TANIM: AN INTELLIGENT AGRICULTURAL FRAMEWORK FOR CROP RECOMMENDATION AND SOIL HEALTH MONITORING

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CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Agriculture is important in the Philippines since it serves as the foundation of food security, livelihood, and rural development. In a traditional soil management practices in the Philippines, such as those endorsed by the Department of Agriculture (DA), it relies on generalized soil health monitoring and fertilizer recommendations; they are using manual tools like the Minus-One Element Technique (MOET) and Rapid Soil Test Device (RST). These approaches often fail to address field-specific variability, crop diversity, and seasonal dynamics, leading to suboptimal resource use based on the Department of Agriculture Region 10 (2023). Historically, the method of soil testing requires transporting soil samples to the nearest laboratories located in the office of the Department of Agriculture, which was supported by the article of Pagaduan, J.L. (2025) which states that the need for farmers to transport soil samples is often expensive, time-consuming, and inaccessible in some remote places. In relation to that, the Department of Agriculture - Regional Field Office 10 (Aggie 10) conducted a soil sampling drive for soil health monitoring sites of rice and corn production areas in the towns of Sugbongcogon, Binuangan, Magsaysay and Gingoog City last March 26-28, 2025. The Aggie 10 targets to muster soil sampling and testing in priority sites across Region 10 by May 2025, in time with the wet cropping calendar based on the article from the Aggie 10 site. With the mentioned traditional method of soil testing, farmers often rely on ocular observations which was supported by the study of Samaniego, A.L. & Gallego, M. (2024) which states that only about 1.03% use a soil-test kit and another 1.03% use government lab services, while the remaining 97.94% rely on observational methods (eyeballing the soil or plant). According to Sarma, A. et. al. (2024) crop selection decisions are frequently based on historical practices rather than data-driven insights, limiting adaptability to changing soils and climate conditions. With the use of technological advancements such as IoT it would be a great aid for the farmers to have a better crop yield and reduce loss.

The soil health is a fundamental pillar for sustainable agriculture, underpinning crop productivity, food security, and environmental resilience. According to Lal, R. (2024), degraded soils, marked by nutrient deficiencies, imbalanced pH, or reduced organic matter, lead to diminished yields, increased pest vulnerability, and economic losses for farmers. In Region 10 (Northern Mindanao, Philippines), a key agricultural hub producing rice, corn, banana, and cacao, optimal levels of nitrogen (N), phosphorus (P), potassium (K), and a pH range of 6.0–7.5 are essential for nutrient availability and robust crop growth which was mentioned on the study of Morgan & Connolly (2013) and (Sondhiya & Singh, 2024). According to the data from the Department of Agriculture in Region 10 last 2024, acidic soils in Bukidnon limit phosphorus uptake, while nitrogen shortages in rice fields can reduce yields by up to 20%. Furthermore, selecting appropriate crops for specific zones and seasons, coupled with precise fertilizer application, is critical to maximizing productivity and minimizing environmental impacts like nutrient runoff (Patil et al., 2023).

Advancements in Internet of Things (IoT) technologies and machine learning (ML) offer innovative solutions for precision agriculture. IoT-based sensors, such as NPK, pH, and moisture probes, enable soil monitoring, while ML algorithms analyze complex datasets to deliver tailored recommendations stated in the study of (Kumar et al., 2024), (Lavanya et al., 2024). Multi-Criteria Decision Analysis (MCDA) algorithms, such as Analytic Hierarchy Process (AHP) or Weighted Sum Model (WSM), further enhance decision-making by integrating multiple factors like soil nutrient profiles, climate data, and crop suitability supported by the study of Kumar & Singh (2024). According to Elbasi et. al (2023), the modern farming methods utilizes technology to optimize crop production and minimize waste. Smart farming aids in increasing yield outputs and crop productivity. By combining IoT, ML, and MCDA with data of soil suitability maps and agricultural zoning data, systems can optimize both crop selection and fertilizer application for specific zones and seasons in Region 10.

This study proposes a Soil Health Monitoring and Recommendation System that leverages IoT sensors and a Multi-Criteria Decision Analysis (MCDA) algorithm to provide zone-specific, and season-specific recommendations for multi-cropping and fertilizer application in Region 10. Targeting key crops such as Maize (Corn), Mungbean (Mongo), Peanut, Soybean, Squash (Kalabasa), Sweet Potato (Camote), Cassava, Taro (Gabi), Eggplant, Tomato, Pechay, and Cabbage, the system integrates soil health data (NPK, pH, moisture, humidity and temperature) and agri-weather data, online data resources, and DA's zoning maps to predict optimal crops for planting and recommend precise fertilizer strategies. By addressing field-specific variability and seasonal dynamics, the system aims to enhance agricultural productivity, reduce resource waste, and promote sustainable farming practices. Aligned with Sustainable Development Goals (SDGs) 2 (Zero Hunger), 12 (Responsible Consumption and Production), and 15 (Life on Land), this research contributes to food security, environmental conservation and goods production, and sustainable agriculture in the Philippines.

1.2 Statement of the Problem

Traditional soil management and crop selection practices in Region 10 lack precision, leading to reduced yields, resource waste, and environmental degradation (Lal. R., 20234. Generalized manual tools from Department of Agriculture tools lack accuracy to account for field-specific variability, crop diversity, and seasonal dynamics. Ultimately, the absence of data-driven fertilization recommendations and crop prediction systems limits optimal land use, particularly for Region 10's diverse crops like Maize (Corn), Mungbean (Mongo), Peanut, Soybean, Squash (Kalabasa), Sweet Potato (Camote), Cassava, Taro (Gabi), Eggplant, Tomato, Pechay, and, Cabbage. Key challenges include:

1. Ensuring accuracy of IoT sensors in monitoring soil health indicators (pH, NPK, salinity, moisture, and temperature) across farming zones in Region 10.

2. Integration of MCDA and machine learning algorithms with soil health, climate, and zoning data to predict suitable crops and generate optimized fertilizer recommendations.

3. Designing a mobile interface that delivers user-friendly crop and fertilizer recommendations tailored for farmers in Region 10.

4. Evaluating the accuracy and scalability of an IoT–MCDA system in supporting agricultural practices for farmers in Region 10.

1.3 Objectives of the Study

The main objective of this study is to develop an IoT-based crop recommender system integrated with machine learning for crop recommendation based on soil health parameters (NPK levels, pH, and moisture content) and weather data for farmers, specifically the following:

1. Implement a machine learning model to predict suitable crops and recommend fertilizers for multi-cropping in Region 10 based on soil, climate, and zoning data.

2. Develop a mobile application to monitor soil health, crop predictions, fertilizer schedules, and multi-cropping planning for farmers.

3. Develop a website application to monitor soil health insights for different zoning, farmers data and information on their farming patterns, and multi-cropping information for each zoning.

4. Evaluate the IoT-based crop recommender system's accuracy and usability in agricultural settings in Region 10.

1.4 Significance of the Study

The significance of this study lies in its potential to transform agricultural practices in Region 10 by developing an integrated IoT and Multi-Criteria Decision Analysis (MCDA) with a machine learning model system for soil health monitoring, crop recommendation with multi-cropping, and fertilizer recommendation. Traditional methods of soil testing provided by the Department of Agriculture are not often used by farmers due to inaccessibility and time-consuming, farmers often rely on ocular observations that may involve risk in planting crops (Samaniego, A.L. & Gallego, M., 2024). This research addresses critical limitations of traditional soil management methods, such as generalized recommendations and lack of zone-specific insights, which often lead to inefficient resource use.

By providing precise soil data and tailored crop and fertilizer suggestions for crops, the system enables farmers to optimize yields and reduce costs. Furthermore, the incorporation of DA's zoning maps and credible online datasets enhances land use efficiency, promoting sustainable farming practices that align with environmental conservation goals. The study also contributes to precision agriculture by offering a scalable IoT-MCDA framework, facilitating data-driven decision-making for farmers. Ultimately, this research has the potential to significantly improve agricultural productivity, environmental sustainability, and food security in Region 10, supporting Sustainable Development Goals (SDGs) 2, 12, and 15.

Farmers, the system will greatly help the farmers in optimizing crop yield providing soil health monitoring data, and data-driven crop recommendations and optimized fertilizer use. This helps farmers to reduce risk, and maximize crop yield.

Department of Agriculture, the study will aid the Department of Agriculture in Region 10 by providing real-time soil health insights, improving the accuracy of their fertilizer distribution programs, and enhancing the effectiveness of agricultural zoning. Also, it can serve as a tool for planning interventions, and monitoring soil health trends for sustainable agriculture.

Agriculturist, this research benefits agriculturists by serving as a reliable reference for analyzing soil conditions and crop suitability. It enhances their capacity to provide professional recommendations to farmers, reducing reliance on manual or generalized methods.

Future Researchers, The study will serve as a foundation for future innovations in smart farming and precision agriculture. It opens opportunities for further research in areas such as integrating remote sensing data, advanced predictive analytics, and climate-smart agriculture techniques. Future researchers can expand this system into other regions or crop categories, making it a scalable model for national and even global agricultural applications.

1.5 Scope and Limitations

This study focuses on the agricultural areas that are located in Region 10, Philippines, where specific crops such as: Maize (Corn), Mungbean (Mongo), Peanut, Soybean, Squash (Kalabasa), Sweet Potato (Camote), Cassava, Taro (Gabi), Eggplant, Tomato, Pechay, and Cabbage are produced since these crops are the focus of this study. The system was designed to analyze data input for soil health parameters such as (1) Nitrogen, (2) Phosphorus, (3) Potassium, (4) temperature, (5) soil moisture, (6) pH level, and (7) soil salinity. These parameters are integrated with agri-weather data like leaf wetness, precipitation, temperature, and wind speed to be retrieved via a weather API that will serve as the foundation for crop recommendation and fertilizer optimization. By implementing machine learning algorithms with Multi-Criteria Decision Analysis (MCDA) methods, the system aims to promote sustainable agriculture and maximize crop yields in multi-cropping scenarios.

This study is geographically limited to farms across Bukidnon, ensuring relevant soil parameters accuracy, climate conditions, and agricultural zoning. This development emphasizes the integration of IoT, machine learning, and

MCDA systems. On the other hand, the sensor that will be used for this system is limited to only seven (7) soil parameters excluding factors like micronutrients and the organic matter. Real-time soil health monitoring is not implemented, as the system focuses on periodic data analysis rather than continuous monitoring.

