American Journal of Smart Technology and Solutions (AJSTS)

ISSN: 2837-0295 (ONLINE)

VOLUME 5 ISSUE 1 (2026)

PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

American Journal of Smart Technology and Solutions (AJSTS)

Volume 5 Issue 1, Year 2026
ISSN: 2837-0295 (Online)
DOI: https://doi.org/10.54536/ajsts.v5i1.7318
https://journals.e-palli.com/home/index.php/ajsts

Soil and Crop Production Analyzer: Advancing Agricultural Revolution through Random Forest Algorithm

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Article Information

Received: January 07, 2026

Accepted: March 24, 2026

Published: June 18, 2026

Keywords

Agricultural Technology, Crop Recommendation System, General Santos City, IoT Sensors, Machine Learning, Precision Agriculture, Random Forest Algorithm, Soil Fertility Classification, Soil Nutrient Analysis, Sustainable Farming

ABSTRACT

This study responds to the challenge faced by many farmers in accessing reliable methods of soil testing to ascertain nutrient levels in the soil and recommend the crops that best suit the area for planting. Guesswork and experience make farmers in most rural areas depend on long waiting for laboratory results, as well as traveling to distant testing facilities, which mostly yield poor results. This study, therefore, tries to solve this problem by suggesting a portable Soil and Crop Production Analyzer that uses accessible information on soil nutrients and machine learning techniques to offer recommendations in real-time. The system integrates WiFi-enabled IoT sensors with a mobile application in measuring the following key parameters in the soil: Nitrogen (N), Phosphorus (P), Potassium (K), and pH levels. The Random Forest algorithm classifies the fertility level of the soil and recommends suitable crops from the measured parameters that were used to process the gathered data on soil. Historical data tracking, offline capability, and a farmer-friendly interface are some additional features of the mobile application to ensure usability even at the remotest areas. By making soil testing and crop recommendations more accessible, the system encourages better farming practices and enhances agricultural productivity. The present study is targeting specifically farmers in General Santos City to gain access to more resilient and data-based agricultural communities as a consequence of its implementation.

INTRODUCTION

One of the most difficult hurdles that meet today's farmers is understanding the actual composition of soil. There are many farms which growers are not aware of planting with soil that lacks the required nutrients such as nitrogen, phosphorus, potassium, and pH which are important for the healthy and strong growth of the crops. But without soil nutrient analysis, it is nearly impossible to tell what is lacking. The issue is, the majority of farmers do not have easy access to testing. There are lab-based soil tests, but they take too long or are too far from farming areas. Even if soil testing is performed, the condition of the soil may alter with time; thus, one test is not sufficient for giving guidance throughout the entire planting season. Sadly, some farmers find themselves depending on their intuition or old methods by just doing what has always been done to survive.

In General Santos City, this issue is very clear. Farmers need better tools that can tell them, right away, what their crops fit to their soil. While some portable nutrient analyzers are available, there are still limitations like far from testing areas that made them go just to test their soils. This leads the farmers left trying to make the best decisions they can with limited information, which often leads to wrong crop planting and low crop yields. This kind of guesswork doesn't just lower crop yields; it can also make farming more expensive.

To address these issues, this research explores the use of device and mobile app machine learning techniques, in this instance, a crop recommendation system, to know parameters of soil nutrient and recommend crop to plant using algorithm machine learning. By using these computational methods, the system outlined in this paper targets to enhance soil nutrient measurement and suggest farmers to select the appropriate crops to plant. This algorithm called random forest algorithm allows for the automation of soil nutrient analysis, which is a most suitable and consistent method of soil classification. It will classify the most suitable crops depending on the soil nutrient analyzed by the system. The records of soil testing will be recorded to the admin for soil data analysis in different areas in the city.

Applications of machine learning in precision agriculture is an excellent challenge towards better soil assessment, crop selection, and resource utilization. This study utilizes a crop recommendation device that takes into account the soil properties and makes suitable predictions based on such parameters. This system device analyzes many interrelated variables together and gives a complete and data-driven assessment of the soil.

The proposed model encompasses all the components of the soil nutrient, pH, N, P, K, and pH level-all playing very crucial roles in the development of plants. Soil testing was applied to establish soil fertility and what to grow. This model is trained on already existing data on soil that helps in coming up with the best possible recommendations depending on the specific parameters of the given soil. The system combines soil nutrient into different levels: most, moderate and least suitable potential productivity and these are the basis for crop

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recommendation. High nitrogen soil is ideal for leafy vegetables while high phosphorus soil is ideal for root crops. Similarly, a well-balanced NPK soil will be adequate for staple crops to reach their potential yield without compromising long-term soil viability.

This tool provides farmers with reliable recommendations on soil management and crop selection by processing enormous data sets of soil parameters. With the continuous update of the system with new data on soils recommendations become more relevant and fitting. Besides facilitating decisions in agriculture this solution supports agriculture by reducing resource loss in this vital sector.

Precision farming using machine learning is a good way to manage the soil for more productivity and sustainable agriculture. This research based on the use of the crop recommendation tool proposes a science-informed yet practical solution to improve the assessment of soil fertility and selection of crops. Using computational techniques in soil assessments aims to equip farmers with decision-making that improves agricultural sustainability and resource-use efficiency amidst resource-constrained conditions. This is also an innovation to the soil laboratory, that is, the administration, through the introduction of technological advancements in their department, making the testing and records of soil nutrient data across the city more efficient.

Statement of the Problem

The limitations of manual and traditional soil analysis method make it difficult for farmers to maintain soil nutrient and choose which crops to grow. This study tackles these problems. Lack of quick and effective methods for identifying soil nutrients has led to inconsistent crop yields and wasteful crop use. Therefore, the study intends to investigate the following problems:

1.How do conventional soil testing methods impact the accuracy and effectiveness of soil fertility assessment and crop selection?

2.What constraints of access and turnaround time limit farmers ability to obtain frequent soil tests and timely recommendations throughout the planting season?

3.How does a system with machine learning, specifically the Random Forest Algorithm improve the precision and accessibility of soil fertility analysis and crop recommendation for farmers?

Objectives of the Study

The main goal of this study is to develop a soil nutrient analyzer and crop recommendation system that will helps farmers better understand their soil's condition and plant the right crop. By using the Random Forest Algorithm, the system analyzes nutrient levels such as nitrogen, phosphorus, potassium, and pH to determine soil health. Based on the results, it suggests the most suitable crops for planting:

1.Develop and validate a Random Forest Algorithm based soil fertility classifier using N, P, K, and pH level.

2.Assess the effectiveness of the ML-based soil analysis versus traditional methods in terms of accuracy, turnaround time, and accessibility for farmers.

3.Optimize crop recommendations based on soil composition helping farmers maximize productivity while promoting sustainable agricultural practices.

Scope and Limitation

The system blends hardware with software elements to support agricultural decision-making based on data. Employing an The Raspberry Pi Pico's NPK and pH level sensor allow the system to identify soil pH, phosphorus (P), potassium (K), and nitrogen (N). By inserting into the soil, the device will scan and get the nutrient levels. The data is then wirelessly sent via Wi-Fi connectivity to mobile application. Soil data received is processed through random forest machine algorithm organically classifying the NPK and pH status and other factors with bioavailability contact of the crop. Based on this analysis, the procedure recommends the best crops for the respective soil type and conditions. These suggestions can be shown using a mobile app and store to admin the history, which helps the farmers to see the past recommendations and soils laboratory for reporting and data analysis. This system does have some limitations, crop recommendations based on NPK and pH sensors depend on their accuracy, which can be significantly affected by calibration and the environment. To deliver suitable readings, it requires calibration and maintenance. Additionally, Wi-Fi communication has a limited coverage area and susceptible to interfering conditions, resulting in data loss or communication failure. For such a crop outside the dataset, the recommendation may be missing owing to a recommendation restricted to fixed database of crops. Finally, the device uses an external mains power supply and will likely not be workable in places with no access to the electricity grid (unless you have a battery- or solar-based solution for powering it). Environmental factors, such as changes in soil moisture and temperature, may also need additional calibration of sensor readings. It is also context-aware, but only for this location: the soil datasets and recommendations are based on soil collected from General Santos City. Consequently, its efficiency might not be similar when used in different areas with various soil complexions and climatic situations. While it has its own limitations, crop recommendation system is an effective tool for precision farming and this will allow the farmers to make better decisions by enabling accessible analysis. It improves agricultural efficiency and sustainability by using sensor technology, Wi-Fi connectivity, and machine learning algorithms.

