

IoT-Driven Crop and Fertilizer Recommendation System

by

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Under the supervision of

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DECLARATION

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We declare that this capstone project report entitled *"IoT-Driven Crop and Fertilizer Recommendation System"* is the result of our own work except as cited in the references. The capstone project report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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Date: May 12, 2025

Dedicated to my friends
for being my support and
to the farmers who works
hard for more sustainable
agriculture and ensure
food security of the world.

– *Md. Tarek Mahamud Rashik*

Dedicated to my beloved
family for being my
strength.

– *Nazia Afrin Titly*

Dedicated to my beloved
family for being
supportive and the farmers
who works hard to fed us.

– *Sanjida Tasnim Oishi*

Dedicated to my family
for being my support and
to my supervisor Professor
Muhammad Golam Kibria,
a good soul

– *Faisal Kabir Taj*

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ABSTRACT

Bangladesh is an agricultural country with a large portion of the country's economy and livelihood dependent on agriculture . Though it is repeatedly facing various challenges and setbacks leading to lower crop yield, degradation of soil quality and decreased production.As a response to these challenges, an IoT based system for soil data collection and periodic monitoring of soil, integrated with machine learning models for precisely recommending crops and fertilizers , as well as soil health report based on soil information and notable suggestions has been proposed. The system integrates IoT sensors for periodic monitoring of soil parameters -pH, moisture, temperature,salinity and nutrient levels. Multiple machine learning models, SVM, CatBoost, Bagging Regressor and Random Forest, analyze and process the data to recommend suitable crops and fertilizer with a accuracy of 98% by CatBoost in crop recommendation and 97.3% by Random Forest in fertilizer recommendation, exceeding other models.In addition pH status, moisture and salinity almost 99% accuracy has been achieved by CatBoost.A web application will works as user interface. Unlike traditional systems that are dependent on environmental parameters and lab tests, our system develops solutions through periodic monitoring, standardized data collection, time efficiency, and timely recommendations.The system's architecture combine IoT and machine learning to improve soil health, optimize crop productivity, reduce costs, increase crop yields , enhancing food security and economic growth through enabling periodic maintenance and advanced decision-making.

Keywords: IoT ,CatBoost, Support Vector Machine, Random Forest, Bagging Regressor, Fertilizer Recommendation, Crop Prediction, Soil Health, Web application.

Chapter 1

Introduction

Bangladesh is an agricultural country, with almost 11.2% of its GDP , 37% of its labor force engaged in agriculture *Fertilizer Recommendation Guide-2018* (2018). The sector plays a significant role in ensuring food security and economic stability. However, agriculture in Bangladesh faces challenges, including the overuse of fertilizers, repetitive crop planting without proper soil care, and a lack of awareness of the maintenance of nutrients. These issues contribute to hampering soil health, reduced productivity and increased costs for farmers. Sustainable agriculture depends on effective soil nutrient management. Current soil analysis methods, such as colorimetric analysis provide reliable results but are inefficient due to their time consuming nature which discourages farmers from utilizing them. Other services lack access to large datasets for comprehensive analysis and do not always work with authorized data sources. Most available services operate on a limited scale and provide fertilizer recommendations all at once, without ongoing monitoring based on real time soil data. To address these challenges our project integrates IoT technology into agriculture, allowing farmers to receive immediate data driven recommendations. IoT is a network of sensors and machines that are useful for collecting , receiving and sending soil data for further analysis to recommend crop and fertilizer. The IoT system consists of a sensor that collects nine soil parameters: nitrogen, phosphorus, potassium, temperature, pH, moisture, salinity, humidity and total dissolved solids. In addition , region plays a significant role in precise crop and fertilizer recommendation. IoT devices transmit the data using the MQTT protocol which was chosen for its low power consumption and bandwidth efficiency. The ESP32 microcontroller is used for its capability to store phone numbers, which helps us keep track of the farmers using our device and organizing them. A web

application enables farmers to monitor their soil conditions and receive tailored crop and fertilizer recommendations from anywhere and at any time, making it highly convenient for farmers. The web application also stores previous recommendations, soil health reports and notable suggestions. This helps farmers to track soil conditions over time and refine their agricultural practices. We created a large dataset from various authorized sources and used with our consistent supervised machine learning model. For crop recommendation, classification models were used like Support Vector Machine (SVM) and CatBoost achieved accuracy rates of 97% and 98%. In addition 99% in pH status, 98% in moisture and 99% in salinity accuracy achieved by CatBoost. For precise fertilizer recommendations regression models such as Random Forest and Bagging Regressor were used which obtained R^2 scores of 97.3% and 97.1%. These models ensure reliable recommendations and reduce the guesswork in fertilizer application and crop selection. Our system can recommend suitable crops- Boro, Maize, T. Aman, Potato, Cauliflower, Cucumber, Cabbage, Radish, Maize, Tomato and Jute. For fertilizer, our system recommends Urea, TSP and MoP. By Integrated IoT and Machine Learning together ensures determining the most appropriate crops and fertilizers with immediate decision making, enabling sustainable agriculture.

1.1 Background Study

Sustainable agriculture depends on careful soil nutrient management. Existing lab-based soil tests are often time-consuming and lack authorized data. Furthermore, many current systems are limited to environmental parameters, leading to inefficiency in addressing agricultural needs and providing recommendations all at once, without ongoing monitoring based on real time soil data. IoT and machine learning offer a strong collaboration by allowing reliable periodic monitoring of soil elements like nitrogen, phosphorus, potassium, pH, moisture, temperature and salinity and recommend farmers suitable crops to grow and how much fertilizer to use. In addition, region plays a significant role in precise crop and fertilizer recommendation and has been taken into consideration. Through a web application, farmers will be able to access soil data, receive reliable crop prediction, timely fertilizer recommendations, soil health report as well as some notable suggestions while

currently data is processed and stored in the cloud. The result is a scalable, data-driven approach to enhance crop yield, increase productivity, reduce environmental impact, and support sustainable agriculture.

1.2 Problem statement

Bangladesh is an agricultural country and an extensive portion of its economy and livelihood dependent on agriculture. Bangladesh's agriculture sector faces numerous challenges that threaten food security, soil health and its economic stability. The overuse of fertilizers, repetitive crop planting without proper soil care, and a lack of awareness regarding nutrient deficiencies are damaging the land and reducing productivity. There exist crop and fertilizer recommendation systems dependent on Laboratory tests, while they are accurate but are time-consuming and often dependent on environmental parameters, sometimes lack authorized data and fail to provide fertilizer recommendations based on crop yield optimization, leading to inefficiencies and environmental harm. Existing recommendation systems provide suggestions about fertilizers and its amount all at once which create misuse of fertilizers. An "IoT-Driven Crop and Fertilizer Recommendation System" can offer a suitable solution to these challenges by providing the appropriate crop for the soil, recommending the optimal amount of fertilizer, monitoring soil health periodically which will benefit agriculture in Bangladesh in increasing productivity and crop-yield, reducing improper usages on fertilizer, guaranteeing long-term farm viability.

1.3 Aims, objectives & Motivation

1.3.1 Aims

"IoT-Driven Crop and Fertilizer Recommendation System" aims to improve soil health, increase productivity and economic growth, and ensure food security by periodic monitoring and collecting real-time soil data on nutrients(nitrogen, phosphorus, potassium), pH, moisture, salinity and temperature using IoT sensors, predict crops as well as periodically recommending fertilizer based on soil information using machine learning models- Support Vector Machine(SVM), Random

Forest(RF), Bagging Regressor(BR) and CatBoost which will provide to the farmers via web application. This project also provide soil health report and notable suggestions.

1.3.2 Objectives

This system focuses on periodic monitoring and collecting data, recommending crops as well as provide soil health reports and notable suggestions to farmers. The main objectives of this project are:

- To collect a standard-size sample of the soil for better accuracy.
- To monitor and collect soil nutrients (NPK), pH, temperature, salinity and moisture level using IoT sensors [ESP32 Soil Sensor RS485, Rs485-to-uart, 16x2 LCD .
- To collect soil data and send to the cloud through ESP32 and will be analyzed with an existing optimal dataset consisting of optimal soil nutrients, pH, moisture , salinity, and temperature needed for a crop with fertilizer and crop recommendations using machine learning models- [SVM, CatBoost, Random Forest and Bagging Regressor] and conditions of the soil.
- To provide crop prediction and fertilizer recommendation , region differnces has been taken into consideration.
- To provide soil health information and recommendations to the farmers through a web application, while currently data is processed via API and stored in MySQL database.

1.3.3 Motivation

The agriculture sector of Bangladesh faces numerous challenges due to improper use of fertilizers, repeated farming,unawareness about nutrient significance in the soil and soil health and many more hampering the soil health , productivity and crop quality, leading to skyrocketing prices of foods, lack of nutrition in foods, the poor livelihood of farmers and the shrinking availability of food supply [M. S. Islam et al. \(2024\)](#). The project strengthens the need to focus on particular actions that

contribute to the application of IoT and machine learning-based technology in the agriculture sector of Bangladesh, allowing specialized solutions for the challenges. The scalability and accuracy offered by this project will help to balance the nutrient level of the soil and soil health, optimal use of fertilizers in the crop yield, ensures productivity growth, introduce crop variety, balance food security and increase economic growth; as well as reduces the cost and robustness of the lab tests.

1.3.4 Significance

Agriculture of Bangladesh faces numerous challenges because of - repeated farming, improper use of fertilizers, and unawareness about soil nutrients and soil health which degrade the soil quality. In 1980, the total usage of fertilizers was almost 8,751,79, which increased to 2,991,264 in 2000 and it became 4,333,800 in 2012, according to the Fertilizer Recommendation Guide-2018 (2018). If this increasing fertilizer is not maintained properly it will continuously impact the soil negatively.” IoT-Driven Soil Monitoring And Fertilizer Recommendation Systems” will -

- Monitor soil elements such as pH, NPK, Salinity, Temperature and Moisture periodically.
- Recommends suitable crops for the soil.
- Recommends fertilizers with proper amounts.
- Provide soil health report and notable suggestions.
- Will offer an user-friendly web application for the farmer while currently data is processed via API and stored in the MySQL database. This will ensure maintaining soil nutrients and soil health, ensure food security by optimizing crop yield, increase productivity and economic growth and reduce improper dependency on fertilizers.

1.4 Scope and Limitation

1.4.1 Design specifications and success criteria

To understand the design specifications of the system this part utilizes requirements and success criteria of the system design.

1. Sensor Measurement

- **Requirement:** The applied sensor measurement should be- pH between , Nitrogen between, Phosphorus between , Potassium between , Moisture between , Salinity between , Temperature between which are acceptable agronomic range.

- **Success criteria:** The sensor measures pH between , Nitrogen between, Phosphorus between , Potassium between , Moisture between , Salinity between , Temperature between ranges.

2. Soil monitoring and data flows

- **Requirement:** The system should collect and transmit data intervals in 10 seconds per readings for each of the parameters

- **Success criteria:** The system collects and transmits data with intervals of 2/3 seconds per readings for each of the parameters and implements for continuous monitoring not more than 1% data loss.

3. Recommendation accuracy

Requirement: The applied machine learning models should achieve accuracy above 90%.

- **Success criteria:** For crop recommendation, classification models were used like Support Vector Machine (SVM) and CatBoost achieved accuracy rates of 97% and 98%. In addition 99% in pH status, 98% in moisture and 99% in salinity accuracy achieved by CatBoost. For precise fertilizer recommendations regression models such as Random Forest and Bagging Regressor were used which obtained R^2 scores of 97.3% and 97.1%.

4. Power efficiency and time consumption

- **Requirement:** The average power consumption of the system should be below 100mA and time consumption should be not more than limited time.

- **Success criteria:** The average power consumption of the system is 5.5 v and needed time is not more than 2/3 seconds per readings.

5. User interface and accessibility

- **Requirement:**The web application must follow a user friendly interface accessible to the farmers from anywhere.
- **Success criteria:**The web application of our system have user friendly interface while data is processed via an API and is accessible to the farmers from anywhere.

1.4.2 Scope

This study aims to develop an IoT-driven soil monitoring, fertilizer and crop recommendation system focusing on precise sustainable agriculture in Bangladesh. The scope includes the following:

- The study will offer crop and fertilizer recommendations across different selected areas, allowing an extensive analysis of soil conditions and fertilizer needs within these areas.
- This system generally focuses on crops like rice, wheat, maize and potato, T.Amana, Radish, Cauliflower, Cucumber and Jute because of their importance in the country's agricultural sector.
- Recommendations will be provided based on soil nutrient levels and specific to each crop and soil's needs.
- The study provide soil health report based on soil parameters and notable suggestions.

1.4.3 Limitations

This study has several defined limitations to ensure feasibility and maintain a focused scope:

- This system will focus on primary nutrients -nitrogen, phosphorus, and potassium (NPK)-based fertilizers only. It will not provide recommendations for additional macronutrients such as zinc and sulfur.

- The system does not specify crop varieties or species; for example, it will suggest "potato" as suitable for a particular soil type but not indicate which species or cultivar of potato to plant.
- The scope is limited to a timeline, and adjustments outside this period are not addressed.
- The device only takes an 11 digit number as input for registration; it is not able to identify if the number is a proper phone number or not.

1.5 Report Layout

Chapter 1 :Introduction This chapter introduces the core idea behind the project, laying out the problem, objectives, significance, motivation, objectives, limitations, design specification with success criteria and outlining the research as a crop and fertilizer recommendation for soil.

Chapter 2 :Literature Review A comprehensive review of the related literature is presented, including studies on the application of IoT in soil monitoring, the role of machine learning in soil monitoring, fertilizer and crop recommendation, MQTT, and collaboration of IoT, machine learning and web application in agriculture . It examines the importance of fertilizer in soil and, based on the soil, what type of crop will be suitable, and the proper amount of fertilizer to use.

Chapter 3 :Design and Development This chapter focuses on the project design, methods, and development process. It covers the work breakdown structure, financial consideration, project requirements, tools and techniques, data flowing process, methodology, solution design, and implementation.

Chapter 4 :Result Analysis This chapter shows the analysis of data collected through IoT-based systems. It evaluates the performance of various machine learning models. Comparative analysis of the accuracy , effectiveness of different models and outlining efficient machine learning models for the system is also discussed.

Chapter 5 :Conclusions The final chapter summarizes the research findings and

discusses the impact of the project in the country's agriculture as well as on environment and sustainability. This part also discusses professional and ethical standards that has been followed. It highlights the project contributions on improving soil health and increasing productivity.

Chapter 2

Literature Review

2.1 Introduction

Bangladesh is an agricultural country with a large portion of its economy and livelihood dependent on agriculture but has to face numerous challenges that threaten food security, soil health and its economic stability. This is because of repeated farming, misuse of fertilizers and unawareness. Traditional methods of crop and fertilizer recommendation usually give poor decisions because of unauthorized data, dependency of environment parameters only, lack of real time data collection, time consuming and don't follow harvesting schedule. Recently, the IoT devices and ML has provided an efficient data-driven approach to agriculture, which enables real-time soil monitoring, crop prediction, and fertilizer recommendation promoting precision agriculture. Several studies have been conducted this part, exploring various methods for IoT and ML-based agricultural systems. Such as- *Fertilizer Recommendation Guide-2018* (2018) guidelines for optimizing proper fertilizer for specific crops, soil conditions and soil type to improve soil quality and increase crop yields and productivity for sustainable farming have been proposed. Also, optimize crop based on soil and land information, about soil health, NPK toxicity, and causes of deficiency.

Kashyap & Kumar (2021) reviews important sensing technologies for soil nutrient monitoring and to see how useful their application is in precision agriculture. They show advanced methods like ion selective membrane based electrochemical sensors, biosensors and capillary electrophoresis systems for detecting necessary nutrients like nitrogen, phosphorus and potassium. Recent developments in solid state sensors and iot usage allow real-time, portable and field ready nutrient moni-

toring. It increases sustainability by reducing excessive and unnecessary fertilizer use. But the paper points out some problems like high costs, complexity and sensor specific calibration requirements.

