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Advancing Agriculture with IoT and a Smart Fertilizer Recommendation System

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Abstract

Agriculture is a key contributor to Pakistan's GDP, and optimizing fertilization is crucial for enhancing crop yield and ensuring food security. This research presents a real-time, IoT-based soil analysis model that replaces traditional off-site testing, providing instant and site-specific fertilizer recommendations. The system integrates an IoT-enabled device to assess soil nutrient levels and employs a regression algorithm to predict the required NPK quantities. A realistic soil dataset is used to train and validate the model, ensuring accurate predictions. With an 88-92% accuracy rate, the system effectively recommends fertilizers, enabling precision farming and optimizing resource utilization. This reduces reliance on conventional soil testing methods, minimizing fertilizer wastage and improving soil sustainability. The real-time analysis supports data-driven farming decisions, ensuring balanced nutrient application and promoting sustainable agricultural practices. Additionally, this innovation aligns with the Sustainable Development Goals (SDGs) by modernizing agricultural techniques, enhancing food security, and supporting economic growth in farming communities.The IoT-based smart fertilizer recommendation system offers a cost-effective, accurate, and sustainable solution to improve agricultural productivity and promote precision farming.

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1 Introduction

Agriculture has been a cornerstone of human progress since ancient times, shaping civilizations and driving economic growth. In Pakistan, this sector plays a vital role, contributing nearly 40% of the country's GDP [1]. However, despite its significance, agricultural advancements remain limited in approximately 40% of the country's regions. Natural disasters and environmental changes have disrupted soil fertility, causing fluctuations in nutrient levels and reducing agricultural productivity. These challenges demand innovative solutions to ensure sustainable crop yields and economic stability.

A fundamental aspect of agriculture is maintaining the right balance of essential nutrients in the soil, particularly nitrogen (N), phosphorus (P), and potassium (K), collectively known as NPK. These macronutrients are critical for plant growth: nitrogen promotes leaf development, phosphorus supports root and flower growth, and potassium enhances disease resistance and water regulation [12]. However, soil nutrient levels tend to diminish over successive growing seasons due to nutrient mining. Factors such as soil moisture, pH, and organic carbon also influence nutrient absorption, often varying with specific crops. Imbalances or excesses in any one of these nutrients can disrupt plant health and growth, emphasizing the need for precise soil management.

In practice, many farmers struggle to select the appropriate fertilizers for their fields. Decisions are often based on intuition, past experiences, or recommendations from peers, rather than on scientific analysis. Limited access to soil testing facilities and the perception that soil analysis is an unnecessary or time-consuming effort further hinder the adoption of best practices. As a result, disorganized and inconsistent farming practices persist, leading to suboptimal crop yields and soil degradation.

To address these issues, this research proposes a modern, technology-driven solution: an IoT-based system to monitor soil conditions and recommend precise fertilizer applications [11]. By deploying sensors to measure NPK levels, temperature, humidity, and moisture, the system will provide farmers with real-time data on soil health [2]. Based on this information, it will offer targeted recommendations for fertilizers tailored to specific crop needs and soil conditions. This approach not only simplifies the decision-making process for farmers but also minimizes the risks of over-fertilization and nutrient imbalances, promoting sustainable farming practices.

The proposed model is designed to overcome the limitations of traditional methods, such as reliance on trial-and-error or generalized recommendations, by offering a science-backed, precision farming solution. Through rigorous testing and validation, this system aims to ensure its effectiveness in enhancing agricultural productivity, stabilizing soil conditions, and supporting farmers in making informed decisions for sustainable agriculture.

2 Literature Review

Soil characteristics play a fundamental role in agricultural productivity, enabling crops to absorb nutrients effectively while minimizing energy consumption. Fertility and crop yields are sustained through the balanced application of fertilizers, but over time, soils can become depleted of essential nutrients. To address this challenge, new technologies are being developed to analyze soil fertility in real-time and provide precise nutrient recommendations. This section reviews recent advancements in nutrient recommendation systems that use advanced algorithms and technologies to optimize fertilizer application, particularly for nitrogen (N), phosphorus (P), and potassium (K).

