IoT Based Soil pH Detection and Crop Recommendation System

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Abstract:- Agricultural productivity hinges on soil fertility, influenced by key factors like nitrogen, phosphorus, potassium, pH level, and soil moisture. Yet, achieving optimal crop growth is challenging due to limited farmer knowledge and difficulties in determining precise fertilizer quantities. Conventional soil analysis methods involve manual sampling and costly lab tests, which are subjective. To address this, aproposed solution integrates IoT-enabled soil nutrient monitoring with machine learning algorithms for croprecommendations. Sensors collect data on crucial parameters like nitrogen, phosphorus, and soil temperature, transmitting it to a cloud-based database. Machine learning analyzes this data to suggest ideal crops, minimizing fertilizer use, reducing labor, and enhancing overall productivity. This innovative approach streamlines crop selection, minimizing unnecessary inputs while maximizing yields. By harnessing IoT and machine learning, farmers gain valuable insights into soil health, enabling precise fertilization and crop selection. This not only boosts agricultural productivity but also contributes to economic growth by fostering sustainable practices and increased yields.

Keywords:- *Agriculture Yields, Crop Recommendation, Machine Learning, Soil Behavior Analysis.*

I. INTRODUCTION

In agricultural settings, farmers often grapple with economic challenges stemming from suboptimal crop selection, resulting in financial losses and crop disorders. Soil fertility plays a pivotal role in addressing this issue, aslow-nutrient soils can lead to various plant disorders and diminished yields. To enhance profitability, farmers must accurately assess the nutritional status of their soil and select crops accordingly. The problem of crop selection is particularly pronounced in rural areas, where the adoption of IoT technologies can offer viable solutions. Utilizing an IoT-based approach, an array of sensors including those for Nitrogen (N), Phosphorus (P), Potassium (K), pH, temperature, moisture, and humidity are deployed to ascertain soil nutrient levels. These sensors continuously collect data from the agricultural field and transmit it to a cloud-based platform via wireless communication protocols. A significant advantage of utilizing a cloud-based database is its accessibility from anywhere and at any time, enabling seamless integration with various smart devices. Data stored in the cloud encompasses crucial factors such as soil moisture, temperature, rainfall, pH levels, and nutrient concentrations (N, P, K), facilitating informed decision-making. To recommend suitable crops, machine learning algorithms such as Linear Regression (LR), K Nearest Neighbor (K-NN), Decision Tree (DT), Random Forest Regression (RFR), Neural Network (NN), Support Vector Machine (SVM), and XGBoost are leveraged. The overarching objective of this system is to alleviate farmers' workload, enhance profitability, and facilitate data-driven decision- making. Real-time data pertaining to nitrogen, phosphorus, potassium, pH, temperature, moisture, and humidity sourced from the cloud database serves as inputs for the machine learning algorithms, enabling dynamic and context-aware crop recommendations.

II. LITERATURE SURVEY

The classification algorithm used to predict the crop suitablefor the soil based on the nutrients level present on that is described in most of the existing literature for precision and smart agriculture. This section includes several articles that are predicted to illustrate the benefits of adopting precision and smart agriculture as well as the areas that require

