Project Report

on

Crop Recommendation Using Machine Learning

Submitted in the partial fulfillment for the requirements
For the award of the degree of

Bachelor of Engineering
in
Electronics and Telecommunication Engineering

By

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Academic Year 2023-24

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Department of Electronics and Telecommunication Engineering

CERTIFICATE

This is to certify that the project entitled **"Crop Recommendation using Machine Learning"** is a bonafide work of **Shweta Bachute (Roll No. 806), Ekta Bhowad (Roll No. 811), Omkar Gosavi (Roll No. 819), Kedar Sawant (Roll No. 832)** under the supervision of **Prof. Ragini Bhoyar** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **Bachelor of Engineering in Electronics and Telecommunication Engineering.**

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REPORT APPROVAL FOR B.E.

This project report entitled **"Crop Recommendation using Machine Learning"** by **Shweta Bachute, Ekta Bhowad, Omkar Gosavi and Kedar Sawant** is approved for the degree of Bachelor of Engineering in **Electronics and Telecommunication Engineering from University of Mumbai, in academic year 2023-24**.

Examiners:

1.Internal: ____________________

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Date: / / 2024
Place: Mumbai

DECLARATION

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Acknowledgments

It is indeed a matter of great pleasure and proud privilege to be able to present this project on "Project Title". We would like to express our regards and gratitude to the Principal **Dr. Sanjay U. Bokade** and Head of Department **Dr. Sanjay. D. Deshmukh**. The completion of this project work is a milestone in student life and its execution is inevitable in the hands of a guide. We are highly indebted to the project guide **Prof. Ragini Bhoyar** for her invaluable guidance and appreciation for giving from and substance to this report. It is due to her enduring efforts, patience and enthusiasm, which has given a sense of direction and purposefulness to this project and ultimately made it a success. We would also like to tender our sincere thanks to the staff members for their cooperation.

Abstract

The requirement for sustainable practices to guarantee effective crop cultivation is posing an increasing challenge to the agriculture sector. To address this, this study presents a novel project aimed at putting into practice a cutting-edge crop recommendation system. Using real-time data on important environmental parameters like as temperature, moisture content of soil, weather, and contextual subtleties, the system utilises machine learning models that have been trained beforehand to examine complex inputs. To ensure precision and accuracy, the training process makes use of modern technologies such as support vector machines (SVM), random forests, decision trees, and others. With the use of data-driven insights, the robust model that is produced offers farmers customised and optimised crop suggestions that will increase agricultural production and promote sustainable farming methods. This approach is a big step forward because it highlights the agriculture sector's efficiency and resilience.

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Chapter 1

Introduction

1.1 About Project

In the context of agricultural sustainability, knowing how important environmental variables—like temperature and soil moisture—interact dynamically is essential to crop cultivation's success. Our innovative response centres on the application of a state-of-the-art crop recommendation system. This method leverages real-time data on soil moisture content, outside temperature, meteorological conditions, and the month-specific contextual details. Through the utilisation of pretrained machine learning models, our approach aims to thoroughly examine these diverse inputs and provide customised suggestions regarding which crops would be best suited for a certain soil type.

This creative method makes use of a variety of machine learning algorithms, such as support vector machines (SVM), random forests, and decision trees. By means of rigorous training and careful assessment, we seek to determine the model's accuracy and precision and then choose the best deployment strategy. After completing this intensive training, a very clever and resilient model will be created that can generate predictions based on the information provided by the customer, making it easier to provide customised and optimised crop suggestions.

Our programme aims to provide farmers with timely, accurate, and data-driven information so they may make well-informed decisions to increase agricultural output by promoting a data-driven strategy. Our system's main goals are to increase total crop productivity and promote sustainable farming techniques. By strengthening the agricultural sector's resilience, we hope to bring in a new era of agricultural wealth and advancement.

1.2 Motivation

The motivation for building a crop recommendation system stems from several factors, all aimed at addressing challenges faced by farmers and improving agricultural productivity and sustainability.

1)**Optimizing Crop Selection:** Farmers need to select crops that are well-suited to their specific environmental conditions, including soil type, climate, and water availability. A crop recommendation system helps optimize crop selection by providing personalized recommendations based on data analysis and predictive modeling, thereby maximizing yields and profitability.

2)**Increasing Productivity:** By selecting the most appropriate crops for a given set of conditions, farmers can maximize productivity and minimize the risk of crop failure. A crop recommendation system leverages historical data, scientific research, and machine learning algorithms to identify patterns and relationships between environmental factors and crop performance, leading to more informed decision-making and improved outcomes.

3)**Resource Efficiency:** Agriculture accounts for a significant portion of water usage, fertilizer application, and land utilization globally. By recommending crops that require fewer resources or are more resilient to environmental stressors, a crop recommendation system can help farmers optimize resource usage, waste management, and minimize environmental impact.

4)**Mitigating Risks:** Farmers face various risks, including weather fluctuations, market volatility, and pest infestations, which can impact crop yields and financial stability. A crop recommendation system provides risk mitigation strategies by diversifying crop portfolios, adapting to changing environmental conditions, and offering real-time insights into market trends and demand.

5)**Empowering Smallholder Farmers:** Smallholder farmers, especially in developing countries, often lack access modern agricultural technologies and expertise. A crop recommendation system democratizes access to agricultural knowledge and resources by providing user-friendly interfaces, actionable recommendations, and decision support tools tailored to the needs of small-scale farmers, thereby empowering them to improve their livelihoods and resilience.

6)**Promoting Sustainable Agriculture:** Sustainable agriculture aims to balance economic profitability with environmental stewardship and social equity. A crop recommendation system promotes sustainable agriculture by encouraging practices such as crop rotation, soil conservation, and biodiversity conservation, which contribute to long-term soil health, ecosystem resilience, and community well-being.

7)**Harnessing Technology and Innovation:** In the era of digital transformation, technology plays a critical role in revolutionizing agriculture and addressing global food security challenges. A crop recommendation system harnesses the power of data analytics, machine learning, and remote sensing technologies to unlock insights, optimize decision-making, and drive innovation across the agricultural value chain.

1.3 Different Techniques of Crop Recommndation

Crop recommendation systems utilize various techniques and methodologies to provide farmers with personalized recommendations for crop selection. These techniques leverage data analysis, machine learning, and expert knowledge to assess environmental conditions and identify suitable crops. Here are some different techniques commonly used in crop recommendation systems:

1)**Rule - Based Systems:** Rule-based systems use a set of predefined rules and heuristics to recommend crops based on specific criteria. These rules are typically derived from agronomic knowledge, best practices, and expert opinions. For example, if the soil pH is acidic and the climate is humid, recommend crops such as rice or certain varieties of vegetables that thrive in these conditions.

2)**Expert Systems:** Expert systems integrate domain-specific knowledge from agricultural experts into a knowledge base and use inference engines to make recommendations. These systems mimic the decision-making process of human experts by reasoning with the available knowledge to generate crop recommendations. Expert systems can handle complex decision-making scenarios and provide explanations for their recommendations.

3)**Statistical Analysis:** Statistical analysis techniques analyze historical crop yield data, soil properties, climate data, and other relevant factors to identify correlations and patterns. Statistical models such as regression analysis, correlation analysis, and cluster analysis can be used to uncover relationships between environmental variables and crop performance. These insights can inform crop recommendations based on statistical trends and associations.

4)**Machine Learning:** Without the need for explicit programming, machine learning approaches use algorithms to extract relationships and patterns from data and generate predictions or suggestions. With the use of historical data, supervised learning algorithms such as decision trees, random forests, support vector machines, and neural networks can be taught to forecast crop yields or suggest crops based on input characteristics like soil composition, climate, and management techniques. Algorithms for unsupervised learning, such clustering algorithms, can recognise clusters of related farms or areas and suggest crops based on these commonalities.

5)**Data Fusion:** Data fusion techniques integrate information from multiple sources, such as satellite imagery, weather forecasts, soil surveys, and sensor data, to provide a comprehensive assessment of environmental conditions. By combining heterogeneous data sources, data fusion techniques can improve the accuracy and reliability of crop recommendations. Techniques such as Bayesian networks and fuzzy logic can be used to combine and interpret diverse datasets for crop recommendation.

6)**Geographic Information Systems (GIS):** GIS techniques analyze spatial data related to soil types, elevation, land use, and climate patterns to generate spatially explicit crop recommendations. GIS tools can map the suitability of different crops to specific geographic regions based on environmental constraints and crop requirements. Spatial analysis techniques, such as suitability modeling and spatial interpolation, can be used to generate maps and visualize crop recommendation results.

7)**Hybrid Approaches:** Hybrid approaches combine multiple techniques, such as rule-based systems, expert systems, statistical analysis, and machine learning, to leverage the strengths of each approach and improve the robustness and accuracy of crop recommendations. By integrating complementary techniques, hybrid approaches can overcome limitations and exploit synergies to provide more effective crop recommendations.

1.4 Scope of Project

The scope of crop recommendation using machine learning is vast and encompasses various aspects of agriculture, data science, and technology.

1)**Personalized Recommendations:** Machine learning enables the development of crop recommendation systems that provide personalized recommendations tailored to the specific conditions of each farm. By analyzing data on soil properties, climate conditions, historical crop yields, and farmer preferences, machine learning models can generate customized recommendations that optimize crop selection and maximize yields.

2)**Environmental Monitoring:** Machine learning models can analyze environmental data from sources such as satellite imagery, weather stations, and soil sensors to monitor changes in soil health, weather patterns, and pest infestations. By integrating real-time data streams with historical data, crop recommendation systems can adapt to dynamic environmental conditions and provide timely recommendations to farmers.

3)**Precision Agriculture:** Precision agriculture relies heavily on machine learning to enable focused interventions and efficient resource management. Crop recommendation systems have the ability to suggest crop types, planting dates, and irrigation plans that conserve resources, lessen their negative effects on the environment, and optimise returns on investment. In order to deliver useful insights for farm management, machine learning models can also evaluate sensor data from precision agriculture technology like drones and IoT devices.

4)**Risk Assessment and Management:** Crop selection, market volatility, and climatic unpredictability are hazards that machine learning models can evaluate and reduce. Crop recommendation systems examine past data on crop yields, market prices, and weather patterns to detect risk factors and suggest management plans that minimise losses and optimise profits. Farmers can make well-informed decisions by using machine learning approaches like risk analysis and predictive modelling, which can quantify and prioritise risks.

5)**Decision Support Tools:** Throughout the crop production cycle, crop recommendation systems function as instruments for decision support, helping farmers make well-informed choices. Machine learning models offer insights and suggestions that maximise decision-making and raise agricultural productivity, from crop planning and planting to harvest and marketing. Crop recommendation systems facilitate data collecting, analysis, and decision-making by integrating with IoT platforms and farm management software.

6)**Research and Innovation:** Research and advancement in crop recommendation systems and methodology are made possible by machine learning. Crop recommendation systems can be made more accurate, scalable, and user-friendly by investigating new algorithms, data sources, and development strategies. A sustainable food supply can be achieved by machine learning researchers by working with agricultural stakeholders and utilising new technology to solve urgent issues in agriculture.

7)**Global Impact:** Machine learning-based crop recommendation has the potential to significantly impact the world by boosting food security, increasing agricultural production, and encouraging sustainable farming methods. Crop recommendation systems enable farmers to make informed decisions by providing them with data-driven insights. This helps tackle global issues including resource scarcity, climate change, and population expansion. Stakeholders in agriculture may collaborate to create a more resilient and sustainable food system for coming generations by utilising technology and machine learning.

Chapter 2

Literature Survey

In [1] the Smart Irrigation and Monitoring System integrates DHT11 and YL100 Soil Moisture sensors with a WeMos board to effectively monitor air temperature, humidity, and soil moisture levels. The collected data is then transmitted to an IoT Hub for in-depth analysis. This system leverages machine learning algorithms to process the sensor data alongside weather forecasts, enabling it to make informed decisions about when irrigation is needed. The system can alert farmers in a timely manner, ensuring efficient water management for their crops. To provide a user-friendly experience, both web and mobile applications are developed, allowing farmers to customize irrigation schedules and parameters tailored to different plant types. This innovative solution promises to enhance agricultural practices by optimizing water usage and increasing crop yield.

