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Advancing crop recommendation system with supervised machine learning and explainable artificial intelligence

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Agriculture is one of the most important sectors, as many countries' economies depend on it. At the same time, meeting the food requirements of the increasing population is also challenging, as the land for agriculture is curtailed everywhere. Thus, there is a need to increase crop productivity, and machine learning (ML) techniques are very helpful in recommending suitable crops based on soil, weather, and other parameters. This work presents a crop recommendation model based on Gradient Boosting trained on a crop recommendation dataset. The model can accurately recommend crops based on nutrients and environmental parameters. The proposed method shows promising results in agricultural crop recommendation, with a 99.27% accuracy rate, 99.32% precision, 99.36% recall, and 99.32% F1 score. This proposed model is pertinent because, further, the amalgamation of Explainable Artificial Intelligence (XAI) helps to provide detailed explanations to give agronomists a reliable and steady tool for fast and accurate recommendation of crops.

Keywords Agriculture, Crop recommendation, Explainable artificial intelligence, Gradient boosting, Machine learning

Agriculture plays a multifaceted role in augmenting social well-being, the development of rural areas, environmental sustainability, poverty reduction, food security, and is also interlinked with several United Nations Sustainable Development Goals. According to UN forecasts, there will be 8.1 billion people in the world by the year 2030, 8.5 billion by 2030, and 9.9 billion by the year 2050[1]. As the global population is continuously increasing, there is a vigorous demand for both food and employment opportunities[2,3]. Thus, the agriculture sector has an imperative role in nourishing the growing population worldwide[4,5]. Agronomists all over the world are working on novel techniques and methods for enhancing crop yields. In the past few decades, farmers have increased the use of chemicals such as pesticides, herbicides, and fertilizers for the increase in crop productivity but at the same time, these chemicals produce negative impacts on the crops as well as soil[6,7]. The weather conditions, water availability and quality, soil fertility, crop pricing, and other related factors should be taken into consideration for the betterment of crops[8,9].

Thus, there is a need to find sustainable solutions for enhancing crop yields and for this purpose, data can play a vital role. In the present time, data is produced everywhere and is exponentially increasing. The emerging technologies can be employed for the improvement in crop productivity by ignoring traditional farming and moving towards precision agriculture by utilizing the data related to soil nutrition, crop health, field variability, and meteorological factors[10,11]. Precision Agriculture is often used for the optimal use of resources to increase crop productivity and at the same time to minimize wastage and costs[12–15]. It heavily relies on the advancements of information technology, like sensors, satellite imagery, drones, and other cutting-edge methods for the collection of data. Furthermore, for data-driven decision-making learning in agriculture, advanced analytical techniques of Machine Learning (ML) have been utilized by various researchers. The use of ML optimizes various aspects of agriculture by utilizing vast amounts of data collected through precision farming. ML algorithms like random forests, decision trees, gradient boosting (GB), naïve bayes (NB), support vector machine (SVM), and logistic regression work on complex and gigantic datasets for the extraction of meaningful insights and for

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making decisions and predictions. These algorithms may be used to extract trends, correlations, and patterns from agricultural data to suggest crops for a certain growing season.

The farmers need to choose the right crop, otherwise, it leads to a decrease in crop productivity and financial losses[16,17]. Further, there is a need to consider the various parameters including soil conditions, and meteorological factors for high productivity and undoubtedly, ML can be quite useful to recommend the right crop for sowing according to these factors. This will recommend farmers the right crop as per the conditions that will help increase productivity in the realm of agriculture. Thus, by employing the techniques and algorithms of ML[18], it is possible to reduce the use of pesticides and chemicals and at the same time, it can be useful for increasing crop yields, optimizing resource allocation, and enhancing agriculture sustainability.

Various researchers have developed crop recommendation systems using different aspects[19]. have proposed a crop recommender system using the Mamdani Fuzzy Inference model where they predict the production of rice based on three parameters rainfall, humidity, and temperature. Using MapReduce and K-means clustering[20], introduced a crop recommendation system on multiple crops and production per area in addition to the type of soil and seeds, depending on the varieties used in a specific area. In another study[21], worked on soil and meteorological parameters by utilizing the models, viz. KNN, DT, RF, XGBoost, and SVM for the recommendation of the crops, where these models achieved an accuracy of 96.36%, 86.64%, 97.18%, 95.62%, and 87.38%. The many parameters, such as location, season, area, and production, were employed in addition to assessment measures including Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared were used by[22] for improving agricultural practices and enhancing crop recommendation systems with explainable artificial intelligence (XAI). For accurate recommendations to the farmers and to promote sustainable farming[23], has presented a recommendation system that utilizes two ML algorithms, Random Forest and KNN, with accuracy values of 98% and 96%, respectively.

To help farmers and the agriculture sector achieve high crop productivity, a crop recommender system that uses ML algorithms based on important nutrients found in soil, like nitrogen (N), phosphorus (P), and potassium (K), as well as meteorological factors like temperature, humidity, wind, and rainfall, can be used[24]. The present work will focus on providing recommendations based on these factors for the upcoming season, based on the best ML-based model utilized for the study. Among the ten ML methods, gradient boosting (GB) yields the highest results and is used to categorize numerous crops to suggest the best crop for the future season. Furthermore, it has been shown that the ideal model for guaranteeing interpretability and transparency in agricultural decision-making is XAI. XAI is used for providing detailed explanations in a manner that is understandable to humans[25]. It provides a better understanding of the outcomes of ML algorithms. Thus, by exploiting explainable agricultural intelligence, the current work optimizes crop recommendations by integrating ML algorithms, ensuring transparency, trustworthiness, and accountability in decision-making processes. The key gaps identified in existing studies are outlined below to highlight areas for improvement and future research.

1. Most existing studies rely on a single supervised machine learning algorithm, lacking a comparative analysis across multiple classifiers.
2. Explainable AI techniques such as LIME have not been employed, limiting the interpretability and transparency of model predictions.
3. Gradient Boosting, a powerful ensemble method, has not been adequately explored in prior works for the given problem domain.
4. Existing studies do not conduct detailed exploratory data analysis (EDA) or provide class-wise performance evaluation, especially for datasets with a large number of classes (e.g., 22 classes).

This paper presents an experimental study to optimize crop recommendation by utilizing various ML techniques and XAI. "Literature review" includes a detailed literature study that highlights existing research. In "Materials and methods", the methods and methodology are detailed, encompassing various aspects such as dataset description and data analysis through various graphs. In addition, the suggested methodology is described in "Proposed research methodology". "Experiment evaluation and results" describes the experimental study conducted to evaluate the performance of various ML algorithms. Moreover, "Comparative analysis" gives the comparative analysis of various algorithms used in the present study and also with the existing works, elucidating the strengths of the proposed method. Furthermore, in "XAI (LIME)", XAI is used on the best model for its explanation. In Discussion, the findings are discussed, considering implications for further research. Finally, "Conclusion and future work" highlights future research directions and stresses the significance of ongoing agricultural improvements.

Literature review

The present section examines existing research about the use of emerging technologies for crop recommendation systems in particular and agriculture in general.

