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Applicability of Machine Learning and Internet of Things-Based for Crop Selection

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Abstract

Agriculture plays a big role in ensuring global food security and sustainability. To optimize crop yields, it is essential to understand the soil and weather conditions of a farm. In this study, we developed a Crop Selection System that leverages the IoT and ML, specifically the Random Forest algorithm, to assist farmers of Rwanda in choosing the most suitable crops for their piece of land. The system makes recommendations based on measurements of nitrogen, phosphorus, potassium, pH, humidity, rainfall, and temperature before cultivation begins. Real-time field data was gathered using IoT sensors deployed in farm areas to collect soil and environmental information. Our device utilized soil sensors to measure nitrogen, soil pH, humidity, phosphorus, temperature, and potassium. The NodeMCU microcontroller preprocessed the data and uploaded it to a cloud database. The data collection took place in Gicumbi District, and the collected samples were analyzed using our crop selection model. The model was developed using the Random Forest algorithm to evaluate soil compatibility and rank the crops based on their probability of successful growth. By training the model with a dataset of crops' ecological requirements, we achieved an accuracy of 96%. We then tested the model with newly collected data from the field. Over a period of seven days, the model's predictions indicated that potatoes had the highest growing probability at 56%, followed by beans at 43%, carrots at 33%, tomatoes at 33%, and rice at 17%. This data-driven approach significantly enhances farmers' decision-making by enabling them to make informed choices about crop selection. This technology can boost agricultural productivity while reducing unnecessary costs, such as excessive fertilizer use, by ensuring crops are cultivated based on the available ecological conditions. The system helps farmers assess nutrient levels and implement corrective measures to restore soil fertility. This method advances precision agriculture and contributes to the overall modernization of farming practices.

Keywords: *IoT, Machine Learning, Random Forest, Soil Assessment, Crop Selection*

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1. Introduction

The production of food and crops is crucial due to the high growth of the global population. Over the past decades, the agricultural sector has witnessed significant technological advancements, introducing various techniques for crop cultivation and storage (Senapaty et al., 2023). Modern agricultural practices increasingly incorporate IoT, wireless sensor networks, AI, and automated materials, playing a key role in smart agriculture (Senapaty et al., 2023). Various agricultural research initiatives was launched with the primary aim of improving crop yields to support population sustenance (Senapaty et al., 2023). However, despite these ongoing efforts, challenges remain within the agricultural industry, particularly for small-scale farmers (Misaki et al., 2018a).

A major challenge faced by small-scale agriculture is the incorrect selection of suitable crops that can fit with their land, considering the ability of the existing soil parameters and climatic conditions on their farms. This issue arises due to a lack of knowledge about soil characteristics and environmental weather patterns (Maku & Muriira, 2022). Soil properties vary due to both natural and human-induced factors, including land degradation, soil erosion, crop rotation, and climate change. As a result, the ability of land to support specific crops fluctuates and does not remain constant. Given this variability, multiple processes of data collection and analysis related to soil and meteorological conditions are necessary (Misaki et al., 2018b).

Ongoing soil changes mean that the all properties of soil, along with environmental factors, may not always be in the right balance to support a specific crop. Several factors can contribute to reduced crop yields, including abnormal changes or deficiencies in essential minerals such as potassium, nitrogen, and phosphorus. Continuous cultivation of the same crops over time (In Numbers, n.d.). The indiscriminate application of fertilizers without understanding the soil's actual deficiencies and the best corrective measures can further degrade the soil instead of resolving the issue. These complexities require extensive research from multiple data sources to address the factors influencing crop yield. Consequently, selecting the most suitable crop is not a simple task but rather a series of complex steps. Crop recommendation algorithms, based on the optimal ecological conditions of a given farmland, can now predict the most suitable crop to cultivate. Several approaches have been proposed to enhance crop prediction tasks. In this study, regression and classification algorithms were employed to model and predict different crops for local farmers, considering soil properties (pH, nitrogen, potassium, phosphorus) along with ambient temperature and humidity.

Agriculture is one of the economic sectors for developing nations, especially those in Africa's Sub-Saharan region, such as Rwanda. Most households depend on agriculture both for their food supply and as their main source of income. Additionally, agriculture plays a crucial role in the GDP of Sub-Saharan African countries. Over the past 24 years, these nations have led the crop sector, contributing approximately 85% of the total production (Suwadu & Ibrahima, 2020)

Rwanda is a home of over 13 million people and 69% of households are engaged in agriculture activities (crop production or animal husbandry). In 2022 the 5th Rwanda Population and Housing Census (PHC) confirmed that Nearly 64% of Rwandans are employed in both agriculture and animal rearing, stressing the importance of the sector in creating jobs and lowering poverty (National Institute of Statistics of Rwanda, 2022). Agriculture is a cornerstone of Rwanda's economy, with the majority of the population relying on it for their livelihoods. In the fiscal year 2023-2024, the agriculture and livestock sectors contributed 25% to the national GDP, achieving an annual growth rate of 7%. The current agricultural policy focuses on fostering a market-oriented and professional approach to agriculture, aiming to enhance yields, improve the quality and quantity of produce, and promote the adoption of modern technologies and innovations.

The National Strategy for Transformation 2 (NST2) sets an ambitious target of achieving an average annual real GDP growth of 9.3% over five years, driven by productivity improvements across all sectors and a shift toward value-added activities. Key focus areas include agriculture, with growth propelled by innovation and increased private investment. During this period, agriculture is projected to grow at an average rate above 6% (*Summary_of_the_NST2 (1)*, n.d.).

Crop production in Rwanda is hampered by a number of issues that have been recognized and persist. These difficulties can be divided into two primary groups: those caused by technology and those impacted by people. Lack of knowledge and technical expertise, restricted extension services and training, poor research, and insufficient experience providing agricultural services are some of the issues associated with technology (Semwenda, 2016, n.d.), Meanwhile, soil erosion, land degradation, ongoing farming, leaching, deforestation, and temperature and weather unpredictability are examples of both natural and human-influenced variables (East African Community, n.d.).

The problem of local farmers choosing the wrong crops has been exacerbated by their inability to match crops to the unique soil and environmental conditions of their farms due to a lack of technical and natural agronomic understanding. Based on its biological, chemical, and physical characteristics, every crop has unique ecological needs. Because it gives farmers the information, they need to choose the best crops for optimizing yields, it is crucial to comprehend soil properties and weather patterns before making planting selections (Senapaty et al., 2023).

