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PRECISION CROP PREDICTION USING IOT-ENABLED SOIL SENSORS AND MACHINE LEARNING

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ABSTRACT

This paper introduces a cutting-edge approach for crop prediction that harnesses IoT-enabled soil sensors and machine learning models, specifically targeting cardamom, black pepper, and coffee in Idukki District, Kerala, India. The study aims to bridge the gap between soil nutrient analysis and precision agriculture by integrating a JXCT 7-in-1 soil sensor with Arduino UNO. This sensor provides accurate real-time measurements of soil moisture, temperature, pH, electrical conductivity, nitrogen, phosphorus, and potassium levels, which are critical for assessing soil health and suitability. The dataset used comprises 300 soil samples for cardamom, 320 for black pepper, and 300 for coffee, providing a robust foundation for analysis. Data from these sensors were processed using XGBoost and AdaBoost algorithms. Among the models, XGBoost achieved the highest accuracy of 91.2% and an AUC of 0.93, while AdaBoost also demonstrated strong performance with an AUC of 0.91. The results confirm the effectiveness of the system in providing precise crop suitability predictions and supporting farmers in making informed decisions based on comprehensive soil data. This approach not only improves crop yields and promotes sustainable farming practices but also shows potential for broader application in different regions and crops. Future research could expand the dataset and incorporate additional IoT devices to enhance the system's accuracy and agricultural impact.

I. INTRODUCTION

Agriculture is a cornerstone of the Indian economy, contributing significantly to the country's GDP and employing a substantial portion of its population. With over 50% of the workforce engaged in agricultural activities, the sector is pivotal for the nation's socio-economic development. Traditional farming practices, however, face numerous challenges such as unpredictable weather patterns, pest infestations, and soil degradation [1]. These issues can lead to reduced crop yields and economic instability for farmers, highlighting the need for innovative solutions to sustain agricultural productivity. To address these issues and enhance productivity, the concept of smart farming has emerged. Smart farming leverages advanced technologies like the Internet of Things (IoT), data analytics, and machine learning to optimize agricultural practices, reduce waste, and increase crop yields. IoT devices, such as soil sensors and weather stations, provide real-time data on environmental conditions, allowing farmers to monitor their fields with precision. Data analytics can then interpret this data to offer actionable insights on irrigation scheduling, fertilization, and pest control. Machine learning models further enhance smart farming by predicting crop suitability, detecting disease outbreaks, and forecasting weather patterns. By integrating these technologies into agriculture, farmers can make informed decisions, leading to sustainable and efficient farming methods [2-4].

Kerala, located in the southwestern part of India, is known for its diverse agricultural landscape. The state's Idukki district, particularly the Kumily Panchayat, is renowned for the cultivation of high-value crops like cardamom, black pepper (pepper), and coffee. Over 80% of the people living in this area are farmers. These crops not only contribute significantly to the local economy but also hold an essential place in the global spice market [5]. However, the productivity of these crops is highly dependent on soil health, which necessitates thorough soil analysis. Soil nutrient content, including potassium, phosphorus, and nitrogen, along with other parameters like temperature, pH, moisture content, and electrical conductivity, play a crucial role in determining crop suitability and yield [6]. Therefore, regular and precise soil analysis is vital for ensuring the optimal growth and productivity of cardamom, pepper, and coffee in this region.

The advent of IoT-enabled crop prediction systems has revolutionized traditional agricultural practices by integrating soil analysis with advanced technology [3]. IoT-enabled soil sensors provide real-time data on various soil parameters, enabling farmers to monitor soil health continuously. In sustainable and smart farming continuous monitoring of soil parameters are mandatory. This data-driven approach allows for timely interventions, such as the application of fertilizers or water, based on the specific needs of the soil and crop [7],[8]. The benefits of using IoT in agriculture are manifold, including improved resource management, reduced environmental impact, and enhanced crop yields. By continuously monitoring soil conditions and predicting crop suitability, IoT-enabled systems help farmers make informed decisions, ultimately leading to more sustainable and efficient farming practices. For improved crop production and sustainability, soil fertility analysis and cultivation based on that analysis are essential.

