



KLE Technological University | Creating Value,
Leveraging Knowledge

Dr. M. S. Sheshgiri Campus, Belagavi

2024-2025

**Department of
Electronics and Communication Engineering**

**Minor Project Report
on
Smart Agriculture Powered by Intelligence
Robot**

By:

- | | |
|-----------------------|------------------|
| 1. Sanskruti Mirajkar | USN:02FE22BEC084 |
| 2. Shraman Kanthi | USN:02FE22BEC092 |
| 3. Swati Patil | USN:02FE22BEC112 |
| 4. Darshan Modekar | USN:02FE22BEC119 |

Semester: VI, 2024-2025

Under the Guidance of

Prof. Shivaling Hunagund



KLE Technological University | Creating Value,
Leveraging Knowledge

Dr. M. S. Sheshgiri Campus, Belagavi

2024-2025

DEPARTMENT OF ELECTRONICS AND COMMUNICATION
ENGINEERING

CERTIFICATE

This is to certify that project entitled “Smart Agriculture Powered by Intelligence Robot ” is a bonafide work carried out by the student team of ” Sanskruti Mirajkar (02FE22BEC084) , Shraman Kanthi (02FE22BEC092) ,Swati Patil (02FE22BEC112),Darshan Modekar (02FE22BEC119)”. The project report has been approved as it satisfies the requirements with respect to the minor project work prescribed by the university curriculum for B.E. (6th Semester) in Department of Electronics and Communication Engineering of KLE Technological University Dr. M. S. Sheshgiri CET Belagavi campus for the academic year 2024-2025.

Prof.Shivaling Hunagund
Guide

Dr. Dattaprasad A. Torse
Head of Department

Dr. S. F. Patil
Principal

External Viva:

Name of Examiners

Signature with date

1.

2.

ACKNOWLEDGMENT

We sincerely thank our Principal, Dr. S. F. Patil, and our Head of Department, Dr. Dataprasad Torse, for providing us with the opportunity and support to carry out our project titled “Smart Agriculture Powered by Intelligence Robot.” We extend special thanks to our guide, Prof. Shivaling Hunagund, for his invaluable guidance and continuous support throughout the project. We acknowledge the collective efforts of our team members, each of whom contributed significantly to the success of the project. We also thank KLE Dr. M. S. Sheshgiri College of Engineering and Technology, Belagavi, for providing the necessary resources and infrastructure, and the faculty and staff of the Electronics and Communication Department for their constant support.

-The project team

ABSTRACT

This project introduces a smart agriculture system designed to automate both seed recommendation and sowing processes using real-time environmental data. The first component involves predicting the most suitable seed for a given condition based on soil moisture, temperature, and humidity, which are measured using sensors connected to an ESP32 microcontroller. The data is sent to ThingSpeak, where it is accessed by a JavaScript-based application running in Visual Studio Code. A machine learning model, trained with historical agricultural data and achieving 70 percentage accuracy, processes this input to recommend the optimal seed. The predicted seed type, along with real-time sensor values, is displayed through a user interface (UI) to provide farmers with clear and actionable insights. The second component is an autonomous seed-sowing vehicle that places seeds at crop-specific intervals—such as 25 cm for rice—without using distance sensors. Instead, it relies on calibrated motor timing to estimate travel distance and trigger seed placement accordingly. This integrated system provides a low-cost, scalable solution to enhance precision agriculture, reduce manual effort, and support informed decision-making in the farming process.

Contents

| | |
|---|-----------|
| List of Abbreviations | 1 |
| 1 Introduction | 2 |
| 1.1 Motivation | 2 |
| 1.2 Objectives | 3 |
| 1.3 Literature Survey | 3 |
| 1.4 Problem statement | 4 |
| 1.5 Application in Societal Context | 4 |
| 2 Project planning | 5 |
| 2.1 Gantt chart | 5 |
| 2.2 Work Breakdown Structure(WBS) | 6 |
| 3 Design specifications | 7 |
| 3.1 Input specifications | 7 |
| 3.1.1 ESP32 :- | 7 |
| 3.2 DHT11 (Temperature and Humidity Sensor) | 8 |
| 3.3 SOIL MOISTURE SENSOR | 8 |
| 3.4 Output specifications | 9 |
| 3.5 L298N Motor Driver | 9 |
| 3.6 DC Motor (100 RPM) | 10 |
| 3.7 Seed Recommendation (via UI) | 11 |
| 3.8 Software specifications | 11 |
| 3.8.1 Arduino IDE | 11 |
| 3.8.2 Visual Studio Code (VS Code) | 12 |
| 3.8.3 ThingSpeak | 12 |
| 3.8.4 Resource Specifications | 13 |
| 3.9 List of tools used | 13 |
| 4 Methodology | 14 |
| 4.1 Dataset Description and Model Training | 14 |
| 4.2 Seed Placement Strategy | 14 |
| 4.3 Methodology | 15 |
| 4.3.1 Hardware Design | 15 |
| 4.3.2 Testing and Calibration | 16 |
| 4.3.3 Optimization and Scalability | 16 |
| 4.4 Functional Block Diagrams | 16 |
| 5 Results and Discussion | 18 |
| 5.1 Machine Learning Model Performance | 18 |
| 5.2 User Interface Output | 18 |
| 5.3 Seed Sowing Vehicle Results | 19 |

| | | |
|----------|-------------------------------------|-----------|
| 5.4 | ThingSpeak Cloud Output | 20 |
| 5.5 | App Interface | 21 |
| 5.6 | Discussion | 21 |
| 6 | Conclusions and future scope | 22 |
| 6.1 | Conclusion | 22 |
| 6.2 | Future Scope | 22 |
| | References | 23 |

