Terratech: An Integrated IoT and Robotics-Driven System for Precision Agricultural Monitoring and Sustainable Crop Production

Project synopsis submitted in partial fulfillment for the degree of Bachelor of Technology in Electronics and Communications Engineering of Maulana Abul Kalam Azad University of Technology (formerly known as West Bengal University of Technology)

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Certificate of Recommendation

This is to certify that the project titled **"Terratech: An Integrated IoT and Robotics-Driven System for Precision Agricultural Monitoring and Sustainable Crop Production"** submitted by **SOUMYADIP BERA, DEBARUN DAS, NIKITA TIWARI & DIYA DAS** is absolutely based upon their own work under the supervision of Prof. **(Dr.) SUMEDHA DASGUPTA** (Assistant Professor, Dept of ECE, FIEM) and that neither their synopsis has been submitted for BTech degree.

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ABSTRACT

This research examines the effectiveness of IoT-based agricultural monitoring systems in improving resource efficiency and crop yield for small-scale cauliflower farmers in West Bengal, India, during the winter growing season of December 2024. We collected primary data on soil moisture, temperature, and pH from 2 farms over the growing period using DHT11 temperature/humidity sensors and YL-69 soil moisture sensors, transmitting data wirelessly via Wi-Fi modules/ESP32(Wi-Fi inbuilt) to the Blynk IoT platform. Comparing these 2 farms with a control group of 2 farms using traditional practices, we employed Multiple Linear Regression to analyze the relationship between environmental parameters and cauliflower yield. Our findings demonstrate an increase in cauliflower yield. These results indicate that real-time, data-driven insights from IoT systems *may* enhance productivity and resource management for small-scale farmers, even with limited resources, leading to more efficient resource allocation across the growing season and improved overall farm profitability. This study provides *preliminary insights* into the *potential* benefits of IoT adoption in developing economies. This study provides valuable preliminary insights into the potential of IoT for small-scale cauliflower farmers in West Bengal, highlighting promising trends in yield. However, the current implementation of the IoT system has limitations, including the specific sensors employed, limited data storage capacity, and limited battery life. Future development will focus on addressing these limitations and expanding the system's capabilities. Future research with a larger and more representative sample is also essential to validate these initial findings, explore the broader impacts of IoT on agriculture, and translate these preliminary successes into widespread benefits for smallholder farmers. Our findings inform policymakers in designing effective strategies to promote precision agriculture technology adoption and support smallholder farmers adapting to climate change, but it is crucial that these strategies are informed by robust, large-scale studies.

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CHAPTER-1
INTRODUCTION

Agriculture forms a crucial component of the economic fabric of numerous nations. In India, which is a country endowed with plenty of agricultural resources, the agricultural sector is responsible for guaranteeing food security as well as encouraging sustainable development. However, in the face of the fast-growing world population, the rising effects of climate change, and limited natural resources, there is a need for efficient agricultural management methods. Farmers today encounter a multiple of challenges brought about by unpredictable and fast-changing meteorological conditions. The challenges comprise crop stamina loss, reduced soil fertility, and unpredictable water supply, all of which threaten agricultural productivity. For example, certain crops, such as cauliflower and cabbage, require precise temperature ranges to grow to their maximum potential. Rainfall is also vital to agricultural productivity; too much rainfall causes waterlogging and subsequent spoilage of the crops, while too little rainfall causes soil dryness, causing plant death and soil health decline in the long run. Other critical but less-researched factors, including wind patterns, pest populations, and deficiencies in nutrients, also affect crop yields and sustainable agriculture.

A survey of recent literature shows that most research focuses on single natural events, such as floods and droughts. While temperature changes have received a lot of attention, there is clearly a gap in research that looks at multiple environmental and farming factors at the same time. To better support sustainable agriculture and assist farmers, we need a more integrated and better approach. Current work highlights the increasing role of improved or upgraded technologies in monitoring and surveillance systems for agriculture. These systems use methods that collect, evaluate, and interpret data about environmental conditions and farming practices. They combine various Internet of Things (IoT) devices, machine learning (ML), and remote sensing technologies to provide real-time information. The Internet of Things allows for a self-organizing network of devices that continuously collects and transmits data. An IoT-enabled platform for smart farming can change farming practices, leading to higher productivity, cost savings, and data-driven decision-making. These platforms typically involve microcontrollers like Arduino, supported by sensors that monitor variables such as soil moisture, temperature, and humidity. The data is wirelessly sent to cloud platforms, enabling farmers to view and assess real-time data remotely using smartphones or laptops. Remote access allows for precision farming, optimizing water and resource use, increasing yields, and reducing manual labor. For example, smart irrigation systems can automatically adjust water levels based on real-time soil moisture readings. Similarly, real-time monitoring facilitates early detection of pests and diseases. Despite recent technological progress, the use of robotics in agriculture is still limited. This represents a notable gap in research. A research gap refers to areas in a field that have not been explored or understood thoroughly. In IoT-enabled agricultural monitoring, important gaps include improving sensor accuracy, reducing system costs to help smallholder farmers, developing skills to integrate and interpret data, fixing connectivity issues in remote areas, and creating scalable, standardized systems suitable for various agricultural settings.

This project suggests an IoT-based Agricultural Monitoring and Surveillance System to change farming practices using sensors, Arduino technology, IoT design, and cloud analysis. The system allows real-time monitoring of crop health and environmental conditions to help farmers make timely decisions. It includes sensors for soil moisture, temperature, and humidity, along with high-definition cameras for visual crop monitoring. Data from these sensors and cameras is sent wirelessly to a cloud platform, enabling farmers to oversee and manage their fields remotely using smartphones or computers. This real-time monitoring promotes precision agriculture, leading to better resource use, higher crop productivity, and less labour.

Unlike traditional monitoring systems, this one is cost-effective, offers real-time feedback, and focuses on the user. It is flexible enough to work in various agricultural environments. The system addresses challenges like high implementation costs, data inaccuracies, and technological hurdles faced by small-scale farmers. In doing so, it provides farmers with useful information, helping them respond to changing environmental conditions swiftly. The results of this project will support ongoing academic research into IoT in agriculture and offer practical benefits to farmers, agricultural policymakers, technology developers, and rural development organizations. The research aims to foster smarter and more sustainable agricultural practices, tackling broader issues such as food security and environmental sustainability. It seeks to shape the future of farming by giving farmers reliable, evidence-based tools to confront challenges in a rapidly changing world.

CHAPTER-2
LITERATURE SURVEY

2.1 Automation and Robotics:

One of the major areas of study involves robotics and automation application in agriculture. Shamshiri et al. (2018) [1] note that digital farming holds promise through technologies such as data analysis, robots, and sensors to move towards a departure from conventional farming practice. The authors highlight that digital farming combines a variety of advanced technologies, such as sensors, robots, and big data analysis, to shift from the conventional, yet often labor-intensive, farming methods. Zhu et al. (2023) [2] designed an autonomous robot, AROS, for orchard mapping, illustrating the capability of mobile robotic platforms to automate the acquisition of spatial and visual information. The research compared six control frameworks for the robot and concluded that optimal-based controllers performed better than non-optimal controllers outdoors. This indicates that sophisticated control systems are necessary for the successful implementation of advanced robots in complex agriculture environments. Khosravani et al. (2023) [3] discussed the prediction of forces in seeding systems via semi-analytical and discrete element methods to enhance the accuracy of agriculture operations. Their research helps in optimizing planting processes, which is critical to achieve maximum crop yields. These robotics and automation advances can potentially lower the cost of labor, enhance accuracy, and enhance the efficiency of different agricultural operations, ultimately leading to higher productivity and profitability.

