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XGBoost Outperforms Traditional Models in Crop Recommendation Accuracy and Reliability

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Abstract - Crop recommendation plays a vital role in modern agriculture, enabling farmers to make informed decisions that enhance yield and sustainability. With advancements in machine learning, various algorithms have been applied to predict the most suitable crops based on soil and environmental parameters such as nitrogen, phosphorus, potassium, pH, temperature, humidity, and rainfall. This study presents a comparative analysis of several supervised learning models, including Decision Tree, Naïve Bayes, Support Vector Machine (SVM), Logistic Regression, Random Forest (RF), and XGBoost. Performance was evaluated using accuracy, precision, recall, and F1-score. The results demonstrate that while traditional models achieved strong performance, XGBoost outperformed them all, achieving the highest accuracy (99.31%), precision (100%), and reliability across metrics. Its ability to capture complex, non-linear relationships within soil data underscores its effectiveness for precision agriculture. The findings highlight XGBoost as a robust and scalable solution for enhancing crop recommendation systems.

Keywords - XGBoost, Crop Recommendation, Machine Learning, Soil Data Analysis, Precision Agriculture.

I. INTRODUCTION

Agriculture remains the backbone of many economies, providing food security and livelihood for a large portion of the global population. However, the sector faces growing challenges due to climate change, population growth, and resource constraints. To meet increasing food demands, farmers are required to make data-driven decisions rather than relying solely on traditional practices or intuition. Among these decisions, crop recommendation—identifying the most suitable crop for a given soil and environmental condition—plays a critical role in optimizing productivity and sustainability. Accurate crop recommendation ensures efficient utilization of natural resources, reduces the risk of crop failure, and supports better economic returns for farmers.

The effectiveness of crop recommendation systems largely depends on the integration and analysis of diverse parameters such as soil nutrients (nitrogen, phosphorus, potassium), pH levels, temperature, humidity, and rainfall. These factors interact in complex and non-linear ways, making manual analysis difficult. Traditional statistical methods often fall short in capturing such intricate relationships. This has led to the increasing adoption of machine learning (ML) techniques, which can process large datasets, identify hidden patterns, and generate accurate predictions.

Over the years, a wide range of supervised learning algorithms has been applied in crop recommendation research. Decision Trees, Logistic Regression, Naïve Bayes, Support Vector Machines (SVM), and Random Forests (RF) are among the most widely used. Decision Trees are simple and interpretable but often prone to overfitting. Logistic Regression works well for linearly separable data but struggles with complex, non-linear interactions. Naïve Bayes, though efficient, makes strong independence assumptions that rarely hold in real-world agricultural datasets. SVMs and Random Forests have shown stronger performance by handling higher-dimensional data and non-linear relationships, but they too have limitations in scalability and optimization.

In contrast, XGBoost (Extreme Gradient Boosting) has emerged as a powerful alternative, demonstrating superior performance in various machine learning applications. XGBoost is an advanced implementation of gradient boosting that builds an ensemble of decision trees sequentially, where each tree corrects the errors of the previous one. It incorporates regularization techniques to prevent overfitting, a specialized split-finding algorithm to handle missing or sparse data, and supports parallel and distributed computing, making it both efficient and scalable. Its ability to model complex, non-linear interactions makes it particularly suitable for agricultural datasets that involve multiple interdependent soil and environmental parameters.

The comparative results from this study further highlight XGBoost's dominance. While traditional models achieved high levels of performance with Random Forest and Naïve Bayes both recording 99.09% accuracy XGBoost surpassed them, achieving 99.31% accuracy, 100% precision, and 99% recall and F1-score. This not only demonstrates its predictive strength but also its reliability in minimizing both false positives and false negatives. Such consistency is crucial in crop recommendation, where errors can lead to wasted resources, reduced yields, and economic losses for farmers.