In [2] data preprocessing was conducted, followed by the extraction of polarimetric parameters to create a comprehensive soil moisture database. Machine-learning models were then trained and assessed with feature selection techniques to enhance the accuracy of soil moisture estimation. The results highlight the effectiveness of machine learning when integrated with polarization decomposition parameters, with the Random Forest (RF) model showing particular promise. However, the study does acknowledge certain limitations, notably the constraints posed by a relatively small sample size and limited coverage of diverse crop types. To address these constraints, future research should focus on exploring broader geographical areas and employing advanced methodologies like deep learning. In sum, this approach provides valuable support for modeling soil moisture in agricultural contexts, offering potential benefits for optimizing irrigation and crop management.

In [3] a pH meter is connected to an Arduino while a temperature sensor, specifically the DHT11, is linked to a Raspberry Pi. The pH meter provides crucial data that aids in assessing nutrient levels in the soil. Simultaneously, the soil moisture sensor readings determine when the water pump should be activated. The primary objective of this research is to develop an automated monitoring system that enables real-time tracking of soil pH, temperature, and moisture. This system not only controls valves based on soil moisture levels but also delivers valuable pH and nutrient information. By facilitating real-time analysis, this innovative system offers the potential to significantly enhance agricultural productivity and profitability by optimizing resource usage, ultimately benefiting both the environment and farmers.

Chapter 3

Problem Statement and Objective

3.1 Problem Statement

The problem revolves around developing a robust and accurate crop recommendation system using machine learning techniques to provide personalized crop suggestions to farmers based on their specific agricultural and environmental conditions.

1)**Data Collection and Preprocessing:** Gathering relevant data including soil characteristics (e.g., pH levels, nutrient content), climatic data (e.g., temperature, rainfall patterns), geographical information, historical crop yields, and farmer preferences. Preprocessing the collected data to handle missing values, outliers, and inconsistencies, and ensuring data quality and reliability.

2)**Feature Selection and Engineering:** Identifying and selecting the most informative features (e.g., soil type, temperature, precipitation) that influence crop growth and yield. Engineering new features or transforming existing ones to enhance the predictive power of the model.

3)**Model Development:** Designing and implementing machine learning algorithms capable of learning patterns from the collected data to predict suitable crops for given environmental conditions. Exploring various algorithms such as decision trees, random forests, support vector machines, or neural networks to determine the most effective approach for crop recommendation.

4)**Model Evaluation and Validation:** Evaluating the performance of the developed models using appropriate metrics such as accuracy, precision, recall, and F1-score. Validating the model predictions through cross-validation techniques and comparing them against historical crop performance and expert recommendations.

5)**Deployment and Integration:** Building a user-friendly interface that allows farmers to input their location, soil characteristics, climate data, and other relevant information. Integrating the developed crop recommendation model into the interface to provide real-time, personalized crop suggestions based on user inputs. Deploying the system on scalable and accessible platforms such as web applications or mobile apps to reach all farmers.

3.2 Objective

The primary objectives of the machine learning-based crop recommendation system are as follows:

1)Provide accurate and personalized crop recommendations to farmers based on their specific Humidity, Temperature, Soil, and Climate Conditions.

2)Optimize crop selection to maximize yields, minimize resource usage, and increase profitability for farmers.

3)Facilitate data-driven decision-making in agriculture, leveraging machine learning techniques to enhance crop management practices.

4)Empower farmers with actionable insights and recommendations to improve overall farm productivity and sustainability.

Chapter 4

Block Diagram

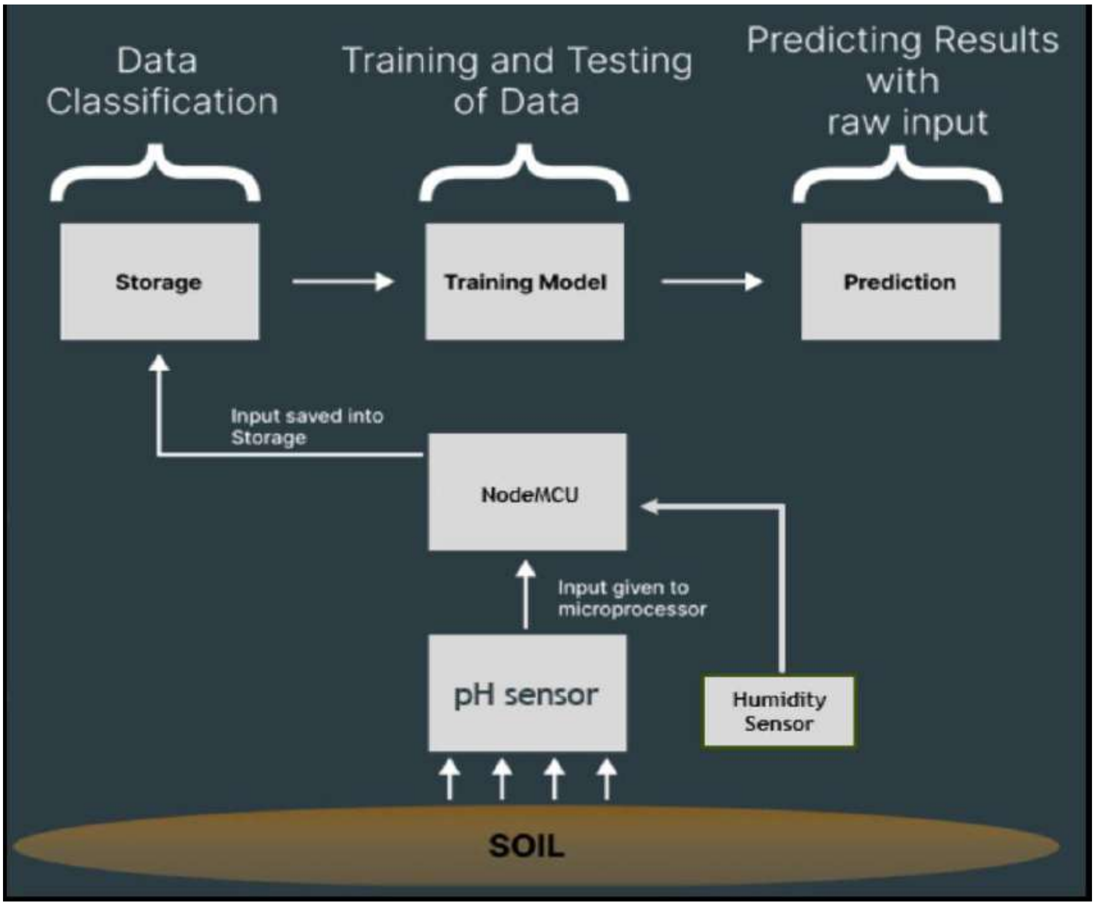

Figure 4.1: Block Diagram

1]Data Collection:

The crop recommendation system is based on data collection. A microcontroller device called NodeMCU, which has Wi-Fi capability, serves as the main hub for gathering data from several sensors placed across the agricultural area. The pH sensor determines the soil's acidity or alkalinity, giving vital information about the health of the soil, while the humidity sensor determines the soil's moisture level, which is critical for crop growth.

NodeMCU gathers information on soil conditions in real time by gathering data at regular intervals. Temperature, humidity, pH, and other pertinent environmental factors are included in this data. Farmers are able to make well-informed judgments regarding the health and condition of their crops by consistently monitoring these indicators and take informative decisions about irrigation, fertilization and crop selection.

2)Data Processing:

Preprocessing is done on the data after it is gathered to make sure it is suitable for analysis and of high quality. Preprocessing data entails the following steps:

Step 1:-Handling Missing Values: Sensor failures or transmission mistakes frequently result in missing data points in real-world datasets. One of the two approaches to dealing with these missing values is imputation or deletion.

Step 2:-Eliminating Outliers: Data points that drastically differ from the remainder of the sample are known as outliers, and they can skew the study. To find and eliminate these anomalies, outlier detection techniques are used.

Step 3:-Normativeization: By ensuring that every feature has an equal magnitude, normalizing the data helps to avoid specific features from taking center stage in the analysis because of their greater size.

We guarantee that the data is clear, consistent, and error-free by preprocessing it, setting the foundation for accurate machine learning model tarining.

3. Feature Selection and Engineering:

Feature selection involves identifying the most relevant attributes from the collected data that contribute significantly to the prediction task. In the context of crop recommendation, features may include soil pH levels, humidity levels, temperature, soil type, geographical location, and historical crop yields.

Feature engineering goes a step further by creating new features derived from existing ones or transforming features to enhance the predictive power of the model. For example, we may calculate additional features such as the average pH level over a specific time period or the variation in humidity levels throughout the day.

The goal of feature selection and engineering is to maximize the information content of the dataset while minimizing redundancy, thereby improving the performance of the machine learning model.

4. Model Selection:

Selecting a machine learning technique that best fits the features of the dataset and the requirements of the prediction task is known as model selection. The selection of a model is influenced by various aspects, such as:

Size of the Dataset: While simpler models like decision trees or random forests may perform well for smaller datasets, complicated models like deep learning neural networks may be appropriate for larger datasets.

Character of the Issue: Certain kinds of challenges are better suited for different machine learning techniques. Regression models are used to predict continuous variables, whereas decision trees are interpretable and appropriate for classification problems.

Computing Capabilities: Taking into account the model's computational complexity is crucial, particularly when implementing the system on hardware with limited resources such as NodeMCU.

Neural networks, support vector machines (SVM), decision trees, and random forests are popular machine learning algorithms for crop recommendation. To get good generalization performance and high prediction accuracy, the right algorithm must be used.

5. Model Training:

After the model is chosen, the preprocessed data is used to train it. In order to minimize the prediction error on the training data, the model parameters are adjusted iteratively throughout model training. Usually, optimization algorithms like gradient descent are used for this process.

The model picks up on the underlying patterns and connections between input variables (such as soil pH and humidity levels) and goal labels (crop suggestions) during training. The objective is to create a model that can make trustworthy predictions on data that hasn't been seen and that appropriately depicts these relationships.

To assess the model's performance and avoid overfitting; a situation in which the model memorizes the training data without generalizing well to new data; the training process may entail dividing the dataset into training and validation sets.

6. Model Evaluation:

Following training, a different dataset known as the testing data is used to assess the model's performance. This dataset offers an objective evaluation of the model's generalization capacity since it includes samples that the model hasn't encountered during training.

To measure the performance of the model, evaluation measures including accuracy, precision, recall, and F1-score are calculated. These metrics assess how well the model uses input characteristics to categorize or predict crop suggestions.

The assessment procedure aids in locating any flaws or vulnerabilities in the model and offers insightful input for adjusting its settings or investigating substitute algorithms.

7. Model Deployment:

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The assessment procedure aids in locating any flaws or vulnerabilities in the model and offers insightful input for adjusting its settings or investigating substitute algorithms.

8. Continuous Improvement:

The crop recommendation system is retrained, monitored, and given feedback in order to continuously improve. In order to adjust to changing circumstances and enhance its forecast accuracy over time, the model can be updated and retrained as new data becomes available and the system receives input from users and stakeholders.

Continual development could include:

i] Gathering more information in order to improve the training dataset and identify any new trends or patterns.

ii] Adjusting the model's parameters in light of domain expertise and performance feedback.

iii] Investigating cutting-edge machine learning methods or algorithms to improve forecast precision.

iv] Addressing particular agricultural concerns and improving the crop recommendation process by incorporating user feedback and subject expertise. The crop recommendation system can develop and get better at helping farmers make decisions by adopting a cycle of continuous improvement.

In summary, the machine learning-based crop recommendation block diagram consists of a number of interrelated phases, each of which is vital to the creation, implementation, and enhancement of a successful crop recommendation system. Farmers may maximize agricultural production and make educated decisions by utilizing sensors and NodeMCU hardware components in conjunction with cutting-edge machine learning techniques.