1.5.1 Conceptual Framework

In this section, the study's conceptual framework is presented through an Input-Process-Output (IPO) model, which outlines the structure of the soil health monitoring, crop and fertilizer recommendation system. The framework integrates multiple components, each playing a vital role in developing an efficient, data-driven solution for sustainable agriculture.

Figure 1.1

IPO Model

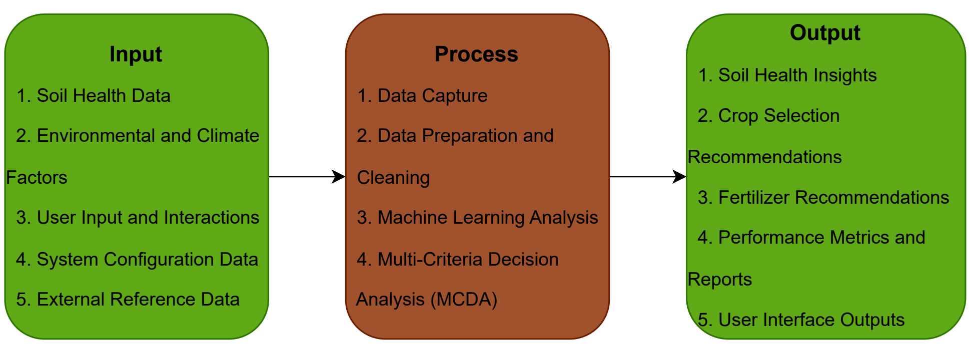


Figure 1 outlines the input, process, and output for a system designed to process soil health data and support agricultural decision-making in Region 10, Philippines. The inputs include readings from lot sensors (NPK levels, pH, moisture, salinity, and temperature) collected via ESP32 microcontroller and Soil Sensor, zoning data from Department of Agriculture (DA) maps, historical soil data from DA Region 10 reports, environmental and climate data, online data, and farmer-defined parameters.

These inputs are then processed through data capture, cleaning, and integration with external sources, followed by machine learning analysis using LightGBM and a multi-criteria decision analysis (AHP-TOPSIS) for crop and fertilizer recommendations. The system then produces outputs such as soil health insights, zone-specific crop recommendations, fertilizer recommendations, performance metrics, and a user-friendly dashboard with analytics, alerts, and reports. This data-driven approach enables farmers to make informed decisions, improving efficiency, yield, and resource management while reducing waste.

1.5.2 Theoretical Framework

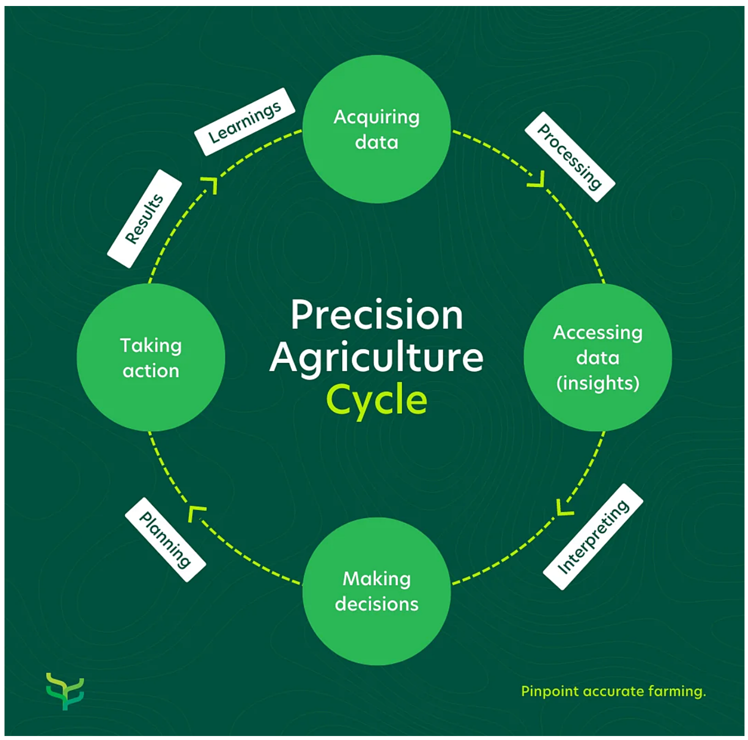
This study utilized Precision Agriculture Theory, a strategy that gathers, processes data driven insights to optimize farming practices based on conditions rather than relying on generalized farming practices recommendations, which is supported by the study of Pierre C. Robert states that an integrated farming approach designed to enhance long-term production efficiency, productivity, and profitability while minimizing environmental impacts. It involves using technology and data to optimize farming practices at a site-specific level. The theory highlights the importance of applying the right input, at the right place, at the right time, and in the right amount to maximize productivity while conserving resources.

With the integration of IoT sensors which will provide measurements of soil health parameters the precision agriculture theory will be fully operational. The soil parameters will serve as a foundation for the Multi-Criteria Decision Analysis methods to generate actionable recommendations for farmers. Moreover, machine learning boosting algorithms will be used to analyze soil and environmental patterns to predict crop suitability and yield potential.

Figure 2 explains the Precision Agriculture Cycle on how farming decisions become data-driven. It starts with acquiring data through IoT sensors and other tools that measure soil and environmental conditions. This data is then processed into insights to understand soil fertility and crop needs. Using these insights, decisions are made with the help of Machine Learning (ML) for prediction and Multi-Criteria Decision Analysis (MCDA) for evaluating multiple factors like soil parameters, climate, and zoning. The next step is taking action, where farmers apply precise fertilizers, choose suitable crops, or adjust irrigation. Finally, the results and learnings feed back into the system, ensuring continuous improvement in productivity, efficiency, and sustainability.

Figure 1.2

IPO Model



By combining ML's predictive capability with MCDA's structured decision making process, the study applies the principles of precision agriculture in a holistic manner. This ensures that recommendations for crop selection and fertilizer application are data-driven, addressing the variability of soils and seasonal conditions in Region 10. Thus, Precision Agriculture Theory serves as the guiding lens that connects IoT-based data collection, Machine Learning prediction, and MCDA supported decision-making, ultimately promoting sustainable and efficient farming practices.

1.6 Definition of Terms

This study defined the following terms that are mentioned in this study.

Agriculture The science, art, and practice of cultivating plants and livestock, serving as the foundation for food security, livelihoods, and rural development in regions like the Philippines.

Agricultural Zoning The practice of designating specific areas for agricultural use to conserve farmland, prevent urban conflicts, and promote orderly rural growth, often including minimum lot sizes and restrictions on non-farm activities.

Analytic Hierarchy Process (AHP) A structured decision-making technique that organizes complex problems into a hierarchy of goals, criteria, and alternatives, using pairwise comparisons to derive priorities and rank options.

Boosting Algorithms A family of machine learning techniques that convert weak learners into strong ones by iteratively training models to correct errors from previous ones, commonly used in regression and classification tasks.

Crops Plants or plant products grown and harvested extensively for profit or subsistence, categorized into food, feed, fiber, oil, ornamental, and industrial types based on their uses.

Fertilizer A natural or synthetic substance added to soil to supply essential nutrients like nitrogen, phosphorus, and potassium, enhancing plant growth and productivity in agriculture.

Internet of Things (IoT) in Agriculture The integration of connected sensors, devices, and networks in farming to monitor soil, weather, crops, and livestock, enabling data-driven decisions for improved efficiency and sustainability.

Machine Learning A subset of artificial intelligence that enables computers to learn from data and improve performance on tasks without explicit programming, often using algorithms to identify patterns and make predictions.

Multi-cropping The practice of growing two or more crops on the same piece of land in a single year, either sequentially or simultaneously, to enhance productivity, diversify income, and improve soil health.

Multi Criteria Decision Analysis (MCDA) A decision-making approach that evaluates alternatives based on multiple conflicting criteria, using techniques like weighting and ranking to support complex choices in fields such as agriculture.

NPK The abbreviation for the three primary macronutrients in soil and fertilizers: nitrogen (N), phosphorus (P), and potassium (K), essential for plant growth, development, and overall health.

Precision Agriculture A farming management strategy that uses data from sensors, GPS, and analytics to optimize inputs like water and fertilizers, responding to variability in crops for improved efficiency and sustainability.

Soil Health The continued capacity of soil to function as a vital living ecosystem that sustains plants, animals, and humans, encompassing biological, physical, and chemical properties.

Soil pH A measure of soil acidity or alkalinity on a scale from 0 to 14, indicating hydrogen ion concentration, which influences nutrient availability and plant growth.

Soil Salinity The accumulation of soluble salts in soil that can impair plant growth, often measured by electrical conductivity, with levels above 4 dS/m considered saline.

Sustainable Agriculture Farming practices that meet current food needs while preserving resources for future generations, balancing environmental health, economic viability, and social equity.

CHAPTER 2

REVIEW OF RELATED LITERATURE

This chapter presents some preliminary concepts and known results that are needed in this study.

2.1 Soil Health in Northern Mindanao

The literature underscores the critical role of soil health in sustainable agriculture and the limitations of traditional methods. Lal, R. (2024) emphasizes soil degradation's impact on global food security, while Morgan & Connolly (2013) detail nutrient uptake mechanisms and challenges in imbalanced soils. In the Philippine context, DA Region 10 (2023, 2024) highlights regional soil issues, such as acidity in Bukidnon and nutrient shortages in rice fields, alongside generalized zoning maps. According to the study of Timario, A., & Lapoot, C. (2024), which assessed soil fertility in irrigated lowland areas across Northern Mindanao, revealing strongly to moderately acidic soils (pH 4.5-6.0) with variable organic matter content, peaking in Bukidnon at up to 3.5%. The study employed soil sampling and laboratory analysis to monitor key parameters like pH, and NPK, highlighting deficiencies in phosphorus and potassium that limit rice yields. This underscores the need for regular soil health monitoring to track degradation trends and inform site-specific interventions in Region 10's rice-dominated landscapes; this is supported by the study of Sani et. al.(2023) which uses several factors of crops and uses those inputs for random forest algorithms.

Crop production trends in Northern Mindanao, note that fertilizer inefficiencies in Bukidnon and Misamis Oriental contribute to yield gaps in corn and rice, with average applications exceeding recommendations by 15-20% based on the study of Alipio (2015). The review recommends precision fertilizer strategies, such as variable-rate applications, to optimize nutrient use efficiency and minimize environmental impacts in Region 10's diverse agroecosystems. On the other hand, Hauswirth et al. (2014) reviewed soils and crop suitability in Bukidnon Highlands, highlighting how volcanic-derived soils support high-value crops like pineapple and coffee, but require lime amendments for acidity management to sustain productivity. The study links soil properties to crop performance, advocating for diversified cropping systems to enhance resilience in Northern Mindanao.