Smart farming, sometimes referred to as precision agriculture, has become a cutting-edge strategy to solve current issues with agricultural sustainability. The Internet of Things (IoT) and machine learning (ML) are the driving forces behind this development (De Dieu Hagenimana & Sumbiri, n.d.). A branch of artificial intelligence called machine learning permits autonomous skill development and learning in machines without the need for explicit programming (Sharma et al., 2021). Conversely, the Internet of Things is a network of intelligent devices that are connected and have the ability to share resources and data, self-organize, and react to changes in their environment (Intelligent Techniques for Cyber-Physical Systems, n.d.). The next agricultural revolution, especially in farm management, will heavily rely on machine learning and the Internet of Things. These technologies are essential for collecting and evaluating soil and environmental data before suggesting the best crops to grow (World Bank, 775, n.d.)

In this study, we developed an optimized crop selection system utilizing machine learning and IoT, employing seven soil analysis parameters as an effective solution to assist Rwandan farmers. The system enables real-time collection and analysis of soil and weather attributes, including soil pH, nitrogen, phosphorus, potassium, temperature, humidity, and calcium. By comparing these attributes to the ecological requirements of various crops, the system uses a machine learning algorithm to recommend the best crops for optimal growth on a given farmland.

1.1 Problem Statement

Changes in soil's physical, chemical, and biological characteristics, including soil erosion, land degradation, ongoing farming, climate and weather fluctuation, leaching, loss of organic matter, and deforestation, all contribute to the depletion of vital nutrients (AYUB JOSHUA SEMWENDA, 2016). As a result, the soil's ability to provide the necessary ecological conditions for plant growth may decline or be significantly affected, ultimately reducing its capacity to support certain crop varieties. A major concern among local farmers is the lack of fundamental knowledge and appropriate methods for assessing soil conditions. Farmers typically cultivate crops based on their personal preferences. In some cases, they achieve high yields when the soil naturally meets the crops' ecological requirements, but at other times, they experience lower yields or must rely on fertilizers to enhance soil productivity (Kuradusenge et al., 2023).

Given this challenge, a reliable method for data collection and analysis is essential before beginning crop cultivation to evaluate the soil's current condition across the farmland. However, the majority of Rwandan farmers do not have access to up-to-date information about soil and weather conditions, which is a persistent problem (Omar et al., 2024). They thus find it difficult to choose the best crops for their property. The inability to assess soil conditions and crop requirements negatively impacts agricultural productivity by reducing crop yields. Another pressing issue is the excessive and unnecessary application of chemical fertilizers due to the lack of real-time knowledge about soil and environmental conditions. This not only increases costs for farmers but also contributes to soil degradation (Michelson et al., 2021).

1.2. Research Objectives

1.2.1. General Objective

The main objective of this study is to develop a system that helps the farmer perform the selection of the most suitable crop for his/her piece of land based on the seven soil analysis parameters measurement of nitrogen, phosphorous, potassium, pH, humidity, calcium, and temperature using Internet of Things and Machine Learning.

1.2.2. Specific Objectives

i. To design and deploy IoT device to collect real-time soil and environmental weather data based on nitrogen, phosphorous, potassium, pH, humidity, temperature, and calcium.

ii. To develop a machine learning algorithm that processes and provides crop recommendations, optimizing crops based on the specific soil characteristics and environmental conditions of the piece of land.
iii. To develop a user-friendly web application that allows farmers to easily receive crop recommendations.

1.3 Research Questions

i. How can an IoT device collect real-time soil and environmental data?
ii. What type of machine learning algorithm can optimize crop recommendations?
iii. How can a web application effectively deliver crop recommendations to farmers?

1.4 Hypotheses

Seven soil analysis parameters along with IoT and ML tools for crop selection will enhance crop productivity and eliminate unnecessary expenses by providing farmers with precise recommendations on crops that can thrive based on the existing soil and weather conditions.

2.0

2. Materials and Methods

This study employed IoT and Wireless Sensor Networks to collect real-time soil and weather data from Rwandan farmlands, aiming to provide informed crop recommendations using machine learning. The research covered the study area, data collection methods, dataset organization, and model integration. A Random Forest Classifier was used to analyze the data and suggest suitable crops based on ecological conditions. The collected parameters included soil pH, nitrogen, phosphorus, potassium, temperature, humidity, and calcium levels. The data was processed using an Arduino Uno R3 and a NodeMCU for wireless transmission to a cloud server via HTTP. The data collection process involved initializing the microcontroller for peripheral communication, activating sensors to read environmental characteristics, and displaying preprocessed data on a system dashboard. An API established an HTTP connection to transmit data to the cloud, after which the device entered sleep mode for 28,800 milliseconds before restarting the process. This automated system ensured continuous and efficient data gathering for precise crop recommendations.