To optimize crop production[4], has proposed a crop prediction model that uses 15 ML algorithms, such as Bayes Net, Naïve Bayes, Multilayer Perception, Simple Logistic, Logistic Regression, IBK, KSTAR, LWL, Ada BoostM1, Regression, Decision Table, Random Forest, Random Tree, Hoeffding Tree, and J48, to help inform decision-making. The crop recommendation dataset has been collected from Kaggle, having 2200 records and 22 classes. To facilitate training and testing, the dataset has been partitioned into a 70:30 ratio. Out of these 15 algorithms, Bayes Net produced an accuracy of 99.59%, kappa of 0.995, MAE of 0.0010, RMSE of 0.018, RAE of 1.14, and RRSE of 8.64. The building time and test time of Bayes Net are 0.48 and 0.25 s respectively[24]. have worked on the same dataset and used two methods, including RBF neural network with SMO and SMO algorithm for network optimization. For training and testing, the dataset has been divided into 80:20 ratios. The RBF model's accuracy was 91.5%, whereas the RBF model with SMO had a 98.2% accuracy rate. A method for recommending agricultural practices based on temperature, water requirements, farm size, and soil type helps estimate which crops and fertilizers will be needed for a given season. Multi-criteria CRS showed accuracy, precision, recall, and F1-score of 95.85%, 92%, 88%, and 89.9%, respectively, among the five prediction approaches used. The other four methods included SVM, Neural Network, Random Forest, and FRS[26].

Compared to on-field surveys, remote sensing data and methodologies are also useful for crop recommendation[27]. Remote Sensing data has been used by[28] with three methods including PBIL-optimized neural networks (NNs), multiple linear regression (MLR), and a suggested Artificial Neural Network (ANN) are utilized to estimate agricultural productivity. RMSE, average difference, and correlation coefficient for corn and soybeans have been used to assess the approaches' performance. The outcomes demonstrated that compared to MLR and ANN, the suggested ANN optimized using PBIL produced superior results[29]. have collected a dataset of three cultivation crops viz. jowar, paddy, and ragi from the Economics and Statistics Department, Government of Karnataka, for crop yield prediction. Five methods, including CNN, DNN, RNN, GAN, and proposed LSTM with Attention Mechanism, have been utilized and achieved an accuracy of 83.78%, 86.39%, 89.56%, 91.67%, and 94.24%, respectively. The LSTM with Attention Mechanism has also exhibited fewer errors in terms of R2 as 0.43, MAE as 0.131, MSE as 0.054, and RMSE as 0.232. Inter-fused ML with the Advanced Stacking Ensemble model (IML-ASE) has been proposed by[30] for precise crop prediction. With seven characteristics, the secondary dataset for the crop recommendation system was gathered from Kaggle. As base learners, six algorithms such as DT, NB, RF, XGBR, SVM, ABR, and ABR were used. The meta-learner then received the average prediction outcomes from these algorithms to determine the final prediction. Metrics including mean absolute error (0.23%), mean square error (2.73%), root mean square error (1.65%), recall (97.12%), specificity (100%), precision (97.03%), and F1-score (97.09%) were used to evaluate the model's performance. Utilizing six distinct ML algorithms, which are Decision Tree, Naïve Bayes, Support Vector Machine, Logistic Regression, Random Forest, and XGBoost[18], recommended the best harvest. XGBoost was the most successful of these six algorithms and was finally used for recommendation. To forecast the best crops with an accuracy rate of more than 95%, several crop recommendation models have been created using Logistic Regression, Decision Tree, Random Forest, K-Nearest Neighbor, Naïve Bayes, SVM, and Neural Networks. This is carried out to safeguard farmers' welfare and to assist the agriculture industry's decision-making process with knowledge[31]. The best among them are Random Forest and Naïve Bayes, exhibiting 99.5% accuracy.

For increasing the productivity of crops in the agriculture sector, a crop recommendation system can be helpful to a large extent. In this regard, a crop recommendation system has been proposed by[32] where they applied 5 different ML algorithms, including Gradient Boosting, Random Forest, Naïve Bayes, KNN, and Decision Tree. Gradient Boosting, one of these algorithms, yielded a 98.18% accuracy rate when proposing the best crop to plant on the specified soil. A fuzzy deep learning (DL) based crop yield prediction model has been developed by[33] using the Vellore district's dataset of rice crops, which has 29 parameters. K-fold cross-validation has been used to separate the data into training and validation sets. Other deep learning models, such as LSTM, GBDBN, BANN, MLNN, SLNN, RNN, and GAN, have also been compared to the suggested model (fuzzy DBM), and RBM fared better with 92% accuracy. Under the regime of NPK, soil pH, and 3 climatic parameters[34], suggested an ML-based proposal for crop growing, both agricultural and horticultural. The Indian Chamber of Food and Agriculture gathered the dataset over a period, which consists of 2100 records. The training and test sets are split 70:30 between 11 agricultural and 10 horticulture crops. XGBoost, the optimal model, has a total accuracy of 98.51%, surpassing the results of other commonly used methods such as Random Forest (96.98%), Decision Tree (87.62%), Support Vector Machine (95.71), and K-nearest neighbor (92.24). Similarly[35], has presented a web-based crop recommendation system utilizing four ML algorithms: Random Forest, Decision Tree, XGBoost, and Logistic Regression. for the recommendation of crops. Random Forest fared the best among these algorithms, achieving an accuracy of 98.86%. Through crop recommendations[36], offered a predictive method for raising agricultural output in Morocco. The 1800 records in the dataset were split into training (70%) and test (30%) groups. Five distinct machine learning algorithms, which are Random Forest, Naive Bayes, Support Vector Machine, Logistic Regression, and Decision Tree, were also trained using the training dataset. Random Forest outperformed the others in terms of accuracy (97%), precision (97%), recall (97%), and F1-score (97%). An ensemble ML-based recommendation system for effective prediction of suitable agricultural crop cultivation has been proposed by[37] and The information covering several seasons was gathered from four distinct Bangladeshi agricultural groups. The suggested model, K-nearest Neighbor Random Forest Ridge Regression (KRR), outperformed the other training models in terms of recommendation performance.

To identify weeds and crops in two target fields of strawberry and pea, a method was developed by[38]. The study's goal is to ascertain the most accurate technique for weed identification in these two agricultural sectors. The study's goal is to ascertain the most accurate technique for weed identification in these two agricultural sectors. The average weed identification accuracy of the developed method is 95.3%, which is better than the accuracies of Yolo-v3, Faster R-CNN, KNN, and SVM[39]. tried to diagnose deficiency of nutrients, including potassium (K), nitrogen (N), and phosphorus (P) in rice crops by applying various DL models. The five pre-trained models have been modified by adding a few layers to improve the prediction performance. Out of five modified pre-trained models, three models including modified DenseNet169, DenseNet201, and InceptionV3, have been chosen for improving the performance by making their ensemble using weighted averaging. Outperforming all previous models, the authors proposed the DECNN ensemble model produced results of 98.33% accuracy, 98% precision, 98% recall, and an F1-score. By using data mining[40], outlined an algorithm, namely Adaptive Lemuria, for the prediction of crops using agricultural data collected from various government departments. In terms of performance, this algorithm outperformed SVM, CLARA, Decision Tree, DBSCAN, KNN, K-means, and PAM. Metrics such as precision (97%), recall (96.2%), f-measure (96.49%), and accuracy (98.35%) were among the metrics that showed improvement. For the recognition of agricultural pests automatically, a mobile application has been proposed by[41] using DL. The public IP102 dataset of pest images, along with the BP neural network, SSD MobileNet, and the proposed faster R-CNN, has been used for recognizing pest images. Among these three methods, the proposed faster R-CNN classifier showed better performance and achieved an accuracy of 98.9%. This algorithm outperformed CLARA, DBSCAN, KNN, SVM, Decision Tree, K-means, and PAM in terms of accuracy, recall, f-measure, and precision, scoring 98.35%, 96.2%, and 97%, respectively.

Materials and methods

This section outlines the dataset source, structure, and preprocessing steps, followed by exploratory analysis to identify key patterns and relationships. It then describes the supervised machine learning algorithms applied and concludes with the proposed research methodology that integrates data processing, model training, and interpretability.