2.1.1 Zoning in Agriculture

In agriculture, zoning is the process of dividing land into management areas based on topographic features, soil fertility, and climate–all of which have a direct impact on crop suitability. Zoning has been used in several areas of the Philippines to maximize land use and improve site-specific agricultural recommendations. Watson et al. (2025) used the Food and Agriculture Organization of the United Nations (FAO) land evaluation to characterize and categorize soil series in Ilocos Norte and perform crop suitability assessments for rice, maize, garlic, onion, and tomato. According to their research, morphological characteristics and soil physicochemical characteristics are important factors in determining whether an area is considered highly suitable (S1), moderately suitable (S2), or marginally suitable (S3).

The use of zoning for particular crops is further illustrated by regional studies. In Samar Province, Poliquit et al. (2020) evaluated crop suitability and soil fertility, identifying nutrient deficiencies like low levels of organic matter, phosphorus, and nitrogen as productivity-limiting factors. The significance of mapping local soil fertility for focused input management was highlighted by their findings. Similarly, Bato (2018) created a Geographic Information System (GIS) based banana cultivation suitability map that illustrates the spatial variations in suitability across the Philippine landscape. Slope, elevation, rainfall, and soil properties were all integrated in the study to create a visual guide that farmers and policymakers could use to identify the best places to grow bananas.

These zoning studies together make a strong case for creating smart frameworks that combine soil and crop suitability with cutting-edge technologies to give site-specific crop and fertilizer recommendations.

2.2 Machine Learning

Machine learning (ML) is becoming very useful in agriculture, it enables researchers and farmers to process huge amounts of data. It provides predictive insights related to soil health, crop recommendation, fertilizer and so on. Unlike traditional methods that rely on generalized formulas or manual observations, ML can accommodate complex and internal relationships between the soil, climate and crop parameters. This will enable them to make site-specific recommendations which will increase productivity, reduce costs and improve sustainable farming practices.

As noted by Islam et al. (2023), ML enabled systems are flexible. They not only analyze nutrient levels of soil but also suggest crops that can be grown in various environments. They do this with more accuracy and precision than manual assessments. According to Parganiha and Verma (2024), optimized ML models like LightGBM can yield predictive accuracies as high as 97% for crop yield forecasting. These models are easily scalable for larger agricultural zones like Northern Mindanao.

2.2.1 Random Forest

Random Forest (RF) is an ensemble algorithm that constructs multiple decision trees and aggregates their outputs through majority voting (classification) or averaging (regression). Incorporating bootstrapped data subsets and randomly selected features minimizes overfitting and enhances the RF model's resilience to the inaccurate data typical of many agricultural applications. This is useful in examining soils, where data quality is often compromised due to sparse sampling and other uncontrolled environmental factors.

In predicting fertilizer amounts and estimating crop inputs, Sani et al. (2023) demonstrated its capability in capturing nonlinear relationships integrated among soil parameters and environmental factors. The study found that RF outperformed linear models in terms of accuracy, showing its adaptability across diverse farming conditions. Islam et al. (2023) integrated RF into a crop recommendation framework, successfully suggesting suitable crops based on soil nutrient levels and weather data.

2.2.2 Boosting Algorithms

With the current technologies, Islam et. al.. (2023) developed an ML-enabled system for soil nutrient monitoring, and crop recommendations, evaluated through field experiments to enhance productivity and sustainability.

This approach supports multi-crop applications relevant to Region 10. Parganiha and Verma (2024) proposed an optimized LightGBM model for soil analysis and crop yield prediction, incorporating data preprocessing, feature selection, and hyperparameter tuning, achieving up to 97% predictive accuracy. LightGBM's efficiency, as noted by Data Overload (2024), makes it ideal for large-scale agricultural tasks in Region 10.

Table 1: Parameters for Different Gradient Boosting Algorithms **??**

Algorithm	**Parameter**	**Value**
Adaptive Boosting (AdaBoost)	learning_rate	0.5
	n_estimators	200
Cat Boosting (CatBoost)	depth	4
	iterations	300
	iterations	300
Gradient Boosting Machine (GBM)	learning_rate	0.3
	max_depth	3
	n_estimators	300
Light Gradient Boosting Machine (LightGBM)	learning_rate	0.1
	n_estimators	200
	num_leaves	31
Extreme Gradient Boosting (XGBoost)	learning_rate	0.3
	max_depth	3
	n_estimators	300

Table 1 outlines the hyperparameters used for training the different gradient boosting algorithms considered in this study. Each model was configured with commonly used parameter settings based on literature benchmarks and preliminary tuning to balance performance and computational efficiency. For AdaBoost, the number of estimators was set to 200 with a relatively high learning rate of 0.5 to speed up convergence. CatBoost employed a maximum tree depth of 4, 300 boosting iterations, and a learning rate of 0.3. This reflects its ability to handle categorical features effectively. The Gradient Boosting Machine was configured with a learning rate of 0.3 and a tree depth of 3, alongside 300 estimators to control complexity while maintaining accuracy. LightGBM used a lower learning rate of 0.1 with 200 estimators and 31 leaves, capitalizing on its efficiency in handling large datasets. Lastly, XGBoost was set with 300 estimators, a learning rate of 0.3, and a maximum depth of 3, representing a balanced configuration widely adopted in classification tasks.

2.2.3 Decision Tree Analysis

Decision tree analysis is a supervised machine learning approach that uses a tree-like model of decisions and their possible consequences to classify or predict outcomes. It is widely applied in agriculture because of its simplicity, interpretability, and ability to handle both categorical and numerical data. By splitting data into smaller subsets based on key attributes such as soil nutrients, moisture, pH, and climatic conditions, decision trees can provide farmers with clear and actionable recommendations.

A study of Lavanya et al., 2024 employed Gradient Boosting Decision Trees for multi-crop fertilizer recommendation, integrating soil and climate data, and reported 95% accuracy. This highlights the method's strength in managing Region 10's diverse cropping systems where multiple environmental factors interact.

Similarly, Bishnoi, S., & Hooda, B. K. (2022). examined the applicability of decision tree algorithms in agriculture for classification tasks, emphasizing their effectiveness in handling diverse datasets related to crop type, soil fertility, and environmental conditions. Their study concluded that decision trees not only enhance prediction accuracy but also improve the interpretability of agricultural data, enabling researchers and farmers to make evidence-based decisions. This demonstrates that decision tree-based models are reliable tools for optimizing fertilizer management, predicting yields, and supporting sustainable farming practices.

2.2.4 Multi-Criteria Decision Analysis (MCDA)

Multi-Criteria Decision Analysis (MCDA) is a decision-making tool that evaluates and compares different alternatives based on multiple, often conflicting, criteria. In agriculture and environmental management, MCDA is particularly useful for addressing complex problems where decisions must balance productivity, sustainability, cost, and environmental impact. A study of Cicciù, Schramm, F., & Schramm,V., (2022) analyzed 41 papers from 1999 to 2021, revealing a surge in MCDA applications for agricultural sustainability since 2016, with France and China leading research output. The Analytic Hierarchy Process (AHP) was the most used method (11 papers), favoring compensatory approaches, while non-compensatory outranking methods like ELECTRE and PROMETHEE were less common. The Triple Bottom Line (economic, social, environmental) was applied in 68% of studies, often at the farm level, highlighting MCDA's potential to support sustainable farming systems, though its application remains underexplored, particularly for non-compensatory and hybrid methods.

MCDA integration is supported by Saaty (2008) for AHP and Kumar & Singh (2024) for IoT-ML in tropical fertilization. Yuan et al. (2022) systematically reviewed MCDA methods for rural spatial sustainability, emphasizing AHP, SAW, and TOPSIS for complex evaluations involving soil health and environmental factors. These methods enhance decision-making for crop selection and fertilizer recommendations by weighing multiple criteria like soil nutrients, climate, and zoning data.

2.3 Crop and Fertilizer Recommendation Systems

In the Philippines, crop and fertilizer recommendations remain very general and imprecise. According to Samaniego and Gallego (2024), it was found that as much as 97.94% of farmers rely on ocular observations or visual inspection of plants and soil, while only 1.03% use soil-test kits or government laboratories. This reliance on manual methods ends up either over or under-application of fertilizer, contributing to low yields and unnecessary costs. Farmers typically follow broad guidelines or personal judgement in fertilizer management, but these approaches lack the precision required to account for variations in soil health, nutrient level, and crop demands.

To address these inefficiencies, several studies have explored machine learning and data-driven approaches for fertilizer optimization. Sani et al. (2023) employed Random Forest algorithms to predict fertilizer requirements with various soil and crop inputs, achieving high accuracy. Lavanya et al. (2024) demonstrated Gradient Boosting Decision Trees (GBDT) could yield multi-crop fertilizer recommendations with an accuracy of 95% by integrating the soil and climate data. Alipio (2015) also recommended precision fertilizers, like using different amounts of fertilizers based on location, to avoid nutrient waste and environmental impact. These findings demonstrate the potential of ML models to provide more efficient and tailored fertilizer recommendations compared to traditional methods.

Crop recommendation systems are equally important for optimizing agricultural practices. Islam et al. (2023) developed a machine learning enabled soil monitoring and crop recommendation system that uses and analyzes soil nutrient levels and environmental conditions to suggest suitable crops across multiple environments. The study highlighted the adaptability of ML in multi-cropping systems, showing that intelligent algorithms can go beyond input optimization to guide farmers in selecting crops that align with specific soil and climatic conditions.

2.4 Soil Health Sensor in Agriculture

Soil sensors play a critical role in modern agriculture as they provide accurate and real-time data about soil conditions. By measuring key parameters such as soil moisture, temperature, pH, salinity, and nutrient levels, these sensors help farmers assess overall soil health and make informed decisions for crop management. This is supported by the study of Yin et al., (2021), in which they highlighted the four aspects that will be the main focuses for future soil sensing. First is to improve the sensing performance (e.g., sensitivity and specificity) and reliability for key soil parameters, with little interference from background noise; Second is to develop a sufficient low-power consumption

WSN with powerful data processing and long-range wireless communication capability; Third is to develop versatile soil sensing platforms that can be distributed in large-scale to collect real-time soil microenvironment data continuously; and the Fourth is to develop self-powered or power-independent sensors and sensing platforms that are low-cost, reliable, and maintenance free.

