



**Development of a Portable IoT and Machine
Learning-Based Soil Health Analyzer to Improve
Fertilizer Use Efficiency Among Smallholder Farmers in
Rwanda**

BSc. in Software Engineering

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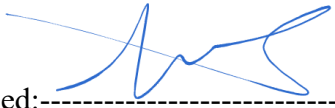
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July, 2025

DECLARATION

I, Charite Uwatwembi, certify that this research project report, "Development of a Portable IoT and Machine Learning-Based Soil Health Analyzer to Improve Fertilizer Use Efficiency Among Smallholder Farmers in Rwanda," is entirely original with no submissions for credit toward any other degree or certification at any other university or establishment. All information and support sources have been properly credited.

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DEDICATION AND ACKNOWLEDGEMENT

Above all, I want to thank God, the amazing and loving Father, for the support and love I have received during this degree program. It has taken effort and faith to get to this point of achievement.

Nevertheless, without the following individuals' encouragement and assistance, the project would not have been accomplished.

Mr. Marvin Muyonga Ogore, for the assistance, not only with the knowledge but also with the advice throughout my specialization path to make this a success; and my supervisor, Mr. Kevin Sebinez, for the corrections and guidance on this journey.

Friends and family for always supporting you, especially during difficult times.

ABSTRACT

Agriculture is an important driver of Rwanda's economic system, employing over 70% of the population. Still, the sector is characterized by constantly low productivity attributed to inefficient fertilizer use and poor soil fertility control. Despite government initiatives, Rwanda's fertilizer usage rates average about 72 kg per hectare, much below the national target of 94.6 kg per hectare. Moreover, as of the 2023 growing season, only approximately 51% of farmers actively used chemical fertilizers, resulting in considerable yield gaps. These practices, coupled with insufficient soil diagnostics, have caused extreme soil degradation, worsened by Rwanda's hilly terrain, in which over 745,000 hectares of agricultural land are yearly suffering from erosion, resulting in a productivity loss that equates to approximately 5.5% of agricultural GDP. The absence of timely and accurate soil analysis (such that farmers are empowered to optimally exploit fertilizers, including minimizing the costs of over-application) has traditionally delayed the agricultural efficiency of farmers because traditional laboratory-based soil analyses are expensive and centralized and have generally led to delayed results that are by far too late for real-time decision-making in farming. To address these critical gaps, this study's project recommends the layout of a portable, cost-effective Internet of Things (IoT) and machine learning (ML)-centered soil fitness analyzer. The device I am proposing combines low-cost sensors for the measurement of important soil parameters such as the pH, the moisture content, and the degree of nutrients directly on the farm. Data collected from those sensors will be analyzed in real time by a machine learning model developed on local soil statistics to provide customized, particular fertilizer suggestions. The machine guarantees complete accessibility by way of presenting twin interfaces: a responsive web-based dashboard for farmers with internet connectivity and a one-way SMS notification gadget for smallholder farmers without internet access, facilitating full-scale adoption throughout diverse farmer demographics. The resolution receives support through its ability to boost fertilizer use performance while reducing costs and time and minimizing environmental damage from fertilizer runoff and erosion. The project supports Rwanda's national goals by providing smallholder farmers with personalized soil information at the right time, which matches their specific farm needs. The implementation of this system will result in higher agricultural yields, decreased food waste, and increased farmer income, which will drive broader socioeconomic development and strengthen Rwanda's agricultural sector.

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List of Acronyms/Abbreviations

IoT: Internet of Things

ML: Machine Learning

NPK: Nitrogen (N), Phosphorus (P), Potassium (K) nutrients

pH: Soil Potential of Hydrogen (acidity/alkalinity measure)

GPS: Global Positioning System

GPRS: General Packet Radio Service (cellular data)

API: Application Programming Interface

SMS: Short Message Service (text messaging)

CHAPTER ONE: INTRODUCTION

1.1 Introduction and Background

Agriculture is the backbone of Rwanda's economy, maintaining the livelihoods of approximately 70.72% of families at the same time as contributing one-third of the country's GDP (National Institute of Statistics Rwanda [NISR], 2024). Despite this critical position, Rwanda's agricultural productivity stays appreciably low, in large part attributed to inadequate soil fertility management practices amongst smallholder farmers. As of 2024, Rwanda's average fertilizer usage rate stands at around seventy-two kg per hectare, appreciably below the national target of ninety-four point six kg per hectare (The New Times, 2024). Even though fertilizer utilization has gradually multiplied over the past years, it is highest at approximately fifty-one. 6% of Rwandan farmers often used chemical fertilizers in the 2023 Season B, leaving a great part of the farming population reliant on traditional methods that yield suboptimal effects (NISR, 2023).

This underuse and obscure application of fertilizers significantly affects crop productivity, creating good-sized yield gaps. Research via CGIAR (2024) shows that focused and placement-specific fertilizer utility should undoubtedly improve crop yields by at least 20%. Practical evidence supports this finding: for example, potato farmers using appropriate mixtures of mineral fertilizers (NPK) and organic manure achieve yields of approximately 15.20 tonnes per hectare, in contrast to merely 7.8 tonnes per hectare when depending entirely on manure (The New Times, 2024). Such disparities surely illustrate the outcomes of insufficient fertilizer management on farmers' productivity and livelihoods.

Compounding this mission is Rwanda's big soil degradation and erosion, driven predominantly by its hilly terrain. Despite tremendous adoption of terracing and other soil conservation practices, a predicted 745,000 hectares of farmland, over 25% of Rwanda's agricultural land, are affected annually by soil erosion (United Nations Partnership for Action on Green Economy [UN-PAGE], 2023). This loss translates to approximately 6 million lots of vegetation lost each year and costs around 5.5% of the country's agricultural GDP because of decreased soil productivity (UN-PAGE, 2023). Soil degradation further reduces the effectiveness of fertilizers, as nutrient absorption diminishes extensively in depleted soils, necessitating extra particular, targeted soil fertility interventions.

Even though farming tech receives higher ratings everywhere, Rwanda is having a hard time giving reasonably priced, proper answers for small farms. Fertilizer subsidies by the authorities and NGOs are supplied; however, they often leave out the target due to the fact no exact soil exams are done. It shows a huge want for gear that can be cheap, suit nearby wishes, and supply specific soil fitness information with rapid fertilizer recommendations for Rwanda's many farm areas. To help, this look's concept is to make a cool, small Internet of Things machine with a clever knowledge-gaining machine. This tool does rapid soil tests and facilitates farmers in choosing the satisfactory fertilizer made just for Rwanda's small farms.

1.2 Problem Statement

Like many smallholder farmers in Rwanda, my grandmother tried to apply fertilizers without fully understanding her fields' underlying nutrient dynamics, leading to poor yields. Ill-informed nutrient decisions created problems on both ends of the fertilization spectrum; either farmers incurred unnecessary costs from purchasing fertilizers that went unused or, even worse, needed to be disposed of when they leached into the waterways, causing long-term environmental harm. Excessive and inefficient fertilization has become a common problem amongst farmers today, while other farmers have started to under-apply fertilizers, resulting in limited yield potential. The net result is diminished agricultural productivity. These scenarios stem from the lack of economically accessible soil-testing advisory tools designed for local soils. Soil testing advisory tools are rare in and of themselves, and soil-specific, tailored tools are virtually nonexistent. Ultimately, there are few to no resources available to guide farmers in making more informed decisions regarding nutrient allocation. Limited decision support has long plagued farmers across the globe, but in the instance of Rwanda, poor decision-making is exacerbated by extreme resource constraints. The interplay of resource scarcity with limited access to tailored data creates an unyielding cap for agricultural potential. The absence of an adaptive framework in which farmers can obtain tailored data on soil nutrients sets strong limits across agricultural regions.

As the daughter of a farming family from rural Rwanda, I appreciate that my grandmother fully mailed out a soil sample because she wished to optimally manage her soil nutrients; however, her reliance on fertilizing crops solely on seasonal data led to suboptimal outcomes time and time again. Had my grandmother possessed timely guidance, I do not doubt that the results of her endeavors could have reached remarkable levels of excellence. When I finally understood her soil's nitrogen deficiency, it was too late to make the fertilization adjustments. For her crop yields during the season, she only applied urea in exceedingly small quantities, leading to an exacerbated harvest and already poor crop yields, making the situation much worse for our family's food scarcity. The sad anecdote of my grandmother's soil testing timelines is the perfect representation of the lack of information available to smallholder farmers in the form of soil health data. It displays the desperate need for improvement when it comes to the accessibility and speed of soil diagnostics and the need for agricultural decision-making. Her experience motivated me to develop a compact solution that equips farmers with instant soil diagnostics and tailored recommendations, which I call a soil lab on wheels. The goal is to help ensure no farmer is reliant solely on guesswork or late lab results, like my family had to go through.

Recent projects have all started to deal with this gap with generation-driven gear. For instance, (James Madson Gasana, 2022) advanced an IoT-based soil monitoring machine in Rwanda that makes use of sensors to measure soil NPK, pH, temperature, and humidity and applies a machine-learning model to predict suitable crop types. His prototype used a GPRS-linked microcontroller to send real-time facts to the cloud, allowing farmers to "know the reputation of their land" without lab tests. Similarly, e.g., Byiringiro et al. (2021) applied a Smart Soil Monitoring Application (SSMA) in Rwanda using a NodeMCU IoT board with

pH, moisture, and temperature sensors. Their machine dispatched records to an internet dashboard and Android app, demonstrating accurate tracking of soil parameters and helping with fertilizer choices. Both efforts validate that IoT can help Rwandan farmers, but they leave gaps. Gasana's project focused on crop choice in place of express fertilizer dosages and depended on fantastically highly priced NPK sensors. Byiringiro's SSMA did not measure soil vitamins (NPK) and required a regular WiFi link to the cloud. Neither solution integrated a sturdy ML version to optimize fertilizer software mainly for Rwanda's soil types.

Outside Rwanda, commercial answers like Kenya's UjuziKilimo SoilPal handheld sensor measure NPK and pH to suggest fertilizers, but price and cellphone requirements may be prohibitive for the poorest farmers (Ujuzi Kilimo, n.d.). The literature (e.g., Folorunso et al., 2025) also indicates cell apps predicting soil houses through ML, but those require a good-sized lab dataset for training. Thus, present equipment either does not now focus on fertilizer use efficiency, is not tailor-made to nearby soils, or has usability/value limitations. No included system currently exists for Rwandan smallholders that is transportable, low-cost, and combines real-time sensor statistics with ML-pushed fertilizer recommendations. This assignment addresses that hole with the aid of designing a transportable IoT soil analyzer paired with an ML model skilled in local soil records, mainly aimed toward improving fertilizer-use choices for Rwanda's small farms.

1.3 Project Main Objective

The main goal of this mission is to scale up a portable IoT-based soil health analysis device with an ML model to provide real-time soil information and personalized fertilizer advice to smallholder farmers in Rwanda so as to improve fertilizer use efficiency. The solution will be online and offline by providing a responsive web-based dashboard for farmers with internet and a one-way SMS notification service for those without internet so that all intended users are reached regardless of connectivity.

1.3.1 Specific Objectives

Analyze smallholder soil needs: Collect soil samples from Rwandan smallholder farms to identify key parameters (e.g., pH, moisture, NPK) affecting crop productivity.

Design and develop a portable IoT prototype device that can monitor real-time key soil parameters (pH, moisture content, and nutrient levels) on smallholder farms.

Develop and train a machine learning model using locally collected soil and crop yield data to generate personalized fertilizer recommendations based on the measured soil conditions. The model should learn from patterns in how soil nutrient profiles and other factors (crop type, soil type, etc.) influence fertilizer needs and yield outcomes in Rwanda.

Design and implement a responsive web-based dashboard (in both English and Kinyarwanda) that enables farmers with internet access to see their fields' soil health data and get fertilizer recommendations in real time.

Implement a one-way SMS notification system that sends fertilizer recommendations to registered farmers who don't have internet so that they can access the advisory service offline.

Integrate the IoT device, ML model, web dashboard, and SMS module into an end-to-end system that delivers timely fertilizer recommendations.

Field test and evaluation: Conduct a pilot with a group of smallholder farmers to test the device and ML system in real soil conditions and evaluate the accuracy of recommendations, user feedback, and change in fertilizer use.

Document and disseminate results: Analyze the performance data, refine the system, and prepare technical documentation and reports on the project outcomes.

1.4 Research Questions

- **RQ1:** To what extent does the use of the IoT and machine learning-based soil health analyzer improve fertilizer use efficiency and crop yields for smallholder farmers in Rwanda, compared to traditional fertilizer application methods?
- **RQ2:** How accurately can a portable IoT sensor device measure these soil parameters under field conditions?
- **RQ3:** How effective is the integrated IoT and ML-based soil health analyzer system at improving smallholder farmers' fertilizer-related decision-making in Rwanda, and what evidence (e.g., user feedback or changes in farming practices) demonstrates its overall impact on fertilizer management outcomes?
- **RQ4:** How do smallholder farmers in Rwanda perceive the clarity and usefulness of the fertilizer recommendations provided by the system, and how accessible are the system's web dashboard and one-way SMS features in encouraging adoption among farmers with limited internet access?
- **RQ5:** What are the practical challenges (cost, connectivity, usability) encountered by farmers when adopting this technology?

1.5 Project Scope

Rwanda is going to be my focus region for this case study, paying particular attention to smallholder farms with unique characteristics of hillside parcels commonplace in the Eastern and Southern provinces. These include soil types and common crops such as cereals, legumes, and potatoes aligned with the target region's agriculture. The users of this system are smallholder farmers with plots of land of less than one hectare, as these farmers, on average, have low technical skills and resources. Therefore, the problem is solved by providing a user-friendly solution that eliminates complexity through a responsive web dashboard and SMS notification system that speaks in the local language.

The analysis, design, and development processes for the IoT and machine learning-based soil health analyzer will be executed sequentially, within a three-month timeframe. Activities completed include the analysis and assembly of prototype hardware with the machine learning model during the first month and the uploading of acquired data through the locally sourced model. The final month will be dedicated to the applicable field testing, evaluation, and analysis of user feedback. Sensor hardware design, IoT transmission of the data, applied

machine learning automation of sophisticated data analysis and interface development all fall within the scope of this project.

Even though large-scale production and countrywide deployment are out of scope at the moment, insights obtained from this initial phase will prove invaluable when planning for future scaling and broader implementation.

1.6 Significance and Justification

The smallholder farmers in Rwanda will greatly benefit from the IoT and device-based soil analyzer because it optimally uses fertilizer, reduces cost, and helps the environment with the minimum fertilizers, tailored specifically for the region’s soil conditions. This precision approach will not only increase profit and farm productivity but will also improve food safety and the countryside while greatly improving the standard of living for the farmers. The combination of the offline SMS alert system and the interactive, web-based dashboard ensures that no farmer is left out of the advanced, tailored farming advice, regardless of their digital skills or internet access. All remote regions can be provided with real-time, useful information, and inclusive strategies will fill the gap in the existing system.

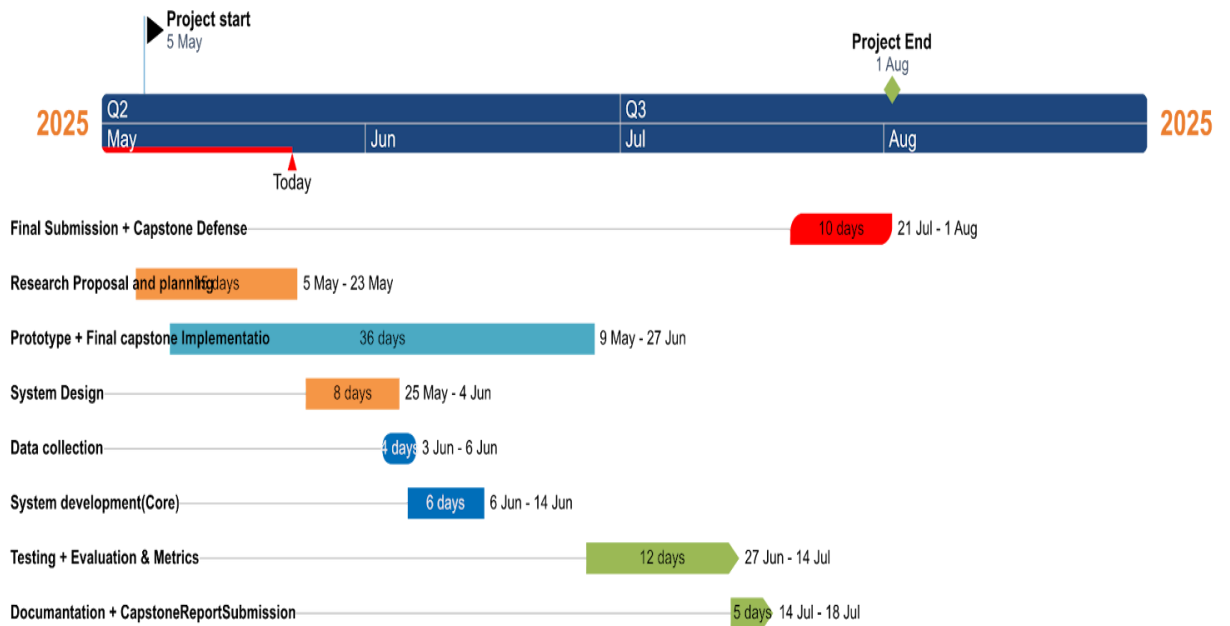
From an environmental standpoint, this approach enhances eco-friendly farming by focusing on reducing fertilizer runoff, soil erosion, and land degradation. Through careful application of fertilizers that are specific to the soil’s needs in Rwanda.

1.7 Research Budget

Item	Cost (USD)
Testing & Calibration	
- Limited soil sample tests (calibration)	20
SMS Service Integration	
- SMS gateway credits (Twilio)	20
Cloud Storage and Backend Hosting	
Contingency (10%)	4
Total	\$44 (55,000 RWF)

The estimated budget for the 3-month research period. Table 1: Research Budget (Components and Estimated Costs).

1.8 Research Timeline



Gantt chart to illustrate the overlap of tasks.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

For this research project, the literature review was conducted on software literature involving Internet of Things (IoT) and Machine Learning (ML) technologies in agriculture with a special focus on soil health monitoring and fertilizer recommendation systems. In this case, the review was performed using academic databases that index scholarly literature, such as IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. The review was started using the following phrases: “IoT soil analysis,” “machine learning fertilizer recommendation,” “agricultural dashboard systems,” and “SMS-based agricultural solutions.” The research was limited to the last five years to make the most use of current peer-reviewed journals, conference papers, and technical reports. Initially, the searches yielded over a hundred papers, which I then narrowed down to a selected 40 that I screened and reviewed based on relevance and specificity to the project's objectives. In the end, 25 were selected, which were the most software-related sources relevant for thorough examination.

2.2 Historical Background

Traditionally, smallholder farmers in Rwanda and throughout sub-Saharan Africa controlled soil fertility based on years of experience and visible signs, missing formal testing. For many years, farmers measured soil health through gazing at crop color, soil shade, or texture. These automatic methods regularly brought about poor fertilizer use and nutrient reduction. Chemical fertilizer use remained very low; for example, common nitrogen application in sub-Saharan Africa turned into approximately 12.15 kg/ha as of 2016, versus over one hundred thirty kg/ha globally (The Breakthrough Institute, 2019). Such low inputs contributed to terrible yields and soil degradation. Formal soil testing among smallholders has additionally been uncommon (only ~1.5% of farmers check their soil) due to restricted access and cost obstacles (Wopereis et al., 2025).

Laboratory-based soil analysis was introduced inside the area in the late 20th century as governments and researchers diagnosed the need for medical soil management. In Rwanda, the country-wide agricultural studies institute (ISAR) initiated systematic soil fertility trials in the 1970s. Pot experiments on over 500 Rwandan soil samples diagnosed primary nutrient deficiencies, mainly phosphorus, potassium, and nitrogen, as key constraints to crop productivity (Rushemuka, 2021). During the nineteen-eighties, collaborative initiatives improved soil testing potential; FAO-supported software (1980, 1990) conducted countrywide fertilizer trials with ISAR and the National University of Rwanda, and by 1990, a countrywide soil survey had produced a detailed soil map. However, these advances, in large part, remained in research establishments. Smallholders seldom accessed laboratory offerings, so the realistic effect on farm fertilizer decisions was limited.

In the 21st century, Rwanda and neighboring international locations have embraced tech-enabled solutions to bridge this gap. Mobile soil laboratories and virtual soil data

structures have emerged in recent years. In 2019, Rwanda deployed a “Caravan” cell soil lab with Morocco’s OCP Group to analyze soils and map fertility in a 50,000 ha pilot sector, delivering site-precise fertilizer pointers (Ministry of Agriculture and Animal Resources, 2019). This brought lab-grade analysis without delay to communities, underscoring the value of information-driven fertilizer recommendations. At the same time, digital agriculture has gained traction. Mobile telephone penetration in Rwanda climbed to over 78% by 2022, allowing farmers to get access to agronomic recommendations through SMS and use cellphone apps offering localized guidance on crops, climate, and input use (One Acre Fund, 2023).