List of Figures

| | | |
|-----|---|----|
| 2.1 | Gantt chart | 5 |
| 2.2 | Work breakdown structure | 6 |
| 3.1 | ESP-32 WROOM | 7 |
| 3.2 | DHT11 Sensor | 8 |
| 3.3 | Soil Moisture Sensor | 8 |
| 3.4 | L298N Motor Driver Module | 9 |
| 3.5 | 100 RPM DC Motor | 10 |
| 3.6 | Arduino IDE | 12 |
| 3.7 | Visual Studio Code Environment | 12 |
| 4.1 | confusion matrix | 14 |
| 4.2 | Hardware Integration | 16 |
| 4.3 | Functional block diagram of predicting seed | 17 |
| 4.4 | Functional block diagram of seed sowing | 17 |
| 5.1 | Model Accuracy | 18 |
| 5.2 | Seed Recommendation Dashboard | 19 |
| 5.3 | Hardware Integration Front View | 19 |
| 5.4 | Hardware Integration Back View | 20 |
| 5.5 | Real-Time Sensor Data on ThingSpeak | 20 |
| 5.6 | App Interface | 21 |

List of Abbreviations

| Abbreviation | Description |
|--------------|---|
| ESP32 | Espressif Systems 32-bit Microcontroller |
| IoT | Internet of Things |
| GPS | Global Positioning System |
| Wi-Fi | Wireless Fidelity |
| WBS | Work Breakdown Structure |
| GPIO | General Purpose Input/Output |
| ML | Machine Learning |
| UI | User Interface |
| IDE | Integrated Development Environment |
| RPM | Revolutions Per Minute |
| DC | Direct Current |
| API | Application Programming Interface |
| EC | Electrical Conductivity |
| HTML | HyperText Markup Language |
| CSS | Cascading Style Sheets |
| .pkl | Pickle File Format (for ML model storage) |

Chapter 1

Introduction

Agriculture is the backbone of many economies and remains a vital sector for global food security. However, traditional farming practices often rely heavily on manual labor, experience-based decision-making, and inefficient methods of seed planting, which can lead to lower productivity and resource wastage. With the increasing challenges of climate change, soil degradation, and labor shortages, there is a growing need for innovative solutions that integrate technology into farming operations.

The rise of embedded systems, Internet of Things (IoT), and machine learning offers new opportunities to revolutionize agriculture. Smart farming solutions can help farmers make informed decisions, automate repetitive tasks, and optimize resource usage. In this project, we propose a two-part smart agriculture system that focuses on enhancing the seed selection process and automating the seed-sowing mechanism.

The first part of the project uses environmental parameters such as soil moisture, temperature, and humidity to predict the most suitable seed for cultivation. Sensor data is collected via an ESP32 microcontroller and uploaded to ThingSpeak, a cloud-based IoT platform. A machine learning model, trained on agricultural datasets, analyzes this real-time data and provides seed recommendations with an accuracy of 70 percentage. These recommendations are displayed on a user-friendly interface developed in JavaScript, allowing users to view both sensor data and prediction results in real time.

The second part of the project involves designing an autonomous seed-sowing vehicle that places seeds at specific intervals based on the predicted crop type. For example, rice requires a spacing of 25 cm. The vehicle does not use distance sensors; instead, it uses motor calibration and timing logic to estimate the distance traveled and trigger seed dispensing accordingly. This approach reduces the complexity and cost of the system while maintaining acceptable precision in seed placement.

By integrating predictive analytics with automation, this project aims to provide a cost-effective and scalable solution that supports precision farming, improves crop planning, and minimizes manual labor—especially beneficial for small and medium-scale farmers.

1.1 Motivation

The motivation behind this project stems from the pressing need to modernize traditional farming practices and address the challenges faced by farmers in today's agricultural landscape. Many farmers still rely on guesswork or manual observation to decide which crop to sow, often leading to poor yield due to mismatched crop-soil conditions or improper planting techniques. Additionally, manual seed sowing is time-consuming, labor-intensive, and often lacks precision, resulting in uneven spacing and inefficient use of land. With the advancement of technology, especially in the areas of embedded systems, IoT, and machine learning, there is an opportunity

to make agriculture smarter, more accurate, and less dependent on manual intervention. This project aims to empower farmers with a predictive tool that recommends the most suitable seed based on real-time environmental data and automates the seed-sowing process using a simple, cost-effective vehicle. By doing so, it hopes to reduce labor costs, increase productivity, and bring intelligent decision-making to even small and medium-scale farms, where resources and access to advanced tools are often limited.

1.2 Objectives

- **Seed Recommendation System:** Develop a system that predicts the most suitable seed for cultivation based on real-time environmental parameters such as soil moisture, temperature, and humidity.
- **Real-Time Data Acquisition:** Use sensors integrated with an ESP32 microcontroller to collect live environmental data from the field and send it to the cloud (ThingSpeak).
- **Machine Learning Integration:** Train and implement a machine learning model with at least 70% accuracy to analyze environmental data and suggest the appropriate crop or seed type.
- **User Interface (UI):** Design a JavaScript-based user interface in VS Code to display sensor readings and predicted crop recommendations in a user-friendly manner.
- **Automated Seed Sowing:** Design an autonomous vehicle that sows seeds at predefined intervals (e.g., 25 cm for rice) based on the predicted seed type.
- **Distance Estimation Without Sensors:** Implement motor timing calibration to estimate travel distance and automate seed placement without using external distance sensors.
- **Cost-Effective Agricultural Automation:** Develop a low-cost, scalable, and efficient system suitable for small and medium-scale farmers to enhance productivity and reduce manual labor.