This paper [M. S. Islam et al. \(2024\)](#) shows the harmful impact of improper fertilizer use. In Eastern Gangetic Plain (EGP) causes yield gaps, soil depletion, and environmental harm because of improper fertilizer use. The study also showed balanced fertilizer use increased crop yields and food security. This project used FRG-2012 guidelines to measure gaps in N, P, K, S, and Zn usage and divided the farmers into overuse and underuse sections. A beta regression model identified the factors influencing these gaps, considering variables like farm size, inputs, and institutional support. The limited data sample for the farmers that underuse fertilizer affect the accuracy and reliability of the analysis.

[Salvi et al. \(2021\)](#) designed an IoT-based soil health monitoring system which will monitor soil health and provide recommendations to improve the quality of soil. The study emphasizes real-time data for practices. The IoT system is designed to monitor soil parameters like moisture content, temperature, nutrients. This innovative technology challenges traditional soil health management and becomes a strengthening pillar for farmers to make proper decisions for farming. Frequent sensor calibration and maintenance are required for this device which increase costs for farmers.

The study uses IoT technology to choose land and processes satellite images from Landsat-8, K-means clustering, random forest, and LSTM to forecast crop yield and healthy plants, while a solar-powered irrigation system controlled by fuzzy logic improves water use with real-time soil monitoring for crop and fertilizer advice. The key limitations are that the system requires validation with larger, varied datasets, integration of real-time weather data for precise irrigation, and field-scale implementation [Saha et al. \(2025\)](#).

This paper mentions a system that has digital twin technology in Agriculture 4.0, integrating weather APIs, GPS modules, NPK soil sensors, and machine learning models to revolutionize agricultural production by leveraging real-time data on soil composition, meteorological dynamics, and geographic coordinates to deliver precise crop growth forecasts, enhance crop recommendation models, and simulate predictive scenarios for optimized water and pesticide management. The key limitation is high initial implementation costs and integration complexity [Banerjee et al.](#)

(2025).

The reviewed paper introduces AgroXAI, a system that integrates IoT, edge computing, and explainable AI methods, specifically ELI5, LIME, SHAP, and counterfactual techniques to generate tailored crop recommendations based on local weather and soil conditions. The key limitation is that the paper identifies a critical trade-off between model accuracy and interpretability, which may hinder the practical adoption of the system in dynamic agricultural environments [Turgut et al. \(2024\)](#).

The study looks into how the use of pesticides and chemical fertilizers is affected by agricultural specialization and large-scale operations. This study fills the information vacuum by examining how specialization leads to inefficient and ignorant use of pesticides and fertilizers, emphasizing the influence of government regulations on agricultural practices. One of the study's limitations is its incapacity to completely account for regional variations in farming methods, which could have an impact on how broadly applicable the findings are [Zhang et al. \(2024\)](#).

2.2 IoT-based Soil Monitoring Systems

Recent developments in agriculture have explored a number of IoT-based soil monitoring systems that use nutrient sensors to measure important factors such as salt, pH, temperature, moisture, and NPK. In order to preserve soil quality, these systems offer real-time data and suggestions. Consequently, IoT-based solutions ensure a healthy environment for crops by automating crucial procedures, reducing human error, and identifying unfavorable conditions more quickly. Several studies have been conducted on how these systems work and the efficiency of these operations.

[M. R. Islam et al. \(2023\)](#) proposed an innovative system which combines both IoT and machine learning to improve crop management through real-time soil monitoring and personalized recommendations. Three sensors JXBS-3001, FC-28, and DHT11 are used in the field to measure necessary parameters like Nitrogen, phosphorus, potassium, moisture, humidity, and temperature. The data is sent to a remote server using NodeMCU and the MQTT protocol. This data is used in machine learning algorithms like Random Forest to give crop and fertilizer recommendations. Which helps farmers make informed decisions. A mobile app

was developed to provide a user-friendly interface where farmers can find sensor readings, track and understand trends and get warnings about critical issues which are nutrient deficiencies, disease outbreaks or bad weather. The Random Forest algorithm which was fine-tuned with GridSearchCV which was able to achieve great results. It got 99.56% accuracy and 100% F1-score in fertilizer prediction. It got better results compared to other models like SVM and Linear Forest. The IoT and machine learning system monitors soil nutrients well, but it does not provide real-time data accuracy and requires a strong internet connection.

A system proposed by [Pyingkodi et al. \(2022\)](#) , uses a range of hardware and software components to monitor soil characteristics like nitrogen, phosphorus, and potassium in real-time. Using that data it provides fertilizer recommendations to help farmers improve their crop growth. The hardware they used for their system is Arduino UNO, a GSM modem, a 16x2 LCD, a voltage regulator and an NPK sensor. The ATmega328P microprocessor is used as its core. The system displays data with the help of IoT and stores it in the cloud for easy access. Kernel Density Estimation is used to analyze the nutrient levels. it generates smooth graphs to understand it better. The IoT-based soil nutrient monitoring system supports smart farming, but it requires regulation frequently and it could be costly for farmers.

[Senapaty et al. \(2023\)](#) presents a cost-effective framework that uses IoT sensors and machine learning to monitor soil nutrients and recommend crops. It employs sensors for soil moisture, temperature, pH and NPK values, all connected to an Arduino board and linked to the cloud via an ESP8266 Wi-Fi module. The data is stored in the Firebase cloud and accessed through an Android app for real-time analysis. The system's multi-class support vector machine which was optimized by the fruit fly algorithm increases the accuracy of crop recommendations. it achieved a high rate of 0.973. This cost-effective system also uses an LDR color sensor instead of a traditional NPK sensor making it cheaper for farmers.

The system described in the paper [Hossain et al. \(2024\)](#) (2024) uses IoT hardware like Arduino UNO, ESP8266, NPK, pH and rain sensors to collect real-time soil data. It is processed and analyzed to recommend crops with the help of a web portal which is user-friendly. The dataset used in this paper contains 8 features which are Nitrogen, Phosphorus, Potassium, temperature, humidity, pH and rainfall. 22 unique crops were represented by 2200 instances. The paper first used four baseline classifiers which were SVM, KNN, Decision Tree and Naive Bayes. They later used

a soft voting ensemble model that combined the predictions from these classifiers based on their probability estimates. This ensemble approach showed superior performance. It got 99% accuracy, precision, recall and F1-score. It outperformed individual models like SVM and Decision Tree. The real-time crop recommendation system uses sensor data effectively, but it may not adjust well to sudden weather changes or extreme conditions like droughts or storms.

A real-time and cloud-based solution for soil analysis by using grid sampling to collect soil samples and measure important nutrients and environmental factors proposed by [Patil et al. \(2021\)](#). The system utilizes sensors like DHT11 for temperature and humidity and an RGB color sensor to find NPK levels with an Arduino and ESP8266 module for data processing and transmission to the cloud via ThingSpeak and Ubidots. This allows farmers to remotely access real-time soil health data through mobile apps. Field tests were done near Pune, India which successfully demonstrated the system's ability to provide real-time monitoring and accurate nutrient assessments. The cloud-based system significantly reduces the delays of traditional lab testing.

[Srivastava et al. \(2020\)](#) paper describes an IoT-based system for remotely monitoring and controlling soil moisture levels using sensors for moisture temperature, and rainfall and DHT-22 for temperature and humidity monitoring. The sensors are interfaced with an Arduino microcontroller which measures main soil parameters and transmits the data wirelessly to a control unit using the Zigbee modules. The data is then processed by a Raspberry Pi (R-pi) and uploaded to the ThingSpeak cloud platform. If the soil moisture falls below a predefined threshold. It causes a trigger signal that activates pumps to maintain optimal moisture levels. The system is powered by solar panels with battery backups. Making sure the operation is uninterrupted. The setup was tested on two artificial fields. The system helps farmers to monitor soil health, but it requires regulation frequently and it could be costly for farmers.

[Anwar et al. \(2023\)](#) project proposes a handheld IoT device that reads soil conditions and sends the data to a server for analysis. The device will have an NPK sensor for detecting soil nutrient levels and a soil moisture sensor for determining irrigation needs. The data collected by the device will be processed by the server. It integrates information from national datasets like the Soil Research Development Institute and agricultural organizations such as the Bangladesh Rice Research Insti-

tute . Recommendations for farmers will be formulated based on these datasets also local soil texture, crop variety, and weather conditions will be used. The Upazila Agriculture Officer plays a key role by ensuring that local farming practices are taken into account. The device will display recommendations for irrigation and fertilizer administration on a simple monitor. The sensing methodologies help to monitor soil moisture and nutrients, but they can not work equally for all soil types and climates. The limitation of this system is the accuracy of it which can vary depending on soil type. It can make the system less effective in different types of farming areas.

Ahmed et al. (2024)proposes a portable IoT-based system to enhance farming efficiency by monitoring soil conditions in real time and providing data-driven recommendations. The system uses multiple sensors to measure soil moisture pH temperature and humidity. The Arduino board acts as the central unit for processing and transmitting data. The Blynk IoT platform is integrated for real-time data visualization and a GSM module sends SMS alerts to farmers. The system classifies soil moisture into three categories dry, moist and saturated. It also assesses the soil's pH is acidic, neutral or alkaline. After analyzing sensor data farmers are notified of the appropriate actions to optimize irrigation and nutrient levels. This machine learning system gives useful crop and fertilizer recommendations, but it can not give sudden environmental changes like unexpected droughts, floods, or pest attacks.

Garg et al. (2021) propose a multimodal system that combines IoT and machine learning for precision agriculture. The research highlights the collaboration between data from IoT devices and machine learning algorithms which enhance agricultural efficiency. The study shows how to improve crop yields by optimizing resource usage. Relies on continuous internet connectivity for real time monitoring and recommendations which limit usability in farming areas with poor network Infrastructure.

The paper presents an IoT-based soil nutrient monitoring system integrated with machine learning for crop recommendations; sensors measure N, P, K, temperature, pH, humidity, and rainfall, transmitting data via WSN to a cloud database where algorithms advise optimal crop selection, reduce fertilizer use, and lower manual labor. The key limitations are that the system lacks Field validation, integration of weather forecasting and extreme event detection, and cost-effectiveness assessments

are needed [Bepery et al. \(2020\)](#).

2.3 Machine Learning For Crop and Fertilizer Prediction

Machine learning performs strongly to predict suitable crops for a soil and recommend fertilizers with proper amounts by properly analyzing soil data which have been explored by agriculture advancement in recent times. There are several studies that conduct significance of machine learning models in agriculture sectors.

[Dipto et al. \(2021\)](#) paper describes a system that gathers NPK values from soil and compares them to the optimal values required for various crops like rice, potato, mustard, wheat and pulse using Euclidean Distance to find the most suitable crop for each soil type. After determining the best crop based on minimal NPK difference the data is split into training and testing sets. Algorithms like SVM, AdaBoost, Random Forest and Logistic Regression are used for crop prediction. Out of all the algorithms, SVM showed the highest accuracy at 98%. Precision, recall, and F1-score were also calculated for each algorithm. SVM outperformed the others while Logistic Regression had the lowest accuracy at 88%. The study focused on the UllahPara sub-district. They have plans for future expansion across Bangladesh. However they were working with a small sample size of 192 data points. It could lead to the risk of overfitting.

A system has been developed to optimize farming in Rwanda using machine learning for crop recommendations and rule-based models for fertilizer advice. It focuses on soil properties like nitrogen, phosphorus, potassium and pH. The authors collected and analyzed soil and crop growth data. They trained a neural network on the dataset to predict the best crops based on soil conditions. It outperforms models like decision trees. Fertilizer recommendations were made using a rule-based system that suggested proper actions for unsuitable pH levels. IoT sensors deployed in fields transmitted real-time soil data to a cloud server. which crop and fertilizer recommendations were generated and communicated to farmers. The system achieved high accuracy in crop prediction which was 99% and demonstrated practical real-world use [Musanase et al. \(2023\)](#).

Priyadharshini et al. (2021) proposed crop recommendation system uses machine learning techniques which include Linear Regression and Neural Networks. Python, Pandas, Numpy, TensorFlow, Keras and Scikit-learn were used. Data preprocessing, like handling missing values and filtering crops based on soil nutrients. It greatly improves prediction accuracy. The neural network implemented with Keras predicts the sustainability of 15 crops based on state, month and soil data. linear regression models crop yield based on rainfall, temperature and pH. various machine learning algorithms were compared. The neural network achieved the highest accuracy of 89.88%. Fewer data samples on underrepresented crops caused the model to overfit to those specific crops.

This Dey et al. (2024) paper shows the uses of five machine learning (ML) models—Support Vector Machine, XGBoost, Random Forest, KNN, and Decision Tree—in making crop and nutrient recommendations based on soil and climatic data. Datasets for train and test has been collected from Kaggle. This approach shows promise for optimizing agricultural practices in varying environmental conditions. The accuracy and F1 scores of XGBoost is 92.71% , 0.927), Random Forest (89.59%, 0.896), SVM (86.58%, 0.863), Decision Tree (83.51%, 0.835), and KNN (81.22%, 0.812). The system relies on unauthorized data from untrusted sources like Kaggle. ML-powered cloud-based crop recommendation platform was developed to assist farmers in selecting optimal crops based on observed parameters, comparing KNN, DT, RF, XGBoost, and SVM to determine the most effective model for precision farming shows in Thilakarathne et al. (2022).

This paper shows TCRM: Transformative Crop Recommendation Model , a ML based system for crop recommendation. It performs better than traditional models with 94% accuracy as well as considering SMS systems for the farmers. This model considers environmental factors, region specific practices and real time data collection which ensures sustainable agriculture. The key limitations of this paper is the need of large and high quality data that might be challenging to collect from low resource areas Singh & Sharma (2025).

This paper highlights a system that integrates with IoT and machine learning models for proper crop yield prediction. Machine Learning models - LightGBM , Decision Tree and Random Forest have been used for better prediction and achieved almost 98% accuracy . This system also considers real time monitoring , enabling increased productivity, sustainability and efficient decision making. The limitation exist in

implementing this system due to limited technological adaptability and awareness [Bouni et al. \(2024\)](#).

The paper proposes an integrated architecture combining IoT sensors, edge computing, and cloud services to support a plant recommendation system for urban microfarms. Soil parameters are monitored and transmitted via LoRa networks to edge processors, where machine learning models, including collaborative filtering, analyze the data for optimal plant selection based on soil and climate conditions. Data management is conducted through open protocols such as AMQP and HTTP, while extensive model training is handled in the cloud. The key limitation is that the system's reliance on a single communication protocol (LoRa) may present scalability and interference challenges in dense sensor environments [Grunewald et al. \(2024\)](#).

An IoT-based cloud framework enhances precision agriculture , by optimizing resources, enabling real-time monitoring, automating decisions, and leveraging AI for yield prediction with 92% accuracy and crop forecasting with 87.38% accuracy using real field data Application [Ali et al. \(2023\)](#),[Rahman et al. \(2023\)](#).

2.4 Integration of IoT and Web Applications For Agriculture

Combination of IoT and use friendly interface conducting a strong enhancement in the agriculture sector . Farmers can get real time soil information and recommendations through a user interface which can ensure a precise agriculture by increased productivity. The significance and process of connecting IoT and user interface is conducted in several studies shown below:

[Shawon et al. \(2024\)](#) study proposes a crop recommendation system using data from Kaggle. The features nitrogen, phosphorus, potassium, temperature, humidity and pH were analyzed through machine learning algorithms to predict the most suitable crops. The system used Random Forest, AdaBoost, Decision Tree, SVM, KNN, Logistic Regression and XGBoost. The Random Forest and Decision Tree achieved the highest accuracy at 99.7%. A web portal was created that allows users like farmers to input soil data and receive crop recommendations based on real time predictions stored in the cloud. This system recommends crops based on soil

nutrients, but it does not consider other factors like pests, weather conditions, or sudden climate changes.