The use of soil health sensors enables precision agriculture, where inputs like water, fertilizers, and pesticides can be applied more efficiently, reducing waste and minimizing environmental impact. In addition, continuous monitoring of soil health through sensors helps in early detection of soil degradation issues such as nutrient depletion, salinization, or compaction. This allows for timely interventions that improve soil productivity and sustainability. The integration of soil sensors with Internet of Things (IoT) platforms further enhances their effectiveness by enabling wireless data transmission, cloud-based analytics, and automated decision-making systems for smart farming.

Numerous studies in the field of agriculture integrate modern advancements like Internet of Things (IoT) , it is supported by the study of Sondhiya & Singh, (2024), which explores Internet of Things (IoT) and Machine Learning (ML) for soil monitoring in Zea mays (corn) in Kibangay, Lantapan, Bukidnon, demonstrating improved nutrient management. The study utilized NPK and pH sensors with an ESP32 microcontroller and LoRaWAN, achieving 95%

agreement with the Department of Agriculture's Soil Test Kit. However, its single-crop focus limits applicability to Region 10's diverse crops like rice, banana, and cacao. Moreover, the study of Kumar et al., (2024) developed an IoT-based soil monitoring system using Arduino-based NPK and moisture sensors for rice and maize, achieving 95% nutrient detection accuracy, validating the potential of IoT for monitoring.

2.5 Synthesis

The reviewed studies provide comprehensive insights into soil health, crop productivity, and machine learning applications in agriculture. Research gained in-depth understanding of the soil health challenges in Northern Mindanao, particularly with issues like soil acidity in Bukidnon and nutrient deficiencies in rice fields. Regional assessments, including those from the Department of Agriculture Region 10 (2023, 2024) and the work of Timario and Lapoot (2024), confirmed the variability of soil properties and their direct impact on yield performance. These findings are consistent with earlier insights from Alipio (2015), who noted the inefficiencies in fertilizer applications, and from Hauswirth et al. (2014), who linked volcanic-derived soils to both opportunities and limitations for high-value crops. Together, these studies stress the importance of site-specific soil health monitoring and precision interventions to counteract degradation and sustain agricultural productivity. However, most of these studies remain limited to general recommendations or crop-specific assessments, leaving a gap in developing integrated, data-driven systems tailored to multiple crops in Northern Mindanao.

Zoning has also emerged as a crucial strategy for sustainable land use. Efforts by Watson et al. (2025) using FAO land evaluation in Ilocos Norte, the crop suitability mapping in Samar by Poliquit et al. (2020), and the GIS-based banana suitability mapping by Bato (2018) demonstrated how soil fertility, topography, and climate can be translated into actionable agricultural zoning. These initiatives underscore the value of integrating spatial data with soil and crop requirements. Yet, these zoning studies are often region-specific and crop-focused, lacking the integration with modern technologies such as machine learning and IoT sensors that could make zoning more dynamic and adaptive to current farming needs.

The incorporation of machine learning adds a new dimension to these agricultural practices. Random Forest applications by Sani et al. (2023) and Islam et al. (2023) showed how nonlinear soil and environmental data can be used to generate accurate fertilizer and crop recommendations, while boosting algorithms such as LightGBM, as explored by Parganiha and Verma (2024), achieved high predictive accuracies in crop yield forecasting. Complementary approaches like decision tree analysis, highlighted in the work of Lavanya et al. (2024) and Bishnoi and Hooda (2022), further support the adaptability and interpretability of ML models. Broader frameworks such as Multi-Criteria Decision Analysis, reviewed by Cicciù et al. (2022) and Yuan et al. (2022), provide systematic ways to balance productivity, environmental sustainability, and economic viability. While these studies prove the potential of ML and decision-support systems, their application in the Philippines context–particularly Northern Mindanao–remains scarce, and most models have yet to be validated in diverse cropping systems beyond rice and maize.

The technological foundation for these innovations is strengthened by the integration of soil health sensors and IoT systems. Yin et al. (2021) emphasized the need for reliable, low-power, and scalable soil sensing technologies, while recent Philippine-based studies such as those by Sondhiya and Singh (2024) in Bukidnon and Kumar et al. (2024) in rice and maize systems demonstrated the practicality of IoT-enabled NPK and pH sensors in monitoring nutrient status. Despite their promise, these sensor applications are still largely crop-specific and small-scale, limiting their ability to provide generalized, multi-crop recommendations across Region 10's diverse agricultural systems.

The literature review establishes a strong foundation for developing a data-driven agricultural framework in Northern Mindanao. Soil health monitoring, zoning approaches, machine learning models, and IoT-based sensors converge to form comprehensive solutions. However, there remains a clear gap: existing studies often treat these components separately–soil fertility studies without advanced analytics, zoning without integration to real-time data, or ML models without validation in local contexts. This study aims to address these gaps by developing an IoT-based Soil Health Monitoring and Recommendation System that integrates real-time soil parameters (NPK, pH, salinity, moisture, and temperature), agri-weather data, and agricultural zoning maps with machine learning and Multi-Criteria Decision Analysis (MCDA). Unlike previous studies that focused on single crops or generalized recommendations, this system will deliver zone-specific and season-specific recommendations for both multi-cropping and fertilizer application in Region 10. By targeting key crops such as maize, mungbean, peanut, soybean, squash, sweet potato, cassava, taro, eggplant, tomato, pechay, and cabbage, the project seeks to optimize yields, reduce resource waste, and promote sustainable agriculture practices aligned with the region's diverse farming systems.

CHAPTER 3

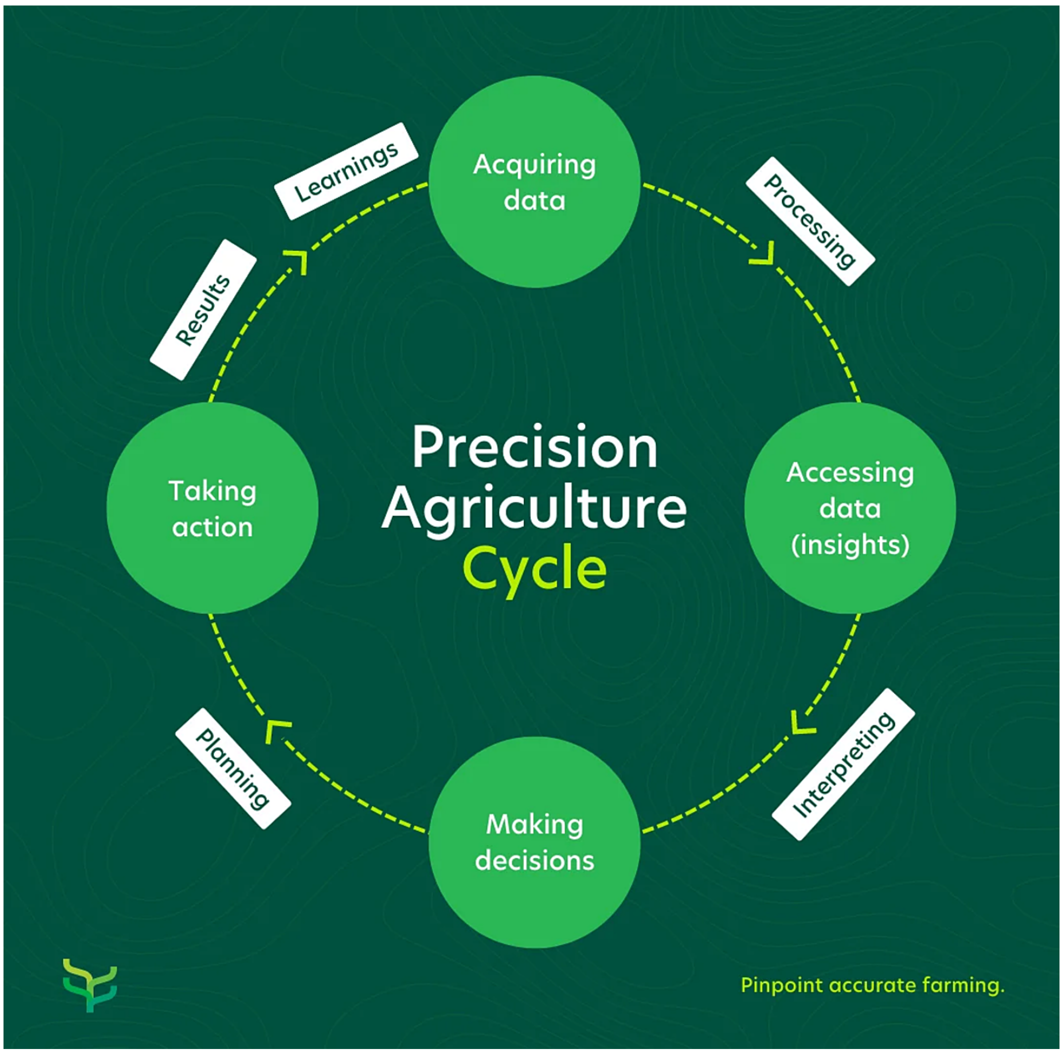
METHODOLOGY

In this chapter, the researchers outlined the methodology used to develop a soil health monitoring and recommendation system, which aimed to enhance sustainable agricultural practices through present data. The study utilized an experimental approach, integrating IoT sensors and machine learning algorithms, to enable continuous and accurate assessment of soil conditions. By focusing on essential soil parameters such as nitrogen, phosphorus, potassium (NPK) and pH this methodology provided insights that supported optimal crop management. This chapter also addressed the rationale behind the chosen experimental design, describing each stage of data collection, system setup, and analysis.

3.1 Research Design

Figure 3.1

Modified Waterfall Model



temporary

This study follows a modified waterfall research model to guide the development of the IoT-MCDA system shown in figure 4. The process begins with the requirements gathering, in which the system will collect comprehensive data from the Department of Agriculture (DA) and credible online datasets. The datasets include zoning information and soil parameters, as well as crop-specific requirements for growth conditions. Moreover, all datasets will be integrated with the DA's zoning information.

It then proceeds to the requirements analysis, which identifies the need for soil health monitoring, crop prediction and fertilizer recommendation in the selected field in Region 10. A gradient boosting algorithm will be employed , using both sensor and zoning data inputs. Soil health prediction will classify soil quality levels, while crop yield forecasting will leverage an optimized machine learning model with metaheuristic-based feature selection to predict expected productivity. Fertilizer recommendations will be generated through a hybrid IoT-MCDA framework.

