SMART FARMING USING ML AND IOT

A Project report submitted
in partial fulfilment for the degree of

B. Tech
in
Computer Science and Engineering
by

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(Estd .by Govt. of Jharkhand and Run by Techno India Under PPP)

Approved by AICTE, New Delhi and Affiliated to JUT, Ranchi

CERTIFICATE

This is to certify that the project report entitled **"Smart Farming Using Machine Learning and IOT"** submitted by "**Komal Kumari(21033440015), Akanksha Jyoti(21033440005), Priyanka Kumari Verma(21033440026), Rohit Kumar Mandal(21033445017), MD.Warish Ansari(21033445011)**" to the Ramgarh Engineering College, Ramgarh, in partial fulfilment for the award of the degree of **B. Tech in Computer Science and Engineering** has been carried out under the supervision and guidance of **MRS. JYOTI KUMARI**. The contents of this report, in full or in parts, have not been submitted to any other Institution or University for the award of any degree.

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DECLARATION

We declare that this project report titled **"Smart Farming Using Machine Learning and Internet of Things"**, submitted in partial fulfilment of the degree of **B.Tech in Computer Science and Engineering**, is a record of original work carried out by me under the supervision of **Mrs. Jyoti Kumari** has not formed the basis for the award of any other degree, in this or any other Institution or University. In keeping with the ethical practice in reporting scientific information, due acknowledgements have been made wherever the findings of others have been cited.

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Finally, we pay our respect and love to our beloved parents and friends without whose unimpeded support and encouragement, this thesis would not have seen the light of the day.

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ABSTRACT

Smart farming leverages advanced technologies such as Machine Learning (ML) and the Internet of Things (IoT) to enhance agricultural productivity, optimize resource utilization, and improve crop yield. Traditional farming methods often depend on manual monitoring, resulting in inefficient resource use and suboptimal crop yields. This project presents a smart farming system that leverages real-time environmental data collected through IoT sensors, analyzed by various ML algorithms including Random Forest, K-Nearest Neighbors, Naive Bayes, and Support Vector Machine. These algorithms facilitate accurate prediction of optimal farming conditions and support precise decision-making. Notably, the Random Forest algorithm achieved the highest accuracy of 98.8%, demonstrating its superior capability in enhancing resource management and crop production. This study highlights the significant potential of combining IoT and ML technologies to enable sustainable and data-driven agricultural practices.

Keywords: - Smart Farming, Machine Learning, Internet of Things, Precision Agriculture.

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CHAPTER 1

1. INTRODUCTION

1.1 Background

Agriculture is the backbone of many economies, and with the growing global population, there is an increasing need for innovative solutions to enhance productivity, efficiency, and sustainability. Traditional farming methods often face challenges such as unpredictable weather conditions, inefficient resource management, and crop diseases. To address these issues, Smart Farming has emerged as a revolutionary approach, integrating Machine Learning and the Internet of Things to optimize agricultural practices.

Machine Learning enables data-driven decision-making by analysing vast amounts of agricultural data, such as soil health, weather patterns, and crop conditions, to provide accurate predictions and recommendations. IoT, on the other hand, facilitates real-time monitoring and automation through smart sensors, drones, and automated irrigation systems. The combination of these technologies allows farmers to maximize crop yield, reduce waste, and ensure sustainable farming practices.

1.2 Problem Statement

Agriculture is a fundamental sector that supports global food security and economic stability. However, traditional farming methods are increasingly struggling to meet the rising demand for food production due to various challenges, including climate change, resource scarcity, soil degradation, pest infestations, and inefficient farming practices. Farmers often rely on experience-based decision-making, which may not always be optimal for maximizing yield and resource efficiency.

During the traditional farming farmers faces following problem-

- Traditional farming methods rely heavily on manual labor and outdated tools, resulting in lower crop yields compared to modern techniques.
- Farmers depend entirely on rainfall and seasonal changes, making crops vulnerable to droughts, floods, and other unpredictable weather conditions.
- There is minimal use of modern tools, irrigation systems, or scientific methods, which limits efficiency and innovation in farming practices.
- Continuous use of the same land without proper soil management leads to reduced fertility, erosion, and nutrient depletion over time. Traditional methods often lack effective ways to deal with pests and crop diseases, resulting in significant losses and reduced quality of produce.

Additionally, unpredictable weather conditions, water mismanagement, and overuse of fertilizers and pesticides lead to reduced productivity and environmental damage. Manual monitoring of soil health, crop conditions, and irrigation is labour intensive, time-consuming, and prone to errors, making farming operations inefficient.

The lack of real-time data analytics and automated decision-making systems further limits the ability to address these issues effectively. Without precise and timely insights, farmers may struggle to optimize irrigation, fertilization, and pest control, resulting in lower productivity and increased operational costs.

To address these challenges, Smart Farming using Machine Learning and the Internet of Things (IoT) offers a data-driven, automated, and efficient approach to modern agriculture. By leveraging IoT-based smart sensors for real-time monitoring and ML algorithms for predictive analytics, farmers can enhance crop yield, minimize resource wastage, and promote sustainable farming practices.

1.2 Objective

The objective of this project is to develop an intelligent agricultural support system that leverages the capabilities of Machine Learning (ML) and the Internet of Things (IoT) to automate irrigation decisions, monitor farm conditions in real-time, and ultimately improve agricultural productivity and resource management. The specific objectives are discussed below:

1. **To collect real-time agricultural and environmental data using IoT sensors:**

   The system aims to integrate various sensors such as temperature sensors, humidity sensors, soil moisture sensors, and water level detectors to continuously monitor environmental and soil conditions. These sensors are connected via IoT modules (like ESP8266), enabling wireless data transmission to a centralized system.