1.3 Literature Survey

- **B. Nagarasu (2022)** presents a smart agricultural system titled “*Automatic Irrigation and Worm Detection for Peanut Field using Raspberry Pi with OpenCV*”, which utilizes Raspberry Pi and OpenCV to automate irrigation and detect worms in peanut fields. This integration of IoT and image processing reduces manual labor, improves crop yield, ensures efficient water usage, and enables early pest detection.
- **Jayakrishna P V S (2020)** introduces an “*Autonomous Seed Sowing Agricultural Robot*” that automates the seed sowing process. It uses sensors and motors to control the sowing mechanism, ensuring uniform seed distribution. The system reduces physical effort, enhances planting accuracy, and minimizes human error.
- **J. Ashok Kumar (2023)** in “*Crop Selection and Yield Prediction using Machine Learning Algorithms*” applies machine learning techniques like Decision Trees and SVM to agricultural datasets. The system assists farmers in selecting suitable crops and predicting yield based on soil, weather, and crop data, thereby improving productivity and optimizing resource usage.

- M. Jyotshna (2023) proposes a system titled “*Implementation of Solar Based Multipurpose Agriculture Robot using Random Forest Algorithm*”, which is a solar-powered robot capable of performing tasks like sowing, plowing, and environmental monitoring. It uses the Random Forest algorithm to make decisions from sensor inputs, thereby promoting sustainability, reducing operational costs, and supporting smart agriculture.

1.4 Problem statement

In the growing generation, there is a need to address challenges in the agricultural sector through an advanced robot that performs essential farming tasks while adapting to varying soil conditions

1.5 Application in Societal Context

- Helps farmers select the right seed based on real-time environmental data like soil moisture, temperature, and humidity.
- Increases crop yield by recommending suitable seeds and maintaining correct planting distance.
- Reduces manual labor through an autonomous seed-sowing vehicle.
- Promotes precision agriculture, leading to efficient use of resources.
- Provides a cost-effective solution suitable for small and medium-scale farmers.
- Supports sustainable agriculture by optimizing seed placement and reducing wastage.

Chapter 2

Project planning

The project begins by identifying the required hardware and software components, designing the system architecture, and integrating environmental sensors with the ESP32 microcontroller. The collected data is transmitted to the ThingSpeak platform for cloud storage and analysis. A machine learning model is used to predict the most suitable seed based on real-time data, and the prediction is displayed on a user-friendly interface. In parallel, an autonomous seed-sowing vehicle is developed to place seeds at specific intervals without using external distance sensors. The entire system is tested for data accuracy, model performance, and reliable vehicle operation to ensure seamless integration and effective deployment in agricultural fields.

2.1 Gantt chart

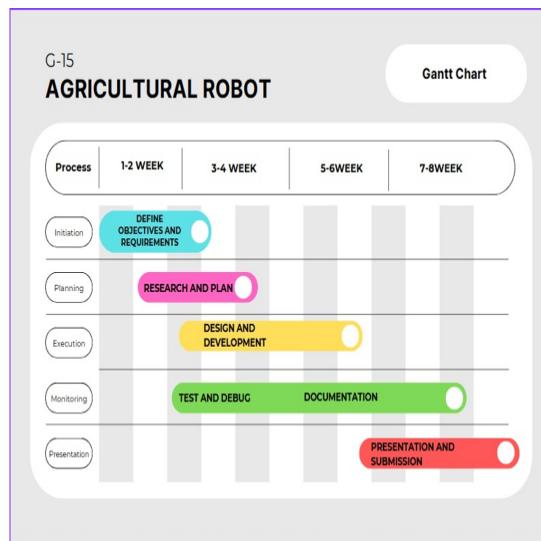


Figure 2.1: Gantt chart

A Gantt chart is a visual project management tool that represents the timeline and progress of tasks or activities in a project. It uses horizontal bars to display tasks, with the length of each bar indicating the duration of the task. The chart provides a clear overview of task sequences, dependencies, and deadlines, helping teams effectively plan, schedule, and monitor progress.

The project is beginning with defining objectives and requirements and is progressing with research and planning, simultaneously designing and developing the system while conducting testing and debugging. Documentation is being prepared alongside, and the process is culminating with the presentation and submission of the final work.

2.2 Work Breakdown Structure(WBS)

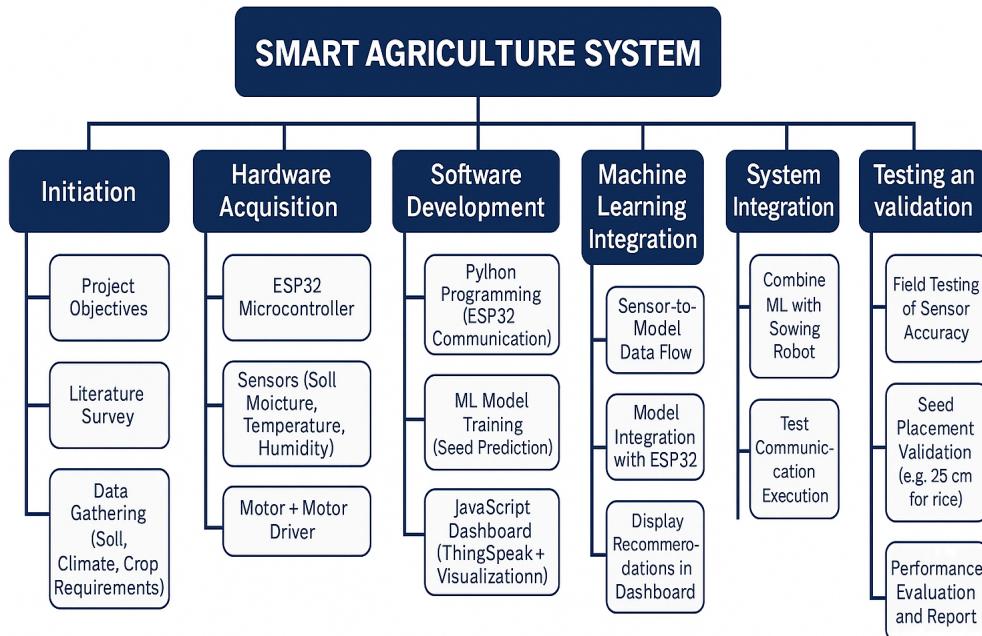


Figure 2.2: Work breakdown structure

The Work Breakdown Structure (WBS) in our project organizes tasks into five key phases: Initiation, Hardware Acquisition, Software Development, Server and Analytics, and Testing and Validation.