Chapter 5

Methodology

5.1 Machine Learning Algorithm

1.**Collect and preprocess data:** Gather data on various crops, including their growth requirements, yield, and other relevant factors. Preprocess the data to ensure it is clean, consistent, and ready for analysis.

2.**Select a machine learning model:** Choose a suitable machine learning model for crop recommendation, such as decision trees, random forests, or support vector machines.

3.**Split the data:** Divide the data into training and testing sets. The training set will be used to train the model, while the testing set will be used to evaluate its performance.

4.**Train the model:** Use the training set to train the machine learning model. This involves feeding the model with input data (such as soil type, climate, and other environmental factors) and the corresponding output (the recommended crop).

5.**Evaluate the model:** Use the testing set to evaluate the performance of the model. This involves comparing the predicted output (the recommended crop) with the actual output (the known recommended crop).

6.**Fine-tune the model:** check for the accuracy, precision and performance score in confusion matrix or in classification report, If the model's performance is not satisfactory, fine-tune it by adjusting its parameters or selecting a different model.

7.**Deploy the model:** Once the model is trained and evaluated, deploy it in a production environment where it can be used to recommend crops based on input data.

8.**Monitor and update the model:** Monitor the model's performance over time and update it as needed to ensure it continues to provide accurate crop recommendations.

5.2 Working Principle

1.**Data Collection**: Various data sources such as soil sensors, historical crop yields, and farmer surveys are collected. This data provides comprehensive insights into factors affecting crop growth such as soil characteristics, climate conditions, and past crop performance.

2.**Data Preprocessing**: The collected data undergoes preprocessing to ensure quality and consistency. This includes handling missing values, outliers, and inconsistencies. Additionally, data normalization and transformation techniques may be applied to standardize the data and make it suitable for machine learning algorithms.

3.**Feature Selection/Extraction**: Relevant features or variables that significantly impact crop growth and yield are selected from the dataset. Feature selection techniques help in identifying the most important factors. Feature extraction methods may also be employed to derive new features that capture complex relationships in the data.

4.**Model Training**: Machine learning algorithm such as random forests is trained on the preprocessed data. During training, the model learns from the input features (e.g., soil type, temperature and humidity) and target variables (e.g., crop yield, crop type) to make accurate predictions.

5.**Validation**: The trained model is validated using a separate dataset to assess its performance. This is crucial for ensuring that the model generalizes well to new data.

6.**Crop Recommendation**: Once the model is validated, it can be deployed to provide crop recommendations. Given input data about a specific location (e.g., soil type, climate conditions), the model predicts the most suitable crops to grow in that area. Recommendations can be customized based on various factors such as maximizing yield, optimizing resource utilization, minimizing risks, or meeting specific farmer preferences.

7.**Feedback Loop**: Continuous feedback is essential for improving the recommendation system. Farmers' feedback, along with updated data on crop performance and environmental conditions, is incorporated into the system to refine the models. This iterative process helps enhance the accuracy and relevance of future crop recommendations.

By leveraging machine learning techniques, crop recommendation systems enable farmers to make informed decisions and optimize agricultural practices for increased productivity, sustainability, and profitability.

Chapter 6

Component Description

6.1 NodeMCU

INTRODUCTION

NodeMCU ESP32 is a powerful development board built on the ESP32 system-on-chip (SoC) by Espressif Systems. This compact yet versatile device is revolutionizing the Internet of Things (IoT) landscape by offering developers a cost-effective, easy-to-use platform for building connected projects. In this document, we'll explore the key features, applications, and advantages of the NodeMCU ESP32.

Key Features:

1.Dual-Core Processing: The ESP32 chip boasts dual-core Ten silica LX6 processors, enabling it to handle complex tasks efficiently.

2.Wireless Connectivity: It supports both Wi-Fi and Bluetooth, allowing seamless integration with various IoT networks and devices.

3.Rich Peripheral Interface: With a wide range of GPIO pins, SPI, I2C, UART, and more, the NodeMCU ESP32 offers extensive interfacing capabilities.

4.Built-in Security Features: Features like secure boot, flash encryption, and cryptographic accelerators enhance the security of IoT applications.

5.Ultra-Low Power Consumption: The ESP32 chip incorporates advanced power management features, making it suitable for battery-operated devices.

6.Arduino Compatibility: NodeMCU ESP32 is Arduino IDE compatible, simplifying the development process for Arduino enthusiasts.

Applications:

1.Home Automation: Control and monitor various home appliances remotely using the NodeMCU ESP32's connectivity features.

2.Smart Agriculture: Deploy sensors in agricultural fields to collect data on soil moisture, temperature, and more, facilitating precision farming practices.

3.Industrial Automation: Monitor and manage industrial equipment and processes wirelessly for improved efficiency and safety.

4.Wearable Devices: Develop wearable gadgets such as fitness trackers, smartwatches, and healthcare monitors using the compact and energy-efficient NodeMCU ESP32.

5.Environmental Monitoring: Deploy sensor networks for real-time monitoring of environmental parameters like air quality, humidity, and pollution levels.

6.Education and Prototyping: NodeMCU ESP32 serves as an excellent educational tool for teaching IoT concepts and rapid prototyping of IoT projects.

Advantages:

1.Cost-Effective: The NodeMCU ESP32 offers an affordable solution for IoT development without compromising on performance.

2.Ease of Use: Its Arduino compatibility and extensive documentation make it accessible even to beginners in the field of embedded systems.

3.Scalability: From simple DIY projects to commercial IoT products, the NodeMCU ESP32 scales effortlessly to meet diverse application requirements.

4.Community Support: A vibrant community of developers contributes libraries, tutorials, and support, enriching the development experience.

5.Versatility: With its rich feature set and connectivity options, the NodeMCU ESP32 can be deployed in a wide range of IoT scenarios.

A few aspects of the NodeMCU ESP32:

1.Dual-Core Processing:

The ESP32 chip powering the NodeMCU ESP32 development board features dual-core Tensilica LX6 processors. These processors are designed for high performance and energy efficiency, making them ideal for handling complex tasks in IoT applications. By leveraging dual cores, developers can implement multitasking functionality, allowing the device to perform multiple tasks simultaneously without sacrificing performance. One core can be dedicated to handling communication tasks such as Wi-Fi and Bluetooth connectivity, while the other core manages data processing and application logic. This division of tasks enhances the overall responsiveness and efficiency of the device, ensuring smooth operation even under heavy workloads.

2.Built-in Security Features: Security is a critical aspect of IoT devices, especially considering the sensitive nature of data they often handle. The NodeMCU ESP32 incorporates several built-in security features to safeguard against various threats:

• Secure Boot: The ESP32 chip supports secure boot functionality, which ensures that only trusted firmware is loaded during the boot process, preventing unauthorized code execution.

• Flash Encryption: Data stored in the flash memory of the NodeMCU ESP32 can be encrypted, protecting it from unauthorized access or tampering.

• Cryptographic Accelerators: Hardware-accelerated cryptographic functions such as AES, RSA, and ECC are available on the ESP32 chip, enabling efficient encryption and decryption of data for secure communication.

By leveraging these security features, developers can build robust and secure IoT applications, protecting both user privacy and device integrity.

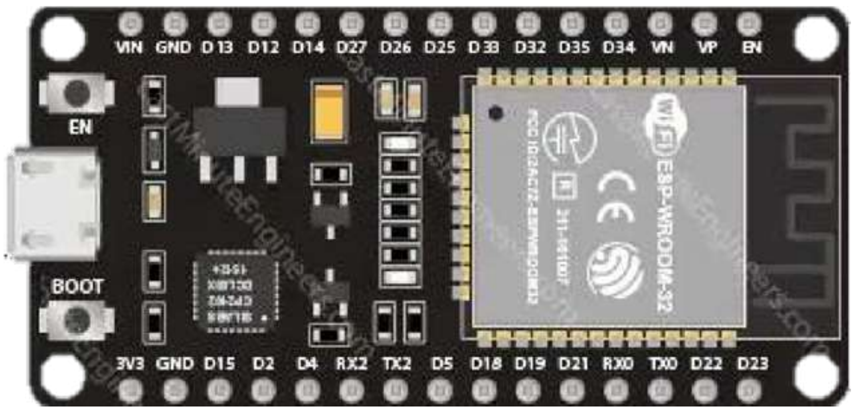

Figure 6.1: ESP32 Wroom

6.2 NodeMCU ESP32 Pin Description

GPIO Pins:

With the right register programming, the 25 GPIO pins on the ESP32 development board can be assigned various functionalities.
GPIOs come in various varieties, such as digital-only, analog-enabled, capacitive-touch-enabled, and so on. Digital GPIOs include both analogenabled and capacitivetouch-enabled GPIOs. The majority of these digital GPIOs can be configured to have high impedance or internal pull-up or pull-down.

Input Only GPIOs:

It is not possible to interpret pins GPIO34, GPIO35, GPIO36(VP), and GPIO39(VN) as outputs. They have additional uses in addition to being digital or analogue inputs. Unlike the other GPIO pins, they also don't have intrinsic pull-up and pull-down resistors.

ADC Pins:

The ESP32 allows measurements on 15 channels (analog-enabled pins) and integrates two 12-bit SAR ADCs. Because the ESP32 has a 12-bit ADC, it can detect 4096 distinct analogue levels. Put differently, it will translate input voltages between 0 and 3.3V (the operational voltage) into integer numbers between 0 and 4095. A resolution of 3.3 volts / 4096 units, or 0.0008 volts (0.8 mV) per unit, is the result of this. Additionally, programmable control over the ADC resolution and channel range is possible.

DAC Pins:

Two 8-bit DAC channels are built within the ESP32 to convert digital signals to real analogue voltages. It can be utilised to control analogue devices by acting as a digital potentiometer. Due to the 8-bit resolution of these DACs, values between 0 and 256 can be translated to an analogue voltage between 0 and 3.3 V.

I2C Pins:

Up to 112 sensors and peripherals can be connected to the ESP32's single I2C bus. By default, the following pins are designated as SDA and SCL pins. Nevertheless, you may use the wire to bit-bang the I2C protocol on any GPIO pin. Start the command (SDA, SCL).

SPI Pins:

Three SPIs (SPI, HSPI, and VSPI) are available in slave and master modes on the ESP32.

UART Pins:

The three UART ports on the ESP32 development board i.e., UART0, UART1, and UART2 supports IrDA at up to 5 Mbps and asynchronous communication (RS232 and RS485).

PWM Pins:

With the exception of input-only GPIOs, the board features 21 channels of PWM pins that are managed by a PWM controller. Digital motors and LEDs can be driven by the PWM output.

Power Pins:

The VIN pin and the 3V3 pin are the two power pins. If your 5V power supply is regulated, you can utilise the VIN pin to power the ESP32 and its peripherals directly. The on-board voltage regulator's output, which can handle up to 600 mA, is located on pin 3V3. Ground pin is GND.

