and relationships that are difficult to discern with traditional methods [1].

These insights enable farmers to make informed choices, optimize asset allocation, and increase crop yields. Leveraging these innovations can significantly boost agricultural efficiency, reduce waste utilization, and yield the most profitable results. This paper presents a Crop Recommendation, Fertilizer Recommendation, Yield Prediction, and Crop possibility prediction system that utilizes machine learning strategies to help farmers make informed, data-driven decisions. The proposed work aims to identify the most suitable crops for agriculture by considering various natural and soil factors, including Temperature, soil type, pH levels, and nutrient levels. Additionally, it predicts anticipated crop yields, enabling farmers to plan their agricultural activities more effectively. Through the integration of distinctive machine learning models, assessing their adequacy, and utilizing the best-performing model, the paper enhances the overall decision-making process in cultivation. Through the examination of natural components such as Temperature, moisture, pH levels, soil supplements, and moisture content, the work proposes the most suitable crops for a particular region, while determining conceivable yields.

Decision Trees define decision rules; Random Forest improves expectation accuracy by joining various trees [2]. Logistic regression analyzes the likelihood of crop compatibility, while naive Bayes assesses the chances of achieving a perfect crop yield. This cohesive methodology enables farmers to optimize resources, mitigate risks, and increase yields, thereby advancing productive and sustainable agricultural practices. The Crop Recommendation, Fertilizer Recommendation, Yield Prediction, and Crop Possibility Prediction system offers various options that may alter rural strategies. By providing data-driven proposals, it empowers farmers to make more informed decisions, ultimately leading to improved crop yields and greater sustainability. A key benefit is the capacity to decrease hazards. Farmers can avoid costly mistakes, such as sowing crops that aren't suited to their soil or climate conditions. The system's determining capacities help decrease vulnerability related to crop yields, allowing farmers to more effectively prepare for changing agricultural costs and environmental conditions. Again, the fertilizer recommendation system suggests the best fertilizer for a particular crop based on the region of cultivation and other factors, utilizing a machine learning algorithm, specifically a random forest algorithm, to make data-driven choices. The yield prediction again uses the random forest algorithm to predict the possible yield of the crop. The crop possibility prediction system utilizes a decision tree algorithm to recommend crops that can be grown in a region, based on the region's cultivation conditions and the optimal cultivation season for each crop.

Agricultural efficiency is crucial for ensuring food security, but farmers often face challenges in selecting the most suitable crops and determining potential yields due to natural and soil factors. Conventional agricultural choices often rely on experience rather than data-driven insights, leading to suboptimal crop decisions and inefficient asset utilization. This activity aims to develop a machine learning-driven crop recommendation system, a fertilizer recommendation system, a yield prediction system, and a crop possibility prediction system to assist farmers in making informed decisions, enhancing efficiency, and promoting economically viable cultivation. In outline, the Crop Recommendation, Fertilizer Recommendation, Yield Prediction, and Crop Possibility Prediction System serve as a vital asset for advancing the agriculture sector. Utilizing information and machine learning enables farmers to make informed choices, resulting in increased efficiency, improved resource management, and a more sustainable agricultural future.

2. Related Work

Agarwal et al. [1] conducted a comprehensive analysis and highlighted the significance of joining soil properties. Different companies utilized machine learning algorithms to analyze soil information and predict the most suitable crops for individual lands. The master plans are also investigated, providing farmers with tailored proposals that are specific to their soil conditions. Sani et al. [2]. This contribution explains the usability of machine learning calculations in progressing trim suggestions. Different calculations, such as SVM, were investigated to predict suitable crops based on soil properties. The significance of soil quality and supplement substances in improving is controlled. Mehta et al. [3] discuss the significance of early and accurate generations in advancing agricultural outcomes. Different machine learning procedures, such as SVM, decision Trees, and random forests, were investigated for edit suggestions and yield prediction. It became apparent that consolidating natural variables, such as Temperature, stickiness, pH, and soil nutrients (N, P, K), essentially improved and enhanced proposal accuracy.

Gayathri et al. [4] report that the soil testing labs regularly report that from insufficient foundation and overworkloads, causing delays that prevent farmers from planting crops at the correct time. Whereas private labs offer faster management, their high costs make them too expensive for several farmers. Gayathri et al. [4] previously explored traditional methods that rely on farmers' experience, which often lead to inaccurate predictions. With advancements in technology, machine learning algorithms have been applied to analyze historical yield data and soil properties, thereby improving the estimated accuracy. Studies have shown that Random Forest outperformed other models in crop prediction due to its ability to handle large datasets effectively. Similarly, K-means clustering has been effectively used to classify soil nutrients and recommend suitable fertilizers. Indira et al. [5] conducted several examinations to enhance agricultural efficiency using machine learning methods. Analysts already relied on routine strategies, but these approaches frequently led to unrealistic expectations and wasteful outcomes. Machine learning models such as XGBoost and K-means clustering were utilized to predict cut reasonableness, prescribe fertilizers, and differentiate plant illnesses.

Mahalakshmi et al. [6] researchers have highlighted the effect of unusual climatic conditions on rural efficiency. Analysts distinguished soil quality, water accessibility, and regular varieties as their key components affecting yield. Information on harvesting approaches has been utilized to analyze authentic rural data and provide beneficial recommendations to farmers. Researchers have demonstrated that significant advances are being made in decision-making and benefit administration in the agricultural sector. Jaichandran et al. [7] have, based on the previous considerations, emphasized the significance of crop production in supporting national economies and taking steps towards food security. Analysts recognized that precise crop determination based on soil and natural conditions significantly enhanced agricultural efficiency. Different machine learning procedures have been investigated to create accurate suggestions on plans, ensuring optimal yield by analyzing soil supplements, Temperature, and rainfall data. Information science has been widely utilized to compile extensive datasets and provide farmers with actionable insights for informed decision-making.

