Journal of Agriculture and Food Research 14 (2023) 100880

Contents lists available at ScienceDirect

Journal of Agriculture and Food Research

journal homepage: www.sciencedirect.com/journal/journal-of-agriculture-and-food-research

Machine learning enabled IoT system for soil nutrients monitoring and crop recommendation

Md Reazul Islam [a], Khondokar Oliullah [a], Md Mohsin Kabir [a], Munzirul Alom [a], M.F. Mridha [b,*]

[a] Department of Computer Science and Engineering, Bangladesh University of Business and Technolog, Rupnagar R/A, Mirpur-2, Dhaka, 1216, Bangladesh
[b] Department of Computer Science, American International University-Bangladesh, Dhaka, 1229, Bangladesh

ARTICLE INFO

Keywords:
Machine learning
Internet of things
Agriculture
Crop recommendation
Soil nutrients
Sensor
Cloud computing
Crop quality assessment

ABSTRACT

Agriculture plays a vital role in feeding the growing global population. But optimizing crop production and resource management remains a significant challenge for farmers. This research paper proposes an innovative ML-enabled IoT device to monitor soil nutrients and provide accurate crop recommendations. The device utilizes the FC-28 sensor, DHT11 sensor, and JXBS-3001 sensor to collect real-time data on soil composition, moisture, humidity, temperature, and for nutrient levels. The collected data is transmitted to a server using the MQTT protocol. Machine learning algorithms are employed to analyze the collected data and generate customized recommendations, including a possible high-yielding crop list, fertilizer names, and its amount based on crop requirements and soil nutrients. Furthermore, the applied fertilizers and treatments to the field during production are stored in the database. As a result, it has become possible to determine the quality of the produce at the consumer level through the mobile app. The system's effectiveness is evaluated through field experiments, comparing its performance with traditional methods. The results demonstrate the device's ability to enhance crop productivity and optimize resource utilization, promoting sustainable agricultural practices and food security. The research contributes to IoT-enabled agriculture, demonstrating the potential of ML techniques in improving soil nutrient management, facilitating informed decision-making about crop fertilizers, and assessing the quality of produced crops at the consumer level.

1. Introduction

The advent of the Internet of Things (IoT) and the rapid advancements in machine learning (ML) techniques, ranging from healthcare to transportation [2,11,20,24,25,34,36,41,50] have opened up new avenues for improving agricultural practices. In recent years, there has been a growing emphasis on leveraging these technologies to address the challenges faced by farmers in optimizing crop production and reducing resource wastage [33]. Among these challenges, the effective management of soil nutrients and accurate crop recommendations [47] play pivotal roles in ensuring sustainable and efficient agricultural practices.

Traditional methods of soil nutrient analysis and crop recommendation have often been labor-intensive, time-consuming, and rely on subjective assessments. As a result, farmers are often left with suboptimal decisions, leading to inefficient use of resources, reduced yields, and increased environmental impact [10]. To overcome these limitations, there is a pressing need for innovative solutions that can provide real-time, accurate data on soil nutrient levels and generate customized recommendations based on the specific requirements of different crops.

This research paper proposes an innovative ML-enabled IoT device that integrates advanced sensor technologies, data analytics algorithms, and crop science knowledge to monitor soil nutrients and provide intelligent crop recommendations. The proposed device harnesses the power of ML algorithms to analyze real-time data collected from sensors embedded in the soil, including moisture, ph, temperature, humidity, and nutrient sensors. These sensors continuously measure and transmit vital information about the soil composition, NPK, temperature, humidity, and moisture content to a central cloud, where the ML algorithms process the data to extract actionable insights.

The ML algorithms employed in this device utilize sophisticated data modeling techniques, such as random forest, logistic regression, LGBM, and neural networks, to identify and understand the intricate relationships between soil nutrient levels, environmental factors, and crop requirements. By leveraging historical data, the ML algorithms are trained

* Corresponding author.
E-mail addresses: reaz.ceo.easytech@gmail.com (M.R. Islam), oli.it.ju@gmail.com (K. Oliullah), mdmkabi@gmail.com (M.M. Kabir), cse.alomb008@gmail.com (M. Alom), firoz.mridha@aiub.edu (M.F. Mridha).

https://doi.org/10.1016/j.jafr.2023.100880
Received 29 June 2023; Received in revised form 1 November 2023; Accepted 14 November 2023
Available online 23 November 2023

to generate accurate predictions and recommendations tailored to specific crops, taking into account their nutrient demands, growth stages, and environmental conditions. Additionally, this system can show the quality of the produce at the consumer level when it will be in the market. The outcomes of this research endeavor have the potential to revolutionize the way farmers manage soil nutrients and make crop decisions. By providing real-time, accurate data on soil conditions and customized crop recommendations, the proposed ML-enabled IoT device aims to empower farmers with the tools and knowledge necessary to enhance productivity, optimize resource utilization, food security, and promote sustainable agricultural practices.

Contributions to this work include.

a) The design and development of an IoT device with integrated machine learning capabilities for continuously monitoring soil moisture, humidity, temperature, and NPK levels using three different sensors. This device provides real-time data, enabling precise and timely agricultural decision-making.
b) The application of machine learning algorithms to analyze the collected data and generate crop recommendations based on observed patterns. These recommendations contribute to optimizing crop growth and maximizing yield potential, promoting efficient resource utilization in agriculture.
c) Thorough evaluation of the developed device through field experiments, including a comparative analysis with existing methods. This assessment highlights the capabilities and advantages of the device over traditional approaches, demonstrating its potential to revolutionize agricultural practices.
d) The development of a mobile application to engage end-users and facilitate crop quality assessment. By providing access to the collected data, consumers can monitor the quality of the crops produced. This feature enhances transparency in the agricultural supply chain, empowering consumers to make informed decisions about the agricultural produce they consume.

The paper is organized as follows: Section 2 comprehensively reviews related work. Section 3 describes the methodology and materials used in the study, including IoT devices and sensors, data transmission and analysis, machine learning model design and implementation, and the proposed framework. Section 4 presents the analysis of the results, including data collection and preprocessing, evaluation metrics, training and testing of the proposed model, and performance analysis. Section 5 provides an in-depth discussion of the study's findings and limitations. Finally, Section 6 presents the conclusion and future directions for research in this field.

2. Related works

The management of soil nutrients and accurate crop recommendations are crucial for sustainable and efficient agricultural practices. Traditional methods of soil nutrient analysis and crop decision-making often rely on subjective assessments and labor-intensive processes, resulting in suboptimal resource utilization and reduced yields. However, the integration of Internet of Things (IoT) technology and machine learning (ML) algorithms has opened up new possibilities for addressing these challenges. This literature review explores the existing research and developments related to ML-enabled IoT devices for soil nutrients monitoring and crop recommendation.

IoT-based soil monitoring systems have gained considerable attention in recent years. These systems employ various sensors, such as moisture sensors, pH sensors, and nutrient sensors, to collect real-time data on soil conditions [3,5,13,14,35,48]. The collected data is transmitted to a central hub for analysis and decision-making. For example, an IoT-based system that utilized soil moisture and nutrient sensors to monitor soil conditions in real-time [7,42]. The data collected was then used to optimize irrigation schedules and fertilizer applications, resulting in improved crop yield and water use efficiency.

[49] proposes a system that utilizes an Internet of Things (IoT) platform for monitoring citrus moisture, temperature, and nutrient levels to provide early warning systems and decision-making support for large-scale citrus cultivation. The system employs a single-point multi-layer detection method to obtain temperature, humidity, and nutrient data, which expands the detection range and improves accuracy. The system uses ARM11-based S3C6410 as the master chip. Additionally, an expert knowledge base tailored to the Three Gorges reservoir area is established, offering guidance for citrus fertilization and irrigation decision support based on local geographical conditions and citrus management experience. Field testing demonstrates that the system enables scientific management decisions based on citrus growth conditions. However, the system still has limitations, such as fragmented solutions and high costs, which need to be addressed.

Machine learning techniques have shown great potential in analyzing soil data and predicting nutrient levels [15,16,32]. ML algorithms can identify patterns and correlations in large datasets, enabling accurate predictions and proactive decision-making. In a study by Ref. [8], an ML model was developed to predict soil nutrient levels based on historical data, environmental factors, and crop requirements. The model achieved high accuracy in predicting nutrient deficiencies and excesses, aiding in the timely adjustment of fertilizer application rates.

[1] proposes a system to predict three essential soil fertility elements (OM, K2O and P2O5) using three machine learning approaches like multiple linear regression (MLR), support vector machine (SVM) and random forest (RF). They collets 400 soils from Doukala, central Morocco. According to the findings, texture, carbonates, and cation exchange capacity were the key factors that significantly influenced the prediction of OM, P2O5, and K2O. They also proposed fertilizer recommendation model.

