AI BASED REAL TIME CROP ADVISORY SYSTEM BY LEVERAGING IOT TECHNOLOGY

Abstract:

This paper proposes an AI and IOT-based Crop Advisor integrated with a chatbot interface to revolutionize smart agriculture, by combining AI-IOT and conversational interfaces, the system demonstrates its potential as an inclusive and efficient approach to modern agriculture... IOT sensors deployed in the field continuously monitor key environmental parameters such as soil moisture, temperature, humidity, pH, and nutrient levels. The real-time data is processed using machine learning algorithms to recommend the most suitable crops and provide timely agricultural advice. The system has been evaluated for Toor Dal (Pigeon Pea) and Wheat, two widely cultivated crops with distinct growth requirements. Toor Dal thrives in moderately fertile soils with a pH of 6.0–7.5 and temperature between 25–35 °C. As a legume, it fixes atmospheric nitrogen and thus requires relatively lower nitrogen supplementation (20–25 kg/ha) but responds strongly to phosphorus (50–60 kg/ha) and potassium (20–25 kg/ha) for improved root development and pod formation. Wheat, in contrast, grows best under cooler conditions with a temperature range of 15–25 °C, soil pH between 6.0–7.0, and higher soil moisture levels of 60–80%. It requires substantial nitrogen input (100–120 kg/ha) for grain development, along with phosphorus (50–60 kg/ha) and potassium (40–50 kg/ha) for root establishment and disease resistance. Maintaining a balanced nutrient supply is essential, as nutrient deficiencies delay growth while excess nitrogen increases susceptibility to pests and fungal infestations. Preventive strategies such as crop rotation, balanced Nitrogen(N), Phosphorous(P), Potassium(K) fertilization, use of resistant seed varieties, biological pest control, and timely irrigation management are integrated into the advisory framework to minimize plant and stem diseases. A user-friendly chatbot interface enables farmers to interact with the system in natural language, asking questions related to crop suitability, irrigation schedules, fertilizer recommendations, and pest or disease management. With a response time of less than 1.5 seconds and a crop prediction accuracy of 92%, the proposed system empowers farmers with personalized and accessible recommendations, enhances crop yield, reduces resource wastage, and bridges the digital divide in rural communities.

Keywords: **IOT, Crop, Fertilizer, Chat Bot, Irrigation and Machine Learning.**

I. INTRODUCTION

Agriculture plays a vital role in sustaining human life, yet traditional farming methods are increasingly challenged by climate change, resource scarcity, and unpredictable weather patterns. To meet the growing food demand and ensure sustainable agricultural practices, there is an urgent need for innovative solutions that combine technology with real-time decision-making. The integration of Artificial Intelligence (AI) and the Internet of Things (IOT) in agriculture known as Smart Agriculture — offers promising advancements by enabling farmers to make data-driven choices.

This project introduces an AI and IOT-based Crop Advisor system that empowers farmers with intelligent crop selection and cultivation recommendations based on real-time environmental conditions. IOT sensors are used to monitor soil parameters like moisture, pH, temperature, and humidity, which are crucial for plant growth. The data collected is analyzed using machine learning models to recommend the most suitable crops for a specific field or season, thereby improving yield and resource efficiency.

To make this system user-friendly and accessible, especially in rural areas, a conversational chatbot interface is integrated. This allows farmers to interact with the system in natural language, ask queries, and receive personalized farming advice without needing deep technical knowledge. By merging sensor-based monitoring, AI-based predictions, and chatbot communication, the system offers a comprehensive solution to modernize agriculture, improve productivity, and support informed decision-making in farming communities. [1], the survey explores the application of deep learning technologies in smart agriculture, focusing on data processing and decision-making enhancements [2] this critical review examines the integration of machine learning, remote sensing, and IOT in crop yield prediction, discussing the potential of these technologies in enhancing agricultural productivity. [3], [4], [5], [6] Developed an AI-driven system to recommend crops based on environmental conditions, aiming to enhance precision agriculture. Utilized machine learning algorithms, including CatBoost, with feature selection and SMOTE for data balancing [8] Proposed a system tailored for Maharashtra to recommend crops and forecast yields using advanced machine learning techniques. Implemented Long Short-Term Memory (LSTM) networks combined with a novel expectation-maximization technique.

Machine Learning

A subset of artificial intelligence known as machine learning focuses primarily on the creation of algorithms that enable a computer to independently learn from data and previous experiences. Arthur Samuel first used the term "machine learning" in 1959. It could be summarized as follows:

Without being explicitly programmed, machine learning enables a machine to automatically learn from data, improve performance from experiences, and predict things.

Machine learning algorithms create a mathematical model that, without being explicitly programmed, aids in making predictions or decisions with the assistance of sample historical data, or training data. For the purpose of developing predictive models, machine learning brings together statistics and computer science. Algorithms that learn from historical data are either constructed or utilized in machine learning. The performance will rise in proportion to the quantity of information we provide.

BLOCK DIAGRAM FOR REAL TIME CROP ADVISORY SYSTEM

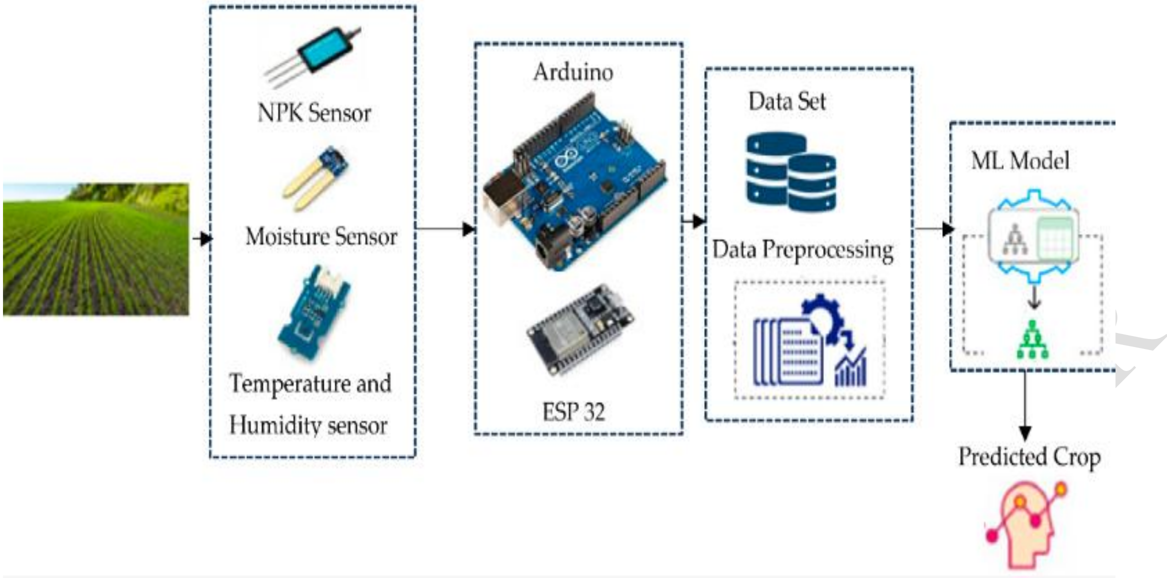


Figure – 1: The image displays a block diagram outlining a Real-Time Crop Advisory System, which is a conceptual framework for using technology to provide informed advice to farmers for optimal crop management.

