



Real-Time Soil Monitoring for Optimal Crop Growth via Interactive

Dashboard

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Abstract - This abstract introduces a soil monitoring system designed to enhance agricultural practices through real-time monitoring of soil moisture and nutrition levels. The system employs industry-standard sensors, including a soil moisture sensor and an NPK sensor, along with an ESP8266 microcontroller equipped with a MAX485 TTL to RS-485 interface module. These sensors are embedded in the soil, providing continuous data on soil conditions. The soil moisture sensor assesses soil water content, while the NPK sensor measures vital nutrients like nitrogen, phosphorus, and potassium. To enable wireless data transmission, the ESP8266 microcontroller acts as a central node, interfacing with the sensors via the RS-485 protocol, known for its reliability in long-distance and multi-node communication. Moreover, the system incorporates machine learning to analyze collected data, constructing a model that identifies patterns and correlations between soil parameters, crop types, and required fertilization based on historical data. This model generates predictions, recommendations, and early alerts for optimal irrigation schedules and fertilizer applications. The processed data, machine learning insights, and recommendations are presented through a user-friendly monitoring dashboard accessible via web or mobile interfaces. This dashboard offers real-time visualizations, alerts, and analytics, enabling farmers to make informed decisions remotely. Overall, this soil monitoring system offers benefits such as real-time data collection, wireless connectivity, and a userfriendly dashboard. By merging sensor technology with advanced communication modules and machine learning, it empowers farmers with actionable insights, leading to improved crop yield, reduced water usage, and optimized fertilizer utilization.

Keywords: Soil moisture, Nutrient levels, Real-time sensors, Fertilizer recommendations, Crop guidance, Interactive dashboard.

1.INTRODUCTION

One of the oldest and important human activities, agriculture has undergone substantial evolution over time, incorporating technical developments to satisfy the rising demands of a rapidly expanding global population. In this pursuit, real-time monitoring of crucial soil parameters has emerged as a cornerstone for effective agricultural practices, enabling farmers to make informed decisions and optimize resource management. This abstract unveils a novel soil monitoring system designed to provide continuous and precise measurements of soil moisture and nutrition levels, which are vital factors governing crop health and productivity. The heart of this innovative soil monitoring system lies in the integration of industrial-

standard sensors, specifically a soil moisture sensor and an NPK sensor, coupled with the ESP8266 microcontroller equipped with a MAX485 TTL to RS-485 interface module. The combination of these elements allows the system to gather critical data directly from the soil, facilitating accurate and reliable measurement of both water content and the concentration of essential nutrients like nitrogen, phosphorus, and potassium. Leveraging the ESP8266 as a central node and employing the RS-485 protocol for longdistance communication, the collected sensor data is wirelessly transmitted, ensuring seamless connectivity and multi-node support. However, beyond real-time data collection lies an even more powerful aspect of this system is the incorporation of machine learning. By harnessing the capabilities of machine learning algorithms, the soil monitoring system becomes more than just a datagathering tool, it transforms into an intelligent agricultural advisor. Through the analysis of historical data, the machine learning model identifies intricate patterns and relationships between soil moisture, nutrient levels, and crop health. Armed with these insights, the system generates predictions, personalized recommendations, and early warnings, empowering farmers to make informed decisions remotely, fostering optimal crop growth, and efficient resource management. The proposed soil monitoring system offers real-time insights into the dynamic soil conditions, eliminating the need for manual labor-intensive measurements. The wireless connectivity streamlines data collection, making it easily accessible for prompt decision-making. Furthermore, the user-friendly monitoring dashboard, accessible through web and mobile interfaces, presents data visualization, alerts, and analytics in a comprehensible manner, ensuring ease of use for farmers and agricultural professionals.As we move towards more technology-driven agricultural landscape, а innovations like this soil monitoring system stand as a testament to the potential of transforming traditional farming practices into smarter, more efficient and environmentally conscious operations.