Singh et al. [2] implemented a soil-test-based NPK recommendation system for mulberry farming in the acidic soils of Lohardaga, Jharkhand. Conducted between 2012 and 2013, the study evaluated the fertility status of 30 farmers' fields across seven villages. The soils were highly acidic, with pH values ranging from 4.32 to 5.07, and had low to medium levels of organic carbon (0.36% to 0.69%). The study compared nutrient management practices, including soil-test-based doses (STBD), farmers' existing practices (FEP), and recommended practices (RP). STBD significantly outperformed FEP and RP in crop productivity, demonstrating the effectiveness of site-specific fertilizer recommendations in addressing soil acidity and organic matter variability. Despite these promising results, the study's small sample size and context-specific findings suggest the need for broader validation in diverse soil and climatic conditions.

In a different context, Chuan et al. [3] investigated sustainable fertilization methods for Chinese cabbage, one of China's most widely cultivated vegetables. Their multi-year, multi-site trials explored yield responses and agronomic returns against varying nutrient input levels. They found that excessive application of NPK fertilizers negatively impacted crop yields, particularly when nutrient additions exceeded the soil's uptake capacity. For instance, the indigenous nutrient balances for nitrogen, phosphorus, and potassium were 132 ha¹, 35.03 ha¹, and 213.15 ha¹, respectively. The study emphasized the importance of balancing nutrient inputs with soil absorption capacities, underscoring the need for precision nutrient management to enhance fertilizer use efficiency. However, implementing these findings in diverse agricultural settings remains challenging due to variability in soil nutrient dynamics.

Abdullah et al. [4] focused on maize production in the wet tropics, where nutrient deficiencies pose significant challenges to crop yields. Their study evaluated various NPK-compound fertilizers and their effects on maize productivity through field experiments conducted at the Indonesian Cereal Research Institute. Using a randomized block design, they tested two dosages of NPK+urea combined with five different NPK-compound fertilizers. The results indicated that a dosage of 450 kg/ha of NPK 15:15:15 mixed with 250 kg/ha of urea produced the highest yield probability of 12 t/ha, compared to slightly lower yields from other formulations. This study highlights the importance of balancing nutrient ratios for optimal crop production. However, the context-specific findings may have limited applicability in regions with differing climatic and soil conditions, and the study primarily focuses on yield outcomes, potentially overlooking long-term soil health implications [13, 14].

Addressing the need for efficient and practical soil analysis, Soitong et al. [5–8] developed a rapid soil test for field-based determination of NPK levels. Their method demonstrated a strong correlation between extractable nitrogen (ammonium and nitrate) and corn dry weight, with an R^2 value of 0.74. Using Mehlich 1 as the most effective extractant for NPK, they designed a soil test kit that allows farmers to obtain real-time data on soil nutrient levels. This innovation significantly reduces the time and cost of traditional laboratory testing. Additionally, the researchers integrated a modeling program to provide nutrient recommendations based on soil test results. While this approach enhances the efficiency of nutrient management, the accuracy of these models requires further validation in diverse agricultural contexts to ensure reliability.

These studies collectively underscore the importance of site-specific fertilizer recommendations and real-time soil analysis in improving agricultural productivity. By addressing challenges such as soil acidity, nutrient variability, and excessive fertilizer application, they demonstrate the potential for precision farming technologies to optimize nutrient use efficiency. However, limitations such as context-specific findings, the scalability of soil-test-based systems, and the adaptability of nutrient recommendation models highlight areas for future research. Robust, adaptable systems are needed to support diverse agricultural practices, ensuring sustainable and effective fertilizer management across varying agro ecological settings [15, 16].

3 Design and Methodology

The project aims at developing a real-time soil nutrients detection and fertilizer recommendation model for farmers. The flowchart below shows implementation of various parts combined in order to form the complete working model for this project.

The project is divided into three parts:

Hardware Section: A real-time IoT device that analyzes soil nutrients.

Machine Learning Algorithm: This [19] algorithm takes the analyzed soil data to forecast the required NPK and the amount of fertilizer needed.

User-Friendly Website: A platform for farmers to interact with the ML algorithm and receive predictions. The design and development of each part are discussed in detail below

3.0.1 IOT-BASED SOIL MONITORING IN REAL-TIME

The first component of our project is a physical hardware module that is able to measure contents of the soil. The Crop Factor or yield depends on numerous chemical and physical properties of the soil such as moisture, temperature and Nitrogen phosphorus and potassium content. The soil, including its moisture content, temperature, and levels of nitrogen, phos-