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improvement. It focuses on the management challenges in IoT-based agricultural systems and how it might best benefit users. According to [1], agriculture is dependent on the geographic locations and climatic conditions in the designated places. This article covered potential weather changes and forecasted which weather would be best for the given place during the particular season. According to Chlingaryana et al. 2017 [2], the level of nitrogen in the soil is a key component in predicting crop yield. These days, decision-making is where most remote sensing devices are used. Farmers can increase crop production by using these remote sensing data. A choice is made using a vast amount of remote sensing data. Nitrogen is used to enhance agricultural yield and cultivate the soil. The choice is madeusing methods for machine learning. The three main variables we will take into account are nitrogen, soil type, and yield. Analyzing prior data on these variables will helpus make informed decisions, predict yields, and assistfarmers. In [3] and [4], the clustering and classification process to grouping, the common users are discussed. These approaches facilitate the identification of common crops that supports the farmers to use some kind of cultivation method. The procedure of "smart terrace gardening" is described in [5], which demonstrates the effective water-conservation methods used. This system's use of intelligent rules encourages less consumption while simultaneously supporting improved plant development. The geographically based customized crop suggestion system is presented in [6]. It collects user input and offers customized recommendations that are pertinent to their location and previous farming. A cloud-based IoT system for precision gardening is proposed in [7]. Through the use of cloud computing technology, this system delivered the sensor data that had been assessed to the user's mobile device or system. The research cited in [8] analyses the present weather and soil moisture content and offers recommendations for needed water level and weather conditions. It's an Internet of Things-based project that helps intelligent and precise agriculture. The Naive Bayes classification methods and their use in the categorization of the crop suitable for the soil chosen for cultivation are described in another study [9]. Please don't change any of the labels that are currently in place. Another study mentioned in [10] The majority of the study publications that were examined took into account several climate factors, including temperature, humidity, and rainfall. Several agronomic factors, including soil, herbicides, and nutrient levels like N, P, and K. These variables' values have been used as input. A sizable dataset is needed for data mining to be applied successfully. The information obtained from numerous sources is occasionally in raw form. It might include some conflicting, redundant, or incomplete data. Thus, such redundant data needs to be filtered in this step. You should normalize your data. Largedata sets are analyzed using data mining to discover helpful classifications and trends. The main objective of the data mining process is to take the information from a data set and organize it so that it can be used in other ways. Using the data at hand, this research assesses crop yield output.

III. PROPOSED SYSTEMMETHODOLOGY

The IoT-based soil monitoring and machine learning-driven crop recommendation system employs a hierarchical architecture comprising various sensor nodes strategically positioned across agricultural fields. These sensors, encompassing parameters such as nitrogen, phosphorus, potassium, pH, soil temperature, and moisture, continuously gather data on soil conditions. Through a Wireless Sensor Network (WSN), this data is transmitted wirelessly to a centralized cloud database for storage and analysis. Within the cloud infrastructure, machine learning algorithms are deployed to conduct comprehensive analysis of both steady-state and transient soil behavior. Additionally, environmental parameters including temperature,humidity, and precipitation are integrated into the analysis. Thisholistic approach enables the system to generate precise recommendations for crop cultivation tailored to the specific land parcel, accounting for its nutrient composition and prevailing environmental conditions. By leveraging this analytical framework, the system assists farmers in optimizing fertilizer application, mitigating manual intervention, and ultimately enhancing agricultural output. Through the provision of accurate crop recommendations, the system not only fosters operational efficiency but also contributes to the overall economic advancement of the agricultural sector.

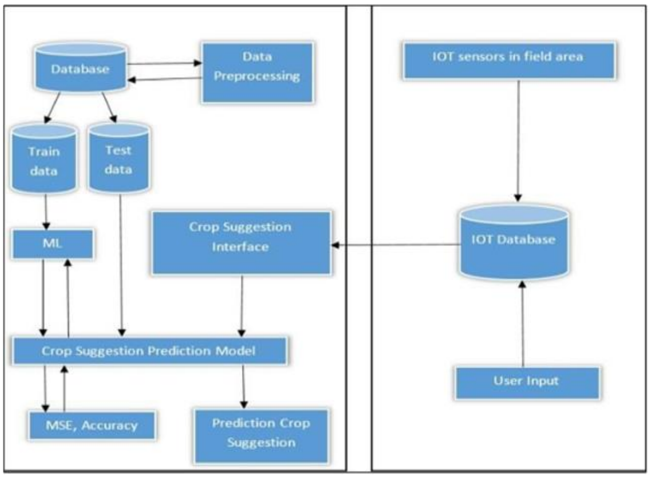

Fig 1 Architecture for Soil PH Detection and Crop Recommendation

➢ *pH Sensor:*

- *Input: Soil Sample Preparation:*

The pH sensor receives a soilsample extracted from the field. Preparation of the soil sample is crucial for ensuring accurate pH measurement. This preparation typically involves creating a soil-water slurry by mixing the soil with distilled water in a standardized ratio.