Dataset description

The dataset used for this study is sourced from Kaggle[42]. It consists of 2,200 samples with 8 features and no missing values. This dataset is designed for multi-class classification with 22 distinct crop categories. The features in the dataset are categorized into soil nutrients and meteorological variables. The three nutrients found in soil are potassium (K), phosphorus (P), and nitrogen (N). Meanwhile, the meteorological features comprise temperature (in degrees Celsius), humidity (as a percentage), pH level, and rainfall (measured in millimeters). Rice, chickpeas, pigeon peas, grapes, papaya, mung beans, lentil, pomegranate, banana, moth beans, watermelon, black gram, mango, kidney beans, cotton, muskmelon, black gram, orange, maize, coconut, jute, apple, and coffee are among the crop labels included in the dataset. The research challenge is by nature a multi-class classification job given these labels.

Exploratory data analysis

Exploratory Data Analysis (EDA) is an essential first step in comprehending the structure of a dataset, finding patterns, and summarizing its key. It involves visualizing the distribution of features and examining relationships between them to gain insights that can inform model development. Through EDA, one can detect potential anomalies, assess feature interactions, and understand the underlying patterns that may influence crop recommendations.

Pair plot

An efficient visual aid for examining pairwise correlations between several characteristics in a dataset is a pair plot. Pair plots may be used to find trends, clusters, and correlations by comparing each feature against every other feature. Additionally, they enable the display of class separability between the various crop categories. Figure 1 represents the pairwise relationships between seven features of the dataset, showing patterns and relationships across the 22 crops (22 class labels).

Joint plot

Joint plots, which combine scatter plots and histograms, offer a thorough understanding of the connection between two continuous variables. They provide both the individual distributions along each axis and the correlation between the variables, providing a dual viewpoint. A greater comprehension of the interactions between the traits in various crop classes is made possible by this method. For instance, Fig. 2 illustrates the joint plot of rainfall and humidity, showing their relationship across the 22 crop classes. To optimize crop suggestions, patterns and correlations that may be crucial can be found with the use of this graphic.

Correlation between features

To determine which factors may be very important or redundant, correlation analysis evaluates the direction and strength of the linear connection between pairs of attributes. This data is essential for feature selection and dimensionality reduction since it makes it easier to determine which features have the most effects on crop type prediction. Potential multicollinearity problems can be found and the characteristics used for model training can be influenced by analyzing the correlation matrix. Figure 3 represents the correlation matrix for the features of the dataset, highlighting the strength of relationships between soil nutrients, meteorological factors, and their combined effect on different crop classes.

Supervised machine learning algorithms

An approach known as supervised machine learning trains the model using labeled data, which means that every training sample has both the input feature and the matching output label. Learning an input-to-output mapping that can be applied to fresh, unobserved data predictions is the aim. This work used ten supervised learning algorithms to categorize twenty-two crop labels. K-Nearest Neighbors (KNN) offers interpretability and simplicity by classifying occurrences according to the majority label among the nearest neighbors. It is highly sensitive to feature scaling and may struggle with high-dimensional data. Decision Tree (DT) builds a model using tree-like decisions, allowing for easy visualization of the classification process. However, it can be prone to overfitting if not properly pruned. Random Forest (RF) enhances decision trees by aggregating multiple trees to improve accuracy and control overfitting. This ensemble method provides robustness and reduces variance but may require considerable computational resources. With high independence assumptions between features, Naïve Bayes (NB) implements the Bayes theorem and is appropriate for probabilistic classification. Even with its irrational independence assumption, it may perform very well given its simplicity. Support Vector Machine (SVM) effectively divides classes into distinct groups by determining the best hyperplane in high-dimensional environments. By applying kernel methods, it can handle non-linear interactions, although it might require a lot of computing power. Logistic Regression (LR) models the probability of class membership

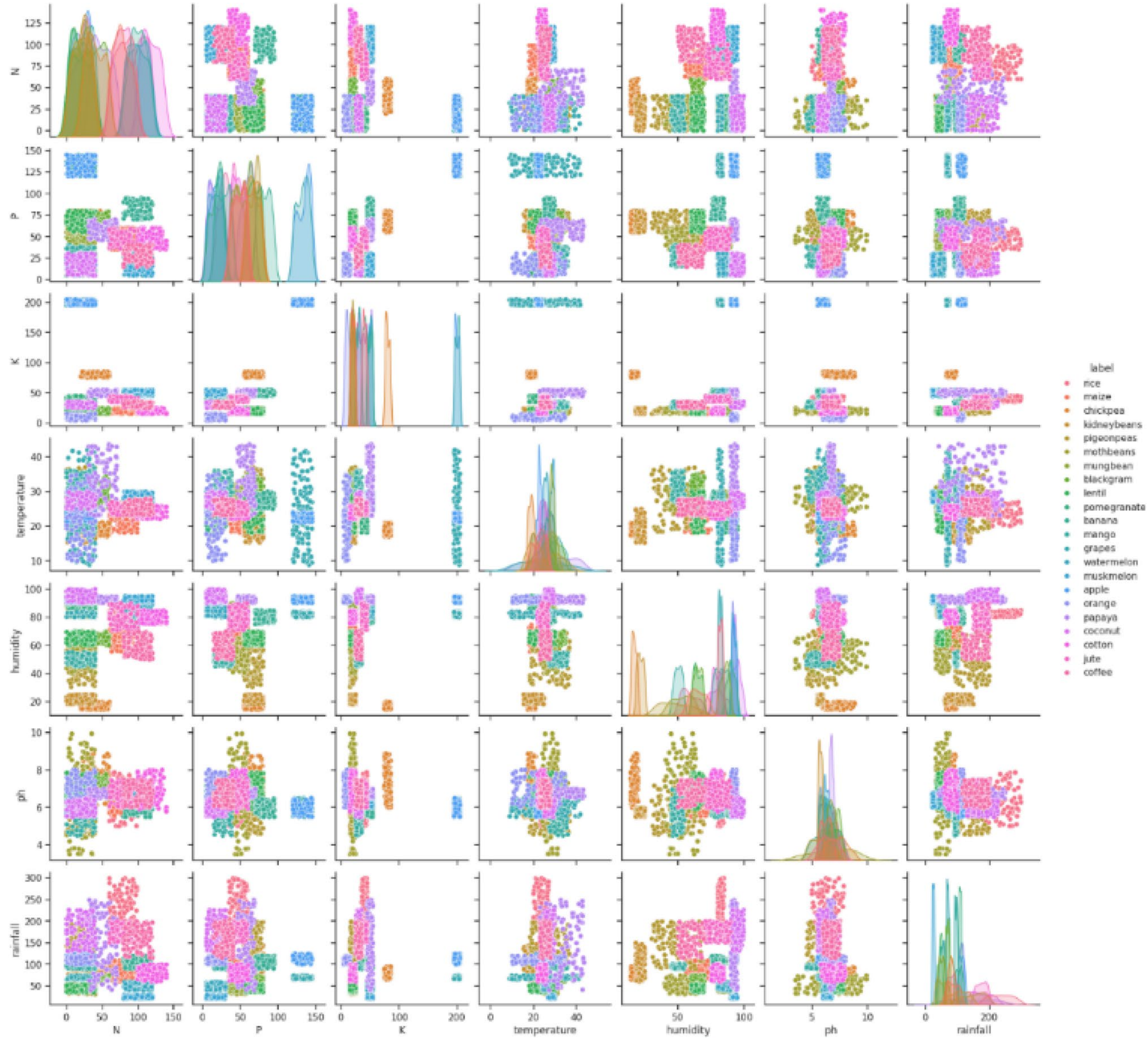

Fig. 1. Pair plot.

through a logistic function, offering a straightforward and interpretable approach. It is particularly useful for binary classification but can be extended to multi-class problems. Neural Network (NN) uses interconnected nodes (neurons) to model complex relationships, capable of capturing intricate patterns. It requires careful tuning of hyperparameters and can be prone to overfitting if not regularized. Gradient Boosting (GB) improves prediction performance by iteratively building models to fix prior models' flaws. Although quite successful, this strategy might be susceptible to outliers and noisy data. To optimize class separability, a crucial property for dimensionality reduction, Linear Discriminant Analysis (LDA) projects feature onto a lower-dimensional space. It may not always be true that classes are normally distributed and have identical covariance matrices. By simulating class-specific covariance matrices, Quadratic Discriminant Analysis (QDA) expands on LDA and provides more adaptable decision bounds. When there are notable differences in the spread of class distributions, this method works well.