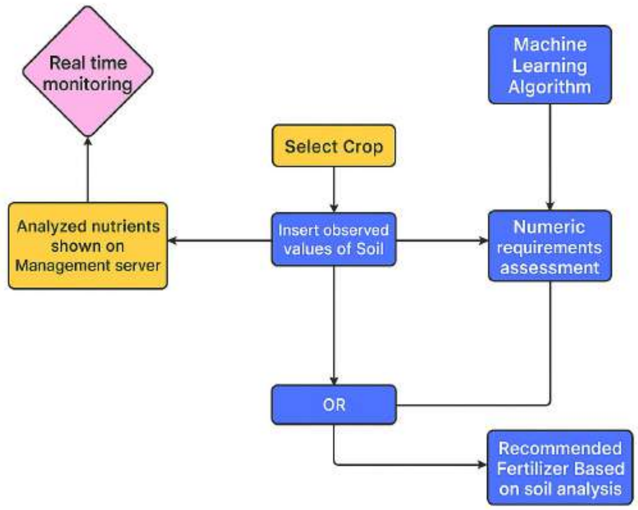

Figure 1. Flow Chart

phorus, and potassium. All these [9, 10] properties can be sensed by the open-source hardware and they can be used in the field. Consequently, in this stage, the monitoring and analysis system of soil nutrient is established, farmers can wirelessly view all these parameters on a smartphone or a computer system.

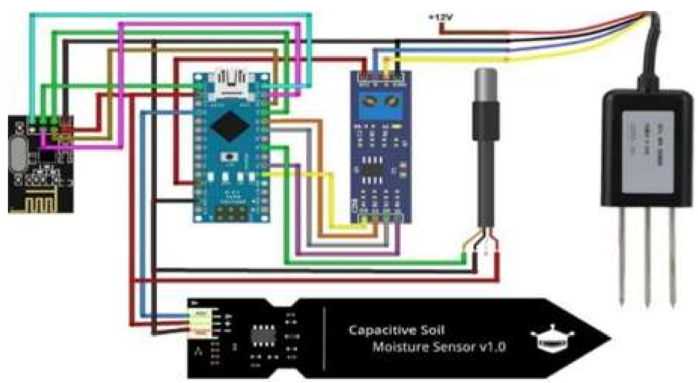

Figure 2. Circuit Diagram

3.0.2 IMPLEMENTATION

To measure soil moisture, we use a soil moisture sensor, while the DS18B20 waterproof temperature sensor measures soil temperature. A soil NPK sensor assesses nutrient levels. All sensors interface seamlessly with Arduino. The hardware section is divided into two circuits for our IoT-based soil nutrient monitoring using Arduino and ESP32. The first circuit, a Sensor Node, includes an Arduino Nano, NPK sensor, and NRF24L01 Transceiver Module. The second circuit, the gateway, utilizes the ESP32 Wi-Fi Module and NRF24L01 Transceiver Module. Data from the Sensor Node is sent to the gateway, which uploads it to the ThingSpeak server for graphical and numerical monitoring. To address connectivity issues in agricultural fields lacking GSM or Wi-Fi, we use the NRF24L01 module to transmit data wirelessly up to a kilometer. The ESP32 receiver then connects to a Wi-Fi network to upload the data to ThingSpeak.3.1.1.1 SENSOR NODE CIRCUIT The NRF24L01 Transceiver Module, the Arduino Nano Board, the Soil Moisture Sensor, the DS18B20 Temperature Sensor, and the Soil NPK Sensor make up the Sensor Node or Sensor Circuit which detects or analyzes the soil. The circuit and connection schematic for the sensor node is shown below

Above is a table showing how the NRF24L01 and Arduino Nano Board are connected. Besides the NRF24L01 Arduino Connections, Sensor is connected to the Arduino analogue as well as to the digital ports. The Capacitive Soil Moisture Sensor Analog pin is connected to the Arduino's A0 pin. Analogous to the BME280 and HTU21D sensors, the DS18B20 sensor is connected to Arduino's D5. And the Modbus Pins 2,

NRF24L01 Pin	Arduino Pin
VCC	3.3V
CSN	10
MOSI	11
GND	GND
CE	9
SCK	13
MISO	12

Table 1. NRF24L01 and Arduino Nano Board

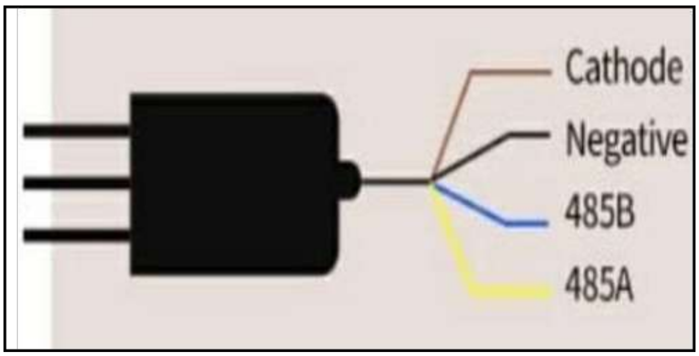

Figure 3. NRD24L01

3, 7, and 8 are used to connect the NPK Sensor with the Arduino. It is also remarkable that the NPK Sensor works at the voltage of 9V – 24V. A second source is therefore required for the circuit. The 5V/3.3V Pin of the Arduino can supply power to the other peripherals.

