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NOMENCLATURE

ABBREVIATIONS AND ACRONYMS

- AI - Artificial Intelligence
- ML - Machine Learning
- RL - Reinforcement Learning
- NPK – Nitrogen, Phosphorus, Potassium
- API - Application Programming Interface
- MERN - MongoDB, Express.js, React, Node.js
- JS - JavaScript
- HTML - HyperText Markup Language
- CSS - Cascading Style Sheets
- REST - Representational State Transfer
- CRUD - Create, Read, Update, Delete
- IDE - Integrated Development Environment
- UI - User Interface
- UX - User Experience
- DB - Database
- OOP - Object-Oriented Programming
- CI/CD - Continuous Integration/Continuous Deployment
- HTML5 - HyperText Markup Language version 5
- CSS3 - Cascading Style Sheets version 3
- HTTP - HyperText Transfer Protocol
- DNS - Domain Name System
- GPU - Graphics Processing Unit
- IoT - Internet of Things
- SDK - Software Development Kit
- SQA - Software Quality Assurance

CHAPTER 1
INTRODUCTION

1.1 PROBLEM STATEMENT

Agriculture faces significant challenges in meeting the demands of a rapidly growing global population while managing diminishing resources, especially freshwater. With the global population projected to reach 9.7 billion by 2050, the demand for food is expected to rise significantly. Agriculture, as a primary source of food production, already consumes about 85% of the world's freshwater resources. This extensive consumption of water, coupled with inefficient traditional irrigation practices, has led to unsustainable agricultural practices and environmental degradation. The pressure on water resources is particularly acute in regions prone to water scarcity, where droughts and unpredictable weather patterns exacerbate the challenge.

Traditional irrigation methods, such as flood and furrow irrigation, are often inefficient, leading to a substantial amount of water wastage due to evaporation, runoff, and poor soil absorption. This results in over-irrigation or under-irrigation, both of which negatively affect crop yields and lead to unsustainable water consumption. In many regions, farmers also lack the necessary tools and real-time information to make informed decisions about irrigation schedules and water distribution, leading to mismanagement of water resources.

In addition to water wastage, improper crop selection and soil management further exacerbate the problem. Farmers often do not have access to accurate data on soil health, including nutrient composition and pH levels, leading to the selection of unsuitable crops for their soil conditions. This mismatch between crop requirements and soil characteristics not only reduces crop yields but also depletes soil nutrients, further diminishing agricultural productivity in the long term.

1.2 OBJECTIVES

The Smart Farming System project is designed to address the inefficiencies in agricultural practices, particularly concerning water management and crop selection. To achieve this, the project sets several initial goals that are critical to its development and success:

1.2.1 Develop A Comprehensive System Architecture

The first goal is to create a robust system architecture that integrates IoT sensors, edge devices, cloud computing, and AI-driven algorithms. This architecture will enable seamless data collection, transmission, and processing, providing real-time insights into soil health, moisture levels, temperature, and nutrient content..

1.2.2 Deploy IoT Sensors In The Agricultural Field

Installing and configuring sensors such as NPK, pH, temperature, and soil moisture sensors is essential for collecting the relevant environmental data. These sensors will be deployed in various areas of the agricultural field to ensure accurate and representative data collection.

1.2.3 Ensure Seamless Data Flow And Processing

The next goal is to ensure that data flows smoothly from sensors to edge devices and cloud storage for further processing. This includes establishing wireless networks that allow continuous data transmission from the field to the backend systems.

1.3 Expected Outcomes

1.3.1 **Soil Health Recommendation:** The model essentially calculates deviations of the readings obtained in real time from the data set to determine the health of the soil. To make the model more detailed, it shows enumerated nutrient levels N, P, and K and the soil's pH and reveals existing deficits and unevenness in resources.

1.3.2 **Crop Suitability Recommendation:** Based on the level of soil health, the model decides which modern crops can be suitably grown in a particular set of soil conditions. It compares the current nutrient and pH to the needs of the crops and suggests the best that would suit a particular farming

1.3.3 **Fertilizer Recommendations:** Therefore, depending on the nitrogen, phosphorus, and potassium levels, the model recommends the right fertilizers to improve the nutrients of the soil. These fertilizer recommendations are given based on the nutrient inadequacies that have been found in the soil.

1.3.4 **Water Require Prediction:** The proposed system combines the information from the moisture sensor with the temperature and humidity values obtained from the Google Maps API in real time. This API gives details on the current humid and precipitation conditions in a particular region such as Temperature, pressure, humidity, precipitation, dew point, wind chill, and heat index among others. The features include the current relative humidity in the atmosphere, the amount of moisture in the ground, and the expected weather forecast. If the drying of the soil has occurred and rain is out of the question then the system suggests to the farmer that he water the field. On the other hand, if humidity is high, or if rain is expected, the system recommends not to water the crops as it is likely to flood. They wanted to find out how farmers could effectively and efficiently use water in growing crops while at the same time, soil moisture was well conserved

CHAPTER 2

REVIEW OF LITERATURE

2.1 OVERVIEW OF EXITING KNOWLEDGE MANAGEMENT SYSTEM

The integration of advanced technologies such as the Internet of Things (IoT) and Machine Learning (ML) in agriculture has given rise to innovative solutions known as smart farming or precision agriculture. This literature review explores various studies and findings related to the development, implementation, and impact of smart farming systems on agricultural productivity, resource efficiency, and sustainability. Registration of optical and IR images for the automated plant water stress quantification is an essential prerequisite on the path to design automatic irrigation management systems, where plant water data is acquired thermographically. The work done by [4] introduces an efficient image registration approach that does not require any intervention from a user since it uses Pearson's cross-correlations to registration optical and IR images. The main problems such as translation, rotation, and small scale changes are managed by this computationally efficient technique and provides a non-interventional means of collecting the plant water stress data that can be directly used in an automated irrigation system.

A description of a system that utilizes soil moisture and temperature nodes mounted on a wireless sensor network to regulate irrigation depending on some set values are proposed by Joaquín Gutiérrez in his paper "Automated Irrigation System Using a Wireless Sensor Network and GPRS Module" [3]. This innovation vested after 136 days of field trials where it demonstrated 90 per cent water conservation efficiency than conventional means, making it appropriate for the areas that are spatially isolated and policy water scarce.

The idea presented in the paper of Amarendra Goap, "An IoT-based Smart Irrigation Management System Using Machine Learning and Open Source Technologies" [2] is designed to solve the global water shortage problem through the application of IoT-based data on soil moisture and climate to the optimization of irrigation practices. A low power sensor node and a machine learning algorithm to estimate the irrigation requirements and/or weather conditions in order, therefore, improve the usage of water in the production of crops.

In the paper "Internet of Underground Things in Precision Agriculture"[6] Vuran examines the use of concealed sensors and communication related objects for monitoring soil in real time. The Internet of Underground Things approach presented in the work improves interaction between growers and agronomists to create effective, economically, and ecologically sound farming practices. An understanding of wireless underground communication provides benefits towards increasing crop yields and resource utilisation.

In the paper titled ''An Irrigation Supporting System for Water Use Efficiency Improvement in Precision Agriculture" [1], the author, A. Bonfante also singles out DSS a as well as IAS as means to enhance water use efficiency in the discussed perspective. The system combines in-situ sensors (W-Tens), remote sensing (IRRISAT®), and physiologically-based computer simulation (W-Mod) to properly control irrigation. Measurements made during field trials asserted that the application of these tools can enhance the water use efficiency by as much as fifty percent, whereas, IRRISAT® worked at the tract without using the soil spatial data.