Proposed research methodology

The research methodology for this study is structured into five distinct steps, as illustrated in Fig. 4 to ensure a comprehensive approach to crop recommendation using ML.

Step 1: Data Input and Loading: The process begins by loading the crop recommendation dataset from a CSV file. This dataset, which consists of 2,200 entries with 8 features, is prepared for further analysis.

Step 2: EDA, **Data Preprocessing**, **and Data Partitioning**: Following data loading, EDA is conducted to understand the dataset's characteristics. Then, data preprocessing involves checking for and addressing any null values, missing data, outliers, and noisy entries. After that, a 75–25% split of the dataset is made into training and

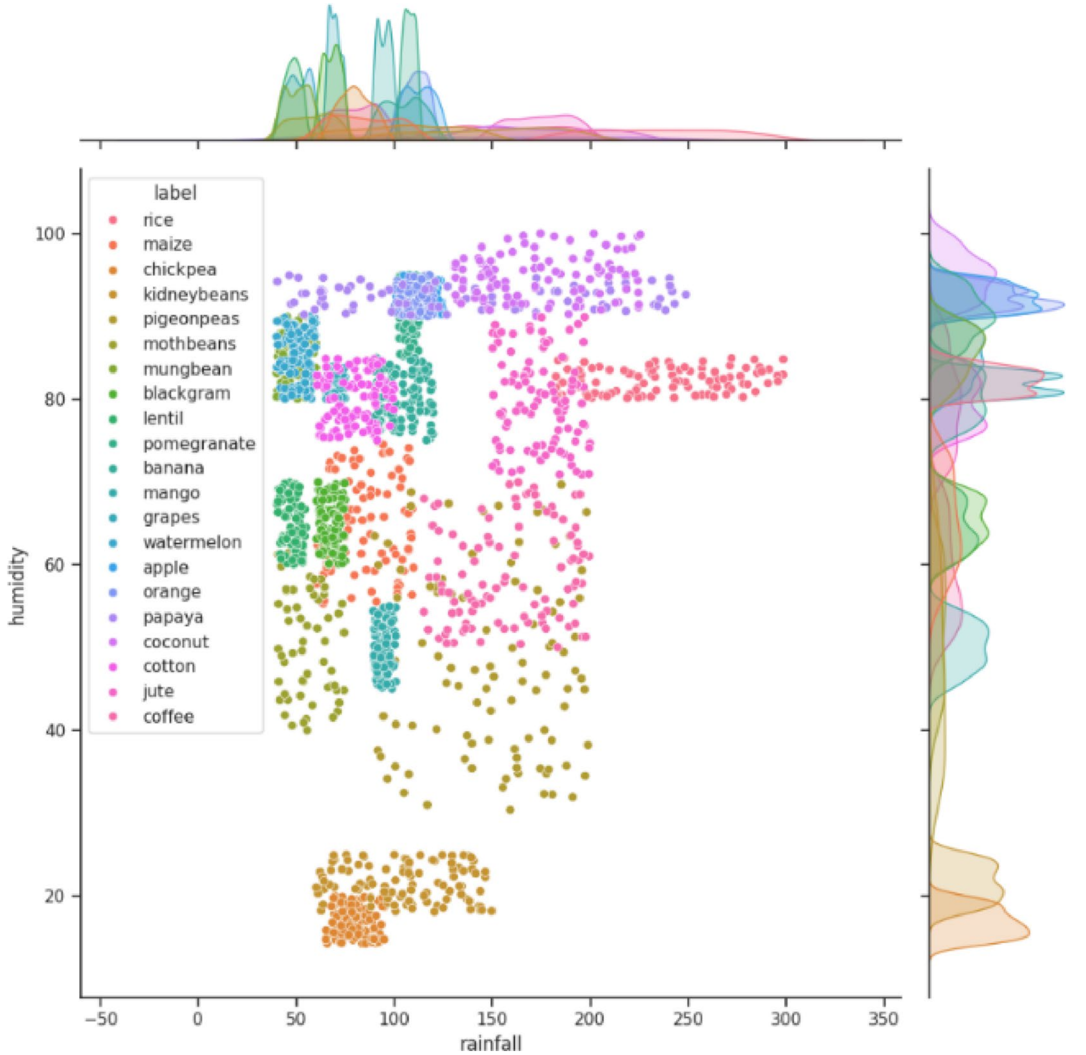

Fig. 2. Join plot.

test sets, yielding 1,650 rows for training and 550 rows for testing. With this partitioning, a significant amount of the data is reserved for performance evaluation and the remaining piece is used to train the model.

Step 3: Model Training: Several supervised ML algorithms are trained on the training set. A variety of models are used, such as Gradient Boosting (GB), K-Nearest Neighbors (KNN), Neural Network (NN), Linear Discriminant Analysis (LDA), Decision Tree (DT), Random Forest (RF), Naïve Bayes (NB), Support Vector Machine (SVM), Logistic Regression (LR), Quadratic Discriminant Analysis (QDA). Based on the given characteristics, these algorithms are trained to categorize the 22 crop labels.

Step 4: Model Evaluation: Once trained, the models are evaluated using the test data, which constitutes 25% of the original dataset. The evaluation metrics include:

- ***Confusion Matrix***: A Confusion matrix is a table that displays the counts of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) to illustrate the performance of a classification model.
- ***Accuracy***.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

- ***Precision***:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

- ***Recall***:

