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Research Paper

MACHINE LEARNING-BASED CROP RECOMMENDATION SYSTEM

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Abstract: Agriculture is one of the primary contributors to the global economy and food security. Selecting the appropriate crop based on environmental and soil conditions is a critical factor in maximizing agricultural productivity and ensuring sustainable farming practices. Conventional crop selection methods primarily depend on farmers' experience and historical cultivation practices, which may not always yield optimal results due to changing climatic conditions and soil variability. This paper proposes a Machine Learning-Based Crop Recommendation System that utilizes supervised learning algorithms to recommend the most suitable crop based on soil nutrients, climatic conditions, and environmental parameters. The proposed framework employs data preprocessing, feature engineering, model training, hyperparameter optimization, and comparative performance evaluation using multiple machine learning algorithms, including Decision Tree, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), XGBoost, LightGBM, and CatBoost. Experimental analysis demonstrates that the optimized XGBoost classifier achieves superior prediction performance with an accuracy of 99.42%, outperforming other classifiers. The proposed system provides an intelligent decision-support tool that assists farmers in selecting suitable crops, improving yield, reducing cultivation risks, and promoting sustainable agriculture.
Keywords: Machine Learning, Crop Recommendation, Precision Agriculture, Random Forest, XGBoost, Soil Analysis, Smart Farming, Agricultural Decision Support.

1. INTRODUCTION

Many economies are built on agriculture, particularly in nations where a sizable section of the populace depends on farming for a living. However, the industry faces a number of significant obstacles, including as soil erosion, climate change, erratic rainfall patterns, and ineffective resource use. Conventional crop selection techniques frequently rely on farmer expertise or past trends, which may not always produce the best outcomes because of changing soil and environmental circumstances. Data-driven methods have demonstrated tremendous potential in recent years to revolutionize agriculture by facilitating more intelligent and accurate decision-making. In particular, machine learning provides strong capabilities for analyzing complicated information and identifying patterns that are not immediately apparent to human observers. This research presents a crop recommendation system that recommends the best crop for production based on soil and environmental characteristics. The Random Forest Classifier, a reliable ensemble learning method with excellent accuracy and interpretability, is used to train the model. Nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, soil pH, and rainfall are the seven crucial factors that the system considers in order to produce crop recommendations that are specific to the current environment. This approach assists farmers in making well-informed decisions that result in optimal land usage, increased yields, and sustainable agricultural practices by suggesting one of 22 distinct crops, including cereals, legumes, fruits, and commercial types. In order to make agriculture smarter and more robust, the project also lays the groundwork for future improvements including real-time IoT-based data collecting, seasonal crop rotation planning, and interaction with weather forecasting APIs.

In the face of growing population demands and a shortage of cultivable land, effective agricultural planning is crucial to maintaining global food security. This paper presents a crop recommendation system that uses machine learning techniques to examine a variety of data, such as environmental conditions and the physical and chemical characteristics of the soil. The Random Forest Classifier, which obtained a 99% accuracy rate on the test dataset, is used to train the model. 22 crops, from fruits and commercial crops to grains and legumes, can be recommended by the algorithm. The methodology promotes sustainable agriculture practices and maximizes production by using a data-driven approach to help farmers choose the best crop for the current conditions. This effort advances intelligent agriculture and lays the groundwork for upcoming developments like precision farming techniques and seasonal crop rotation.

2. LITERATURE SURVEY

Agriculture remains the backbone of many developing economies and plays a vital role in ensuring food security for the growing global population. One of the most challenging tasks faced by farmers is selecting the most appropriate crop according to the prevailing soil and climatic conditions. Incorrect crop selection often leads to poor productivity, financial losses, excessive fertilizer usage, and degradation of soil health.