2.LITERATURE SURVEY

Supachai Puengsungwan (2020) has introduced IoT environment for smart farming, according to the literature review. The ESP8266 NodeMCU has been introduced as the connected device to deploy the IoT-based connected sensor. The task of the linked sensor built on the ESP8266 platform is to measure and update the soil moisture data on the cloud platform. Additionally, the user interface has been developed to link to the IoT environment for real-time data monitoring and analysis. MATLAB connected to the cloud has been utilized to examine the real-time moisture data for data analytics.[1]



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might be applied to other industries, such as agriculture. [4]

majority of modern technology focuses on high-end machinery and robots that assist in completing the fundamental agricultural operation and enable farmers to eradicate weeds and apply pesticides and chemicals to the field. With this technology, we are focusing more on the issues that farmers are most worried about, such as the health of the farming land, the quantity of pesticides needed for the field without negatively compromising the crop's lifetime and the nutrient value of the soil. Compared to earlier work in this field, our top priority in this project has been to use the enormous potential of distributed, coordinated systems and sensors to revolutionize soil testing systems. We have attempted to improve our system relative to others by integrating Machine Learning into the system and using a variety of other effective sensors to reduce measurement errors. They have used a variety of sensors, including soil moisture sensors, pH values, temperature, and humidity sensors, and placed them stationary on the field, which results in inadequate coverage of the field and poor data collection. We have overcome this by using higher-quality sensors and making them mobile, which is a system that does not require human intervention in contrast to ours, which is automatic.[2]

Nachiket Kulkarni et al., (2019) investigated on the

Shilpa Mangesh Pande et al., (2021) has emphasized the limits of current technologies and their usefulness for yield. The proposed solution then introduces a workable yield forecast system to the farmers, connecting them via a mobile application. Users of the smartphone application can choose from a variety of features to help them choose a crop. The built-in prediction technology aids farmers in forecasting crop yields. The built-in recommender system enables the user to investigate potential crops and their yield in order to make more informed judgments. On the provided datasets from the states of Maharashtra and Karnataka, many machines learning algorithms, including Random Forest, ANN, SVM, MLR, and KNN, were deployed and assessed for yield to accuracy. The accuracy of the various algorithms is contrasted. The results show that Random Forest Regression, which has a 95% accuracy rate, is the best standard algorithm when applied to the presented datasets. The suggested model looked into when fertilizers should be applied and suggested a suitable time frame. Future work will concentrate on periodically updating the datasets to generate reliable predictions, and the procedures can be automated. The provision of the appropriate type of fertilizer for the specified crop and area is another service that needs to be provided. To put this into practice, a detailed investigation of the available fertilizers and their interactions with soil and climate must be conducted. It is necessary to conduct a statistical data analysis. [3]

Rafael Hernández Moreno et al., (2018) says that there is a wealth of research that shows machine learning (ML) algorithms are quite effective at handling categorization and prediction issues. In the recommendation of fertilizers and nutrients for the production of cold climate pastures, artificial neural networks are used. To determine whether the algorithm can be used to other places and different kinds of crops, further research needs gather more data from observations. The outcomes also demonstrated that

Harsh V.P. Singh et al., (2015) said that in this paper, two straightforward, useful, and scalable architectures are shown that enable the streaming of sensor data in real time for cloud applications. In situations where the sensor or system status is time-variant, real-time sensor data is essential. Sensor-related applications often transfer realtime data values to cloud-based software programs that rely on real-time data feeds to provide real-time analytics, multi-user collaboration, processing, and re-transmission. For the purpose of facilitating the transmission of real-time sensor data, the suggested architectures make use of the most recent HTML5 WebSocket framework and NODE.JS API. Our architectures' strength is in how they make use of the huge ubiquitous computing capabilities that are both on the cloud and at the client end to quickly construct a scalable, affordable real-time communication link. [5]

Rebecca Vivian et al.,(2015) says the project makes a contribution to the field of learning analytics as well as the creation of collaborative and software engineering tools. This dashboard for teamwork combines tried-and-true methods with innovative ideas based on educational philosophy. This tool may help team leaders and instructors monitor online collaboration more effectively and efficiently, and it also supports current communication technologies used in both business and education. The creation of this tool opens up new avenues for research and presents chances to evaluate and improve its features to meet the demands of team managers and educators. [6]