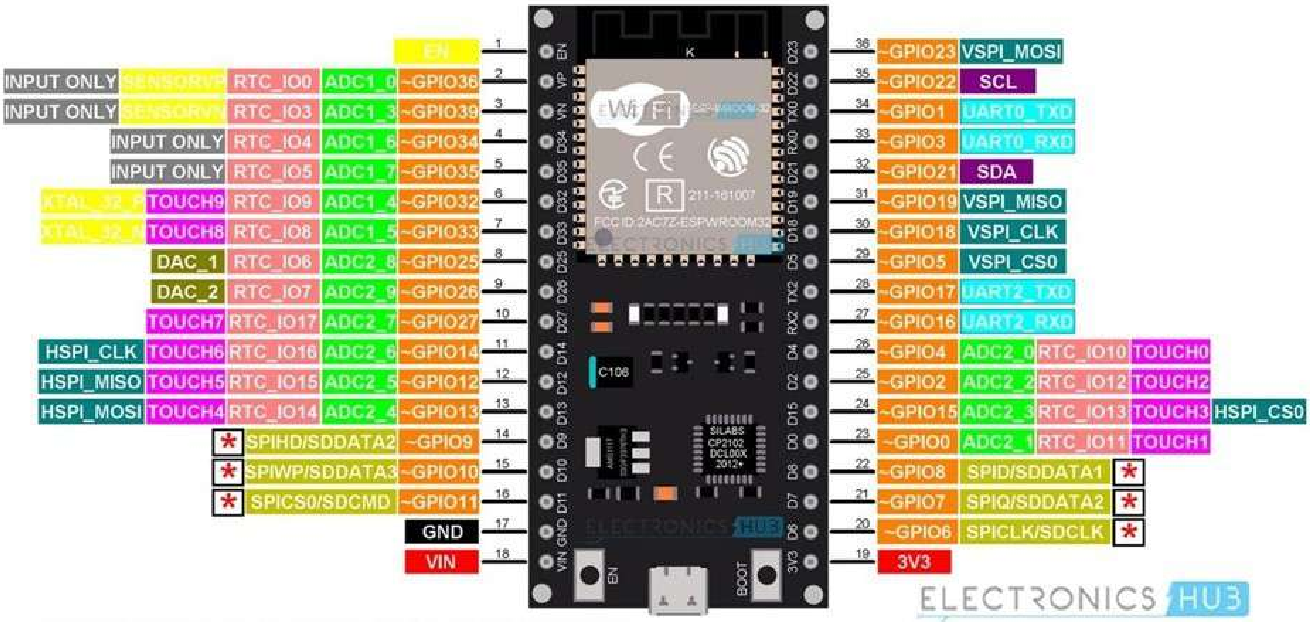

Figure 6.2: Pin Description

6.3 DHT11

Sensor Specification

Temperature Range: 0°C to 50°C (32°F to 122°F)
Humidity Range: 20 to 90 perent
Operating Voltage: 3.3V to 5V DC
Sampling Rate: Approximately 1 reading per second
Operating current: 0.3mA (measuring) 60uA (standby)
Resolution: Temperature and Humidity both are 16 bit
Accuracy: –1 C and –1
Output: Serial data

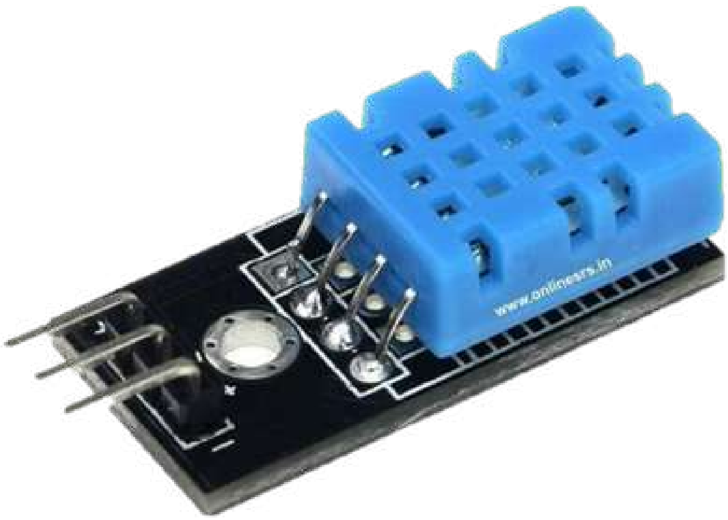

Figure 6.3: DHT11

Introduction

The DHT11 is a popular and cost-effective sensor widely used for measuring temperature and humidity in IoT (Internet of Things) projects. Developed by Aosong Electronics, this sensor offers a simple yet reliable solution for monitoring environmental conditions in various applications. In this document, we'll explore the key features, working principle, applications, and advantages of the DHT11 sensor.

Key Features:

1.Temperature and Humidity Sensing: The DHT11 sensor is capable of measuring temperature ranging from 0°C to 50°C with a ±2°C accuracy and relative humidity ranging from 20 percent to 90 percent with a ±5 percent accuracy.

2.Digital Output: It communicates with microcontrollers via a single-wire digital interface, making it easy to integrate into IoT projects.

3.Low Cost: The DHT11 is a low-cost sensor, making it accessible for hobbyists, students, and developers on a budget.

4.Compact Design: With its small form factor, the DHT11 can be easily deployed in various environments and applications where space is limited.

Working Principle:

The DHT11 sensor utilizes a thermistor to measure temperature and a capacitive humidity sensor to measure relative humidity. These sensors are integrated into a single package along with signal processing circuitry. When prompted by a microcontroller, the DHT11 sensor initiates a measurement cycle. During this cycle, it measures temperature and humidity and converts the analog signals into digital data. The digital data is then transmitted serially to the microcontroller, which can interpret the values and take appropriate actions based on the environmental conditions sensed by the DHT11.

Applications:

1.Home Automation: The DHT11 sensor is commonly used in home automation projects to monitor indoor temperature and humidity levels, enabling the control of HVAC systems, fans, and humidifiers.

2.Weather Stations: DIY weather stations often incorporate DHT11 sensors to collect data on temperature and humidity, providing users with real-time weather information.

3.Greenhouses and Agriculture: In greenhouse environments, DHT11 sensors help monitor and control temperature and humidity to create optimal growing conditions for plants.

4.HVAC Systems: Heating, ventilation, and air conditioning (HVAC) systems can use DHT11 sensors to adjust temperature and humidity levels for comfort and energy efficiency.

5.Data Logging: DHT11 sensors are used in data logging applications to record temperature and humidity data over time for analysis and monitoring purposes.

Advantages:

1.Affordability: The low cost of the DHT11 sensor makes it an attractive option for projects with budget constraints.

2.Ease of Use: With its digital output and simple communication protocol, the DHT11 sensor is easy to interface with microcontrollers, requiring minimal external components.

3.Reliability: Despite its low cost, the DHT11 sensor offers reliable performance for measuring temperature and humidity in a wide range of environments.

4.Wide Availability: The DHT11 sensor is readily available from various suppliers, making it easily accessible to hobbyists, students, and professionals alike.

Some additional aspects of the DHT11 sensor:

1.Limitations and Considerations:

While the DHT11 sensor offers simplicity and affordability, it's essential to consider its limitations when designing IoT applications: Limited Accuracy: The DHT11 sensor provides moderate accuracy for temperature and humidity measurements. However, for applications requiring higher precision, alternative sensors with better accuracy may be necessary. Slow Response Time: The DHT11 sensor has a relatively slow response time, especially when compared to more advanced sensors. This delay can impact the real-time monitoring of rapidly changing environmental conditions. Limited Operating Range: The operating range of the DHT11 sensor is optimized for typical indoor environments. Extreme temperatures or humidity levels outside its specified range may affect its performance. Understanding these limitations allows developers to make informed decisions when selecting sensors for their IoT projects and ensures that the DHT11 sensor is used appropriately in suitable applications.

2.Calibration and Calibration Factors:

Calibration is a crucial step in ensuring the accuracy of temperature and humidity measurements obtained from the DHT11 sensor. While the sensor comes pre-calibrated from the manufacturer, environmental factors and component aging can affect its performance over time. Calibration involves comparing the sensor readings to those obtained from a reference instrument and applying correction factors if necessary.

Developers can calibrate the DHT11 sensor by exposing it to known temperature and humidity conditions and adjusting its output accordingly. Calibration factors can be stored in the microcontroller's firmware or applied in real-time during data processing to compensate for any deviations from the expected measurements.

3.Power Consumption and Battery Life:

The DHT11 sensor operates at low power, making it suitable for battery-powered IoT devices. Its simple design and digital output contribute to minimal power consumption, extending the battery life of portable and remote monitoring applications. By optimizing the sensor's sampling intervals and sleep modes, developers can further reduce power consumption and maximize battery life, ensuring prolonged operation without frequent battery replacements.

4.Interfacing with Microcontrollers:

The DHT11 sensor communicates with microcontrollers using a single-wire digital interface, making it easy to interface with popular development platforms such as Arduino, Raspberry Pi, and ESP8266/ESP32. Libraries and code examples are available to simplify the integration process, allowing developers to focus on application logic rather than low-level sensor communication.

Additionally, the DHT11 sensor's compact size and lightweight design make it suitable for integration into various form factors, from small IoT nodes to wearable devices, enabling a wide range of innovative applications. By considering these additional factors and insights, developers can leverage the DHT11 sensor effectively in their IoT projects, ensuring accurate measurements, optimized performance, and enhanced reliability.

In summary, the DHT11 sensor provides a convenient and cost-effective solution for measuring temperature and humidity in IoT applications. Its simplicity, reliability, and affordability make it a popular choice among hobbyists, students, and professionals for monitoring environmental conditions in various projects. Whether used in home automation, weather stations, agriculture, or other applications, the DHT11 sensor continues to play a valuable role in the world of IoT.

Pin Description

Vcc: Power supply 3.5V to 5.5V
Data: Outputs both Temperature and Humidity through serial Data
Ground: Connected to the ground of the circuit

6.4 PH Sensor

Figure 6.4: PH Sensor

Sensor Specification

Working Current: 5-10 mA
Detection Concentration Range: pH 0-14
Response Time: <= 5 s

Stability Time: <= 120 s
Power Consumption: <= 0.5 W
Size: 42mm x 32mm x 20 mm
Weight: 25 g

Introduction

An analog pH sensor is a critical component in pH measurement systems, offering precise and accurate monitoring of acidity or alkalinity levels in liquids. These sensors find extensive use in various fields, including environmental monitoring, agriculture, water treatment, and food production. In this document, we'll explore the working principle, features, applications, and advantages of analog pH sensors.

Working Principle:

An analog pH sensor operates based on the principle of electrochemistry, specifically the measurement of the potential difference between a reference electrode and a sensing electrode immersed in the solution being tested. The sensing electrode typically consists of a glass membrane sensitive to hydrogen ion concentration (pH), while the reference electrode maintains a constant potential. When the glass membrane comes into contact with the solution, it generates a voltage proportional to the pH of the solution. This voltage is then measured and converted into a pH value using appropriate calibration techniques.

Key Features:

1.High Accuracy: Analog pH sensors offer high accuracy and precision, enabling reliable measurement of pH levels in a wide range of liquids.

2.Wide pH Range: These sensors can typically measure pH values across a broad range, from highly acidic to highly alkaline solutions.

3.Stability: Analog pH sensors exhibit excellent long-term stability, maintaining their calibration over extended periods of use.

4.Fast Response Time: With rapid response times, analog pH sensors provide real-time monitoring of pH fluctuations, enabling timely intervention in critical processes.

5.Compatibility: Analog pH sensors are compatible with various measurement devices and systems, including pH meters, data loggers, and process control systems.

Applications:

1.Environmental Monitoring: Analog pH sensors are used to assess water quality in natural bodies of water, wastewater treatment plants, and industrial discharge sites, aiding in pollution control and environmental conservation efforts.

2.Agriculture: In agriculture, pH sensors help optimize soil pH levels for crop cultivation, ensuring optimal nutrient uptake and plant growth.

3.Water Treatment: Analog pH sensors play a crucial role in monitoring and controlling pH levels in water treatment processes, such as drinking water purification, swimming pool maintenance, and industrial water treatment.

4.Food and Beverage Industry: These sensors are employed in food and beverage production to monitor pH levels during fermentation, brewing, and other manufacturing processes, ensuring product quality and safety.

5.Laboratory Research: Analog pH sensors are essential tools in scientific research laboratories for studying chemical reactions, enzymatic processes, and biological systems where pH regulation is critical.

Advantages:

1.Precision: Analog pH sensors offer high precision and accuracy, allowing for precise control and monitoring of pH levels in diverse applications.

2.Versatility: With their wide pH measurement range and compatibility with various liquids, analog pH sensors are versatile instruments suitable for a range of industries and research fields.

3.Reliability: Analog pH sensors exhibit excellent stability and durability, providing reliable performance even in harsh or demanding environments.

4.Ease of Use: These sensors are relatively easy to calibrate and maintain, making them accessible to both professionals and enthusiasts in various fields.

5.Cost-Effective: While offering high performance, analog pH sensors are available at competitive prices, making them cost-effective solutions for pH measurement applications.