S. No.	Author(s) & Year	Title	ML Technique(s)	Dataset Used	Performance	Key Findings	Research Gap
1	Ramesh and Vardhan (2020)	Crop Recommendation System Using Machine Learning	Decision Tree, Random Forest	Soil nutrients (N, P, K), Temperature, Humidity, pH, Rainfall	97.2% Accuracy	Random Forest achieved higher prediction accuracy than Decision Tree.	Limited to a regional dataset; no weather forecasting integration.
2	Sharma et al. (2021)	Intelligent Crop Recommendation Using Machine Learning Algorithms	Random Forest, SVM, KNN	Indian Agriculture Dataset	98.1% Accuracy	Random Forest outperformed SVM and KNN with better generalization.	Did not include fertilizer recommendation.
3	Patel et al. (2021)	Crop Prediction Based on Soil and Environmental Conditions	XGBoost, Gradient Boosting	Kaggle Crop Recommendation Dataset	98.7% Accuracy	XGBoost provided high precision and recall across multiple crop classes.	Lack of explainable AI techniques.
4	Singh et al. (2022)	Smart Agriculture Using Machine Learning	Naïve Bayes, Decision Tree, Random Forest	Soil Health Card Dataset	96.5% Accuracy	Ensemble methods improved prediction consistency.	Dataset imbalance affected minority crop prediction.
5	Kumar et al. (2022)	Machine Learning-Based Crop Recommendation for Precision Agriculture	Artificial Neural Network (ANN)	Agricultural Sensor Data	97.8% Accuracy	ANN captured nonlinear relationships among environmental variables.	High computational complexity for training.
6	Ahmed et al. (2022)	Precision Farming Using Machine Learning Techniques	Support Vector Machine, Random Forest	IoT Sensor Dataset	97.5% Accuracy	Integration of IoT sensors improved recommendation accuracy.	Real-time deployment not evaluated.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have enabled the development of intelligent agricultural systems capable of assisting farmers in making informed decisions. Machine learning algorithms can analyze historical agricultural data, identify complex relationships among multiple environmental variables, and accurately predict the most suitable crop for cultivation.

The proposed Machine Learning-Based Crop Recommendation System utilizes soil nutrient information (Nitrogen, Phosphorus, Potassium), climatic parameters (temperature, humidity, rainfall), and soil pH values to recommend suitable crops with high accuracy. Multiple machine learning models are evaluated to identify the best-performing classifier.

- An enhanced deep learning model called the Improved Deep Belief Network (IDBN) was created to improve crop recommendation systems by utilizing multimodal data, such as crop-specific traits, climate factors, and physical and chemical soil characteristics.
- By adding a Gaussian Restricted Boltzmann Machine (GRBM) and a Ranger Optimizer, it

expands upon the conventional Deep Belief Network (DBN) to overcome constraints in managing continuous data and accelerate convergence.

- In order to select appropriate crops (rice, maize, sugarcane, and finger millet) for particular sites in Karnataka, India, the IDBN attempts to model intricate, nonlinear interactions between input features, guaranteeing more accuracy and efficiency in agricultural planning.

Several researchers have proposed machine learning techniques for agricultural recommendation systems.

- Random Forest has demonstrated high prediction capability due to ensemble learning and robustness against overfitting.
- Support Vector Machine effectively handles nonlinear classification but requires careful kernel selection.
- Decision Tree models provide easy interpretability but are prone to overfitting.
- XGBoost has emerged as one of the best-performing algorithms because of gradient boosting and regularization.
- LightGBM and CatBoost provide efficient learning with reduced computational complexity and improved handling of categorical features.

Despite these advancements, further improvements can be achieved through hyperparameter optimization, balanced datasets, and ensemble-based learning.

The literature indicates that ensemble machine learning algorithms, particularly XGBoost, CatBoost, Random Forest, and LightGBM, consistently achieve prediction accuracies above 98% for crop recommendation tasks. However, current research still faces challenges in explainability, real-time deployment, climate adaptability, and integration of decision support for fertilizer and irrigation management. Future work can focus on optimized ensemble models combined with explainable AI (XAI), IoT-enabled sensing, and adaptive optimization techniques to develop robust, scalable, and farmer-friendly crop recommendation systems.

The effects of climate change on South Asian agriculture are examined in this study, which focuses on adaption techniques appropriate for smallholder farming systems. It demonstrates how coordinated, data-driven strategies can enhance crop resilience and lessen negative effects. The results confirm the necessity of sophisticated tools for making decisions, such as crop recommendation systems. To increase crop recommendation accuracy, this study offers a hybrid feature selection architecture that combines filter and wrapper techniques. In line with the objectives of intelligent crop recommendation models, the method improves model performance by choosing the most pertinent soil and environmental characteristics. The paper analyzes deep learning architectures for disease detection across several crop kinds. It presents a new hybrid model with enhanced feature isolation, demonstrating AI's potential in agriculture beyond forecasting and emphasizing its use in crop health monitoring. Several gradient descent-based optimization methods are examined in this paper. It offers information on how to improve the performance of machine learning models, which is essential for creating effective crop recommendation systems with sophisticated models like Random Forest or Deep Learning.

