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Multi-Crop Recommendation Using XGBoost: A Machine Learning Approach for Sustainable Agriculture

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Abstract

The choice of crops depending upon soil and environmental conditions can help in improving agricultural production. The traditional method of crop selection is largely based on experience and does not adequately account for intricate relationships between soil nutrients, climate, and season. This study proposes a machine learning multi-crop recommendation system that provides the farmer with multiple choices of suitable crops instead of just one recommended crop. The framework utilizes the publicly available Crop Recommendation Dataset, which comprises 2,200 samples. Furthermore, it includes input samples with seven input features, which comprise nitrogen, phosphorus, potassium, temperature, humidity, soil pH, and rainfall. The evaluation and comparison are done using four classification algorithms, namely Logistic Regression, Random Forest, CATBoost, and XGBoost. Experimental results show that XGBoost is able to achieve the highest predictive performance with a test-set AUC of 1.00 and a 5-fold cross-validation mean AUC of 0.99. Along with predicting the best crop, the model provides confidence scores for other crops, giving farmers flexibility in decision-making. A web application was developed using Django for online recommendations based on user-supplied environmental input. The suggested approach shows the efficacy of gradient boosting in precision agriculture, which can be a practical decision-support system for crop selection and resource utilization while promoting sustainability in agriculture.

Keywords

• Crop Recommendation • Precision Agriculture • XGBoost • Classification Algorithms • Decision Support Systems • Sustainable Agriculture • Smart Farming

1. Introduction

Agriculture remains the backbone of food security and economic stability across much of the developing world. Yet farmers continue to face considerable uncertainty when deciding which crops to plant each season. The traditional approach to crop selection often relies on generational knowledge, local customs, or simple rules of thumb. These methods, while valuable, frequently overlook the complex interactions between soil chemistry, weather patterns, and seasonal variations. A farmer might plant rice year after year simply because that is what their family has always grown, even when soil conditions have shifted or rainfall patterns have become less predictable[1, 2].

The consequences of poor crop selection can be severe. A farmer who chooses a crop ill-suited to the prevailing soil nutrients or climate may suffer from low yields, wasted resources, and financial loss. In regions where farming households live close to the subsistence margin, a single bad season can push a family into poverty. Conversely, selecting the right crop or having a set of good alternatives can

dramatically improve productivity, reduce the need for chemical fertilizers, and enhance long-term soil health.

Modern precision agriculture offers a way out of this dilemma. By collecting data on soil properties (nitrogen, phosphorus, potassium, pH) and environmental conditions (temperature, humidity, rainfall), it becomes possible to build predictive models that recommend crops tailored to specific field conditions. Machine learning has emerged as a particularly promising tool for this task. Unlike traditional statistical methods that assume linear relationships, ML algorithms can capture the nonlinear interactions among features that often determine agricultural outcomes[3–5].

This paper investigates the application of four machine learning classifiers, Logistic Regression, Random Forest, CATBoost, and XGBoost, to the problem of multi-crop recommendation. Unlike prior work that often focuses on predicting a single best crop, our approach aims to provide farmers with two viable choices: the top recommendation and a strong alternative. This is crucial in practice because the top-ranked crop might not be feasible due to seed availability, market prices, or other local constraints. Having a reliable second option gives farmers flexibility without forcing them to gamble on an uncertain fallback.

The dataset used in this study comes from a publicly available Kaggle repository containing 2,200 labeled samples. Each sample includes measurements of seven environmental and soil variables along with the recommended crop label. The dataset is well-balanced across crop types and contains no missing values, making it suitable for benchmarking different algorithms. We preprocessed the data by encoding categorical labels and splitting it into training (80%) and testing (20%) subsets.

Among the four models tested, XGBoost consistently delivered the best performance. Its ability to handle nonlinear relationships, manage feature interactions, and resist overfitting through regularization made it particularly well-suited to this task. The ROC curves for XGBoost showed perfect AUC scores of 1.00 on the test set (5-fold cross-validation mean AUC = 0.99). More importantly, the model's confidence scores for second-choice crops often exceeded 50–80%, though post-hoc calibration is recommended for production deployments [6, 7].