1.Electrochemical Mechanism:

Analog pH sensors operate based on an electrochemical mechanism involving the generation of a potential difference between the sensing and reference electrodes immersed in the solution. The sensing electrode typically consists of a glass membrane that selectively interacts with hydrogen ions ($H+$) in the solution. When the glass membrane comes into contact with the solution, it establishes an equilibrium potential proportional to the logarithm of the hydrogen ion concentration, which is directly related to the pH of the solution. This potential is measured against a reference electrode, which maintains a stable potential, providing a baseline for comparison. The voltage difference between the sensing and reference electrodes is then converted into a pH value using established calibration curves or equations.

2.Calibration and Maintenance:

Calibration is a crucial step in ensuring the accuracy and reliability of analog pH sensors. Calibration involves exposing the sensor to buffer solutions with known pH values and adjusting the sensor's output accordingly to match the expected readings. Calibration should be performed regularly, especially if the sensor is subjected to harsh or variable conditions, to maintain accuracy over time. Additionally, proper maintenance, including cleaning and storage according to manufacturer guidelines, helps prolong the lifespan of analog pH sensors and ensures consistent performance.

3.Temperature Compensation:

Temperature has a significant impact on pH measurements due to its influence on the ionization equilibrium of water and the sensitivity of pH-sensitive materials. Analog pH sensors often incorporate temperature compensation mechanisms to correct for temperature variations and ensure accurate pH measurements across a range of temperatures. Temperature sensors integrated into the sensor assembly or external temperature probes provide temperature data, which is used to adjust the pH readings based on temperature-dependent calibration curves or algorithms.

4.Sensor Selection and Considerations:

When selecting an analog pH sensor for a specific application, several factors should be considered:

Measurement Range: Choose a sensor with a measurement range suitable for the expected pH levels in the target environment or sample.

Chemical Compatibility: Ensure that the sensor's materials are compatible with the sample solution to prevent corrosion or contamination.

Response Time: Consider the required response time for monitoring dynamic pH changes and select a sensor with an appropriate response time.

Installation and Mounting: Choose a sensor design and mounting configuration suitable for the application's requirements, such as immersion, insertion, flow-through, or surface measurement.

By carefully considering these factors and selecting the appropriate analog pH sensor, users can optimize pH measurement accuracy and reliability for their specific applications.

5.Integration with Data Acquisition Systems:

Analog pH sensors can be integrated into data acquisition systems and control loops to automate pH monitoring and control processes. These sensors typically provide analog voltage or current outputs proportional to the measured pH value, which can be interfaced with data acquisition devices such as pH meters, data loggers, PLCs (Programmable Logic Controllers), or SCADA (Supervisory Control and Data Acquisition) systems. Integration with data acquisition systems allows for real-time monitoring, data logging, alarms, and automated control of pH levels, enhancing process efficiency and reliability.

By incorporating these additional insights, users can deepen their understanding of analog pH sensors and their integration into various applications, enabling more informed decisions and optimized performance in pH measurement and control processes.

Some advanced features and emerging trends related to analog pH sensors:

1.Smart Sensor Technologies:

Advancements in sensor technology have led to the development of smart pH sensors equipped with additional functionalities and capabilities. These sensors may include built-in microcontrollers, digital signal processing capabilities, and communication interfaces such as I2C, SPI, or UART. Smart pH sensors can provide enhanced features such as onboard calibration, self-diagnosis, temperature compensation algorithms, and digital communication protocols, making them easier to integrate into automated systems and IoT (Internet of Things) networks. Additionally, smart sensors may offer features like data logging, remote monitoring, and wireless connectivity, allowing for real-time access to pH data and enabling advanced analytics and predictive maintenance strategies.

2.Miniaturization and Microfluidic Integration:

The trend towards miniaturization and integration of sensing technologies has influenced the design of analog pH sensors, leading to the development of compact and portable devices suitable for point-of-care diagnostics, wearable technologies, and microfluidic systems. Miniaturized pH sensors offer advantages such as reduced sample volume requirements, faster response times, and increased sensitivity, making them ideal for applications where space, weight, and power constraints are critical. Integration of pH sensors into microfluidic platforms enables lab-on-a-chip systems for high-throughput screening, biomedical diagnostics, and environmental monitoring, opening up new possibilities for point-of-use pH analysis in diverse settings.

3.Multi-Parameter Sensing:

In addition to measuring pH, modern analog sensors may incorporate additional sensing elements to enable multi-parameter analysis. For example, pH sensors integrated with ion-selective electrodes (ISEs) can simultaneously measure other ions such as chloride, fluoride, or potassium, providing comprehensive chemical analysis of the sample solution.

Multi-parameter sensing capabilities offer advantages in applications requiring comprehensive water quality monitoring, process control, or environmental analysis, where multiple parameters influence the overall system performance or regulatory compliance.

4.Remote Sensing and IoT Integration:

Analog pH sensors are increasingly being integrated into IoT platforms and remote monitoring systems to enable real-time monitoring and management of pH levels across distributed networks. IoT-enabled pH sensors can transmit data wirelessly to cloud-based platforms, where it can be accessed, analyzed, and visualized by stakeholders via web-based dashboards or mobile applications. Remote sensing capabilities enable proactive maintenance, early warning alerts, and predictive analytics, allowing for timely intervention and optimization of pH-related processes in various industries, including agriculture, aquaculture, and industrial manufacturing.

5.Sustainable Sensor Technologies:

The development of sustainable sensor technologies is a growing trend in sensor design and manufacturing. Analog pH sensors may incorporate eco-friendly materials, energy-efficient designs, and recyclable components to minimize environmental impact throughout their lifecycle. Additionally, advancements in sensor fabrication techniques, such as additive manufacturing and green chemistry approaches, are reducing resource consumption, waste generation, and hazardous chemical usage in sensor production. Sustainable sensor technologies contribute to environmental sustainability goals and promote the adoption of green practices in sensor manufacturing and deployment.

By embracing these advanced features and emerging trends, users can leverage the full potential of analog pH sensors to address complex challenges, improve process efficiency, and drive innovation in pH measurement and control applications.

In summary, Analog pH sensors are indispensable tools for precise and accurate pH measurement in a wide range of industries and research fields. Their high precision, versatility, reliability, and cost-effectiveness make them essential instruments for environmental monitoring, agricultural management, water treatment, food production, and scientific research. By leveraging the capabilities of analog pH sensors, professionals and researchers can ensure optimal pH control and quality assurance in their respective domains, contributing to improved efficiency, productivity, and sustainability.

Chapter 7

Result

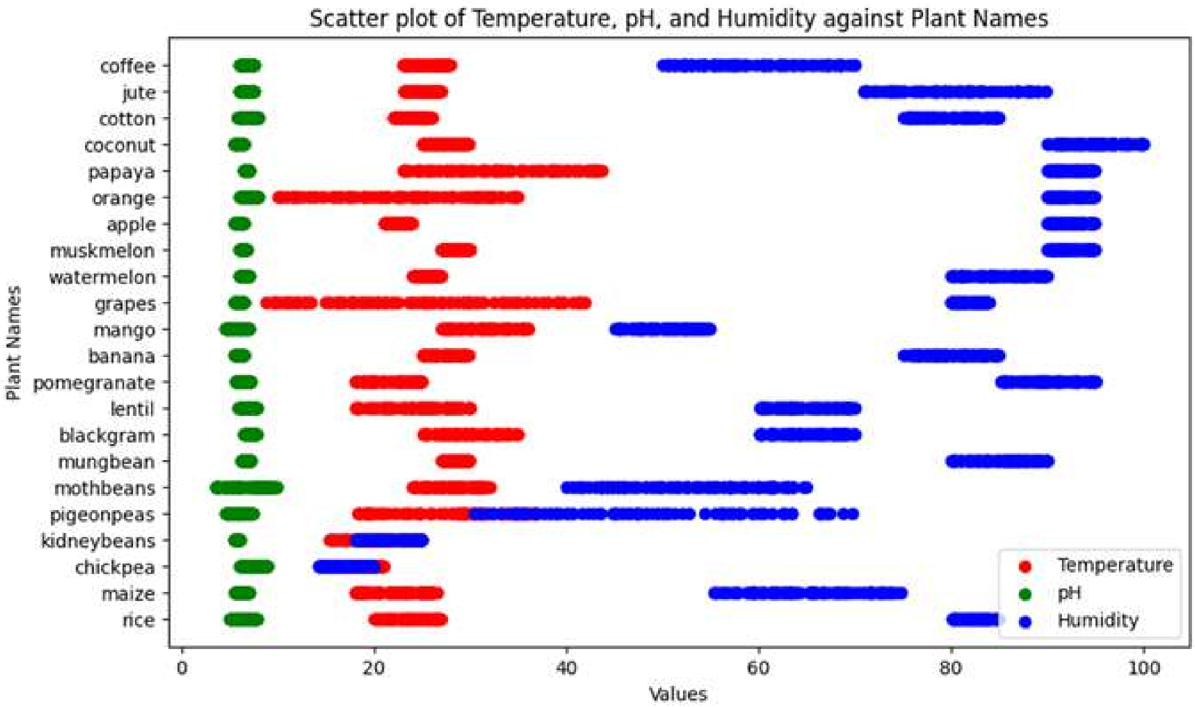

Figure 7.1: Output

The graphical representation of the dataset offers a concise yet insightful overview of the environmental preferences of various plant species. With plant names meticulously annotated along the Y-axis and ranges for humidity, temperature, and pH levels delineated along the X-axis, the graph provides a clear visualization of each plant's optimal environmental conditions.

Each plant species is represented as a distinct data point, positioned along the X-axis according to its preferred ranges of environmental variables. This arrangement allows for the identification of patterns and similarities among plants, facilitating the recognition of clusters with overlapping environmental requirements.

This graph serves as a valuable tool for refining machine learning models aimed at recommending optimal care practices for plants. By analyzing the patterns embedded within the graph, researchers can develop more sophisticated algorithms that generate targeted recommendations tailored to the specific needs of different plant clusters.

Furthermore, the graph enables researchers to validate and refine existing models by visually comparing their predictions with the observed ranges depicted in the graph. This iterative process of validation and refinement ensures the accuracy and effectiveness of the models in providing actionable insights for plant care.

In essence, the graphical representation of the dataset is a powerful resource for understanding and optimizing the care of plant species across diverse environmental conditions. Its visual clarity and rich informational content make it an invaluable tool for researchers, horticulturists, and enthusiasts alike, enabling informed decision-making to promote the health and vitality of plants in various settings.