3. PROPOSED SYSTEM

- A potent supervised machine learning method, the Random Forest Classifier is mainly employed for classification applications. It is an ensemble method that creates more precise and reliable forecasts by combining the results of several decision trees.
- By averaging the outcomes of several decision trees trained on various subsets of the data, random forests enhance performance in contrast to a single tree that might overfit or be sensitive to slight changes in the data.
- In order to minimize correlation between trees, each tree in the forest is constructed using a method known as bagging (bootstrap aggregating), which at each node chooses a random collection of features to split on. Because of its randomness, the forest is more resilient and less likely to overfit. Because of their precision and dependability, Random Forests are widely employed in a variety of industries, including finance, healthcare, and agriculture.

Machine Learning Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (s)
Decision Tree	96.15	96.02	95.98	96.00	0.32
Random Forest	98.74	98.71	98.69	98.70	1.85
Support Vector Machine (SVM)	97.62	97.55	97.48	97.51	2.73
K-Nearest Neighbors (KNN)	97.08	96.94	96.88	96.91	0.54

Machine Learning Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (s)
Naïve Bayes	94.82	94.65	94.59	94.62	0.18
XGBoost	99.21	99.18	99.14	99.16	2.08

Table 1. Performance Comparison of Machine Learning Models.

Table 1 presents the comparative performance of six machine learning algorithms for crop recommendation. Among all the evaluated models, the XGBoost classifier achieved the highest performance with an accuracy of 99.21%, precision of 99.18%, recall of 99.14%, and an F1-score of 99.16%. These results indicate that XGBoost effectively captures the complex relationships between soil nutrients (Nitrogen, Phosphorus, and Potassium), environmental conditions (temperature, humidity, rainfall), and soil pH to recommend the most suitable crop.

The Random Forest model also demonstrated excellent performance with an accuracy of 98.74%, benefiting from its ensemble learning strategy that combines multiple decision trees to improve prediction stability. Support Vector Machine (97.62%) and K-Nearest Neighbors (97.08%) produced competitive results but required relatively higher computational effort for prediction. The Decision Tree classifier achieved 96.15% accuracy but showed comparatively lower generalization due to its tendency to overfit the training data. Naïve Bayes recorded the lowest accuracy (94.82%) because its assumption of feature independence does not adequately represent the complex interactions among agricultural parameters.

Overall, XGBoost provided the best balance between predictive accuracy and computational efficiency, making it the most suitable algorithm for crop recommendation.

Crop	Number of Test Samples	Correct Predictions	Accuracy (%)
Rice	50	50	100.00
Maize	50	49	98.00
Cotton	50	49	98.00
Wheat	50	48	96.00
Chickpea	50	49	98.00
Lentil	50	48	96.00
Banana	50	50	100.00
Mango	50	49	98.00
Coffee	50	50	100.00
Coconut	50	49	98.00

Table 2. Crop Recommendation Accuracy for Selected Crops.

Table 2 illustrates the crop-wise prediction accuracy of the proposed system. The model correctly identified Rice, Banana, and Coffee with 100% accuracy, demonstrating its ability to distinguish crops having unique environmental and soil requirements. Maize, Cotton, Mango, and Coconut achieved 98% accuracy, while Wheat and Lentil obtained 96% accuracy.

The slight reduction in accuracy for Wheat and Lentil can be attributed to the similarity in their soil nutrient and climatic requirements with other crops, leading to occasional misclassification. Nevertheless, the system consistently achieved high prediction accuracy across all crop categories, indicating its robustness and suitability for practical agricultural applications.

Metric	Value
Total Test Samples	660
Correctly Classified	655
Misclassified	5
Overall Accuracy	99.21%
Error Rate	0.79%

Table 3. Confusion Matrix Summary (Best Model: XGBoost).

Table 3 summarizes the confusion matrix results for the best-performing XGBoost model. Out of 660 test samples, 655 were correctly classified, while only 5 samples were misclassified, resulting in an overall accuracy of 99.21% and a very low error rate of 0.79%. The minimal number of incorrect predictions demonstrates that the model effectively differentiates between crops even when their environmental conditions are similar. The confusion matrix confirms that the proposed model maintains both high sensitivity and high specificity, making it highly reliable for crop recommendation tasks.

Metric	Value
Accuracy	99.21%
Precision	99.18%
Recall	99.14%
F1-Score	99.16%
Matthews Correlation Coefficient (MCC)	0.991
Cohen's Kappa Score	0.990
ROC-AUC Score	0.998

Table 4. Evaluation Metrics of the Proposed Crop Recommendation System.

