



A PROJECT REPORT ON

“CROP PREDICTION USING IOT AND ML”

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BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE & ENGINEERING

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that phase-II of the project work, entitled “ **CROP PREDICTION USING IOT AND ML**” is carried out by **AARADHYA R(1MJ20CS002)**,**ADITI JAISWAL (1MJ20CS008)** ,**ARCHANA S(1MJ20CS028)** and **BINDHU K B (1MJ20CS045)** who are bonafide students of MVJ College of Engineering, Bengaluru, in partial fulfilment for the award of Degree of **Bachelor of Engineering in Computer science and Engineering** of the Visvesvaraya Technological University, Belagavi during the year 2023- 2024. It is certified that all corrections/suggestions indicated for the Internal Assessment have been incorporated in the major project report deposited in the departmental library. The major project report has been approved as it satisfies the academic requirements in respect of major project work prescribed by the institution for the said Degree.

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DECLARATION

We, **AARADHYA R (1MJ20CS002)**, **ADITI JAISWAL (1MJ20CS008)**, **ARCHANA S (1MJ20CS028)** and **BINDHU K B (1MJ20CS045)** Here by declare that the entire Phase-II work of the project titled “**CROP PREDICTION USING IOT AND ML**” embodied in this project report has been carried out by us during the 8th semester of B.E. degree at MVJCE, Bangalore under the esteemed guidance of **Dr. Kiran Babu T.S, Head Of Department, Department of CSE**, MVJCE affiliated to Visvesvaraya Technological University, Belagavi. The work embodied in this dissertation work is original and it has not been submitted in part or full for any other degree in any University.

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So, with gratitude we acknowledge all those whose guidance and encouragement served as a beacon of light and crowned our effort with success.

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We are also thankful to our HOD, **Dr. Kiran Babu T.S, Department of CSE** for his incessant encouragement & all the help during the project work.

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ABSTRACT

The project, titled "CROP PREDICTION USING IOT AND ML" is dedicated to modernizing agriculture through cutting-edge technologies like the Internet of Things, Artificial Intelligence, and data analytics. The primary focus is on developing sensor-based monitoring systems for real-time data collection on soil conditions, weather patterns, and crop health. AI algorithms will analyze this data to offer actionable insights to farmers, enabling informed decisions on irrigation, fertilization, and pest control. Integration of drones and robotics will enhance precision agriculture, optimizing resource use. A user-friendly interface, accessible through mobile or web platforms, empowers farmers with real-time information and control. Smart irrigation systems, informed by weather forecasts and soil moisture data, contribute to water conservation. The project's significance lies in its potential to increase agricultural productivity, reduce resource wastage, and promote sustainable farming practices, ultimately revolutionizing farming for a more resilient and technologically advanced agricultural sector.

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CHAPTER 1

INTRODUCTION

In recent years, agriculture has undergone a transformative evolution, embracing cutting-edge technologies to address the challenges posed by a growing global population, climate change, and resource limitations. Among these technologies, the integration of the Internet of Things (IoT) and Machine Learning (ML) has emerged as a game-changer, propelling traditional farming practices into the realm of precision and efficiency.

The traditional agricultural landscape is characterized by unpredictable environmental conditions, resource constraints, and the need for sustainable practices. Smart agriculture aims to mitigate these challenges by employing a network of interconnected devices and advanced analytics, creating an intelligent ecosystem capable of real-time monitoring, decision-making, and optimization.

IoT forms the backbone of smart agriculture, fostering connectivity between various devices and sensors deployed across the agricultural landscape. These devices collect a plethora of data, including soil moisture levels, temperature, humidity, crop health indicators, and even livestock behavior. This real-time data is transmitted to a central hub, creating a comprehensive picture of the farm's conditions.

The influx of data generated by IoT devices is where Machine Learning steps in. ML algorithms analyze this data, identifying patterns, correlations, and anomalies that may elude human observation. By leveraging historical and real-time data, these algorithms enable predictive modeling for crop yield, pest infestations, and optimal irrigation schedules. Farmers can make informed decisions, enhancing productivity and resource allocation.

One of the remarkable outcomes of this integration is the concept of precision farming. Instead of adopting a one-size-fits-all approach, precision farming tailors agricultural practices to specific conditions within a farm. For instance, ML algorithms can optimize irrigation schedules based on soil moisture levels, ensuring water is used efficiently and reducing the environmental impact. IoT sensors and ML algorithms collaborate to monitor crop health, detecting early signs of diseases or nutrient deficiencies.

CROP PREDICTION USING IOT AND ML

Drones equipped with cameras and sensors can survey vast fields, capturing high-resolution images that ML algorithms analyze to identify areas of concern. This proactive approach allows farmers to take timely corrective actions, preventing widespread crop damage. Beyond crops, IoT and ML contribute to smart livestock management.

Wearable devices on animals track vital signs, behavior patterns, and overall health. ML algorithms process this information, alerting farmers to potential health issues or optimizing feeding schedules for optimal livestock growth. Smart agriculture is not only about maximizing yields but also ensuring sustainability.

ML algorithms optimize resource usage, minimizing waste and environmental impact. By precisely tailoring irrigation, fertilization, and pest control measures, farmers can reduce the ecological footprint of their operations. The convergence of IoT and ML in smart agriculture marks a pivotal moment in the history of farming.

This holistic approach empowers farmers with actionable insights, fosters sustainability, and ensures that agriculture evolves in tandem with the demands of a dynamic world. As we celebrate the one-year milestone of this project, the journey towards a more efficient, sustainable, and intelligent agricultural future continues. Happy farming!

Summary:

In this chapter we have explained the introduction of our project in detail, our project is going to predict the crop based on the sensor data we are getting from the farm field. We have used so many sensors like dht, water level, soil moisture and light intensity sensors. From these sensors using Arduino and node MCU we send the data to database and using ML model in front end it will predict and display the crop.

CHAPTER 2

LITERATURE SURVEY

2.1 Smart Agriculture Using Internet of Things with Raspberry Pi.

Authors: Zuraida Muhammad, Muhammad Azri Asyraf Mohd Hafez, Nor Adni Mat Le, Zakiah Mohd Yusoff , Shabinar Abd Hamid .

Published On:

This system uses 2 sensors connected to a Digital output relative humidity and temperature (DHT22) and soil moisture sensor. This system used a Raspberry Pi as its processor and connected to Analog and Digital Converter (ADS1115).Ubidots Cloud connected to the Raspberry Pi through Wi-Fi connectivity.For irrigation system, water pump will be turn on when specified condition is satisfied.

2.2 Machine Learning and Internet of Things based Smart Agriculture.

Authors: Prince Samuel S , Malarvizhi K,Karthik S ,Mangala Gowri S G

Published On:

The algorithm is trained with lot of previously available data. These algorithms can build the model of the system based on the information and yield information. The application of machine learning and machine vision by using descriptors of textures and contours, and the usage of algorithms for deep learning would allow plant species recognition from RGB images especially in the problem of weed detection in agricultural fields.

2.3 Design of an Internet of Things (Iot) Based Smart Irrigation and Fertilization System Using Fuzzy Logic for Chili Plant.

Authors: Nor Syafikah Pezol,Ramli Adnan, Mazidah Tajjudin

Published On:

The moisture sensor, flowrate sensor and pH sensor act as input of the project. Hence, the inputsensor was connected to the controller where the controller used in this project was Arduino and Node Micro Controller Unit (Node MCU). The Arduino will follow the decision instructed by Fuzzy membership and determine the output values. For Node MCU, this the component act as a device to interface the system to mobile phone.

From the controller, the water pump and valve as output device to flow out the solution. Data logging was used to record the data while mobile apps display the data from sensor.

2.4 Renewable Energy Integration Into Cloud & IoT-Based Smart Agriculture.

Authors: Et-Taibi Bouali, Mohamed Riduan Abid, Tareq Abu Hamed

Published On:

Here the aim is to contribute towards the smooth penetration of Smart Agriculture into underprivileged sub-Saharan countries. We are further envisioning, through this work, to set a solid cornerstone for establishing a dedicated Cloud-based and HPC (HighPerformance Computing) platform to collect real-time data about water-table usage. This data, which falls under the big data category, as it bears the big data 3Vs (Volume, Velocity, and Variety).

2.5 Smart Irrigation System for Precision Agriculture—The AREThOU5A IoT Platform.

Authors: Antonis Gotsis, Shaohua Wan, Spyridon Nikolaidis, Maria S. Papadopoulou, Achilles D. Boursianis

Published On:

The smart irrigation systems of the literature that present different techniques in water management, by notating the origin of the demonstrations of these systems in the field, the adopted technologies, and the various communication protocols that include in their implementations. There are several water management models or platforms presented in the literature that combine various technologies to deliver smart irrigation systems in agriculture.

2.6 Smart Secure Sensing for IoT-Based Agriculture: Blockchain Perspective.

Authors: Anusha Vangala, Ashok Kumar Das, Mamoun Alazab, Neeraj Kumar

Published On:

The United Nations provides a very thorough and detailed study of several statistical methodologies and models that can accurately calculate the cost of wasted food.

2.7 Towards Paddy Rice Smart Farming: A Review on Big Data, Machine Learning, and Rice Production Task.

Authors: Rayner Alfred 1, Joe Henry Obi 1, Christie Pei-yee Chin 1

Published On:

The algorithm is trained with lot of previously available data. These algorithms can build the

model of the system based on the information and yield information. The application of machine learning and machine vision by using descriptors of textures and contours, and the usage of algorithms for deep learning would allow plant species recognition from RGB images especially in the problem of weed detection in agricultural fields.

2.8 Deep Learning and Smart Contract-Assisted Secure Data Sharing for IoT Based Intelligent Agriculture.

Authors: Randhir Kumar, Prabhat Kumar, Ahamed Aljuhani , A. K. M. Najmul Islam ,Alireza Jolfaei , Sahil Garg

Published On:

We exploit deep learning and smart contract to propose a new IoT-enabled IA framework for enabling secure data sharing. First we develop new authentication and key management scheme to ensure secure data transmission in IoT-enabled IA. The encrypted transactions are used by the CS to analyze and detect intrusions by a deep learning architecture. In CS, the SC-based consensus mechanism is executed on legitimate transactions that verifies and adds the formed blocks into blockchain by a peer-to-peer CSs network .

2.9 Energy efficient edge fog cloud architecture for IoT based smart agriculture environment.

Authors: Hatem A.Alharbi,Mohammad Aldossary

Published On:

The methodology adopts a four-layered edge-fog-cloud architecture for an energyefficient smart agriculture system. Utilizing low-power IoT sensors and technologies like LoRa, the design optimizes local processing in the Edge and Fog Layers, reducing latency and costs. The Cloud Layer handles heavy data processing, ensuring scalability and secure storage for IoT agriculture applications.

2.10 Internet of things for the future of smart agriculture:A comprehensive survey of emerging technologies.

Authors: Othmane Friha ,Mohamed Amine Ferrag,Lei Shu,Leandros Maglaras,Xiaochan Wang

Published On:

The methodology employed in this study involves a comprehensive review of existing

literature on smart farming and agricultural IoT. The search criteria focused on key aspects such as IoT applications, network technologies, hardware devices, and emerging trends in agricultural technology. The collected information was then synthesized and organized based on thematic categories. Critical analysis and synthesis of the reviewed literature were conducted to identify gaps, challenges, and emerging technologies in the field of smart agriculture.

2.11 IoT equipped and AI enabled next generation smart agriculture:A critical review,current challenges and future trends.

Authors: Sameer Qazi,Bilal A.Khawaja,Qazi umar Farooq

Published On:

The methodology involves deploying wireless sensors, including temperature, humidity, soil, and fluid level sensors, in smart agriculture systems. These sensors facilitate crucial monitoring of environmental conditions and soil parameters. Communication between these sensors and smart farming machinery occurs through various wireless technologies, such as LoRa, RFM69, Zigbee, Bluetooth, NB-IoT, SigFox, Wi-Fi, WiMAX, and cellular technologies. Microcontroller platforms like ATMEGA328P, 18F458 PIC, and ESP8266 NodeMCU coordinate sensor data and actuation in IoT-based smart agriculture systems. Smart irrigation strategies, including soil-based and soil-less techniques, leverage algorithms like fuzzy logic, majority vote, time-controlled, exponential weight moving average, PID control, and neural networks.

2.12 Artificial Intelligence and Internet of Things for Sustainable Farming and Smart Agriculture.

Authors: Ahmad Ali Alzubi, Kalda Galyna

Published On:

The following models are implemented:A. smart greenhouses in agriculture ,B.Drones for agriculture.C. Systems for precision farming,D. Solutions for tracking and monitoring livestock,E. Sensors for crop and soil monitoring,F. Current weather monitors,G. Robots for agriculture,H. Devices for estimating future harvests and prices.

Summary:

In this chapter, whatever the IEEE papers we referred for our project has explained in detail. Totally 12 papers we referred and has explained those above. All those papers were related to our project based only and all those papers published after the year 2020.

CHAPTER 3

PROBLEM ANALYSIS

Weather is always a wildcard in agriculture however it is one of the most important aspects to consider for crop expansion. The crop prediction is the toughest task for agricultural domain. Farmer or Agriculturist tends to choose the non-favourable crop without considering the market or weather risks and bears crop lose and sometimes it leads to bankrupt situation. Recognizing these challenges, the implementation of cutting-edge technologies, specifically the integration of the Internet of Things (IoT) and Machine Learning (ML), becomes imperative to revolutionize agriculture. This project aims at predicting the crop yield at a particular weather condition and thereby recommending suitable crop for that field.