Suresh G et al., conducted a study that harnessed the potential of Supervised Machine Learning Algorithms, a robust tool in the realm of artificial intelligence. This algorithm, extensively trained on a comprehensive dataset encompassing various crop-related information, including growth patterns, environmental requisites, and yield outcomes, serves the purpose of delivering highly precise and dependable recommendations for optimal harvests. It achieves this through meticulous scrutiny of key data points like soil type, climate conditions, and geographical location. Employing machine learning techniques, the algorithm absorbs insights from historical crop performance data, discerning patterns that enable it to forecast future crop outcomes. [7]

Thilakarathne NN et al. investigated Random Forest, KNN, Decision Tree, XGBoost, and SVM as machine learning algorithms for classification problems. Each of these methods boasts distinct advantages and disadvantages, with performance depending on the particular issue at hand. The accuracy rates in this situation were as follows: Random Forest was in first place with 97%, followed by KNN at 96%, XGBoost at 96%, SVM at 87%, and Decision Tree at 83%. Random Forest, an ensemble learning technique, excels at managing large datasets with high complexity by combining many decision trees to improve accuracy and prevent overfitting. Random Forest's excellent performance in this situation can be due to its skill at handling complex data and addressing overfitting issues. [8]



In



order to promote plant growth and maximize crop yields, Siva F et al.'s research focused on agriculture, where the availability of crucial nutrients including nitrogen, phosphorus, and potassium (NPK) is crucial. The appropriate amounts of these nutrients, however, differ based on the type of crop, the soil's makeup, and the current weather. In order to achieve the best results, farmers must decide which fertilizers to use and when to apply them. A recent study suggested using an Artificial Neural Network (ANN) model to address this problem. Based on weather predictions, this ANN model is intended to estimate NPK nutrient levels and offer suggestions for the best fertilizer kind and application schedule. An ANN is a sort of machine learning model that draws inspiration from the structure and operation of the human brain. Nodes or neurons that are coupled together process incoming data and produce output make up this system. In this particular instance, historical data covering NPK levels, weather, and fertilizer treatment schedules were used to train the ANN model in order to understand the underlying patterns and correlations among these factors. [9]

Shinde K et al., have delved into the challenges encountered in agriculture, which include fluctuations in weather patterns, soil degradation, and the imperative need to enhance crop yields while minimizing input costs. In recent times, the agricultural sector has witnessed a growing adoption of data mining techniques to address these challenges effectively. The authors harnessed various data mining methods, such as clustering, decision trees, and association rule mining. Clustering facilitates the grouping of similar data points together, while decision trees are employed to identify data patterns and make predictions based on these patterns. Association rule mining is instrumental in uncovering connections between different variables within a dataset. [10]

3.METHODOLOGY 3.1 Problem Identification

➤ In order to enhance the income of farmers while preserving soil quality, it is crucial to increase productivity on the same plot of land.

➤ Indian farmers often face challenges in selecting the most suitable crops for their fields, considering factors like Nitrogen (N), Phosphorus (P), Potassium (K) levels, temperature, humidity, rainfall, and pH.

➤ There is a lack of awareness among farmers regarding the appropriate use of organic and conventional fertilizers based on their soil's specific requirements.

> Insufficient and unbalanced fertilization practices contribute to soil degradation, resulting in nutrient depletion and the emergence of second-generation issues in nutrient management.

3.2 Proposed Work

This project is designed to classify soil nutrients and provide precise crop recommendations for the field of precision agriculture. It comprises several key components: sensor-based data acquisition, cloud-based data storage, classification algorithm, fertilizer suggestion and crop recommendation. Figure 3.1 illustrates the flow diagram representing the Real-time soil monitoring system for optimal crop growth, while the subsequent sections provide an in-depth explanation of its operational processes and functionality.

