

Crop recommendation system based on soil moisture sensor

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Abstract – This paper presents a crop recommendation system leveraging soil moisture sensors to optimize agricultural decision-making. The system collects real-time soil moisture data, which, along with environmental factors, is analyzed to identify suitable crops for specific soil conditions. By utilizing machine learning algorithms, the model can predict optimal crop choices, enhancing productivity and water resource management. The proposed system aims to support farmers in selecting crops that align with current soil moisture levels, thus promoting sustainable farming practices and resource efficiency. Preliminary results demonstrate the system's effectiveness in improving crop yield predictions and aiding informed crop selection

1.INTRODUCTION (Size 11, Times New roman)

Agriculture plays a vital role in sustaining populations and supporting economies worldwide. However, the increasing demand for food, coupled with environmental challenges like water scarcity, soil degradation, and climate change, has placed significant pressure on agricultural practices. In response, precision agriculture has emerged as an innovative approach, employing technology to improve productivity and efficiency. One critical aspect of precision agriculture involves understanding and managing soil moisture, as it directly impacts plant health, crop yield, and resource utilization. This paper introduces a crop recommendation system based on soil moisture sensors, aiming to assist farmers in making data-driven crop choices that align with real-time soil conditions.

Soil moisture is a fundamental factor in agriculture, influencing plant growth, nutrient availability, and soil structure. Traditionally, farmers rely on experience or basic measurements to determine moisture levels, which may not accurately reflect the conditions necessary for optimal crop selection and yield. Integrating soil moisture sensors with data-driven algorithms offers a more precise and actionable approach. Soil moisture sensors monitor the water content in the soil, providing continuous, real-time feedback that can be used to inform agricultural decisions. The data collected through

these sensors serves as a foundation for this crop recommendation system, enabling farmers to select crops that are well-suited to current moisture levels, soil characteristics, and other environmental factors.

This crop recommendation system leverages machine learning algorithms to analyze sensor data and recommend crops based on specific moisture conditions. By incorporating additional environmental data, such as temperature, humidity, and historical weather patterns, the system can enhance the accuracy of crop predictions. Using supervised learning techniques, the model is trained on historical data, learning to correlate moisture levels and other parameters with successful crop outcomes. This process ensures that the recommendations provided are grounded in data patterns relevant to specific soil and climate conditions.

The development of such a system has significant implications, especially in regions where traditional farming methods have become unsustainable due to climate variability. With real-time data and informed crop recommendations, farmers can shift from reactive to proactive decision-making, which may improve crop resilience and productivity even under challenging conditions. While some similar systems exist, this approach stands out by focusing on the integration of soil moisture sensors with machine learning for more localized and adaptive recommendations.

Ensemble models like J48 and support vector further demonstrate the potential of combining different network architectures, such as CNNs and Long Short-Term Memory (LSTM) networks, to predict suitable crop. These models achieved over 90% accuracy across various datasets. However Random forest algorithm got highest accuracy around 98%.

2. WORKING PRINCIPLE

The system uses two main sensors: a soil moisture sensor to gauge the water level in the soil, and a DHT11 sensor to measure temperature and humidity in the surrounding environment. These readings provide key insights into the soil's hydration level and the microclimate. Both sensors are connected to an ESP8266 microcontroller, which is responsible for collecting, processing, and transmitting the data.

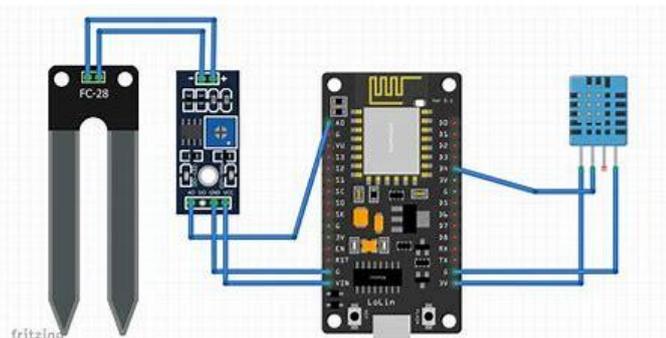
Once the ESP8266 receives data from the sensors, it transmits this data over Wi-Fi to a cloud server or a local database. By sending data in real-time, the system can provide a continuous, up-to-date profile of soil and environmental conditions, essential for accurately assessing the suitability of different crops.

On the server, the collected data is processed. The soil moisture level, temperature, and humidity readings are compared to the optimal growth conditions for various crops. This can be done using machine learning algorithms trained on environmental data and crop suitability or through rule-based logic that references ideal conditions for each crop type.

Based on the analysis, the system generates a list of recommended crops that can thrive in the current soil and climate conditions. Additional factors, such as soil pH or historical crop data, may also be integrated into the recommendation model to improve accuracy and personalization for different types of farms and soil compositions.