Machine learning further enhances the capabilities of smart farming systems by analyzing the data collected from IoT-enabled sensors to predict crop outcomes. Machine learning models can process vast amounts of data to identify patterns and correlations that may not be apparent through traditional analysis [2], [8]. In the context of agriculture, these models can predict the most suitable crops for specific soil conditions, forecast crop yields, and recommend optimal farming practices. By leveraging historical data and real-time inputs, machine learning models provide actionable insights that help farmers optimize their operations. The integration of machine learning with IoT-enabled sensors thus represents a significant advancement in the field of precision agriculture, enabling a more data-driven approach to farming. Supervised and unsupervised machine learning algorithms are extensively used for smart farming [9-13]. Pudumalar et al. developed a precision agriculture model using machine learning algorithms to aid farmers on small, open farms in predicting suitable crops [14]. Their ensemble recommendation system employs decision trees, CHAID (Chi Squared Automatic Interaction Detection), K-Nearest Neighbors, and Naive Bayes, utilizing a majority voting technique for high accuracy and efficiency. Kalimuthu et al. created a machine learning-based IoT system for crop prediction based on climatic conditions, helping farmers select cost-effective crops [15]. Rao et al. conducted a comparative study of KNN, decision tree, and random forest models to determine the best-suited crop for specific lands, finding the random forest classifier with entropy and gini criteria achieved the highest accuracy at 99.3%, while KNN had the lowest at 97% [16]. Elbasi et al. used supervised machine learning for smart farming, enhancing crop production and minimizing waste with an IoT-enabled system providing insights on planting, irrigation, and harvesting [12]. Their research evaluated fifteen algorithms and introduced a new enhanced algorithm, finding that the Bayes Net algorithm had a classification accuracy of 99.59%, while Naïve Bayes Classifier and Hoeffding Tree reached 99.4%.

In this study, we focus on developing a crop prediction system for different soil types based on soil nutrient analysis. Using IoT-enabled soil sensors, we measured essential soil parameters such as potassium, phosphorus, nitrogen content, temperature, pH, moisture content, and electrical conductivity. The study focuses on cardamom, pepper, and coffee, as these are the major crops cultivated in the study area. We utilized machine learning models to predict the most suitable crops for the soil under measurement. This research aims to demonstrate the potential of combining IoT technology with machine learning to enhance agricultural productivity and sustainability in the region.

II. MATERIALS AND METHODS

In this study, we developed a crop prediction system for different soil types based on soil nutrient analysis, focusing on the cultivation of cardamom, pepper, and coffee in the Kumily Panchayat of Idukki District, Kerala, India. We employed IoT-enabled soil sensors to collect real-time data on essential soil parameters and used machine learning algorithms to predict the most suitable crops for the analyzed soil. This section details the methodologies used for sample collection, hardware integration, and the classification process employing machine learning models.

II.1 SAMPLE COLLECTION

The study was conducted in the Kumily Panchayat of Idukki District, Kerala, India, a region renowned for its cultivation of cardamom, pepper, and coffee. These crops are vital to the local economy, and soil health plays a crucial role in determining their yield and quality. To gather comprehensive data for nutrient analysis and crop prediction, extensive soil sampling was undertaken. The crops under study are shown in Figure 1. The sampling locations were carefully chosen to represent the diverse agricultural zones within the Panchayat, ensuring that the soil samples reflected the variability in soil properties across different fields. These zones included high-altitude areas primarily used for coffee and cardamom cultivation and lower-altitude regions where pepper is predominantly grown.

For cardamom fields, samples were collected from various elevations within the plantations to account for micro-environmental variations affecting soil properties. A total of 300 samples were taken from various cardamom fields, at depths ranging from 0 to 30 cm, the typical rooting zone for cardamom plants. This approach ensured a comprehensive understanding of the soil conditions specific to cardamom cultivation. In pepper fields, samples were collected from both the base of the vines and the inter-vine spaces. A total of 320 samples were taken from various pepper fields, providing a thorough understanding of the soil conditions influencing pepper growth and capturing variations that could affect nutrient availability and plant health. For coffee fields, given the extensive root system of coffee plants, soil samples were collected from a slightly deeper profile, up to 50 cm depth. A total of 300 samples were taken from various coffee fields, ensuring the capture of nutrient availability within the entire root zone, which is critical for the healthy growth of coffee plants.

