ABSTRACT

Agriculture remains the foundation of human survival and the global economy, providing essential food resources and employment. However, it continues to face serious challenges from pest infestations, which significantly reduce crop yield, quality, and farmer income. Traditional pest detection methods depend on manual observation, which is slow, error-prone, and inefficient. To overcome these challenges, this project introduces an AI-Based Smart Pest Detection and Advisory System that integrates Artificial Intelligence (AI), the Internet of Things (IoT), and Robotics to deliver a modern, efficient, and sustainable solution for pest monitoring.

The system features an autonomous rover powered by a Raspberry Pi 4 and Arduino Uno, equipped with a high-resolution auto-shutter camera and multiple sensors including DHT22, LDR, HC-SR04, MAX4466 bio-acoustic mic, and NEO-6M GPS module. The rover autonomously navigates the crop field, captures high-quality images, and records environmental parameters. Through IoT connectivity, the data is transmitted to a cloud-based platform, where an AI detection model (YOLOv11) processes the images to accurately identify and classify pest species. Based on the detection results, the web dashboard provides farmers with appropriate organic and non-organic pesticide recommendations, along with detailed pest information.

This integrated system promotes precision agriculture, reduces chemical misuse, and minimizes environmental damage while saving farmers time and labor. By combining AI-driven image analysis, IoT-based real-time monitoring, and robotic automation, the project provides an intelligent, scalable, and eco-friendly approach to pest management. It empowers farmers with data-driven insights for timely decision-making, thus fostering sustainable agriculture and improving overall crop productivity.

Keywords:

AI, IoT, Robotics, Raspberry Pi, Smart Pest Detection, YOLOv11, Cloud Computing, Precision Agriculture, Organic Pesticides, Sustainable Farming.

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CHAPTER - 1

INTRODUCTION

Agriculture forms the backbone of human civilization, providing food, raw materials, and livelihood to a large portion of the global population. However, agricultural productivity is continually threatened by pest infestations, which are among the most significant causes of crop loss worldwide. Pests damage crops at various growth stages, leading to reduced yield, poor quality produce, and severe economic losses. Traditional pest detection and management practices rely heavily on manual observation and the widespread use of chemical pesticides. These approaches are often inefficient, time-consuming, and environmentally unsustainable, as they contribute to soil degradation and loss of beneficial organisms.

With the advancement of technology, the integration of Artificial Intelligence (AI), Internet of Things (IoT), and Robotics has opened new avenues for smart and sustainable agriculture. Modern precision farming techniques enable farmers to monitor field conditions, detect pests early, and apply targeted treatments with minimal resource wastage. Among these innovations, AI-based pest detection systems play a critical role by automating the identification of pest species through image and sensor data analysis, helping farmers make informed decisions and preserve ecological balance.

The proposed project, AI-Based Smart Pest Detection and Advisory Rover, aims to revolutionize pest management through intelligent automation and real-time advisory support. The system employs a mobile robotic rover equipped with multiple sensors, including a high-resolution camera, DHT22 temperature and humidity sensor, LDR for light intensity measurement, GPS for location tracking, ultrasonic sensors for obstacle avoidance, and a bio-acoustic microphone for sound-based pest detection. A Raspberry Pi 4 serves as the central controller, managing sensor data acquisition and communication. Captured crop images and environmental parameters are transmitted to the cloud via IoT modules, where an AI-based deep learning model (YOLOv11) processes and classifies pest species with high accuracy.

Once pests are identified, the system provides the farmer with suitable organic and non-organic pesticide recommendations through a web dashboard or mobile interface. This ensures eco-friendly pest control, minimizes chemical overuse, and supports precision agriculture and sustainable farming practices. By combining AI analytics, IoT communication, and robotic mobility, the system empowers farmers to protect crops efficiently and enhance agricultural productivity.