Therefore, this paper focuses on exploring why XGBoost outperforms traditional models in terms of accuracy and reliability for crop recommendation systems. By leveraging soil and environmental data, XGBoost provides a robust framework for precision agriculture, paving the way for smarter, data-driven farming practices that enhance productivity while ensuring sustainability.

II. LITERATURE REVIEW

A deep learning–based model was developed using fine-tuned transfer learning algorithms such as VGG-16, VGG-19, Inception-V3, and Xception to detect cotton leaf diseases. Among these, the Xception model achieved 98.70% accuracy and was integrated into a web application to support real-world disease prediction. This solution helps farmers detect plant diseases early, preventing crop losses. The study highlights how AI and deep learning are driving smart farming and precision agriculture, improving diagnostic accuracy and boosting agricultural sustainability [1].

Another study explored the use of machine learning in agricultural crop selection (CS) through recommender systems (RSs). It reviews how RSs have evolved, their features, and the challenges they face in supporting farmers' decisions. The work points out a lack of a clear classification scheme for crop recommendation algorithms and features, aiming to close this gap. By discussing trends, evaluation criteria, and emerging challenges, the study emphasizes the growing role of RSs in optimizing crop choices and improving efficiency in farming [2].

An innovative system was also proposed to enhance crop production efficiency by combining Internet of Things (IoT), cloud computing, and machine learning. The IoTSNA-CR model collects data from IoT sensors, stores it in the cloud, and analyzes it using a custom algorithm. Farmers can access recommendations via an Android application, receiving continuous guidance rather than relying solely on traditional methods. Its unique algorithm, MSVM-DAG-FFO, demonstrated high accuracy in recommending crops, optimizing soil nutrient usage, and improving productivity while minimizing resource use [3].

Another study emphasized the importance of soil fertility management and integrated nutrition management in crop recommendation systems. It employed multiple machine learning algorithms and evaluated 14 classifiers. CatBoost achieved the highest accuracy (99.51%), while Gaussian Naive Bayes (GNB) performed best in ROC and MCC scores.

The research demonstrates how AI can help address key agricultural challenges, including climate variability, population growth, food security, and employment issues, by improving soil and crop management [4].

A Crop Recommender System using the Random Forest algorithm was proposed to help farmers decide the best crops based on soil and rainfall conditions. Unlike traditional intuition-based decisions that often lead to losses, this system offers data-driven recommendations. It features a user-friendly web application, integrates GPS for environmental data, and compares accuracy across different algorithms. By averaging results across multiple decision trees, the Random Forest method improves reliability. The study concludes that such systems can enhance agricultural productivity and guide stakeholders toward better decisions [5].

Another paper applied clustering algorithms and k-Nearest Neighbor (k-NN) to analyze temperature and humidity data, identifying patterns useful for climate prediction and crop categorization. The study further integrates techniques such as neural networks, image processing, and remote sensing, showing the value of machine learning in crop yield prediction and climate modeling [6].

A separate study highlighted the limitations of traditional farming practices and proposed a machine learning–based crop selection system. Unlike conventional approaches, this system factors in soil conditions, market value, and sustainability, which farmers often overlook. By leveraging machine learning and deep learning, the system offers more accurate crop recommendations, aiming to increase profitability and yield outcomes [7].

Finally, research focusing on Indian farmers addressed the challenge of declining agricultural productivity caused by poor crop selection. The solution, grounded in precision agriculture, used data on soil type, pH, temperature, moisture, and humidity to recommend optimal crops. An intelligent system was designed with sensors and implemented on a STM32 ARM Processor, simulated on Proteus, and tested on a Nucleo board. Recommendations were displayed via the Blynk app and LCD display, demonstrating its practical potential to help farmers make better crop choices and improve productivity [8].

A novel hybrid deep learning model called Cap-DiBiL was introduced, combining a Channel Capsule Network with a Stacked Dilated Bi-LSTM to predict crop water requirements and recommend suitable crops. The model processes IoT data through normalization, missing value imputation, and one-hot encoding, followed by feature extraction and selection. It also incorporates a Gated Residual Autoencoder and the Chaotic Northern Goshawk Optimization algorithm, achieving high performance across metrics such as accuracy, precision, and F1 score. Results show that Cap-DiBiL outperforms existing approaches, offering more accurate water requirement predictions and crop recommendations [9].