LITERATURE REVIEW

Related Literature

In crop yields soil nutrient levels are a key factor. They directly affect the growth, quality and yield of plants making them crucial to long-term agricultural sustainability. Because of the absence of a proper nutrient analysis of the soil, farmers ran the risk of planting on a nutrient-poor soil. Low yields and high disease incidence characterized this type of scenario. Nitrogen (N), phosphorus (P), and potassium (K) are primary nutrients that are crucial for plant health; low content of any one of them, as a result, excessive use of fertilizers leads to deterioration of soil quality while under-fertilization is limiting to crop growth. The lack of accessible soil testing has forced many farmers to rely on visual assessment, experience, and traditional farming practices, resulting in poor crop management decisions about the land they farm. By failing to correctly evaluate the health of the soil scientifically, our production costs are rising with suffering crop yields unable to rise.

The Bureau of Soils and Water Management (2024) said that many Filipino farmers lack access to laboratory-based soil testing due to high costs, long processing times, and limited testing facilities. This results in the continuation of traditional methods of evaluating soil that depend on visual examination, which frequently lead to misconceptions regarding the health of the soil. Farmers who forgo soil testing typically plant crops using their intuition and prior knowledge, which may lead to fairly suitable crops planting that causes low crop yields. The cost associated with soil testing can be very costly, making laboratory analyses unaffordable for low-income farmers. Without prompt or easy access to information regarding the composition of their soil, these farmers find it difficult to make educated choices about which crops to plant, when to plant them, and how much fertilizer to use to employ, which eventually results in decreased yields and profits.

Kai *et al.*, (2025) soil nutrient conditions from organic vegetable farms in Sariaya, Quezon and Los Banos Laguna have been investigated. In many of these organic farms there are nutrient deficiencies that eventually limit the production. They analyzed the chemistry and biological activity of the soil using SOFIX (Soil Fertility Index). They measured microbial diversity and function as indicators of soil health. In addition, it showed that key macronutrients such as nitrogen phosphorus and potassium were below the recommended level for organic farming. They were found in organic farms that switched from conventional to organic practices in an effort to maintain soil nutrient levels. Understanding soil nutrients is important for maintaining productivity and producing high crop yields. Proper management of the soil supports not only plant growth but also the long-term sustainability of the farming system.

Various initiatives have been introduced to improved awareness of soil fertility and support better crop management through accessible soil testing. University of the Philippines Los Banos (2020), introduced a portable soil testing kit designed to measure key nutrients which is the NPK and pH or Nitrogen, Phosphorus, Potassium, and pH level. The kit contains pre-measured chemical solutions and visual indicators that allow soil chemists to mix soil samples with reagents, observe color changes, and compare them to a chart to estimate nutrient levels and soil pH level. This simplified the testing method, helping farmers and field technicians to make basic but accessible assessments of soil testing in minutes. Despite its accessibility and ease of use, the process still requires up to eight to ten days not because of the kit, but because of the waiting time since many farmers tested their soil, the reason the result is delayed.

Tiwari (2023) emphasized that soil testing is one of the major means by which agriculture has been made sustainable. In practice such practices will facilitate economic gains among farmers conserve environmental resources and ensure food security. Knowing exactly what one's soil needs can help farmers avoid excessive applications of fertilizers thereby maintaining soil health and growing disease-resistant crops. The repeated soil testing in this case prevents land deterioration over time and productivity for future generations. We must enhance access to such testing services and provide farmers with the knowledge and skills needed to facilitate informed decisions and better respond to difficulties.

Conventional methods for testing soil have several disadvantages. So, scientists are exploring new technologies in the form of IoT-based soil sensors and machine learning for soil analysis. They are also developing websites and apps through which people can easily test their soil. These may offer farmers the required information about soil nutrients and help solve all problems related to the testing of soils. The farmers could improve crop yields by using new technologies for testing soils, while ensuring sustainability.

Soil health assessment and management have become easier for farmers with recent developments in soil testing technologies, mobile apps, and IoT-based monitoring systems. Testing for soil required sending samples to labs, waiting for results, and interpreting complex data, which took weeks. Modern tools now let farmers instantly and accurately test the quality of the soil in the field. Using portable sensors key soil parameters such as nitrogen phosphorus potassium NPK and pH levels can be measured in real time while smartphone apps do the analysis. IoT monitoring systems even allow the continuous observation of soil conditions automatically collecting and sending these data to mobile devices or cloud platforms.

This information will enable farmers to make faster, evidence-based decisions on when and how to apply fertilizers, which crops to plant on their lands and how to increase yields with minimal waste. They not only increase productivity but also ensure that agriculture becomes sustainable. By fully understanding the exact requirements of soil farmers can avoid over-fertilization, reduce costs and prevent environmental damage. All these technological advances have turned traditional soil testing into an accessible, efficient and smart process that enables farmers to raise healthier crops and make more informed decisions about agriculture.

Raj *et al.*, (2021) researched how machine learning could make recommendations on crops based on soil conditions. A system wherein IoT devices monitor important parameters in soil such as pH temperature humidity and moisture. These readings are derived from several sensors attached to a microcontroller that processes data using a machine learning algorithm. A web-based graphical interface allows farmers to make more informed decisions by displaying recommendations. It is however not practical since a laptop or computer must be used to get the results.

Similarly, Karuna *et al.*, (2024) developed an IoT-based crop recommendation and monitoring system that monitors real-time soil conditions. In their work, they used pH and moisture sensors connected to the ESP8266 microprocessor for continuous soil monitoring. Then, by using Wi-Fi, data would be transmitted to a cloud platform, which, based on an integrated rule-based algorithm, would recommend suitable crops. Farmers would access the recommendations remotely through an online interface and respond in real time.

Reddy *et al.*, (2024) proposed a low-cost smart agricultural equipment supported by sensors for soil moisture, pH, and color. The inventors used an Arduino Uno as the base microcontroller that communicated with the sensors to collect the soil data. A real-time display of the readings was shown on the LCD screen, and the power was ensured by a battery pack. The system also has features for crop and fertilizer recommendations based on collected data, along with a yield estimation module to assist in pricing.

Jayapriya *et al.*, (2023) developed an IoT-based nutrient analysis model. In the prototype nitrogen, potassium and phosphorus concentrations were measured using an Arduino Uno-based sensor node equipped with soil NPK sensors. They were wirelessly sent to a remote computer where the data were processed using the decision tree and k-nearest neighbor algorithms. Results were presented in a web-based dashboard accessible to farmers.

Rathore *et al.*, (2021) developed a machine learning based recommendation system incorporating various ambient and soil sensors. It also included a temperature-humidity sensor DHT11, a capacitive moisture sensor and NPK sensors that were connected to a Raspberry Pi controller. The data was stored locally and was sent to a Firebase database for analysis using random forest, CNN and KNN algorithms. The end of the crop's recommendations were presented on a mobile-friendly dashboard.

Gottemukkala *et al.*, (2023) proposed a hardware system for NPK analyses. In this paper the authors presented a soil probe with integrated NPK sensors connected to a Raspberry Pi which communicated data via MQTT protocol. It consisted of a crop database that correlated the current levels of nutrients with those required by the crop thus coming up with rapid recommendations through a web application optimized for mobile phones.