- **Climate Uncertainty and Agricultural Risks:**

Climate change has introduced unprecedented levels of uncertainty into agricultural practices. Fluctuating weather patterns, extreme temperatures and irregular precipitation events pose significant risks to crop yields. Farmers need a solution that provides real-time monitoring and adaptive strategies to mitigate the impact of climate related challenges.

- **Resource Inefficiency:**

Traditional farming practices often rely on generalized approaches to resource management, leading to inefficiencies in water usage, fertilizer application, and energy consumption. The need for more precise and targeted resource allocation is crucial to optimize yields, reduce waste, and enhance overall sustainability.

- **Lack of Data-Driven Decision Making:**

Agriculture has historically been reliant on experiential knowledge and conventional methods. The absence of real-time, data-driven decision-making processes hinders the ability to respond promptly to emerging challenges.

- **Crop Monitoring and Early Detection:**

Detecting crop diseases and nutrient deficiencies at an early stage is pivotal for preventing

extensive damage and ensuring a successful harvest. Conventional methods often fall short in providing timely and accurate information. The project aims to address the gap in efficient crop monitoring and early detection, leveraging IoT sensors and ML algorithms to analyze vast amounts of data for proactive decision-making.

- **Sustainability Concerns:**

With a growing emphasis on sustainable agriculture, there is a need to minimize the environmental impact of farming practices. Traditional methods often contribute to soil degradation, water pollution, and excessive use of chemical inputs. The project aims to tackle these sustainability concerns by introducing precision farming techniques that optimize resource usage and reduce the ecological footprint.

The problem statement for "Smart Agriculture Using IoT and ML" revolves around addressing the complex challenges faced by traditional agriculture. By leveraging the combined power of IoT and ML, the project seeks to provide a comprehensive solution to climate uncertainty, resource inefficiency, data-driven decision-making gaps, crop monitoring issues, livestock management challenges, limited connectivity, and sustainability concerns. The successful implementation of this project promises a paradigm shift in agriculture, ensuring a more resilient, efficient, and sustainable future for farmers worldwide.

Summary:

The traditional methods of crop prediction in agriculture are inefficient and prone to inaccuracies due to reliance on historical data and manual observation. Environmental challenges such as climate change and water scarcity further complicate the prediction process. By integrating IoT and ML technologies, this project aims to revolutionize crop prediction by leveraging real-time data from sensors to provide farmers with actionable insights and recommendations for optimizing crop selection and resource allocation.

CHAPTER 4

EXISTING AND PROPOSED SYSTEM

4.1 EXISTING SYSTEM

Soil Sensors:

Incorporate soil sensors to monitor moisture content, pH levels, temperature, and nutrient composition.

Weather Stations:

Include more advanced weather sensors to gather real-time data on temperature, humidity, precipitation, wind speed, and sunlight exposure.

Increase Dataset Size:

Expand the dataset by including data from various geographical locations, different crop varieties, diverse weather conditions, and multiple seasons. This can make our ML model more robust and adaptable.

High-Resolution Imaging:

Incorporating high-resolution images for training the ML model to enable more detailed analysis of crop health, pest infestations, and disease identification.

Historical Data:

Integrate historical agricultural data, including crop yield, pest outbreaks, and climate patterns, to enhance the model's predictive capabilities.

Feature Engineering:

Identify and include additional relevant features in the dataset that could significantly impact crop growth and yield prediction. Optimize the model's hyperparameters to fine-tune its performance and increase accuracy.

Real-time Learning:

Implement models capable of continuous learning using incoming data, allowing the model to adapt and improve over time.

User-Friendly Interface:

Design an intuitive dashboard or mobile application that provides easy-to-understand insights and recommendations based on the ML model's predictions.

DISADVANTAGES:

1.High Costs: The inclusion of soil sensors, weather stations, high-resolution imaging, and advanced infrastructure for real-time learning can significantly increase costs for farms. This financial burden can be challenging, especially for smaller operations.

2.Data Management Complexity: Collecting and processing large datasets from various sources, including high-resolution images and historical data, requires advanced infrastructure and skilled data engineers. This increases operational complexity and costs.

3.Maintenance and Calibration: Systems with multiple sensors and weather stations require regular maintenance and calibration to ensure accuracy. This ongoing requirement adds to the workload and operational costs.

4.Overfitting and Model Instability: With complex feature engineering and continuous learning, there's a risk of overfitting, where the model performs well on training data but poorly in real-world scenarios. Real-time learning can also lead to model instability due to frequent updates.

5.Data Privacy Concerns: High-resolution imagery and extensive sensor data could raise privacy issues if they include identifiable landmarks, property boundaries, or sensitive information. This concern could lead to legal and ethical challenges.

6.Technical Expertise Required: Implementing and maintaining advanced systems with soil sensors, weather stations, and real-time learning requires significant technical expertise. This need for specialized skills can be a barrier for smaller farms or those with limited technical resources.

7.Inconsistent Weather Data: Weather stations might produce inconsistent data due to local microclimates or environmental changes. This inconsistency can affect the accuracy and reliability of predictions, leading to unreliable insights for farmers.

8.Energy and Resource Consumption: High-resolution imaging and real-time learning demand substantial computing power, leading to increased energy consumption. This can result in higher operational costs and a larger environmental footprint, which can be a concern for sustainable farming practices.

These additional disadvantages further highlight potential challenges and complexities in the implementation and maintenance of advanced ML-based agricultural systems.

4.2 PROPOSED SYSTEM

The Main theme of the project is to predict the crop which can be grown efficiently. This system collects various environmental parameters from the agricultural field like Precipitation, Humidity, Temperature, Soil moisture, Soil pH, Soil Nutrients, Sun light intensity. Some are sensor collected data and some are chemically tested data after which the system suggests the agriculturalist or farmer what crops can be grown efficiently.

The proposed system aims to revolutionize traditional agriculture by leveraging the synergies between the Internet of Things (IoT) and Machine Learning (ML). It seeks to create an intelligent, interconnected ecosystem that monitors, analyzes, and optimizes various facets of agricultural operations. This comprehensive solution addresses the challenges outlined in the problem statement, providing farmers with the tools needed for precision farming, data-driven decision-making, and sustainable agricultural practices.

The programming languages used in this project are Python with Flask, HTML/CSS/PHP- Front end languages and C++ for Arduino ID.

Python with Flask (Backend):

- Python is a versatile and readable language, making it an excellent choice for backend development. It has a vast ecosystem of libraries and frameworks, perfect for implementing complex functionalities.
- Flask is a lightweight web framework that integrates seamlessly with Python. It's modular, easy to use, and ideal for building RESTful APIs, which is crucial for communication between the frontend and backend in your smart agriculture project.

HTML/CSS/PHP (Frontend):

- HTML provides the structure, and CSS adds styling to your web pages. They are fundamental for creating a user-friendly interface. Since they are standard web technologies, they ensure compatibility across different browsers and devices.
- PHP is a server-side scripting language that complements HTML. It helps in dynamic content generation and database interactions. In your smart agriculture project, PHP can facilitate real-time data updates and seamless integration between the frontend and backend.

C++ for Arduino (Embedded Systems):

- Arduino, being a microcontroller platform, requires a language that provides lowlevel control and efficient resource management. C++ is well-suited for embedded systems due to its performance and proximity to hardware.

Arduino IDE:

- The Arduino Integrated Development Environment simplifies C++ programming for microcontrollers. It offers a user-friendly interface and a vast community, making it easier to find support and resources for your smart agriculture project.

By combining these technologies, you create a robust and integrated system for smart agriculture. Python and its associated frameworks offer flexibility, while HTML/CSS/PHP handle the frontend seamlessly. C++ on Arduino ensures efficient control of embedded systems, and the inclusion of IoT and ML technologies enhances the precision and intelligence of the system.

NodeMCU is a cost-effective and efficient microcontroller based on the ESP8266 Wi-Fi module. It enables seamless connectivity to the internet, facilitating communication between sensors and the backend (Python/Flask) of your smart agriculture system.

The backend server can query the database for real-time information, enabling immediateactions or alerts. For example, if the ML model detects a potential crop disease, an alert can be sent to the farmer for quick intervention.

Apache server and MySQL play integral roles in the smart agriculture project by managing the web interface, handling backend communication, storing and retrieving data efficiently, ensuring security, and supporting historical analysis. Together, they form a robust architecture that supports the seamless integration of IoT, ML, and database functionalities for effective crop detection and agricultural decision-making.

The decision tree algorithm serves as a powerful tool for classifying and interpreting crop conditions in a smart agriculture project. Its transparency, interpretability, and real-time decision-making capabilities make it a valuable component for farmers seeking to optimize their agricultural practices based on machine learning insights.

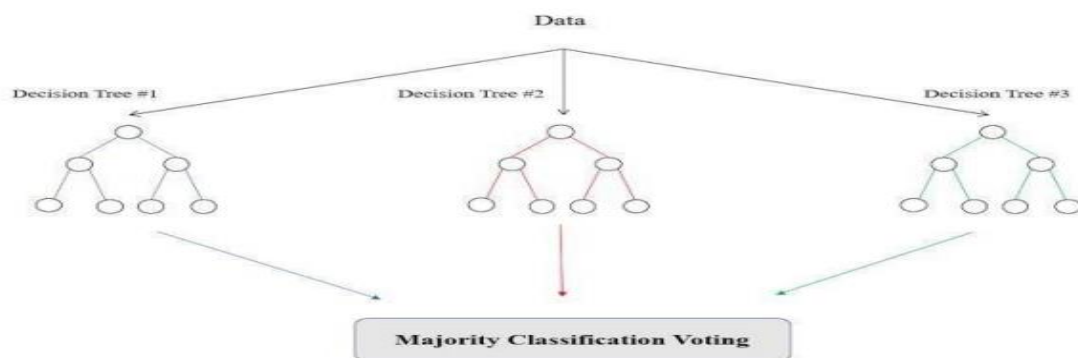


Fig:4.1 Decision Tree

The proposed system for "Smart Agriculture Using IoT and ML" envisions a holistic intelligent ecosystem that empowers farmers with data-driven insights, precision farming recommendations, and sustainable practices. By seamlessly integrating IoT and ML technologies, the system addresses the complexities of modern agriculture, paving the way for a more resilient, efficient, and sustainable future for farmers worldwide.

4.3 SYSTEM ARCHITECTURE

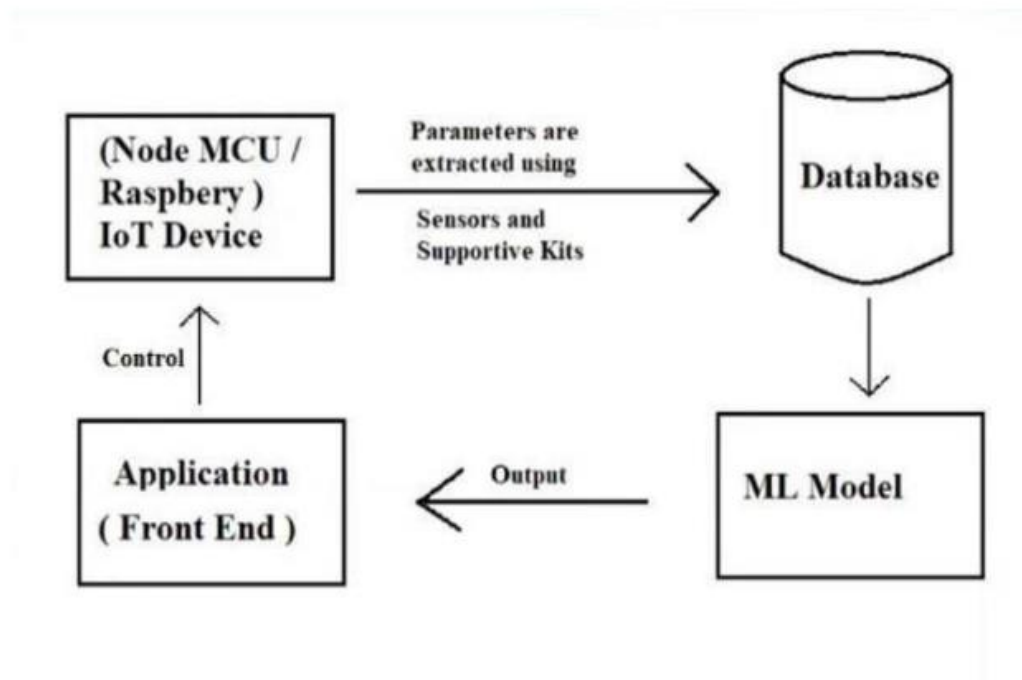


Fig:4.2 System Design

The proposed system follows Naive Bayes classifier, the supervised learning algorithm consist of the four levels to calculated and predict the crop for the suitable climate in phenomenon such as:

- **Data Collection:** Data is composed from a different source and optimized for data sets. Kaggle, Google weather forestation and data government, provide the data for up to 10years in series. The data sets such as soil nature, climatic conditions and seed data are used for the crop prediction and better crop yields.
- **Preprocessing Step:** It involves adding the missing values, the correct set of data, and extracting the functionality.
- **Feature Extraction:** It reduce the data size involved to characterize a wide collection of data. This selects the features based on the correlation matrix.
- **Data Prediction:** By applying the Naïve Bayes Gaussian classifier the data is trained with available input and output data. In the test phase, the data are tested if the accuracy of e model is satisfied. Then the new data is predicted by machine learning module.

