Bachelor of Science in Computer Science & Engineering

IoT Based Crop and Fertilizer Recommendation System

by

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by

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Finally, I would like to dedicate my thesis work to my father and mother.

Abstract

In modern agriculture, the integration of Internet of Things technologies has revolutionized traditional farming practices by enabling real-time monitoring and data-driven decision-making. This thesis focuses on the development and implementation of an innovative IoT-based Crop and Fertilizer Recommendation System that harnesses a comprehensive array of environmental parameters for optimized agricultural management. A farmer will be able to make decisions and not rely solely on the local agriculture office by utilizing the support system. The suggested system makes use of the Internet of Things (IoT)-enabled sensors to collect vital information such as soil pH, air humidity, soil temperature, soil moisture levels, and soil values for phosphorus (N), potassium (K), and nitrogen (N). Through seamless connectivity and data transmission, these parameters are continuously monitored and transmitted to a centralized system for analysis and recommendation generation. Machine learning algorithms are employed within this framework to process the collected data and generate actionable insights. By establishing correlations between environmental variables and crop fertilizer requirements, predictive models are developed to provide tailored recommendations for optimal fertilizer compositions and application rates. The development process encompasses data acquisition, preprocessing, and model training stages. IoT sensors deployed across agricultural fields capture real-time environmental data, which undergoes preprocessing to ensure accuracy and consistency. Here data is collected using IoT cloud Thingspeak Server. Feature engineering techniques are utilized to identify the most influential parameters for fertilizer recommendation. The crop and fertilizer recommendation system employs a variety of machine learning algorithms, including regression, decision trees, and ensemble methods, to construct robust predictive models. These models are trained on historical data and refined iteratively to adapt to changing environmental conditions and crop-specific requirements. Here data is collected from field of particular crop.The data which is collected from thr field of a certain crop, it is labeled by this crop.

For labeling fertilizer,the fertilizer which is used in the field for production is labeled with the data. Performance metrics such as accuracy, efficiency, and scalability are evaluated to assess the system's effectiveness in improving crop yield and resource utilization. The findings demonstrate the viability and efficacy of the developed IoT-based Crop and Fertilizer recommendation system in enhancing agricultural productivity and sustainability. Here We have found the highest accuracy for the random forest method which is 97.86 percent for crop prediction. On the other hand, we have found 98.78 percent for Fertilizer prediction. The precision, recall and F1 score value is also best for the Random Forest Classifier. We have found the lowest for the Naive Bayes classifier which is 77.61 for crop prediction and 75.22 for fertilizer prediction. We have deployed This model in Flask Framework with a user interface. For this, we have created user friendly interface using bootstrap. We also have done the comparison using different machine learning algorithms. By providing farmers with timely and precise fertilizer recommendations tailored to specific environmental conditions, this research contributes to the advancement of smart farming practices, facilitating informed decision-making and optimizing resource management in agriculture

Keywords: Internet of Things(IoT), WiFi, Flask, Machine Learning, Thingspeak Server.

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Chapter 1

Introduction

1.1 Introduction

A farming management idea called "smart farming" aims to improve both the quantity and quality of agricultural products. Farmers today have access to technology for data management, soil scanning, GPS, and the Internet of Things.

The goal of research on smart agriculture is to lay a strong basis for a decision-support system for farm management. Smart farming argues that there are three concerns that need to be addressed: labor, climate change, and population growth. This includes everything from crop planting and irrigation to health and harvesting [1]. The country's economic status cannot be improved without the increase of the agriculture industry. Sadly, a lot of farmers still work their land with antiquated methods, which lowers the yields of fruits and crops. But in all cases where automation has been employed and autonomous machinery has taken the place of humans, the yield has increased. Therefore, the agricultural industry needs to apply modern science and technology in order to enhance productivity. Even though technology advances quickly and new innovations are made daily, farmers continue to have many issues with their land. It is everyone's responsibility to establish an atmosphere that encourages farmers to work comfortably, produce well, and safeguard their crops from various creatures [2]. The IoT as smart agricultural architecture consists of three layers: a sensor layer, a transport layer, and an application layer. The sensor layer is used to gather real-time data from the field and digitally modify the information to make analysis easier. In general, sensors like temperature sensors, humidity sensors, pressure sensors, etc., are used to collect data. Real-world sensing techniques must be used by the sensor layer to manage a variety of data before sending it to the processing system. A transport layer is utilized for data transfer, gathering all of the sensor data. In the Internet of Things applications, the transport layer—which consists of data processing centers, active internet access, and communication centers—is crucial. Ultimately, the decision is given to the user by the application layer, which analyses the data gathered. It is regarded as a combination of intelligence systems and the Internet of Things that gives the farmer a clear display of the analysis results [3]. In IOT-based smart agriculture, a system is developed to monitor the agricultural field using sensors (soil moisture, light, humidity, temperature, etc.) and automate the irrigation system. IOT (Internet of things) in agriculture refers to the process of turning every aspect and action associated with farming into data through the use of sensors, cameras, and other devices [4]. Agriculture, which controls a large share of the world economy, has widespread applications of IoT. Our work can be applied in several areas, including maximizing profit and soil monitoring. In developing our proposed system, several challenges arose, including data collection from ESP32 micro-controllers, data preprocessing, and feeding the data to models. We also faced a problem in deploying the model in the flask.

This platform's goal is to show off how well machine learning techniques can be used to assist in choosing crops and fertilizer applications for optimal results in intelligent farming.

1.2 Proposed IoT-Based Crop and Fertilizer Recommendation System

Our proposed system is illustrated in fig. 1.1. The framework is composed of the significant steps that follow: (1) Establishing experimental setup, (2) Raw data collection, (3) Preprocessing the Raw data, (4) Data splitting(train-validation-test), (5) Training the ML Models, (6) Evaluate the model on test data, (7)Deployment of the best model in Flask Framework, (8)finally recommend the crops and fertilizer.

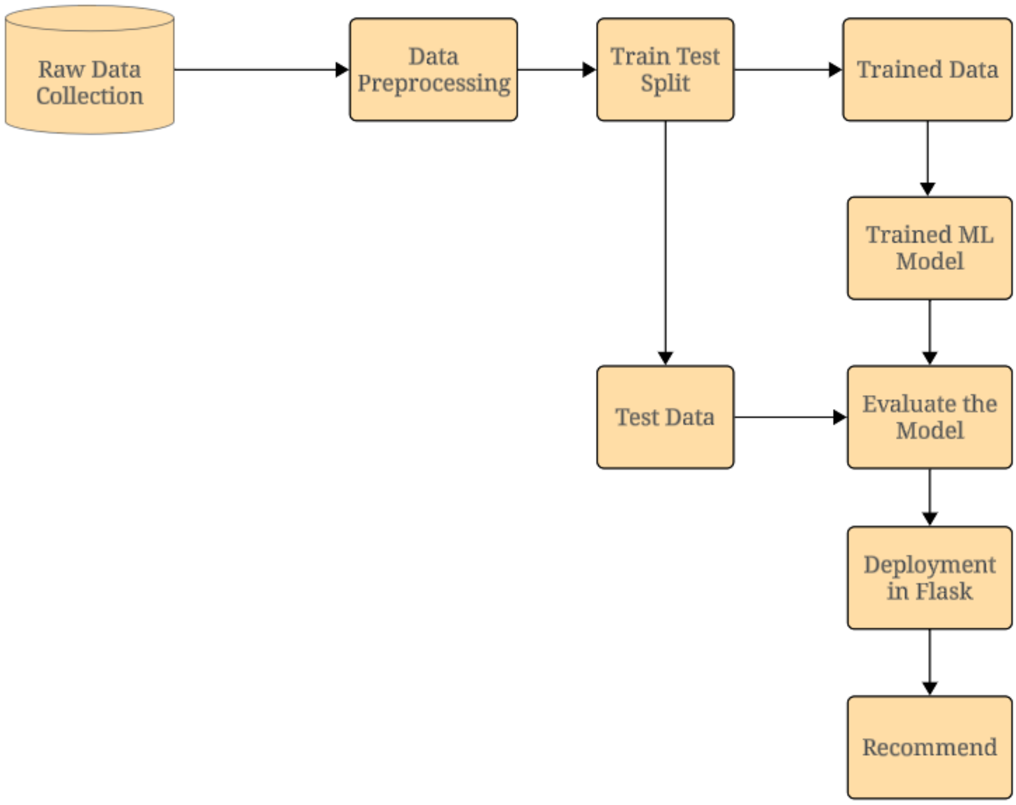

Figure 1.1: Overview of the proposed framework

For the work, we collected the raw data from the soil of different fields of different parameters. Then we labeled them using crop and fertilizer names. Then we ran a model on the dataset. Then we have deployed the model in Flask and created a user interface using HTML and CSS[5].

1.3 Objectives

The key objective and possible outcomes of this work are mentioned below:

1. To collect the required data from the constructed setup using thingspeak.
2. To apply the machine learning model and evaluate the result and accuracy and make the prediction.
3. To develop a system that can recommend crop and fertilizer types for farmers to increase profit.

1.4 Motivation

The motivation behind the development of the IoT-based Crop and Fertilizer Recommendation System (CFRS) stems from the pressing need to address the challenges facing modern agriculture, including the imperative to enhance productivity, sustainability, and resource efficiency in the face of growing global food demand and environmental pressures.

Traditional farming practices often rely on generalized approaches to crop management and fertilizer application, which can lead to inefficiencies, resource wastage, and environmental degradation. Moreover, the variability in soil conditions, weather patterns, and crop requirements presents significant challenges for farmers in making informed decisions to optimize yields while minimizing inputs.

In this context, the integration of IoT technologies and advanced data analytics offers a transformative opportunity to revolutionize agricultural practices through real-time monitoring, analysis, and decision-making. By leveraging IoT-enabled sensors to capture granular data on soil nutrients, moisture levels, temperature, and other environmental parameters, this system provides farmers with valuable insights into the dynamic conditions of their fields, enabling proactive and precise management strategies.

Furthermore, the development of predictive models within this framework empowers farmers to move beyond reactive approaches to crop management, towards proactive decision-making based on data-driven insights. By harnessing the power of machine learning algorithms to analyze complex relationships among environmental variables and crop fertilizer requirements, this system facilitates the generation of tailored recommendations for optimal fertilizer compositions and application rates, thereby maximizing yields while minimizing environmental impact. The overarching goal of the Crop and Fertilizer recommendation system is to empower farmers with the tools and knowledge needed to unlock the full potential of their agricultural operations, by enabling them to make informed decisions that enhance productivity, profitability, and sustainability. By promoting precision agriculture practices that are responsive to the unique needs of each field and crop, the Crop and Fertilizer recommendation system aims to contribute to a more efficient, resilient, and sustainable agricultural ecosystem, capable of meeting the challenges of feeding a growing global population while safeguarding the planet for future generations.

1.5 Contribution of The Thesis

Our thesis is about recommending crops and fertilizer at the same time taking some parameters like N, P, K, soil moisture and temperature, Air humidity, and temperature. We have used raw data which collected using IoT device configuration and implemented machine learning techniques for the prediction. In this thesis, the main motive was to establish an improved framework for recommending crops and fertilizers based on parameters. The primary contribution of this thesis is the following:

1. We collected data from different fields.
2. We fed our dataset into the Machine learning Model and then Evaluated the model based on accuracy, precision, recall, and F1 score.
3. Finally we deployed our model which gives the best accuracy, precision, recall, and F1 score into the Flask framework. Then we created user-friendly and easy-to-navigate user interface.

1.6 Thesis Organization

The subsequent sections of this thesis report are structured in the following manner:

- Chapter 2 provides an overview of the existing works concisely, that have been done using different sensor and then shows their results and limitations.
- Chapter 3 describes the methodology proposed to recommend crops and fertilizers along with appropriate diagrams. The details about hardware

and experimental setup, data collection, preprocessing of the data, and the implementation of the models have been described in this section.

- Chapter 4 discusses the experimental results and visualization of collected data. Also, a brief comparison of machine learning models has been on focus in this chapter. Here we also discussed about confusion matrix of our model. Also discussed about the user interface of the application.
- Chapter 5 contains the conclusion of this work which includes an overall overview of our system and also mentions some limitations & future work.