Prabavathi *et al.*, (2024) developed an affordable and compact soil pH detection system with an Arduino Uno and a soil pH sensor. Sensor data was transmitted using the ESP8266 Wi-Fi module to ThingSpeak-a cloud data platform-for real-time monitoring and analysis of soil pH. Crop recommendations based on acidity levels were displayed on a web-based dashboard.

Varshitha *et al.*, (2022) proposed a system which was based on the use of machine learning, AI techniques such as decision trees, random forests, and KNNs. Their framework required no sensors, but rather depended on pre-available measured data on soil that was kept in CSV format, processed through Python Scripts with associated classifiers. It can suggest suitable crops based on historical data patterns and communicate the results to farmers through text format.

John *et al.*, (2022) designed a mobile application that makes recommendations on crops to be planted in relation to the soil classification to assist farmers in making better decisions on planting. Their study used soil recordings from local agricultural areas analyzed using a Random Forest classifier implemented in Python. This system, without the use of physical sensors, was focused on the creation of a decision-support model that would identify the soil types and recommend suitable crops for the respective categories. Farmers can check their soil quality using the application to minimize lab consultations. By using their smartphones to select the best crops for their types of soils, farmers could achieve better yields. Trained with a large dataset, this should provide an increased level of accuracy in its predictions, hence a suitable, user-friendly tool for farmers aiming at optimizing the usage of their land through data-driven recommendations.

Thanushree *et al.*, (2023) proposed a rule-based system, in which physical sensors of pH, NPK, and moisture were connected to an Arduino Nano microcontroller that transferred that data, via Wi-Fi, to the backend implemented using Firebase. In order to recommend crops and monitor trends in soil quality, the system used real-time data comparisons with predefined rule-based thresholds, whereas it stored data for all the tested areas.

Ramzan *et al.*, (2024) developed an IoT-based prediction system using different ensemble machine learning techniques. Their system consisted of environmental sensors, including DHT11 (temperature and humidity) and capacitive moisture sensors, all connected to an ESP32 board for power and data transfer. The data tested at the soil was sent to the cloud, which used various methods, such as bagging and boosting, to enhance crop yield prediction. The farmers accessed the system through a device display that provided recommendations on crops to be cultivated.

Garg *et al.*, (2021) developed an agriculture system by integrating IoT technologies, ML, and DL in order to enhance farming productivity and sustainability. The suggested multimodal system adopts IoT sensors for acquiring real-time data on soil moisture and NPK levels; thus, enabling smart irrigation and fertilizer management. It further exploits several ML techniques such as Random Forest LightGBM, XGBoost Decision Tree and K-Nearest Neighbor in predicting crop damage.

In parallel the system detects crop diseases using several deep learning models namely VGG16 ResNet50 and DenseNet121. The data is relayed to the cloud-based web interface that offers farmers helpful insights into resource use optimization and enhanced crop yields.

Ferreira *et al.*, (2022) also developed a mobile soil nutrient analysis system with a AI and IoT sensors that sends soil nutrient test through a smartphone application. It reduces farmers to go to soils laboratory just to test their soil, thus making precision farming quite feasible even for small-scale farmers. Integrating IoT and AI for predictive modeling helps farmers understand their soil condition and optimize planting for high yields and sustainability.

Dey *et al.*, (2024) proposed an AI-based crop recommendation system to identify the best crop a farmer could cultivate at specific locations based on the history of soil and climatic data. These authors used machine learning methods Random Forest SVM XGBoost KNN and Decision Trees to analyze the NPK level of soil pH. AI-enhanced models optimize fertilizer application, boost yields and reduce dependence on experience-based decisions in agriculture. These findings are indicative of the potential.

Soberano *et al.*, (2023) applied Machine Learning in order to assess the suitability of soil for banana, maize and papaya on Negros Occidental in the Philippines. In addition, fourteen factors were used: pH, organic matter, phosphorus, potassium and salt content which showed the relationship between soil properties and optimal crop performance. In the analyzed algorithms Random Forest outperformed the other models with an accuracy of 94.6% and recommendations were communicated via physical reports, field visits or direct interactions with local agricultural extension personnel.

The algorithm has been recognized for its accuracy in classifying soil fertility recommending crops and predicting yields. Geetha *et al.*, (2020) examined the ability of the RF algorithm to identify the most suitable crops with respect to soil characteristics and climate variables. Using the RF algorithm researchers manually gathered data about soil and climate variables. This study presented that RF models outperform traditional prediction methods since multiple decision trees are combined into a single model thus producing more accurate selections of crops. Data-driven agricultural predictions outperform traditional intuition-based farming and establish RF as a useful tool for enhancing agricultural decision-making.

In another related analysis, Paithane (2023) proposed a random forest-based crop recommendation system that considers soil nutrient content and rainfall patterns to recommend scientifically appropriate crops for given conditions. A new algorithm has been developed using historical agricultural data including soil fertility levels, precipitation patterns and regional crop performance. RF models were then used to predict optimal crop selections with the intention of reducing financial losses from poor crop choices. It achieved a prediction accuracy of 99.03% confirming that this model is effective in helping farmers develop better ways of crop selection.

Folorunso *et al.*, (2023) in assessing levels of macronutrients in the soil using lab-analyzed soil samples compared Decision Trees Random Forest and SVM models. Their research shows AI-based approaches outperform traditional methods of testing soil and therefore may enable farmers to monitor nutrient levels, adjust fertilizer applications and prevent soil degradation over multiple growing seasons. The results support the fact that machine learning provides cost-effective and scalable solutions for assessing soil fertility.

Awais *et al.*, (2023) developed an artificial intelligence-driven framework for soil testing using deep learning techniques to anticipate complex patterns of soil degradation and nutrient inconsistencies. In their system they identified trends in nutrient depletion suggesting corrective actions against each to maintain soil health. Findings show that artificial intelligence optimizes fertilizer distribution and supports long-term soil sustainability besides how predictive analytics can prevent land degradation and increase productivity.

Ahmed *et al.*, (2024) Using Long-Short-Term Memory (LSTM) networks (2024) combined the nutritional data of the soil with climatic information to estimate crop yield. It discussed seasonal changes in soil fertility weather conditions and historical data for yield prediction which provided highly accurate predictions. Findings showed that the LSTM models aid farmers in foreseeing weather-related risks and planning their planting accordingly thus showing how machine learning can alleviate uncertainties of crop production.

Suresh *et al.*, (2021) considered the effectiveness of Random Forest in crop yield prediction by analysis of soil nutrient levels, previous crop yields and climatic factors. The proposed RF model was designed to handle all agricultural variables simultaneously and yielded highly accurate forecasts. The results suggested that the RF model enhances data-driven farming practices in reducing the risks associated with unpredictable environmental conditions. The results of this study show that machine learning can support farmers in predicting possible yield outcomes and adjusting the planting strategies accordingly. The algorithm of random forest has technical advantages in addition to classification and prediction which increase its application in agriculture.

In addition to classification and prediction, the algorithm of Random Forest has technical advantages which enhance its applicability in agriculture. Therefore, Kalimuthu *et al.*, (2020) RF classifiers improve the prediction accuracy by combining multiple decision trees thus helping to select the best crop. They have established that RF-models are robust, scalable and efficient for handling large datasets and thus suitable for AI-enhanced agriculture.

Priyadharshini *et al.*, (2021) The RF model was enhanced by incorporating feature selection methods into an Intelligent Crop Recommendation System. They examined the impacts of different environmental and soil variables on crop growth while optimizing the predictive performance of the RF model. Machine learning-based predictions improve agricultural effectiveness because they reduce farmers' dependence on traditional farming knowledge by offering insights to make informed decisions.

This transformative change in modern agriculture is brought about by the combination of sensor-based soil analysis IoT technologies and machine learning. They allow for the real-time monitoring of the condition; better fertilizer use and data-driven crop advice. In a recent study AI-driven models tend to outperform conventional approaches. These techniques ensure better precision in the soil fertility assessment and proper crop selection. The Random Forest algorithm has emerged as the best algorithm to enhance accuracy in the improvement of classification and give reliable recommendations of crops among the machine learning algorithms. By collecting real-time data in real-time IoT soil monitoring systems further enhance the efficiency and sustainability in farming.