The Initiation phase is focused on defining objectives, reviewing literature, and gathering crop and soil data. In the Hardware Acquisition phase, components like ESP32, sensors, and motors are being assembled. The Software Development phase involves Python programming, model training, and dashboard setup using ThingSpeak. The Machine Learning Integration phase connects sensor data to the model for real-time seed recommendations. In the System Integration phase, all modules are synchronized for accurate seed placement. Finally, the Testing and Validation phase ensures system accuracy through field testing and performance evaluation.

Chapter 3

Design specifications

3.1 Input specifications

3.1.1 ESP32 :-



Figure 3.1: ESP-32 WROOM

The ESP32 microcontroller is a versatile and powerful development board widely used in IoT projects. It features a dual-core processor that allows for efficient multitasking and higher performance in various applications. The ESP32 includes built-in Wi-Fi and Bluetooth capabilities, enabling seamless communication with other devices and networks.

Additionally, the ESP32 provides a variety of General Purpose Input/Output (GPIO) pins, which are useful for interfacing with sensors, actuators, and other peripherals. Its design for low power operation makes it ideal for battery-powered applications, and it offers various power modes to extend battery life.

3.2 DHT11 (Temperature and Humidity Sensor)

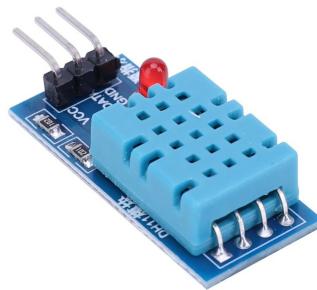


Figure 3.2: DHT11 Sensor

The DHT11 is a digital sensor used for measuring temperature and humidity. It provides accurate and reliable readings, making it suitable for various environmental monitoring applications. The DHT11 features a single-wire communication interface, which allows for easy integration with microcontrollers. The sensor is housed in a compact package, making it ideal for space-constrained projects.

Specifications

- **Temperature Range:** 0°C to 50°C
- **Temperature Accuracy:** ±2°C
- **Humidity Range:** 20% to 80% RH
- **Humidity Accuracy:** ±5% RH
- **Power Supply:** 3.5V to 5.5V
- **Package Type:** 4-pin package

3.3 SOIL MOISTURE SENSOR

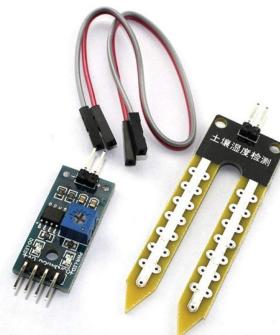


Figure 3.3: Soil Moisture Sensor

The Soil Moisture Sensor is used to measure the volumetric water content in soil. It helps in determining whether the soil has sufficient moisture for plant growth. This information is essential for precision agriculture, allowing efficient irrigation management and crop health monitoring. The sensor works by measuring the resistance or voltage drop between two probes inserted into the soil, where the output varies with soil moisture content. It provides an analog signal that can be easily read by a microcontroller like the ESP32.

Specifications

- **Operating Voltage:** 3.3V to 5V
- **Output Type:** Analog
- **Sensor Type:** Resistive
- **Probe Material:** Corrosion-resistant metal
- **Typical Usage:** Detect moisture level for irrigation control
- **Interface:** 2-pin analog signal output

3.4 Output specifications

3.5 L298N Motor Driver



Figure 3.4: L298N Motor Driver Module

The L298N is a dual H-Bridge motor driver module that allows control of the direction and speed of two DC motors independently. It is widely used in robotics and embedded systems due to its simplicity and effectiveness. In this project, the L298N motor driver is used to control the movement of the seed-sowing vehicle. Based on the calibrated time intervals, the motors are triggered to move forward and activate the seed dispenser mechanism at specific distances, such as every 25 cm for crops like rice.

The L298N receives control signals from the ESP32 microcontroller and translates them into appropriate voltage and current outputs to drive the motors. It supports both forward and reverse motor control, making it ideal for maneuvering the vehicle in the field.

Specifications

- **Operating Voltage:** 5V to 35V
- **Logic Voltage:** 5V
- **Current per Channel:** 2A (max)
- **Number of Channels:** 2 (can control two motors)
- **Control Interface:** ENA, ENB, IN1–IN4 for motor control
- **Use in Project:** Controls forward movement and timing-based seed dispensing of the sowing vehicle

3.6 DC Motor (100 RPM)



Figure 3.5: 100 RPM DC Motor

The 100 RPM DC motor is a low-speed, high-torque motor commonly used in robotic and automation applications. In this project, four such motors are used to drive the wheels of the seed-sowing vehicle. The relatively low speed of 100 revolutions per minute (RPM) ensures controlled movement, which is crucial for accurate seed placement at fixed intervals (e.g., 25 cm).