1.7 Conclusion

In this chapter, a basic overview of the system to recommend right crop and fertilizer is provided. We also mentioned some basics of IoT. Along with the purpose of this work and contributions, a brief description of the obstacles and problems was provided. In the succeeding chapter, a thorough explanation of the background information regarding the issue will be provided.

Chapter 2

Literature Review

2.1 Introduction

The modern agricultural landscape is undergoing a transformation driven by technological advancements, with the Internet of Things (IoT) emerging as a powerful tool to revolutionize farming practices. In recent years, IoT-based systems have gained considerable attention for their potential to enhance agricultural productivity, sustainability, and efficiency. One such application is the development of crop and fertilizer recommendation systems, which leverage IoT technologies to provide personalized guidance to farmers, enabling them to make informed decisions about crop cultivation and soil management. The significance of crop and fertilizer recommendation systems lies in their ability to address the challenges faced by farmers in optimizing crop yield while minimizing resource usage and environmental impact. By harnessing real-time data from IoT sensors deployed in fields, these systems offer insights into crucial factors such as soil moisture, temperature, nutrient levels, and weather conditions. Through data analytics and machine learning algorithms, they can generate tailored recommendations for crop selection, planting schedules, and fertilizer application, tailored to the specific needs of each farm plot. While the potential benefits of IoT-based crop and fertilizer recommendation systems are evident, their effective implementation requires a comprehensive understanding of the existing research landscape. This literature review aims to explore and synthesize the body of knowledge surrounding this topic, encompassing relevant studies, methodologies, technologies, and challenges. By examining prior research efforts and identifying gaps in the current literature, this review sets the stage for the development of a novel IoT-based recommendation system tailored to the needs of agricultural stakeholders.

In this chapter, we will go through different methods that have been developed for crop and fertilizer recommendation systems. The advantages and disadvantages of the methods mentioned above that are applied in recommendation will also be briefly discussed.

2.2 Overview of Internet of Things(IoT)

The Internet of Things, or IoT, is a new and revolutionary technology paradigm that has the potential to completely change a number of industries, including agriculture. IoT is essentially a network of networked devices that are integrated with software, actuators, and sensors that allow them to exchange, gather, and act upon data without the need for human interaction. These devices, often referred to as "smart" or "connected" devices, can range from simple sensors monitoring environmental conditions to complex machinery controlling autonomous operations. In the context of agriculture, IoT holds promise for optimizing resource utilization, improving crop yield, and enhancing overall farm management practices. By deploying IoT-enabled sensors throughout agricultural fields, farmers can gather real-time data on key parameters such as soil moisture levels, temperature, humidity, light intensity, and crop growth status. This granular data provides valuable insights into the health and condition of crops, allowing farmers to make timely and informed decisions to optimize cultivation practices.

IoT technology offers several advantages for agriculture, including:

Precision Agriculture: IoT enables precision agriculture techniques by providing farmers with detailed information about the variability of soil and crop conditions within their fields. This makes it possible to implement tailored interventions with greater agricultural output and resource efficiency, such as precision fertilization, irrigation, and insect control.

Remote Monitoring and Control: Farmers can use Internet of Things (IoT) devices to remotely monitor and manage agricultural activities from any location with an internet connection. This capacity allows for resource optimization, prompt response to changing conditions, and proactive control of agricultural operations.

Data-Driven Decision Making: By collecting and analyzing vast amounts of data from IoT sensors, farmers can gain valuable insights into crop health, environmental conditions, and productivity trends. This data-driven strategy makes evidence-based decisions easier to make, which results in more productive and sustainable farming methods.

Predictive Analytics: IoT data can be leveraged to develop predictive models that forecast future trends and events, such as crop yield, disease outbreaks, and weather patterns. These predictive insights enable farmers to anticipate challenges and take proactive measures to mitigate risks and optimize outcomes.

2.3 IoT Devices Used for Data Collection

Our device for data collection is previously established by a previous student of CUET using different sensors according to parameters. Here we have used this device for data collection. Here we have used the NPK sensor, soil moisture sensor, soil temperature sensor, Ph sensor, air temperature sensor, and humidity sensor. We have used the Arduino for data collection purposes. Here we have used the Thingspeak server for data collection.

2.3.1 Arduino

In the realm of IoT-based agriculture, Arduino [6] serves as a versatile and accessible platform for deploying sensor nodes, collecting data, and implementing control mechanisms. Arduino's [6] open-source hardware and software ecosystem make it an attractive choice for agricultural applications, enabling farmers and researchers to customize and scale their IoT solutions according to specific needs and requirements. Arduino boards [6], equipped with a variety of sensors and communication modules, can be deployed in agricultural fields to monitor a wide range of environmental parameters such as soil moisture, temperature, humidity, light intensity, and atmospheric conditions. These sensor nodes continuously collect data from their surroundings and transmit it wirelessly to a central gateway or cloud-based server for analysis and processing. Arduino's [6] compatibility with various communication protocols, including Wi-Fi, Bluetooth, LoRa[7], and GSM, enables seamless integration with existing farm infrastructure and data networks. This interoperability facilitates real-time data transmission, remote monitoring, and control of agricultural operations from anywhere with an internet connection[8]. Farmers can receive alerts and notifications on their smartphones or computers, enabling timely intervention and decision-making to optimize farm management practices. Overall, Arduino [6] plays a vital role in democratizing IoT-based agriculture by providing a cost-effective, customizable, and accessible platform for deploying sensor networks, collecting data, and implementing smart farm solutions. As we explore the literature on IoT-based crop and fertilizer recommendation systems, it is essential to consider the role of Arduino[6] as a foundational technology driving innovation and sustainability in modern agriculture.

Figure 2.1: Arduino Board

2.3.2 Sensors Used

In the context of IoT-based agriculture, sensors play a pivotal role in capturing real-time data related to soil, environmental conditions, and plant health. These sensors provide valuable insights that enable farmers to make informed decisions about crop management, irrigation, fertilization, and pest control. In this section, we will discuss the significance of various sensors commonly used in agricultural IoT systems, including NPK sensors, soil moisture sensors, pH sensors, soil temperature sensors, air temperature sensors, and air humidity sensors.

NPK Sensor: NPK sensors measure the concentration of essential nutrients nitrogen (N), phosphorus (P), and potassium (K) in the soil [9]. These sensors provide critical information about soil fertility levels, enabling farmers to optimize fertilizer application and nutrient management practices. By monitoring NPK levels in real-time, farmers can prevent nutrient deficiencies or excesses, resulting in improved crop yield and quality.

Figure 2.2: NPK Sensor

Soil Moisture Sensor: Soil moisture sensors measure the water content in the soil [10], indicating the availability of water for plant uptake. These sensors help farmers determine the optimal timing and amount of irrigation, preventing under- or over-watering of crops. By monitoring soil moisture levels, farmers can conserve water resources, reduce irrigation costs, and minimize the risk of water stress in plants.

Figure 2.3: Soil Moisture Sensor

Soil Temperature Sensor: Soil temperature sensors measure the temperature of the soil at various depths below the surface [10]. Soil temperature influences seed germination, root development, microbial activity, and nutrient availability in the soil. By monitoring soil temperature, farmers can optimize planting schedules, manage crop growth stages, and mitigate risks associated with temperature extremes.

Figure 2.4: Soil Temperature Sensor

pH Sensor: pH sensors measure the acidity or alkalinity of the soil, which directly affects nutrient availability and plant growth In [11]. Maintaining the correct soil pH is essential for optimal nutrient uptake by plants and microbial activity in the soil. pH sensors enable farmers to monitor soil pH levels and make appropriate adjustments through lime application or soil amendments to create an ideal growing environment for crops.

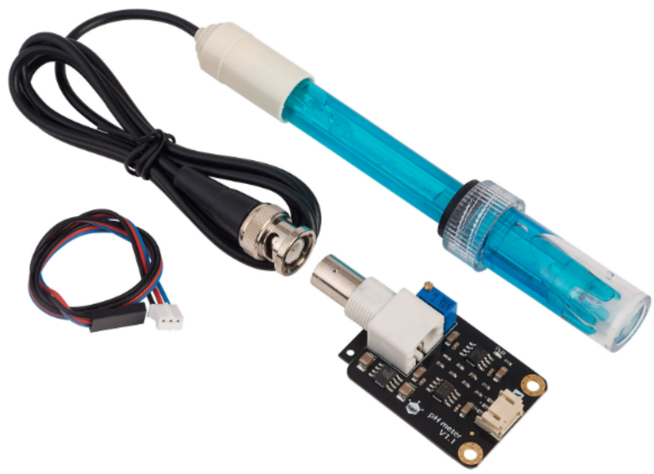

Figure 2.5: pH Sensor

DHT11 Sensor: A simple, incredibly affordable digital temperature and humidity sensor is the DHT11. It measures the air quality using a thermistor and a capacitive humidity sensor, then outputs a digital signal on the data pin. [10]. It can collect data for both air humidity and air temperature. A resistive-type humidity measurement component where the resistance of the sensor changes with the change in humidity levels. This change is converted into a digital signal that is sent to the microcontroller. A thermistor, a type of resistor whose resistance varies significantly with temperature. This variation is also converted into a digital signal. By monitoring air humidity and air temperature, farmers can adjust irrigation schedules, implement ventilation strategies, and prevent moisture-related crop diseases.

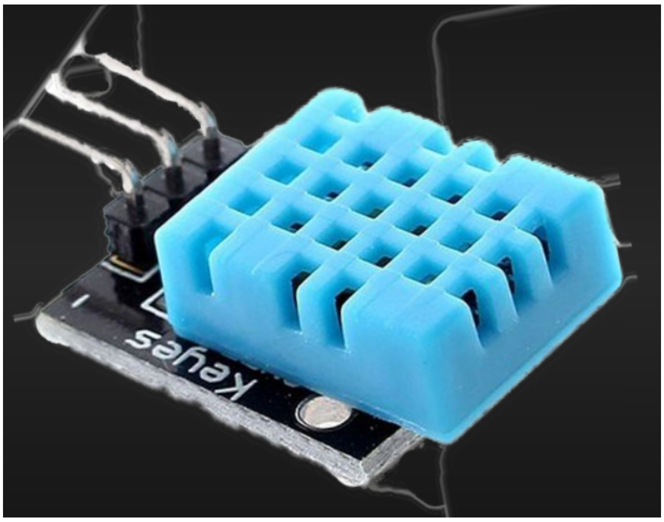

Figure 2.6: Air Humidity Sensor

2.3.3 Thingspeak Server

ThingSpeak is a popular IoT platform that enables the collection, analysis, and visualization of sensor data in real-time [12]. It provides a user-friendly interface for managing IoT devices, storing sensor data, and developing custom applications for data analysis and visualization. In the context of IoT-based agriculture, ThingSpeak [12] serves as a powerful tool for farmers and researchers to monitor and manage farm operations efficiently.

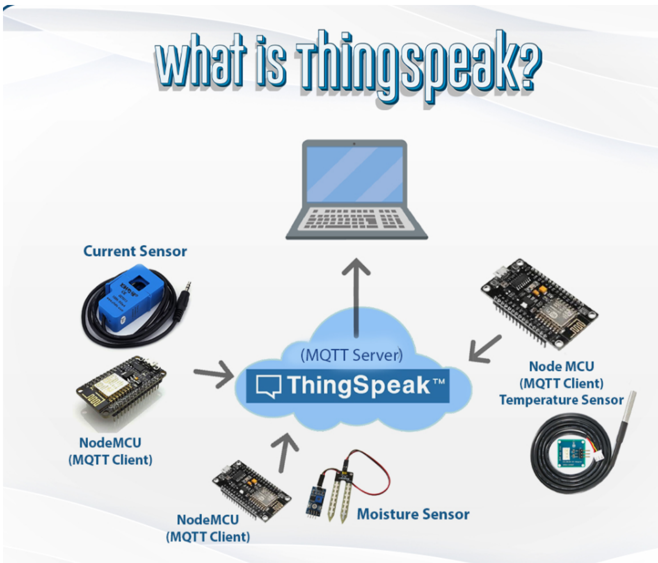

Figure 2.7: Thingspeak Server

2.4 Machine Learning Techniques for Crop and Fertilizer Recommendation System

Random Forest Classifier: The Random Forest classifier is a popular and versatile ensemble learning method used for classification and regression tasks [13]. It operates by constructing a multitude of decision trees during training and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random Forest is an ensemble learning technique based on the "wisdom of crowds" principle, where multiple decision trees are combined to improve predictive accuracy and reduce overfitting. Decision trees are the building blocks of Random Forests, where each tree learns to predict the target variable based on feature values by recursively partitioning the feature space. Random Forest uses bootstrapping, a sampling technique where multiple random subsets of the training data are generated with replacement.