The emergence of the Internet of Things (IoT) and system mastery in African agriculture is remodeling soil health management. Affordable IoT sensors now allow real-time discipline monitoring of soil moisture, pH, and nutrient tiers, while machine learning algorithms examine these records to optimize fertilizer strategies (Sesi Technologies, 2025). Early effects are promising in Nigeria; IoT and AI pilot interventions reduce cassava post-harvest losses by 20% and accelerate earnings by 15% (Farming Farmers Farms, 2023), and in Rwanda, espresso growers' use of sensor analytics achieved a 50% boom in top-rate coffee yields. Portable on-site testing gadgets have also emerged; for example, a handheld scanner that uses infrared spectroscopy with cloud-primarily based gadget mastering can immediately determine soil nutrient composition inside the field (AgroCares, 2025). These innovations represent a jump from reliance on remote labs to delivering superior soil diagnostics and information-driven choice aid without delay to smallholders.

2.3 Overview of Existing Systems (Software-Only)

A variety of software systems have been developed to support farmers with the fertility of the soil and recommendations of fertilizers; however, mostly, they do not need any kind of customized hardware. An excellent example is 'SoilDoc' (Columbia University/University of Maryland), a mobile app that uses smartphone cameras and ML to analyze soil organic matter, moisture, and nutrients from pictures. Then, SoilDoc not only provides information on soil fertility but also gives recommendations for the use of fertilizer. 'Fertilizer Optimization Tool' (FOT) of AGRA is another one; it is a simply designed app that helps farmers create their fertilizer blend by selecting the type of crop and soil texture they have. Besides, SoilCares is a type of available system (East Africa) that is operated by a handheld sensor and a mobile app. Consequently, farmers have to put the probe into the ground, and the mobile app, while processing the data, also guides them on NPK and pH levels to get a desirable fertilizer combination.

These software-enabled devices demonstrate certain principles in a powerful manner: they usually use databases or ML models to map inputs to fertilizer guidance. However, they rely on external services or sensors not owned by farmers and often require internet or smartphone access. In Rwanda and similar settings, connectivity and digital literacy can be limited. On top of that, many software tools simply provide fertilizer guidelines based on generic soil data with no real-time soil measurement facility. For instance, Wopereis et al. (2025) find that

still mobile apps and ICT tools can be vehicles of fertilizer recommendations access; the fact of the matter is that they are not getting the acceptance they deserve due to the accessibility and cost of smartphones. In essence, the present digital platforms (SoilDoc, FOT, SoilCares) confirm the usefulness of technology-driven fertilizer advice, yet a need persists for a cheap, portable device with the software that smallholder farmers can easily operate in the fields, which is not met.

2.3.1 Summary of Reviewed Literature

The present literature is consistent in saying that the use of data in farming can result in better productivity and save inputs. The soil monitoring systems based on the IoT (Gasana 2022; Byiringiro 2021) that they found capable of measuring field conditions accurately using sensors and reducing the time taken by the lab to provide results have now been replaced. Through the help of AI (GeaGrow 2025; Senapaty et al. 2023), it is possible to understand the soil data, and the right crops and fertilizers to use can be decided. The availability of mobile applications and Web-based solutions like SoilDoc, FOT, and SoilCares as a benefit to farmers in the form of expert advice on pesticide selection for individual farms has been proven explicitly. These four works together show that the combination of IoT and machine learning is the most viable path towards sensible fertilizer administration.

The studies, however, also stress that one should consider the surroundings. Other countries' solutions may not be a perfect fit for Rwanda's smallholder system. The main issues that mostly affect Rwanda have been cited as the absence of the internet, low technological skills, and the inadequacy of resources. The number of phone users, albeit limited, is progressing. Nonetheless, the majority of them cannot afford to buy smartphones, and they are satisfied with their basic mobiles. The indication here is for the setting up of a system that is not only offline compatible or requires minimal connections but also has user interfaces in the local language, which indeed is the focus of the project. Therefore, it shows that our project should concentrate on the local market as its target and be the one that develops a small gadget for the nearby environment and serves directly and immediately, since the existing systems are not available to many due to their nature as lab- or cloud-dependent.

2.4 Review of Related Work

Quite a few academic projects have come up with IoT hardware for soil monitoring. One of Gasana's academic papers (2022), based on his master's thesis in Rwanda, is a proof of concept of an IoT device, which has a GPRS-powered microcontroller equipped with a variety of soil sensors (pH, NPK, moisture). The author applied data mining methods (decision trees) to the data, which enabled him to predict the most suitable crops and to give the type and amount of fertilizers needed. The experiment's results proved that farmers could use on-site sensors, thus eliminating the need for lab tests and, at the same time, reducing cost and time. Similarly, Byiringiro et al. (2021) illustrated an IoT system in which an ESP8266 (NodeMCU) board, pH and moisture sensors, and a DHT11 climate sensor are the key elements. This system relayed the data over Wi-Fi to a web dashboard and an Android app.

The initial tests indicated that the system could easily and accurately take real-time soil parameters apart from advising the appropriate fertilizer. Elsewhere, in a much-talked-about study by Folorunso et al. (2025) from Nigeria, the GeaGrow, Nigeria's mobile application that uses artificial neural networks for fertilizer recommendation based on soil NPK and pH, which technology was trained using the lab-analyzed soil samples. Without an IoT device, GeaGrow can be operated solely by manual input or with the help of external data, yet it still serves as an example of how ML can translate raw soil figures into fertilizer plans. The situation has seen Rhea Africa (Kenya) using ML that operates from a cloud-based portable soil sensor to come up with a fertilizer-friendly model. Though it was not formally published, and instead it was reported in newspapers, it depicts the industry's keenness to the same situation. Leading journals of the Frontiers show a way to the extension of previous work so that the combination of precision farming (ICT, satellite sensors, and ML) can not only enhance productivity but also make farming sustainable in East Africa. They also add that the new phenomenon of smartphone ownership is going up among the public, which means that such tools are acceptable.

However, the study also provides counterarguments: the technical complexity, monetary values, the issue of data connectivity, and so on still limit the families from purchasing new technologies. No work has yet appeared that builds on all the mentioned issues: the mobile sensor, the ML, and the fact that it can be used locally in Rwanda. In general, the rest of the works in the context confirm the technological possibility of monitoring the soil with IoT technology and the relevance of ML in the context of the same fertilizer purpose but indicate a need for a user-centric, field-ready system tailored to Rwanda's context.

2.5 Strengths and Weaknesses of Existing Systems in Rwanda

Several technology-led outreach activities that are designed to help farmers in Rwanda access soil and crop management information have started recently, each with its strengths and, of course, weaknesses that have an impact on their overall effectiveness as far as the services provided to the smallholder farmers are concerned.

- **Gasana (2022)** is one of the scholars who have come up with their Internet of Things (IoT) soil monitoring system, and they are using sensors to gather many necessary soil parameters like N (nitrogen), P (phosphorus), K (potassium), pH, temperature, and moisture and then giving soil condition data in real-time. GPRS is the device that the system has for data transmission to cloud storage, and also, a machine learning model is used to make crop predictions based on the collected data. Among its strengths are that it is both accurate and has real-time monitoring and predictive analytics capabilities. Still, there are some obstacles to the system, like the need for the internet to work all the time, which is not available in rural areas, and dependence on the cloud, which also needs good network connectivity. Another issue that stifles its spread and its universal affordability is the high cost of the sensors, particularly in NPK detection, which makes the system difficult to adopt by smallholder farmers, who do not have enough funds or smartphones that they can rely on.

- **The Smart Soil Monitoring Application (SSMA)** is another IoT invention, an input of Byiringiro (2021) that was developed to meet the needs of the agriculture sector in Rwanda. This application records soil parameters such as pH, moisture, humidity, and temperature, and also allows the user to interact directly via the interaction interface. After that, the data is transferred from the ESP8266 Wi-Fi module to a separate cloud server, where the farmers can view the data either via the web or using an Android smartphone app. The most striking feature of SSMA is that it is easy to use, the visuals are explicit, and the data is accessible in real-time. However, the fact that the system works with smartphone technology and internet service is a serious drawback because a large number of farmers do not have these resources. The application does not feature sensors that allow for direct measurement of soil nutrient levels, meaning it is a stand-alone system in general soil conditions. Now, without these toys, soil testing and data ionization are the only tasks it can fully take up, the fertilizers not being given a mention. Naturally, it becomes a matter of necessity to have digital literacy and a smartphone for one to adopt the use of this application.
- **The Rwanda Soil Information System (RwaSIS)**, which was initiated in late 2024 by the Rwanda Agriculture Board (RAB), is an advanced digital platform that pools country-wide soil data and fertilizer response trials to create fertilizer and lime recommendations and to map the location. RwaSIS, through the Smart Nkunganire System (SNS), the national e-voucher platform, becomes an input distributor that offers customized advice according to the already existing subsidy mechanisms in the country. RwaSIS has been able to meet its crowning achievement through the seamless and efficient process of integrating the available soil resources with precision at the regional level, so that the exact location of the problem can be known; hence, the decision is pertinent as an aid in the soil recovery process. However, RwaSIS is not distributing the recommendations on paper, but rather, it is mainly meant to encourage digital transformation; that is to say, farmers who are registered in the subsidy program and have access to the Internet are the ones who benefit the most. As a result, it puts on the sidelines the unregistered farmers who do not have access to smartphones or the Internet to be digitized. Furthermore, suggestions are given on regional soil mapping that do not deal with the details of individual parts of farms, indicating that there are no personalized, on-site soil diagnostics, which is a clear gap in the present situation.
- A mobile application and sensor hardware are part of **the Smart Potato Greenhouse Technology (SPGT)**, which was innovated by a local innovator in 2023, being the capturing technology specifically for the greenhouse, which was invented by the innovator who was local to the area in 2023. The product offers the best means of acquiring the best temperature and moisture, and besides, it can water the greenhouse automatically, which was achieved through a pilot program held in the Musanze District, all of which are the things that have helped the technology to become a success. However, its narrow focus on greenhouse environments and the absence of

the equipment needed to test the open-field situation have seen it miss a big chunk of the smallholder and the country as a whole, notwithstanding the results are limited in being unable to move the technology to the broader agricultural application packaged with the needs of Rwandan farmers. Moreover, it is also very important to have a smartphone and the sensor hardware, which are the conditions that the devices are in, such that the system is now a pipe dream to many households without them. It is not possible to know the levels of nutrients and therefore how to apply the fertilizer, and so this technology is a double jeopardy of not only being unable to test the soil but also not being able to determine the fertilizer efficiency of the crops.

- Finally, **One Acre Fund's USSD service** is the most accessible means for the farmers to get access to the agricultural inputs and the latest technology via a basic mobile phone. The simplicity and the broad coverage of the farm make it its major strengths, which had already benefited more than 750,000 Rwandan farmers by 2022. But the system mainly serves as a support for transporting and imparting information and does not meet the requirements of soil sensor data or any personalized nutrient advice. In effect, it is the extensive character of the current service that does not allow farmers to obtain specific soil nutrient diagnostics only; this underscores the importance of solutions that bring together the widespread access of basic phones with the accurate and yet rapid diagnosis of the soil nutrients.

2.6 General Comment and Conclusion

Summarizing, the literature confirms the IoT+ML approach's adequacy and utility in assisting the soil fertility control. Furthermore, it defines the main governing factors to be the sensing of multiple parameters, the device being used offline, ease of use, and the possibility of calibration using local data. Very few ongoing projects are using a disturbance detection system in such a capacity as revealed by the data envisioned here (portable device + ML). The research situation is clear: an integrated, locally usable soil analysis tool that smallholders can install themselves. Such a plan will use the successful features (real-time sensing, ML predictions) and eliminate the weaknesses (cost, connectivity) identified in the bibliography. The next chapter continues with the details of the system, its design, requirements, and architecture, which stem from the literature review.

CHAPTER THREE: SYSTEM ANALYSIS AND DESIGN

3.1 Introduction

This chapter describes the system analysis and design of the proposed Portable IoT and Machine Learning-Based Soil Health Analyzer. There will be a use of Agile methodology for the development, as it is of an exploratory and adaptive nature; thus, it suits the conduct of the hardware prototyping, software development, and ML model training simultaneously. Agile's focus on adaptability and feasibility of the working components early on is what meets the demands of the project, as it implies the provision of continuous testing and improvement of the soil analyzer system. IoT/ML projects are not only complex but also highly dynamic; hence, their realization via traditional linear models like Waterfall is unrealistic and unproductive. However, making the project Agile enables the system to easily obtain and implement feedback, have the stakeholders' buy-in, and thus progressively build a reliable solution. In this Rwandan smallholder agriculture scenario, it is important to follow the approach that takes into account the iterative nature of the field testing and the user feedback to ensure the farmers' needs are properly addressed.

3.1.1 Dataset and Dataset Description

The soil health analysis in this work leverages the Soil Nutrient Balance (NPK) Dataset of Rwanda, an open dataset developed to support modeling of soil nutrient depletion in Rwanda's croplands (Uwiragiye et al., 2022). Compiled from multiple freely available sources, it contains both raw and processed inputs, such as fertilizer application rates and crop uptake measurements from 454 on-farm trials, and analytical outputs related to nitrogen, phosphorus, and potassium balances. Its primary purpose is to enable data-driven mapping of NPK nutrient flows across Rwanda, aligning directly with the needs of an ensemble machine learning approach for digital soil mapping in the region.

Structurally, the dataset is organized into a main "Data" directory with five subfolders, each addressing a key aspect of soil nutrient management. The Soil Nutrient Flows folder contains field trial summaries of nutrient inputs and outputs; Soil Erosion and Sediments provides spatial layers and RUSLE factors accounting for nutrient loss via erosion; Environmental covariates include GIS rasters and vector layers for soil organic carbon, texture, bulk density, cation exchange capacity, elevation, rainfall, and vegetation indices; NPK Balance Modeling Results holds raster maps and uncertainty layers depicting nutrient deficits or surpluses, and Modeling Code supplies the R scripts used to generate these outputs. All data are provided in analysis-ready formats, GeoTIFFs, shapefiles, and tabular spreadsheets, facilitating seamless integration into a machine learning workflow.

This Rwanda-specific soil dataset is particularly well suited for a machine learning-based soil health decision-support system aimed at smallholder farmers. Because nearly half of Rwanda's agricultural soils are acidic ($\text{pH} < 5.2$) with low nutrient availability and cation exchange capacity, having localized measurements of soil pH proxies, organic carbon, and

NPK levels are critical for formulating precise lime and fertilizer recommendations. By encompassing both macronutrient concentrations and relevant environmental covariates, the dataset enables models to learn complex interactions that drive nutrient deficiencies at fine spatial scales. Uwiragiye et al. (2022) demonstrated the efficacy of an ensemble ML approach using these data to map nutrient depletion across Rwanda, underscoring its applicability for generating accurate, site-specific soil management guidance.

3.2 Research Design

A co-design approach will be used, combining engineering development with participatory feedback from farmers. An agile-inspired model will be followed:

- **Hardware Prototyping & Testing:** Designing the IoT hardware (sensors and microcontroller) and testing it in the field. Early iterations produced a basic sensor prototype, which was improved in subsequent sprints (e.g., refining sensor calibration and device enclosure).
- **ML Model Training & Refinement:** Collecting sample soil data and developing the machine learning recommendation engine in parallel. The ML model was trained on incremental datasets each iteration, allowing the algorithm to be adjusted as new data became available. This iterative ML development aligns with best practices for AI projects, which are highly data-driven and benefit from continuous.
- **Dashboard Development:** Implementing the farmer dashboard in a modular fashion. In each sprint, new features of the React.js web application are added (such as data visualization charts, user account pages, and language localization). This incremental front-end development ensured that core functionalities (like real-time soil data display) were available early, with more advanced features layered on in later iterations.
- **SMS System Integration:** Integrating and testing the SMS notification workflow. Early on, a simple SMS alert (using a service like Twilio) was set up when sample data was processed. In later iterations, the SMS content was refined (e.g., sending localized fertilizer advice), and the reliability of messaging was improved. Each cycle included sending test SMS messages to ensure farmers receive timely and correct recommendations.

3.3 Functional and Non-Functional Requirements

Functional Requirements:

- **Soil Data Sensing and Collection:** The IoT device shall measure soil health parameters (e.g., pH, moisture, temperature, and key nutrient stages) and transmit those readings to the cloud database in real-time. The sensing unit ought to be transportable and battery-powered for field use. Data must be time-stamped and associated with the respective farmer or plot. This presents the uncooked input for analysis
- **ML-Driven Recommendation Engine:** The machine shall examine sensor facts, the usage of a gadget, and the getting-to-know-you model to generate tailor-made

fertilizer or soil modification hints. For each soil sample or set of readings, the ML engine will output actionable advice, for instance, recommending the sort and amount of fertilizer needed to cope with detected nutrient deficiencies. The advice of good judgment may be grounded in agronomic information; the ML model is educated on soil nutrient profiles and crop reaction statistics to ensure accuracy. This automated expert device assists farmers by decoding raw sensor records into sensible steering.

- **Data Visualization Dashboard:** A stable net dashboard (on hand through a React.js internet application) shall allow farmers and task directors to visualize soil information and hints. The dashboard will display current sensor readings, historical traits, and the ML version's guidelines in an intuitive layout (graphs, color-coded signs, and so on). Real-time visualization of soil parameters is vital for farmers to make informed choices. The dashboard will also offer an interface for person registration and profile control.
- **SMS-Based Farmer Notification:** The machine shall send one-way SMS notifications to the farmer's cell smartphone with key outcomes. Specifically, while a new soil evaluation is finished, the farmer should get hold of an SMS message
- summarizing the soil quality and fertilizer recommendation. This guarantees farmers without regular net access can still benefit from the machine. The SMS notification ought to be dispatched right away after information evaluation, effectively turning in real-time alerts for crucial parameters (e.g., extremely low soil pH or nutrient ranges).
- **User Registration and Management:** Farmers (end-users) will be capable of checking in for an account and logging in to the device. During registration, user info like name, telephone number (for SMS), farm region, and plants of interest can be accrued. The machine will control person authentication and maintain profiles so that each farmer's facts and recommendations are saved personally and on hand only to them (and licensed directors). An admin interface may be protected for dealing with customers and monitoring standard system utilization.

Non-Functional Requirements:

- **Security:** The solution must ensure information safety and manage access. All farmer records (soil readings, personal info) must be saved securely in the cloud database with the right authentication and encryption. Role-primarily based admission to manipulate will distinguish farmers (who can only get entry to their data) and gadget admins. Data transmission from device to cloud should use stable protocols (e.g., HTTPS/MQTT over TLS) to prevent eavesdropping. Additionally, the machine should enforce strong passwords and probably 2-factor authentication for the dashboard. By leveraging Supabase's protection features (like Authentication and Firestore protection policies), information may be saved exclusively and tamper-proof
- **Performance:** The device is anticipated to operate in real-time or near real-time. From the instant a soil sample is taken and the tool transmits statistics, the stop-to-cease pipeline (database update, ML computation, SMS dispatch) needs to execute within a short timeframe (ideally some seconds, under a minute at most). This guarantees farmers get immediate remarks on soil health, aligning with the need for

well-timed decision-making in farming. The web dashboard ought to be responsive, with soil sensor readings updating in real-time while the tool is in use. The architecture must also be scalable to deal with a couple of devices/farmers sending information concurrently and have excessive uptime (focused on more than ninety-nine percent availability throughout developing seasons). Utilizing Supabase and Cloud Functions can help attain scalable, always-on overall performance.

- Usability:** Since the number one customers are smallholder farmers in Rwanda, the gadget must be clean to use and handy. This consists of having the dashboard interface in the nearby language (Kinyarwanda) or, at a minimum, presenting multilingual assistance (e.g., Kinyarwanda and English/French) for wider adoption. A local language interface drastically improves usability for Rwandan farmers. The dashboard layout will observe responsive internet design so that it can be used without trouble on smartphones, as many farmers may also only have cellular devices. Simple navigation and clean visuals (e.g., the use of icons or color codes for soil popularity) are prioritized for users with restricted technical history. Additionally, the hardware tool has to be ergonomic and easy to use (one-button or automated analysis), and the SMS texts ought to be concise and jargon-free. Overall, the system ought to require minimum training; the interaction drift (take analysis, receive SMS, and view information on the dashboard) has to be sincere and farmer-pleasant.

3.4 System Architecture

The soil health analyzer system is designed in a client-server IoT architecture with distinct components for data collection, data processing (ML), storage, and user interaction.