Features:

- Enable farmers to monitor and control field conditions remotely through a mobile app or web interface. This includes sensor data visualization, system health checks, and manual control of irrigation or other systems.
- Implement machine learning models to predict crop yield based on historical data and current environmental conditions. This can help farmers make informed decisions about planting and harvesting schedules.
- Integrate IoT sensors with automated irrigation systems that adjust watering based on soil moisture levels, temperature, and humidity, ensuring optimal water use and crop health.
- Integrate weather forecast data to help farmers plan their activities and anticipate changes in weather that could impact crop health or irrigation needs.
- Use computer vision and ML algorithms to detect pests and diseases in crops through camera feeds or drone-based imagery, allowing for early intervention and targeted treatment.
- Add sensors for continuous monitoring of soil pH, nutrient levels, and other soil health indicators. This can help farmers apply fertilizers more efficiently and sustainably.
- Develop an intelligent recommendation system that suggests the most suitable crops based on current soil conditions, climate, and market trends, helping farmers optimize their crop choices.
- Implement field zoning based on soil conditions and other factors to allow precision farming techniques, optimizing resource use and crop yields.
- Create an alert system that notifies farmers of critical changes in field conditions, such as low soil moisture or impending weather events, allowing for quick response.
- Implement blockchain technology to ensure the traceability of crops, providing transparency and accountability throughout the supply chain.
- Develop a platform where farmers can share insights, best practices, and data, fostering community collaboration and knowledge exchange.

CROP PREDICTION USING IOT AND ML

- Create a real-time analytics dashboard that provides comprehensive visualizations of field data, enabling farmers to quickly assess the status of their fields and make informed decisions.
- Use IoT sensors and ML algorithms to predict when farm equipment might require maintenance or replacement, reducing downtime and improving efficiency.
- Include features to monitor the environmental impact of farming practices, such as carbon footprint and water usage, promoting sustainable agriculture.

4.4 MODEL DESCRIPTION

The Smart Agriculture system integrates Internet of Things (IoT) devices, Machine Learning (ML), and data analytics to create a robust platform for modern, data-driven agriculture. The system encompasses various components working in harmony to provide farmers with actionable insights, enabling precision farming and sustainable agricultural practices.

IoT Sensors and Data Collection

- The system relies on a network of IoT sensors distributed across the agricultural field to collect real-time data. These sensors measure environmental parameters such as precipitation, humidity, temperature, soil moisture, soil pH, soil nutrients, and sunlight intensity. The sensors are connected to NodeMCU microcontrollers (based on ESP8266), which facilitate wireless data transmission to the backend server.

Embedded Systems

- The microcontrollers (Arduino with C++) serve as the bridge between the sensors and the backend. They process sensor data and send it to the backend server via Wi-Fi. These embedded systems are responsible for ensuring efficient data collection and communication.

Backend Processing and Machine Learning

- The backend, developed in Python with Flask, receives sensor data and performs various tasks. It processes the data, applies machine learning models, and makes predictions. The decision tree algorithm is employed for crop classification and recommendation. The backend can also detect anomalies or potential issues, triggering alerts for immediate action.

Data Storage and Management

- The system uses MySQL for data storage. This database holds historical sensor data, environmental conditions, crop information, and ML model outputs. Apache server manages the communication between the frontend and backend, providing a secure and efficient platform for data storage and retrieval.

Frontend User Interface

- The frontend, developed with HTML/CSS/PHP, provides an intuitive user interface for farmers. It displays real-time sensor data, crop recommendations, and ML model outputs. The frontend enables farmers to interact with the system, visualize data, and receive alerts.

Features and Functionalities

- Remote Monitoring and Control: Farmers can monitor field conditions and control systems remotely through the web-based interface.
- Automated Irrigation: IoT sensors and backend algorithms control irrigation systems based on soil moisture and other parameters.
- Crop Recommendation: The ML model recommends crops to plant based on environmental conditions and soil health.
- Alerts and Notifications: The system sends alerts to farmers for critical events like low soil moisture, pest detection, or weather changes.
- Data Analytics Dashboard: A real-time dashboard provides comprehensive visualizations of field data for informed decision-making.
- Predictive Analytics: The system uses ML to predict crop yield and detect potential issues in advance, allowing for proactive measures.

Integration and Connectivity

- The system integrates seamlessly with other technologies and platforms. Weather forecasts can be integrated to provide additional insights for planning. The NodeMCU microcontrollers ensure efficient connectivity, while the backend processes data and communicates with the frontend in real-time.

Future Extensions

The model can be extended with additional features like blockchain for crop traceability, community platforms for farmer collaboration, and advanced ML algorithms for enhanced predictions. Sustainability monitoring and environmental impact analysis can also be integrated to promote eco-friendly farming practices.

4.5 ABOUT THE ALGORITHM

Random Forest is a popular ensemble learning technique used in supervised machine learning tasks, such as classification and regression. It is known for its robustness, versatility, and ability to handle a wide range of data types and features. The core concept behind Random Forest is to combine multiple decision trees to create a more reliable and accurate predictive model.

How Random Forest Works

The Random Forest algorithm operates by creating a collection of decision trees, each built from a random subset of the training data. The key steps involved in building a Random Forest model are:

1. Bootstrap Sampling: The training data is randomly sampled with replacement to create multiple subsets, each of which is used to train a single decision tree. This process is known as "bootstrapping."

2. Random Feature Selection: At each node in the decision tree, a random subset of features is chosen to determine the best split. This introduces variability and helps prevent overfitting, ensuring that the trees in the forest are diverse.

3. Tree Construction: Each decision tree is built using its respective subset of the training data, typically to the point where the tree cannot be split further or a predefined depth limit is reached.

4. Ensemble Voting: Once the forest of trees is created, predictions are made by aggregating the results of individual trees. For classification tasks, the majority vote of the trees determines the final prediction. For regression tasks, the predictions are averaged to produce a final outcome.

Advantages of Random Forest in Crop Prediction:

Resilience to Noise: The randomization and bootstrapping process used by Random Forest reduce sensitivity to noisy data and outliers, making it suitable for real-world applications like crop prediction.

Handling of Complex Data: Random Forest can work with both numerical and categorical features, allowing for flexibility when modeling diverse agricultural datasets.

High Accuracy and Robustness: By combining multiple decision trees, Random Forest can achieve high accuracy while mitigating the risk of overfitting.

Application in Crop Prediction

In the context of crop prediction, Random Forest can be used to predict various outcomes, such as crop yield, crop type, or optimal planting times, based on input features like weather conditions, soil properties, historical yield data, and more. The algorithm's ensemble approach helps ensure that the predictions are accurate and robust, even in the presence of variable and noisy agricultural data.

Tuning and Optimization

To optimize the performance of Random Forest for crop prediction, various hyperparameters can be tuned, including:

- The number of trees in the forest (`n_estimators`)
- The maximum depth of each tree (`max_depth`)
- The minimum number of samples required to split a node (`min_samples_split`)
- The minimum number of samples required at a leaf node (`min_samples_leaf`)
- The number of features to consider at each split (`max_features`)

Hyperparameter tuning can be done through techniques like grid search or random search, allowing you to identify the optimal configuration for your specific crop prediction task.



Fig:4.3 Random Forest Algorithm

Random Forest is a popular ensemble learning technique used in supervised machine learning tasks, such as classification and regression. It is known for its robustness, versatility, and ability to handle a wide range of data types and features. The core concept behind Random Forest is to combine multiple decision trees to create a more reliable and accurate predictive model.

Summary:

Currently, agricultural decision-making relies heavily on manual observation and historical data, resulting in inefficiencies and limited accuracy in crop prediction. In the proposed system, IoT sensors are deployed to gather real-time environmental data, while ML algorithms analyze this data to predict crop performance. This integration of IoT and ML technologies offers a transformative approach, providing farmers with timely and precise insights to optimize crop selection and resource management, thus enhancing agricultural productivity and sustainability.

CHAPTER 5

METHODOLOGY

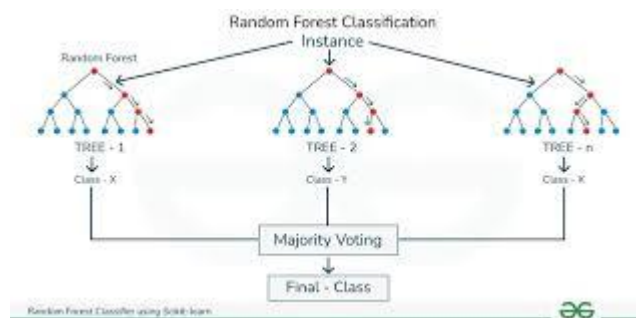


Fig:5.1 Random Forest classifier

Random Forest is a popular ensemble learning technique used in supervised machine learning tasks, such as classification and regression. It is known for its robustness, versatility, and ability to handle a wide range of data types and features. The core concept behind Random Forest is to combine multiple decision trees to create a more reliable and accurate predictive model.

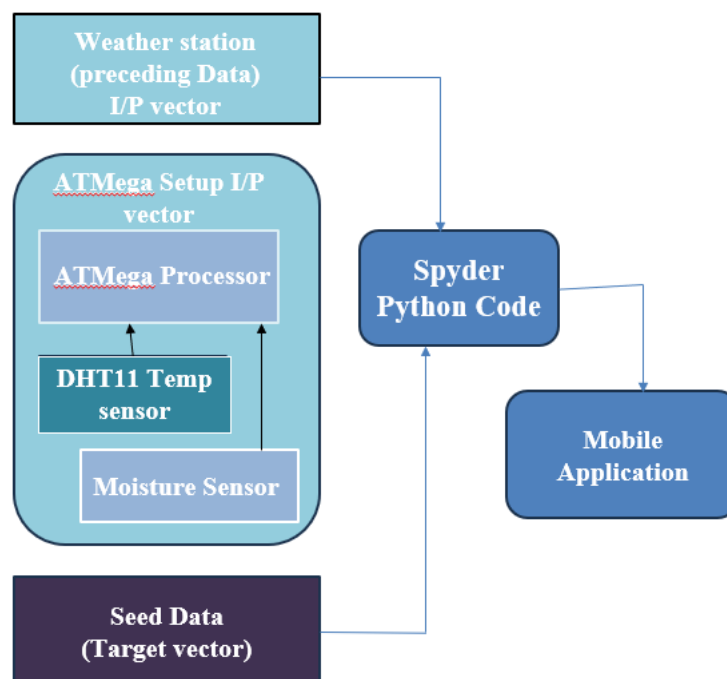


Fig5.2 System Architecture

The Main theme of the project is to predict the crop which can be grown efficiently. This system collects various environmental parameters from the agricultural field like Precipitation, Humidity, Temperature, Soil moisture, Soil pH, Soil Nutrients, Sun light intensity. Some are sensor collected data and some are chemically tested data after which the system suggests the agriculturalist or farmer what crops can be grown efficiently. The proposed system aims to revolutionize traditional agriculture by leveraging the synergies between the Internet of Things (IoT) and Machine Learning (ML). It seeks to create an intelligent, interconnected ecosystem that monitors, analyzes, and optimizes various facets of agricultural operations. This comprehensive solution addresses the challenges outlined in the problem statement, providing farmers with the tools needed for precision farming, data-driven decision-making, and sustainable agricultural practices.

PYTHON:

Python is a versatile and widely used high-level programming language known for its simplicity and readability. It features a clean and concise syntax that makes it easy to learn and understand, even for beginners. With its cross-platform compatibility, Python code can be executed on different operating systems without modification. Python's large and active community provides extensive documentation and resources, making it easy to find support and guidance. The language offers an extensive standard library with a wide range of modules and functions, reducing the need for external dependencies. Python's dynamic typing allows for flexible variable assignment, although careful attention to variable types is necessary. Being an interpreted language, Python allows for quick development, testing, and debugging of code. Additionally, Python integrates well with other languages, facilitating code reuse and leveraging existing libraries. Overall, Python's simplicity, versatility, and extensive ecosystem have contributed to its popularity as a go-to language for various applications, including web development, data analysis, artificial intelligence, and more.

Advantages of Python:

1. Readability and Simplicity
2. Versatility and Flexibility

- 3.Cross-Platform Compatibility
- 4.Large Standard Library and Third-Party Packages
- 5.Productivity and Rapid Development
- 6.Strong Community and Support
- 7.Integration Capabilities
- 8.Scalability

VS CODE:

Visual Studio Code (VS Code) is a highly popular and versatile code editor developed by Microsoft. It has gained widespread adoption among developers due to its powerful features, user-friendly interface, and extensive customization options. Available for Windows, macOS, and Linux, VS Code provides a consistent experience across different platforms. Despite its rich feature set, it remains lightweight and fast, ensuring a smooth coding experience even with large projects. With built-in support for numerous programming languages and a vast library of extensions, developers can tailor their environment to their specific needs. VS Code offers features like IntelliSense, providing intelligent code completion and suggestions, as well as robust code navigation capabilities. It also includes an integrated terminal for executing commands and running scripts, making it a comprehensive development environment. Debugging capabilities, Git integration, and task automation further enhance productivity. With its combination of performance, flexibility, and an active community contributing to its ecosystem, VS Code has become a go-to choice for developers across different domains and platforms.

