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Optimizing Fruit Crop Recommendations via Soil Analysis with XGBoost and Supervised Learning Techniques

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Abstract. The importance of soil composition in determining suitable crops selection cannot be emphasized enough in the quest for increasing precision agriculture. The presence of soil components such as pH, nitrogen, phosphorus, and potassium levels significantly affect the growth and productivity of crops. Building upon this, the present work provides a cohesive strategy that merges the powerful XGBoost algorithm with conventional supervised learning techniques to improve crops recommendation systems. The study systematically utilizes machine learning techniques to surpass the limitations of conventional heuristic-based methods by examining the complex relationships between soil variables and crops performance. The research employs a large dataset including many soil properties to perform a thorough comparison analysis of numerous well-known machine learning algorithms, such as Decision Trees, SVM, Logistic Regression, Random Forest Naive Bayes and XGBoost. The findings evaluated is based on four important performance measures - accuracy, recall, precision, and F1-score - clearly demonstrate the better performance of the XGBoost model. With exceptional accuracy (99.31%), precision (100%), recall (99%), and an F1-score (99%), this system surpasses its competitors in precisely forecasting and proposing the best crops based on soil composition, demonstrating its unmatched effectiveness. The findings not only confirm the strong capability of XGBoost in managing intricate prediction tasks, but also emphasize its potential in promoting more sustainable and productive farming methods. The study's results have important implications for the creation of intelligent agronomic decision-making tools. These tools will use data to help farmers and agronomists achieve higher crops yields that are customized to the unique requirements of their soil conditions.
Keywords: Decision Trees, Svm, Logistic Regression, Random Forest Naive Bayes And Xgboost, Crop Recommendations

I. INTRODUCTION

The convergence of agriculture and technology has ushered in a new era of precision farming, whereby data-driven analysis is used to make well-informed choices that improve agricultural productivity, effectiveness, and ecological soundness. An essential aspect of this agricultural revolution is the examination of soil composition, a crucial factor in determining the well-being and efficiency of crops. [1] The soil's pH, nutritional composition, moisture levels, and organic matter concentration have a considerable impact on the kind of crops that may flourish in a particular setting. Hence, the capacity to precisely suggest suitable crops via thorough soil research has the potential to revolutionize agricultural methods, resulting in enhanced yields and reduced ecological footprint. To address this difficulty, the use of sophisticated machine learning methods, including XGBoost and supervised learning algorithms, presents a viable resolution. These technologies possess the capability to analyze intricate soil data, detect trends, and forecast crops compatibility with unparalleled precision. XGBoost is distinguished by its efficiency, scalability, and performance [2]. It excels in managing the complex connections between different soil characteristics and crops success rates. The combination of supervised learning algorithms, which acquire knowledge from labelled data to generate predictions, results in a potent tool for improving crops recommendations. In this study, we compare and contrast several machines learning algorithms, including XGBoost, Naive Bayes, Logistic Regression, SVM, Decision Trees and Random Forest. The present study utilizes a large dataset that includes soil components all across the world. the third Using this approach, we can be sure that any algorithm's predictive power in identifying crops suitability, including all of the unique soil characteristics, will be thoroughly evaluated. By focusing on performance metrics such as accuracy, recall, precision and F1-score, we assess each model's merits and shortcomings in the particular setting of crops recommendation. The results of the research show that XGBoost is quite effective in all parameters that were tested. The system's impressive F1-score, recall, accuracy, and precision prove its worth in providing reliable crops recommendations based on soil analysis. The findings shed light on the potential for XGBoost and supervised learning to revolutionize crops recommendation systems. Better crops management, higher yields, and more sustainable agriculture might be the outcome of agronomists' and farmers' use of advanced machine learning algorithms to inform decision-making.

Our present research is aimed at developing user-friendly, cost-effective technologies can bridge this gap, making these innovations more inclusive and beneficial for a broader range of farmers. Real-time data processing and predictive analysis in agriculture are areas ripe for development. The ability to make immediate, informed decisions based on real-time data can significantly enhance agricultural efficiency and responsiveness to changing conditions.

