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Development of Real-Time Crop Cultivation and Nutrient Recommendation System

A Minor Project Report (18EC64)

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CERTIFICATE

Certified that the minor project(18EC64) work titled ***Development of Real-Time Crop Cultivation and Nutrient Recommendation System*** is carried out by **Gopalkrishna Hegade M** (**1RV20EC065**), **M Kaushik** (**1RV20EC094**) and **Gopal Vaman Naik** (**1RV21EC406**) who are bonafide students of RV College of Engineering, Bengaluru, in partial fulfillment of the requirements for the degree of **Bachelor of Engineering** in **Electronics and Communication Engineering** of the Visvesvaraya Technological University, Belagavi during the year 2022-23. It is certified that all corrections/suggestions indicated for the Internal Assessment have been incorporated in the minor project report deposited in the departmental library. The minor project report has been approved as it satisfies the academic requirements in respect of minor project work prescribed by the institution for the said degree.

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DECLARATION

We, **Gopalkrishna Hegade M** , **M Kaushik** and **Gopal Vaman Naik** students of sixth semester B.E., Department of Electronics and Communication Engineering, RV College of Engineering, Bengaluru, hereby declare that the minor project titled '**Development of Real-Time Crop Cultivation and Nutrient Recommendation System**' has been carried out by us and submitted in partial fulfilment for the award of degree of **Bachelor of Engineering** in **Electronics and Communication Engineering** during the year 2022-23.

Further we declare that the content of the dissertation has not been submitted previously by anybody for the award of any degree or diploma to any other university.

We also declare that any Intellectual Property Rights generated out of this project carried out at RVCE will be the property of RV College of Engineering, Bengaluru and we will be one of the authors of the same.

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ABSTRACT

Soil characteristics are of paramount importance in agricultural production as they directly influence fertility and the success of crop development. The balance of essential nutrients, such as Nitrogen (N), Phosphorus (P), and Potassium (K), collectively known as NPK is critical for crop growth and development. These nutrients play pivotal roles in crucial physiological processes including photosynthesis, nutrient uptake and overall plant metabolism, which ultimately determines crop productivity. Lab based soil tests are not only time-consuming and expensive but also fail to capture the diversity and complexities of real-world farming conditions. Current market lacks a portable device for the nutrient recommendation or soil testing, which gives instant results for a user-specified crop.

This project presents a real-time crop prediction and nutrient recommendation system with the prime objective of creating a portable device for crop prediction and additional nutrient recommendation. The approach utilizes an NPK sensor to collect input data, which is then transmitted to the Firebase database using ESP32 controller for further processing using Naive Bayes algorithms deployed in AWS Elastic Compute Cloud (AWS EC2). A mobile application is developed for ease of interfacing. The system provides farmers with accurate predictions regarding the most suitable crops for their specific land based on the NPK values obtained, the system offers precise recommendations for additional nutrients required to optimize crop productivity and achieve maximum yield. The application also integrates a visual map, enhancing the user experience by offering a clear representation of the precise locations where soil samples were analyzed.

This novel system addresses the challenges faced by farmers in optimizing crop choices and nutrient management by providing real-time and data-driven insights. By efficiently utilizing NPK sensor data, Naive Bayes algorithm based ML model gives an accuracy of 98.8% aims to revolutionize traditional agricultural practices. Further, the integration of Spectroscopic Soil Analysis can be done based on location and holds the potential to provide invaluable insights into the variations of soil nutrient content across diverse sections of a farmer's land.

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ABBREVIATIONS

AI Artificial Intelligence

AIML Artificial Intelligence and Machine Learning

AWS Amazon Web Services

AWS EC2 AWS Elastic Compute Cloud

CCNRS Crop Cultivation and Nutrient Recommendation System

DNN Deep Neural Network

DSSAT Decision-Support System for Agro-technology Transfer

ER Exponential Regression

IGA Improved Genetic Algorithm

IoT Internet of Thing

K Potassium

LiDAR Light Detection and Ranging

LR Linear Regression

ML Machine Learning

MSE Mean Squared Error

N Nitrogen

NB Naive Bayes

NPK Nitrogen-Phosphorus-Potassium

P Phosphorus

PR Polynomial Regression

RADAR Radio Detection And Ranging

RFR Random Forest Regression

SQL Structured Query Language

SVR Support Vector Regression

XGBoost Extensive Gradient Boosting

Chapter 1

Introduction to Crop prediction and Nutrient Recommendation System

CHAPTER 1

INTRODUCTION TO CROP PREDICTION AND NUTRIENT RECOMMENDATION SYSTEM

1.1 Introduction

The county's economic growth is mainly influenced by the agricultural industry. More than half of India's population is employed in the agricultural sector. More than half of global GDP is accounted for by agricultural output. It is proved that agricultural enhancement upshots poverty reduction. Agricultural productivity and sustainability are increasing with the development of technology with innovative solutions. Factors like nutrient content, irrigation, soil type, and fertilizers used impacts crop production. Soil characteristics play a vital role in agriculture in maintaining fertility by allowing crops to develop better through root nutrition. The significant parameters extensively used in agriculture are Nitrogen (N), Phosphorus (P), and Potassium (K). In order to keep the production level high these nutrients are suggested. Inappropriate fertilizer use causes an intriguing issue in nutrient (macro and micro) level imbalance. The drop in yield output occurs due to a crisis of nutrients, directly leading to a rise in the production cost.

According to a report farmers in India are Employing soil at the highest possible density, resulting in the production of two crops per year with no use of soil management technologies. The approach causes nutrient shortages and alterations in the chemical structure of the soil gradually. Plants are unable to undertake development activities when nutrients are low. Hence there is a requirement to assure ongoing soil monitoring with a clear strategy to maintain a high soil organic matter content and nutrient availability. Before fertilization, a soil test for nutrients (including Nitrogen, Phosphorus, and Potassium) can be performed. In the event of a nutritional deficit, the required nutrients should be given. The fertility of the soil is maintained at an adequate level and crop output is boosted. The traditional techniques of assessing soil health often entail the examination of a wide variety of markers (biological, physical, and chemical properties) that rely on Laboratory evaluation involving expenditures for soil sample gathering, shipping, and evaluation, all of which reduce the farmer's profitability. The utilization of data-driven technologies provides accurate, timely, and personalized recommendations for optimizing crop cultivation practices and nutrient management among farmers. The use of Artificial Intelligence and Machine Learning (AIML) has made significant advancements in agriculture, including the cultivation of crops, pruning, and sales. AIML is a sophisticated technology that has the potential to be employed to diagnose and arrive at decisions in place of human intellect. Artificial intelligence, when coupled with the Internet of Thing (IoT), may be used throughout the food chain, that is from agriculture to food waste management. Remote sensing (RS) has transformed into a potent instrument for rapidly collecting large amounts of agricultural data and generating valuable data for crop managers. Normally, indications are primarily associated with chemical fertilizers consisting of N, P, and K, along with other biological markers such as organic matter content. Furthermore, techniques based on Machine Learning (ML) are the most widely used methods to process information from remote sensing systems. Thus ML models such as Linear Regression (LR), Polynomial Regression (PR), Exponential Regression (ER), Random Forest Regression (RFR), Support Vector Regression (SVR), and Deep Neural Network (DNN) can be employed to predict the crop which produces good yield in a specified region considering various factors. By utilizing advanced algorithms and AI-driven analytic, the model can generate personalized nutrient recommendations tailored to specific crop types, and field conditions. By optimizing natural fertilizer usage, farmers can minimize environmental impact, improve resource efficiency, and enhance overall crop productivity.

1.2 Motivation

In today's world, to meet the ever-increasing global food requirements, there is a growing need for efficient crop cultivation practices. To address this challenge, recent advancements in technology, such as remote sensing, the IoT, and Artificial Intelligence (AI), have opened up new possibilities in the field of agriculture. These technologies enable environmental monitoring and real-time crop growth, providing farmers with valuable insights for precise nutrient management, and empowering informed decisions about the nutrient application. By utilizing advanced algorithms and AI-driven analytics, the system can generate personalized nutrient recommendations tailored to specific crop types, and field conditions. By optimizing natural fertilizer usage, farmers can minimize environmental impact, improve resource efficiency, and enhance overall crop productivity. The development of such a system has the potential to revolutionize the agricultural industry, enabling farmers to achieve sustainable and efficient crop cultivation practices while meeting the global demand for food.

1.3 Problem statement

Unavailability of a portable device for the nutrient recommendation which gives instant results for a user-specified crop with sensor data as input.

The project aims to develop a versatile and farmer-friendly system that enables farmers to specify the type of crop they want to cultivate and swiftly provide precise and tailored nutrient recommendations to optimize crop growth and yield based on the sensor data. Device must be portable, allowing farmers to access it conveniently in the field, and it should deliver real-time results to aid farmers in making better decisions for their crops.

1.4 Objectives

The objectives of the project are as follows:

- To develop a system to check if certain crops can be cultivated in a specific acreage and suggest the additional nutrients required if the crop can be cultivated.
- To design a farmer-friendly portable device- Prototype.
- To provide the graphical representation using a location map of the derived analytics.