The next phase is the system design, where the flow of the overall system is defined with detailed descriptions on how the system will work on implementing the IoT-based ML Integration system. This phase involves a comprehensive overview of the system design, architecture, the flowchart of the hardware and software that will be used in this system, as well as the web and mobile interfaces. The design ensures seamless integration of hardware components for data acquisition, software modules for data analysis and prediction, and user interfaces for monitoring control.

This is followed by the implementation phase, which involves the development of the IoT system, training and testing of the machine learning model, in combination with multi-criteria decision analysis methods, and the configuration of hardware and software. Field nodes gather and preprocess soil data, then transmit it to a central server for storage, predictive analytics, and generation of crop suitability and fertilizer recommendations. A web dashboard visualizes soil health, farmer data, nutrient trends, weather, and zoning maps.

Once completed, the testing phase is carried out in the selected area where soil data is gathered and prediction accuracy is measured. In this phase, the zoning-based recommendations are also validated. The validation phase then ensures reliability through quantitative accuracy testing and qualitative feedback on usability. Finally, the deployment and maintenance phase presents possible large-scale applications across Region 10 with recommendations for improvement, scalability, and sustainability.

3.2 Requirements Gathering

The system requires comprehensive data collection to provide accurate, multi-cropping planning and fertilizer recommendation based on farming zoning in Budkinon, Philippines. Data will be sourced from the Department of

Agriculture (DA), and credible online datasets. This includes detailed zoning information and soil parameters. To be included also are crop-specific requirements and growth conditions. Gathering these datasets ensures that the recommendation system is grounded in both environmental and agricultural best practices.

The types of data required encompass zoning information, and detailed crop profiles. Zoning data defines farming area, and land use classifications, while soil parameters include pH levels, matter, texture, and other essential nutrients. To be included as well is climate data such as historical rainfall, temperature, humidity, and forecast models which provide insights into environmental conditions that affect crop growth.

In preparation for system integration, the data will undergo a series of preprocessing steps. Missing sensor readings and data gaps will be addressed through interpolation, while noisy or incorrect data will be identified and removed to maintain integrity. Soil and climate parameters will be normalized into uniform ranges to enhance the performance of predictive models. Once cleaned and standardized, all datasets will be integrated with the Department of Agriculture's zoning information to ensure that recommendations are localized and relevant to the specific conditions in Bukidnon.

3.2.1 Research Setting

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The study will be conducted on specific farms in Region 10, specifically farms in Bukidnon, Philippines. The region is mostly agricultural, with vast lands focused on the cultivation of high-value crops such as Maize (Corn), Mungbean (Mongo), Peanut, Soybean, Squash (Kalabasa), Sweet Potato (Camote), Cassava, Taro (Gabi), Eggplant, Tomato, Pechay, and Cabbage The farms in this region typically employ conventional and semi-modern farming practices, which offers a realistic setting to monitor and assess crop performance under actual farming conditions.

3.3 Requirements Analysis

The system requires the development and implementation of a machine learning component capable of performing soil health prediction, and crop recommendation. Machine Learning boosting algorithms will be employed for these tasks, using both sensor and zoning data. Soil health prediction will classify soil quality levels, while crop yield forecasting will leverage an optimized machine learning model with metaheuristic-based feature selection to predict expected productivity. Fertilizer recommendations will be generated through a hybrid IoT-MCDA framework. Machine learning with Multi Criteria Decision Analysis will be combined to determine the most suitable fertilizer type and dosage for specific conditions. The dataset will be divided into training, validation, and testing subsets with a `70-15-15` split respectively to maximize the predictive accuracy and avoid overfitting.

The system will undergo proper evaluation using both quantitative and qualitative approaches. Quantitative assessment will include metrics such as accuracy, precision, recall, and F1-score for soil health prediction. R^2, RMSE, and MAE for crop yield forecasting and consistency ratios and ranking stability indices for crop recommendation. Cross-validation will ensure model robustness across different crop zones. Qualitative evaluation will involve focus group discussions and structured interviews with farmers and agricultural technicians in Region 10 to assess usability, reliability, and practical value. Feedback from these sessions will guide further refinement of the system to ensure its effectiveness in real-world agricultural applications.

3.3.1 User Definition

Following the requirements analysis, the system's users were defined as follows:

Farmer - Farmers are the primary beneficiaries of the system. Their farms provide localized data inputs through the soil sensor. In return, farmers receive soil health insights, and multi-cropping recommendations.

Department of Agriculture (DA) - The DA serves as both a data provider and a supervisory user of the system. They supply zoning information, and other agricultural zoning datasets that form the foundation of the recommendation system. Through the web-based dashboard, DA officials can visualize regional soil health trends, and monitor farming zones.

The specific user requirements are summarized in Table 1.

Table 2: User Requirements

User	**Requirements**
Farmer	- Access soil health insights (pH, moisture, nutrients) through a mobile app. - Receive crop suitability scores and multi-cropping recommendations. - Get fertilizer schedules tailored to soil condition and crop type.
Department of Agriculture	- Provide zoning maps, soil datasets, and crop profiles to the system. - Access a centralized web dashboard to visualize soil health, nutrient trends, and farmer data across Region 10.

This table summarizes the requirements of the system's two main users. Farmers need accessible insights and recommendations to guide timely crop and fertilizer decisions, while the Department of Agriculture requires integrated data and analytics to support monitoring, reporting, and regional agricultural planning.

3.3.2 System Requirements

The system requirements shown in Table 2, were categorized into Process, Output, Control, and Performance specifications to aid the system design and implementation.

Table 3: System Requirements

Category	**System Requirement**
Input Requirements	- The system shall accept input data directly from farmers and agricultural authorities through the designated interface. - The system shall acquire and process soil data from integrated sensors or external data sources. - The system shall accept soil health data from the sensor as input for hardware operation. - The system shall retrieve weather information from external APIs.
Process Requirements	- The system shall combine weather, soil, and farmer-provided data into a single decision-making framework. - The system shall employ boosting algorithms to enhance the accuracy of predictive crop recommendations. - The system shall apply multi-criteria decision analysis methods to evaluate and rank potential crop options.

Category	System Requirement
	- The system shall analyze data-driven insights to balance yield potential with resource availability. - The system shall determine an appropriate planting timeline based on environmental conditions and crop growth requirements.
Output Requirements	- The system shall present crop recommendations via a visual interface on mobile and web applications. - The system shall display multi-cropping options, which shows compatible crop pairings. - The system shall present localized weather forecasts. - The system shall provide soil health reports with clear visual indicators. - The system shall display information on current crops cultivated by the farmer. - The system shall display farm details of the farmer. - The system shall display the locations and overview of registered farms. - The system shall display a list of all farmers registered. - The system shall present crop rules, including crop rotation guidelines, and companion planting practices.
Control Requirements	- The system shall provide secure login and authentication for farmers and agricultural authorities.

Category	System Requirement
	- The system shall restrict access to sensitive data based on user roles and permissions. - The system shall allow administrators to update crop rules and farm locations.
Performance Requirements	- The system shall scale efficiently to accommodate growth in registered farmers and farms without requiring major redesign. - The system must be able to have offline syncing for farmer features. - The system must provide accurate crop recommendations for farmers.

The system requirements were defined to ensure the effective collection processing, and presentation of farm and soil data to support informed crop management decisions. The primary objective of the system is to assist farmers by integrating farm-specific information, and soil health metrics to generate accurate and actionable crop recommendations. Input requirements focus on collecting data from farmers and sensors, while process requirements involve advanced algorithms. This includes boosting algorithms, and multi-criteria-decision analysis, to evaluate and rank crop options. Outputs are delivered through mobile and web applications, to provide farmers and administrators with visualized recommendations. Control requirements ensure secure access, role-based permissions, and administrative capabilities for managing crop rules and farm records. Lastly, performance requirements address scalability, offline syncing, and recommendation accuracy, to ensure effective decision support in diverse agricultural contexts.

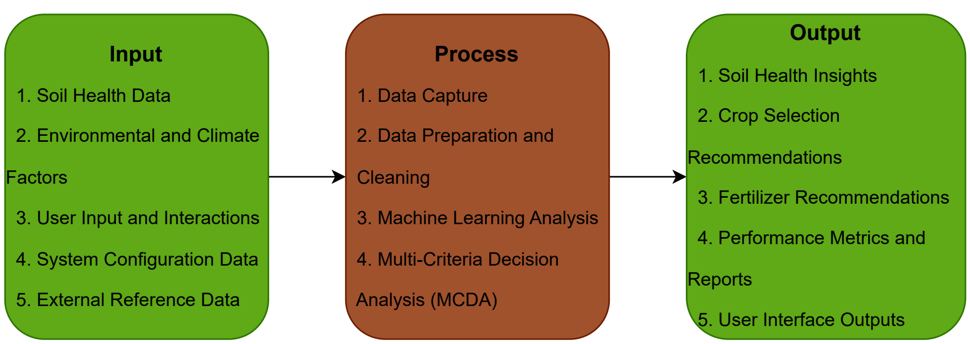
3.4 System Design

In this section, the flow of the overall system is defined with detailed descriptions on how the system will work on implementing the IoT-based ML integration system. This involves a comprehensive overview of the system design and architecture, and the flowchart of the hardware and software that will be used in this system. The design ensures seamless integration of hardware components for data acquisition, software modules for data analysis and prediction, and user interfaces for monitoring and control.

3.4.1 System Architecture

Figure 3.2

System Architecture



The figure 3.2 illustrates the system architecture of Soil Health Monitoring, Fertilizer and Crop Recommendation for Greater Crop Yield. The system begins with a solar-powered IoT sensing unit deployed in the field. A solar panel, managed by a solar charge controller, supplies power to the entire device, ensuring continuous operation even in remote areas. The core sensing component is a soil sensor, which measures parameters such as NPK, pH, electrical conductivity, soil moisture, and temperature. Data from the sensor is transmitted through a TTL MAX485 module, which converts soil sensor signals to TTL levels readable by the ESP32 microcontroller. The ESP32 serves as the central processor, collecting sensor data, performing basic preprocessing such as averaging and sorting, attaching metadata like timestamp and location, and preparing the data for wireless transmission. For communication, the ESP32 uses a LoRa module, which allows the data to be sent over long distances to a gateway with minimal power consumption.