Another study proposed an IoT-based framework that integrates Improved Distribution-based Chicken Swarm Optimization (IDCSO) with Weight-based LSTM (WLSTM) for crop prediction and recommendation. Climate data is collected and preprocessed, with IDCSO used for feature selection and WLSTM for predictive modeling. This system demonstrates better accuracy, precision, recall, and execution time compared to earlier methods, enabling farmers to make more precise crop decisions [10].

Machine learning approaches have also been applied to predict crops based on environmental variables like soil nutrients, temperature, and precipitation. Five algorithms were evaluated, with Random Forest identified as the most effective. Despite challenges related to limited data, the system seeks to provide an open-source, low-cost precision farming solution for Moroccan farmers, fostering sustainable agricultural productivity and economic growth [11].

To address fertilizer management, an Electronic Agricultural Record (EAR) system was proposed. Built using Hive and Elasticsearch, the system integrates multiple datasets into a unified agricultural data warehouse. It extracts fertilizer information and uses statistical models to recommend balanced levels of nitrogen, phosphorus, and potassium for major EU crops. The system aims to optimize fertilizer use, improving yields while minimizing environmental impact from over-application [12].

Another study applied ML algorithms to region-specific weather data for crop recommendation. Models including Decision Tree, Logistic Regression, Naive Bayes, Random Forest, and Support Vector Machines were evaluated. The system provides regionally tailored recommendations, helping farmers select the most suitable crops under varying weather conditions, thereby supporting agricultural sustainability [13].

Research on fertilizers investigated the synthesis of BBFs (Bio-Based Fertilizers) from coffee husk and low-grade phosphate rock. The study analyzed their chemical characteristics, infrared spectroscopy, and phosphorus release kinetics, testing their agronomic performance on maize and Brachiaria grass. Findings demonstrated the potential of BBFs to improve phosphorus efficiency in Oxisols, offering environmentally friendly alternatives to traditional fertilizers [14].

Another work compared bagging, random forest, linear regression, and naive Bayes models for yield prediction, with bagging proving most effective. Boosting algorithms were further emphasized for crop recommendation systems. A graphical interface was developed to demonstrate the system, enabling farmers to visualize recommendations and improve decision-making [15].

Bayesian Belief Networks (BBNs) have also been explored for crop recommendation by integrating climate data, soil properties, and historical yield records. This probabilistic model accounts for uncertainty while incorporating farmer preferences and constraints, making recommendations highly adaptable. The approach achieved strong predictive performance while supporting personalized and sustainable farming strategies [16].

In irrigation-focused research, the limitations of relying solely on evapotranspiration (ET) rates for irrigation scheduling were highlighted. The study showed that ET-based recommendations often fail to reflect actual crop needs due to interactions between soil, crop type, and environmental factors. It calls for a more integrated irrigation strategy that considers these interactions to optimize water use [17].

Finally, macronutrient optimization for greenhouse crops was explored using the VegSyst Decision Support System (VegSyst-DSS). By calibrating VegSyst v3 for nutrient uptake in pepper and muskmelon, the updated DSS (v2) provides fertilizer recommendations for macronutrients such as phosphorus, potassium, calcium, and magnesium. The approach balances nutrient requirements with environmental and cost concerns, aiming to reduce over-fertilization while maintaining crop productivity [18].