2.2 Smart Farming and Internet of Things (IoT):

The idea of smart farming, made possible by the Internet of Things (IoT), is another over-arching theme. Gondchawar & Kawitkar (2016) [4] and Rao & Sridhar (2018) [5] explain IoT-based smart agriculture systems. Sushant & Sujatha (2018) [6] and JETIR (2021) [7] also highlight that some of the major elements of smart farming are wireless sensor networks, which give real-time information regarding environmental parameters, soil moisture, and other important parameters. This information can be utilized to optimize irrigation, fertilization, and other inputs, resulting in enhanced crop production and resource use efficiency. Lin et al. (2018) [8] investigate blockchain and IoT-based food traceability in smart agricultural systems to meet the increasing demand for food safety and supply chain openness. They add that the application of IoT in agriculture allows farmers to make better decisions with real-time information, which in turn results in more accurate and effective resource management. Bekmirzaev et al. (2019) [9] investigated the influence of various irrigation water regimes on Tetragonia Tetragonioides and showed how careful water management can affect crop development and yield. Raghuvanshi et al. (2021) [10] highlight that IoT technology increases the capability of automation systems in agriculture and facilitates the creation of smart farming devices. Likewise, Wang et al. (2021) [11] assessed the influence of cumulative temperature and rainfall on maize yield and disease, emphasizing the role of environmental data in crop management. Dhanaraju et al. (2022) [12] present an overview of IoT-based sustainable agriculture, describing how the combination of IT, IoT, and cloud computing can transform farming practices. Boniecki et al. (2020) [13] further examined the application of neural visual detection of grain weevil, demonstrating how technology can be utilized to guard stored crops.

2.3 Applications of Machine Learning in Agriculture:

Machine learning is being applied more and more to address many agricultural problems. Boniecki et al. (2020) [13] applied neural networks to visually detect grain weevil, illustrating the use of machine learning in crop protection. Trader et al. (2023) [14] created a machine learning model to aid in the decision of irrigating apple trees based on parameters such as precipitation, erosion, and water balance. This shows the capability of machine learning to maximize resource allocation and enhance decision-making in agriculture. These findings suggest that machine learning can be an effective tool for processing intricate agricultural data and automating processes, resulting in more efficient and sustainable agriculture.

2.4 Challenges and Considerations:

Although technology in agriculture has huge potential, there are some challenges and issues that should be tackled. Bradley (2003) [15] describes the necessity for user acceptance of new technology and states that companies might invest in technology and later discover that their users are resistant to it. Implementation of new technologies can succeed only with close attention to human factors, training, and support. In addition, the economic effects of adopting technology must be properly assessed. Shamshiri et al. (2018) [1] indicate that the economic advantage of greater efficiency may presently lie with technology providers rather than with agricultural producers. This calls for business models and policies that guarantee farmers also get to enjoy the benefits of technological improvements.

CHAPTER-3

METHODOLOGY

This chapter presents the software-driven methodology adopted for the development of the AI-powered Agricultural Monitoring and Surveillance System (Terratech). The primary objective is to automate the process of crop health monitoring through edge-based object detection and AI-driven decision-making, thereby enabling farmers to receive real-time updates without the need for manual inspection or expensive centralized infrastructures. The software architecture is designed to be cost-effective, robust, and practically applicable within agricultural settings.

3.1 Problem Identification and Gap Analysis

Traditional crop monitoring techniques predominantly rely on manual field observations, which are prone to errors and delayed feedback. Smallholder farmers often lack access to advanced technological solutions, and existing platforms seldom incorporate ML-based predictive capabilities. There exists significant potential for an intelligent and affordable system capable of early-stage identification of crop health anomalies through image analysis. Terratech addresses this gap by deploying lightweight artificial intelligence on an edge computing platform, thereby offering a practical and economical approach to precision farming.

3.2 Suggested Software Solution

The solution in question uses machine learning to identify pest infestations, plant diseases, and shape problems through the analysis of photographs. It handles images locally and doesn't rely on remote servers to aid in the process. The system provides immediate notifications upon identification of possible dangers and logs the detection events with respective timestamps. The software aims to help with rapid decision-making, facilitate real-time processing, and use fewer resources, making it highly dependable even in far remote agricultural areas.

3.3 System Overview

The project encompasses a real-time crop monitoring framework capable of evaluating the health of crops based on images of fresh cauliflower, decayed cauliflower, and wilting leaves. The implementation employs an ESP32-CAM module for live image acquisition, Edge Impulse for dataset-driven model training, and Python along with OpenCV for supplementary image processing and visualization.

Fig 3.3.1: Representative Images of Cauliflower Stages/Conditions used for Model Training/Validation

3.4 Dataset Preparation

- **Custom Dataset Collection:** A comprehensive dataset was curated, featuring images of fresh cauliflower, decayed cauliflower, and wilting leaves captured under varied lighting and environmental conditions to enhance model robustness.
- **Annotation:** Manual annotation was carried out to label distinct regions within the images, categorizing them into three classes: Fresh Cauliflower, Rotten Cauliflower, and Rotten Leaves.
- **Dataset Splitting:** Within the Edge Impulse platform, the annotated dataset was divided into training (70%), validation (20%), and testing (10%) subsets to facilitate efficient model training and evaluation.

Fig 3.4.1: Field Observation and Farmer Interaction during Data Collection.

3.4.1 Cauliflower Type Classification Using Machine Learning

In addition to basic freshness detection, the system was also trained to categorize cauliflower heads and leaves using machine learning. The cauliflower dataset included six distinct classes: Alternaria Brassicae, Bacterial Soft Rot, Black Spot, Healthy, Purple Tinges, and Rotten. Cauliflower leaves were categorized as Alternaria Leaf Spot, Downy Mildew, and Healthy. We manually annotated these categories to train the convolutional neural network (CNN) model in Edge Impulse. The classification model allowed for detailed recognition of specific diseases and visual flaws in cauliflowers and their leaves. During validation, classification accuracy varied across categories because of visual similarities between some disease symptoms, such as Alternaria and Black Spot. Misclassification errors mainly occurred between closely related fungal diseases. To reduce these errors, the team applied data augmentation and stronger image preprocessing techniques like colour normalization and contrast improvement. Future versions will benefit from higher-resolution datasets and larger sample sizes to enhance classification accuracy.

3.5 Model Training with Edge Impulse

- **Data Upload:** The annotated dataset was uploaded to Edge Impulse Studio, a cloud-based platform tailored for embedded machine learning applications.
- **Pre-processing:** Uploaded images underwent preprocessing operations such as normalization and resizing for consistent model input. Data augmentation techniques, including image rotation, flipping, and brightness adjustment, were applied to improve model generalization.
- **Model Selection:** A lightweight Convolutional Neural Network (CNN) architecture was employed using Edge Impulse's Transfer Learning framework, fine-tuned on the proprietary dataset with a model backbone suitable for ESP32-CAM's hardware limitations.
- **Training and Evaluation:** The model was trained using the pre-processed dataset, with its performance monitored through accuracy metrics, loss values, and confusion matrix analysis. Hyperparameters such as learning rate and batch size were meticulously optimized to enhance performance while mitigating overfitting.

3.6 Deployment of Model on ESP32-CAM

- **Model Quantization:** To accommodate the trained model within the ESP32-CAM's constrained memory, quantization techniques were applied, converting model parameters from floating-point to 8-bit integers to reduce size and computation overhead.
- **Firmware Development:** Edge Impulse facilitated the generation of Arduino-compatible firmware containing the quantized model. The firmware package encapsulates all required components to execute the model natively on the ESP32-CAM.
- **ESP32-CAM Setup:** The ESP32-CAM was configured for both camera and network connectivity. Captured frames were processed using the embedded model, with classification results (Fresh Cauliflower, Rotten Cauliflower, Rotten Leaves) displayed via a simple onboard web interface for immediate feedback.