<u>Key Components and Workflow:</u>

Sensors: The system begins with the collection of real-time environmental data through various sensors.
NPK Sensor: Measures the levels of Nitrogen (N), Phosphorus (P), and Potassium (K) in the soil, which are crucial plant nutrients.
Moisture Sensor: Detects the water content in the soil, vital for irrigation management.
Temperature and Humidity Sensor: Monitors atmospheric conditions that affect crop growth and potential disease outbreaks.
Microcontrollers: These components act as the central processing unit for sensor data and facilitate communication.
Arduino & ESP32: Microcontroller boards (like Arduino and ESP32) are used to collect data from the sensors and can transmit this data wirelessly, often via Wi-Fi (ESP32).
Data Processing & Machine Learning:
Data Set & Data Preprocessing: The collected sensor data forms a dataset that needs to be preprocessed (cleaned, filtered, and formatted) before it can be used for analysis.
ML Model (Machine Learning Model): A machine learning model (e.g., Random Forest Classifier) analyzes the processed data along with historical data to generate predictions or recommendations.

Output & Advisory:
Predicted Crop: Based on the ML model's analysis, the system can predict suitable crops for cultivation based on current conditions, or advise on optimal practices for existing crops.
Advisory: The output could be in the form of alerts, notifications, or specific recommendations delivered to the farmer via a user interface, like a mobile application.
In essence, this system integrates sensor technology with machine learning to provide data-driven insights, enabling farmers to make informed decisions for improved yield, optimized resource use (like water and fertilizer), and better management of potential risks like pests and diseases in real time.

METHODOLOGY

The proposed methodology mainly consists of two phases and many sub-phases. The first phase includes reading nutrient values from soil. The second phase of the methodology gives crop recommendations by the developed model using the values obtained from the soil. Figure 2 represents the architecture diagram that shows the actual flow of execution of the methodology.

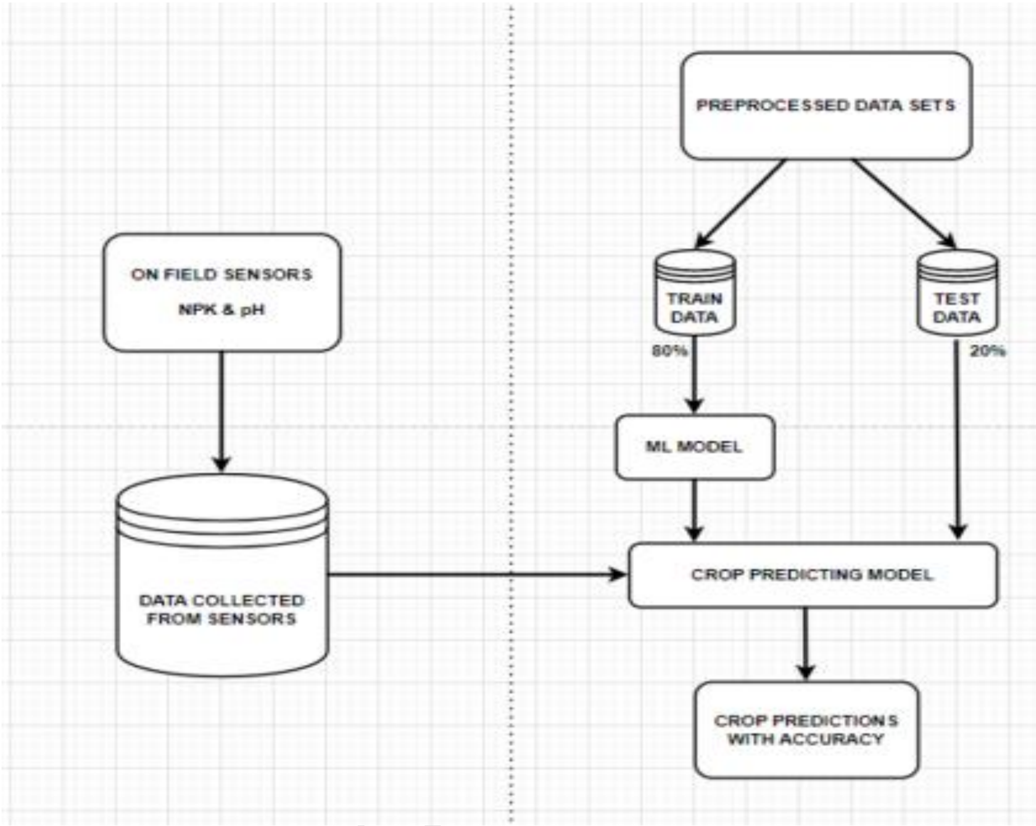


Figure-2: Architecture diagram of the proposed system

A. Hardware Components:

The Arduino Uno board, NPK sensor, and MAX485 module are the three main components required for system development. A popular microcontroller board based on the Atmega328P microcontroller is called the Arduino Uno. The board has 6 analog input pins, 6 PWM output pins, and 14 digital input/output pins, including 6 that can be used as PWM outputs. Both 3.3V and 5V logic levels are supported via the I/O pins, which are used by the board to function at 5V. For programming and communication, the Arduino board can be connected to a computer using its built-in USB port [14-18]. When seen on a PC, it appears as a virtual COM port. In order to communicate serially with external devices using the USB interface, the board contains a hardware serial port (USART)

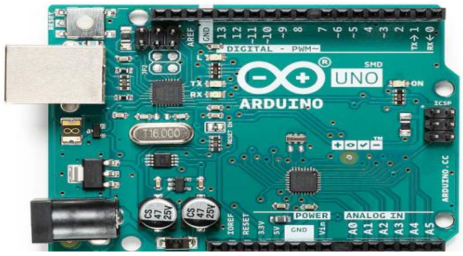


Fig. 3:Arduino Uno Board

Nitrogen, phosphorus and potassium, three crucial elements in soil, are measured using an NPK sensor. These essential nutrients are frequently present in commercial fertilizers and are necessary for plant growth. In order to ascertain nutrient contents, NPK sensors examine the electrical conductivity or spectral characteristics of the soil. The sensor is often made up of soil-based probes that can monitor NPK levels in real time or very close to real time. NPK sensors are available in a variety of configurations, including portable units, handheld devices, and even integrated systems that may be mounted on agricultural equipment for automated soil analysis [19-25]. The VCC pin, which is connected to the 5v-30v power supply, is represented by the brown wire. A differential signal is connected to the MAX485 Modbus Module's A pin via a yellow-coloured wire. Another differential signal, B (blue wire), is linked to the MAX485 Modbus Module's B pin. The Ground pin is designated by the black wire GND.