1.5 Literature Review

Farmers should be aware of crop type that is treatable for soil type and geographical location. Hence, it can be necessary to offer timely-based, accurate data according to the soil type and climatic parameters to the farmer, helping them create better decisions for the soil, resulting in great productivity and profitability as discussed in [1]. During the data categorization, beyond the rough set, the fuzzy logic is used to handle the boundary values of the numerical features to improve the accuracy of the prediction by exploiting all the soil micro and macro-nutrients to predict the crop suitability for a region [2]. The most important factors such as identifying a crop's illness and providing ideas, anticipating a suitable crop for the land, and offering a suitable fertilizer for the crop that affects crop yield. It uses the Extensive Gradient Boosting (XGBoost) model to predict a suitable crop, Random Forest for Fertilizer recommendation and MobileNet for Disease Detection based on the local soil nutrients such as N, P, K and pH values and rainfall. The XGBoost algorithm gives an accuracy of 99% for Crop Prediction, the random forest gives 95.7% for Fertilizer Recommendation, and Mobile Net gives 92% for Disease Detection. The key drawback of this study is that it uses user-provided manual data rather than sensor data as the model's input [3].

The potentialities, advantages and disadvantages of each remote sensing techniques such as Radio Detection And Ranging (RADAR) and Light Detection and Ranging (LiDAR) for crop yield, Aerial photography and crop yield, Satellite imagery for yield prediction and the applicability of these techniques under different agricultural conditions. Parameters derived from multi-sensors help in the evaluation of biophysical and biochemical characteristics related to crops. It is possible to measure crop spectral features using various remote sensing sensors by taking into account certain factors that are directly related to crop vitality [4]. Using synthetic datasets from biophysical crop models to evaluate the impact of the predictive algorithm selection, data volume, and data partitioning techniques on predictive performance. It used OilcropSun and Ceres-Wheat from Decision-Support System for Agro-technology Transfer (DSSAT) to simulate sunflower and wheat data for the years 2001 to 2020 in five different regions of Spain. Farms with various soil depths and farming practices were used for the simulations. Different methods (random forests, regularized linear models, artificial neural networks) were used to analyze the farm yield data set as a function of seasonal weather changes and soil. For neural networks, Keras was used in the analysis, and R packages were used for all other algorithms. In comparison to regularized linear models (64-65%) and artificial neural networks (37-141%), the Random Forest approach performed better (Root Mean Square Error 35-38%) and was simpler to use [5]. The MYRS (Mapping Yield Remote Sensing-based model) to estimate final yield in grain crops using a RS-based approach. The model showed good performance at reproducing final yield in an operational way at field and within-field scales in commercial fields [6]. Using time-series sensor data to recommend different crop settings and makes suggestions regarding nutrition with an Improved Genetic Algorithm (IGA).The algorithm uses a neighborhood exploration and exploitation method as part of its optimization scheme. According to experimental findings, the model can effectively suggest optimizing patterns and yearly yield growth [7].

Through the use of deep learning architectures, this research provides unique AI-based soft sensor techniques that are integrated with remote sensing models. The input has undergone pre-processing to identify values that are missing, data cleaning, and remove noise from the image that was taken on agricultural land. Utilizing a weight-optimized neural network with maximum likelihood (WONN-ML), the features were represented. The classification process has been carried out utilizing ensemble architecture of stacked auto-encoder and kernel-based convolution network (SAE-KCN) after the features have been represented. The proposed technique has produced experimental results for a variety of crops with computing time of 56%, accuracy of 98%, precision of 85.5%, recall of 89.9%, and F-1 score of 86% [8]. Analysis of crop age status is crucial to preventing over-fertilization, figuring out when to harvest, and lowering production costs. Image based analysis using computational intelligence has proved beneficial in estimation of categorical age in the crops. In this study, the application of predictive computational intelligence techniques is highlighted for assessing the Nitrogen condition of wheat crops. While classifying the crop yield age into categories, ANN-based optimized technique can distinguish wheat crops from other undesirable plants and weeds in a considerable way. The results of the experiment produce the maximum validation accuracy of 97.75%, the lowest error rate of 0.22, and a reduction in the loss value of 0.28. The proposed ANN + GA technique offers better performance results while minimizing the error rate as compared to its modern competitors [9]. Crop prediction and crop recommendation are the two key processes that the Multimodal Machine Learning Based Crop Recommendation and Yield Prediction (MMML-CRYP) approach model focuses on. For effective crop recommendation at the beginning, equilibrium optimizer (EO) with kernel extreme learning machine (KELM) technique is used. The random forest (RF) technique was then used to accurately predict the crop production. Results of the experiments showed that the MMML-CRYP technique performed significantly better than the comparison approaches, with a maximum accuracy of 97.91% [1].

The machine learning algorithms, particularly Random Forest, Naive Bayes, and XGBoost, can greatly enhance the ability to predict crop yield and nutrient requirements. This advancement is crucial for efficient agricultural practices and informed decision-making. Additionally, the research highlights the limitations of lab-based tests in monitoring crops over large areas. Such tests are not only time-consuming and expensive but also fail to capture the diversity and complexities of real-world farming conditions. Furthermore, the current survey reveals a significant gap in research concerning soil nutrient enhancement in India. This dearth of knowledge hinders the implementation of effective strategies for improving soil health and optimizing nutrient application. Furthermore it is found that there is insufficient research on determining the suitability of specific crops for cultivation in designated acreage. This lack of information poses challenges for farmers and prevents them from making informed choices regarding crop selection and land utilization. Addressing these issues and developing a real-time crop cultivation and nutrient recommendation system will empower farmers with valuable insights, enabling them to maximize productivity, reduce costs, and promote sustainable agricultural practices.

1.6 Brief Methodology of the project

The user has to insert the Nitrogen-Phosphorus-Potassium (NPK) sensor in the soil. The design incorporates NPK sensors that collect soil nutrient values and transmit them to a cloud database using a microcontroller. Figure 1.1 gives an overview of the architecture employed.

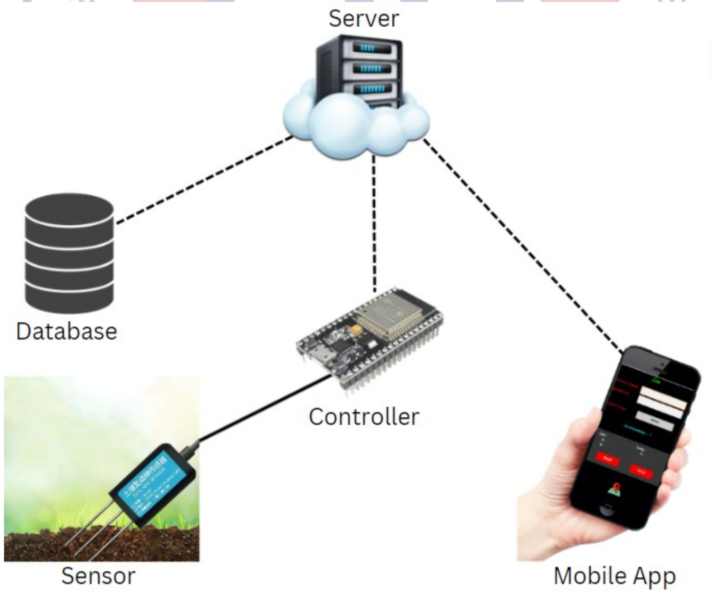

Figure 1.1: Design Overview

The user is provided a mobile application to control the working of the portable system, where the crop name has to be selected from the dropdown provided for which the additional NPK is to be calculated. This data is accessed by Amazon Web Services (AWS) server which processes the data and returns the additional NPK required for the crop to the mobile application. If the crop name is set to null, then the server will return the predicted crop and its probabilities to the mobile application. Overall, the proposed design ensures seamless connectivity between sensors, microcontroller, cloud databases, and mobile applications, offering a robust and efficient solution to support sustainable and productive farming practices.

1.7 Assumptions made / Constraints of the project

- Mean value is the best value for the NPK

  Since the mean presents a fair estimate by taking into account all available data points, the mean value is regarded as the best depiction of NPKlevels for a crop variety. It reduces the impact of extreme values or outliers, resulting in a more consistent and normal measurement. Using the mean also streamlines the process of making decisions and enables easy comparisons between crop samples.

- Considered only NPK values for the evaluation.

  Considered only NPKvalues into account for the evaluation. While acknowledging that other factors such as soil pH, humidity, and temperature also influence plant growth, the focus is placed on NPK as the major contributor. This choice is based on the direct impact of NPK nutrients on crucial biological processes, including protein synthesis, energy transfer, and regulation of water uptake, which are fundamental to plant growth and development.

- The consideration of datasets to train the model is limited to certain regions of India.

  The ideal values of NPKnutrients vary significantly with changes in location and environmental conditions. Different regions have distinct soil compositions, climate patterns, and crop preferences, which directly impact the optimal NPKrequirements.

- The datasets is limited to 22 different crops.

  The dataset's limitation to 22 different crops with 100 samples each is reasonable due to practical constraints and the need for comprehensive data representation. While a broader variety of crops would provide more diversity.

1.8 Organization of the report

This report is organized as follows

- Chapter 2 discusses the Basics of Crop Prediction and Nutrient Recommendation. It elaborates on the necessity of an instant soil testing device and analyzes the fundamentals of the modules used, such as ML, server, microcontroller, and mobile application.
- Chapter 3 delves into the Design and Architecture of the device, providing a detailed explanation of the diverse hardware used and their specifications.
- Chapter 4 encompasses the Implementation of the methodology discussed in Chapter 3.
- Chapter 5 elegantly explores the intricate interplay of results and discussions, rendering a captivating amalgamation of empirical findings and insightful analyses.
- Chapter 6 explores the conclusions drawn from the study, outlines the potential for future advancements, and highlights the key learning outcomes of the research.