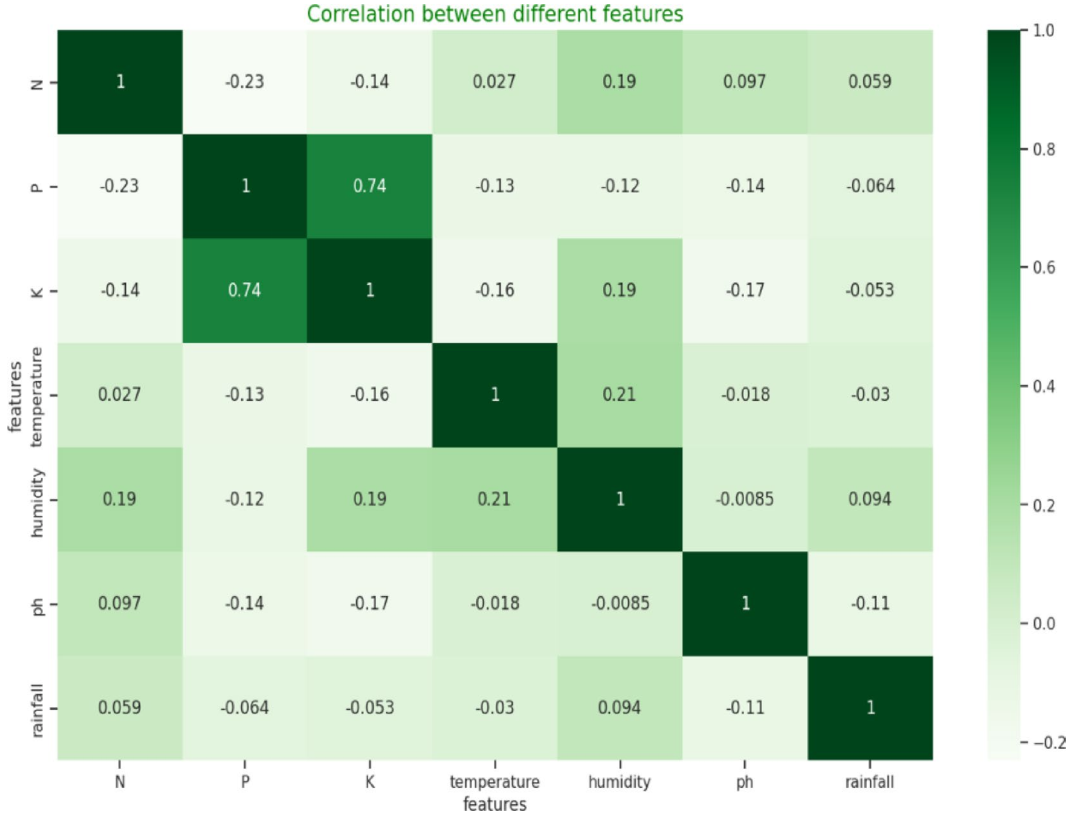

Fig. 3. Correlation between features.

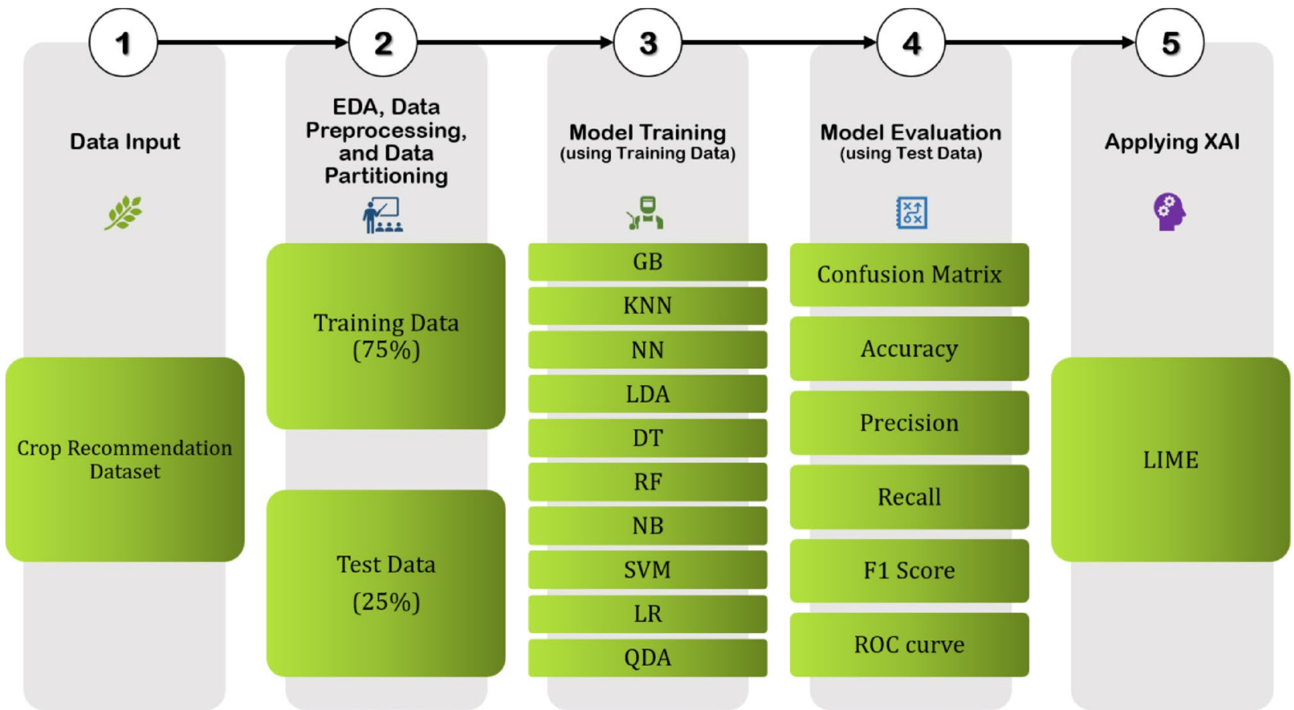

Fig. 4. Proposed research methodology.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

- ***F1 Score***:

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

- ***Receiver Operating Characteristic (ROC) curve***: A graphical depiction called the ROC curve is used to evaluate a classification model's performance. It displays how different threshold values affect the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR).

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} \tag{6}$$

The model's ability to discriminate between the positive and negative classes is assessed with the aid of the ROC curve. Plotting the ROC curve involves placing the False Positive Rate (FPR) on the x-axis and the True Positive Rate (TPR), often referred to as Sensitivity or Recall, on the y-axis. A model with flawless classification of all positives and negatives will have a ROC curve that crosses the top-left corner of the plot, or point (0,1), signifying a low FPR and a high TPR. The model's performance may be summed up with a single scalar value using the area under the ROC curve (AUC). The AUC shows the probability that a randomly chosen positive instance would be scored higher than a randomly chosen negative one. On a scale from 0 to 1, 1 represents perfect performance, while 0.5, or random guessing, indicates a model with poor discriminative ability. The AUC shows the probability that a randomly chosen positive instance would be scored higher than a randomly chosen negative one. On a scale from 0 to 1, 1 represents perfect performance, while 0.5, or random guessing, indicates a model with poor discriminative capacity.

Step 5: Applying Explainable AI (XAI) with LIME: The Local Interpretable Model-agnostic Explanations (LIME) approach is used to improve the models' interpretability. By approximating complicated model predictions with more straightforward, interpretable models locally around the prediction of interest, LIME seeks to explain the predictions of complex models. The core idea involves perturbing the input data 'x' to generate a set of samples (x', y'), where 'y" are the predictions from the black-box model. LIME then fits a local interpretable model 'g' (such as a linear model) to these perturbed samples. The optimization problem for LIME can be formulated as:

$$\text{argmin}_g \left(\sum\nolimits_i L\left(f, g, x_i\right) + \Omega\ (g) \right). \tag{7}$$

where L(f, g, xi) is the loss function measuring the discrepancy between the black-box model 'f' and the local model 'g' around 'x', and $\Omega\ (g)$ is a regularization term to ensure the simplicity of 'g'. The transparency and reliability of the ML models utilized in this work are increased by examining these local explanations, which provide us with insights into how each variable affects the model's predictions.

Experiment evaluation and results

This section outlines the experimental setup, evaluation metrics, and comparative benchmarks to validate the proposed approach. Each subsection highlights a key aspect of the evaluation process. Together, they provide a comprehensive assessment of model performance and interpretability.

Implementation environment

This study was implemented in a high-performance computing environment built to meet the demands of challenging ML tasks. The system utilized an NVIDIA GeForce RTX 4090 GPU, known for its exceptional processing power and efficiency in accelerating DL and computationally intensive tasks. Complementing the GPU, the setup includes 32 GB of RAM and an Intel i9 13th Gen CPU.

Additionally, several significant Python modules were used to make data analysis and model construction easier. Pandas were utilized for preprocessing and data manipulation, offering strong capabilities for managing and examining structured data. For mathematical and statistical computations, NumPy made fast numerical computations and array operations possible. For data visualization, Matplotlib and Seaborn were used, enabling the production of intricate and educational charts to investigate and display data insights. A whole range of ML tools is available for developing and accessing different algorithms with Scikit-learn.