Crop recommendation systems play a critical role in guiding farmers towards optimal crop selection based on soil conditions and market demands. ML algorithms have been successfully employed to develop crop recommendation models that consider various factors, such as soil nutrients, climate conditions, and market trends [4,6,9,27,37]. For instance Ref. [46], proposed a crop recommendation system that utilized ML algorithms to analyze historical crop yield data, weather patterns, and soil nutrient levels. The system provided personalized crop recommendations to farmers, resulting in improved crop productivity and profitability.

The integration of IoT and ML technologies offers a comprehensive approach to soil nutrients monitoring and crop recommendation [26,28,40,45]. By combining real-time soil data collected through IoT devices with ML algorithms, accurate predictions and customized recommendations can be generated. For instance Ref. [18], developed an ML-enabled IoT device that employed various soil sensors and ML algorithms to monitor soil conditions and provide crop-specific recommendations. The device successfully improved crop yields and optimized resource utilization.

A system that consists of sensors, an Arduino board, and an Amazon Web Service has been presented. The used machine learning methods, the cloud, and a mobile application to analyze and visualize data. This approach enables the determination of the availability of soil minerals and the corresponding prescription of fertiliser requirements [38].

Fertilizer recommendation plays a crucial role in optimizing crop productivity and ensuring sustainable agricultural practices. Traditional approaches to fertilizer recommendation often rely on expert knowledge and manual analysis, which can be time-consuming and prone to errors. However, with the advancements in machine learning techniques, there has been growing interest in leveraging these methods [12,21,22,30] to develop more accurate and efficient fertilizer recommendation systems [23]. represented a Machine Learning Approach to Recommend Suitable Crops and Fertilizers for Agriculture. They used different machine learning approaches to perform this task and urged that random forest was the best performer.

The literature review highlights the significant progress made in the field of ML-enabled IoT devices for soil nutrients monitoring and crop recommendation. The integration of IoT technology and ML algorithms has proven to be effective in providing real-time data on soil conditions and generating customized recommendations for farmers. These advancements hold great promise in enhancing crop productivity, optimizing resource utilization, and promoting sustainable agricultural practices. Future research should focus on improving the accuracy and scalability of ML algorithms, food security at the consumer level, as well as integrating additional data sources to further enhance the performance of these innovative works. In the following, we provide a tabular summary of the most recent study in Table 1 to provide a better overview and distinguish our work from theirs.

3. Methods and materials

In this section, we will outline the methodologies and materials employed in this study, encompassing the IoT devices, sensors 3.1, data transmission and analysis techniques 3.2, machine learning model design and implementation 3.3, and the proposed framework 3.4. The hardware used in this research was acquired from techshopbd.com, a company based in Dhaka, Bangladesh. Different components were sourced from various brands. The NodeMCU, produced by Espressif Systems in Shanghai, China, was utilized as the IoT device. The JXBS-3001 sensor, manufactured by Weihai JXCT Electronic Technology Company Ltd in Weihai City, China, was employed for data collection purposes. Guangzhou Aosong Electronic Company Ltd., China manufactures the DHT11 sensor and FC-28 soil sensor is manufactured by various suppliers.

3.1. IoT devices and sensors

This study used three categories sensors like JXBS-3001 3.1.2, FC-28 3.1.3, DHT11 3.1.4, and one NodeMCU 3.1.1. The circuit diagram is presented in Fig. 1. And Table 2 represents the configurations and specifications of the proposed IoT System Components.

3.1.1. NodeMCU

The NodeMCU is an integral component used in this research for the implementation of IoT capabilities. It is a versatile and widely adopted microcontroller board. The NodeMCU board has a voltage regulator to supply a steady 3.3 V power supply as well as a USB interface for programming and powering the device. It is based on the ESP8266 Wi-Fi module, which provides seamless connectivity and enables wireless communication with other devices and the internet. The NodeMCU offers a range of functionalities and features, including 11 GPIO (General Purpose Input/Output) pins, analog-to-digital converters, and programmable interfaces, making it suitable for various applications in the field of IoT. Its compact size, low power consumption, and compatibility with the Arduino development platform, Arduino IDE, make it a popular choice for IoT projects. In this research, the NodeMCU serves as a vital component for collecting sensor data, transmitting it wirelessly using MQTT protocol, and facilitating seamless integration with machine learning algorithms.

3.1.2. JXBS-3001 sensor

The JXBS-3001 sensor plays a pivotal role in this research as a key component for data collection and analysis. This sensor offers advanced capabilities for monitoring and measuring essential soil parameters. Specifically designed for agricultural applications, the JXBS-3001 sensor enables accurate and real-time measurements of soil NPK. These measurements are crucial for assessing soil health, nutrient levels, and overall environmental conditions. The JXBS-3001 sensor boasts a robust construction, high sensitivity, and reliable performance, making it a valuable tool for gathering precise and actionable data. It features quick responses, excellent interchange capabilities, and high precision agriculture sensors. This sensor was chosen because it accurately sense data. Its integration into the research framework facilitates comprehensive soil monitoring, aiding in the development of innovative machine learning algorithms for soil nutrient analysis and crop recommendation.

3.1.3. FC-28 sensor

The FC-28 sensor is a key component utilized in this research for soil moisture monitoring. The FC-28 sensor, based on LM393 design, is widely recognized for its effectiveness in measuring soil moisture content. It has 4 pins for performing its operation. The sensor features two probes that are inserted into the soil, allowing it to determine the moisture level based on the electrical resistance between the probes. With its simple design and ease of use, the FC-28 sensor provides a cost-effective solution for monitoring soil moisture in agricultural and research applications. Its analog output can be easily interfaced with microcontrollers, enabling seamless integration into IoT systems. It has digital output and power Indicator LEDs. With a compact PCB size of 3.2 cm × 1.4 cm, the fire flame sensor offers a compact form factor for easy

Table 1
Summary of the most recent studies.

Study	Purpose/Application Area	Method	Dataset	ML-IoT Enabled	Key Findings	Limitations
[35]	Continuous monitoring system of soil health.	IoT	Real-time data	No	Development and testing of a low-cost (5667 USD) monitoring system.	No Data Analysis technique was conducted.
[13]	Continuously measures variables at the agro-field.	IoT and DSS	Real-time data.	No	Development and testing of IoT-based smartphones platform.	It must be connected with wires.
[48]	An automated remote field monitoring system	LoRaWAN	Real-time data.	No	Visualization in the cloud.	Data Analysis technique is not mentioned.
[42]	Soil monitoring system	IoT	Real-time data.	No	Efficiently identify soil type and display corresponding data graphically.	Data Analysis technique is not mentioned.
[8]	Soil Classification based on micronutrients.	ELM	Private dataset.	Yes	Accuracy 94 %	The dataset consists exclusively of the Tamil Nadu region.
[6]	Crop recommendation	MLP	Kaggle Dataset	Yes	98.22 % accuracy	Detailed analysis was not conducted.
[46]	To assist the farmer by developing crop recommendation platform	RF	Kaggle Dataset	No	Random forest achieved 97.18 % accuracy	Not applicable for real-time data.
[40]	To support farmers with ongoing crop and field information regularly.	MSVM-DAG-FFO	Own dataset	Yes	The proposed mode achieved the accuracy of 97.3 %	Didn't develop any platform from where farmers can get support.
[45]	Crop Recommendation system	RFC	Own dataset	Yes	RFC achieved 99 % accuracy	No detailed discussion about data sensing.
[18]	Correct Selection of Crop	SCS	Dataset from Pakistan.	Yes	Accuracy 97.4 %	Dataset contains only two types of soil. And the technique is only suitable for a few crops.

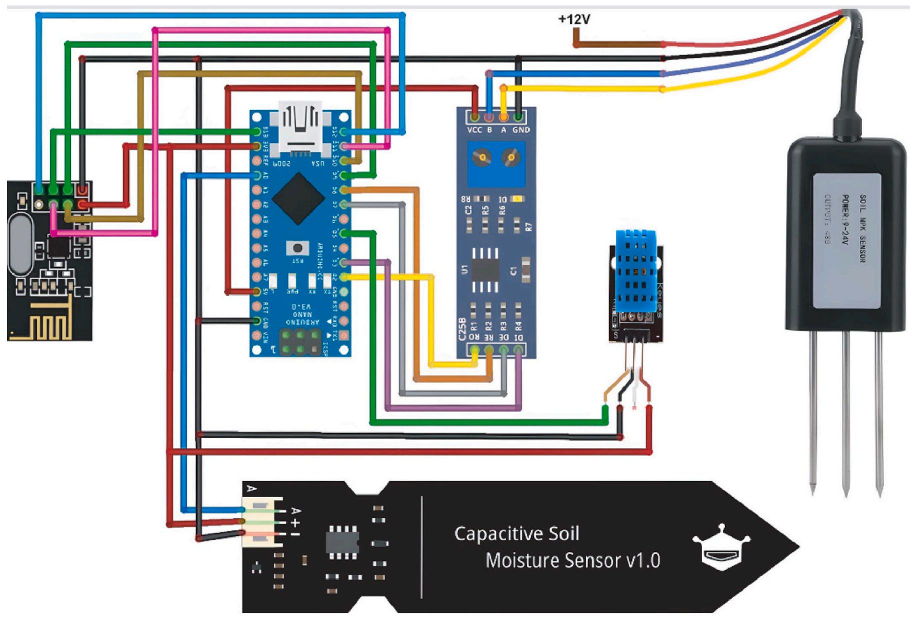

Fig. 1. Circuit diagram of the proposed system.