The Nitrogen (N), Phosphorous (P), and Potassium (K) values can be read using one of the NPK Sensor's three separate inquiry frames (K). The instruction manual and inquiry frame are included.

3.0.3 GATEWAY CIRCUIT

The Gateway is also employed in the IoT-based Soil Nutrient Content Analysis & Monitoring as well. The components used in the construction of the Gateway are ESP32 Wi-Fi Module and NRF24L01 Wireless Transceiver Module. It transfers the data wirelessly to the receiver/gateway portion which is a part of the sensor node circuit. The gateway is responsible for collecting the data and sending it to the ThingSpeak Server. You simply have to navigate to the ThingSpeak Dashboard's private view. You will input your

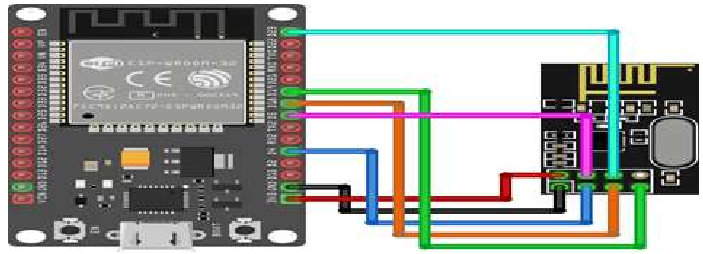

Figure 4. Gateway Circuit Diagram

information into the ThingSpeak Server.

NRF24L01 Pin	ESP32 Pin
VCC	3.3V
CSN	D5
MOSI	D23
GND	GND
CE	D4
SCK	D18
MISO	D19

Table 2. ESP32 Board and NRF24L01 Connections

To process sensor data, we employed an Arduino-based microcontroller due to its efficiency in handling real-time inputs [23]. The ESP32 microcontroller was integrated for wireless communication, leveraging its built-in Wi-Fi and Bluetooth capabilities [24]. The system also includes an NPK sensor to measure soil nutrient levels [25], a capacitive soil moisture sensor for moisture detection [26], and an NRF24L01 transceiver module for long-range wireless data transmission [21].

3.1 MACHINE LEARNING ALGORITHM

The second section of our project involves a machine learning algorithm that predicts the optimal fertilizer recommendations based on the soil analysis data acquired by the hardware component. This algorithm is crucial for translating raw soil data into actionable insights for farmers.

In our project, we employ a supervised learning approach using a regression algorithm. The primary purpose of this machine learning algorithm is to predict continuous numeric output variables (i.e., the required NPK values and fertilizer quantities) from the given input data. The model learns the complex

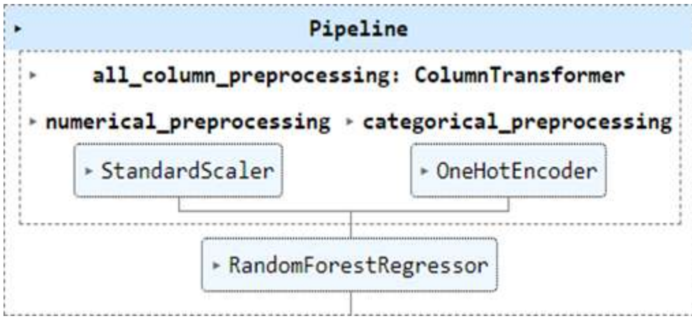

Figure 5. Pipeline

relationships between soil properties and fertilizer needs during the training phase, enabling it to make accurate predictions on new soil data.

3.1.1 IMPLEMENTATION

Regression algorithm takes input features such as soil texture, analyzed NPK values, crop type etc. and after applying mechanism it redirects the output which consists of target variables such as required NPK values, appropriate fertilizer to be used as well as the quantity of the fertilizer to be applied in one acre field.