Avanija et al. [8] crop recommendation system using Ant Lion Optimization and Decision Tree Algorithm. Analysts have utilized decision tree calculations and support vector machines to analyze soil properties, climatic conditions, and asset accessibility for exact crop determination. Nature-inspired calculations, such as Antlion Optimization (ALO), have been widely considered for their efficiency in optimizing complex rural parameters. Rakesh et al. [9] crop recommendation and Prediction System, some of the considerations have examined the role of machine learning and agriculture in improving crop choice and making developments in rural efficiency. Analysts have utilized calculations such as k-Nearest Neighbors (KNN), decision trees, and deep learning models to analyze soil conditions, climate designs, and resource accessibility.

3. Proposed Methodology

A precise approach is pivotal for the effective execution of a solid and compelling framework in our crop management paper using machine learning. This approach comprises three primary stages: gathering a dataset from kaggle, training models with pickle, and creating a web application in visual studio code (Figure 1).

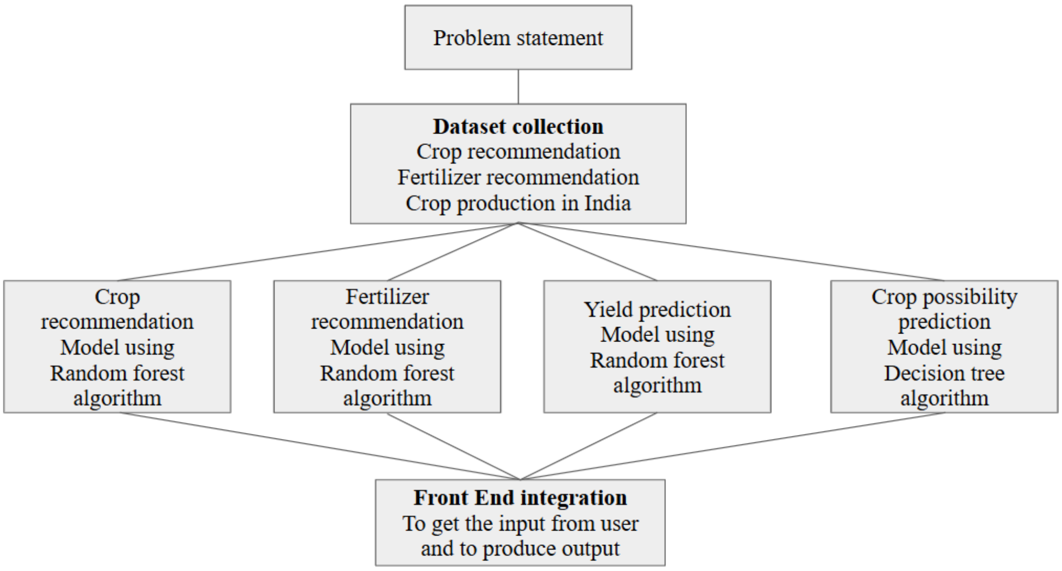

Figure 1: System architecture

3.1. Dataset Collection

The favourable outcome of a machine learning paper is based on the quality and quantity. For this paper, we utilize multiple datasets relevant to agriculture and crop prediction, taken from open-source Kaggle, each containing essential attributes for effective recommendations and predictions. The Crop Recommendation Dataset comprises soil nutrients such as Nitrogen (N), Phosphorus (P), and Potassium (K), as well as environmental factors including Temperature, Humidity, pH, and rainfall, along with the crop name, which facilitates the recommendation of the most suitable crop for a given condition. The Fertilizer Recommendation Dataset includes Temperature, Humidity, soil moisture, soil type, crop type, nitrogen, phosphorus, potassium levels, and fertilizer name, which helps in recommending the most suitable fertilizer for the given conditions. The Yield Prediction Dataset contains state name, district name, crop year, Season, crop type, area, and production, which are crucial for predicting crop yields under given conditions. The Crop Prediction Dataset includes state, district, Season, and crop type, assisting in identifying the likely crops grown in a specific region. The dataset undergoes preprocessing to handle missing values, normalize features, and standardize labels, ensuring high accuracy in model predictions.

3.2. Model Training

This paper contains four modules: Crop Prediction, Crop Recommendation, Fertilizer Recommendation, and Yield Prediction. Each module has a separate, trained model for its predictions and recommendations in precision agriculture.

3.2.1. Crop Recommendation Model

The Crop recommendation model is trained with the algorithm Random Forest classifier, an ensemble learning algorithm to recommend the crop based on the soil properties like Nitrogen (N), Phosphorous (P), Potassium (K), Temperature (TEMP), Humidity (HUM), pH level (pH), Rainfall (RF), as mentioned in equation 1. It operates in two modes: training and predictions. In the training phase, it reads soil properties and weather conditions from the given dataset, trains a Random Forest model with 10 decision trees, and saves it as ‘crop_model.pkl’ using the pickle module. In the prediction phase, the user provides input values, which are processed and fed into a trained model to predict the most suitable crop.

$CM_t(x) = f\ (N, P, K, TEMP, HUM, pH, RF)$ (1)

3.2.1.1. Algorithm for Crop Recommendation

Input: N, P, K, Temperature (TEMP), Humidity (HUM), pH, Rainfall (RF)

Output: Recommended Crop.

- Train a Random Forest Classifier
- Use crop recommendation dataset with features: N, P, K, TEMP, HUM, pH, RF
- Set number of trees (n_estimators) = 10
- Save trained model as 'crop_model.pkl' using pickle
- Load 'crop_model.pkl'
- Accept user input for soil and environmental conditions
- Preprocess inputs:
- Validate and normalize values
- Format input as feature vector X
- Predict: Crop = model.predict(X)
- Return the recommended crop to the user

3.2.2. Fertilizer Recommendation Model

The Fertilizer recommendation model is trained using the Random Forest classifier, an ensemble learning algorithm, to recommend fertilizers based on soil properties. It trains a model using data Nitrogen (N), Phosphorous (P), Potassium (K), Temperature (TEMP), Soil type (ST), Soil moisture (SM), Crop(C), and Humidity (HUM), where Categorical values are encoded using label encoding as mentioned in equation 2. The dataset is divided into training and testing sets. The model trains a Random Forest model with 10 decision trees and saves it as ‘crop_model.pkl’ using the pickle library. The trained model is saved for future use. If the model or encoders are missing, it automatically retrains the model. When a user enters input values, the Python script validates and encodes them, then uses the trained model to predict the ideal fertilizer. In the prediction phase, the user provides eight input values, which are processed and fed into a trained model to predict the most suitable fertilizer.