The system mentioned in the paper [Nuchhi et al. \(2020\)](#) is used for soil testing and focuses on real-time analysis of key nutrients like NPK and also measures soil moisture, temperature and humidity using sensors that are connected to an Arduino board. The data is transmitted via the ThingSpeak cloud platform which allows farmers to access field information through mobile apps. The system helps recommend the necessary fertilizers to improve soil quality and crop yield. Testing was done in the Vijayapur district. The parameters were recorded over time. The results showed how soil moisture, temperature, and humidity varied daily. NPK deficiencies were found. The IoT-based soil testing instrument provides real-time soil analysis, but its accuracy and scalability may be limited, especially for large farms or varied soil conditions.

[Wu et al. \(2023\)](#) introduce the development of Internet-of-Things(IoT) based multiple- sensor monitoring systems for soil information diagnosis using a smart-phone. It highlights existing technologies with some moderation based on real-time emphasis. Soil parameters such as moisture, temperature, and nutrients are collected by IoT device and transmitted to a smartphone application so that farmers can get their soil health evaluation easily on a real-time basis and can make better agricultural decisions. This process discusses the limitations of traditional methods and offers cost-efficient technology for agricultural monitoring. The device usage of cheaper sensors results in lower precision affecting the accuracy of soil health measurements and recommendations.

This paper represents the significance of real time monitoring of soil - temperature, moisture, pH, nutrient levels using IoT . In addition , AI-based mobile applications enable efficient decision making on irrigation, crop health and uses of fertilizer. The key limitation of this paper is its limited analysis of crop metabolism and real time nutrients tracing in a complex environment [Ali et al. \(2023\)](#).

An integrated IoT-based system with a web dashboard for tracking real-time environmental data, including temperature, humidity, soil moisture, wind speed, and rainfall, is presented in this work. Dynamic updates and interactive data display are guaranteed by the Dash framework. The system's dependability in a variety of settings was confirmed by performance analysis, which revealed no discernible

variations in application performance. Scalability and other difficulties in implementing the system across extensive agricultural enterprises are not covered in the paper [Er et al. \(2024\)](#).

2.5 MQTT

MQTT is a reliable messaging protocol used in IoT devices for real time communication between devices. It combines IoT and machine learning to help farmers make data-driven decisions. There are several studies that show the importance of messaging protocols, most specifically MQTT.

A system that combines IoT and machine learning to help farmers make data-driven decisions. It uses DHT-11 and soil moisture sensors connected to NodeMCU and Raspberry Pi 3 via MQTT to monitor temperature, humidity and soil moisture proposed by [Nagaraja et al. \(2019\)](#). Data is transmitted to Firebase and ThingSpeak IoT Cloud for real-time visualization. The crop prediction module uses a Support Vector Machine classifier which is trained on over 700 records. Python libraries like scikit-learn, pandas, and numpy are used for analysis, while Flask hosts the system on Raspberry Pi. The system managed to achieve 97% accuracy in crop prediction and supports real-time data monitoring through mobile and web interfaces. The smart agriculture system improves farm management, but it may not work well in places where the IoT infrastructure is weak or where farmers have lack of technical knowledge to operate it. .

The paper [Kalavaani \(2023\)](#) presents an 'IoT-based Smart Soil Monitoring System', an automated embedded system. It helps reduce manual monitoring and predict real-time data on moisture, pH, nutrients, and temperature by IoT device using sensors connected to an STM32 microcontroller and LoRaWAN gateway. The system ensures proper data process and analysis through cloud-based platforms using Node-RED and MQTT protocols. This helps to increase crop yield, reduces water and fertilizer, and reduces environmental impacts. Costs, power dependency, data privacy concerns, and potential data may cause challenges for this project as per the study. The main limitations of the system are high implementation costs, reliance on

continuous power supply and potential risks to data privacy.

This [Hindy et al. \(2020\)](#) study focuses on building and evaluating Machine Learning ML based Intrusion Detection Systems IDS for MQTT IoT networks, using a novel dataset that includes both benign and attack scenarios aggressive scans, UDP scans, SSH brute force, and MQTT brute force. The dataset, gathered through a simulated network with 12 MQTT sensors and diverse attack setups, emphasizes realistic IoT conditions with packet loss and mixed operations. Key findings show that flow-based features unidirectional and bidirectional outperform packet based features in detecting MQTT-specific attacks, achieving weighted average recall and precision of up to 98.85% and 99.04%, respectively. This shows the need for tailored detection techniques because of MQTT's unique communication patterns and the challenges of distinguishing attacks from normal operations in IoT environments. Distributing MQTT traffic efficiently requires external load balancing.

This [Liu et al. \(2020\)](#) study focuses on IoT systems that rely on cloud based architectures and specialized communication protocols like MQTT, CoAP, AMQP and HTTP for real time and reliable data exchange, with MQTT being particularly efficient due to its lightweight design and publish or subscribe architecture. Wi-Fi technology is vital for wireless IoT communication, offering high transmission rates and adaptability through modes like AP, STA and listening. Advanced methods, such as encoding network credentials within MAC addresses, streamline device connectivity in complex environments, addressing challenges like network efficiency and forgotten credentials. IoT applications span precision agriculture, e-healthcare, remote monitoring and industrial automation, showcasing reduced costs, enhanced efficiency and improved user experiences, though challenges in network complexity and data processing demand scalable solutions for future advancements. MQTT lacks built in security measures. It's vulnerable to snooping and eavesdropping without external encryption and authentication.

This [Patel & Doshi \(2020\)](#) paper explores the MQTT protocol, a lightweight publish-subscribe communication model widely used in IoT applications due to its efficiency and simplicity compared to HTTP. Key components of MQTT include publishers, subscribers, and brokers, with quality of service levels ensuring reliable data transmission. Applications span smart healthcare, smart homes, industries, parking and weather monitoring. The paper addresses security challenges in MQTT communication and emphasizing the need for robust authentication mechanisms. It

proposes a novel framework with user and device registration phases involving encrypted JSON based credential exchange and a user authentication phase using session keys for secure data access. The framework aims to enhance secure MQTT communication and can be adapted for other cryptographic protocols. The broker is overwhelmed with excessive connections or messages which leads to service disruptions.

[Atmoko et al. \(2017\)](#) discuss the application of the MQTT protocol for real-time data collection in IoT systems which focus on its lightweight and efficient communication capabilities. The paper focuses on MQTT's suitability for resource gap environments, enabling reliable and real time data transfer. It mentions advantages of MQTT over HTTP, such as lower bandwidth usage, reduced power consumption, and real-time capabilities. The study highlights practical application and the protocol's advantages to maintain the perfect communication between IoT devices and makes it an essential tool for real-time IoT applications. The findings suggest improved data reliability and quality with MQTT. (2017): MQTT is not optimized for large file transfers or media streaming.

These studies illustrate the growing trend toward using IoT and machine learning technologies in agriculture. The research studies reviewed the importance of soil nutrients in increasing productivity, the importance of real-time soil monitoring, the enhancement of IoT and machine learning in agriculture, the significance of the combination of IoT and machine learning, the need for a user interface, the connection process between IoT and other devices, issues of the traditional method, and more. These studies help to outline the efficiency process and design of our system.

References	Parameters	Data Collection	Crop/Fertilizer Recommendation	Soil Health	User Interface	Real-time	Cost Effective	Limitations
<i>Fertilizer Recommendation Guide-2018 (2018)</i>	NPK, pH, OrgANIC Matter	Lab Analysis	Euclidean distance and Fertilizer Formula	Lab Analysis	PDF and print book	No	No	No real-time monitoring
Salvi et al. (2021)	NPK, Moisture, Temp	IoT Sensors	No	IoT Integration	Web App	Yes	Yes	Lack of calibration
Banerjee et al. (2025)	NPK, Weather Data	IoT Sensors	ML Models	IoT Integration	Web App	Yes	No	Complex integration and high cost
M. R. Islam et al. (2023)	NPK, Moisture, Hum., Temp	IoT Sensors	RF Model	IoT Integration	Mobile App	Yes	Yes	Needs strong internet availability
Senapaty et al. (2023)	NPK, pH, Moisture, Temp	LDR Sensor	SVM Model	Sensor-Based	Android App	Yes	Yes	Not suitable for extreme weather
Hossain et al. (2024)	NPK, pH, Temp, Rainfall	IoT Sensors	SVM, DT Models	IoT Integration	Web App	Yes	Yes	Extreme weather sensitivity
Dipto et al. (2021)	NPK	IoT Sensors	Euclidean + SVM, AdaB, RF, LR	IoT Integration	N/A	N/A	N/A	Risk of Overfitting
Kalavaani (2023)	Nutrients, Moisture, pH, Temp	IoT + MQTT	Prediction Models	IoT Integration	Cloud Based	MQTT Used	Yes	Data privacy issues
Patel & Doshi (2020)	MQTT Only	MQTT Based	N/A	N/A	Dashboard/App	MQTT Used	Yes	Risk of service disruption
Wu et al. (2023)	Nutrients, Moisture, Temp	IoT Sensors	DQN, BiLSTM, OS-ELM, P-ELM	Same ML Models	Smartphone App	IoT Based	Yes	Poor sensor accuracy

Table 2.1: Comparative Analysis

Chapter 3

Design and Development

3.1 Project Management and Financial Activities

Our project is divided into schedule-based manageable phases to keep track of the work; as well as cost-effectiveness is also considered.

3.1.1 Work Breakdown Structure(WBS)

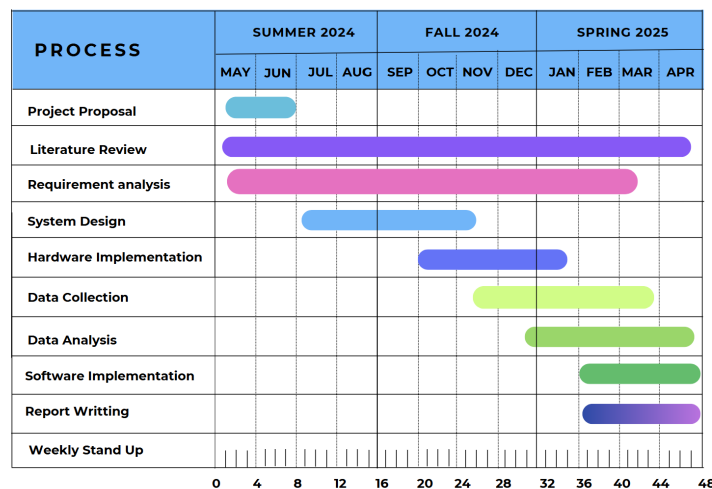


Figure 3.1: Gantt Chart

The Work Breakdown Structure (WBS) has divided the entire project into manageable phases with a schedule to keep track of the work. To ensure a clear progress of all necessary resources, technology and financial strategies , are identified. Risk

management, finding possible risks and planning to reduce the risk will also be on focus. Canva has been used to get proper insights into the organized tasks. The project timeline with specific tasks is shown in Figure 3.1.

3.1.2 Budget Plan

- **Budget Allocation:** A significant portion of the budget needs to be allocated for software hardware development, diverse work and labour as they bring the most impactful responsibility on system functionality.
- **Spending:** Cost distribution should follow the phases(Hardware setup costs →software development costs→ miscellaneous costs).
- **Cost Management:** Cost-saving strategies need to be implemented For example- for software using open source tools, choosing cost-effective cloud-based infrastructure.

Category	Description	Estimated Cost (BDT)
Hardware	- Soil sensor RS485 - 16x2 LCD with I2C interface - RS485-to-UART converter - ESP32 - Routers, cables, antennas, etc. - Batteries for powering sensors - Breadboards	30000
Software	- Communication tools - Cloud Integration - Dashboard/Interface Development	5000
Miscellaneous	- Licenses and Permits	5000
Contingency Fund	- Unexpected costs like delays, equipment failure, etc.	4000
Total		44000

Table 3.1: Budget Estimation

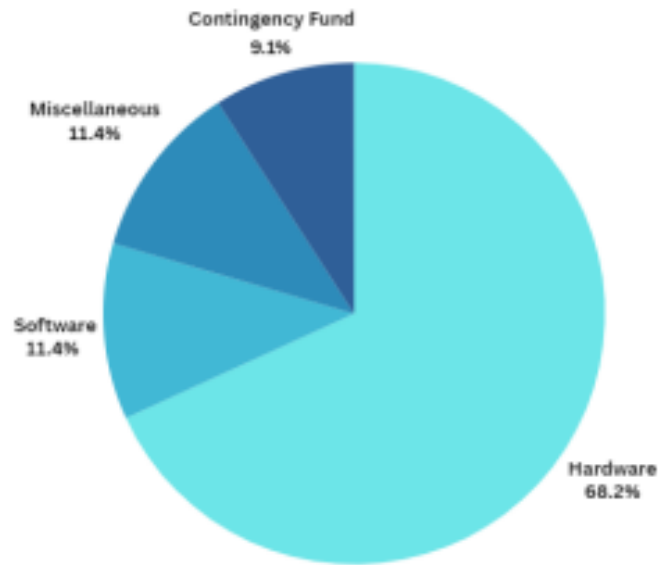


Figure 3.2: Percentage Breakdown of Estimated Costs

3.2 Requirement Analysis

Hardware and software requirements of our system have been chosen following needs , adjustablity and reliability.

3.2.1 Hardware Requirements

- **ESP32** : Wireless module for internet connectivity and communication with IoT device [Senapaty et al. \(2023\)](#).
- **Soil Sensor RS485** : Measures soil parameters such as pH, NPK, temperature, moisture, and salinity [Hossain et al. \(2024\)](#).
- **RS485-to-uart**: Converted the sensor's RS485 signals into UART compatible signals for the ESP32.
- **16x2 LCD with I2C interface**: For display [Pyingkodi et al. \(2022\)](#).

- Model : RS485 Soil Nutrients Sensor
- Measurement Range: Nitrogen(N):56-140 ppm Phosphorus(P):40-100 ppm Potassium(K):15-100 ppm Temperature: 18-30°C Salinity: $0 \leq 20$ ds/m Moisture:0-100% scale pH: 5 to 7
- Energy Consumption: <0.15W
- Response Time: <1s
- Selection Rationale: This multi-sensor is efficient for collection soil parameters-NPK, pH, temperature, salinity and moisture.This sensor supports real time soil data collection and reliable data transmissions. The data collection and transmission process is fast , enabling immediate decision making. This sensor easily integrates with microcontrollers and communication protocols(RS485-to-UART, ESP32) . This sensor is waterproof and easy to carry.

3.3.2 Microcontroller and Communication Modules Configuration

RS485-to-UART

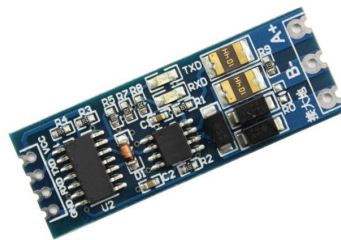


Figure 3.4: RS485-to-UART

- Model:RS485-to-UART
- Voltage:3.3V
- Data Range:<2.5Mbps

- Distance: <1200 meters
- Selection Rationale: This module helps convert the RS485's signals into UART compatible signals. It supports long range , multi devices and serial communication. This is also cost effective.