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Chapter 2

Theory and Fundamentals

CHAPTER 2

THEORY AND FUNDAMENTALS

The implementation of a real-time crop cultivation system requires knowledge of machine learning, cloud database handling, IoT, app development, and different sensors. Machine learning is utilized to train large datasets and make accurate crop predictions. Cloud database handling is essential for storing tested data and using it for further operations. IoT plays a crucial role in sending sensor data to the cloud. App development platforms are used to create an intuitive app through which users can access the results conveniently. Moreover, expertise in sensors and micro-controllers is necessary for interfacing various sensors used in soil testing. This comprehensive combination of skills and technologies will enable the development of an efficient and user-friendly system for crop cultivation and nutrient recommendation.

2.1 Basics of Crop Prediction and nutrient recommendation

Crop prediction is the process of estimating the yield of a crop in a given environment. This can be done using a variety of methods, including statistical analysis, machine learning, and remote sensing [10] The nutrient recommendation is the process of determining the amount and type of nutrients that a crop needs to grow and produce a healthy yield. This can be done by considering the crop's specific requirements, the soil conditions, and the weather forecast [11].

The first step in crop prediction and nutrient recommendation is collecting relevant data. This includes historical crop yield data, weather data (temperature, precipitation, humidity), soil data (nutrient levels, pH), and chemical compositions such as N, P, K, and other environmental variables. [12] Crop prediction and nutrient recommendation using machine learning are vital applications in modern agriculture, aimed at optimizing crop yield and ensuring sustainable agricultural practices. These technologies leverage data analytics and machine learning algorithms to make accurate predictions about crop growth, yield, and nutrient requirements based on historical data, weather patterns, soil conditions, and other relevant factors. The performance of the crop prediction and nutrient recommendation models is evaluated using validation data to ensure accuracy and reliability. Various metrics like Mean Squared Error (MSE) or R-squared are used to assess model performance [13].

For real-time crop prediction and nutrient recommendation, sensor data from the field, such as soil moisture, temperature, and nutrient levels, can be integrated with the model to update recommendations continuously. Crop prediction and nutrient recommendation enable precision agriculture practices, where farmers can apply fertilizers and irrigation in a targeted manner, minimizing waste and maximizing crop productivity. Implementing machine learning-based crop prediction and nutrient recommendation systems can lead to increased crop yield, reduced resource consumption, better resource allocation, and enhanced sustainability in agriculture [14].

2.2 The need for an instant soil testing device

The need for an instant soil testing device arises from the critical role soil plays in agricultural productivity and sustainable farming practices. Soil health directly influences crop growth, yield, and nutrient uptake. Traditional soil testing methods are time-consuming and often require sending samples to a laboratory, leading to delays in obtaining results [14]. An instant soil testing device addresses these challenges by providing real-time and on-site analysis of soil properties. Farmers can quickly assess essential soil parameters, such as nutrient levels (NPK), moisture content, and organic matter, without relying on external laboratories. This instant feedback empowers farmers to make informed decisions promptly. The device's portability and ease of use enable farmers to conduct tests conveniently across various fields and monitor soil conditions regularly. By identifying soil deficiencies or imbalances instantly, farmers can adjust fertilization and irrigation practices efficiently, optimizing resource utilization and reducing costs. Overall, the need for an instant soil testing device arises from the desire to enhance agricultural productivity, sustainability, and resource efficiency. By providing farmers with quick and reliable soil insights, these devices empower them to make data-driven decisions, promoting better crop management and fostering more resilient and productive farming systems [15].

2.3 Machine learning

Machine learning is a subset of artificial intelligence that involves the development of algorithms and statistical models that enable computers to learn from and make predictions or decisions based on data, without being explicitly programmed. The key concept behind machine learning is the use of data to train models and improve their performance over time [16]. There are various types of machine learning, including supervised learning, unsupervised learning, and reinforcement learning. Machine learning finds applications in various fields, such as image and speech recognition, natural language processing, recommendation systems, autonomous vehicles, agriculture, finance, healthcare, and more[17]. The availability of vast amounts of data and advances in computing power have accelerated the growth and adoption of machine learning in real-world scenarios.

2.4 Server

A server is a computer or software program that provides services and resources to other computers or clients on a network, like the Internet. It acts as a central hub for data storage, processing, and communication, allowing clients to access and utilize its capabilities remotely. Servers play a crucial role in modern technology, enabling tasks such as web hosting, data storage, and application deployment. They come in various types, such as web servers, file servers, database servers, cloud servers, and application servers, each serving specific purposes [18]. Servers handle requests from clients, process data, and deliver responses efficiently. They are essential for running websites, handling user interactions, and deploying machine learning models, making them vital components of the digital infrastructure.

2.5 Micro Controller

Microcontrollers are compact integrated circuits that combine a microprocessor, memory, and input/output peripherals on a single chip. They serve as the brain of various embedded systems and electronic devices, offering real-time control and processing capabilities [19]. These low-cost, low-power devices are widely used in robotics, IoT devices, consumer electronics, and industrial automation. Microcontrollers can be programmed to perform specific tasks and respond to inputs from sensors or user interactions. They offer high flexibility and ease of prototyping due to their small size and simplicity. Popular microcontroller families include Arduino, Raspberry Pi, PIC, and ESP32. Microcontrollers play a crucial role in driving the growth of the IoT by enabling connectivity and intelligence in a wide range of smart devices and systems [20].

2.6 Mobile Application

Mobile applications, commonly known as mobile apps, are software programs designed to run on smartphones, tablets, and other mobile devices. They offer a wide range of functionalities and services to users, enhancing their productivity, entertainment, and communication. Mobile apps are available for various platforms, such as iOS, Android, and Windows, developed using different programming languages and tools. They can be downloaded and installed from app stores, providing convenient access to a multitude of services, including social media, gaming, banking, navigation, and more. Mobile apps leverage the device's capabilities, such as GPS, camera, and sensors, to offer personalized and location-based experiences. Their popularity and widespread use have led to a significant shift in digital interactions, making them an integral part of modern life. With continuous advancements in mobile technology, mobile apps continue to evolve and shape the way people interact with technology and each other. development of agricultural applications based on smartphone devices has increased exponentially in the last years[21].

2.7 Internet of Things (IoT)

IoT is a revolutionary concept that connects everyday objects and devices to the Internet, enabling them to collect, exchange, and process data. IoT allows seamless communication between the physical and digital worlds, creating smart and interconnected systems. It encompasses a wide range of applications, including smart homes, wearable, industrial automation, healthcare monitoring, precision agriculture, and environmental sensing. IoT devices are equipped with sensors, actuators, and microcontroller, enabling them to interact with the environment and other connected devices. Through IoT, data can be gathered in real-time, empowering businesses and individuals to make informed decisions and optimize processes. IoT was widely used in agriculture, such as management systems, monitoring systems, control systems, and unmanned machinery [22]. However, the rapid adoption of IoT also raises concerns about data privacy, security, and the potential impact on the environment. As IoT continues to evolve, its transformative impact on industries and society is expected to grow exponentially.

2.8 Cloud Database

Cloud databases are online databases that are hosted and managed on cloud computing platforms. They offer scalable and flexible data storage solutions for businesses and individuals. Cloud databases eliminate the need for on-premises hardware and maintenance, reducing operational costs and complexity. They provide high availability and reliability, ensuring data accessibility from anywhere with an internet connection. Cloud databases support various data models, including relational, New-Structured Query Language (SQL) catering to diverse data requirements. They offer features like automatic backups, data encryption, and data replication for data security and disaster recovery. Cloud databases enable collaborative and real-time data access, fostering teamwork and efficient decision-making. With pay-as-you-go pricing models, users can easily scale their database resources as needed, accommodating changing demands and workloads. Overall, cloud databases empower organizations with agile and cost-effective data management solutions in the digital age.

2.9 Remote Sensing

Remote Sensing is the process of acquiring information about the Earth's surface and atmosphere from a distance, typically using satellites, aircraft, or drones equipped with sensors. It enables the collection of valuable data without direct physical contact with the target area [23]. The sensors capture electromagnetic radiation reflected or emitted by the Earth's surface, which is then processed and analyzed to derive meaningful information. Different types of sensors, such as optical, thermal, RADAR, and LiDAR, are used to capture specific characteristics of the Earth's surface. Remote sensing has revolutionized the way of studying and understanding the Earth, providing valuable insights into global phenomena and helping make informed decisions for sustainable development and resource management [24].

After understanding the fundamentals of crop prediction and nutrient recommendation using machine learning. Crop prediction involves estimating crop yield based on historical data, weather patterns, soil conditions, and other factors. Nutrient recommendation determines the optimal amount and type of nutrients for healthy crop growth. Machine learning algorithms enable accurate predictions and recommendations, facilitating precision agriculture. Real-time sensor data from the field can be integrated into models for continuous updates. Now, integrating a microcontroller, and cloud databases for real-time data collection and processing leads to the development of remote sensing devices. The goal is to provide farmers with instant soil analysis and nutrient recommendations through a mobile application.

Chapter 3

Design and architecture of the Device

CHAPTER 3

DESIGN AND ARCHITECTURE OF THE DEVICE

The system is designed to enhance agricultural productivity and sustainability by providing accurate crop suitability predictions and precise nutrient recommendations based on sensor data. A user-friendly mobile application is developed which allows farmers to interact with the system, select crops, and receive real-time nutrient recommendations. The portable device is built in order to ease the process of soil testing. The current chapter will delve into the discussion of the envisioned intricate design structure of the Crop Cultivation and Nutrient Recommendation System (CCNRS).