The next section (Section-II) in the paper represents the literature review carried, the third section (Section-III) brings out a detailed methodology adopted, the section four (Section-IV) deals with results and discussion and the last section (Section-V) is the conclusion and future scope.

Keywords: Decision Trees, Svm, Logistic Regression, Random Forest Naive Bayes And Xgboost, Crop Recommendations

II. LITRATURE REVIEW

The authors [1] have used a deep learning-based model utilizing fine-tuned Transfer Learning algorithms, like VGG-16, VGG-19, Inception-V3, and Xception, to detect cotton leaf diseases. The Xception model, with a 98.70% accuracy, was integrated into a web application for real-life disease prediction, aiding farmers in early disease detection. This advancement in AI and deep learning showcases its potential in smart farming and precision agriculture, aiming to enhance disease diagnosis accuracy and reduce crops losses.

The application of ML in agricultural crops selection (CS) needs a review on the evolution, main features, and challenges of recommender systems (RSs) in CS, highlighting their importance in aiding farmers' decision-making and enhancing yield outcomes. The authors [2] have identified the lack of a comprehensive classification scheme for algorithms and features in crops recommendation, a gap it aims to address.

There is a need for introducing a fresh approach to maximize the yield of crops. To help farmers make educated choices throughout the growing process, there is a need to combine machine learning, Internet of Things (IoT) and the cloud computing. The data is gathered by Internet of Things (IoT) sensors, stored in the cloud, and analyzed with a bespoke algorithm in the proposed IoTSNA-CR model. This technology, which can be accessed via an Android smartphone, provides ongoing assistance, which lessens the need for conventional farming practice s[3]. The authors [4,5] stress the significance of crops recommendation systems for managing soil fertility, integrated nutrition, and socioeconomic advantages. This study employs a number of machine learning methods to highlight the revolutionary potential of AI in agriculture, namely in defending agricultural production against factors such as climate change, population increase, unemployment, and food insecurity. In order to provide crops recommendations, the suggested technique collects data, processes it, extracts and selects features, and then classes the results. Of the fourteen classifiers tested, Cat Boosting (C-Boost) had the highest accuracy at 99.51%, while Gaussian Naive Bayes (GNB) was the most effective in terms of ROC and MCC values across all three categories of machine learning: classification, regression, and boosting [4,5].

The authors [6,7,8] aim to utilize temperature and humidity data, applying clustering algorithms and k- Nearest Neighbor methods to uncover patterns in large datasets, aiding climate prediction and categorization. The key concepts include crops yield prediction, Remote sensing, Image processing, Neural Networks, and K-Nearest Neighbor method

The paper highlights the challenges in traditional farming practices and proposes a machine learning-based system to assist farmers in crops selection. This system aims to consider various factors like soil conditions, market value, and sustainability, which are often overlooked by farmers.

The authors [9] have introduced Cap-DiBiL, a novel hybrid deep learning model combining Channel Capsule Network and Stacked Dilated Bi-LSTM, for predicting crops water requirements and making suitable crops recommendations. The model uses IoT data, processes it through data normalization, missing value imputation, and one-hot encoding, and applies feature extraction and selection techniques. The model aims to enhance the accuracy of crops water requirement predictions and crops recommendations, comparing favorably with existing methods. Key aspects include IoT data processing, Gated Residual Auto encoder, Chaotic Northern Goshawk Optimization algorithm, and evaluation of performance metrics like accuracy, precision, and F1 score.

The authors [10,11] have suggested a system for crops prediction and recommendation using the Internet of Things (IoT) that makes use of Weight-based Long Short-Term Memory (WLSTM) and Improved Distribution-based Chicken Swarm Optimization (IDCSO). This system gathers weather data, checks it for accuracy, then selects features using IDCSO and crops using WLSTM. This methodology is designed to help farmers make educated crops decisions by providing exact forecasts and suggestions. It improves upon prior approaches in terms of accuracy, precision, recall, and execution time [10].

