



## Agri-Edge: A Result-Oriented Crop Recommendation System

Prof. Kamlesh Kelwade<sup>1</sup>, Prof. Saima Ansari<sup>2</sup>, Reefat Abdul Hafeez<sup>3</sup>, Fiza Khan<sup>4</sup>, Runzzun Kawade<sup>5</sup>, Bushra Sanobar Ansari<sup>6</sup>, Nida Khan<sup>7</sup>

<sup>1,2</sup>Associate Professor, Computer Science and Engineering, A.C.E.T. Nagpur, Maharashtra, India

<sup>3,4,5,6,7</sup>B.TECH Student, Computer Science and Engineering, A.C.E.T. Nagpur, Maharashtra, India

Peer Review Information	Abstract
<p>Submission: 07 Feb 2025 Revision: 16 Mar 2025 Acceptance: 18 April 2025</p> <p><b>Keywords</b></p> <p>Machine Learning Data Analysis IoT-Based Environmental Monitoring System DHT11</p>	<p>Machine learning can offer farmers tailored recommendations to enhance crop production. The selection of crops for this method is influenced by their climatic traits and volume. Data analytics facilitates the extraction of valuable insights from agricultural databases. Crop data analysis leads to recommendations based on productivity and seasonal factors. By analyzing historical data, weather patterns, soil quality, and other relevant variables, machine learning models can provide important guidance for farming choices. This predictive capability is transforming agricultural management, ensuring that crops are cultivated under ideal conditions and maximizing yields. The challenges posed by a rapidly growing global population, along with the issues associated with climate change, underscore the necessity of dependable crop production forecasting systems. This initiative aims to design and implement an IoT-based monitoring system for environmental conditions that utilizes the DHT11 sensor for temperature and humidity along with a soil moisture sensor. The main objective is to develop a system that gathers real-time information on temperature, humidity, and soil moisture and transmits it wirelessly to an IoT platform for remote observation. The ESP8266 microcontroller acts as a communication intermediary, facilitating smooth data upload and interaction with cloud-based applications. This system allows users to monitor and access environmental parameters remotely through devices connected to the internet, offering valuable insights for applications like smart farming, weather tracking, and home automation. The project involves the integration of sensors, data processing, configuration of an IoT platform, and the development of a user interface for data visualization. The objective of the project is to deliver a reliable and user-friendly solution for efficient environmental monitoring and management through thorough testing and validation.</p>

### INTRODUCTION

Agriculture is crucial for maintaining food security and economic stability. Data mining can support farmers in making educated decisions by examining extensive agricultural datasets and

uncovering valuable insights. Recommendations for crops are made based on weather patterns, soil characteristics, and seasonal productivity. By utilizing data analytics, farmers can refine their crop choices, maximize yields, and boost overall

farming efficiency.

Comprehending the Cultivation of Seasonal Crops in India:

India experiences a variety of climatic conditions that influence the cultivation of crops. The agricultural calendar of the country is segmented into four primary seasons:

- Winter (Rabi Crops) (December - February):

Common Crops: Wheat, Barley, Mustard, Peas, Gram

Cultivated in cooler climates with reduced precipitation.

- Summer (March - June):

Common Crops: Vegetables (Pumpkin, Cucumber, Watermelon), Pulses

Needs elevated temperatures and watering.

- Monsoon (Kharif Crops) (July - September):

Common Crops: Rice, Maize, Bajra, Cotton, Sugarcane, Groundnut

Significant reliance on precipitation

- Post-Monsoon (October - November):

Common Crops: Fruits (Guava, Papaya), Late-harvested crops

Transition period from monsoon to winter crops

- A. *Role of Machine Learning in Crop Yield Prediction*

Recently, the farming industry has progressively adopted machine learning (ML) to forecast crop yields. This method utilizes past data, climatic trends, soil characteristics, and market dynamics to offer essential information for growers.

- Enhanced Farming: Aids in choosing the most suitable crop for a particular season and soil condition.
- Resource Management: Effective utilization of water, fertilizers, and pesticides.
- Harvest Estimation: Anticipating agricultural output beforehand
- Market Stability: Balancing crop excess and deficiency, guaranteeing equitable pricing.
- Execution of Decision Tree Classifier for Crop Recommendation.