3.1 Specifications for the Design

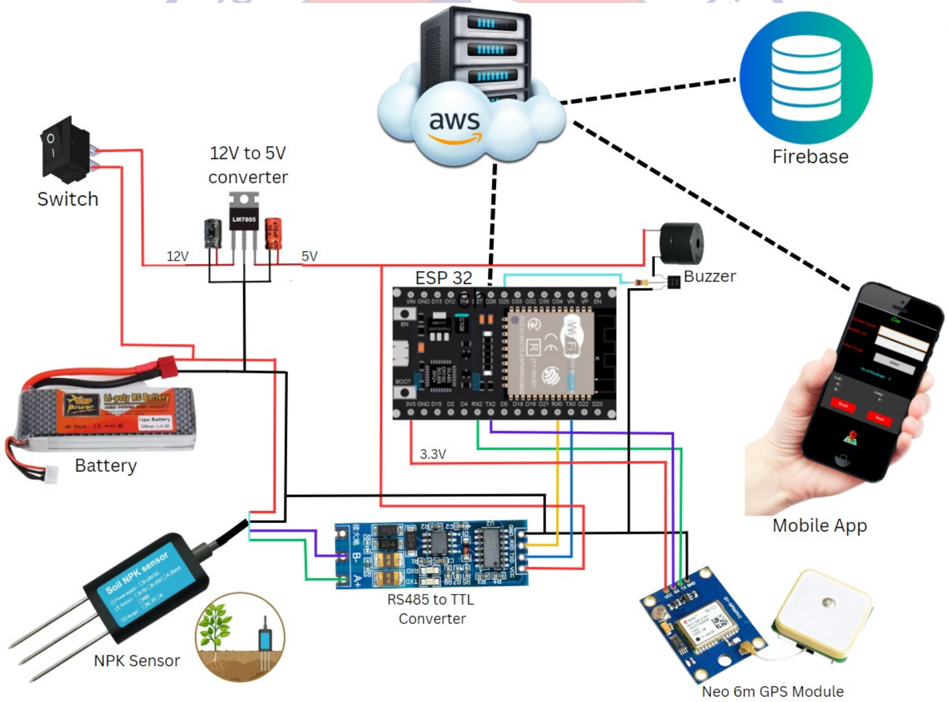


Figure 3.1: Design Architecture

The CCNRS consists of multiple hardware components which are connected to each other. During the design of CCNRS as shown in figure 3.1 , all the specifications of individual parts are taken into consideration to see whether the requirements are fulfilled and the objectives are achieved. Since the components are connected to each other, they must also be verified if they are compatible with each other. The interfacing type should be the same and voltage and current levels must be below the threshold.

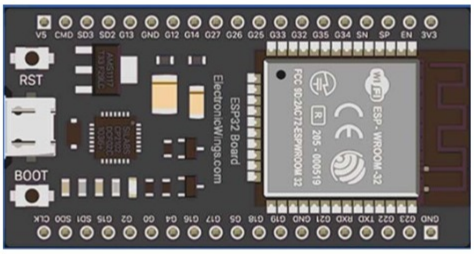
3.1.1 Soil NPK sensor

Driver Model	JXBS-3001-NPK-RS
Operating Voltage (VDC)	12-24
Working temperature (℃)	5-45

Figure 3.2: Soil NPK sensor and it's specifications

The Soil NPK Sensor is utilized to fetch the Nitrogen (N), Phosphorus (P), and Potassium (K) values from the soil. It provides an output signal in RS485 format. The measurement range spans from 0 to 1999 mg/kg.

3.1.2 ESP32 Wi-Fi and Bluetooth MCU



Driver Model	ESP32-WROOM-32D
Operating Voltage (VDC)	2.3 to 3.6
Working temperature (℃)	-40 to 125
Current rating	80mA

Figure 3.3: ESP32 Microcontroller and it's specifications

It is a series of low-cost, low-power systems on a-chip microcontroller with integrated Wi-Fi and dual-mode Bluetooth. The sensor data is sent to the Firebase database using ESP32. The GPS module is also attached to the controller for to provide the location details.

3.1.3 NEO-6M GPS Chip

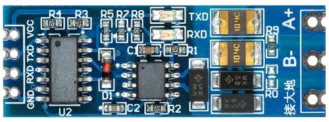
The NEO-6M GPS Chip is employed to determine the precise location of the test sample collected. Subsequently, this location information is utilized to display the position on the map within mobile application.

Driver Model	GY-GPS6MV2
Operating Voltage (VDC)	2.7 - 3.6
Working temperature (°C)	-40 to 85
Current rating	45mA

Figure 3.4: NEO-6M GPS Module and it's specifications

3.1.4 MAX485 TTL To RS485

This module facilitates the conversion of the TTL interface from the microcontroller to the RS485 module. The NPK Sensor's data is in RS485 format.



Dimension	6x3x2 cm^3
Operating Voltage (VDC)	5
Working temperature (°C)	-55 to 70

Figure 3.5: MAX485 TTL To RS485 and it's specifications

3.1.5 Li-poly RC Battery:

Capacity	5500mAh
Output Voltage (VDC)	11.1
weight	480g

Figure 3.6: Li-poly RC Battery and it's specifications

The Li-poly RC Battery serves as the power source for the entire system, including the controller board.

3.2 Pre analysis work for the design or Models used

- Requirement Gathering: Identify and gather the specific requirements of the project, including the functionalities of the real-time crop prediction and nutrient recommendation system, the data needed from NPK sensors, and the desired output for farmers.

- Data Collection: Determine the types of data required for the ML model, such as historical crop yield data, soil data, and NPK sensor data. Explore available datasets and sources for data collection.

- ML Model Selection: Evaluate different ML algorithms suitable for crop prediction and nutrient recommendation tasks, considering factors like accuracy, computational complexity, and interoperability.
- Design of Mobile Application: Plan the user interface and functionalities of the mobile application for farmers to interact with the system, including crop selection, sensor data visualization, and nutrient recommendations.
- Battery Specifications: The battery to be used in CCNRS should continuously provide power supply to the sensors, controller. The NPK sensor output needs to be converted to less than 5V to be compatible with the ESP32.

3.3 Design methodology

The Design encompasses four key phases, each contributing significantly to the system's functionality and effectiveness. These phases confine the integration of NPK sensors with ESP32 microcontroller for seamless data acquisition, the establishment of a secure and scalable cloud database to store sensor data, the deployment of machine learning models on the cloud platform for real-time predictions, and the development of an intuitive mobile application to provide farmers with accessible insights and recommendations.

3.3.1 Sensor Data Integration

The NPK sensors are integrated with the system to collect real-time data on Nitrogen (N), Phosphorus (P), and Potassium (K) levels in the soil. The ESP32 microcontroller is responsible for reading the sensor data, including the NPK values, through analog interfaces. Once the data is acquired, the ESP32 establishes a wireless communication link with the cloud database using its built-in Wi-Fi module. This enables seamless transmission of the collected NPK sensor data to the cloud server for further analysis and storage.

The collected NPK values are processed and analyzed using ML algorithms in the cloud to predict the most suitable crops for the specific soil conditions. The integration of NPK sensors with ESP32 and cloud database enables real-time monitoring of soil nutrient levels, providing valuable insights for precise nutrient recommendations and crop predictions to optimize agricultural productivity and sustainability.

3.3.2 Cloud Database Setup

In this phase of the project, a suitable cloud database is chosen to securely and efficiently store the sensor data. The selected cloud database should offer features like scalability, reliability, data encryption, and high availability to ensure the safe storage of sensor data. Once the cloud database is selected, it is set up with appropriate data structures and configurations to accommodate the incoming sensor data seamlessly. The database schema is designed to capture relevant sensor parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), timestamps, and associated metadata. The configuration also includes setting up data indexes and optimizing query performance for faster data retrieval. Data integrity measures, such as data validation rules and error handling mechanisms, are implemented to ensure the accuracy and consistency of the stored sensor data. Overall, the cloud database setup phase focuses on creating a robust and reliable data storage infrastructure that can handle the influx of real-time sensor data effectively.

3.3.3 Machine Learning Model Integration

For crop prediction and nutrient recommendation, a suitable ML model is chosen based on its performance and ability to handle the dataset [25]. The model is trained using historical crop yield data and relevant soil data, including NPK levels and other environmental factors. The training process involves feeding the model with labeled data, allowing it to learn the patterns and relationships between input features and crop outcomes. Once the model is trained, it is deployed on the cloud platform, allowing it to make real-time predictions based on the incoming sensor data from the NPK sensors. The cloud platform provides the computational resources and scalability needed to handle multiple sensor inputs simultaneously. When new sensor data is received, the deployed ML model processes the data, applies the learned patterns, and generates crop predictions and nutrient recommendations promptly. This real-time prediction capability enhances agricultural decision-making and enables farmers to optimize their crop management strategies for better yield and resource efficiency.

3.3.4 Mobile Application Development

In the Mobile Application Development phase, a user-friendly mobile app is designed and developed to provide farmers with a seamless interface to interact with the real-time crop prediction and nutrient recommendation system. It is designed by adding code blocks as represented in figure 3.7. The mobile app allows farmers to select the desired crop from a user-friendly dropdown menu, enabling them to easily specify their crop of interest. The app presents sensor data visualizations in an easily understandable and visually appealing manner, helping farmers monitor the NPK sensor readings and soil health parameters effectively.