The authors [12] propose an Electronic Agricultural Record (EAR) system to integrate various datasets into a unified dataset. They built a data warehouse using Hive and Elastic search to manage and process agricultural big data, focusing on extracting fertilizer information. Statistical methods based on this data warehouse are used to recommend the right quantities of fertilizer components (Nitrogen, Phosphorus, Potassium) for the most popular crops in the EU. This system aims to balance crops nutrition needs with environmental impact, enhancing crops yield and reducing unnecessary fertilizer use.

Improved crops suggestions using meteorological data particular to regions are the focus of this investigation into machine learning (ML) techniques. In order to forecast the best crops to grow given a set of environmental conditions, the research compares a number of ML algorithms. These include Logistic Regression, Naive Bayes, Decision Tree, Random Forest, and Support Vector Machines (SVM). The end objective is to increase agricultural production and sustainability by empowering farmers to make better crops growing choices [13,14,15].

The Chemical characteristics, infrared spectroscopy, and phosphorus release kinetics are examined, with an emphasis on synthesizing BBFs from coffee husk and low-grade phosphate rock. The research evaluates the effects of different acids and magnesium during synthesis on the agronomic performance of these BBFs on Brachiaria grass and maize. Our research aims to boost crops development by improving phosphorus usage efficiency in Oxisols (*a soil order* best known for their occurrence in tropical rain forest within 25 degrees north and south of the Equator) and providing alternative fertilizer choices [16].

The paper [17] examines several machine learning models, such as Naive Bayes, Random Forest, linear regression, and Bagging, with a focus on bagging for recommendation systems and boosting algorithms for yield prediction. To help farmers make better decisions and increase agricultural output, the system is tested for correctness and shown how to use it using a graphical user interface.

Using Bayesian Belief Networks (BBNs), the model incorporates climatic data, soil properties, and historical yield data. It then provides probabilistic reasoning and evaluates the implications of parameters. It adjusts suggestions according to farmers' preferences and limitations while taking uncertainties into consideration. Agricultural production, sustainability, and personalized decision-making are all improved by the model's high prediction accuracy and flexibility. By combining data, learning, and Bayesian networks, this method is a huge step forward for agricultural recommendation systems [18]. The Table 1, shows the comprehensive literature review carried out.

TABLE 1. Literature review of Improved Productivity through Crops Recommendations machine learning techniques.

Reference	**Year**	**Methods**	**Advantages**	**Limitations**	**Future Work**
[1]	2023	ML Algorithms	- Data integration - High accuracy	- Data quality - Limited to specific crops	- Improved predictive models - Incorporate more environmental factors
[2]	2023	ML Algorithms	- Comprehensive literature review	- Lack of real-world evaluations - Dependency on historical data	- Real-world validation - Enhanced personalization of recommendations
[3]	2023	ML Algorithms	- Real-time data collection - Precision agriculture	- IoT infrastructure deployment challenges - Sensor	- Integration with weather data - Scalability and cost-effectiveness
[4]	2023	AI-based Crops Recommendation System	- Robustness	- Data privacy concerns	- Explainable AI for transparency
[5]	2023	Random Forest Algorithm for Crops Recommendation	- Ensemble learning approach	- Limited interpretability	- Evaluation of model ensembles
[6]	2023	Intelligent Crops Recommendation System	- Deep learning techniques	- Data complexity	- Transfer learning for data efficiency
[7]	2021	Crops Recommendation System	- Early research in the area	- Data quality	- Incorporate recent data sources
[8]	2023	ML Algorithms	- Integration of IoT and ML - Real-time data collection	- IoT infrastructure deployment challenges - Scalability and cost-effectiveness	- Optimization of IoT data collection and processing - Integration with remote sensing data