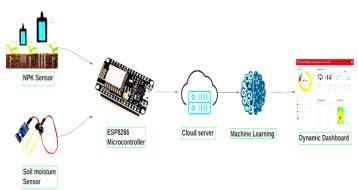


Figure 3.1: Workflow diagram

3.2.1 Data Collection

The most efficient approach to gather and quantify data from different sources, such as Kaggle and the UCI Machine Learning Repository, is through a systematic data collection process. This process involves obtaining a representative sample of data for the system's needs. Data is acquired from diverse locations using sensors and by tapping into existing datasets. In this data gathering effort, Real time sensors are crucial. For assessing nutrient content, we rely on NPK sensors, while industrial sensors are employed to measure soil moisture levels.

The Soil NPK Sensor boasts a measuring range spanning from 0 to 1999 mg/kg and operates effectively within a humidity range of 5% to 95%. Its power consumption remains minimal, capped at \leq 0.15W. These sensors are deployed with stainless steel probes that are embedded into the soil, enabling the precise measurement of values. Subsequently, the acquired data is securely stored in the Firebase cloud service. To streamline data collection, we leverage Excel's data streamer feature, which allows us to capture real-time data and save it in CSV format. The dataset primarily encompasses crucial nutrient values such as Nitrogen, Phosphorus, and Potassium levels, as well as Soil moisture levels. Additionally, for enhanced accuracy in crop prediction, we incorporate pH values into our dataset. These meticulously collected data points serve as the foundation for our crop prediction model, wherein we consider all these factors to make more precise predictions.

3.2.2. Cloud Service

We have established a robust data collection system utilizing sensors integrated with ESP8266, which enables us to gather information and transmit it to the cloud via built-in Wi-Fi capabilities. To efficiently manage this data, we have harnessed Excel's data streamer feature to capture real-time information and store it in CSV format.

The NoSQL database Firebase, which provides smooth storage and real-time data synchronization, is our preferred cloud option. We chose this platform since it is scalable and affordable. Additionally, other farmers have access to our cloud data, enabling group reading and analysis for mutual benefit. In fact, a useful feedback loop



created by feeding the insights gained from this shared data back into the cloud.

However, storage issues could arise as we expand the scope of our real-time data collecting across numerous crop species and production sites. In instance, projecting crop results could be difficult if we don't have enough real-time data. To maintain the accuracy and integrity of our dataset, it is essential to emphasize the regular need for data cleansing.

Furthermore, we have put in place strict access controls to guarantee that only authorized staff can update real-time data in the cloud. We have used machine learning models through an Android app to improve our data analysis skills.

3.2.3 Data Pre-processing

After gathering data from various sources, The obtained dataset must be read as the initial step in the data processing process. Subsequently, data cleaning is performed to enhance the accuracy of crop forecasts. During this data cleaning phase, redundant features are removed from the dataset to streamline it. Additionally, datasets containing missing values are identified, and these missing values are replaced with 'NaN' or undesirable values to ensure that the dataset is complete. This comprehensive preprocessing is essential for optimizing the accuracy of the model.

Once the data has been cleaned and processed, the next step is to define the specific objectives of the model. The dataset is divided into a training set and a test set using the Scikitlearn (Sklearn) program after the objectives of the model have been determined. For the model to be evaluated and trained efficiently, this division is essential.

3.2.4 Feature Selection

Developing systems for recommending crop types and fertilizer usage relies heavily on precise data analysis to determine the appropriate fertilizers and quantities for different crops. One of the pivotal steps in creating these systems is the selection of the most crucial features or characteristics that significantly impact crop production.

Various techniques, such as statistical analysis, domain expertise, and machine learning algorithms, can be employed to pinpoint the relevant features. Statistical analysis aids in establishing the relationships between crop yields and various factors like soil nutrient levels, temperature, rainfall, and other environmental variables.

On the other hand, domain experts in agriculture play a crucial role in identifying the key elements affecting crop growth and yield. Their deep knowledge and experience shed light on the biological and environmental aspects most vital to crop development.