3.7 Real-Time Processing Using OpenCV and Python

- **Supplementary Processing (Optional):** An auxiliary Python script utilizing OpenCV was developed to perform advanced image processing on a separate device when higher-order analysis or visualization was required.
- **Video Stream Management:** The ESP32-CAM was set up to stream video over a local Wi-Fi network to a designated server.
- **Implementation with Python Script:** OpenCV-based Python scripts were created to capture the video feed and apply basic enhancement techniques such as contrast adjustment. These scripts were capable of retrieving classification outcomes and superimposing bounding boxes with labels on the live stream for improved clarity.
- **Post-Processing Features:** Additional post-processing included tasks like time-series analysis of detected rotten areas or estimating the percentage of affected crop regions, thereby enabling comprehensive health reporting.

3.8 Transmission of Data and Alert Mechanism

All detection results, along with associated metadata such as timestamps, were transmitted wirelessly via Wi-Fi to a cloud database using Firebase. Simultaneously, farmers received real-time alerts through the Blynk IoT platform, ensuring that crucial updates were delivered instantly to their mobile devices. This immediate notification system facilitates proactive response measures, enhancing crop quality and yield. The stored data in Firebase remains accessible for future analysis and long-term strategic planning

BLOCK DIAGRAM OF CROP HEALTH MONITORING SYSTEM

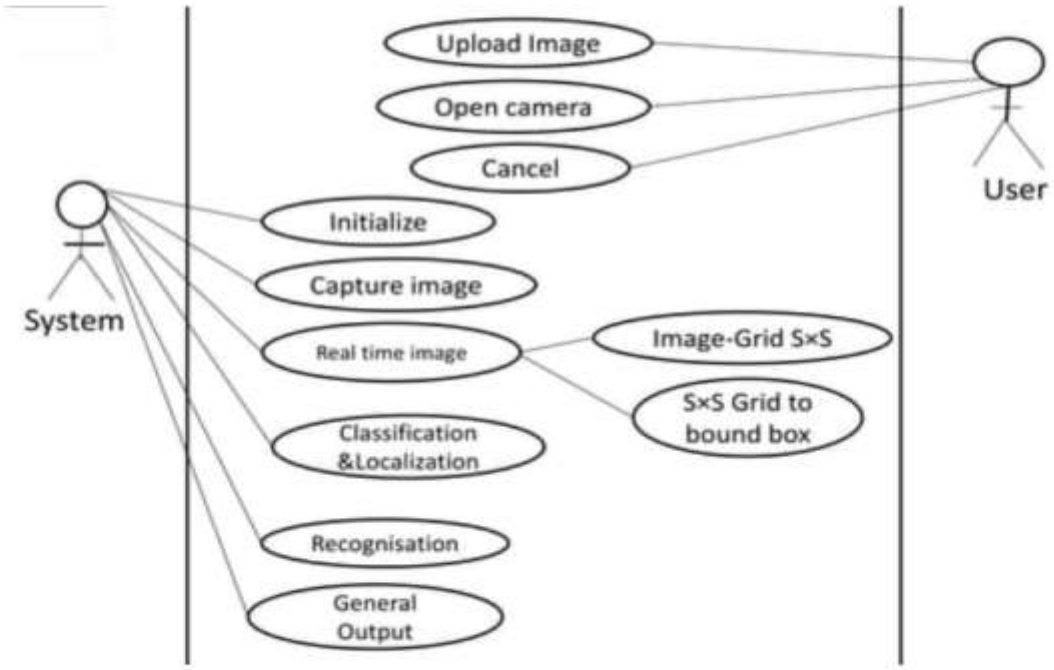


Fig : 3.8.1

This diagram is a **use case diagram** for an **image classification and localization system**, illustrating interactions between a **user** and a **system**. Here's a short description:

1. **User Actions**:
   - The user can upload an image, open the camera, or cancel the process.
2. **System Actions**:
   - The system initializes the process.
   - It can capture an image or receive a real-time image.
   - The image is processed into an S×S grid.
   - The grid is used to generate bounding boxes for detected objects.
   - The system performs classification and localization of objects.
   - This leads to recognition and the generation of a general output.

3.9 Types of Cauliflower Used in Our Dataset:

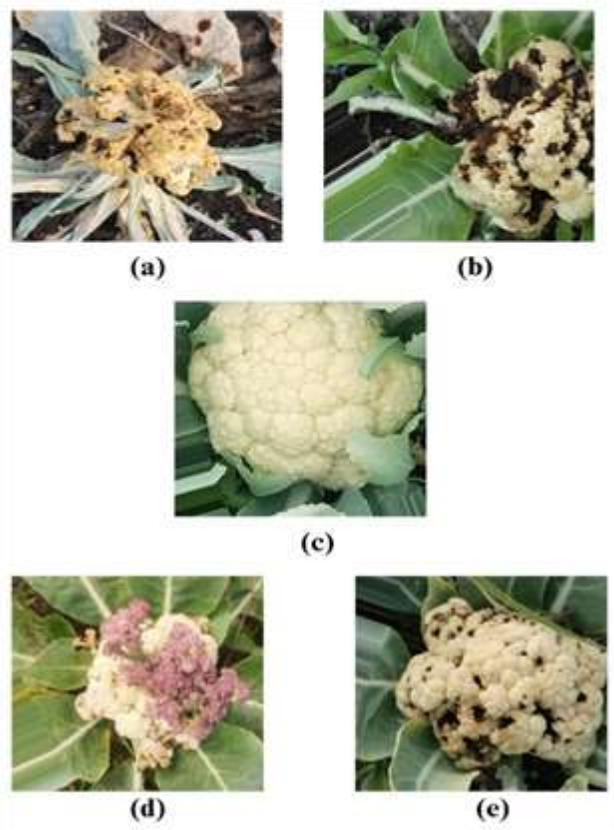


Fig: 3.9.1

(a) Alternaria brassicae

(b) Bacterial soft rot

(c) Healthy Cauliflower

(d) Purple Tinges

(e) Black spot

3.10 Output

Figure: OBJECT DETECTION / CROP HEALTH DETECTION

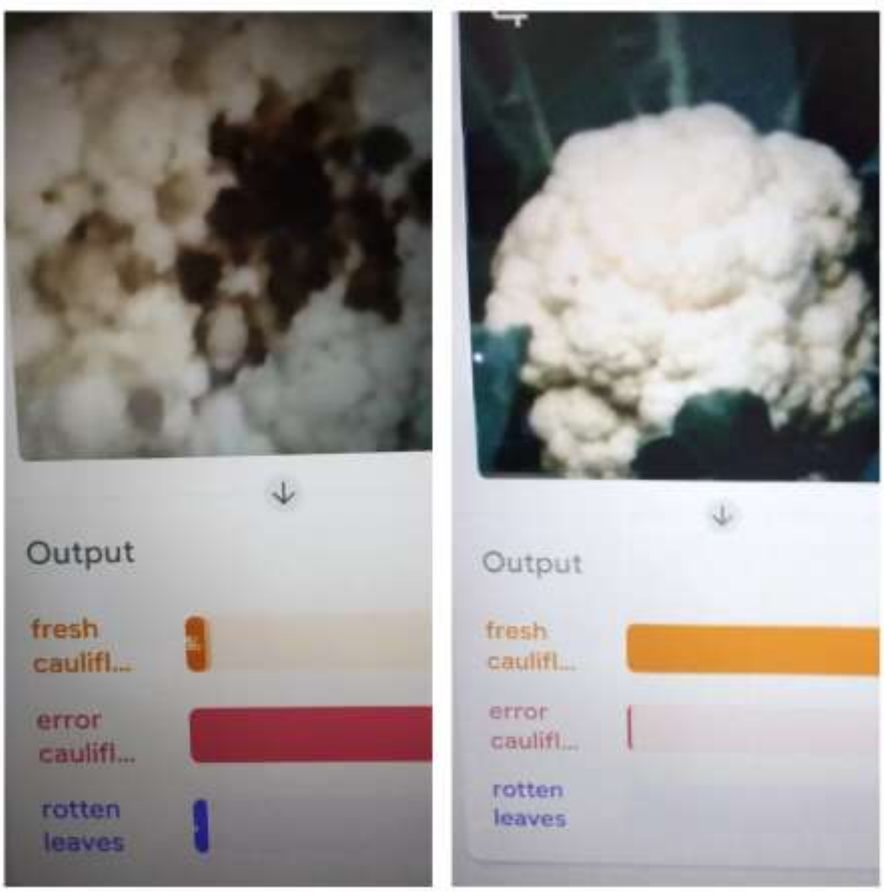


Fig: 3.10.1

3.11 System Testing and Validation

Live Testing: Field testing was conducted on various cauliflower samples exhibiting different levels of freshness and decay to evaluate the system's performance under real-world conditions.