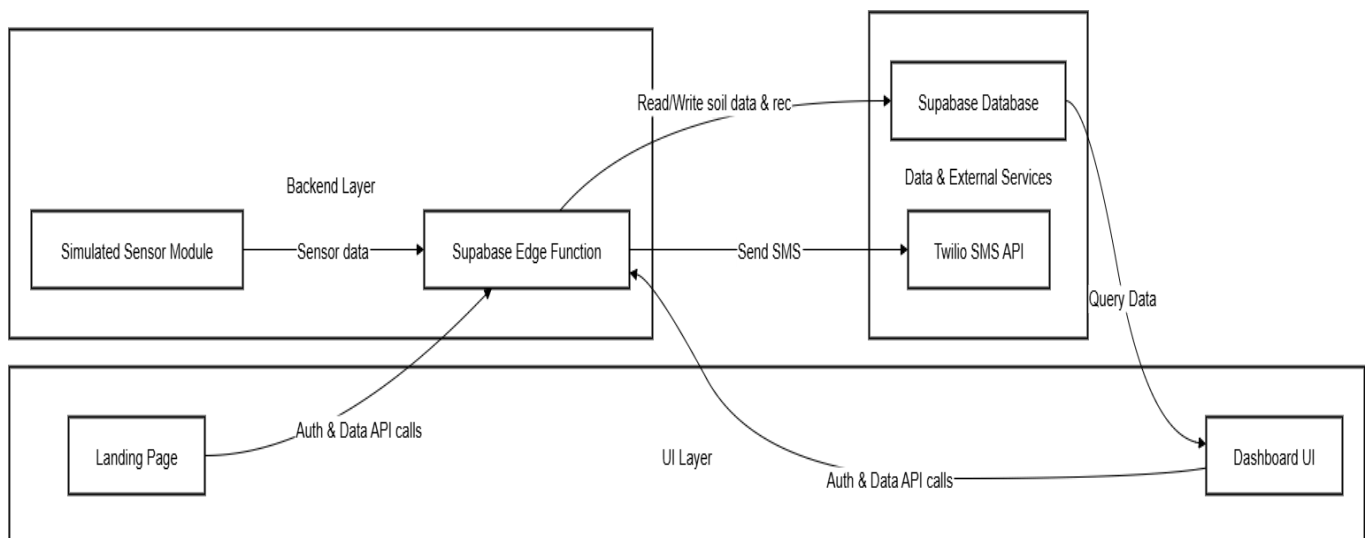


Figure 3.1 illustrates the high-level architecture and data flow of the system.

System Architecture Overview

This architecture diagram shows how the front-end components (Landing Page and Dashboard UI) and the internal Simulated Sensor Module connect to the backend. All business logic resides in Supabase Edge Functions, which handle authentication, data ingestion, ML predictions, database operations in Supabase's PostgreSQL, and invoking the external Twilio SMS API. Arrows indicate API calls, data flows, and command/response paths between layers.

The proposed system architecture integrates four principal components: IoT hardware, cloud backend, machine learning engine, and user interfaces (internet dashboard and SMS notifications) to deliver specific, accessible, and real-time soil fitness insights and fertilizer suggestions to Rwandan smallholder farmers. At the sensing layer, a transportable IoT device ready with inexpensive sensors (pH, soil moisture, temperature, and doubtlessly electrical conductivity or NPK sensors) is deployed immediately in farmers' fields. This tool is powered with the aid of a rechargeable battery, optionally augmented with solar charging capabilities for sustained discipline operations. An ESP32 microcontroller manages sensor readings and transmits information wirelessly to a cloud platform. Connectivity to the cloud makes use of Wi-Fi via the ESP32's onboard module; however, GSM or LoRa modules function as feasible alternatives for remote places missing Wi-Fi infrastructure. Every IoT device includes an individual ID about a specific farmer's debt, thereby enabling customized supervision and record management systems.

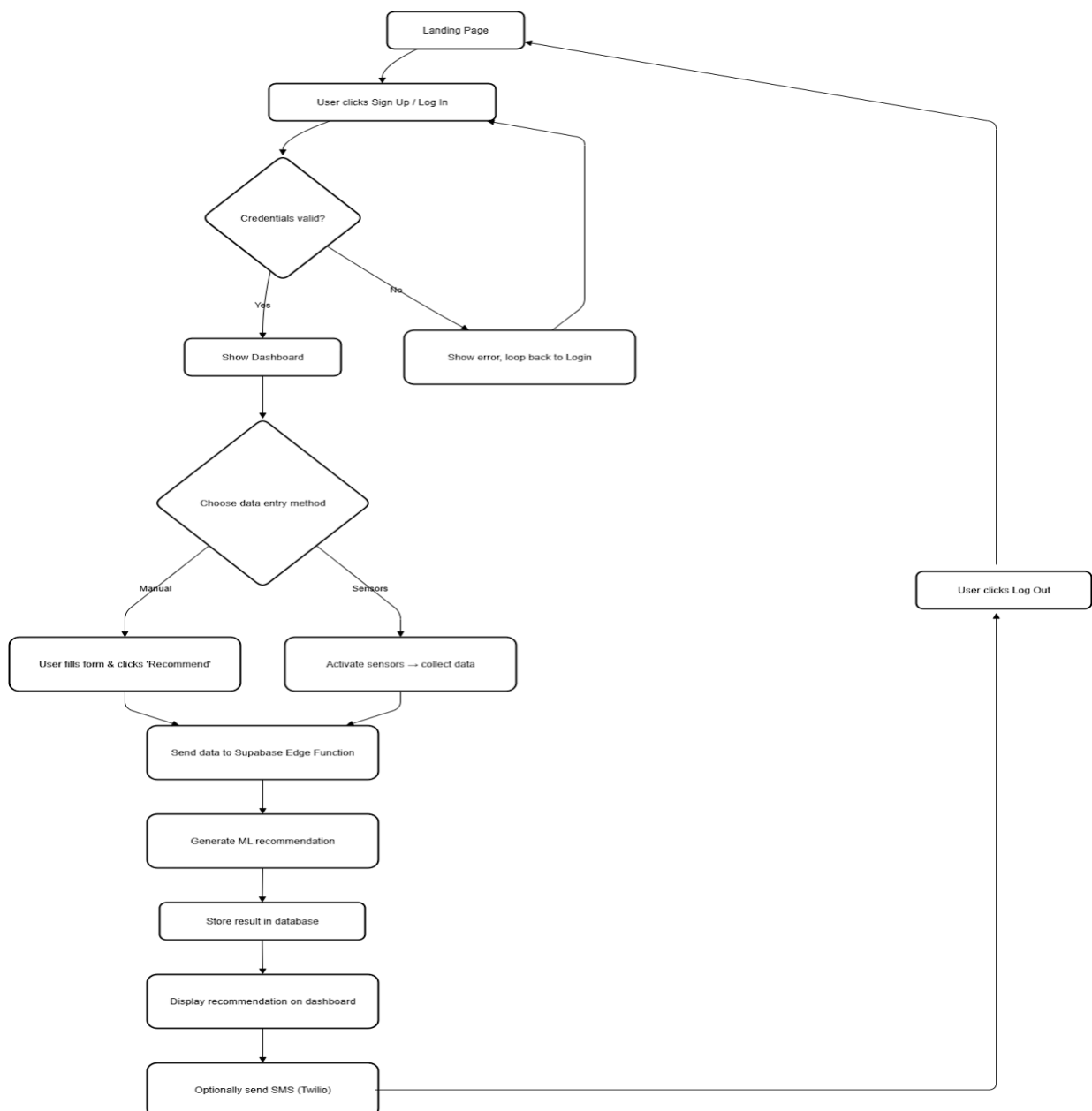
Information accumulated from the IoT sensors is processed using Google Supabase's cloud infrastructure. Soil measurements, along with their corresponding timestamps, farmer IDs, and device IDs, are stored in Supabase's real-time SQL database. Supabase was chosen for its optimal performance in the synchronization of data in real time, its robust security authentication for user access control, and its support of multiple frontend frameworks. Furthermore, backend business logic such as the ML engine execution and SMS alert integration is hosted in Supabase Cloud Functions, which provides serverless data and service delivery, enabling smooth processing and logic execution relied on by hosted functions.

The ML model, constructed in Python, elevates the analytics center of the system to the cloud. With his or her consent, the IoT device drives the ML model by triggering what would be referred to as an event-driven architecture, where a previous Rwandan soil dataset-based model predicts the most suitable types and amounts of fertilizers needed. Recommendations produced, along with "apply 50 kg/ha of nitrogen fertilizer because of low nitrogen levels," are immediately written back into Supabase, triggering the next consumer notifications. Python's choice offers the right of entry to massive ML libraries and flexibility for future model enhancements or integrations. To reach farmers without reliable net access, the machine integrates an SMS notification module through Twilio or a local SMS gateway. Once the ML engine generates fertilizer recommendations, personalized messages are automatically sent to farmers' registered phone numbers in their preferred nearby language, ensuring accessibility and simplicity of expertise.

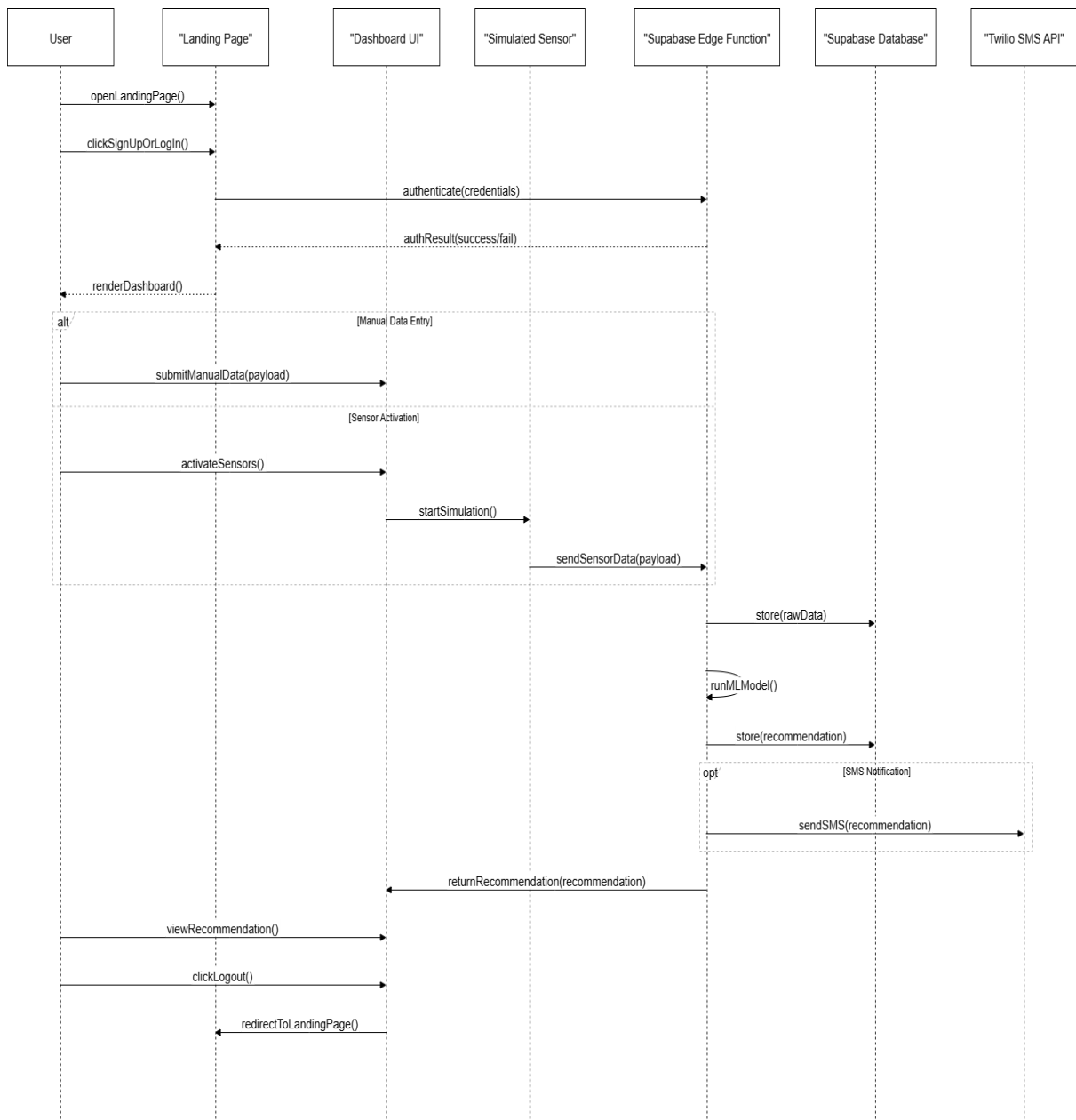
Farmers with internet connectivity access specified statistics via a responsive internet-based dashboard constructed using React.js. The dashboard dynamically interacts with Supabase to display real-time soil health updates, historical fact visualizations (e.g., traits in soil moisture or nutrient tiers), and personalized fertilizer recommendations. React.js ensures the interface is consumer-pleasant and available across diverse devices, supporting both farmers and device administrators with clean, actionable insights.

Overall, the structure employs a modular and cloud-centric approach, ensuring scalability, maintainability, and flexibility. Real-time sensor record integration, speedy ML analysis, and available consumer interfaces (each primarily internet-based and SMS) together supply a strong, cost-effective, and contextually suitable device that considerably complements fertilizer use efficiency among Rwandan smallholder farmers.

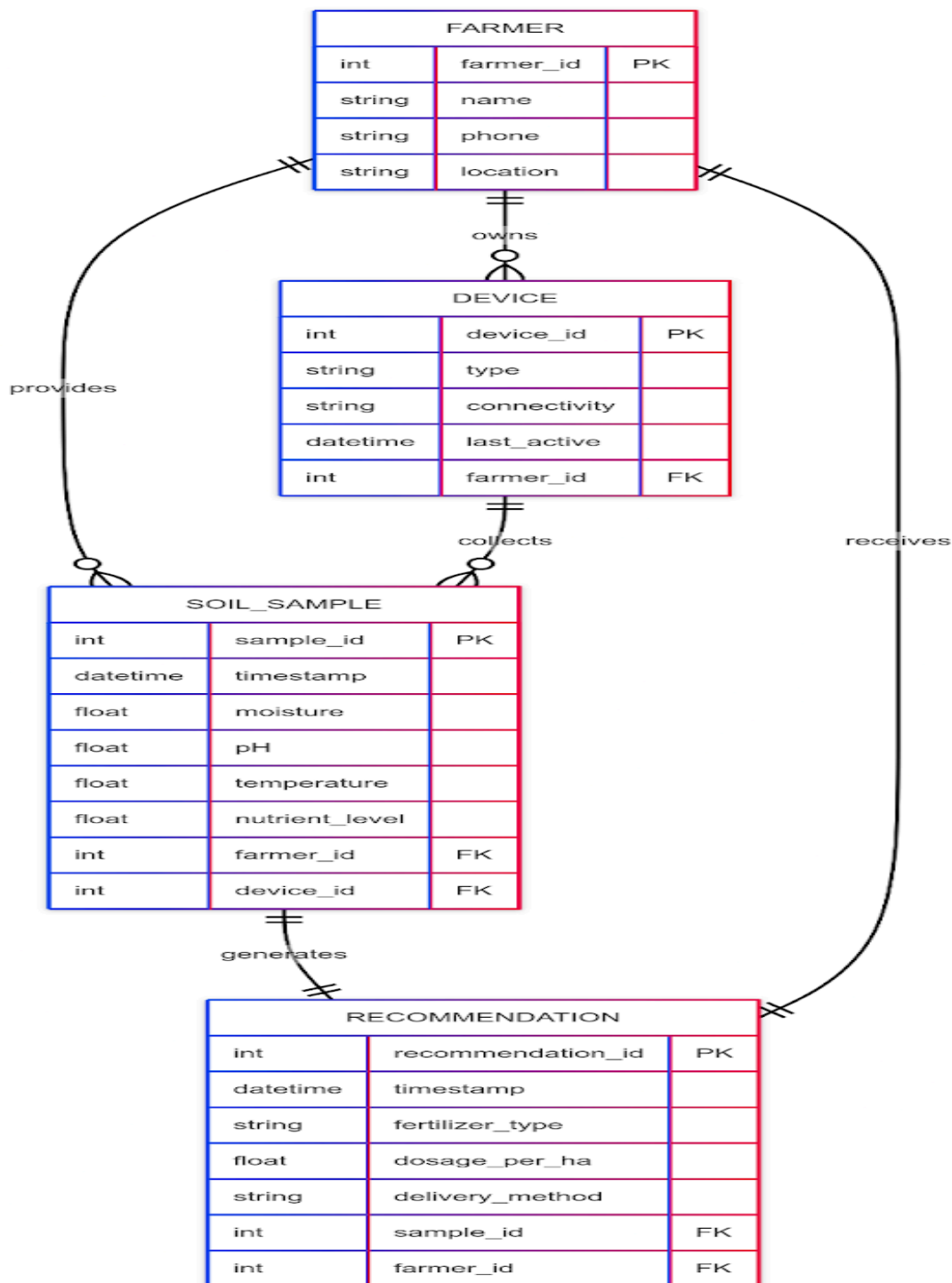
3.5 UML Diagrams



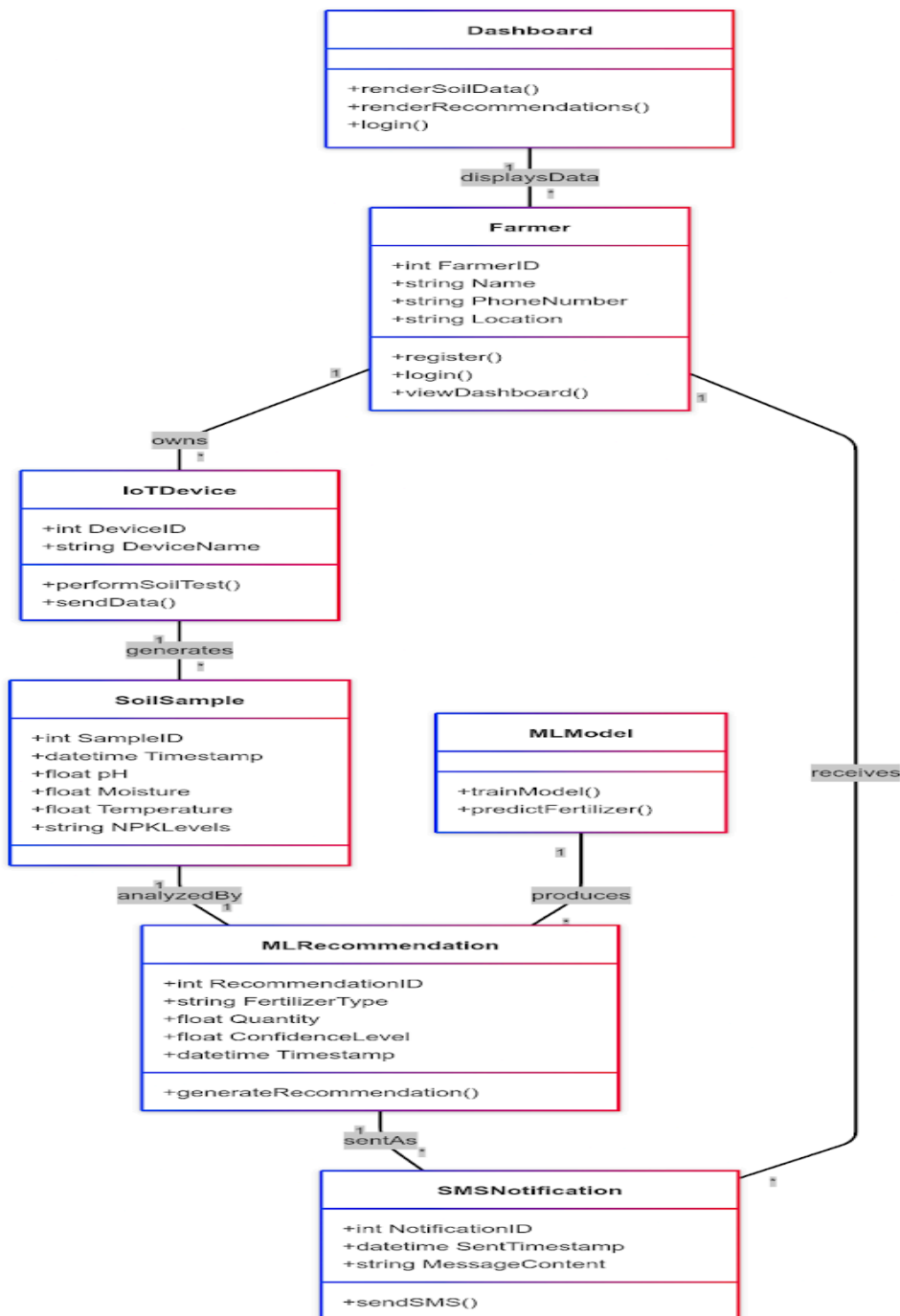
Flowchart of User Journey and Data Pipeline: This flowchart illustrates the end-to-end process starting on the public landing page and ending back at the same page after logout. It shows the user signing up or logging in, choosing between manual data entry or activating the sensor simulation, sending the collected soil parameters to the Supabase Edge Function, running the ML prediction, persisting both input and recommendation in the database, displaying the result on the dashboard, optionally dispatching an SMS notification, and finally logging out. The decision diamonds clarify the “credentials valid” and “data entry method” branching.