Working Principle: Random Forest begins by randomly selecting subsets of the training data with replacements. This process, known as bootstrapping, creates multiple samples of the dataset. For each bootstrap sample, a decision tree is constructed. The decision tree is trained on a random subset of features at each node, typically referred to as feature bagging or feature randomness. Once all decision trees are constructed, predictions are made for each tree using the corresponding test data. For classification tasks, each tree "votes" for the class label of the input sample. The ultimate prediction is given to the class label that receives the most votes throughout all trees. The Random Forest's ensemble forecast is created by combining the predictions made by each individual decision tree.

The below figure depicts very well:

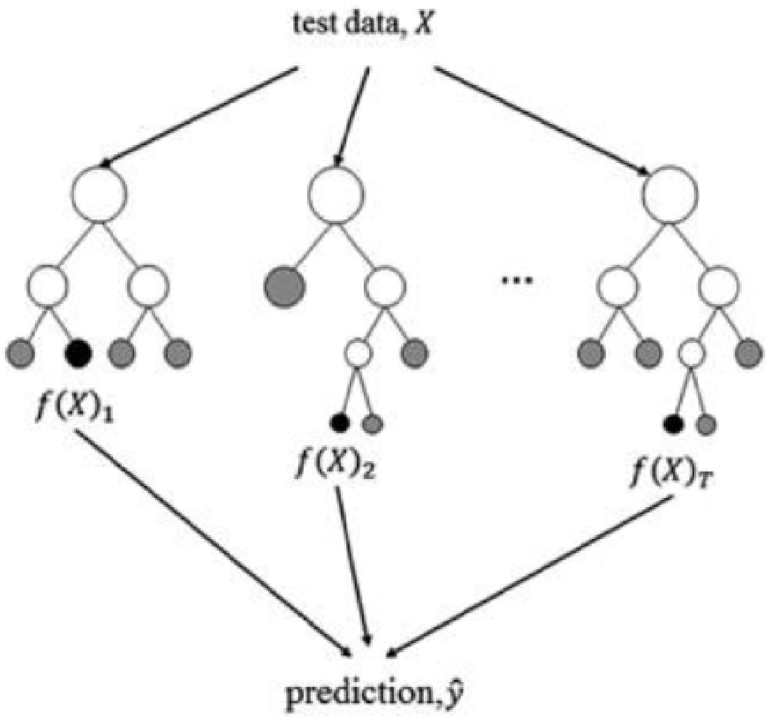

Figure 2.8: Random Forest classifier. (Source: Wikipedia)

Boosting, bagging, and randomized partial regression trees are a few examples of typical ensemble method types. We have used Random Forest Classifier in our thesis work. A common method for training ensemble models is Random forest. we have also compared accuracy results with other ensemble methods.

Naive Bayes Classifier: Naive Bayes is a simple yet powerful probabilistic classifier based on Bayes' theorem with an assumption of independence between features [14]. Despite its simplicity, the Naive Bayes classifier is widely used in various applications, including text classification, spam filtering, sentiment analysis, and medical diagnosis. A key idea in probability theory is the Bayes theorem, which expresses the likelihood of an event depending on past knowledge of its relevant circumstances. In terms of math, it is stated as:

Working Principle: The Naive Bayes classifier uses the Bayes theorem to calculate the posterior probability of each class given the feature values in order to classify an instance with n features. The joint probability of the features can be broken down into the product of the probabilities of each individual feature as it is assumed that the features are conditionally independent given the class label. The anticipated class label is subsequently determined by the classifier by choosing the class with the highest posterior probability..

The below figure depicts very well:

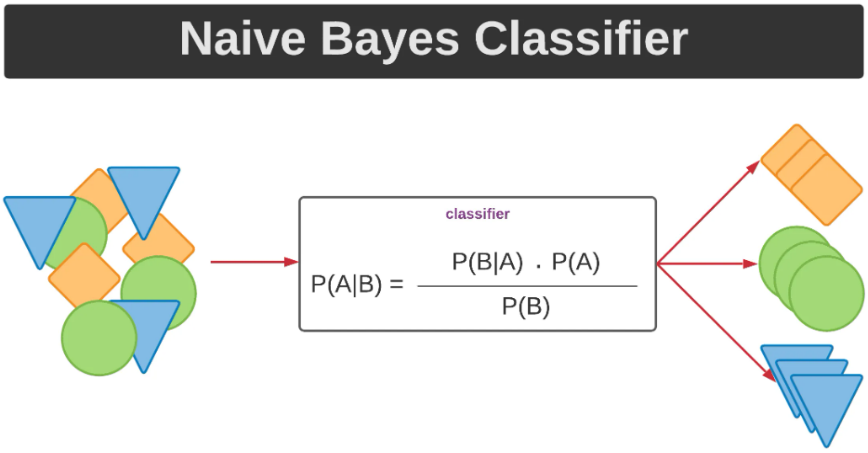

Figure 2.9: Naive Bayes classifier. (Source: Wikipedia)

Gradient Boosting Classifier: Gradient Boosting is a powerful ensemble learning technique that builds a strong predictive model by combining the predictions of multiple weak learners, typically decision trees [15]. It focuses on the residuals of the previous model and trains new models one after the other to fix mistakes caused by the earlier models. Gradient Boosting algorithms, such as Gradient Boosting Machine (GBM), XGBoost, LightGBM, and CatBoost, have become popular in various machine learning tasks due to their high predictive accuracy and robustness.

Working Principle: The Gradient Boosting algorithm minimizes a loss function (e.g., mean squared error for regression, cross-entropy loss for classification) by iteratively adding new models to the ensemble. At each iteration, a new weak learner is trained to predict the residuals (gradient) of the previous models. The predictions of all models in the ensemble are combined to produce the final prediction, typically by summing the individual predictions.

The below figure depicts very well:

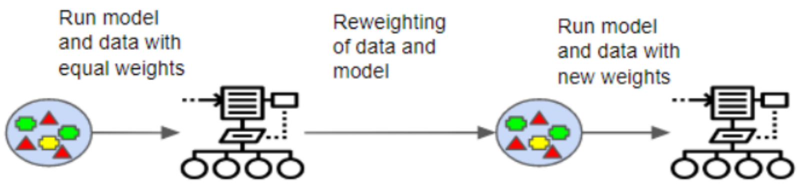

Figure 2.10: Gradient Boosting classifier. (Source: Wikipedia)

SVM Classifier: Support Vector Machine (SVM) is a powerful supervised learning algorithm used for classification and regression tasks [14]. It's particularly effective in high-dimensional spaces and is widely used in areas such as bioinformatics, text classification, image recognition, and more. It is used in different spheres of our work. It is fast and easy to understand. SVM can handle both linearly separable and non-linearly separable datasets using different kernel functions. In the case of linearly separable data, SVM constructs a linear decision boundary to separate the classes. For non-linearly separable data, SVM uses kernel functions to map the original feature space into a higher-dimensional space where the classes become separable.

Working Principle: SVM identifies the hyperplane that maximizes the margin, which is the distance between the hyperplane and the nearest data points from each class, known as support vectors. Mathematically, a hyperplane is defined as the set of points satisfying the equation:

$$wx + b = 0$$

The objective of SVM is to find the hyperplane parameters (w and b) that maximize the margin while satisfying the constraint that all data points are correctly classified.

The below figure depicts very well:

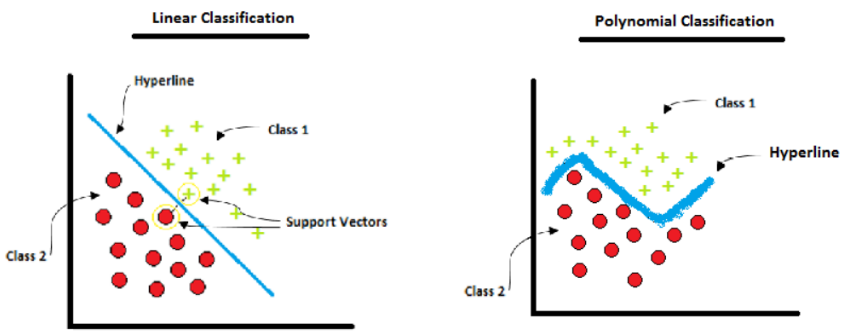

Figure 2.11: SVM classifier. (Source: Wikipedia)

2.5 Background

Here we going to discuss previous work done on this topic. And also we will cover research questions that arise during our work.

2.5.1 Related Works

We present in this section recent research work aimed at the application of IoT based smart farming. Some of they have used AI techniques to enhance the prediction aspect.

This paper [16] proposed a system for recommending crops by taking six parameters as input. These parameters are N, p, k, soil moisture, pH, and temperature. They did performance analysis using different machine learning algorithms.

This paper [13] proposed a system that Can recommend crops using soil temperature, rainfall, and surface temperature. Here they have used random forest, SVM, and naive Bayes model. They have also shown the comparison between this model. Finally, They have made software using this value.

In [17] proposed a system that recommends crops based on soil type and water level. Here They have used SVM and decision tree classifier for predicting crops. Here They found good accuracy.

In [9] proposed a method for optimal nutrition recommendation. Here they have used the regression method. The qualities of the soil are crucial in preserving its fertility; as farming causes the soil's nutrition level to decline annually, this is an appropriate strategy to use in order to maximize soil fertility and boost crop yields.

In [10] proposed a framework for agricultural field monitoring and irrigation control using IoT. Sensor networks and cloud computing platforms are used in the creation of this framework to store and process data in real-time. The system uses a gateway to send data it detects from several field sensors, such as soil moisture, temperature, humidity, and air quality, to the cloud. This technique forecasts the level of dryness in the soil as well as the weather to come. The real-time data collection and weather forecast are used by the system to schedule the irrigation procedure.

In [18] proposed a setup for collecting soil moisture and temperature data through sensing. Here they used Thingspeak to collect data. They also used an Arduino board which controls the high-voltage farming equipment without human intervention.

In [19]proposed a real-time monitoring system for the Measurement Of Soil Fertility Parameters. This system increases crop yield based on pH and humidity parameters. They have used IoT Cloud Thingspeak for monitoring purposes.

In the above research paper, the Researcher has develop a setup for collecting the raw data through different censors such as pH sensor, humidity sensors, temperature sensors, and moisture sensors. Here most of the researcher uses Thingspeak Iot-cloud for raw data collection.

In [20] a solution for the existing automated systems in precision agriculture is developed. Artificial Intelligence (AI) concepts are used in the planned infrastructure to maximise and enhance the outcomes. It can be put into place on both new and existing buildings. To regulate the climate and watering process, two edge nodes and one fog node are suggested. But the fog node is where the AI services are put into practice. Optimizing resources—such as water, energy, etc.—while maintaining production is the ultimate objective.

In [11] presented an automated irrigation system to reduce water utilization in agriculture by combining IoT, cloud computing, and optimization. Their technique consists on the deployment of inexpensive sensors to sense weather, soil type, pH, temperature, and humidity, among other characteristics of interest. Then they proposed a optimization model for reducing water usage.

In [21] presented Iot cloud-based smart agriculture project and then used a transfer learning module in three parameters which is temperature, moisture, and humidity to enhance the performance. Additionally, they emphasized how AI techniques have limitations, particularly when it comes to training speed and accuracy balance, which could impede the integration of machine learning.