Table 2
Configurations and Specifications of the proposed IoT System Components.

Components	Specifications
NodeMCU	ESP8266 Wi-Fi module-based development board with open-source firmware. It includes a USB interface, a voltage regulator for reliable power, 11 digital I/O pins, a pin for analog input, and a UART communication interface. Able to run on the Arduino IDE.
JXBS-3001 Sensor	Designed specifically for soil monitoring applications. Its measurement range of NPK is 0–199 mg/kg. It uses RS485 communication port and requires 5V-24v DC power supply.
FC-28 Sensor	The sensor operates within a voltage range of 3.3V–5V DC and has an operating current of 15 mA, ensuring low power consumption during operation. LM393 based design.
DHT11 Sensor	The sensor provides accurate humidity readings within the range of 20 %–80 % with a precision of 5 %. It is also capable of accurately measuring temperatures within the range of 0 °C–50 °C with an accuracy of ±2 °C. The sampling rate of the sensor is limited to a maximum of 1 Hz.

installation and integration into fire detection systems. Therefore, the FC-28 sensor enables researchers to obtain real-time data on soil moisture, facilitating informed decision-making and efficient water management strategies.

3.1.4. DHT11 sensor

The DHT11 sensor is an essential component used in this research for collecting environmental data. The DHT11 sensor is widely employed for measuring temperature and humidity levels. It offers a cost-effective solution with reliable performance. The sensor utilizes a digital signal output, making it compatible with various microcontrollers and IoT platforms. With its compact size and easy integration, the DHT11 sensor is ideal for applications where monitoring temperature and humidity are critical. Its accuracy and stability ensure precise measurements, enabling researchers to gather valuable data for analysis and decision-making. The DHT11 sensor provides an affordable and efficient solution for environmental monitoring in research studies.

3.2. Data transmission using MQTT protocol

The data transmission section of the research paper focuses on the implementation of the MQTT (Message Queuing Telemetry Transport) protocol for efficient data transmission in the ML-enabled IoT device for soil nutrients monitoring and crop recommendation. This section outlines the methods and techniques used for utilizing the MQTT protocol for data transmission, and storage. A suitable MQTT broker needs to be chosen, considering factors such as scalability, reliability, and support for Quality of Service (QoS) levels. In this project, a cloud-based MQTT broker is chosen, as it provides easy scalability, high availability, and seamless integration with other cloud services. After that, MQTT topics are designed to represent different aspects of soil nutrients and crop-related data, enabling efficient organization and routing of messages. The collected data is formatted into MQTT payloads, encapsulating the relevant soil parameters, crop information, and other contextual data. Based on the criticality and reliability requirements of the data, the appropriate QoS level is selected. QoS levels 0 (at most once), 1 (at least once), or 2 (exactly once) are considered for message delivery. The IoT device is equipped with an MQTT client that connects to the MQTT broker and publishes the collected data to the respective MQTT topics. It publishes data to specific topics, while other devices or subscribers can subscribe to these topics to receive the data in real-time. For the purpose of the secured data storage and management, the MQTT broker is integrated with cloud storage services, enabling the seamless storage and retrieval of MQTT data in scalable storage systems. And, the received MQTT messages are persisted in cloud storage for long-term data retention and subsequent analysis. Finally, raw data received from the MQTT broker undergoes preprocessing steps, including filtering and cleansing, to remove noise, outliers, or erroneous readings and is transformed into a suitable format for analysis, ensuring compatibility with ML algorithms and further processing steps.

3.3. Machine learning methods

This section explains the machine learning algorithms integrated into the analysis pipeline to process the data and generate relevant insights and recommendations for soil nutrients monitoring and crop management. In our study, we used Catboost classifier 3.3.1 and Random Forest classifier with grid SearchCV 3.3.2 to recommend crop, and fertilizer, respectively.

3.3.1. CatBoost Classifier

The CatBoost classifier is a powerful machine learning algorithm employed in the research paper. It is an open-source gradient boosting framework that excels in handling categorical features and large datasets. In the context of the crop recommendation system, CatBoost plays a pivotal role in predicting the most suitable crops for a given set of environmental and soil conditions. Its ability to handle categorical variables without the need for extensive preprocessing makes it a preferred choice for agricultural applications. The algorithm effectively learns from complex patterns and interactions in the data, enabling accurate crop predictions. It addresses gradient bias and prediction shift issues, integrates a gradient boosting decision tree (GBDT) with categorical features, and concentrates on categorical variables [31]. By using all sample datasets in the algorithm for training, it helps to increase the resilience of the algorithms. Assume that we observe a data set of samples (1)

$$S = (X_i, y_i)_{i=1,\ldots,n,} \tag{1}$$

Where $X_i = (x_i^1, x_i^2, \ldots, x_i^k)$ is a vector of k characteristics and response feature $y_i \epsilon F$, which can be encoded as the numerical feature (0,1,2,3, …., m). The distribution of the samples (X_i, y_i) is independently and identically distributed according to an unidentified distribution, $d(., .)$. The learning task's objective is to develop a function A: $F_k \rightarrow F$ that minimizes the estimated loss indicated in equation (2)

$$Los(A) := EL(y, A(X)) \tag{2}$$

where $L(., .)$ is a smooth loss function and (X, y) is a sample of test data drawn from the training data S [17]. Additionally, CatBoost offers features like robust handling of missing values, strong regularization techniques, and customizable parameters that can be fine-tuned for optimal performance. By leveraging the capabilities of CatBoost, the research paper's crop recommendation system aims to provide farmers and agricultural stakeholders with valuable insights and informed decision-making tools to enhance crop productivity and sustainability.

3.3.2. Random forest with grid SearchCV

Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. In the context of the fertilizer recommendation, Random Forest plays a crucial role in analyzing various factors such as soil properties, crop characteristics, and environmental conditions to suggest the most appropriate fertilizer for optimal plant growth. The algorithm's ability to handle complex interactions and nonlinear relationships between variables makes it well-suited for this task. By utilizing an ensemble of decision trees, Random Forest reduces overfitting and improves prediction accuracy. It also provides insights into feature importance, aiding in understanding the factors that influence fertilizer recommendations. The base classifiers can be defined as (3)

$$\{t(x, \varphi_m), m = 1, \ldots\ldots.., \} \tag{3}$$

Where, x is input vector and $\{\varphi_m\}$ are the independent and identically distributed random vectors [39]. Then, the random forest approach can be defined as (4)

$$Rf = majorityVote\{t(x, \varphi_m), m = 1, \ldots\ldots.., \} \tag{4}$$

In this research paper, we explore the application of the Random Forest algorithm in combination with grid search for optimizing fertilizer recommendation systems. Random Forest is a popular ensemble learning method that combines multiple decision trees to make accurate predictions. Grid search, on the other hand, is a hyperparameter tuning technique that systematically searches through a specified parameter grid to find the optimal combination of hyperparameters for a machine learning model. By utilizing grid search, we aim to fine-tune the Random Forest model to improve its performance in fertilizer recommendation. We conduct experiments on a comprehensive dataset containing soil properties, climate data, and crop information. The grid search technique allows us to explore various hyperparameter combinations, such as the number of trees, maximum depth, and minimum sample split, to find the best configuration for our model. Through rigorous evaluation and comparison with other models, we demonstrate the effectiveness and efficiency of the Random Forest algorithm with grid search in accurately predicting the optimal fertilizer recommendation for different crops and soil conditions. The results highlight the potential of this approach in supporting precision agriculture and enhancing crop yield and sustainability. With its robustness and ability, it is an essential component of the research paper's fertilizer recommendation system, providing valuable guidance to farmers and helping them make informed decisions to optimize crop productivity while minimizing the environmental impact.