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Vol. 5||Issue 2||pp 23-43||April||2025
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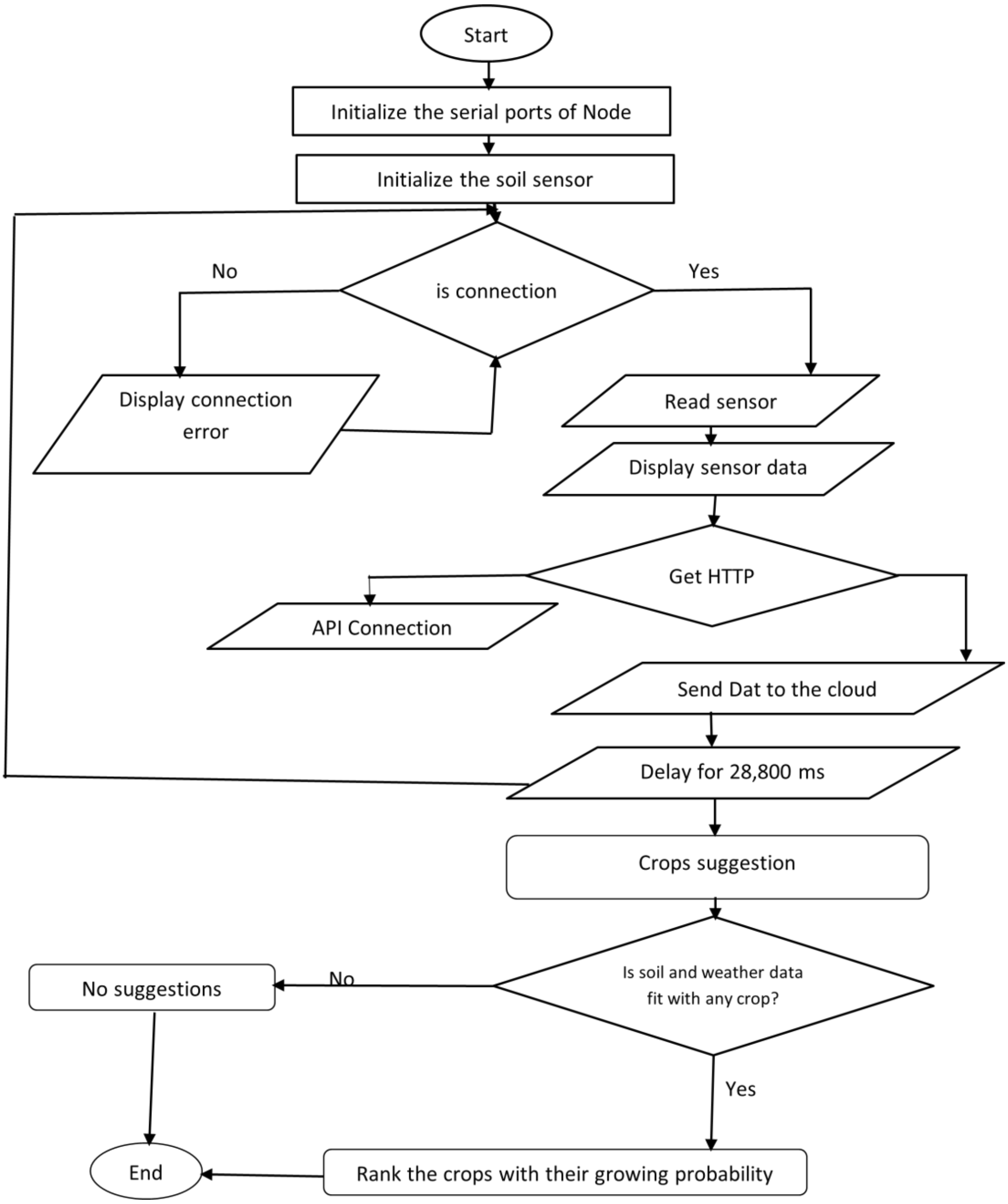

Figure 1: Data collection workflow

2.1. Ecological requirements range

We investigated the minimum and maximum ecological requirements ranges of each crop under observation using the dataset. Table 1 below provides the requirement ranges for each crop considering soil nutrients (NPK), soil pH, temperature, humidity, and rainfall.

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Vol. 5||Issue 2||pp 23-43||April||2025
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Table 1: Ecological requirement average

	Potassium(kg/ha)	Phosphorus(kg/ha)	Soil pH	Nitrogen(kg/ha)	Moisture	Temperature(^{0}c)
Tomatoes	68.0	39.7	6.2	50.3	73.1	21.0
Potatoes	62.8	37.2	6.2	47.1	72.9	20.7
Beans	61.8	35.5	6.2	46.2	72.8	21.0
Rice	59.9	36.1	6.1	43.7	74.6	21.3
Carrots	58.3	33.7	6.3	43.2	72.3	21.6

2.2. Model Selection and Training

To identify the most suitable model for our dataset, we examined various machine learning techniques, including Support Vector Machine, Decision Trees, and Random Forests. Cross-validation techniques were employed to assess the performance of these models, leading to the selection of the Random Forest model as the optimal choice for our dataset. The model was trained using the selected features and its performance was evaluated on the test dataset. The Figure below shows the result of model's selection and performance comparison.

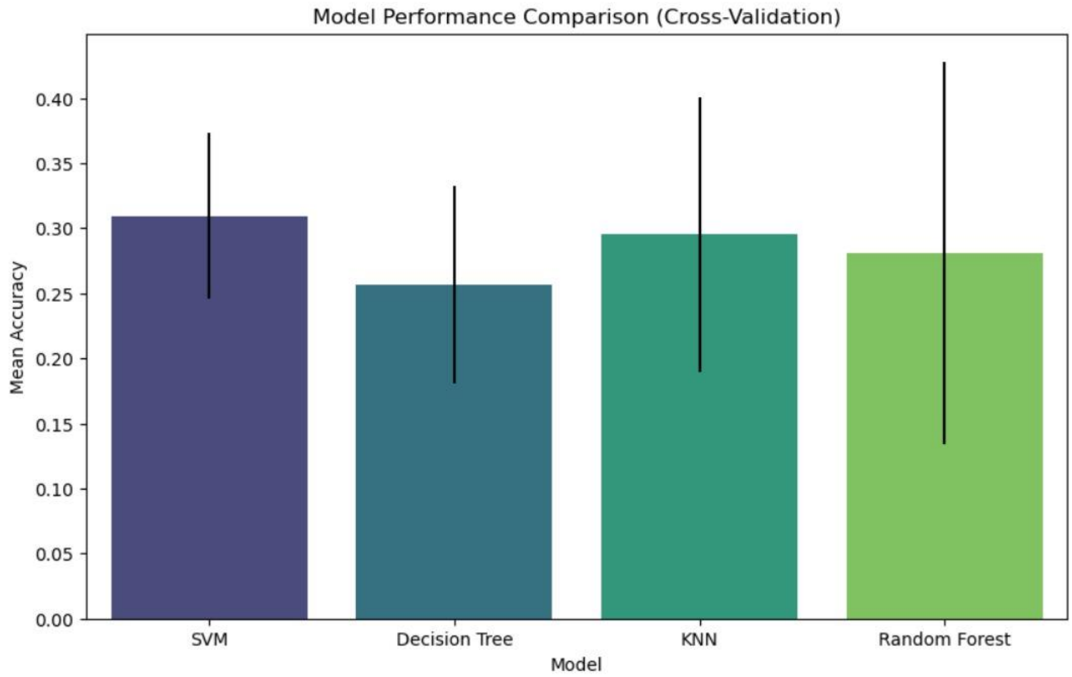

Figure 1: Models performance comparison

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Vol. 5||Issue 2||pp 23-43||April||2025
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2.3. Prediction Model

After training and evaluating multiple models, the Random Forest model was chosen due to its superior accuracy of 96% compared to the alternatives. This outcome suggests that the model can be effectively applied in real-world scenarios. Following this, a prediction system was developed to forecast the most suitable crops and rank them based on their probability of successful growth. The ranking process considers key ecological factors such as soil nutrients, pH levels, and environmental weather attributes, utilizing the Random Forest Classifier. The model was tested using new, unseen sensor-collected data, where it demonstrated satisfactory performance. The model was set up on a cloud server to improve accessibility, allowing users to engage with it without any problems. Users can use the web application to enter average weather and soil data into the machine learning model, which interprets the data and, taking into account the particular agricultural circumstances produces a ranked list of crops based on their likelihood of growing. The figure below illustrates the architecture and workflow.