Performance evaluation

This section details the assessment of 10 ML algorithms' effectiveness using key metrics, such as accuracy, precision, recall, F1 score, and ROC to evaluate their predictive performance on the crop recommendation dataset. Further, we assign natural numbers to class labels to streamline result evaluation and improve clarity in reporting the findings. Class 1 denotes Apple, Class 2 denotes Banana, Class 3 denotes Blackgram, Class 4 denotes Chickpea, Class 5 denotes Coconut, Class 6 denotes Coffee, Class 7 denotes Cotton, Class 8 denotes Grapes, Class 9 denotes Jute, Class 10 denotes Kidneybeans, Class 11 denotes Lentil, Class 12 denotes Maize, Class 13 denotes Mango, Class 14 denotes Mothbeans, Class 15 denotes Mungbean, Class 16 denotes Muskmelon, Class 17 denotes Orange, Class 18 denotes Papaya, Class 19 denotes Pigeonpeas, Class 20 denotes Pomegranate, Class 21 denotes Rice, and Class 22 denotes Watermelon.

The class-wise test classification report of each algorithm, which includes precision, recall, f1-score, and overall accuracy, is detailed in Tables 1, 2 and 3, and 4 respectively. The confusion matrix and ROC curve for the best-performing ML algorithm, Gradient Boosting (GB), are shown in Figs. 5 and 6, respectively, with an overall training accuracy of 100% and a test accuracy of 99.27%.

Comparative analysis

The performance comparison (in terms of accuracy) of the 10 supervised learning algorithms used for the experimentation is shown in Fig. 7. Gradient Boosting, with a testing accuracy of 99.27% and a training accuracy of 100%, performs the best out of these ten classifiers. where the F1 score, recall, and total test precision are, respectively, 99.32%, 99.36%, and 99.32%. The comparison between the current study's findings and previous research on a similar kind of dataset is presented in Table 5.

XAI (LIME)

Making AI systems' decision-making processes visible and intelligible to humans is the primary objective of the area of Explainable Artificial Intelligence (XAI). XAI creates methods to clarify forecasts by emphasizing critical characteristics affecting results as AI models get more intricate. Improving interpretability and aligning AI behavior with human ideals increases user trust, makes debugging easier, and guarantees ethical deployment. Local Interpretable Model-agnostic Explanations (LIME), which we used in this work, is one of the greatest XAI techniques.

LIME is a method that offers local explanations for complicated ML models. The basic principle of LIME is to use a smaller, more interpretable model, like a decision tree or linear model, to simulate the behavior of a complicated model locally around the prediction of interest. This enables us to determine which traits are most important for a certain forecast. The first row of the dataset's predictions from a Gradient Boosting model has been interpreted using LIME.

Explanation of row 1 (index 0) of the crop recommendation dataset

- **Prediction Probabilities**: Prediction probabilities of the row in illustrated in Fig. 8. Here, the model predicts with 100% confidence that the crop is "coffee." This is reflected in the prediction probability bar where "coffee" has a full green bar indicating high confidence.

- **Class Labels** (NOT Banana vs. Banana): LIME tries to explain the prediction of "coffee" by showing features that indicate why the prediction is not "banana" (since "banana" might be a potentially confusing class).

	Precision									
Class	KNN	DT	RF	NB	SVM	LR	NN	GB	LDA	QDA
1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
3	0.95	0.61	0.95	1.00	0.95	0.88	0.94	1.00	0.74	1.00
4	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
5	1.00	0.93	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
6	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
7	0.96	1.00	1.00	0.96	0.96	0.88	0.92	1.00	0.96	1.00
8	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
9	0.90	0.50	0.89	0.89	0.86	0.85	0.84	0.97	0.83	0.91
10	0.96	0.00	1.00	1.00	0.96	1.00	1.00	1.00	0.96	1.00
11	0.96	0.62	1.00	1.00	0.96	0.87	0.89	1.00	0.85	0.96
12	1.00	1.00	1.00	1.00	1.00	0.92	0.96	1.00	1.00	1.00
13	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	0.97	1.00
14	1.00	0.00	1.00	1.00	1.00	0.81	0.85	0.96	1.00	1.00
15	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
16	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
17	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
18	1.00	1.00	1.00	1.00	1.00	1.00	0.96	1.00	1.00	1.00
19	1.00	0.53	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96
20	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
21	0.85	0.46	1.00	1.00	1.00	0.91	1.00	0.92	0.95	0.92
22	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 1. Precision report.

Class	Recall									
	KNN	DT	RF	NB	SVM	LR	NN	GB	LDA	QDA
1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
3	1.00	1.00	1.00	1.00	1.00	0.70	0.80	1.00	0.85	1.00
4	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
5	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
6	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
7	1.00	1.00	1.00	1.00	1.00	0.92	0.96	1.00	1.00	1.00
8	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
9	0.87	0.03	1.00	1.00	1.00	0.94	1.00	0.94	0.97	0.94
10	1.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96
11	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.96	0.88	1.00
12	0.96	1.00	1.00	0.96	0.96	0.88	0.92	1.00	0.96	1.00
13	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
14	0.92	0.00	0.96	1.00	0.92	0.84	0.88	1.00	0.84	0.96
15	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
16	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
17	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
18	1.00	1.00	1.00	1.00	1.00	0.91	1.00	1.00	1.00	1.00
19	0.96	1.00	1.00	1.00	0.96	1.00	1.00	1.00	0.92	1.00
20	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
21	0.88	0.96	0.84	0.84	0.80	0.80	0.72	0.96	0.76	0.88
22	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 2. Recall report.

Class	F1-Score									
	KNN	DT	RF	NB	SVM	LR	NN	GB	LDA	QDA
1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
3	0.98	0.75	0.98	1.00	0.98	0.78	0.86	1.00	0.79	1.00
4	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
5	1.00	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
6	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
7	0.98	1.00	1.00	0.98	0.98	0.90	0.94	1.00	0.98	1.00
8	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
9	0.89	0.06	0.94	0.94	0.93	0.89	0.91	0.95	0.90	0.92
10	0.98	0.00	1.00	1.00	0.98	1.00	1.00	1.00	0.98	0.98
11	0.98	0.76	1.00	1.00	0.98	0.93	0.93	0.98	0.87	0.98
12	0.98	1.00	1.00	0.98	0.98	0.90	0.94	1.00	0.98	1.00
13	1.00	1.00	1.00	1.00	1.00	0.98	1.00	1.00	0.98	1.00
14	0.96	0.00	0.98	1.00	0.96	0.82	0.86	0.98	0.91	0.98
15	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
16	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
17	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
18	1.00	1.00	1.00	1.00	1.00	0.95	0.98	1.00	1.00	1.00
19	0.98	0.70	1.00	1.00	0.98	1.00	1.00	1.00	0.96	0.98
20	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
21	0.86	0.62	0.91	0.91	0.89	0.85	0.84	0.94	0.84	0.90
22	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 3. F1-score report.

Overall Accuracy									
KNN	DT	RF	NB	SVM	LR	NN	GB	LDA	QDA
0.98	0.85	0.99	0.99	0.98	0.96	0.97	0.99	0.96	0.99

Table 4. Accuracy score.