ESP32

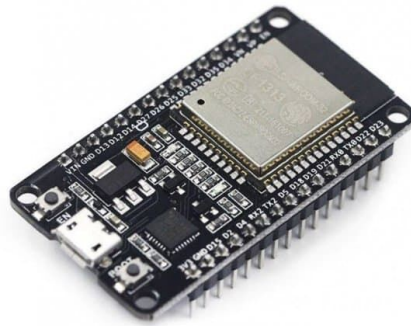


Figure 3.5: ESP32

- Model: ESP32
- Voltage: 3.0 to 3.3 V
- I/O Pins: 34 GPIO
- Ports: 3
- Communication: wifi, UART, bluetooth, I2C.
- Selection Rationale: This is a powerful , cost-effective and energy efficient microcontroller . It has built-in wifi , bluetooth, UART, I2C that enable reliable wireless communication.

3.4 Communication Protocols and Data Flows

An ESP32 microcontroller orchestrates both data acquisition and transmission by interfacing with an NPK sensor breakout via an RS-485 module and RS-485-to-UART converter and driving a 16×2 I²C LCD for real-time display, while a membrane keypad allows users to register their phone number by pressing button A or trigger MQTT data publishing by pressing button D. Upon activation, the ESP32 assembles calibrated, timestamped soil parameters which are nitrogen, phosphorus, potassium, moisture, temperature, salinity and TDS into a JSON payload and transmits it via MQTT to a PHP-based web application hosted on InfinityFree. The incoming data is only accepted when sensor and user phone numbers match and then they are formatted into their appropriate data types alongside user-supplied context fields which are season, crop type and soil texture because they cannot be picked up by the sensor. Then those data are stored in MySQL tables which are used as feature data. Through the web interface, each user may retrieve only their own historic or current entries, which are then forwarded over HTTPS to a PythonAnywhere API hosting our pretrained machine-learning models; these models generate tailored crop, fertilizer and soil-health recommendations that are returned to the site, rendered for the user, and stored in a Recommendations table for future reference.

3.5 Design the Solution

3.5.1 Design and Development

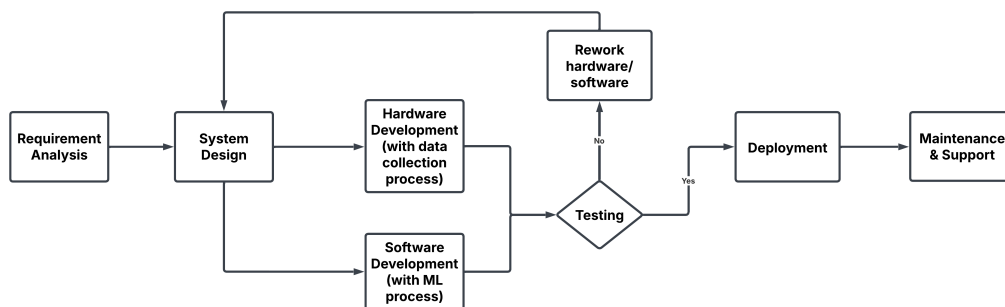


Figure 3.6: System Development Process

The design and Development process gives insights into important progressing chunks needed for the project, which is essential for a successful project to specify the steps individually and clarification of what we are doing sequentially. It helps to make final decisions. The flowchart of the process is shown in Figure 3.2.

- **Requirement analysis:** We first identify the stakeholder needs, and requirements for both functional and non-functional needs, and determine key features. Then we can make a formal requirement document for guiding the project.
- **System Design:** In system design, we are going to make an architectural design where we define the system architecture, specify technologies, create a data flow diagram to visualize data movement and moreover design a user interface. Once the system design is complete, we see the process branches in two parallel streams.
- **Hardware Development:** Selecting components (e.g., sensors, microcontrollers, wireless communication modules etc.), creating prototypes, calibrating sensors to ensure the adjustment with environmental factors, and making a successful data collection setup are the main key points of hardware design.
- **Software Development:** In this process, we write code to gather data from sensors, set up a cloud to store and collect data from sensors and manage the communication between the sensors and cloud. Processed data is used for machine learning to train the system and recommend the fertilizer based on the conditions. Also, we introduce a web application to visualize the real-time data and recommendations
- **Testing:** Here are some types of testing including unit testing, integration testing, system testing, and user acceptance testing. If the system successfully passes all tests, it will take a step forward.
- **Rework hardware/software:** If any errors in hardware or software or the whole system, it will make a loop back to system design because maybe we have to make changes to the system design also.

- **Deployment:** After successfully testing, it can be deployed to farms, and handed to the farmers or users. Also to train the user on how to operate the system.
- **Maintenance support:** It is required to plan for regular updates of the system and maintenance as needed. Also, user feedback is most important for the system for continuous improvement.

3.5.2 Methodology

We start by collecting multiple soil samples from Sher-e-Bangla Agricultural University to provide a detailed understanding of soil conditions, ensuring our dataset captures local variability; an RS485 sensor then measures N, P, K, moisture, pH, temperature, and salinity it's corrosion-resistant, waterproof, and built for rough soil while an ESP32 wirelessly transmits all readings to a MySQL database for instant, anywhere access. Four machine learning models SVM, Random Forest, Bagging Regression, and CatBoost Classifier are trained on data from the Good Growth Plan (2014–2024), the FAO, and the 2018 BARC Fertilizer Recommendation Guide, which defines optimal nutrient, pH, temperature, salinity, and moisture levels for various crops; land type and seasonal conditions are also factored in, since specific environmental features significantly impact recommendations. In addition, n Sensor data is published via MQTT to a PHP-based web app hosted on InfinityFree, where it's authenticated by matching sensor and user phone numbers, cast to the correct data types, and augmented with user-supplied season, crop type, and soil texture before being stored in MySQL feature tables; through the web interface, users retrieve their own historic or current entries, which are forwarded over HTTPS to a PythonAnywhere API running our pretrained models, and the API returns tailored crop, fertilizer, and soil-health recommendations that are rendered on-site and stored in a Recommendations table for future reference.

3.5.3 System Architecture

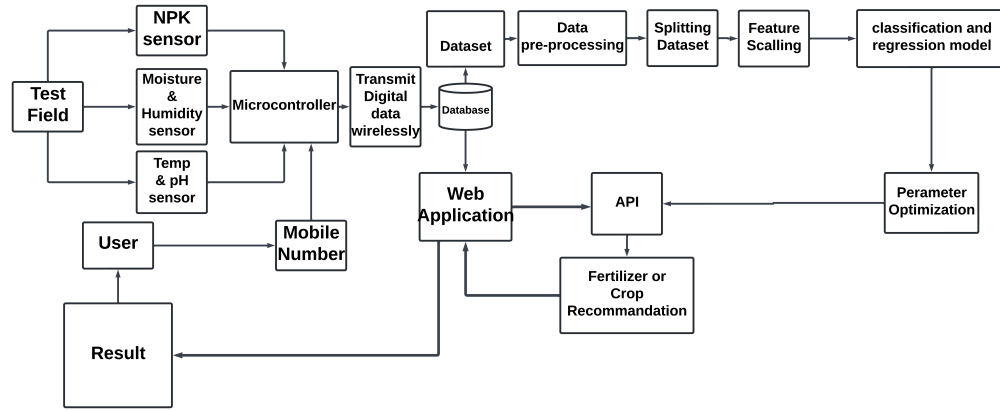


Figure 3.7: System Diagram

Multiple soil samples will be collected based on land size. rs485 5pin measure NPK, temperature, humidity, moisture and pH. Using ESP32 a request has been sent to the register for collecting sensed data using code. Readings were continuously captured and displayed on the 16x2 LCD, providing immediate feedback to the user through localhost. The local host will store and analyse the data using multiple machine-learning models-SVM, CatBoost, Random Forest and Bagging Regressor models for crop and fertilizer recommendations. The models will be trained on authorized datasets and collected data will be used as the test set. To improve accuracy various preprocessing techniques will be used. Farmers will also be notified through our application on soil health report and notable suggestions.

3.6 Use Case Diagram

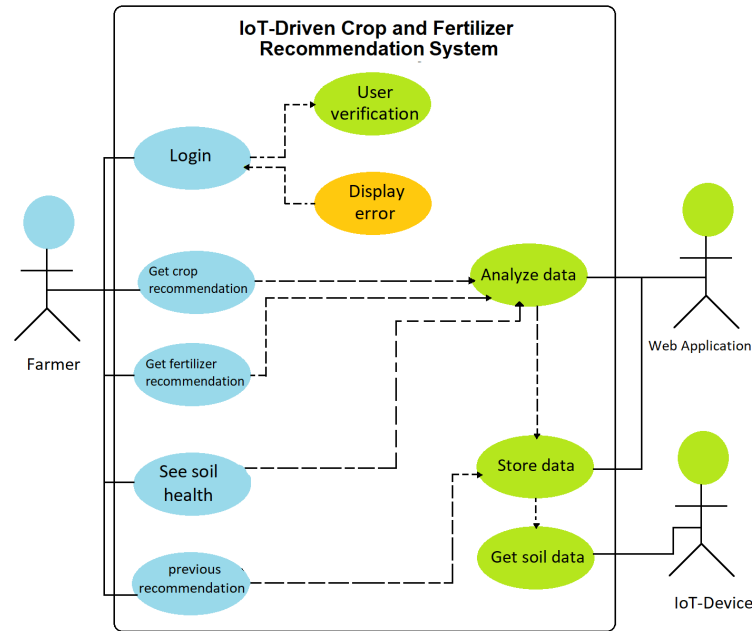


Figure 3.8: Use Case Diagram

The following use case diagram shows the functional requirements of a system where farmers, cloud application and IoT devices work as actors. Use cases or actions of these diagrams are - login, user verification, display error, analyze data, crop and fertilizer recommendation , see soil health and nutrient levels, get soil data , store data timely reminders and notify users. Lines that connect actors with the use cases known as association , shows connectivity. Users will login and be verified ; if not there will be an error on the display. After login, users can get crop and fertilizer recommendations , see soil health and suggestions. Web application will analyze the data collected from IoT devices, give fertilizer and crop recommendation soil health and suggestions.

3.7 Activity Diagram

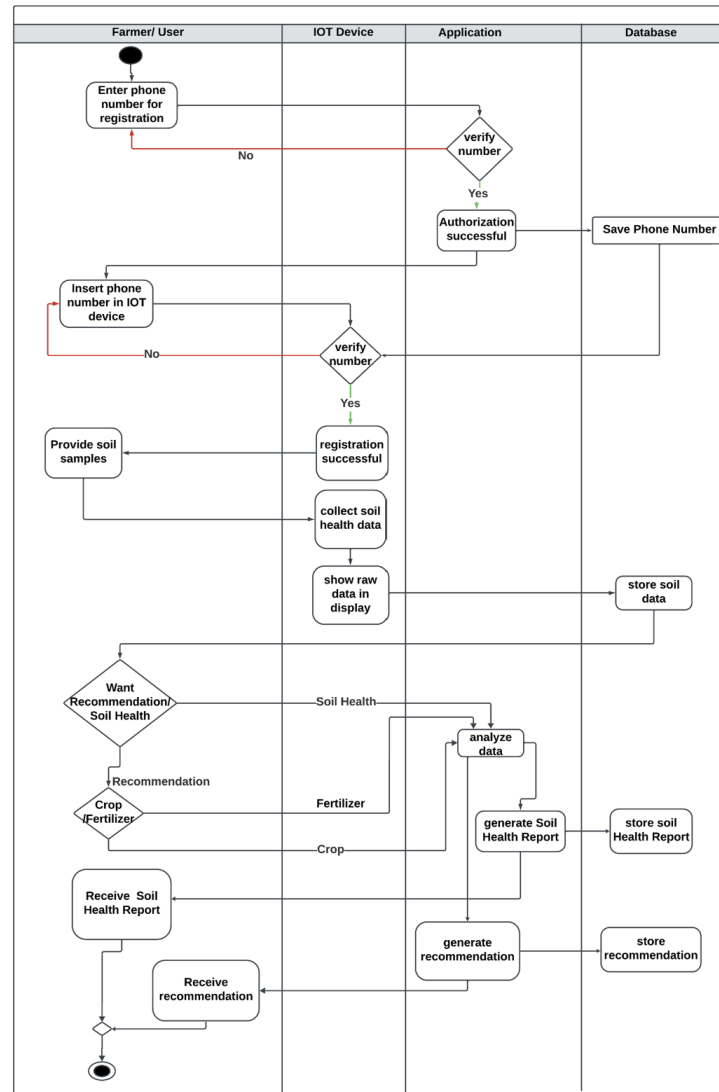


Figure 3.9: Activity Diagram

The following activity diagram shows the sequential workflow of the systems. Farmers will insert their phone number for registration or signUP to the application. If not verified or authorized farmers need to try again. Once the registration is successful the IoT device will provide soil information to the farmers. Web application will analyze the data and generate fertilizer and crop recommendations to the user as well as soil health update and suggestions.

3.8 ER Diagram

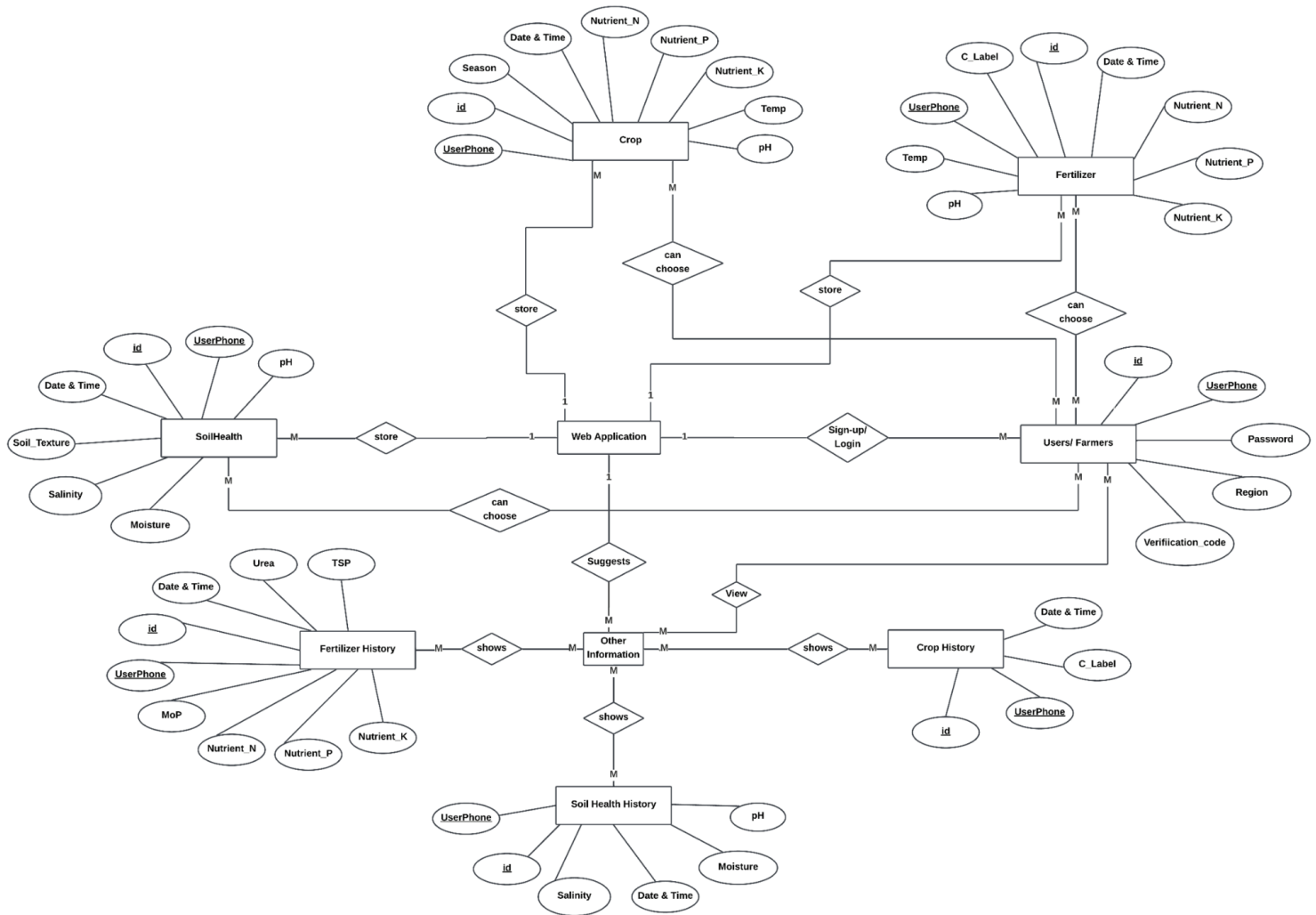


Figure 3.10: ER Diagram

The following ER diagram visually representing connections of: Entities- Admin, User, Application, Soil Records, Fertilizer, Crop, Soil Health and Others. Attributes- N, P, K, Temperature, Humidity, pH; For user- name, phone number, ID, PIN. For Admin- ID, Name, Phone Number, Email. Relationships of the system to understand the models structure. In the ER diagram, Admin and User(Farmers) can signUP/Login to application, Admin authorized users as, device have a limitation of identifying proper phone numbers,

web application shows the recommendation of crop and fertilizers as well as evaluates soil health and other information. Soil records will be store in the mySQL database. Soil records will analyze the attributes or parameters and evolves the recommendation of crop and fertilizers as well as predicts soil health .Admin can update/analyze fertilizer, crop, soil health and other information. User can view fertilizer and crop recommendation ; as well as soil health and other information. User can be identified with their phone number which work as a primary key and Admin can identified with their IDs which also works as a primary key.