To streamline data pre-processing and model training, we utilized Scikit-learn pipelines. Furthermore, we used the Random Forest Regressor algorithm to train the model. Finally, the trained models are saved using the Pickle library in Python to enable efficient reuse of the models for future predictions. Saving the models allows us to avoid retraining them every time we need to make a prediction, which is essential for real-world deployment.

When using the Scikit-learn library for machine learning, trained models must be saved to a file and restored later. This process, known as serialization, allows us to persist the model's learned state. We use the Pickle library to serialize and deserialize the model objects.

3.1.2 RANDOM FOREST REGRESSOR: DETAILED EXPLANATION

We chose the Random Forest Regressor for its ability to handle non-linear relationships in the data, its robustness to overfitting, and its capacity to manage a relatively large number of input features. Random Forest is an ensemble learning method that combines the predictions of multiple decision trees to make more accurate and stable predictions.

3.1.3 Ensemble Learning and Decision Trees

At its core, Random Forest relies on the concept of ensemble learning. Instead of using a single decision tree, it grows a "forest" of many decision trees. A decision tree is a tree-like structure where each internal node represents a test on an input feature, each branch represents the outcome of the test, and each leaf node represents a prediction. Decision trees recursively partition the data based on feature values, aiming to create subsets that are increasingly homogeneous with respect to the target variable.

3.1.4 Randomness in Random Forest

Random Forest introduces randomness in two key ways to promote diversity among the trees:

Bootstrap Aggregating (Bagging): Each tree is trained on a random subset of the original data, sampled with replacement. This technique, known as bootstrapping, creates different training sets for each tree, leading to a variety of trees.

Random Subspace: At each node when building a tree, only a random subset of the input features is considered for splitting. This prevents any single feature from dominating the predictions and further increases tree diversity.

3.1.5 Prediction Mechanism

For a regression task, the Random Forest makes a prediction by averaging the predictions of all the individual decision trees in the forest. Mathematically, the prediction can be represented as:

$$\text{Prediction} = \frac{1}{n_{\text{trees}}} \sum_{i=1}^{n_{\text{trees}}} \text{prediction}_{\text{tree}_i}$$

where n_trees is the number of trees in the forest, and prediction_tree_i is the prediction of the i-th tree.

3.1.6 Advantages of Random Forest

Random Forest offers several advantages for our fertilizer recommendation system:

Sr#	Crop Name	Soil Texture	Nitrogen (%)	N Status	Phosphorus (ppm)	P Status	Potassium (ppm)	K Status
1	Wheat	Silty Clay Loam (Medium)	0.050	Low	5	Very Low	280	Very High
2	Tomato	Silty Clay Loam (Medium)	0.057	Low	5	Very Low	260	Very High
3	Tomato	Silty Clay Loam (Medium)	0.054	Low	5	Very Low	200	High
4	Tomato	Silty Clay Loam (Medium)	0.530	Low	5	Very Low	192	High
5	Onion	Silty Clay Loam (Medium)	0.075	Medium	7	Low	216	Very High

Table 3. Input Features

Required N (kg/acre)	Required P (kg/acre)	Required K (kg/acre)	Sona Urea (Bags/acre)	Sona DAP (Bags/acre)	FFC SOP (Bags/acre)
63	45	0	2.00	2.00	0.00
53	35	4	1.75	1.50	0.25
53	35	8	1.75	1.50	0.25
53	35	5	1.75	1.50	0.25
43	33	5	1.25	1.50	0.25

Table 4. Output Features

- It can effectively model complex, non-linear relationships between soil properties and fertilizer requirements.
- It is less prone to overfitting than individual decision trees, leading to better generalization performance.
- It can handle a large number of input features without requiring extensive feature selection.
- It provides a measure of feature importance, which can help in understanding the relative influence of different soil parameters on fertilizer recommendations.

3.1.7 DATA PREPROCESSING

Before training the Random Forest Regressor, we applied several preprocessing steps to the input data to ensure optimal model performance. These steps were implemented using Scikit-learn pipelines to maintain a structured and efficient workflow.

3.1.8 Handling Missing Values

We examined the dataset for missing values. If any missing values were present, we addressed them using an appropriate imputation technique (e.g., replacing them with the mean or median of the respective feature).

3.1.9 Feature Scaling

We used the Standard Scaler from Scikit-learn to standardize the numerical features. This scaling process transforms the features to have a mean of 0 and a standard deviation of 1. Feature scaling is crucial because it prevents features with larger ranges from dominating the model training process, ensuring that all features contribute equally to the final prediction.