$CM_t(x) = f\ (N, P, K, TEMP, HUM, SM, ST, CT)$ (2)

3.2.2.1. Algorithm for Fertilizer Recommendation

Input: N, P, K, Temperature (TEMP), Humidity (HUM), Soil Moisture (SM), Soil Type (ST), Crop Type (CT)

Output: Recommended Fertilizer

Train a Random Forest Classifier,

- Use fertilizer dataset with relevant features
- Encode categorical variables (ST, CT) using Label Encoding
- Set n_estimators = 10
- Save model as 'crop_model.pkl' using pickle
- Load 'crop_model.pkl'

Accept user inputs and preprocess them,

- Encode categorical values
- Normalize and structure input
- Predict: Fertilizer = model.predict(X)
- Return the recommended fertilizer to the user

3.2.3. Yield Prediction Model

The Yield Prediction model is trained using a random forest regression algorithm to predict crop yield (production) based on various input features. It begins by loading the dataset and identifying categorical columns, such as State name, District name, Season, Crop name, and Crop year. These categorical features are converted into numerical values using Hot Encoding, ensuring the model can process them effectively. The dataset is split into two parts, training (X) and testing (y), where production is the target variable. The dataset is divided into 80% training and 20% testing sets utilizing train_test_split(). A random forest regression model with 100 decision trees (estimators=100) is trained on the training data (X_train, y_train), learning the relationship between input features and edit crop production. After training, the trained model is saved as crop_production_model.pkl, and the hot encoder is saved as label_encoders_yield.pkl using joblib.dump() for future predictions.

For Prediction, the script takes six command-line inputs: State_Name, District_Name, Crop_Year, Season, Crop, and Area. It verifies the input count and loads the trained model and One Hot Encoder. The categorical inputs are transformed using Hot Encoding, and the numerical feature (Area) is added. The script ensures the input features align with those used during training by reindexing the DataFrame. Finally, the trained model predicts the crop yield, which is displayed as the anticipated yield in quintiles. This structured approach, as mentioned in equation 3, guarantees precise data encoding and dependable yield prediction for different input conditions.

$$CM_t(x) = f\,(\text{State, District, Crop Year, Season, Crop, Area}) \quad (3)$$

3.2.3.1. Algorithm for Yield Prediction

Input: State, District, Crop Year, Season, Crop, Area

Output: Predicted Yield (in quintals).

Train a Random Forest Regressor,

- Use the yield prediction dataset with categorical and numerical features
- Apply One Hot Encoding to categorical columns
- Set n_estimators = 100
- Save trained model as 'crop_production_model.pkl'
- Save encoder as 'label_encoders_yield.pkl'
- Load both the model and the encoder

Accept user input,

- Encode categorical inputs
- Append Area and reindex to match training features
- Predict: Yield = model.predict(X)
- Return the predicted yield in quintals

3.2.4. Crop Prediction Model

The crop prediction model is trained using a decision tree classifier to provide information about crop growth in a specific region and Season. The decision Tree Classifier for crop prediction employing the pre-processed dataset ‘preprocessed2.csv’. The dataset is split into training data (80%) and testing data (20%). Functions like unique_vals (), class_counts (), parcel (), gini (), and info_gain () analyze data and determine the optimal split using find_best_split (). The decision Tree structure is defined using the question, leaf, and decision node classes, and build_tree () recursively develops the tree. The trained model is saved as ‘filetest2.pkl’. The model's prediction takes the input values of state, district, and Season as command-line arguments. It classifies the crop using classify(), retrieves prediction probabilities using print_leaf(), and prints the predicted list of crops for that specific region and Season. The decision tree model facilitates data-driven decision-making by categorizing crops based on patterns in the dataset, thereby enhancing agricultural productivity and efficiency.

$$CM\_\ (x)=f\ (x_1, x_2, x_3) \tag{4}$$

Where x_1, x_2, x_3 represent the various inputs like state, district, season

3.2.4.1. Algorithm for Crop Possibility Prediction

Input: State, District, Season

Output: List of Possible Crops

Train a Decision Tree Classifier,

- Use preprocessed dataset ‘preprocessed2.csv’
- Split dataset (80% train, 20% test)
- Build decision tree using Gini index and information gain
- Save model as 'filetest2.pkl'
- Load 'filetest2.pkl'
- Accept user inputs and preprocess if necessary

Predict,

- Use classifies (X) to get the Prediction
- Use print_leaf () to get crop probabilities
- Return a list of suitable crops for the given region and Season

3.3. Frontend Development

To provide an interactive and user-friendly interface, we developed the frontend using PHP. The process began with designing a structured layout using HTML and CSS to ensure a clean and responsive user interface. Bootstrap was incorporated to enhance responsiveness across different devices. The primary focus was on creating a seamless user experience by structuring multiple pages for input and output display. User inputs were captured through well-designed forms using PHP, which validated and processed the data before passing it to the backend model for predictions. JavaScript and AJAX were utilized to improve interactivity, allowing dynamic content updates without requiring page reloads. The machine learning models discussed in sections 3.2.1, 3.2.2, 3.2.3, and 3.2.4 were formatted and displayed effectively using PHP, ensuring clarity in presenting recommendations and predictions. Error-handling mechanisms were implemented to manage invalid inputs gracefully. CSS styling and JavaScript animations were utilized to enhance user engagement, resulting in a smooth and visually appealing experience.