The crop recommendation in this project utilizes the Decision Tree Classifier. This algorithm is a type of supervised machine learning technique that:

1. Accepts input characteristics such as soil type, rainfall, temperature, pH, and season.
2. Divides the data into branches according to decision-making criteria.
3. Categorizes crops based on historical data and environmental conditions.

This machine learning-driven crop recommendation system guarantees that farmers receive tailored, data-informed advice,

promoting greater productivity and sustainable agricultural practices.

## LITERATURE REVIEW

The Crop and Yield Prediction Model was developed by Kalyani A. Bogawar and Shreya S. Bhanose. To forecast crop yields and assist farmers in making optimal decisions for improving farming practices, the agricultural industry requires a coherent and organized method. Predicting the most suitable crops can be difficult without a foundational understanding of agricultural data. One proven approach to increase revenue and improve farming standards is through crop prediction. Data clustering algorithms serve as an effective means to extract valuable insights and facilitate predictions within the realm of data mining. Various techniques have been utilized so far, either aimed at crop prediction or for other purposes. A crop forecasting model supports farmers in making well-informed decisions.

2) Forecasting agricultural pests and diseases using data mining and wireless sensor networks. A. K. Tripathy remarks that dynamic crop-weather information is essential for data-driven precision agriculture components, particularly for pest and disease management. An experiment was conducted in a semi-arid area utilizing wireless sensors and field monitoring data to gain insights into the interconnected dynamics of the pest (Thrips) and disease (Bud Necrosis) affecting groundnut crops. To convert the data into useful insights, knowledge, relationships, trends, and correlations along the crop-weather-pest-disease continuum, data mining techniques were applied. The dynamics obtained through these data mining methods and modeled mathematically were verified with relevant surveillance data. Findings from the kharif (monsoon) season of 2009–2010 and the rabi (post-monsoon) seasons of 2009–10 and 2010–11 can be utilized to create models that are accurate or nearly accurate.

3) An Analysis of Agricultural Soils Utilizing Data Mining Techniques Ramesh Babu Palepu emphasized that agriculture is the most basic solution to satisfy global food demands, which is particularly critical for developing countries like India. The use of data mining tools in agriculture, especially for examining soils, can enhance crop yields and transform the scenario for commitments in farming. Soil testing is vital for addressing a variety of issues related to agriculture. This paper not only reviews several data mining methods and the pertinent studies of various authors concerning soil analysis but also explores the role of data mining in relation to soil

assessment within the agricultural industry.

4) Shakir and Choi (2019) created a remote monitoring system based on GSM technology, intended to track environmental factors such as temperature and humidity. Their system utilizes GSM technology to send real-time information to a centralized server, enabling remote monitoring and access. Testing was conducted in various settings, proving the system's efficiency in delivering timely and precise measurements of temperature and humidity levels. The research emphasizes the benefits of GSM in remote regions where conventional communication infrastructure is scarce (Shakir & Choi, 2019).

5) Patel and Patel (2020) examined the combination of Bluetooth Low Energy (BLE) with environmental sensors to create a smart monitoring system. Their system captures temperature and humidity data using sensors and sends this information through BLE to a mobile app. This method improves user accessibility and allows for real-time monitoring. The authors highlight BLE's effectiveness in minimizing power consumption while ensuring reliable communication between sensors and mobile devices (Patel & Patel, 2020).

6) Kumar and Agarwal (2021) investigated the merger of GSM and Wi-Fi technologies for the remote monitoring and regulation of environmental conditions. Their research introduces a dual-mode system that utilizes GSM for emergency notifications and Wi-Fi for regular data transfer. The system tracks temperature, humidity, and moisture levels, offering users a detailed view of environmental data. Their findings indicate that the integration of GSM and Wi-Fi improves the system's reliability and adaptability, making it applicable in a wide range of scenarios (Kumar & Agarwal, 2021).