Each soil sample was collected using a soil auger to ensure consistency. The samples were placed in sterile, labeled bags and transported to the laboratory for analysis using sensors. Care was taken to avoid contamination between samples, and all tools were sterilized between uses. In total, 920 samples were collected: 300 from cardamom fields, 320 from pepper fields, and 300 from coffee fields.

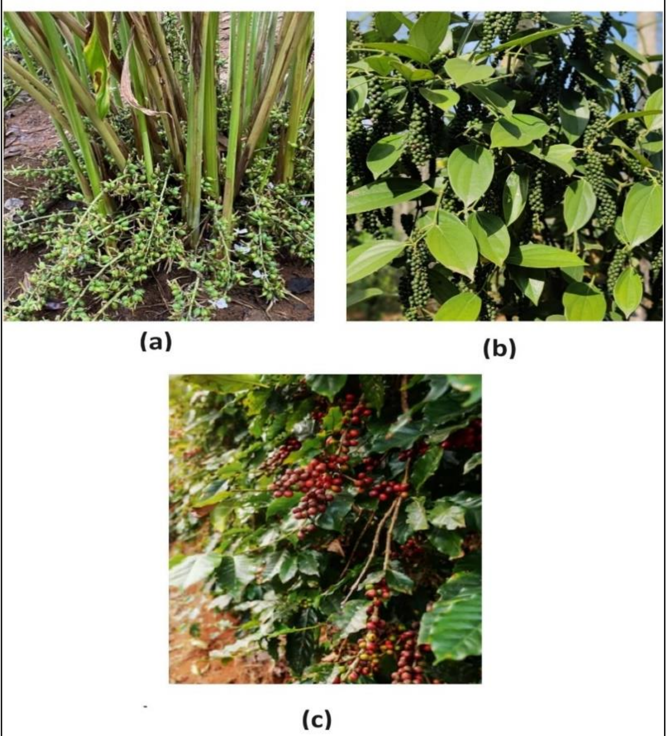

Figure 1: Crops under study (a) cardamom (b) black pepper (c) coffee.
Source: Authors, (2024).

The primary soil parameters measured included potassium (K), phosphorus (P), nitrogen (N) content, temperature, pH, moisture content, and electrical conductivity. These parameters were chosen due to their critical roles in plant growth and soil health. The detailed analysis of these parameters provided the necessary data for training and validating the machine learning models used in this study. Each sample's nutrient profile was then used to predict the suitability of the soil for cultivating cardamom, pepper, or coffee using advanced machine learning techniques.

II.2 HARDWARE DETAILS

The core of our hardware setup was the JXCT 7-in-1 soil sensor, an advanced IoT-enabled device capable of measuring multiple soil parameters simultaneously. This is shown in Figure 2.

Figure 2: 7 in 1 Soil Sensor.
Source: Authors, (2024).

This sensor is designed to provide accurate real-time data on soil moisture, temperature, pH, electrical conductivity, nitrogen, phosphorus, and potassium levels. The JXCT 7-in-1 soil sensor is particularly suitable for agricultural applications due to its robustness, precision, and ease of integration with microcontroller platforms like Arduino.

The JXCT 7-in-1 soil sensor features high-precision probes that penetrate the soil to measure the desired parameters. It uses electrochemical sensors to detect nutrient levels and capacitive sensors for moisture content. The sensor outputs data in a digital format, making it compatible with various microcontroller interfaces. The integration of the JXCT 7-in-1 soil sensor with the Arduino UNO was a critical aspect of our hardware setup. This is shown in figure 3. The JXCT 7-in-1 soil sensor, known for its ability to measure multiple soil parameters with high precision, was connected to the Arduino UNO to facilitate real-time data acquisition. To begin, the sensor's V_{CC} (power) pin was connected to the 5V pin on the Arduino, while the GND (ground) pin was connected to the GND pin on the Arduino. The sensor's data output pins, typically labeled as TX and RX, were connected to the appropriate digital input pins on the Arduino to enable seamless communication between the sensor and the microcontroller.