CROP PREDICTION USING IOT AND ML

DATASETS:

	N	P	K	Temperature	Humidity	pH	Rainfall	Moisture	Light	Label
1										
2		5.6	3.2	4.8	30	48	6.5	600	300	1500 Cucumber
3		6.2	3.5	5	32	46	6.3	660	350	1600 Cucumber
4		5.8	3	4.5	28	50	6.8	540	280	1400 Cucumber
5		6	3.2	4.7	31	44	6.6	570	320	1550 Cucumber
6		5.5	2.8	4.6	29	46	6.4	630	290	1450 Cucumber
7		5.7	3.1	4.9	30	42	6.7	690	310	1520 Cucumber
8		6.3	3.4	4.8	33	45	6.2	720	330	1620 Cucumber
9		5.9	3.3	4.6	29	48	6.9	630	320	1580 Cucumber
10		6.1	3.1	5.1	31	43	6.5	660	340	1600 Cucumber
11		5.5	2.9	4.7	28	47	6.6	600	300	1500 Cucumber
12		5.3	3	4.8	30	46	6.4	630	310	1550 Cucumber
13		5.7	3.2	4.5	32	41	6.6	660	320	1620 Cucumber
14		5.9	3.5	4.7	33	44	6.8	690	330	1680 Cucumber
15		6	3.4	4.6	31	45	6.7	620	340	1700 Cucumber
16		5.8	3.2	4.9	32	43	6.9	690	330	1650 Cucumber
17		5.4	2.8	4.7	29	48	6.7	660	300	1600 Cucumber
18		6.2	3.1	5	31	42	6.8	630	320	1580 Cucumber
19		6.1	3.3	4.8	33	45	6.6	690	340	1620 Cucumber
20		5.6	3	4.5	30	43	6.4	660	310	1550 Cucumber
21		5.7	3.2	4.6	32	46	6.7	630	320	1600 Cucumber
22		6	3.1	4.9	31	44	6.9	690	330	1650 Cucumber
23		5.8	2.9	4.7	29	48	6.8	660	300	1580 Cucumber
24		5.5	3	4.8	30	46	6.6	630	310	1550 Cucumber

Fig 5.3 Dataset 1

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
27	6.2	3.3	4.7	31	45	6.8	720	340	1700	Cucumber									
28	5.6	3.1	4.6	32	43	6.9	690	330	1650	Cucumber									
29	5.8	3.2	4.9	33	42	6.7	660	320	1600	Cucumber									
30	6	3	4.8	30	44	6.8	690	330	1650	Cucumber									
31	5.7	3.3	4.7	31	46	6.6	630	310	1550	Cucumber									
32	5.9	3.1	4.6	32	41	6.7	660	320	1620	Cucumber									
33	5.6	3.2	4.8	20	43	6.5	300	300	1000	Lettuce									
34	6.2	3.5	5	22	46	6.3	330	350	1100	Lettuce									
35	5.8	3	4.5	18	50	6.8	270	280	950	Lettuce									
36	6	3.2	4.7	21	44	6.6	312	320	1050	Lettuce									
37	5.5	2.8	4.6	19	46	6.4	288	290	980	Lettuce									
38	5.7	3.1	4.9	20	42	6.7	318	310	1000	Lettuce									
39	6.3	3.4	4.8	23	45	6.2	342	330	1150	Lettuce									
40	5.9	3.3	4.6	22	48	6.9	294	320	1100	Lettuce									
41	6.1	3.1	5.1	24	43	6.5	324	340	1120	Lettuce									
42	5.5	2.9	4.7	21	47	6.6	282	300	1050	Lettuce									
43	5.3	3	4.8	20	46	6.4	312	310	1080	Lettuce									
44	5.7	3.2	4.5	22	41	6.6	336	320	1150	Lettuce									
45	5.9	3.5	4.7	23	44	6.8	348	330	1200	Lettuce									
46	6	3.4	4.6	21	45	6.7	360	340	1220	Lettuce									
47	5.8	3.2	4.9	22	43	6.9	330	330	1170	Lettuce									
48	5.4	2.8	4.7	19	48	6.7	318	300	1100	Lettuce									
49	6.2	3.1	5	21	42	6.8	288	320	1120	Lettuce									
50	6.1	3.3	4.8	23	45	6.6	318	340	1150	Lettuce									

Fig 5.4 Dataset 2

CROP PREDICTION USING IOT AND ML

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
51	5.6	3	4.5	20	43	6.4	330	310	1080	Lettuce									
52	5.7	3.2	4.6	22	46	6.7	306	320	1120	Lettuce									
53	6	3.1	4.9	21	44	6.9	318	330	1170	Lettuce									
54	5.8	2.9	4.7	19	48	6.8	312	300	1100	Lettuce									
55	5.5	3	4.8	20	46	6.6	294	310	1080	Lettuce									
56	5.9	3.2	4.5	22	41	6.7	300	320	1150	Lettuce									
57	6.1	3.4	4.8	23	44	6.9	324	330	1200	Lettuce									
58	6.2	3.3	4.7	21	45	6.8	348	340	1220	Lettuce									
59	5.6	3.1	4.6	22	43	6.9	306	330	1170	Lettuce									
60	5.8	3.2	4.9	23	42	6.7	336	320	1120	Lettuce									
61	6	3	4.8	20	44	6.8	318	330	1170	Lettuce									
62	5.7	3.3	4.7	21	46	6.6	300	310	1080	Lettuce									
63	5.9	3.1	4.6	22	41	6.7	330	320	1150	Lettuce									
64	5.6	3.2	4.8	25	48	6.5	37.5	300	1800	Okra									
65	6.2	3.5	5	27	46	6.3	40	350	1900	Okra									
66	5.8	3	4.5	23	50	6.8	35	280	1700	Okra									
67	6	3.2	4.7	26	44	6.6	36.25	320	1850	Okra									
68	5.5	2.8	4.6	24	46	6.4	38.75	290	1750	Okra									
69	5.7	3.1	4.9	25	42	6.7	41.25	310	1800	Okra									
70	6.3	3.4	4.8	28	45	6.2	42.5	330	1950	Okra									
71	5.9	3.3	4.6	27	48	6.9	38.75	320	1900	Okra									
72	6.1	3.1	5.1	29	43	6.5	40	340	1920	Okra									
73	5.5	2.9	4.7	26	47	6.6	37.5	300	1800	Okra									
74	5.3	3	4.8	25	46	6.4	38.75	310	1850	Okra									

Fig 5.4 Dataset 3

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
70	6.3	3.4	4.8	28	45	6.2	42.5	330	1950	Okra									
71	5.9	3.3	4.6	27	48	6.9	38.75	320	1900	Okra									
72	6.1	3.1	5.1	29	43	6.5	40	340	1920	Okra									
73	5.5	2.9	4.7	26	47	6.6	37.5	300	1800	Okra									
74	5.3	3	4.8	25	46	6.4	38.75	310	1850	Okra									
75	5.7	3.2	4.5	27	41	6.6	40	320	1920	Okra									
76	5.9	3.5	4.7	28	44	6.8	41.25	330	1980	Okra									
77	6	3.4	4.6	26	45	6.7	42.5	340	2000	Okra									
78	5.8	3.2	4.9	27	43	6.9	41.25	330	1950	Okra									
79	5.4	2.8	4.7	24	48	6.7	40	300	1900	Okra									
80	6.2	3.1	5	26	42	6.8	38.75	320	1920	Okra				4					
81	6.1	3.3	4.8	28	45	6.6	40	340	1950	Okra									
82	5.6	3	4.5	25	43	6.4	41.25	310	1880	Okra									
83	5.7	3.2	4.6	27	46	6.7	40	320	1920	Okra									
84	6	3.1	4.9	26	44	6.9	41.25	330	1980	Okra									
85	5.8	2.9	4.7	24	48	6.8	40	300	1900	Okra									
86	5.5	3	4.8	25	46	6.6	38.75	310	1880	Okra									
87	5.9	3.2	4.5	27	41	6.7	40	320	1950	Okra									
88	6.1	3.4	4.8	28	44	6.9	41.25	330	2000	Okra									
89	6.2	3.3	4.7	26	45	6.8	42.5	340	2020	Okra									
90	5.6	3.1	4.6	27	43	6.9	40	330	1950	Okra									
91	5.8	3.2	4.9	28	42	6.7	41.25	320	1900	Okra									
92	6	3	4.8	25	44	6.8	41.25	330	1950	Okra									
93	5.7	3.3	4.7	26	46	6.6	40	310	1880	Okra									
94	5.9	3.1	4.6	27	41	6.7	41.25	320	1950	Okra									

Fig 5.5 Dataset 4

ARDUINO UNO:

Arduino Uno is a highly versatile microcontroller board that is at the heart of many DIY electronics projects. To program the Arduino Uno, developers use the Arduino Integrated Development Environment (IDE), a user-friendly platform that allows them to write, compile, and upload code to the board. The Arduino IDE features a code editor with helpful tools like syntax highlighting and auto-indentation, making it easier for developers to write and manage their code. It also has built-in functionality to upload code to the board through a USB connection, simplifying the programming process.

The core structure of an Arduino program, known as a "sketch," revolves around two main functions: `setup()` and `loop()`. The `setup()` function is executed once when the Arduino Uno starts, allowing you to initialize hardware components and set configurations. The `loop()` function contains the main logic of the program and runs repeatedly as long as the board is powered.

Overall, the Arduino Uno software environment is designed to be accessible to users of all skill levels. It benefits from a large community of developers who contribute tutorials, libraries, and projects, providing a wealth of resources for learning and experimentation. This makes Arduino Uno a popular choice for hobbyists, students, and professionals seeking to create innovative electronics projects.

Summary:

The methodology of the project encompasses data collection through IoT sensors, capturing real-time environmental factors like temperature, humidity, soil moisture, and light intensity. Following data preprocessing to ensure quality, relevant features influencing crop growth are selected. ML algorithms, such as Random Forest or Support Vector Machines, are then trained on these features to develop predictive models for crop performance. Subsequent model evaluation via cross-validation ensures accuracy and generalization. Finally, validated models are utilized to predict crop yields and furnish farmers with tailored recommendations for optimized crop selection and resource management strategies, thus facilitating informed decision-making in agriculture.

CHAPTER 6

SYSTEM REQUIREMENTS

Functional requirements: describe what the system must accomplish. At its core, the system needs to collect real-time data from various IoT sensors, measuring key environmental parameters such as temperature, soil moisture, humidity, soil pH, and sunlight intensity. This data must be transmitted to the backend server via Wi-Fi for processing. The backend, developed in Python with Flask, is responsible for processing this data, applying machine learning models, and generating outputs like crop recommendations, predictive analytics, and alerts for events like low soil moisture or potential crop diseases. Data storage and management are facilitated by a MySQL database, ensuring efficient data retrieval and historical analysis.

The frontend, built with HTML/CSS/PHP, must offer an intuitive interface for farmers to monitor field conditions, receive alerts, and control certain functionalities, including automated irrigation. The system also needs to support remote monitoring and control, allowing farmers to access information and make decisions from a web interface or mobile app. Integration with weather forecasts and a real-time analytics dashboard further enhance the system's functionality.

Non-functional requirements: focus on the system's performance, reliability, security, and usability. The system must be reliable and scalable, handling large volumes of data with high uptime and minimal downtime. Security is crucial, with mechanisms for secure communication and data encryption to protect against unauthorized access. The frontend must be user-friendly and accessible across different platforms, while the backend must be maintainable and adaptable for future updates or additional features. Interoperability with other systems and a focus on sustainability are also key, ensuring the system can adapt to different agricultural settings and promote eco-friendly practices. Together, these functional and non-functional requirements provide a comprehensive framework for building a robust, efficient, and user-friendly smart agriculture system.

6.1 Operating System :

- Windows 7 or Higher
- Arduino IDE 1.8.0 or Higher
- Arduino Libraries for various sensors
- MySQL Server with phpMyAdmin
- Apache Server with PHP Parser
- Pycharm IDE with Flask Framework

6.2 Hardware Requirements:

- Operating System : Windows 7 or Higher
- Processor : Intel Duo 1.2Ghz or Higher
- RAM : 1GB or Higher
- Hard disk: Min 10GB Free Space

6.3 Programming Languages :

- Python with Flask
- HTML/CSS/PHP - Front end languages
- C++ for Arduino ID

6.4 IOT Requirements:

- Arduino UNO R3
- NodeMCU ESP8266

- DHT11 Temperature and Humidity Sensor
- Light Intensity Sensor
- Soil Moisture Sensor
- Soil PH Sensor
- Precipitation Sensor
- Jumper wires
- Soldering Gun
- 9v Power Adapter

Summary:

The system requires IoT sensors capable of capturing real-time environmental data, including temperature, humidity, soil moisture, and light intensity, from agricultural fields. Additionally, it necessitates a reliable network infrastructure to facilitate seamless communication between sensors and data processing units. Robust data preprocessing algorithms are essential for cleaning and preparing collected data for analysis. Furthermore, the system mandates the availability of ML frameworks and tools for model development and training, along with sufficient computational resources for executing complex algorithms. Lastly, user-friendly interfaces, such as web or mobile applications, are needed to deliver predictive insights and recommendations to farmers in an accessible manner.