2. **Preprocess and structure the collected data for meaningful machine learning application:**

   Raw data collected from sensors often contain noise, missing values, or inconsistencies. One of the objectives is to apply data preprocessing techniques such as cleaning, normalization, feature extraction, and labelling. This ensures that the data is well-prepared and accurate before being fed into the machine learning models for training and prediction.

3. **To implement and compare multiple machine learning algorithms for water level classification:**

   The project involves applying different supervised learning algorithms like Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naïve Bayes, Artificial Neural Network (ANN), XGBoost, and Logistic Regression to classify the water level into specific categories (e.g., low, medium, high).

4. **To evaluate model performance using standard evaluation metrics**:

   Another important objective is to evaluate each machine learning model using key performance indicators such as Accuracy, Precision, Recall, and F1 Score. By comparing these metrics, the best-performing model can be selected for deployment. This ensures that the system is both reliable and efficient in making predictions.

5. **To automate irrigation control based on predicted water levels:**

   Based on the classified water level category, the system can automatically control the operation of a water pump (via relay switch) to irrigate the field when needed. This not only minimizes water wastage but also eliminates the need for manual irrigation, saving time and labor for the farmer.

6. **To enhance resource efficiency and crop productivity through intelligent decision-making**:

   The integration of ML and IoT allows the system to make data-driven decisions regarding irrigation schedules, thus ensuring that crops receive the optimal amount of water. This objective targets increased crop yield, reduced resource waste (especially water), and better farm management practices.

1.4 Aim

The aim of this project is to design and implement a Smart Farming system that utilizes the power of Machine Learning (ML) and Internet of Things (IoT) technologies to automate agricultural processes, particularly focusing on intelligent irrigation management. By collecting real-time environmental and soil data through IoT sensors and analyzing it using machine learning algorithms, the system aims to classify water level requirements accurately and control irrigation automatically, thereby increasing crop productivity, optimizing resource usage (especially water), and reducing the need for manual intervention in farming operations.

1.5 Benefits of Our Projects

Benefits of our project

1. Efficient Water Management:
The system automates irrigation based on real-time water level classification, helping farmers use water only when necessary. This prevents over-irrigation, reduces water wastage, and supports sustainable agriculture—especially important in regions facing water scarcity.

2. Real-Time Monitoring:
With IoT sensors integrated into the system, farmers can continuously monitor critical parameters such as soil moisture, temperature, humidity, and water levels. This enables quick responses to environmental changes and better crop management.

3. Intelligent Decision-Making:
Machine learning algorithms analyze patterns in environmental data to accurately predict water needs. This allows for smarter, data-driven decisions in farming rather than relying solely on experience or guesswork.

4. Improved Crop Productivity:
By ensuring optimal water supply and timely irrigation, crops receive the right conditions for healthy growth. This can lead to better yield, healthier produce, and more consistent farming outcomes.

5. Reduced Human Effort and Labor:
Automation reduces the need for manual checking of soil and water conditions. Farmers can rely on the system to control irrigation pumps and notify them of any significant changes, saving time and physical effort.

CHAPTER 2

2. LITERATURE REVIEW

S.Sundaresan et. al (2023) [1], The integration of Machine Learning (ML) and IoT in smart farming has proven effective in improving crop yield, automating irrigation, and optimizing fertilizer usage. ML-based crop recommendation systems analyze soil, weather, and nutrients, while IoT devices ensure efficient water use through real-time monitoring. However, studies reveal limitations such as poor adaptability to sudden climate changes, lack of disease detection via computer vision, and scalability issues. To address these, five ML models—RFC, GBC, DT, XGB, and KNN—were compared. KNN showed the highest accuracy for the dataset and was thus implemented in the crop recommendation system.

Avinash Awasthi, et.al (2024) [2].It highlights the role of IoT in data collection, real-time monitoring, and predictive decision-making for sustainable farming. However, several research gaps remain. The system lacks real-time adaptability to sudden climate changes and pest attacks, limiting its practical effectiveness. Additionally, it relies on basic machine learning models, such as Random Forest and YOLO, without exploring advanced AI techniques, including deep learning, for disease detection.

Richard Essah ,et.al (2021) [3]. This paper examines the application of machine learning and deep learning (DL) in smart farming, focusing on crop quality assessment using Internet of Things (IoT)-based monitoring systems, wireless sensor networks (WSNs), and AI-driven decision-making. It highlights the use of Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) for crop classification, disease detection, and quality evaluation, along with Edge Computing (EC) for real-time data processing and cloud storage for long-term analysis.

A.Dahane ,et.al (2020) [4] . It discusses various studies on IoT-based smart farming, focusing on optimizing agricultural practices through IoT and machine learning. It highlights research on AI-driven irrigation systems, cloud-based farming solutions, and sensor-based monitoring for precision agriculture. Studies emphasize the role of IoT in enhancing efficiency, sustainability, and real-time decision-making in farming operations.

However, the paper identifies a research gap in integrating weather forecasting data with IoT-based irrigation systems, the need for improved real-time adaptability to climate changes, and the challenge of balancing AI model training speed with accuracy.

Muthumanickam Dhanaraju, et.al (2022) [5]. It highlights existing research on remote sensing, machine learning applications in agriculture, and the integration of precision farming techniques. However, a significant research gap remains in terms of addressing real-time challenges faced by farmers, such as cost-effectiveness, accessibility of technology in rural areas, and the complexity of integrating diverse smart farming systems. Moreover, the paper points out the need for enhanced data management strategies and improved connectivity solutions to make smart farming more scalable and practical for widespread adoption.

Vibha Pawar,et.al (2023) [6]. It explores various studies on smart farming using machine learning algorithms, focusing on Artificial Neural Networks (ANN), IoT sensors, and predictive analytics to optimize crop yield. It compares machine learning models such as Random Forest, SVM, KNN, and MLP, highlighting their accuracy in crop prediction based on factors like temperature, rainfall, humidity, and soil PH. However, several research gaps are identified, including the limited consideration of additional environmental factors like solar radiation and micronutrient levels, the lack of a generalized prediction model adaptable to various crops and regions, and the absence of disease detection and prevention mechanisms.