These motors are powered and controlled via the L298N motor driver, with direction and timing signals provided by the ESP32 microcontroller. By calculating the duration each motor must run to cover a specific distance, the system avoids the need for external distance sensors. This makes the entire vehicle setup more affordable and simpler to implement, while still maintaining reasonable accuracy.

Specifications

- **Operating Voltage:** 6V to 12V DC
- **Speed:** 100 RPM (at 12V)
- **Torque:** High torque suitable for small robotic platforms
- **Shaft Diameter:** 6 mm (approx.)
- **Number of Motors:** 4 (for 4-wheel movement)

- **Use in Project:** Provides motion to the seed-sowing vehicle with accurate timing-based movement

3.7 Seed Recommendation (via UI)

The seed recommendation system in this project is designed to help farmers select the most suitable seed for cultivation based on real-time environmental data. The ESP32 microcontroller collects data from sensors measuring soil moisture, temperature, and humidity. This data is sent to the ThingSpeak platform and processed by a machine learning model trained to predict the optimal crop.

The prediction result is displayed on a user-friendly web interface developed using JavaScript in Visual Studio Code. The UI fetches the latest sensor readings and displays the predicted seed or crop type clearly and accessibly, enabling farmers to make informed decisions quickly. This visualization component bridges the gap between raw data and actionable insight, making smart agriculture more approachable and effective.

Key Features

- **Real-Time Prediction:** Displays crop recommendations based on live sensor data.
- **Web-Based UI:** Developed using JavaScript for easy access via browser.
- **Data Integration:** Fetches data from ThingSpeak and processes it through a connected ML model.
- **Ease of Use:** Intuitive design tailored for field use by non-technical users.

3.8 Software specifications

3.8.1 Arduino IDE

The Arduino IDE (Integrated Development Environment) is an open-source platform used for writing, compiling, and uploading code to microcontroller boards. In this project, it is used to program the ESP32 microcontroller, which interfaces with various sensors such as the DHT11 and soil moisture sensor. The Arduino IDE supports the ESP32 board through additional board manager packages and provides a simple environment for implementing the logic that collects sensor data, controls motor movement, and communicates with the ThingSpeak cloud platform. The code is written in C/C++ and directly uploaded to the ESP32 via USB, making it an essential tool for the development and testing of both the seed prediction and seed-sowing systems.

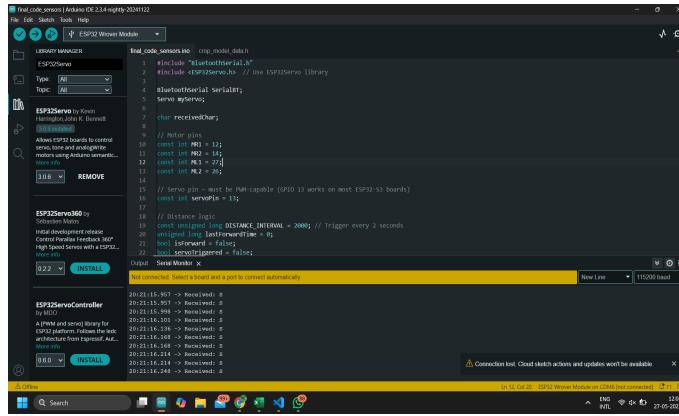


Figure 3.6: Arduino IDE

3.8.2 Visual Studio Code (VS Code)

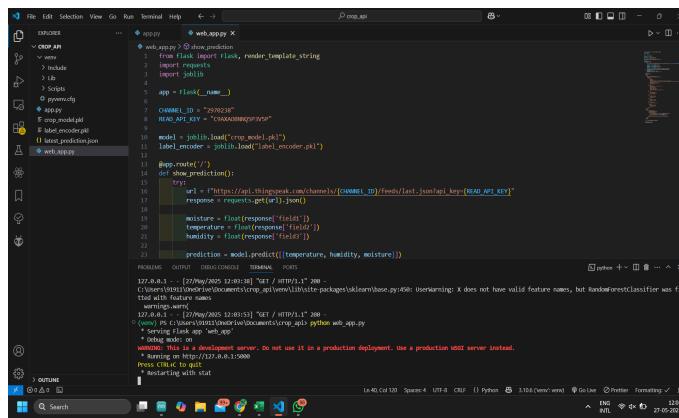


Figure 3.7: Visual Studio Code Environment

Visual Studio Code (VS Code) is a powerful source-code editor developed by Microsoft. In this project, VS Code is used to build the front-end user interface for seed prediction. Using JavaScript, HTML, and CSS, a dynamic UI is created to fetch real-time data from ThingSpeak and display the recommended seed type based on environmental conditions. VS Code also integrates well with various extensions that support JavaScript development, API testing, and real-time updates, making it an ideal tool for building the user-friendly, browser-based dashboard that interacts with the machine learning model.

3.8.3 ThingSpeak

ThingSpeak is an open-source IoT analytics platform used to collect, store, analyze, and visualize sensor data in real-time. In this project, ThingSpeak acts as a cloud-based intermediary between the ESP32 microcontroller and the machine learning prediction interface. Environmental data such as soil moisture, temperature, and humidity are sent from the ESP32 to ThingSpeak using its RESTful API.

From there, JavaScript running in the web interface fetches the latest data through ThingSpeak's public channel API to display real-time values and seed recommendations. Additionally, ThingSpeak allows for historical data tracking and basic analysis, which can be useful for optimizing crop decisions and understanding environmental trends over time.