3.3.1. Whole Paper Workflow Algorithm

Input: User input data X (soil properties, climate, crop type, region details)

Output: Recommended Crop, Fertilizer, Yield, or Crop Possibility

Preprocess input X

- Normalize numerical values (e.g., N, P, K, TEMP, HUM, pH, Rainfall, Area)
- Encode categorical values (e.g., Soil Type, Crop, State, District, Season)

Select a module based on the user request.

If Module = Crop Recommendation

- Train Random Forest Classifier with 10 trees on the crop recommendation dataset.
- Save model as 'crop_model.pkl'
- Load 'crop_model.pkl'

Else If Module = fertilizer recommendation

- Train Random Forest Classifier with 10 trees on the fertilizer dataset
- Encode categorical variables (Soil Type, Crop Type)
- Save model as 'crop_model.pkl'
- Load 'crop_model.pkl'

Else If Module = yield Prediction

- Train a Random Forest Regressor with 100 trees on the yield dataset
- Apply One Hot Encoding to categorical inputs
- Save model as 'crop_production_model.pkl' and encoder as 'label_encoders_yield.pkl'
- Load both the model and encoder.

Else If Module = Crop Possibility

- Train Decision Tree Classifier on preprocessed2.csv
- Build a tree using Gini and Information Gain
- Save model as 'filetest2.pkl'
- Load 'filetest2.pkl'
- Format user input as feature vector X
- Perform Prediction
- Y = Model.predict(X)
- Display output Y (Recommended crop, fertilizer, yield, or list of crops) to the user via web interface

4. Results and Discussion

To achieve precise results, we employ an ensemble learning approach. This approach selects the best model for the given dataset to produce precise results. Comparing the Decision tree algorithm, Random forest algorithm, Logistic regression algorithm, Naive Bayes algorithm, K Nearest Neighbours, and Random forest, the Random forest algorithm is more accurate for the given dataset, as per the result received in Figure 2. Figure 2 shows that the comparison of algorithms, including Decision Tree, Naive Bayes, Logistic Regression, K-Nearest Neighbors, and Random Forest Algorithm, yields more accuracy for the given dataset.

Random Forest was chosen for the Crop Management System due to its superior accuracy compared to other algorithms. Random forest combines multiple decision trees to improve prediction performance and reduce overfitting. It is highly reliable for classifying crops based on soil and weather parameters. Overall, it offers robust, accurate, and interpretable results ideal for precision agriculture. The proposed Crop Management System was tested across all four modules — Crop Recommendation, Fertilizer Recommendation, Yield Prediction, and Crop Possibility Prediction — to evaluate its performance in real-world agricultural scenarios.

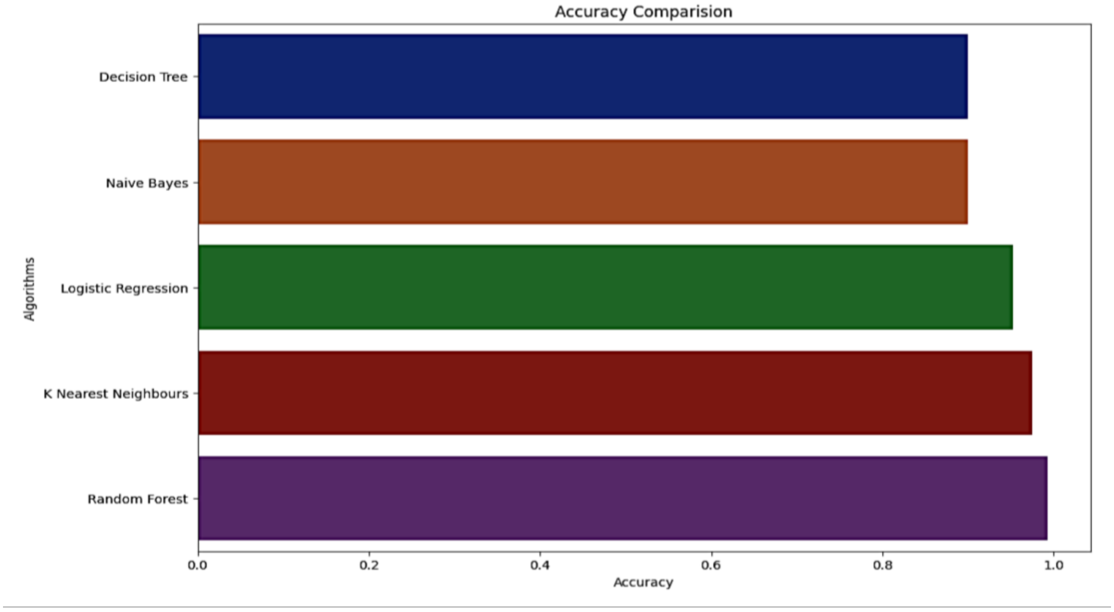

Figure 2: Comparison of the model with random forest

Each model was trained using reliable datasets and validated through sample inputs. The results demonstrate accurate, consistent, and interpretable outputs aligned with agronomic best practices. The following subsections present module-wise results, accompanied by representative examples and analysis.