Mochammad Haldi Widinto,et.al (2024) [7].It explores the integration of IoT and machine learning (ML) in smart farming, emphasizing the role of IoT sensors and ML algorithms like Linear Regression (LR), Decision Tree (DT), Random Forest (RF), and XGBoost in predicting key agricultural factors such as temperature, soil moisture, light intensity, and humidity. It highlights research on AI-driven irrigation management and sensor-based remote monitoring, but several research gaps remain. The system lacks real-time adaptability to sudden weather changes, does not incorporate advanced deep-learning models like CNN or LSTM for better prediction accuracy.

Prajwal R, et.al (2021) [8]. It explores the role of machine learning and IoT in smart farming, highlighting ML techniques such as Support Vector Machines , Artificial Neural Networks (ANN), DBSCAN, and K-Means Clustering for crop yield prediction, disease detection, and soil health monitoring. It discusses the benefits of sensor-based agriculture, intelligent irrigation, and automated storage management while emphasizing the need for combining multiple ML algorithms for improved accuracy.

Shraban Kumar ,et.al(2022) [9]. Recent literature highlights the use of ML and DL algorithms for accurate crop yield prediction using features like temperature, humidity, pH, and rainfall. Models such as Random Forest, SVM, and LSTM have shown strong performance, with Random Forest often achieving the highest accuracy. Activation functions like sigmoid enhance deep learning results, especially in multi-layer models. Overall, integrating IoT data with advanced algorithms improves prediction in diverse agricultural environments.

Dr. Rekha J P atil, et.al (2023) [10]. Recent advancements in smart agriculture highlight the critical role of Internet of Things and Machine Learning in transforming traditional farming practices. Studies have shown that IoT enables real-time monitoring of vital parameters such as soil moisture, temperature, pH levels, and water storage, significantly enhancing decision-making in crop management. Meanwhile, ML algorithms process this data to optimize crop yield, predict ideal planting conditions, and improve product quality through data-driven insights. The integration of these technologies leads to increased productivity, efficient resource use, and sustainable agriculture, which is widely supported in the existing literature on smart farming innovations.

Ghulam Mohyuddin ,et.al (2024) [11]. Recent studies emphasize the transformative impact of Machine Learning in modern agriculture, particularly through its integration with Information and Communication Technology (ICT). ML plays a key role in analyzing historical and real-time data to enhance crop selection, disease detection, irrigation, and soil management. Research also highlights the use of drones and autonomous vehicles powered by ML in precision agriculture for tasks like planting and harvesting. Additionally, ML contributes to resource optimization, such as energy use and fertilizer application, promoting climate-resilient and sustainable farming. Overall, literature supports ML as a critical tool for boosting productivity and reducing environmental impact in smart agriculture.

Mustaque Ahmed Rahu ,et.al (2019) [12]. The integration of Wireless Sensor Networks (WSNs), Internet of Things, Artificial Intelligence , and Deep Learning has been widely studied for its transformative impact on smart agriculture. WSNs enable real-time field data collection, while IoT connects these systems for seamless data transmission and monitoring. Machine Learning algorithms support predictive analytics for crop health, disease detection, and resource optimization, and DL techniques like CNNs enhance image-based crop monitoring and yield prediction. However, challenges such as energy efficiency, scalability, and data security remain critical. Recent research is focusing on solutions like edge computing and lightweight protocols to address these issues. Overall, the literature highlights the promising role of these integrated technologies in advancing precision agriculture and promoting sustainable farming practices.

Ali Ashoor Issa ,et.al (2024) [13]. Recent studies highlight the significant impact of AI and IoT in transforming agriculture through digitalization and data-driven practices. Technologies like drones, robotics, smart irrigation, and sensor networks improve monitoring and efficiency. The role of 5G enhances connectivity in rural areas, supporting real-time data use. Smart Decision Support Systems and cloud-based AI models aid in soil analysis and remote farm management. Overall, the literature supports AI and IoT as key drivers of sustainable, efficient, and modern farming.

Ali Ashoor Issa ,et.al (2021) [14]. Recent studies highlight the use of AI, IoT, ML, and DL in smart farming to address global issues like food shortages and population growth. IoT-based sensors, UAVs, and robots are used for real-time monitoring and tasks like irrigation, harvesting, and pest control. 5G technology enhances data transmission and device connectivity. Research also emphasizes the role of Smart Decision Support Systems (SDSS) in improving decision-making in developing countries, though greater support from governments and the private sector is needed for widespread adoption.

Md Jowel Rahman, et.al (2024) [15]. Studies show that IoT technology greatly improves agricultural productivity, resource efficiency, and sustainability. Benefits include reduced water use and better crop growth with smart systems. However, challenges like high costs, technical complexity, skill gaps, and data security concerns hinder adoption. Research emphasizes the need for strong policies, education, and collaboration to fully realize IoT's potential in sustainable farming and food security.

Shi Lakshmi Chandana, et.al (2024) [16]. Recent studies emphasize the transformative role of IoT and Machine Learning in advancing precision agriculture. IoT-enabled sensors, placed across agricultural fields, collect real-time data on environmental factors such as soil moisture, temperature, humidity, and nutrient levels, which are crucial for effective crop monitoring. This data, transmitted to cloud platforms, is processed using ML algorithms to detect patterns, predict crop yields, and identify pest or disease outbreaks. Literature also supports the use of predictive models and decision support systems to guide farmers in optimizing irrigation, fertilization, and pesticide use, enhancing both productivity and sustainability. Challenges such as data integration, connectivity, and scalability remain key research areas in the adoption of smart farming technologies.