- *Output: pH Measurement:*

The pH sensor provides an outputin the form of the pH value of the soil sample. This value quantifies the acidity or alkalinity of the soil and is expressed ona numerical scale ranging from 0 to 14. A pH of 7 indicates neutrality, values below 7 signify acidity, while values above 7 indicate alkalinity.

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➢ *Working of pH Sensor:*

- *Sensor Calibration and Setup:*

Calibrate the pH sensor according to the manufacturer's instructions to ensure accurate readings.Connect the pH sensor to the Arduino Uno using the RS485interface. Use appropriate wiring and ensure proper electricalconnections. Set up the Arduino Uno with necessary libraries and configurations to communicate with the pH sensor via RS485.

- *Initialization and Configuration:*

Initialize the Arduino Uno and configure the serial communication parameters for RS485 communication. Set up the pH sensor for data acquisition, includingconfiguring measurement intervals and calibrationsettings if necessary. Implement error handling mechanisms to detect andhandle communication errors with the pH sensor.

- *Data Acquisition:*

Periodically request pH measurements from the sensor using the RS485 communication protocol. Receive pH data packets from the sensor via RS485 anddecode them to extract pH values. Implement error-checking mechanisms to ensure theintegrity of received data and handle any transmission errors.

- *Data Processing and Storage:*

Process the received pH data to convert it into a usable format, such as floating-point values representing pH levels.Store the processed pH data locally on the Arduino Uno'smemory or an external storage device, depending on the storage requirements and available resources. Implement buffering mechanisms to manage data storageefficiently and prevent data loss in case of temporary storage unavailability.

- *Communication with Iot Module:*

Establish communication between the Arduino Uno and the IoT module (e.g., using UART, SPI, or I2C interface). Transfer the processed pH data from the Arduino Uno tothe IoT module for further transmission to the cloud platform. Ensure compatibility and interoperability between the Arduino Uno and the IoT module by configuring communication protocols and data formats accordingly.

- *Cloud Platform Integration:*

Configure the IoT module to connect to the internet and establish communication with the cloud platform. Implement protocols and security mechanisms (e.g., MQTT, TLS) to ensure secure and reliable datatransmission to the cloud. Send pH data packets from the IoT module to the cloud platform at regular intervals, adhering to predefined communication protocols and data formats.

- *Data Analytics and Crop Recommendation:*

On the cloud platform, receive and process the incoming pH data packets from multiple Arduino Uno devices. Analyze the pH data using statistical methods andmachine learning algorithms to identify trends, patterns,and anomalies. Generate crop recommendations based on the analyzed pH data, considering factors such as soil pH levels, crop requirements, and environmental conditions.Provide real-time feedback and updates to farmers through the user interface or other communication channels.

- *User Interface and Interaction:*

Develop a user interface (e.g., web application, mobile app) tovisualize soil pH data and crop recommendations for farmers.Enable farmers to access the user interface using their devices (e.g., smartphones, tablets, computers) and authenticate securely.Display real-time soil pH measurements, historical trends, and personalized crop recommendations based on the farmer's location and preferences. Implement interactive features for farmers to customize settings, provide feedback, and receive notifications/alertsrelated to soil pH and crop management.

- *Maintenance and Monitoring:*

Implement monitoring mechanisms to track the health and performance of the entire system, including Arduino Uno devices, IoT modules, and cloud platform components.Set up automated alerts and notifications to inform administrators of any system anomalies, errors, or failures that require attention.Conduct regular maintenance tasks such as updating firmware/software, calibrating sensors, and replacing faulty components to ensure the smooth operation of the system.

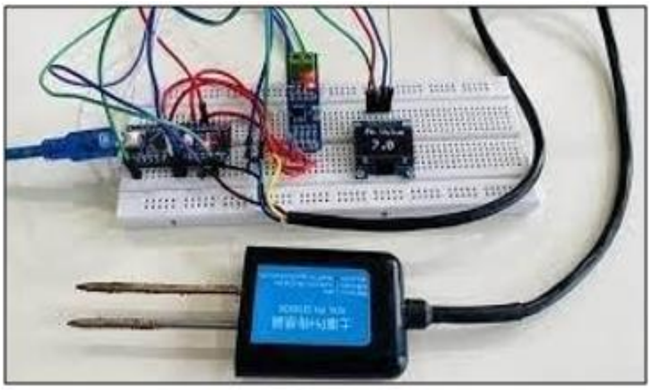

Fig 2 pH Sensor Connection

A. Decision Trees:

➢ *Input:*

The Decision Trees algorithm takes soil parameters such as nitrogen, potassium, phosphorus, and pH levels as input features.