CHAPTER – 2

EXISTING SYSTEM

2.1 LITERATURE REVIEW

S. No.	TITLE OF PAPER	AUTHORS	YEAR	PUBLISHER/ SOURCE	Key Highlights / Findings
1.	Advancing Crop Health with YOLOv11 Classification of Plant Diseases	E.H.I. Eliwa, T. Abd El-Hafeez	2025	Springer – Neural Computing and Applications	Introduces YOLOv11 for classifying 37 pest species and 8 crop diseases with high precision; emphasizes agricultural sustainability and food security.
2.	YOLOv11-RCDWD: A New Efficient Model for Detecting Maize Leaf Diseases Based on Improved YOLOv11	J. He, Y. Ren, W. Li, W. Fu	2025	MDPI – Applied Sciences	Proposes an optimized YOLOv11 architecture for maize leaf disease detection, achieving higher efficiency and accuracy in smart agriculture applications.
3.	Multiclass Weed and Crop Detection Using Optimized YOLO Models on Edge Devices UAV Detection and Tracking in	A. Upadhyay, G.C. Sunil, S.	2025	Elsevier – Journal of	Employs YOLOv11n and YOLO11 models for identifying multiple crop and weed

	Challenging Aerial Environments Using YOLOv11	Das, J. Mettler		Agricultural Informatics	species, enabling intelligent mechanical and smart spraying systems.
4.	UAV Detection and Tracking in Challenging Aerial Environments Using YOLOv11	S.M. Almuhannadi	2025	ProQuest Database	Evaluates YOLOv11 for drone-based detection and tracking, demonstrating robustness in aerial image analysis and object tracking accuracy.
5.	RDW-YOLO: A Deep Learning Framework for Scalable Agricultural Pest Monitoring and Control	J. Song, K. Cheng, F. Chen, X. Hua	2025	MDPI – Insects Journal	Develops a pest detection model based on the YOLOv11 framework for scalable agricultural pest monitoring and intelligent pest management.

2.2 LIMITATIONS OF THE EXISTING SYSTEM

Although several advanced studies have utilized YOLOv11 and other deep learning models for pest and disease detection, most of the existing systems remain limited to controlled laboratory or dataset environments rather than real-world field deployment. Research by Eliwa et al. (2025) and He et al. (2025) demonstrates high detection accuracy for crop diseases and pests but lacks integration with IoT-based real-time data acquisition and autonomous field mobility.

Furthermore, existing models primarily focus on image-based pest detection, ignoring other critical environmental parameters such as temperature, humidity, and light intensity, which significantly influence pest activity. Systems like RDW-YOLO (Song et al., 2025) and YOLOv11-RCDWD (He et al., 2025) provide valuable algorithmic improvements but are not coupled with field-deployable hardware for continuous monitoring.

Another limitation is the absence of automated farmer advisory systems. Most studies stop at detection and do not provide contextual recommendations for pesticide selection or pest management strategies. Additionally, few works address resource constraints, such as low-power operation and network connectivity challenges, which are crucial for rural agricultural environments.

Hence, despite promising detection accuracy, the existing systems lack the end-to-end integration of sensing, processing, communication, and decision-support that real-world precision agriculture demands.

2.3 UNIQUENESS OF THE PROPOSED PROJECT

The AI-Based Smart Pest Detection and Advisory Rover introduces several unique innovations that bridge the gaps found in existing systems. Unlike prior research limited to stationary or dataset-based detection, this project integrates AI, IoT, and Robotics into a single autonomous platform capable of real-time field operation.

The system uses a mobile rover equipped with a high-resolution camera and multi-sensor array (DHT22, LDR, GPS, ultrasonic, and bio-acoustic mic) to capture both visual and environmental data directly from the crop field. This multi-modal data is transmitted via IoT to a cloud-based YOLOv11 model for pest identification, ensuring high accuracy and adaptability to various crop conditions.

A major novelty lies in the web-based advisory dashboard, which provides farmers with organic and non-organic pesticide recommendations based on pest species and infestation severity. This end-to-end automation — from detection to decision support — makes the system both smart and actionable.

Additionally, the project emphasizes sustainability and eco-friendliness by promoting targeted pest control, minimizing pesticide misuse, and protecting beneficial insects. Its modular hardware design and scalable architecture make it suitable for deployment across different crop types and field conditions, ensuring both scientific innovation and practical applicability.