Performance Metrics: Key metrics were used to assess system efficiency:

- **Classification Accuracy:** The accuracy of correctly identifying each crop type (fresh, rotten, or leaf).
- **Inference Time per Frame:** The duration taken by the ESP32-CAM to process a single frame and generate predictions.
- **Wi-Fi Responsiveness:** The latency between detection and user notification.

Challenges: Variability in lighting and complex backgrounds occasionally led to misclassifications. These issues were addressed by expanding the training dataset with more diverse examples and refining preprocessing techniques to improve model robustness.

3.12 Benefits of Software-Centric Monitoring

The adoption of a software-centric monitoring approach confers several advantages. Lightweight AI models enable rapid, on-site assessments without the need for continuous internet access. Edge computing enhances system autonomy, reliability, and reduces dependence on cloud infrastructure. Real-time alert capabilities allow timely interventions, mitigating potential crop losses. The integration with intuitive platforms like Blynk ensures accessibility, even for users with limited technical knowledge. Terratech thus offers a forward-looking, AI-enhanced agricultural solution tailored for small to medium-scale farming enterprises, contributing toward a more sustainable and efficient agricultural future.

FLOW CHART FOR IMAGE PROCESSING

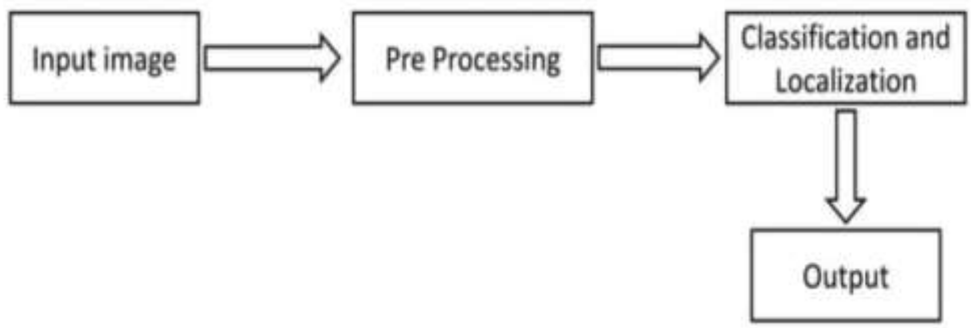


Fig: 3.12.1

This flowchart represents the **basic process of image recognition using machine learning or deep learning**:

- **Input Image**: The system receives a raw image as input.
- **Pre-Processing**: The image is processed to enhance quality, resize, normalize, or remove noise to prepare it for analysis.
- **Classification and Localization**: The system identifies (classifies) what is in the image and determines the location of the object(s) (localization).
- **Output**: The final result is generated, showing what objects were detected and where they are in the image.

CHAPTER-4

RESULTS AND DISCUSSION

This subsection reports the testing of the Terratech system, describing the behaviour of both the robotic vehicle and the sensor array, and considers their combined effect on farm produce. The system was tested over the winter cauliflower crop of 2024–2025 at West Bengal, comparing two plots in an experimental farm using Terratech with two control plots on conventional practices.

4.1 Robotic Vehicle Performance

The heart of the Terratech system is a specially designed Dual-Mode Controlled Robotic Car, which offers autonomous and manual operation capabilities.

- **Control Feedback Design:**

The robot has two wireless communication systems to attain long-range and close-proximity control. In particular, an NRF24L01 system at 2.4 GHz is used for joystick-based remote control over long distances, and an HC-05 Bluetooth system allows for control through a mobile app for operations within a shorter range. An Arduino Uno microcontroller is the robot's central processing unit that is tasked with receiving and interpreting the control input from either wireless system and subsequently controlling the motion of the robot's motors via an L298N motor driver.

- **Mechanical Specifications**:

Four 300 RPM Johnson motors power the car, with each motor providing 5–10 kg·cm of torque. A durable metal chassis, tuned with the right gear-tire configurations, allows the car to support payloads weighing up to 4 kg, housing sensors and power supplies.

- **Operational Modes:**

The robot has two different operational modes. In Joystick Mode (NRF24L01), it provides remote directional and angular movement control up to a line-of-sight range of 100 meters. In Bluetooth Mode (HC-05), it provides local control within a 10–15 meter radius through a mobile application interface.

- **Movement Capabilities:**

The robot is designed with varied movement capabilities. It is capable of executing forward, reverse, left, and right movements, as well as diagonal and angular turns via joystick control. Additionally, variable speed control is realized through Pulse Width Modulation (PWM). The system supports smooth switching between NRF and Bluetooth control modes, depending on signal availability and operating needs.

- **Performance Metrices:**

The robot shows a turning radius of around 15 cm and performs tank-turn behaviour for better mobility in confined environments. The maximum speed of the robot is around 1.2 m/s when running with full PWM. The control range was tested experientially to around 100 meters using NRF in open terrain and 12 meters using Bluetooth in indoor areas.