In [22] proposed a solution for the water crisis using Iot based smart farming. Here they collect data of soil moisture, temperature, and humidity using Iot cloud and then apply decision tree algorithm which gives answer in yes or no to farmers emails about when to use water in crops.

This paper [23] proposed a model to predict apple diseases. Here use wsn and sensor for collecting raw data using Iot cloud. Here they also identify the problem faced by the apple farmers in Kashmir. They have collected raw data and processed this using transfer learning to predict disease. They have got good accuracy in disease prediction.

This paper [24] proposed a system that recommend both crop and fertilizer based on Ph value and soil moisture. Here the system is integrated with wifi module 8266 for transfer of data. It also analyses soil nutrient content in real-time. This paper [25] proposed a smart decision support system that acquires the input parameters based on real-time monitoring to optimize the yield. It has three basic units smart irrigation unit, intelligent sensor module, and fertilizer module.

In [14] proposed a system that predicts which crops fit well with the factors that influence crop growth, such as soil nutrients, soil pH, humidity, and rainfall. For this purpose, they have used different machine learning algorithm like decision tree, SVM, Naive Bayes, and Logistic Regression.

here above paper gives us a view of the application of Iot based smart farming. An IoT-based agricultural system can provide comprehensive solutions across various applications such as crop and fertilizer recommendations, water crisis management, disease prediction, weather monitoring, and irrigation management. Here several application is covered such as Crop and fertilizer recommendation system, water crisis solving, disease prediction, weather monitoring, and irrigation monitoring.

A summary of some related works is given in the following table 2.1.

Table 2.1: Summary of Related Works

Ref no.	Methods	Algorithms Used	Input Data	Output
[16]	Classifier	SVM,Random Forest,Naive Bayes,DT	soil moisture,N,P,K,pH,Temperature	Crop recommendation
[13]	Classifier	SVM,Random Forest and Naive Bayes	soil temperature,Rainfall	Crop recommendation
[17]	Classifier	SVM and Decision Tree	Soil Type,Water level	Crop recommendation
[9]	Regression	Exploration and exploitation method and improved genetic algorithm	Soil nutrient data	Optimal nutrition recommendation
[10]	Classifier	Rule-based classifier	soil moisture,temperature,air quality	Weather prediction
[18]	Classifier	Rule Based Classifier	Soil moisture and humidity	crop recommendation
[19]	No Methods	No Algorithm	Ph,humidity	Monitoring purpose
[20]	Regression	SVM	Soil data	Optimize water use
[22]	Classifier	Decision tree	Soil data and air data	When to use water
[23]	Regression	SVM	Soil data	Apple disease prediction
[14]	Classifier	SVM,DT,Naive Bayes	soil nutrients,Ph,Humidity,Rainfall	Crop prediction

2.5.2 Research Questions

Our thesis work is about establishing a System for recommending crop and fertilizer. In this work, we have collected data using Thingspeak server. To implement the task there are some research questions have been raised and we have tried to solve these throughout our work. Addressing these questions is critical to developing a robust and effective system. They are the following:

- How to accurately collect and process environmental and soil data using IoT devices?
- How A machine learning model is deployed in Flask?
- What are the potential drawbacks and difficulties of using an ESP32 microcontroller?
- What are the effects and real-world uses of the suggested System?

2.6 Conclusion

The literature review presented in this chapter provides a comprehensive overview of the existing research and knowledge relevant to the development of an IoT-based Crop and Fertilizer Recommendation System. Through an exploration of various studies, methodologies, technologies, and challenges, key insights have been gained into the current landscape of agricultural IoT solutions and their potential applications in enhancing crop management practices. The review highlighted the significance of IoT technology in modern agriculture, offering a transformative approach to farm management through real-time monitoring, data-driven decision-making, and automation. By leveraging IoT-enabled sensor networks, farmers can collect valuable data on soil conditions, environmental parameters, and crop health, enabling them to optimize resource usage, improve productivity, and promote sustainable farming practices. Furthermore, the review identified several essential components of IoT-based agricultural systems, including NPK sensors, soil moisture sensors, pH sensors, soil temperature sensors, air temperature sensors, and air humidity sensors. These sensors play a crucial role in capturing real-time data on soil and environmental conditions, providing farmers with insights to make informed decisions about irrigation, fertilization, pest control, and crop management. Moreover, the review discussed the integration of the ThingSpeak server as a central hub for collecting, storing, analyzing, and visualizing sensor data in IoT-based agriculture systems. ThingSpeak's user-friendly interface, real-time data visualization tools, advanced analytics capabilities, and integration with external services make it a valuable platform for farmers, researchers, and agricultural professionals to monitor and manage farm operations effectively.

Chapter 3

Methodology

3.1 Introduction

This chapter includes our proposed methodology for our proposed system for recommending crops and fertilizers for real-time data. The entire procedure of data collection with experimental setup and then processing the data then applying the machine learning model. Furthermore, the deployment of the developed model within a Flask framework provides a user-friendly interface, allowing farmers and agricultural stakeholders to access personalized crop and fertilizer recommendations seamlessly. The integration of a visually appealing and intuitive interface enhances the usability and adoption of the system, thereby bridging the gap between advanced technological solutions and end-users in the agricultural domain. Overall, this thesis aims to contribute to the advancement of precision agriculture by offering a practical and efficient solution for crop management and fertilizer optimization.

3.2 Proposed Crop and Fertilizer Recommendation System

In this thesis, we tried to create a system for Recommending crop and fertilizer type. We have proposed a fully operational approach that can be used to apply our method. The entire functionality can be divided into five parts:

1. Hardware Configuration

2. Data Collection

3. Data Preprocessing

4. Approched Models

5. Deployment of the model in Flask framework

3.2.1 Hardware Configuration

The most important and primary step in our proposed framework is the hardware configuration. Here Different types of sensors are connected to the Arduino Uno board. Using this hardware configuration we have collected real-time data from the soil of different crops field. Here parts of different sensors are connected to Arduino board in different configurations.

3.2.1.1 NPK Sensor Configuration

At first, we connected the ground pin to the ground of Arduino and display and then connected the VCC pin to the VCC of Arduino and Display. We have connected the two wires which are colored Yellow and Blue with RS-485 A and B pins respectively. We have connected Arduino A4 and A5 pins to the display. Finally, we have connected RS-485 with Arduino for collecting data through the ESP-32 module.

The connection is given below:

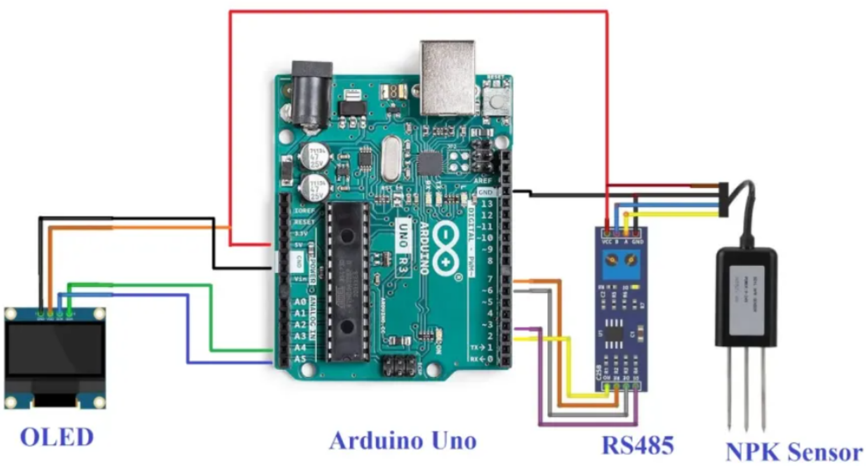

Figure 3.1: NPK Sensor Configuration

3.2.1.2 pH Sensor Configuration

The connection is given below:

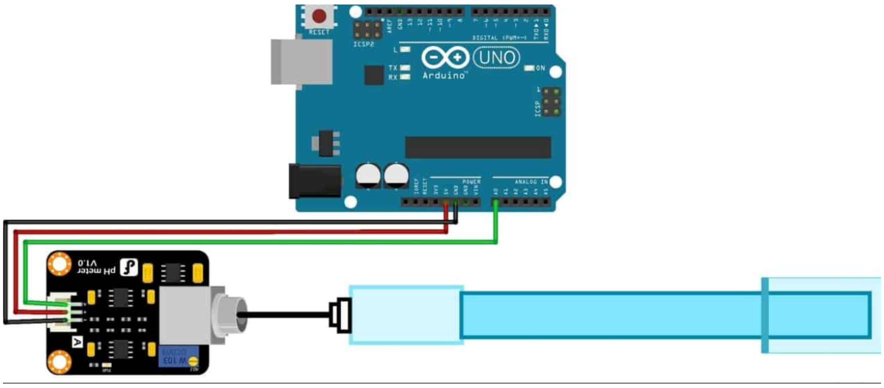

Figure 3.2: pH Sensor Configuration

3.2.1.3 Soil Moisture Sensor Configuration

The connection is given below:

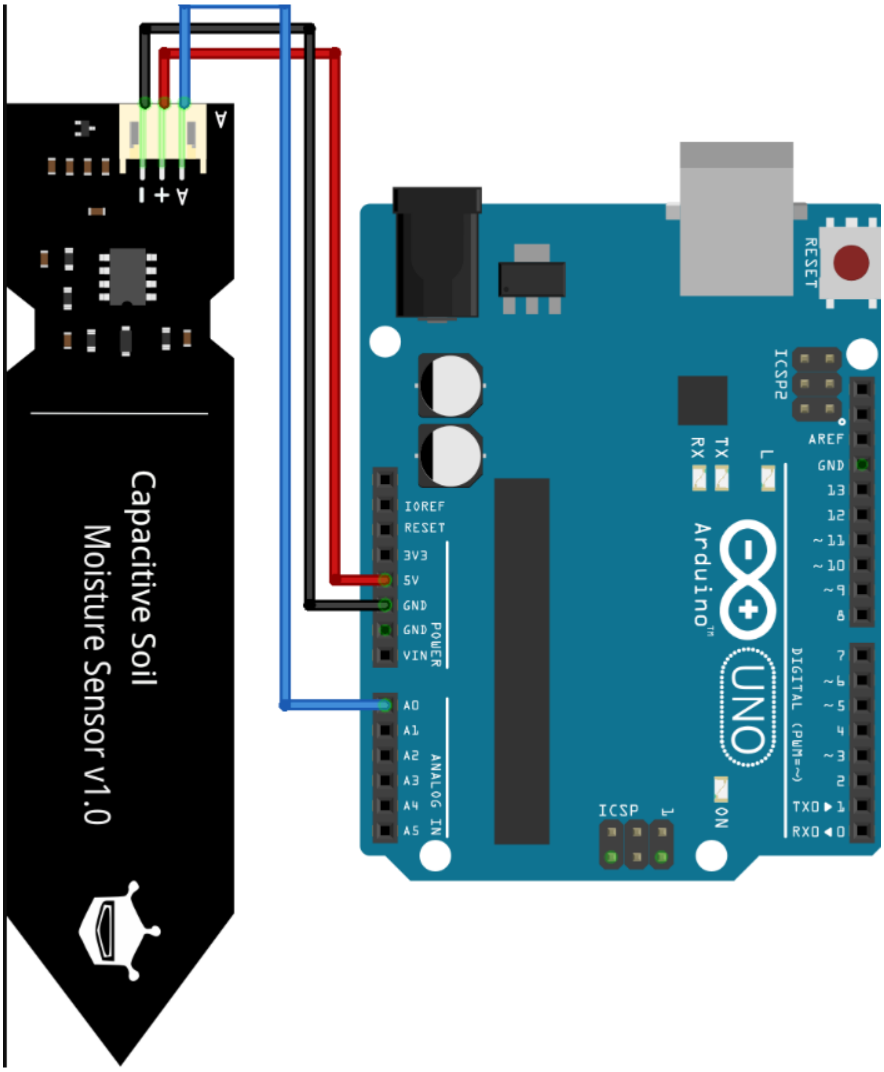

Figure 3.3: Soil Moisture Sensor Configuration

3.2.1.4 Soil Temperature Sensor Configuration

The connection is given below:

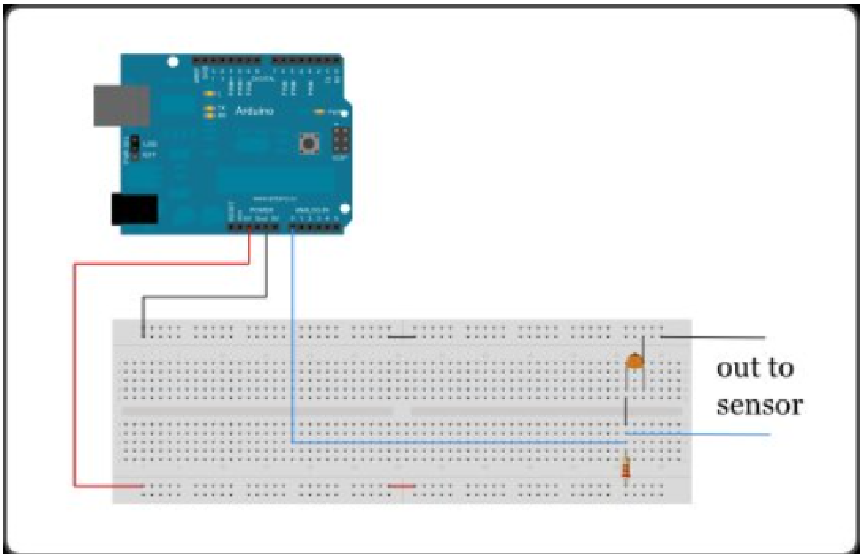

Figure 3.4: Soil Temperature Sensor Configuration

3.2.1.5 DHT11 Sensor Configuration

The connection is given below:

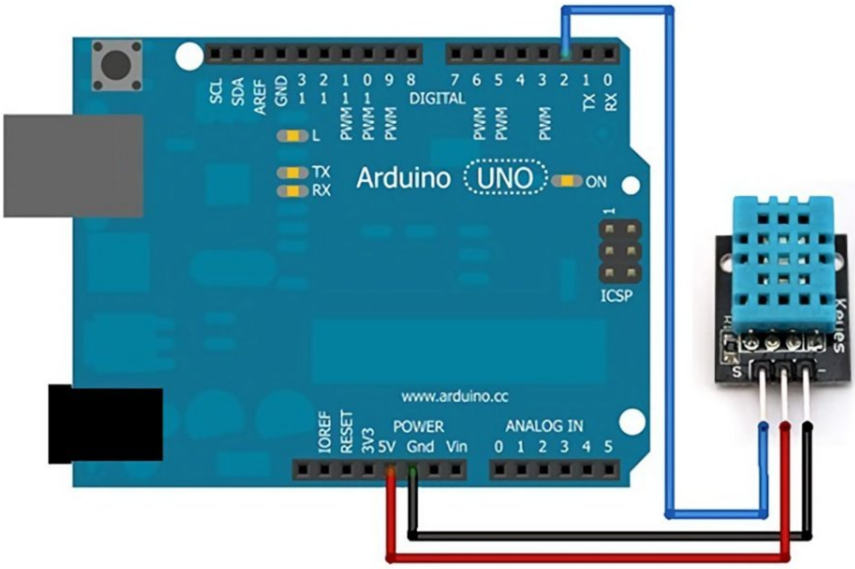

Figure 3.5: DHT11 Sensor Configuration

3.2.2 Data Collection

Here we have collected data using two ESP-32 receiver and transmitter. The transmitter is connected to Arduino. Here we have used the ThingSpeak server for collecting the data. For this, we have run two codes on our Arduino IDE software in our company. One code is for the transmitter another is for the receiver. Here all the sensor is touched with soil.

3.2.3 Data Preprocessing

Here, preprocessing is performed before training the model. Specifically, the following preprocessing steps are carried out:

Min-Max Scaling: MinMaxScaler is used to scale the features to a specific range, usually between 0 and 1. Here we have done it to increase the performance of model [26].

Standardization: StandardScaler is used to standardize the features by removing the mean and scaling to unit variance. Here we also have done this to increase the performance of our model [27].

3.2.4 Approached Models for Crop and Fertilizer Prediction

Here we have fed our dataset with different machine learning models. At first, we tried linear regression classifier. Then we tried the Random Forest classifier and then Naive Bayes classifier. After some days we have fed Gradient Boosting and SVM classifier. Here we have compared accuracy. The model which have largest accuracy, we have deployed using Flask framework to make the app.

3.2.5 Deployment of Model in Flask Framework

For deployment in the Flask framework, we have selected the Random Forest classifier. For this, at first, we created a folder, where we created a file name app where we wrote Flask code. In this folder, we created an index file,where we created an intuitive user interface using HTML and CSS[5]. Finally, we ran the code and we found the output in our browser.

3.3 Implementation Procedure

As we mentioned earlier that we have five major steps that are required to establish the proposed system of recommending crop and fertilizer types. But at first, we have to fulfill some software and hardware requirements.

3.3.1 System Setup

In this section, we have described the required equipment for the experiment, the hardware, and the software requirements that are needed to implement the proposed framework.

3.3.1.1 Hardware Setup

Here we have used a previously made IoT device setup to collect the data from different fields. Here we have used the NPK sensor for collecting Nitrogen, Potassium, and Calcium data from the soil. We have used a Soil moisture sensor for collecting soil moisture data. Soil temperature sensor for collecting soil temperature data. We have used a pH sensor for collecting the pH of soil and a DHT 11 sensor for collecting air humidity and air temperature data. We have used two pairs of ESP-32 transmitter and reciever for collecting data[28]. The whole device is connected to a laptop.

3.3.1.2 Software Setup

We have used Arduino IDE and Iot cloud Thingspeak Server to collect data[19]. After collecting data we have used google colab to run our model. Here we have used it to see how our model performs based on Accuracy, Precision, Recall, and F1 score[29]. We have used pycharm community addition for deploying our model in Flask. We have used HTML(Hyper Text Markup Language) and CSS(Cascading Style sheets) for making the user interface[5].

3.3.2 Steps of Implementation

For the implementation of our system, we have done different things in steps. Here at first, we have collected the data from different fields. Then we preprocessed data. After that, we split the dataset into train and test. Here we have used a trained set for training the model. On the other hand test set for evaluating the model. The model that gives the best performance, we deployed it in Flask[5]. Finally, we got the recommendation in the user interface. From the overall methodology, we can understand how our system works for recommending crops and fertilizer. The overall methodology of our system is given below:

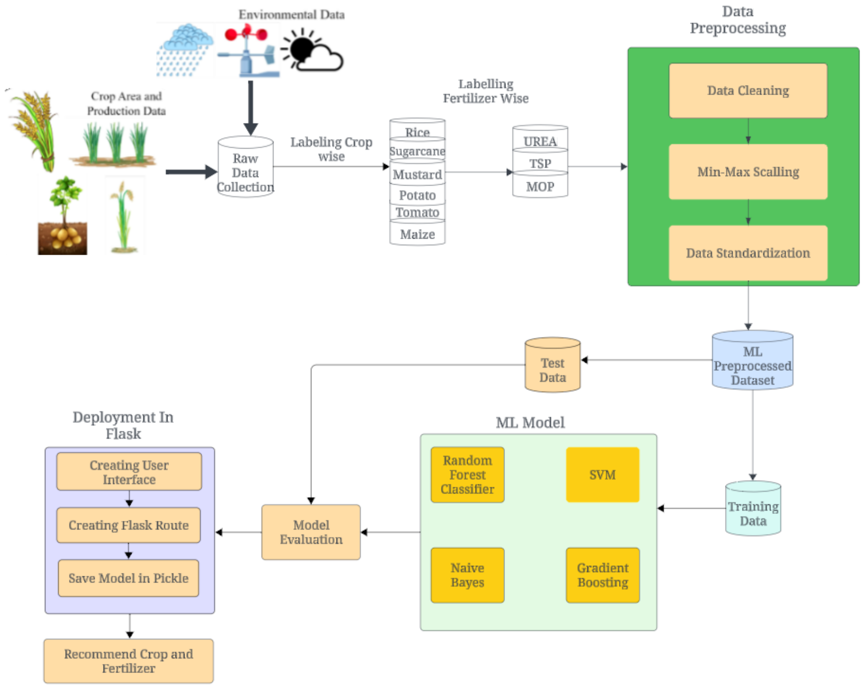

Figure 3.6: Proposed Methodology

The steps are discussed below:

Data Collection: At first, we have collected data from the field of different crops which we have selected. For this, we have used an Iot device configuration. For this, we have used ESP-32 receiver and transmitter. Also, we have used the Thingspeak server as IoT cloud. After Data collection we have labeled them with corresponding crops and fertilizers. In this way, we have made our final dataset.

Data Preprocessing: Here we have done feature scaling using min-max scaling and standardization. We have done it for greater performance.

Splitting Dataset into Train and Test: In this step, we have split the dataset into train and test. Here we have taken 40 percent for tests and 60 percent for training. We have done it for performance measurement.

Trained Model: Here we have trained the model. Here we have used different machine learning algorithms. Here we have used Random Forest, Naive Bayes, Gradient Boosting, and SVM Classifier.

Evaluate Model: Here we have evaluated the model on the testing dataset. Here after model training accuracy, precision, recall, and F1 score for the model are evaluated[29]. After all evaluation, we have taken a decision on which model, we should deploy in Flask framework[5].

Deployment in Flask Framework: Here we have deployed the trained model which has the highest accuracy, precision, recall, and F1 score[29] value is deployed in Flask framework[5]. In flask framework [5] at first model is saved in pickle. Then model is reloaded in model. Here user gives input to the Flask [5] API. After that Flask [5] API gives feature to the model. Then the model predicts the value in Flask[5] API. Then user can see the output in the front end.

To do this, we have to perform some work. They are given below:

User Interface Design: Here We have designed the user interface using HTML and Bootstrap. In order to make the user interface easy to use for farmers and other agricultural stakeholders, it is meant to be straightforward, engaging, and visually appealing. Here are the key elements of the user interface:

Input Fields: The application presents input fields for users to enter values for parameters such as N, P, K levels, soil moisture, soil temperature, pH, air humidity, and air temperature. Each input field may include tooltips or hints to guide users in providing accurate information.

Submit Button: A prominent "Submit" button allows users to submit their input data for processing and recommendation generation.

Output Display: The application displays the recommended crop types and corresponding fertilizer types based on the input parameters. This output is presented clearly and prominently to ensure users can easily interpret and act upon the recommendations.

Creating Flask App Here at first, we had imported the necessary library which needed for our system. Then we created a flask [5] route through which we can access our user interface. Here we have written the code using which we can predict or recommend particular crops and fertilizers.

this diagram shows how Flask [5] recommend certain things:

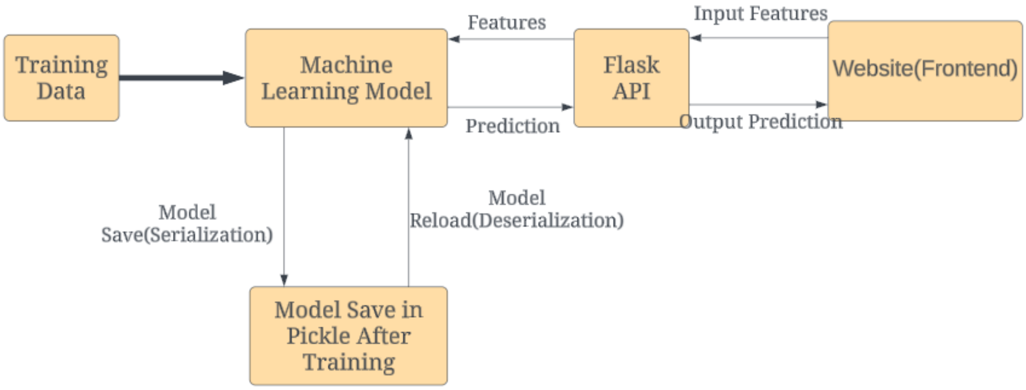

Figure 3.7: Flask Working

This image describes the flask [5] framework more easily.