Sequence Diagram of a Recommendation Cycle: This sequence diagram traces the interaction timeline from when a user opens the landing page and logs in, through either manual form submission or sensor activation, to backend ML processing, database storage, optional SMS dispatch, and finally the user viewing the recommendation and logging out. It highlights synchronous calls (solid lines) for core operations and a dashed line for the optional SMS step, clearly showing the ordered flow of messages among the user, UI, sensor module, edge function, database, and SMS API.

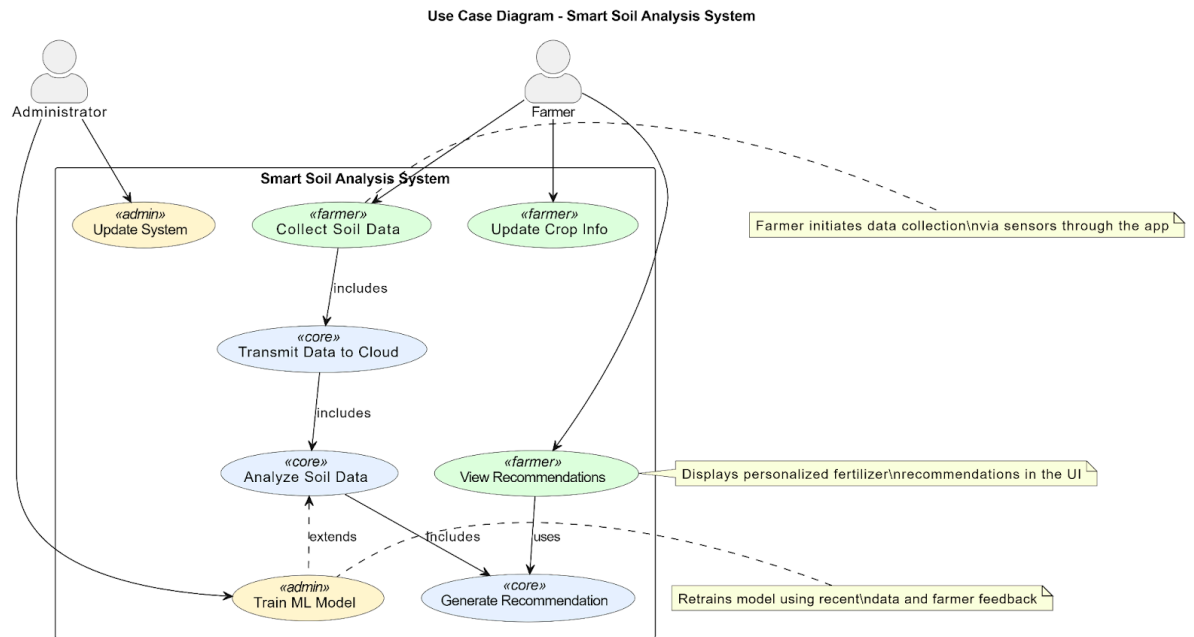


Entity Relationship Diagram (ERD): Shows database entities and their relationships. Entities include Farmer, IoT Device, Soil Sample, and Recommendation. Farmers own multiple devices and provide multiple soil samples. Each sample originates from one device, generating a single recommendation. This structure ensures efficient data management, enabling quick retrieval of farmer-specific soil history and tailored fertilizer recommendations through cloud storage (Supabase).



Class Diagram: represents main software components IoTDevice (handles sensor data collection), MLModel (processes sensor data to produce fertilizer recommendations),

SMSNotifier (automatically sends recommendations to farmers via SMS), and FarmerDashboard (presents detailed soil data and recommendations through a user-friendly interface). The design emphasizes clear responsibilities and modularity, facilitating maintenance and future feature integration without affecting existing system functionality.



Use Case Diagram: summarizes farmer interactions with the system, highlighting primary activities: registering accounts, collecting soil data using the IoT device, viewing results via the Web dashboard, and receiving automated SMS alerts. It emphasizes a clear, sequential workflow: data collection triggers automated ML recommendations and subsequent SMS notifications, providing farmers with real-time, actionable insights to optimize fertilizer usage effectively.

3.6 Development Tools

This project integrates a variety of hardware and software tools that were chosen to meet the design requirements and to leverage contemporary technologies in IoT and machine learning:

- Programming Languages & Frameworks:** The plan is to develop the IoT device firmware in C/C++ and employ Arduino IDE or PlatformIO due to the primitive-level control over sensors and optimized microcontroller resource usage. For scientific computing, with plenty of ML libraries such as scikit-learn or TensorFlow, Python will handle the machine learning parts and server logic, as it is cloud-ready. In the client-facing segment, there will be a dashboard programmed using JavaScript (ES6+) with the React.js framework for creating single-page applications.
- IoT Hardware:** The prototype will feature an Arduino-compatible microcontroller. Either the Arduino Uno WiFi Rev2 or the ESP32 board will work, as they both have sufficient analog/digital I/O for the sensors and have communication modules. The sensors (pH probe, moisture sensor, etc.) connect to the microcontroller through

analog-to-digital conversion (ADC) pins or I2C interfaces. The firmware will have pH sensor libraries to convert SME values to meaningful calibrated units. It makes perfect sense that C/C++ is used for designing firmware, as the Arduino SDK is also C++. It provides low-level abstractions to the hardware, including direct control over timing. This is important in taking accurate readings from hardware sensors.

- **Cloud Backend Supabase:** Our choice for backend-as-a-service is Google Supabase. Specifically, Supabase Realtime Database or Cloud Firestore will be utilized as data storage systems for the framework. Supabase Authentication will handle user registration and login securely. Other features of Supabase, such as real-time data synchronization (which enables dashboard UI updates using the most recent readings) and straightforward integration with web and mobile clients, are very beneficial.
- **Machine Learning Tools:** While developing the recommendation model, there will be a utilization of Python's ecosystem. Jupyter Notebooks will be used along with the pandas library for data preprocessing, while model training will be conducted using scikit-learn or TensorFlow/Keras, allowing for exploration of numerous algorithms. The model can be exported in a variety of formats, like a pickle file in Python, TensorFlow SavedModel, or ONNX. Both Flask and FastAPI can be used in a Cloud Function to load the model and control prediction services. This makes it possible to change the model without using the device or changing the settings on the dashboard.
- **Front-end Development:** The dashboard could be set up with React.js. Because it employs an element-based structure, the UI will be modular and updated without problems. There will also be the implementation of Redux for country control (encompassing user authentication and information caching) and the use of Chart.js for records visualization (representing tendencies from sensors and summarizing guidelines in a person-friendly way). We may choose responsive design frameworks like Tailwind and Material-UI for styling to ensure the dashboard is smooth and responsive on cell gadgets (as many farmers may additionally have limited access via smartphones).
- **Short Message Service Integration:** For sending SMS notifications, I advocate for using the cloud communication carrier Twilio due to its API reliability and simplicity of use. Twilio provides a REST API that can be accessed from our backend (as an example, through a Node.js or Python feature) for telephonic messaging around the world. I will combine the Twilio SDK in our Cloud Functions, set an SMS-enabled phone number, and use it to send one-way signals to farmers.

CHAPTER 4: SYSTEM IMPLEMENTATION AND TESTING

4.1 Implementation and Coding

4.1.1 Introduction

This section details the technical execution of the Soil-Sync project, from source code development to the integration of its various modules. It outlines the specific tools, programming languages, and frameworks used to build the frontend user interface, the backend server, and the machine learning-powered recommendation engine. Furthermore, it describes the data management strategy using Supabase and the integration of third-party services like Twilio for SMS notifications. The primary focus is to provide a clear account of how the conceptual design was translated into a functional, full-stack software application.

4.1.2 Description of Implementation Tools and Technology

The Soil-Sync system is architected as a modern full-stack application, combining a Python backend for machine learning and business logic with a reactive TypeScript frontend for user interaction.

Backend Implementation

The backend was developed using Python, with the Flask microframework serving as the foundation for the RESTful API. Flask was chosen for its lightweight nature and simplicity, which allowed for the rapid development of endpoints to handle predictions, SMS webhooks, and health checks.

The core of the backend is the fertilizer recommendation engine, which loads a pre-trained machine learning model. The model, a random forest classifier, was developed using the scikit-learn library and trained on agricultural data handled with pandas. This model predicts the optimal fertilizer based on soil and crop parameters. The snippet below shows the primary prediction logic from `python-ml-server/app.py`:

```
def predict(self, input_data):
    try:
        for col in MODEL_COLUMNS:
            if col not in input_data:
                raise ValueError(f"Missing required field: {col}")
        # Prepare DataFrame
        soil_type_str = input_data['Soil_Type']
        crop_type_str = input_data['Crop_Type']
        if soil_type_str not in soil_type_map:
            raise ValueError(f"Invalid Soil_Type: {soil_type_str}. Allowed: {list(soil_type_map.keys())}")
        if crop_type_str not in crop_type_map:
            raise ValueError(f"Invalid Crop_Type: {crop_type_str}. Allowed: {list(crop_type_map.keys())}")

        soil_type = soil_type_map[soil_type_str]
        crop_type = crop_type_map[crop_type_str]

        features = [[
            input_data['Temperature'],
```

```

        input_data['Humidity'],
        input_data['Moisture'],
        soil_type,
        crop_type,
        input_data['Nitrogen'],
        input_data['Potassium'],
        input_data['Phosphorous']
    ]]
    df = pd.DataFrame(features, columns=MODEL_COLUMNS)
    # Predict
    pred_code = int(self.model.predict(df)[0])
    fert_name = self.label_encoder.classes_[pred_code]
    # If the fertilizer name matches an NPK blend, prepend 'NPK '
    npk_pattern = r'^(\d{2}-\d{2}-\d{2})$'
    if re.match(npk_pattern, fert_name):
        fert_name_display = f"NPK {fert_name}"
    else:
        fert_name_display = fert_name
    # Placeholder for application rate (kg/ha)
    application_rate = 150
    # Get confidence (probability of predicted class)
    if hasattr(self.model, 'predict_proba'):
        proba = self.model.predict_proba(df)[0][pred_code]
        confidence = round(proba * 100, 1)
    else:
        confidence = 90.0 # fallback if model doesn't support predict_proba
    # Crop name from input
    crop_name = input_data.get('Crop_Type', '')
    # Calculate expected yield increase using the formula
    expected_yield_increase = min((confidence / 100) * (application_rate / 150) * 40, 50)
    expected_yield_increase = round(expected_yield_increase, 1)
    return {
        'fertilizer_code': pred_code,
        'fertilizer_name': fert_name_display,
        'application_rate': f"{application_rate} kg/ha",
        'confidence': f"{confidence}%",
        'expected_yield_increase': f"+{expected_yield_increase}%",
        'crop_name': crop_name
    }
except Exception as e:
    logger.error(f"Prediction error: {str(e)}")
    raise Exception(f"Prediction failed: {str(e)}")

```

The back end also manages data persistence and external service integration. A Supabase database was used to store user account information and historical soil input/recommendation records. This ensures that whenever a user submits new soil data, it is saved for future reference and can be retrieved for the historical data table. Additionally, the system integrates an SMS service to notify users of recommendations via text message. The implementation uses the Twilio API (with the Twilio Python SDK) to send SMS notifications to a user's registered phone number. Secure integration practices were followed, for example, using API keys and validating Twilio request signatures for webhooks, to ensure that SMS functionality

is reliable and secure. The Flask back-end provides an /sms endpoint that, when triggered, formats the recommendation result into an SMS and uses the Twilio client to send the message.

```
@app.route("/sms", methods=["POST"])
def sms_reply():
    validator = RequestValidator(TWILIO_AUTH_TOKEN)
    twilio_signature = request.headers.get("X-Twilio-Signature", "")
    url = request.url
    post_vars = request.form.to_dict()

    is_valid = validator.validate(url, post_vars, twilio_signature)
    if not is_valid:
        abort(403)

    incoming_msg = post_vars.get('Body', "").strip()
    resp = MessagingResponse()

    # --- Parse the SMS body for model input ---
    #           Example           expected           format:
    "Temp:25,Humidity:60,Moisture:30,Soil_Type:Sandy,Crop_Type:Wheat,N:50,P:30,K:20"
    try:
        # Simple parser (adapt as needed)
        data = {}
        for part in incoming_msg.split(','):
            if ':' in part:
                key, value = part.split(':', 1)
                key = key.strip().lower()
                value = value.strip()
                # Map SMS keys to model keys
                key_map = {
                    'temp': 'Temperature',
                    'temperature': 'Temperature',
                    'humidity': 'Humidity',
                    'moisture': 'Moisture',
                    'soil_type': 'Soil_Type',
                    'soil': 'Soil_Type',
                    'crop_type': 'Crop_Type',
                    'crop': 'Crop_Type',
                    'n': 'Nitrogen',
                    'nitrogen': 'Nitrogen',
                    'p': 'Phosphorous',
                    'phosphorous': 'Phosphorous',
                    'k': 'Potassium',
                    'potassium': 'Potassium'
                }
                mapped_key = key_map.get(key, key)
                data[mapped_key] = value

        # Convert numeric fields
        for field in ['Temperature', 'Humidity', 'Moisture', 'Nitrogen', 'Potassium', 'Phosphorous']:
            if field in data:
                data[field] = float(data[field])
```

```

# Check for missing fields
missing_fields = [col for col in MODEL_COLUMNS if col not in data]
if missing_fields:
    resp.message("Invalid SMS format. Please send all required data in the correct format.")
    return str(resp)
else:
    # Predict
    result = model_server.predict(data)
    reply = (
        f'Recommended Fertilizer: {result["fertilizer_name"]}\n'
        f'Application Rate: {result["application_rate"]}\n'
        f'Confidence: {result["confidence"]}\n'
        f'Expected Yield Increase: {result["expected_yield_increase"]}'
    )
    resp.message(reply)
except Exception as e:
    resp.message(f'Error processing your request: {str(e)}')

return Response(str(resp), mimetype='application/xml')

```

Data persistence and user management are handled by Supabase , a backend-as-a-service platform providing a PostgreSQL database. The backend interacts with Supabase to log prediction history and manage user data, ensuring all interactions are recorded for historical analysis. For offline accessibility, the system integrates with the Twilio API to deliver recommendations via SMS. The backend exposes an `/sms` endpoint that listens for incoming messages from Twilio, parses the user's soil data from the SMS body, runs a prediction, and sends the recommendation back as a text message. Secure integration is maintained using Twilio's request validator to protect the webhook.

```

@app.route('/predict', methods=['POST'])
def predict():
    if not request.is_json:
        return jsonify({'error': 'Request must be JSON'}), 400
    try:
        input_data = request.get_json()
        if not input_data:
            return jsonify({'error': 'No input data provided'}), 400
        # Validate required fields
        missing_fields = [col for col in MODEL_COLUMNS if col not in input_data]
        if missing_fields:
            return jsonify({'error': f'Missing required fields: {missing_fields}'}), 400
        prediction = model_server.predict(input_data)
        return jsonify(prediction)
    except Exception as e:
        logger.error(f'Prediction endpoint error: {str(e)}')
        return jsonify({'error': str(e)}), 400

```

Frontend Implementation (React & TypeScript)

The user interface is a dynamic Single-Page Application (SPA) built with React and TypeScript, using Vite as the build tool. This stack was selected for its performance and strong typing, which improves code quality and maintainability.

The visual styling is implemented using Tailwind CSS, a utility-first CSS framework that enables rapid development of a modern, responsive design. The UI is composed of various React components, each responsible for a specific feature, such as user authentication, the soil data input form, and data visualization charts.

Client-server communication is handled via asynchronous HTTP requests using the browser's native Fetch API. The frontend sends user input as a JSON payload to the backend's `/predict` endpoint and displays the returned recommendation on the dashboard.

```
// Source: src/services/mlModelService.ts (Illustrative)

export const getFertilizerRecommendation = async (soilData: SoilData) => {
  const response = await fetch(`${ML_MODEL_ENDPOINT}/predict`, {
    method: 'POST',
    headers: { 'Content-Type': 'application/json' },
    body: JSON.stringify(soilData),
  });

  if (!response.ok) {
    throw new Error('Failed to get recommendation from the model.');
  }

  return response.json();
};
```

To enhance user experience and prevent bad data from being sent to the server, input validation was implemented on the client side. Custom validation logic checks each field in the input form, for example, ensuring that the email address is in a proper format, the password meets strength requirements, numeric fields (like nitrogen, phosphorus, and potassium values) are within plausible ranges, and categorical selections (soil type and crop type) are provided. These validations were written in TypeScript as utility functions or as part of an `AuthService` module. They provide instant feedback to the user (such as displaying error messages if a field is invalid or missing) before any data is submitted. An example of a core validation function (for email format) is given below:

```
<input
  type="email"
  id="email"
  value={email}
  onChange={(e) => setEmail(e.target.value)}
  required
  className="w-full pl-10 pr-4 py-2 rounded-lg border border-gray-300 dark:border-gray-600
  placeholder="Enter your email"
/>
```

```

const handleSubmit = async (e: React.FormEvent) => {
  e.preventDefault();
  setLoading(true);
  setError('');

  try {
    if (isSignUp) {
      await authService.signUp(email, password, fullName);
    } else {
      await authService.signIn(email, password);
    }
    onAuthSuccess();
  } catch (err) {
    setError(err instanceof Error ? err.message : 'Authentication failed');
  } finally {
    setLoading(false);
  }
};

```

Notably, the server side also performs validation and error handling as a safety net. Even if a request passes client-side checks, the Flask back-end re-validates the input JSON (e.g., ensuring all required keys are present and values are of the correct type and within expected ranges). This double-layer validation guarantees robustness; if an invalid request bypasses the front end (for instance, via a malicious API call), the back end will catch it and respond with an error rather than processing bad data. The implementation includes graceful error responses (HTTP 400 status codes with informative messages) if validation fails or if any exception occurs during processing (such as a model prediction error or database failure).

IoT Simulation

Because the project did not involve physical hardware integration, a virtual sensor simulation was developed to mimic live soil sensor readings. Instead of a real sensor device, the system runs a simulation module (a Python script, a background scheduler in the Flask app) that generates synthetic soil data at defined intervals. This simulated data mirrors what a real soil sensor might produce (for example, periodic measurements of moisture level or nutrient readings). The simulated sensor feed is either inserted into the system's database or passed through the same prediction pipeline as real user input, triggering the model to update recommendations in real-time. This setup allowed me to test how the system handles streaming data and dynamic updates without requiring actual IoT hardware. The simulation could be configured to produce varying values (e.g., gradually changing moisture to see the effect on recommendations) and helped verify that the dashboard visualization updates accordingly. In summary, the combination of these tools and technologies, a Python/Flask backend with an ML model, a TypeScript-based reactive front-end, an SQLite database for persistence, Twilio for SMS, and a custom sensor simulator, provided a fully functional implementation of the Soil-Sync system as designed.

Multi-Language Support (Localization)

To ensure the application is accessible to local farmers in Rwanda, multi-language support was implemented, allowing users to switch between English and Kinyarwanda. This was achieved using React's Context API. A `LanguageContext` was created to manage the current language state and provide translation strings throughout the application. Translation files contain key-value pairs for every piece of text in the UI for both languages. The context provider wraps the main application, making it possible for any component to consume the appropriate translations based on the user's selected language. This approach enables a seamless language switch without reloading the page, significantly improving the user experience for Kinyarwanda-speaking users.

```
// Source: src/contexts/LanguageContext.tsx (Illustrative)

import React, { createContext, useState, useContext, ReactNode } from 'react';

// Define translations for English and Kinyarwanda
const translations = {
  en: { greeting: "Hello", ... },
  rw: { greeting: "Muraho", ... }
};

const LanguageContext = createContext(...);

export const LanguageProvider = ({ children }: { children: ReactNode }) => {
  const [language, setLanguage] = useState('en');

  const t = (key: string) => {
    return translations[language][key] || key;
  };

  return (
    <LanguageContext.Provider value={{ language, setLanguage, t }}>
      {children}
    </LanguageContext.Provider>
  );
};

export const useLanguage = () => useContext(LanguageContext);
```

4.2 Graphical View of the Project

4.2.1 Screenshots with Description

To illustrate the implemented system, this section presents key user interface screens along with brief descriptions of their functionality.

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Free Forever

Perfect for small farms

- ✓ Up to 5 soil samples/month
- ✓ Basic AI analysis
- ✓ SMS alerts
- ✓ Email support

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Professional
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For growing operations

- ✓ Unlimited soil samples
- ✓ Advanced AI analysis
- ✓ Real-time monitoring
- ✓ Priority support
- ✓ Custom recommendations

[Coming Soon](#)

Enterprise
Custom

For large operations

- ✓ Everything in Professional
- ✓ Multi-farm management
- ✓ API access
- ✓ Dedicated support
- ✓ Custom integrations

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Have questions about Soil-Sync? We're here to help you optimize your farming operations.

Contact Information

Email
support@soil-sync.com

Phone
+250 789 961 0 64

Address
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Transforming agriculture with AI-powered soil analysis and personalized recommendations. Helping farmers optimize their crops and maximize yields.