7) Zhang and Wang (2022) conducted an in-depth analysis of diverse IoT-driven monitoring systems designed for temperature and humidity. Their analysis includes systems that utilize GSM, Bluetooth, Wi-Fi, and other communication methods. They assess the advantages and drawbacks of these technologies across various areas, including agriculture and industrial uses.

### Summary of Literature Review

This collection of research papers illustrates the growing role of technology and data analytics in agriculture.

Bogawar and Bhanose concentrate on predicting crop yields through data clustering techniques, with the goal of aiding farmers in their decision-making processes. Tripathy highlights the use of

data mining and wireless sensor networks to forecast agricultural pests and diseases, particularly in groundnut crops. Palepu underscores the significance of soil analysis utilizing data mining to boost cultivation yields. Furthermore, various studies investigate remote environmental monitoring systems employing GSM, Bluetooth Low Energy, and Wi-Fi, with an emphasis on tracking temperature and humidity. These systems improve access to real-time data and monitoring capabilities, especially in remote locations, and demonstrate the advantages of combining different communication technologies for dependable and adaptable agricultural applications.

## METHODOLOGY

### Software Module:



Figure 1 : Diagram of the Software Module Flowchart

#### 1. Data Collection:

This marks the initial significant move toward the genuine advancement of a machine learning model: the gathering of data. This essential phase will have a significant impact on the model's quality; the greater and higher-quality data we obtain, the more effectively our model will operate. There are multiple methods for gathering data, such as web scraping, manual efforts, and others.

#### 2. Dataset:

The dataset contains 821 individual entries. There are 14 columns present in the dataset, which are detailed below.

- States: the total number of states in India
- Rainfall: measured rainfall in mm
- Ground Water: overall ground water level
- Temperature: temperature expressed in

degrees Celsius

- Soil type: number of different soil types
- Season: the season that is optimal for crop growth
- Crops: varieties of crops present
- Fertilisers required: types of fertilisers needed
- Cost of cultivation: overall expense for cultivation
- Expected revenues: projected total revenues
- Quantity of seeds per hectare: amount of seeds needed per hectare
- Duration of cultivation: number of days required for cultivation
- Demand of crop: level of crop demand (high or low)
- Crops for mixed cropping: which crops can be used for mixed cropping

### 3. Data Preparation:

Prepare and organize the data for training. Cleanse any data that requires attention (eliminate duplicates, fix errors, address missing values, perform normalization, and convert data types, etc.) Randomize the data to eliminate any influence from the specific order in which it was collected or processed. Visualize the data to identify significant relationships between variables or uncover class imbalances (bias alert!), or conduct other exploratory analyses. Divide the data into training and evaluation subsets.

### 4. Model Selection:

A decision tree is a tree-like diagram resembling a flowchart, where internal nodes signify features (or attributes), branches denote decision rules, and each leaf node indicates the outcome. The node at the top of the decision tree is referred to as the root node. It learns to divide based on the values of the attributes. This tree is partitioned recursively through a process known as recursive partitioning. This flowchart structure aids in decision-making. Its visualization resembles a flowchart diagram, which closely reflects human thought processes. Therefore, decision trees are straightforward to understand and interpret.

The Decision Tree is classified as a white box machine learning algorithm. It provides insight into its internal decision-making processes, which is often lacking in black box algorithms like Neural Networks. Its training duration is quicker when compared to neural network algorithms. The time complexity of decision trees is contingent on the number of records and attributes present in the dataset. Decision trees are considered distribution-free or non-parametric methods, as they do not rely on assumptions of probability distributions. They

are capable of managing high-dimensional data with impressive accuracy.

The decision rules are typically expressed as if-then-else statements. As the tree grows deeper, the rules become more intricate, and the model becomes more finely tuned.

Before we delve deeper, let's familiarize ourselves with a few key terms:

**Candidate Concept:** This refers to a concept we believe to be the target concept.

**Testing Set:** This is akin to the training set and is utilized to evaluate the candidate concept and assess its performance.