CHAPTER 6

IMPLEMENTATION

- Firstly, the Arduino UNO R3 connected with various Analog sensors sends the sensor data to the ESP8266 (NodeMCU) Module
- ESP8266 along with other parameters data sends an HTTP POST Request to the Apache server to store the sensor data on to the MySQL Database
- The Same Sensor data insertion on to the database is done repeatedly for over a period of time/Seasons.
- Then this data from the database along with the other lab tested parameters is sent to the M.L Model for the Prediction.

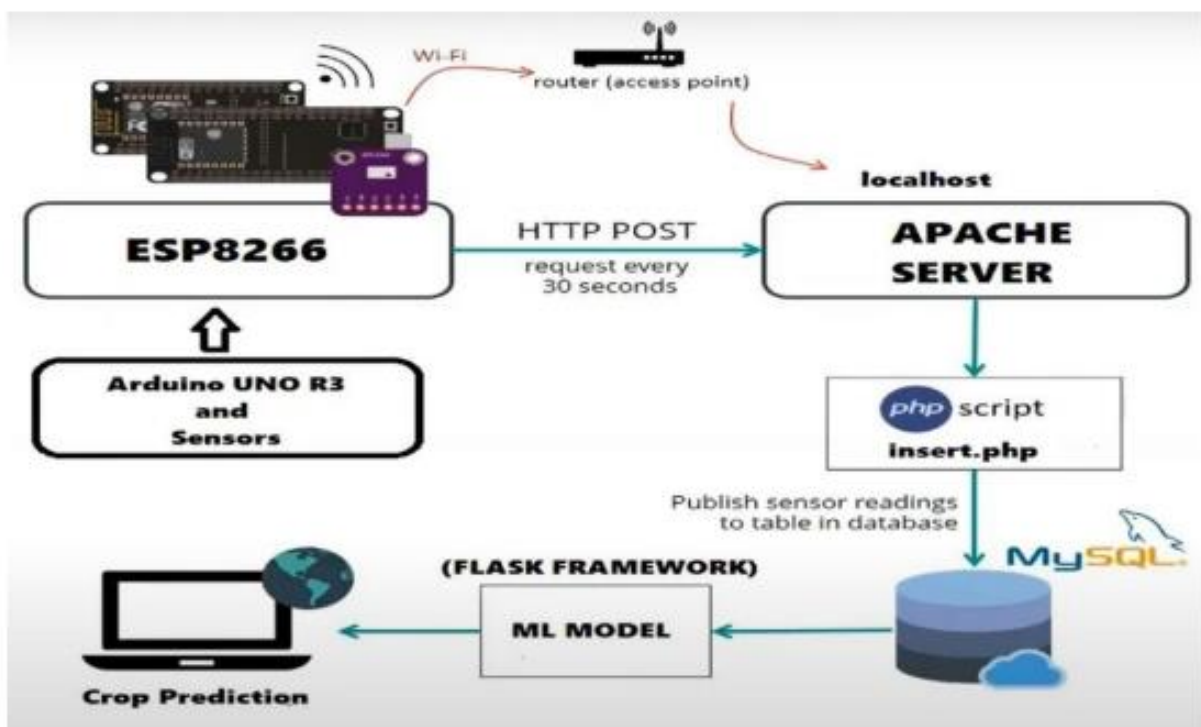


Fig:6.1 System Design

- Decision tree can be used to visually and explicitly represent decisions and decision making. It uses a tree-like model of decisions. Though a commonly used tool in data mining for deriving a strategy to reach a particular goal, its also widely used in ml.

CROP PREDICTION USING IOT AND ML

ESP8266 and Arduino UNO R3 are the two boards which are used for Sensor data extraction.

- Arduino Uno is a microcontroller board based on the ATmega328P.
- The ESP8266 is a low-cost Wi-Fi microchip, with a full TCP/IP stack and microcontroller capability and is based on the ESP-12 Module

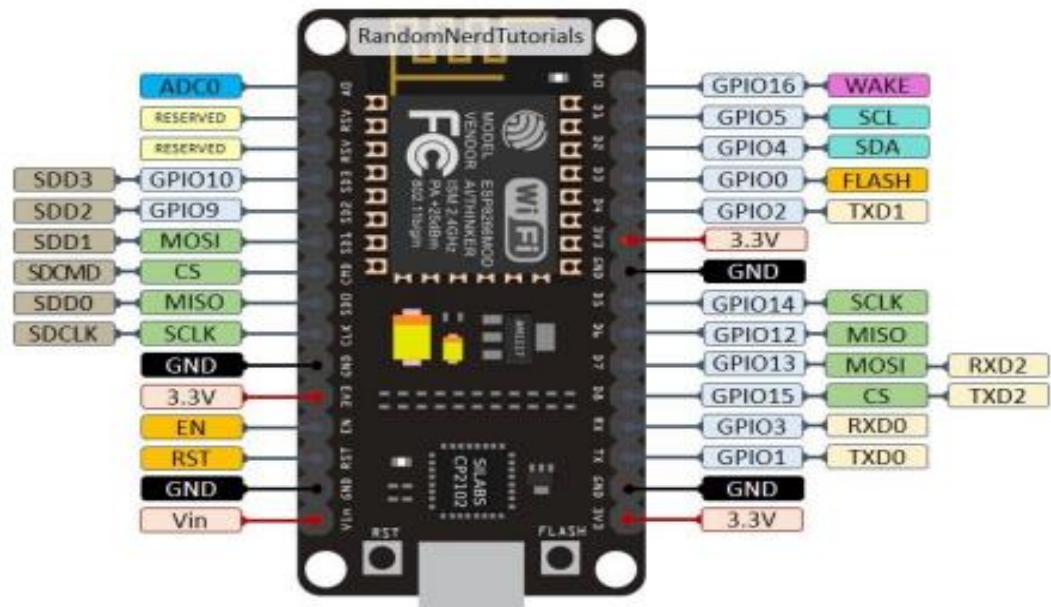


Fig 6.2 ESP8266 -Node MCU

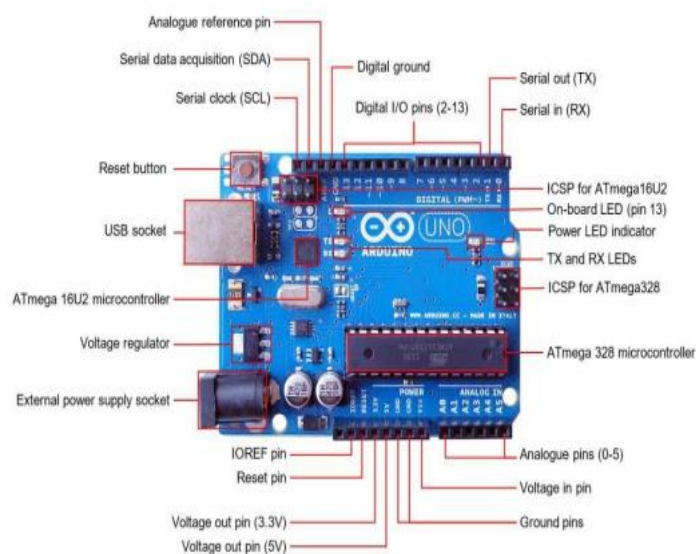


Fig:6.3 Arduino UNO

Weather and Soil Factors affecting crop production are:

Sensor Collected Parameters:

1. Temperature
2. Humidity
3. Precipitation
4. Soil pH range
5. Soil moisture
6. Sunlight Intensity

Lab-Tested/Physical parameters:

1. Nitrogen Content
2. Phosphorus Content
3. Potassium Content

DHT11

The DHT11 Humidity and Temperature Sensor consists of 3 main components. A resistive type humidity sensor, an NTC (negative temperature coefficient) thermistor (to measure the temperature) and an 8-bit microcontroller, which converts the analog signals from both the sensors and sends out single digital signal.



Fig 6.4 DHT11 sensor

Rain Sensor

A rain sensor is composed of a rain detection plate with a comparator who manages intelligence. The sensor acts as a variable resistance that will change status: the resistance increases when the sensor is wet and the resistance is lower when the sensor is dry. The comparator has 2 outputs connected to the rain sensor, a digital output (0/1) and an analog output (0 to 1023).



Fig 6.5 Rain Sensor

BH1750

BH1750 is a Digital Ambient Light Sensor or a Light Intensity Sensor, which can be used to auto adjust the brightness of display in mobiles, LCD displays, or to turn on/off the headlights in cars based upon the outdoor lighting conditions.



Fig 6.6 BH1750 Sensor

Soil Moisture

Sensor Soil Moisture Sensor measures the volumetric content of water inside the soil and gives us the moisture level as output. The sensor is equipped with both analog and digital output, so it can be used in both analog and digital mode.

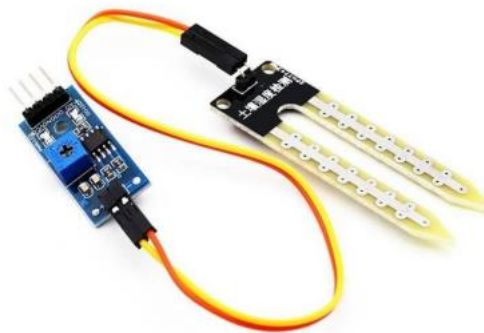


Fig 6.7 Soil Moisture Sensor

pH Sensor

The pH Sensor, pH stands for potential Hydrogen, and it tells us whether a solution or substance is BASIC, ACIDIC or NEUTRAL based on the pH Value. The optimal pH range for most common hydroponic crops is between 5.5 and 6.0



Fig 6.8 Ph Sensor

6.2 SOURCE CODE

ARDUINO :

It seems the code snippet for reading data from a DHT11 temperature and humidity sensor, an analog moisture sensor, and a BH1750 light sensor. In the code, you also read an additional analog input for water level and then print the collected data to the serial monitor.

SNIPPET OF CODE:

```
#include "dht.h"
#include <BH1750.h>
#include <Wire.h>
#define DHT_PIN A1
#define WATER_PIN A2
#define MOISTURE_PIN A0
BH1750 lightMeter;
dht DHT;
void setup() {
    Serial.begin(9600);
    Wire.begin();
    lightMeter.begin();
    delay(1500);
}
void loop() {
    float lux = lightMeter.readLightLevel();
    DHT.read11(DHT_PIN);
    Serial.print(DHT.temperature); Serial.print(",");
    Serial.print(DHT.humidity); Serial.print(",");
    Serial.print(analogRead(WATER_PIN)); Serial.print(",");
    Serial.print(analogRead(MOISTURE_PIN)); Serial.print(",");
    Serial.println(lux);
    delay(5000);
}
```

ALGORITHM:

1. Initialization:

- Set up the necessary communication protocols (Serial, I2C).
- Initialize the BH1750 light sensor.
- Wait a few seconds to allow sensors to stabilize.

2. Main Loop:

CROP PREDICTION USING IOT AND ML

- Read sensor data at regular intervals.
- Measure the light level using the BH1750 sensor.
- Measure the water level and soil moisture using analog sensors.
- Read temperature and humidity from the DHT sensor.
- Print the collected sensor data to the Serial monitor.
- Delay before repeating the loop to avoid excessive readings.

In summary, the algorithm collects environmental data (light, soil moisture, water level, temperature, humidity) and outputs these values to the Serial monitor every 5 seconds.

NODE MCU:

The provided code is an Arduino sketch that connects an ESP8266 module to a Wi-Fi network, then sends sensor data received via serial communication to a specified URL using HTTP POST requests. It continuously reads sensor values for temperature, humidity, water level, moisture level, and light intensity from a connected Arduino. If the HTTP request is successful, it logs the response; otherwise, it reports an error.

SNIPPET OF CODE:

```
#include <ESP8266WiFi.h>
#include <ESP8266HTTPClient.h>
#define SSID "Seenu"
#define PASSWORD "07989391"
#define URL "http://192.168.0.110/CropPrediction/sensor_data.php"
void setup() {
    Serial.begin(9600);
    WiFi.begin(SSID, PASSWORD);

    while (WiFi.status() != WL_CONNECTED) {
        Serial.print(".");
        delay(500);
    }
    Serial.println("Connected, IP: " + WiFi.localIP().toString());
}
void loop() {
    if (WiFi.status() == WL_CONNECTED && Serial.available()) {
        String data = Serial.readStringUntil('\n');
        String postData = "Temp=" + data.split(',')[0] +
            "&Humidity=" + data.split(',')[1] +
            "&Water=" + data.split(',')[2] +
            "&Moisture=" + data.split(',')[3] +
```

```
        "&Light=" + data.split(',')[4];
    HTTPClient http;
    http.begin(WiFiClient(), URL);
    http.addHeader("Content-Type", "application/x-www-form-urlencoded");
    int httpCode = http.POST(postData);
    String response = http.getString();
    Serial.println("HTTP Code: " + String(httpCode));
    Serial.println("Response: " + response);
    http.end();
}
delay(5000);
}
```

ALGORITHM:

1. Wi-Fi Connection

- Start Serial communication.
- Connect to a Wi-Fi network (SSID, password).
- Wait for the connection to be established.
- Print the local IP address when connected.