3.9 Sequence Diagram

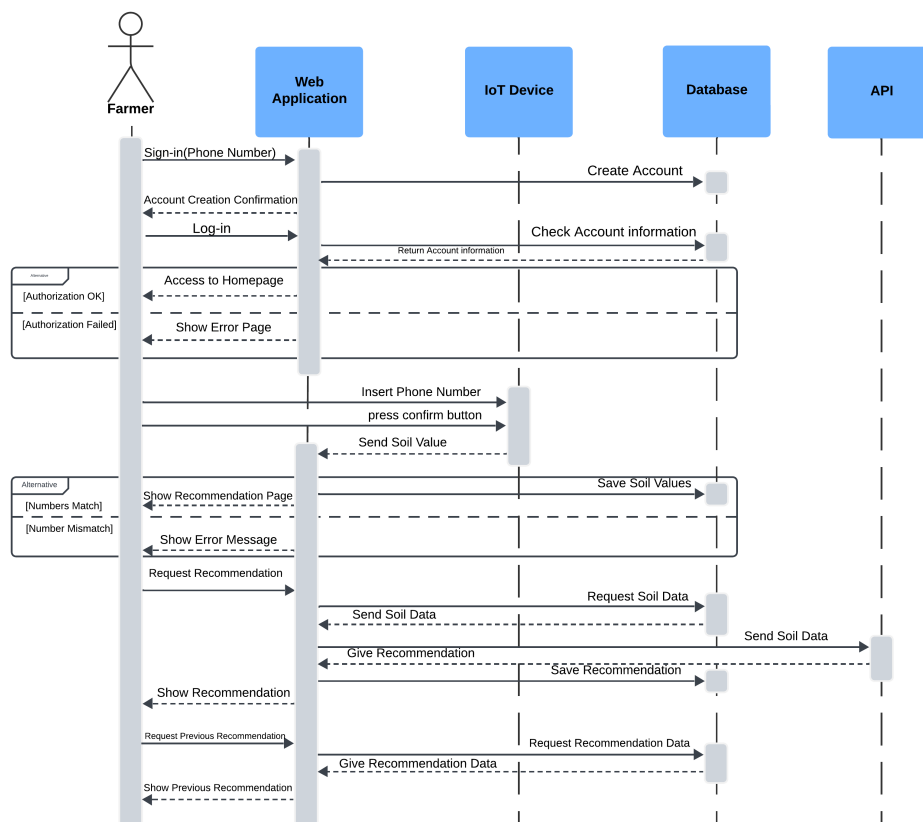


Figure 3.11: Sequence Diagram

The following sequence diagram shows the flow of information between

admin, IoT device and web application in the system. Farmers will register to the application with a phone number and get verified . If not authorized an error message will be shown to the user. Once authorized the phone no. will be saved and a confirmation message will be displayed to the user and the IoT device will save the phone number and collect the soil samples. Users can request for fertilizer and crop recommendation , soil health and other information. Web application will provide recommendation and soil information to users.

3.10 Data Flow Diagram

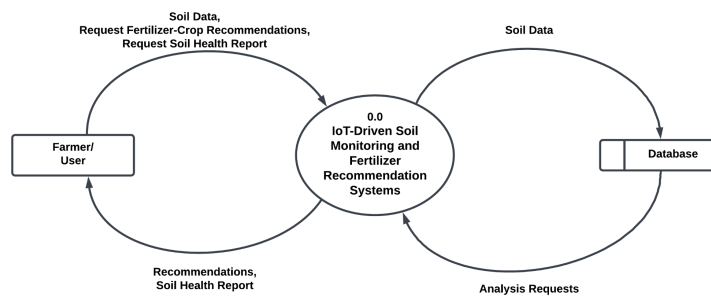


Figure 3.12: 0-Level-DFD

0-Level-DFD showing an overview of the system. Soil information input from the farmers which transferred to the web, processed using ML models there and recommendations sent back to users/farmers. Admin Validate the results.

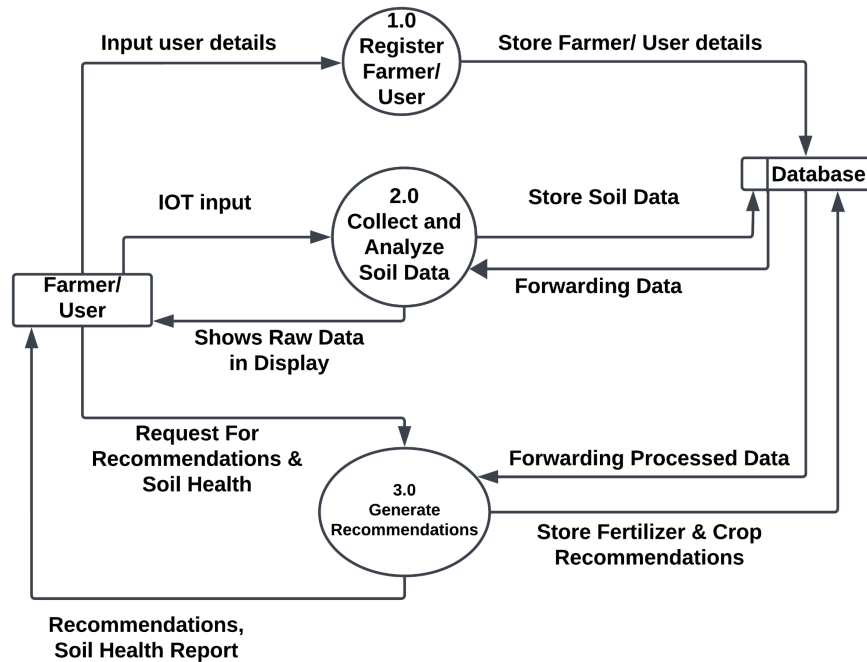


Figure 3.13: 1-Level-DFD

1-Level-DFD representing a more detailed breakdown of the system by showing- farmers information and soil data (IoT input) will be collected and stored in a MySQL database, but raw data will be visible in the display. Admin will verify the data. Users can request for recommendation , soil health and suggestions which will be analyzed and validated ;then sent back to the user.

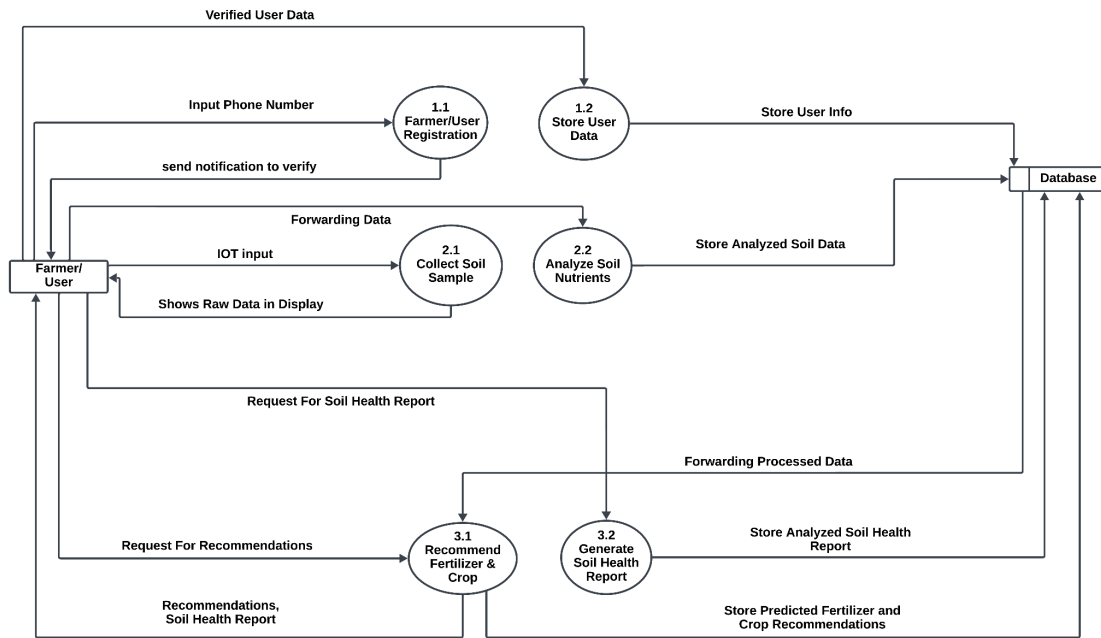


Figure 3.14: 2-Level-DFD

2-Level-DFD representing the full breakdown of the system. Admin and User(Farmers) can signUP/Login to application , Admin authorized users.Users and soil information will be stored in MySQL database.Web application shows the recommendation of crop and fertilizers as well as evaluates soil health and other information. Soil records will be stored in the MySQL database. Soil records will analyze the attributes or parameters and evolve the recommendation of crop and fertilizers as well as predict soil health and other information.Admin can update/analyze fertilizer, crop, soil health and other information. Users can request for fertilizer and crop recommendation ; as well as soil health and other information and after validation provided by the results.

3.11 Implementation

3.11.1 Hardware Implementation

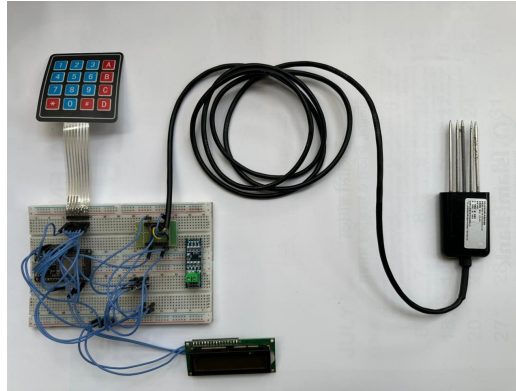


Figure 3.15: Circuit Diagram

IoT devices include - NPK sensor Breakout board, rs485-to-uart Breakout board, 16x2 LCD with I2C interface, ESP32 and Keypad connected to each other as per connection regulation. The IoT system consists of an ESP32, NPK sensor, RS485-to-UART module, 16x2 LCD with I2C and a keypad, all connected per standard regulations. The ESP32 supplies 3.3V power to the NPK sensor, LCD and RS485 module. Since ESP32 and RS485 cannot communicate directly, the RS485-to-UART module converts sensor signals for ESP32 via TX and RX pins. The NPK sensor's VCC and GND connect to ESP32 ports, while the LCD connects via I2C using GPIO 21 to SDA and GPIO 22 to SCL. Soil data is captured and displayed on the LCD, with the keypad's rows linked to ESP32 pins 12, 13, 14, 27 and columns to 25, 26, 32 and 33. An I2C module allows the ESP32 to drive the LCD with fewer wires. Users can register their phone numbers via keypad button "A" which is then stored in the sensor's memory, while pressing "D" transmits sensor data to an MQTT server to a web application, processed data with sensor based and contextual data via API and stores it in our MySQL dataset and then used to give various recommendations, soil health report and suggestions.

3.11.2 Sensor Tuning

The ESP32 may access the calibration registers of the NPK sensor by using the rs485 module to deliver data requests. Tuning is accomplished by mapping raw data from the registers to actual nutrient concentrations using standard NPK solutions. RS485 to UART module converted the sensor RS485 signals into UART compatible signals for ESP32 to measure accuracy. The calibration parameters in the sensor's registers can be changed to make adjustments for better accuracy. For reliable performance, make sure the probes are clean.

3.11.3 Software Implementation

- **Data Collection Transmission:** The ESP32 development board continuously reads calibrated soil parameters (N, P, K, pH, temperature, salinity, moisture) via the RS-485 sensor and RS-485-to-UART converter. Each reading is timestamped, JSON-encoded, and published over MQTT to a PHP-based web application hosted on InfinityFree.
- **Web App Ingestion Validation:** The PHP MQTT library on the server accepts incoming payloads only when the embedded sensor phone number matches the user's registered number. Validated measurements are cast to their proper data types alongside user-entered context fields (season, crop type, soil texture) and stored in MySQL tables for recommendation lookup.
- **Data Preprocessing:** Raw soil data retrieved via serial or API undergoes cleaning to remove anomalies, followed by standard scaling and linear encoding to normalize feature ranges, ensuring consistency across historical and real-time datasets.
- **Model Hosting:** Four pretrained machine-learning models (CatBoost Classifier, Support Vector Machine, Random Forest, Bagging Regressor) reside on a PythonAnywhere API. When a user requests recommendations through the web interface, their selected dataset current or historical

is sent over HTTPS to this API.

- **Recommendation Delivery:** The API returns tailored crop, fertilizer, and soil-health recommendations based on the combined sensor and contextual inputs. These results are displayed in the user's secure portal and logged in a Recommendations MySQL table for auditability and future reference.

3.11.4 System Integration and data collection Process

3.11.4.1 Integration Process

To integrate soil nutrient measurement sensors into a soil monitoring system, we utilized an ESP32 development board, a 16x2 LCD with I2C interface, an RS485 to UART chip and an NPK sensor. The system was designed to capture and process data related to soil nutrients, displaying the results locally while enabling remote access via serial communication. The power supply configuration was set up to provide the necessary voltages for each component. The ESP32 board supplied 3.3V to components such as the NPK sensor and the I2C LCD module. The RS485 to UART chip was also powered through the ESP32's 3.3V output, ensuring a stable power source for all components. Ground connections were established to maintain a common reference point. For sensor connections, the NPK sensor's communication lines A and B were interfaced with the RS485 to UART module, which converted the sensor's RS485 signals into UART compatible signals for the ESP32. The RS485 module was linked to the ESP32 via its TX and RX pins, ensuring seamless data flow between the sensor and the microcontroller. The LCD display was connected to the ESP32 using its SDA and SCL lines assigned to pins 21 and 22, for I2C communication. Power and ground connections for the LCD were provided by the ESP32's 3.3V and GND pins. The display was used to show nutrient levels and other necessities. A keypad was incorporated for user interaction, allowing farmers to insert multiple samples. The keypad rows were connected to ESP32 pins 12, 14, 27 and 26, the columns were connected to pins 25, 33, 32 and 35. To ensure portability and field usability, a battery pack

was connected to the ESP32's power input. This setup allowed the system to function autonomously making it suitable for on-site soil analysis. The software configuration enabled the ESP32 to process data from the NPK sensor via the RS485 to UART module. Sensor readings were captured and displayed on the 16x2 LCD, providing feedback to the user. The keypad allowed users to insert multiple soil samples and average them to get a better understanding of the soil condition. By clicking A in the keypad of the IoT device users can register with their phone number which has been saved as the sensor has memory and using D on the keypad censored data transmitted to MQTT protocol to a web application hosted on InfinityFree. API processed data in the background to be shown on the web application. The serial communication capability of the ESP32 ensured that the data could also be sent to a connected computer for further analysis.