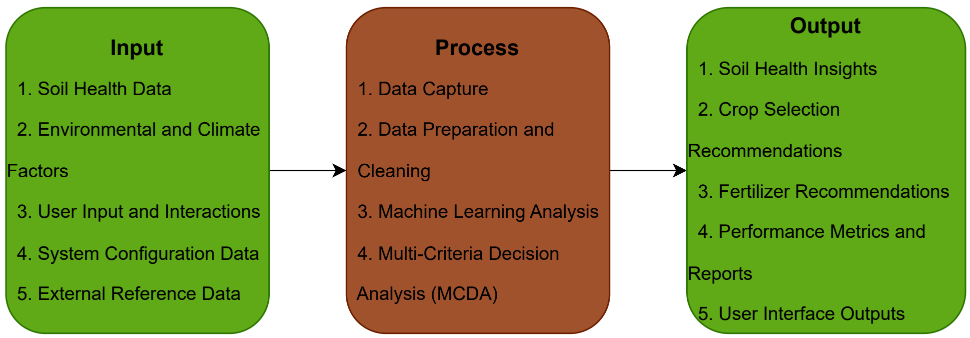
The gateway acts as a bridge between the field device and the cloud, receiving the LoRa packets and forwarding them to the internet via Wi-Fi, Ethernet, or cellular connectivity. From there, the data is securely transmitted to Firebase, which serves as the cloud database for real-time storage and access. Once in the cloud, the raw sensor readings undergo preprocessing, validation, and enrichment with additional context such as weather or crop stage information. This cleaned data is then passed to the machine learning engine, which analyzes soil health and generates actionable outputs. Using both agronomic rules and predictive models, the system provides fertilizer recommendations, crop suggestions, and soil health scores tailored to specific field conditions.

The results are delivered through two applications: the TANIM Web App and the TANIM Mobile App. The Web application is designed for agricultural authorities, providing dashboards, maps, and analytics tools to monitor soil conditions across regions and guide agricultural programs. Meanwhile, the Mobile application is aimed at farmers, offering simple and actionable insights such as soil health insights, crop recommendation and fertilizer optimization for multi-cropping. Both apps also support real-time notifications for critical issues like soil stress or device malfunctions. Importantly, farmers can provide feedback through the app, reporting crop outcomes and applied practices. This feedback, together with sensor data, is fed back into the system to retrain machine learning models and refine recommendations, creating a continuous improvement loop. Through this integration of IoT, cloud computing, and machine learning with multi-criteria decision analysis, the system enables data-driven decision-making that supports both farmers and agricultural authorities in achieving higher crop yields and sustainable farming practices.

3.4.2 Flowchart

Figure 3.3

System Flowchart



The figure 3.3 presents the operational workflow of the proposed soil health monitoring and recommendation system, highlighting the data flow from the field device to the end-user applications. The process initiates at the sensing stage, where the ESP32 microcontroller, powered through a solar energy management unit, interfaces with soil sensors to capture essential soil parameters, including Nitrogen, Phosphorus, and Potassium (NPK), pH, moisture, temperature, and soil salinity. These parameters are critical indicators of soil fertility and crop suitability. Once collected, the data is processed locally by the ESP32 to ensure efficient packaging before transmission. Leveraging LoRa technology, the device transmits the data wirelessly over long distances to a gateway, which serves as the intermediary link between the sensing unit and the cloud infrastructure. The gateway then forwards the collected data to a cloud database, ensuring reliable and scalable data storage for subsequent analysis.

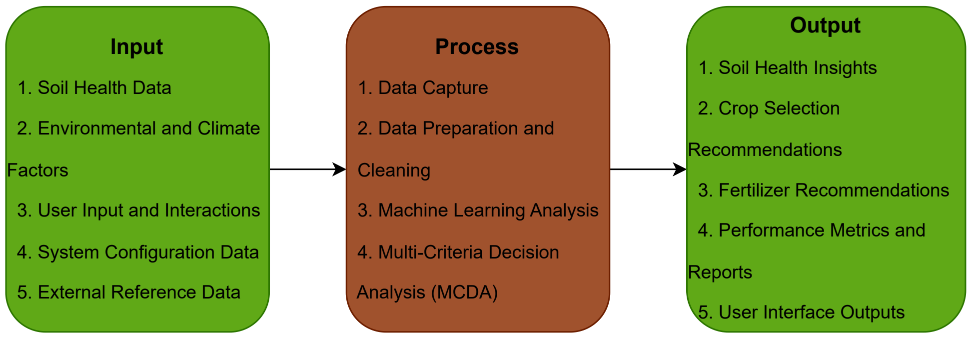
Within the cloud environment, the raw soil data undergoes processing and analysis through machine learning models. These models are trained on historical soil and crop datasets to identify patterns, classify soil conditions, and predict nutrient deficiencies. By transforming raw sensor readings into interpretable outputs, the system generates actionable insights regarding soil health and crop management. The analytical results include fertilizer recommendations and crop suitability assessments, enabling evidence-based decision-making for end users. This layer of intelligence ensures that data collected from the field is not merely stored but is also transformed into knowledge that directly supports precision agriculture practices.

The processed insights are subsequently disseminated through two primary platforms: a web application and a mobile application. The web application is designed for agricultural authorities and extension officers, providing comprehensive monitoring dashboards, spatial analysis tools, and regional soil health reports. This enables decision-makers to track soil conditions at scale, identify priority intervention areas, and develop region-specific agricultural strategies. The mobile application targets farmers as the primary stakeholders, offering a user-friendly interface to access real-time soil health status, recommended fertilizer dosages, and crop-specific advisories. Notifications and alerts are integrated into the system to provide timely guidance, particularly in scenarios requiring immediate action.

An integral component of the workflow is the feedback mechanism incorporated within both platforms. Farmers and users are able to submit observations, report crop outcomes, and validate system recommendations. This feedback not only enhances farmer engagement but also provides valuable data for iterative improvements of the machine learning models. As a result, the system establishes a continuous learning cycle wherein recommendations are refined over time, leading to greater accuracy and contextual relevance. Overall, the workflow described in Figure 3.3 demonstrates how the integration of IoT sensing, cloud computing, and machine learning facilitates a comprehensive, data-driven approach to soil health management and crop productivity enhancement.

Figure 3.4

Software Mobile Application



The figure 3.4 illustrates the workflow of the farming recommendation system, highlighting the interaction between farmers and the application in obtaining crop suggestions tailored to soil and weather conditions. The process begins with user authentication, wherein the farmer logs into the system using their credentials. The application validates these credentials against the stored records in the database, ensuring secure access. If the credentials are incorrect, the system prompts the user to re-enter valid information, thereby safeguarding the platform against unauthorized access. Upon successful login, the farmer is redirected to the dashboard, which serves as the central interface for accessing personalized farm data and system functionalities.

From the dashboard, the farmer navigates to the "My Farms" section, where the application consolidates and displays farm-specific data. This includes soil health parameters gathered from IoT-enabled sensors and environmental information derived from integrated weather forecasting services. The system then processes this combined dataset using its analytical and decision-making algorithms to generate a list of recommended crops that are most suitable for the prevailing soil and weather conditions. By leveraging both real-time and contextual data, the system ensures that the recommendations are accurate, adaptive, and relevant to the farmer's specific location and situation. Once the recommendations are presented, the farmer can review the options and select the crop that aligns with their goals, preferences, and available resources. Following this selection, the system provides advanced features designed to further support farm management. These include multicrop suggestions, which propose crop diversification strategies for risk mitigation and sustainable land use, as well as a detailed crop planting timeline that outlines optimal planting and cultivation schedules. Such features are aimed at enhancing farming efficiency, improving resource allocation, and maximizing yield potential.

The final stage of the workflow involves the farmer applying the recommendations provided by the system. By combining data-driven crop selection with structured guidance on crop management, the system enables farmers to initiate the farming process with greater confidence and scientific support. This workflow underscores the system's capacity to guide users from initial login and farm data access to informed decision-making and implementation in the field. Ultimately, the integration of secure user access, real-time soil and weather data, intelligent recommendation algorithms, and decision support tools demonstrates how the farming recommendation system contributes to improved agricultural productivity and long-term sustainability.

Figure 3.5

Web Application Flowchart

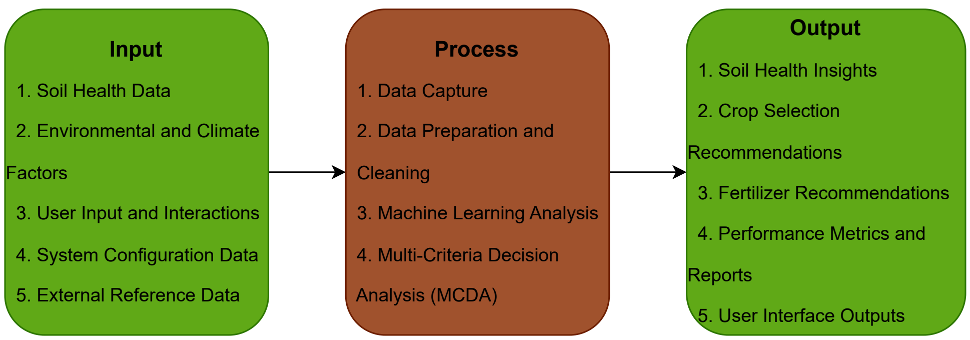


Figure 3.5 illustrates the workflow of the Farm Management Web Application, which is specifically designed to support agriculture administrators in managing and monitoring farming activities at a broader scale. The process begins with a secure login mechanism, wherein the administrator is required to enter valid credentials. The system validates these credentials against stored records to ensure authorized access. If the login attempt is unsuccessful, the administrator is prompted to re-enter the correct credentials, thereby maintaining both system integrity and data security. Once authenticated, the ad-

ministrator is directed to the main dashboard, which functions as the central control panel for the application.

From the dashboard, administrators are provided with access to several key modules, each serving a distinct role in farm management. The Farms module enables the management of farm records, including details such as farm size, location, and soil health data. The GIS Map module provides geospatial visualization, allowing administrators to monitor farm distribution, analyze spatial patterns, and make data-driven decisions at the regional level. The Farmers module consolidates and manages farmer profiles, enabling oversight of farmer registration, activity logs, and engagement with advisory services. The Crop Rules module supports the definition, modification, and enforcement of agricultural guidelines, such as fertilizer application standards, crop suitability rules, and sustainability practices. These modules are seamlessly integrated with the dashboard, ensuring smooth navigation and centralized administration.