3.4. Proposed framework

The proposed framework involves the installation of three sensors—the JXBS-3001, FC-28, DHT11 sensor—in the crop field to collect various types of data, including soil nutrient concentrations (NPK), moisture, humidity, and temperature. The collected data is then transmitted to a remote server through the NodeMCU using the MQTT protocol for further processing. These sensors provide real-time data, allowing farmers to monitor soil health and make informed decisions regarding fertilization strategies and irrigation schedules. This data is passed to the proposed machine learning model, which generates personalized crop recommendations, including ideal planting times, suitable crop varieties, and precise fertilization plans. This empowers farmers to optimize their crop selection and improve overall productivity. Besides, it ensures the health and safety of harvested produce by soil monitoring and assesses nutritional content, pesticide residues, and potential contaminants in the food by analyzing data from embedded sensors. The proposed framework offers a User-Friendly Mobile App, which can provides farmers with seamless access to their device and data, allowing them to remotely monitor and control their agricultural operations. Users can view real-time sensor readings, track historical trends, receive actionable insights, and access crop recommendations and food health reports, all within the app's intuitive interface. It also delivers real-time alerts and notifications to farmers regarding critical conditions such as water stress, nutrient deficiencies, disease outbreaks, or adverse weather conditions, and presents comprehensive data visualization and analysis tools. Farmers can view sensor data in intuitive graphs and charts, identify patterns, and gain valuable insights into soil health, crop performance, and food quality. Overall, the proposed framework utilizes a combination of IoT sensors and machine learning algorithms to enable remote agro-field monitoring and crop recommendation. By leveraging the power of machine learning, the system can accurately analyze vast amounts of data and makes informed decisions about agro-field conditions, leading to better outcomes, food safety, and improved food production. The proposed framework is illustrated in Fig. 2.

4. Experimental results

In this section, we will provide an explanation of the outcomes achieved in our study. This will encompass field deployment design 4.1 and information about the techniques employed for data collection and processing 4.2, along with a summary of the accuracy measures 4.3 employed to assess the effectiveness of our system. Lastly, we will conduct an analysis of the acquired results 4.4 and introduce an IoT-ML enabled agriculture platform 4.5.

4.1. Experimental setup

The study was conducted using an 8th generation Intel Corei7 with a 6600U processor clocked at up to 3.1 GHz and 16 GB of RAM. Numerous tests were conducted using various machine learning techniques using the Anaconda tool. To gather diverse data from the crop field, three sensors—the JXBS-3001, FC-28, and DHT11 sensors—are deployed.

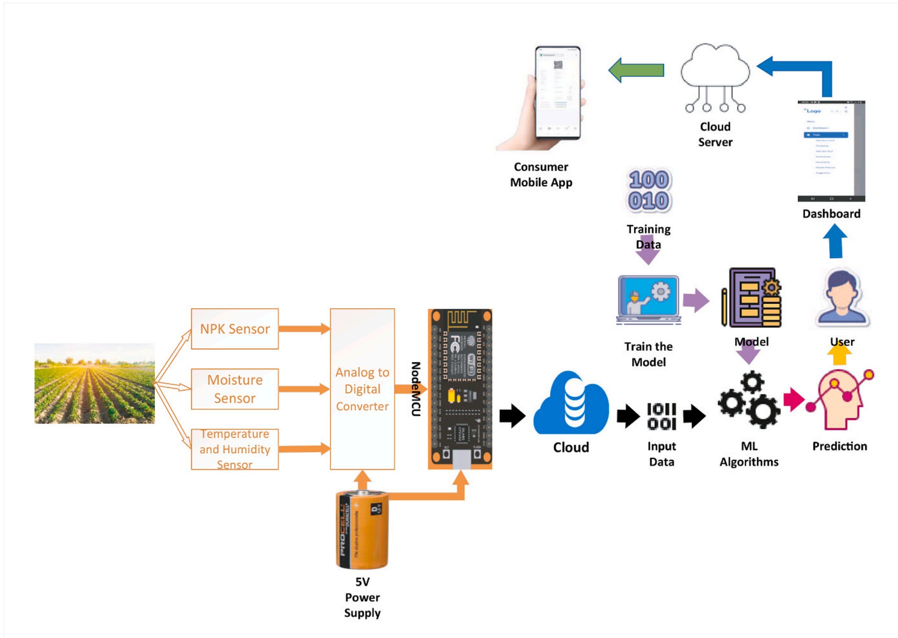

Fig. 2. Proposed framework of an innovative ML-Enabled IoT system for soil nutrients monitoring and crop recommendation.

Deploying sensors and controllers in an IoT-based agricultural system is crucial for precise data collection. The key considerations of the deployment in field include strategic sensor placement (at various depths in the soil) to monitor soil properties at different levels, even distribution for accurate data capture, node controllers (NodeMCU) near sensors, power supply via solar panels for remote areas, reliable communication networks (LoRaWAN), weatherproofing for durability, regular calibration and maintenance, centralized data storage, user-friendly interfaces, and scalability. These sensors enable the collection of information such as soil nutrient concentrations (NPK), moisture levels, humidity, and temperature. The acquired data is subsequently transmitted to a remote cloud via the NodeMCU device, utilizing the MQTT protocol. Fig. 3 illustrates the field experimental design of the ML-Enabled IoT system for monitoring soil nutrients and crop recommendations.

4.2. Data collection and pre-processing

To initiate the learning and validation process of the proposed framework, we initially utilized a combined dataset compiled from Ref. [19] and our own collected dataset from diverse regions of Bangladesh for crop recommendation which contains 2299 records. A diverse set of 22 crop types data, including apple, banana, black gram, grapes, kidney bean, chickpea, coconut, coffee, cotton, jute, lentil, maize, moth beans, mung beans, pomegranate, pigeon peas, musk-melon, orange, papaya, rice, and watermelon, was collected and utilized for the development of our crop recommendation system. This comprehensive dataset represents a wide spectrum of crops commonly cultivated in various agricultural regions, ensuring the system's applicability across different farming contexts. This combined dataset allows us to recommend a suitable crop for the agri-field based on its 7 features, such as Nitrogen (N), Potassium (K), Phosphorus (P), Temperature, Humidity, and soil Moisture. Additionally, we employed a distinct

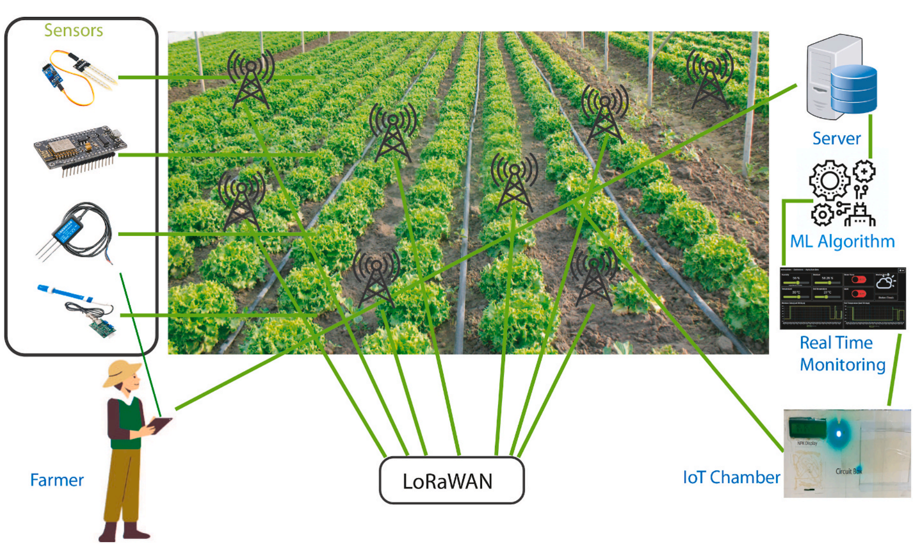

Fig. 3. Field Experimental Design of the ML-Enabled IoT System for monitoring soil nutrients and crop recommendations.

dataset to learn and validate our proposed system specifically for fertilizer recommendation based on its 9 features, such as Nitrogen (N), Potassium (K), Phosphorus (P), Temperature, Humidity, Soil type, Crop type, and soil Moisture. This dataset contains 152 entries prepared from our own data and a Kaggle dataset [43]. By using the chi-squared test (5), we can evaluate the independence or dependence between features, identify patterns or relationships, and make informed conclusions about the significance of associations within the data.

$$Ci_2 = \sum \frac{(Ob_i - Ex_i)}{Ex_i} \tag{5}$$

Where, Ob_i is the observed value, and Ex_i is the expected value. Table 3 represents the chi-squared score of the crop recommendation dataset, where the score of ph is worst compared with other features. Therefore, we eliminate the ph from the dataset for further processing. Then, we apply the Z-score (6) to remove outliers from the dataset.

$$Z = \frac{(x - \mu)}{\sigma} \tag{6}$$

Where, x is value, μ is mean, and σ is standard deviation. We have established a threshold to identify and exclude outliers from the dataset. Any data point with a z-score less than 3 is considered an outlier and removed. Through this process, we detected 9 outliers, resulting in a revised dataset size of 2299 instances, compared to the original 2290 instances. Fig. 4 shows the correlation among the features of the crop recommendation dataset.

We convert the categorical features of the fertilizer prediction dataset into numerical values. Then, we performed Z-score methods to remove outliers. We did not find any outliers from the dataset. To convert the ppm unit of soil nutrients into *Kg/HA* the following equation (7) is used [44].

$$Nutrient(kg / HA) = 2.5 * \lambda \tag{7}$$

Where, λ is PPM(parts per million) of Nutrient.

After preprocessing, the data set was split into a training set (80 %) and a test set (20 %). Although the model was primarily trained and assessed using the combined Dataset, we also conducted tests using real-time data collected in our laboratory.