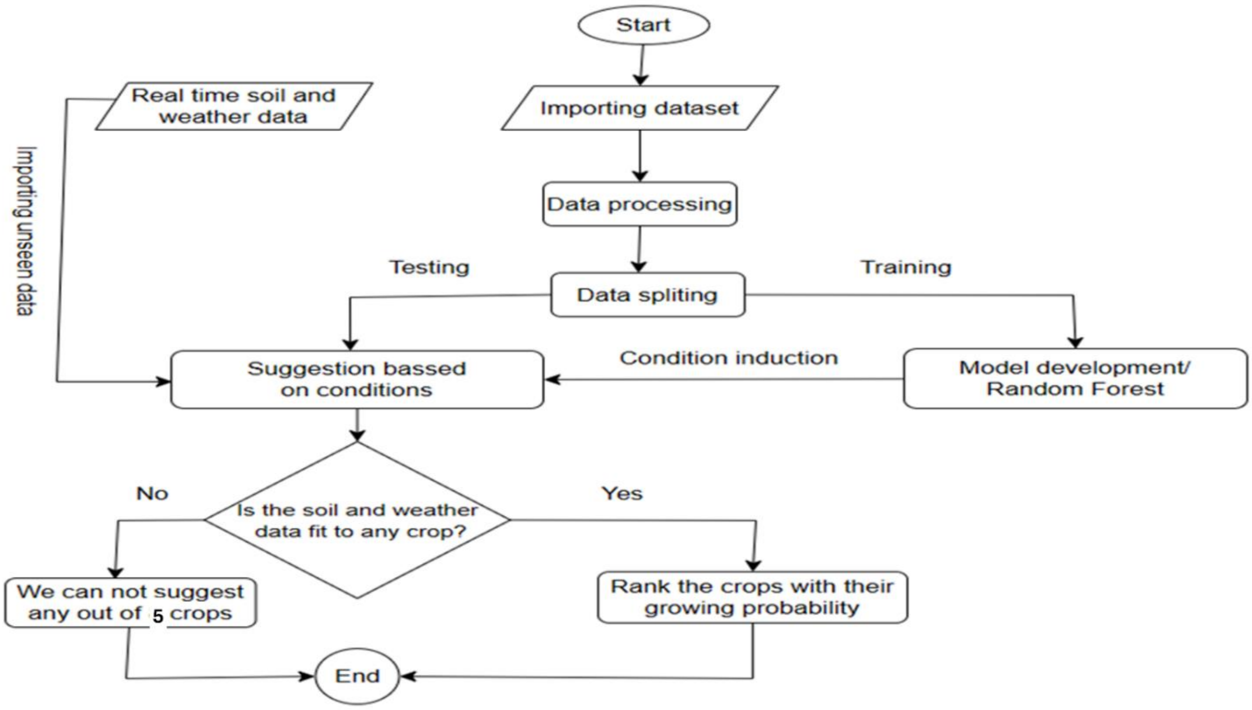

Figure 3: Architecture and workflow of the crop selection model

2.2. Tools used

2.2.1. NodeMCU

NodeMCU is a versatile and low-cost development platform for IoT projects, featuring robust processing, built-in Wi-Fi, and extensive GPIO pin support for sensor integration. It supports various programming environments, including Arduino IDE and Mongoose OS, and enables seamless communication between sensors, actuators, and cloud-based systems. In the context of "Optimizing Crop Selection Through Machine Learning and IoT Using Seven Soil Analysis Parameters," NodeMCU can act as the central processing unit for collecting real-time soil data (e.g., pH, moisture, and temperature) through sensors, transmitting the data wirelessly to a machine learning model for analysis, and facilitating precise crop recommendations based on soil health and environmental factors(Singh Parihar & Parihar, 2019)

Figure 4: NodeMCU(esp8266)

2.2.2. Soil-integrated Sensor

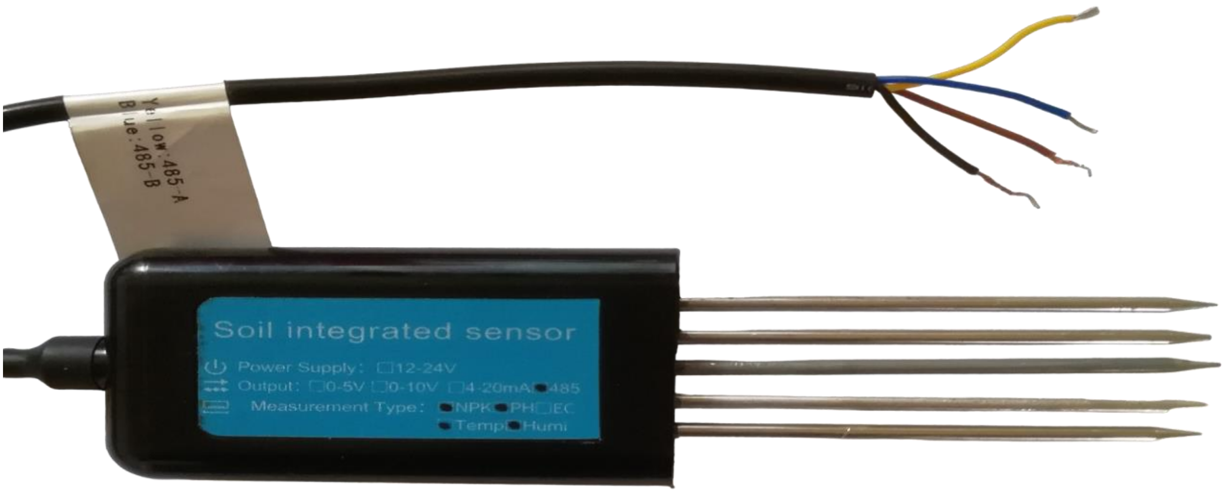

Figure 5: Soil-integrated Sensor

The soil-integrated sensor is designed to measure four essential soil parameters, including pH levels and the amounts of phosphorus, potassium, and nitrogen. This sensor is known for its reliable performance, quick response time, and high accuracy (Kumar et al., 2024). It has premium stainless-steel probes that are resistant to electrolysis rust, and corrosion from salts and alkalis. Fully waterproof and compatible with various soil types, the sensor is suitable for long-term soil embedding or quick measurements by inserting its stainless-steel rods into the ground. The NPK concentration varies from 0 to 1999 mg/kg, with an accuracy of ±2%, while the pH measurement ranges from 3 to 9 with an accuracy of ±0.3pH. The sensor delivers an efficient response time of less than one second (*In-Depth: Interfacing Soil NPK Sensor with Arduino*, n.d.). It features four wire connections: the VCC wire (brown) connects to a 12V-24V DC power source, the GND wire (black) connects to the NodeMCU ground terminal, and the B (blue) and A (yellow) wires correspond to the B and A pins of the MAX485/RS485 Modbus module, respectively.