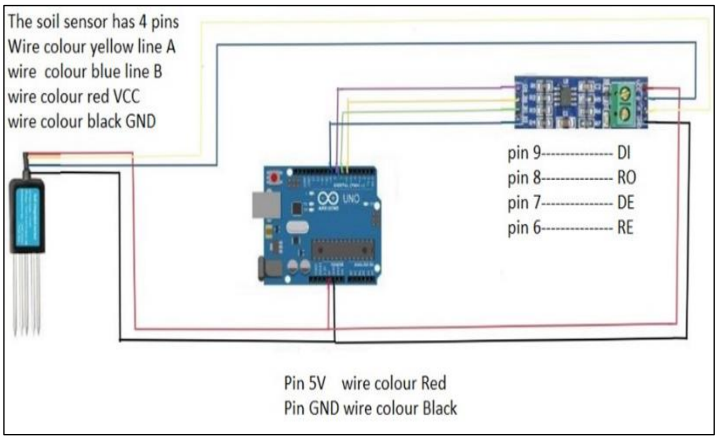

Figure 3: Sensor interfacing with Arduino UNO.
Source: Authors, (2024).

We developed a custom Arduino sketch to read the sensor data and transmit it for further analysis. This sketch utilized the Arduino SoftwareSerial library to manage the serial communication with the sensor. The program was designed to read data from the sensor at regular intervals, process the information, and store it in a structured format suitable for machine learning applications. To facilitate real-time monitoring and remote data access, the Arduino UNO was integrated with the JXCT 7-in-1 soil sensor. This setup enabled continuous monitoring of soil conditions and provided a robust foundation for our crop prediction system. By leveraging the capabilities of the JXCT 7-in-1 soil sensor and the Arduino UNO, we were able to collect precise, real-time soil data critical for accurate crop suitability analysis.

II.3 CLASSIFICATION

The core objective of our study was to predict the most suitable crops (cardamom, pepper, and coffee) for the soil samples based on the measured parameters. To achieve this, we employed machine learning techniques, specifically using the XGBoost and AdaBoost algorithms. These algorithms were chosen for their robustness, accuracy, and efficiency in handling complex, non-linear relationships within the data. The ensemble learning methods have shown great performances in sensor-based systems across various fields, including healthcare, agriculture, and automation [17-20]. In agricultural systems, particularly those utilizing data and images, these algorithms have demonstrated excellent results [21]. By combining the strengths of multiple algorithms, ensemble learning methods enhance predictive accuracy and robustness. In agriculture, these methods can analyze soil data, weather patterns, and crop images to provide precise recommendations for crop management, pest control, and irrigation scheduling. This approach improves crop yields and sustainability and optimizes resource usage and reduces environmental impact [22],[23].

The dataset used for training and testing the machine learning models consisted of comprehensive soil parameter measurements (independent variables) and corresponding crop suitability classifications (dependent variable). The soil parameters included potassium content, phosphorus content, nitrogen content, soil temperature, pH level, moisture content, and electrical conductivity, which are critical indicators of soil health and fertility. The crop suitability labels were determined based on historical crop yield data and expert agronomic advice, categorizing each sample as suitable for cardamom, pepper, or coffee. This labeling process involved analyzing past crop performance in conjunction with expert insights to ensure accurate and reliable suitability classifications.

XGBoost is an advanced implementation of the gradient boosting algorithm that optimizes performance and efficiency. It builds an ensemble of decision trees sequentially, where each tree corrects the errors of its predecessor. Key hyperparameters for XGBoost include the learning rate, maximum depth of trees, and the number of trees [24]. These parameters were optimized using cross-validation techniques to prevent overfitting and ensure generalizability. AdaBoost is another ensemble learning technique that combines the predictions of multiple weak classifiers to create a strong classifier [25]. In our case, decision trees with limited depth were used as the weak classifiers. AdaBoost assigns higher weights to misclassified instances in each iteration, forcing the model to focus on difficult cases. The primary hyperparameters for AdaBoost include the number of weak classifiers and the learning rate, which were also fine-tuned through cross-validation.