Consequently, soil analysis and informed crop recommendations are crucial components of modern agriculture. Nevertheless, it is a big challenge for farmers especially in resource-poor regions. In most cases it is not easy for farmers to obtain reliable and timely soil testing services. Traditional methods available, which involve ocular or laboratory tests, are generally too inaccurate or too impractical for frequent use.

Therefore, many of them must guess when deciding on planting and fertilizing due to the lack of real-time soil data. Nutritional imbalances deteriorating soil health poor fertilizer use lower yields and economic instability are among the major negative effects caused by such issues. Without technological interventions efforts towards supporting sustainable and profitable farming are severely hampered.

Recently developed developments in this field aim to overcome these issues by integrating IoT devices, machine learning and data analysis into agriculture. The majority of methods are collecting soil data on sensors, processing it using predictive models and recommending the type of crops to grow on different standalone devices, web platforms or mobile applications. Despite these innovations being great milestones, they usually carry major drawbacks with them. Most solutions rely on constant internet availability which severely limits their use in rural areas due to poor infrastructure. Others focus on a narrow range of soil parameters and give delayed recommendations due to centralized processing or require farmers to access complex online systems or hardware they may find difficult to manage.

In this paper we propose a system utilizing an IoT sensor enabled by WiFi combined with machine learning to provide soil analysis and exact recommendations on crops. Unlike systems dependent on uninterrupted internet availability or merely the central server farmers can perform local soil testing with our approach. In areas where internet connectivity is limited advice can be received directly on their mobile devices. An IoT sensor collects important soil parameters including nitrogen (N), phosphorus (P), potassium (K) and pH levels. It then sends the data to a backend server that uses a machine learning model to match the information with a locally available crop recommendation database. By enabling instant on-site analyses without laboratory tests and complicated online systems which have become a concern for small farmers we address the issues of cost, accessibility, speed and ease of use.

Integrate IoT sensors, machine learning, and mobile-friendly technology to move modern agriculture closer to being one that is more productive, resource-efficient, and sustainable. It offers farmers all over the world the ability to make informed, data-driven decisions that encourage economic stability, environmental health, and long-term agricultural success.

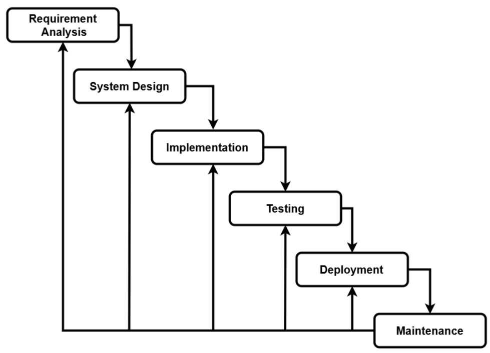


Figure 1: Iterative Waterfall Model of SDLC

MATERIALS AND METHODS

In the creation of the Soil Testing Device, the researchers have employed the Iterative Waterfall Model development method. This methodology follows a structured sequence, starting with defining high-level requirements and progressing through stages of requirement analysis, system design, implementation, testing, integration, delivery, and maintenance. Notably, it incorporates feedback loops linking each phase to its preceding stage, distinguishing it from the traditional waterfall model.

Requirements Analysis

The Requirements phase consisted entirely of data collection, analysis, and planning. It had the very important objective of discerning the needs for both the device and the system currently under development. To obtain results very close to real life, and to ensure that this system meets expectations, the research team conducted a survey with the Farmers and Soils Laboratory at the City Agriculturist Office of General Santos City. This approach allowed for a better understanding of what issues need to be resolved, the parameters needed regarding the features to be included in the device, and such a design would meet the actual needs of the users and provide functionality relevant to them.

The survey was done to understand the challenges faced by farmers and soils laboratory chemists. Collected data were studied to identify the best technologies, methods, and steps for the next phase of development. From the survey results, important constituents of the prototype Crop Recommendation System were determined. With simple functionality and recommended or predictive crops, this system is meant to be user-friendly for farmers. It also gives soil chemists an easy and effective way to analyze soil data databases.

The survey aimed to find out the current challenges that farmers and soil lab chemists encounter with soil analysis. The data was then examined to help guide potential technologies, methods, and processes for the next development phases.

After conducting the survey, we identified several key features needed to create an accessible and efficient soil testing and crop recommendation prototype. These include:

1.NPK and pH Level Sensing: a device has sensors that can detect Nitrogen (N), Phosphorus (P), and Potassium (K) levels, as well as the pH of the soil. This provides data on soil nutrients to assess nutrient availability.

2.Wireless Wi-Fi Connectivity: device connects easily to the mobile application via Wi-Fi. It transmits data from the sensor to the app without needing an internet connection.

3.Data Processing: Soil data collected is immediately processed and displayed on the mobile application, hence reducing the waiting time for farmers to get the result of the soil analysis.

4.Mobile App Integration: Device sends the nutrient levels to the Android mobile application, which in turn matches the data to a pre-loaded crop database to give recommendations on crops that should be grown.

5.Admin Data Management: The mobile app and admin record the soil tests. This enables farmers and soil laboratories to monitor, over time, changes in soil fertility and make informed decisions on farming for the long term.

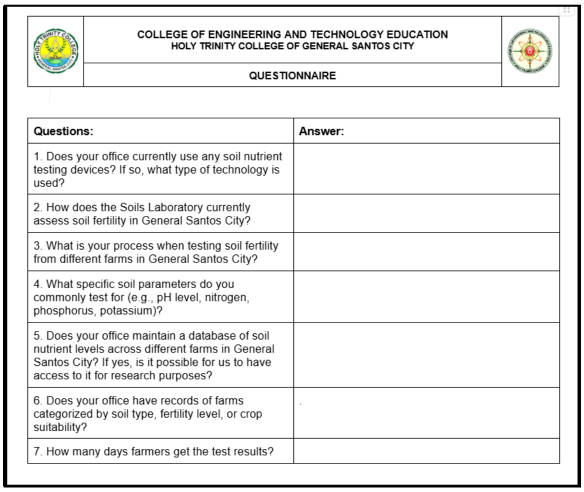
6.User-friendly Interface: The device is designed to be very simple, hence easy to use, for farmers who do not have heavy technical backgrounds.

7.Compact and Portable Design: The sensor device is lightweight and portable, hence making it easy for the farmer to carry and use in different locations where soil testing is to be done.

8.Rechargeable Battery: A rechargeable battery powers the device, enabling its extended use in the field, therefore limiting the replacement frequency of batteries.

9.Offline Functionality: A device can work without internet connectivity; hence, it is reliable in remote farming areas where the network is poor or completely absent.

The features mentioned above are targeted by the Crop Recommendation System for enhancing precision in agriculture, informing farmers about appropriate crop choices, and optimizing soil management for sustainable farming.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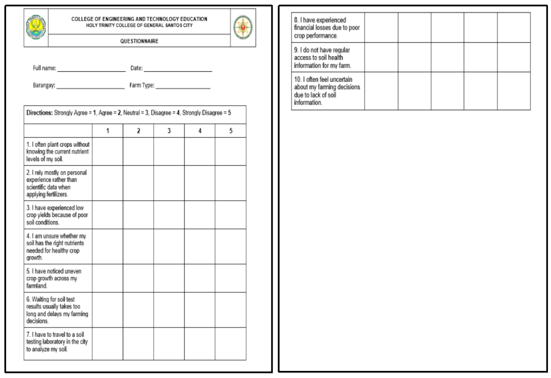
HOLY TRINITY COLLEGE OF GENERAL SANTOS CITY
QUESTIONNAIRE

Questions:	Answer:
1. Does your office currently use any soil nutrient testing devices? If so, what type of technology is used?	
2. How does the Soils Laboratory currently assess soil fertility in General Santos City?	
3. What is your process when testing soil fertility from different farms in General Santos City?	
4. What specific soil parameters do you commonly test for (e.g., pH level, nitrogen, phosphorus, potassium)?	
5. Does your office maintain a database of soil nutrient levels across different farms in General Santos City? If yes, is it possible for us to have access to it for research purposes?	
6. Does your office have records of farms categorized by soil type, fertility level, or crop suitability?	
7. How many days farmers get the test results?	