4.3. Model evaluation metrics

Prior to implementing our model on simulated data, it is essential to enhance its overall predictive capability by assessing its performance using diverse criteria. It is important to evaluate an ML model using various metrics [29] and not solely relying on accuracy when applying it to new data, as this can result in inaccurate predictions. To evaluate the effectiveness of our research, we employ the following evaluation criteria (Accuracy 4.3.1, Precision 4.3.2, Recall 4.3.3, F1-Measur 4.3.4) with TP- True Positive, TN- True Negative, FP- False Positive, and FN- False Negative.

4.3.1. Accuracy

Accuracy refers (8) to the proportion of accurately classified samples compared to the total number of samples within the dataset:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{8}$$

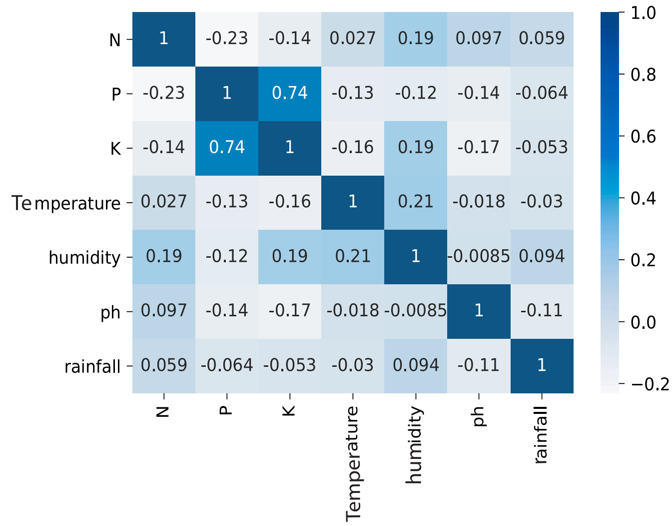

Fig. 4. Correlation among the features of the crop recommendation dataset.

4.3.2. Precision

Precision 9 is determined by dividing the number of true positive samples by the total number of positive samples predicted by the model:

$$Precision = \frac{(TP)}{(TP + FP)} \tag{9}$$

4.3.3. Recall

Recall (10), also known as the true positive rate (TPR), is calculated by dividing the number of correctly recommended or predicted crops or fertilizers by the total number of crops or fertilizers. It can be defined as:

$$Recall = \frac{(TP)}{(TP + FN)} \tag{10}$$

4.3.4. F1-measure

It is the precision and recall's harmonic mean (average) defined in equation (11).

$$F1 - Score = \frac{(2 * Precision * Recall)}{(Precision + Recall)} \tag{11}$$

4.4. Results analysis

The results obtained from the implementation of the CatBoost classifier in the crop recommendation 4.4.1 and from the implementation of the Random Forest classifier with Grid Search in the fertilizer prediction 4.4.2 are analyzed in this subsection. The performance of the classifiers was evaluated using various evaluation metrics, including accuracy, precision, recall, and F1-score.

4.4.1. Crop recommendation

The accuracy metric indicates the overall correctness of the crop recommendations provided by the system. Precision represents the proportion of correctly recommended crops out of all the crops suggested by the system, while recall measures the system's ability to identify and recommend the relevant crops. The F1-score combines both precision and recall to provide a balanced assessment of the classifier's performance.

Table 3
Chi-squared score of the crop recommendation dataset.

N	P	K	temperature	humidity	ph	rainfall
53144.69	42500.13	116710.53	1092.42	14755.48	74.88	54808.13

Fig. 5 represents the comparisons of 3 different model evaluation metrics which indicate the effectiveness of the applied CatBoost Classifier with Voting and Bagging classifiers in terms of accuracy, precision, Recall, and F1- measure. The CatBoost classifier achieved the best performance with an accuracy of 97.5 %, precision of 98 %, recall of 96 %, and F1-score of 97.5 %. Other models also perform well. The bagging classifier obtained the accuracy of 95 %, precision of 96 %, recall of 95 %, and F1-score of 95 %, while the voting classifier acquired the accuracy of 96 %, precision of 94 %, recall of 96 %, and F1-score of 97 %.

Additionally, the confusion matrix was analyzed to gain insights into the specific types of classification errors made by the system presented in Fig. 6. Upon analyzing the results, it is evident that the model exhibits a significant number of accurate positive and negative predictions across various classes. Nonetheless, there are instances where the model generates incorrect outputs. Specifically, there are 52 occurrences where the model misclassifies certain classes. These errors may have the potential to impact crop selection decisions within the agricultural domain.

Table 4 represents a comparative performance analysis of different machine learning algorithms used in the recent literature to recommend the suitable crop for the cultivation in the agri-field. It indicates that the CatBoost classifier demonstrates promising performance with 97.5 % accuracy and 97 % F1 score in accurately recommending crops based on the given input parameters. These findings validate the effectiveness of the implemented crop recommendation system and highlight the potential of the CatBoost classifier in agricultural decision-making processes.

4.4.2. Fertilizer prediction

After several iterations and fine-tuning, we successfully developed a fertilizer prediction model using the Random Forest algorithm combined with grid searchCV. The hyperparameters of the model were carefully adjusted to achieve optimal performance. To determine the best values for these hyperparameters, we conducted a cross-validated grid search, as depicted in Table 5 of our study. This process involved systematically exploring different combinations of hyperparameters and evaluating their performance using cross-validation techniques. The resulting model with the identified optimal hyperparameter values demonstrates promising potential for accurate fertilizer prediction in our research.

The confusion matrix was analyzed to gain insights into the specific types of classification errors made by the system presented in Fig. 7. Upon analyzing the results, it is evident that the model exhibits a significant number of accurate positive and negative predictions across various classes. It is mentionable that there is only one instance where the model generates incorrect output.

Table 6 presents the precision, recall, and f1-score for each class, indicating the model's performance. It is evident that the model exhibits strong performance for most classes, with a precision of 1.00 and a recall value of 0.99. This suggests that the model excels at accurately

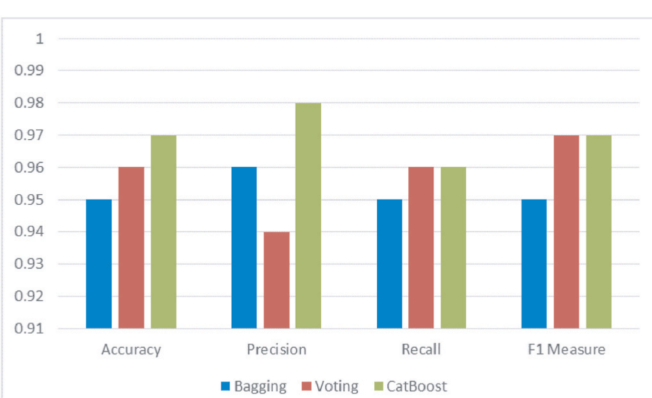

Fig. 5. Comparisons of 3 different model's evaluation metrics.

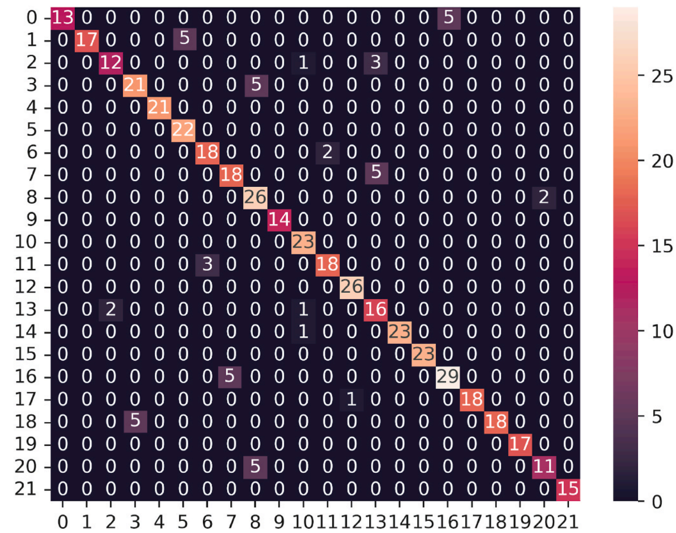

Fig. 6. Confusion matrix of CatBoost classifier.

predicting the appropriate fertilizer for optimal crop cultivation.

Fig. 8 represents a comparative performance analysis of different machine learning algorithms used in the recent literature to predict the suitable fertilizer for crop cultivation in the agri-field. It indicates that the Random Forest with Grid SearchCV demonstrates promising performance with 99.56 % accuracy and 100 % F1 score in accurately predicting fertilizers based on the given input parameters. In comparison to alternative machine learning methods like SVM, Random Forest, and Linear Forest, the proposed approach exhibited higher accuracy and F1-score, demonstrating its superior performance in fertilizer prediction. To illustrate, previous studies by Ref. [12] achieved an accuracy of 0.97 and an F1-score of 0.95 using Linear Forest, while [22] reported an accuracy of 0.95 and an F1-score of 0.95 with Random Forest. The proposed method surpassed these approaches, including advanced techniques such as support vector machines. For instance Ref. [30], achieved an accuracy of 0.95 and an F1-score of 0.894 with an SVM model. Overall, these findings validate the effectiveness of the implemented fertilizer prediction system and highlight the potential of the Random Forest with Grid SearchCV classifier in agricultural decision-making processes.