2. Main Loop

- If Wi-Fi is connected and Serial data is available:
 - Read and split the Serial data into sensor values.
 - Create HTTP POST data from the sensor values.
 - Send HTTP POST request to a specified URL.
 - Print HTTP response code and response message.
 - Delay for 5 seconds.

SENSOR DATA:

The PHP code connects to a MySQL database, checks if certain POST variables are set (temperature, humidity, water level, moisture level, light intensity), and inserts their values into a `sensors_data` table. If the data is inserted successfully, it returns a success message; otherwise, it reports an error. If the connection fails, it stops with an error message. Finally, it closes the database connection.

SNIPPET OF CODE:

```
<?php
// Database connection settings
$hostname = "localhost";
$username = "root";
$password = "";
$databse = "sensor_db";
// Connect to the database
$conn = mysqli_connect($hostname, $username, $password, $database);
// Check for connection error
if (!$conn) {
    die("Connection failed: " . mysqli_connect_error());
}
echo "Database Connection Success";
// Check if POST variables are set
if (isset($_POST["Temperature"], $_POST["Humidity"], $_POST["WaterLevel"],
$_POST["MoistureLevel"], $_POST["LightIntensity"])) {
    $t = (float)$_POST["Temperature"];
    $h = (float)$_POST["Humidity"];
    $w = (float)$_POST["WaterLevel"];
    $m = (float)$_POST["MoistureLevel"];
    $l = (float)$_POST["LightIntensity"];
    // Insert data into the database
    $sql = "INSERT INTO sensors_data (Temperature, Humidity, WaterLevel,
MoistureLevel, LightIntensity) VALUES ($t, $h, $w, $m, $l)";
    // Execute the query and provide feedback
    if (mysqli_query($conn, $sql)) {
        echo "New record created successfully";
    } else {
        echo "Error: " . $sql . "<br>" . mysqli_error($conn);
    }
} else {
    echo "Required data not provided";
}
// Close the connection
mysqli_close($conn);
?>
```

ALGORITHM:

1. Database Setup:

- Configure connection parameters: `hostname`, `username`, `password`, `database`.
- Connect to the database.

2. Connection Validation:

- If connection fails, stop with an error message.

3. POST Data Check:

- Ensure `Temperature`, `Humidity`, `WaterLevel`, `MoistureLevel`, `LightIntensity` are set in the POST request.

4. Data Insertion:

- Insert POST data into the `sensors_data` table.

5. Result Handling:

- If insertion is successful, return success message.
- If it fails, return an error message.

6. End:

- If POST data is missing, return a message or do nothing.

AVERAGE DATA:

This code connects to a MySQL database and retrieves all rows from a table called sensors data. It calculates the average values for five sensor readings: Temperature, Humidity, Water Level, Moisture Level, and Light Intensity. It does this by summing each value across all rows and then dividing by the row count. These averages are stored in an associative array, which is converted to JSON and echoed as the output. If no rows are found, it returns "0 results". Finally, the database connection is closed.

SNIPPET OF CODE:

```
<?php
$conn = mysqli_connect("localhost", "root", "", "sensor_db");
if ($conn) {
    $result = mysqli_query($conn, "SELECT * FROM sensors_data");
    if (mysqli_num_rows($result) > 0) {
        $sums = ["Temperature" => 0, "Humidity" => 0, "WaterLevel" => 0,
"MoistureLevel" => 0, "LightIntensity" => 0];
        $count = 0;
        while ($row = mysqli_fetch_assoc($result)) {
            foreach ($sums as $key => &$value) {
                $value += $row[$key];
            }
            $count++;
        }
    }
}
```

```
        $averages = array_map(fn($sum) => $sum / $count, $sums);
        echo json_encode($averages);
    } else {
        echo json_encode([]);
    }
    mysqli_close($conn);
} else {
    die("Connection failed: " . mysqli_connect_error());
}
?>
```

ALGORITHM:

1. Connect to Database:

- Connect to the MySQL database.
- If connection fails, terminate with an error message.

2. Query Data:

- Execute SQL query to get all rows from `sensors_data`.
- If no rows, output "0 results".

3. Calculate Averages:

- Initialize sums and row count to zero.
- Loop through rows, adding sensor values to sums and incrementing row count.
- Calculate averages by dividing sums by row count.

4. Output Results:

- Encode the average values in JSON format and output.

5. Close Connection:

- Close the database connection.

CROP PREDICTION ML:

This Flask web application predicts crop types based on sensor data and user inputs. It fetches sensor averages from a PHP endpoint, trains a Random Forest classifier on a pre-defined crop dataset, and then predicts crop types given specific input parameters. The app has three main

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routes: `^` for the home page, `/getsensordata` to retrieve sensor averages, and `/submit` to handle user input for prediction. Depending on the predicted crop type, it displays a different template (for example, `Lettuce-display.html` for lettuce). The `predict_crop` function does the prediction and returns the result with accuracy.

SNIPPET OF CODE:

```
from flask import Flask, render_template, request
import requests, json, pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
app = Flask(__name__)
# Fetch sensor data
response = requests.get('http://172.20.10.12/CropPrediction/average_data.php')
if response.status_code == 200:
    data = json.loads(response.text)
    avg_vals = {
        "temperature": float(data["averageTemperature"]),
        "humidity": float(data["averageHumidity"]),
        "water_level": float(data["averageWaterLevel"]),
        "moisture_level": float(data["averageMoistureLevel"]),
        "light_intensity": float(data["averageLightIntensity"])
    }
@app.route('/')
def home():
    return render_template('home_page.html')
@app.route('/submit', methods=['POST'])
def submit():
    # Get user input from the form
    sensor_inputs = {
        "n": float(request.form['n_val']),
        "p": float(request.form['p_val']),
        "k": float(request.form['k_val']),
        "ph": float(request.form['ph_val'])
    }
    # Merge averages and form inputs
    inputs = list(avg_vals.values()) + list(sensor_inputs.values())
    # Predict the crop
    predicted_crop, accuracy = predict_crop(inputs)
    # Display correct page based on prediction
    crop_pages = {
        "Lettuce": 'Lettuce-display.html',
        "Cucumber": 'Cucumber-display.html',
        "Okra": 'Okra-display.html'
    }
    return render_template(crop_pages.get(predicted_crop[0], 'Okra-display.html'), crop=predicted_crop[0], acc=accuracy)
```

ALGORITHM:

1. Initialize Flask:

- Create a Flask application and import necessary libraries (Flask, HTTP requests, data processing, machine learning).

2. Fetch Sensor Data:

- Retrieve average sensor data via a GET request to a PHP endpoint and extract values from the JSON response.

3. Train Random Forest Classifier:

- Load crop dataset from Excel.
- Train a Random Forest classifier on the dataset.

4. Define Routes:

- Define endpoints for the home page (^/), sensor data retrieval (^/getsensordata`), and form submission for crop prediction (^/submit`).

5. Predict Crop:

- Use form data and sensor averages to predict the crop type with the trained classifier.
- Render the appropriate HTML template with the prediction result and accuracy.

6. Run Flask Application:

- Start the Flask app in debug mode.

Summary:

The implementation of the project involves deploying IoT sensors across agricultural fields to capture real-time environmental data. This data is then transmitted to a central data processing unit, where it undergoes preprocessing to ensure quality and consistency. ML algorithms are trained using the preprocessed data to develop predictive models for crop performance. These models are integrated into a user-friendly interface, such as a web or mobile application, allowing farmers to access predictive insights and recommendations for crop selection and resource management. Continuous monitoring and refinement of the system ensure its effectiveness and reliability in supporting agricultural decision-making

CHAPTER 7

RESULTS

ARDUINO UNO:

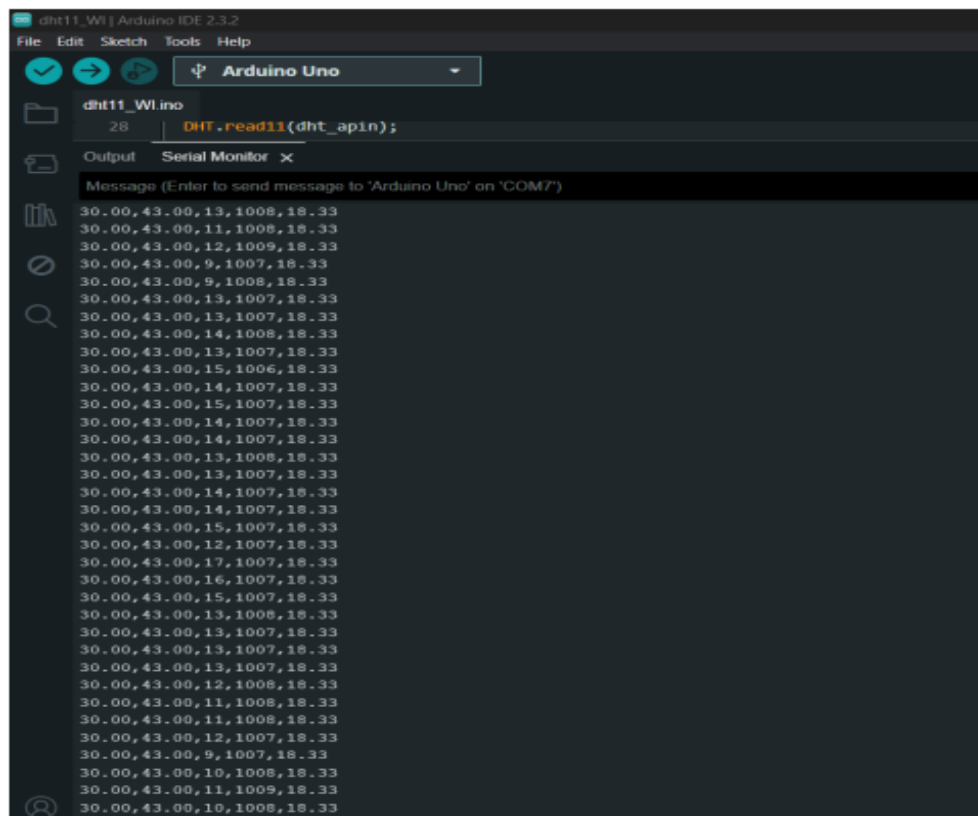
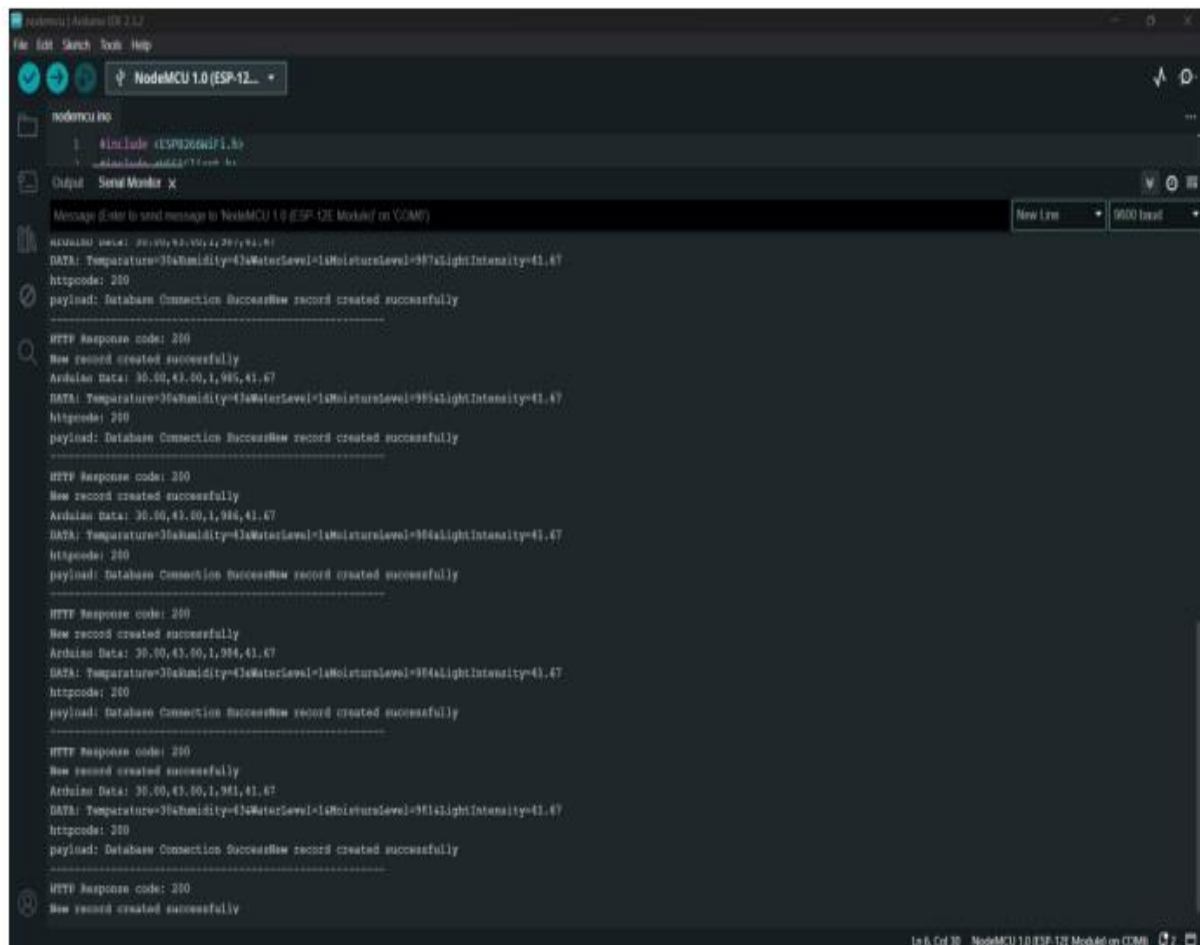


Fig 7.1 Arduino output

All the sensor output collecting from the Arduino and sending to the node MCU using wifi connection. This Arduino code measures environmental conditions using various sensors. It initializes a serial communication and begins interacting with a BH1750 light sensor for light level measurement. In the `loop` function, it reads sensor values: temperature and humidity from a DHT sensor, light intensity from the BH1750, and moisture and water levels from two analog inputs. The code prints these readings—temperature, humidity, water level, soil moisture, and light intensity—to the serial console, providing a simple environmental monitoring system. The `delay(5000)` at the end of the loop sets a 5-second interval between sensor readings, avoiding excessive data generation.