➢ *Output:*

It provides a recommended crop based on the input soil parameters.

➢ *Steps:*

- Data Collection and Preprocessing: Soil data, including pH, nitrogen, potassium, and phosphorus levels, is collected and preprocessed to ensure consistency and suitability for analysis.
- Dataset Splitting: The dataset is divided into training and testing subsets to facilitate model training andevaluation, respectively.

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- Model Training: A decision tree classifier is trained using the training dataset. The classifier employs soil parameters as features and crop types as labels to learn the underlying relationships between soilcharacteristics and suitable crops.
- Model Evaluation: The trained decision tree model's performance is assessed using the testing dataset through metrics such as accuracy, precision, recall, and F1-score, among others.
- Prediction: Upon successful training and evaluation, the trained decision tree model is employed to predict the recommended crop based on the input soil parameters provided by the user. The model utilizes its learned decision-makingprocess to classify the input data into the most appropriate crop category.

B. Support Vector Machines (SVM):

➢ *Input*:

The Support Vector Machines (SVM) algorithmaccepts soil parameters such as nitrogen, potassium, phosphorus, and pH levels as input features.

➢ *Output*:

It offers a recommended crop based on the input soil parameters.

➢ *Steps*:

- Data Preprocessing and Splitting: Initially, the soil data undergoes preprocessing to address missing values and outliers. Subsequently, the dataset is partitioned into training and testing subsets. This division facilitates model training and subsequentevaluation.
- Feature Scaling: To ensure uniformity and comparability among features, they undergo scaling to bring them within a similar range. This step enhances the convergence speed and effectiveness of the SVM classifier.
- Model Training: Using the training dataset, an SVM classifier is trained. This classifier leverages soil parameters as features and crop types as labelsto discern the optimal decision boundary that segregates various crop categories effectively.
- Parameter Tuning: Fine-tuning of SVM parameters, including the kernel type and regularization parameter (C), is executed. Techniques such as grid search or randomized search, coupled with cross-validation, are employed to optimize the model's performance.
- Model Evaluation: The trained SVM model undergoes evaluation using the testing dataset to gauge its performance metrics. These metrics encompass accuracy, precision, recall, F1-score, among others, providing insights into the classifier's efficacy.
- Prediction: Upon successful training and evaluation, the trained SVM model is deployed to predict the recommended crop based on the input soil parameters furnished by the user. By applyingthe acquired decision boundary, the model classifies the input data into the most suitable crop category, facilitating informed agricultural decisions.

C. k-Nearest Neighbors (k-NN):

➢ *Input*:

The k-Nearest Neighbors (k-NN) algorithm utilizes soil parameters such as nitrogen, potassium, phosphorus, and pH levels as input features.

➢ *Output:*

It offers a recommended crop based on the input soil parameters.

➢ *Steps:*

- Data Preprocessing and Splitting: The soil data undergoes preprocessing to address missing values and outliers. Subsequently, it is partitioned into training and testing sets to facilitate model training and evaluation.
- Feature Standardization or Normalization: To ensure uniformity in feature scales, the features are standardized or normalized. This step is crucial for accurate distance computation in the k-NN algorithm.
- Model Training: Using the training dataset, the k-NN classifier is trained. The parameter 'k' denotes the number of nearest neighbors considered during classification.
- Parameter Selection: The optimal value of 'k' is selected utilizing techniques such as cross-validation to enhance the model's performance.
- Model Evaluation: The trained k-NN model is evaluated using the testing dataset to assess its performance metrics. These metrics include accuracy,precision, recall, and F1-score, providing insights intothe classifier's effectiveness.
- Prediction: Upon successful training and evaluation, the trained k-NN model is employed to predict the recommended crop based on the input soil parameters provided by the user. The model identifies the 'k'nearest neighbors in the feature space and determines the majority class among them as the predicted crop category, thereby facilitating informed agricultural decisions.