3.8.4 Resource Specifications

The system used for the development and integration of the smart agriculture project is specified as follows:

- **Operating System:** Windows 11 (64-bit)
- **Processor:** Intel® Core™ i5-13420H (up to 4.6 GHz, 8 cores, 12 threads) – Enables efficient multitasking and fast machine learning model training.
- **Memory:** 16 GB DDR4-3200 MT/s (2 × 8 GB) – Supports real-time processing and development environments.
- **Storage:** 512 GB PCIe® Gen4 NVMe™ M.2 SSD – Ensures high-speed data access and storage.
- **Graphics:** NVIDIA® GeForce RTX™ 2050 Laptop GPU (4 GB GDDR6 dedicated) – Suitable for any GPU-accelerated computation needs and future enhancements.
- **Power Supply:** A continuous 12V regulated DC power supply is provided to the ESP32 microcontroller to support uninterrupted sensor data acquisition and motor operations.

3.9 List of tools used

1. Arduino IDE
2. Think-Speak
3. Visual Studio Code (VS Code)
4. Google Colab

Chapter 4

Methodology

4.1 Dataset Description and Model Training

The dataset used for training the ML model consists of entries with characteristics including temperature ($^{\circ}$ C), humidity, and soil moisture. The data set consists of 55001 entries and 4 characteristics. The data set includes labeled results that represent suitable crop types (for example, rice, wheat, and maize). It was preprocessed by normalizing the value of features and handling missing data. The data set was divided into 80 percent for training and 20 percent for testing. The model achieved an accuracy of approximately 70 percentage with Random Forest and is saved as a .pk1 file for integration into the JavaScript-based interface.

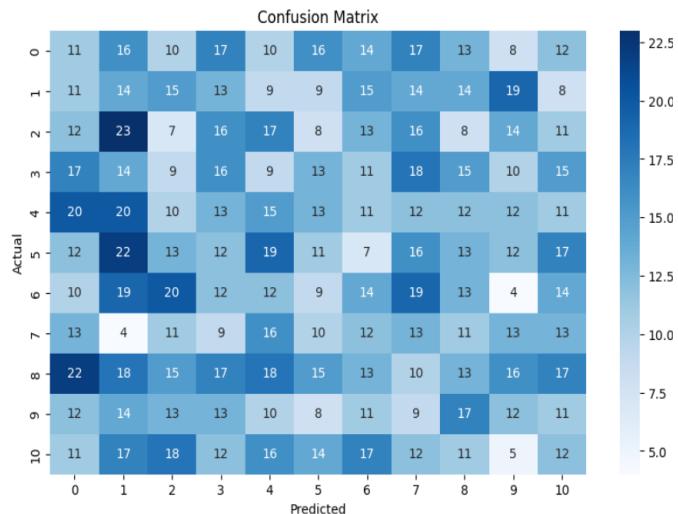


Figure 4.1: confusion matrix

4.2 Seed Placement Strategy

Seed placement plays a critical role in determining plant growth, spacing efficiency, and overall crop yield. Different crops require specific spacing between seeds to ensure optimal sunlight exposure, nutrient absorption, and root development. In this project, seed placement is automated by calibrating motor movement on the basis of time intervals rather than using expensive

distance sensors.

The required spacing for each crop is used to calculate the time duration the motor should run before the next seed is sown. This timing logic is embedded into the ESP32 microcontroller, allowing the seed-sowing vehicle to place seeds accurately in real-time.

The following table outlines the recommended distances for various crops and the approximated values used in the system calibration:

| SL NO. | CROP | DISTANCE REQUIRED | DISTANCE (Used) |
|--------|-----------|-------------------|-----------------|
| 1. | Barley | 15–20 cm | Approx 20 cm |
| 2. | Cotton | 30–45 cm | Approx 40 cm |
| 3. | Groundnut | 10–15 cm | Approx 15 cm |
| 4. | Maize | 20–25 cm | Approx 25 cm |
| 5. | Rice | 20–25 cm | Approx 25 cm |
| 6. | Wheat | 10–15 cm | Approx 15 cm |
| 7. | Pulse | 15 cm | Approx 15 cm |

Table 4.1: Recommended and Applied Seed Placement Distances for Various Crops

4.3 Methodology

4.3.1 Hardware Design

The hardware setup involves interfacing the ESP32 with sensors to collect environmental data (soil moisture, temperature, and humidity) for seed prediction and controlling motors for automated seed placement. The DHT11 sensor is connected to the ESP32 via a digital GPIO pin to monitor ambient temperature and humidity. Similarly, the soil moisture sensor is connected through an analog input. A regulated 12V DC power supply is used to power the ESP32 and motors.

The ESP32 collects sensor readings and transmits them in real-time to the ThingSpeak platform using its built-in Wi-Fi module. This data is then used by the ML model (integrated in JavaScript) for seed prediction, which is displayed on a user-friendly dashboard. Simultaneously, the ESP32 also controls a motor-based seed dispensing unit that moves at calibrated intervals (e.g., 25 cm for rice) to place seeds precisely in the field.



Figure 4.2: Hardware Integration

4.3.2 Testing and Calibration

Sensor readings were tested for consistency and accuracy against standard reference data. Motor timing was calibrated by measuring distances travelled during motor operation to match required seed spacing. Wireless data transmission was validated using ThingSpeak's real-time channel dashboard.

4.3.3 Optimization and Scalability

The system's scalability is supported by the ESP32's versatile I/O capabilities. Optimizations include minimizing power usage and enabling future integration of more sensors like soil pH or GPS. The ML model can also be retrained with a larger dataset to enhance prediction accuracy.

4.4 Functional Block Diagrams

A Functional Block Diagram (FBD) represents the interaction between system components. It illustrates data flow from sensors to ESP32, transmission to ThingSpeak, ML-based seed prediction, and seed sowing through motor control.