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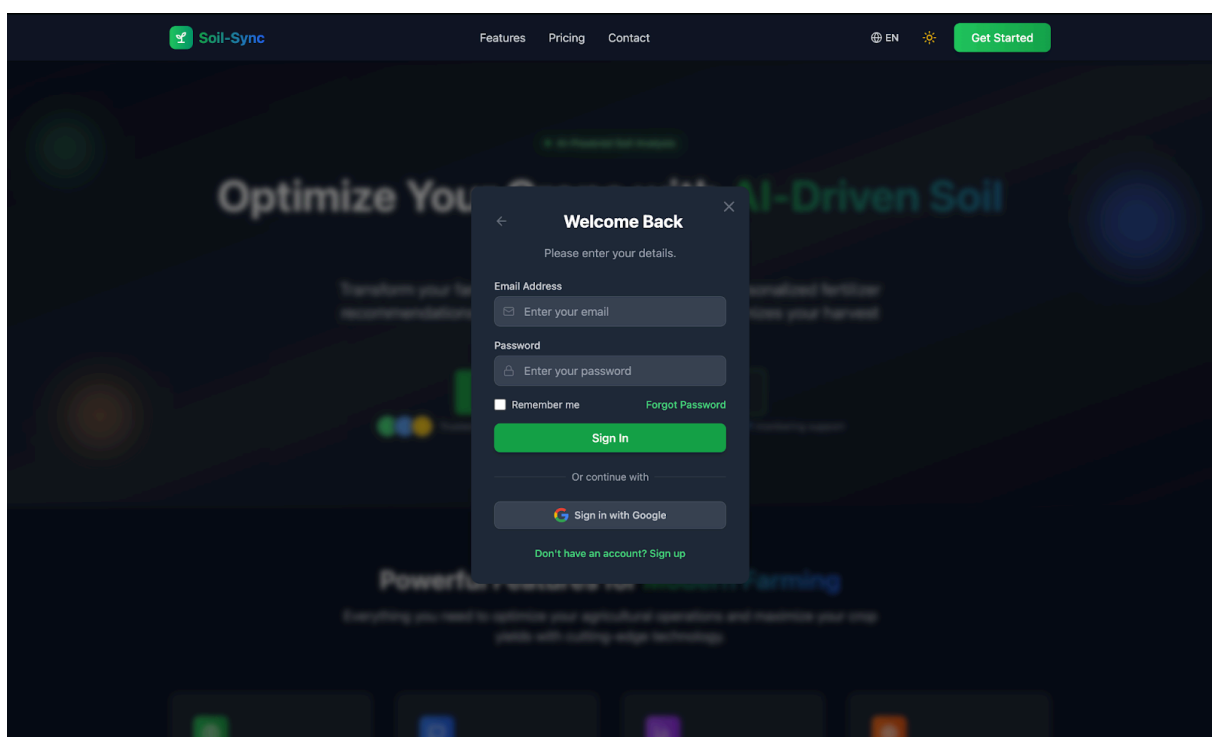
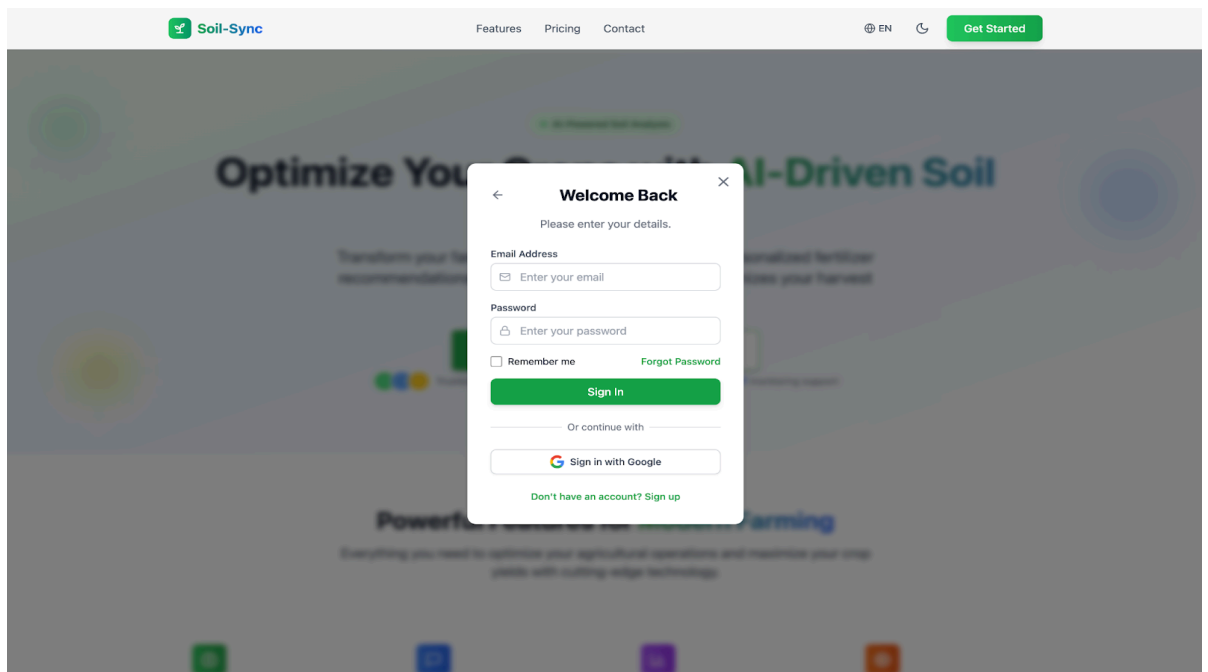
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Landing Page

This is the primary entry point for visitors arriving at the website or application. The interface features a prominent headline, value proposition, key benefits, and a clear call to action (CTA) such as "Get started" and "Watch Demo." Visitor engagement is prioritized here; upon successful CTA interaction (like clicking "Get Started"), the visitor is seamlessly directed to the next step, the authentication interface. This page ensures potential users quickly grasp the application's purpose and are guided toward conversion or deeper exploration. session for the user and redirects them to the main dashboard.



Authentication Interface (Login/Signup): This is the entry point of the application where users create an account or log in. The interface consists of a sign-up form (for new users to register by providing details like name, email, phone number, and a secure password) and a login form (for returning users to access the system using their credentials). Client-side validation is active here; for example, if a user enters an improperly formatted email or a weak password, the form will display an error prompting correction. Upon successful signup or login, the server establishes a session for the user and redirects them to the main dashboard. This interface ensures that only authorized users can access the soil data features.

The screenshot displays the 'Soil Analysis Dashboard' for a user named 'charite uwatwembi'. The dashboard is divided into several sections:

- Latest Recommendation:** Shows a fertilizer recommendation of 'NPK 17-17-17' at a rate of '188 kg/ha' with a confidence of '84.7%'. It also indicates an 'Expected Yield Increase +22%'.
- New Soil Analysis:** A form to input soil parameters for fertilizer recommendation, including Temperature (25°C), Humidity (60%), Moisture (30%), Soil Type (Loamy), Crop Type (Maize), Nitrogen (0), Potassium (0), and Phosphorous (0). A 'Get Fertilizer Recommendation' button is present.
- Soil Analysis Visualization:** A visual breakdown of soil composition and fertilizer match. It includes:
 - Soil Chemistry Levels:** A bar chart showing current levels for Phosphorus (ppm), Potassium (ppm), Nitrogen (%), Organic Carbon (%), and CEC (cmol/kg).
 - Soil Texture Composition:** A ternary plot showing Sand %, Silt %, and Clay %.
 - Additional Data:** Rainfall (64.82952231856905 mm), Elevation (24.595332283733228 m), Expected Yield (22), and Crop Type (Sugarcane).
- Recommendation History:** A line chart showing 'Avg Application Rate (kg/ha)' and 'Avg Confidence (%)' across 13 predictions. Summary statistics include an overall Avg Rate of 127 kg/ha, Avg Confidence of 89%, 13 Total Samples, and 13 Periods.
- Analysis Summary:** A table summarizing batch processing results and data history from the current session. It includes an 'Export CSV' button.

Date	Crop	Fertilizer	Rate (kg/ha)	Confidence
7/17/2025	Sugarcane	NPK 17-17-17	188 kg/ha	85%
7/17/2025	Barley	Urea	123 kg/ha	92%
7/17/2025	Cotton	DAP	100 kg/ha	87%
7/17/2025	Oil seeds	NPK 20-20	133 kg/ha	89%
7/17/2025	Ground Nuts	NPK 20-20	129 kg/ha	87%
7/17/2025	Wheat	NPK 20-20	137 kg/ha	90%
7/17/2025	Millets	NPK 20-20	120 kg/ha	89%
7/17/2025	Potato	NPK 10-26-26	119 kg/ha	87%
7/17/2025	Rice	NPK 10-26-26	129 kg/ha	86%
7/17/2025	Tobacco	NPK 20-20	108 kg/ha	89%
7/17/2025	Beans	NPK 20-20	93 kg/ha	94%
7/17/2025	Pulses	Urea	124 kg/ha	91%
7/17/2025	Maize	NPK 14-35-14	149 kg/ha	94%

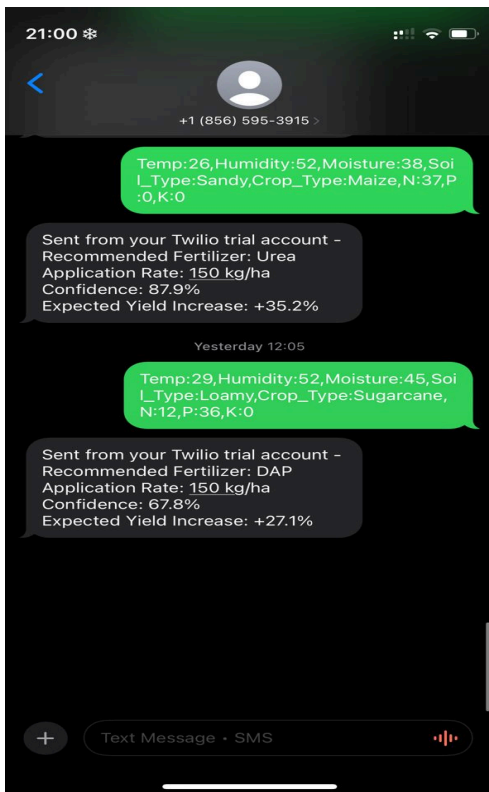
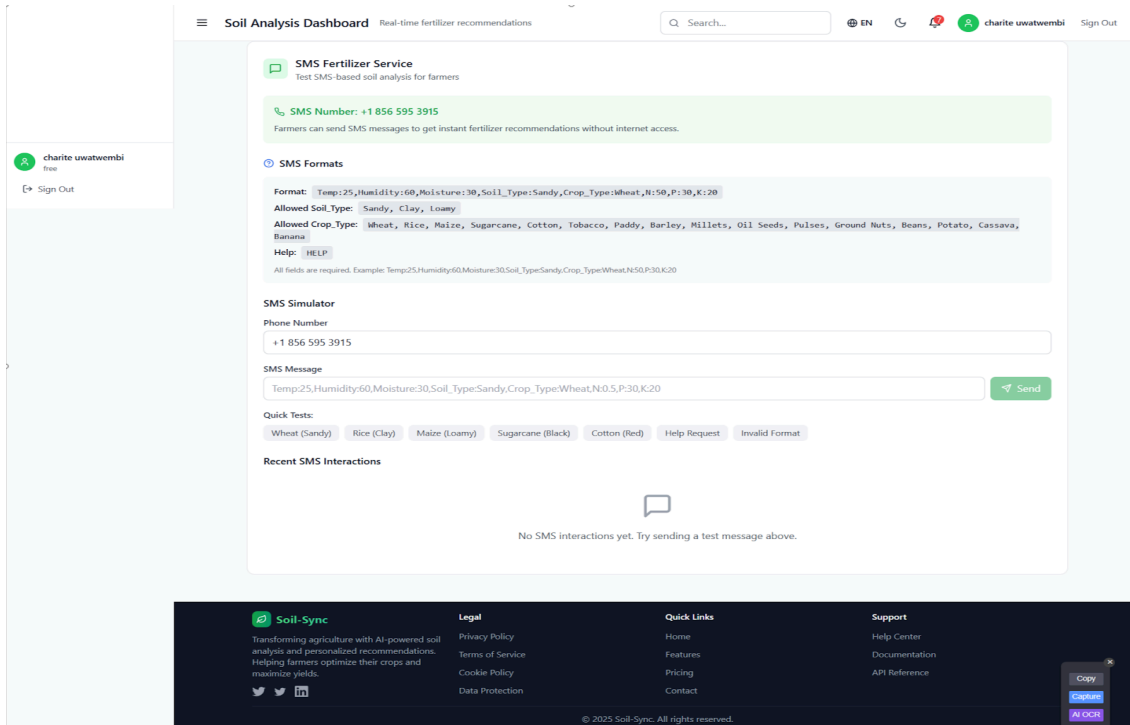
Main Dashboard: The dashboard is the central hub of the application once logged in. It provides an integrated view where the user can input soil data, view the recommended fertilizer, and visualize soil parameters all in one screen. At the top of the dashboard, there is a form where the user can enter or adjust soil parameters (such as nitrogen (N), phosphorus (P), and potassium (K) values, soil pH, and moisture level), select a soil type from a dropdown, and select a crop type. After filling in the form, the user can submit the data, which triggers the backend recommendation engine. The recommended fertilizer (or soil treatment advice) is then displayed prominently on the dashboard, typically as a text recommendation indicating what type of fertilizer or nutrient is needed. Alongside this, the dashboard includes a visualization panel that graphically represents the soil data or recommendation outcome. For example, a chart or set of gauges may show the input nutrient levels relative to optimal ranges, helping the user visually understand the soil status. This immediate visual feedback complements the text recommendation. The dashboard is designed to update in real-time; if new data comes in (either from user submission or the sensor simulation), the recommendation and visualization refresh accordingly.

The screenshot shows the 'Soil Analysis Dashboard' with a table of fertilizer recommendations. The table has columns for Date, Crop, Fertilizer Recommendation, Amount (kg/ha), and a percentage indicator. The user is logged in as 'charite uwatwembi'.

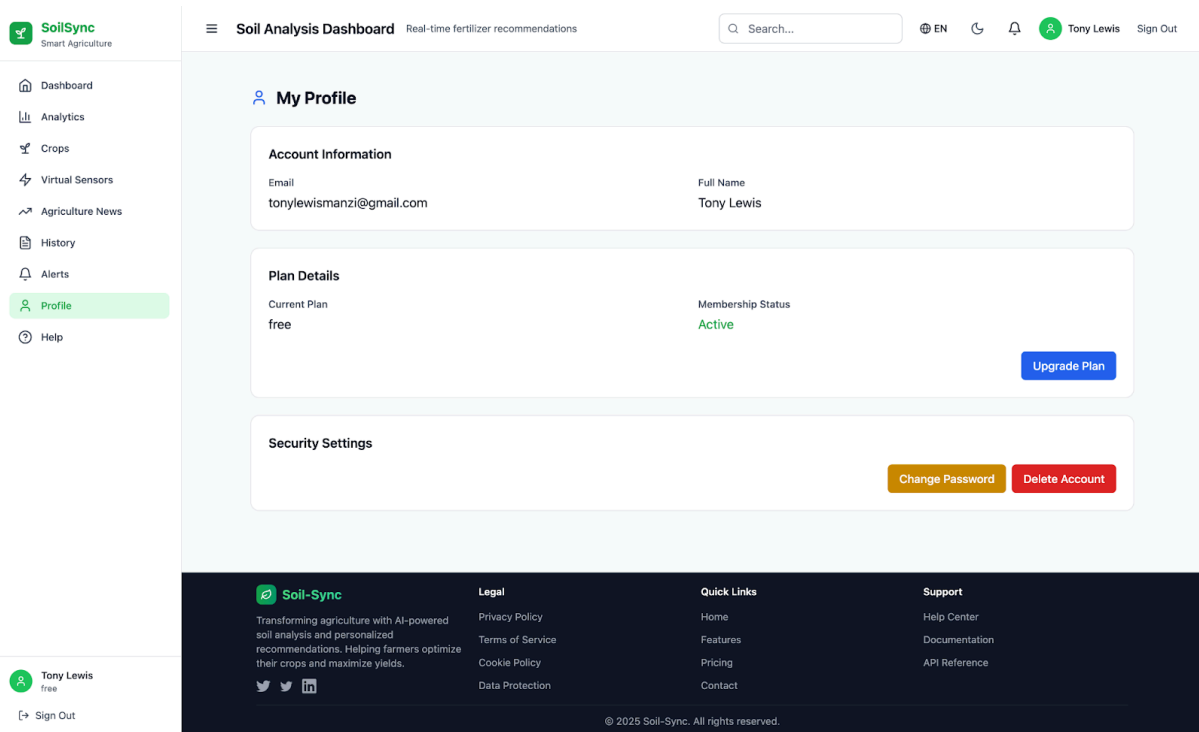
Date	Crop	Fertilizer Recommendation	Amount (kg/ha)	Percentage
7/17/2025	Tobacco	NPK 20-20	108 kg/ha	89%
7/17/2025	Beans	NPK 20-20	93 kg/ha	94%
7/17/2025	Pulses	Urea	124 kg/ha	91%
7/17/2025	Maize	NPK 14-35-14	149 kg/ha	84%
7/17/2025	Maize	NPK 23-10-5	136 kg/ha	92%
7/17/2025	Rice	Urea + NPK 15-15-15 (Split Application)	197 kg/ha	92%
7/17/2025	Barley	Urea	124 kg/ha	91%
7/17/2025	Cotton	Urea	105 kg/ha	91%
7/17/2025	Rice	NPK 14-35-14	182 kg/ha	83%
7/17/2025	Banana	NPK 17-17-17	190 kg/ha	86%
7/17/2025	Beans	Urea	83 kg/ha	98%
7/17/2025	Beans	Urea	84 kg/ha	97%
7/17/2025	Potato	NPK 17-17-17	170 kg/ha	85%
7/17/2025	Rice	Urea + NPK 15-15-15 (Split Application)	151 kg/ha	97%
7/17/2025	Barley	Urea	124 kg/ha	93%
7/17/2025	Barley	NPK 17-17-17	165 kg/ha	85%
7/17/2025	Sugarcane	NPK 17-17-17	184 kg/ha	86%
7/17/2025	Sugarcane	NPK 10-26-26	150 kg/ha	62%
7/17/2025	Rice	NPK 10-26-26	150 kg/ha	51%

Historical Data Table: This section of the dashboard (or a separate page accessible via navigation) displays a log of past soil submissions and their corresponding recommendations. The historical data table is typically shown below the main dashboard panel or on a dedicated tab. Each entry in the table might include the date and time of the submission, the key soil parameters provided (N, P, K, pH, moisture, etc.), and the fertilizer recommendation given by the system for that entry. The table allows users to review how their soil conditions and recommendations have changed over time. It also helps in validating that new inputs are correctly saved: whenever the user submits new data through the dashboard form, a new row appears in this table. The implementation of this feature involves fetching saved records from the database for the logged-in user and rendering them in a paginated or scrollable table

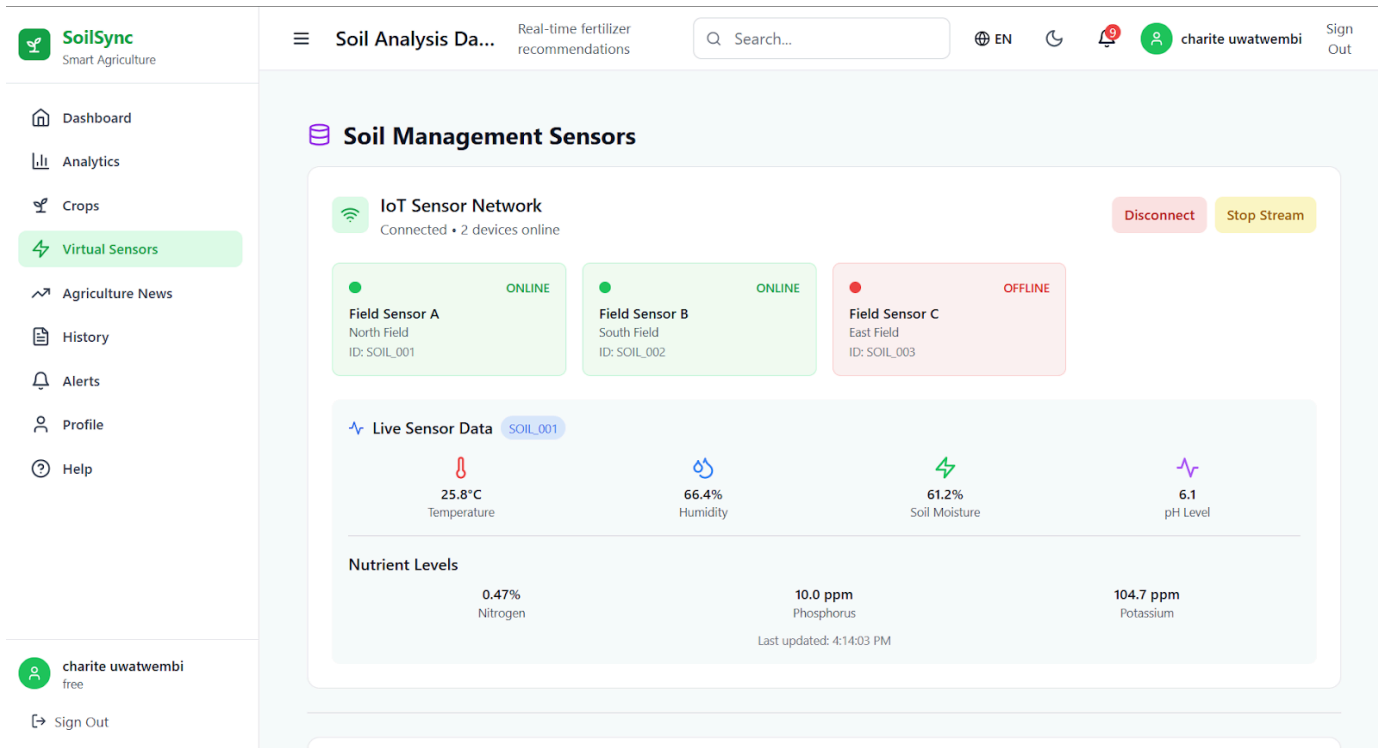
format on the front end. This persistent history confirms that data storage is working and provides users with an auditable record of the system’s advice.