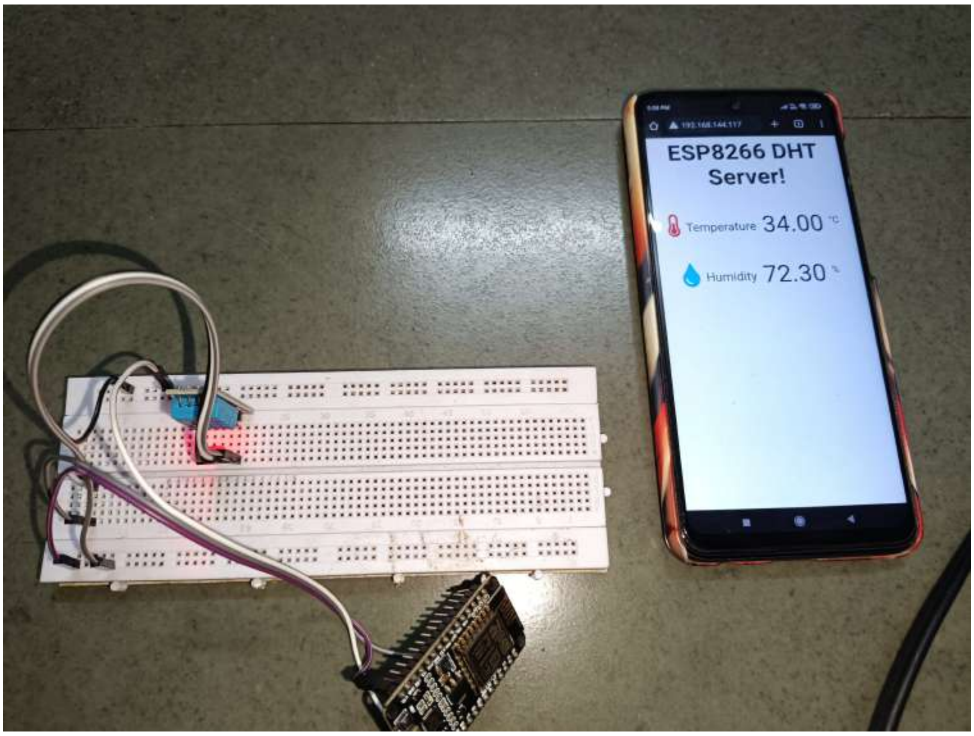

Figure 7.2: DHT Connection

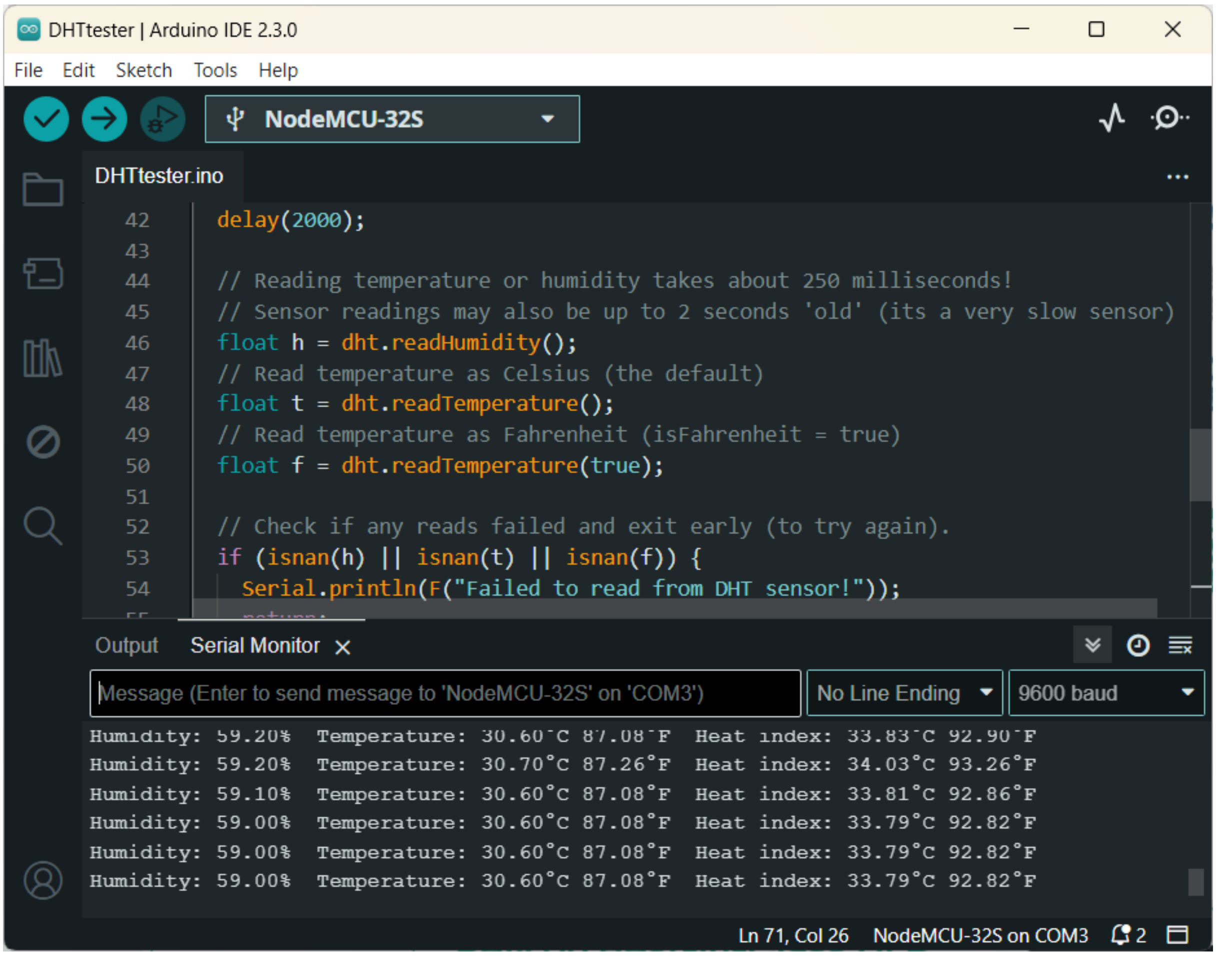

Figure 7.3: DHT11 Output

The process for connecting a DHT11 sensor to an ESP32 for measuring temperature and humidity:

1. Gather Components:

• ESP32 board

• DHT11 temperature and humidity sensor

• Breadboard and jumper wires

2. Understand Pinout:

• The DHT11 sensor typically has three pins: VCC (power), data, and GND (ground).

• The ESP32 board will have multiple GPIO pins for data input.

3. Connect DHT11 to ESP32:

• Connect the VCC pin of the DHT11 sensor to a 3.3V pin on the ESP32 board.

• Connect the GND pin of the DHT11 sensor to a ground (GND) pin on the ESP32 board.

• Connect the data pin of the DHT11 sensor to a GPIO pin on the ESP32 board. Choose any available GPIO pin; for example, GPIO 4.

4. Check Connections

5. Upload Code:

• Write the Arduino code for reading temperature and humidity values from the DHT11 sensor.

• Upload the code to the ESP32 board using the Arduino IDE or another compatible programming environment.

6. Testing:

• Power up the circuit.

• Open the serial monitor to view the temperature and humidity readings.

- Wait a few moments for the sensor to stabilize and provide accurate readings.

The code initializes the DHT11 sensor, reads temperature and humidity values, and prints them to the serial monitor every 2 seconds. Adjust the pin numbers and delay time as needed for your setup.

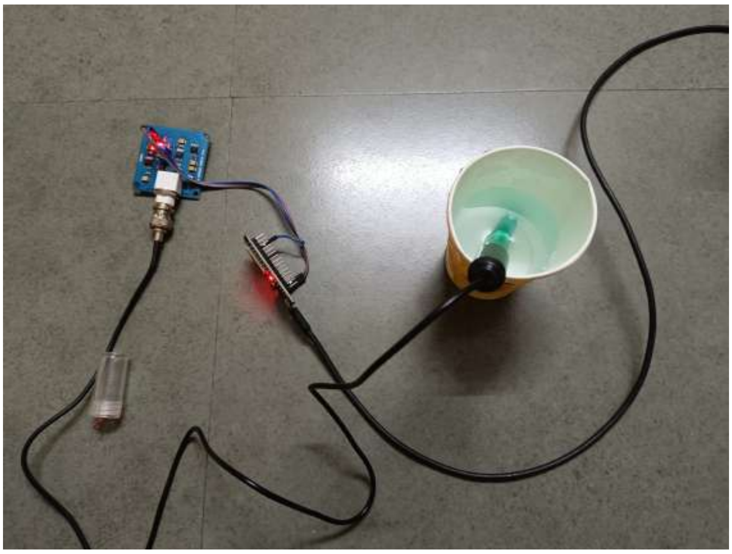

Figure 7.4: Testing pH of water

Figure 7.5: Water Output

The process for connecting an analog pH sensor to an ESP32:
1. Gather Components:

- ESP32 board

- Analog pH sensor kit

- Breadboard and jumper wires

- 9V battery pack (if the sensor requires it)

2. Understand Pinout:

- Identify the analog output pin of the pH sensor. This pin will provide the pH reading as an analog voltage.

- Identify the ground (GND) pin of the pH sensor.

- If your ESP32 board does not have a built-in ADC reference voltage, you may need to connect the reference voltage pin of the pH sensor to a stable voltage source (e.g., 3.3V or 5V).

3. Connect Analog Output:

- Connect the analog output pin of the pH sensor to one of the analog input pins (e.g., VP) on the ESP32 board.

- Connect the ground (GND) pin of the pH sensor to the ground (GND) pin on the ESP32 board.

4. Power Supply:

- If the pH sensor requires a separate power supply (e.g., 9V battery), connect it to the appropriate power input pin on the sensor.

- Connect the ground (GND) of the power supply to the ground (GND) pin on the ESP32 board.

5. Optional: Reference Voltage Connection (if needed):

- If the pH sensor requires a reference voltage, connect it to a stable voltage source on the ESP32 board, if available.

6. Check Connections

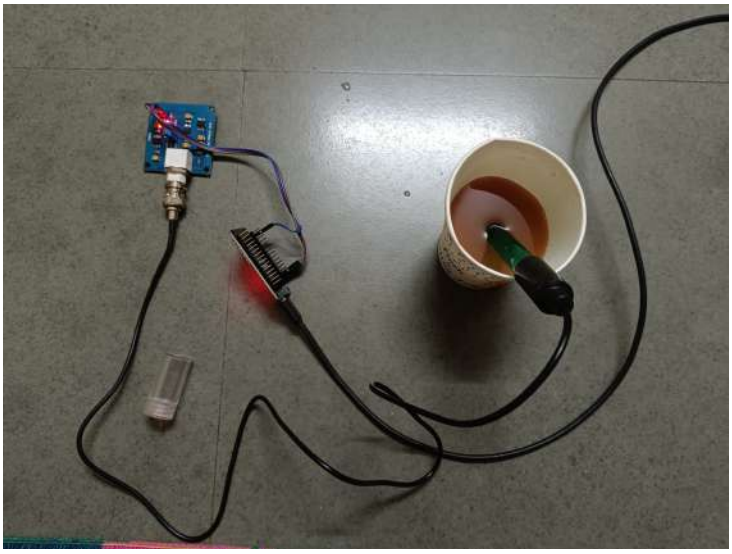

Figure 7.6: Testing pH of soil

Figure 7.7: Soil Output

7. Upload Code:

• Write or download the Arduino code for reading analog sensor values.

• Upload the code to the ESP32 board using the Arduino IDE or another compatible programming environment.

8. Testing:

• Power up the circuit.

• Open the serial monitor to view the pH readings.

• Dip the pH sensor into different solutions to observe changes in pH readings.

Remember to handle the pH sensor carefully, especially the sensitive glass membrane, to avoid damage. Additionally, ensure proper calibration of the sensor for accurate pH readings.

Chapter 8

Conclusion

Crop recommendation systems powered by machine learning represent a transformative approach to optimizing agricultural practices. By harnessing the capabilities of machine learning algorithms to analyze diverse datasets encompassing soil properties, climate conditions, historical crop performance, and farmer preferences, these systems offer personalized recommendations tailored to specific agricultural contexts. The adoption of precision agriculture principles allows for efficient resource allocation while minimizing environmental impact. Furthermore, these systems contribute to maximizing crop yields and profitability by suggesting the most suitable crops based on various factors such as soil type, moisture levels, temperature, and disease prevalence. They also serve as invaluable tools for risk mitigation, aiding farmers in adapting to challenges posed by climate change, market fluctuations, and pest outbreaks. As accessibility to these systems improves, particularly in remote or resource-constrained areas, their potential impact on global food security becomes increasingly significant. Moving forward, ongoing advancements in technology, such as the integration of real-time data from IoT sensors alongside continued research into more sophisticated machine learning algorithms, will further enhance the accuracy and effectiveness of crop recommendation systems.

Chapter 9

Future Scope

1.Integration of IoT and Remote Sensing: Incorporating real-time data from IoT sensors and satellite imagery can enhance the accuracy of crop recommendation systems by providing up-to-date information on soil moisture, crop health, and weather conditions.

2.Multi-criteria Decision Making: Future systems can employ advanced multi-criteria decision-making techniques to consider diverse factors such as economic viability, social impact, and environmental sustainability in crop recommendations.

3.Machine Learning Algorithms: Continued research into more advanced machine learning algorithms, such as deep learning and reinforcement learning, can further improve the predictive capabilities of crop recommendation systems, especially in handling complex and nonlinear relationships.

4.Localized Solutions: Tailoring recommendations to the specific needs and constraints of local communities can enhance the adoption and effectiveness of crop recommendation systems, considering factors like cultural practices, market demand, and infrastructure availability.