III. PROPOSED METHOD

Proposed flowchart

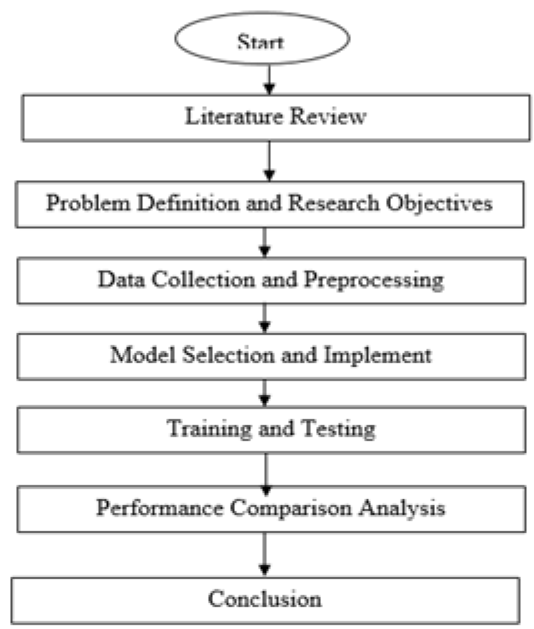

Figure 1. Proposed flowchart

The research process shows in figure 1 begins with a literature review, which helps in understanding existing work and identifying knowledge gaps. Based on this, the problem definition and research objectives are formulated to establish a clear direction. Next, data collection and preprocessing are carried out to gather relevant datasets, clean them, and prepare them for analysis. After preprocessing, appropriate models are selected and implemented, followed by the training and testing phase to evaluate how well the models perform. Once trained, the models are subjected to a performance comparison analysis where their accuracy and efficiency are measured using various evaluation metrics. Finally, the findings are synthesized into the conclusion, summarizing the research outcomes, highlighting the contributions, and pointing to possible directions for future work. This structured approach ensures a systematic progression from problem identification to validated results and meaningful insights.

Methods of Dataset Preprocessing

Data Cleaning

- Handling Missing Values: Address missing entries by filling them with statistical measures (mean, median, mode) or using advanced approaches such as predictive imputation. In some cases, rows or columns with excessive missing values may be removed.
- Outlier Removal: Detect and eliminate outliers that distort results. Techniques like Z-score and Interquartile Range (IQR) can be used to identify extreme values.

Data Integration

- Merging Data Sources: Combine information from multiple datasets to form a unified dataset, ensuring consistency across scales, units, and measurement systems.
- Resolving Inconsistencies: Correct discrepancies such as different labels or naming conventions for the same soil attributes or crop types.

Data Transformation

- Normalization: Rescale numerical values (e.g., soil pH, nutrient levels) into a fixed range, usually 0–1, so that no variable disproportionately influences the model.
- Standardization: Adjust features by centering around the mean and scaling to unit variance, ensuring comparability across soil parameters.

Feature Engineering

- New Feature Creation: Generate additional features, such as nutrient ratios or interaction terms, to capture complex soil–crop relationships.
- Categorical Encoding: Transform categorical attributes (e.g., soil type, crop variety) into numerical form using one-hot encoding or label encoding for model compatibility.

Proposed XGBoost Model

Designing an XGBoost model for crop recommendation based on soil composition requires a structured workflow, from dataset understanding to model evaluation. The following steps outline the proposed approach:

Step 1: Understanding the Dataset

- Analyze Soil Components: Examine key soil parameters such as pH, nitrogen (N), phosphorus (P), potassium (K), and organic matter.
- Study Crop Requirements: Identify the specific soil conditions necessary for different crops to achieve optimal growth.

Step 2: Data Preprocessing

- Data Cleaning: Manage missing values and eliminate outliers.
- Data Transformation: Normalize or standardize soil variables to ensure comparability.
- Feature Engineering: Create derived features (e.g., nutrient ratios, interaction terms) to better capture soil–crop relationships.
- Data Encoding: Convert categorical attributes (e.g., soil type) into numerical form using encoding techniques.
- Data Splitting: Divide the dataset into training and testing subsets, typically using an 80:20 or 70:30 ratio.

Step 3: Model Preparation

- Base Model Selection: Initialize a standard XGBoost classifier as the starting point.
- Parameter Initialization: Define core parameters such as learning rate, maximum depth of trees, and number of estimators.
- Cross-Validation Setup: Employ k-fold cross-validation to fine-tune parameters and ensure robustness.