3.1.10 Encoding Categorical Features

Categorical features, such as soil texture and crop type, were encoded using One-Hot Encoding. This technique converts each categorical variable into a set of binary (0 or 1) variables, where each binary variable represents a unique category. For example, if the "soil texture" feature has categories like "sandy," "clay," and "loam," One-Hot Encoding would create three new binary features: "is_sandy," "is_clay," and "is_loam." This encoding allows the Random Forest Regressor to effectively handle categorical inputs.

3.1.11 MODEL TRAINING AND EVALUATION

3.1.12 Training and Validation Split

The dataset was divided into training and validation sets to evaluate the model's performance. We used a typical 80/20 split, where 80% of the data was used for training the Random Forest Regressor, and 20% was held aside for validation. This split allowed us to assess how well the model generalizes to unseen data.

3.1.13 Hyperparameter Tuning

We employed a grid search approach with cross-validation to optimize the hyperparameters of the Random Forest Regressor. Key hyperparameters tuned included the number of trees in the forest (n_estimators) and the maximum depth of the trees (max_depth). Cross-validation helped us to select the best combination of hyperparameters that yielded the best performance on the validation set, reducing the risk of overfitting.

3.1.14 Evaluation Metrics

The performance of the Random Forest Regressor was evaluated using the following regression metrics:

Mean Squared Error (MSE): This metric calculates the average of the squared differences between the predicted and actual fertilizer values. Lower MSE values indicate better model performance. Root Mean Squared Error (RMSE): The RMSE is the square root of the MSE. It provides a measure of the average magnitude of the errors in the same units as the target variable, making it more interpretable than MSE. R-squared (Coefficient of Determination): This metric measures the proportion of the variance in the dependent variable that is predictable from the independent variables. An R-squared value of 1 indicates a perfect fit, while a value of 0 indicates that the model does not explain any of the variance

3.1.15 Libraries Used for ML Algorithm

In this project, several Python libraries were essential in training and optimizing our machine learning model. Below is an overview of each library and a description of its specific role and use case in our model's development.

- **NumPy**
  NumPy was used extensively for array manipulation, which formed the foundation for managing data and calculations within our model. Specifically, we relied on NumPy to handle large datasets efficiently, especially during feature engineering, where it helped to create, manipulate, and transform multi-dimensional arrays [17, 18]. For instance, we used it for matrix operations when calculating input data transformations, which improved processing speed and streamlined linear algebra tasks required for training.
- **Pandas**
  We used Pandas for loading, cleaning, and manipulating our dataset prior to feeding it into the model. Data preparation was crucial, so we leveraged Pandas to handle missing values, normalize datasets, and structure data effectively for analysis. Using Pandas, we could handle large, complex datasets, enabling smooth transitions between raw data and the finalized, pre-processed format required for accurate model input.
- **Scikit-Learn (sklearn)**
  Scikit-Learn was central to our machine learning workflow, offering tools for both training and evaluating the model. We used Scikit-Learn's classification and regression modules to develop a Random Forest model tailored to our dataset's specific characteristics. Additionally, we relied on its cross-validation and model evaluation tools to fine-tune our algorithm, ensuring optimal accuracy and consistency.
- **Sklearn Pipelines**
  Scikit-Learn Pipelines were used to streamline our workflow by chaining multiple data transformation and model training steps together. We constructed pipelines to manage our preprocessing steps—such as one-hot encoding, scaling, and model training—within a single workflow. This approach not only reduced code complexity but also minimized the risk of error by ensuring that each step in the workflow was consistently applied.
- **Random Forest Regressor**
  We implemented the Random Forest Regressor from Scikit-Learn to perform regression tasks in a supervised learning context. Random Forest was chosen due to its robustness with large datasets and its ability to handle non-linear data relationships. It was particularly effective in our project as it reduced over fitting through its ensemble of decision trees and provided a more accurate prediction model [22].
- **One-Hot Encoding**
  One-Hot Encoding was applied to convert cate-

gorical data into a format usable by the machine learning model. Using Scikit-Learn's One Hot Encoder, we transformed categorical variables into binary vector format. This allowed the model to interpret categorical inputs effectively and improved its prediction accuracy for data features that were non-numeric in nature [20].

3.1.16 Standard Scaler

We used the Standard Scaler from Scikit-Learn to normalize our feature set, ensuring that all variables had a mean of 0 and a standard deviation of 1. This normalization process was necessary to prevent features with larger ranges from dominating the model. By standardizing our data, we achieved a more stable and faster convergence during model training.