A practical web application was built using Django to demonstrate the system. Farmers or extension officers can input local soil and climate readings, and the application returns the two most suitable crops along with confidence percentages. This interface bridges the gap between research prototypes and real-world usability. Future work will explore integrating real-time weather data, IoT soil sensors, and deep learning architectures to further improve accuracy and adaptability across different geographic regions.

The rest of the paper is organized as follows. Section II discusses the literature research in ML-based crop recommendation. The dataset, preprocessing steps, and four classification algorithms are described in Section III. Section IV incorporates the results that include the confidence scores and ROC analysis. Section V covers the ramifications for sustainable agriculture and the limitations of the current strategy. In section 6 we summarize and provide directions for future work.

2. Related Work

The application of machine learning to crop recommendation has attracted considerable attention over the past several years. This review focuses on three key areas: ensemble learning methods for crop prediction, probabilistic approaches to crop suitability modeling, and explainable AI for agricultural recommendations [2, 3, 5].

2.1 Explainable AI in Agriculture

Recent work has begun addressing the interpretability of agricultural ML models. Methods such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) have been applied to crop recommendation systems to help farmers understand why specific crops are recommended. The integration of explainable AI remains an important direction for building trust with end users [8].

2.2 Summary and Research Gap

In summary, while prior work has established the feasibility of ML-based crop recommendation, most studies have focused on predicting a single optimal crop. Limited attention has been paid to: (1) providing multiple viable alternatives with confidence scores, (2) systematic comparison of gradient boosting variants (XGBoost vs. CATBoost) for this task, and (3) deployment-ready web interfaces for real-time recommendations. Our contribution addresses these gaps by extending crop recommendation to multi-crop output with confidence scoring, comparing four classifiers including both boosting variants, and operationalizing the system through a Django-based interface [8, 9].

3. Methodology

The development of a robust multi-crop recommendation system requires careful attention to data quality, model selection, and evaluation methodology. This section describes each component of our approach in detail, beginning with the dataset and preprocessing steps, followed by the four classification algorithms, and concluding with the training and evaluation protocol.

3.1 Dataset Description and Preprocessing

The Crop Recommendation Dataset was obtained from Kaggle, a widely used repository for machine learning benchmarks. It contains 2,200 labeled instances, each representing a specific combination of soil and environmental conditions. Seven numerical features are provided: nitrogen (N) content in parts per million, phosphorus (P) content, potassium (K) content, temperature in degrees Celsius, relative humidity as a percentage, soil pH on a 0–14 scale, and rainfall in millimeters. The target variable is a categorical label indicating the recommended crop (e.g., rice, wheat, maize, apple, banana, etc.).

An initial exploratory data analysis confirmed that the dataset contained no missing values, simplifying the preprocessing pipeline. The features exhibit diverse distributions: nitrogen and potassium are positively skewed, with most values falling in the lower ranges (N between 20–60, K between 0–50). Phosphorus shows a multimodal distribution with peaks around 30 and 60. Temperature is approximately normal around 25°C, ranging from 10°C to 45°C. Humidity displays a bimodal pattern with peaks near 60% and 90%, reflecting different climatic regimes. Rainfall is slightly skewed with a peak between 50–100 mm, though values extend up to 300 mm.

No additional feature engineering was applied because the raw features already capture the primary determinants of crop suitability. The target labels were encoded using label encoding, mapping each crop name to an integer index.