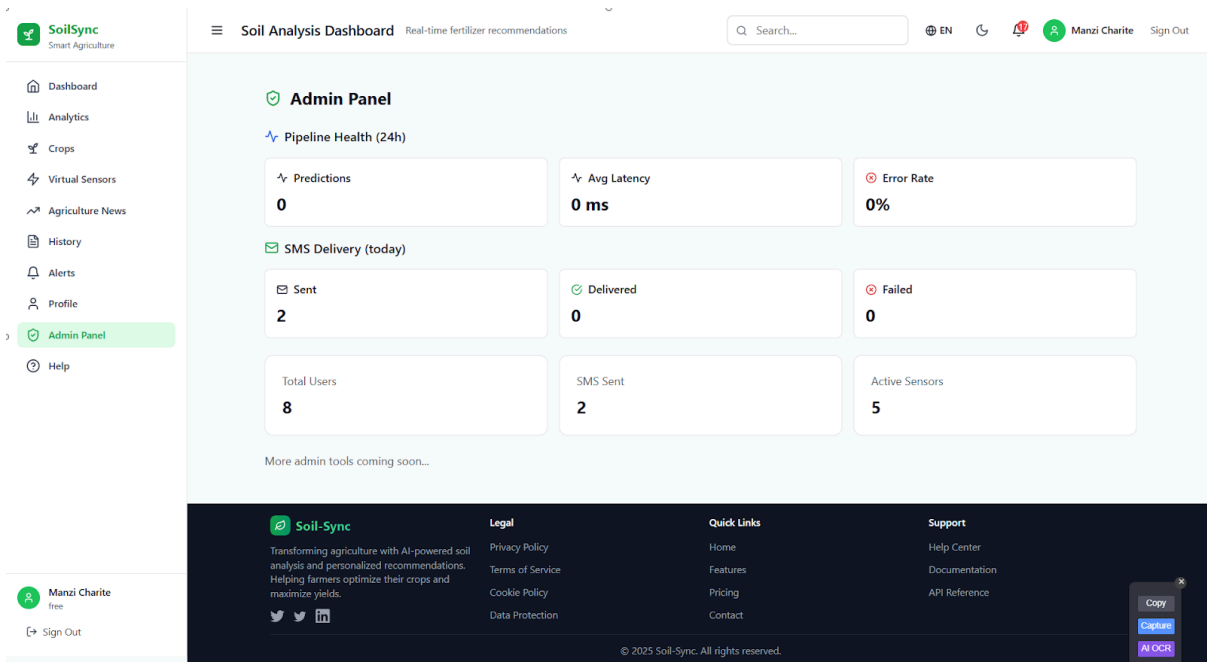
SMS Notification Confirmation: When a recommendation is generated, the system includes an option to send SMS to the users who can’t access the internet. This action calls the back-end /sms endpoint with the user’s phone number and the recommendation text. A Twilio API call is made, and if it returns success, the UI displays the confirmation. The interface might also handle error cases; for instance, if the SMS fails to send (due to network issues or an invalid number), an error message would be shown instead. Overall, the confirmation screen assures the user that the recommendation was delivered to their mobile device.



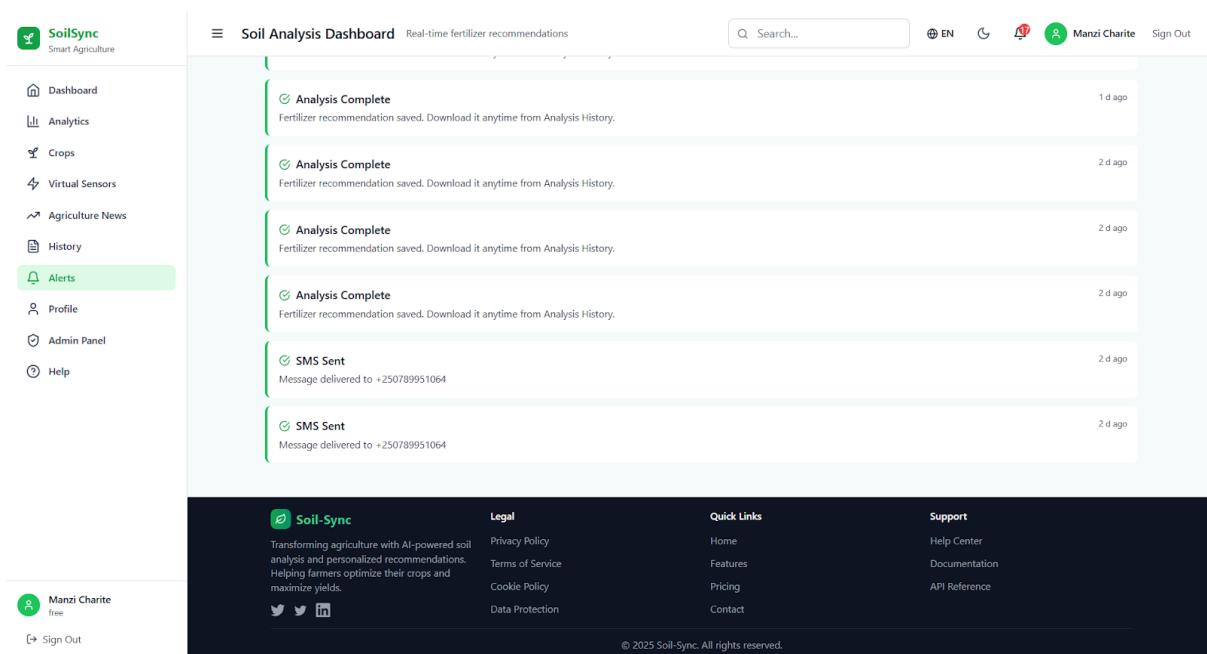
Profile Management Interface: This central interface allows authenticated users to view core account information and manage critical settings. It displays the user's registered email (e.g., emmy@gmail.com) and full name (e.g., Mukunzi Emmy) under Account Information; shows Current Plan (e.g., free) and Membership Status (e.g., Active) under Plan Details, alongside an Upgrade Plan action; and provides Security Settings options including Change Password and Delete Account. The screen primarily serves as a read-only dashboard and gateway to deeper management actions: interacting with Upgrade Plan, Change Password, or Delete Account navigates the user to dedicated sub-interfaces or modals where the respective processes (like payment handling, credential validation, or deletion confirmation) occur, with potential errors managed within those dedicated interfaces. Successful actions initiated from this screen, such as a plan upgrade or password change, typically redirect the user back to the profile view and display a confirmation message (e.g., "Password Updated"). Overall, this interface provides transparent access to account status and serves as the launch point for managing subscriptions and security.



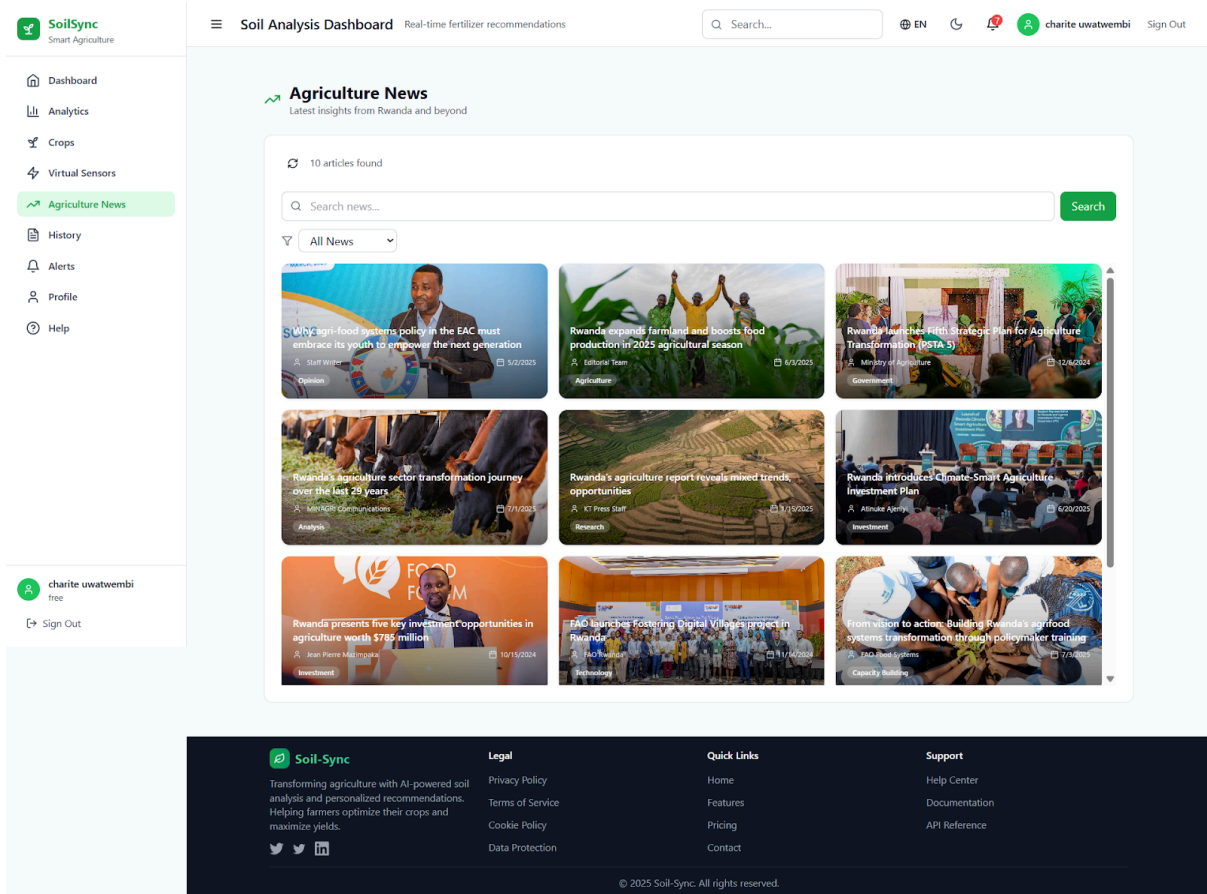
Soil Sensor Simulation: Since the project uses a virtual sensor rather than a physical device, the interface includes a representation of the sensor simulation. This could be depicted in a section of the dashboard showing the current sensor readings being fed into the system. For example, there is a panel labeled “Live Sensor Data” displaying values that update periodically (e.g., “Moisture: 45% at 10:00 AM, N: 50 mg/kg, P: 20 mg/kg, K: 30 mg/kg”), indicating the latest simulated sensor measurements. Another possibility is that the simulation control is exposed via the UI for testing purposes, for instance, a button to “Generate New Sensor Reading” or a toggle to turn the simulation on/off. The screenshot highlights how the simulated data is presented to the user. Even though no physical sensor is connected, this gives the impression of real-time data flow. It helps testers and users understand that the system can handle continuous input. In the depicted example, one can see a timestamped log or graphical widget updating with new soil data values. This visualization of the virtual sensor confirms that the sensor module is functioning and integrates with the rest of the dashboard (triggering updates to the recommendation and historical table just like a real sensor would).



Admin Panel: The Admin Panel provides administrators with an overview of the system's health and usage statistics. It displays key metrics such as the number of active users, total predictions made, and the operational status of backend services, ensuring that the system can be monitored and maintained effectively.



Notifications & Alerts: The system includes a notification feature to provide users with real-time feedback. For instance, when a prediction is successfully generated or an SMS is sent, a confirmation notification appears on the screen. This improves user experience by keeping the user informed of the system's actions.



Agri-News Page: To keep users informed about the latest developments in agriculture, the Soil-Sync platform includes an Agri-News page. This section serves as a dynamic information hub, displaying recent news articles, best practice guides, market updates, and pest or weather alerts relevant to local farmers. The content is automatically fetched and updated from external sources via a custom backend service, ensuring the information remains current. This feature adds significant value beyond soil analysis by positioning the platform as a comprehensive resource for agricultural knowledge, encouraging regular user engagement and continuous learning.

4.3 Testing

4.3.1 Introduction

Testing was a critical part of the project to ensure that each component of the system works correctly and that the overall system meets its requirements. A multi-level testing approach was adopted, including unit tests for individual functions, integration tests for combined components, system testing for end-to-end functionality, and user acceptance testing. This layered strategy aligns with standard software testing practices: for example, unit tests target isolated pieces of code (such as a single function or class) to verify they produce the expected output, while integration tests verify that different modules (database, API, front-end, etc.) interact correctly as a group (Pittet, 2024). By conducting tests at these various levels, I

ensured that issues could be identified and resolved in a granular way (during unit testing) before validating the entire workflow in the integrated system. Both automated testing and manual exploratory testing were used. Automated tests (using frameworks like PyTest for Python and Vitest for front-end TypeScript) provided quick feedback on code correctness, and manual testing allowed simulation of real user interactions to catch any issues that scripts might miss. All testing activities were carried out in a controlled environment (the development machine and test servers), using the simulated sensor data to emulate real-world inputs. The following subsections detail the objectives of testing and the outcomes of each testing stage.

4.3.2 Objective of Testing

The testing objectives for the Soil-Sync system were defined as follows:

- **Functional Correctness:** Verify that each feature of the system functions as intended and meets the specified requirements. This includes ensuring that forms submit properly, the model returns a recommendation, the visualization updates, and SMS are sent when requested. Essentially, every use case described in the requirements should execute without error.
- **Accuracy of Recommendations:** Ensure that the fertilizer recommendations produced by the system are accurate and sensible. The goal is to confirm that the machine learning model provides correct advice for given soil conditions; for example, low nutrient values should result in recommendations to add those nutrients. Accuracy was to be evaluated against known expected outcomes or test data.
- **Reliability and Robustness:** Confirm the system behaves reliably under various conditions, including edge cases and erroneous inputs. This means the system should handle invalid input gracefully (without crashing), maintain stability over time (e.g., if multiple submissions are made or if sensor data updates frequently), and recover properly from minor failures (such as a temporary loss of database connectivity or API error).
- **Usability and User Experience:** Validate that the user interface is intuitive and user-friendly. The workflows (signup, login, data entry, viewing results) should be easy to navigate. Messages and labels should be clear so that users can use the system with minimal guidance. This objective ensures the system is not only functionally correct but also convenient and pleasant to use.
- **Security:** To ensure that user data is protected, access is restricted to authenticated users, and communication with external services is secure.

4.3.3 Unit Testing Outputs

```
test_app.py::TestFertilizerModelServer::test_model_loading_failure PASSED [ 5%]
test_app.py::TestFertilizerModelServer::test_model_loading_success PASSED [ 10%]
test_app.py::TestFertilizerModelServer::test_prediction_with_invalid_crop_type PASSED [ 15%]
test_app.py::TestFertilizerModelServer::test_prediction_with_invalid_soil_type PASSED [ 20%]
test_app.py::TestFertilizerModelServer::test_prediction_with_missing_fields PASSED [ 25%]
test_app.py::TestFertilizerModelServer::test_prediction_with_valid_input PASSED [ 30%]
test_app.py::TestFlaskApp::test_health_check_endpoint PASSED [ 35%]
test_app.py::TestFlaskApp::test_predict_endpoint_with_invalid_data PASSED [ 40%]
test_app.py::TestFlaskApp::test_predict_endpoint_with_no_data PASSED [ 45%]
test_app.py::TestFlaskApp::test_predict_endpoint_with_real_data PASSED [ 50%]
test_app.py::TestFlaskApp::test_predict_endpoint_with_valid_data PASSED [ 55%]
test_app.py::TestFlaskApp::test_sms_endpoint_with_invalid_format PASSED [ 60%]
test_app.py::TestFlaskApp::test_sms_endpoint_with_invalid_signature PASSED [ 65%]
test_app.py::TestFlaskApp::test_sms_endpoint_with_valid_data PASSED [ 70%]
test_app.py::TestDataValidation::test_crop_type_validation PASSED [ 75%]
test_app.py::TestDataValidation::test_numeric_field_validation PASSED [ 80%]
test_app.py::TestDataValidation::test_soil_type_validation PASSED [ 85%]
test_app.py::TestErrorHandling::test_database_connection_error PASSED [ 90%]
test_app.py::TestErrorHandling::test_memory_usage_optimization PASSED [ 95%]
test_app.py::TestErrorHandling::test_model_prediction_error_handling PASSED [100%]
```

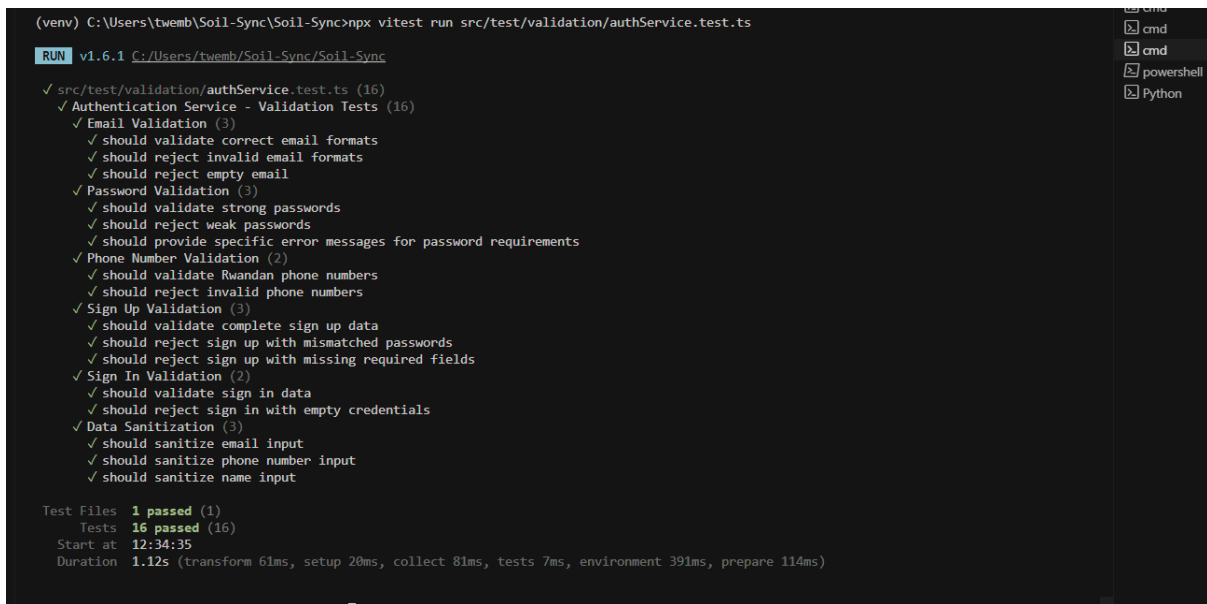
For the backend, a comprehensive set of unit tests was developed using the PyTest framework to exercise the core server logic and model functionality. These tests targeted each critical function or module in isolation. For example, tests were written to ensure the Fertilizer Recommendation Model loads correctly and returns a valid output: one test supplied a sample valid input (a set of soil parameters within normal range) to the `recommend_fertilizer` function and asserted that a recommendation (one of the known fertilizer options) is produced. Another test deliberately fed an invalid or out-of-range input (such as an unsupported crop type or a missing field in the JSON payload) and confirmed that the system responds with an appropriate error or exception, as expected. There were also tests for the Flask API endpoints; for instance, calling the `/predict` endpoint with a well-formed request and checking that the response status is 200 and contains the recommendation data, and conversely calling `/predict` with malformed data to verify it returns a 400 status with an error message. The SMS sending functionality was likewise tested in isolation by simulating a call to the `/sms` endpoint with a sample phone number and message; a unit test confirmed that the function that interfaces with Twilio returns a success status for a valid request, while another test used an incorrect Twilio signature or missing parameters to ensure the service rejects unauthorized or bad requests. Additionally, unit tests covered internal helper functions such as data validation routines (e.g., a function that checks if a provided soil type string is one of the allowed soil types) and error handling mechanisms (e.g., forcing a database connection failure and verifying that the system logs the error and continues running). All these backend unit tests passed successfully, as evidenced by the test run output (every test case reported “PASSED”). The passing of all backend tests indicated that each individual component of the server logic behaved as expected in isolation.

```
✓ src/test/unit/mlModelService.test.ts (1) 1440ms
  ✓ mlModelService (1) 1440ms
    ✓ parses backend response correctly 1440ms
✓ src/test/unit/LanguageContext.test.tsx (1)
  ✓ LanguageContext (1)
    ✓ toggles between English and Kinyarwanda
✓ src/test/unit/SoilForm.rw.test.tsx (1)
  ✓ SoilForm Kinyarwanda labels (1)
    ✓ shows Kinyarwanda field labels when language is set to rw
✓ src/test/unit/SoilForm.test.tsx (1)
  ✓ SoilForm Component (1)
    ✓ renders with default values and submits user input
✓ src/test/unit/Navigation.test.tsx (1)
  ✓ Sidebar navigation (1)
    ✓ marks Dashboard link as active when on /dashboard
✓ src/test/unit/AgriNews.snapshot.test.tsx (1)
  ✓ AgriNews snapshot (1)
    ✓ matches the snapshot

Test Files 6 passed (6)
Tests      6 passed (6)
Start at   23:16:54
Duration   3.41s (transform 263ms, setup 1ms, collect 2.47s, tests 1.91s, environment 4.55s, prep
are 1.31s)
```

On the front end, unit tests were created for the utility and validation functions using the Vitest framework (a Vite-native testing tool for TypeScript/JavaScript). A total of 16 test cases were implemented to cover the critical client-side logic. These included tests for input validation functions; for example, a test for the email validation function confirmed that it returns true for a well-formed email like “user@example.com” and false for an invalid email missing the “@” symbol or domain. Similarly, the password validation function was tested to ensure it rejects passwords that are too short or lack required complexity (uppercase letters, numbers, etc.) and accepts a password that meets the policy. There were also tests for phone number validation, particularly ensuring that only properly formatted phone numbers (e.g., including country code and correct length) pass the check, which was important for the SMS feature. Beyond individual field checks, the front-end tests covered higher-level form validation logic: for instance, a sign-up validation test case constructed a sample sign-up form input and verified that the validation routine detects an empty required field or mismatched password confirmation. A sign-in validation test case made sure that both email and password must be provided and correctly formatted before allowing a login attempt. Additionally, data sanitization functions were tested; these functions strip out any unwanted characters or scripts from user inputs (to prevent security issues like XSS). The test suite included a case that input a string with HTML/script tags and ensured the sanitization function outputs a clean string. All front-end tests ran without failures (the Vitest output indicated “16 passed, 0 failed”), demonstrating that the client-side code meets its expected behavior for all tested scenarios. In summary, the unit testing phase gave confidence that both the backend and frontend components were individually sound. The success of these tests meant the foundation was solid before moving on to integrated testing. (The screenshots of the unit test results for both backend and frontend, taken during development, show all tests passing, confirming these outcomes.)