Finally, in the present topic "Arduino Based Smart Irrigation Using Water Flow Sensor, Soil Moisture Sensor, Temperature Sensor & ESP8266 WiFi Module" by Pushkar Singh [5], the author proposed a low-cost smart irrigation system based on Arduino. Water flows, temperature, and soil moisture sensors are used to help users to monitor the irrigation process remotely over the internet connection located in the system. Lab tests then proved the prototype workable and can be extendible to other farming communities to ensure the crops grow the ideal conditions.

2.2 GAPS IN CURRENT SOLUTIONS

Despite significant advancements in precision agriculture, there are still several gaps in current solutions that prevent them from fully addressing the challenges faced by modern agriculture, particularly in the areas of water management, crop selection, and sustainability. These gaps highlight the need for more integrated, intelligent, and scalable approaches to farming practices. The Smart Farming System seeks to address these shortcomings by developing a comprehensive solution that leverages IoT, AI, and real-time data analytics. Below are some of the key gaps identified in existing solutions:

2.2.1 Limited Scope of Precision Irrigation Systems

Many existing precision irrigation systems focus solely on monitoring soil moisture levels to automate water distribution. While these systems help reduce water wastage, they often lack a comprehensive approach that considers multiple environmental factors such as temperature, humidity, and soil composition. These systems may also fail to dynamically adjust to varying crop requirements, weather changes, and soil characteristics, which can lead to suboptimal water usage and crop health.

2.2.2 Lack of Integration With Crop Selection

Most current solutions focus on optimizing water usage without addressing the equally important issue of crop selection based on soil conditions. Farmers often lack the tools to determine which crops are best suited for their specific soil characteristics, resulting in suboptimal yields and wasted resources. Crop selection is critical, as different crops have varying water, nutrient, and soil pH requirements, and growing an unsuitable crop can lead to poor outcomes despite efficient irrigation.

2.2.3 Poor Data Connectivity And Accessibility

One of the major challenges in deploying precision agriculture solutions is the lack of reliable connectivity, particularly in rural or remote farming areas where high-speed internet access is limited. Many current solutions rely heavily on continuous cloud connectivity for data processing and storage, which may not always be feasible. This limitation can result in delayed or lost data, making real-time decision-making difficult and reducing the effectiveness of these systems.

CHAPTER 3

PROBLEM STATEMENT AND PROPOSED SOLUTION

3.1 PROBLEM STATEMENT

The increasing scarcity of freshwater resources, combined with the growing global demand for food, presents a significant challenge for modern agriculture. Traditional irrigation systems, which are often based on fixed schedules, fail to account for real- time environmental factors such as soil moisture, temperature, and weather conditions. As a result, they frequently lead to over-irrigation or under-irrigation, causing water wastage and suboptimal crop growth. With agriculture consuming 85% of the world's freshwater, there is a pressing need for more efficient and sustainable water management solutions. The lack of precision in current irrigation methods has broader implications. As the global population is expected to reach 9.7 billion by 2050, the demand for food will surge, increasing the pressure on farmers to produce more with limited water resources. Additionally, climate change has made weather patterns less predictable, exacerbating the difficulty of ensuring crops receive adequate water. Farmers, particularly those managing large areas, often struggle to monitor soil and crop conditions manually, leading to inefficient water use and lower productivity.

A Smart Farming System that leverages IoT (Internet of Things) and AI (Artificial Intelligence) technologies can address these challenges. IoT sensors can provide real-time data on soil moisture, temperature, and humidity, allowing for precise monitoring of field conditions. AI algorithms can analyze this data to predict irrigation needs, ensuring that crops receive the right amount of water at the right time. This data-driven approach eliminates guesswork, reducing water wastage and enhancing crop yields. However, implementing such a system comes with its own set of challenges. Accurate and reliable data collection from various sensors, data management, and seamless integration of IoT with AI models are critical for success. The system must also support real-time monitoring and provide actionable insights through an easy-to-use interface. In addition, the solution must be energy-efficient, scalable for different farm sizes, and affordable, particularly for smallholder farmers in developing regions.

In conclusion, the development of a Smart Farming System offers a promising solution to the challenges of water management in agriculture. By optimizing irrigation schedules and improving water efficiency, such a system can not only boost agricultural productivity but also promote sustainability. The use of advanced technologies like IoT and AI in farming will play a crucial role in meeting the world's growing food demands while conserving precious water resources.

3.2 PROPOSED SOLUTION

The proposed solution for the Smart Farming System focuses on leveraging the power of IoT and AI to address critical challenges in modern agriculture, particularly water management and crop health monitoring. By deploying IoT sensors in the field, the system collects real-time data on soil moisture, temperature, humidity, and other environmental factors. This data is then processed using advanced AI algorithms that predict optimal irrigation schedules based on real-time conditions, weather forecasts, and crop requirements. The integration of these technologies will ensure efficient water usage, reduce wastage, and enhance crop yields, ultimately promoting sustainable agricultural practices.

3.2.1 IoT Sensors for Real-Time Monitoring: The system will deploy a variety of IoT sensors, such as NPK (nitrogen, phosphorus, potassium), soil moisture, pH, and temperature sensors, across the agricultural field. These sensors will provide real-time data on the environmental and soil conditions, offering precise information to farmers on the health and requirements of their crops.

3.2.2 Cloud-Based Data Management and Storage: Data from the IoT sensors will be transmitted wirelessly to a centralized cloud platform. This cloud storage will securely manage and organize the vast amounts of data generated by the sensors. The cloud- based infrastructure will ensure that data is readily available, accessible, and safe from any loss, enabling remote monitoring from anywhere.

3.2.3 Dynamic and Automated Irrigation Control: Based on the AI's predictive analysis, the system will dynamically adjust irrigation schedules in real-time. This automation will ensure that crops are irrigated precisely when needed, reducing the human effort required for manual irrigation while optimizing water delivery, preventing both over- and under-irrigation.

3.2.4 User-Friendly Interface for Farmers: A dashboard will be designed to display critical data such as soil health, weather conditions, crop moisture needs, and irrigation recommendations. The interface will be simple and accessible, allowing farmers with minimal technical expertise to interact with the system and make decisions based on data insights. Reports on soil health and weather-based crop predictions will further aid decision-making.

3.2.5 Scalability, Cost-Effectiveness, and Flexibility: The solution is designed to be scalable, allowing it to be implemented on both small farms and large agricultural operations. The hardware components, such as sensors and microcontrollers, will be selected for cost-effectiveness, ensuring that the system remains affordable for farmers in various regions, especially those in developing areas. The system’s modular design will allow for future upgrades and adaptations as technology evolves.

3.3 BENEFICIARY COMMUNITY

The Smart Farming System aims to positively impact various beneficiary groups, starting with farmers who will experience enhanced crop yields and reduced water costs through optimized irrigation. Rural communities will benefit from improved food security and economic stability as agricultural outputs increase. Agricultural cooperatives can leverage shared resources to strengthen their market position, while environmental stakeholders will appreciate the system's focus on sustainable practices that conserve water and reduce waste. Finally, consumers will enjoy fresher, higher- quality produce, contributing to a more resilient food supply chain. Together, these communities will promote sustainability and innovation in agriculture.