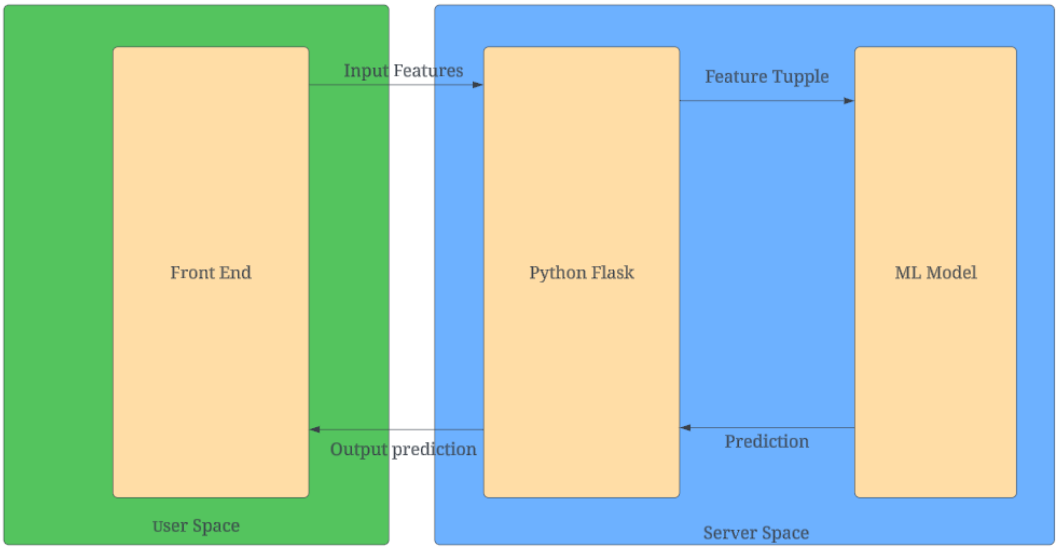

Figure 3.8: Flask Framework

3.4 Conclusion

In conclusion, the methodology outlined in this chapter presents a comprehensive framework for the development and deployment of an IoT-based Crop and Fertilizer Recommendation System. Through a systematic approach encompassing data collection, processing, model application, and user interface design, our proposed system aims to address the complexities of modern agricultural management while facilitating seamless interaction for end-users. By bridging the gap between advanced technological solutions and end-users in the agricultural domain, our proposed system aims to democratize access to precision agriculture tools and empower stakeholders with actionable insights for enhanced productivity and sustainability.

Chapter 4

Results and Discussions

4.1 Introduction

The technique for developing the system for recommending crops and fertilizers was explained in depth in the previous chapter. We implemented the methodology and now it's time to assess the outcomes. Discussion about the results of the used models and the performance evaluation of the method will be analyzed in this chapter. As our system deals with crop and fertilizer recommendations which is a string so accuracy is the performance indicators that will be used to evaluate the model. Graphs and charts of the results have been also covered in this chapter. We also covered user interface of our app that has been created after deployment in Flask. A comparison between the implemented models has been included at the end of this chapter.

4.2 Evaluation Measures

For the evaluation of this thesis, several evaluation measures can be employed to assess the performance and effectiveness of the system in providing accurate crop and fertilizer recommendations. Here are some evaluation measures that we have considered:

Accuracy: Accuracy measures the proportion of correct predictions made by the recommendation system [29]. It is computed as the ratio of the total number of guesses to the number of right forecasts. The following is the accuracy formula:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.1}$$

Precision: Precision measures the accuracy of positive predictions made by the system [29]. The ratio of actual positive forecasts to all positive predictions is used to compute it. The following is the precision formula:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4.2}$$

Recall: Recall calculate the ability of the system to correctly identify positive instances [29]. The ratio of genuine positive forecasts to the total number of real positive occurrences is used to compute it. The following is the recall formula:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4.3}$$

F1 Score: The F1 score is the harmonic mean of precision and recall [29]. It offers a harmony between recall and precision. Below is the formula for the F1 score:

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4.4}$$

4.3 Dataset Analysis

Here we will analyze our dataset. Here in our dataset, at first, we have collected 8 parameters using an Iot device configuration. These 8 parameters are N, P, K, soil moisture, soil temperature, pH, air temperature, and humidity. After collecting this data from differnt field near our university, we have labeled the data with 6 crops where we have collected data. For example, if we collected data from rice field we have labeled it with rice. Here 6 crops are rice, sugar cane, tomato, mustard, potato, and maize. After labeling with crop then we labeled with fertilizer types. Here we have used three fertilizers. They are UREA, TSP, MOP. For example, if the field from where we collected data if they use urea we will label it with urea.

The snapshot of our data set is given below:

	N	P	K	temperature	humidity	ph	moisture	soil temp	crops	Fertilizer
0	90	42	43	20.879744	82.002744	4.502985	30.4	25.6	rice	urea
1	85	58	41	21.770462	80.319644	5.038096	30.5	25.7	rice	urea
2	60	55	44	23.004459	82.320763	4.840207	30.4	25.6	rice	urea
3	74	35	40	26.491096	80.158363	4.980401	30.5	25.5	rice	urea
4	78	42	42	20.130175	81.604873	4.628473	30.6	25.4	rice	urea

Figure 4.1: Dataset

Heatmap: Here we are showing how all the numerical parameter of our system is correlated. Here the red one denotes the positive correlation and the blue one denotes the negative correlation. The snapshot of the heatmap is given below:

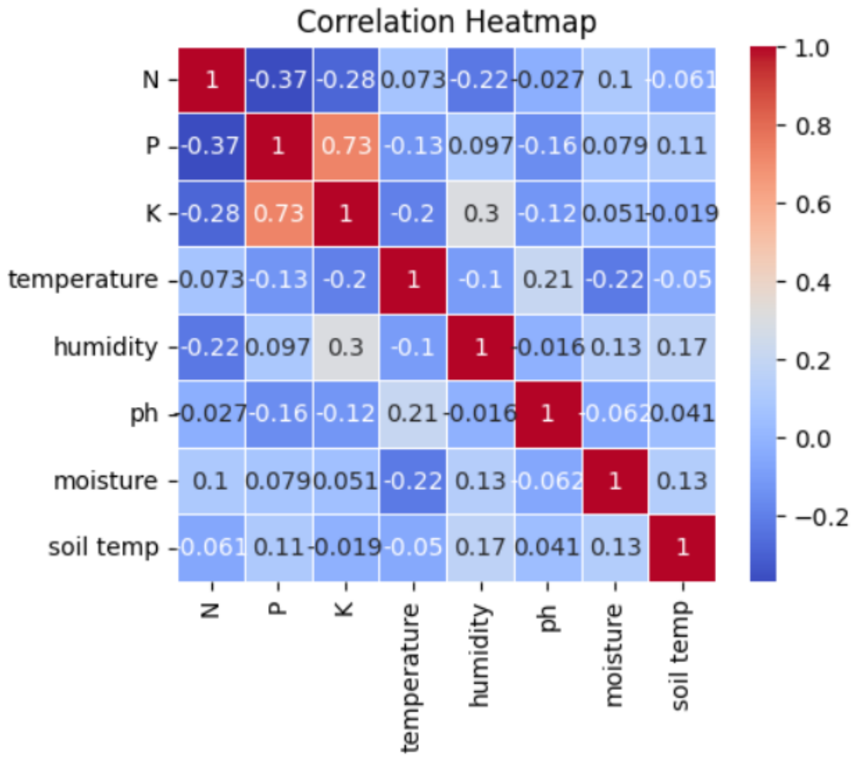

Figure 4.2: Heatmap

Distribution of Crops:

Here how many datasets of different crops are collected. Here we have taken the most data for maize followed by potato.

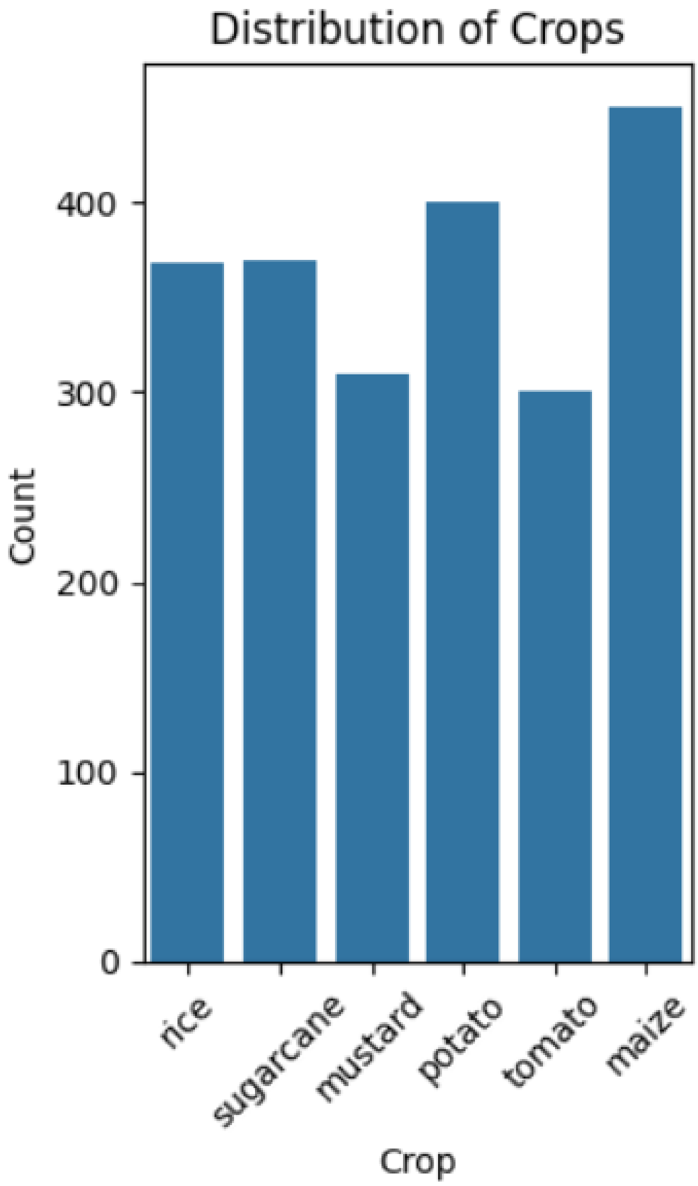

Figure 4.3: Distribution of Crops

Distribution of Fertilizer:

Here how many datasets of different Fertilizers are collected.