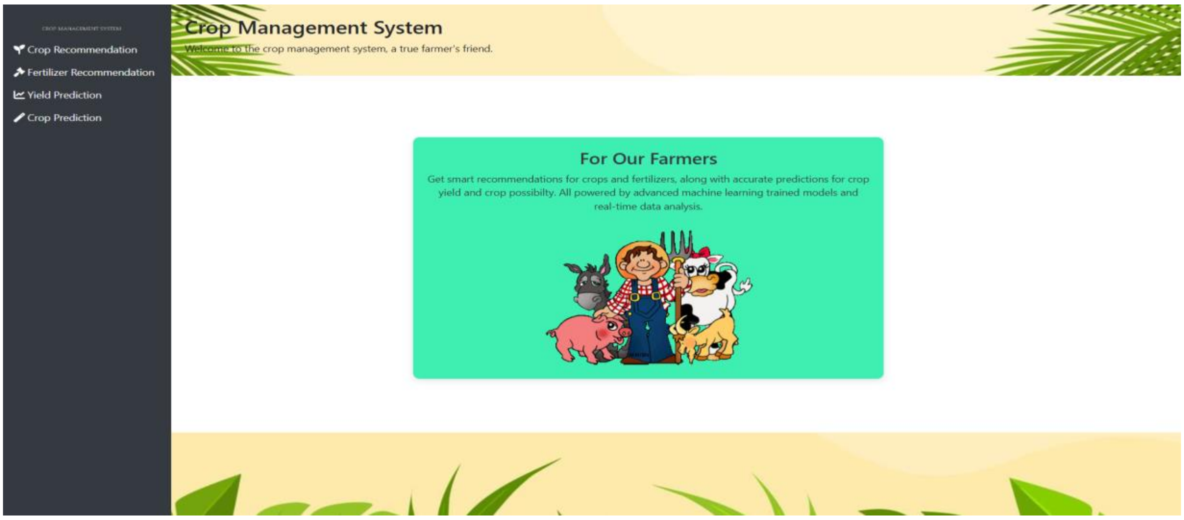

Figure 3: Home page for the crop management system

In Figure 3, we can see the interactive user home page, which allows access to all four modules listed in the navigation bar on the left side.

4.1. Crop Recommendation – Sample Result

This module predicts the most suitable crop based on soil nutrients and environmental conditions. It utilizes a Random Forest Classifier trained on features such as Nitrogen (N), Phosphorus (P), Potassium (K), Temperature, Humidity, pH, and Rainfall. The model applies ensemble learning to recommend the optimal crop for maximizing yield in specific conditions. Substituting the values in equation 1, N as 90, P as 48, K as 52, TEMP as 22, HUM as 85, pH as 6.5, and RF as 225. we received the updated equation 5 as:

$$CM_t\ (90,48,52,22,85,6.5,225) = \text{Crop recommended}(y) \quad (5)$$

The solution of Decision trees is:

- Decision tree 1, $CM_1(x)$= Rice
- Decision tree 2, $CM_2(x)$= Rice
- Decision tree 3, $CM_3(x)$= Maize
- Decision tree 4, $CM_4(x)$= Wheat
- Decision tree 5, $CM_5(x)$= Rice

$$y = \text{mode}\ \{CM_1(x), CM_2(x), CM_3(x), CM_4(x), CM_5(x)\} \qquad (6)$$

Substitute CMt values in equation 65, Rice appears 3 times; Maize appears 1 time; Wheat appears 1 time. Now, using the Ensemble learning approach, the most repeated outcome from the decision trees will be a recommended crop. Equation 7 is a recommended crop.

$$y = \text{Rice} \qquad (7)$$

Where: $CM_t(x)$ is the predicted crop from the t-th decision tree

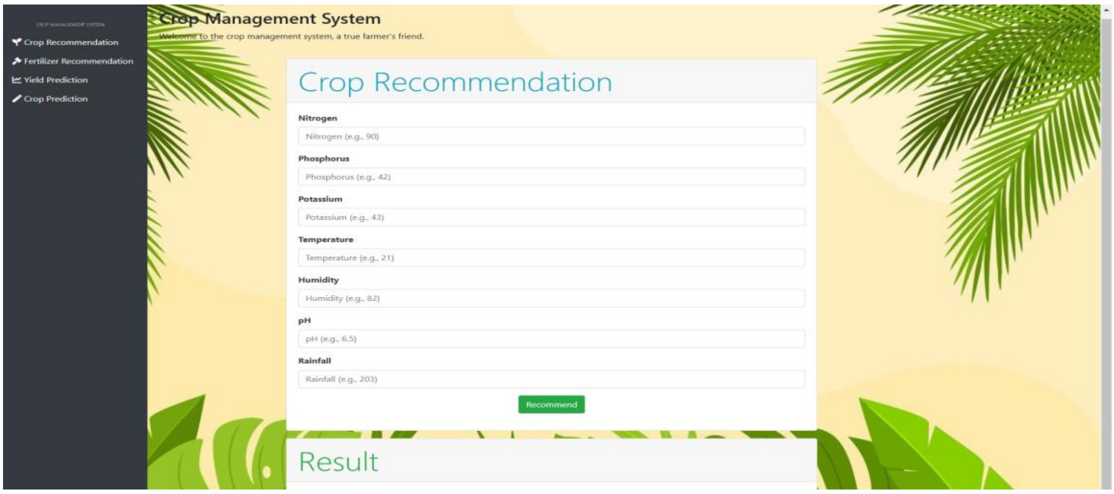

Figure 4: Crop recommendation page

In Figure 4 we can see the crop recommendation system webpage, in provided text box user can give inputs that are asked in the provided text field, for example we can see in Figure 5: Nitrogen value is given as 90, Phosphorus value is given as 48, Potassium value is given as 52, Temperature is given as 22, Humidity is given as 85, pH value is given as 6.5 and Avg Rainfall as 225 mm, Here the recommended crop is “rice” (Figure 5).