3.3.1 Farmers: Smallholder and large-scale farmers will experience enhanced productivity and efficiency through optimized irrigation practices. This will lead to reduced water costs and increased crop yields, directly impacting their income and livelihoods.

3.3.2 Rural Communities: The implementation of the Smart Farming System will bolster food security in rural areas, leading to improved local economies. Increased agricultural output will support the community's self-sufficiency and reduce dependency on external food sources.

3.3.3 Researchers and Innovators: Academics and tech developers involved in agricultural technology research will benefit from data generated by the system. The insights gathered can inform future innovations and advancements in precision farming.

3.3.4 Agricultural Cooperatives: Groups of farmers can collaborate more effectively using the system, sharing insights and resources. This collective approach will enhance their bargaining power and foster a sense of community among cooperative members.

3.3.5 Consumers: Ultimately, consumers will gain access to fresher, higher-quality produce as a result of improved farming practices. The focus on sustainability will also ensure healthier food options and a more resilient food supply chain.

3.3.6 Environmental Stakeholders: The system will promote sustainable agricultural practices by conserving water and reducing resource wastage. Environmental organizations and advocates will benefit from the positive impact on natural resources, contributing to broader sustainability goals.

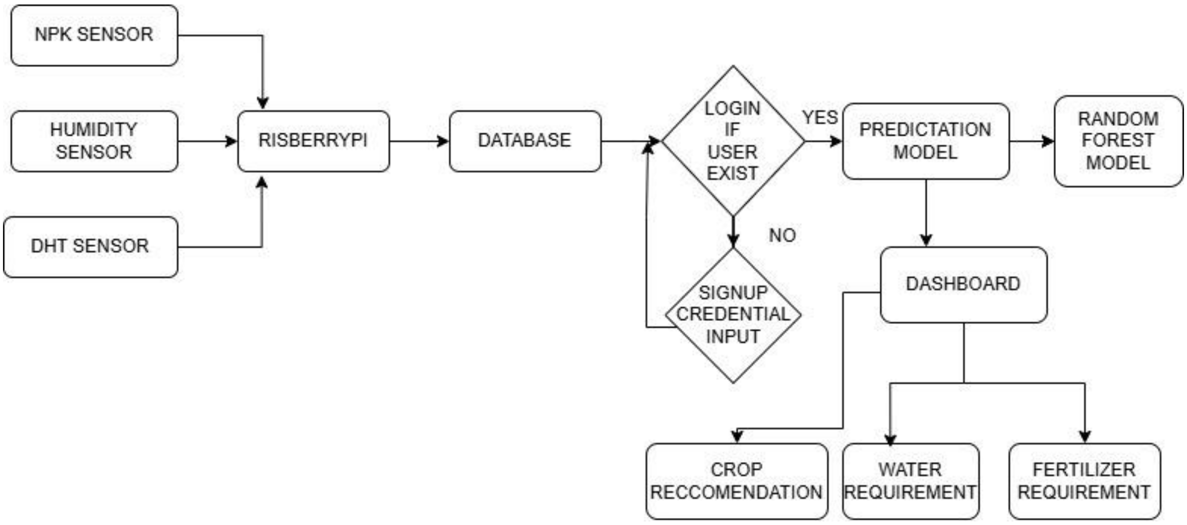
CHAPTER 4

SYSTEM DESIGN AND ARCHITECTURE

4.1 SYSTEM OVERVIEW

Smart Farming System comprises the following key subsystems and components:

4.1.1 Data Flow Diagram



Here is a more detailed, pointwise breakdown of your data flow diagram description:

4.1.1.1 Data Collection:

The system starts by collecting real-time data using various sensors placed in the soil. These sensors are: NPK Sensor: Measures the levels of nitrogen (N), phosphorus (P), and potassium (K) in the soil. Humidity Sensor: Measures the moisture levels in the air surrounding the soil. DHT Sensor: Measures temperature and humidity directly from the environment.

4.1.1.2 Microcontroller (Raspberry Pi Pico W):

To control the entire system, a Raspberry Pi Pico W microcontroller is used. The programming language for the microcontroller is MicroPython. The microcontroller collects the data from all sensors and passes it to the backend for further processing.

4.1.1.3 Data Storage (MySQL Database):

All data collected from the sensors is stored in a MySQL database.

This ensures that the data is structured, retrievable, and accessible for future predictions and recommendations.

4.1.1.4 User Interaction (Frontend Web Interface):

The user interacts with the system via a web-based frontend, which is created using:

HTML: For structuring the web pages.

CSS: For styling and layout of the web pages.

JavaScript (JS): For adding dynamic behavior and interactions.

The homepage contains a login screen where the user enters their credentials.

Once logged in, the user is directed to the dashboard that provides:

Information about three recommendation systems.

A general data system showing real-time sensor data.

4.1.1.5 Main Functional Tabs:

After logging in, the user can navigate to four main tabs, each providing different functionalities:

I. Overall Dashboard: Displays a summary of all collected data and system recommendations.

II. Predict Crop: Provides crop prediction based on soil conditions and other environmental factors.

III. Water Requirement: Recommends optimal water requirements based on the current moisture levels and weather conditions.

IV. Fertilizer Requirement: Suggests fertilizer needs based on the NPK sensor data.

4.1.1.6 Prediction Models:

The system's prediction models are powered by Random Forest algorithms.

These algorithms analyze the collected sensor data to make accurate predictions.

The models are written in Python and utilize the Django framework for backend functionality.

4.1.1.7 Recommendation System:

The recommendation system works by comparing real-time sensor data with standardized datasets already stored in the system.

Based on this comparison, the system provides tailored recommendations for crop selection, water, and fertilizer usage.

4.1.1.8 Outputs to the User:

After selecting their requirements from the tabs, the user receives:

Predictions: Outputs related to crop choice, water needs, or fertilizer requirements.

Dashboard View: A visual representation of sensor data and system recommendations, all displayed on the user interface.

4.2 MACHINE LEARNING MODEL

Random Forest is the type of ensemble learning that is majorly used in the classification and numerical prediction fields. It can then grow one or multiple decision trees which produces a more accurate forecast. Random Forest can be integrated with the scope of your Smart Farming System to forecast a range of scenarios such as best crops/selection, watering regime, or yield estimation employing input parameters like soil moisture, pH temperature, and total nutrient content (NPK).

4.2.1 Working of Random Forest

A Random Forest is built from multiple decision trees where each tree is trained from sample data of this original data in a random manner. The last forecast is obtained by applying the voting method by choosing the class with the highest frequency in the case of classification, or by averaging the predicted value in the group of generated decision trees for regression problems.

The core steps for building a random forest are:

4.2.1.1 Random Subset Selection (Bagging): Regardless of the underlying dataset, for each tree a number of data points are randomly selected from the initial set with replacement. That is why this method is called bootstrapping and enables us to reduce the case of overfitting.

4.2.1.2 Feature Randomness: When performing the splits in a decision tree, a criterion is not chosen from all possible features but only from a randomly chosen part of them. This brings diversity in among the trees.

4.2.1.3 Tree Creation: The difference is that each decision tree is created utilising a greedy algorithm (just as in the case of traditional decision trees) where revealing the feature and the threshold offering the most effective separation of data points is the aim, usually employing Gini impurity for classification purposes or variance reduction for regression problems.

4.2.1.4 Prediction Aggregation: After creating multiple trees, their outputs are combined:

Classification: The majority class is chosen as the final prediction.

Regression: On average, all trees would have made such a prediction, and the average of that prediction is taken.