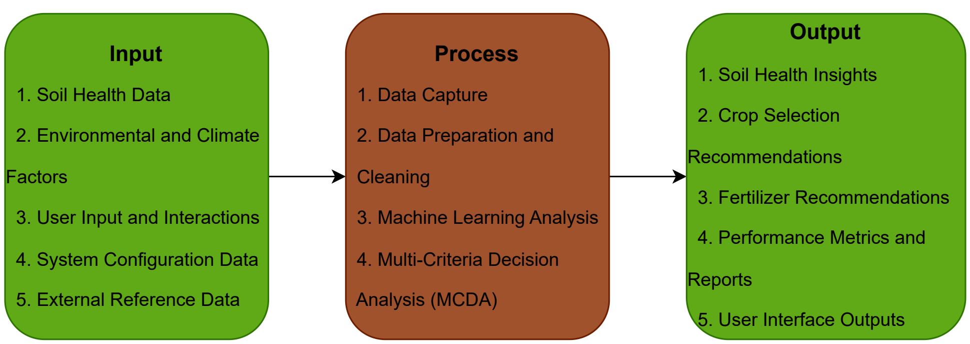
Additionally, the system provides administrators with the option to securely terminate their session at any point through the logout function, further reinforcing data protection and privacy. By integrating secure access control with comprehensive management modules, the Farm Management Web Application ensures that administrators maintain full oversight of agricultural data, farmer engagement, and policy implementation. This workflow demonstrates how the system empowers administrators to efficiently coordinate farm-level operations while supporting evidence-based decision-making, regional monitoring, and sustainable agricultural governance.

3.4.3 Context Level Diagram

The Context-Level Diagram provides a high-level view of how the TANIM system interacts with its primary stakeholders: Agricultural Authorities and Farmers. It illustrates how data flows into and out of the system without detailing internal processes.

Figure 3.6

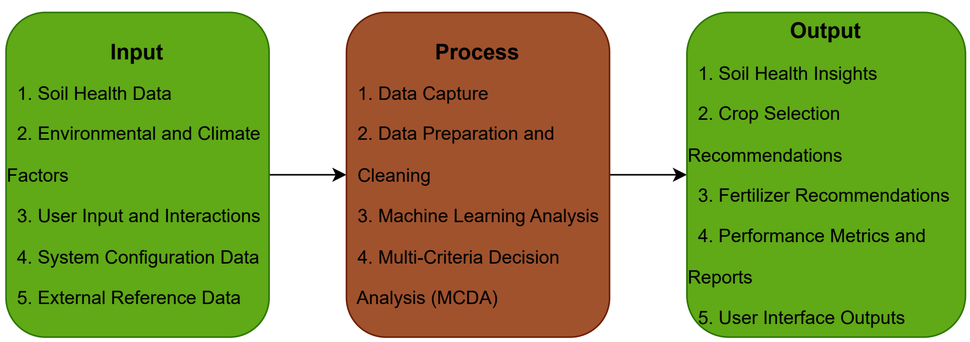
Context-Level Diagram Between the System And Agricultural Authorities



The Figure 3.6 presents the interaction between Agricultural Authorities and the TANIM Web Application from the perspective of informational input and decision-making output. While authorities do not directly generate the raw data, they receive processed insights derived from IoT devices deployed in the field. These insights include soil analysis reports, GIS-based farm visualization, farmer profiles, and crop recommendation results. Each of these outputs enables corresponding benefits such as evidence-based policy-making, targeted resource allocation, compliance tracking, and improved agricultural planning. In this way, TANIM translates raw field data into actionable intelligence, empowering authorities to make informed, timely, and sustainable decisions that support both farmers and national food security goals.

Figure 3.7

Context-Level Diagram Between the System And Farmers



The figure 3.7 illustrates the interaction of the TANIM Mobile Application with farmers and IoT devices. IoT devices act as data sources, providing soil and environmental information to the system, which then processes the data to deliver outputs such as soil analysis reports, planting schedules, fertilizer guidance, crop recommendations, and farming practice records. Farmers, as external entities, contribute by supplying inputs like crop yield feedback, farming activity logs, fertilizer usage records, and crop preferences. This exchange of data ensures that the system can generate accurate recommendations, supporting sustainable farming practices and helping farmers improve productivity and decision-making

3.4.4 Data Flow Diagram

The Data Flow Diagram visually represents how data flows within the TANIM system. It highlights the interactions between IoT devices, farmers/agricultural authorities, and the system's core processes, demonstrating how data is retrieved, stored, and analyzed to provide soil health insights and crop/fertilizer recommendations.

Figure 3.8

Data Flow Diagram

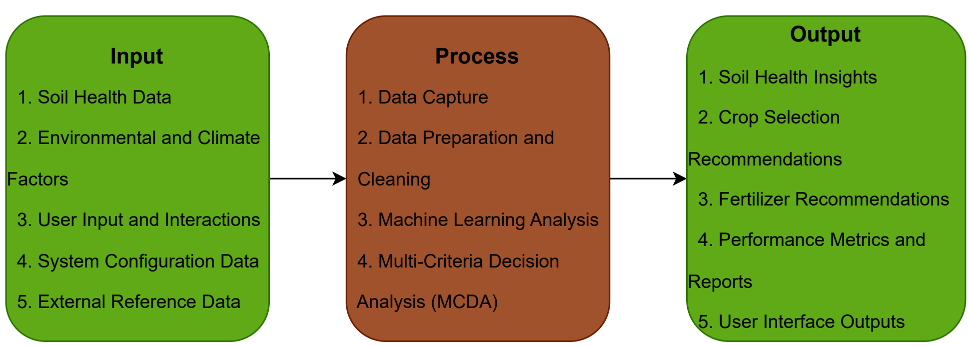


Figure 3.8 shows the Data Flow Diagram (DFD) of the TANIM system.

The data flow between the user and the system is divided into two main processes: retrieval and analysis. The "retrieve" process is responsible for collecting soil and farm data from IoT devices, as well as crop and fertilizer inputs from the users. These data are then stored in the system's database for access and processing. The "analysis" process uses the stored data to assess soil health conditions and generate crop or fertilizer recommendations. Finally, the processed results are delivered to farmers or agricultural authorities in the form of soil data analysis reports and practical recommendations to support better agricultural decision-making.

3.4.5 Use Case Diagram

The Use Case Diagram visually represents how different actors interact with the system of TANIM. It illustrates both passive and active engagements that facilitate data collection and system utilization.

Figure 3.9

Use Case Diagram

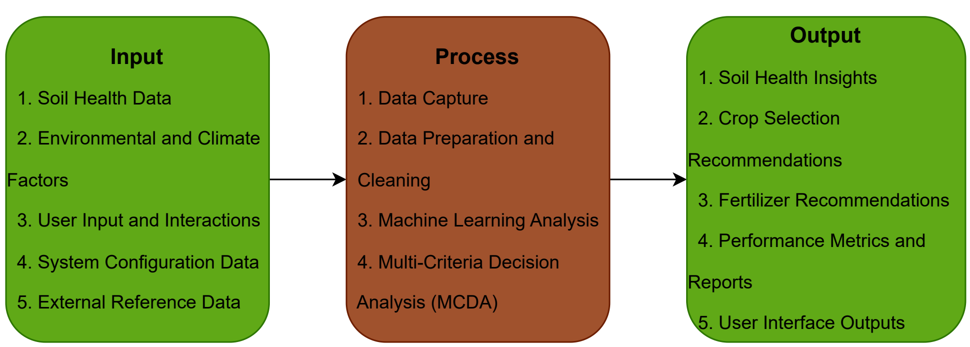


Figure **??** shows how Farmers interact with the system. Farmers can use the system to view a list of their own farms, which helps them keep track of their agricultural activities in an organized manner. They are also able to check the status of their crops in the corresponding farm. This allows them to stay updated on growth progress and overall crop status. In addition, the system enables farmers to monitor soil health, Farmers can also access weather updates directly through the platform, which is essential for planning day-to-day tasks and preparing for potential challenges. Lastly, the system provides personalized crop recommendations, giving farmers guidance that is tailored to their specific conditions and needs. Together, these features create a comprehensive tool that supports farmers in managing their farms more effectively.

Figure 3.10

Use Case Diagram

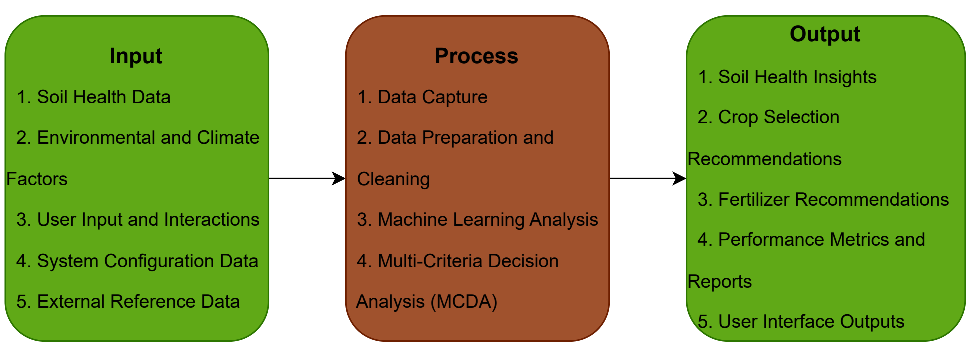


Figure 3.10 shows how the Department of Agriculture interacts with

the system. The Department of Agriculture can access everything the farmer has access to, in addition, the Department of Agriculture can utilize a comprehensive dashboard that provides weather insights, which gives a clear overview of conditions that may affect multiple farms at once. It also has the ability to manage all farm listings. Another important function is the use of GIS maps to view farm locations, allowing for a view of agricultural activity across different areas. Lastly, the Department can oversee crop-related regulations, ensuring that standards are properly implemented.

3.4.6 Hardware Design Flowchart

Figure 3.11

Hardware Design Flowchart

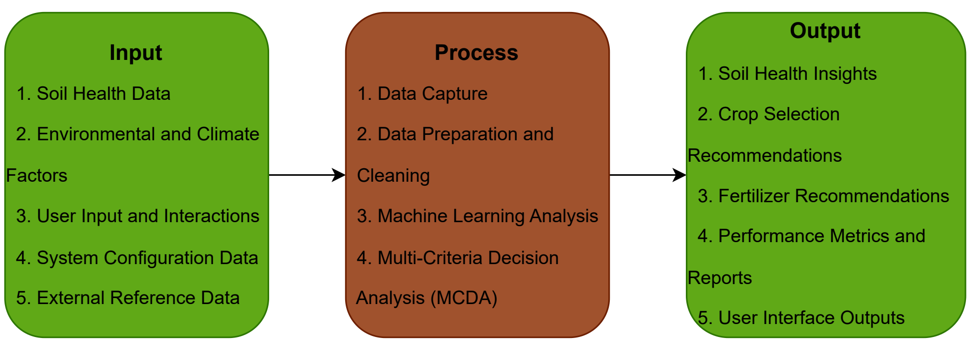


Figure 3.11 illustrates the workflow of the hardware components. Figure 15 illustrates the workflow of the hardware components. The process begins at the "Start" node, followed by the initialization of the central micro-

controller. Next, the sensor is initialized to prepare for data collection. Once the sensor retrieves data, the process moves to the transceiver module, which handles the transmission of the collected data. The transmitter module then processes and sends the data, concluding the workflow at the "End" node.