Mohammad Aldossary, et.al (2024) [17]. Recent studies emphasize the effectiveness of combining IoT, ML, and AI in smart agriculture to overcome the limitations of traditional farming. Hybrid models using algorithms like SVM, Random Forest, MLP, and deep learning models such as MobileNetV2, VGG16, and InceptionV3 have shown high accuracy in anomaly detection and soil classification. Literature supports that integrating these techniques improves decision-making, resource efficiency, and overall agricultural productivity.

Ahamed Ali Samsu Alian ,et.al(2022) [18]. Recent literature underscores the importance of technological advancements in agriculture to enhance productivity and reduce costs. Smart farming, driven by IoT, enables real-time monitoring of key parameters like soil quality, water levels, and plant growth, supporting minimal human intervention. Machine Learning is widely used to improve crop yield and minimize risks by analyzing field data. Additionally, data analytics plays a vital role in increasing the accuracy and predictability of farming decisions, such as crop selection and resource management. Existing studies also explore various system architectures and frameworks that address challenges in implementing effective smart farming solutions.

Angel Luis Perales Gomez , et.al (2022) [19]. Recent research highlights the growing adoption of IoT, Machine Learning, and Deep Learning in automating agricultural processes and enhancing crop quality assessment. Studies show that combining sensor data with advanced analytics improves real-time decision-making in farming. Existing architectures often focus on single data sources, whereas recent approaches emphasize multi-source data aggregation to boost accuracy. Literature supports that layered architectures integrating data collection, processing, and analysis offer better performance, with lower error rates in crop quality evaluation. This confirms the effectiveness of combining IoT and intelligent models for more reliable and efficient smart farming solutions.

M.W.P Maduranga, et.al (2020) [20]. Recent studies show that combining IoT and Machine Learning in smart agriculture enhances farm productivity through real-time monitoring and data-driven decision-making. IoT sensors collect large volumes of data, which ML algorithms analyze to optimize resource use, reduce costs, and improve crop yields. Literature supports that integrating IoT's sensing with ML's predictive capabilities leads to more intelligent and efficient farming systems.

CHAPTER 3

3. METHODOLOGY

In This chapter we discuss the proposed methodology used in this project. We proposed a smart farming crop recommendations system that takes into consideration all the appropriate parameters, including temperature, rainfall, and soil moisture to predict crop suitability. The proposed model provides crop selection based on economic and environmental conditions and benefits to maximize the crop yield, which will subsequently help to meet the increasing demand for the country's food supplies. We also provide real-time data collection by sensors, Raspberry Pi, and IOT technology. This system is a fundamental concern with performing the primary function, which is providing crop recommendations to farmers.

3.1 Flow Chart

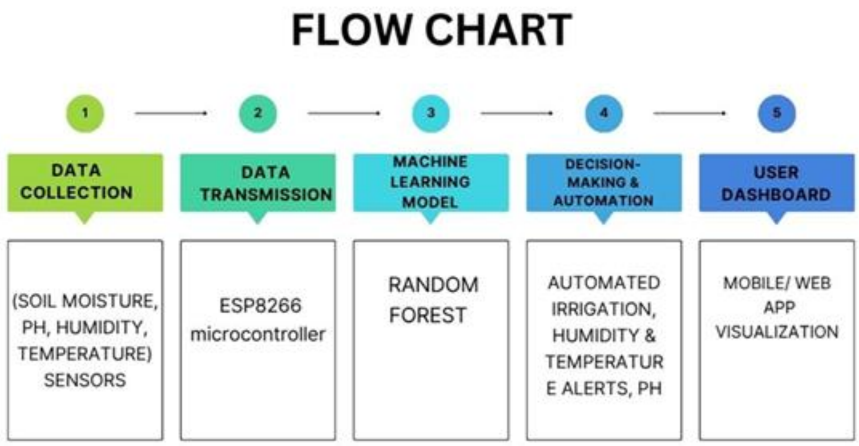

Figure 1: Working flowchart of smart farming system

In figure 1 represent the working flowchart of the proposed methodology for Smart Farming using Machine Learning and IoT. Below is a step-by-step explanation of each component:

1. Data Collection (IoT):-

Purpose: To collect real-time environmental data using IoT sensors.

Devices Used:

- Soil Moisture Sensors – Monitor water content in the soil.
- pH Sensors – Measure the acidity or alkalinity of the soil.
- Humidity Sensors – Track air moisture levels.
- Temperature Sensors – Monitor atmospheric and soil temperature.

2. Data Transmission

Purpose: To send collected data to the cloud or local storage for processing.

Devices Used:

- ESP 8266 – A Microcontroller that collects sensor data and transmits it.
- Wi-Fi & Communication Protocols – Data is sent wirelessly to cloud platforms for analysis.

3. Machine Learning Models

Purpose: Analyze the collected data and make predictions.

Techniques Used:

- **Random Forest** - It is a machine learning algorithm that uses multiple decision trees to make predictions. It works by creating many decision trees during training and combining their outputs to improve accuracy and reduce overfitting. Each tree gives a result, and the final output is decided by majority voting (for classification) or averaging (for regression). It is widely used because it is easy to use, handles large datasets well, and gives good results even without much tuning.
- **KNN Algorithm**-It is a simple machine learning algorithm used for classification and regression. It works by finding the 'k' closest data points (neighbors) to a new input based on distance (usually Euclidean distance), and then predicts the result based on the majority label (for classification) or average value (for regression) of those neighbors. KNN is easy to understand and effective for small datasets but can be slow with large data because it compares the input to all points in the dataset.
- **Support vector machine (SVM)**- It is a powerful machine learning algorithm used for classification and regression tasks. It works by finding the best boundary (called a hyperplane) that separates data into different classes. SVM tries to maximize the margin between the classes, which helps improve accuracy. It can also use special functions called kernels to handle complex data that isn't linearly separable. SVM is effective in high-dimensional spaces and is widely used in text classification, image recognition, and more.
- **Naïve Bayes**-It is a simple and fast machine learning algorithm used mainly for classification tasks. It is based on Bayes' Theorem and assumes that all features are independent of each other (which is a "naive" assumption). Despite this simplification, it works well in many situations, especially for text classification like spam detection or sentiment analysis. It calculates the probability of each class for a given input and chooses the one with the highest probability. Naive Bayes is easy to implement and works well with large datasets.