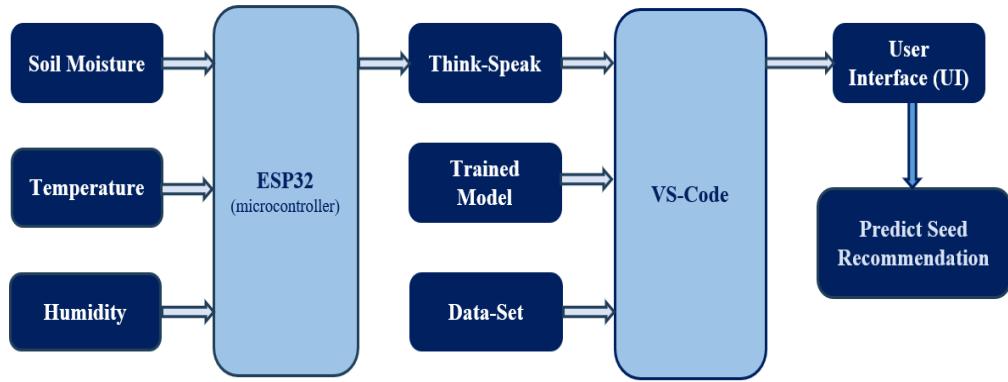


Figure 4.3: Functional block diagram of predicting seed

Seed Sowing System

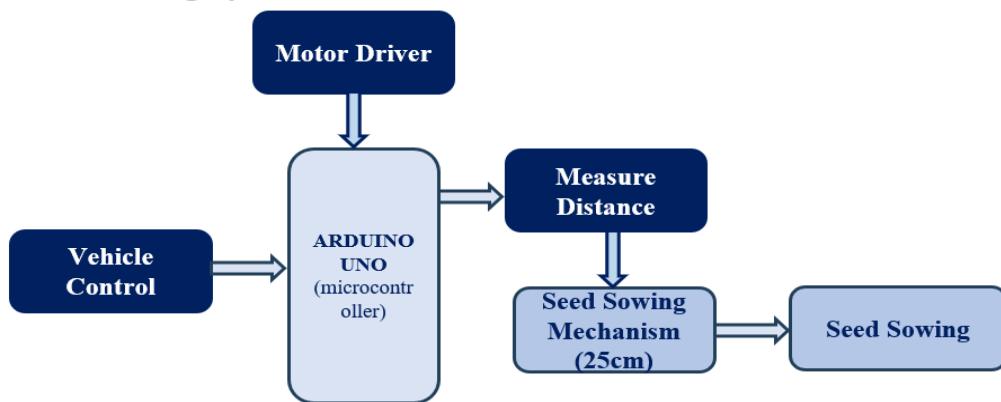


Figure 4.4: Functional block diagram of seed sowing

Chapter 5

Results and Discussion

The smart agriculture system was successfully developed and tested in real-world conditions, demonstrating the integration of environmental data acquisition, machine learning-based seed prediction, and autonomous seed sowing.

5.1 Machine Learning Model Performance

The machine learning model trained using environmental parameters—soil moisture, temperature, and humidity—achieved an accuracy of approximately 70% on the test dataset. The dataset was preprocessed and split in an 80:20 ratio for training and testing. The model was exported as a .pk1 file and integrated into the user interface using JavaScript. Seed predictions generated by the model were validated with expected results and expert guidance.

| Final Test Accuracy: 0.7132727272727273 | | | | |
|---|-----------|--------|----------|---------|
| | precision | recall | f1-score | support |
| 0 | 0.71 | 0.69 | 0.70 | 967 |
| 1 | 0.71 | 0.71 | 0.71 | 998 |
| 2 | 0.71 | 0.73 | 0.72 | 997 |
| 3 | 0.72 | 0.72 | 0.72 | 1035 |
| 4 | 0.73 | 0.71 | 0.72 | 988 |
| 5 | 0.72 | 0.72 | 0.72 | 974 |
| 6 | 0.69 | 0.69 | 0.69 | 969 |
| 7 | 0.71 | 0.70 | 0.70 | 1014 |
| 8 | 0.71 | 0.71 | 0.71 | 1057 |
| 9 | 0.71 | 0.72 | 0.71 | 983 |
| 10 | 0.70 | 0.74 | 0.72 | 1018 |
| accuracy | | | 0.71 | 11000 |
| macro avg | 0.71 | 0.71 | 0.71 | 11000 |
| weighted avg | 0.71 | 0.71 | 0.71 | 11000 |

Figure 5.1: Model Accuracy

5.2 User Interface Output

The JavaScript-based user interface, integrated with ThingSpeak and hosted in Visual Studio Code, successfully displayed:

- Real-time sensor data (temperature, humidity, soil moisture)
- Predicted suitable seed based on current conditions
- A clean, user-friendly dashboard layout



Figure 5.2: Seed Recommendation Dashboard

5.3 Seed Sowing Vehicle Results

The autonomous vehicle was tested for seed placement at various calibrated distances. The timing-based motor logic allowed accurate placement for crops like rice (25 cm), wheat (15 cm), and maize (25 cm). The sowing mechanism operated smoothly across test plots with consistent spacing.



Figure 5.3: Hardware Integration Front View



Figure 5.4: Hardware Integration Back View

- DC motors were calibrated to run for specific durations to achieve desired distances.
- Field testing confirmed the vehicle could reliably place seeds with minimal deviation from target spacing.

5.4 ThingSpeak Cloud Output

Live environmental data was visualized in real-time through the ThingSpeak channel. Graphs showed variations in humidity, temperature, and moisture levels, confirming reliable data transmission from ESP32.