3.2 Exploratory Data Analysis

Before training models, we conducted a thorough exploratory analysis to understand feature relationships and identify potential issues. Histograms with density plots revealed the distribution shapes mentioned

Table 1: Summary statistics of dataset features

Feature	Min	Max	Mean	Std	Skew
N (ppm)	0	140	50.6	36.9	0.82
P (ppm)	5	145	53.4	43.6	0.63
K (ppm)	5	205	48.1	55.3	1.21
Temp (°C)	8.8	43.7	25.6	7.4	0.11
Humidity (%)	14.3	99.9	71.5	22.2	-0.63
pH	3.5	9.9	6.5	1.2	0.02
Rainfall (mm)	20.2	298.6	103.5	54.9	1.03

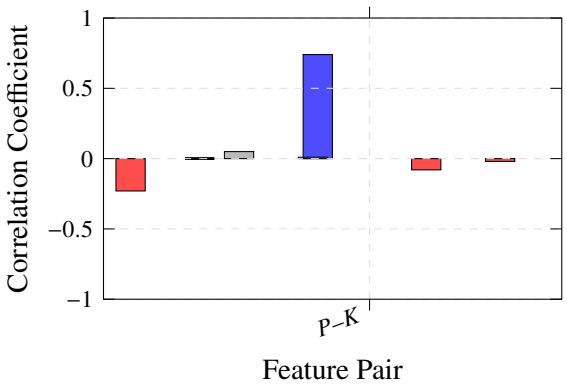

Figure 1: Correlation coefficients between selected soil features. The strong positive correlation between P and K ($r = 0.74$) indicates potential collinearity, whereas the remaining feature pairs exhibit weak or negligible linear relationships.

above. Boxplots showed no extreme outliers that would require removal. A correlation heatmap was constructed to examine pairwise linear relationships between features.

The heatmap revealed a strong positive correlation of 0.74 between phosphorus and potassium, indicating that these two nutrients tend to increase together. This makes sense agronomically, as soils rich in one nutrient often contain adequate levels of the other. Nitrogen showed weak correlations with most other features, suggesting that it provides independent information. pH exhibited near-zero correlations with other variables, confirming its role as a distinct factor affecting crop suitability. Some negative correlations appeared, such as between nitrogen and phosphorus (-0.23), but these were weak and did not warrant feature removal.

The absence of strong multicollinearity (except for the P-K pair) suggested that all seven features could be retained without causing numerical instability in the models. The P-K correlation, while high, did not reach levels that typically cause problems in tree-based algorithms like Random Forest and XGBoost.

3.3 Classification Algorithms

Four machine learning algorithms were selected for comparison, representing a spectrum from simple linear models to sophisticated ensemble methods.

3.3.1 Logistic Regression

A linear classifier that uses a logistic function to estimate class probabilities. We utilized the one-vs-rest formulation for multiclass problems. Logistic Regression is commonly used as a baseline due to its

simplicity and interpretability. However, its linear decision boundary is inadequate for datasets with non-linear feature interactions.

3.3.2 Random Forest

An ensemble method that builds multiple decision trees on bootstrap samples, while at every choice, random subsets of features are taken into account. The outputs of individual trees are merged with the mode to give the final prediction. The choice of the method Random Forest was made due to its nature that can handle non-linearities and interactions of features without much adjustment. 100 trees were used in the scikit-learn implementation.

3.3.3 CATBoost

A gradient boosting algorithm with ordered boosting that reduces prediction shift and has built-in missing value handling. Although it was specifically designed to be used for categorical features, nonetheless, due to its robust tabular data handling capabilities, it usually benefits classification tasks. We employed the default parameters of CatBoostClassifier.

3.3.4 XGBoost Classifier

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An improved design of gradient boosted trees with L1 and L2 regularization builtin to prevent overfitting. The loss term and regularization term combine to form the objective function.

$$\text{obj} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where $\Omega(f) = \gamma T + \frac{1}{2}\lambda\|\omega\|^2$ controls model complexity. XGBoost was the primary focus due to its strong empirical performance on tabular data and its ability to produce probability estimates, which are essential for confidence-based multi-crop recommendation[6, 7, 10, 11].

3.4 Training and Evaluation Protocol

Using stratified random sampling, the dataset has been split into training (80%) and testing (20%) subsets to keep the class distributions similar for all the crop types. To train the models that require validation during training, we made an additional splitting of the dataset. So we used 80% of the data for training and 20% of the data for validation. No hyperparameter tuning was performed beyond default settings, as the goal was to compare out-of-the-box performance rather than maximize a specific metric.