3.1.17 Pickle

To save and reuse our trained model, we used the Pickle library for serializing and deserializing the model object. After training, the model was serialized with Pickle, allowing us to save it as a file. This was essential for preserving the model in its final state, enabling us to load and deploy it efficiently without retraining.

4 RESULTS AND DISCUSSION

This seciton includes experimental results of finalized project as well as some performance metrics in order to evaluate our working model.

4.1 ASSEMBLING:

As a result, now we may start testing the gadget once the code has been successfully uploaded to the Arduino & ESP32 Board. Place all the sensors in the soil as indicated in the figure below to achieve this.

Open both Serial Monitors in Arduino at this point to see if data transfer is occurring or not. The serial monitor on the sensor node displays data from the sensor, such as the percentage of soil moisture, the temperature, and the mg/kg NPK content. The data is gathered and uploaded to the ThingSpeak Server by the gateway. You just need to access the ThingSpeak Dashboard's private view. Your information will be recorded on the ThingSpeak Server.

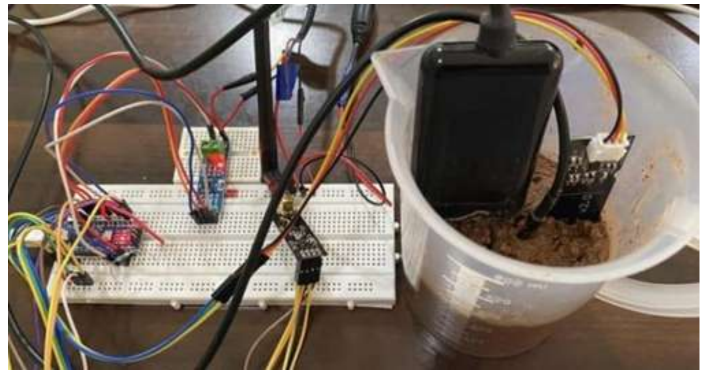

Figure 6. Project

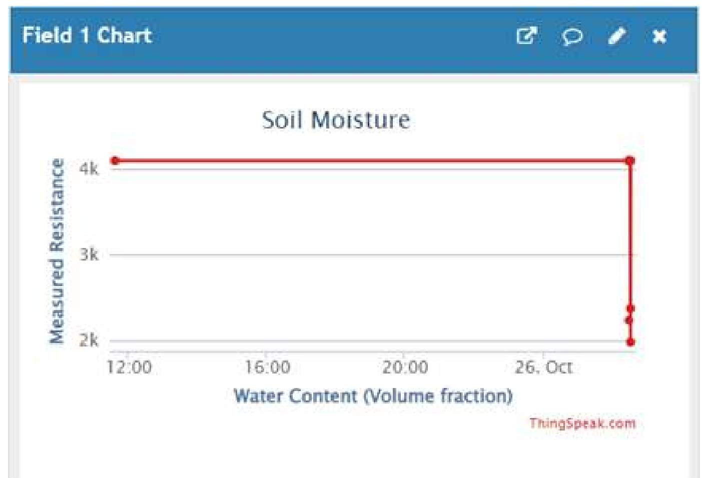

Figure 7. Soil Moisture Result on Server

These are the results obtained from soil analysis. Note the values NPK and insert these values in fertilizer calculator provided on our website to predict the best fertilizer based on soil nutrients.

Our machine learning model implemented on the backend of our website takes these analyzed values as input and forecasts following results as prediction:

4.2 Accuracy Scores of Predictors

Predictor	Accuracy (%)
Urea Predictor	91%
DAP Predictor	88%
FFC Predictor	95%
Nitrogen Predictor	89%
Phosphorous Predictor	87%
Potassium Predictor	95%