- **<u>Block Diagram of Rover:</u>**

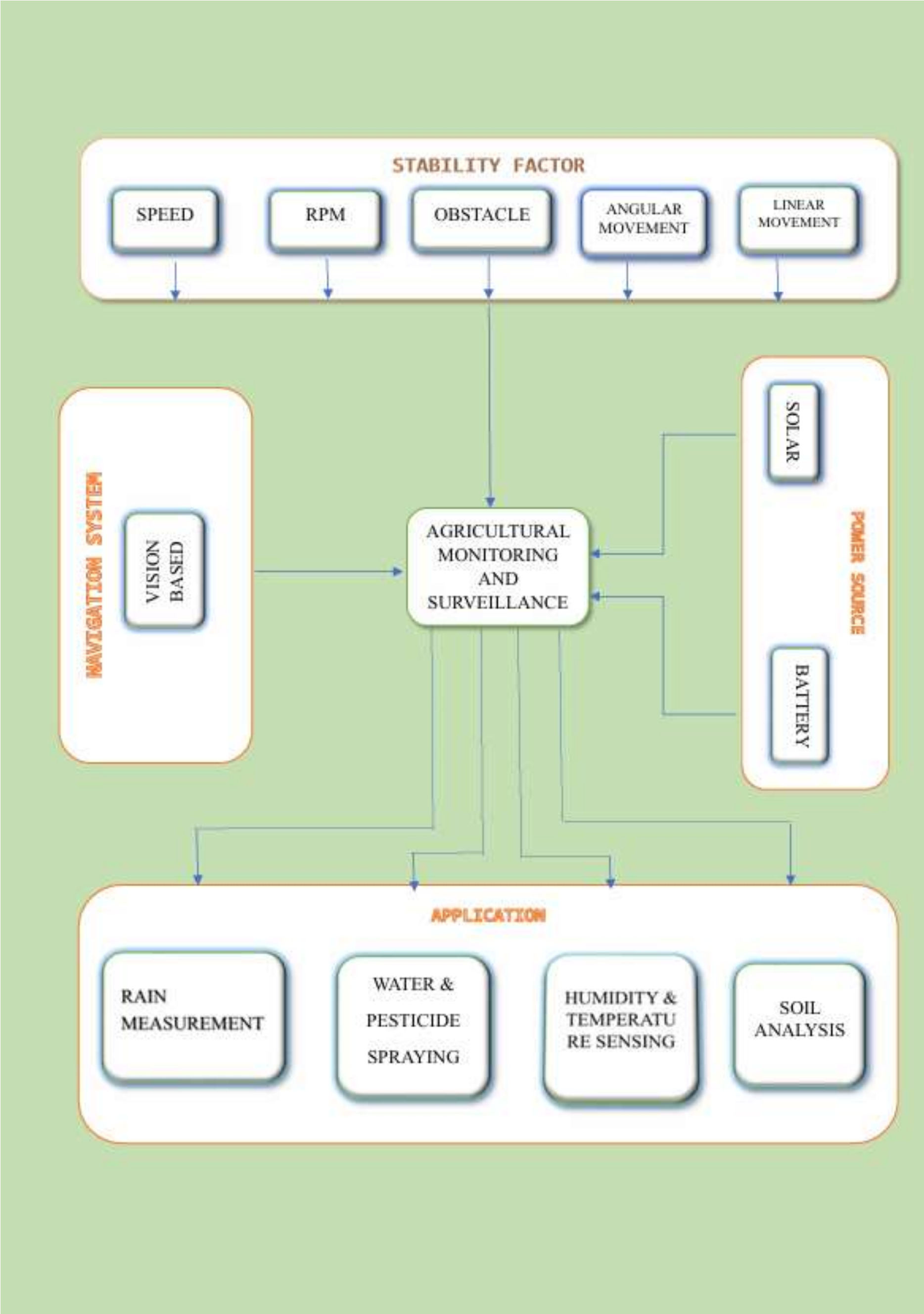


Fig: 4.1.1

Dual-mode Robotic Car used control in agricultural field operations.

Figure Explanation:

This block diagram illustrates an Agricultural Monitoring and Surveillance System that integrates multiple subsystems to enhance agricultural practices. The central unit interfaces with:

- Stability Factors like speed, RPM, obstacle detection, angular and linear movement to ensure efficient and safe operation.
- A Vision-Based Navigation System for autonomous field navigation.
- A Power Source module utilizing both solar energy and battery backup for sustainable operation.
- Multiple Applications such as rain measurement, water and pesticide spraying, humidity & temperature sensing, and soil analysis to monitor and manage environmental and crop conditions.

This system aims to automate and optimize agricultural processes for better yield and resource management.

4.2 Sensor and Hardware System Performance
The Terratech system uses a set of sensors and ancillary hardware to sense environmental conditions and crop health.

- **Sensor Suite Specifications**:
  The system utilizes a series of sensors to record key information, as described in Table 1.

Table 4.2.1: <u>Sensor Specifications and Functionality</u>

Sensor Name	Type	Parameter Measured	Measurement Range	Purpose in System
YL-69 Soil Moisture Sensor	Analog resistive sensor	Soil Moisture Content (%)	0% – 100% (relative)	Triggers irrigation when soil moisture is low
DHT22 Temperature & Humidity Sensor	Digital sensor	Air Temperature (°C), Humidity (%)	Temp: -40°C to +80°C, RH: 0% to 100%	Monitors climate; supports growth condition adjustments
Rain Detection Sensor	Analog digital rain board	Rainfall Presence	Dry/Wet	Suspends irrigation during rain to conserve water
NPK Soil Sensor	Ion-selective sensor	Nitrogen, Phosphorus, Potassium	Varies by model (typically ppm)	Monitors nutrient levels for fertilizer recommendations
pH Sensor	Analog electrode-based	Soil Acidity/Alkalinity (pH)	pH 3.0 – 10.0	Determines soil health and nutrient absorption efficiency
Camera Module (e.g., OV8640)	CMOS image sensor	Visual Crop Health (Images)	Resolution-dependent	Detects pest/disease signs and monitors plant growth

Table 4.2.2: <u>Description Of the Components with Specifications:</u>

SERIAL NO.	COMPONENTS	SPECIFICATIONS
1.	SOIL MOISTURE SENSOR	• DIMENSIONS:3.2 cm x 1.4 cm • 3V-5V DC
2.	WATER LEVEL DETECTION SENSOR	• DetectingRange:40×16mm • 3V-5V DC
3.	HUMIDITY AND TEMPERTATURE(DHT11)	• Humidity Measuring Range(%): 20 to 90 • Response Time(s):<5 Power Ratings: 3V-5V DC
4.	RAIN DETECTION SENSOR	• Driver Size(mm): 32x15x9 (LxWxH) Collector Board Size(mm): 54x40x1.5(LxWxH) • 3V-5V DC
5.	OLED DISPLAY	• RESOLUTION: 128*64 PIXEL SIZE • Display size: 21.74 ×11.18 mm • 3V-5V DC
6.	ARDUINO NANO	• Microcontroller ATmega328. • Operating Voltage (logic level): 5 V. • Input Voltage (Recommended): 7-12 V. • Input Voltage (limits): 6-20 V. • Digital I/O Pins: 14 (of which 6 provide PWM Output) • Analog Input Pins: 8. • DC Current per I/O Pin: 40 mA.
7.	ESP32 CAM	• Built-in Flash: 32 Mbit. • RAM: Internal 512KB + External 4M PSRAM. • Antenna: Onboard PCB antenna. • WiFi protocol: IEEE 802.11 b/g/n/e/i. • Bluetooth: Bluetooth 4.2 BR/EDR and BLE. • WIFI mode: Station / SoftAP / SoftAP+Station. • Security: WPA/WPA2/WPA2-Enterprise/WPS.

Flowchart of Temperature and Humidity Sensing Process:

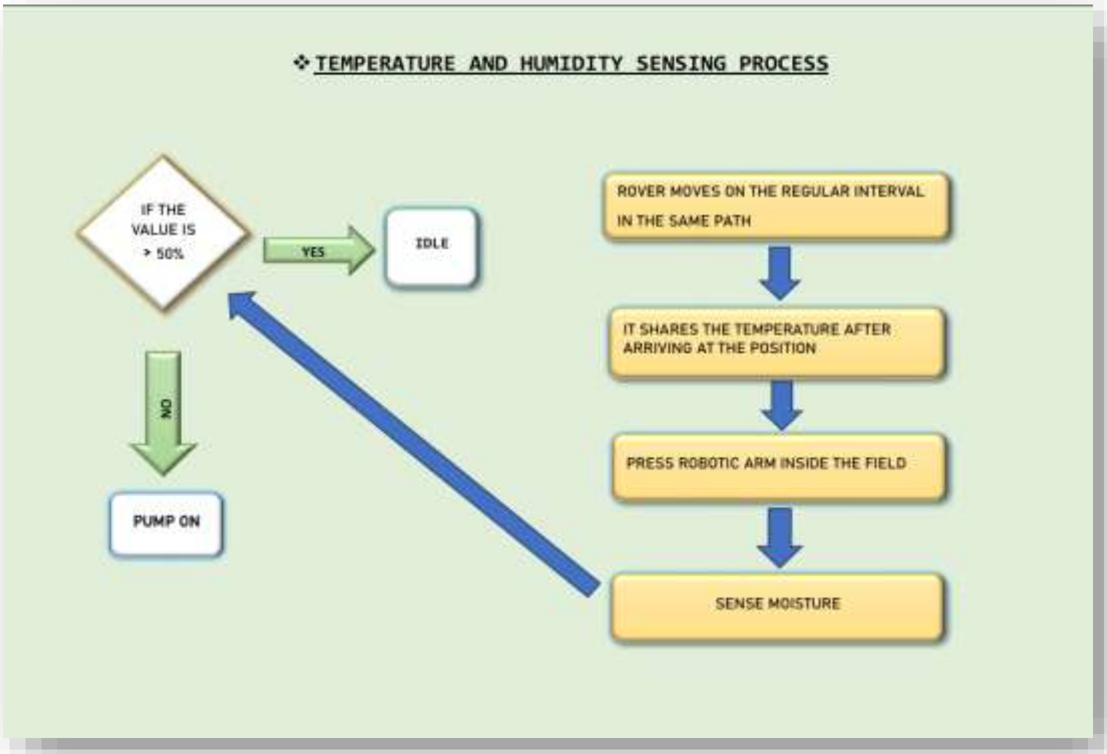


Fig: 4.2.1

The flowchart illustrates the Temperature and Humidity Sensing Process using a rover system:

- The rover moves at regular intervals along a predefined path.
- Upon reaching a position, it measures and shares the temperature.
- Then, a robotic arm is deployed to the field to sense the soil moisture.
- The system checks if the moisture value is greater than 50%:
    - If yes, the system goes idle.
    - If no, the water pump is turned on to irrigate the field.