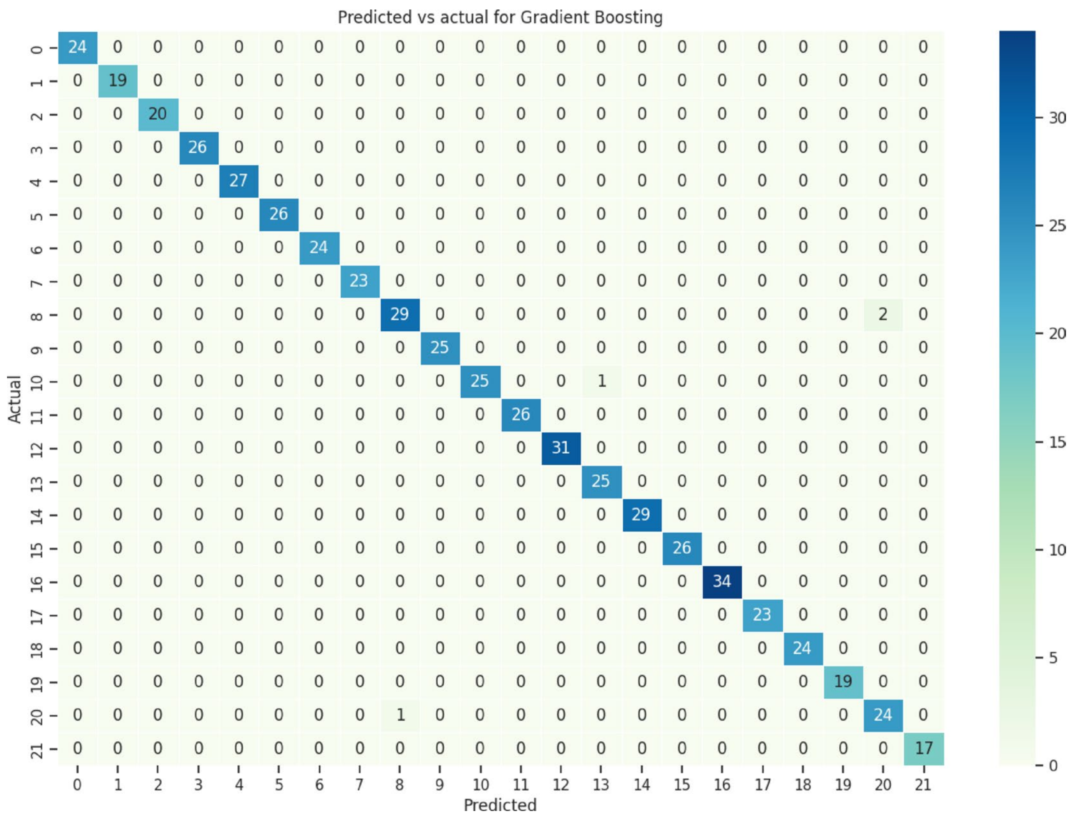

Fig. 5. Confusion matrix (GB).

- **Feature Contributions**: Table 6 depicts the features and their values for the first row.
- **Explanation of Features**:

  a). ***P < = 28.00***: The amount of phosphorus is below 28. This condition slightly decreases the likelihood of being "banana" (weight: 0.04).
  b). ***Rainfall > 122.21***: High rainfall contributes against the prediction of "banana" (weight: 0.02).
  c). ***21.00 < K < = 33.00***: Potassium levels being within this range further support "not banana" (weight: 0.01).
  d). ***37.00 < N < = 85.00***: This nitrogen range weakly suggests against "banana" (weight: 0.01).
  e). ***60.47 < Humidity***: High humidity plays against "banana" (weight: 0.00).
  f). ***pH > 6.91***: pH levels above 6.91 contribute minimally against "banana" (weight: 0.00).
  g). ***Temperature < 25.55***: This feature slightly lowers the chance of being "banana" (weight: 0.00).

- **Interpretation**: The prediction is strongly in favor of "coffee" due to the combination of these features, primarily because none of the conditions significantly align with those that would lead to a "banana" prediction. The LIME explanation highlights the importance of rainfall and nutrient levels (P, K, N) as decisive factors in distinguishing between "coffee" and potential competing crops like "banana."
- **Feature Influence**: Rainfall and nutrient levels are critical in determining the crop type, suggesting that the model has learned to rely heavily on these environmental and soil features for classification.

Discussion
The current study presents a recommendation system in the agriculture sector for various crops by utilizing ML algorithms and XAI. The experiment focused on classifying agricultural data into 22 categories of crops. The data used for the study has been shown using various visualization tools, including pair plot, box plot, joint plot, heat map, and correlation matrix. Gradient Boosting fared better than the other nine ML algorithms out of ten that were used for the experiment. The comparative analysis of the proposed work is also compared with other

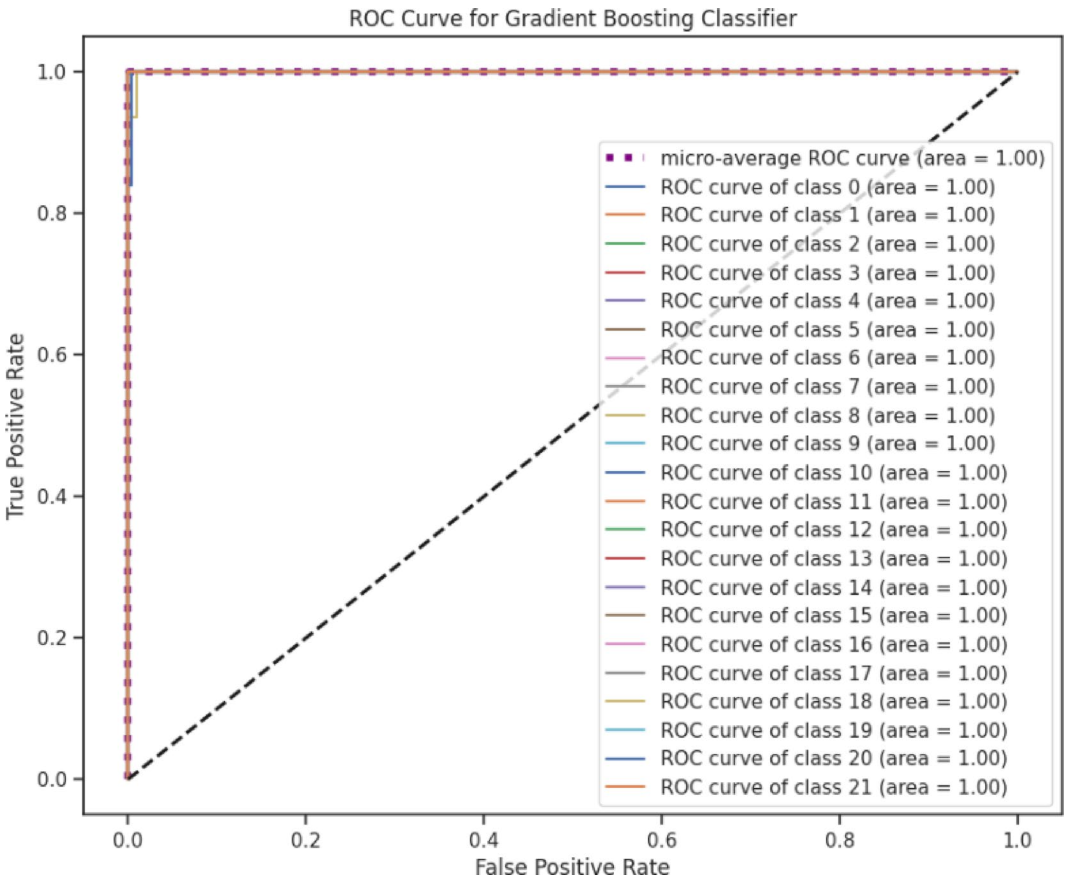

Fig. 6. ROC curve (GB).