Figure- 4: NPK Sensor

Working:

The initial phase of reading nutrient values from the soil requires interfacing of NPK sensor with Arduino board. The semantic diagram for interfacing between the hardware components is shown in figure 5.

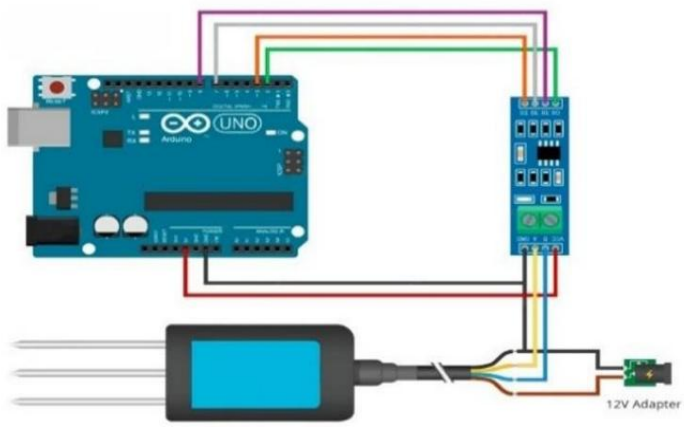


Figure-5: Arduino – NPK interfacing.

- The NPK sensor has four wires. The brown power line needs to be attached to the 5V-30V power supply.
- The black ground wire needs to be attached to a common ground.
- The RS485 module’s A pin should have the yellow wire of the NPK sensor connected, and the B pin should have the blue wire connected.
- The digital pins 2 and 3 of the Arduino should be connected to the RS485 module’s R0 and DI pins.
- The DE and RE pins should be linked to digital pins 7 and 8, respectively, and the VCC pin of the RS485 module should be connected to the Arduino’s 5V output.
- Finally, the Arduino and the circuit should have a common ground.

D. Model Training

- Firstly, the dataset that is being used is preprocessed by removing the redundant columns and duplicate values that are present.
- Secondly, the data and the labels are to be initialized.
- Divide the processed dataset 75:25 into training and testing datasets.
- Now, create a KNN classifier with k=3 as nearest neighbors.
- Once the model is created, train the model with train dataset and save it to the disk. Metrics like

E. Model Classification and Recommendations

- The data collected from the soil using NPK sensor and Arduino board are supplied to the trained model.
- The input data is then classified into labels based on existing dataset.
- Recommendations are then made with an average accuracy of 99.67% that are displayed using a web application developed using python-based web development framework, flask.

CALCULATION:

1. Data Collection (IOT Sensors)

IOT devices are used to collect various environmental parameters from the soil, which serve as input features for the prediction model. These parameters include:

- Soil pH x_1
- Soil Moisture x_2
- Temperature x_3
- Humidity x_4

The feature vector for a given time is:

X=[x1, x2, x3, x4] …Equation-1

This is used to represent data at a given time, including temperature(X3) and humidity(X4)

2. Data Preprocessing

Collected sensor data is normalized to bring values to a uniform scale: values are normalised to a uniform scale, typically between 0 and 1.

, $$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$ ….Equation-2

where x is the original value, min(x) is the minimum value in the dataset, and max(x) is the maximum value**.** This normalized feature vector is then passed to the machine learning model.

3. Crop Prediction using Random Forest

Let D={(X_1,y_1),(X_2,y_2),...,(X_n,y_n)}is used where Xi is the normalised feature vector for the i-th record and yi is the corresponding crop labl (**toor dal , wheat**)to be the trained data set where:

- X_i is the normalized feature vector of the i-th record
- y_i is the corresponding label (e.g., Toor Dal, Wheat)

Random Forest Construction:

- A number of decision trees T1,T2,...,Tk are built using different bootstrapped samples and random subsets of features.
- Each tree Tiproduces a prediction hi(X)

Final Crop Prediction (Majority Voting):

Equation-3….

$$\hat{y} = \text{mode}(h_1(X), h_2(X), \dots, h_k(X))$$

This means the most common prediction among all decision trees is selected as the final crop recommendation.

4. Feature Importance Calculation

To interpret which sensor features affect prediction the most, Random Forest calculates Gini Importance or Information Gain:

$$\text{Gini}(t) = 1 - \sum_{i=1}^{C} p_i^2 \quad \text{…. Equation-4}$$

Where:

Gini (t): Represents the Gini impurity of a node ‘t’ in a decision tree.

C : Denotes the total number of classes or categories present in the dataset at that node

- p_i is the probability of class iii at node ttt
- C is the total number of crop classes

The reduction in Gini impurity after a split indicates the importance of a feature.

5. Chatbot Integration

Let user input be a natural language query Q, such as:

“What crop should I grow in this season?”

Using Natural Language Processing (NLP), the chatbot:

- Extracts intent and entities from Q
- Maps query to function call:

predict_crop(x1,x2,x3,x4))

- Fetches and returns the AI-predicted result in simple language:

“Based on current soil and weather conditions, Rice is the most suitable crop.”

6. System Summary Flow

Example:
For input:

- Soil pH = 6.8
- Moisture = 45%
- Temp = 27°C
- Humidity = 65%

After normalization and model input:

X=[0.68,0.45,0.27,0.65]X = [0.68, 0.45, 0.27, 0.65]X=[0.68,0.45,0.27,0.65]
Random Forest trees vote:

- Tree1: Toor
- Tree2: Toor
- Tree3: Wheat

→ Majority = Toor

II. System Architecture

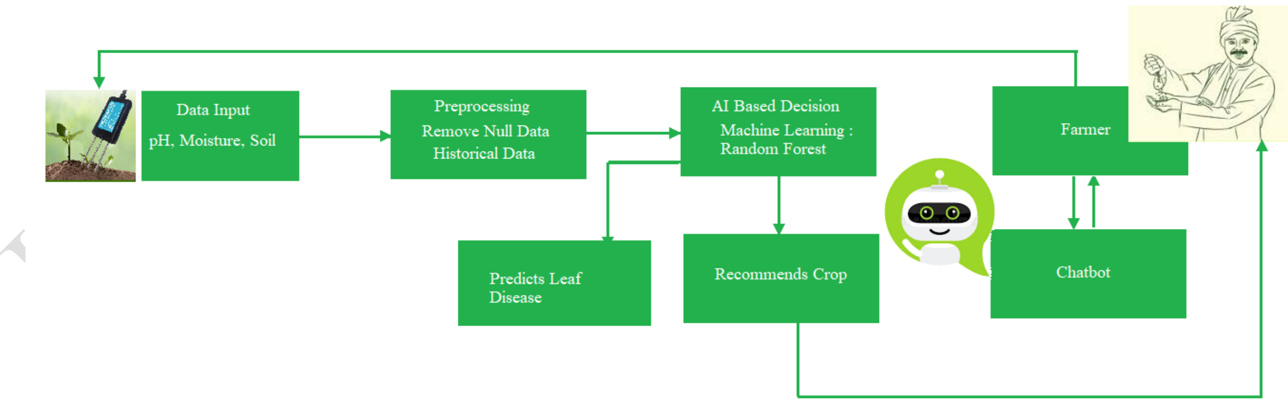


Figure 6: System Architecture

The image displays a document outlining the system architecture and the workflow of an AI-based crop recommendation system with disease prediction and a chatbot for farmer interaction.