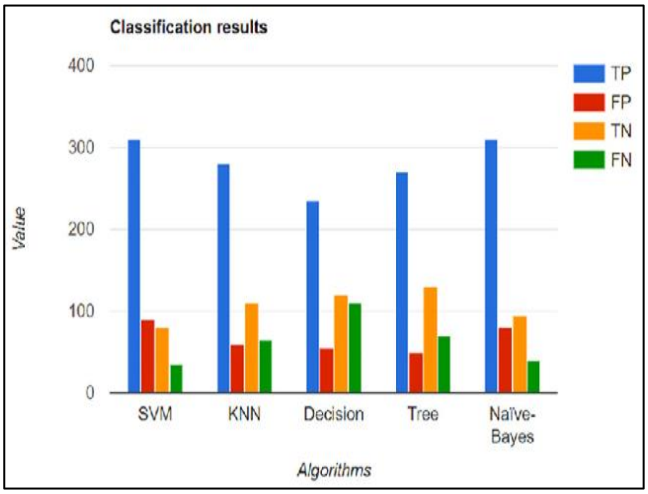

Fig 3 Algorithm analysis

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IV. EXPERIMENTAL SETUP AND RESULT ANALYSIS

The IoT-based soil pH detection and crop recommendation project integrates sensor technology, data analysis, and agricultural expertise to offer farmers actionable insights for optimized crop growth. Through a web interface, farmers input soil parameters including nitrogen, potassium, phosphorus, and pH levels, allowing the system to analyze this data and recommend suitable crops tailored to the given conditions. Additionally, the system identifies soil deficiencies and suggests appropriate fertilizers to enhance crop productivity. Leveraging IoT sensors for real-time data collection, advanced algorithms for crop recommendation, and user-friendly web-based interfaces, this project empowers farmers with personalized recommendations for sustainable agricultural practices.

A. Soil Behavior Observations and Analysis:

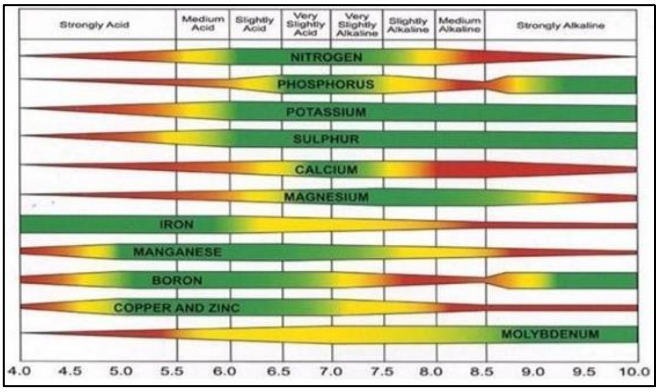
In the IoT-based soil pH detection and crop recommendation project, soil pH analysis involves employing pH sensors to measure soil acidity or alkalinity. These sensors detect hydrogen ion concentrations in the soil solution, providing a pH value indicative of the soil's chemical balance. NPK analysis entails evaluating nitrogen (N), phosphorus (P), and potassium (K) levels in the soil, critical nutrients for plant growth. Soil samples are typically collected and analyzed using laboratory methods or portable soil testing kits to ascertain nutrient content accurately. By integrating IoT sensors and data analysis techniques, the project facilitates real-time monitoring of soil pH and nutrient levels. This enables informed decisions regarding crop selection and fertilizer application, optimizing crop growth and yield.