4.2.2 Mathematical Formulation

Let's break this down with the specific elements:

4.2.2.1 Bootstrapping: Assuming a dataset D = {(x_1, y_1), (x_2, y_2) …… (x_N, y_N)} ; where, (x_i) is the feature space (say, soil moisture, pH, temperature) while (y_i) is the target figure of interest (such as yield or moisture) a random forest employs bagging. A new data set (D_b) is formed by randomly choosing a set of points (D) and substituting the chosen points back in the set (D).

4.2.2.2 Decision Tree Training: In the case of each tree (T_i) of the ensemble, the training process tries to split the data points depending on the feature values in each node using measures such as Gini indices or variance. Mathematically, for regression, the split at node (t) is chosen by minimizing the variance of the two resulting subsets:

$$\mathbf{var}(\boldsymbol{s}) = \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{\boldsymbol{t}=\mathbf{1}}^{\boldsymbol{N}} (\boldsymbol{y}_{\boldsymbol{i}} - \overline{\boldsymbol{y}})^{\mathbf{2}}$$

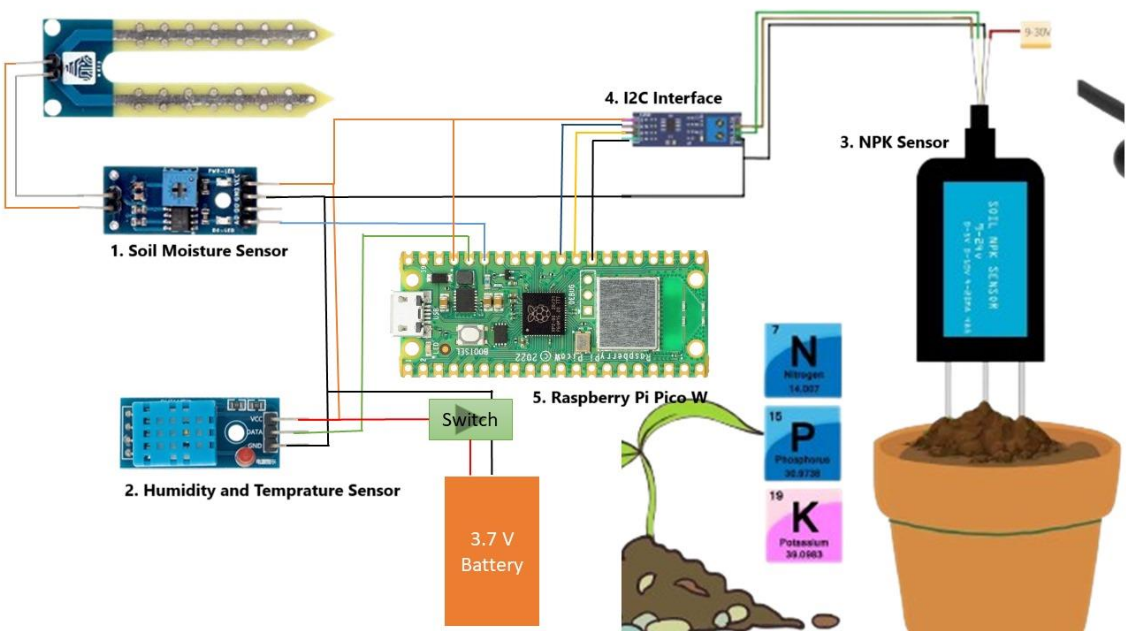
4.2.2.3 Prediction: Once the forest is trained, the predictions are aggregated for classification: The overall prediction (hat{y}) is the majority voting, that is the mode, of birch tree predictions. [For the estimated value of the target function symbolically represented by hat{y} we take the mode value of the set consisting of the results of the actions realized by the following transforms $T_1(x)$, $T_2(x)$, …, $T_n(x)$

For regression: The last forecast (hat{y}) is then the average of all the four: [y_{hat} = Mean($T_1(x)$, $T_2(x)$, …., $T_n(x)$)]

This article provides information on Random Forest Algorithm such as:

- **Decision Trees:** The base learners in random forest which are individuals models are themselves over-fit and when their results are averaged they are fairly good.
- **Bagging (Bootstrap Aggregating):** In a method where in several samples of the data are created by employing random sampling with replacement as well as constructing different trees by training them on these different sets in an orderly manner, some sort of variance is imposed to forestall overtraining.
- **Feature Subset Selection:** In the case of decision trees, Random Forest takes a random sample of features using which it decides the best way for splitting. This avoids domination by having strong independently predictors and increases diversities.
- **Gini Impurity (for Classification):** [Detailed below is the general formula for G(t) $\boldsymbol{G(t) = 1 - \sum_{i=1}^{G} p_i^2}$ where (p_i) is the likelihood of a data point of class (i) at node (t), and (C) is total number of classes.
- **Variance Reduction (for Regression):** This rates how much variability of the output is reduced by the split
- **Out-of-Bag Error (OOB Error):** Some of the images are omitted because each tree is trained on a randomly selected sub-sampling of the data. These are used to estimate the error without having to set aside a validation set in advance.

4.3 DESIGN AND ARCHITECTURE



4.3.1 Soil Moisture Sensor: This sensor detects the moisture level in the soil. It has three pins: VCC (power), GND (ground), and DATA. The sensor is connected to the Raspberry Pi Pico W's appropriate GPIO pins for data transmission and power supply.

4.3.2 Soil NPK Sensor: This sensor measures the Nitrogen (N), Phosphorus (P), and Potassium (K) levels in the soil. It appears to use three electrodes placed in the soil to assess the nutrient concentration. The sensor is powered by a 9-30V source, with its data pins connected to the Raspberry Pi Pico for data input.

4.3.3 Humidity and Temperature Sensor: This sensor monitors the environmental humidity and temperature. The sensor has three main pins: VCC (power), DATA, and GND (ground), and it is connected directly to the Raspberry Pi Pico to provide climate data .

4.3.4 I2C Interface: This module is likely an I2C or UART interface to communicate with one or more sensors (probably the NPK sensor or any sensor requiring additional modules).It is connected to both the power and data lines of the microcontroller.

4.3.5 Raspberry Pi Pico W: The Raspberry Pi Pico W serves as the microcontroller, interfacing with all the sensors. It uses Micro Python for processing the inputs and sending data to the backend or database. A 3.7V battery powers the Pico, and there is a switch connected to control the power flow to the Pico.3.7V

4.3.6 Battery: This battery powers the entire system, supplying voltage to the Raspberry Pi Pico and, through it, the other connected components. A switch is connected between the battery and the Pico to control the power supply manually.

4.3.7 Voltage Divider/Resistor: There is a small resistor (labeled as 9-30V) connected to the NPK sensor, likely used to drop the voltage to safe levels for other components or to stabilize current.