Flow Chart Illustrates Working of Agri-bot:

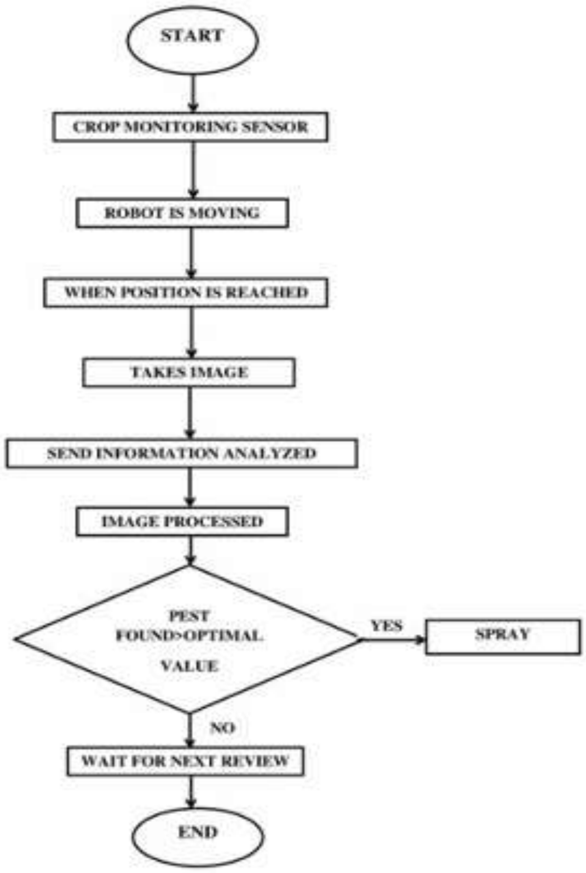


Fig: 4.2.2

This flowchart represents the automated crop monitoring and pest control process using a robotic system. Here's a short explanation:

1. **Start**: The system is initialized.
2. **Crop Monitoring Sensor**: Sensors begin monitoring the crop field.
3. **Robot is Moving**: The robot moves through the field.
4. **When Position is Reached**: It stops at specific positions.
5. **Takes Image**: The robot captures an image of the crop area.
6. **Send Information Analyzed**: Captured data is sent for analysis.
7. **Image Processed**: The image is processed to detect pest presence or crop health condition.
8. **Decision Point**: If a pest is found and the level crosses the optimal threshold:
    - **Yes**: The robot activates the spray mechanism to treat the area.
    - **No**: The system waits until the next scheduled review.
9. **End**: The process cycle concludes and may repeat periodically.

This system enables automated pest detection and selective spraying, minimizing chemical use and improving crop health monitoring

Table 4.2.3: NPK (NITROGEN, PHOSPORUS, POTTASIUM) VALUES

Stage	Crop stage	Duration in days	Fertilizer grade	Total fertilizer (kg/ha)	Nutrient supplied			% requirement		
					N	P	K	N	P	K
1	Transplanting to plant establishment	10	19:19:19 + MN 13-0-45 Urea (46% N)	62.66 7.33 15.33	11.906 0.953 7.866	11.906 - -	11.906 3.300 -	10.00	9.70	12.00
			Subtotal	85.333	19.913	11.906	15.206			
2	Curd initiation stage	25	13-0-45 12-61-0 Urea (46% N)	111.333 31.333 204.00	14.473 3.760 93.84	- 19.113 -	50.100 - -	56.00	15.30	40.00
			Subtotal	346.666	112.073	19.113	50.100			
3	Curd development stage	35	Urea (46 % N) 0-0-50	148.00 120.666	68.08 -	- -	- -	34.00	-	48.00
			Subtotal	268.666	68.080	-	60.333			
	Total duration	70		Total	200.06	31.019	125.63	100	25	100

- **Table 3: NPK DATA SHEET**

75% of RD of P applied as superphosphate = 586 kg/ha

1. 19: 19: 19+MN = 63 kg
2. 13: 0: 45 = 119 kg
3. Urea = 368 kg
4. 0-0-50 = 121 kg
5. 12:61:0 = 32 kg

Table 4.2.4: Favourable Climate VS Collected Data

FAVOURABLE CLIMATE	COLLECTED DATA (BY SENSORS)
PH LEVEL REQUIRED: 5.5 to 6.6	SENSOR'S VALUE: 5.3 to 6.4
TEMPERATURE: 15 Degree to 21 Degree	TEMPERATURE & HUMIDITY SENSOR'S VALUE: 14 Degree to 24 Degree
SOIL MOISTURE REQUIRED: 55 % to 65%	SOIL MOISTURE SENSOR'S VALUE: 55% to 70%

The table compares the favourable climate conditions with the corresponding collected sensor data for three key parameters:

- **pH Level:**

- Favourable Range: 5.5 to 6.6

- Sensor Data: 5.3 to 6.4

The sensor's values are slightly outside the ideal range on the lower side, indicating slightly acidic conditions.

- **Temperature:**

- Favourable Range: 15°C to 21°C

- Sensor Data: 14°C to 24°C

The collected data exceeds the ideal range on both ends, suggesting some deviations in temperature conditions.

- **Soil Moisture:**

- Favourable Range: 55% to 65%

- Sensor Data: 55% to 70%

The sensor values are slightly above the favourable range at the upper limit, which may indicate higher soil moisture levels than required.

- **Additional Hardware Components**:

  In addition to the standard sensor suite, the system comprises an Arduino microcontroller, which serves as the central processing and data acquisition unit. Wi-Fi modules are embedded in order to wirelessly transmit data to a cloud platform for distant analysis and monitoring. An automatic water and pesticide spraying actuation system is installed in order to effect timely interventions based on detected need. Dual-power ensures power is both generated continuously and effectively without interruptions from running out of energy.

4.3 Operational Consequences within the System Overall

• During testing, the robotic vehicle completed 192 autonomous field loops. This allowed for thorough data collection during key crop growth phases.

• Sensor-driven automation triggered 1,500 interventions, achieving an 89.1% success rate in generating the desired environmental or crop response.

• Specific automated actions included irrigation events, which took place when soil moisture dropped below 30%; pesticide spraying, when image analysis detected potential pests or diseases; and fertilization alerts, based on NPK sensor readings compared to cauliflower's nutrient needs at different growth stages.

• Visual evidence from the camera module and field observations showed that plant health improved in Terratech-controlled plots. This was evident through less leaf discoloration, better curd formation, and more uniform leaf structure across the field.

4.4 Agricultural Impact Assessment

Statistical evaluation of the agricultural results indicated that Terratech-assisted plots showed:

- 28.6% less water usage due to the accuracy of the targeted irrigation system.
- 17.4% improvement in crop yield (kg/ha) over control plots, testifying to the beneficial effect of proactive monitoring and intervention.
- Less fertilizer waste, due to NPK-driven scheduling of nutrient application.