Step 4: Model Training

- Fit the Model: Train the XGBoost model on the prepared training dataset.
- Hyperparameter Tuning: Apply grid search or random search to identify optimal hyperparameter values.
- Feature Importance Analysis: Evaluate feature contributions and retain the most relevant predictors.

Step 5: Model Evaluation

- Cross-Validation Testing: Assess the consistency and stability of the model using cross-validation.
- Performance Metrics: Measure model performance on the testing dataset using accuracy, precision, recall, and F1-score.

XGBoost Model

XGBoost (Extreme Gradient Boosting) is an advanced gradient boosting framework that has become widely recognized for its speed, accuracy, and efficiency, especially when dealing with structured tabular data such as soil composition for crop recommendation. Its foundation lies in an ensemble of decision trees, built sequentially, where each new tree is designed to reduce the errors of the previous ones. Using gradient descent optimization, XGBoost minimizes prediction loss at each iteration, steadily improving performance. One of its major strengths is its ability to handle sparse and heterogeneous data. XGBoost uses a specialized split-finding algorithm and a weighted quantile sketch to efficiently manage missing values and approximate splits. To prevent overfitting, it incorporates regularization terms directly into its objective function, which helps maintain a balance between model complexity and accuracy.

In the context of crop recommendation, XGBoost can analyze soil features such as pH, nitrogen, phosphorus, potassium, and moisture content, capturing both linear and nonlinear interactions between these variables and crop suitability.

This makes it particularly effective for modeling the complex relationships between soil parameters and yield outcomes. Moreover, its scalability is enhanced by parallel and distributed computing, making it well-suited for large agricultural datasets. XGBoost also provides built-in cross-validation techniques, ensuring robust evaluation during training and improving model generalization. Its ability to efficiently process different feature types, handle missing values, and capture intricate patterns enables it to generate highly accurate and reliable crop recommendations, ultimately supporting precision agriculture and sustainable farming practices.

Table 2. Comparison table outlining the different features of the algorithms.

Feature	Decision Tree	Naive Bayes	SVM	Logistic Regression	Random Forest (RF)	Proposed XGBoost
Model Type	Non-parametric, supervised	Probabilistic, supervised	Non-probabilistic, supervised	Parametric, supervised	Non-parametric, ensemble	Non-parametric, ensemble (boosting)
Suitability for Non-Linear Problems	Yes	No	Yes (with kernel trick)	No	Yes	Yes
Handling of High Dimensional Space	Low	High	High	Medium	High	High
Robustness to Noisy Data	No	Yes	No	No	Yes	Yes
Computational Performance	Fast for small datasets, slow for large	Very fast	Medium to slow (depends on the kernel used)	Fast	Medium (requires more computational resources for	Fast (optimized gradient boosting)

					large ensembles)	
Interpretability	High (easy to visualize and interpret)	Medium (based on probability distributions)	Low (hard to interpret the high-dimensional space)	High (model coefficients can be interpreted)	Medium (ensemble model can be harder to interpret)	Medium (model can be interpreted using feature importance)
Ability to Handle Missing Data	Yes	No	No	No	Yes	Yes
Prone to Overfitting	Yes (without proper pruning)	No	Yes (without proper regularization)	Yes (without proper regularization)	No (ensemble method reduces overfitting risk)	No (regularization terms help prevent overfitting)

Implementation and Result Discussion

Python Library for Implementation

- Pandas: A powerful Python library for data manipulation and analysis. It provides flexible data structures, such as DataFrames, along with functions for handling numerical tables and time series data.
- NumPy: A fundamental scientific computing library in Python that supports large, multi-dimensional arrays and matrices. It also offers a wide collection of high-level mathematical functions for efficient array operations.
- Scikit-learn: A dedicated machine learning library in Python that includes tools for classification, regression, clustering, and dimensionality reduction. Algorithms such as support vector machines, random forests, gradient boosting, k-means, and DBSCAN are implemented, and it integrates smoothly with NumPy and SciPy.
- XGBoost: A highly efficient, scalable, and portable implementation of distributed gradient boosting. It enhances machine learning performance by leveraging advanced optimization techniques within the Gradient Boosting framework.
- Matplotlib and Seaborn: Popular visualization libraries in Python used to create static, interactive, and highly informative visualizations. While Matplotlib provides a solid foundation for plotting, Seaborn builds on it to generate more visually appealing statistical graphics.