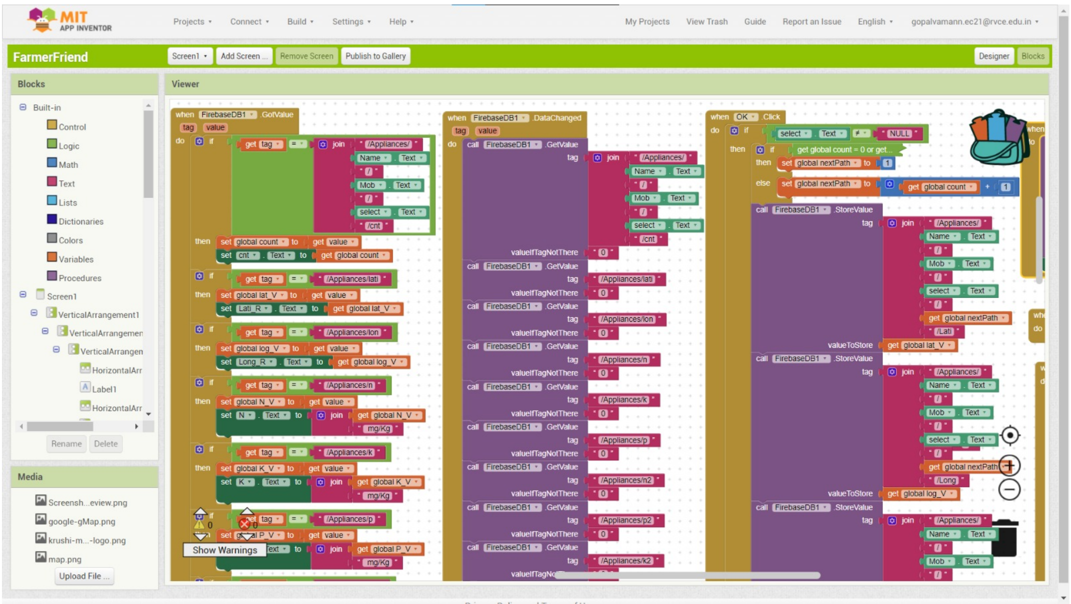


Figure 3.7: Mobile Application Development Environment

Based on the ML model's output, the mobile app generates precise nutrient recommendations tailored to the selected crop. These recommendations are displayed to the farmers, providing user with valuable insights into the additional nutrients required to enhance crop productivity and achieve maximum yield. The app ensures that the nutrient recommendations are clear and concise, making it easier for farmers to implement the suggested changes in their farming practices. Overall, the mobile application development phase focuses on delivering a user-friendly and intuitive interface that empowers farmers to make data-driven decisions for sustainable and productive agricultural practices.

3.3.5 Experimental Techniques

The NPK sensors undergo calibration to ensure accurate and reliable data readings before deployment in the field. Calibration involves comparing the sensor's output to known reference values and adjusting it accordingly. This step ensures precise measurements of Nitrogen, Phosphorus, and Potassium levels in the soil. ML models are trained using historical crop yield data, soil characteristics, and nutrient levels. The training process involves providing labeled data to the models and adjusting their parameters to minimize prediction errors. Various ML algorithms, such as Random Forest, Naive Bayes, or Support Vector Machines, are tested to build accurate prediction models for recommending suitable crops and nutrient requirements based on sensor data. The Naive Bayes (NB) algorithm is used as it has highest accuracy for predicting crop. Deploying the ML models on the cloud server for real-time data processing and analysis. Testing is conducted to evaluate the models' performance and accuracy. Test data, including sensor data from different locations and crop types, is fed into the cloud server, and the system's responses are analyzed to validate the accuracy of crop predictions and nutrient recommendations. This iterative testing process helps optimize the models and ensure the system's practical applicability in agricultural settings.

This chapter discussed the design methodology for the CCNRS. It outlines the integration of hardware components such as the GPS chip, NPK sensor, and ESP32 MCU. The cloud database setup is explained, along with the integration of machine learning models for real-time crop predictions and nutrient recommendations. The chapter also covered. the development of a user-friendly mobile application for farmers to interact with the system and receive personalized recommendations. Experimental techniques, including sensor calibration and testing, are outlined to validate the system's accuracy and performance.

Chapter 4

Implementation of Real-Time Crop Cultivation and Nutrient Recommendation System

CHAPTER 4

IMPLEMENTATION OF REAL-TIME CROP CULTIVATION AND NUTRIENT RECOMMENDATION SYSTEM

Focuses on the integration and utilization of hardware and software components in the real-time CCNRS. It combines NPK sensors and ESP32 microcontroller to collect and transmit soil nutrient data, while the NEO-6M GPS chip captures geographical locations. The cloud database, Firebase, securely stores real-time sensor data, and the AWS Elastic Compute Cloud (AWS EC2) server deploys the ML model for crop prediction. The mobile application **'E-Dharani'** created using MIT App Inventor, provides farmers with intuitive access to soil health data, crop predictions, and nutrient recommendations. The seamless collaboration of these elements empowers farmers to make data-driven decisions, optimize resources, and embrace sustainable farming practices.

4.1 Utilization of Hardware

The strategic utilization of hardware components that form the core of soil testing and transmitting sensed values to the cloud database. The instrumental roles of NPK sensors, ESP32 microcontroller, and the NEO-6M GPS chip collectively enable seamless data collection, wireless communication, and geospatial tagging, culminating in a sophisticated system that empowers farmers with real-time insights into soil health, nutrient levels, and precise crop recommendations.

4.1.1 NPK sensors

NPK sensors play a pivotal role in collecting essential soil data required for crop prediction and nutrient recommendation. The NPK sensors are deployed in the soil at the testing locations to measure the levels of Nitrogen (N), Phosphorus (P) and Potassium (K). These sensors are equipped with probes that penetrate the soil and measure the concentration of nutrient levels. The NPK sensors are interfaced with microcontroller (e.g., ESP32) that read the sensor values and convert them into digital data. The microcontroller then wirelessly transmit this data to the cloud server using the ESP32 Wi-Fi module.

Once the NPK sensor data reaches the cloud server, it undergoes further processing.

The cloud server hosts a machine-learning model that is trained on historical crop yield data, weather data, and soil data. The incoming NPK sensor data is fed into the ML model, which then predicts the suitable crop based on nutrient levels and environmental factors. Additionally, the ML model provides precise nutrient recommendations for the selected crop to achieve maximum yield. The utilization of NPK sensors in this project enables real-time monitoring of soil health and nutrient levels, allowing farmers to make informed decisions about crop selection and nutrient management. This data-driven approach enhances agricultural productivity and sustainability by optimizing resource usage and promoting precision farming practices.

4.1.2 ESP32

ESP32 microcontroller play a crucial role in collecting sensor data and enabling wireless communication between the NPK sensors and the cloud server. The ESP32 interfaces with the NPK sensor through analog or digital pins, depending on the sensor type. Once the sensor data is obtained, the ESP32 establishes a Wi-Fi connection using its built-in Wi-Fi module. This enables the microcontroller to transmit the real-time sensor data to the cloud server, where further processing and analysis take place.

The ESP32 also acts as a data aggregator, collecting sensor data from sensors deployed across different soil samples or fields. It efficiently handles data synchronization and error handling during the data transmission process. The microcontroller's low-power capabilities ensure minimal power consumption, making it suitable for prolonged usage in agricultural settings. Additionally, the ESP32 can be easily programmed using Arduino IDE, making it accessible to developers with varying levels of expertise. Overall, the utilization of ESP32 microcontroller enables seamless data acquisition, reliable communication, and cost-effective deployment in the real-time crop prediction and nutrient recommendation system.

4.1.3 NEO-6M GPS Chip

The NEO-6M GPS chip is utilized to capture the latitude and longitude of the testing soil sample location. The GPS chip is interfaced with the microcontroller (e.g., ESP32) to enable location tracking and geo-tagging of the sensor data. When the NPK sensors collect soil data, the microcontroller retrieves the GPS coordinates from the NEO-6M GPS chip, associating the specific soil data with its geographical location. This information is crucial for providing location-specific nutrient recommendations and crop predictions.

The GPS data obtained from the NEO-6M chip is then transmitted to the cloud server along with the sensor data. The cloud server processes this combined data to provide accurate nutrient recommendations and crop predictions that take into account both the soil characteristics and the geographical location. By leveraging the NEO-6M GPS chip's capabilities, the system ensures that the nutrient recommendations and crop predictions are tailored to the specific soil and environmental conditions of each testing site. This enhances the precision and effectiveness of the system, enabling farmers to make data-driven decisions and optimize crop management practices based on the unique characteristics of their fields.

4.2 Utilization of Software

The integration of crucial software tools like Firebase, AWS EC2, and MIT App Inventor, each with a specific role at different stages of the system's operation, a robust and expandable infrastructure is formed. This integration creates a powerful platform that equips farmers with real-time data insights, accurate predictions, and practical recommendations, thus promoting improved farming techniques and sustainable yields.

4.2.1 Firebase

Firebase database is utilized as the cloud database to store the real-time sensor data received from the NPK sensors. Firebase provides a scalable and secure cloud-based database solution that allows easy integration with the project's microcontroller and cloud servers. The microcontroller, equipped with Wi-Fi modules, transmit the sensor data to the Firebase database, where it is stored in real-time. Firebase's real-time database feature enables seamless data synchronization between the microcontroller and the cloud, ensuring that the latest sensor readings are accessible to the cloud server and the mobile application.