CHAPTER – 3
PROPOSED SYSTEM

3.1 SYSTEM OVERVIEW

The proposed system, titled Smart pest detection and instent remedial system using YOLOv11 algorithm for sustainable crop production, is designed to revolutionize agricultural pest management through the integration of Artificial Intelligence, Internet of Things, and Robotics. The system aims to automate the process of pest detection, analysis, and pesticide recommendation, providing farmers with real-time, data-driven insights for effective and sustainable pest control.

At the core of the system is an autonomous rover equipped with a Raspberry Pi 4 as the main processing unit and an Arduino Uno for motor and sensor control. The rover is fitted with a high-resolution auto-shutter camera that captures real-time images of crops. Alongside, several sensors — including DHT22 (temperature and humidity), LDR (light intensity), GPS module (location tracking), ultrasonic sensors (obstacle avoidance), and MAX4466 mic module (bio-acoustic pest detection) — gather environmental data.

Captured images and sensor readings are transmitted to a cloud-based platform using IoT communication modules. The cloud platform hosts a YOLOv11 deep learning model, which performs object detection to identify pests from the received images. Once a pest is identified, the system cross-references the pest data with a knowledge base and provides organic and non-organic pesticide recommendations through a web dashboard. The dashboard serves as a decision-support tool, giving farmers clear insights into pest type, density, and control methods.

This integrated system bridges the gap between field-level pest monitoring and AI-driven analytics, offering a complete solution that minimizes manual labor, reduces chemical misuse, and enhances productivity in precision agriculture.

3.2 OBJECTIVES

The main objectives of this project are as follows:

1. Develop an autonomous rover equipped with a camera and sensor suite capable of field navigation and environmental data collection.
2. Implement IoT-based real-time communication between the rover and cloud server for seamless data transfer and monitoring.
3. Integrate AI (YOLOv11) for pest detection, classification, and analysis using image data captured by the rover.

4. Provide smart advisory support through a web-based dashboard recommending both organic and non-organic pesticides based on pest species and infestation severity.
5. Promote sustainable agriculture by reducing the excessive use of harmful pesticides and encouraging data-driven pest management.
6. Enhance system scalability and usability, allowing it to adapt to various crops, terrains, and pest types.

3.3 PROBLEM DEFINITION

Pest infestation remains one of the leading causes of crop loss and productivity decline in agriculture. Traditional methods for pest identification rely on manual observation, which is time-consuming, error-prone, and non-scalable. Additionally, the use of broad-spectrum chemical pesticides without accurate pest identification leads to environmental pollution, pesticide resistance, and destruction of beneficial insects.

Existing research in AI-based pest detection focuses primarily on image classification models but lacks a field-deployable, integrated hardware system that can operate autonomously in real agricultural environments. There is also an absence of IoT-enabled advisory mechanisms that can suggest specific pesticide treatments in real time.

Therefore, the problem addressed by this project is:

"To design and implement an AI-based and IoT-based autonomous rover system capable of real-time pest detection and providing intelligent pesticide recommendations to support precision and sustainable agriculture."

This system directly addresses the shortcomings of existing manual and semi-automated pest detection methods by combining robotic automation, AI-driven detection, and IoT-based communication into a cohesive and scalable solution.

CHAPTER 4
SYSTEM WORKFLOW & METHODOLOGY

4.1 SYSTEM ARCHITECTURE OVERVIEW

The AI-Based Smart Pest Detection and Advisory Rover is designed as a multi-layered intelligent system integrating IoT, AI, and robotics. The system operates through four primary stages — data acquisition, communication, processing, and user interaction.

The rover, equipped with multiple sensors and a high-resolution camera, autonomously navigates through crop fields and captures environmental and visual data. This raw data is transmitted to the cloud via IoT modules, where the YOLOv11 deep learning model processes the images to identify pests.

The processed results are then made accessible on the web dashboard, allowing farmers to view pest types, infection severity, and suggested control methods in real time.

The architecture emphasizes modularity, scalability, and automation, ensuring smooth data flow between hardware, cloud, and user interface components.