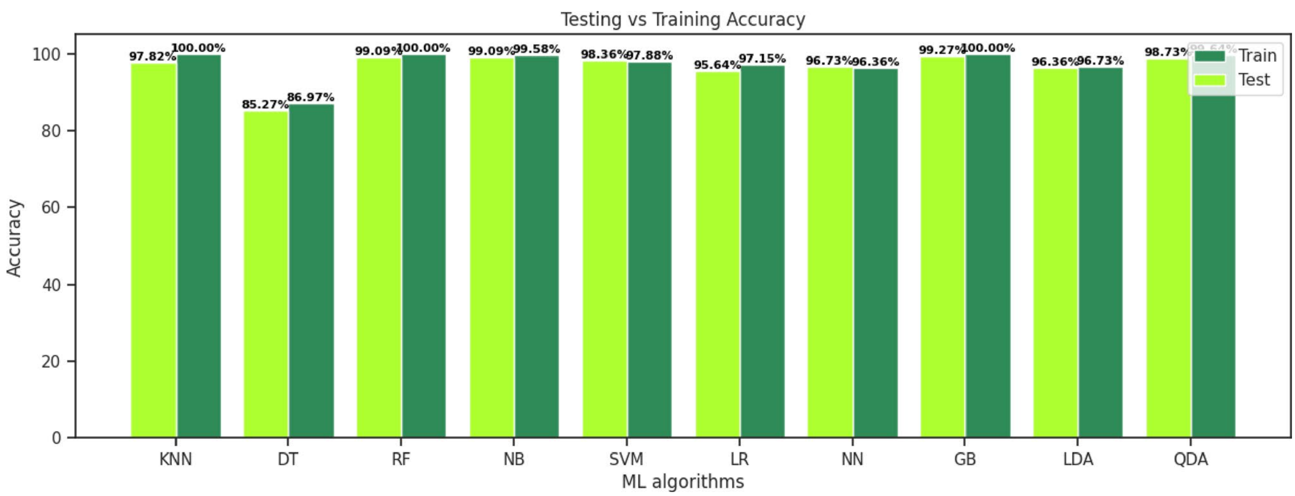

Fig. 7. Overall accuracy comparison of ML algorithms used in the experiment.

existing works, as shown in Table 5 and it revealed that the present work achieved good performance in terms of performance metrics, including 99.27% accuracy rate, 99.32% precision, 99.36% recall, and 99.32% F1 score. According to the findings of this study, the GB model can be a useful tool for crop recommendation since it can quickly and accurately recommend crops based on nutrient and environmental parameters. The augmentation of XAI with ML gives a detailed explanation of the predictions of the present study.

Reference	# Models Used	Best Method	Dataset	Split Ratio	#Classes	Precision	F1-Score	Recall	Accuracy
10	5	Random Forest	Kaggle (Crop Recommendation)	70:30	22	97%	97%	97%	97.18%
12	2	K-Nearest Neighbour	Kaggle	75:25	-	-	-	-	98%
13	2	RBF + SMO	Kaggle (Crop Recommendation)	80:20	22	-	-	-	98.2%
15	5	Multi-Criteria CRS	Soil Health Card Data (5000 land samples of Gujarat)	-	-	92%	89.9%	88%	95.85%
18	7	IML-ASE (Ensemble)	Kaggle (Crop Recommendation)	-	22	97.03%	97.09%	97.12%	97.1%
21	5	Gradient Boosting	Kaggle (Crop Recommendation)	-	22	-	-	-	98.18%
22	9	Fuzzy DBN	Paddy crop dataset of Vellore district	k-fold cross validation	-	-	-	-	92%
23	5	XGBoost	Kaggle	70:30	21	97.33%	97.49%	97.99%	98.51%
24	4	Random Forest	Kaggle (Crop Recommendation)	-	22	-	-	-	98.86%
25	5	Random Forest	-	70:30	-	97%	97%	97%	97.18%
43	3	Modified ResNeXt	Public dataset	-	3	99.38%	99.18%	99.18%	98.92%
28	6	DECNN	Rice Dataset (Kaggle)	75:20:05	3	98%	98%	98%	98.33%
29	8	Adaptive Lemuria	-	-	-	97%	96.49%	96.2%	98.35%
30	3	Faster R-CNN	Public IP102 dataset	70:30 and 90:10	5	-	-	-	98.90%
44	3	Improved ResNeXt	Public dataset	-	4	99.40%	99.20%	99.20%	98.94%
Proposed Model	**10**	**Gradient Boosting**	**Kaggle (Crop Recommendation))**	**75:25**	**22**	**99.32%**	**99.32%**	**99.36%**	**99.27%**

Table 5. Comparison with existing work.

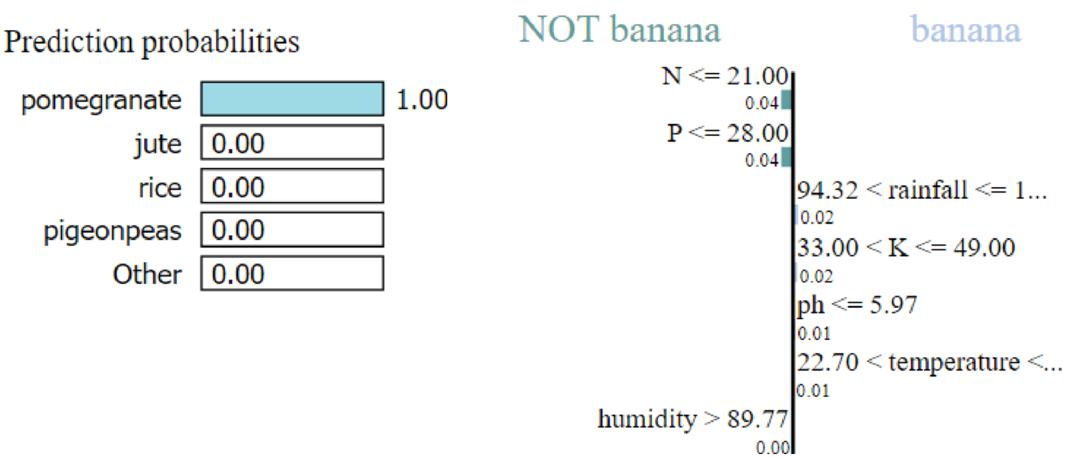

Fig. 8. Prediction probabilities using XAI (LIME) (Row 1).

Conclusion and future work

Agriculture is the most important industry as it feeds the world's population. The involvement of technology has transformed traditional ways and included new innovative methods that are beneficial for the increase in the production of crops. The use of data-driven technologies, such as artificial intelligence and machine learning, has given farmers and agronomists a new viewpoint. The involvement of these state-of-the-art techniques gathers real data from the farms and then discovers trends, patterns, and correlations for decision-making. In recent years, almost all countries have been moving towards precision agriculture, which involves innovative methods for data-driven decisions to improve the fertility of farms and increase crop yield. This study addresses several gaps in existing crop yield prediction research by applying multiple supervised machine learning algorithms, including Gradient Boosting, to improve predictive accuracy and robustness across diverse crop types. A detailed exploratory data analysis was conducted to better understand the dataset, guiding effective feature selection and model development. Importantly, the integration of Explainable AI techniques, specifically LIME, provided transparent and interpretable insights into model decisions, which are largely absent in prior works. Class-wise performance evaluation across 22 crop categories further demonstrates the model's effectiveness in handling

Feature	Value
N (Nitrogen)	1.00
P (Phosphorus)	27.00
Rainfall	104.99
K (Potassium)	36.00
pH	5.68
Temperature	23.99
Humidity	93.34

Table 6. Feature contributions (Row 1).

multi-class prediction problems. The current study aims to propose crop yield models based on environmental and nutrient factors, helping farmers and agricultural specialists make quicker and more accurate decisions. While the results show strong prediction performance. Thus, this work lays a robust foundation for developing explainable, reliable, and practical ML-based tools to enhance agricultural productivity.

Data availability
This study does not produce any particular data. We made use of the publicly accessible dataset available at: https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset.

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Declarations

Competing interests
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