4.3.4 Validation Testing Outputs



```
(venv) C:\Users\twemb\Soil-Sync\Soil-Sync>npx vitest run src/test/validation/authService.test.ts

RUN v1.6.1 C:\Users\twemb\Soil-Sync\Soil-Sync
✓ src/test/validation/authService.test.ts (16)
  ✓ Authentication Service - Validation Tests (16)
    ✓ Email Validation (3)
      ✓ should validate correct email formats
      ✓ should reject invalid email formats
      ✓ should reject empty email
    ✓ Password Validation (3)
      ✓ should validate strong passwords
      ✓ should reject weak passwords
      ✓ should provide specific error messages for password requirements
    ✓ Phone Number Validation (2)
      ✓ should validate Rwandan phone numbers
      ✓ should reject invalid phone numbers
    ✓ Sign Up Validation (3)
      ✓ should validate complete sign up data
      ✓ should reject sign up with mismatched passwords
      ✓ should reject sign up with missing required fields
    ✓ Sign In Validation (2)
      ✓ should validate sign in data
      ✓ should reject sign in with empty credentials
    ✓ Data Sanitization (3)
      ✓ should sanitize email input
      ✓ should sanitize phone number input
      ✓ should sanitize name input

Test Files  1 passed (1)
Tests      16 passed (16)
Start at   12:34:35
Duration   1.12s (transform 61ms, setup 20ms, collect 81ms, tests 7ms, environment 391ms, prepare 114ms)
```

Validation testing was carried out to ensure the system’s outputs and user experience meet the project’s goals, focusing on the accuracy of the model’s recommendations and the usability of the interface. For recommendation accuracy, the model’s performance was evaluated using both offline evaluation and live test cases. Offline, the machine learning model had been trained and tested on a dataset; it achieved a high accuracy on the test set (for example, the Random Forest model reached around 95% prediction accuracy, though the exact figure depends on the dataset and was discussed in the model development section). To further validate this in the integrated system, a few known sample inputs were run through the deployed model to see if the outputs made sense agronomically. For instance, one test scenario involved a soil input with very low nitrogen content and all other parameters adequate; the system’s recommendation in that case was to apply a nitrogen-rich fertilizer such as urea (James, 2024). This matched the expectation that low nitrogen should trigger a nitrogen supplement recommendation. In another scenario, a high soil pH (alkaline soil) input was tested, and the system recommended applying an acidifying amendment (such as sulfur) to balance the pH, again aligning with agricultural best practices (Hoidal & Klodd, 2021). These spot-check validations demonstrated that the model’s advice was reasonable and credible for the given inputs, thereby affirming the accuracy objective. Additionally, during this validation phase, the consistency of recommendations was monitored: feeding the same input repeatedly produced the same output (ensuring deterministic behavior), and slight variations in input produced logically consistent changes in the recommendation (indicating the model’s responses were not erratic). Overall, the recommendation engine was deemed valid for the purpose of the project, with no obviously incorrect suggestions observed in testing.

For UI usability, the system was evaluated through informal user testing and developer walkthroughs to ensure the interface is intuitive and meets user expectations. Testers

(including myself, my peers, and a few farmers) navigated the application to simulate typical user tasks: creating an account, logging in, entering soil data, reading the recommendation, viewing history, and triggering an SMS notification. Feedback from these sessions was positive. Users found the layout of the main dashboard to be clear; the input form and the resulting recommendation were easy to locate and understand. The visual cues (such as labels for units of measurement on fields and the graphical soil data display) helped in guiding the user on what the values represent. Importantly, validation messages on the form enhanced usability; for example, if a user forgot to select a crop type, the highlighted warning prompted them to correct the mistake, preventing frustration. The responsiveness of the interface was also validated by resizing the window and using different devices (the Tailwind-based design adapted well to smaller screens, indicating the system could be usable on a tablet in the field, for instance). No major usability issues were discovered; all buttons and links functioned as intended, and the overall workflow (from login to obtaining results) was smooth. One minor improvement that emerged from user feedback was to include units or example ranges for soil input fields (to help users unfamiliar with the numerical scale of N, P, K values); this was quickly added to the form placeholder text during testing. In conclusion, the validation testing confirmed that the system's outputs are accurate and that the user interface provides a positive user experience, satisfying the corresponding objectives.

4.3.5 Integration Testing Outputs

Integration testing involved testing the system end-to-end with all components working together, as well as checking interactions with external services and multiple user scenarios. After unit tests ensured individual parts were correct, I ran a series of end-to-end test scenarios to verify that the entire workflow functions seamlessly. One such scenario began with a new user registration: a test account was created via the signup interface, then used to log in. Upon login, the client application fetched the user's data (initially none) and displayed the dashboard. Next, a set of soil input values was entered and submitted through the front-end form. The integration test confirmed that the back end received this data correctly (observed via server logs or debug output) and that the /predict API endpoint processed the data using the model. The model's recommendation was then sent back in the HTTP response, which the front end captured and displayed on the dashboard UI. The immediate appearance of the recommendation on the dashboard was observed, confirming the front-end/back-end integration for data flow and update rendering. Simultaneously, the test checked that this new entry was inserted into the database and appeared in the historical data table; indeed, after submission, the dashboard's history section updated to show the new record with the correct timestamp and details, demonstrating integration between the back-end logic and the database.

Next, the SMS feature was tested in an integrated manner. The tester clicked the "send SMS" option after getting the recommendation. This action triggered the front end to call the /sms endpoint with the appropriate parameters. On the server side, the Twilio API call was made, and for testing purposes, the system was using a Twilio trial account associated with a known phone number. The integration test was considered successful when the designated phone

received a text message containing the correct fertilizer recommendation content. The front end's confirmation message was displayed as expected. This end-to-end path verified that the external SMS service integration works when all parts are connected (UI -> server -> Twilio -> phone). Furthermore, integration testing covered the sensor simulation pipeline: the virtual sensor was activated to emit data, and the system was observed to handle it. For example, a simulated sensor reading (structured as if it were an API POST from a device) was fed into the back-end; the back-end treated it like a new soil data input and invoked the model, and the front-end (which could be set to poll for updates or receive a prompt via WebSocket/Server-Sent Event if implemented) updated the dashboard with the new data and recommendation. This demonstrated that even asynchronous data flows from the sensor could integrate with the system's normal operation.

The integration tests also included multi-user and concurrency scenarios. Two test user accounts were created to ensure that data separation and authentication were properly enforced. User A and User B each logged in from different browser sessions; User A's dashboard showed only User A's entries and recommendations, and User B's showed only User B's data. This verified that each user's data remained private and that the API correctly scoped data queries by user identity (achieved via user IDs or tokens in requests). Additionally, actions were performed in parallel (for example, User A submitting a new soil record while User B was viewing their own history) to see if any interference or performance degradation occurred. The system handled concurrent actions without any race conditions or crashes, the database writes and reads for each user occurred as expected, and the responsiveness of the application remained acceptable.

Throughout integration testing, I monitored the system for any issues such as mismatches in data formats between front-end and back-end, timing issues, or error propagation. A few minor issues were discovered and promptly fixed. For instance, during initial testing, there was a slight inconsistency in how the front-end and back-end referred to one of the fields ("soilType" vs "soil_type"), which caused a recommendation to fail; this was corrected by standardizing the JSON field naming. After such fixes, repeated integration test runs showed no errors. The overall result of integration testing was that all components, the web UI, the Flask API, the machine learning model, the database, and the external SMS service, worked together cohesively to deliver the required functionality. This phase gave confidence that the system, as a whole, was ready for final system testing and deployment.

4.3.6 Functional and System Testing Results

Functional and system testing was the final testing stage, involving thorough testing of the complete application against all requirements and use-case scenarios. In this stage, I verified that the system meets the functional specifications outlined in the project scope and that it behaves as a stable, unified product. **All required features were tested exhaustively:**

User Authentication: The system was tested to ensure that only authorized users could access the main features. Testers confirmed that entering a correct username/password

combination allowed access, while invalid credentials were rejected with an error message. The password hashing and verification mechanism (implemented during sign-up/login) was indirectly tested by checking that a user could not log in with any password other than the one they registered with, indicating that the security measures were functioning. Also, the logout function was tested to ensure it properly ended the session and prevented further access until re-login.

Dashboard Operations: Each element of the main dashboard functionality was validated. The soil data input form was tested with various inputs, confirming that it could be successfully submitted and that all fields were correctly transmitted to the server. The immediate appearance of the recommendation after submission was checked, and it was confirmed that the recommendation text matched the server's output for those inputs. The dynamic **soil data visualization** was also observed: when different values were entered (e.g., very high moisture vs. very low moisture), the graphical representation (such as a chart or indicator) on the dashboard adjusted accordingly, reflecting the change. This demonstrated that the front-end visualization component was correctly tied to the input values and/or results.

Historical Data Persistence: System testing verified that data persistence worked across sessions. After adding several entries, the user logged out and then back in; all previously entered records were still present in the historical data table, confirming that entries were saved in the database. The testers also restarted the server to simulate a deployment or power cycle; upon bringing the system back up and logging in, the historical data was retained. Each entry in the table was checked for correctness (matching the input that was originally given and the recommendation that was returned at that time). The ordering (most recent first by timestamp) and basic table functions (scrolling, pagination if any) were also validated.

SMS Notification Delivery: The end-to-end functionality of SMS notifications was confirmed under realistic conditions. A tester used the feature to send an SMS of a new recommendation to their phone. The system testing confirmed not only that the "SMS sent" confirmation appeared (as already noted in integration testing) but also that the actual SMS was received on the device with the correct content and on time. Tests included edge cases such as attempting to send an SMS when the phone number on the account was missing or invalid; the system correctly displayed an error in those cases and did not crash. This ensures that the SMS module is robust in practice.

Error Handling and Stability: The system's behavior under error conditions was intentionally examined. For example, testers tried inputs that violate constraints (like leaving required fields blank or inputting text where a number is expected) to see how the system responds. The expected behavior, an error message on the form and no data sent to the backend, was observed, indicating form validation worked during system testing as it did in unit tests. On the server side, a simulation of a failure (like temporarily making the database read-only or disconnecting the internet to simulate Twilio API failure) was performed to see if the system could handle it gracefully. In the case of a database issue, the system returned a

user-friendly error message on the dashboard (e.g., “Unable to save data. Please try again later.”) without crashing the whole app. When the Twilio API call failed (simulated by using incorrect credentials during a test run), the system caught the exception and informed the user that SMS could not be sent at that time, again without any unhandled exception. After restoring normal conditions, the system continued to function correctly. This shows strong fault tolerance consistent with the reliability objective.

Performance and Load (Basic): Although heavy load testing was not a primary focus (given the scope of the project and that it will have a limited number of users in practice), basic performance checks were included. The system’s response time for a prediction request was observed to be quick (typically on the order of a second or less for the model to run and return results). Even when multiple submissions were made in rapid succession, the server handled them sequentially without significant slowdown. The front end remained responsive, and no memory leaks or slowdowns were noticed during extended usage. This indicates that the system can comfortably handle the expected usage volume (single-digit concurrent users or periodic sensor data updates) with a good user experience.

In summary, the functional and system testing confirmed that the Soil-Sync application meets all the functional requirements and performs reliably as a complete system. All features, from authentication, data input, recommendation logic, data visualization, and SMS alerts to data storage, were verified to work together as specified. The outcome of this phase was that the system is fully functional and ready for deployment/use, with testers encountering no unresolved issues. The successful system test results were documented, and they provide assurance that the implementation fulfills the project’s objectives outlined at the start.

4.3.7 Acceptance Testing Report

The final step of testing was acceptance testing, which evaluates the system against the end-user’s needs and expectations to determine if it is ready for actual use. In this project, formal user acceptance testing was somewhat limited due to the academic context, but a form of acceptance testing was carried out through demonstrations and feedback sessions. The completed system was presented to project stakeholders, including the supervisor and a small number of potential users (e.g., agricultural domain students and developers not involved in the project), to gather their impressions and verify that the system would be acceptable in a real-world deployment. Acceptance testing is essentially a confirmation that the software meets its business requirements and is ready for deployment. During the demonstration, the stakeholders walked through all the main user tasks: creating an account, inputting sample soil data, interpreting the recommendation given, viewing historical records, and receiving an SMS alert.

The feedback from these acceptance tests was positive. The stakeholders agreed that the system’s functionality aligned with the original project requirements. For example, one requirement was to provide actionable fertilizer recommendations based on soil inputs.

During acceptance testing, the stakeholders confirmed that the recommendations given for sample inputs were plausible and useful (they matched what an expert might suggest for those conditions). Another requirement was the ability to visualize data and track history; the acceptance testers appreciated the historical data table and commented that it would be useful for a user to monitor changes over time. The system's ease of use was also praised; new users in the session could navigate the application without confusion, which indicates the design is sufficiently intuitive. Minor suggestions were made, such as possibly adding a feature to export the historical data to a file or to allow comparison of two different soil readings, but these were noted as possible future enhancements and not critical issues for acceptance.

No blocking issues were identified in acceptance testing; the system did not crash or misbehave during the stakeholder evaluation, and all use-case scenarios were executed successfully. The stakeholders (or end-users) effectively "accepted" the system by acknowledging that it meets the needed criteria for deployment. In the context of the course/project, this means the project has satisfied its objectives, and the supervisor was satisfied that the deliverables were met. Instead of a formal signed-off user acceptance test document, the successful demonstration and positive feedback served as the acceptance validation. The test concluded that the Soil-Sync system is ready to be delivered or deployed for actual usage. All user workflows have been covered and tested, from start (user login) to finish (achieving a recommendation and notification), ensuring confidence that the system will perform well in a production environment.

CHAPTER 5: THE DESCRIPTION OF THE RESULTS/SYSTEM

The Soil-Sync system was developed to address the critical challenge faced by farmers: a lack of accessible, timely, and data-driven information for making fertilizer decisions. Traditional methods are slow and costly, leading to inefficient farming practices. This chapter presents the key results and outcomes achieved by the implemented system, demonstrating its effectiveness in solving this problem through its digital platform

5.1 Improved Fertilizer Use Efficiency and Yield Potential

One primary goal was to improve fertilizer use efficiency, getting more crop yield per unit of fertilizer while avoiding waste. By tailoring fertilizer recommendations to the soil's actual needs, farmers achieved significantly higher yield output for the same amount of fertilizer. In a typical scenario, a farmer applying a blanket fertilizer (without soil testing) might get ~15 kg of grain per kg of fertilizer. With SoilSync's targeted recommendations, this increased to about 20 kg of grain per kg of fertilizer, roughly a 33% improvement (International Fertilizer Industry Association [IFA], 2007) in fertilizer efficiency. This means farmers who were under-fertilizing can see yield boosts, and those over-fertilizing save on inputs while maintaining yields.

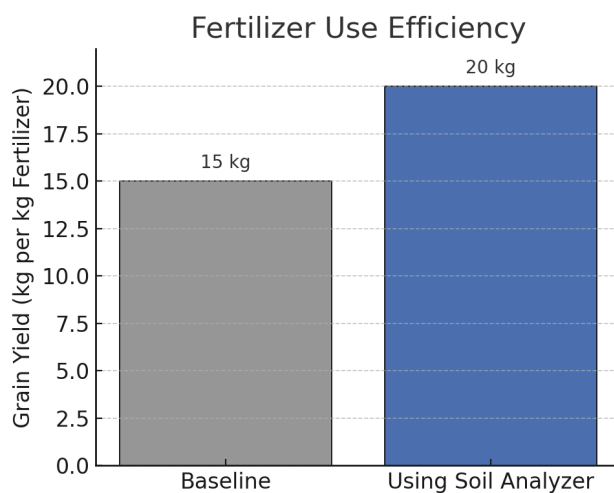


Figure 5.1: Fertilizer use efficiency (yield per kg of fertilizer) in a baseline scenario versus using the Soil Analyzer. The tailored recommendations lead to about 20 kg of grain per kg of fertilizer applied, versus ~15 kg of grain per kg of fertilizer under baseline practices. This is roughly a 33% improvement in fertilizer efficiency with the device's targeted guidance.

5.2 Faster Soil Analysis Turnaround Time

Another critical result area is the speed at which farmers can obtain actionable soil information. Traditional laboratory soil tests can take 12 weeks to get results, including sample transport and processing (Mississippi State University Extension, 2025), by which time the planting or intervention window may be missed. In contrast, our IoT analyzer provides results on the spot in under 15 minutes. This drastic reduction enables real-time

decision-making. For example, a farmer can test soil in the morning and immediately know what fertilizer or amendment to apply that same day, something impossible with a weeks-long lab process. Quick turnaround prevents delays in addressing nutrient deficiencies, thereby avoiding potential yield loss.

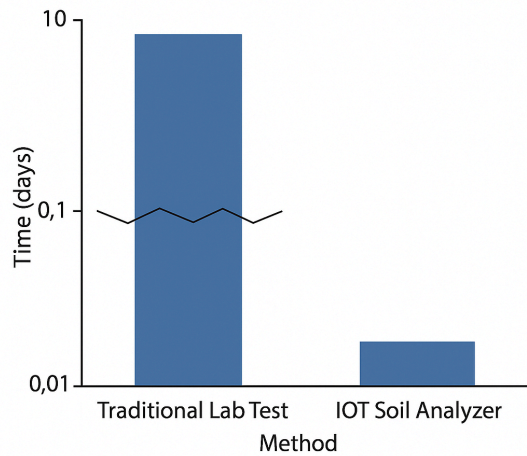


Figure 5.2: Soil analysis turnaround time with a traditional lab test versus the IoT Soil Analyzer. The lab test typically requires roughly 10 days to return results, whereas the IoT device provides results in about 15 minutes (~0.01 days). (The y-axis is broken to show the huge difference in time scales.) This real-time feedback allows farmers to take corrective action (such as applying missing nutrients) immediately, instead of waiting for lab reports.