Figure 2: Soil Laboratory Examiner Questionnaire


COLLEGE OF ENGINEERING AND TECHNOLOGY EDUCATION
HOLY TRINITY COLLEGE OF GENERAL SANTOS CITY
QUESTIONNAIRE

Full name: ____________ Date: ____________

Barangay: ____________ Farm Type: ____________

Directions: Strongly Agree = 1, Agree = 2, Neutral = 3, Disagree = 4, Strongly Disagree = 5

	1	2	3	4	5
1. I often plant crops without knowing the current nutrient levels of my soil.					
2. I rely mostly on personal experience rather than scientific data when applying fertilizers.					
3. I have experienced low crop yields because of poor soil conditions.					
4. I am unsure whether my soil has the right nutrients needed for healthy crop growth.					
5. I have noticed uneven crop growth across my farmland.					
6. Waiting for soil test results usually takes too long and delays my farming decisions.					
7. I have to travel to a soil testing laboratory in the city to analyze my soil.					
8. I have experienced financial losses due to poor crop performance.					
9. I do not have regular access to soil health information for my farm.					
10. I often feel uncertain about my farming decisions due to lack of soil information.					

Figure 3: Farmers Questionnaire

System Design

After a comprehensive requirements evaluation, it is assured that specifications are met for the development of the application. This system incorporates both hardware and software to provide an accessible soil nutrients analyzer and crop recommendations. The processing unit is Raspberry Pi Pico, which handles data from the RS-NPK-N01-TR Sensor that measures Nitrogen (N), Phosphorus (P), Potassium (K), and pH level. The data will be transmitted through the RS485 to UART Converter Module and will appear on a Flutter mobile app through Wi-Fi Serial Communication using Python or Micro Python with the use of the Wi-Fi Module. It will run on a 12V DC Power Adapter regulated by a 12V to 5V DC Buck Converter, and to make it mobile in the field, it also has a LiPo Battery. Components are protected with an Enclosure from environmental factors. The crop recommendation model is created in Python, using the Scikit-learn Random Forest Algorithm, where data of previous soil analysis is stored in Firebase SDK.

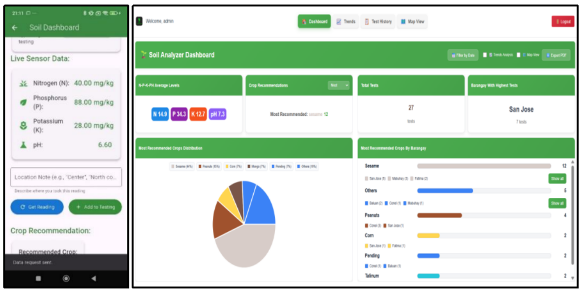


Figure 4: System Design of Crop Recommendation

Within the System Design phase, the architecture of the Crop Recommendation System is developed to outlines how the system components interact and work together.

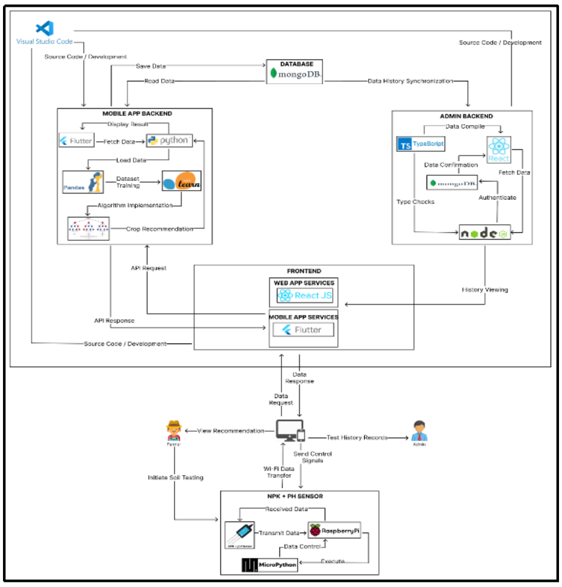


Figure 5: System Architecture

The solution consists of two parts that work together: a mobile app for farmers and a read-only web dashboard for the soil laboratory. In the field, the farmer opens the Flutter app and connects to the device's Wi-Fi name (SSID). The device, an RS-NPK-N01-TR probe wired to a Raspberry Pi Pico running MicroPython, takes a soil reading for nitrogen, phosphorus, potassium, and pH. It then transmits the data directly to the phone over Wi-Fi. On the phone, a lightweight, mobile-designed Random Forest model converts the reading into clear Soil Nutrient Results and a Crop Recommendation Set. The app also saves each test in a local history, so that results are viewable even without internet. When that phone comes online, the application syncs those test records to MongoDB using simple Node.js/Express APIs. The React and TypeScript web dashboard reads from this central history to show past tests, basic trends, and allows staff to download CSV or PDF reports. Most importantly, the admin doesn't create the recommendations; they simply view history, see analytics, and export files. his setup works because farmers receive guidance on the spot, without needing a network connection, while the laboratory still gets an organized and searchable record once everything syncs. It's fast to use in the field, reliable for long-term tracking, and easy for both farmers and staff to maintain. This approach also reduces delays, prevents data loss, and supports better decision-making since everyone has timely access to accurate soil information. Overall, the system creates a smooth, practical workflow that fits the real conditions farmers experience every day.

Implementation of the Random Forest Algorithm

The system uses a Random Forest algorithm, which specializes in the data available for the soil composition of General Santos City. This approach minimizes error and overfitting by using the NPK and pH levels measured by the sensors. Each decision tree uses this data to determine what crop should be planted, and a majority vote decides which crop should be recommended. The system then displays the name of the crop and its corresponding confidence level.

This approach helps local farmers make well-informed decisions, ensuring that their farming practices are eco-friendly and provide the highest yield based on the composition of the soil in their barangay.

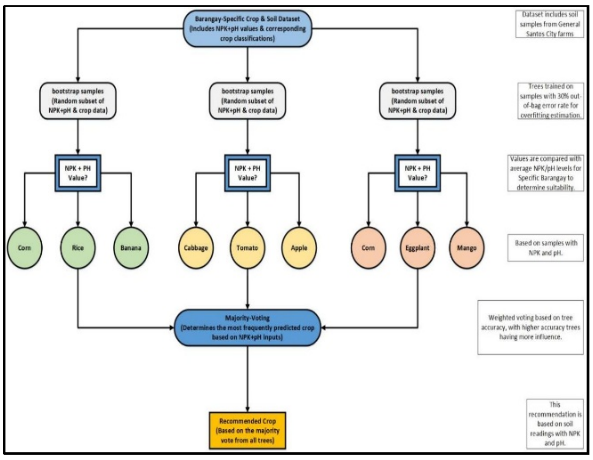


Figure 6: Implementation of the Random Forest Algorithm

$$G(t) = 1 - \sum_{i=1}^{c} p(i|t)^2$$

Equation 1. Gini Impurity

Formula Explanation for Crop Recommendation

Think of a "box" (the node 't' in the formula) which holds a set of soil samples. This box is a collection of soil samples and each soil sample has a tag to show what type of crop did well in it.

1. G(t): This says how much the crops in this box of soil samples are "mixed up." If G(t) is low, the box is filled mostly with samples for which that same crop grew really well ("purity"). A high G(t) means that the box has a good mixture of samples in which different crops do well ("impurity" is high).

2. 1−...: We begin with 1 (as high a mixed-up-ness as we can). Next it is subtracted something to show how "un-mixed" (pure) the box is getting.