Leveraging large datasets of historical crop yield data, machine learning algorithms can uncover pertinent features. These algorithms can uncover patterns and correlations among different factors influencing crop yield, contributing valuable insights.

Once the relevant features are determined, a detailed analysis of their impact on crop output ensues. This analysis helps identify the factors with the most substantial influence on crop yield, facilitating more precise recommendations for crops and fertilizer usage.

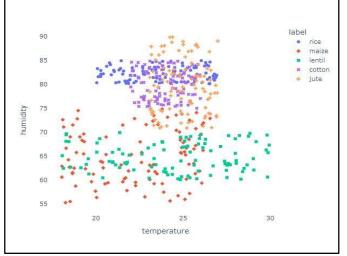


Figure 3.2 Relationship between temperature and humidity of various crops

3.2.5 Model Development

Deep learning, machine learning, and neural networks are three examples of artificial intelligence (AI) approaches that are used to build models specifically designed for tasks like image categorization, natural language processing, and predictive analytics. The initial step in model development is the identification of pertinent data features essential for the model's intended purpose.

Once these features are identified, data preprocessing is carried out to ensure it aligns with the required format for model training. Tasks like data normalization and conversion into numerical formats may be necessary. Subsequently, the prepared data is utilized to train the model.

The model learns to identify patterns in the data during the training phase. The ultimate goal is to create a model that can correctly predict intended results when fresh data is introduced. The performance of the model is assessed using a number of metrics, including as accuracy, precision, and recall.

Precision examines the model's capacity to make accurate positive predictions, recall evaluates how well the model can identify positive outcomes, and accuracy measures how well the model predicts outcomes properly. These metrics measure the model's performance as a whole and identify potential areas for improvement.

To sum up, artificial intelligence methods like deep learning, machine learning, and neural networks are effective tools for building models that can handle challenging tasks. Making models that generate precise predictions and wise decisions is attainable by identifying relevant features and getting the data ready for model training.

3.2.6 Model Validation

Ensuring the accuracy of our crop and fertilizer recommendation model on new, unseen data is crucial. This process, known as model validation, involves assessing the model's performance using a separate dataset after it has been trained on historical data.



A subset of the training data is reserved for validation purposes. It's essential that this validation dataset is representative of the entire dataset and covers various conditions and scenarios.

3.2.7 Machine Learning Prediction Algorithm

Making accurate predictions based on previously learned data is a strength of machine learning predictive algorithms. To calculate the chance of future events, predictive analytics uses data, statistical algorithms, and machine learning approaches. We use supervised machine learning in our strategy, specifically classification and regression. The best strategy for our system is categorization.

We use machine learning techniques including XGBoost, Random Forest, and K-Nearest Neighbors (KNN) for crop prediction and Support Vector Machines (SVM) and Random Forest for fertilizer recommendation in order to forecast the best crop and fertilizer.

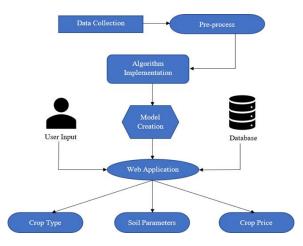


Figure 3.3: Flow diagram for Machine Learning prediction

3.2.8 Crop Prediction

In the crop prediction process, we utilize input factors like nitrogen (N), phosphorus (P), potassium (K) levels, temperature, humidity, and rainfall to determine the specific crop to be cultivated. The initial step involves importing external agricultural datasets. Subsequently, the data undergoes various preprocessing stages, as detailed in the data preprocessing section. Once the data is preprocessed, we create a training dataset and train the models using KNN and Random Forest classifiers.

Our crop prediction takes into consideration several variables, including temperature, humidity, soil pH, and expected rainfall, as inputs. These parameters can be entered manually or obtained from sensors. To assist in the forecast process, we also keep a list of input parameter values and expected rainfall totals.