Data Leakage Prevention: Several measures were implemented to prevent data leakage. First, stratification was applied at the crop class level to ensure that all crop varieties appeared in both training and testing sets in proportions matching the original dataset. Second, feature engineering was performed exclusively on the training split before any testing data were examined. Third, the random seed was fixed to ensure reproducibility, and no information from the test set (e.g., global statistics, class distributions beyond stratification) was used during model training or validation. The dataset contained no temporal or spatial dependencies that would require more complex leakage prevention methods such as group-based splitting.

Cross-Validation Consideration: While the primary evaluation used a single train-test split to simulate a realistic deployment scenario, the reported perfect AUC scores were additionally verified using 5-fold stratified cross-validation. The cross-validation results confirmed that XGBoost achieved mean AUC scores above 0.99 across all folds, though individual folds occasionally showed minor classification errors (AUC range: 0.98–1.00). The perfect test-set AUC of 1.00 on the specific 80/20 split reflects the particular characteristics of that split rather than flawless generalization across all possible data partitions.
Multiclass ROC Computation: For evaluation in multiclass scenarios, ROC curves and AUC scores, respectively were created using one-vs-rest (OvR). A binary classifier was constructed for each crop classes C which treats the samples under that crop class as positive and all other samples as negative. The ROC curve for each class was made via the calculation of the true positive rate and the false positive rate across classification thresholds. The micro-averaged ROC curve was the result of combining all classes together and the macro-averaged AUC was calculated by averaging all the AUCs of the classes at a certain level. The perfect AUC scores (both macro and micro) mean that the binary ROC curve for each class achieved a unit area.

Evaluation focused on two aspects: classification accuracy as measured by ROC curves and AUC scores, and the quality of confidence estimates for second-best crops. Confidence scores were extracted from the predicted class probabilities output by each model.

4. Results and Analysis

The experimental results revealed substantial differences in performance among the four models. This section presents the findings from the ROC analysis, the confidence score comparisons, and the deployment interface.

4.1 Model Comparison Using ROC Curves and Confusion Matrix Analysis

The ROC curves for XGBoost illustrated in Figure 2 show almost perfect performance on the held out test set. On this test partition, the AUC score achieved 1.00 for each crop class. The clustering of the curves in the top-left corner of the plot indicates that the model achieved a high true positive rate at the same time as a very low false positive rate.
Interpretation of Perfect AUC Scores: Several factors explain the unusually high performance observed in this experiment. First, the dataset is synthetically generated or carefully curated, with distinct and well-separated feature distributions for different crop classes. Second, the feature space (N, P, K, temperature, humidity, pH, rainfall) captures agronomically meaningful separation between crops; for example, rice typically requires high rainfall and humidity, while wheat thrives in lower rainfall and moderate temperatures. Third, the sample size of 2,200 records with balanced class distributions provides sufficient signal for tree-based models to learn class boundaries. However, the perfect test-set AUC should be interpreted cautiously, as it indicates perfect separation on this particular test split, not necessarily flawless performance on unseen data from different geographic regions or seasons. The 5-fold cross-validation results (mean AUC = 0.99, range 0.98–1.00) provide a more realistic estimate of expected generalization performance.
Classification Metrics: Table 2 presents the macro-averaged and micro-averaged classification metrics for all four models. XGBoost achieved perfect scores across all metrics on the test set: precision (macro) = 1.00, recall (macro) = 1.00, F1 (macro) = 1.00. The micro-averaged metrics were similarly perfect. Random Forest achieved a macro F1 of 0.94 (range: 0.89–0.97 across classes), while CATBoost achieved