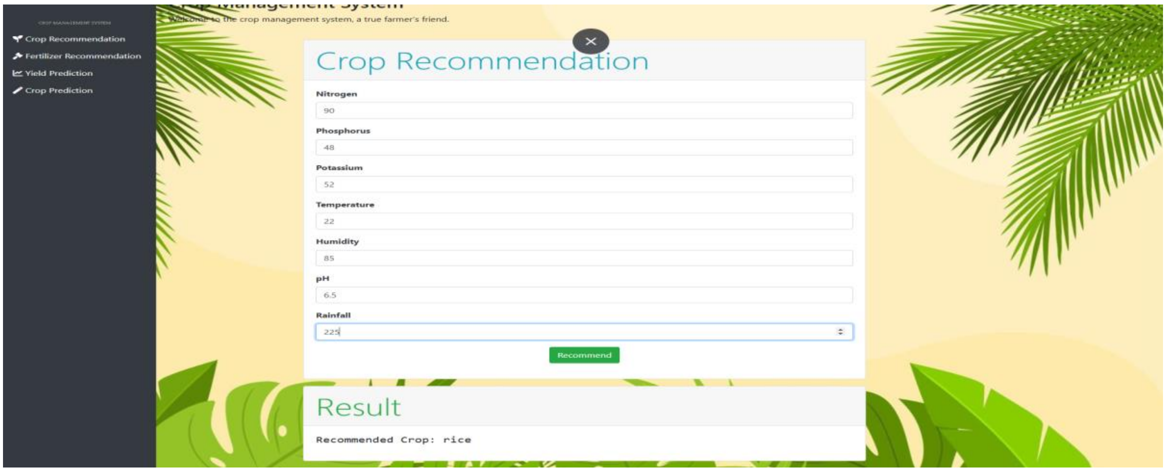

Figure 5: Recommendation of crops in the crop recommendation system

4.2. Fertilizer Recommendation – Sample Result

The fertilizer recommendation module assists farmers in identifying the most suitable fertilizer for a specific crop and soil profile. It considers factors such as soil nutrients (N, P, K), Temperature, Humidity, soil type, crop type, and soil moisture. A Random Forest Classifier is trained on labelled data to provide data-driven fertilizer suggestions that improve crop growth and soil health. Substituting the values in Equation 2, N as 30, P as 5, K as 6, TEMP as 28, HUM as 54, SM as 41, ST as Loamy, and CT as paddy. We received the updated equation 8 as:

CM_t (30, 5, 6, 28, 54, 41, Loamy, Paddy) = Fertilizer(y) (8)

- Decision tree 1, $CM_1(x)$=Urea
- Decision tree 2, $CM_2(x)$=Urea
- Decision tree 3, $CM_3(x)$=DAP
- Decision tree 4, $CM_4(x)$=Urea
- Decision tree 5, $CM_5(x)$=MOPh

$y = \text{mode}\ \{CM_1(x), CM_2(x), CM_3(x), CM_4(x), CM_5(x)\}$ (9)

Substitute CMt values in equation 9, Urea appears 3 times; DAP appears 1 time; MOP appears 1 time. Now, using the Ensemble learning approach, the most repeated outcome from the decision trees will be a recommended crop. Equation 10 is a recommended fertilizer.

y = Urea (10)

Where: $CM_t(x)$ is the recommended fertilizer from the t-th decision tree.

Figure 6: Fertilizer recommendation page

In Figure 6 we can see the fertilizer recommendation system webpage, in provided text box user can give inputs that are asked in the provided text field, for example we can see in Figure 7: Nitrogen value is given as 30, Phosphorus value is given as 5, Potassium value is given as 6, Temperature is given as 28, Humidity is given as 54, Soil Moisture is given as 41 and Soil type given as loamy, Crop type given as paddy, Here the recommended crop is “Urea”.

Figure 7: Recommendation of fertilizer in the fertilizer recommendation system

4.3. Yield Prediction – Sample Result

This module estimates the expected crop yield in quintals based on historical agricultural data. A Random Forest Regressor is trained on features such as state, district, crop year, Season, crop name, and area under cultivation. The model employs Hot Encoding for categorical features and predicts yield with high accuracy, thereby aiding farmers in their production planning. Substituting the values in Equation 3, with State as Andhra Pradesh, District as Guntur, year as 2026, Season as Rabi, Crop as Rice, and Area as 250, we obtain the updated Equation 11.

CM_t ("Andhra Pradesh", "GUNTUR",2026, "Rabi", "Rice" ,250) = Predicted Yield (y) (11)

- Decision tree 1, $CM_1(x)$=220.1 quintal
- Decision tree 2, $CM_2(x)$=228.4 quintal
- Decision tree 3, $CM_3(x)$=225.6 quintal
- Decision tree 4, $CM_4(x)$=230.2 quintal
- Decision tree 5, $CM_5(x)$=228.4 quintal

$$y = \text{mode}\ \{CM_1(x), CM_2(x), CM_3(x), CM_4(x), CM_5(x)\} \quad (12)$$

Substitute CM_t values in equation 12, 228.4 appears twice, 220.1 appears once, 230.4 appears once,225.6 appears once. Now, using the Ensemble learning approach, the most repeated outcome from the decision trees will be a recommended crop. Equation 13 is the predicted yield of the crop in quintals.

$$y = 228.4 \text{ quintals} \quad (13)$$

Where: $CM_t(x)$ is the predicted yield from the t-th decision tree.

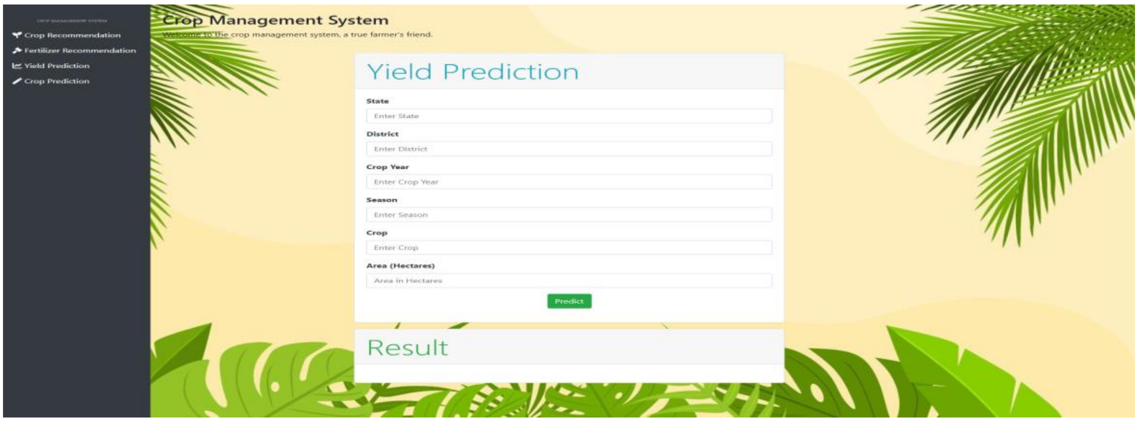

Figure 8: Yield prediction page

In Figure 8, we can see the yield Prediction system webpage. In the provided text box, the user can enter inputs that match the fields specified.