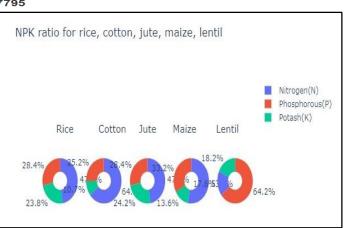


Figure 3.4 NPK values for various crops

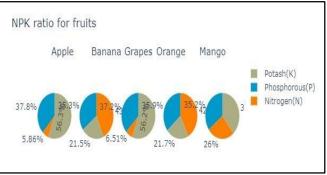


Figure 3.5 NPK values for various fruits

3.2.9 Fertilizer Recommendation

We employ input variables such as N, P, K levels, temperature, humidity, moisture content, and soil type, alongside the specific crop intended for cultivation, to make accurate predictions regarding the optimal fertilizer to be utilized. The initial phase of our fertilizer prediction process involves loading external fertilizer datasets. Following the import of the dataset, the various steps of data pre-processing described in the preceding section will be carried out. We create a training dataset after preprocessing the data, then we use Support Vector Machine (SVM) and Random Forest classifiers to train machine learning models.

Our fertilizer prediction system takes into consideration multiple factors, including temperature, humidity, soil pH, and the intended crop variety, in order to make informed fertilizer recommendations. These system input parameters can be directly input by the user or retrieved from sensors. The values for these input parameters, along with the predicted crop, are then recorded in a list for reference.

N	Р	К	Temperatur e	Humidity	Crop
90	42	43	20.87	82.00	rice
85	58	41	21.77	80.31	rice
60	55	44	23.00	82.32	rice
74	35	40	26.49	80.15	rice

Table 3.1: Given Input Parameters Values with Output forCrop Prediction

ng KNN and Random Forest classifiers. prediction takes into consideration severa





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3.2.10 Support Vector Machine

This process involves optimizing the separation of data into distinct categories, and it relies on a key concept: distance. In numerous fields, such as agriculture, SVM (Support Vector Machine) algorithms have proven to be remarkably effective in tasks like crop yield prediction, disease outbreak forecasting, and soil fertility assessment.

Specifically in the context of crop and fertilizer recommendation, SVM algorithms excel at categorizing available data and making predictions about the most suitable crops for cultivation on a particular piece of land. This predictive capability takes into account various factors like temperature, soil type, and nutrient content to ensure accuracy.

To harness the power of SVM algorithms for such tasks, extensive data is required, including historical weather records, soil samples, and crop yield data. With this knowledge, the SVM algorithm builds a high-dimensional space and places a hyperplane inside of it to divide the data into various groups. Highly precise crop suggestions are produced as a result of optimizing the spacing between these categories on the hyperplane.

One of the primary advantages of SVM algorithms in this context is their ability to handle vast datasets with precision. Their adaptability to diverse environmental conditions makes them versatile and effective tools for providing farmers with precise guidance.

In summary, leveraging SVM algorithms for crop and fertilizer recommendations is a potent machine learning technique that delivers farmers precise insights and guidance. These algorithms excel in creating highdimensional spaces with hyperplanes and analyzing extensive data to offer accurate suggestions regarding the optimal crop choices and nutrient requirements for achieving maximum yield.

Here's a breakdown of the steps involved:

Step 1: Select relevant feature groups from various data classes.

Step 2: Identify the intersections of each feature class with specific plot locations. Repeat for all data features.

Step 3: Eliminate data points that intersect with multiple feature classes and the corresponding features.

Step 4: Plot the hyperplanes for the remaining data points.Step 5: Determine hyperplane distances for different classes of items.

Step 6: Select the hyperplane that consistently applies across all data classes.

 After the model has been trained, it will interface with a web application that is constructed using the following technologies:
React.js for Frontend

Node.js for Backend Firebase for Database

Once the development is complete, the application will be deployed within a Docker container for ease of deployment and scalability.