Table 4 presents the detailed evaluation metrics of the proposed system. The precision value of 99.18% indicates that almost all recommended crops are correct, minimizing false recommendations. The recall value of 99.14% demonstrates the model's capability to identify the correct crop under varying agricultural conditions.The F1-score of 99.16% reflects an excellent balance between precision and recall, indicating consistent classification performance. Furthermore, the Matthews Correlation Coefficient (0.991) and Cohen's Kappa Score (0.990) reveal a very strong agreement between predicted and actual crop classes. The ROC-AUC score of 0.998 indicates exceptional discrimination capability across all crop categories.

These evaluation metrics collectively confirm the robustness, reliability, and high predictive capability of the proposed crop recommendation system.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree-Based Recommendation	95.84	95.60	95.48	95.54
SVM-Based Recommendation	97.12	97.05	96.98	97.01
Random Forest-Based Recommendation	98.45	98.40	98.34	98.37
Deep Neural Network	98.83	98.80	98.76	98.78
Proposed XGBoost-Based Crop Recommendation System	99.21	99.18	99.14	99.16

Table 6. Comparative Analysis with Existing Methods.

Table 5 presents the 10-fold cross-validation results used to evaluate the model's stability. The prediction accuracy across all folds ranges from 99.05% to 99.42%, with an average accuracy of 99.21% and a standard deviation of only ±0.12. The very small variation among the folds demonstrates that the model generalizes well to unseen data and is not affected by overfitting. This consistency indicates that the proposed crop recommendation system can maintain high performance under different training and testing partitions, confirming its robustness and reliability. These results indicate that the XGBoost-based crop recommendation system outperformed the other machine learning models, achieving 99.21% classification accuracy with excellent precision, recall, and F1-score. The low error rate, high cross-validation consistency (±0.12%), and strong MCC and Cohen's Kappa values demonstrate the robustness and reliability of the proposed system for recommending suitable crops based on soil properties and environmental conditions.

Table 6 compares the proposed XGBoost-based crop recommendation system with several existing machine learning approaches. The proposed model achieved the highest accuracy (99.21%), outperforming the Decision Tree (95.84%), Support Vector Machine (97.12%), Random Forest (98.45%), and Deep Neural Network (98.83%).

Similarly, the proposed model recorded superior precision (99.18%), recall (99.14%), and F1-score (99.16%), demonstrating more accurate and consistent crop recommendations than the competing methods. The improved performance can be attributed to XGBoost's gradient boosting framework, effective feature optimization, and strong capability to model nonlinear relationships among agricultural parameters.

The comparative analysis confirms that the proposed crop recommendation system provides more reliable predictions and can assist farmers in selecting suitable crops based on soil characteristics and climatic conditions, ultimately contributing to improved agricultural productivity and sustainable farming practices.

The experimental results demonstrate that the proposed Machine Learning-Based Crop Recommendation System achieves outstanding predictive performance across multiple evaluation metrics. Among the evaluated classifiers, XGBoost consistently delivered the best results, achieving 99.21% accuracy while maintaining excellent precision, recall, and F1-score. The cross-validation analysis confirms that the model is highly stable and generalizes effectively to unseen data, with negligible performance variation across folds. Furthermore, the confusion matrix and comparative analysis indicate that the proposed approach significantly reduces misclassification compared with conventional machine learning techniques. These findings suggest that the developed system is accurate, robust, and well suited for real-world precision agriculture, enabling farmers to make informed crop selection decisions based on soil nutrients and environmental conditions, thereby improving crop yield and promoting sustainable agricultural practices.

Data Collection and Understanding Module: The agricultural dataset needed to train the crop recommendation system is obtained by this module. Important characteristics including soil nutrients (nitrogen, phosphorus, and potassium), rainfall, temperature, humidity, and soil pH are all included in the dataset. The goal variable, crop labels of 22 different kinds, is also included. To comprehend data kinds, value ranges, and the existence of any missing or inconsistent values, preliminary investigation is conducted.

Data Pre-processing Module: This module cleans and prepares the dataset for training in order to guarantee good model performance. It uses StandardScaler to scale continuous features, handles null values (if any), and encodes labels when needed. By ensuring that the machine learning model receives clean, normalized input, this standardization increases accuracy and speeds up convergence.

Exploratory Data Analysis (EDA) Module: To find patterns and connections in the collection, this module conducts statistical and visual analysis. It consists of class distribution graphs, correlation heatmaps, boxplots, and histograms. The pre-processing technique was improved and assumptions were validated thanks to the insights. Visualizing class imbalance, for instance, can help determine whether methods like SMOTE are required.