Finally, the farmer can access the crop recommendations through an online platform, mobile app, or IoT dashboard linked to the system. By having this information at their fingertips, farmers can make informed decisions about which crops to plant, optimizing both yield and resource efficiency based on real-time, data-driven insights.

3. CIRCUIT DIAGRAM



4. ELEMENT OF A SYSTEM

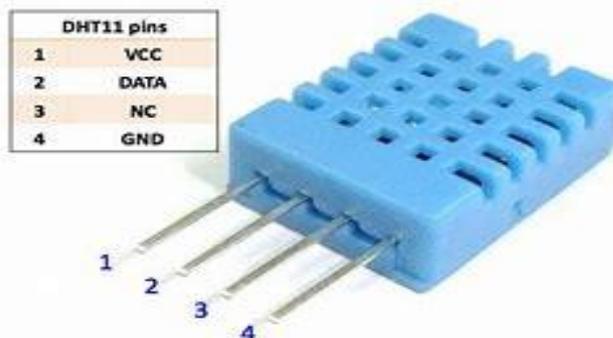
4.1 SOIL MOISTURE SENSOR



A soil moisture sensor is used to detect the amount of water present in the soil. Unlike traditional gravimetric methods, which require removing, drying, and weighing a soil sample, these sensors determine water content indirectly. They do this by analyzing soil properties that shift with moisture, such as dielectric constant, electrical resistance, or neutron interaction, which correspond with soil water levels.

The accuracy of the sensor's readings may need to be adjusted, as they can vary with environmental factors like soil type, temperature, and electrical conductivity. Additionally, microwave emissions influenced by soil moisture are often used in agriculture and hydrology for remote moisture sensing over broad areas. Most soil moisture sensors detect volumetric water content, while other types, known as soil water potential sensors (like gypsum blocks and tensiometers), measure the energy status of water in the soil.

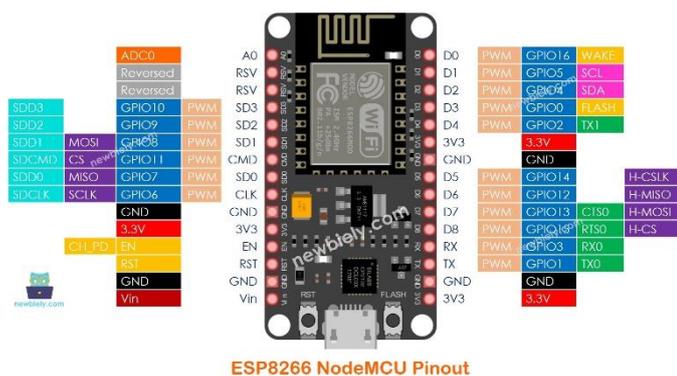
4.2 DHT11



The DHT11 sensor is an affordable digital sensor commonly used to measure temperature and humidity. It combines a thermistor for detecting temperature and a capacitive element for humidity sensing, offering reasonably accurate readings within a specific range. Due to its simplicity, low cost, and compatibility with microcontrollers like Arduino and ESP8266, the DHT11 is a popular choice for beginners.

This sensor provides digital output, making it easy to connect to microcontrollers without requiring complex analog-to-digital conversion. It measures temperatures from 0 to 50°C with an accuracy of ±2°C and humidity levels from 20% to 80% with an accuracy of ±5%, making it suitable for basic indoor and moderate environmental monitoring. For applications needing higher precision or broader measurement ranges, other sensors may be more suitable.

4.3 ESP8266



that may not follow simple linear patterns. Random Forest, being an ensemble of decision trees, can capture nonlinear relationships effectively.

For crop recommendation, where feature variations can lead to different crop suggestions, Random Forest’s ensemble approach provides stable and reliable predictions without memorizing the training data.

In some regions, agricultural data can be sparse or imbalanced, meaning that certain crop types or environmental conditions are underrepresented. Random Forest performs well even with limited or imbalanced datasets due to its bootstrap sampling technique.

Crop recommendation data can have multiple environmental and agronomic factors. Random Forest handles high-dimensional data effectively because each decision tree within the forest only uses a subset of features for splitting, which reduces the risk of overfitting.

Compared to models like SVMs, which require careful tuning of kernel functions and hyperparameters, or neural networks, which need significant architecture and parameter adjustments, Random Forest can achieve solid results with less complexity.

Agricultural datasets often contain missing values or noisy data. Random Forest is relatively robust to both, as the model can use different subsets of the data and ignore missing values when training individual trees.

Comparison with Other Models

SVM: Effective for classification, but not as flexible in handling high-dimensional, noisy, or imbalanced data. It can also be slow on larger datasets and challenging to interpret.

K-Nearest Neighbors (KNN): KNN is simple but can struggle with high-dimensional data, making it less efficient and harder to interpret in complex, multidimensional agricultural data.