3. ∑i=1c: This is the sum sign. It instructs us to sum a calculation for each different type of crop that we consider. The 'c' is the number of total distinct crop types being recommended (ex: if you're recommending 5 types of crops c=5).

4. p(i|t): the proportion of soil samples in the current box 't' where specific crop 'i' grows well. For instance, if in our 100 samples of soil, 60 of our samples grew Corn, then p(Corn|t)=60/100=0.6. If there were 20 who grew Rice, then p(Rice|t)=20/100=0.2 and so forth with all the other crops.

5. p(i|t)2: We square this value. Squaring "squares up" the crops that are heavier in the box. More of them, when squared, become bigger next to the squared smaller ones. This makes the algorithm concentrate on boxes where a single or few crops are dominant.

6. ∑i=1cp(i|t)2 (The Summation Part): We then sum the squared conditional proportions of the crop at the box and add them up for all c crops. When the box is perfectly pure (each sample grew the same crop), one of the elements in p(i|t) will be 1, and the rest will be 0. and then when you square them and sum them you get 12+02+02+... =1. If the box is jumbled, then the proportions will be fractions, and when you square them and sum, you should end up with a number less than 1.

7. 1 - (The Sum) (The Final Calculation) We subtract the sum of the proportions squared from 1. If the box is pure (sum = 1), G(t) = 1−1 = 0 (low "mixed-up-ness" – good!). And

if the box is mixed (sum < 1), then G(t) will be negative value (more the negative – more mixed-up-ness), say 2, indicating that the box is not pure (shaded here and shaded there). The more intermixed the crops on the tray again, the closer G(t) will be to high values, (but still within (0, 1)).

$$Gini_{split} = \frac{D_{left}}{D}\, Gini(t_{left}) + \frac{D_{right}}{D}\, Gini(t_{right})$$

Equation 2. Gini Split

The goal is always to find the split that produces the absolute lowest Gini split value.

1. Symbol Meanings and Uses Gini split: This is the score the algorithm uses to rank potential splits. The split with the minimum Gini split is selected, as this maximizes the reduction in disorder (Gini Gain).

2. D|: It serves as the denominator for the weighting factors, representing the size of the data being evaluated.

3. |Dleft|: It acts as the numerator to calculate the weight (|D||Dleft|) of the left node's impurity in the overall split score.

4. |Dright|: It acts as the numerator to calculate the weight (|D||Dright|) of the right node's impurity.

5. Gini(tleft): This value is calculated using the primary Gini Impurity formula (Gini(t)=1−∑pi2) based on the class distribution found only in the Dleft subset.

6. Gini(tright): This value is calculated using the primary Gini Impurity formula based on the class distribution found only in the Dright subset.

7. Individual Impurity (Gini(tleft) and Gini(tright)): These terms quantify the disorder that remains in the data after the split. The lower the value (closer to 0), the purer the resulting node. A perfect split would result in both of these being 0.

8. Weighting (|D||Dleft| and |D||Dright|): This is the key distinguishing factor. A split might make one node perfectly pure, but if it only sends a tiny fraction of the data (say, 1 sample) to that pure node, it's not a very useful split. The weighting factor ensures that the impurity of a node containing a larger proportion of the data contributes more heavily to the final Ginisplit score.

$$Final\ Classification = \left(\sum_{t-1}^{T} ⬚ \prod = (Prediction_t = k) \right)^{n}$$

Equation 3. Majority Voting

The Process When a new, unseen data point enters the trained Random Forest, the following steps occur:

1. Individual Prediction: The data point is passed through every single tree in the forest, from Tree 1 to Tree T.

2. Collection of Votes: Each tree follows its own unique set of rules (learned from its random sample of data and random subset of features) until the data point lands in a final leaf node. The class label of that leaf node is the tree's vote (its individual prediction).

3. Tallying: All the votes for each possible class (e.g., 'Apple', 'Orange', 'Banana') are collected and counted.

4. Final Decision: The class that receives the highest number of votes the simple majority is the final prediction of the Random Forest model.

2.The Formula/Rule While it's a counting process, it can be formally represented by the Mode calculation (finding the most frequent value) over the set of all tree predictions:

3. Predictiont: The individual class predicted by Tree t.

4. I(…): The Indicator Function, which equals 1 if the tree's prediction matches class k, and 0 otherwise.

5. kargmax: This returns the class label (k) that maximizes the count (the sum)

Implementation

Following the system design phase, the Crop Recommendation System progresses from concept to a fully functional software system during the implementation stage. By incorporating the technologies and algorithms previously discussed,

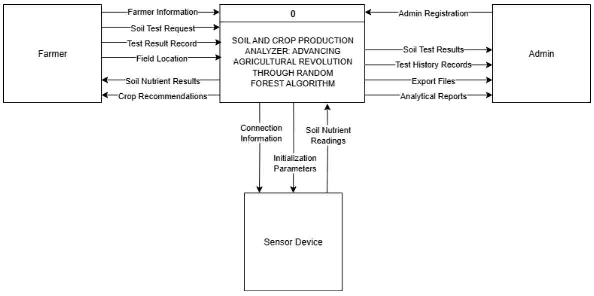


Figure 7: Context Diagram

The context diagram for the Soil & Crop Production Analyzer illustrates a clear collaboration of three parties: the Farmer, the Sensor Device, and the admin at the soil laboratory. The process is initiated when the phone connects to the Wi-Fi name of the device using the connection details. The application sends initialization parameters, places the probe in the soil, and on tapping Test by the farmer, the sensor streams the Soil Nutrient Readings to the system. After the application is completed, the farmer receives Soil Nutrient Results and a Crop Recommendation Set. A test result record is also created associated with the farmer's information and the location. The such records are compiled as Test History Records for the administrator. There are also analysis summary and export files in CSV/PDF format for storage and reporting. Admin focuses on storing history, viewing analytics and exporting report.

Testing

One very critical stage of our cycle in software development, actually a checkpoint, is testing. Testing verifies that all the functional requirements have been met, and both device, application, and admin interact with each other properly to provide the right user experience. Testing goes further to identify and isolate any problems that might exist, adapting their solutions so that Soil Analyzer and Crop Recommendation ensure the efficiency. This stage is very important because it assures overall flow, ensures the system will meet user needs, and prepares the system for deployment

Development

The development phase is at the heart of creating the Soil Analyzer and Crop Recommendation System. Here, we turn ideas into real solutions. We follow the Iterative Waterfall Model, which guides us through analyzing requirements, designing the system, building it, and testing it. Each step builds on the feedback from the previous one. By working together and sticking to good coding practices, we aim to create a system that is flexible, efficient, and packed with features, giving farmers the tools, they need for soil analysis. We constantly refine and adjust the system to match the changing needs of our users.

To better visualize the interactions among the system's users, the following use case diagram illustrates the primary actions and roles within the Soil Analyzer and Crop Recommendation System. This diagram highlights the key interactions between Farmers, Device, and Admins in managing screen time for children's devices.

This use case diagram below illustrates the interactions for Farmers, Device, and Admins in Soil Analysis and Crop Recommendation. Farmers will log in by entering only their name and location then connect the mobile to the device and test the soil. Admins will see the lists of history tested by the farmers. "Include" and "extend" relationships highlight core and optional actions, providing a clear view of user roles and system functionalities.