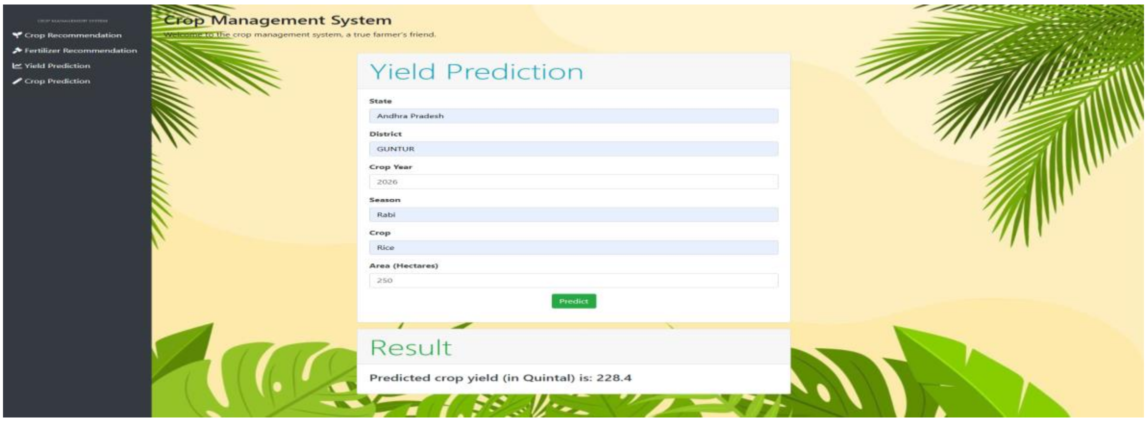

Figure 9: Prediction of yield in the yield prediction system

For example, we can see in Figure 9: State name is entered as Andhra Pradesh, District name is entered as Guntur, Crop year is entered as 2026, Season is entered as Rabi, Crop is entered as Rice, and Area(Hectors) is entered as 250. Here, the predicted crop yield is “228.4 Quintal”.

4.4. Crop Possibility Prediction – Sample Result

The crop possibility prediction module identifies all feasible crops that can be grown in a particular region during a specific season. Using a Decision Tree Classifier, this module analyses patterns in regional and seasonal crop data to classify and list all compatible crops, helping farmers choose from multiple viable cultivation options. In Equation 4, the x1, x2,..., xn are feature values provided by the user, such as state, district, and Season, for determining the possibility of crop prediction shown in Equation 14.

$$CM(x) = y \tag{14}$$

Table 1: Accuracy table

Module Name	Algorithm Name	Accuracy
Crop Recommendation	Random Forest	99%
Fertilizer Recommendation	Random Forest	98%
Yield Prediction	Random Forest	98%
Crop Possibility Prediction	Decision Tree	95%

Table 1 shows the module names in the crop management system, the algorithm used, and their module accuracy.

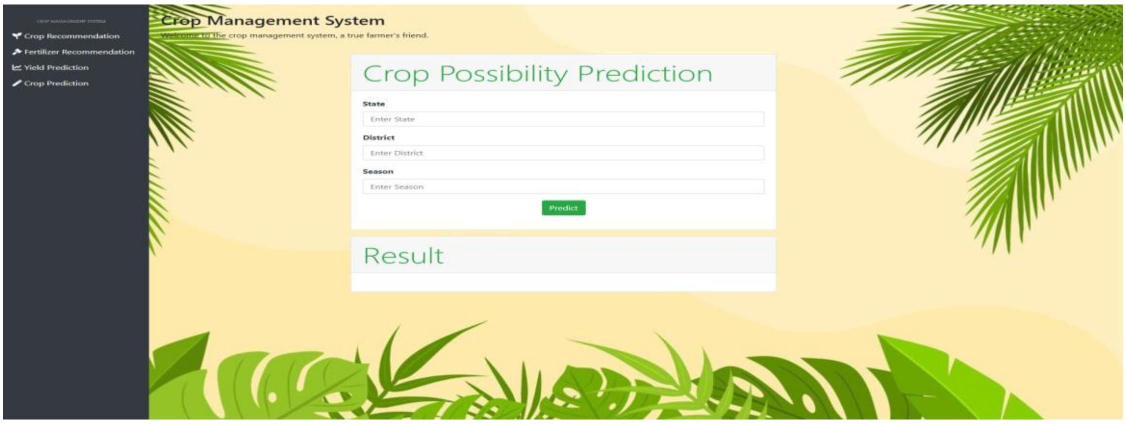

Figure 10: Crop possibility prediction page

In Figure 10, we can see the Yield Prediction system webpage. In the provided text box, the user can enter inputs that match the fields specified.