NODE MCU:



```
nodemcu.ino
1 #include <ESP8266WiFi.h>
2 #include <Arduino.h>

// Serial Monitor

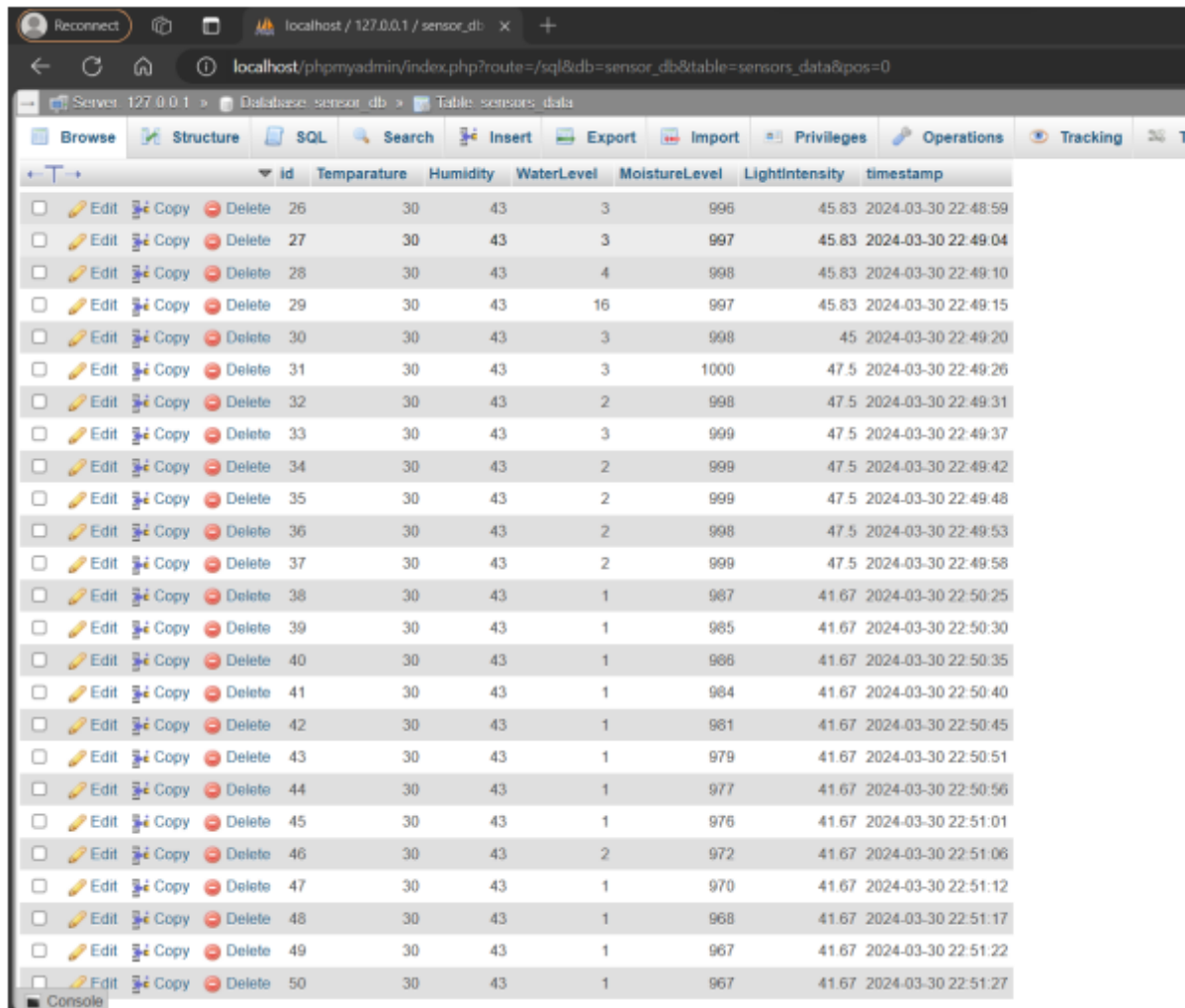
// Message (Enter to send message to NodeMCU 1.0 (ESP-12E Module) on COM6)
// New Line 9600 baud

// Arduino Data: 30.00,43.00,1,985,41.67
// DATA: Temperature=30.00Humidity=43.00WaterLevel=1MoistureLevel=985LightIntensity=41.67
// httpcode: 200
// payload: Database Connection SuccessNew record created successfully
// -----
// HTTP Response code: 200
// New record created successfully
// Arduino Data: 30.00,43.00,1,985,41.67
// DATA: Temperature=30.00Humidity=43.00WaterLevel=1MoistureLevel=985LightIntensity=41.67
// httpcode: 200
// payload: Database Connection SuccessNew record created successfully
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// HTTP Response code: 200
// New record created successfully
// Arduino Data: 30.00,43.00,1,984,41.67
// DATA: Temperature=30.00Humidity=43.00WaterLevel=1MoistureLevel=984LightIntensity=41.67
// httpcode: 200
// payload: Database Connection SuccessNew record created successfully
// -----
// HTTP Response code: 200
// New record created successfully
// Arduino Data: 30.00,43.00,1,984,41.67
// DATA: Temperature=30.00Humidity=43.00WaterLevel=1MoistureLevel=984LightIntensity=41.67
// httpcode: 200
// payload: Database Connection SuccessNew record created successfully
// -----
// HTTP Response code: 200
// New record created successfully
// Arduino Data: 30.00,43.00,1,981,41.67
// DATA: Temperature=30.00Humidity=43.00WaterLevel=1MoistureLevel=981LightIntensity=41.67
// httpcode: 200
// payload: Database Connection SuccessNew record created successfully
// -----
// HTTP Response code: 200
// New record created successfully
```

Fig 7.2 Node MCU output

This code for an ESP8266 microcontroller connects to a Wi-Fi network, reads sensor data from another Arduino through serial communication, and sends this data to a web server via HTTP POST requests. After connecting to Wi-Fi, the code checks if data is available on the serial line. If it finds sensor readings (temperature, humidity, water level, moisture level, and light intensity), it parses them and sends them to a PHP script on a remote server. If the server responds with a success message, the code confirms that a new record was created; otherwise it reports errors. The loop repeats every 5 seconds, ensuring regular data transmission.

DATABASE:



The screenshot displays a web browser window with the URL `localhost/phpmyadmin/index.php?route=/sql&db=sensor_db&table=sensors_data&pos=0`. The interface shows a table named `sensors_data` with the following columns: `id`, `Temperature`, `Humidity`, `WaterLevel`, `MoistureLevel`, `LightIntensity`, and `timestamp`. The table contains 25 rows of data, each with a unique ID and corresponding sensor readings. Each row has interactive icons for Edit, Copy, and Delete.

	id	Temperature	Humidity	WaterLevel	MoistureLevel	LightIntensity	timestamp
<input type="checkbox"/>	26	30	43	3	996	45.83	2024-03-30 22:48:59
<input type="checkbox"/>	27	30	43	3	997	45.83	2024-03-30 22:49:04
<input type="checkbox"/>	28	30	43	4	998	45.83	2024-03-30 22:49:10
<input type="checkbox"/>	29	30	43	16	997	45.83	2024-03-30 22:49:15
<input type="checkbox"/>	30	30	43	3	998	45	2024-03-30 22:49:20
<input type="checkbox"/>	31	30	43	3	1000	47.5	2024-03-30 22:49:26
<input type="checkbox"/>	32	30	43	2	998	47.5	2024-03-30 22:49:31
<input type="checkbox"/>	33	30	43	3	999	47.5	2024-03-30 22:49:37
<input type="checkbox"/>	34	30	43	2	999	47.5	2024-03-30 22:49:42
<input type="checkbox"/>	35	30	43	2	999	47.5	2024-03-30 22:49:48
<input type="checkbox"/>	36	30	43	2	998	47.5	2024-03-30 22:49:53
<input type="checkbox"/>	37	30	43	2	999	47.5	2024-03-30 22:49:58
<input type="checkbox"/>	38	30	43	1	987	41.67	2024-03-30 22:50:25
<input type="checkbox"/>	39	30	43	1	985	41.67	2024-03-30 22:50:30
<input type="checkbox"/>	40	30	43	1	986	41.67	2024-03-30 22:50:35
<input type="checkbox"/>	41	30	43	1	984	41.67	2024-03-30 22:50:40
<input type="checkbox"/>	42	30	43	1	981	41.67	2024-03-30 22:50:45
<input type="checkbox"/>	43	30	43	1	979	41.67	2024-03-30 22:50:51
<input type="checkbox"/>	44	30	43	1	977	41.67	2024-03-30 22:50:56
<input type="checkbox"/>	45	30	43	1	976	41.67	2024-03-30 22:51:01
<input type="checkbox"/>	46	30	43	2	972	41.67	2024-03-30 22:51:06
<input type="checkbox"/>	47	30	43	1	970	41.67	2024-03-30 22:51:12
<input type="checkbox"/>	48	30	43	1	968	41.67	2024-03-30 22:51:17
<input type="checkbox"/>	49	30	43	1	967	41.67	2024-03-30 22:51:22
<input type="checkbox"/>	50	30	43	1	967	41.67	2024-03-30 22:51:27

Fig 7.3 Database interface

The database is having all the sensor data collected from the NODE MCU using the php script. The data collection system retrieves sensor readings for temperature, humidity, water level, soil moisture, and light intensity from Arduino devices. This data is then transmitted via HTTP POST requests to a remote PHP-based web server. Successful transmissions indicate data is accurately stored in a database, providing a foundation for further analysis and monitoring.

FRONT ENDS:



Fig:7.4 Frontend page1

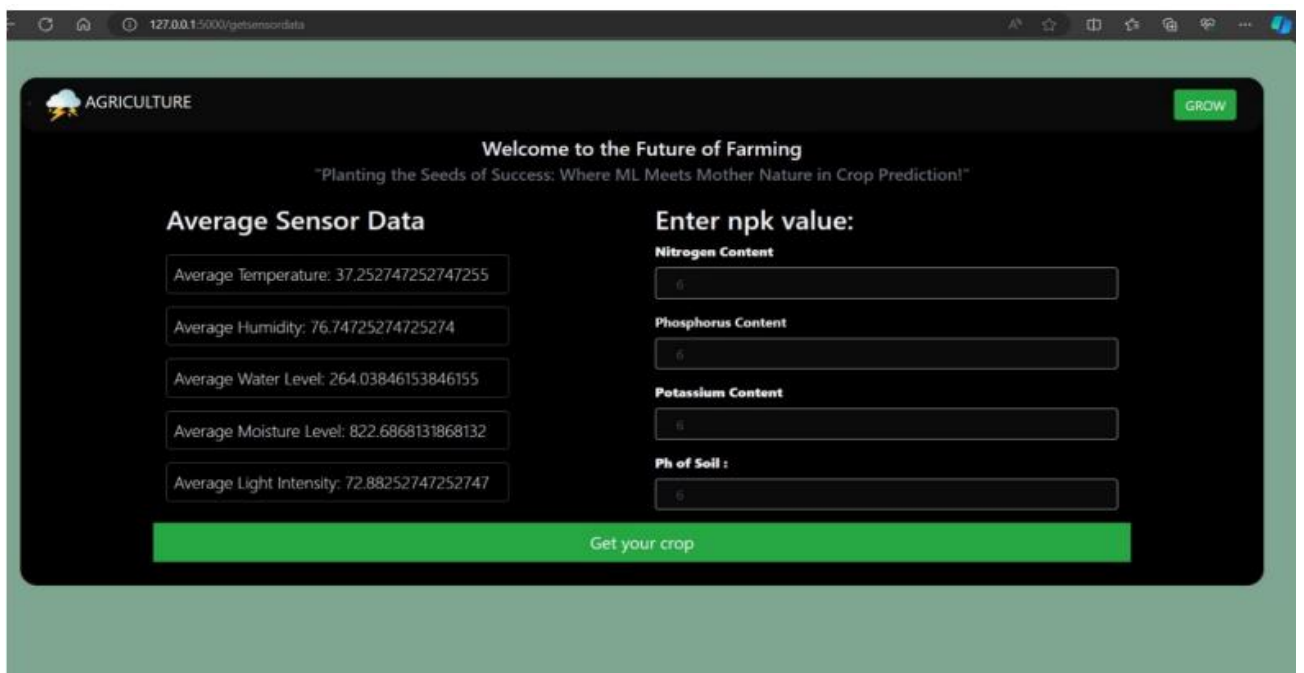


Fig 7.5 Frontend page 2

This JavaScript code handles user interaction with dropdown menus and a navigation button on a webpage. When a parent menu item in the navigation bar is clicked, it toggles the display of the associated dropdown menu. If the dropdown is visible, it is hidden; if hidden, it's made visible. A second event listener ensures that if a user clicks outside the dropdown, any open dropdowns are hidden to maintain a tidy interface.