4.4 IMPLEMENTATION

A Smart Farming System is integrated with a set of consecutive processes that apply IoT and Machine Learning to enhance farming activities. The heart of this system comprises connecting IoT sensors with Raspberry Pi Pico W and Wi-Fi connectivity boards to ensure that the results are transmitted wirelessly over the wireless network and analyzed in a real-time manner with regard to the soil state. In the first phase, several IoT sensors, including NPK (Nitrogen, Phosphorus, Potassium), pH, and moisture sensors, are deployed directly into the soil to capture critical agricultural data: NPK sensors quantify the levels of nitrogen, phosphorus, and potassium ions, ions which are basic plant nutrients. pH Measuring indicates the soil's Acidity or alkaline value that has a direct influence on nutrient availability as well as crop compatibility. These sensors help monitor the amounts of moisture in a specific area of the garden, important when ascertaining the need for water in the soil. These sensors are able to collect data from the soil every day such as nitrogen, phosphorus, and potassium levels, pH of the soil, and moisture level. This data is wireless transmitted and the information is stored in a final database for further research. The second phase is analysis where the raw data collected by the sensors are converted into something that can be utilized. This is an important phase in which data is fed to a machine learning (ML) model with the ability to analyze it. The model used in this research is the ML model that uses the Random Forest algorithm, which is an innovative and prominent method of learning algorithms that are fundamental to ensemble learning. Random Forest works on the model where during the training process several decision trees and at the end of training, gather the results and have final prediction in this way eliminates overfitting. The Random Forest-based ML model is built by considering a dataset of soil characteristics and their impact on crops.

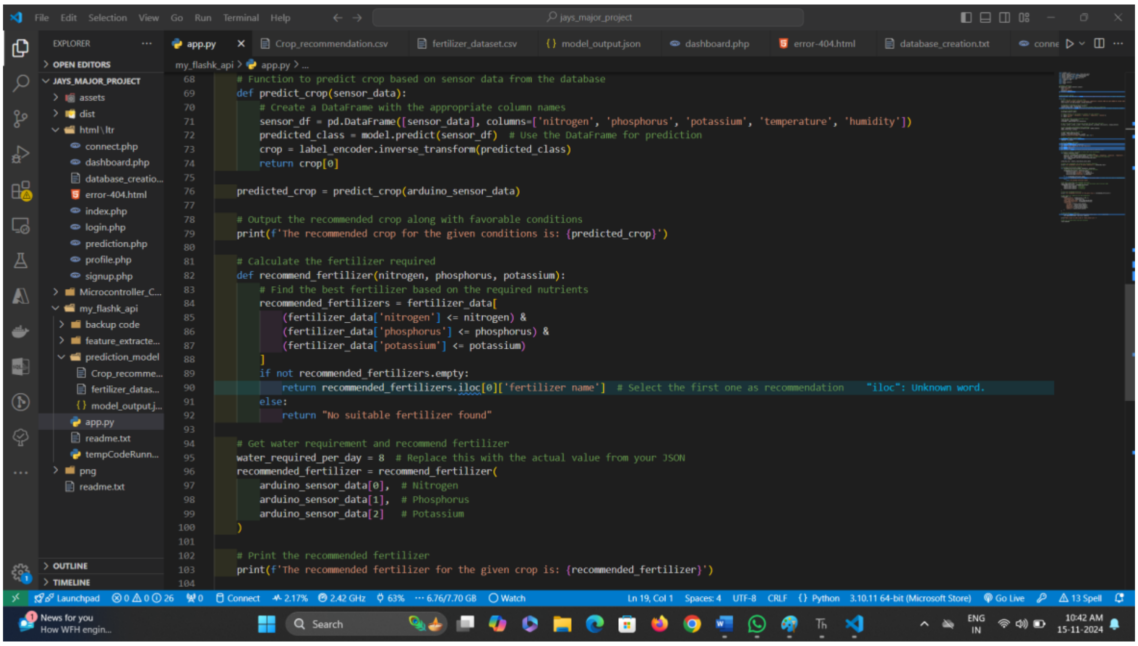


Figure 4.4 : Code section

4.5 PROJECT WALKTHROUGH :

This chapter focuses on the features and functionalities of SMART FARMING SYSTEM as presented to a user. A detailed walkthrough with screenshots and explanations is provided to give a comprehensive understanding of the system's capabilities.

Links to hosted versions, source code, project documentation, and other relevant resources are provided in Appendix A.

4.5.1 LANDING PAGE

The landing page is the first point of contact for users visiting SMART FARMING SYSTEM. It provides an overview of the system's features and functionalities, guiding users on how to get started. The landing page includes a brief description of SMART FARMING, key benefits, and a call-to-action to sign up or log in.

Figure 4.5.1: Landing Page

The landing page allows users to move to the authentication page or scroll down to learn more about SMART FARMING SYSTEM features.

4.5.2 AUTHENTICATION PAGE

SMART FARMING SYSTEM has a simple and intuitive authentication page that allows users to sign up or log in to the system. Users can create an account by providing their email address and password.

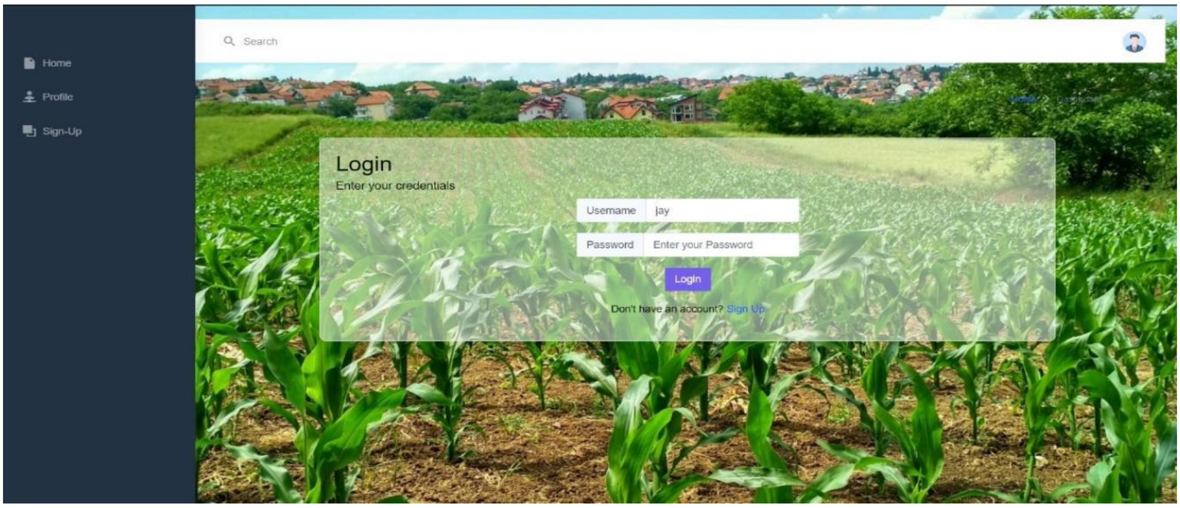
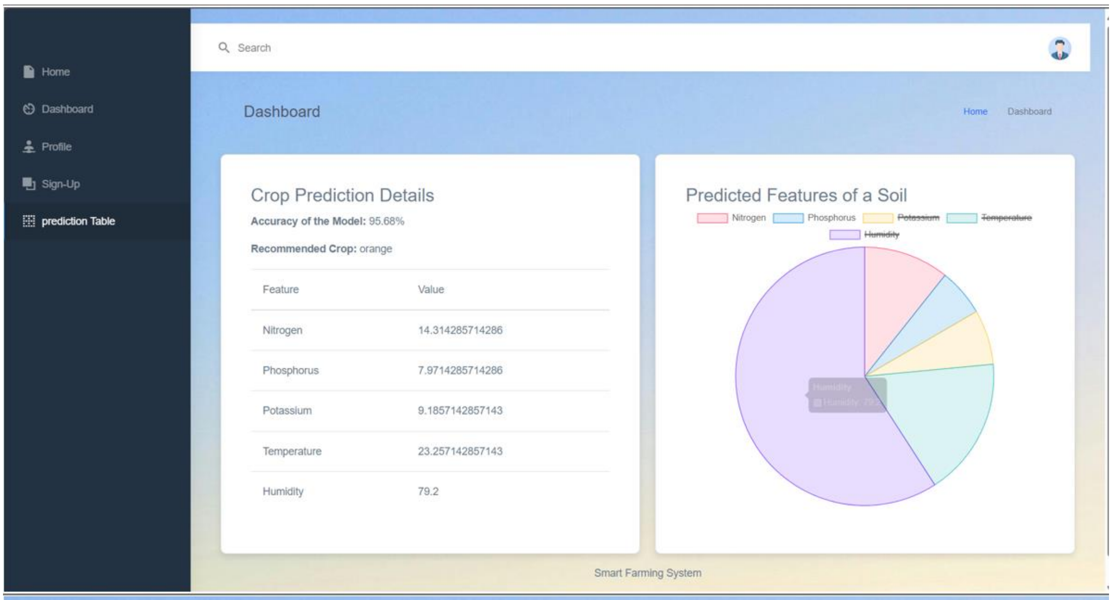