<u>System Architecture working procedure :</u>

1. Data Input (pH, Moisture, Soil)

- Description: IOT sensors are deployed in the field to collect real-time agricultural parameters like:
  - Soil pH (acidity/alkalinity level)
  - Moisture content (water level in soil)
  - Soil Type or other characteristics
- Purpose: These inputs form the raw data needed for making intelligent crop recommendations.

2. Preprocessing (Remove Null Data, Historical Data)

- Description: The collected data is cleaned and prepared for analysis.
  - Remove Null Data: Any missing or invalid sensor readings are filtered or interpolated.
  - Historical Data: Past datasets of crops, soil conditions, and outcomes are used to enrich the dataset.
- Purpose: Ensures that only accurate, consistent data is passed to the AI models.

3. AI-Based Decision (Machine Learning: Random Forest)

- Description: A Random Forest machine learning model is used to:
  - Analyze current and historical sensor data
  - Learn patterns between conditions and successful crops
  - Predict the best crops for current conditions
- Purpose: This is the core intelligence of the system that enables smart decision-making.

4. Predicts Leaf Disease

- Description: An optional module (usually via image analysis using CNN or ML) that:
  - Detects signs of leaf disease from uploaded plant leaf images
  - Identifies conditions like fungal infections, blight, rust, etc.
- Purpose: Helps farmers take early action to treat or prevent crop diseases.

5. Recommends Crop

- Description: Based on predictions from the Random Forest model, the system:
  - Suggests the most suitable crop(s) to grow under current conditions
  - May also recommend ideal planting time, fertilizers, and irrigation needs
- Purpose: Provides actionable guidance to the farmer.

6. Chatbot

- Description: An interactive AI chatbot interface that:
  - Allows farmers to ask questions in natural language (e.g., "What crop should I plant?")
  - Converts the question into machine-readable form, fetches the response, and delivers it back in human language
- Purpose: Makes the system accessible and user-friendly, especially for non-technical rural users.

7. Farmer

- Description: The end-user who interacts with the system via the chatbot.

    - Receives advice on which crops to grow
    - Gets alerts on disease risks and farming practices
- Purpose: Empowers farmers to make informed decisions based on AI and sensor data.

III. RESULTS AND DISCUSSION

Figure 7.1 [a]: Final outcome showcasing the crop advisory system .

The figure displays both the hardware and software are connected through Arduino-Uno board using the NPK , soil moisture, temperature and ph sensors. The developed real-time crop advisory system integrates both hardware and software to assist farmers in making data-driven decisions. The hardware setup consists of an Arduino Uno board connected to NPK, soil moisture, temperature, and pH sensors, which continuously monitor essential soil and environmental parameters. The collected sensor data is processed and transmitted to the software interface, where AI algorithms analyze the inputs and provide crop-specific recommendations. The results are displayed in real time on both the LCD module and the computer interface, ensuring farmers receive timely insights regarding soil health, nutrient levels, and suitable crop choices. This seamless integration of sensors, microcontroller, and advisory software creates an intelligent decision-support system for precision agriculture.

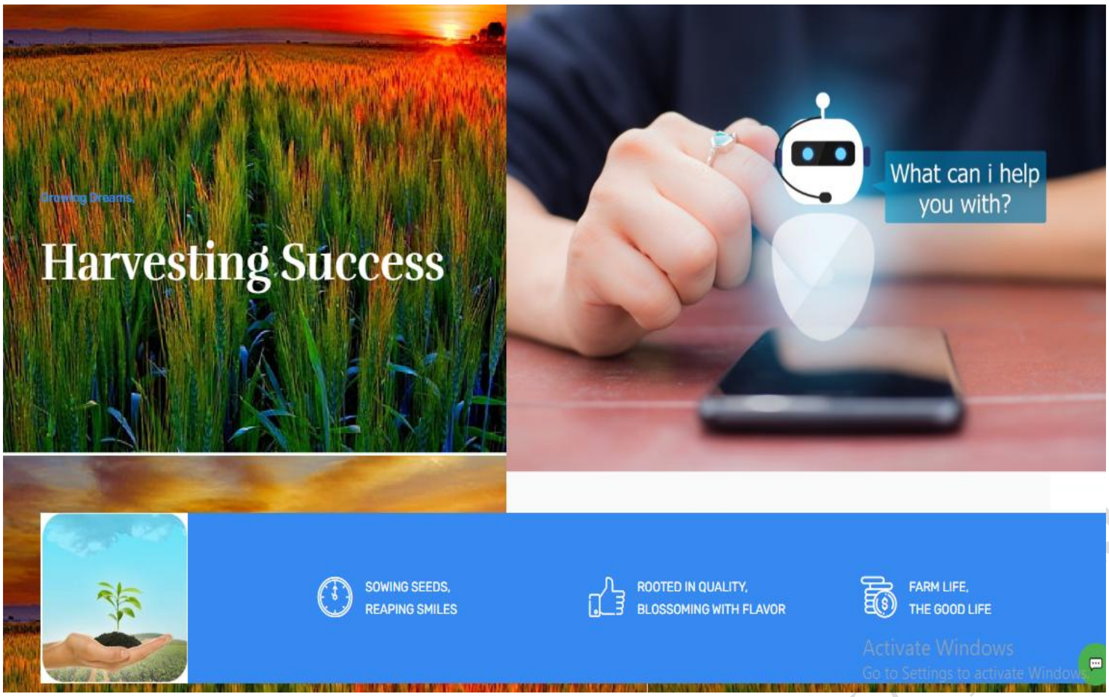


Figure 7.2 [a]: The front page of the software with the chatbot where the user/farmer can ask any sort of queries