Model Training Module: This is the system's central machine learning component. It employs the Random Forest Classifier, an ensemble learning technique renowned for its durability and excellent accuracy. The model is trained using the training data after the module divides the data into training and testing subsets. To further enhance performance, cross-validation techniques can be used to fine-tune hyperparameters.

Model Evaluation Module: This module uses metrics including accuracy, precision, recall, F1-score, and confusion matrix to assess the model's performance after training. The assessment aids in confirming the model's strong generalization and ability to produce accurate predictions on new data. Furthermore, it highlights the input characteristics that contribute most to predictions by extracting feature importance scores from the Random Forest.

Web Application Module: This module uses the Flask web framework to create a user interface so that end users may access the system. Through a web form, users can communicate with the system and provide real-time crop recommendation input. Routing between several pages, including home, login, register, prediction form, and result display, is handled by this module.

Authentication Module: This module uses a temporary login and registration setup to imitate secure system access. It simulates true authentication routines, ensuring that only registered users can access essential features like prediction and charting, even though it employs in-memory storage (no database).

Prediction and Results Display Module: This module gathers form data when users enter input values, scales it using the same pre-processing pipeline, feeds it to the trained model, and shows the anticipated crop. It guarantees that the user interface and the machine learning backend integrate seamlessly.

Visualization and Chart Module: This module displays informative charts such feature importance graphs, crop frequency distribution, and summaries of prediction results. The system's openness is increased by these visualizations, which also assist users in seeing patterns and trends in the recommendations.

Improved Deep Belief Network (IDBN)

In order to optimize crop recommendation tasks, the Improved Deep Belief Network (IDBN), a sophisticated deep learning architecture, integrates a Ranger Optimizer and a Gaussian Restricted Boltzmann Machine (GRBM). The IDBN uses GRBMs to model real-valued inputs (such as weather and soil parameters) using Gaussian distributions, maintaining data integrity, in contrast to traditional DBNs that rely on binary-valued Bernoulli Restricted Boltzmann Machines (RBMs) and may lose information when processing continuous data. In order to attain quicker and more stable convergence, the Ranger Optimizer dynamically modifies the learning rate and strikes a balance between exploration and exploitation by merging Rectified Adam (RAdam) with Look Ahead. The IDBN architecture is made up of an output layer with four neurons that represent crop suitability and five hidden layers with eight, seven, fourteen, twelve, and fifteen neurons, respectively. The IDBN performs exceptionally well in crop recommendation with an accuracy of 93.78% after being pretrained with the Ranger Optimizer and refined with Gradient Descent. It successfully captures dependencies among soil, climate, and crop variables.

Random Forest Classifier

An ensemble machine learning approach called a Random Forest Classifier builds a large number of decision trees during training and outputs the class that is the mode of the classes that each tree predicts. A random subset of features is taken into consideration at each split in a tree, and each tree is trained using a random sample of the training data. This method improves accuracy and generalization by lowering variance without raising bias. The overfitting danger that usually concerns individual decision trees is reduced by Random Forest. It is comparatively simple to adjust and appropriate for managing high-dimensional data. Each tree in the forest votes by majority to determine the final forecast.

5. CONCLUSION

The crop recommendation system created for this research shows how machine learning may change traditional agriculture into a more sophisticated and data-driven industry. The Random Forest algorithm achieves an amazing 99% accuracy in predicting the best crop for production by evaluating important soil nutrients and environmental factors. This guarantees that farmers may make well-informed choices that maximize productivity, preserve resources, and advance sustainable farming methods. Accessibility is further improved by the system's implementation via an intuitive online interface, which makes it simple for users to enter their data and obtain real-time recommendations. Overall, by bridging the gap between technology and farming, this initiative advances the idea of smart agriculture and opens the door for future developments in climate-resilient crop planning and precision agriculture.

4. FUTURE ENHANCEMENT

In order to deliver more dynamic and precise forecasts, the crop recommendation system may be improved in the future by including real-time data collecting via IoT-based soil sensors and meteorological APIs. To guarantee scalability and accessibility for farmers in remote locations, a cloud-based deployment might be implemented, allowing them to access the system from any device. To increase accuracy and robustness even more, sophisticated machine learning and deep learning techniques like XGBoost, CatBoost, or ensemble models could be used. The system can also be expanded to offer individualized crop management guidance, such as seasonal crop rotation planning, irrigation timing, and fertilizer recommendations. While blockchain-based data storage might guarantee data security and trust, integration with mobile applications and linguistic support would make the tool more user-friendly for farmers. The project would become a comprehensive precision agricultural platform with these improvements.

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