[9]	2021	Crops Recommendation System	- Early research in the area	- Data quality	- Incorporate recent data sources
[10]	2023	IoT-Based Crops Recommendation System	- IoT integration	- IoT infrastructure deployment	- Integration with weather data and remote sensing
[11]	2023	Predictive Approach for Agricultural Productivity through Crops Recommendations	- Predictive modeling - Local context	- Limited to Morocco - Data availability	- Adaptation to different regions and crops - Real-world validation
[12]	2023	Predictive Approach for Agricultural	- Predictive modeling	- Limited to Morocco	- Adaptation to different regions and crops
[13]		Productivity through Crops Recommendations	- Local context	- Data availability	- Real-world validation
[14]	2023	ML Algorithms	- Utilizes weather data - Machine learning techniques	- Weather data availability - Data quality	- Improved weather data quality - Enhanced predictive models
[15]	2023	Biochar-Based Phosphate Fertilizers for Crops Grown in Oxisols	- Agricultural research - Soil nutrient management	- Limited to fertilizer recommendations - Limited to specific soil types	- Field trials and validation - Impact on crops yields and soil health
[16]	2023	Organic Manures in Tamil Nadu	- Precision agriculture - Organic farming practices	- Limited to oilseed crops - Data availability	- Expansion to other crops types - Real-world validation
[17]	2023	Sustainable Agriculture	- Bayesian networks - Sustainable agriculture	- Limited to recommendation optimization	- Integration with IoT for real-time data - Evaluation in diverse agricultural contexts
[18]	2023	Irrigation Rate	- Utilizes evapotranspiration - Irrigation optimization	- Limited to irrigation - Data quality	- Evaluation in different regions and crops - Incorporate soil moisture data

While going through the different journal papers, it was observed that despite significant advancements in machine learning and deep learning techniques for agricultural applications, a notable research gap exists in the development of highly accurate and region-specific crops recommendation systems based on soil composition. The current models often lack the ability to fully integrate and analyze the complex interactions between various soil parameters such as pH, nutrient levels, moisture content, and texture and their impact on different crops yields. Moreover, most systems do not adequately address the variability in soil composition across different geographical areas and climates, which can greatly affect crops suitability and productivity.

Additionally, there is a scarcity of comprehensive datasets that include a wide range of soil types and corresponding crops performance data, which limits the ability of machine learning models, including advanced algorithms like XGBoost, to learn and predict with high precision. This gap underscores the need for more sophisticated models that can leverage deep learning to uncover intricate patterns in soil-crops relationships and for the collection of more diverse and extensive soil composition data to train these models effectively. Such improvements could significantly enhance the accuracy of crops recommendations, leading to optimized agricultural productivity and sustainability. As per the agriculture standards and details gathered from the papers, the Table2 and Table 3 display the standard parametric values needed for appropriate growth of the crops. The Table 2 represents the environmental standard data and Table 3 represents the Standard fertilizer data.

TABLE 2. Environment standard data

Environment	**Temperature(°C**		**Humidity (%)**		**pH**		**Rainfall(mm)**	
CROP ↓	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**
Banana	14	35	58	89	5.5	7.1	1510	2520
Orange	5	34	52	78	6.1	7.6	810	1530
Grapes	14	35	62	81	6.2	7	510	820
Papaya	14	38	64	85	5.4	6.6	1200	2010
Watermelon	18	36	61	90	5.5	7	500	890
Apple	0	26	60	80	6.4	7.8	850	1250
Mango	24	30	52	65	5.4	7	750	2550

TABLE 3. Standard fertilizer data

Fertilizer →	**N(Kg/H)**		**P(Kg/H)**		**K (Kg/H)**	
CROP ↓	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**
Banana	110	295	32	100	200	300
Orange	109	182	45	66	142	182
Grapes	32	98	22	52	60	122
Papaya	115	210	49	102	152	252
Watermelon	51	102	26	52	75	152
Apple	63	99	31	60	62	125
Mango	101	202	40	61	102	205

III. METHODOLOGY ADOPTED

In the present research work, we need to design a system which is based on statistical parameters which are very essential for the overall design of the crop recommendation system. The dataset for the present research work was collected from Kaggle, which contains essential parameters like NPK(nitrogen, phosphorus, potassium) values, the additional important parameters like temperature, humidity, rainfall and pH have also been included. All these parameters are collected for different crop varieties. The Figure1 shows the overall design flow adopted for implementing the present research