4.5. IoT-ML enabled agriculture platform

Based on the evaluation criteria discussed earlier, it is evident that CatBoost demonstrates superior performance compared to the other machine learning algorithms considered in predicting the optimal crop for harvesting. Therefore, for our crop recommendation platform, we plan to utilize CatBoost to predict the most suitable crop based on user-input parameters such as N, P, K, air temperature, air humidity, soil pH level, moisture, and rainfall. Similarly, it has been observed that RF with gridsearchCV yields the best results in predicting the appropriate fertilizer for field application. Hence, for our platform, we will employ RF with gridsearchCV to recommend the most suitable fertilizer for the earlier recommended crop, considering user-provided parameters such as Nitrogen (N), Potassium (K), Phosphorus (P), Temperature, Humidity, Soil type, Crop type, and Soil Moisture. Once the optimal models have been selected, they will be saved separately for the development of the crop recommendation platform using Flutter as the subsequent step. Following successful local testing, we deployed our locally tested mobile app on Google Cloud App Engine, which offers Platform as a Service (PaaS) capabilities, ensuring high uptime of nearly 99.9 % and convenient access from any device around the clock. For demonstration purposes, we utilized their free tier service, which does not incur any charges. Fig. 9 provides a glimpse of the fully functional

Table 4
A comparative performance analysis of ML algorithms used in the recent literature to recommend the suitable crop.

Ref	Year	Dataset	Sensors Used	Methodology	Performance
Bakthavatchalam et al. [30]	2022	Kaggle dataset	Yes	MLP	Accuracy: 98 %, F1 Score:
Thilakarathne et al. [31]	2022	Kaggle dataset	No	Random Forest	Accuracy: 97.18 %, F1 Score: 97 %
Senapaty et al. [32]	2023	Field data of India	Yes	MSVM-DAG-FFO	Accuracy: 97.3 %, F1 Score: 96 %
Sundaresan et al. [33]	2022	Own data	Yes	KNN	Accuracy: 97 %, F1 Score:
Ikram et al. [36]	2022	Own data	Yes	Ensemble approach	Accuracy: 97.4 %, F1 Score: 97 %
Proposed Model	2023	Kaggle dataset + own dataset	Yes	CatBoost	Accuracy: 97.5 %, F1 Score: 97.5 %

Table 5
The hyperparameter tuned with a grid search for the random forest.

Hyperparameter	Grid Search Parameter
Number of trees	200, 500
Maximum features	auto, sqrt, log2
Maximum tree depth	4,5,6,7,8
Cross Validation	5

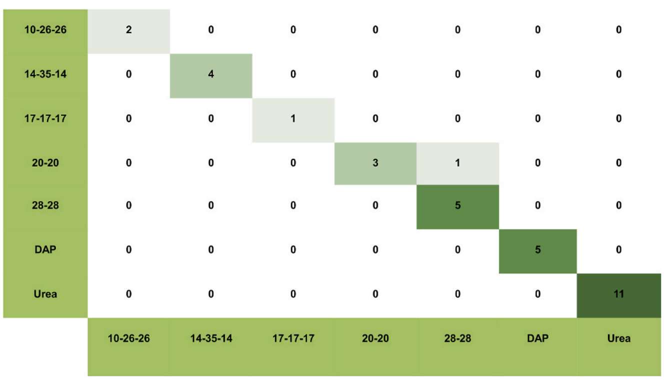

Fig. 7. Confusion Matrix of Random Forest Classifier with gridSearchCV.

Table 6
Classification Report for the proposed model performance.

Class	precision	recall	f1-score	Support
10-26-26	1.00	1.00	1.00	2
14-35-14	1.00	1.00	1.00	4
17-17-17	1.00	1.00	1.00	1
20–20	1.00	0.75	0.86	4
28–28	1.00	1.00	1.00	5
DAP	1.00	1.00	1.00	5
Urea	1.00	1.00	1.00	11
accuracy			0.99‘	32
macro avg	1.00	0.96	0.98	32
weighted avg	1.00	0.99	1.00	32

recommendation platform hosted in the cloud. The platform can determine the name and quantity of applied fertilizers and the list of potential high yielding crops according to the soil fertility test and test results. Fertilizers and treatments applied to the field during production are stored in the database. As a result, it has become possible to determine the quality of the produce at the consumer level through the mobile app when it is marketed. The use of QR codes allows farmers to market their crops effectively. Therefore, consumers have the ability to access detailed crop history information, such as the planting time, and the type and quantity of fertilizers used, etc.

5. Discussion and future research

The aim of this study was to develop an innovative ML-enabled IoT device for soil nutrients monitoring and crop recommendation. The results obtained from our research indicate that the proposed device and framework have significant potential in the field of precision agriculture.

One of the key contributions of our study is the integration of IoT technology with machine learning algorithms for real-time soil nutrient monitoring. By deploying sensors such as JXBS-3001, FC-28, and DHT11 in the crop field, we were able to collect essential data related to soil nutrient concentrations (NPK), moisture, humidity, and temperature. This data was then transmitted to a remote server using the NodeMCU and MQTT protocol, enabling continuous monitoring and analysis.

The use of machine learning algorithms, particularly CatBoost and Random Forest, played a crucial role in the crop recommendation process. These algorithms were trained on merged datasets and optimized through hyperparameter tuning, resulting in accurate predictions for the most suitable crops and fertilizers. The CatBoost algorithm exhibited superior performance in predicting the optimal crop based on input parameters such as N, P, K, air temperature, air humidity, soil pH level, moisture, and rainfall. On the other hand, the Random Forest algorithm with grid search excelled in recommending the most appropriate fertilizer based on parameters such as Nitrogen (N), Potassium (K), Phosphorus (P), Temperature, Humidity, Soil type, Crop type, and Soil Moisture.

The performance evaluation of our models revealed high precision, recall, and F1-scores for most classes, indicating the effectiveness of our approach in crop and fertilizer recommendation. However, it is important to note that there were instances where the models made errors, which could have implications for crop selection and fertilization decisions. Further research and refinement are necessary to minimize these errors and improve the overall accuracy of the system.

The integration of the ML-enabled IoT device with a cloud-based recommendation platform provides convenient access and scalability. By deploying the locally tested mobile app on Google Cloud App Engine, we ensured high uptime and easy accessibility from any device. The cloud-hosted platform offers a fully functional recommendation system for farmers, enabling them to make informed decisions regarding crop selection and fertilizer application.

Future research directions for the paper include.

1. Expanding capabilities: The device and platform should be further developed to accommodate a broader range of crops and geographic locations. This expansion would allow farmers cultivating different types of crops in various regions to benefit from the device's monitoring and recommendation functionalities.
2. Integration of satellite imagery and weather data: To provide more comprehensive and precise recommendations, future research should focus on incorporating satellite imagery and weather data into the system. By leveraging these additional sources of information, the device can offer more accurate insights into crop health, growth patterns, and environmental conditions.
3. Enhancing scalability and usability: The device's scalability and usability should be improved to cater to the needs of farmers in different regions with varying technological infrastructures. This includes ensuring that the device can adapt to different communication networks and power sources, as well as developing user-

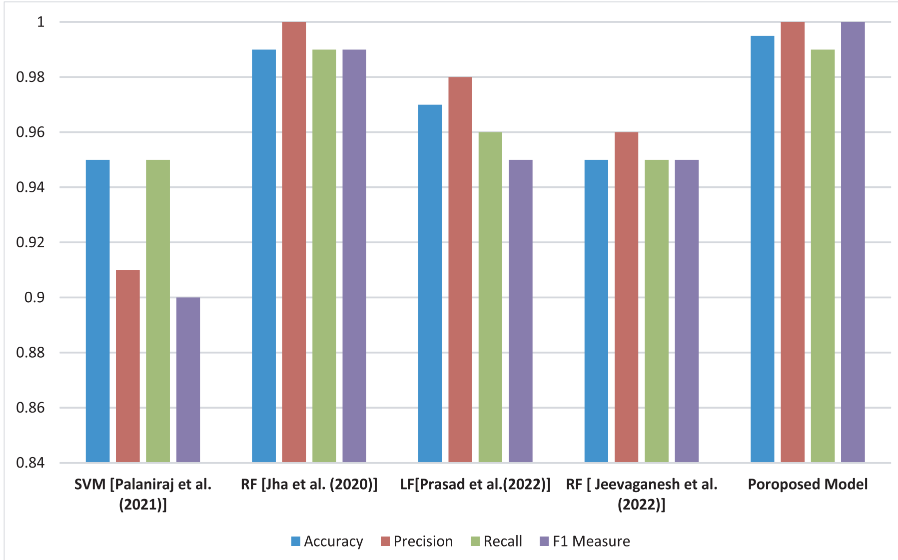

Fig. 8. A comparative performance analysis of ML algorithms used in the recent literature to predict the suitable fertilizer.