When the NPK sensors collect soil data, the microcontroller communicates with the Firebase database using the Firebase API to store the sensor data. The data is organized in a structured format, including the Farmer's name, mobile number, fetched NPK, location, and the timestamp of data collection as represented in figure 4.1. The processed values like the additional NPK, and predicted probabilities are stored. The real-time nature of Firebase ensures that the sensor data is instantly stored and can be accessed

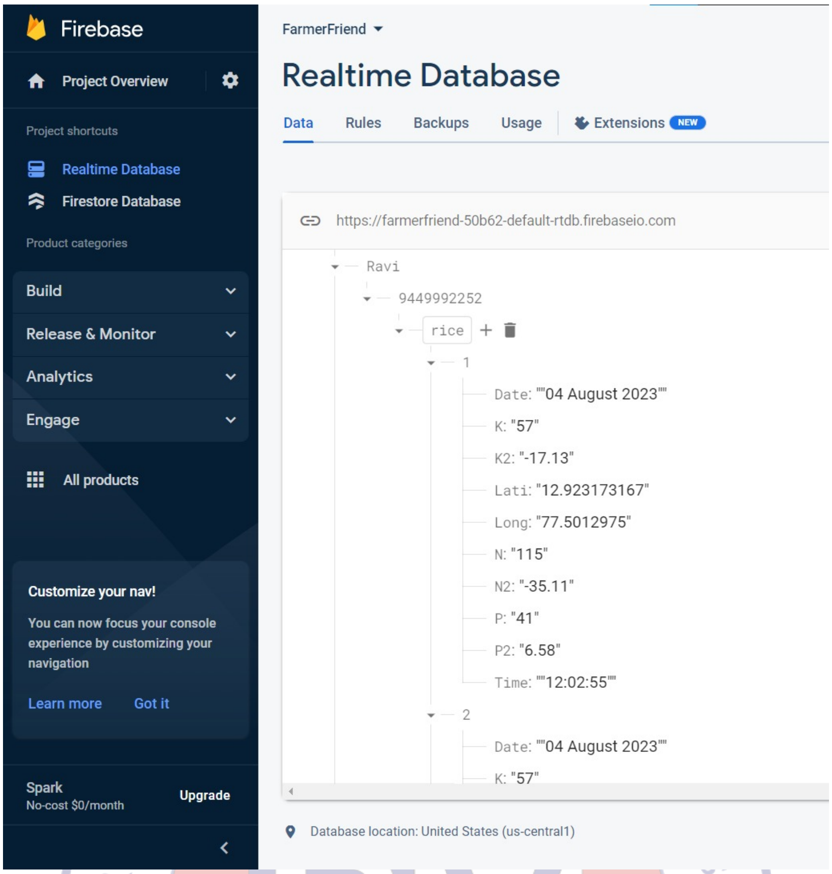


Figure 4.1: Cloud Database setup

securely from anywhere with an internet connection.

These outputs are then stored in a separate collection within the Firebase database. Each record in the output collection contains the predicted crop, the probabilities of different crops, and the recommended additional NPK values for the selected crop. By utilizing the Firebase database for both sensor data storage and processed output storage, the system ensures that all relevant information is available in real-time to the mobile application, enabling farmers to access and act upon the recommendations promptly. Additionally, the Firebase database's secure authentication features provide data privacy and access control, ensuring that only authorized users can interact with the stored information. Overall, the Firebase database plays a crucial role, by facilitating efficient data storage, retrieval, and management for the crop prediction and nutrient recommendation system, enhancing its usability and effectiveness for farmers.

4.2.2 AWS EC2

AWS EC2 server is utilized as the cloud computing infrastructure to host and deploy the ML model for real-time crop prediction and nutrient recommendation. The EC2 server offers scalable computing resources, enabling the system to handle a large number of incoming sensor data requests efficiently. The EC2 instance is configured with the necessary computational power and memory to run the machine-learning algorithms effectively. The trained ML model is deployed on the EC2 instance, making it accessible to receive real-time sensor data from the field. The EC2 server processes the incoming data from Firebase using the ML model to predict the most suitable crop based on the NPK sensor values. Additionally, the EC2 server calculates the precise amount of additional nutrients required for optimal crop growth and yield. The scalability of the EC2 instance ensures that the system can handle multiple sensor data streams simultaneously, enabling real-time predictions for numerous farming locations.

The AWS EC2 server cloud offers robust and scalable computing resources, allowing for the deployment and management of the ML model effectively. The seamless integration with the Firebase database ensures a smooth data flow, enabling the ML model to access the latest sensor data and provide timely and accurate crop predictions and nutrient recommendations. Once the ML model processes the sensor data, it generates the output, which is then sent back to the Firebase database for easy accessibility to the mobile application and other stakeholders. The utilization of the AWS EC2 server cloud not only ensures the availability and reliability of the ML model but also provides a cost-effective and scalable solution for handling the computational demands of real-time crop prediction and nutrient recommendation in agriculture.

4.2.3 MIT App Inventor

MIT App Inventor is utilized as the tool to develop the mobile application for the real-time crop prediction and nutrient recommendation system. MIT App Inventor is a user-friendly visual programming platform that allows for the creation of Android applications without the need for traditional coding. MIT App Inventor was used to design the mobile app's user interface and functionality. This allowed farmers to interact with the cloud server, granting them access to real-time data visualizations, crop predictions, and nutrient recommendations. The mobile application was integrated with the cloud server to retrieve sensor data, display crop suitability based on the ML model's output, and provide accurate nutrient recommendations to farmers. This simplified and intuitive development environment facilitated the rapid creation of the mobile app, making it accessible and easy to use for farmers.

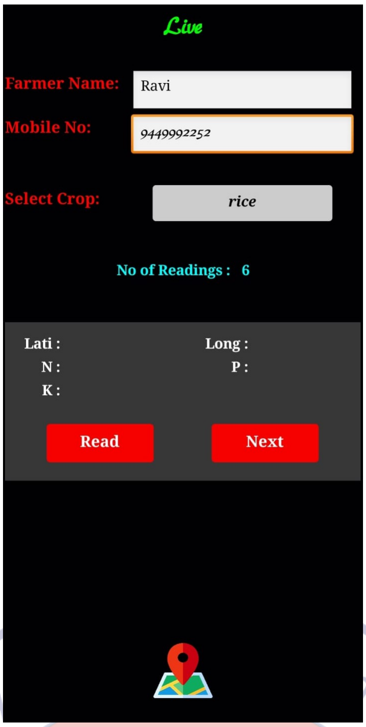


Figure 4.2: Front-end of the Application

The mobile app **'E-Dharani'** offers a range of features to empower farmers in optimizing their agricultural practices. It allows farmers to input their name and mobile number, enabling personalized interactions and data storage for future reference. The app seamlessly integrates real-time sensor data from NPK sensors, providing farmers with instant access to their soil nutrient levels. Based on this data, ML model offers crop suitability predictions, helping farmers make informed decisions on crop selection. The app also recommends precise nutrient requirements for maximum crop yield, minimizing resource wastage and promoting sustainable farming. The mobile app's user-friendly interface makes it easy for farmers to visualize their soil health on a map, displaying tested locations for better decision-making. With the convenience of portability, 'E-Dharani' empowers farmers to access critical information on the go, revolutionizing agricultural practices and driving the adoption of precision farming techniques for enhanced productivity and sustainability.

4.3 Integration of software and hardware

The integration of the project involves the seamless collaboration of various software and hardware components to create a comprehensive real-time crop prediction and nutrient recommendation system. The hardware components, including the NPK sensor and ESP32 microcontroller as shown in Figure 4.3, it plays a vital role in collecting and transmitting soil nutrient data to the cloud.

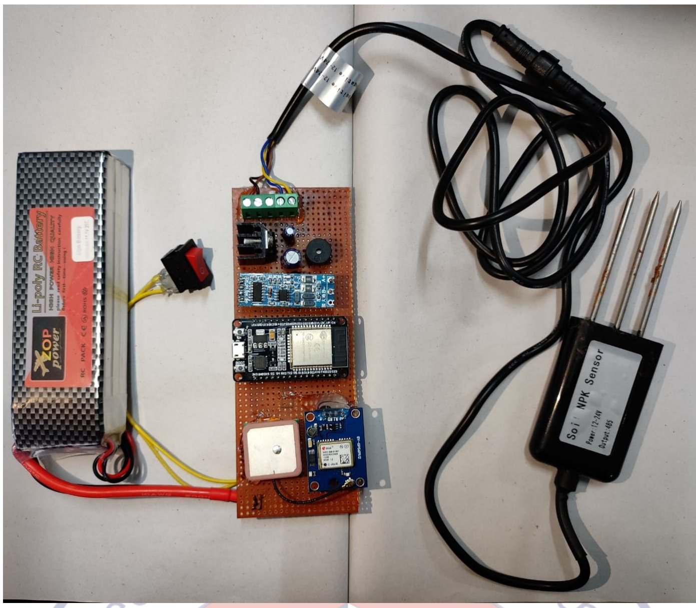


Figure 4.3: Hardware Integration

The NPK sensor measures the Nitrogen, Phosphorus, and Potassium levels in the soil, while the ESP32 microcontroller facilitates the communication between the sensor and the cloud server. The cloud server, deployed on AWS, receives and processes the sensor data using ML algorithms to predict crop suitability and nutrient requirements. This integration ensures that farmers have access to real-time soil health information and accurate crop recommendations on their mobile devices through the mobile application developed using MIT App Inventor.

The mobile application acts as a user-friendly interface, allowing farmers to interact with the cloud server and access the crop prediction and nutrient recommendation system. Through the app, farmers can input their crop preferences and receive instant feedback on the most suitable crops for their soil conditions. The app also provides precise nutrient recommendations, enabling farmers to optimize fertilizer application and ensure optimal crop growth. The mobile app communicates with the cloud server to retrieve and display sensor data, crop predictions, and nutrient recommendations in a visually appealing and easy-to-understand format. This integration of hardware and software components enables farmers to make informed decisions and implement precision farming techniques, ultimately leading to increased crop yield, resource efficiency, and sustainable agricultural practices. With the data-driven insights provided by the integrated system, farmers can enhance their productivity and profitability while promoting environmentally responsible farming practices.