2.2.3. 3Max485 Chip RS-485 Module /TTL to RS-485 Module

Using the NodeMCU 5V supply as power, the MAX485 TTL to RS-485 interface module serves as a bridge between the Soil Sensor and the NodeMUCU. Up to 2.5 MB/sec of data transfer is supported, although speed drops with increasing device distance. On the data side, the module has four male connectors: the RE (Receiver Enable) pin is connected to the Arduino's digital output pin, and the RO (Receiver Output) pin is connected to the Arduino's RX pin. Also known as "Active High," the DE (Driver Enable) pin is attached to the RE pin. The NodeMCU's TX pin is connected to the DI (Driver Input) pin. There are four male headers on the RS-485 output side: the GND pin is connected to the NodeMCU's GND pin, and the VCC pin receives 5V from the NodeMCU. The blue (B) and yellow (A) wires of the Soil Sensor module are represented by the B and A pins (*7 in One Multiparameter Soil Sensor with*

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Vol. 5||Issue 2||pp 23-43||April||2025
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Esp32 - Other Hardware / Sensors - Arduino Forum, n.d.). The RS-485 module is depicted in Figure 4.5. In Figure 6, the RS-485 module is displayed.

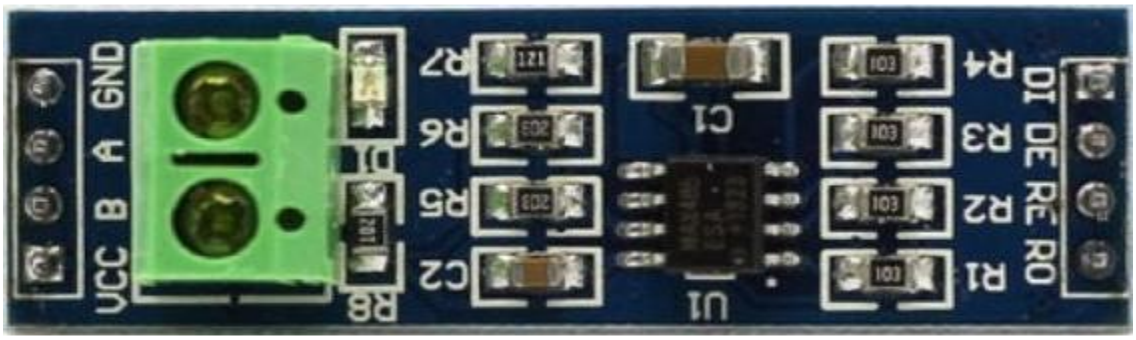

Figure 6: 3Max485 Chip RS-485 Module /TTL to RS-485 Module

2.2.4. 12V DC Power Cable

A 12V power cable supplies 12 volts when fully charged. It is both economical and ecologically

Figure 7: 12V DC Pawer Cable

good because it can be recharged several times and stores electrical energy as direct current (DC) [39]. Three 3V DC batteries are used in the system; when completely charged, they produce 12V. A 12V battery powers the soil-integrated sensor (Kübra Seda Kimyager & Yasin Ömer Bıdık, 2022). To supply 12V to the sensor module, the battery's 12V VCC is connected to the brown wire of the soil-integrated sensor, whereas the Arduino board runs on 5V(*12V DC MICROFIT POWER SUPPLY - WM Systems LLC - Innovation in Smart IoT / M2M Systems*, n.d.).

2.2.4. API

An API, or application programming interface, is a set of protocols that allows different applications to communicate with each other. It acts as a middle layer for transferring data between various systems (Nadim Iqbal, 2012). In our study, we have implemented an API to facilitate the transmission of data from the sensor model to the cloud server using the HTTP protocol. The data sharing and storage process involves several steps after data collection by the sensors.

I. First, the ESP8266 establishes an HTTP connection to provide internet access for the sensor model.
II. Second, the API initiates an HTTP request and sends it to the control system.
III. Third, the sensor model uses the HTTP protocol to react with the data via the API.
IV. The API then waits until a new request is initiated after sending the data to the cloud server for storage.

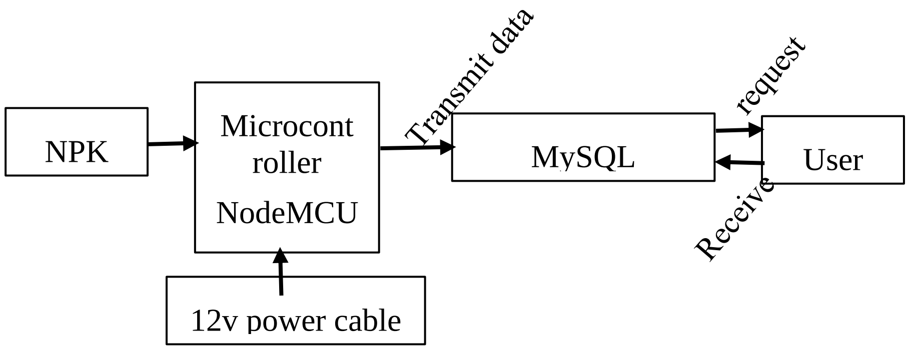

Figure 8: Sensor model block diagram

2.3. Crop Suggestion Model

The model in this study was developed using supervised machine-learning algorithms. To find the most efficient algorithm, four were tested: The accuracy of the Support Vector Machine (SVM) was 87%, the K-Nearest Neighbor was 90%, the Decision Tree Classifier was 95%, and the Random Forests were 96%. Using the ecological needs dataset for eight crops, the Random Forest Classifier was chosen based on this comparison and used to train the model before being put on the cloud server. A backend function in the web application determines the daily average of the sensor data over seven days during farm setup and cultivation after the sensor model gathers data and sends it to the cloud server. The daily averages are then added up to determine the overall average, which is subsequently entered into the model for processing and analysis. In the end, the algorithm generates a ranking of the best crop suggestions.