3.11.4.2 Data Collection Process



Figure 3.16: Soil Sample Collection

Our soil sampling process was conducted across the popular agricultural fields in Sher-e-Bangla Agricultural University and Kernaiganj farming area. A total of two hundred ten soil samples were collected. The data collection was done in December, January, February and April with sampling taking place mostly Thursday and Saturday. The sampling process was carried out properly, ensuring that each sample represented the soil conditions accurately. The collected data manually entered into a Google Spreadsheet for organized and accessible data management.

Chapter 4

Result Analysis

4.1 Sampling Measurement



Figure 4.1: Sampling Measurement

- For dividing the land into small portions ,we chose the Grid Sampling method which is a uniform grid section. Each grid is 180 square feet. So, for one sample the device is recommending 720 square feet.This approach helps us achieve precise and accurate results for smaller land areas.
- First, we dug a hole to measure the plough depth, around 8-10 cm deep. We then marked our tools to maintain this depth throughout the sampling process. For each sample, we took a 7-8 cm slice of soil from one side of the hole. Using a soil probe or spade, we ensured that samples

were collected straight down.

- To streamline the process, we collected 1 soil sample per grid section and averaged them. This provided us with a composite sample that accurately represents each grid while minimizing effort and analysis costs.
- After collecting all the samples for a grid, we mixed them thoroughly in a clean bucket. We broke up clumps of soil, removed any stones or crop residue, and ensured the sample was consistent. If the soil was wet, we allowed it to air dry naturally but avoided using a microwave or oven to preserve the integrity of the sample.
- Finally, we filled the sample bag with the well-mixed, averaged soil sample and labeled it carefully. By following this method, we ensured our soil sampling process was efficient and provided reliable data for crop and fertilizer recommendations.

4.2 Dataset Overview

N	P	K	Temperatu	pH	Region	Season	pH_Status	C_label	Urea	TSP	MoP	Nutrient_T	Nutrient_F	Nutrient_K
90	42	43	20.8797	6.50299	Rangpur	Rabi	V_s_alkali	Maize	135.5	28.496	84.8	62.4424	5.6992	42.4
85	58	41	21.7705	7.0381	Rajshahi	Kharif-1	Neutral	Maize	138	25.936	85.3333	63.5945	5.1872	42.6667
60	55	44	23.0045	7.84021	Rajshahi	Kharif-2	SI_alkaline	T.Aman	100.333	11.0067	88.0556	46.2366	2.20133	44.0278
74	35	40	26.4911	6.9804	Rajshahi	Rabi	Neutral	Radish	143.5	37.02	142.667	66.129	7.404	71.3333
78	42	42	20.1302	7.62847	Rajshahi	Rabi	SI_alkaline	Radish	141.5	35.62	141.778	65.2074	7.124	70.8889
69	37	42	23.058	7.07345	Mymensingh	Rabi	Neutral	Cauliflowe	97.3333	36.62	88.6111	44.8541	7.324	44.3056
69	55	38	22.7088	5.70081	Rajshahi	Kharif-2	SI_acidic	T.Aman	97.3333	11.0067	89.7222	44.8541	2.20133	44.8611
94	53	40	20.2777	5.71863	Dhaka	Rabi	SI_acidic	Maize	133.5	26.736	85.6	61.5207	5.3472	42.8
89	54	38	24.5159	6.68535	Rajshahi	Kharif-1	Neutral	Maize	136	26.576	86.1333	62.6728	5.3152	43.0667
68	58	38	23.224	6.33625	Rajshahi	Kharif-2	SI_acidic	T.Aman	97.6667	10.8067	89.7222	45.0077	2.16133	44.8611
91	53	40	26.5272	5.38617	Khulna	Kharif-1	S_acidic	Boro	120	13.368	89.1667	55.2995	2.6736	44.5833
90	46	42	23.979	7.50283	Mymensingh	Rabi	SI_alkaline	Maize	135.5	27.856	85.0667	62.4424	5.5712	42.5333
78	58	44	26.8008	5.10868	Khulna	Rabi	S_acidic	Cauliflowe	94.3333	32.42	88.0556	43.4716	6.484	44.0278
93	56	36	24.015	6.98435	Khulna	Kharif-1	Neutral	Maize	134	26.256	86.6667	61.7512	5.2512	43.3333
94	50	37	25.6659	6.94802	Khulna	Rabi	Neutral	Maize	133.5	27.216	86.4	61.5207	5.4432	43.2
60	48	39	24.2821	7.0423	Rajshahi	Rabi	Neutral	Cauliflowe	100.333	34.42	89.4444	46.2366	6.884	44.7222

Figure 4.2: Primary Dataset

Our project utilizes three main datasets which used to train predictive models for crop- fertilizer recommendations and soil health analysis .The datasets are- a primary dataset with 14,719 entries for crop and fertilizer recommendations and pH status, a salinity dataset with 5,382 entries, and a moisture dataset

Soil_Text	Moisture	S_Moisture
Sand	6.57	O_M
Loam	20.12	O_M
Sandy Clay	19.89	M_D
Silty Clay	18.38	M_D
Sandy Loam	0.18	L_D
Sandy Clay	5.47	L_D
Sandy Clay	42.09	M_E
Sand	10.71	O_M
Loam	30.84	M_E
Loam	2.36	L_D
Silty Clay	17.01	L_D
Silty Clay	27.39	O_M
Silty Clay	30.09	O_M
Sandy Clay	34.16	O_M
Loam	14	M_D
Silt Loam	16.35	M_D
Sandy Loam	18.5	O_M
Silt Loam	37.77	M_E
Sandy Clay	22.8	O_M

Salinity	S_Salinity
0.700668	N_Saline
9.222961	M_Saline
8.284197	M_Saline
1.951718	N_Saline
8.885674	M_Saline
9.676545	M_Saline
15.52925	S_Saline
18.26995	V_S_Saline
19.54797	V_S_Saline
17.79883	V_S_Saline
19.04745	V_S_Saline
10.77751	M_Saline
6.70297	Sl_Saline
9.229153	M_Saline
12.47272	S_Saline
7.214458	Sl_Saline
12.46731	S_Saline
19.65996	V_S_Saline
11.43142	M_Saline

Figure 4.3: Moisture Dataset Figure 4.4: Salinity Dataset

Moisture	Temperature	Conductivity	pH	Nitrogen	Phosphorus	Potassium	Salinity	TDS
115.66	31.39	528.14	4.86	65.92	172.17	208.37	25.37	263.69
88.79	28.2	547.86	5.76	71.88	162.4	206.66	28.71	275.57
101.27	29.83	457.93	4.59	65.04	214.94	181.91	31.68	234.9
85.24	29.73	501.11	6.97	64.48	168.82	186.72	21.47	273.59
107.75	29.19	439.2	5.57	68.02	202.94	180.2	32.39	257.62
90.7	24.49	473.74	4.28	59.34	172.06	207.41	25.38	259.7
94.86	27.73	525.76	7.38	57.73	179.07	198.57	28.22	222.55
106.35	28.98	555.13	6.61	58.38	183.73	175.42	23.54	257.37
105.67	19.06	476.53	5.01	62.66	174.17	162.05	30.96	214.29
83.24	21.44	438.6	5.64	67.2	174.88	159.4	23.89	249.25
117.75	29.78	514.63	4.42	52.59	177.13	202.98	32.25	235.52
109.84	20.21	499.51	7.26	65.12	186.8	185.71	32.51	222.33
105.62	22.2	468.38	6.33	71.36	193.41	166.49	26.91	244.49
92.03	25.67	490.13	7.64	69.97	191.97	166.29	26.19	241.79
113.17	27.62	416.73	7.64	51.81	181.71	164.33	32.89	271.92
116.68	25.36	415.73	6.8	55.18	198.94	168.8	28.29	214.46

Figure 4.5: Sensor Data

with 5,412 entries. The primary dataset includes key features such as nitrogen (N), phosphorus (P), and potassium (K) measured in mg/kg, temperature in °C, pH (indicating soil acidity/alkalinity), and season, all of which are crucial for assessing soil fertility and environmental conditions affecting crop growth. Additional soil health features include salinity, soil texture, and moisture, which are vital for evaluating water uptake, retention, and overall soil structure. The labels in the primary dataset are crop types (C.label: maize, T. Aman, radish, cauliflower, cauliflower, boro, cabbage, jute, tomato, cucumber, and potato) for crop recommendations; urea, TSP, MoP, Nutrient_N, Nutrient_P, and Nutrient_K for fertilizer recommendations, indicating the specific amounts required in kg/ha; and pH.Status to classify soil pH as balanced, acidic, or alkaline. In the salinity and moisture datasets, the labels S.Salinity and S.Moisture monitor soil salt levels and water holding capacity. The data collected from BARC (20%), FAO (30%), BRRI (10%), and other

sources (40%), offers information on crop-specific nutrient requirements, soil fertility, and environmental conditions to maximize yields, optimize fertilizer use, and promote sustainable agriculture. We have collected 210 data using sensor that works as a validation set.

4.3 Data Preprocessing

To ensure the dataset's quality and consistency for machine learning, multiple preprocessing steps were applied for improving data reliability, updating labels and preparing the features for improved model performance as dataset was compiled from multiple sources. To address this, we converted all units to a standardized format missing values were removed to ensure the dataset's seamless integration and avoid inaccuracies in model predictions. For crop recommendations, we used the Euclidean Distance formula from the research paper [Dipto et al. \(2021\)](#) This formula calculates the distance between the soil's nutrient levels N, P, K and the nutrient requirements of different crops, providing scientifically informed crop recommendations.

$$d_{crop} = \sqrt{(n_s - n_c)^2 + (p_s - p_c)^2 + (k_s - k_c)^2} \quad (4.1)$$

d_{crop} = EuclideanDistance

n_s = Nitrogenofsoil

n_c = Nitrogenofcrop

p_s = Phosphorussoil

p_c = Phosphorusofcrop

k_s = Potassiumsoil

k_c = Potassiumofcrop

$$F_r = U_r - \frac{C_n}{C_s} \times (S_t - L_s) \quad (4.2)$$

Where, F_s = Fertilizer nutrient amount (kg/ha)

C_n = Fertilizernutrientclassinterval

C_s = SoilTestValueIndex(STVI)classinterval

S_t = Soiltestvalue

$L_s = \text{Lower limit of soil test value in the same STVI class}$

$$\text{Urea (kg/ha)} = N \text{ (kg/ha)} \times 2.17$$

$$\text{TSP(kg/ha)} = P \text{ (kg/ha)} \times 5.00$$

$$\text{MoP(kg/ha)} = K \text{ (kg/ha)} \times 2.00$$

These formulas were applied only to data from untrusted sources which is 40% of the dataset to improve reliability. This method ensures the fertilizer recommendations align with soil test values and specific crop requirements, enabling precise nutrient management for better yields.

4.4 Classification Performance

4.4.1 Support Vector Machine

Support vector machine(SVM) is highly effective for multi class classification problems. SVM separates classes by finding an optimal hyperplane that separates the classes and using the radial basis function(RBF) kernel. It allows models to learn non-linearity. It can manage high dimensional spaces and ensure robust classification, even with complex large datasets. The model achieved strong performance in classifying crops across 10 labels with an overall accuracy of 97%. The f1-score of .96 reflects the model's ability to classify the majority of the samples correctly , while maintaining good generalization across different levels. Also it emphasizes its reliability and accuracy [Dipto et al. \(2021\)](#).

- **Boro Potato:** With near-perfect metrics precision, recall and F1-score all at 0.99, the model performs exceptionally well in classifying this majority class.
- **Cabbage :**exhibit strong performance, with f1-score, precision, f1-score and recall exceeding 0.95.
- **Cauliflower:** Exhibit strong performance, with precision and exceeding

0.95, but Cauliflower shows a slightly lower recall at 0.95.

- **Cucumber:** These classes maintain high precision, recall and f1-scores of 0.97,0.98 and 0.97, showing robust classification.
- **Maize:** Despite its limited data support, the precision .95 indicates correct identification. the low recall 0.62 and f1-scores .46 suggests challenges in capturing for all instances.
- **Raddish:** With a recall and F1-score of 0.90, the model somehow handles this minority class.

4.4.2 CatBoost Classifier

CatBoost is a gradient boosting algorithm which excels in classification tasks and offers high accuracy with robust performance. It has the ability to handle categorical features directly, it simplifies preprocessing while achieving impressive results. Using this model, the classification task achieved an impressive accuracy of 98.30% across multiple crop categories. The model also achieved a Precision Score of 0.9830 and an F1 Score of 0.9829. These scores highlight the model's effectiveness in managing both majority and minority classes. Also it emphasizes its reliability and accuracy.

- **Boro:** With near-perfect metrics precision, recall and F1-score all at 0.99, the model performs exceptionally well in classifying this majority class.
- **Cabbage and Cauliflower:** Both classes exhibit strong performance, with precision and recall exceeding 0.95, but Cauliflower shows a slightly lower recall at 0.95.
- **Cucumber and Radish:** These classes maintain high F1-scores of 0.97 and 0.94, showing robust classification.
- **Tomato:** Perfect precision, recall, and F1-score at 1.00 showing the model's perfect classification for this small class.

- **Jute:** Despite its limited data support, the precision 1.00 indicates correct identification. the low recall 0.50 suggests challenges in capturing for all instances.

- **Maize:** With a recall of 0.97 and F1-score of 0.95, the model effectively handles this minority class. The macro average F1 score of 0.94 indicates that, while the model performs well across most classes, there is room for improvement in handling categories with less data, such as Jute. The weighted average F1 score of 0.98 reflects the model's strong overall performance. It ensures accurate classification for the majority of the dataset.

CatBoost's ability to maintain high accuracy and generalization across diverse crop types makes it a reliable choice for this multi class classification problem.

4.4.3 Random Forest

The Random Forest Regressor is a powerful ensemble learning method that is great in predicting continuous outcomes by combining multiple decision trees. Its robustness and ability to handle non-linear relationships make it a good choice for regression tasks [Dey et al. \(2024\)](#).

- **Mean Absolute Error:** 1.05, this low value shows that the model's average deviation from the true values is minimal. Which means the model is able to do precise predictions.

- **MSE:** 14.07, While slightly higher due to the squaring of errors, remains within an acceptable range, demonstrating the model's strong predictive capability.

- **R² Score:** An R² score of 0.97 means that the model explains 97% of the variance in the target variable. It highlights its amazing performance and reliability in capturing the patterns in the data.

The Random Forest Regressor balances accuracy and generalization making it a great solution for regression tasks where both precision and reliability are

important.

4.4.4 Bagging Regressor

Bagging regression is a powerful ensemble learning method designed to improve accuracy of machine learning model's classification and regression tasks. Decision Tree Regressor has been used as a base estimator which helps to reduce variance in non-linear data.

- **Mean Absolute Error:** 1.04 ,this low MAE value shows that the model's average deviation from the true values is minimal and able to do precise predictions.
- **Mean Squared Error:** 14.18,the MSE remained in acceptable range , demonstrating the model's strong predictive capability.
- **R² Score:** An R² score of 0.97 means that the model explains 97% of the variance in the target variable. It highlights its stable performance and reliability in capturing the patterns in the data.

The Bagging Regression balances accuracy and generalization making it a great solution for regression tasks where both precision and reliability maintained except MSE is slightly higher than Random Forest Regression.