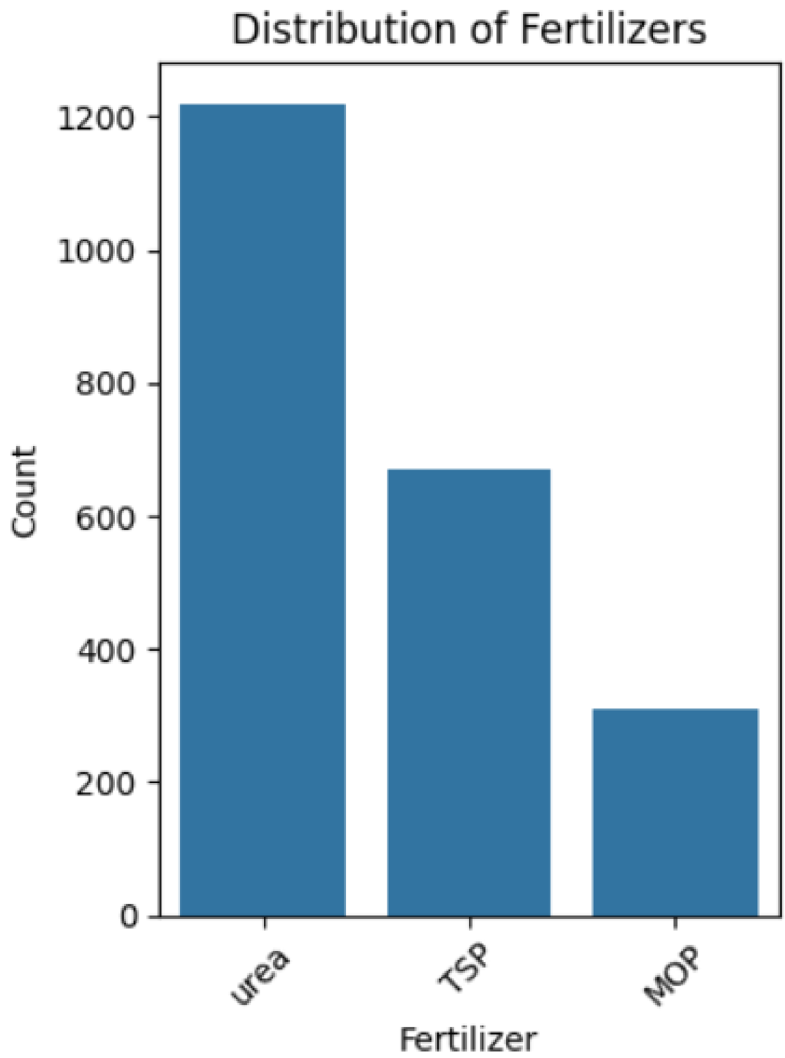

Figure 4.4: Distribution of Fertilizer

4.4 Evaluation of Performance

In this thesis work after collecting data from different field and then by labeling with crops and fertilizer type. Then we had fed this dataset into a machine learning model. Here we have used different machine learning model. Here we have used Random Forest classifier, Naive Bayes classifier, Gradient Boosting classifier, and SVM classifier. In the latter part of this section, we have presented some performance comparisons and analyses.

4.4.1 Model Performance Illustration

We have used different machine learning classifier models for our system. Here we have shown the Accuracy, precision, recall, and F1 score of our implemented model as its overall performance[29]. Each of these metrics provides different insights into how well the model is performing.

In this table, we are giving model performance for crop prediction.

Table 4.1: Overall Model Performance for crop prediction

Model	Accuracy	precision	Recall	F1 Score
Random Forest Classifier	97.86	0.973	0.973	0.974
SVM Classifier	88.97	0.891	0.889	0.889
Naive Bayes Classifier	77.61	0.802	0.776	0.770
Gradient Boosting Classifier	97.75	0.977	0.977	0.978

In this table, we are giving model performance for Fertilizer prediction.

Table 4.2: Overall Model Performance for Fertilizer prediction

Model	Accuracy	precision	Recall	F1 Score
Random Forest Classifier	98.78	0.994	0.994	0.995
SVM Classifier	82.61	0.824	0.826	0.824
Naive Bayes Classifier	75.22	0.784	0.752	0.760
Gradient Boosting Classifier	97.31	0.972	0.971	0.973

4.4.2 Confusion Matrix

Here we all show the confusion matrix for all our model[30]. These matrices will help you understand how well the model is performing in terms of true positives, false positives, true negatives, and false negatives for each prediction [30].

Random Forest Classifier: Here given the Confusion Matrix[30] for Crop and Fertilizer recommendation:

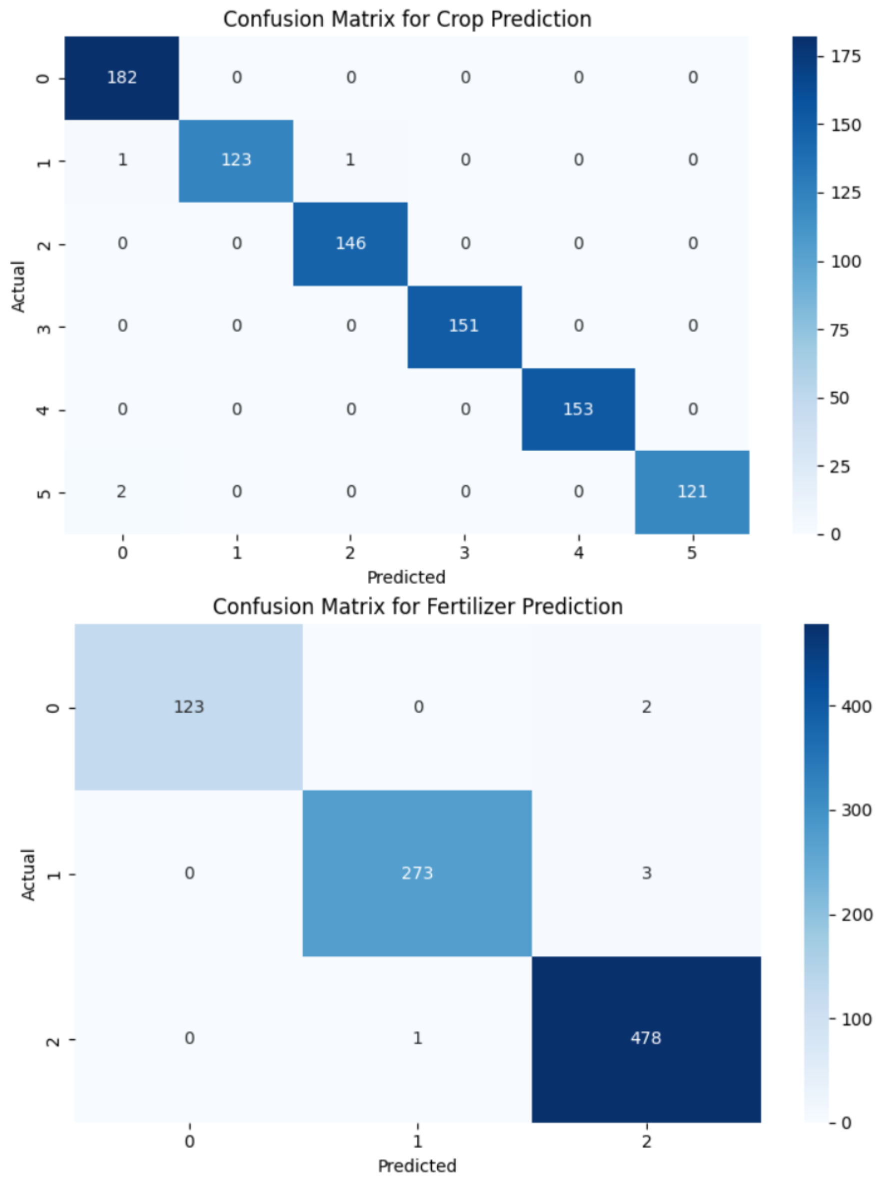

Figure 4.5: Confusion Matrix for Random Forest Classifier

SVM Classifier: Here given the Confusion Matrix[30] for Crop and Fertilizer recommendation:

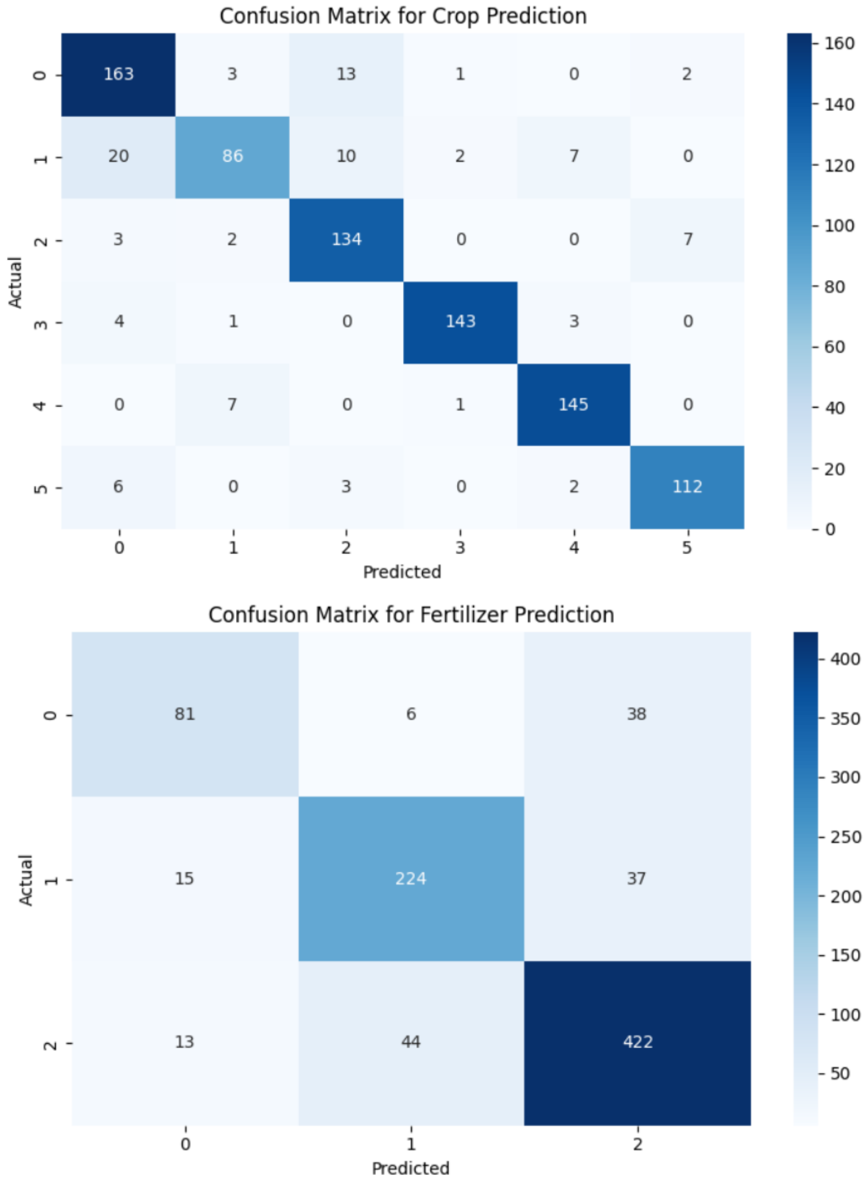

Figure 4.6: Confusion Matrix for SVM Classifier

Naive Bayes Classifier: Here given the Confusion Matrix[30] for Crop and Fertilizer recommendation:

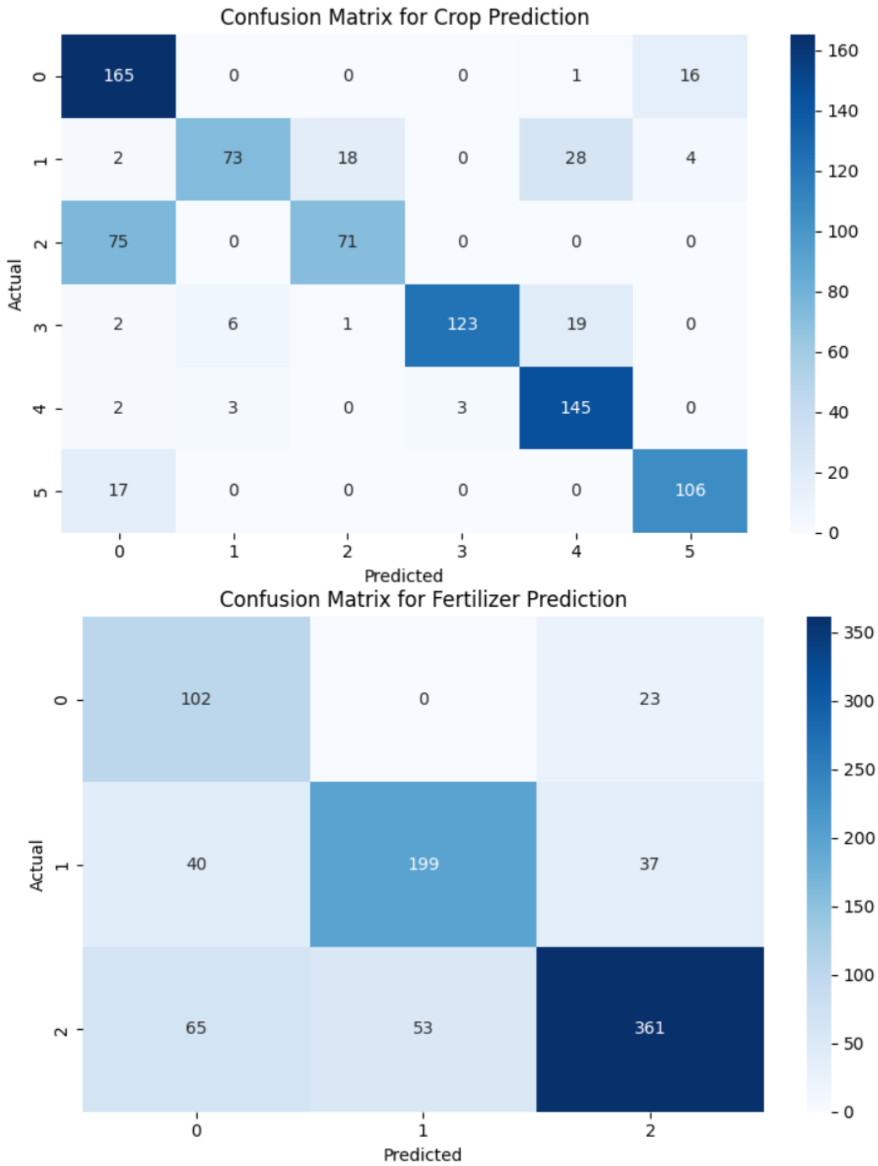

Figure 4.7: Confusion Matrix for Naive Bayes classifier

Gradient Boosting Classifier: Here given the Confusion Matrix[30] for Crop and Fertilizer recommendation:

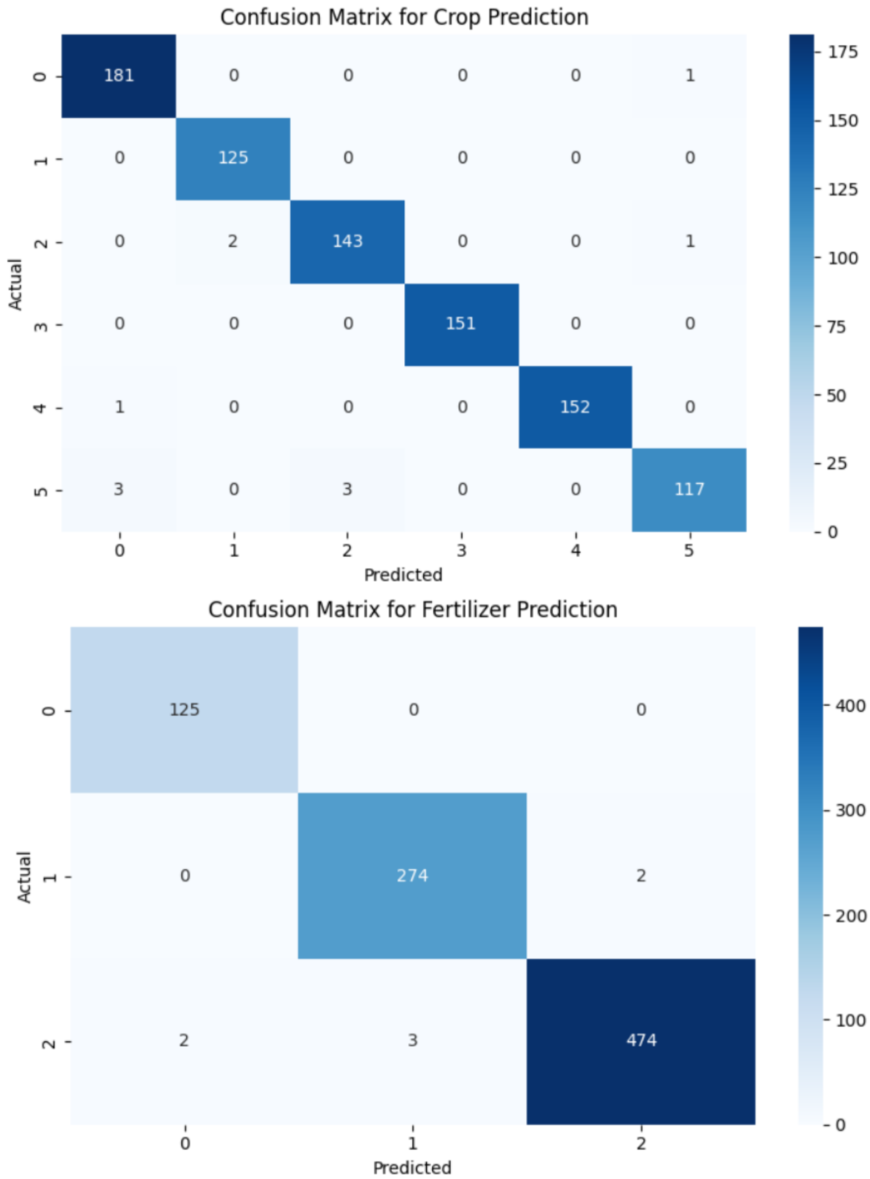

Figure 4.8: Confusion Matrix for Gradient Boosting Classifier

4.4.3 Discussion

From the above analysis, we have found that the Random Forest classifier give the best performance. Its accuracy is 97.86 percent for crop prediction. But for fertilizer prediction, its accuracy is 98.78 percent. The precision, recall and F1 score values are also good for the Random Forest classifier. This gives the worst result for Naive Bayes Classifier which is 77.61 for crop and 75.22 for fertilizer. As here our dataset is very low we got better results with machine learning. That's why we haven't tried the deep learning approach. We have deployed the Random Forest classifier as our model in the Flask framework.

4.5 User Interface

In the user interface section of this thesis, the focus is on designing an intuitive and user-friendly application using Flask [5]. The application serves as a platform for users to input various parameters related to soil and environmental conditions, such as N, P, and K levels, soil moisture, soil temperature, pH, air humidity, and air temperature. Based on these inputs, the application provides recommendations for suitable crop types and corresponding fertilizer types. Our user interface contains:

The snapshot of our user interface is given below:

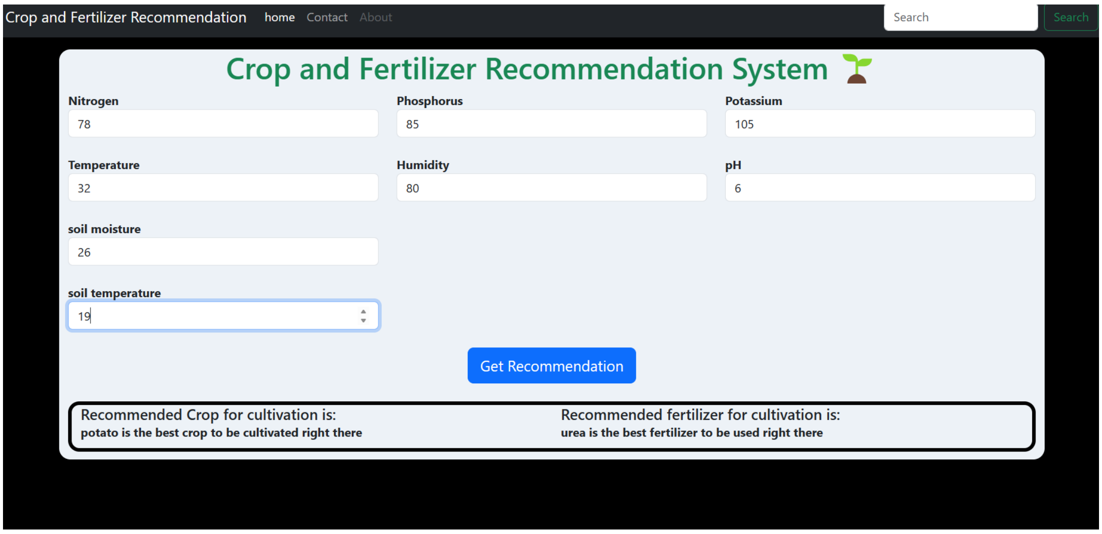

Figure 4.9: User Interface

4.6 Comparison Analysis

Here we will do the comparison between existing system and my proposed system. It is depicted in the table below:

Table 4.3: Comparison Analysis

Comparison Parameter	Existing Method [16]	Proposed Method
No. of Parameter Used	6	8
Crop Prediction	Yes	Yes
Fertilizer Prediction	No	Yes
Accuracy for Crop Prediction	97.18 percent	97.86 percent
Accuracy for Fertilizer Prediction	No	98 percent
No. of Crops Used	4	6
No. of Fertilizer Used	No	3
Application Made	No	Yes

4.7 Conclusion

In this thesis work our main goal was to establish a system for predicting crop and fertilizer using an IoT device configuration. In order to do so, at first we configured our hardware and collected raw data using two pairs of ESP32 microcontrollers[28]. We also preprocessed the raw data. The entire process has been discussed in the previous chapter. Our datasets have been fed to machine learning methods. In this chapter, we discussed about result found after running our dataset in Machine Learning model. We got the best results using the Random Forest classifier of the machine learning method for recommending crops and fertilizers. Using this classifier we have created an app using Flask framework. For this, we have created an intuitive user interface. Here we have also discussed about precision, recall, and F1 score [29] of our all model. Here we also discussed about confusion matrix of our model. In conclusion, we can say that our model gives the best result for the Random Forest irrespective of any parameter.

Chapter 5

Conclusion

5.1 Conclusion

In conclusion, the development and implementation of the IoT-based Crop and Fertilizer Recommendation System represent a significant advancement in precision agriculture, offering farmers a powerful tool for enhancing productivity, sustainability, and resource efficiency. Through the integration of Internet of Things technologies and advanced machine learning algorithms, this system facilitates real-time monitoring, analysis, and decision-making based on a comprehensive array of environmental parameters. The successful implementation of this system has been demonstrated through extensive field trials and validation studies, which have highlighted its effectiveness in providing accurate and timely fertilizer recommendations tailored to specific crop and soil conditions. By leveraging IoT-enabled sensors to capture real-time data on soil nutrients, moisture levels, temperature, and other environmental factors, the system enables proactive management of agricultural resources, minimizing waste and optimizing crop yields. The predictive models developed within this framework utilize machine learning techniques to analyze complex relationships among environmental variables and crop fertilizer requirements. Through iterative training and refinement, these models exhibit robust performance in predicting optimal fertilizer compositions and application rates, thereby empowering farmers to make data-driven decisions for maximizing agricultural output while minimizing environmental impact.Furthermore, this system offers scalability and adaptability, capable of accommodating diverse crop types, soil profiles, and climatic conditions. Its flexibility allows for seamless integration with existing farm management systems, facilitating smooth adoption and utilization by farmers across different regions and scales of operation. Overall, the IoT-based Crop and Fertilizer recommendation system represents a significant step forward in the evolution of precision agriculture, offering a holistic approach to crop management that combines real-time data monitoring, predictive analytics, and actionable recommendations. This system can recommend crops and fertilizers with high accuracy. The Random Forest classifier can recommend at accuracy of over 97 percent for crop. On the other hand for fertilizer, it can be recommended at over 98 percent. By harnessing the power of IoT and machine learning technologies, this system holds great potential for revolutionizing agricultural practices, promoting sustainability, and addressing the challenges of feeding a growing global population in the face of climate change and resource constraints. As we continue to refine and expand upon this technology, it is ready to play a pivotal role in shaping the future of farming towards a more efficient, and sustainable agricultural ecosystem.

5.2 Limitations & Future Work

While the proposed IoT-based Crop and Fertilizer Recommendation System offers significant advancements in agricultural management, it is important to acknowledge its limitations. Understanding these limitations is crucial for further improvement and effective deployment. Our proposed IoT-based Crop and Fertilizer Recommendation System has several limitations. Some of them are mentioned below,

- This system has been developed in a real environment. So, there might be some environmental disturbance present in our setup.
- Our system is trained for only 6 crops and three fertilizers.
- The proposed system could not include a large number of parameters.
- The proposed system hasn't covered the large area. Here we collected our data from some certain area which is small.

It is nowadays popular. some of the future works of our system are mentioned below:

- It can be updated with more crops and fertilizers.
- Accuracy also can be increased.
- A more efficient system can be made.
- Data can be collected from different areas not particularly one area.

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