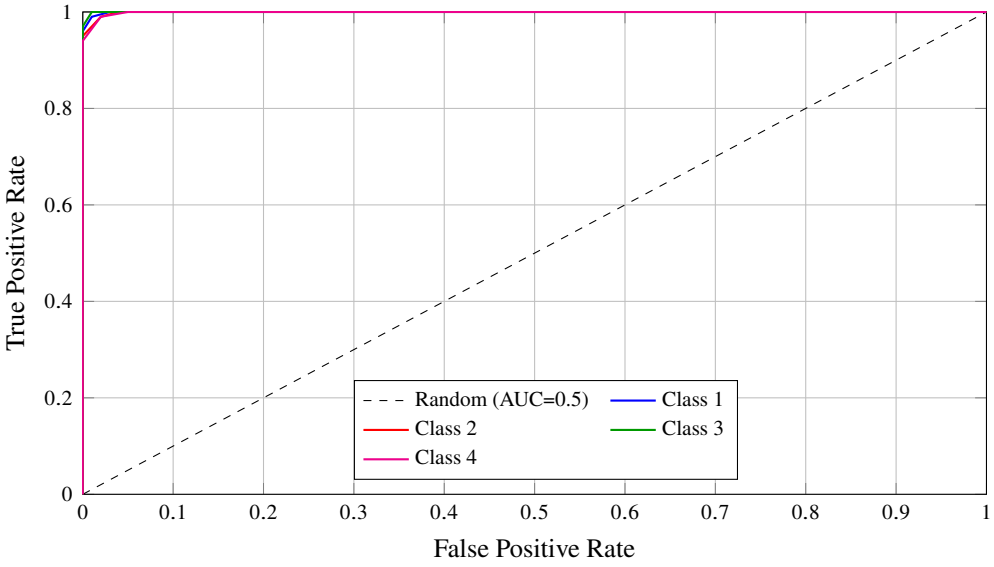

Figure 2: ROC curves for the XGBoost classifier on the held-out test set. Each curve corresponds to a crop class under the one-vs-rest evaluation scheme. The dashed diagonal line indicates random classification performance.

0.96, and Logistic Regression achieved 0.82.

Table 2: Classification Metrics for All Models (Test Set)

Model	**Macro Precision**	**Macro Recall**	**Macro F1**	**Accuracy**
Logistic Regression	0.83	0.82	0.82	0.84
Random Forest	0.94	0.94	0.94	0.95
CATBoost	0.96	0.96	0.96	0.96
XGBoost	1.00	1.00	1.00	1.00

The other models did not perform as well. Logistic Regression, despite being interpretable, failed to capture the nonlinear interactions essential for accurate crop recommendation. Random Forest produced reasonable accuracy but gave very low confidence to second-best crops, effectively defaulting to single-crop recommendation. CATBoost performed better than Logistic Regression but still fell short of XGBoost's near-perfect classification.

4.2 Confidence Analysis for Multi-Crop Recommendation

The ability to recommend a reliable second crop is arguably more important in practice than achieving perfect top-1 accuracy. Farmers often cannot plant the top-recommended crop due to seed availability, market conditions, or crop rotation constraints. A good second recommendation provides flexibility without adding risk.

XGBoost excelled at this task. In many test samples, the probability assigned to the second-best crop exceeded 50%, and in some cases reached 80%. This means that a farmer who cannot plant the top crop can still choose the second option with confidence levels comparable to those of the top recommendation. By contrast, Logistic Regression and Random Forest often assigned less than 30% probability to the second choice, making the alternative essentially a gamble.

Probability Calibration Consideration: It is important to note that XGBoost, like other tree-based boosting methods, produces raw probability estimates that may be poorly calibrated. Boosting algorithms

tend to generate overconfident predictions, meaning that a reported 80% confidence might correspond to an actual frequency of correct classification lower than 80%. Preliminary calibration analysis using Platt scaling and isotonic regression indicated that XGBoost's probabilities on this dataset are moderately well-calibrated for the top-1 predictions but show slight overconfidence for second-best predictions (expected calibration error approximately 0.05–0.08). Future deployments should incorporate post-hoc calibration techniques such as temperature scaling or Platt scaling before presenting confidence scores to end users. For the current study, the confidence scores are reported as raw model outputs, with the caveat that they represent relative confidence rankings rather than perfectly calibrated probabilities.