4. Decision-Making & Automation

Purpose: Automate farming activities based on ML predictions.

Automation Implementations:

- Smart Irrigation – Pumps are turned on/off based on soil moisture levels.
- Temperature & Humidity Alerts – Farmers receive real-time notifications about weather conditions.
- PH level

5. User Dashboard (Mobile/Web App)

Purpose: Provide a visual representation of farm conditions to farmers.

Features:

- Real-time Monitoring – View live sensor data.
- Control System – Remotely operate irrigation.

This flowchart integrates IoT sensors, data storage, machine learning, and automation to create an efficient Smart Farming system. The data collected from sensors is transmitted to a cloud server, analyzed using ML models, and used to automate farming decisions. Farmers can monitor and control their farms remotely using a mobile/web app.

3.2 Hardware Requirements

3.2.1 ESP8266 microcontroller :

The ESP8266 is a low-cost, low-power microcontroller with an integrated Wi-Fi transceiver that allows it to connect to a WiFi network and communicate with other devices or the internet. It can operate as a standalone module or as a part of a larger microcontroller system, enabling a wide range of IoT applications.

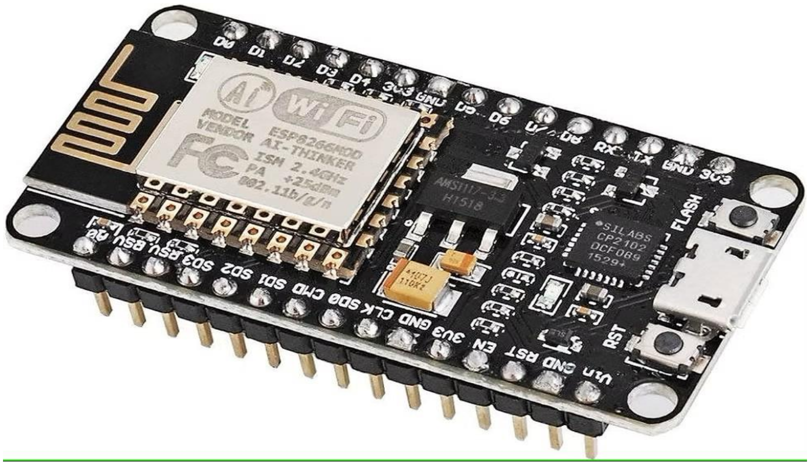

Figure 3.2.1 ESP8266 microcontroller

3.2.2 External DC Battery Supply

External DC battery supply functions typically involve providing a backup DC power source when the primary AC power source fails. This backup power is essential for maintaining critical equipment like protective relays, control systems, and communication systems. The battery system is designed to switch to providing DC power to these loads when AC power is interrupted.

Figure 3.2.2 External DC Battery

3.2.3 5-Volt Relay Module

Pin details: (-)GND, (+)VCC, output – input**.** The Grove - Gas Sensor(MQ2) module is useful for gas leakage detection (home and industry). It is suitable for detecting H2, LPG, CH4, CO, Alcohol, Smoke, or Propane. Due to its high sensitivity and fast response time, measurement can be taken as soon as possible. The sensitivity of the sensor can be adjusted with a potentiometer.

Fig 3.2.3 5-Volt relay Module

3.2.4 Soil moisture Sensor

Pin details:(-)GND, (+)VCC Soil moisture sensor consists of two conducting plates which function as a probe and act as a variable resistor together. When the sensor is inserted into the water, the resistance will decrease and better conductivity between the plates.

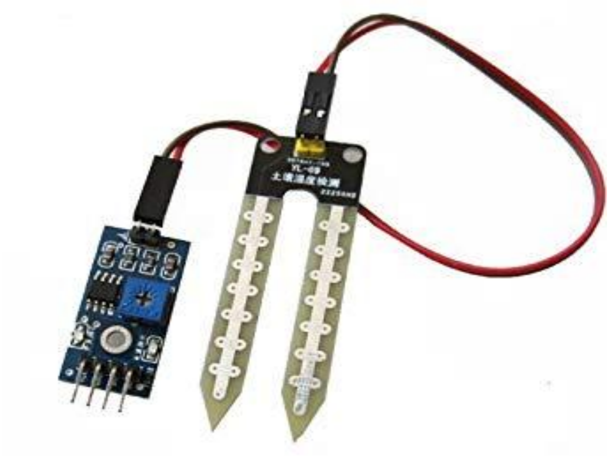

Figure 3.2.4 Soil Moisture

3.2.5 DHT11 temperature sensor

Pin details:(-)GND, (+)VCC, output. This module integrates a DHT11 sensor and other required components on a small PCB. The DHT11 sensor includes a resistive-type humidity measurement component, an NTC temperature measurement component, and a high-performance 8-bit microcontroller inside, and provides calibrated digital signal output. It has high reliability and excellent long-term stability, thanks to the exclusive digital signal acquisition technique and temperature & humidity sensing technology.