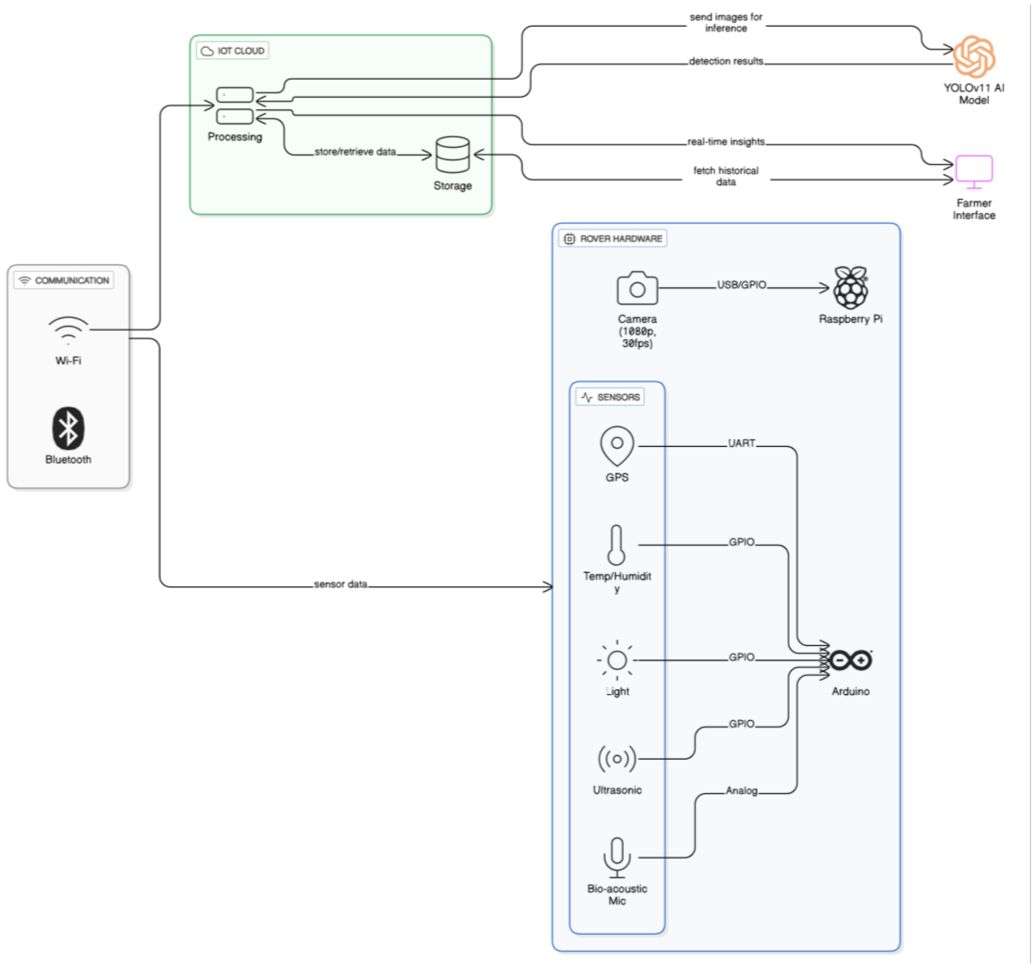

Figure 4.1: System Architecture of AI-Based Smart Pest Detection and Advisory Rover.

4.2 SYSTEM ARCHITECTURE DESCRIPTION

The system comprises four main components, each performing specific functions:

1. Rover Hardware Layer:

The rover includes a Raspberry Pi 4 for image processing and communication, and an Arduino microcontroller for managing sensors such as DHT22 (temperature & humidity), LDR (light intensity), GPS (location), ultrasonic (obstacle avoidance), and a bio-acoustic microphone (sound-based pest detection).

The camera (1080p, 30 fps) captures high-quality images of crops. The rover uses Wi-Fi/Bluetooth for data transmission to the IoT cloud and can operate autonomously within the field.

2. IoT Cloud Layer:

The IoT cloud handles data reception, temporary storage, and transmission to the AI model for analysis. It manages real-time communication and ensures that environmental data and images are securely stored in a cloud database for future retrieval and training updates.

3. AI Processing Layer:

At this stage, the YOLOv11 object detection algorithm identifies and classifies pests from the transmitted crop images. It provides pest name, confidence score, and image location of infestation. This processed output is forwarded to the web dashboard for user interpretation.