Table 1 Soil behavior analysis

Crop	Ideal pH range	Nitrogen (N) (kg/ha)	Potassium (K) (kg/ha)	Phosphorus (P) (kg/ha)
Rice	5.5 - 7.5	100 - 150	50 - 100	20 - 40
Maize	6.0 - 7.5	150 - 200	100 - 150	40 - 60
Cotton	6.0 - 7.5	80 - 120	50 - 80	20 - 30
Pomegranate	6.5 - 7.5	100 - 150	100 - 150	50 - 70
Coffee	5.5 - 6.5	150 - 200	200 - 300	50 - 80
Black gram	6.0 - 7.0	25 - 35	20 - 30	10 - 15
Potato	5.5 - 6.5	150 - 200	150 - 200	70 - 100
Tomato	6.0 - 6.8	100 - 150	100 - 150	50 - 100

B. The Impact of Soil pH on Plant Nutrient Availability:

Soil pH significantly modulates the availability of plant nutrients by influencing their chemical speciation and solubility. In acidic soils (pH below 7), key nutrients suchas phosphorus (P), potassium (K), calcium (Ca), and magnesium (Mg) undergo increased solubility, rendering them more readily accessible to plants. Conversely, micronutrients like iron (Fe), manganese (Mn), and zinc (Zn) may experience heightened concentrations, potentially leading to toxicity issues. On the contrary, in alkaline soils (pH above 7), nutrients such as phosphorus (P), iron (Fe), and zinc (Zn) may exhibit reduced availability due to precipitation or formation of insoluble compounds. To address soil pH disparities and optimize nutrient accessibility, farmers can employ strategic fertilization practices. In acidic soils, the application of lime-containing fertilizers facilitates pH elevation, thereby ameliorating nutrient availability. Conversely, in alkalinesoils, sulfur-containing fertilizers aid in lowering pH levels. Additionally, targeted fertilization strategies involving the application of nutrient-specific formulations help supplement deficiencies induced by pH-related nutrient imbalances. Byrectifying soil pH and optimizing nutrient availability, these practices ensure conducive conditions for robust plant growth and development.



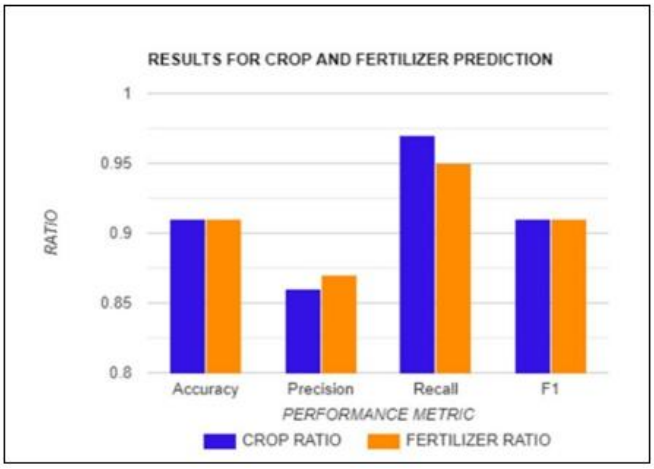


Fig 4 Performance Analysis

Fig 5 Outcomes

V. CONCLUSION

In summary, the IoT-based soil pH detection and crop recommendation project heralds a transformative solution for contemporary agriculture by harnessing technological advancements to elevate farming methodologies. Through the provision of real-time soil pH, nitrogen, potassium, and phosphorus data, coupled with tailored crop recommendations and fertilizer guidance, the initiative aspires to enhance crop yields, optimize resource allocation, and attenuate environmental impact. By integrating IoT sensors, web-based interfaces, and dataanalytics algorithms, the project empowers farmers to make data-driven choices regarding crop selection and nutrient management. Through targeted remediation of soil deficiencies and customized fertilizer prescriptions aligned with crop requirements, the initiative endeavors to streamline input expenditures while maximizing agricultural output. Moreover, the project's scalability and adaptability render it suitable for deployment across diverse agricultural landscapes, spanning from small-scale farms to expansive commercial enterprises. Through collaborative engagement with agricultural stakeholders and continual integration of emerging sensor technologies, machine learning methodologies, and precision agriculture techniques, the initiative stands poised to evolve and contribute substantially to sustainable agricultural practices and global food security endeavors. Ultimately, the IoT-based soil pH detection and crop recommendation project epitomizes a pivotal instrument within the contemporary agricultural arsenal, empowering farmers with actionable insights to cultivate resilient crops, fortify soil vitality, and forge a more robust and productive food ecosystem for future generations.

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