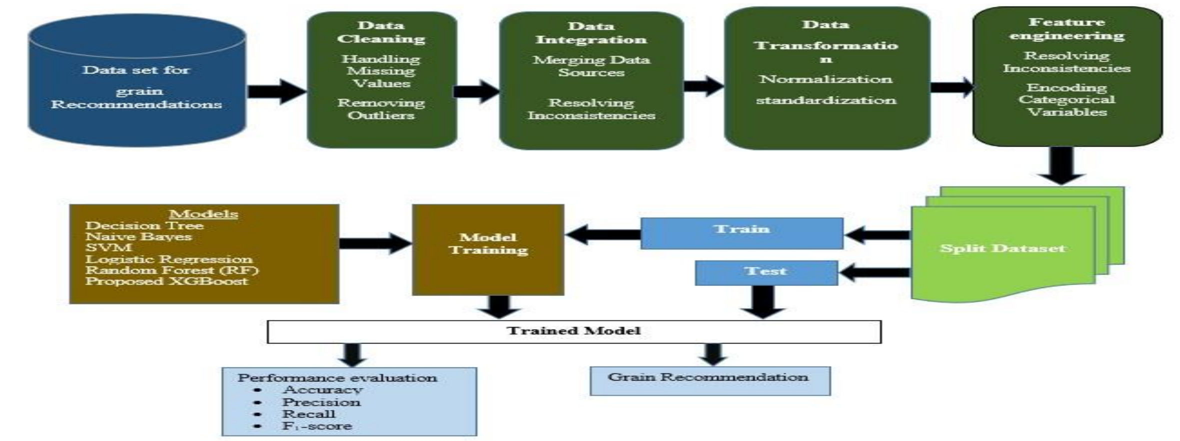


FIGURE 1. Proposed flowchart for Crops Recommendation

The provided Figure 1 presents a methodical approach for conducting research in the field of machine learning, beginning with the inception of the project and culminating in its final conclusion.

Step1: Dataset preprocessing:

As the data was collected from Kaggle, the CSV file (Comma Separated Values) was carefully observed for missing values, misspelt values, outliers and other unwanted numeric values or symbols etc.

Step2: Integration and Data-transformation:

Once the step1 was completed, the next step involves the process of integration which further involves the resolution of inconsistencies. Further the data was subjected to the process of normalization which involves scaling numeric fields like pH levels and nutrient concentration to a standard range, typically 0 to 1, to ensure that no variable dominates due to its scale.

Step3: Feature Engineering and Application of XGBoost Model:

The process of feature engineering involves the derivation of new relevant features from the existing ones, such as the ratio of certain nutrients, to capture more complex relationships in the data. Further the categorical variables, like soil type, were converted into a numeric format through one-hot encoding. The next step involves the understanding of the different tuning parameters available in the XGBoost algorithm.The core data structures used are:

- **DMatrix**: It used for Feature and Labels, it also supports sparsity of the matrix.
- **Gradient Stats**: It is a set of arrays used for holding gradients (g_i) and hessians(h_i) values.
- **Histogram Bins**: Used for storing quantized feature values for faster split finding in the process.
- **Tree Structure**: These are the nodes with gain, split feature, split value etc.
- **Prediction Buffer**: It stores current ensemble predictions for fast updates
- **Priority Queue**: Used for best-first split search.

The input and the three steps involved in the XGBoost algorithm are as shown in the Figure 2.