4. PROPOSED WORK MODULES

On the basis of workflow, we divided the project into four major parts followed as

- 1. Data Gathering using an IoT Sensory System
- 2. Cloud Service
- 3. Data Pre-processing and Analysis for Recommendations on Crops and Fertilizers
- 4. Dynamic Dashboard for detailed Insights

4.1 Data Gathering using an IoT Sensory System

For data collection from agricultural fields, the system consists of real-time, industrially standard sensors such an NPK sensor and a soil moisture sensor. The soil moisture sensor assists in estimating the quantity of soil moisture while the NPK sensor is utilized to analyze the soil's nitrogen, phosphorous, and potassium content levels. By inserting the sensor's probes into the soil, you may determine the NPK values and moisture content. To transfer sensor data to the cloud, these sensors are connected to an ESP8266 Wi-Fi module. The data gathered by the moisture sensor aids farmers in effectively managing irrigation systems. Real time data were collected from different fields for further analysis and those data will be stored as a CSV file in a cloud storage.

4.2 Cloud Service:

A cloud service is accessible to multiple users and provides resource availability for users regardless of location. We link the sensors to the cloud in a way that allows the cloud to save the sensor data as a CSV file. An Arduino board is connected to the Wi-Fi-capable microcontroller ESP8266. The ESP8266's Wi-Fi module was used to transfer the data to the Firebase cloud service, a NoSQL database for synchronizing real-time data that is simple to connect with Android. on order to help other farmers, we may also share the data on our cloud, providing them with real-time crop insights and recommendations for the best crops and fertilizers.

4.3 Data Pre-processing and Analysis for Recommendations on Crops and Fertilizers

Upon compiling information from a variety of sources. Preparing the dataset is a prerequisite for model construction. Reading the collected dataset is the first step in data preprocessing, which is followed by data cleaning. To enable crop projections, some redundant characteristics are removed from the datasets during data cleaning. Based on taught data, machine learning predictive algorithms have highly optimized forecasts of likely outcomes. Using data, statistical algorithms, and machine learning approaches, predictive analytics determines the likelihood of future outcomes based on historical data. The technique for crop prediction starts with loading external agricultural datasets. Following the reading of the dataset, various preprocessing steps—which are covered in the section on data pre-processing-will be taken. After preprocessing the data, create a training sample and train the models. The SVM algorithm is used to categorize the available data and forecast the best crop to cultivate on a particular plot of land in the instance of crop and fertilizer recommendation.





4.4 DYNAMIC DASHBOARD FOR DETAILED INSIGHTS

After the model gets trained. It will interact with the web application. For Web Application we use the Tech stacks as follows

- Frontend React.js
- Backend -Node.js
- Database Firebase

Finally, the web application will be deployed in docker. From the application, farmers can view the field insights and can-do prior activities according to the crop prediction and fertilizer recommendation.

5. OVERALL IMPLICATIONS AND DISCUSSION

The integration of machine learning models for crop and fertilizer recommendations based on soil parameters and environmental conditions offers a promising approach to precision agriculture.

Crop output, resource use, and environmental effect can all be enhanced by real-time monitoring and data-driven decision-making. Centralized cloud-based storage and data sharing promote knowledge exchange among farmers and agricultural experts. The user-friendly dashboard empowers farmers with actionable insights, contributing to more sustainable and profitable agricultural practices. The system's capabilities may be enhanced in the future by adding more sensors and improving machine learning models to adjust to shifting environmental circumstances. Here is our Dashboard.



Figure 5.1 Home Page

This is the actual web application of this project. The UI shows the home tab, Crop Recommender tab and Fertilizer Recommender tab. The web application is named as AgroBRAIN.

Agro <mark>SIGHT</mark>		Home	CropRecommender	FertilizerRecommender
	Cro	p Predictor	- 1241-	
	Amount of Nitrogen	1948	Dalesco - St	
	Amount of Phosphorus			
	Amount of Potassium			
	Moisture level(in %)			
	Humidity level(in %)			
	Temperature(in Celsius)			

Figure 5.2 Crop Recommendation Page

shown in the figure 5.2, the Crop Recommender will have the input fields for the user to enter Nitrogen, Phosphorus and Potassium levels in the soil. Including the fields of Temperature, Humidity, pH and Rainfall value in the certain region of the crops.