5.User Interface and Adoption: Developing user-friendly interfaces and providing adequate training and support to farmers are crucial for the widespread adoption and successful implementation of crop recommendation systems.

6.Collaborative Platforms: Creating collaborative platforms where farmers, agronomists, researchers, and policymakers can exchange knowledge and insights can foster innovation and continuous improvement in crop recommendation techniques.

7.Climate Resilience: As climate change continues to impact agricultural productivity and patterns, crop recommendation systems will play a vital role in helping farmers adapt to changing conditions by recommending resilient crop varieties and management practices.
[1] [2] [3]

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Title of Paper	:	CROP RECOMMENDATION SYSTEM USING MACHINE LEARNING
Impact Factor	:	7.95 (Calculate by Google Scholar)
DOI	:	
Published in	:	Volume 11 | Issue 4 | 2024-04-30
Publication Date	:	2024-04-30
Page No	:	n572-n577
Published URL	:	http://www.jetir.org/view?paper=JETIR2404D69
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JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
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CROP RECOMMENDATION SYSTEM USING MACHINE LEARNING

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Abstract: **The requirement for sustainable practices to guarantee effective crop cultivation is posing an increasing challenge to the agriculture sector. To address this, this study presents a novel project aimed at putting into practice a cutting-edge crop recommendation system. Using real-time data on important environmental parameters like as temperature, moisture content of soil, weather, and contextual subtleties, the system utilizes machine learning models that have been trained beforehand to examine complex inputs. To ensure precision and accuracy, the training process makes use of modern technologies such as support vector machines (SVM), random forests, decision trees, and others. With the use of data-driven insights, the robust model that is produced offers farmers customized and optimal crop suggestions that will increase agricultural output and promote sustainable farming methods. This approach is a major step toward a new era of agricultural growth and wealth since it emphasizes the resilience and efficiency of the agricultural sector.**

Index Terms - **Data Collection, Feature Engineering, Algorithm Selection, Model Training, Validation, Recommendation Generation, User Interface.**

INTRODUCTION:

In the context of agricultural sustainability, knowing how important environmental variables like temperature and soil moisture interact dynamically is essential to crop cultivation's success. Our innovative response centers on the application of a state-of-the-art crop recommendation system. This method leverages real-time data on soil moisture content, outside temperature, meteorological conditions, and the month-specific contextual details. Through the utilisation of pretrained machine learning models, our system aims to thoroughly examine these diverse inputs and provide customized suggestions for the best crops to grow in each soil type. Crop cultivation performance in the context of agricultural sustainability depends on an understanding of the dynamic interactions between key environmental variables, such as temperature and soil moisture. Our creative solution focuses on using a cutting-edge crop recommendation algorithm. This approach makes use of current information on soil moisture content, ambient temperature, weather, and month-specific contextual information. Our approach uses pretrained machine learning models to analyse these many inputs in detail and generate tailored recommendations for which crops might do well in a particular type of soil.

Our program aims to provide farmers with timely, accurate, and data-driven information so they may make well-informed decisions to increase agricultural output by promoting a data driven strategy. Our system's primary goal is to increase overall crop productivity and promote sustainable farming methods. By strengthening the agricultural sector's resilience, it hopes to usher in a new era of agricultural wealth and advancement.

PROBLEM STATEMENT:

Agriculture is crucial to meeting the needs of a growing population and preserving the world's food supply. However, because of variable weather patterns, different types of soil, and ever-changing environmental factors, farmers have significant challenges when choosing the finest crops. To address this issue, a precise and effective machine learning-based crop recommendation system that considers important parameters including soil moisture, pH level, temperature, and the month of the year is needed.

OBJECTIVE:

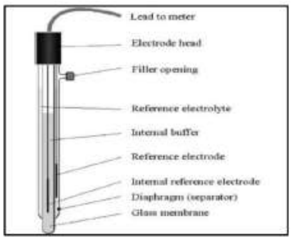
This project's main goal is to create a reliable, data-driven crop recommendation system that makes use of both historical and current data to make recommendations for appropriate crops depending on agricultural criteria. We will be able to obtain soil-related data, including pH value, by using soil sensors. These values will then be utilized to train a prediction-focused machine learning model. By encouraging crop diversity and resource-efficient cultivation methods, the crop recommendation system's success will not only improve agricultural output but also advance sustainable farming practices.

SOLUTION:

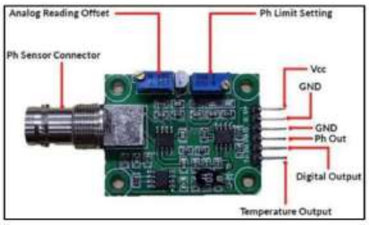
We intend to address the given problem statement by combining the technologies of microcontroller and machine learning. Sensors such as the Dht11 and soil pH sensor are connected to the NodeMCU-Esp32, allowing us to measure the temperature, humidity, and pH of the soil. The measured values are then fed into a pre-trained machine learning model that was trained through supervised learning. The algorithm recommends the best plant for a given soil type based on the variables provided. Because it is composed of a metallic conductor, the reference electrode is unaffected by the solution's pH. This conductor is immersed in an electrolyte solution, usually potassium chloride, which interacts with the test solution through a porous ceramic membrane.

NodeMCU: ESP-32

The NodeMCU ESP32 module, a microcontroller that runs on the ESP32 chip, boasting a diminutive form and pocket-friendly price. This little device enables developers to forge connections with the cyberspace and govern their projects from afar. It cooperates with the Arduino Integrated Development Environment, and allows for scripting in the Lua language or the Arduino programming language. It is a staple in lot ventures, with potential to construct gadgets for domiciles, remote manipulation, and more.

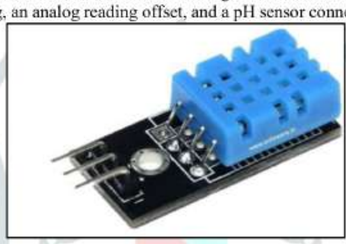


Soil pH Sensor Probe



Transducer

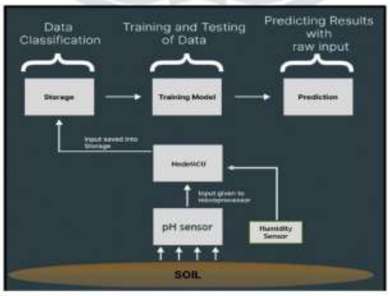
The transducer known as the transmitter, also known as the signal conversion board, is attached to this pH sensor. This board has six IO pins, a PH limit setting, an analog reading offset, and a pH sensor connector that is attached to the sensor probe.



DHT11 Sensor

The DHT11 sensor stands out for its affordability and simplicity in measuring temperature and humidity digitally. It communicates through a single-wire digital interface, making integration straightforward. Its temperature accuracy is within ±2°C, and humidity accuracy is within ±5%. With an operating voltage range of 3.3V to 5V, it is compatible with a variety of microcontrollers and development boards. Although it's widely used for basic environmental monitoring projects due to its cost-effectiveness and ease of implementation, its lower accuracy compared to other sensors should be noted for applications requiring precise measurements.

BLOCK DIAGRAM:



Working of Project

WORKING:

Step 1: Gathering data:
By connecting soil moisture sensors with NodeMCU we will collect soil pH levels, Temperature and Humidity.

Step 2: Data Preprocessing:
We will use different soil sample and their data to make one dataset. Ensure that the collected data is in a consistent format and free from errors or missing values.

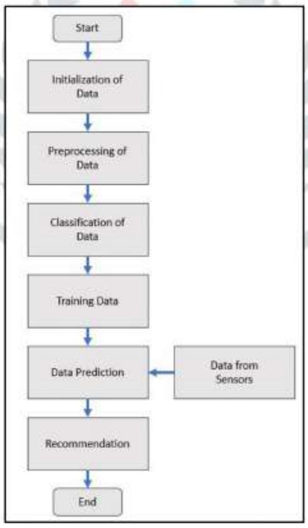
Step 3: Classification of data:
Classify the crops into different categories based on their tolerance to soil pH levels, temperature, and Humidity.

Step 4: Crop Selection Criteria:
Soil Moisture: Choose crops that match the measured soil moisture levels within their optimal range.

Soil pH: Select crops that prefer the soil pH value. Temperature & Humidity: Choose crops that thrive within the current temperature & Humidity range.

Step 5: Crop Recommendation Algorithm:
Develop an algorithm that takes the collected data as input and provides crop recommendations based on the predefined crop selection criteria. The algorithm should be able to prioritize the crops based on how well they match the environmental conditions.

FLOW CHART:



Flow Chart of Model Trading and Prediction

OUTPUT:

```
Humidity: 59.20%  Temperature: 30.70°C
Humidity: 59.10%  Temperature: 30.60°C
Humidity: 59.00%  Temperature: 30.60°C
Humidity: 59.00%  Temperature: 30.60°C
Humidity: 59.00%  Temperature: 30.60°C
```

DHT11 Output from NodeMCU

```
pH:9.47
pH:9.46
pH:9.45
pH:9.41
pH:9.39
pH:9.36
```

PH output from NodeMCU

```
#prediction for new values
new_temperature = 30
new_ph = 7
new_humidity = 59
```

Entering above values to pre-trained model

```
# Printing Predicted Result
print("Predicted Label for the given values:", new_prediction[0])

Predicted Label for the given values: blackgram
```

Recommendation from model

CONCLUSION:

Using supervised machine learning and a random forest classifier, we have successfully trained the machine learning model. We have also developed a prototype system that makes plant recommendations based on soil pH, temperature, and humidity levels. In the future, recommendations based on season can also be implemented to make this project more scalable.