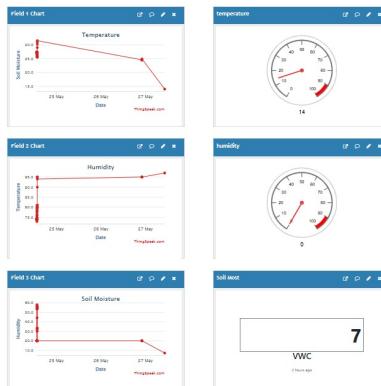


Figure 5.5: Real-Time Sensor Data on ThingSpeak

5.5 App Interface

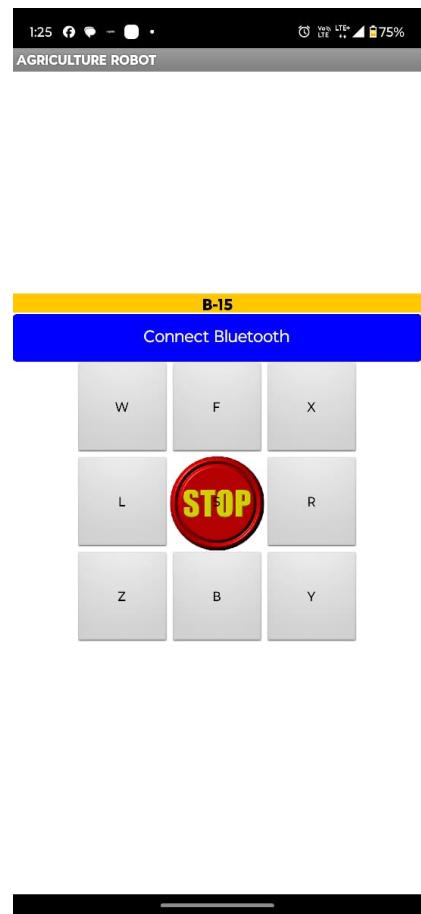


Figure 5.6: App Interface

5.6 Discussion

The results demonstrate the viability of using affordable IoT components and machine learning for smart farming. While the model accuracy and mechanical performance are satisfactory, future improvements such as more advanced models and terrain-aware navigation could further enhance system reliability. Overall, the system successfully reduces manual labor, supports better decision-making, and encourages precision agriculture practices.

Chapter 6

Conclusions and future scope

6.1 Conclusion

This project successfully integrates Internet of Things (IoT), machine learning, and automation technologies to develop a smart agriculture system aimed at assisting farmers in crop selection and efficient seed sowing.

By using real-time environmental data such as soil moisture, temperature, and humidity, the system predicts the most suitable crop using a trained machine learning model with an accuracy of approximately 70%. This model is seamlessly integrated into a JavaScript-based interface, which retrieves data from the ESP32 via the ThingSpeak platform and presents recommendations to the user.

The second major achievement of the project is the development of an autonomous seed-sowing vehicle. Using calibrated motor timing instead of expensive distance sensors, the vehicle places seeds at optimal intervals for each crop type. This approach offers a cost-effective solution for precision farming and reduces manual labor.

The overall system is designed to be scalable, low-cost, and user-friendly, making it a viable solution for small and medium-scale farmers. It promotes sustainable farming practices through data-driven decisions, resource optimization, and automation.

This project demonstrates the potential of technology to modernize agriculture and support food security in a scalable and affordable manner.

6.2 Future Scope

While the current implementation demonstrates the effectiveness of integrating machine learning, IoT, and automation in agriculture, there are several opportunities to enhance and expand the system:

- **Addition of More Sensors:** Integrating sensors for soil pH, electrical conductivity (EC), and nutrient levels can improve seed prediction accuracy and support fertilizer recommendation systems.
- **GPS Integration:** Incorporating GPS modules would enable precise location tracking and route planning for large-scale farms, making the seed sowing vehicle more autonomous and reliable over wide areas.
- **Enhanced ML Model:** The machine learning model can be improved with a larger and more diverse dataset, possibly using ensemble techniques or deep learning models to increase prediction accuracy.

- **Crop Health Monitoring:** Future versions can integrate cameras and computer vision to detect crop diseases or monitor growth stages using image analysis.
- **Solar Power Utilization:** To enhance sustainability and reduce energy dependence, the entire system could be powered using solar panels.

These enhancements will further increase the adaptability, scalability, and efficiency of the system, supporting smart farming practices and maximizing agricultural productivity.

Bibliography

- [1] Rehman, A. U., Alamoudi, Y., Khalid, H. M., Morchid, A., Muyeen, S. M., & Abdellaziz, A. Y. (2024). Smart agriculture technology: An integrated framework of renewable energy resources, IoT-based energy management, and precision robotics. *Cleaner Energy Systems*, 9, 100132.
- [2] Kose, U., Prasath, V. B., Mondal, M., Podder, P., & Bharati, S. (Eds.). (2022). *Artificial intelligence and smart agriculture technology*. CRC Press.
- [3] Chand, A. A., Prasad, K. A., Mar, E., Dakai, S., Mamun, K. A., Islam, F. R., Mehta, U., & Kumar, N. M. (2021). Design and analysis of photovoltaic powered battery-operated computer vision-based multi-purpose smart farming robot. *Agronomy*, 11(3), 530.
- [4] Doshi, M., & Varghese, A. (2022). Smart agriculture using renewable energy and AI-powered IoT. In *AI, Edge and IoT-based Smart Agriculture* (pp. 205–225). Academic Press.
- [5] Eissa, M. (2024). Precision agriculture using artificial intelligence and robotics. *Journal of Research in Agriculture and Food Sciences*, 1(2), 35.
- [6] Patil, D. D., Singh, A. K., Shrivastava, A., & Bairagi, D. (2022). IOT sensor-based smart agriculture using agro-robot. In *IoT Based Smart Applications* (pp. 345–361). Cham: Springer International Publishing.