Fertilizer Recomme		
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Figure 5.3 Fertilizer Recommendation Page

The Fertilizer Recommender page will have the same input fields as the Crop Recommender page. Additionally, it also has the dropdown box to select the Soil type and Crop type. The predicted result of the Crop recommender and Fertilizer recommender is shown in the figure 5.4. The inputs given by the user are validated and trained using the ML recommendation model and gives a result with high accuracy and prediction.

			н	2N NH2	
Prediction: Rice	Crop		Prediction: Urea	Fertilizer	
Depending on the natiety, and days after crop establishment handling, threshing, dearing,	colocting the mature noe ongo or coop usually reaches maturi t. Harvesting activities include (and hauling. Good harvesting imme grain damage and deten	ily at around 105–150 outling, statoking, methods help	The agricultural industry wide percent introgen as an animal role as a nitrogen tertilizer. In replaced ammonium nitrale a	feed add/live and fert the past decade, ursa	Filter. Here, we'll focus on its
XCBoost Model Prediction	RandomForest Model Prediction	KNN Model Prediction	XGBoost Model Prediction	RandomForest Model Prediction	SVM Model Prediction
109 (19.84353164700012%)	rice (95%)	rice (100%)	Unexa (97.40227460861206%)	Ureir (RS%)	Unus (86.48782827957325%)
BA	CK TO PREDICTION		BA	CK TO PREDICT	ION

Figure 5.4 Predicted Result Page

5. CONCLUSIONS

The provided soil monitoring system is a significant development in precision agriculture, providing a comprehensive answer to the problems that plague today's farmers. The following are some of this system's main contributions and highlights:

Precision agriculture and real-time monitoring: The system is aware of how crucial it is for agricultural practices to continuously monitor soil moisture and nutrient levels. It gives farmers the ability to decide on irrigation, fertilization, and crop health in an informed manner, which ultimately improves crop productivity and resource management.

Advanced Sensor Integration: By incorporating industrialstandard sensors, such as soil moisture and NPK sensors, the system enables continuous measurement of essential soil parameters. These sensors, embedded in the soil, provide accurate data on soil moisture and nutrient concentrations, ensuring precise data collection.





Wireless Connectivity and Communication: Leveraging the ESP8266 microcontroller and the RS-485 protocol, the system ensures efficient wireless data transmission. This not only facilitates real-time data collection but also allows remote access and control of the monitoring system.

Machine Learning for In-depth Analysis: The integration of machine learning techniques adds a layer of intelligence to the system. By processing historical data, the machine learning model learns complex patterns and relationships between soil parameters, crop types, and fertilizer requirements. This enables the system to offer valuable predictions, recommendations, and early warnings to farmers.

User-friendly Dashboard: The user-friendly monitoring dashboard, accessible through web and mobile interfaces, democratizes access to critical agricultural insights. It provides real-time visualizations, alerts, and analytics, empowering farmers to make informed decisions remotely. Optimized Resource Management: By providing actionable insights, the system contributes to optimized crop management, reduced water consumption, and judicious fertilizer usage. This not only benefits the farmers economically but also promotes sustainable agriculture practices.

Cloud Integration and Data Sharing: The system seamlessly integrates with cloud services like Firebase, ensuring secure storage of sensor data. Furthermore, it supports data sharing with other farmers, fostering a collaborative and knowledge-sharing agricultural community.

Comprehensive Methodology: The methodology outlined in this abstract demonstrates a systematic approach, covering data acquisition, cloud services, data pre-processing, machine learning, and dynamic dashboard development. Each phase is crucial in achieving the system's objectives.

In essence, this soil monitoring system is a big step toward the technological modernization of agriculture. It enables farmers to make wise decisions that can result in higher crop productivity, sustainable farming methods, and improved livelihoods by giving them access to real-time data and insightful insights. In tackling the changing difficulties facing the agricultural sector, this comprehensive approach to precision agriculture shows considerable promise.

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