4.5 Comparative Analysis

4.5.1 Clasification Models Comparative Analysis For Crop

Between CatBoost Classifier and the Support Vector Machine, it's clear that the CatBoost model performed better through comparison.

- **Accuracy:** The CatBoost Classifier achieved an impressive accuracy of 98.30% and SVM's 97.19%, slightly lower than CatBoost. This indictes that CatBoost was more effective at correctly classifying the data.

- **Precision, Recall, and F1-Score:** The CatBoost Classifier had a precision of 0.9830 and an F1 score of 0.9829, which shows a strong balance between precision and recall and performed well across most crop categories, even for rare categories like Jute. But challenges faced in perfectly identifying all examples in these smaller groups. On the other hand, the SVM model had a precision of 0.9688 and an F1 score of 0.9694. While these are good performances, SVM struggled with rare categories such as Jute, Tomato and Wheat where it failed to make any correct predictions. This resulted in zero precision, recall and F1-scores for these categories.

- **Handling Smaller Categories:** The difference between handling minority classes is concernable. The CatBoost Classifier was able to classify some examples of less frequent categories even though its recall for Jute was only 0.50. On the other hand SVM completely failed for minority classes providing no predictions for them at all.

- **Overall Averages:** The CatBoost Classifier achieved a macro average F1-score of 0.94 and a weighted average F1-score of 0.98. These averages show that it performed consistently well across both majority and minority classes. SVM, had a lower macro average F1-score of 0.62 because of its poor performance on rare categories and weighted average F1-score of 0.97 shows its good performance for more frequent classes.

The CatBoost Classifier perform well than SVM in terms of accuracy, precision and its ability to handle imbalanced data. While SVM performed well for common classes like Boro and Potato, it struggled with rarer categories making it less reliable for datasets with class imbalances.

The CatBoost Classifier is the better choice for this classification task especially when dealing with both majority and minority classes effectively.

4.5.2 Clasification Models Comparative Analysis For pH

The SVM algorithm employs kernel methods to capture nonlinear relationships in sensor readings of pH. Its inherent margin maximization contributes

to stable performance of noisy data. CatBoost leverages decision trees to efficiently model complex patterns, offering built-in regularization that curbs overfitting and accelerates convergence.

- **Accuracy:** The high accuracy of 97% indicates the SVM reliably assigns the correct pH category in most instances. Nearly perfect accuracy 99 % shows that CatBoost almost never misclassified pH readings. This indicates that CatBoost was more effective at correctly classifying pH.
- **F1 Score:** An F1 score of 96% reflects a strong equilibrium between recall and precision, meaning the model both finds true positives and limits false negatives effectively. With an F1 score of 99 %, CatBoost excels at balancing sensitivity and specificity across all classes.
- **Precision:** With 96% precision, the SVM demonstrates robustness in minimizing false alarms when predicting specific pH levels. A precision of 98% highlights CatBoost's reliability in its positive pH predictions, keeping false positives to a minimum.

Although the SVM delivers very strong results, CatBoost slightly outperforms it on every metric, making it the preferred classifier for precise pH categorization in IoT-enabled water quality monitoring.

4.5.3 Clasification Models Comparative Analysis For Moisture

The SVM classifier constructs an optimal hyperplane in a high-dimensional space to separate moisture classes. Its ability to maximize the margin between classes makes it particularly effective for multiclass classification tasks. CatBoost is a gradient-boosted decision tree algorithm that efficiently handles categorical features. Its built-in regularization and oblivious tree structure yield fast convergence and strong generalization, even on smaller datasets.

- **Accuracy:** This high accuracy of 96% indicates that the SVM correctly classifies moisture levels in the vast majority of samples. 98% surpassing the SVM by 2%, this top-line accuracy indicating CatBoost perform better

in capturing complex patterns in moisture data.

- **F1 Score:** A near-perfect F1 score 95% demonstrates that the SVM maintains an excellent balance between precision and recall, minimizing both false positives and false negatives. An F1 score of 98% reflects CatBoost's exceptional balance of precision and recall, ensuring highly reliable classification across all moisture classes.

- **Precision:** 95% high precision shows the model's strong capability to avoid false alarms when predicting a given moisture class. With precision at 98%, CatBoost highlights positive predictions and reducing the false positive classifications risks.

Overall, both of the models perform well, but CatBoost outperform Support Vector Machine across every metric, making it the efficient choice for high-stakes moisture classification tasks.

4.5.4 Clasification Models Comparative Analysis For Salinity

The SVM classifier finds the optimal separating hyperplane in feature space to distinguish salinity levels, leveraging kernel tricks to handle non-linear separations. Its strong regularization helps prevent overfitting on sensor noise. CatBoost is a gradient-boosting algorithm optimized for categorical data and small to medium-sized datasets. Its ordered boosting scheme and oblivious trees reduce prediction shift and deliver stable, high-quality models.

- **Accuracy:** 98 % very high accuracy shows that the SVM correctly classifies nearly all salinity samples. Achieving 99 % accuracy, CatBoost slightly outperforms the SVM. That indicates CatBoost correctly labeling nearly every salinity sample.

- **F1 Score:** An F1 score of 97 % indicates an excellent balance between precision and recall, with few misclassifications in either direction. With an F1 score of 98%, CatBoost demonstrates superior harmony of precision and recall, minimizing both false negatives and false positives.

- **Precision:** 97 % high precision reflects the model's reliability in avoiding false positives when predicting salinity classes. A precision of 98 % highlights CatBoost's strong performance in classifying salinity .

Both classifiers perform well, CatBoost outperform Support Vector Machine across all metrics, making it the reliable choice for salinity classification .

4.5.5 Regression Models Comparative analysis

- **Accuracy (R^2 Score):** Both models achieved a high R^2 score explaining a similar proportion of the variance in the target variable. Random Forest(0.9708) slightly outperformed the Bagging Regressor (0.9704). As the models achieved nearly 1 R^2 score indicating a good performance in predicting actual data.
- **MAE:** values for both models are very close, with the Bagging Regressor showing a slightly lower MAE 1.0444 than Random Forest MAE 1.0463. This means that on average the Bagging Regressor's predictions are slightly closer to the actual values.
- **MSE:** Which gives higher weight to larger errors, the Random Forest model has 14.0749 and the Bagging Regression is 14.1879. This shows that Random Forest handles larger errors better than the Bagging Regressor.

The Random Forest slightly perform better than Bagging Regressor in R^2 and MSE which make it more reliable for minimizing large errors in predictions. The Bagging Regressor achieves a marginally better MAE, suggesting it may be better at handling smaller and consistent deviations in predictions. Both models performed exceptionally well with small differences in their metrics.

The choice between Random Forest and Bagging Regressor depends on the specific use case. But minimizing large errors is critical, That is why Random Forest is our preferred choice.

4.6 Correlation Matrix analysis

We analyzed the relationships between environmental and biological factors, as visualized in our heatmap:

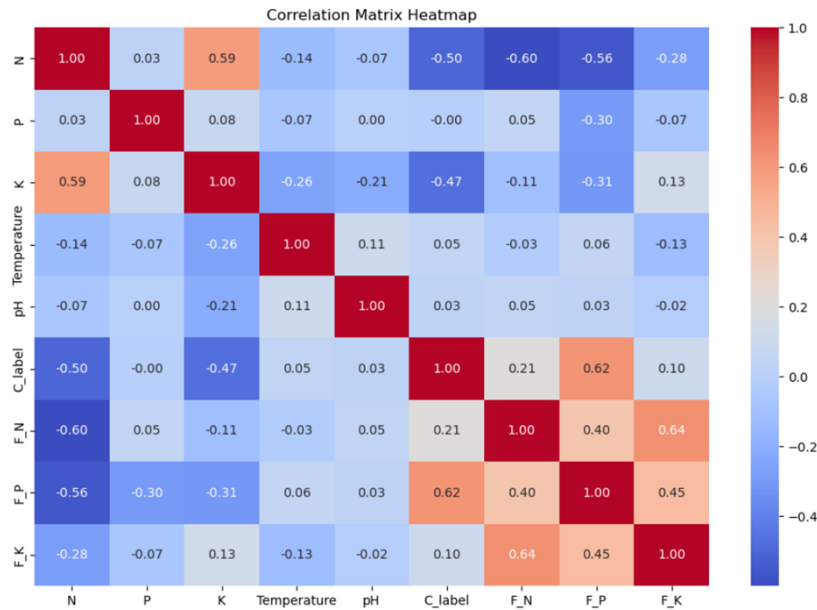


Figure 4.6: Correlation Matrix Heatmap

- **Nitrogen (N):** Nitrogen has a moderate positive correlation with Potassium K which was 0.59, which suggests that soils high in Nitrogen may also contain higher Potassium levels. Negative correlations are observed with crop labels C_label which was -0.50, Fertilizer N (-0.60), and Fertilizer P (-0.56), indicating that higher Nitrogen levels might reduce the need for these fertilizers or influence crop requirements.
- **Phosphorus (P):** Phosphorus shows very weak positive correlations with Temperature (0.05) and pH (0.00), suggesting minimal influence on these factors. There is a negative correlation with Fertilizer P (-0.30), it shows that higher soil phosphorus levels reduce the demand for phosphorus based fertilizers.
- **Potassium (K):** Moderate correlations are observed with Nitrogen

(0.59) and Fertilizer K (0.13), suggesting an interrelationship between these nutrients in the soil. Strong negative correlations exist with crop labels (-0.47) and Fertilizer P (-0.31), it highlights the role of Potassium in influencing fertilizer needs and crop compatibility.

- **Temperature:** Temperature shows weak positive correlations with pH (0.11) and Fertilizer K (0.06), indicating slight environmental influences on soil and crop conditions. Correlation with Nitrogen (-0.14) and Potassium (-0.26) indicates a possible inverse relationship with nutrient levels under varying temperatures.

- **pH:** pH has a negligible positive correlation with most variables, indicating limited influence on crop and fertilizer metrics. Weak correlations with Potassium (-0.21) and Nitrogen (-0.07) suggest slight nutrient dependencies on soil alkalinity.

- **Crop Labels:** Crop recommendations are closely tied to phosphorus fertilizer (0.62) needs. Negative correlations with Nitrogen (-0.50) and Potassium (-0.47) influencing crop selection.

- **Fertilizer-N, P and K:** Fertilizer N shows a strong positive correlation with Fertilizer K (0.64), indicating interdependency. Also, Fertilizer P and Fertilizer K (0.45) are moderately correlated. Fertilizer P has the strongest positive correlation with crop labels (0.62), phosphorus plays an important role in determining crop recommendations. Nitrogen, Phosphorus and Potassium exhibit strong interactions influencing both crop labels and fertilizer requirements. Environmental factors like pH and Temperature have weaker yet notable correlations

4.7 Confusion Matrix Analysis

4.7.1 Confusion Matrix Analysis For Crop

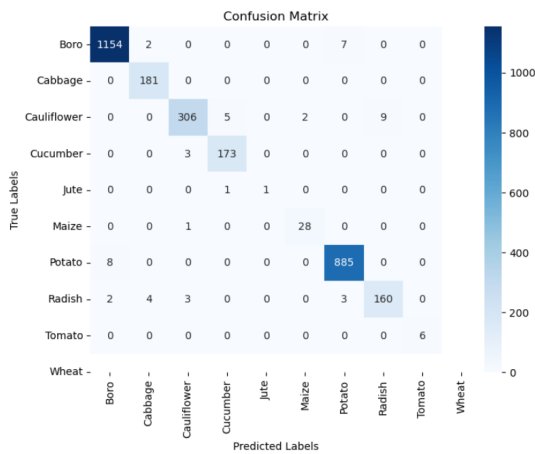


Figure 4.7: Crop: CatBoost

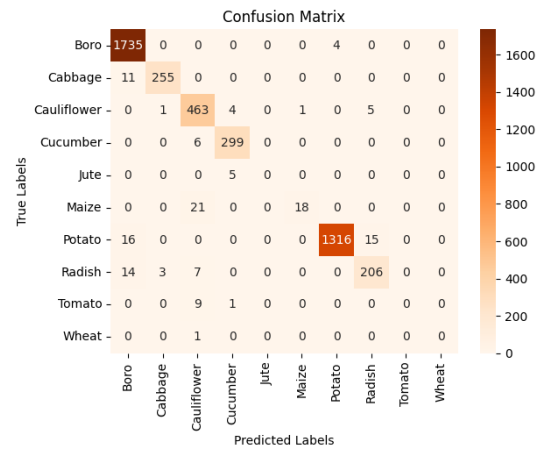


Figure 4.8: Crop: SVM

Fig.4.7 confusion matrix evaluates the performance of CatBoost classification model on ten crop categories. The matrix highlights that the model performs well for frequent crops like Boro, Cauliflower, Cucumber and Potato, as seen by the high numbers along the diagonal 1154, 306, 173 and 885. Minor misclassifications are seen for Cabbage and Cauliflower, where a few instances. Eight Potato samples were classified incorrectly as Boro. Misclassifications are visible more in smaller classes like Maize and Radish, with some overlap between these categories. Radish has 11 misclassified samples as Cabbage, Potato and Cauliflower. Maize sees slight confusion with other categories like Cauliflower. The matrix shows strong overall performance, but refinement is needed for less frequent crops. Fig.4.13 evaluates the performance of SVM classification model on ten crop categories. The matrix highlights that the model performs well for frequent crops like Boro, Cauliflower, Cucumber and Potato, as seen by the high numbers along the diagonal 1753, 463, 299 and 1316. Minor misclassifications are seen for certain crops, such as Cabbage and Radish. 4 Boro samples were misclassified as potato and 31 Potato samples misclassified as Boro and Radish. 5 jute samples are classified but all are incorrect. 18 maize samples are classified correctly and 21 samples misclassified

as cauliflower. Samples of tomato classified only 10 and mis- classified as cucumber and cauliflower.For wheat only one sample is classified and it is mis- classified as cauliflower. The overall performance is slightly underperformed than CatBoost.