Dataset

The crop recommendation dataset is available at recommendation-dataset/data The crop recommendation dataset used in this research captures several key factors that directly affect rainfall levels and crop productivity in a given region. The dataset includes the following variables: phosphate (P), nitrogen (N), potassium (K), temperature, humidity, soil pH, precipitation, and crop label. These parameters together provide a comprehensive view of soil composition, climatic conditions, and environmental influences, enabling the development of machine learning models to recommend the most suitable crops for cultivation under specific conditions.

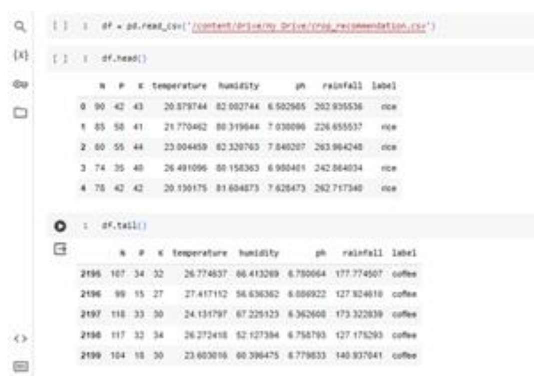

Figure 2. Dataset description.

Illustrative example

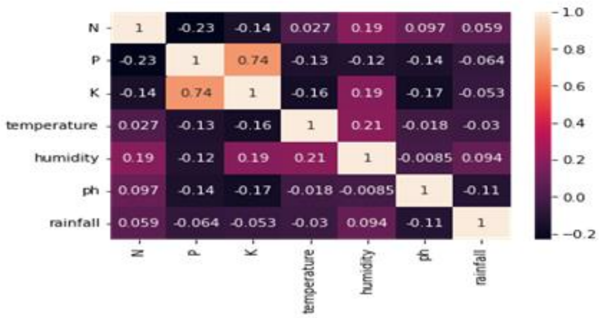

Figure 3: Correlation of dataset features.

The heatmap shown figure 3 represents the correlation matrix of the crop recommendation dataset, where each cell indicates the degree of correlation between two variables. Most of the features exhibit low to moderate correlation values, suggesting that they contribute unique information to the dataset. A strong positive correlation of 0.74 is observed between nitrogen (N) and phosphate (P), implying that these two nutrients often vary together in the dataset. Other variables, such as temperature, humidity, pH, and potassium (K), show weaker or near-zero correlations, reflecting minimal linear dependence.

This overall pattern highlights that the dataset contains diverse and relatively independent features, which is beneficial for training machine learning models, as it reduces redundancy and helps capture more meaningful patterns for accurate crop recommendation.

Result and Discussion

Table 3. Comparative Study of Proposed model with existing

Algorithm	Accuracy	Precision	Recall	F1-score
Decision Tree	90	91	90	90
Naive Bayes	99.09	99	98	99
SVM	97.95	98	97	97
Logistic Regression	95.22	95	95	96
RF	99.09	99	98	99
XGBoost	99.31	100	99	99