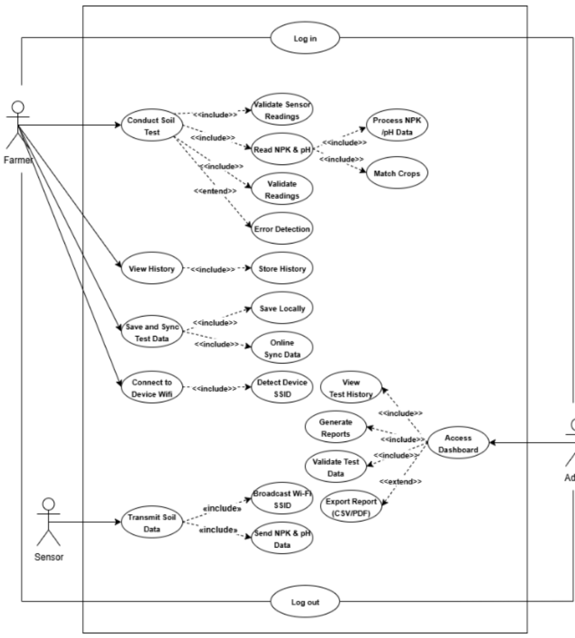


Figure 8: Use Case Diagram

Deployment

Deployment is the final step where we roll out the Soil Analyzer and Crop Recommendation System to users. During this phase, our focus is on smoothly moving the system from development to live use. We ensure that it's easy for users to access and use the system. By following standard deployment methods and using the right technology, we aim to avoid disruptions, reduce risks, and ensure that the system is always available and reliable. Through careful planning and execution, our goal is to deliver a strong and user-friendly tool that helps farmers use the system smoothly.

To provide a clearer understanding of the operational framework supporting the deployment of the system, the following Figure 8: Organization Operational Framework diagram illustrates how the various components of the Soil Analyzer and Crop Recommendation System come together to create a seamless user experience. This framework highlights the critical steps in Soil Analyzer and Crop Recommendation usage.

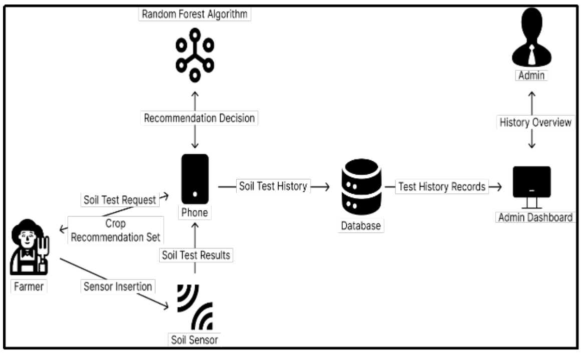


Figure 8: Organization Operational Framework

Maintenance

Maintenance involves continuously ensuring that the Soil Analyzer and Crop Recommendation System stays relevant and functional over time. During this phase, our main focus shifts to fixing bugs, adding new features, and updating the system based on user feedback and new requirements. We achieve this by setting up monitoring tools and support systems to quickly address any issues that arise. Our goal is to keep the system running smoothly, secure, and easy to use. By constantly refining and enhancing the system, we aim to provide farmers with a reliable tool to know their soil health and what crops are best to plant on their area.

Implementation Result

The Soil Analyzer and Crop Recommendation System was tested during the implementation phase to assess its readiness and gather preliminary user feedback. Although the system may not yet be in its final deployment stage, the researchers prioritized collecting insights from actual users which is the farmers in General Santos City. Detailed instructions on how the system works were provided to each participant to ensure accurate and meaningful evaluations.

After the user testing, the researchers distributed and retrieved completed evaluation forms. The survey instrument was designed to assess four major aspects of the system: Effectiveness, Efficiency, Functionality, Interface, Usability, and Satisfaction. A total of 50 farmers respondents participated in this evaluation.

Pre-Evaluation Tool

The evaluation focused on collecting user feedback based on the aforementioned four key areas. Each section of the questionnaire contained statements that respondents rated using a 5-point Likert scale, where 1 indicated Not at All Satisfied and 5 indicated Extremely Satisfied.

The following tables (Table 1 to Table 5) present the specific questions in each category along with the respective rating scale. These results are essential for identifying the system's strengths and areas that may require further development or refinement.

Table 1: Evaluation of the Effectiveness of the Soil Analyzer and Crop Recommendation System

Section 1: Effectiveness (This section measures how well the system achieves its purpose in terms of accuracy, reliability, and helping farmers complete tasks successfully.)	1	2	3	4	5
1.How fast were the soil fertility results (N, P, K, pH) provided by the system?					
2.How helpful were the crop recommendations in deciding what to plant?					
3.To what extent did the system help you understand your soil better?					
4.To what extent did using the system lead to better crop selection for your land?					
5.Overall, how effective was the system in providing useful agricultural insights?					

Table 2: Evaluation of the Efficiency of the Soil Analyzer and Crop Recommendation System

Section 2: Efficiency (This section measures how quickly and smoothly the system helps farmers complete tasks and obtain results.)	1	2	3	4	5
1. How quickly did you get the soil analysis results after scanning?					
2. How easy was it to connect and use the soil sensors with the mobile app?					
3. To what extent did the system save you time in getting soil information compared to old methods?					
4. How efficient was the system in helping you get the information you needed?					
5. How quick and smooth was the process of getting recommendations from the system?					

Table 3: Evaluation of the Functionality of the Soil Analyzer and Crop Recommendation System

Section 3: Functionality(This section measures the system's features operate, including consistency, accuracy, and stability during use..)	1	2	3	4	5
1.To what extent did all the features in the mobile application work correctly?					
2.How fast was the system able to read data from the soil sensors?					
3.How consistently did the system provide crop recommendations based on the soil data?					
4.How easy and accurate was the historical data tracking feature to use?					
5.How often did the system crash or show errors while you were using it?					

Table 4: Evaluation of the Interface of the Soil Analyzer and Crop Recommendation System

Section 4: Interface (This section evaluates the user interface of the Soil and Crop Production Analyzer.)	1	2	3	4	5
1.How easy is the mobile application to navigate?					
2.How clear and easy to read are the text and images on the screen?					
3.How appealing do you find the overall look and feel of the app?					
4.How easy was it to find the information you were looking for in the app?					
5.To what extent does the design of the system help you use it effectively?					

Table 5: Evaluation of the Usability of the Soil Analyzer and Crop Recommendation System

Section 5: Usability (This section looks at the ease of use and responsiveness of the system.)	1	2	3	4	5
1.How easy is it to grasp what the system does and what each element means at first glance?					
2.How easy is it for a new user to learn common tasks without assistance?					
3.How easy and reliable is it to use the controls and complete tasks efficiently?					
4.How appealing and professional does the interface look and feel overall?					
5.To what extent does the product follow recognized usability/accessibility standards and platform guidelines?					

Table 6: Evaluation of the Satisfaction of the Soil Analyzer and Crop Recommendation System

Section 6: Satisfaction(This section measures your overall satisfaction with the system.)	1	2	3	4	5
1.How satisfied are you with the overall performance of the system?					
2.How easy was the system to use and understand?					
3.How likely are you to recommend this system to other farmers?					
4.To what extent did the system meet your expectations?					
5.How would you rate your overall experience with the "Soil and Crop Production Analyzer?					

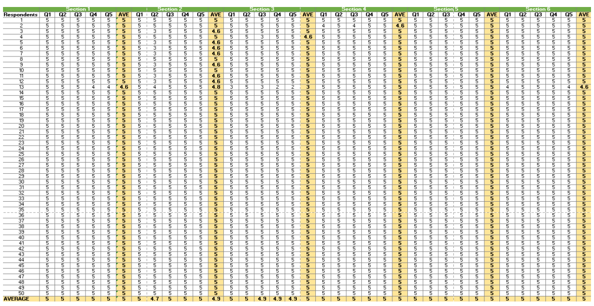
RESULTS AND DISCUSSION

Survey Responses

The following are the raw survey responses collected from 50 farmers in General Santos City on October 1, 2025. Each item was rated on a 5-point scale:

5 – Extremely Satisfied
4 – Very Satisfied
3 – Somewhat Satisfied
2 – Not so Satisfied
1 – Not at All Satisfied

These responses are compiled in Results and Discussion, and form the basis for the subsequent evaluation.



Figute 9: Tools and Software

System Evaluation Results

The summarized findings from the survey are categorized into Effectiveness, Efficiency, Functionality, Interface, Usability, and Satisfaction. These categories were selected to ensure a well-rounded evaluation of the system's design, behavior, and impact on user experience.