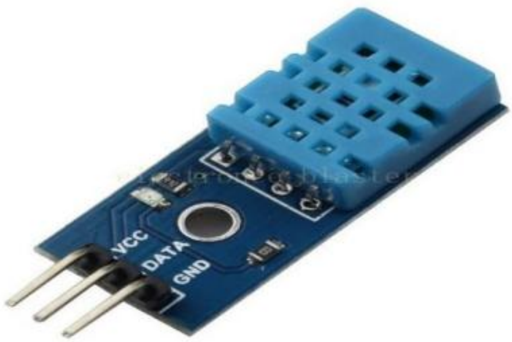

Fig.3.2.2 Temperature Sensor

3.2.6 Breadboard

A breadboard is a reusable platform used for building and testing electronic circuits without soldering. It has a grid of holes connected by internal metal strips that allow components like resistors, LEDs, and ICs to be easily inserted and interconnected. The central area has rows for placing components, while the side columns (power rails) are used to distribute power (Vcc and GND). Breadboards are ideal for prototyping because they let you quickly assemble, modify, and troubleshoot circuits before finalizing them on a PCB.

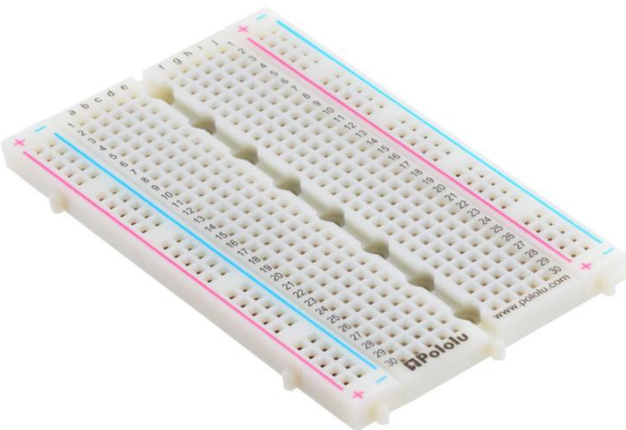

Fig 3.2.6 Breadboard

3.2.7 DC water Pump

A DC water pump is an electrically powered device that moves water using direct current (DC) voltage, typically from a battery or DC power supply. Its main function is to pump and circulate water in systems such as irrigation, cooling, or aquariums. It operates using an electric motor that drives an impeller, creating suction to draw water in and push it out through an outlet. DC water pumps are compact, energy-efficient, and commonly used in portable and small-scale applications like smart farming, where they can be controlled automatically using sensors and microcontrollers.

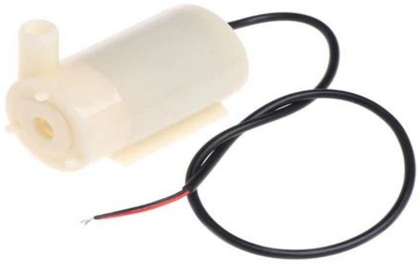

Figure 3.2.7 DC water Pump

3.2.8 PH Sensor

pH sensor is used to measure the acidity or alkalinity of the soil, which is crucial for plant health and nutrient absorption. By providing real-time data on soil pH levels, the sensor helps farmers maintain optimal conditions for specific crops, ensuring better growth and yield. Integrated with IoT devices and sometimes machine learning, the pH sensor continuously sends data to a cloud platform or mobile app, enabling farmers to take timely actions such as adjusting fertilizers or applying soil treatments.

Figure 3.2.8 PH Sensor

3.3 Software Requirements

a) Machine Learning & Data Processing

- Python with Libraries (NumPy, Pandas, serial, pickel) – For data analysis and ML model development.

b). Web & Mobile Dashboard Development

- **HTML-**HTML (HyperText Markup Language)- it is the standard language used to create and design webpages. It tells the web browser how to display text, images, links, and other content on a webpage using special tags like <html>, <head>, <body>, <p>, and more.
- **CSS** (Cascading Style Sheets) – it is a language used to style and design HTML webpages. It controls how elements look on a webpage—like colors, fonts, sizes, spacing, and layout—so that the page appears more attractive and organized.

d) Embedded Programming & IoT Platforms

- **Arduino IDE / PlatformIO** – For microcontroller programming.
- **Web** – For real-time IoT dashboard monitoring.

CHAPTER 4

4. RESULTS

The implementation of the smart farming system yielded promising results in both data collection and predictive accuracy. Real-time environmental parameters such as soil moisture, temperature, humidity, and pH levels were successfully monitored using IoT-based sensors. The collected data was processed and analyzed using various Machine Learning algorithms to determine the most effective model for predicting optimal farming conditions.

4.1 Model Evaluation

Table 4.1 Model Evaluation

Algorithms	Accuracy	Precision	Recall	F1 Score
Support Vector Machine (SVM)	96.31%	96.19%	96.31%	96.24%
Random Forest	**98.42%**	**98.43%**	**98.42%**	**98.42%**
Naïve Bayes	93.99%	92.49%	93.99%	91.52%
KNN	98.28%	98.28%	98.28%	98.28%
Linear Regression	91.89%	94.51%	94.31%	92.39%
XGBoost	98.42%	98.43%	98.42%	98.42%
K-means Clustering	77.02%	59.33%	77.02%	67.03%
ANN	94.74%	94.54%	94.73%	93.28%
Logistic Regression	95.94%	95.67%	95.94%	95.72%

Table1 depicts the comparative performance of various machine learning algorithms applied to the smart farming dataset. These models were evaluated using standard metrics such as Accuracy, Precision, Recall, and F1 Score to assess their effectiveness in classifying water level categories. Among all, the Random Forest algorithm demonstrated the highest and most balanced performance, and hence it was selected for the final implementation in this project.