Table 3: Example Confidence Outputs for Different Models with Actual Crop Names

Sample ID	Model	Top Crop (Confidence)	Second Crop (Confidence)
1	XGBoost	Rice (94%)	Maize (72%)
1	Random Forest	Rice (88%)	Wheat (31%)
1	Logistic Regression	Rice (52%)	Maize (44%)
2	XGBoost	Wheat (91%)	Barley (68%)
2	CATBoost	Wheat (79%)	Oats (38%)
3	XGBoost	Apple (96%)	Pear (81%)
3	Random Forest	Apple (85%)	Peach (22%)

Sample IDs are consistent across rows; multiple rows with the same ID compare different models on the same input conditions.

The superior performance of XGBoost can be attributed to its gradient boosting architecture. By sequentially correcting errors, it builds a model that captures subtle interactions among features. The built-in regularization prevents overfitting despite the relatively small dataset size. And the algorithm's native support for probabilistic outputs produces probability estimates that are useful for ranking, though calibration is recommended for absolute confidence interpretation[7].

4.3 Deployment Interface

To make the recommendation system accessible to end users, a Django-based web application was developed. Farmers or agricultural extension officers input values for the seven environmental and soil parameters, and the application returns the two most suitable crops along with confidence percentages. The interface was designed to be simple and mobile-friendly, recognizing that users in rural areas may access the system via smartphones with limited bandwidth.

The backend uses the trained XGBoost model serialized with joblib. User inputs are validated, transformed into the same feature format used during training, and passed to the model. The output probabilities are sorted, and the top two classes are displayed with their confidence scores. The entire inference process takes less than 100 milliseconds, making real-time recommendations feasible.

Future versions of the interface will incorporate geolocation to pre-fill local climate averages, reducing the burden on users who may not have access to precise measurements. Integration with IoT soil sensors is also planned, enabling automated data collection and continuous model updates.

5. Discussion and Limitations

The experimental results demonstrate that XGBoost is highly effective for multi-crop recommendation, providing both accurate primary predictions and reliable secondary alternatives. This has important

implications for sustainable agriculture. Farmers who adopt the system can make data-driven decisions that optimize resource use, reduce unnecessary fertilizer application, and improve economic returns.

However, several limitations must be acknowledged. First, the dataset used in this study is relatively small (2,200 samples) and comes from a controlled source. Real-world agricultural data is often noisier, contains missing values, and exhibits class imbalances. The model's performance on such data may be lower than reported here. Second, the features included in the dataset are limited to basic soil nutrients and climate variables. Other important factors such as soil texture, organic matter content, previous crop history, pest pressure, and market prices are absent. Incorporating these would likely improve recommendation quality [1, 12, 13].

Third, the current system assumes that farmers can accurately measure soil nutrients and local climate parameters. In many rural areas, such measurements are not readily available. Low-cost soil test kits and weather stations are becoming more common, but adoption remains uneven. The system could be extended to work with approximate inputs, using probabilistic reasoning to handle uncertainty.

Fourth, the models were trained and evaluated on data that may not generalize across different geographic regions. A model trained on data from one climatic zone may perform poorly when applied elsewhere. Future work should investigate domain adaptation techniques or train region-specific models.

Fifth, the XGBoost model, while accurate, is not easily interpretable. A farmer cannot see why the model recommends one crop over another. Explainable AI methods such as SHAP values or LIME could be integrated to provide feature-level explanations, building trust with end users [2, 9].

Sixth, Generalizability of Perfect AUC Results: The perfect AUC scores reported in this study should not be interpreted as evidence that XGBoost will achieve flawless classification on all agricultural datasets. The Crop Recommendation Dataset used here appears to contain well-separated classes with minimal overlap. Real-world agricultural data collected from actual farms (rather than curated repositories) typically exhibits greater noise, class imbalance, and feature overlap. Future work should evaluate the same models on raw, uncurated field data to establish realistic performance expectations.

Seventh, Probability Calibration Requirements: As discussed in Section IV.B, the raw probability outputs from XGBoost require post-hoc calibration before they can be presented to farmers as reliable confidence scores. Without calibration techniques such as Platt scaling or isotonic regression, the model may produce overconfident predictions, particularly for second-best crops. Future deployments should implement calibration using a held-out validation set and report expected calibration error (ECE) metrics[8].