Tables 3 to 8 present the computed mean scores for each item in the survey. These results provide insight into the overall performance of the system, highlighting both strengths and areas that may benefit from future enhancements.

1. For Effectiveness, 99.9% of the respondents were Extremely Satisfied that the system provided accurate soil fertility results (N, P, K, pH) and helpful crop recommendations, achieving a total mean of 4.99, indicating that users found the system highly effective in delivering reliable agricultural insights.

2. In terms of Efficiency, 94% of the respondents were Extremely Satisfied that the system provided quick soil analysis results, saved them time compared to traditional methods, and offered a smooth process for obtaining crop recommendations. The system attained a total mean of 4.94, reflecting a high level of efficiency. 3. Regarding Functionality, 95% of the respondents were Extremely Satisfied with the system's functionality, stating that its features worked correctly, sensor readings were accurate, and crop recommendations were consistent and reliable. The system achieved a total mean of 4.95.

4. For Interface, 99.9% of the respondents were Extremely Satisfied with the application's interface, finding it visually clear, easy to navigate, and user-friendly. With a total mean of 4.99, users praised its appealing and well-structured design.

5. In Usability, 100% of the respondents were Extremely Satisfied with the system's usability, finding it easy to understand and operate even without assistance. It earned the highest total mean of 5.00, demonstrating its intuitive and accessible design.

6. Lastly, under Satisfaction, 99.9% of the respondents expressed Extreme Satisfaction with the system's overall performance, ease of use, and ability to meet their expectations, resulting in a total mean of 4.99. Many also indicated they would recommend the system to other farmers. 7. The overall total mean of 4.97 indicates an overwhelmingly positive response, demonstrating that the system was highly effective, efficient, functional, and user-friendly. This suggests that the Soil and Crop Production Analyzer successfully met its objectives of providing accurate soil data, useful crop recommendations, and an excellent user experience for its target users.

Table 1: System Evaluation Results - Effectiveness Criteria

Section 1: Effectiveness	Mean	Description
1. How accurate were the soil fertility results (N, P, K, pH) provided by the system?	5	Extremely Satisfied
2. How helpful were the crop recommendations in deciding what to plant?	5	Extremely Satisfied
3. To what extent did the system help you understand your soil better?	5	Extremely Satisfied
4. To what extent did using the system lead to better crop selection for your land?	4.98	Extremely Satisfied
5. Overall, how effective was the system in providing useful agricultural insights?	4.98	Extremely Satisfied
Total Mean	4.99	Extremely Satisfied

Table 2: System Evaluation Results - Efficiency Criteria

Section 2: Efficiency	MEAN	Description
1. How quickly did you get the soil analysis results after scanning?	5	Extremely Satisfied
2. How easy was it to connect and use the soil sensors with the mobile app?	4.7	Extremely Satisfied
3. To what extent did the system save you time in getting soil information compared to old methods?	5	Extremely Satisfied
4. How efficient was the system in helping you get the information you needed?	5	Extremely Satisfied
5. How quick and smooth was the process of getting recommendations from the system?	5	Extremely Satisfied
Total Mean	4.94	Extremely Satisfied

Table 3: System Evaluation Results- Functionality Criteria

Section 3: Functionality	MEAN	Description
1. To what extent did all the features in the mobile application work correctly?	4.96	Extremely Satisfied
2. How accurately was the system able to read data from the soil sensors?	5	Extremely Satisfied
3. How consistently did the system provide crop recommendations based on		
the soil data?	4.92	Extremely Satisfied
4. How easy and accurate was the historical data tracking feature to use?	4.94	Extremely Satisfied

5. How often did the system crash or show errors while you were using it?	4.94	Extremely Satisfied
Total Mean	4.95	Extremely Satisfied

Table 4: System Evaluation Results- Interface Criteria

Section 4: Interface	MEAN	Description
1. How easy is the mobile application to navigate?	4.98	Extremely Satisfied
2. How clear and easy to read are the text and images on the screen?	5	Extremely Satisfied
3. How appealing do you find the overall look and feel of the app?	4.98	Extremely Satisfied
4. How easy was it to find the information you were looking for in the app?	5	Extremely Satisfied
5. To what extent does the design of the system help you use it effectively?	5	Extremely Satisfied
Total Mean	4.99	Extremely Satisfied

Table 5: System Evaluation Results- Usability Criteria

Section 5: Usability	MEAN	Description
1. How easy is it to grasp what the system does and what each element means at first glance?	5	Extremely Satisfied
2. How easy is it for a new user to learn common tasks without assistance?	5	Extremely Satisfied
3. How easy and reliable is it to use the controls and complete tasks efficiently?	5	Extremely Satisfied
4. How appealing and professional does the interface look and feel overall?	5	Extremely Satisfied
5. To what extent does the product follow recognized usability/accessibility standards and platform guidelines?	5	Extremely Satisfied
Total Mean	5	Extremely Satisfied

Table 6: System Evaluation Results- Satisfaction Criteria

Section 6: Satisfaction	**MEAN**	**Description**
1. How satisfied are you with the overall performance of the system?	4.98	Extremely Satisfied
2. How easy was the system to use and understand?	5	Extremely Satisfied
3. How likely are you to recommend this system to other farmers?	5	Extremely Satisfied
4. To what extent did the system meet your expectations?	5	Extremely Satisfied
5. How would you rate your overall experience with the "Soil and Crop Production Analyzer"?	4.98	Extremely Satisfied
Total Mean	4.99	Extremely Satisfied

Overall Result

The result of the system evaluation conducted with farmers, based on six categories: Effectiveness, Efficiency, Functionality, Interface, Usability, and Satisfaction. Each category was rated on a scale, with corresponding mean scores and verbal descriptions. The Effectiveness received a mean score of 4.99 which is Agree, indicating that users generally agreed the interface was satisfactory. Efficiency has a mean of 4.94, which indicate that efficiency was approved by the farmer. Functionality was rated at 4.95, showing that users found the system easy to navigate. Usability rated with the highest 5 indicating that the system is easy to use and understand. The Satisfaction with the score of 4.99, showing that users were especially pleased with their overall experience. This indicates a strong level of contentment among the respondents. The total average score of 4.97 demonstrates that users agreed that the system met their expectations.

Table 7: System Evaluation - Overall Results

CATEGORY	**MEAN**	**VERBAL DESCRIPTION**
Effectiveness	4.99	Extremely Satisfied
Efficiency	4.94	Extremely Satisfied
Functionality	4.95	Extremely Satisfied
Interface	4.92	Extremely Satisfied
Usability	5	Extremely Satisfied
Satisfaction	4.99	Extremely Satisfied
TOTAL	4.97	Extremely Satisfied

CONCLUSIONS

The development and implementation of the Soil & Crop Production Analyzer can be considered one of the major breakthroughs in localized agricultural technology that has succeeded in providing soil information and crop recommendations to users. The results of this study clearly show that the system has been extremely well received, with an average score of 4.97. This clearly indicates that users are extremely satisfied with all aspects of the system. For instance, the system has scored almost perfect on all aspects of its effectiveness and design interface, with 99.9% of users agreeing that the system can offer NPK and pH values along with agricultural information. The usability of the system has been clearly demonstrated through its perfect average score of 5.00 on its usability aspect.

Moreover, the analyzer functioned not only as a functional tool but also as a highly efficient substitute for traditional methods of soil analysis. The analyzer greatly reduced the time needed for farmers to acquire useful information. By successfully providing farmers with reliable sensor results and a user-friendly interface, the analyzer effectively met the requirements for accessibility and technical precision that were established for it. Based on this information, it is possible to draw a conclusion that the Soil & Crop Production Analyzer is a highly efficient tool for modernizing farming practices. By effectively bridging the gap between sophisticated science and practical farming needs, this tool enables the agricultural community to make informed decisions that may result in optimized crop production and economic benefits.

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