Table 5. Accuracy Scores of Fertilizer Predictors

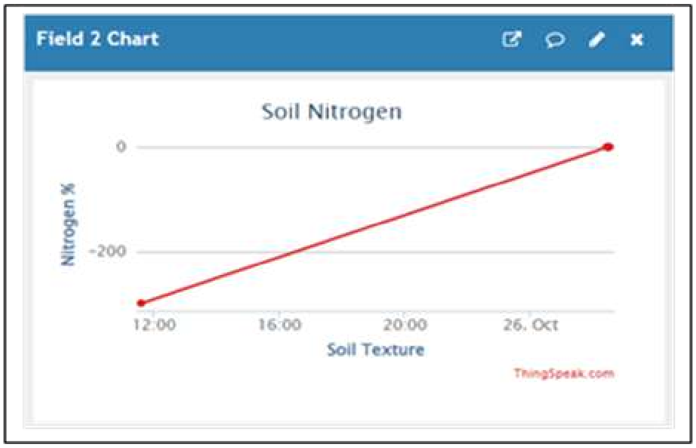

Figure 8. Soil Nitrogen Result on Server

Figure 9. Soil Phosphorous Result on server

Figure 10. Soil Potassium Result on Server

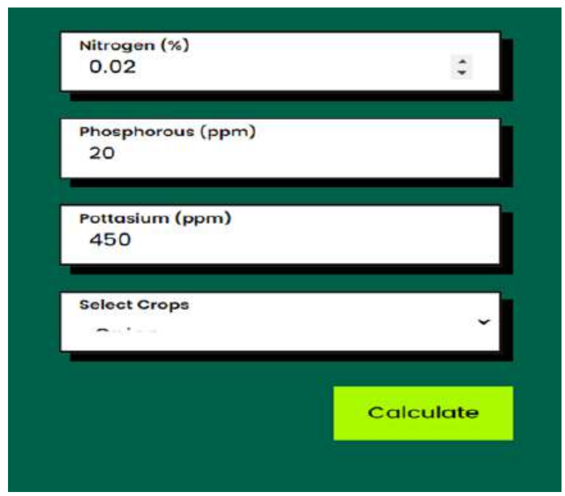

Figure 11. Nutrient Calculator

5 CONCLUSION AND FUTURE RECOMMENDATIONS

Natural disasters and climate-induced soil changes significantly reduce agricultural production. Farmers often rely on outdated or generalized advice for crop management and fertilizer application, leading to inefficiencies. Traditional soil testing requires inconvenient trips to labs, discouraging many farmers from testing their soil regularly. This results in the use of inappropriate fertilizers, causing low yields and soil contamination due to the overabundance of fertilizers available on the market. To address these challenges, we have developed a model that utilizes various sensors to measure soil temperature, moisture, humidity, and nutrient levels. This model provides real-time recommendations for optimal fertilizer application to enhance soil quality and crop yield. By offering remote, real-time soil analysis, our system enables farmers to better understand their soil's specific needs and make informed decisions about fertilization. This research outlines the application and development process of this model and aims to guide researchers in advancing agricultural practices through innovative solutions targeted at improving soil management and crop production.

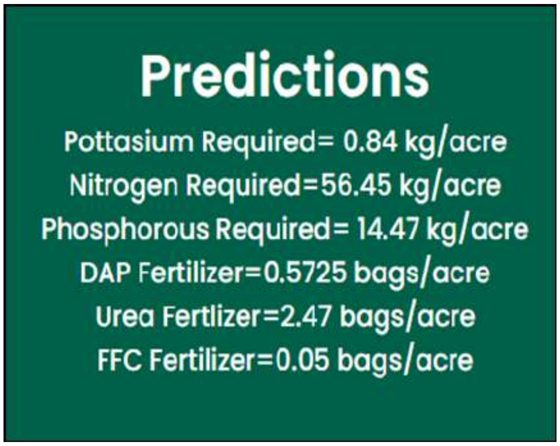

Figure 12. Fertilizer Predictions

6 Future Recommendations

We still have a long way to go in this area of research because we need to make the device more portable, lightweight, and affordable to farmers. The massive potential of agriculture is still unexplored. The technology will help farmers by giving them the necessary guidance on crops, their growth, and other fundamental knowledge. Additionally, it will provide the location of the closest store where farmers can buy fertilizers and other supplies. By giving precise information on market prices and merchant details, it would also help farmers sell their goods to merchants. The accuracy of the device can be increased even further by including specialized cameras in the disease detection feature. Future research can examine at the soil materials that destroy nutrients needed and develop strategies to prevent their appearance, such as aluminum and sodium, as well as how irrigation can assist to remove excess nutritional elements or the said harmful elements. Future research can concentrate on farm management and post-harvest nutrient management to ensure an increase in nutrients prior to upcoming drilling schedules.

Author Contributions

Asim Irfan: Conceptualization, Supervision, Methodology, System Design, IoT Implementation, Manuscript Writing, and Corresponding Author. **Muhammad Hashim**: Data Collection, Dataset Preparation, Model Training, Algorithm Development, and Performance Evaluation. **Hammadullah**: Literature Review, Technical Validation, Editing and Reviewing, and Visualization. **Ahmed Muhammad Shaikh**: Critical Review, Writing Assistance, and Final Approval of the Manuscript.

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

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