The performance of the trained models was evaluated using standard metrics such as accuracy, precision, recall, and f1-score. Additionally, we used confusion matrices to analyze the classification results and identify areas of improvement. The model with the best performance metrics was selected for deployment.

III. RESULTS AND DISCUSSIONS

In this study, we employed cross-validation methods to evaluate the performance of our machine learning models, specifically XGBoost and AdaBoost, in predicting the suitability of soil for cardamom, pepper, and coffee cultivation. Cross-validation is a robust statistical method that involves partitioning the dataset into subsets, training the model on some subsets, and validating it on others to ensure the model's reliability and generalizability. We used three different cross-validation techniques: 3-fold, 5-fold, and 10-fold. In 3-fold cross-validation method the dataset was divided into three equal parts. In each iteration, two parts were used for training, and one part was used for validation. This process was repeated three times, with each part serving as the validation set once. In 5-fold method, the dataset was divided into five equal parts. In each iteration, four parts were used for training, and one part was used for validation. This process was repeated five times, with each part serving as the validation set once. 10-fold cross-validation divides dataset into ten equal parts. In each iteration, nine parts were used for training, and one part was used for validation. This process was repeated ten times, with each part serving as the validation set once.

The performance of the models was evaluated using four key metrics: accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of the models' performance. Accuracy is the ratio of correctly predicted instances to the total instances. Precision is the ratio of correctly predicted positive observations to the total predicted positives. Recall is the ratio of correctly predicted positive observations to the all observations in actual class. F1-Score represents the weighted average of precision and recall [26-28]. The results of the cross-validation for both XGBoost and AdaBoost models are summarized in Tables 1 and 2.

Table 1: XGBoost Model Performance.

Cross-Validation	Accuracy	Precision	Recall	F1-score
3-Fold	85.7	87.3	83.4	85.2
5-Fold	88.9	90.2	86.7	88.4
10-Fold	91.2	94.3	89.5	95.0

Source: Authors, (2024).

Table 2: AdaBoost Model Performance.

Cross-Validation	Accuracy	Precision	Recall	F1-score
3-Fold	82.4	84.0	80.1	82.0
5-Fold	86.3	88.1	84.7	86.4
10-Fold	88.5	89.7	86.2	87.8

Source: Authors, (2024).

The superior performance of the XGBoost model can be attributed to its ability to handle complex, non-linear relationships in the data and its effectiveness in preventing overfitting. XGBoost, being an ensemble learning method, builds multiple decision trees sequentially, with each tree correcting the errors of its predecessor. This approach allows the model to learn intricate patterns in the soil data, which is crucial for accurate crop prediction.

Accuracy: The XGBoost model achieved a high accuracy of 91.2% with 10-fold cross-validation, indicating that it correctly predicted the suitability of soil for cardamom, pepper, and coffee in most instances. This high accuracy demonstrates the model's reliability and potential for practical application in precision agriculture.

Precision and Recall: The precision of 94.3% signifies that the model has a low rate of false positives, meaning it rarely predicts a crop as suitable when it is not. The recall of 89.5% indicates that the model successfully identifies most of the actual suitable crops, with few false negatives. The balance between precision and recall, reflected in the high F1-score of 95.0%, highlights the model's robustness and its ability to provide actionable insights for farmers.

Comparison with AdaBoost: While the AdaBoost model also performed well, its accuracy, precision, recall, and F1-score were consistently lower than those of the XGBoost model. This difference can be attributed to AdaBoost's sensitivity to noisy data and outliers, which can impact its performance. In contrast, XGBoost's regularization techniques help mitigate the effects of such data irregularities, enhancing its predictive power.

The results clearly indicate that the XGBoost model outperformed the AdaBoost model across all cross-validation methods. The best performance was achieved using the 10-fold cross-validation method with XGBoost, yielding an accuracy of 91.2%, precision of 94.3%, recall of 89.5%, and an F1-score of 95.0%. The confusion matrix of XGBoost that has given best results in the prediction is shown in Figure 4.