The flowchart represents a sequential hardware operation where each step is dependent on the successful completion of the previous one. The microcontroller acts as the brain, controlling the sensor initialization and data retrieval. The transceiver module facilitates communication, while the transmitter module ensures the data is sent effectively, completing the hardware cycle.

3.4.7 3D Design

Figure 3.12

3D Container Design

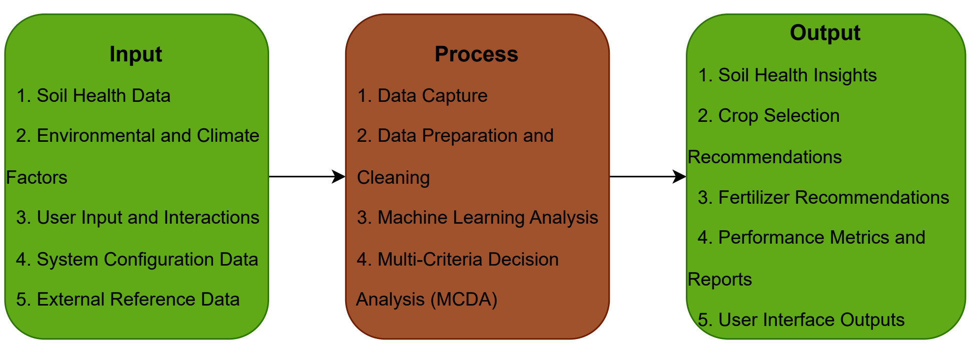


Figure 3.12 displays the 3D container design that will be 3D printed for the container of the hardware. This will contain the hardware components which are etched in a PCB board that will be used in this system. The container should be durable to ensure that it can secure the hardware components inside of it.

3.4.8 Materials and Cost

Table 4: Hardware Components and Cost

Component	**Price**
Microprocessor	₱150
Soil Sensor	₱1,654.90
Solar Power Manager	₱860
Solar Panel	₱320
Lithium Ion Battery	₱120
Transceiver Module	₱163
Transmitter Module	₱180
Miscellaneous (Cable, Mounts)	₱1,500
Total	**₱4,947.90**

3.5 Implementation

The Implementation phase involves developing the software and hardware components. Each function was ensured to function according to the design specifications.This phase intends to transform the conceptual design into a working prototype that can perform data acquisition, processing, and output for TANIM.

3.5.1 Software Implementation

The software implementation for TANIM is designed to provide an efficient, reliable, and user-friendly platform that caters to the needs of both the Farmer and The Department of Agriculture. To ensure optimal accessibility and performance, the frontend for farmers is developed using React Native, a framework well-suited for creating responsive mobile applications. While the frontend for the Department of Agriculture is implemented using React.js, which allows for seamless web application experience. Both user interfaces interact with a shared backend developed in Flask, which centralizes data management and ensures consistent functionality across platforms. This architecture aids in efficient communication between the mobile and web applications. It also supports scalability, and maintainability and ease of integration with additional features or services in the future.

3.5.2 Hardware Implementation

The hardware implementation of the TANIM system is centered on an IoT-based device designed to collect soil data and send it to the cloud for processing and analysis. The core of the device is an ESP32 microcontroller, due to its high processing capability, built-in Wi-Fi, and compatibility with multiple sensor modules. A soil sensor is used to monitor key soil parameters such as NPK, moisture, temperature, and pH. Meanwhile a TTL MAX485 module facilitates reliable communication between the sensors and the ESP32. Data transmission is handled via a LoRa module, which provides long-range, and low-power communication to a central gateway. The system is to be powered by a solar panel managed through a dedicated solar panel manager. The modular design of the hardware makes the system scalable and adaptable to changing agricultural environments.

3.5.3 Data Acquisition and Storage

The sensor is tasked with acquiring data by measuring a variety of critical indicators of soil health. The collected data is then sent to a cloud storage, which provides a secure, scalable, and easily accessible repository for large volumes of environmental data. This cloud-based storage solution not only ensures data integrity and reliability but also facilitates seamless integration with processing stages. The stored data is then utilized as input for the trained machine learning model, which analyzes the information to generate precise insights, predictions, and recommendations regarding soil conditions. Overall, this supports informed decision-making for agricultural management.

3.5.4 Machine Learning Model

The TANIM system will use a boosting algorithm as the core of its predictive model, chosen for its efficiency, scalability, and high accuracy in handling large and complex datasets. This machine learning approach is combined with Multi-Criteria Decision Analysis (MCDA) methods, to provide crop recommendations that consider multiple factors such as soil type, weather conditions, and historical yield data. By integrating machine learning boosting algorithms and Multi-Criteria Decision Analysis, the system is able to deliver personalized and data-driven crop recommendations that optimize productivity and efficient crop utilization.

3.6 Test and Evaluation

Testing and evaluation will be conducted to verify the system's effectiveness, accuracy, and usability for crop recommendation and soil health monitoring. This process will be designed to ensure that the hardware components, software components, and machine learning models will function according to what we aim for this study, which involves hardware testing and calibration, functional testing, system integration testing, performance testing, and usability testing. Hardware testing and calibration will focus on verifying the accuracy of the sensors to ensure reliable soil data. Functional testing will examine whether the mobile and web applications operate correctly and deliver the expected outputs of each feature. To ensure that the hardware, cloud database, machine learning, and applications works together with proper data flow and error handling, system integration will be implemented. For measuring the responsiveness of the system and to evaluate the system's predictive accuracy of the machine learning models using various performance metrics we will be conducting performance testing. Moreover, usability testing will assess the practicality and user-friendliness of the system by involving farmers and agricultural experts in field trial and feedback collection.

3.6.1 Hardware Testing and Calibration

Hardware testing and calibration will ensure that the IoT sensors will provide accurate measurements of soil health parameters such as nitrogen, phosphorus, potassium, pH, moisture, salinity, and temperature. To conduct this testing, the sensors will be deployed in field testing on the actual farms in Region 10, also to ensure consistency under varying field conditions the readings will be recorded at different time and day. Cross checking will be applied by using the Department of Agriculture's soil testing laboratory and soil test kits of the same soil samples from the same farms to ensure reliability and accuracy.

Through statistical measures such as Mean Absolute Error (MAE) the sensor readings will be compared against laboratory results. a maximum allowable error threshold of ± 5 will be set, if the difference between the sensor and laboratory values exceeds this threshold error, calibration adjustments will be applied to the sensors until acceptable accuracy will be achieved. It will be calculated by:

EQUATION DIRI

This process ensures that the data generated by the hardware is reliable enough to be used in machine learning models and the recommendation system.

3.6.2 Functional Testing

Functional testing involves verifying whether each feature of the mobile and web applications operates correctly according to the system design. For the mobile application, the following features will be tested: secure login and authentication, retrieval of soil health readings, display of crop recommendation for multi-cropping, fertilizer optimization, and offline data synchronization. For the web application, features like farm visualization, farmer profile management, and crop rules will be tested.

Each feature will be executed under controlled test cases and the outcomes will be analyzed against the desired output. Additionally, stress tests will be conducted by simulating multiple user logins and farm entries simultaneously to evaluate the application performance. Through this process it ensures that the mobile and web applications behave correctly as intended and is reliable for real-world scenarios of farmers and agricultural authorities.

3.6.3 System Integration Testing

System integration testing will evaluate whether the hardware, software, cloud database, and machine learning model communicates seamlessly with each other as a single system. The system integration testing will be tested by following the full flow of the system: soil health readings captured by the sensor and processed by the ESP32 microcontroller, then transmitted by via the LoRa module to the gateway, forwarded to the cloud database, then processed by the machine learning models, and finally displayed on the mobile and web applications.

This process confirms that the system works together as one reliable system. Furthermore, tests will be conducted to observe how the system handles incomplete or corrupted data to ensure that it can manage error to prevent misleading recommendations to farmers.

3.6.4 Performance Testing

For the system level performance, it is to determine if the system could handle multiple data acquisition and provide timely feedback to the users. The data transmission success rate will be monitored by comparing the successful sensor to cloud uploads against the attempted uploads over multiple trials. Latency tests measure the time from the sensor data capture to its display in the mobile and web application, with an acceptable range set to 30 seconds. Scalability will be evaluated by simulating multiple farms connected simultaneously to ensure that the cloud database and applications could handle increased workloads without delays and crashes. These will ensure that the system is reliable and efficient under real-world agricultural conditions where multiple users operate.

For the machine learning evaluation, it verifies the predictive capability of the machine learning models that will be used on crop recommendation for multi-cropping and fertilizer optimization. The dataset will be split into 70-15-15 for training, evaluation, and testing for maximizing the predictive accuracy and avoiding overfitting.

For the crop recommendation, the machine learning models will be evaluated using accuracy, precision, recall, F1-score, and confusion matrices to determine the effectiveness of the system. The following formulas are going to be use:

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The Multi-Criteria Decision Analysis (MCDA) process will be tested by computing the Analytic Hierarchy Process (AHP) consistency ratio, which was required to be less than 0.1 for validity, and by checking the stability of crop rankings produced through TOPSIS. These evaluation steps confirm that the machine learning models not only provide scientifically sound predictions but also deliver recommendations that are consistent and stable under different scenarios.

3.6.5 Usability Testing

The usability testing will assess the practicality, accessibility, and user satisfaction of the system. For this, farmers will be asked to log into the mobile application, review soil health data, view crop and fertilizer recommendations, and simulate updating their farm records. Meanwhile, DA officials will use the web dashboard to access farmer profiles, view GIS-based maps, and manage crop rules.

After completing the navigation of the system, the System Usability Scale (SUS) developed by Brooke (1995) will be employed. The interactions of the users will be observed and the difficulties they encountered will be recorded. Also, feedback will be collected to gain insights into what features were most useful, and which feature needs improvement. This testing ensures that the system will be accessible, user-friendly, and is beneficial to the users.

APPENDICES

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References