3. Results & Discussion

3.1. Implementation of Prototypes

Six soil and weather parameters—soil nitrogen, phosphorus, potassium, pH, ambient temperature, and humidity can be measured by the prototype embedded device. Its main control unit, a NodeMCU, is in charge of overseeing a number of functions, such as data processing, sensor and actuator interface, power consumption monitoring, and enabling wireless connectivity for data transmission. Three nutrients potassium, phosphorus, and nitrogen as well as pH levels are measured via soil-integrated sensors. While the NodeMCU module sends the data to a MySQL cloud server, the gathered data is shown on a system dashboard. The prototype is powered by a 12V source. The figure below shows the implemented prototype.

Figure 9: Prototype implementation

Dataset features Analysis

Five crops were subjected to feature analysis based on their environmental and soil needs. We contrasted the attribute needs of the eight crops in this investigation. The top five crops with the greatest attribute needs were determined by the model. The outcomes of the feature analysis are as follows:

The model identified the crops with the highest nitrogen (N) requirements, and the results showed that rice required the highest concentration of N (74.5 kg/ha), followed by tomatoes (73 kg/ha), potatoes (72.8 kg/ha), beans (72.5 kg/ha), and carrots (kg/ha)

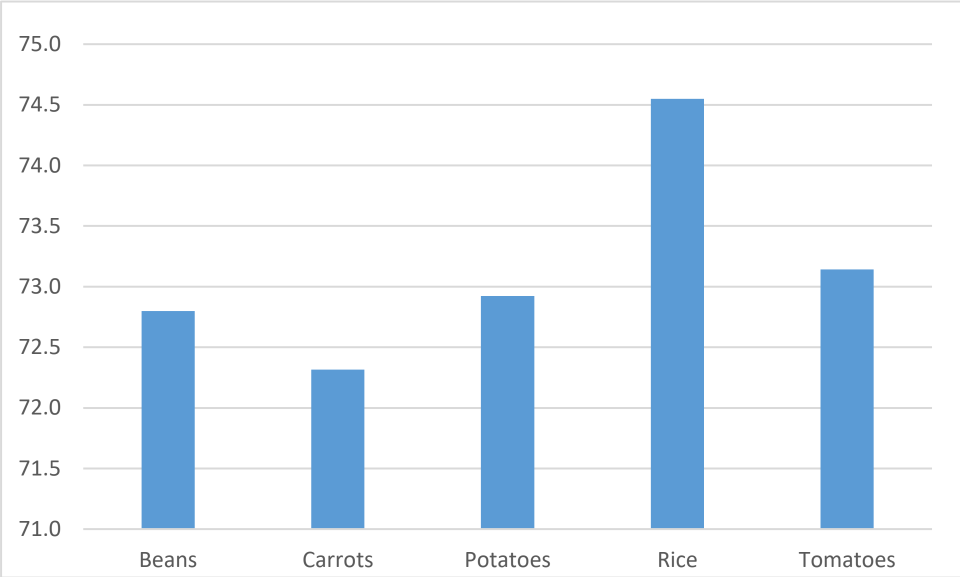

Figure 10: Crops with high nitrogen requirement

For Phosphorous (P), Once more, tomatoes are the most important crop that needs a high concentration of phosphorus (39.5mg/kg) compared to other crops followed by potatoes (37.8 mg/kg), rice (36.0mg/kg), beans (34.8mg/kg) and carrots (32.8mg/kg). The figure below shows the five topmost crops with high phosphorous requirement.

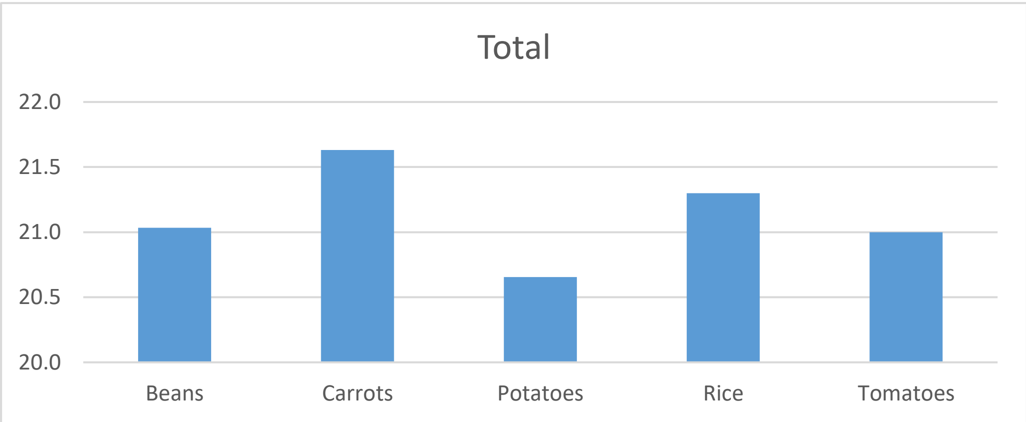

Figure 11: Crops which require high phosphorous concentration

For Potassium (K), rice has become the topmost crops which require high potassium concentration (74.6mg/kg) compared to other crops followed by Potatoes (73.3mg/kg), tomatoes (72.8mg/kg), beans (73.6mg/kg) and carrots (72.4mg/kg).

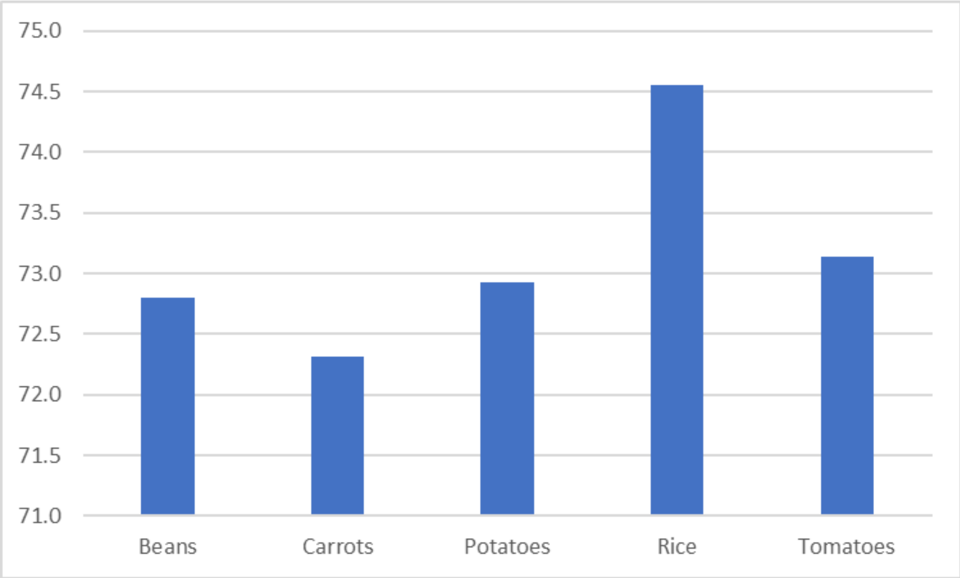

Figure 12: Crops with high potassium requirement

When it comes to hydrogen potential (pH), rice has emerged as the crop that needs the highest pH level (74.5 pH) among all crops, followed by tomatoes. (73.2pH), potatoes (72.8pH), beans (72.6pH) and carrots (72.3pH)