### 5. Analyze and Prediction:

In the current dataset, we selected just 7 attributes:

- I. States: total count of states in India
- II. Rainfall: precipitation measured in mm
- III. Ground Water: total groundwater level
- IV. Temperature: measured in degrees Celsius
- V. Soil type: variety of soil types
- VI. Season: the season that is optimal for crops
- VII. Crops: categories of crops

### 6. Accuracy on test set:

We achieved an accuracy of 90.7% on the test dataset.

### 7. Saving the Trained Model:

When you feel ready to deploy your trained and validated model in a production environment, the initial action is to save it as a .h5 or .pkl file using a library such as pickle. Ensure that pickle is installed in your environment. After that, import the module and save the model into a .pkl file.

### Hardware Module:

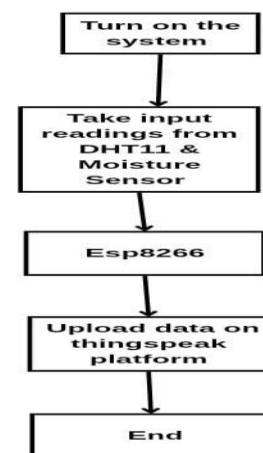


Figure 2 : Flowchart Diagram of Hardware Module

### 1. ESP8266 (Wi-Fi Module & Microcontroller)

The ESP8266 is an affordable microcontroller chip equipped with a complete TCP/IP stack and microcontroller functionality. It is commonly utilized in Internet of Things (IoT) applications.

#### Key Features:

- Integrated Wi-Fi capability
- Facilitates TCP/IP protocol for web connectivity
- Offers GPIO, I2C, SPI, and UART communication interfaces
- Operates with low power usage, making it ideal for battery-operated devices
- Compatible with programming in Arduino IDE, MicroPython, or Lua

#### Common Applications:

- Home automation technology
- Control and monitor from a distance
- Data logging via wireless connections
- Projects based on the Internet of Things (IoT)

- Functions on 3.3V or 5V, ensuring compatibility with ESP8266 and Arduino

#### Common Applications:

- Meteorological stations
- Greenhouse surveillance
- Climate control systems
- Intelligent home initiatives

#### Output Screenshots of Software Module:

ID	Region	State	District	Crop	Season	Duration (Days)	Yield (kg/ha)	Water (mm)	Fertilizer (kg/ha)	Pesticide (kg/ha)
001	North	West Bengal	North 24 Parganas	Jute	Kharif	120-150	1500	1000	100	100
002	West	West Bengal	West 24 Parganas	Jute	Kharif	120-150	1500	1000	100	100
003	West	West Bengal	South 24 Parganas	Jute	Kharif	120-150	1500	1000	100	100
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Figure 3 : Crop Recommendation Data Preview

Figure 4 : Jute Duration of cultivation : 120-150

Figure 5 : Coco Duration of cultivation : 150-180

### 2. Moisture Sensor

readings for temperature and humidity. The collected data will be transmitted to ThingSpeak, a cloud-based IoT platform, allowing for remote monitoring and analysis. The entire system will be programmed through the Arduino IDE, ensuring it is user-friendly and manageable. The DHT11 sensor, which outputs temperature and humidity measurements as digital signals, will connect to a digital I/O pin. A reliable 5V power source, such as a USB adapter or battery pack, will be necessary to power the system and guarantee continuous operation. After the hardware setup is complete, the subsequent step involves programming the ESP8266 using the Arduino IDE. Essential libraries will be incorporated into the project, including the "DHT" library for retrieving data from the DHT11 sensor, along with the "ESP8266WiFi" and "ThingSpeak" libraries to facilitate Wi-Fi communication and interaction with the ThingSpeak API.



*Figure 6 : IoT Soil Moisture Sensor*



*Figure 7 : Real – Time Soil Moisture Sensor Testing in Soil and Saltwater*

## CONCLUSION

The objective of the project is to implement a decision tree classifier that suggests appropriate crops for farmers. The main procedure includes preprocessing data gathered from the software module, while the hardware component serves as a data logging device for a specific farm or client. The project has been successfully finalized concerning software execution, hardware design, and integration of hardware. The hardware module operates as a data recorder, tracking three essential parameters for a specific farm and keeping a record of this data for future use. In parallel, the software module.

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