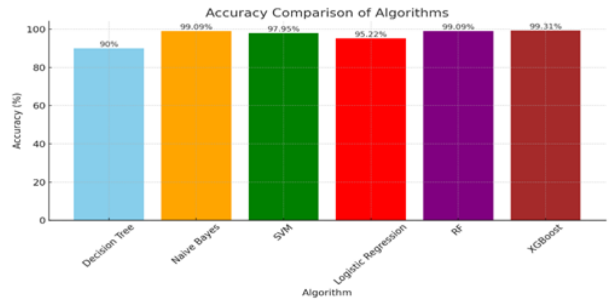

Figure 4: The accuracy of various machine learning algorithms

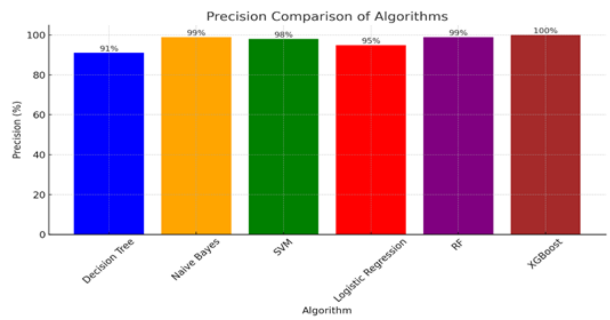

Figure 5: The precision of various machine learning algorithms

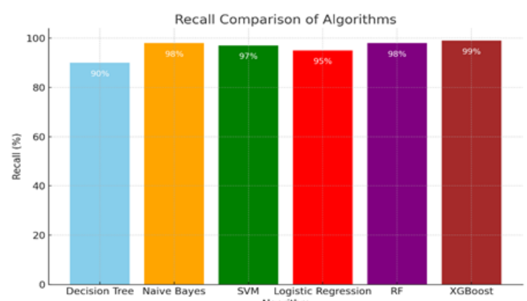

Figure 6: The recall metric for a selection of prominent machine learning algorithms

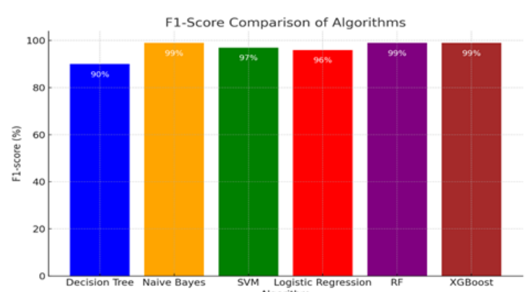

Figure 7: The F1-scores across different algorithms

The performance comparison table 3 and figure 4,5,6,and 7 presents the evaluation of multiple machine learning algorithms on the crop recommendation dataset using four key metrics: accuracy, precision, recall, and F1-score. Among the models, Decision Tree showed the lowest performance with 90% accuracy and balanced precision, recall, and F1-score values of 90–91. Naïve Bayes and Random Forest (RF) both achieved strong results with 99.09% accuracy, high precision (99), and recall (98), reflecting reliable classification. Support Vector Machine (SVM) and Logistic Regression performed slightly lower, with accuracies of 97.95% and 95.22%, respectively, though both maintained high precision and recall in the range of 95–98. XGBoost emerged as the best-performing model, attaining the highest accuracy of 99.31%, precision of 100%, recall of 99, and an F1-score of 99, highlighting its superior ability to capture complex patterns and deliver highly reliable crop recommendations.

IV. CONCLUSION

This study demonstrated the effectiveness of machine learning algorithms in building accurate and reliable crop recommendation systems using soil and environmental parameters such as nitrogen, phosphorus, potassium, pH, temperature, humidity, and rainfall. Traditional models, including Decision Trees, Logistic Regression, Naïve Bayes, SVM, and Random Forest, provided strong predictive results, with accuracies ranging from 90% to 99.09%. However, the findings clearly establish XGBoost as the most robust and reliable model, achieving the highest accuracy (99.31%), perfect precision (100%), and strong recall and F1-scores (99%). Its ability to capture complex, non-linear relationships, handle missing values, and minimize overfitting underscores its superiority over other models in the context of crop recommendation. By providing farmers with highly accurate predictions, XGBoost contributes to optimizing agricultural productivity, reducing crop failure risks, and supporting sustainable farming practices.

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