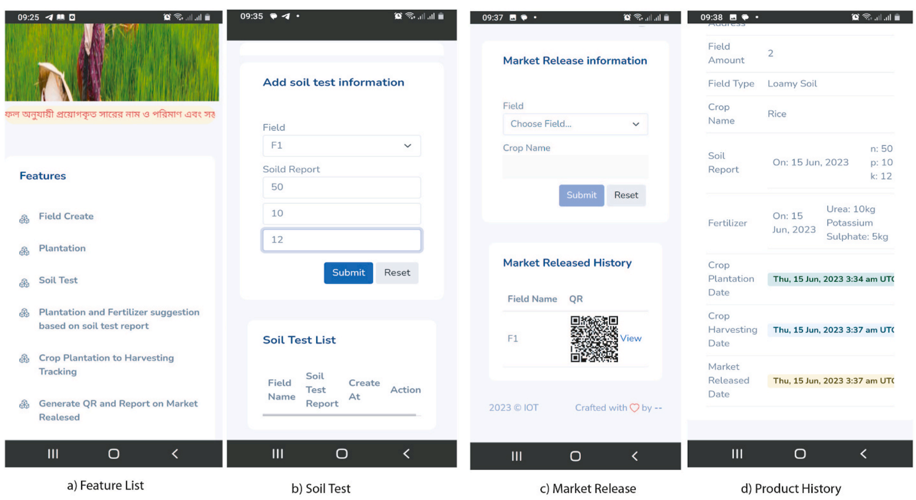

Fig. 9. Crop recommendation platform hosted in the cloud.

friendly interfaces that are accessible to farmers with varying levels of technological literacy.

By addressing these future research directions, the paper can contribute to the advancement of the ML-enabled IoT device and its applicability in agriculture, enabling farmers to make more informed decisions and improve crop productivity.

Overall, our research demonstrates the potential of ML-enabled IoT devices in precision agriculture. The integration of sensor data, machine learning algorithms, and cloud-based platforms enables real-time monitoring, analysis, and decision-making for improved crop management practices. This innovative system offers numerous benefits, including unparalleled precision, real-time monitoring capabilities, adaptability, user-friendliness, support for safe food production, and the potential for sustainability. However, it also faces challenges related to data availability, sensitivity to errors, system complexity, cost considerations, and ongoing maintenance requirements. The system's suitability is dependent on the unique demands and resources of the specific agricultural context in which it is deployed. Furthermore, when comparing our system with the conventional approach, it becomes evident that the proposed system excels in terms of precision, adaptability, and real-time decision support. Nonetheless, traditional methods retain their inherent merits, encompassing simplicity, reliability, cost-effectiveness, transparency, and wide applicability. The selection between the traditional and ML-Enabled IoT approaches hinges on factors such as the precise requirements of the agricultural context, data and resource availability, and the users' technical expertise. Notably, this system holds substantial promise in assisting the many farmers worldwide who lack comprehensive agricultural knowledge, making it especially valuable for such individuals. Future research endeavors should concentrate on fine-tuning the system and broadening its capabilities to cater to the diverse needs of farmers and agricultural stakeholders.

6. Conclusion

In this study, the combination of IoT technology, sensor data collection, and machine learning algorithms has demonstrated promising results in precision agriculture through an innovative ML-enabled IoT device for soil nutrient monitoring and crop recommendation. By utilizing various sensors and transmitting data to a remote server in real-time, crucial information on soil nutrient concentrations, moisture, humidity, and temperature was collected and analyzed. The application of machine learning algorithms, such as CatBoost and Random Forest, proved effective in predicting suitable crops and recommending appropriate fertilizers. While there is room for improvement in minimizing errors and refining the models, this ML-enabled IoT device has shown great potential in providing farmers with real-time insights and recommendations for optimal crop management. By addressing the challenges and further exploring research directions, we can continue to enhance the capabilities of this device and contribute to the advancement of precision agriculture.

CRediT authorship contribution statement

Md. Reazul Islam: Conceptualization of this study, Methodology, Software, Data curation. Khondokar Oliullah: Conceptualization of this study, Data curation, Writing - Original draft preparation, Methodology, Investigation. Md Mohsin Kabir: Writing - Original draft preparation, Investigation, Supervision, Visualization, Writing- Review & Editing. Munzirul Alom: Data curation, Methodology, Investigation. M. F. Mridha: Investigation, Supervision, Visualization, Writing- Review & editing.

Declaration of competing interest

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Data availability

Data will be made available on request.