The components of the CCNRS are successfully integrated to create a robust and efficient platform. The NPK sensor and ESP32 microcontroller work together to collect and transmit soil nutrient data to the cloud server. The cloud server, deployed on platforms like AWS, processes the sensor data using NB algorithm to predict crop suitability and nutrient requirements. The mobile application developed using MIT App Inventor acts as a user-friendly interface, enabling farmers to access real-time soil health information and receive accurate crop recommendations on their mobile devices. The seamless collaboration of hardware and software components ensures that farmers can make informed decisions and implement precision farming techniques, leading to increased crop yield, resource efficiency, and sustainable agricultural practices. The system's reliability and effectiveness ensure that farmers can optimize crop productivity and make data-driven decisions for better agricultural outcomes.

Chapter 5

Results & Discussions

CHAPTER 5

RESULTS & DISCUSSIONS

The comprehensive and insightful results are derived from the experimental phase. It elaborates on the tested performance of the CCNRS system, shedding light on its accuracy, real-time capabilities, customization options, and resource efficiency. The subsequent sections provide a thorough examination of the system's outputs when specific crops are chosen and present a comparative analysis of its performance against conventional methods, showcasing its potential to revolutionize agricultural practices.

5.1 Experimental Results

During the experimental phase, a series of rigorous tests were conducted to validate the operational efficiency of all hardware components and ensure their seamless intercommunication. Thorough examinations were carried out to affirm the robust integration of the NPK sensor with the ESP32 microcontroller, guaranteeing dependable data transmission to the cloud database. The performance evaluation of the ML model involved historical crop data and sensor inputs, with parameter adjustments made to enhance accuracy. Furthermore, extensive testing was executed on the mobile application developed through MIT App Inventor, confirming its user-friendly interface and efficient data retrieval from the cloud. The obtained experimental outcomes solidified the successful amalgamation of hardware and software constituents, thereby providing real-time soil nutrient information and crop recommendations to farmers, consequently amplifying agricultural productivity and sustainability.

Farmer is prompted to input his name and mobile number. Upon clicking the "Next" button as shown in 5.1, the system fetches real-time data from the cloud and displays the current values of NPK on the screen. After clicking on the "Next" button, the additional nutrients required for optimal crop growth are displayed. This output data will be stored in the cloud for future uses . The system also provides a comprehensive map showing the farmer's location, including all his previous test values, locations allowing for easy visualization and analysis of soil health trends over time. This user-friendly interface empowers farmers to make data-driven decisions, ensuring proper nutrient management and promoting sustainable agricultural practices. With instant access to vital information and visual representations of soil health, farmers can efficiently plan their farming

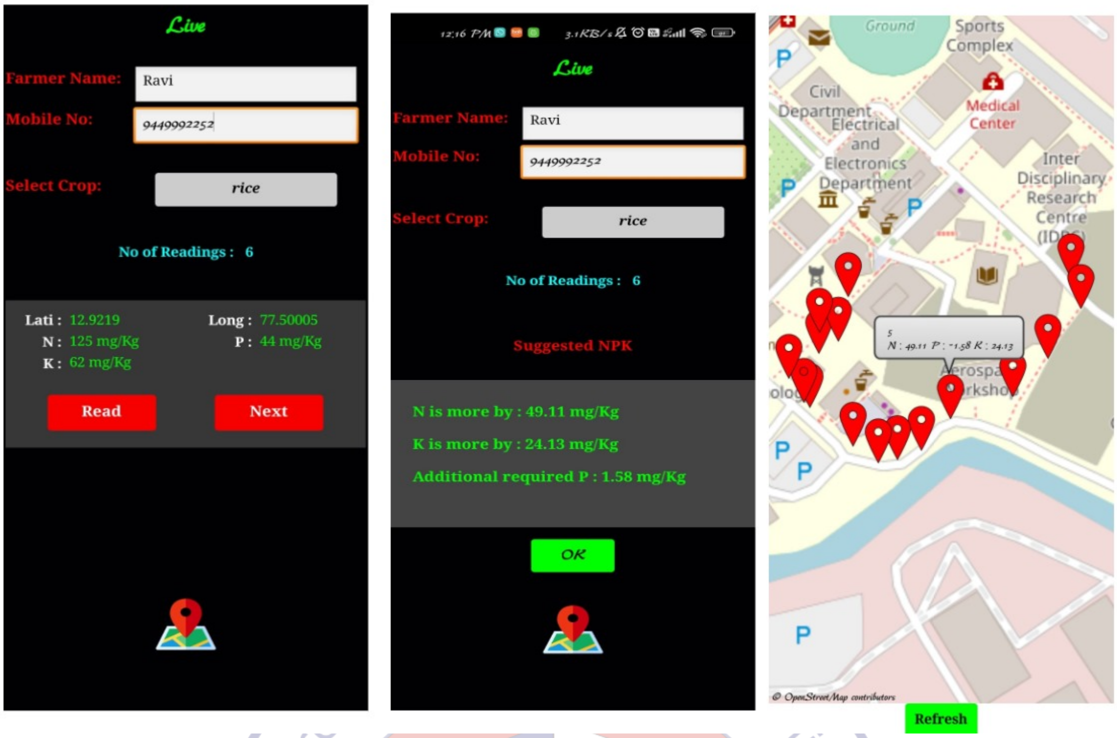


Figure 5.1: Image of Mobile application Interface

activities and enhance crop productivity while minimizing resource wastage.

5.1.1 Implementation Cases

The mobile application is embodied with two cases for the crop type. If the user wish not to select crop, then it is set to null, otherwise crop is selected from the dropdown.

1. NULL as crop:

   When user selected crop name as null, the system predicts first three possible crops that are best suit based on the soil characteristics.

Table 5.1: N, P, K Values and Suggested Crops (Probabilities)

N	P	K	Crop-1	Crop-2	Crop-3
110	45	40	Rice (70.22%)	Jute (28.89%)	Coffee (0.86%)
90	35	30	Coffee (99.39%)	Jute (0.35%)	Rice (0.15%)
115	41	57	Watermelon (54.91%)	Muskmelon (45.08%)	Banana (0.005%)
85	31	34	Coffee (86.07%)	Jute (7.283%)	Rice (6.641%)

The outcomes of the project are presented in the form of NPK values and the suggested crops with their corresponding probabilities. For instance, with NPK values of 110, 45, and 40, the predicted probabilities for crops are 70.22% for Rice, 28.89% for Jute, and 0.86% for Coffee. These outcomes offer valuable insights into the most suitable crops for specific soil compositions, assisting farmers in making informed decisions for optimal crop cultivation strategies

2. When user selects a particular crop:
   Based on the crop, the additional nutrients required and excessive available nutrients are displayed in the mobile application

Table 5.2: Additional NPK Suggested

Selected Crop	Sensed N	Sensed P	Sensed K	Additional N	Additional P	Additional K
Rice	95	34	48	-15	13	-8
Jute	100	35	36	-21	11	3
Watermelon	80	26	25	19	-9	25
Grapes	90	34	33	-66	98	167
Coconut	81	40	35	-59	-23	-4

Upon user's selection of the desired crop, the system presents the sensed NPK values derived from the soil samples, providing insights into the nutrient composition of the soil. Additionally, the system calculates and presents the required additional NPK values for optimal crop growth. For instance, in the case of Rice cultivation, the sensed NPK values are 95 for Nitrogen, 34 for Phosphorus, and 48 for Potassium, indicating the existing soil nutrient levels. The system further recommends adjustments of -15 units of Nitrogen, 13 units of Phosphorus, and -8 units of Potassium to achieve an ideal nutrient balance. The Negative values indicates the excessive availability of the nutrients. Similarly, for Jute cultivation, the sensed NPK values are 100, 35, and 36 respectively, with corresponding recommended adjustments of -21, 11, and 3 units. This pattern continues for other crops like Watermelon and Grapes, where sensed NPK values are provided, along with the necessary additional nutrient adjustments for optimal crop growth. This information equips farmers with actionable insights for nutrient management, enabling them to make informed decisions to enhance crop yield and sustainability.

5.2 Performance Comparison

The implemented CCNRS system, utilizing real-time sensor data and ML algorithms, underwent thorough testing to evaluate its performance. The ensuing performance assessment highlights the system's merits as follows:

1. Accuracy: The crop recommendation system, employing the Naive Bayes algorithm, achieved a noteworthy accuracy of 98.86%, outperforming conventional approaches.

```
from sklearn.naive_bayes import GaussianNB
target = df['label']
labels = df['label']
acc = []
model = []
from sklearn.model_selection import train_test_split
Xtrain, Xtest, Ytrain, Ytest = train_test_split(
    features,target,test_size = 0.2,random_state =2)
NaiveBayes = GaussianNB()
NaiveBayes.fit(Xtrain,Ytrain)
predicted_values = NaiveBayes.predict(Xtest)
x = metrics.accuracy_score(Ytest, predicted_values)
acc.append(x)
model.append('Naive Bayes')

print("Naive Bayes's Accuracy is: ", format(x*100, f".{3}f"), "%")
# print(classification_report(Ytest,predicted_values))
```

```
Naive Bayes's Accuracy is:  98.864 %
```

Figure 5.2: Accuracy of Naive Bayes Algorithm

Drawing insights from historical data and prevailing soil conditions, the ML model generated precise predictions on crop suitability, thereby enhancing crop selection and overall yield.

2. Real-time Recommendations: In contrast to time-consuming conventional practices involving laboratory analysis of soil samples, the system provided instant nutrient recommendations grounded in sensor data. This prompt feedback empowered farmers to swiftly adjust fertilization and optimize crop health, translating to enhanced productivity.

3. Customization: Farmers enjoyed the freedom to personalize crop recommendations according to their distinct requirements. By inputting desired crops or assessing predictions for multiple options, users could make well-tailored decisions aligned with their unique farming strategies.