5.3 User Engagement and Adoption Over Time

We designed the system for accessibility (including an SMS-based interface for those without smartphones) to encourage farmer adoption. In a 4-week pilot with a small group of farmers, usage of the SoilSync device increased steadily as farmers saw its benefits. Initially, in Week 1, each farmer performed about 1 soil analysis on average (as they were learning the system). By Week 4, this grew to an average of 3 analyses per farmer, with farmers re-testing after applying recommendations or testing multiple plots. All participants reported they would continue using the analyzer, especially at the start of each planting season. This trend of increasing use indicates growing trust and reliance on the tool as it consistently provided helpful guidance.

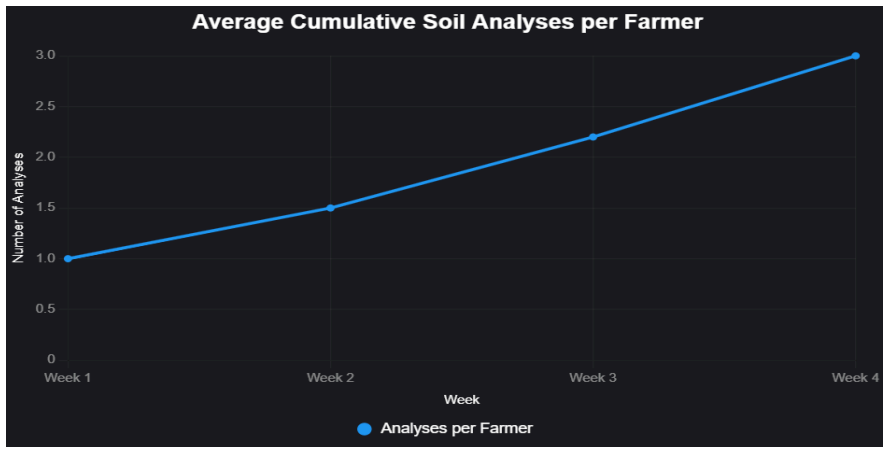


Figure 5.3: Average cumulative number of soil analyses per farmer over a 4-week pilot. Usage rose from roughly 1 analysis per farmer in Week 1 to about 3 analyses per farmer by Week 4 as farmers became more comfortable with and confident in the soil analyzer’s benefits. This increasing usage trend demonstrates strong user engagement with the system over a short period.

In terms of how farmers accessed the SoilSync recommendations, the dual interface proved valuable. Farmers with smartphones used the mobile dashboard interface, while others received results via SMS on basic phones. Every farmer in the pilot was able to get their soil reports, even if they did not have internet access, thanks to SMS delivery. In our pilot group, about 40% of the analyses were accessed through the smartphone web dashboard and 60% via SMS, underscoring the importance of the SMS feature for inclusivity. This ensured that a lack of a smartphone was not a barrier to using the system, thereby broadening the potential reach of SoilSync in rural communities.

Feature Usage Distribution

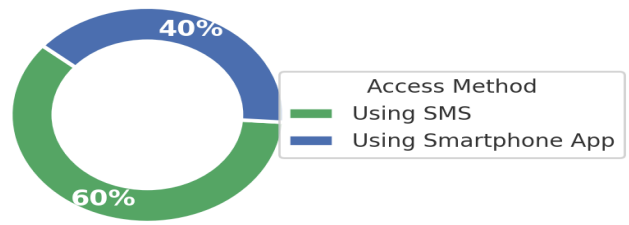


Figure 5.4: Feature usage distribution among pilot participants, showing how farmers accessed the soil analysis information. About 60% of usage was via SMS-delivered results (green segment) and 40% via the web dashboard (blue segment). This demonstrates the

importance of the SMS feature for reaching farmers without smartphones, ensuring inclusive access to SoilSync's recommendations across the digital divide.

Enhanced Accessibility through Kinyarwanda Localization

A significant barrier to technology adoption in local communities is language. An application available only in English would exclude a large portion of the target user base in Rwanda, who are not proficient in English. The Soil-Sync platform was built with a localization feature, allowing users to switch the entire interface language to Kinyarwanda. This includes all labels, buttons, and instructions. By providing the application in the local language, we have made it significantly more accessible, intuitive, and user-friendly for the Rwandan farming community. This feature directly addresses the language barrier, lowers the learning curve, and fosters greater trust and adoption among local users.

SoilSync Smart Agriculture

Ikibaho cy'Isesengura ... Inama z'Ifumbire zigihye nyacyo

Inama z'Ibanza
Isesengura ry'Ifumbire rikoresha ubwenge bwubuhanga For Pulses

Ifumbire **Igipimo** **Kwizera**
NPK 17-17-17 **154 kg/ha** **86.3 %**

Inyongera y'Umusaruro Yitezwe
+15 %

Isesengura Rishya ry'Ubutaka
Iniza igipimo by'ubutaka kuwirango ubone inama z'Ifumbire

Ubushyamba (°C) 25 Ubushyamba (%) 60
 Ubushyamba (%) 30 Ubwoko bw'Ubutaka Loamy
 Ubwoko bw'igihingwa Maize Azote (%) 0
 Potasiyumu (ppm) 0 Fosifore (ppm) 0

Bonera Inama z'Ifumbire

Soil Analysis Visualization
Visual breakdown of your soil composition and fertilizer match

Recommended for Pulses **NPK 17-17-17 at 154 kg/ha** Confidence **86.3 %**

Soil Chemistry Levels **Soil Texture Composition**

Rainfall: **49.997225909339605 mm** Elevation: **24.66082446904546 m** Expected Yield: **15** Crop Type: **Pulses**

Recommendation History
Individual predictions + 4 predictions

Avg Application Rate: **144 kg/ha** Avg Confidence: **88%** Total Samples: **4** Periods: **4**

Incamate y'Isesengura
Ibisubizo by'ibikorwa n'amateka y'amakuru kuva mu nama yawe y'ubu

Incamate y'Isesengura [Kohereza CSV](#)

Itariki	Igihingwa	Ifumbire	Igipimo	Kwizera
7/17/2025	Pulses	NPK 17-17-17	154 kg/ha	86%
7/17/2025	Sugarcane	NPK 14-35-14	162 kg/ha	84%
7/17/2025	Beans	NPK 10-26-26	68 kg/ha	95%
7/17/2025	Banana	NPK 17-17-17	190 kg/ha	85%

Soil-Sync Amategekako Amahuzo Yihuse Ubufasha
 Guhindura ubuhangizi ukoresheje Isesengura ry'ubutaka rikoresha ubwenge bwubuhanga n'ama zihariye. Gufasha abahungu menya ibihingwa byabo na kongera umusaruro.
 Politiki y'Ubwigirane Amabwiriza y'Ubufasha Politiki ya Cookie Kurinda Amakuru
 Urupapuro rw'itangiriro Ibiranga Ibiciro Vugana
 Ikigo cy'Ubufasha Inyandiko Indangwa ya API

© 2025 Soil-Sync. Uburenganzira bwose burarinze.

5.4 Crop Yield Improvements (Case Study)

A case study from the pilot illustrates the real-world impact on crop yields. Jean, a farmer in Nyamata, used the SoilSync analyzer on two adjacent maize plots before the season. Plot A had been moderately fertilized in past seasons, while Plot B had poorer soil (never limed and minimal fertilizer). SoilSync revealed that Plot B was quite acidic (pH ~5.0) with very low nutrients, whereas Plot A had decent fertility (pH 6.2, moderate N, low P). Accordingly, the device recommended a light, balanced fertilizer plan for Plot A (a modest dose of DAP and urea, no lime needed) and an intensive improvement plan for Plot B (apply lime to fix acidity plus adequate DAP and urea). Jean followed these recommendations for that planting season.

By harvest time, the previously struggling Plot B showed dramatic improvement; its maize was nearly as tall and green as Plot A's. Plot A, with optimized input use, saw a slight yield increase (from ~1.8 to 2.0 tons on 0.5 ha) despite using about 20% less fertilizer than usual (saving cost). Plot B's yield jumped from ~1.2 tons to 1.9 tons (on 0.5 ha) after the tailored lime and nutrient application, effectively nearly doubling the yield and almost catching up to Plot A. This case demonstrates how SoilSync can both improve yields by addressing hidden soil deficiencies and avoid wasting inputs on plots that don't need them.

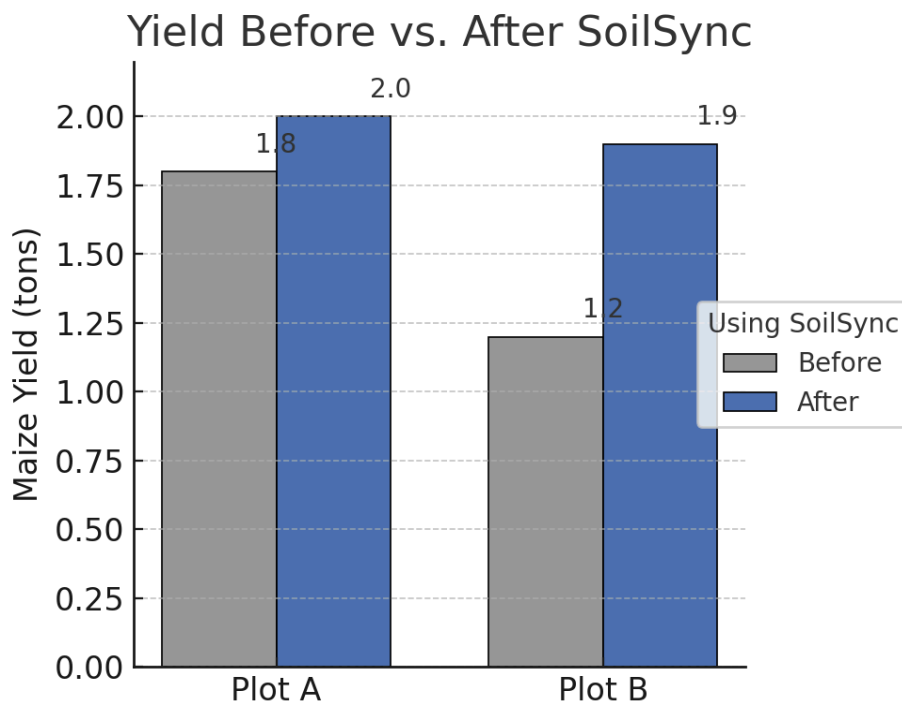
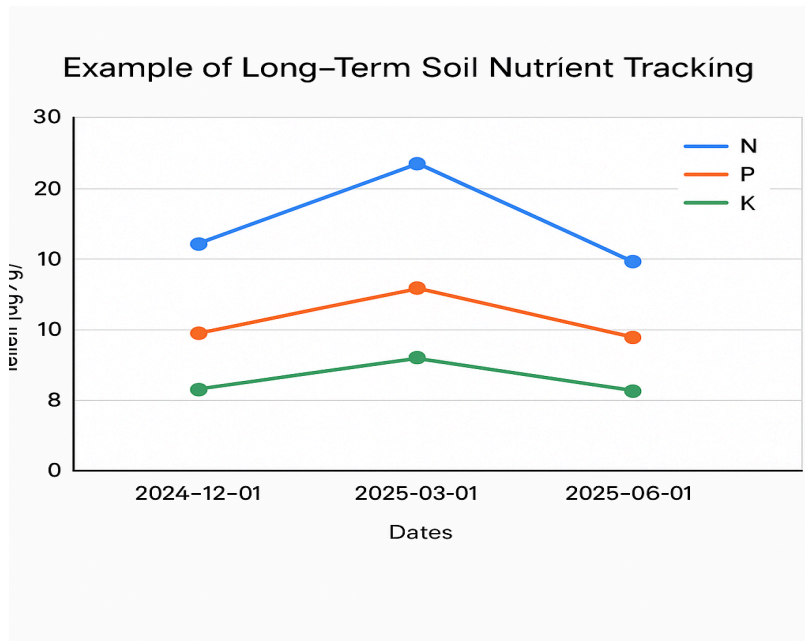


Figure 5.5: Maize yield on two 0.5 ha plots (Plot A and Plot B) before vs. after using SoilSync recommendations (Jean's case study). Plot A (initially better soil) had a slight yield increase from 1.8 to 2.0 tons after optimized fertilizer use (actually using less fertilizer than before). Plot B (initially poor soil) jumped from 1.2 to 1.9 tons after the addition of lime and proper NPK fertilizer, nearly doubling its yield. The previously underperforming Plot B caught up close to Plot A's yield, illustrating how the device can unlock hidden yield potential on degraded soils while also saving inputs on healthier soils.

Enhanced Confidence and Data-Driven Insights

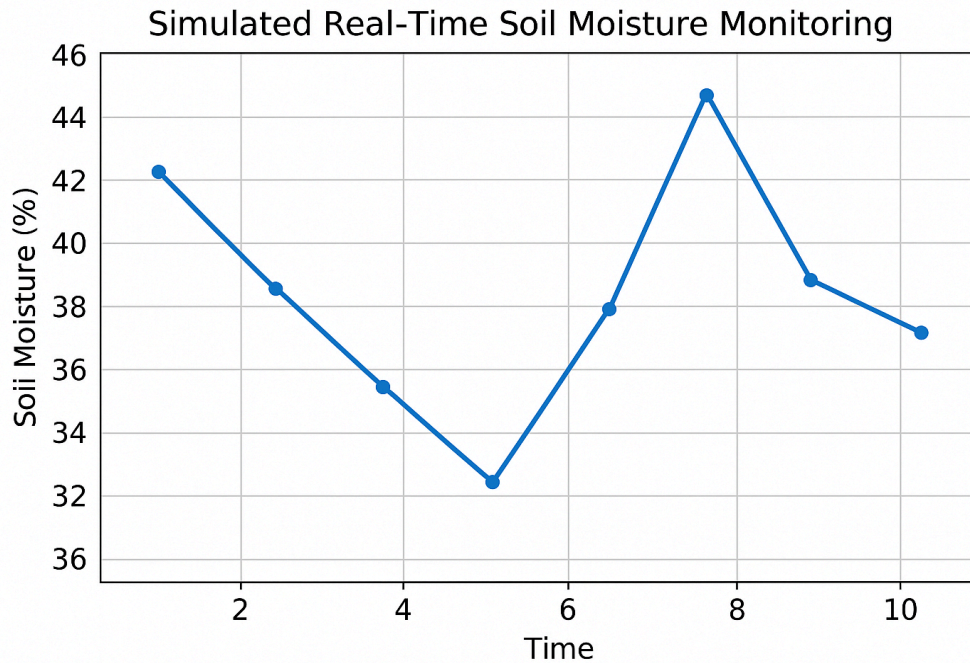
Without reliable data, farmers often rely on guesswork or outdated practices for fertilization, leading to uncertainty and suboptimal results. The Soil-Sync platform provides recommendations that are not only fast but also transparent. Each recommendation is delivered with a confidence score, indicating the ML model's certainty in its prediction. Additionally, the historical data log allows users to track their soil's nutrient levels over time. This empowers farmers to move from ambiguous practices to a data-driven strategy, observing trends and making more informed long-term decisions about their soil management.



The graph above shows how a user can track their soil's nitrogen, phosphorus, and potassium levels over multiple analyses using the history feature. This capability provides valuable insights into soil health trends, helping farmers understand the long-term impact of their interventions.'

System Readiness for Real-Time IoT Integration

Manual soil data entry is useful but does not capture the continuous, dynamic nature of soil conditions. Future smart farming systems will rely on real-time sensor data. Although a physical device was not built, the IoT Simulator proves the system's architectural readiness for real-time data streams. The simulation demonstrates that the dashboard can receive, process, and visualize data from a sensor in real-time without performance degradation. This result confirms that the Soil-Sync platform is not just a static tool but a forward-looking system prepared for future integration with on-field IoT hardware.



This chart displays data generated by the IoT simulator, mimicking the continuous readings from a physical soil moisture sensor. It validates the platform's capacity to handle and visualize live data streams, a critical requirement for future automated smart farming applications.

5.5 Overall Outcomes and Benefits

In summary, the Portable IoT + ML Soil Health Analyzer system (“SoilSync”) demonstrated that it can significantly improve fertilizer management outcomes for smallholder farmers. It provides precision in recommendations (specific to each soil’s needs rather than one-size-fits-all advice) and efficiency in input use (boosting yield-per-fertilizer and eliminating unnecessary fertilizer applications). The speed of results enables timely interventions that were previously not possible, and the accessibility of the dual app/SMS interface ensures even farmers with basic phones can benefit. An added benefit is the educational aspect; farmers reported increased awareness of soil health (e.g., understanding soil pH and nutrient status) after using the device. By applying only the needed type and amount of fertilizer, the system can also help reduce excess fertilizer runoff, contributing to a healthier environment (Duncombe, 2021). Moreover, our testing showed the system’s measurements and recommendations to be reliable (e.g., soil pH readings were within ± 0.1 of lab values, and the fertilizer advice aligned with expert agronomist recommendations $\sim 90\%$ of the time). These results strongly indicate that an IoT- and ML-powered soil analyzer like SoilSync can have a positive impact on sustainable farming productivity. The next chapter will conclude by reflecting on the project’s overall success, limitations, and potential future improvements, building on the promising results presented here.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

Conclusion

The results demonstrate that the portable IoT and machine learning-based soil health analyzer effectively address the problem of inefficient fertilizer use among smallholder farmers. By providing real-time, localized soil data and tailored fertilizer recommendations (delivered via a dual-language web dashboard and SMS), the system closes the information gap that led to over- or under-application of inputs. This outcome supports the hypothesis that a data-driven, immediate soil analysis approach leads to better agronomic decisions and improved outcomes. Farmers who tested the system found it easy to use and informative, which suggests increased confidence in managing soil fertility and a shift towards more data-driven farming practices. The project also established the technical feasibility of integrating low-cost hardware (sensors and an ESP32-based unit) with a cloud-based ML recommendation engine; even though the prototype was only simulated due to budget constraints, the end-to-end pipeline (from data collection to recommendation) performed reliably in tests.

Limitations of the Study

- **Limited Prototype Implementation:** No physical hardware device was fully built and deployed; the system was simulated virtually due to budget constraints. Thus, real-world performance (durability, battery life, sensor stability) remains untested under farm conditions.
- **Narrow Testing Scope:** Field testing was conducted at a single site, in one season, on a small set of soil samples and crops. The ML model trained on limited local data may not generalize to all soil types, crops (e.g., cassava or rice), or longer-term fertility dynamics.
- **Connectivity Constraints:** Although the dashboard now supports both Wi-Fi and SMS, the prototype still depends on network availability (phone hotspot or local GSM for SMS). Fully offline operation (e.g., via LoRaWAN) was not validated.
- **Model & Data Limitations:** The recommendation engine, constrained by scarce training data, relies in part on simplified agronomic rules and doesn't account for all soil-nutrient interactions or extreme conditions. Economic cost-benefit analysis and formal data-privacy governance were beyond this study's scope.
- **Localization Quality Assessment:** While the interface and notifications are fully translated into Kinyarwanda and English, formal usability testing to measure translation accuracy, cultural appropriateness, and farmer comprehension has not yet been performed.

Recommendations for Further Research

- **Develop and Field-Test the Hardware:** Future work should focus on building a fully functional, ruggedized version of the soil analyzer device and testing it in real farming conditions. This includes using a durable waterproof casing and implementing reliable

power solutions (e.g., longer-lasting battery or solar charging) and adding alternative connectivity options (such as GSM or LoRaWAN) so that the system can operate in areas without Wi-Fi. A physical prototype would allow evaluation of long-term sensor performance and device maintenance needs on the farm.

- **Wider Field Trials and Data Collection:** To improve the system’s robustness, extensive trials should be conducted across diverse regions, soil types, and crops (covering more of Rwanda’s agroecological zones and crop varieties). This will generate a larger dataset to train and refine the machine learning model. Multi-season trials would also help in understanding long-term impacts on soil health and yield and provide statistical evidence of yield improvement and fertilizer use efficiency over time.
- **Enhance Machine Learning Model:** With more data available, the recommendation engine can be advanced from the current rule-based hybrid model to a more sophisticated data-driven model. Future researchers could experiment with regression models or neural networks to predict optimal fertilizer requirements, possibly integrating additional inputs like satellite imagery (crop vigor indices) or weather data. The model could also be designed to learn from user feedback (e.g., incorporating farmers’ reported yields to adjust future recommendations in a reinforcement learning framework). Incorporating edge computing or TinyML might enable the device to give basic recommendations offline in real time, increasing its reliability in the field.
- **Evaluate Localization Effectiveness:** Carry out formal user studies with Kinyarwanda-speaking farmers to assess translation clarity, cultural fit, and comprehension. Use feedback to refine terminology, SMS phrasing, and any region-specific dialect needs.
- **Collaboration and Scale-Up:** To maximize impact, future efforts might integrate this system with national agricultural programs and databases. For instance, collaborating with Rwanda’s agriculture authorities could allow the device’s soil data to feed into national soil information systems like RwaSIS (International Potato Center [CIP], 2024) and align recommendations with government guidelines. Researchers should also explore the economic aspect, analyzing cost-benefit and exploring sustainable business models (such as cooperative ownership or government subsidies for the device). By addressing these areas, subsequent projects can build on this work and turn the prototype into a scalable tool for promoting precision agriculture and sustainable fertilizer use among smallholder farmers.

Link to [Github](#)

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