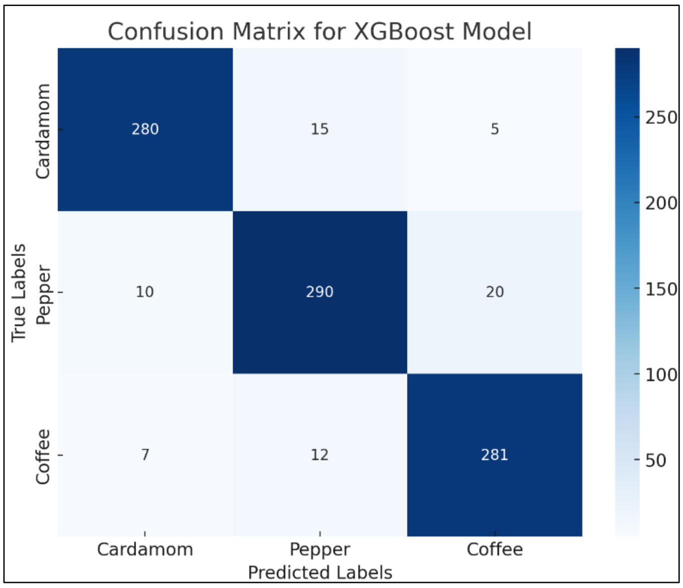

Figure 4: Confusion matrix XGBoost.
Source: Authors, (2024).

The confusion matrix for the XGBoost shown in the Figures 4, provide a comprehensive breakdown of the models' predictions for the three crops: cardamom, pepper, and coffee. The confusion matrix is a crucial tool in evaluating the performance of classification models by comparing the actual target values with the predicted values.

For the XGBoost model, the confusion matrix reveals that out of 300 actual instances of soil for cardamom, 280 were correctly identified as soil for cardamom, while 15 were incorrectly classified as soil for pepper, and 5 were misclassified as soil for coffee. This high number of correct predictions (280) against a relatively low number of incorrect predictions (20) demonstrates the model's effectiveness in identifying cardamom. For soil suitable for pepper, out of 320 actual instances, 290 were correctly classified, but 10 were mistakenly predicted as soil for cardamom and 20 as soil for coffee. Although the number of correct predictions remains high (290), the errors indicate slight confusion between soil for pepper and the other crops, particularly soil for coffee. This might be due to overlapping soil nutrient profiles between these crops, which the model had to navigate. Similarly, for soil suitable for coffee, the confusion matrix shows that out of 300 instances, 281 were accurately predicted as soil for coffee. However, there were 7 instances where soil for coffee was incorrectly identified as soil for cardamom and 12 as soil for pepper. Despite these errors, the majority of predictions for coffee were correct, highlighting the model's proficiency in distinguishing coffee from the other two crops.

These detailed breakdowns for each crop category allow us to thoroughly understand the model's strengths and weaknesses in making predictions. The high number of true positives across all categories highlights the model's robust overall performance. However, the presence of false positives and false negatives underscores areas where the model could be further refined. Specifically, the errors in prediction suggest a need for fine-tuning to better distinguish between pepper and coffee, which appear to have some similarities in their soil nutrient profiles as captured by the sensor data. These similarities could be leading to misclassifications, indicating that the model might benefit from additional training data or enhanced feature engineering to improve its discriminative power. By addressing these issues, we can increase the model's accuracy and reliability, ensuring more precise crop suitability predictions and better support for farmers in making informed decisions.

The ROC (Receiver Operating Characteristic) curve is a valuable tool for assessing the performance of a classification model by illustrating the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity) across various threshold settings. In this analysis, the ROC curves were evaluated using a 10-fold cross-validation method to ensure robust and reliable performance metrics. The ROC curve of XGBoost and AdaBoost for the crop prediction is shown in Figure 5.