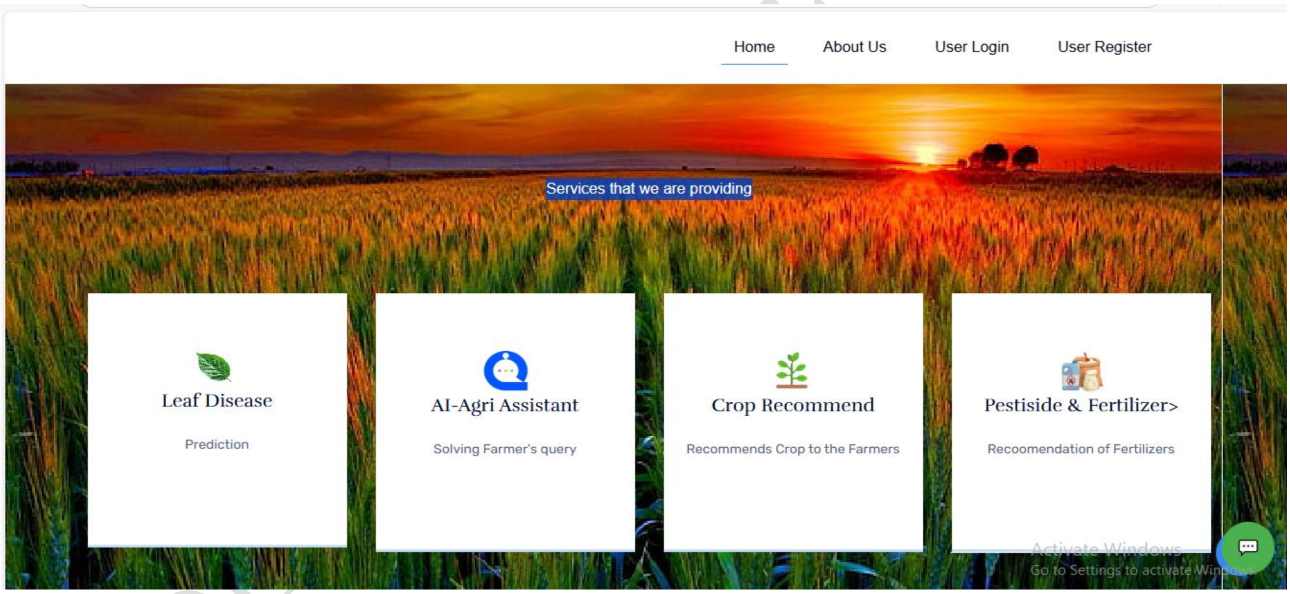


Figure 7.2[b]: shows the services provided by the software as listed in the above image.

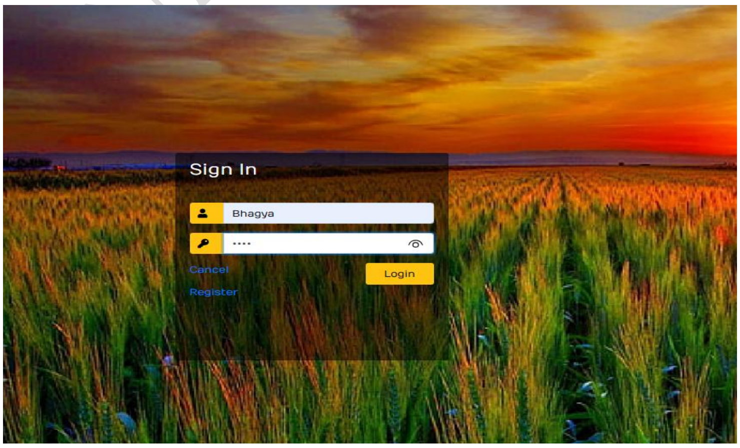


Figure 7.2 [c]: shows the login information submitted by the users in the website page.

Figure 7.2 [d]: The above image displays the home page

Dataset

ID	N	P	K	temperature	humidity	ph	rainfall	ly	village	city	state
1	98	42	43	25.000000	80.000000	6.000000	200.000000	Rice	Aland	Kalaburagi	Karnataka
2	90	42	43	27.000000	78.000000	6.000000	150.000000	Toor	Jewragi	Kalaburagi	Karnataka
3	90	42	43	20.879744	82.002744	6.502985	202.935536	rice	Sedam	Kalaburagi	Karnataka
4	85	58	41	21.770462	80.319644	7.038096	226.655537	rice	Chincholi	Kalaburagi	Karnataka
5	60	55	44	23.004459	82.320763	7.840207	263.964248	rice	Chitapur	Kalaburagi	Karnataka
6	74	35	40	26.491096	80.158363	6.980401	242.864034	rice	Afzalpur	Kalaburagi	Karnataka
7	78	42	42	20.130175	81.604873	7.628473	262.717340	rice	Aland	Kalaburagi	Karnataka
8	69	37	42	23.058049	83.370118	7.073454	251.055000	rice	Jewragi	Kalaburagi	Karnataka
9	69	55	38	22.708838	82.639414	5.700806	271.324860	rice	Sedam	Kalaburagi	Karnataka
10	94	53	40	20.277744	82.894086	5.718627	241.974195	rice	Chincholi	Kalaburagi	Karnataka
11	89	54	38	24.515881	83.535216	6.685346	230.446236	rice	Chitapur	Kalaburagi	Karnataka
12	68	58	38	23.223974	83.033227	6.336254	221.209196	rice	Afzalpur	Kalaburagi	Karnataka
13	91	53	40	26.527235	81.417538	5.386168	264.614870	rice	Aland	Kalaburagi	Karnataka
14	90	46	42	23.978982	81.450616	7.502834	250.083234	rice	Jewragi	Kalaburagi	Karnataka

Figure 7.2 [e] The image displays the given dataset which reads the historical data of all the crops from various places with their respective parameters such as temperature, humidity, Ph, rainfall etc.

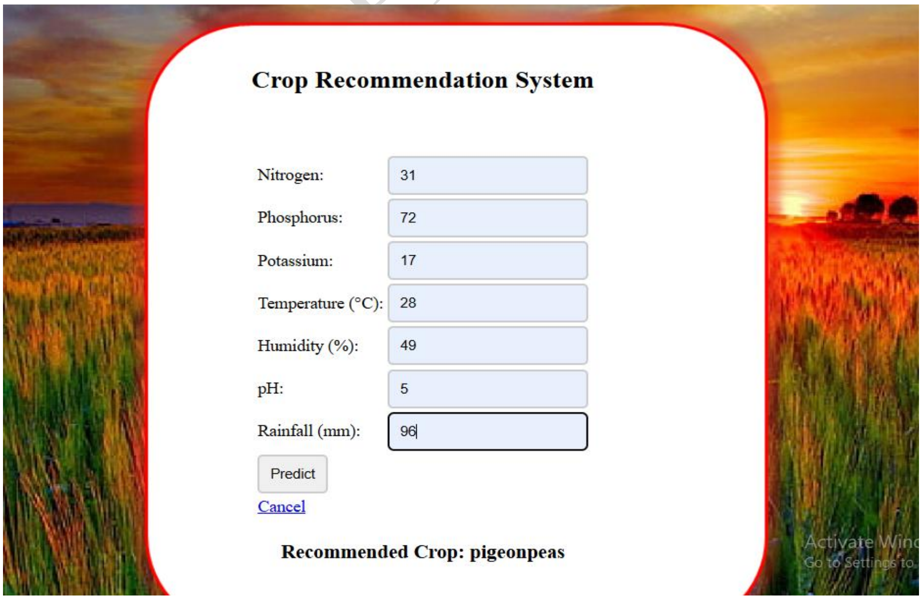


Figure 7.2 [f]: Represents the crop recommendation system which stores the data of NPK, temperature, humidity, pH and rainfall given by the farmer.