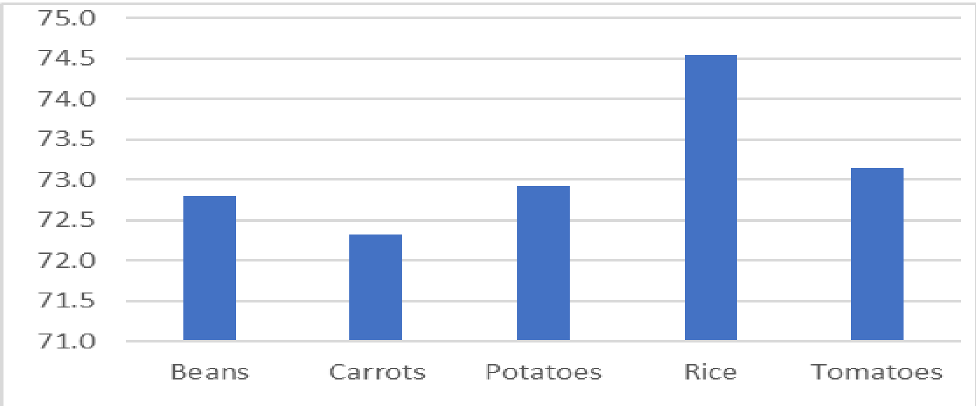

Figure 13: Crops with high nitrogen requirement

The results show that rice has become the topmost crop which requires high humidity level (74.6%) compared to other crops followed by tomatoes (73.3%), potatoes (72.8%), beans (72.6%), and carrots (72.4%).

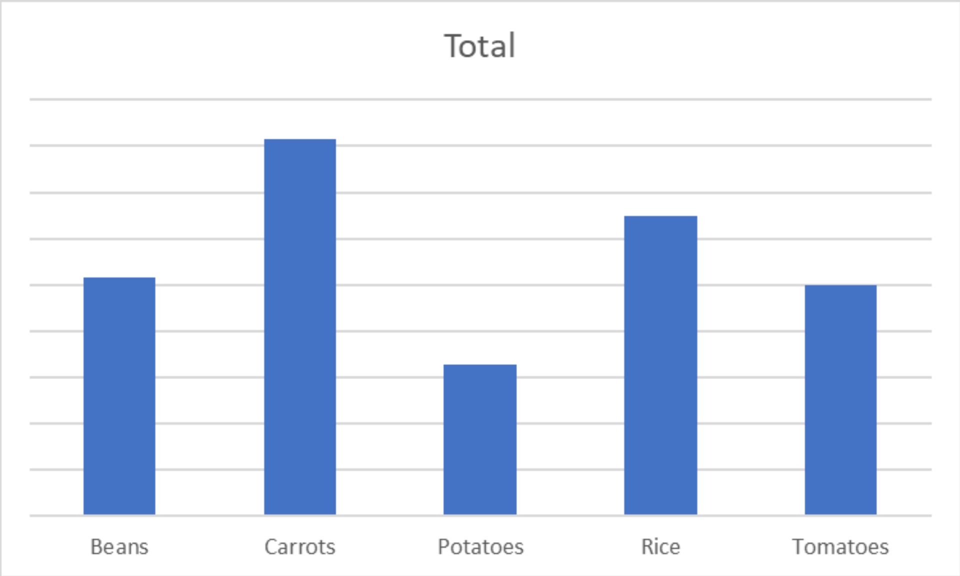

Figure 14: Top most crop that requires high temperature

The results show that rice has become the topmost crop that requires a high humidity level (74.6%) compared to other crops followed by tomatoes (73.3%), potatoes (72.8%), beans (72.6%) and carrots (72.4%).

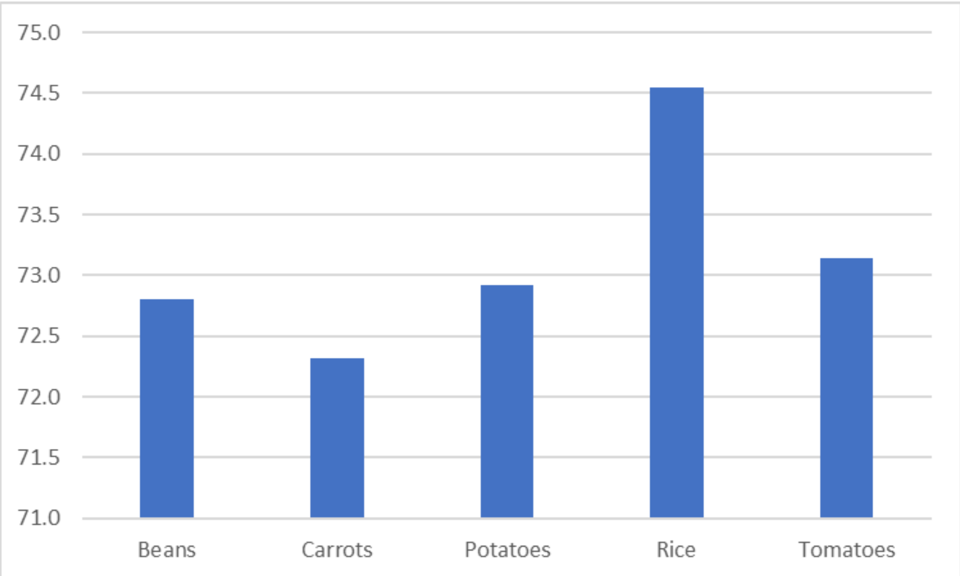

Figure 15: Topmost crop which requires high humidity level

3.2. Field data processing and analysis

The figure below shows the process a field data exportation from database to Machine Learning model.