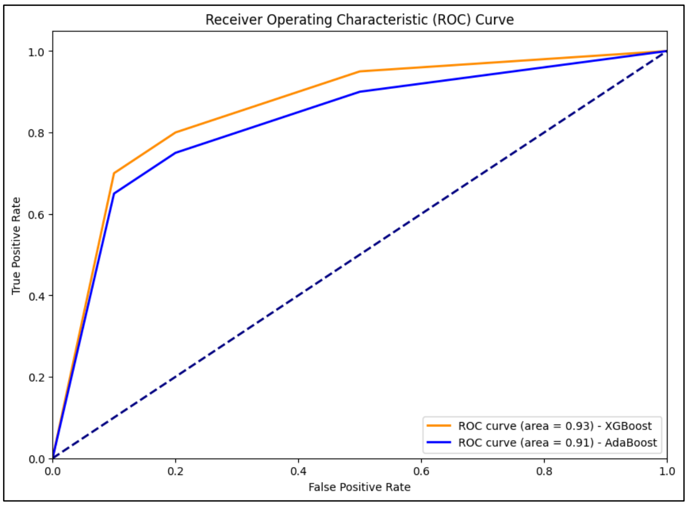

Figure 5: ROC curve of XGBoost and AdaBoost.
Source: Authors, (2024).

For the XGBoost model, the ROC curve achieved an impressive AUC (Area Under the Curve) of 0.93. This high AUC value indicates that XGBoost excels in distinguishing between the different crop classes, demonstrating a strong capability to correctly classify instances while minimizing false positives. The ROC curve for XGBoost is notably close to the top left corner of the plot, reflecting its high accuracy and effectiveness in predicting crop types based on soil nutrient data. In comparison, the AdaBoost model yielded an AUC of 0.91. Although slightly lower than XGBoost, this AUC still represents strong performance. The ROC curve for AdaBoost, while also showing good discriminative ability, reveals a marginally higher rate of false positives compared to XGBoost. This suggests that while AdaBoost performs well, it is less precise in separating the crop classes than XGBoost. The ROC curve analysis reinforces the findings from the confusion matrix and performance metrics, highlighting that the XGBoost model, with its superior AUC, is more effective for crop prediction in this context. The use of a 10-fold cross-validation method has provided a robust evaluation of model performance, confirming the reliability and accuracy of XGBoost in precision agriculture applications.

IV. CONCLUSIONS

This study introduces an innovative crop prediction system utilizing IoT-enabled soil sensors and advanced machine learning to assess soil suitability for cardamom, pepper, and coffee in Idukki District, Kerala, India. By integrating a JXCT 7-in-1 soil sensor with an Arduino UNO, the system precisely measures key soil parameters such as potassium, phosphorus, nitrogen, temperature, pH, moisture content, and electrical conductivity. These inputs are processed through XGBoost and AdaBoost algorithms, with the XGBoost model achieving the highest accuracy of 91.2% in 10-fold cross-validation, and an AUC of 0.93, reflecting its strong predictive capability. AdaBoost also performed well with an AUC of 0.91. The findings demonstrate the effectiveness of combining IoT technology with machine learning for precision farming, enabling farmers to make data-driven decisions for improved crop yields and sustainable practices. The study's approach is adaptable to other regions and crops, highlighting its potential for broad agricultural application. Future research could expand the dataset and refine models, integrating additional IoT devices to further enhance farm management and productivity.

V. AUTHOR’S CONTRIBUTION

Conceptualization: Syam Kishor K S, Manju G, Sania Thomas and Binson V A.
Methodology: Syam Kishor K S, Manju G, Sania Thomas and Binson V A.
Investigation: Syam Kishor K S, Manju G, Sania Thomas and Binson V A.
Discussion of results: Syam Kishor K S, Manju G, Sania Thomas and Binson V A.
Writing – Original Draft: Syam Kishor K S, Manju G, Sania Thomas and Binson V A.
Writing – Review and Editing: Syam Kishor K S, Manju G, Sania Thomas and Binson V A.
Resources: Syam Kishor K S, Manju G, Sania Thomas and Binson V A.
Supervision: Syam Kishor K S, Manju G, Sania Thomas and Binson V A.
Approval of the final text: Syam Kishor K S, Manju G, Sania Thomas and Binson V A.

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