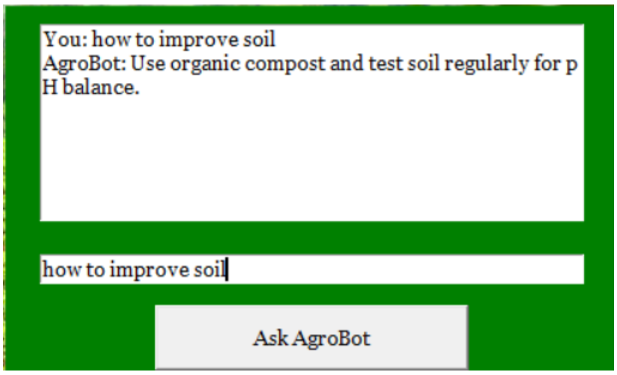


Figure 3:Agri AI-Chatbot

The image displays a simulated interaction with an “Agri AI-Chatbot” named “AgroBot, ” demonstrating how a user might ask about improving soil and receive a response. The chatbot’s advice aligns with common agricultural practices for enhancing soil health.

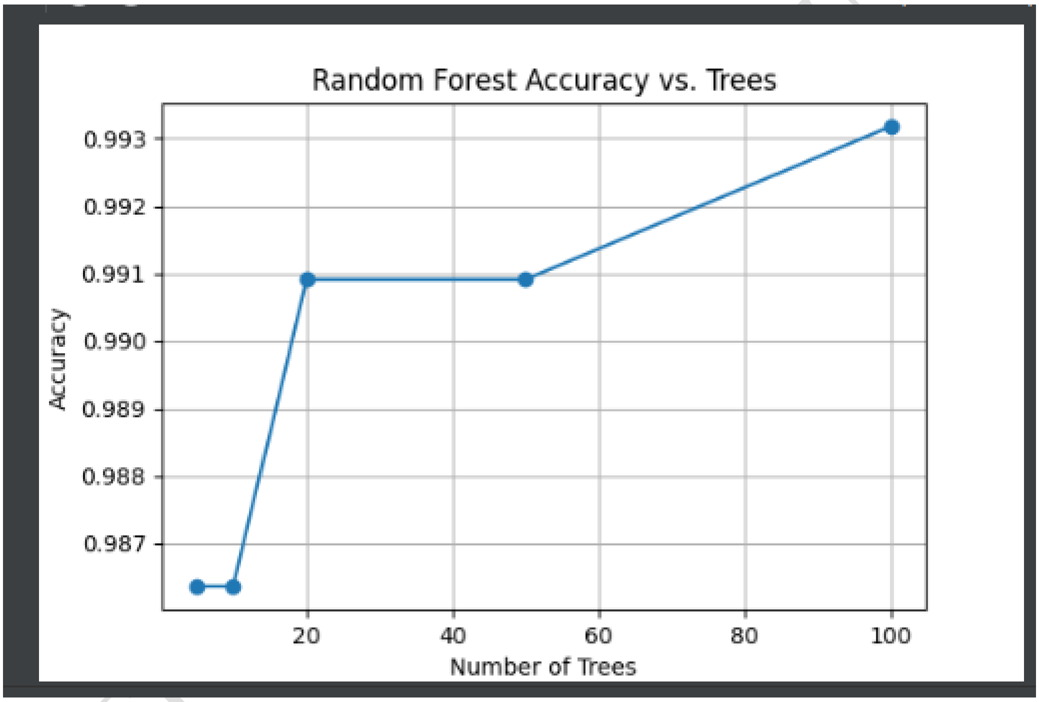


Figure 4: Random forest Accuracy vs Trees

The image displays a graph that illustrates how the accuracy of a Random Forest model changes with the increasing number of decision trees used in the ensemble.

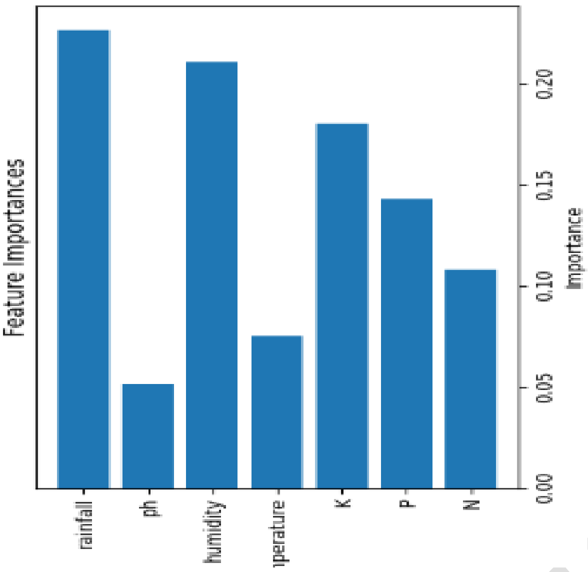


Figure 5: Feature Importance of Model

The image displays a horizontal bar chart which visualizes the relative importance of different features in a model and the chart shows the importance of various environmental and chemical factors which includes Rainfall, pH, Humidity , Temperature, and N, P, K values

Using following sensors the data is collected :

1.NPK sensors

- **Purpose**: Detects the contents of Nitogen (N), Phosphorous (P) and Pottasium (K) in the soil'
- **Working Principle:**
  - An NPK sensor measures the levels of nitrogen (N), phosphorus (P), and potassium (K) in soil to determine soil fertility and guide nutrient management.
- **Importance:**
  - These sensors typically use electrochemical principles, such as ion-selective electrodes, to provide real-time data on soil nutrient content. Their primary application is in precision agriculture, helping farmers optimize fertilizer application, improve crop yields, and reduce environmental impact by preventing over-fertilization and water waste.

2. Soil pH Sensor

Purpose: Measures the acidity or alkalinity of the soil, which affects nutrient availability and crop suitability.

- **Common Sensor**: Analog pH Sensor (e.g., Gravity: Analog pH Sensor by DFRobot)
- **Working Principle**:
  - Uses a glass electrode and a reference electrode to measure hydrogen ion concentration in the soil.
  - Output is a voltage that corresponds to pH levels, typically 0–14 scale.
- **Importance**:
  - Most crops prefer pH between 6.0 to 7.5.
  - Helps recommend crops suited to acidic, neutral, or alkaline soils.

3. Soil Moisture Sensor

Purpose: Detects the water content in the soil, critical for irrigation planning and crop recommendation.

- **Common Sensor**: Capacitive Soil Moisture Sensor (e.g., v1.2 or v2.0)
- **Working Principle:**

- Measures the dielectric permittivity of the soil.
- Water has high permittivity; more moisture means higher capacitance.
- Provides analog or digital output proportional to soil moisture.