References

[1] Y. Al Masmoudi, Y. Bouslihim, K. Doumali, L. Hssaini, K. Ibno Namr, Use of machine learning in moroccan soil fertility prediction as an alternative to laborious analyses, Modeling Earth Systems and Environment (2021) 1–11, https://doi.org/10.1007/s40808-021-01329-8.
[2] J. An, F. Le Gall, J. Kim, J. Yun, J. Hwang, M. Bauer, M. Zhao, J. Song, Toward global iot-enabled smart cities interworking using adaptive semantic adapter, IEEE Internet Things J. 6 (3) (2019) 5753–5765, https://doi.org/10.1109/JIOT.2019.2905275.
[3] N. Ananthi, J. Divya, M. Divya, V. Janani, Iot based smart soil monitoring system for agricultural production, in: 2017 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR), IEEE, 2017, pp. 209–214.
[4] A. Ashwitha, C. Latha, Crop recommendation and yield estimation using machine learning, Journal of Mobile Multimedia (2022) 861–884, https://doi.org/10.13052/jmm1550-4646.18320.
[5] G. Babu Loganathan, E. Mohan, R. Siva Kumar, Iot based water and soil quality monitoring system, Int. J. Mech. Eng. Technol. 10 (2) (2019) 537–541.
[6] K. Bakthavatchalam, B. Karthik, V. Thiruvengadam, S. Muthal, D. Jose, K. Kotecha, V. Varadarajan, Iot framework for measurement and precision agriculture: predicting the crop using machine learning algorithms, Technologies 10 (1) (2022) 13.
[7] V. Bhatnagar, R. Chandra, Iot-based soil health monitoring and recommendation system, Internet of Things and Analytics for Agriculture 2 (2020) 1–21, https://doi.org/10.1007/978-981-15-0663-5_1.
[8] T. Blesslin Sheeba, L. Anand, G. Manohar, S. Selvan, C.B. Wilfred, K. Muthukumar, S. Padmavathy, P. Ramesh Kumar, B.T. Asfaw, Machine learning algorithm for soil analysis and classification of micronutrients in iot-enabled automated farms, J. Nanomater. (2022), https://doi.org/10.1155/2022/5343965.
[9] D.A. Bondre, S. Mahagaonkar, Prediction of crop yield and fertilizer recommendation using machine learning algorithms, International Journal of Engineering Applied Sciences and Technology 4 (5) (2019) 371–376.
[10] A. Chehri, H. Chaibi, R. Saadane, N. Hakem, M. Wahbi, A framework of optimizing the deployment of iot for precision agriculture industry, Procedia Comput. Sci. 176 (2020) 2414–2422.
[11] F. Cirillo, D. Gómez, L. Diez, I.E. Maestro, T.B.J. Gilbert, R. Akhavan, Smart city iot services creation through large-scale collaboration, IEEE Internet Things J. 7 (6) (2020) 5267–5275, https://doi.org/10.1109/JIOT.2020.2978770.
[12] K. V. P. Dr Kalli Srinivasa Nageswara Prasad, S.V.V.D. Venu Gopal, Suitable fertilizer recommendation system using linear forest classifier, Ymer 21 (2022).
[13] S.V. Gaikwad, A.D. Vibhute, K.V. Kale, S.C. Mehrotra, An innovative iot based system for precision farming, Comput. Electron. Agric. 187 (2021), 106291.
[14] L. García, L. Parra, J.M. Jimenez, J. Lloret, P. Lorenz, Iot-based smart irrigation systems: an overview on the recent trends on sensors and iot systems for irrigation in precision agriculture, Sensors 20 (4) (2020) 1042, https://doi.org/10.3390/s20041042.
[15] X. Ge, J. Wang, J. Ding, X. Cao, Z. Zhang, J. Liu, X. Li, Combining uav-based hyperspectral imagery and machine learning algorithms for soil moisture content monitoring, PeerJ 7 (2019), e6926, https://doi.org/10.7717/peerj.6926.
[16] T. Hengl, J.G. Leenaars, K.D. Shepherd, M.G. Walsh, G.B. Heuvelink, T. Mamo, H. Tilahun, E. Berkhout, M. Cooper, E. Fegraus, et al., Soil nutrient maps of sub-saharan africa: assessment of soil nutrient content at 250 m spatial resolution using machine learning, Nutrient Cycl. Agroecosyst. 109 (2017) 77–102.
[17] A.A. Ibrahim, R.L. Ridwan, M.M. Muhammed, R.O. Abdulaziz, G.A. Saheed, Comparison of the catboost classifier with other machine learning methods, Int. J. Adv. Comput. Sci. Appl. 11 (11) (2020).
[18] A. Ikram, W. Aslam, R.H.H. Aziz, F. Noor, G.A. Mallah, S. Ikram, M.S. Ahmad, A. M. Abdullah, I. Ullah, Crop yield maximization using an iot-based smart decision, J. Sens. (2022), https://doi.org/10.1155/2022/2022923.
[19] A. Ingle, Crop recommendation dataset. https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset, 2020.
[20] M.R. Islam, M.M. Kabir, M.F. Mridha, S. Alfarhood, M. Safran, D. Che, Deep learning-based iot system for remote monitoring and early detection of health issues in real-time, Sensors 23 (11) (2023) 5204, https://doi.org/10.3390/s23115204.
[21] D. Jayashree, O. Pandithurai, L. Paul Jasmin Rani, P.K. Menon, M.V. Beria, S. Nithyalakshmi, Fertilizer recommendation system using machine learning, in: Disruptive Technologies for Big Data and Cloud Applications: Proceedings of ICBDCC 2021, Springer, 2022, pp. 709–716.
[22] R. Jeevaganesh, D. Harish, B. Priya, A machine learning-based approach for crop yield prediction and fertilizer recommendation, in: 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI), IEEE, 2022, pp. 1330–1334.
[23] G.K. Jha, P. Ranjan, M. Gaur, A machine learning approach to recommend suitable crops and fertilizers for agriculture. *Recommender System with Machine Learning and Artificial Intelligence: practical Tools and Applications in Medical*, Agricultural and Other Industries (2020) 89–99, https://doi.org/10.1002/9781119711582.ch5.
[24] F. Kiani, A. Seyyedabbasi, S. Nematzadeh, F. Candan, T. Çevik, F.A. Anka, G. Randazzo, S. Lanza, A. Muzirafuti, Adaptive metaheuristic-based methods for autonomous robot path planning: sustainable agricultural applications, Appl. Sci. 12 (3) (2022) 943, https://doi.org/10.3390/app12030943.
[25] W. Li, T. Logenthiran, V.-T. Phan, W.L. Woo, A novel smart energy theft system (sets) for iot-based smart home, IEEE Internet Things J. 6 (3) (2019) 5531–5539.
[26] M. Mulge, M. Sharnappa, A. Sultanpure, D. Sajjan, M. Kamani, Agricultural crop recommendation system using iot and ml, Int. J. Anal. Exp. Modal Anal. 12 (6) (2020).
[27] K. Nischitha, D. Vishwakarma, M.N. Ashwini, M. Manjuraju, Crop prediction using machine learning approaches, Int. J. Eng. Res. Technol. 9 (8) (2020) 23–26.
[28] K. Oliullah, S. Tarafdar, M. Whaiduzzaman, Fog computing and iot based modern agricultural system, Topics in Intell Comput Ind Design 2 (1) (2020) 88–92, https://doi.org/10.26480/cic.01.2020.88.92.
[29] K. Oliullah, A. Barros, M. Whaiduzzaman, Analyzing the effectiveness of several machine learning methods for heart attack prediction, in: Proceedings of the Fourth International Conference on Trends in Computational and Cognitive Engineering: TCCE 2022, Springer, 2023, pp. 225–236.
[30] A. Palaniraj, A. Balamurugan, R.D. Prasad, P. Pradeep, Crop and fertilizer recommendation system using machine learning, IRJET 8 (2021).
[31] L. Prokhorenkova, G. Gusev, A. Vorobev, A.V. Dorogush, A. Gulin, Catboost: unbiased boosting with categorical features, Adv. Neural Inf. Process. Syst. (2018) 31.
[32] Z. Qiu, F. Ma, Z. Li, X. Xu, H. Ge, C. Du, Estimation of nitrogen nutrition index in rice from uav rgb images coupled with machine learning algorithms, Comput. Electron. Agric. 189 (2021), 106421, https://doi.org/10.1016/j.compag.2021.106421.
[33] V.K. Quy, N.V. Hau, D.V. Anh, N.M. Quy, N.T. Ban, S. Lanza, G. Randazzo, A. Muzirafuti, Iot-enabled smart agriculture: architecture, applications, and challenges, Appl. Sci. 12 (7) (2022) 3396, https://doi.org/10.3390/app12073396.
[34] V.K. Quy, V.H. Nam, D.M. Linh, N.T. Ban, N.D. Han, Communication solutions for vehicle ad-hoc network in smart cities environment: a comprehensive survey, Wireless Pers. Commun. (2022) 1–25.
[35] S.J. Ramson, W.D. León-Salas, Z. Brecheisen, E.J. Foster, C.T. Johnston, D. G. Schulze, T. Filley, R. Rahimi, M.J.C.V. Soto, J.A.L. Bolivar, et al., A self-powered, real-time, lorawan iot-based soil health monitoring system, IEEE Internet Things J. 8 (11) (2021) 9278–9293.
[36] S. Rani, S.H. Ahmed, S.C. Shah, Smart health, A novel paradigm to control the chickungunya virus, IEEE Internet Things J. 6 (2) (2018) 1306–1311, https://doi.org/10.1109/JIOT.2018.2802898.
[37] D.A. Reddy, B. Dadore, A. Watekar, Crop recommendation system to maximize crop yield in ramtek region using machine learning, International Journal of Scientific Research in Science and Technology 6 (1) (2019) 485–489, https://doi.org/10.32628/IJSRST196172.
[38] R. Reshma, V. Sathiyavathi, T. Sindhu, K. Selvakumar, L. SaiRamesh, Iot based classification techniques for soil content analysis and crop yield prediction, in: 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC), IEEE, 2020, pp. 156–160.

[39] V.F. Rodriguez-Galiano, B. Ghimire, J. Rogan, M. Chica-Olmo, J.P. Rigol-Sanchez, An assessment of the effectiveness of a random forest classifier for land-cover classification, ISPRS J. Photogrammetry Remote Sens. 67 (2012) 93–104, https://doi.org/10.1016/j.isprsjprs.2011.11.002.

[40] M.K. Senapaty, A. Ray, N. Padhy, Iot-enabled soil nutrient analysis and crop recommendation model for precision agriculture, Computers 12 (3) (2023) 61.

[41] D. Shin, K. Yun, J. Kim, P.V. Astillo, J.-N. Kim, I. You, A security protocol for route optimization in dmm-based smart home iot networks, IEEE Access 7 (2019) 142531–142550, https://doi.org/10.1109/ACCESS.2019.2943929.

[42] V. Shukla, S. Dixit, P. Dixit, An iot based user authenticated soil monitoring system, Ad Hoc Sens. Wirel. Netw. 53 (2022).

[43] M. Singh, Fertilizer Prediction Dataset, 2022. https://www.kaggle.com/datasets/mohitsingh1804/fertilizer-prediction-dataset.

[44] K.S.R. Subramanian, Design and implementation of fertilizer recommendation system for farmers, Test Eng. Manag. 83 (2020) 8840–8849.

[45] S. Sundaresan, S.D. Johnson, V.M. Bharathy, P.M.P. Kumar, M. Surendar, Machine learning and iot-based smart farming for enhancing the crop yield, in: Journal of Physics: Conference Series vol. 2466, IOP Publishing, 2023, 012028.

[46] N.N. Thilakarathne, M.S.A. Bakar, P.E. Abas, H. Yassin, A cloud enabled crop recommendation platform for machine learning-driven precision farming, Sensors 22 (16) (2022) 6299.

[47] A. Vangala, A.K. Das, V. Chamola, V. Korotaev, J.J. Rodrigues, Security in iot-enabled smart agriculture: architecture, security solutions and challenges, Cluster Comput. 26 (2) (2023) 879–902, https://doi.org/10.1007/s10586-022-03566-7.

[48] B.M. Zerihun, T.O. Olwal, M.R. Hassen, Design and analysis of iot-based modern agriculture monitoring system for real-time data collection, in: Computer Vision and Machine Learning in Agriculture, Springer, 2022, pp. 73–82, https://doi.org/10.1007/978-981-16-9991-7_5, 2.

[49] X. Zhang, J. Zhang, L. Li, Y. Zhang, G. Yang, Monitoring citrus soil moisture and nutrients using an iot based system, Sensors 17 (3) (2017) 447.

[50] Z. Zhou, H. Yu, H. Shi, Human activity recognition based on improved bayesian convolution network to analyze health care data using wearable iot device, IEEE Access 8 (2020) 86411–86418, https://doi.org/10.1109/ACCESS.2020.2992584.