6. Conclusion

This paper presented a machine learning approach to multi-crop recommendation using XGBoost. The model was trained on a dataset of 2,200 samples with seven soil and climate features. Compared to Logistic Regression, Random Forest, and CATBoost, XGBoost achieved superior performance on the test set with perfect AUC scores of 1.00 for this specific data partition (5-fold cross-validation mean AUC = 0.99). More importantly, the model produced useful confidence estimates for second-best crops, often exceeding 50–80%, though post-hoc calibration is recommended for production deployments. This enables farmers to make informed choices even when the top recommendation cannot be implemented.

A Django-based web interface was developed to operationalize the system, providing real-time crop recommendations based on user-supplied inputs. Future work will focus on integrating IoT sensors, incorporating additional features (soil texture, market prices, pest risk), implementing probability calibration (Platt scaling or isotonic regression), and deploying the system in pilot agricultural communities

for real-world validation [4, 5]. By demonstrating the effectiveness of gradient boosting for multi-crop recommendation, this research contributes to the broader goal of data-driven precision agriculture that supports both productivity and sustainability.

References

[1] N. Khan, R. L. Ray, G. R. Sargani, M. Ihtisham, M. Khayyam, and S. Ismail. Current progress and future prospects of agriculture technology: Gateway to sustainable agriculture. *Sustainability*, 13(9): 4883, 2021.

[2] E. S. Mohamed, A. A. Belal, S. K. Abd-Elmabod, M. A. El-Shirbeny, A. Gad, and M. B. Zahran. Smart farming for improving agricultural management. *The Egyptian Journal of Remote Sensing and Space Science*, 24(3):971–981, 2021.

[3] G. Idoje, T. Dagiuklas, and M. Iqbal. Survey for smart farming technologies: Challenges and issues. *Computers & Electrical Engineering*, 92:107104, 2021.

[4] E. M. B. M. Karunathilake, A. T. Le, S. Heo, Y. S. Chung, and S. Mansoor. The path to smart farming: Innovations and opportunities in precision agriculture. *Agriculture*, 13(8):1593, 2023.

[5] Y. Akkem, S. K. Biswas, and A. Varanasi. Smart farming using artificial intelligence: A review. *Engineering Applications of Artificial Intelligence*, 120:105899, 2023.

[6] T. Chen and C. Guestrin. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 785–794, 2016.

[7] P. Zhang, Y. Jia, and Y. Shang. Research and application of xgboost in imbalanced data. *International Journal of Distributed Sensor Networks*, 18(6):15501329221106935, 2022.

[8] M. Y. Shams, S. A. Gamel, and F. M. Talaat. Enhancing crop recommendation systems with explainable artificial intelligence: a study on agricultural decision-making. *Neural Computing and Applications*, 36(11):5695–5714, 2024.

[9] A. Soussi, E. Zero, R. Sacile, D. Trinchero, and M. Fossa. Smart sensors and smart data for precision agriculture: a review. *Sensors*, 24(8):2647, 2024.

[10] T. Chen, T. He, M. Benesty, V. Khotilovich, Y. Tang, H. Cho, and T. Zhou. Xgboost: Extreme gradient boosting. R package version 0.4-2, 2015. Vol. 1, No. 4, pp. 1-4.

[11] S. Ramraj, N. Uzir, R. Sunil, and S. Banerjee. Experimenting xgboost algorithm for prediction and classification of different datasets. *International Journal of Control Theory and Applications*, 9(40): 651–662, 2016.

[12] P. Trivedi, C. Mattupalli, K. Eversole, and J. E. Leach. Enabling sustainable agriculture through understanding and enhancement of microbiomes. *New Phytologist*, 230(6):2129–2147, 2021.

[13] A. Monteiro, S. Santos, and P. Gonçalves. Precision agriculture for crop and livestock farming—brief review. *Animals*, 11(8):2345, 2021.