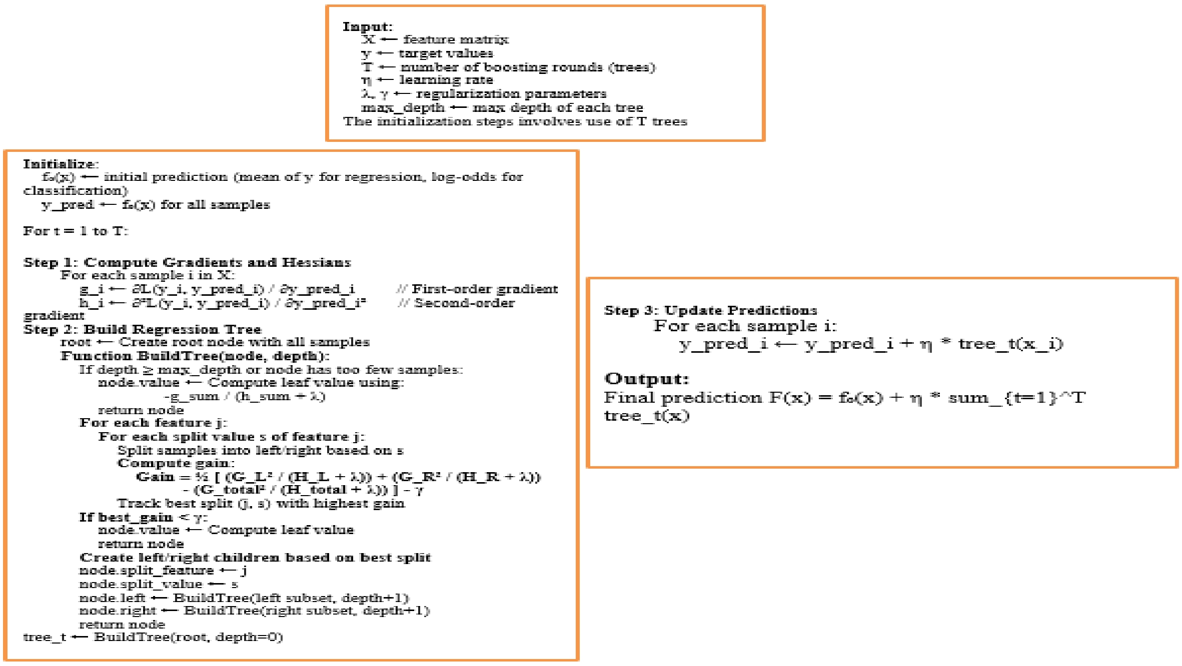


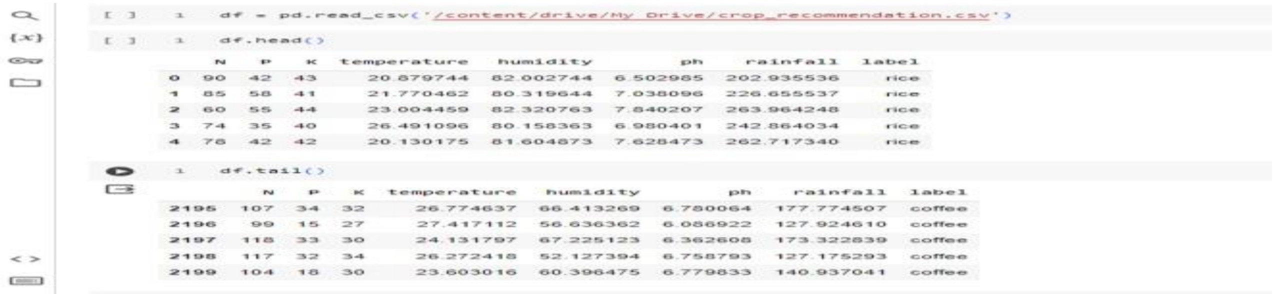
Figure2: XGBoost Model Developed with its algorithm for the research work

Step4: Application of Random Forest, Decision Tree, Naïve Bayes, Logistic Regression and SVM:

For proper comparison of the efficacy of XGBoost with that of the other available machine learning algorithms, the data set was further subjected to testing of other machine learning based algorithms including Random Forest, Decision Tree, Naïve Bayes, Logistic Regression and SVM. The different statistical values for depicting the output were evaluated using the mentioned algorithm.