Neural Networks: Suitable for large and complex datasets but requires significant tuning, large data volumes, and computational resources. It can be hard to interpret, which is a disadvantage for agricultural applications where understanding the decision-making process is essential.

Gradient Boosting Models (e.g., XGBoost, LightGBM): These can outperform Random Forest in certain cases and are also effective with structured data. However, they are more sensitive to hyperparameter tuning and may take longer to train.

4.4 RANDOM FOREST ALGORITHM FOR CROP RECOMMENDATION

Crop recommendation involves complex interactions between features (soil type, rainfall, temperature, etc.)

5. SOFTWARE AND IMPLEMENTATION

5.1 SYSTEM OVERVIEW

To create a crop recommendation system based on soil moisture and environmental conditions, we use an ESP8266 Wi-Fi microcontroller, a DHT11 sensor (for temperature and humidity), and a soil moisture sensor. The system collects data from these sensors, sends it to a cloud platform like ThingSpeak, and provides crop recommendations based on ideal growing conditions for specific crops. This system helps farmers monitor their environment and make informed decisions on which crops to plant.

5.2 SENSOR SETUP

DHT11: Connect the VCC to 3.3V, GND to ground, and the data pin to a digital pin (e.g., D2) on the ESP8266.

Soil Moisture Sensor: Connect the analog output to the A0 pin on the ESP8266. The VCC and GND should go to 3.3V and ground, respectively. The system uses these sensors to measure soil moisture, temperature, and humidity, which are then processed to recommend suitable crops.

5.3 PROGRAMMING THE ESP8266

The code for the ESP8266 uses the ESP8266WiFi library to connect to a Wi-Fi network, the DHT library to read data from the DHT11 sensor, and the ThingSpeak library to send data to the cloud. The setup() function connects to Wi-Fi and initializes the sensors. The loop() function reads the sensor data (temperature, humidity, and soil moisture), processes it, and sends the data to ThingSpeak for further analysis. The code can be customized to recommend crops based on predefined ranges of temperature, humidity, and soil moisture levels.

```
#include <ESP8266HTTPClient.h>
#include <ESP8266WiFi.h>
#include <WiFiClient.h>
#include <DHT.h>

#define DHTPIN 5 // Digital pin D1 connected to the DHT sensor
#define DHTTYPE DHT11 // DHT 11

DHT dht(DHTPIN, DHTTYPE);

WiFiClient client;
const char* ssid = "iPhone";
const char* password = "Mahim1409";

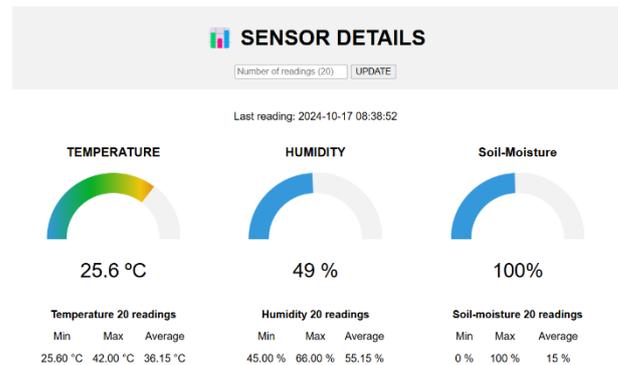
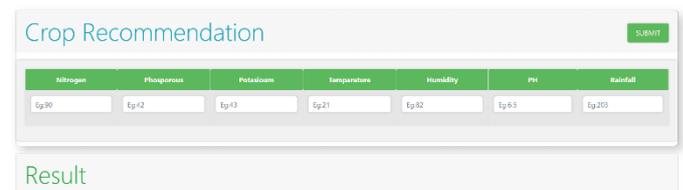
const char* serverName = "http://172.20.10.2/farmtech-master/post-data.php";

String apiKeyValue = "#54321";

String sensorName = "Sensor";
String sensorLocation = "In room";
int valuel;
int sensor = A0;
```

5.4 CONNECTION WITH MACHINE LEARNING ALGORITHM USING UI

To recommend crop some details are required like soil, moisture, temperature, potesium etc, Making suitable user interface it earse workload. It also helps to know flow of system. In this technology, soil moisture sensor gets data and send to machine learning algorithm for finding suitable crop.

4. CONCLUSIONS

Farming and Agriculture website project has cultivated a rich landscape of insights, collaboration, and transformative potential at the intersection of framing and agriculture. This dynamic platform serves not only as a repository of knowledge but as a catalyst for positive change in the way we perceive and practice agriculture globally. Through engaging content, interactive tools, and a commitment to sustainability, the website stands as a testament to the collective efforts of farmers, researchers, policymakers, and enthusiasts. As we reap the collective harvest of diverse perspectives, the conclusion is not an endpoint but a milestone in an ongoing journey.

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