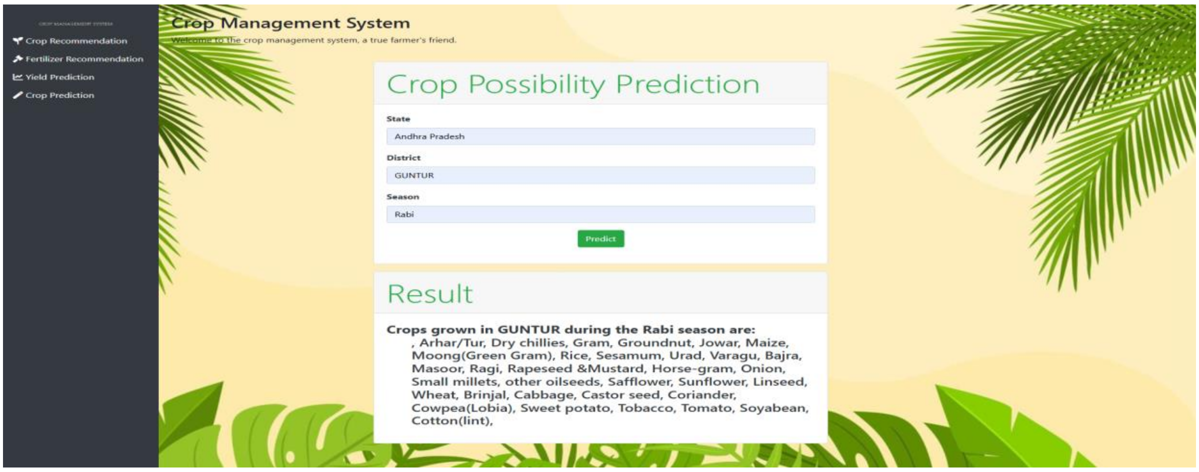

Figure 11: Possibility of predicted crops in the crop possibility prediction system

For example, as shown in Figure 11, the State name is entered as Andhra Pradesh, the District name is entered as Guntur, and the Season is entered as Rabi. Here, the predicted crops list of crops is "Arhar, Dry Chillies, Gram, Groundnut, Jowar, Maize, Moong, Rice, Sesamum, and so on as shown in Figure 11.

4.5. Discussion and Findings

The implementation of the Crop Management System demonstrated the effectiveness of machine learning techniques in solving real-world agricultural problems. Among the various algorithms tested, the Random Forest Classifier delivered the highest accuracy for crop and fertilizer recommendations, reaching 99% and 98% respectively. This validates its robustness in handling diverse input features and classifying complex, non-linear relationships in agricultural data. The Decision Tree model, used for crop possibility prediction, also performed effectively with a 95% accuracy, offering interpretable outputs that help farmers choose the most viable crops for a specific region and Season. The yield prediction model, trained with a Random Forest Regressor, produced precise estimates that enable better planning and resource allocation for upcoming agricultural cycles.

The system's modular design ensured that each function—recommendation or Prediction—could operate independently, allowing scalability and ease of updates. Testing on various input scenarios proved the model's reliability, and the results were consistent with expected agronomic outcomes. Additionally, the web-based interface provided a seamless and user-friendly experience for farmers, bridging the gap between data science and practical farming. Overall, the findings indicate that integrating AI into agriculture not only improves decision-making but also promotes sustainable farming practices. These results confirm that the system has strong potential for deployment at scale, particularly in rural areas where technical advisory support is limited.

5. Conclusion

The paper effectively developed a real-time crop management system utilizing random forest and decision tree algorithms, with a focus on accessibility and practical application for farmers. The system effectively recommends and predicts based on the input provided by the user, as shown in the Figure, where the recommended crop is rice. 5, we can see the recommended Fertilizer is Urea for the given inputs shown in the Figure. 7, we can see the predicted yield of the crop is 228.4 quintal for the given inputs shown in Figure. 9, we can see the possible crops grown in a particular region are Arhar, Dry Chillies, Gram, Groundnut, Jowar, Maize, Moong, Rice, Sesamum and so on for the given user input as shown in Figure.11. Future enhancements could concentrate on improving the model to ensure quicker and more precise processing, enhancing its functionality in various real-world settings. In general, this paper represents a significant achievement in making Crop management system technology more accessible and feasible for regular use.

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References

1. A. Agarwal, S. Ahmad, and A. Pandey, "Crop Recommendation Based on Soil Properties: A Comprehensive Analysis" *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Delhi, India, 2023.
2. S. R. Sani, S. V. Sekhar Ummadi, S. Thota, N. Muthineni, V. S. Srinivas Swargam, and T. S. Ravella, "Crop Recommendation System using Random Forest Algorithm in Machine Learning" *2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*, Salem, India, 2023.
3. M. Mehta, A. Saha, S. Fulia, T. Jain, and N. Shekokar, "An innovative model for soil testing with intelligent crop recommendation system," *in 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Delhi, India, 2023.
4. B. Gayathiri, P. Brindha, I. Karthika, E. Saranya, G. Rajeshkumar, and P. Rajesh Kanna, "Machine learning based crop suitability prediction and fertiliser recommendation system," *in 2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC)*, Coimbatore, India, 2023.
5. D. N. V. S. L. S. Indira, M. Sobhana, A. H. L. Swaroop, and V. P. Kumar, "Krishi Rakshan - A Machine Learning based New Recommendation System to the Farmer", *2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS), IEEE*, Madurai, India, 2022.
6. B. Mahalakshmi, V. Sakthivel, B. Sumitha Devi, and S. Swetha, "Agricultural crop and fertilizer recommendations based on various parameters," *in 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS)*, Coimbatore, India, 2023.
7. R. Jaichandran, T. M. Krishna, S. Harsha Arigela, R. Raman, N. Dharani, and A. Kumar, "Light GBM Algorithm based Crop Recommendation by Weather Detection and Acquired Soil Nutrients," *International Conference on Power, Energy, Control and Transmission Systems*, Chennai, India, 2022.
8. J. Avanija, K. Ambati, L. Naraganti, S. S. Derangula, and T. Nashina, "Crop Recommendation System using Antlion Optimization and Decision Tree Algorithm," *in 2024 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC), IEEE*, Salem, India, 2024.
9. D. Rakesh, V. Vardhan, B. Bhavani Vasantha, and G. Sai Krishna, "Crop Recommendation and Prediction System," *in 9th International Conference on Advanced Computing and Communication Systems (ICACCS), IEEE*, Coimbatore, India, 2023.