Figure 4.5.2: Authentication Page

Once logged in, users are redirected to the dashboard.

4.5.3 DASHBOARD

The dashboard provides users with an overview of their uploaded entities, search functionality, and other key features. The dashboard includes a visualization of user's activities.



Overall Data

ID	HUMIDITY	TEMPERATURE	NITROGEN	PHOSPHORUS	POTASSIUM
7	77.4	22.7	14.1	8.1	9.4
6	79.5	23	14.8	7.8	9.5
5	81.1	24.5	13.9	8.3	9.2
4	78.9	22.3	14.2	8	9.1
3	82.3	23.8	15	7.9	8.8
2	80	24	13.7	7.5	9
1	75.2	22.5	14.5	8.2	9.3

Figure 4.5.3: Dashboard

4.5.4 ADD REVIEW

The add review page provides you the option to add reviews on particular courses you can also give ratings to the IoT kit. The Smart Farming System integrates IoT and ML to optimize water use and boost crop yields. It offers real-time monitoring and predictive insights, improving farming efficiency. This system is a practical solution for sustainable, tech-driven agriculture.

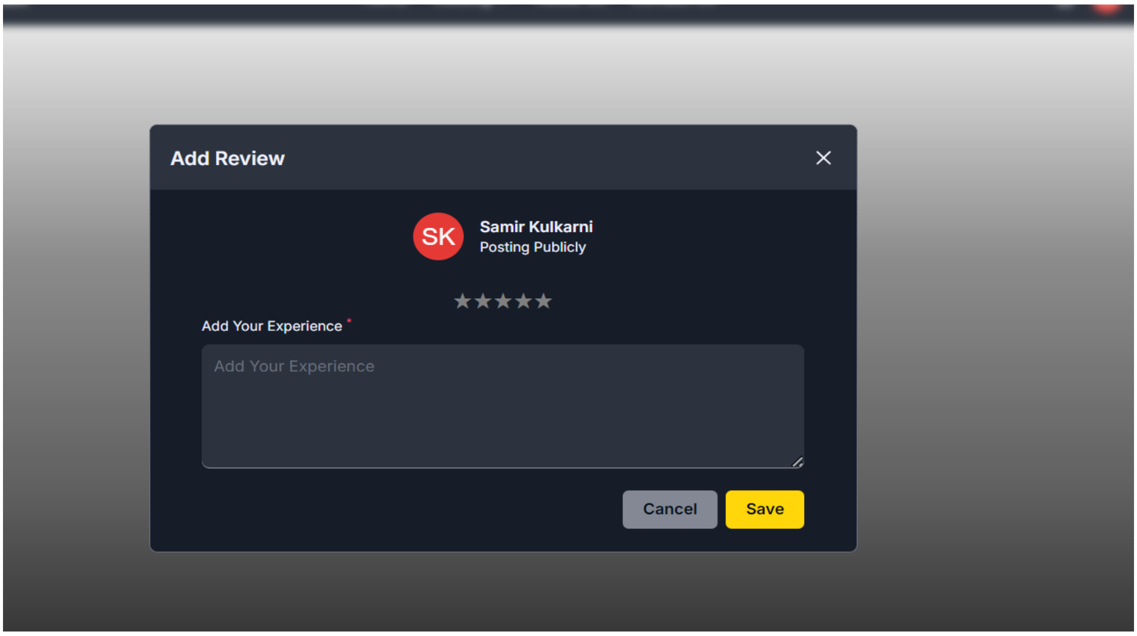
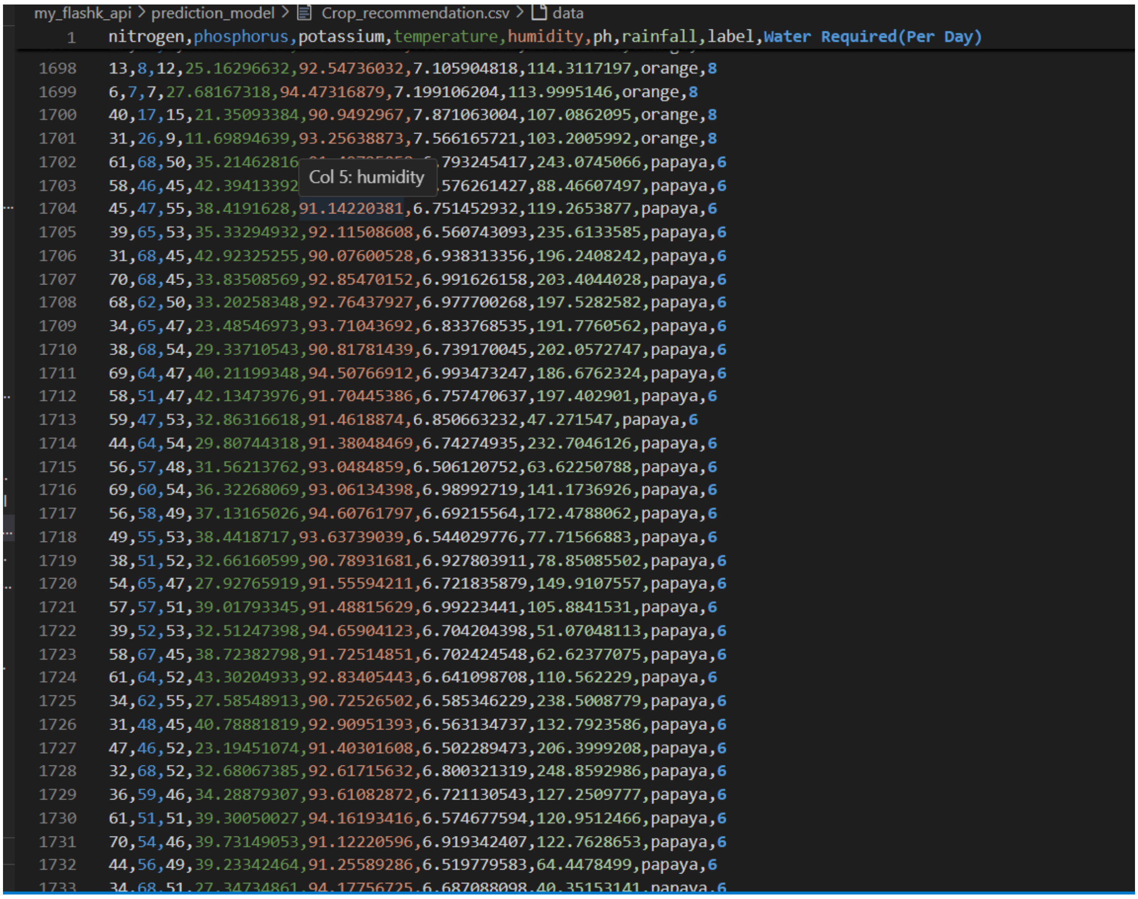