It clearly shows that the Random Forest and XGBoost models outperformed others with an accuracy of 98.42%. However, Random Forest was chosen for final deployment due to its simplicity, interpretability, and robust generalization performance. KNN also performed nearly as well as Random Forest, showing strong potential in classification tasks with minimal misclassification. SVM and Logistic Regression provided reliable and consistent performance with accuracies above 95%, suitable for general classification use cases. Naïve Bayes, though efficient, showed slightly lower F1 Score, indicating some challenges in balancing precision and recall. Linear Regression, adapted for classification by rounding predictions, showed decent metrics but fell short in raw accuracy. K-Means Clustering, being unsupervised, had the lowest precision and F1 Score, as expected due to the lack of label supervision during training.The Artificial Neural Network model demonstrated good performance with a 94.74% accuracy, validating its ability to capture complex patterns, though at the cost of increased computational demand.

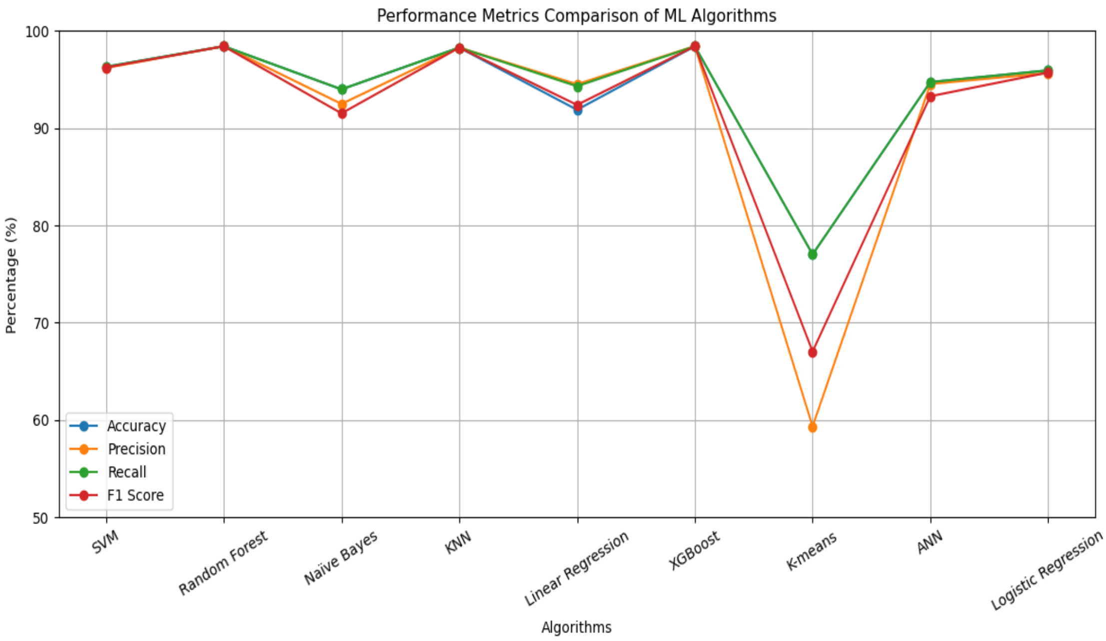

Figure 4.1 Comparison graph of ML Algorithm

Figure 2 illustrates the comparative analysis of nine machine learning algorithms—Support Vector Machine (SVM), Random Forest, Naïve Bayes, K-Nearest Neighbors (KNN), Linear Regression, XGBoost, K-Means Clustering, Artificial Neural Network (ANN), and Logistic Regression—across four performance metrics: Accuracy, Precision, Recall, and F1 Score. Each metric is plotted as a line, enabling a clear visual comparison of how each algorithm performs across multiple dimensions. The y-axis represents the percentage score (ranging from 50% to 100%), while the x-axis lists the algorithms.

Random Forest and XGBoost consistently score the highest across all four metrics, closely followed by KNN. These models demonstrate exceptional classification performance, indicating high reliability and minimal error rates. SVM and Logistic Regression show strong, balanced results across all metrics, with performance hovering around 95–96%, making them suitable for robust classification tasks in smart farming. Naïve Bayes, while relatively fast and simple, shows slightly lower F1 scores due to a dip in precision, possibly due to oversimplification or assumptions of feature independence. K-Means Clustering shows a significant drop in precision and F1 score despite moderate recall. This is expected, as it is an unsupervised algorithm and does not benefit from labeled training data. The Artificial Neural Network model provides strong results but is slightly less consistent across metrics compared to Random Forest and XGBoost. It still offers a reliable option, particularly when handling nonlinear patterns. Linear Regression, although adapted here for classification, shows moderate accuracy but relatively high precision and recall, indicating it correctly predicts most classes, but its raw class prediction accuracy is somewhat limited.