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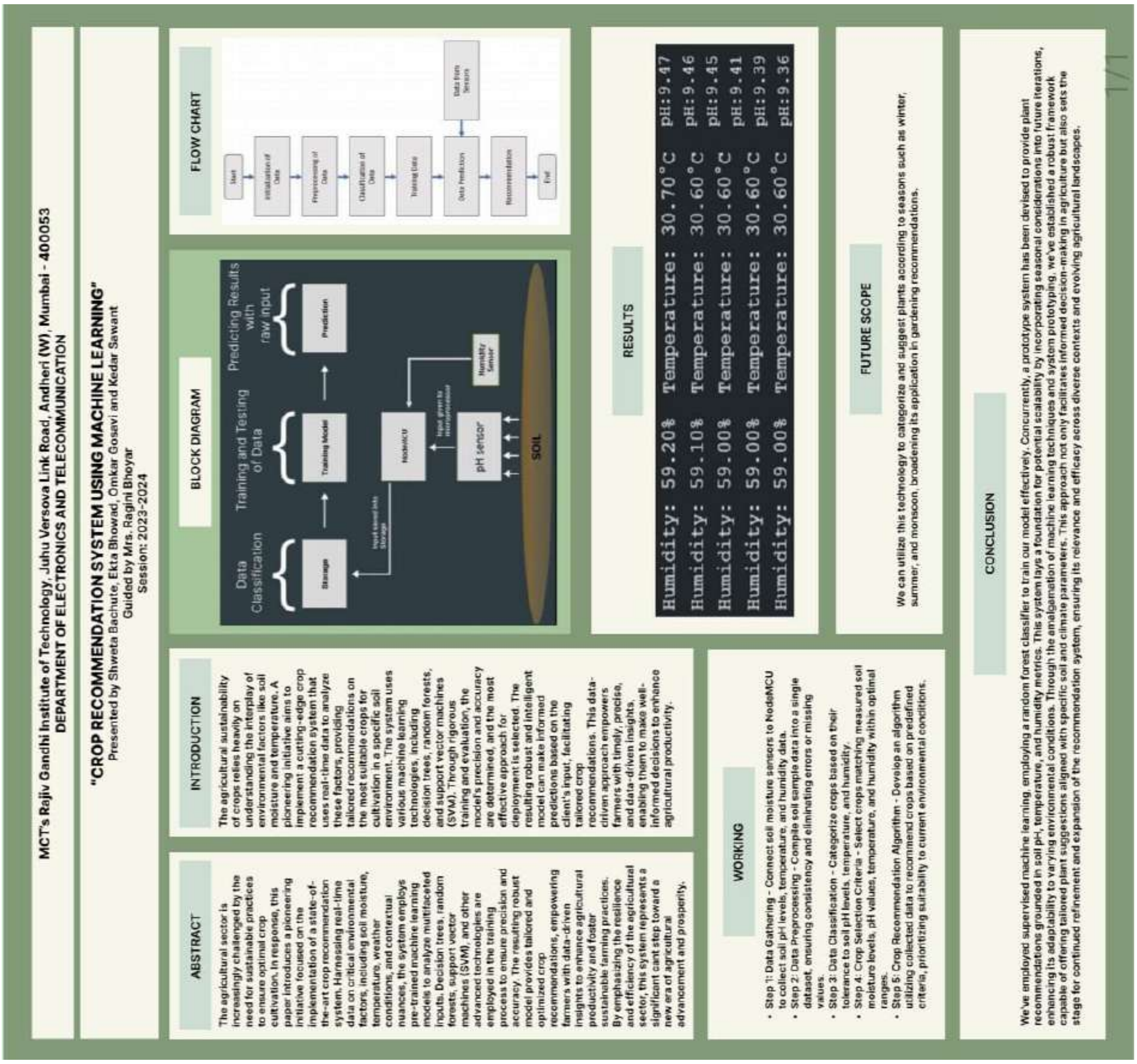
Poster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DEPARTMENT OF ELECTRONICS AND TELECOMMUNICATION
"CROP RECOMMENDATION SYSTEM USING MACHINE LEARNING"
Presented by Shweta Bachute, Ekta Bhowad, Omkar Gosavi and Kedar Sawant
Guided by Mrs. Ragini Bhoyar
Session: 2023-2024
ABSTRACT
The agricultural sector is increasingly challenged by the need for sustainable practices to ensure optimal crop cultivation. In response, this paper introduces a pioneering initiative focused on the implementation of a state-of-the-art crop recommendation system. Harnessing real-time data on critical environmental factors, including soil moisture, temperature, weather conditions, and contextual nuances, the system employs pre-trained machine learning models to analyze multifaceted inputs. Decision trees, random forests, support vector machines (SVM), and other advanced technologies are employed in the training process to ensure precision and accuracy. The resulting robust model provides tailored and optimized crop recommendations, empowering farmers with data-driven insights to enhance agricultural productivity and foster sustainable farming practices. By emphasizing the resilience and efficiency of the agricultural sector, this system represents a significant cant step toward a new era of agricultural advancement and prosperity.
INTRODUCTION
The agricultural sustainability of crops relies heavily on understanding the interplay of environmental factors like soil moisture and temperature. A pioneering initiative aims to implement a cutting-edge crop recommendation system that uses real-time data to analyze these factors, providing tailored recommendations on the most suitable crops for cultivation in a specific soil environment. The system uses various machine learning technologies, including decision trees, random forests, and support vector machines (SVM). Through rigorous training and evaluation, the model's precision and accuracy are determined, and the most effective approach for deployment is selected. The resulting robust and intelligent model can make informed predictions based on the client's input, facilitating tailored crop recommendations. This data-driven approach empowers farmers with timely, precise, and data-driven insights, enabling them to make well-informed decisions to enhance agricultural productivity.
BLOCK DIAGRAM
Data Classification
Training and Testing of Data
Predicting Results with raw input
Storage
Training Model
Prediction
Input saved into Storage
NodeMCU
Input given to microprocessor
pH sensor
Humidity Sensor
SOIL
FLOW CHART
Start
Initialization of Data
Preprocessing of Data
Classification of Data
Training Data
Data Prediction
Data from Sensors
Recommendation
End
RESULTS
Humidity: 59.20% Temperature: 30.70°C pH:9.47
Humidity: 59.10% Temperature: 30.60°C pH:9.46
Humidity: 59.00% Temperature: 30.60°C pH:9.45
Humidity: 59.00% Temperature: 30.60°C pH:9.41
Humidity: 59.00% Temperature: 30.60°C pH:9.39
pH:9.36
WORKING
• Step 1: Data Gathering - Connect soil moisture sensors to NodeMCU to collect soil pH levels, temperature, and humidity data.
• Step 2: Data Preprocessing - Compile soil sample data into a single dataset, ensuring consistency and eliminating errors or missing values.
• Step 3: Data Classification - Categorize crops based on their tolerance to soil pH levels, temperature, and humidity.
• Step 4: Crop Selection Criteria - Select crops matching measured soil moisture levels, pH values, temperature, and humidity within optimal ranges.
• Step 5: Crop Recommendation Algorithm - Develop an algorithm utilizing collected data to recommend crops based on predefined criteria, prioritizing suitability to current environmental conditions.
FUTURE SCOPE
We can utilize this technology to categorize and suggest plants according to seasons such as winter, summer, and monsoon, broadening its application in gardening recommendations.
CONCLUSION
We've employed supervised machine learning, employing a random forest classifier to train our model effectively. Concurrently, a prototype system has been devised to provide plant recommendations grounded in soil pH, temperature, and humidity metrics. This system lays a foundation for potential scalability by incorporating seasonal considerations into future iterations, enhancing its adaptability to varying environmental conditions. Through the amalgamation of machine learning techniques and system prototyping, we've established a robust framework capable of offering tailored plant suggestions aligned with specific soil and climate parameters. This approach not only facilitates informed decision-making in agriculture but also sets the stage for continued refinement and expansion of the recommendation system, ensuring its relevance and efficacy across diverse contexts and evolving agricultural landscapes.
1/1

Chapter 10

Annexure

Machine Learning Code

```
data = pd.read_csv('Crop_recommendation.csv')
# importing our data set
X = data[['temperature', 'ph', 'humidity']]
# Storing value of temperature,
humidity and ph value data to X variable
Y = data['label']
# Storing Label names (Plant names) in Y variable
plt.figure(figsize=(10, 6))
plt.scatter(X['temperature'],
Y, color='r', label='Temperature')
# red color for Temperature
plt.scatter(X['ph'], Y, color='g', label='pH')
# green color for pH value
plt.scatter(X['humidity'], Y, color='b', label='Humidity')
# blue color for Humidity
plt.xlabel('Values')   # name of x axis
plt.ylabel('Plant Names') # name of Y axis
plt.title('Scatter plot of Temperature,
pH, and Humidity against Plant Names')
# name of Chart
plt.legend()
# printing legend on Graph
plt.show()
# plotting actual Graph
# Dividing X and Y data in 80:20 ratio
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2,
    random_state=42)
# (test size is 0.2 means 20)
# Create a Random Forest Classifier
with 100 estimators
clf = RandomForestClassifier
(n_estimators=100, random_state=42)
```

```
#fitting trained data
clf.fit(X_train, y_train)
# using x-test data for prediction
so that it can be used for comparision with y-test
y_pred = clf.predict(X_test)
# creating classfication report based
on y-test (labels) abd y-pred
(predicted result based on x-test)
print("Classification Report:\n",
classification_report(y_test, y_pred))
# Printing Accuracy
print("Accuracy:", accuracy_score(y_test, y_pred))
Accuracy: 0.7727272727272727
#prediction for new values
new_temperature = 25
new_ph = 7
new_humidity = 54
# Making prediction for the new values
new_prediction = clf.predict
([[new_temperature, new_ph, new_humidity]])
# Printing Predicted Result
print("Predicted Label for the
given values:", new_prediction[0])
```

Arduino Code

```
#include <WiFi.h>
#include <WebServer.h>
#include <DHT.h>

#define PH_OFFSET -1.00 //if there is an offset
#define SensorPin A0      // the pH meter Analog output is connected with the
   Arduinos Analog
unsigned long int avgValue; // Store the average value of the sensor feedback
float b;
int buf[10], temp;

const char *ssid = "Redmi Note 12 Pro 5G";
const char *password = "om@475786007";


WebServer server(80);
DHT dht(4, DHT11); // For ESP8266, DHT sensor data pin is D2

void handleRoot() {
   char msg[1500];

   snprintf(msg, 1500,
   "<html>\
```

```
    <head>\
    <meta http-equiv='refresh' content='4'/>\
    <meta name='viewport' content='width=device-width, initial-scale=1'>\
    <link rel='stylesheet'
       href='https://use.fontawesome.com/releases/v5.7.2/css/all.css'
       integrity='sha384-fnmOCqbTlWIlj8LyTjo7mOUSt-
    jsKC4pOpQbqyi7RrhN7udi9RwhKkMHpvLbHG9Sr' crossorigin='anonymous'>\
    <title>ESP8266 DHT pH Server</title>\
    <style>\
    html { font-family: Arial; display: inline-block; margin: 0px auto;
       text-align: center;}\
    h2 { font-size: 3.0rem; }\
    p { font-size: 3.0rem; }\
    .units { font-size: 1.2rem; }\
    .dht-labels{ font-size: 1.5rem; vertical-align:middle; padding-bottom:
       15px;}\
    </style>\
    </head>\
    <body>\
    <h2>ESP32 DHT pH Server!</h2>\
    <p>\
    <i class='fas fa-thermometer-half' style='color:#ca3517;'></i>\
    <span class='dht-labels'>Temperature</span>\
    <span>%.2f</span>\
    <sup class='units'>&deg;C</sup>\
    </p>\
    <p>\
    <i class='fas fa-tint' style='color:#00add6;'></i>\
    <span class='dht-labels'>Humidity</span>\
    <span>%.2f</span>\
    <sup class='units'>&percnt;</sup>\
    </p>\
    <p>\
    <i class='fas fa-flask' style='color:#0080ff;'></i>\
    <span class='dht-labels'>pH Value</span>\
    <span>%.2f</span>\
    </p>\
    </body>\
    </html>",
    readDHTTemperature(), readDHTHumidity(), readPHValue()
    );
    server.send(200, "text/html", msg);
}

void setup() {
    Serial.begin(115200);
    dht.begin();

    WiFi.mode(WIFI_STA);
```

```
  WiFi.begin(ssid, password);
  Serial.println("");

  // Wait for connection
  while (WiFi.status() != WL_CONNECTED) {
    delay(1000);
    Serial.print(".");
  }

  Serial.println("");
  Serial.print("Connected to ");
  Serial.println(ssid);
  Serial.print("IP address: ");
  Serial.println(WiFi.localIP());

  server.on("/", handleRoot);

  server.begin();
  Serial.println("HTTP server started");
  pinMode(13, OUTPUT); // assuming LED output for pH indication
}

void loop() {
  server.handleClient();
  delay(20); // allow the CPU to switch to other tasks
}

float readDHTTemperature() {
  // Sensor readings may also take up to 2 seconds
  // Read temperature as Celsius (the default)
  float t = dht.readTemperature();
  if (isnan(t)) {
    Serial.println("Failed to read from DHT sensor!");
    return -1;
  }
  else {
    Serial.println(t);
    return t;
  }
}

float readDHTHumidity() {
  // Sensor readings may also take up to 2 seconds
  float h = dht.readHumidity();
  if (isnan(h)) {
    Serial.println("Failed to read from DHT sensor!");
    return -1;
  }
  else {
```

```
    Serial.println(h);
    return h;
  }
}

float readPHValue() {
  for(int i = 0; i < 10; i++) {   // Get 10 sample value from the sensor
      for smoothing the value
    buf[i] = analogRead(SensorPin);
    delay(10);
  }
  for(int i = 0; i < 9; i++) {    // Sort the analog values from small to
      large
    for(int j = i + 1; j < 10; j++) {
      if(buf[i] > buf[j]) {
        temp = buf[i];
        buf[i] = buf[j];
        buf[j] = temp;
      }
    }
  }
  avgValue = 0;
  for(int i = 2; i < 8; i++) {                        // Take the average value of
      6 center samples
    avgValue += buf[i];
  }
  float phValue = (float)avgValue * 5.0/4095/6; // Convert the analog value
      into millivolts
  phValue = 3.5 * phValue;                            // Convert the millivolts
      into pH value

  phValue = phValue + PH_OFFSET;

  Serial.print("pH: ");
  Serial.println(phValue, 2);
  return phValue;
}
```