4.7.2 Confusion Matrix Analysis For pH

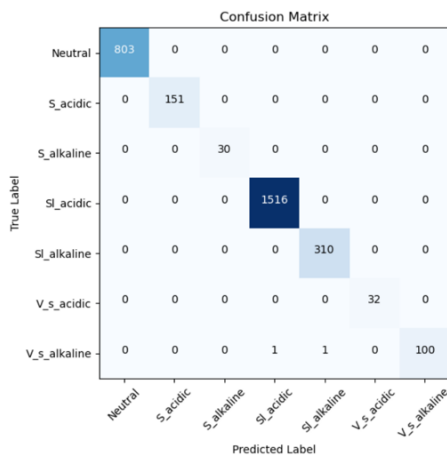


Figure 4.9: pH: CatBoost

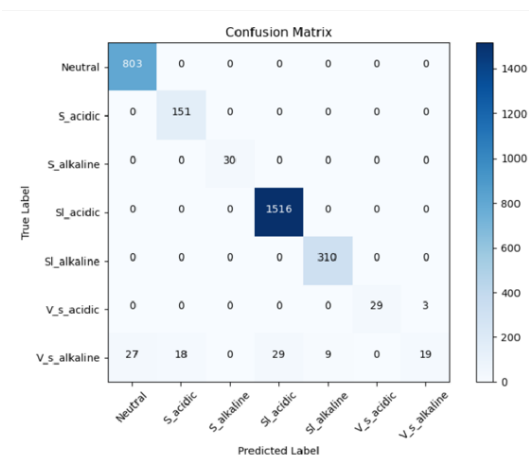


Figure 4.10: pH: SVM

Fig.4.9 confusion matrix evaluates the performance of the CatBoost classification model that exhibits near-perfect classification for neutral, slightly acidic, and slightly alkaline classes, with minimal misclassifications in very acidic and very alkaline categories. The diagonal part shows handling of typical and borderline pH levels strongly . It shows near zero misclassification.Different classes does not have any major confusion.The following classifications are accurate: neutral (803), S_acidic (151), S.alkaline (30), Sl_acidic (1516), Sl.alkaline (310), V_s_acidic (32), and V_s_alkaline (100).Fig.4.10confusion matrix evaluates the performance of the Support Vector Machine model which performs well for noted classes but misclassifies very acidic soils as slightly acidic or slightly alkaline. Another noticeable misclassification visible for V_s_alkaline as Neutral(27),S_acidic(18),S_alkaline(29),Sl_acidic(9), V_s_acidic(19).The SVM performs well but major confusion visible in feature similar pH classes..This indicates less flexible decision boundaries compared to CatBoost, making it the more reliable model for soil pH prediction. CatBoost outperforms SVM in

pH classification, offering higher accuracy and more consistent performance across all categories,

4.7.3 Confusion Matrix Analysis For Moisture

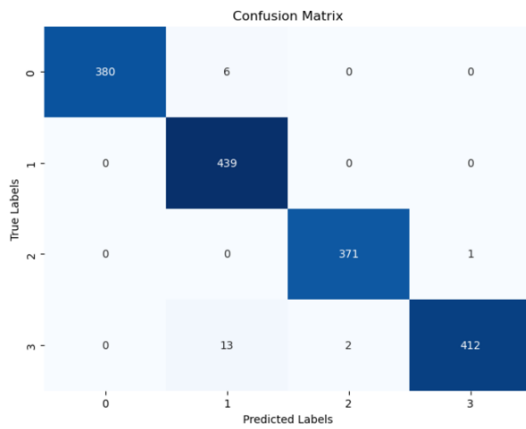


Figure 4.11: Moisture: CatBoost

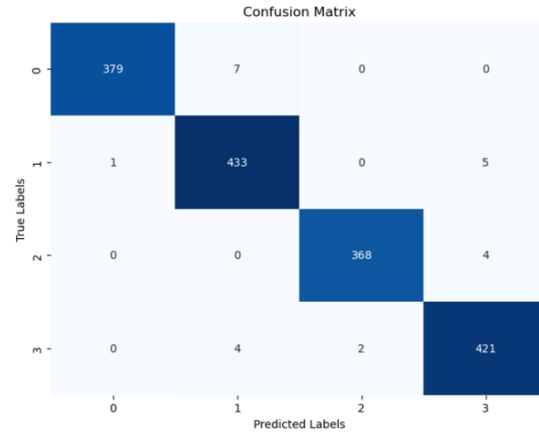


Figure 4.12: Moisture: SVM

Fig.4.11 confusion matrix evaluates the performance of the CatBoost classification model in: Optimal Moisture (O.M), Moisture Deficit (M.D), Long Drought (L.D), and Moisture Excess (M.E), shows minimal misclassifications even in closely related classes. The following classification are accurate Optimal Moisture (380), Moisture Deficit (439), Long Drought (371), and Moisture Excess (412). 17 samples are wrongly predicted. Fig.4.12 confusion matrix evaluates the performance of the Support Vector Machine model which performs well for major categories but shows moderate confusion between Long Drought (L.D) and Moisture Deficit (M.D). CatBoost demonstrates a stronger performance in moisture classification than SVM, with higher accuracy and more proper handling of different moisture conditions. The following classification are accurate Optimal Moisture (379), Moisture Deficit (433), Long Drought (368), and Moisture Excess (421). 18 samples are wrongly predicted. SVM remains competitive but struggles slightly with subtle distinctions among drought and excess states as well as occasional misclassifications involving Moisture Excess (M.E). While the diagonal remains strong, these off-diagonal entries indicate some difficulty distinguishing

4.7.4 Confusion Matrix Analysis For Salinity

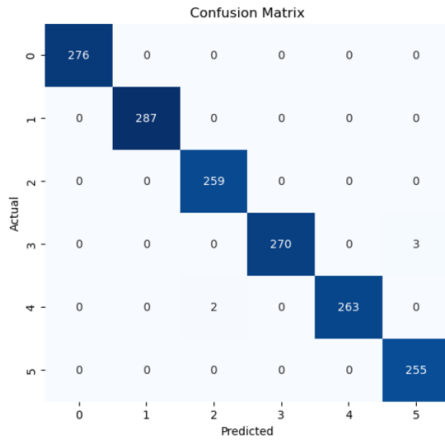


Figure 4.13: Moisture: CatBoost

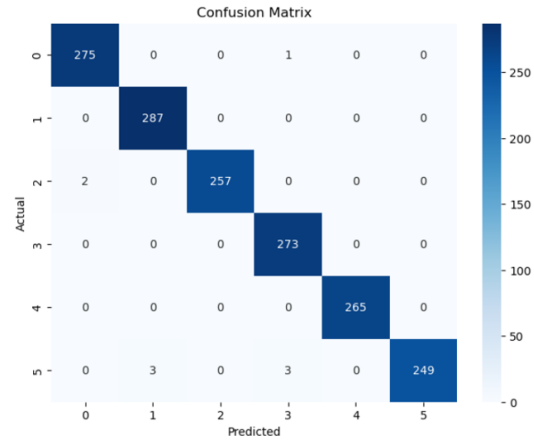


Figure 4.14: Moisture: SVM

Fig.4.13 confusion matrix evaluates the performance of the CatBoost classification model that better captures differences among closely related salinity conditions. Fig.4.14 confusion matrix evaluates the performance of the Support Vector Machine model shows strong diagonal performance, indicating mostly correct predictions for non-saline (N.Saline) and strongly saline (S.Saline). Only minor classifications are visible. CatBoost performs better in salinity classification, with higher accuracy, F1 score, and precision than SVM. Although SVM performs reliably for most classes, it shows slight overlaps in borderline salinity categories, highlighting CatBoost's stronger predictive capability for nuanced salinity levels.

Misclassification may result from overlapping features among the crops, further tuning of the model or feature engineering might improve its ability to distinguish between similar crops.

4.8 Efficient Models for Recommendation

The Catboost model proves to be a highly effective choice for predicting crops. For crop prediction, CatBoost achieved an accuracy of 98.03%, with impressive precision, recall, and F1-scores across multiple classes, demonstrating

its ability to handle the multi-class classification task effectively. CatBoost's advantages include high accuracy, robustness against overfitting, and computational efficiency, making it particularly suitable for predictions where computational cost is a concern. Overall, CatBoost stands out as a strong candidate for both crop prediction due to its high performance and ability to manage complex classification tasks effectively.

For fertilizer recommendation Random Forest significantly effective choice .For fertilizer recommendation, Random Forest achieved an R2 Score : 0.9708 , with impressive MSE and MAE , suggesting better smaller and consistent deviations handling in fertilizer recommendation.The Random Forest Regressor is an excellent choice for regression jobs where accuracy and dependability are crucial since it strikes a balance between the two.Bagging Regression have a good compromise between generalization and accuracy, however Random Forest have slightly higher MSE making it better option for reducing large errors.

4.9 Web Application



A web application has been developed as an user interface for the system. The application has four main features: Crop Recommendation, Fertilizer recommendation, Soil Health and Other information. For authentication the web application considers the signUp/Login system for making the access secure.In this application, sers can manually input soil data or application can automatically collect soil data from sensors which provide real time recommendations and soil health conditions. The application a also has history



Figure 4.15: Web Application

of previous data and recommendation as history. This web application is hosted in infinityfree which connects to a cloud database(MySQL) to store data.This web application is developed efficiently , ensuring easy access from both mobile and desktop making it user friendly.

Chapter 5

Conclusions

5.1 Expected Final Product Outcome

“IoT-Driven Crop and Fertilizer Recommendation System” project develops an IoT-based soil monitoring system that provides real time soil monitoring , crop prediction and fertilizer recommendations to farmers through web application. It also intended to give intuitions into soil health report and notable suggestions. Crop and fertilizer recommendation, soil health report and notable suggestions given based on sensor data-pH,NPK,temperarue, salinity and moisture and machine learning models to improve soil health, reduce excess fertilizer usage, and increase crop productivity by providing data-driven insights.The project strengthens the collaboration of IoT and machine learning-based technology in the agriculture sector of Bangladesh, most specifically for the farmers. We planned to submit this project as a journal.

5.2 Impact on Environment and Sustainability

The “ IoT-driven crop and fertilizer recommendation system” significantly impacts the environment and sustainability. Through real-time data collection, periodic monitoring of soil and machine learning models ensures a more sustainable approach to agriculture. The following points explaining the efficient environmental and sustainability impacts-

- **Improved Soil Health:** The system collect real time data from soil and periodically monitor soil parameters such as- NPK, pH, temperature, salinity and moisture , avoiding problems such as salinity increase or nutrient leaking.This ensure proper soil health for crop growth and more sustainable agriculture practices.
- **Sustainable Nutrient Management:** This system optimizes and recommends fertilizer usages that reduces improper use of fertilizer and ensure sustainable nutrient management in the soil . This also minimizes water pollution by reducing chemical runoff to water sources.
- **Reduce Improper Use of Fertilizer:** This system recommend fertilizer in a proper amount based on real time soil data and periodic monitoring. This ensures reducing overuse or under use of fertilizer into the soil which will reduce chemical spreading into the air , water as well as food.
- **Preservation of Biodiversity:** By maintaining healthy soil conditions and reducing the improper use of fertilizers protect beneficial insects in the soil , promote biodiversity and promotes sustainable agriculture practices.
- **Sustainable Agriculture:** Efficient use of fertilizer and proper crop recommendation improve crop yields while reducing pollution to the environment, which can promote sustainability.
- **Data-driven Efficiency:** Real time soil data collection and periodic monitoring of soil helps track soil health, environment and soil parameters impacts and crop growth,ensuring reducing environmental footprint and informing sustainability policies with eco-agriculture standards.

5.3 Professional and ethical standards

Ethical and Professional Considerations

Several ethical concepts and professional ethics have been followed for “IoT-driven crop and fertilizer recommendation system “ to assure safety, compliance, and environmental sustainability.

1. **Ethical Responsibility:** Engineer’s primary ethical duty is public safety and environment protection .The ethical responsibilities are:

- **Public Safety:** This system will collect real time data and periodically monitor soil parameters to recommend proper use of fertilizer that reduces spreading pollution in the environment and water as well as keeps food healthy.

- **Environmental Protection:** The system is designed to prevent harmful practices, such as the overuse of chemicals or fertilizers, which can damage ecosystems. By using real-time data and machine learning predictions, farmers can maintain optimal soil health, which could devastate local ecosystem.

2. **Safety and Failure Analysis:** To ensure the system is safe to use, the following analysis will be implemented into the design process:

- **Problem Identification:** Sensor failures, communication breakdowns problems were identified which can lead to incorrect predictions, poor soil quality.

- **Failure Analysis:** A broad failure analysis was analyzed to improve potential risks. For example, sensor malfunction could lead to inaccurate data which could hamper soil health and crop growth or lead to harmful

environmental conditions. To reduce these risks, sensor redundancy was implemented and automated system checks would be incorporated.

- **Safety Measures:** Sensor tuning will ensure accurate data collection. Manual overrides will be included to allow for immediate human intervention.

3. **Legal Requirements:** To ensure legal requirements the following steps should be considered:

- **Environmental Regulations:** The system monitors soil health in real time and ensures compliance with soil quality standards. The collected soil parameters- NPK, pH, temperature, salinity and moisture align with soil quality thresholds set by regulatory bodies for safe agriculture operations.

- **Data Privacy Laws:** Since the system will collect and transmit real-time data, it will adhere to data privacy and protection laws, such as the General Data Protection Regulation (GDPR) in Europe or the California 87 Consumer Privacy Act (CCPA) in the US. Data will be encrypted during transmission, and user consent will be taken for data collection.

- **Intellectual Property:** The project will comply with intellectual property laws, ensuring that proprietary technology or software used in the system will be properly licensed or developed in-house. This will protect the project from potential legal disputes.

4. **Integration of Safety:** For design process safety is a core principle. How safety was and will be incorporated into the design is described below:

- **Redundancy and Backup Systems:** To ensure reliability, backup sensors and data processing redundancies will be included. This will prevent any single point of failure from causing critical issues in monitoring or

predictions.

- **User Control:** Farmers have the option to manually override in the system to prevent incorrect fertilizer recommendations when automation or sensor fails.

5. **Ethical Concerns:** Ethical principles were and will be incorporated to ensure that the system benefits society at large following below steps:

- **Sustainability:** By optimizing soil quality and crop growth, the system will support sustainable agriculture practices, reducing the need for harmful chemicals and minimizing waste. This aligns with ethical considerations for environmental sustainability and responsible resource management.

- **Fair Access:** Ethical considerations were also made to ensure that the system can be scaled and adapted for small-scale or local farmers, providing access to technology that promotes sustainable aquaculture, even in resource-limited settings.

6. **Skill Development for Farmers:** The system should be targeted to understand the soil conditions insights and not only look for the recommendations. Local language has been implemented to make them understand. Our ethical concern is not to make the farmers over dependent on the system.

5.4 Societal, Health, Safety, Legal and Cultural aspects

1. **Social Issue:**

- **Issue:** The aim of this system is to increase productivity, economic growth and ensure food security. However, this system can cause confusion that can cause misuse of fertilizer because of unawareness as well as

limited adoption of this system can occur because of limited availability of technical tools most specifically in rural areas.

- **Mitigation:** Arranging ready-made low-cost devices and organizing a free training system can make farmers introduced with new processes of predicting crops and fertilizers can be helpful to reduce these issues.

2. Health Issue:

- **Issue:** The most concerning issue of our system is the amount of fertilizer used. Overuse or misuse of fertilizer can cause chemical reaction that polluted soil and crops which can be harmful for health.

- **Mitigation:**Our system is implemented based on verified datasets from various authorized sources which make our system safe to use .

3. Safety Issue:

- **Issue:** Due to lack of sensor tuning and incorrect sensor integration , incorrect reading can be caused which can lead to inaccurate recommendations.

- **Mitigation:**This issue can be mitigate through proper sensor tuning and checking sensor integration timely .

4. Legal Issue:

- **Issue:**As we collected data from authorized sources and have ownership concern , comply with legal standards on data privacy and protection is must otherwise data branches can occur.

- **Mitigation:** Ensuring data protection regulations such as- GDPR(General Data Protection Regulation) or CCPA (California Consumer Privacy Act) and communication protocol needs to be secured.

5. Cultural Issue:

- **Issue:** As our system is modern technology based , it can conflict with traditional systems and due to lack of awareness farmers may won't use this system.
- **Mitigation:**Creating concern about the significance of technology on agriculture and organizing training can reduce this issue.

5.5 Future Works

The future scopes of this project are -integration of multilingual support in website for easier access,averaging multiple soil samples,implement field tested prototype,implement a cleaner energy source; such as - solar energy.

5.6 Conclusion

The project suggests a new innovative system solution based on strong collaboration of IoT-based technology and multiple machine learning models dedicated to fertilizer and crop recommendations.Region has been considered for precise crop and fertilizer recommendation .A web application contributes to sharing soil related information and fertilizer and crop recommendations with the farmers. The project also intended to give intuitions into soil health report based on predicting soil parameters. This enables efficient and scalable system solutions that deliver three main expected outcomes: periodic soil monitoring, fertilizer and crop recommendations, and web application. Challenges in collecting expertise optimal data for analyzing collected data to recommend fertilizers reduce promptly succeeding obtaining data from FAO,BARC,BRRI and Soil Resource Development Institute, Tangail.Another major challenge is limited availability of sensors in Bangladesh ;for example, soil bulk density sensors for measuring soil porosity .

The successful system implementation will contribute to balancing the nutrient level of the soil and soil health, increase productivity, ensure food security, reduce the cost and robustness of the lab tests and increase economic growth.

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