The code also listens for a click event on a button with ID "goToPage2" and, when triggered, redirects the user to "page2.html." This functionality helps navigate between different sections of a website.

OUTPUTS:

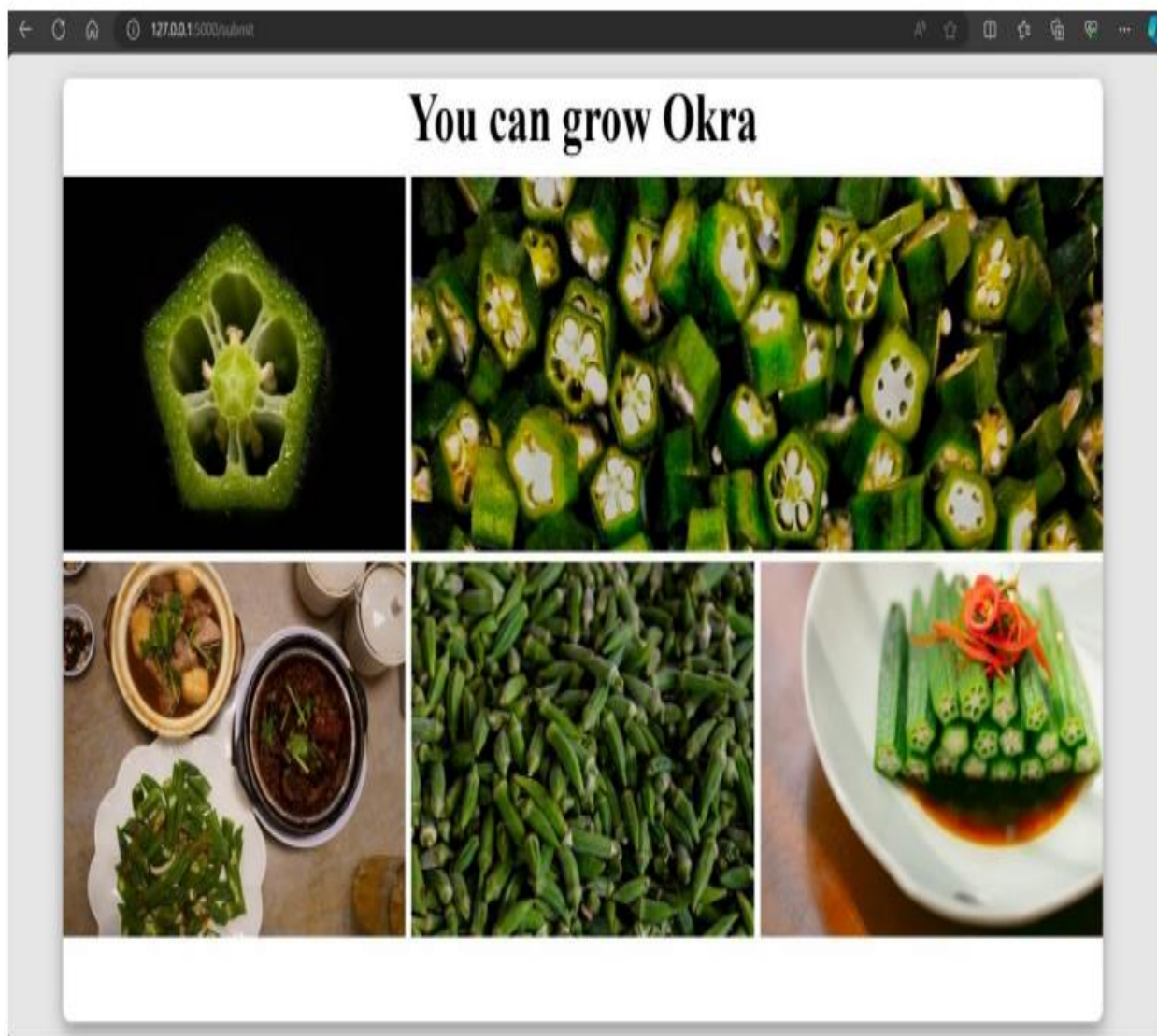


Fig 7.6 Output 1

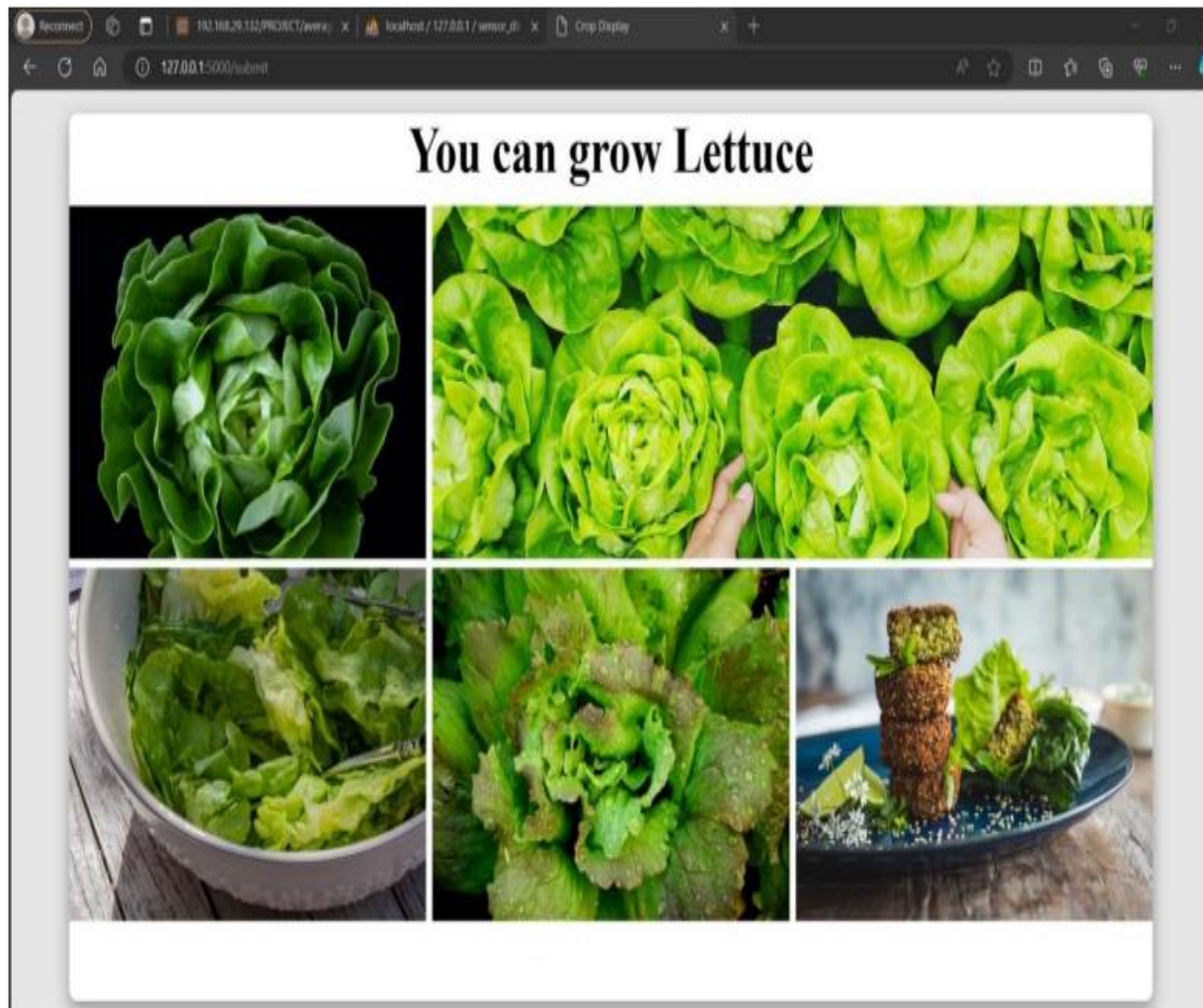


Fig 7.6 Output 2

This Flask application is a crop prediction system that retrieves environmental sensor data and uses it to suggest suitable crops. It interacts with a PHP script to obtain average temperature, humidity, water level, moisture level, and light intensity. This data is sent to the Flask application via a GET request and stored for further use.

Several routes manage the application's logic. The home page is displayed by the root (``) route, while the ``/getsensordata`` route retrieves sensor data from the PHP script and renders it on a webpage. The ``/submit`` route handles POST requests from a form where users input nutrient levels and pH values. This route triggers the ``predict_crop`` function, which trains a Random Forest classifier on a dataset of environmental conditions and crop labels. Using this trained model, the function predicts the best crop based on the sensor data and user inputs.

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The predicted crop and the model's accuracy are then rendered on a specific HTML template. The output displays the suggested crop (e.g., "Lettuce," "Cucumber," or "Okra") and the classifier's accuracy, providing users with recommendations based on real-time data and a trained machine learning model.

Summary:

The results of the project demonstrate the efficacy of the developed system in predicting crop performance and providing actionable insights to farmers. ML algorithms trained on real-time environmental data accurately forecast crop yields and offer tailored recommendations for optimal crop selection and resource management strategies. Farmers using the system experienced improved decision-making capabilities, leading to enhanced agricultural productivity and sustainability. The system's ability to adapt to changing environmental conditions and provide timely recommendations underscores its value in modern agriculture. Overall, the results highlight the potential of IoT and ML technologies to revolutionize crop prediction and decision support systems in agriculture.

CHAPTER 8

FUTURE ENHANCEMENT

In the future, the project could benefit from the integration of advanced sensing technologies to capture a more comprehensive range of environmental parameters. This could include the deployment of hyperspectral imaging cameras to assess crop health and detect diseases at early stages, as well as drones equipped with multispectral sensors for aerial monitoring of large agricultural areas. Additionally, the integration of IoT-enabled soil sensors capable of measuring nutrient levels, soil pH, and organic matter content could provide valuable insights into soil fertility and help optimize fertilizer application. By incorporating these advanced sensing technologies into the existing framework, the project could further enhance the accuracy and granularity of its predictive models, enabling more precise crop predictions and recommendations for farmers.

Another future enhancement could involve the implementation of autonomous farming systems driven by artificial intelligence and robotics. This could include the development of autonomous vehicles equipped with AI algorithms for tasks such as planting, harvesting, and weed control, as well as robotic systems for precision irrigation and crop monitoring. By leveraging IoT sensors and ML algorithms, these autonomous systems could operate in real-time, adapting to dynamic environmental conditions and optimizing agricultural operations with minimal human intervention. Furthermore, the integration of edge computing capabilities could enable on-device processing of sensor data, reducing latency and enhancing the responsiveness of autonomous farming systems. Ultimately, the implementation of autonomous farming systems holds the potential to revolutionize agriculture, increasing efficiency, productivity, and sustainability while reducing labor costs and environmental impact.

CONCLUSION

Our project "Crop Prediction using IoT and ML" stands as a pioneering solution designed to address the persistent challenges encountered in modern agriculture. Through the strategic integration of various sensors, machine learning algorithms, and historical weather data, this initiative aimed to provide farmers with a robust decisionmaking framework for crop selection. By harnessing the capabilities of IoT devices to gather real-time agricultural data and coupling it with sophisticated machine learning models trained on comprehensive datasets, the project sought to offer farmers actionable insights for optimal crop choices. The predictive capacity of this system not only assists in mitigating the impact of unpredictable weather patterns but also aids in maximizing crop yields and resource utilization. The primary objective of this project was to empower farmers by enabling them to make informed decisions regarding crop selection, thereby enhancing agricultural productivity and sustainability. Through the amalgamation of IoT and ML technologies, the project aimed to usher in a new era of precision agriculture, reducing uncertainties and improving agricultural efficiency. Furthermore, the successful implementation of this system signifies a significant stride towards revolutionizing traditional farming practices. By leveraging technology to predict suitable crops based on a confluence of data sources, this initiative offers a pathway to optimize agricultural operations, reduce risks, and promote more resilient farming methodologies. In essence, "Crop Prediction using IoT and ML" embodies the transformative potential of technological innovations in agriculture. It represents a pivotal step towards building a more resilient and efficient agricultural ecosystem, ultimately contributing to the well-being of farming communities and fostering sustainable practices in the realm of agriculture.

Summary:

In conclusion, the project has demonstrated the transformative potential of integrating IoT and ML technologies in agriculture. The system's success in providing accurate predictions and actionable insights underscores its value in enhancing agricultural productivity. Future enhancements will focus on refining algorithms and integrating advanced sensing technologies to address emerging challenges, ensuring the system's continued relevance and impact.

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