Sensor Data Table

Serial Number	Temperature (°C)	Moisture (%)	Nitrogen (mg/kg)	Calcium (mg)	Phosphorus (mg/kg)	Potassium (mg/kg)	Soil pH	Date
ESP123	22.3	65.2	30.0	132.5	36.0	132.5	6.5	2025-01-20 18:09:48
ESP123	22.3	65.2	33.0	112.5	26.0	112.5	6.5	2025-01-20 17:20:05
ESP123	21.4	69.5	1.0	40.0	48.0	40.0	6.5	2024-09-06 12:55:30
ESP123	21.4	67.9	1.0	40.0	48.0	40.0	6.5	2024-09-06 12:55:27
ESP123	21.4	67.9	1.0	40.0	48.0	40.0	6.5	2024-09-06 12:55:23
ESP123	21.4	65.8	1.0	40.0	48.0	40.0	6.5	2024-09-06 12:55:20
ESP123	21.4	67.0	1.0	40.0	48.0	40.0	6.6	2024-09-06 12:55:17
ESP123	21.4	71.3	1.0	40.0	48.0	40.0	6.6	2024-09-06 12:55:13

Figure 16: Crop suggestions result after the completion of data analysis

3.3. Field crop selection findings

After completing the data analysis process, the results showed that potatoes have a 56% likelihood of successful growth, while beans follow with a 43% probability, based on the soil and weather conditions in the field area. The figure below depicts the ranking of crop suggestions following the data analysis.

Select Crop:

Potatoes

Get Suggestions

Soil Nutrient Suggestions

Potatoes
Calcium: Increase Calcium by applying 1.52 kg/ha.
Carrots
Calcium: Increase Calcium by applying 1.80 kg/ha.
Beans
Nitrogen: Decrease Nitrogen, current: 30, recommended: 10-20.
Calcium: Increase Calcium by applying 1.77 kg/ha.
Tomatoes
Nitrogen: Increase Nitrogen by applying 2.00 kg/ha.
Phosphorus: Increase Phosphorus by applying 4.00 kg/ha.
Potassium: Increase Potassium by applying 2.50 kg/ha.
Calcium: Increase Calcium by applying 2.40 kg/ha.

Figure 17: Crop suggestions result after the completion of data analysis

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Journal of Information and Technology
Vol. 5||Issue 2||pp 23-43||April||2025
Email: info@edinburgjournals.org|

The figure below also shows a graphical presentation of crops. In this description, the blue color represents precision which measures the accuracy, the yellow color represents recall which stands for true positive rate and green color combines the average of precision and recall both represent the percentage of growing probability of a specific crop.

A crop selection model was developed using the Random Forest Classifier to analyze and predict suitable crops based on real-time field data collected through an IoT system prototype. This system monitored four soil parameters along with two environmental weather factors. The model demonstrated high reliability for real-world applications, achieving an accuracy of 96% and a precision of 97%. The crop recommendation results were experimentally validated using field input parameters, including temperature, humidity, nitrogen, phosphorus, potassium, pH, and calcium. Data samples were collected from the Gicumbi district. The web application enabled users to manage the collected data and export it to the machine learning model for analysis and crop recommendations. This process involved averaging the data and converting values from PPM to kg/ha, aligning with the dataset's unit scale for NPK data, which is expressed in kg/ha.

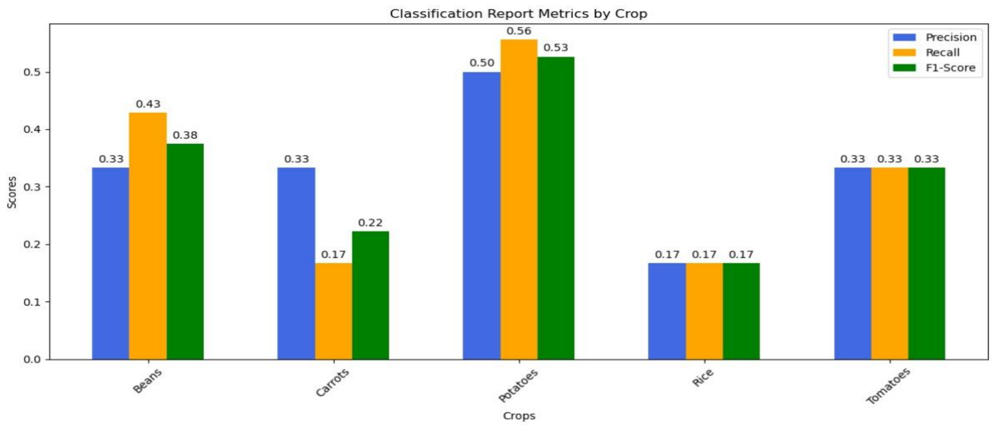

Figure 18: Graphical presentation of crop selection result

Following the data analysis, the results indicated that the average measurements over seven days at this location were 25.152°C temperature, 62.143% humidity, 58 kg/ha nitrogen, 81.714 kg/ha phosphorus, 164.952 kg/ha potassium, and pH level of 5.143. The probability scores for crop growth showed that potatoes had a 56% likelihood of successful cultivation, beans had a 43% probability, both carrots and tomatoes had a 33% chance, and rice had a 17% probability. Consequently, farmers can choose to grow either potatoes or beans in this field. Based on the forecasted results, the existing soil nutrient levels, pH, and environmental conditions at this location are more suitable for potato cultivation than for other crops.

4. Conclusion

The results from the ML algorithms indicated that K-Nearest Neighbors achieved 90% accuracy, while Support Vector Machine reached 87%. A 95% accuracy rate was achieved with the Decision Tree method. However, because the Random Forest Classifier had the best accuracy (96%), we decided to use it to create our crop selection model because it outperformed the other three algorithms in terms of accuracy ratings.

The study was carried out in Rwanda's Northern Province, where field data on soil and meteorological conditions were gathered in the Gicumbi area. The MySQL cloud server was then updated with the collected data. End users may access, manage, and export data to the system's integrated machine-learning model using the web application. Using our crop selection model, the field data was processed and analyzed. The model ranked potatoes as the most suitable crop with a 56% probability of successful growth, followed by beans with a 43% probability. Carrots and tomatoes were both ranked third with a 33% probability, while rice was considered the least suitable, with a 17% probability based on the given soil and weather attributes.

5. Recommendations

This research considered nitrogen, potassium, phosphorus, pH, ambient temperature, calcium, and humidity, with a recommendation to include additional factors rainfall amount for greater accuracy. For future development, we propose a responsive system capable of automatically irrigating the soil when water is needed and mixing fertilizers with water to optimize soil nutrients. Additionally, the system should be designed to predict total harvest production based on soil nutrient levels. This approach will improve efficiency, sustainability, and agricultural productivity.

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