Figure 4.5.4: Add Review

4.6 DATABASE

- The database[7] we are using for our Smart Farming System, sourced from Kaggle, contains over 1,000 entries. Each entry includes data on essential agricultural parameters like Nitrogen (N), Phosphorus (P), Potassium (K), Humidity, and Temperature, providing a robust foundation for data analysis. With this extensive dataset, we can apply AI algorithms to uncover patterns and insights that enhance crop management. The large volume of data supports accurate predictions for soil moisture, fertilization schedules, and other critical agricultural decisions, helping us achieve efficient, sustainable farming practices.



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my_flashk_api > prediction_model > Crop_recommendation.csv > data
nitrogen,phosphorus,potassium,temperature,humidity,ph,rainfall,label,Water Required(Per Day)
13,8,12,25.16296632,92.54736032,7.105904818,114.3117197,orange,8
6,7,7,27.68167318,94.47316879,7.199106204,113.9995146,orange,8
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61,68,50,35.21462816,[illegible].793245417,243.0745066,papaya,6
58,46,45,42.39413392,[illegible].576261427,88.46607497,papaya,6
45,47,55,38.4191628,91.14220381,6.751452932,119.2653877,papaya,6
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31,68,45,42.92325255,90.07600528,6.938313356,196.2408242,papaya,6
70,68,45,33.83508569,92.85470152,6.991626158,203.4044028,papaya,6
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34,68,51,27.34734861,94.17756725,6.687088098,40.35153141,papaya,6
```


Figure 4.6: Crop Database

- The fertilizer recommendation dataset[8] in our Smart Farming System includes data on 100 different fertilizers. This dataset provides detailed information about each fertilizer, such as its composition, suitability for various soil types, and effectiveness for specific crops. By analyzing this dataset alongside soil and environmental data (like Nitrogen, Phosphorus, Potassium, Humidity, and Temperature levels), the system can recommend the most appropriate fertilizer for a given condition. This ensures optimized crop growth, minimizes overuse of fertilizers, and promotes sustainable agricultural practices.

CHAPTER 5

RESULT AND DISCUSSION

This section goes into detail about the development approach, the various "ends" of the system, and the technologies used. It also provides a short overview of the libraries and frameworks used in the development of the Smart Farming System.

5.1 RESULT

5.1.1 Soil Health Recommendation: The model essentially calculates deviations of the readings obtained in real-time from the data set to determine the health of the soil. To state the model is more detailed, they show enumerated nutrient levels N, P, and K and the pH of the soil and reveal existing deficits and unevenness in resources. Crop Suitability Prediction: On the basis of the level of soil health, the model decides which modern crops can be suitably grown in a particular set of soil conditions. It compares the current nutrient and pH to the needs of the crops and suggests the best that would suit a particular farming.

5.1.2 Fertilizer Recommendations: Therefore, depending on the nitrogen, phosphorus, and potassium levels, the model recommends the right fertilizers to improve the nutrients of the soil. These fertilizer recommendations are given based on the nutrient inadequacies that have been found in the soil.

5.1.3 Water Requirement Recommendation: The proposed system combines the information from the moisture sensor with the temperature and humidity values obtained from the Google Maps API in real time. This API gives details on the current humid and precipitation conditions in a particular region such as Temperature, pressure, humidity, precipitation, dew point, wind chill, and heat index among others. The features include the current relative humidity in the atmosphere, the amount of moisture in the ground, and the expected weather forecast. If the drying of the soil has occurred and rain is out of the question then the system suggests to the farmer that he water the field. On the other hand, if humidity is high, or if rain is expected, the system recommends not to water the crops as it is likely to flood. They wanted to find out how farmers could effectively and efficiently use water in growing crops while at the same time, soil moisture was well conserved. The frontend interface of the system is simplified in that it can be operated without much user input. It contains a password-protected login for farmers and offers them full access with all the features which include real-time sensor data, status of soil health, crop suitability index, fertilizer recommendation, and water efficiency data. This interface enables farmers to monitor data generated and decisions made by the system for efficient action to be taken.

5.2 Testing and Quality Assurance

Sr.no	Sample's	Crop suggestion	Fertilizer prediction	Water requirement
1	The pre-defined Standardized data set obtained from Kaggle which contains the value of various parameter.	On the basis of actual values of soil parameters like NPK, PH, it will gives 98 out of 100 correct crops that satisfied the standardized values.	On the basis of values of nitrogen, phosphorus and potassium obtain from soil while comparing with predefined database it suggest the name of fertilizer along with 90% accuracy. It will suggest the name of fertilizer.	Water requirement it suggest the farmer on the basis of real time value of there soil moisture and what actual moisture is required for that particular crop which varies from crop to crop.
2	Black soil (Regur Soil)	Cotton, Maize	Urea	5mm / Day
3	GCOEN Soil	Pigeon Pea	Potash	7mm / Day

5.3 Outcomes

Visuals showing the system in action, demonstrating water-saving irrigation and crop suitability predictions.

5.3.1 Crop Prediction

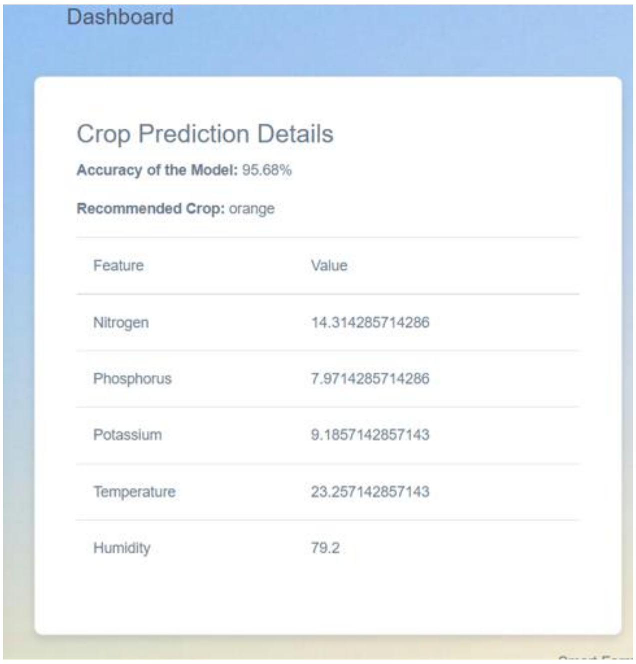


Figure 5.3.1: Crop Prediction