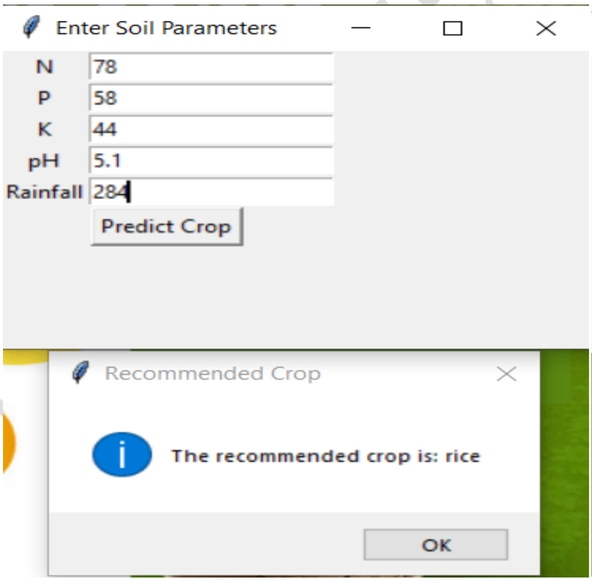
- **Importance**:
  - Ensures crops that require high water (like rice) are only recommended when sufficient moisture is detected.
  - Enables smart irrigation alerts.

4. Temperature Sensor

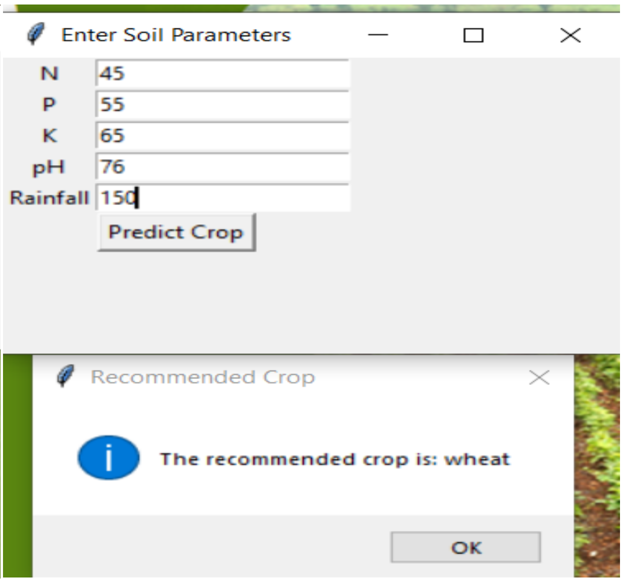
Purpose: Monitors ambient or soil temperature, which affects germination, growth rate, and crop type.

- **Common Sensor**: DHT11 / DHT22 or DS18B20
- **Working Principle**:
  - DHT sensors use a thermistor to measure temperature and a capacitive sensor for humidity (if needed).
  - DS18B20 uses digital output with a unique 1-Wire interface.
- **Importance**:
  - Crops are temperature-sensitive (e.g., wheat thrives in 20–25°C).
  - Real-time temperature ensures seasonal crop suggestions are accurate.

Figure 7.1: Describes the recommendation of the crop which the user wants to know by adding all the N, P, K, Ph and rainfall values.



7.1[a]Recommended Crop is Rice



7.1[b] Recommended crop is Wheat

The system takes into account multiple critical parameters:

- Soil pH: Determines the acidity or alkalinity level; e.g., acidic soil favors crops like potatoes, while alkaline soil suits barley.

- Soil Moisture: Indicates water availability; crops like paddy require high moisture, whereas millets can grow in dry conditions.
- Temperature: Affects crop growth cycles and germination; wheat grows best in cooler climates, whereas maize prefers warmer temperatures.
- Humidity (optional): Can influence pest activity and crop disease risks.

2. Role of Machine Learning

The Random Forest algorithm is used to train a model using historical datasets, which include environmental parameters and the crops successfully grown under those conditions. When real-time sensor data is input, the model:

- Matches patterns with the training data
- Predicts crops with the highest probability of success
- Returns a ranked list or single best crop suggestion

Example :

Input: pH = 6.7, Moisture = 40%, Temperature = 28°C

Predicted Output: Crop = *Rice*

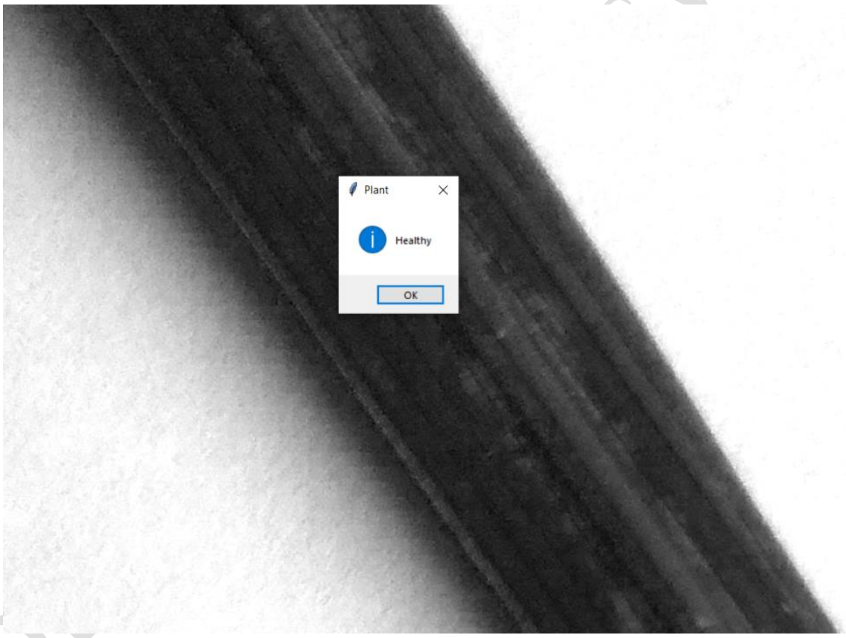


Figure 8: Healthy Leaf

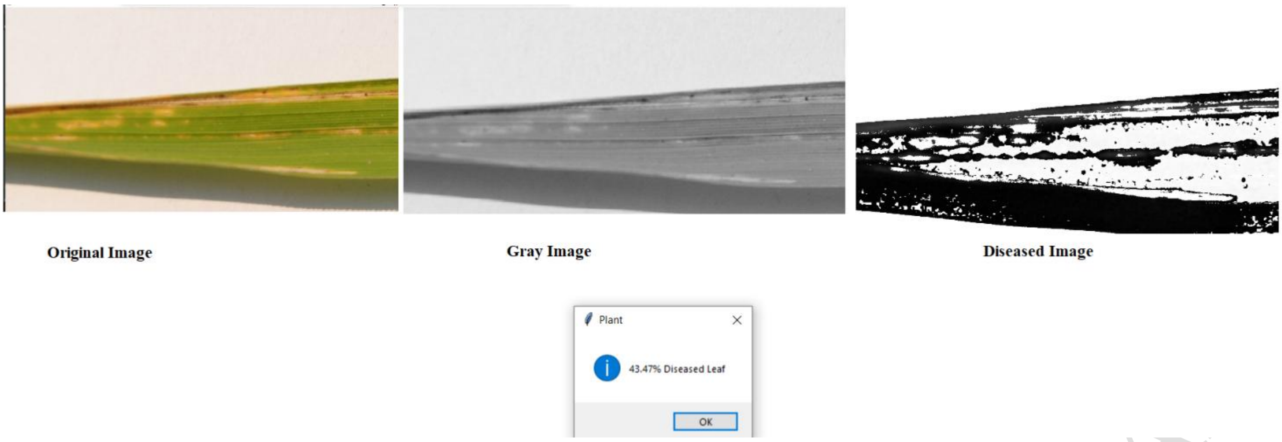


Figure 9: Diseased Leaf

The leaf disease prediction system typically follows these steps:

a. Image Acquisition

- Farmers upload or capture real-time images of crop leaves using a smartphone or camera.