4. Resource Efficiency: The ML model's accurate nutrient recommendations fostered resource optimization, minimizing unnecessary fertilizer usage and mitigating environmental impact. This facet endorsed sustainable agricultural practices while

ensuring cost-effectiveness.

Overall, CCNRS demonstrated superior performance compared to traditional methods, offering accurate, real-time, and customized recommendations to farmers. The integration of IoT sensors, ML algorithms, and cloud computing enabled the development of a powerful tool that empowers farmers to make data-driven decisions for optimal crop management and increased agricultural productivity.

Chapter 6

Conclusion and Future Scope

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

The CCNRS using ML and IoT technologies holds significant promise in revolutionizing modern agriculture.Leveraging the capabilities of NPK sensor, microcontroller, cloud databases, and ML algorithms, an innovative system has been developed to empower farmers with real-time soil health insights and crop recommendations. This enables the adoption of precision farming practices, optimizing resource utilization and improving crop productivity.

The integration of hardware components like NPK sensors and ESP32 microcontroller has led to the development of a portable and user-friendly solution, ideal for effortless deployment in agricultural fields. The data collected by the sensors is efficiently transmitted to the cloud server, where powerful ML algorithms process the information and generate accurate crop predictions and nutrient recommendations. The mobile application developed using MIT App Inventor serves as a convenient interface for farmers, allowing them to access vital information on smartphones and make informed decisions based on real-time soil health data.

The implementation of this system offers numerous benefits to farmers, including increased crop yield, reduced resource wastage, and enhanced sustainability in agriculture. By adopting precision farming techniques based on real-time soil health data, farmers can optimize the application of fertilizers, water, and other inputs, resulting in cost savings and environmental conservation. Furthermore, the ability to receive timely crop recommendations ensures that farmers can adapt their cultivation practices to changing soil conditions and weather patterns, mitigating risks and maximizing agricultural productivity. Overall, the project contributes to the advancement of smart agriculture and establishes a foundation for a more efficient and resilient farming ecosystem.

6.2 Future Scope

1. Enhanced Software and Hardware: Upgrading the NPK sensor with more advanced cameras and high-resolution sensors can improve the accuracy and quality of soil nutrient data. Additionally, incorporating multicore processors and dedicated GPUs can boost the system's processing power and efficiency, leading to faster and more

precise crop predictions. Upgraded motors and improved software can also be implemented to reduce latency and enhance overall system performance.

2. Disease Detection Using Image Analysis: Implementing an AI-based computer vision system for disease detection in crops can significantly enhance the system's capabilities. By analyzing images of the plants, the AI model can identify symptoms of diseases or pest infestations at an early stage. This feature would allow farmers to take timely preventive measures, such as targeted pesticide application or disease-resistant crop selection, reducing crop losses and improving overall yield. Early disease detection can also support sustainable agricultural practices by minimizing the use of chemicals and ensuring better resource management. The integration of image-based disease detection would be a valuable addition to the real-time crop prediction and nutrient recommendation system, contributing to more efficient and healthy crop cultivation.

3. Integration of Advanced Sensors: The system can be extended by incorporating additional electronic or chemical sensors, such as chemical sensors for detecting specific nutrient levels, radioactive sensors for identifying radioactive contaminants, and RF spectrum analyzers for detecting any wireless signals. This integration will expand the system's functionalities and enable more comprehensive soil analysis.

4. Autonomous Capabilities: Providing the system with autonomous capabilities would enable it to navigate and collect data without constant human intervention. Autonomous navigation using computer vision or electronic sensors can help the system avoid obstacles and accurately trace paths, making data collection more efficient. Utilizing a comprehensive database containing maps of various soil conditions can further enhance autonomous operation, streamlining the process of crop prediction and nutrient recommendation.

5. Spectroscopic Soil Analysis based on Location: By incorporating spectroscopic soil analysis in conjunction with the latitude and longitude of the test locations, the system can provide farmers with valuable insights into soil nutrient variations across different areas of their land. Spectroscopic analysis involves analyzing soil samples using infrared or near-infrared spectroscopy to determine nutrient levels, organic matter content, and other soil properties. With this feature, farmers can create

nutrient maps of their fields, identifying nutrient-rich and nutrient-deficient zones. By understanding spatial variations in soil nutrients, farmers can implement site-specific nutrient management strategies, applying fertilizers and other inputs precisely where needed. This targeted approach not only optimizes nutrient utilization but also minimizes environmental impacts and reduces costs. The integration of spectroscopic soil analysis based on location would enable farmers to make data-driven decisions and implement precision agriculture practices, ultimately leading to improved crop health and higher yields.

Overall, these potential enhancements can elevate the real-time crop prediction and nutrient recommendation system to new heights, enabling precision agriculture practices, maximizing crop productivity, and promoting sustainable farming techniques. With continuous advancements in technology and data analytics, the system's future holds great promise in revolutionizing the agricultural sector and empowering farmers with cutting-edge tools for improved decision-making and crop management.

6.3 Learning Outcomes

1. Develops expertise in integrating sensor data from NPK soil sensors, involves understanding the collection, processing, and transmission of real-time sensor data to the cloud for further analysis.

2. Familiarity with various ML algorithms used for crop prediction and nutrient recommendation, acquire practical experience in training and deploying ML models to make accurate predictions based on sensor data.

3. Provides knowledge of cloud computing principles and database management for efficient storage and retrieval of sensor data and ML model predictions, explores the utilization of cloud platforms for scalable and reliable data processing.

4. Expertise in mobile app development using MIT App Inventor. It includes creating user-friendly interfaces, implementing features like viewing soil nutrient levels and receiving crop recommendations, and integrating the app with cloud databases for real-time data access.

5. Gains an understanding of precision farming techniques that leverage technology and data-driven approaches for optimizing crop yield and resource utilization. It explores the application of these techniques for sustainable and efficient agricultural practices.

6. Enhances practical problem-solving skills by addressing real-world challenges in agriculture. It involves analyzing data, identifying patterns, and deriving meaningful insights to make informed decisions for crop management and nutrient recommendation.

7. Fosters a collaborative environment where team members work together to design, implement, and test the system. It emphasizes the importance of effective communication and teamwork in achieving project goals.

8. Provides hands-on experience in integrating hardware components, such as NPK sensors and ESP 32, into the system. It explores the process of interfacing hardware with software to create a functional and reliable agricultural monitoring system.

Appendix A

Code

APPENDIX A

CODE

A.1 First Appendix

Python is used as the programming language for server.

```
import firebase_admin
from firebase_admin import credentials,db
import pandas as pd
import numpy as np
import time
from sklearn.naive_bayes import GaussianNB
from sklearn import metrics
from sklearn import tree
import warnings
warnings.filterwarnings('ignore')

if not firebase_admin._apps:
# Initialize Firebase app
cred = credentials.Certificate("/root/project/FarmerFriend.json")
firebase_admin.initialize_app(cred,
{'databaseURL':
'https://farmerfriend-50b62-default-rtdb.firebaseio.com/'})
ref= db.reference("/")
data=ref.get()
#PATH of the dataset file
PATH = '/root/project/Crop_recommendation.csv'
df = pd.read_csv(PATH)
precision = 3

if data['Appliances']['RunML'] == "1":
db.reference("/Appliances").update({"/RunML" :0})
```

```
#fetching the data from the firebase
crop_name = data['Appliances']['label']
crop_name = crop_name[1:-1]
user_N = int(data['Appliances']['n'])
user_P = int(data['Appliances']['p'])
user_K = int(data['Appliances']['k'])
if crop_name== "NULL" :
# Extract features and target
features = df[['N', 'P', 'K']]
target = df['label']
# Train a Naive Bayes classifier
NB = GaussianNB()
NB.fit(features, target)
# User input
user_input = [[user_N, user_P, user_K]]

# Make predictions on the user input
predicted_probabilities = NB.predict_proba(user_input)[0]
predicted_classes = NB.classes_

# Sort the predicted probabilities
sorted_indices = np.argsort(predicted_probabilities)[::-1]
index = sorted_indices[0]
class_label = predicted_classes[index]
probability = format(predicted_probabilities[index]*100,
                                        f".{precision}f")+"%"
db.reference("/Appliances").update({"prob1": class_label})
db.reference("/Appliances").update({"prob1v": probability})
index = sorted_indices[1]
class_label = predicted_classes[index]
probability = format(predicted_probabilities[index]*100,
                                        f".{precision}f")+"%"
db.reference("/Appliances").update({"prob2": class_label})
```

```
db.reference("/Appliances").update({"prob2v": probability})
index = sorted_indices[2]
class_label = predicted_classes[index]
probability = format(predicted_probabilities[index]*100,
                                f".{precision}f")+"%"
db.reference("/Appliances").update({"prob3": class_label})
db.reference("/Appliances").update({"prob3v": probability})
#delay
time.sleep(1)
db.reference("/Appliances").update({"/Done" : 1})


else:
# Get the rows corresponding to the crop name
crop_data = df[df['label'] == crop_name][['N', 'P', 'K']]
# Calculate the mean NPK values for the crop
mean_N = crop_data['N'].mean()
mean_P = crop_data['P'].mean()
mean_K = crop_data['K'].mean()
# Calculate the difference between user input and mean values
diff_N =format(mean_N- user_N, f".{precision}f")
diff_P = format(mean_P- user_P, f".{precision}f")
diff_K = format(mean_K- user_K, f".{precision}f")
#sending results to the database
db.reference("/Appliances").update({"/n2" : diff_N})
db.reference("/Appliances").update({"/p2" : diff_P})
db.reference("/Appliances").update({"/k2" : diff_K})
time.sleep(1)
db.reference("/Appliances").update({"/Done" : 1})
```

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