IV. RESULTS AND DISCUSSION

As mentioned in the earlier section-III, the present research work has utilized the crops recommendation dataset [19] which is available on Kaggle. It has total of 2200 number of rows with different crops of data with 100 rows each i.e., wheat, rice, maize, chickpea etc. The dataset contains soil components such as Nitrogen(N), Phosphorus(P) and Potassium(K) levels for significant corresponding temperature, humidity, pH and rainfall which affect the growth and productivity of particular fruits crops like banana watermelon, grapes, apple, papaya, orange and mangoes. The data description has been displayed through Figure3.



```
df = pd.read_csv('/content/drive/My Drive/crop_recommendation.csv')
df.head()
```

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice

```
df.tail()
```

	N	P	K	temperature	humidity	ph	rainfall	label
2195	107	34	32	26.774637	66.413269	6.780064	177.774507	coffee
2196	99	15	27	27.417112	56.636362	6.086922	127.924610	coffee
2197	118	33	30	24.131797	67.225123	6.362608	173.322839	coffee
2198	117	32	34	26.272418	52.127394	6.758793	127.175293	coffee
2199	104	18	30	23.603016	60.396475	6.779833	140.937041	coffee

Figure3: Description of the Dataset used

For one such crop, the Table 4, gives the actual values for the banana crop with corresponding NPK, Temperature, Humidity, pH and rainfall values.

TABLE 4. Soil components dataset for Banana crops.

N	**P**	**K**	**Temperatur**	**Humidity**	**ph**	**Rainfall**
91	94	46	29.36792366	76.249001	6.149934	92.82841
105	95	50	27.33368994	83.676752	5.849076	101.0495
108	92	53	27.40053601	82.962213	6.2768	104.9378
86	76	54	29.3159075	80.115857	5.926825	90.10978
80	77	49	26.05433004	79.396545	5.519088	113.2297
93	94	53	25.86632408	84.423793	6.079179	114.5358
90	92	55	27.00932084	80.185468	6.134656	97.32532
108	89	53	29.55054817	78.067628	5.808498	99.34482
108	88	55	26.28845991	83.390039	5.891458	113.873
105	77	52	29.16226551	76.161516	5.816622	100.0076

In order to understand the correlation between the various features, heatmap depicting the correlation values was also generated. This correlation map has values ranging from 0 to 1. The value zero shows no relationship between the variables and the value one shows that the variables are highly correlated.

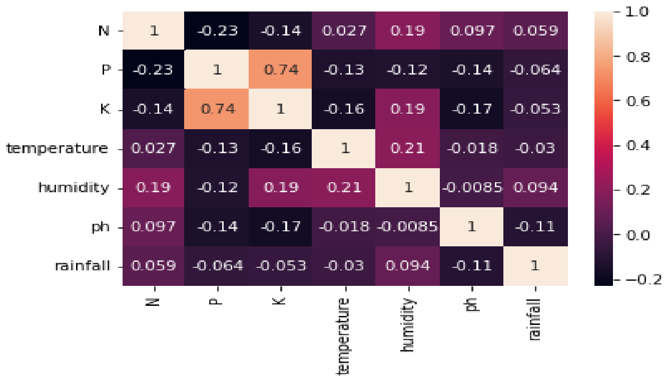


Figure 4:. A heat depiction of Correlation of dataset features.

The Figure4, illustrates a heat map representing the correlation matrix among many soil and environmental parameters, such as nitrogen (N), phosphorus (P), potassium (K), pH, temperature, humidity and rainfall. The heat map employs a color gradient that spans from pale to intense, symbolizing correlation values that vary from weak to strong. The correlation between phosphorus (P) and potassium (K) is notably significant, with a positive value of 0.74. This suggests

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that when the amount of one nutrient grows, the level of the other nutrient also tends to increase. Temperature and humidity have a modest correlation, with a coefficient of 0.21.

The pH has little or negligible association with other variables, since its values are consistently near to zero. The association between rainfall and the other variables is either insignificant or extremely weak. The diagonal, with a value of 1, signifies the ideal positive correlation of each variable with itself. The correlation matrix plays a vital role in comprehending the interconnections among the factors, which can have a substantial impact on crops recommendation systems. It reveals the factors that are likely to influence each other and should be taken into account together when making recommendations.
From the Figure 5, it is clear that the integration of XGBoost with supervised learning for crop prediction based on soil composition yields superior performance. By comparing multiple machines learning algorithms, including Naive Bayes, SVM, Decision Tree, Logistic Regression, Random Forest, and XGBoost, reveals that XGBoost outperforms others in key metrics with 99.31% accuracy, 100% precision, 99% recall, and a 99% F1-score.The present work has also been compared with [2] and [5]. This indicates its exceptional ability to handle complex soil data interactions, enabling accurate crop recommendations. The XGBoost model minimizes false positives and negatives, crucial for maximizing crop yields and guiding agricultural decisions, confirming its effectiveness in precision agriculture.