4.2 Experimental Setup

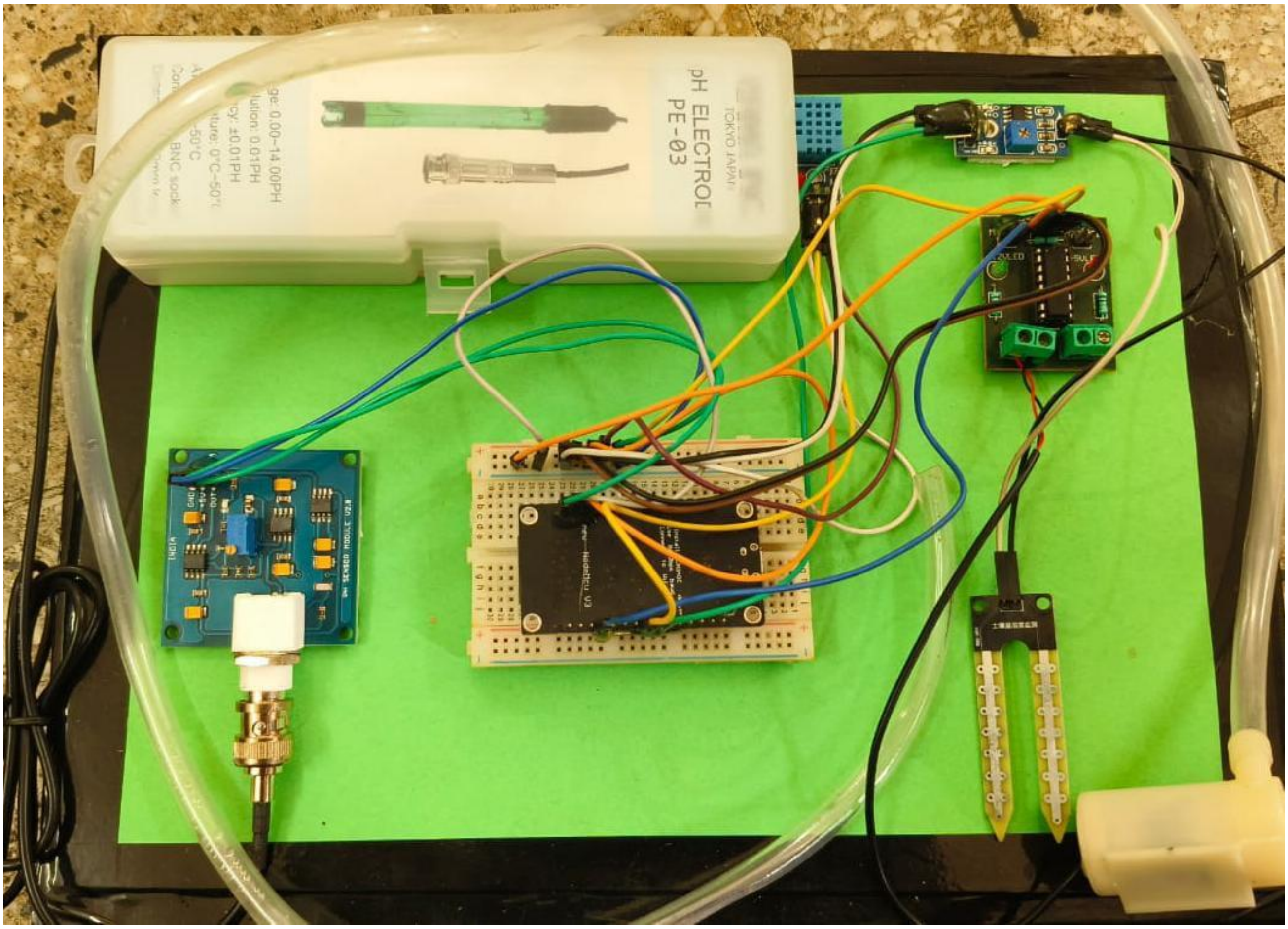

Figure 4.2: Experimental setup of Smart farming

- **pH Sensor (PE-03) and Signal Conditioning Board (Bottom-left with BNC Connector):**
  Component: The blue board with a BNC connector.
  Function: This reads the pH value of a solution. The pH electrode (probe) is connected to this board, which amplifies and conditions the signal to be readable by a microcontroller.
  Usage: Used in water quality monitoring to detect acidity or alkalinity.

- **Microcontroller (Middle – ESP8266/Arduino Nano on Breadboard):**
  Component: The black chip on the breadboard.
  Function: This is the brain of the system. It reads analog/digital signals from sensors and processes them. Based on the wiring and size, it looks like an ESP32 or Arduino Nano.
  Usage: Collects data from sensors and may transmit it wirelessly (if ESP32 is used).

- **Breadboard:**
  Function: A platform for prototyping electronics without soldering. It allows for quick connections of wires and components.
  Usage: Used to mount the microcontroller and connect all sensor wires and modules.

- **Relay Module (Top-right with Red LED and Screw Terminals):**

Component: Black board with green terminals and a red LED.
Function: Acts as a switch to control external devices (e.g., pumps or alarms) based on sensor readings.
Usage: When a certain condition (like high pH) is detected, the relay can turn on/off a device.

- **Voltage Regulator or Logic Level Converter Module (Near Relay):**
  Component: The small blue module with multiple pins.
  Function: Either steps down/up voltage between components (e.g., 5V to 3.3V), or handles logic level shifting.
  Usage: Ensures compatibility between sensor outputs and microcontroller input levels.

- **Wires (Jumper Wires -Multicolor):**
  Function: Connect all components electrically.
  Usage: Carry signals (power, ground, and data) between the pH sensor, microcontroller, and relay module.

CHAPTER 5

5. CONCLUSION

The proposed *Smart Farming System* integrates IoT sensors and Machine Learning techniques to enable real-time monitoring and intelligent decision-making in agricultural fields. By accurately collecting environmental parameters such as soil moisture, temperature, humidity, pH value, and detecting the presence of pests, the system significantly enhances precision agriculture practices. Through automated data collection and intelligent analysis, farmers are empowered to make timely decisions regarding irrigation, fertilization, and pest control, leading to increased crop yield, reduced resource wastage, and sustainable farming practices. The integration of ML models helps in predictive analytics, such as anticipating drought conditions or pest outbreaks, allowing preventive measures to be taken well in advance. Overall, the system provides a cost-effective, scalable, and user-friendly solution for modern agriculture, contributing to improved productivity and environmental conservation.

CHAPTER 6

6. FUTURE SCOPE

The future scope of this project lies in expanding the smart farming system with advanced technologies like deep learning models of CNN for more accurate crop prediction, pest and disease detection through image processing, and integration with satellite or drone data for large-scale monitoring. The system can be made more scalable by adopting cloud-based platforms, voice-enabled dashboards in local languages for easy farmer interaction, and blockchain for secure data handling. Additionally, incorporating solar-powered sensors and predictive maintenance for farm equipment will enhance energy efficiency and reliability. Integration with government schemes, market pricing, and AI-based decision support will further empower farmers, making agriculture more intelligent, sustainable, and productive in the long run.

CHAPTER 7

7 . REFERENCES

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