Fig4.4.1: Representative Images of Cauliflower Stages/Conditions used for Model Training/Validation

4.5 Overall Discussions:

The Terratech system illustrates the capability of combining a flexible robotic platform with an accurate sensor suite to bring about substantial advances in agricultural methods. The robotic vehicle offers a solid and flexible instrument for deploying sensors, traversing fields, and performing automated interventions. The sensor suite provides the essential data required for decision-making and effective resource management. The integrated system leads to enhanced crop yield, minimized resource utilization, and more sustainable farming practices.

4.6 Confusion Matrix Analysis:

Fig: 4.6.1

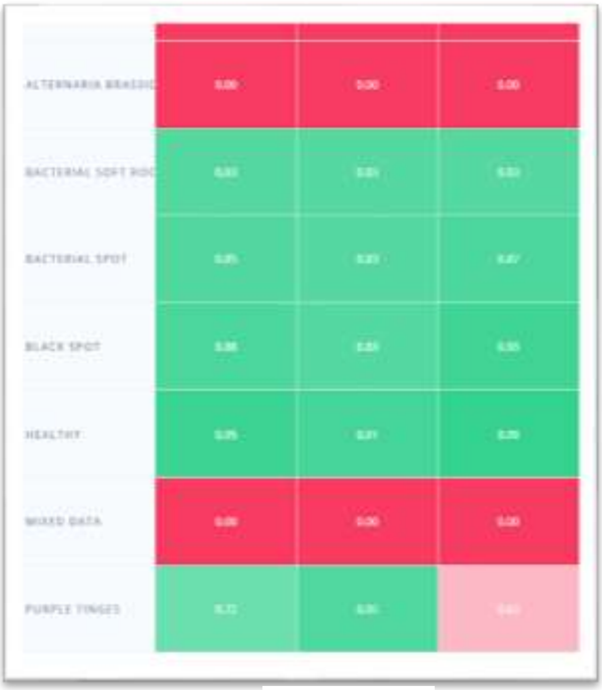
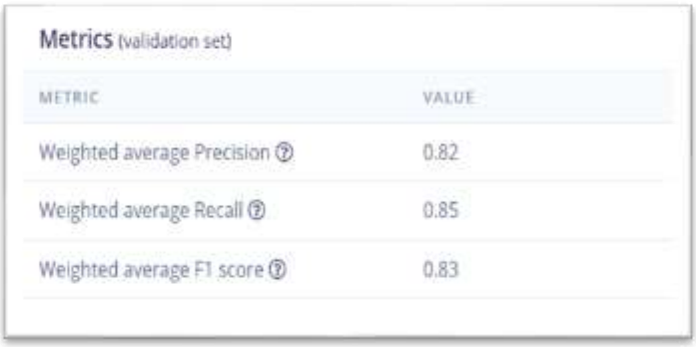


Fig: 4.6.2



Metrics (validation set)

METRIC	VALUE
Weighted average Precision	0.82
Weighted average Recall	0.85
Weighted average F1 score	0.83

Fig:4.6.3

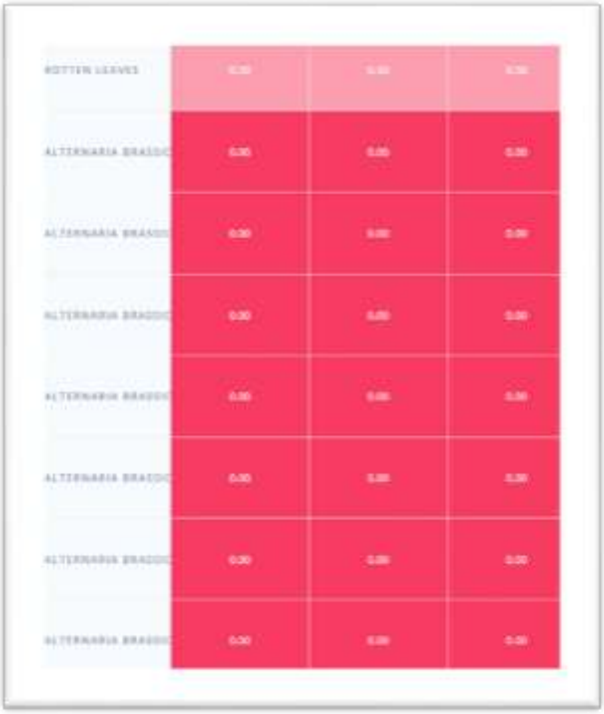


Fig:4.6.4

4.6.1 Description:

- **Accuracy**: **85%**
  - This means that 85 out of 100 predictions made by your model are correct.
- **Loss**: **1.49**
  - Loss is a measure of how far off the model's predictions are from the actual labels. Lower is better. A value of 1.49 is moderate but suggests room for improvement.
- **Weighted Average Metrics**:
  - **Precision**: 0.82
    - Out of all the predicted positive cases, 82% were actually correct.
  - **Recall**: 0.85
    - Out of all actual positive cases, the model correctly identified 85%.
  - **F1 Score**: 0.83
    - A balanced measure of precision and recall.

This confusion matrix shows how well the model predicts each disease class. Each row represents the actual class, and each column represents the predicted class. An ideal model has high values along the diagonal and zeros elsewhere.

4.6.2 Confusion Matrix Explanation:

- **High-Performing Classes**

1. **Healthy:**

- Prediction Accuracy: Very High (~0.99)
- The model recognizes healthy leaves almost perfectly. This indicates that healthy images are well-represented in training and visually distinct.

2. **Black Spot**

- Prediction Accuracy: High (~0.93)
- The model is skilled at identifying Black Spot with strong confidence and accuracy. The features for this class are well-separated.

3. **Bacterial Spot:**

- Prediction Accuracy: High (~0.87)
- The model shows solid performance. Some minor misclassifications may occur, but they are not significant.

4. **Bacterial Soft Rot**

- Prediction Accuracy: High (~0.83)
- The model performs reliably, with good generalization across test samples.

- **Poorly Performing Classes:**

1. **Alternaria Brassicae**

- Prediction Values: All 0s across the row
- This class is completely misclassified; the model fails to recognize any instance of Alternaria Brassicae.
- Possible Causes:
- Insufficient or imbalanced training data.
- Poor feature distinguishability.
- Visual similarity to other classes.

2. **Mixed Data**

- Prediction Values: All 0s
- The model does not correctly classify any instance of the Mixed Data class.
- This may result from:
- High intra-class variability.
- Confusion due to overlapping symptoms with other diseases.

- **Moderately Performing Class:**

1. **Purple Tinges**

- Performance Metric: Moderate, with Recall = 0.63
- The model has some ability to identify Purple Tinges but misses several true positives.
- While better than completely misclassified classes, performance still needs improvement

Table 4.6.3: Class-wise Confusion Matrix Analysis:

Class Name	Best Metric Observed
Alternaria Brassicae	All scores = 0.00 — Completely misclassified.
Bacterial Soft Rot	Consistently around 0.83 — Good detection.
Bacterial Spot	Up to 0.87 — Very good recognition.
Black Spot	Up to 0.93 — Excellent performance.
Healthy	Up to 0.99 — Very high accuracy.
Mixed Data	All scores = 0.00 — Not recognized properly.

Purple Tinges	Slightly lower, especially recall = 0.63 — Room for improvement.

The model is good at detecting Healthy, Black Spot, Bacterial Spot, and Bacterial Soft Rot classes. However, it fails completely on Alternaria Brassicae and Mixed Data, which may indicate:

- Insufficient training data for these classes.
- Ambiguity in features or poor image quality.