- The system will provide accurate recommendations for crop selection based on real-time soil health data (NPK, pH, moisture) and environmental conditions.
- This will enable farmers to choose crops that are best suited for their soil, optimizing yields and reducing the risk of crop failure.

5.3.2 Water Requirement

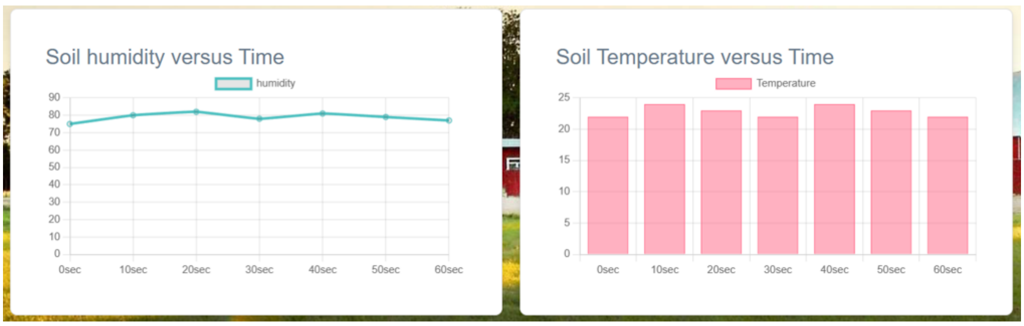


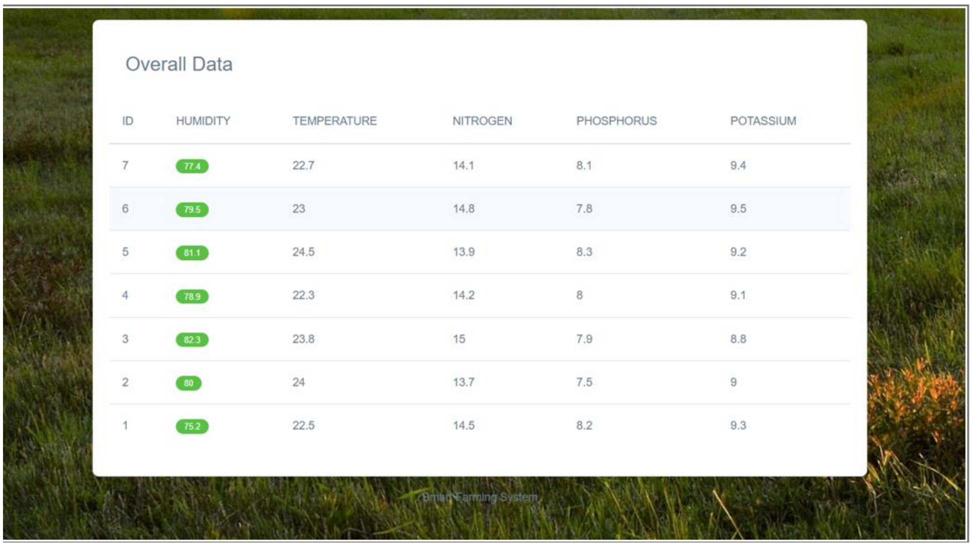
Figure 5.3.2: Water Requirement

- The system will optimize irrigation by predicting the precise water requirements for crops based on soil moisture levels and environmental factors.
- This will lead to more efficient water usage, minimizing waste and supporting sustainable farming practices.

5.3.3 Fertilizer Requirement

- The system will offer targeted fertilizer recommendations, ensuring that nutrients are applied in the right amounts based on soil analysis.
- This will help reduce excessive chemical use, promoting healthier soil, lowering costs, and preventing environmental damage from over-fertilization.

5.3.4 Soil Health Monitoring


Overall Data

ID	HUMIDITY	TEMPERATURE	NITROGEN	PHOSPHORUS	POTASSIUM
7	77.4	22.7	14.1	8.1	9.4
6	79.5	23	14.8	7.8	9.5
5	81.1	24.5	13.9	8.3	9.2
4	78.9	22.3	14.2	8	9.1
3	82.3	23.8	15	7.9	8.8
2	80	24	13.7	7.5	9
1	75.2	22.5	14.5	8.2	9.3

Smart Farming System

Figure 5.3.4: Soil Health Monitoring

- Continuous monitoring of soil health will be facilitated through the collection of comprehensive data on nutrient levels, pH, and moisture content.
- This ongoing analysis will provide farmers with valuable insights into soil conditions, allowing them to make timely adjustments to management practices.
- Improved soil health monitoring will enhance crop productivity, reduce the risk of soil degradation, and promote sustainable agricultural practices that benefit both farmers and the environment.

CHAPTER 6

CONCLUSIONS AND FUTURE SCOPE

6.1 SUMMARY

Precise farming is advanced by a smart farming system that seamlessly integrates the IoT sensor, wireless communication, and machine learning algorithm to provide real-time actionable insights to the farmer. This system differs from other previous models which used only radio images and were not outfitted with wireless modules or modern applications that fail to harvest real-time data essential to continuous monitoring of the soil conditions. It uses NPK, pH, and moisture sensors to read and send valuable soil data, including nutrient levels and moisture content, wirelessly for analysis. A Random Forest-based machine learning model sits at the center of the system, processing this raw data to give an all-around analysis of soil health, crop suitability, fertilizer recommendations, and water needs. With this real-time analysis farmers can make informed decisions that will maximize crop yields, optimize resource use or waste, and reduce environmental impact. Moreover, the system predicts water needs from environmental data for essential aspects like sustainable farming. The Smart Farming System integrates cutting-edge technology with farming practices, all in an effort to increase efficiency, support sustainability, and enable farmers to utilize data to make intelligent decisions that will continue to create success for agriculture in the long term

6.2 CONCLUSIONS

- The Smart Farming System uses IoT sensors and machine learning to provide real-time insights on crop selection, fertilizer application, and water requirements.
  It collects soil data (NPK, pH, moisture) and analyses it with a Random Forest model to offer specific recommendations.

- The system helps farmers choose the most suitable crops, optimize irrigation schedules, and apply fertilizers efficiently.
- Continuous monitoring of soil health allows for early detection of issues, promoting healthier soil and reducing input costs.
- By enabling precision agriculture, the system improves farm productivity, conserves resources, and supports sustainable farming practices.

6.3 FUTURE SCOPE

- **Integration of Advanced AI:** Future iterations of the system can incorporate more advanced AI algorithms, such as deep learning, for even more precise predictions related to irrigation, crop disease detection, and yield forecasting. This will help in further optimizing resource use and increasing productivity.
- **Expansion to Other Agricultural Activities:** Beyond irrigation, the system can be extended to automate and optimize other agricultural processes such as fertilization, pest control, and crop monitoring. By integrating additional sensors for nutrients and pests, the system can offer a holistic solution to farm management.
- **Scalability for Large Farms:** As the technology matures, the system can be scaled for larger agricultural operations. Advanced data processing techniques, such as edge-computing, can be used to handle the vast amounts of real-time data generated by large farms, making it applicable to both smallholder and industrial farming.
- **Cloud Integration and Big Data:** With cloud-based storage and big data analytics, the system could analyze large datasets collected over time, providing insights into regional farming trends, weather patterns, and crop performance. This could benefit agricultural policy-making and regional farming cooperatives.
- **Sustainable Energy Integration:** To make the system even more eco-friendly, future developments could include integration with solar or other renewable energy sources to power IoT devices and sensors in remote areas, reducing the carbon footprint.
- **Blockchain for Supply Chain Transparency:** Blockchain technology can beintegrated to provide transparency in the supply chain, helping farmers track

their produce from farm to market while ensuring that the data is secure and tamper-proof.

- **Global Adoption and Customization:** The system could be adapted for global use by customizing it to suit different climate zones, soil types, and crops, enabling farmers worldwide to benefit from smart farming practices.

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