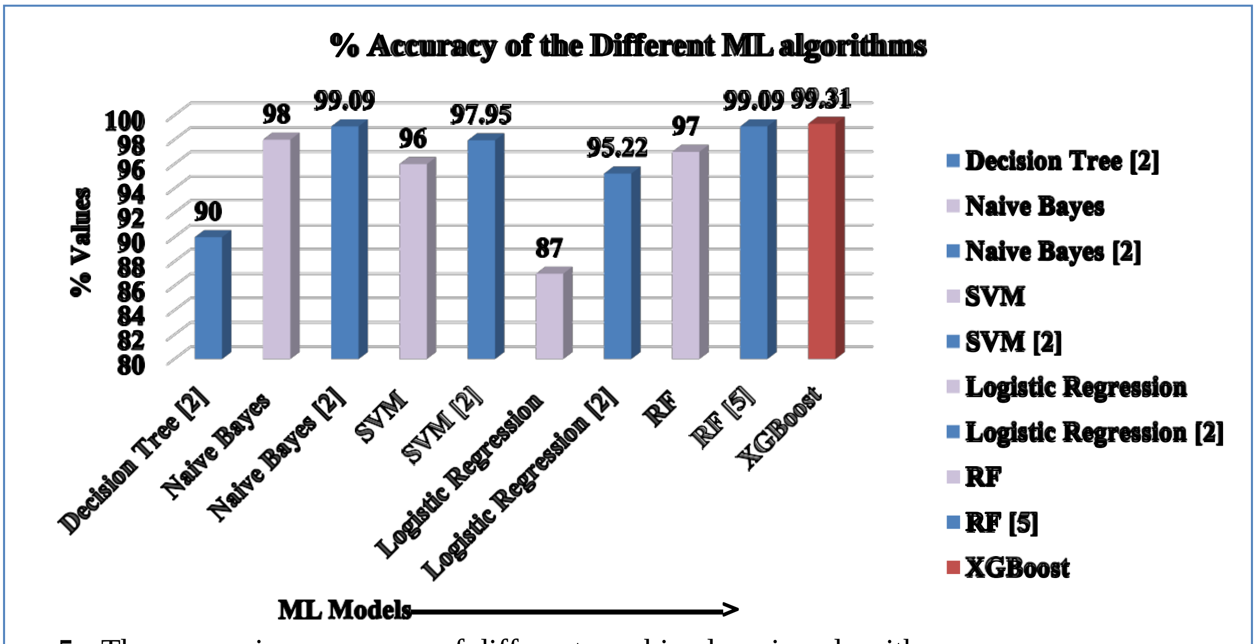

Figure5: The comparison accuracy of different machine learning algorithms

V. Conclusion and Future Scope

In this paper, we have presented a detailed algorithmic breakdown and pseudocode representation of the XGBoost algorithm, emphasizing its internal data structures and decision-making processes. XGBoost stands out as a highly efficient and scalable implementation of gradient boosting, leveraging second-order optimization, regularization, and advanced data handling strategies to deliver state-of-the-art performance on structured data problems.By iteratively constructing decision trees using gradient and hessian information, and by applying regularized loss minimization, XGBoost effectively balances model complexity and predictive accuracy. Key architectural choices such as the use of the DMatrix for optimized data storage, histogram-based split finding for efficiency, and sparsity-aware algorithms for handling missing values, all contribute to its robust performance and widespread adoption.

The presented pseudocode and structural insights aim to demystify the internal workings of XGBoost, providing a foundation for researchers and practitioners to better understand, implement, and tune the algorithm for various machine learning tasks. Future work may explore its extensions to distributed systems, integration with deep learning frameworks, and adaptations to new loss functions and data modalities. Further the deployment of app on cloud could be another solution.

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