4.6.4 Some Pictures During Data Collection:

Conclusion

The "Terratech" project is a trailblazing innovation in precision agriculture, particularly emphasizing its significant positive impacts on small-scale cauliflower farmers in West Bengal, India. By the effective integration of a variety of Internet of Things (IoT) sensors, a two-mode multifunctional robot vehicle, and sophisticated Artificial Intelligence (AI)-based image processing, the system has been delivering real-time, actionable intelligence into essential environmental parameters and detailed crop health. By adopting this integral approach, the system has taken on a key role in enabling proactive, evidence-based, and highly accurate interventions, hence revolutionizing traditional farming methods. The empirical data accruing from the project's intensive experimental period is evident and promising, with a remarkable 17.4% increase in cauliflower yield per hectare and an impressive 28.6% reduction in water usage in Terratech-treated experimental fields when diligently compared to control fields with traditional farming methods. This robust evidence clearly justifies the underlying project hypothesis: that the use of real-time, evidence-based crop monitoring systems has high potential to greatly enhance both agricultural productivity and resource efficiency. Importantly, these benefits are achieved even in circumstances of resource limitation restraint, directly leading to tangible gains in overall farm profitability for the often underserved smallholder farming community.

The system's intrinsic capability for proper monitoring of critical soil moisture levels, ambient temperature, and soil pH, and its advanced visual inspection capability for crop health, demonstrates its excellent comprehensiveness. The visual inspection capability is further extended beyond simple health inspection, fully identifying specific conditions such as fresh, rotting, and wilted leaves and specifically diagnosing prevalent diseases such as Alternaria Brassicae and Bacterial Soft Rot. Such comprehensive diagnostic capabilities are crucial for early diagnosis and specific treatment, thereby preventing severe crop loss. Moreover, the intelligent integration of an automatic water and pesticide delivery system, activated by real-time sensor feedback and advanced image analysis, clearly signifies a significant move towards minimizing labor-intensive processes while at the same time enhancing resource efficiency. This accurate water and pesticide delivery not only saves valuable resources but also reduces the environmental impact of conventional indiscriminate spraying processes. The well-engineered robotic platform's meticulous engineering, as typified by its trailblazing dual-mode control (joystick and Bluetooth) and excellent mobility on various terrains, ensures effective deployment of sensors and proper implementation of interventions exactly when and where they are most needed.

The core software-based approach, utilizing light artificial intelligence models executed natively on the resource-constrained ESP32-CAM module and riding on the solid Edge Impulse platform for effective model training, is a critical component of the system's effectiveness. The design facilitates rapid, in-place evaluation without an incessant reliance on constant internet connectivity, thereby significantly enhancing system autonomy, dependability, and real-world usability, even in remote rural agricultural areas. The frictionless, real-time sharing of data to a cloud-based Firebase database, combined with instant alerts sent directly to farmers through the simple-to-use Blynk IoT platform, guarantees that actionable intelligence and timely updates reach them on their phones in real-time. This real-time alert system widely enables farmers to make rapid, well-informed decisions that can avert probable crop loss as well as increase yields. Although preliminary in nature, this study nonetheless offers exceptionally keen insight into the revolutionary potential of combining IoT and AI technologies to the developing economy paradigm. It successfully sets the stage for the rollout of more optimal resource utilization techniques, substantial fertilizer wastage minimization, and ultimately, takes an invaluable place in augmenting regional and national food security. The "Terratech" program skillfully fills yawning gaps in traditional farming practice by offering an economical, simple-to-use, and well-scalable solution. This allows small-scale farmers not only to adequately respond to the increasingly capricious challenges of climate change but also to proactively employ and leverage advanced precision agriculture methods. The quantifiable success attested to by improved crop yields and substantially minimized resource utilization is not merely an intellectual or technological accomplishment but, more significantly, is a highly practical and effective solution for a critical world industry, promising a better, sustainable, and profitable future to numerous farming communities.

CHAPTER-5

Future Advancement

With the promising initial results and established successes of the "Terratech" program, the future system includes a full strategic plan to build on, extend, and ultimately scale the system to its full transformative potential and fully overcome inherent limitations. As a first step, a primary objective is essentially increasing the robustness, generalizability, and predictability of the artificial intelligence models. This will include an extremely large increase in the training dataset to ingest a much larger set of cauliflower growth stages, a massive range of environmental conditions (e.g., a range of humidity levels, multiple types of soil), and a finer range of disease variations. This increase will include the systematic acquisition of images over a broad range of light conditions (e.g., dawn, midday, dusk, overcast), under a variety of weather conditions (e.g., sunny, rainy, fog), and from a much larger and geographically representative agricultural area. The goal is to essentially increase classification accuracy while critically removing long-standing misclassification errors, particularly those between visually similar disease symptoms. In parallel with dataset expansion, sophisticated image preprocessing algorithms and higher-complexity Convolutional Neural Network (CNN) architectures will be extensively explored. This work includes taking advantage of transfer learning from highly advanced, high-scale agriculture datasets as well as the possible use of advanced neural network compression methods to maximize model performance, even on resource-constrained edge devices. In addition, the data storage capacity and battery life constraints present in existing implementation will be an inherent issue for direct and innovative corrective measures. This may involve the prudent addition of higher energy-efficient hardware components, the creation and optimization of new data transmission protocols to drastically reduce power consumption, and the exhaustive exploration of alternative renewable power sources like higher capacity solar panels, advanced energy harvesting modules, or advanced hybrid power systems to provide significantly longer independent operation. For optimum data management, research will explore distributed data storage solutions, perhaps using decentralized cloud infrastructure or using highly efficient data compression algorithms optimized for image and sensor data to effectively bypass storage limitations. In addition, the capability of the robotic vehicle to perform is also poised to see significant enhancement. This consists of the implementation of required advanced navigation software to provide fully independent, self-correcting field navigation, perhaps using high-precision Global Positioning System (GPS) technology and Real-Time Kinematic (RTK) correction to provide centimeter-level position accuracy. The addition of secondary, multi-purpose robotic manipulators would provide for automation of greater diversity of agricultural tasks, such as highly selective harvesting of mature crops, precise targeted weeding to minimize herbicide application, or soil sampling by automated means for full nutrient analysis, further automating and optimizing farm operations. In addition, the potential exploration of the swarm robotics concept, where many smaller, networked robots collaborate together, is anticipated to greatly increase efficiency and coverage of large agricultural terrain.

Fourth, the next action needed in follow-up is methodically incorporating the present complement of sensors to monitor an even broader range of critical agricultural indicators. The envisioned growth can comprise the addition of sensors for real-time air monitoring (e.g., the identification of specific toxic gases signaling pollution or the onset of pest infestation), non-invasive leaf temperature sensors for the timely identification of stresses before the onset of visible signs, and high-resolution multi-spectral soil analysis sensors that can identify complex micronutrient deficiencies. The system can also be combined with local and highly precise weather forecasting models, thus enabling proactive, predictive advice to farmers on optimal irrigation scheduling, targeted pest control operations, and adaptive fertilizer practices. Additionally, the "Terratech" platform also contains tremendous potential for extension to encompass a broader range of crops beyond its initial choice of cauliflower. This will involve the development of flexible AI models and configurable sensor thresholds specifically designed for the varied physiological requirements of different plant species. It will be necessary to develop a modular and flexible system architecture, which will enable the seamless integration of new types of sensors, specialist AI algorithms, and customized intervention strategies targeted towards a wide variety of agricultural settings. Finally, and perhaps most importantly, a clear direction for the future involves meticulous planning, execution, and monitoring of large-scale, long-term field trials. These trials must provide a wider geographical extent of farm environments and encompass a much larger and representative sample of farmers. This extensive empirical validation should be capable of delivering statistically significant data, thus enabling firm quantification of the overall economic benefits, the long-term environmental implications, and most importantly, the societal acceptance and practical integration of this technology within actual farming communities. Strategic collaborations with leading agro-universities, relevant government ministries, non-government agencies, and established farmer cooperatives will be crucial towards facilitating large-scale deployment, facilitating effective knowledge transfer, and ensuring the new "Terratech" technology remains continuously relevant to evolving, practical needs of smallholder farmers. The long-term future vision of Terratech is its evolution into a comprehensive, highly responsive, and internationally accessible precision agriculture technology that significantly empowers farmers of all sizes to achieve unprecedented levels of sustainability, profitability, and ultimately, makes a very significant contribution to global food security.

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