b. Preprocessing

- Images are resized, enhanced, and filtered to reduce noise.
- Common techniques: grayscale conversion, histogram equalization, and edge detection.

c. Feature Extraction

- Key visual features such as color, texture, shape, and vein pattern are extracted using image processing techniques.

d. Classification using CNN

- A Convolutional Neural Network (CNN) or similar deep learning model is trained on labeled images of healthy and diseased leaves.
- The model outputs a predicted label:

  Disease=f(Leaf Image)

  wheref is the trained neural network function.

For more detailed analysis we have taken an example of the very known famous crop of our land Kalaburagi.

1)Toor Dal

Soil Parameters for Toor Dal

1. Nitrogen (N)

- Toor Dal (Pigeon Pea):
  - Being a legume, it fixes atmospheric nitrogen with the help of rhizobium bacteria in its root nodules.
  - Therefore, it needs minimal nitrogen supplementation (20–25 kg/ha). Too much nitrogen makes it leafy but reduces pod yield.

2) Wheat:

- Requires high nitrogen input (100–120 kg/ha) because nitrogen is crucial for grain filling.
- Low nitrogen leads to pale leaves and poor grain yield, while excess nitrogen can cause lodging (plants falling over).

2. Phosphorus (P)

- Toor Dal: Needs 50–60 kg/ha for strong root development and effective nodulation. Deficiency causes weak plants and poor pod setting.
- Wheat: Requires 50–60 kg/ha, especially during the early growth stage, to promote root establishment and better tillering.

3. Potassium (K)

- Toor Dal: Needs 20–25 kg/ha. Helps in resistance to diseases and improves pod quality. Deficiency leads to weak stems and poor pod filling.
- Wheat: Needs 40–50 kg/ha for stem strength and disease resistance. Deficiency reduces grain weight.

4. Soil pH

- Toor Dal: Prefers slightly acidic to neutral soils, pH 6.0–7.5. Very acidic soils reduce nodulation efficiency.
- Wheat: Grows best in pH 6.0–7.0. Higher alkalinity or acidity affects nutrient uptake.

5. Soil Moisture

- Toor Dal: Requires moderate moisture (50–60%), total water demand about 400–600 mm per season. Waterlogging causes root/stem rot.
- Wheat: Needs higher soil moisture (60–80%), total water demand about 450–650 mm per season. Insufficient water during flowering reduces grain yield.

Water Requirement and Its Effect on Growth

- **Toor Dal (Pigeon Pea):**
  - Requires about 400–600 mm of water per season, usually grown under rainfed conditions.
  - Effect of deficiency: Water shortage during the flowering and pod formation stages leads to poor pollination, flower drop, and reduced pod yield.
  - Effect of excess: Continuous soil saturation or waterlogging causes root rot and stem canker, weakening plants and lowering productivity.
- **Wheat:**
  - Needs around 450–650 mm of water per season, distributed across critical stages (crown root initiation, tillering, flowering, and grain filling).
  - Effect of deficiency: Inadequate irrigation at flowering or grain filling reduces grain size and yield.
  - Effect of excess: Over-irrigation can cause lodging (plants fall over), reduced oxygen availability in the root zone, and fungal diseases.

Precautions to Stop Plant and Stem Diseases

- Toor Dal (Pigeon Pea):
  - Practice crop rotation with cereals to prevent buildup of soil-borne pathogens.
  - Use disease-resistant varieties to combat Fusarium wilt and stem rot.
  - Avoid waterlogging by ensuring proper field drainage.
  - Apply balanced NPK fertilizers; excess nitrogen increases disease risk.
  - Use biological control agents (e.g., Trichoderma spp.) against root and stem pathogens.
- Wheat:
  - Apply timely irrigation—neither drought stress nor waterlogging should occur.
  - Use resistant varieties against rusts, smuts, and stem base diseases.
  - Practice seed treatment with fungicides before sowing to prevent soil- and seed-borne infections.
  - Maintain proper plant spacing to reduce humidity and fungal spread.
  - Apply potassium fertilizers adequately, as potassium strengthens stem tissues and reduces disease incidence.

Parameter	Toor Dal (Pigeon Pea)	Wheat
Optimal Temperature	25–35 °C	15–25 °C
Soil pH	6.0 – 7.5	6.0 – 7.0
Nitrogen (N)	20–25 kg/ha (low, as it fixes N)	100–120 kg/ha (high requirement)
Phosphorus (P)	50–60 kg/ha (supports nodulation & pods)	50–60 kg/ha (supports roots &tillering)
Potassium (K)	20–25 kg/ha (disease resistance, pod quality)	40–50 kg/ha (stem strength, grain weight)
Water Requirement	400–600 mm/season	450–650 mm/season
Effect of Water Deficiency	Flower/pod drop, stunted growth	Reduced grain size & yield
Effect of Excess Water	Root rot, stem canker, fungal attack	Lodging, root oxygen stress, fungal disease
Precautions Against Plant & Stem Diseases	Crop rotation, resistant varieties, proper drainage, balanced NPK, biocontrol (e.g., Trichoderma)	Resistant varieties, seed treatment, proper spacing, balanced irrigation, adequate potassium

Table 1: The Abstract table of Data Monitoring system.

The image displays a "Data Monitoring Table" comparing key agricultural parameters for Toor-Dal and Wheat.

CONCLUSION

The integration of AI and IOT in agriculture offers a transformative approach to sustainable farming by enabling real-time monitoring and intelligent decision-making. Through the deployment of IOT sensors, key soil parameters such as moisture, pH, and nutrient concentrations tracked continuously, while AI-driven models provide accurate crop recommendations and management strategies.. The proposed system, with 92% prediction accuracy and a chatbot response time under 1.5 seconds, demonstrates its effectiveness in bridging the gap between advanced agricultural technology and farmer accessibility. By combining IOT sensing, AI-based analysis, and natural language interfaces, this system empowers farmers with personalized, timely, and practical guidance, ultimately improving crop yield, reducing resource wastage, and fostering a more sustainable and inclusive agricultural ecosystem.

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