4. Web Dashboard/User Interface Layer:

The dashboard displays pest detection results, environmental readings, and recommended pest control measures. It allows farmers to choose between organic and non-organic remedies, monitor field health, and provide feedback for adaptive learning.

4.3 WORKFLOW OF THE SYSTEM

The system workflow follows a sequential and feedback-driven approach:

1. **Data Acquisition:**

   The rover captures images and sensor readings as it moves through the crop field.

2. **Data Transmission:**

   Collected data is sent to the IoT cloud through Wi-Fi or Bluetooth modules.

3. **AI Processing:**

   The YOLOv11 model in the cloud analyzes the images, identifies pests, and classifies them based on trained datasets.

4. **Result Generation:**

   Detection results, including pest name and severity, are stored in the cloud database.

5. **User Interaction:**

   The farmer accesses real-time results via the web dashboard. Recommended control measures (organic and non-organic) are displayed.

6. **Feedback Mechanism:**

   The farmer's feedback helps in continuous improvement of the model through adaptive learning.

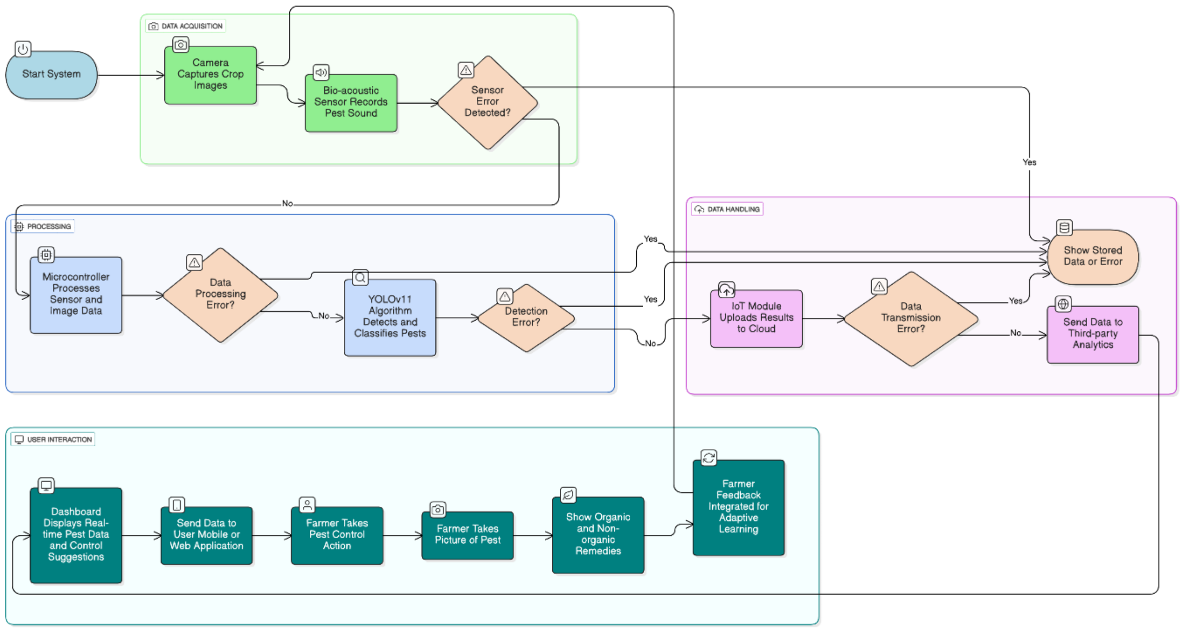

Figure 4.2: Architecture of the Smart Pest Detection and Monitoring System

4.4 Advantages of the Workflow

The designed workflow offers several technical and practical advantages:

- **Automation:** Eliminates manual pest scouting through autonomous rover operation.
- **Accuracy:** YOLOv11 ensures high-precision pest classification and identification.
- **Real-time Monitoring:** Farmers receive immediate updates on pest occurrences.
- **Environmental Sustainability:** Reduces pesticide misuse by suggesting targeted remedies.
- **Scalability:** The modular IoT architecture allows expansion to larger farms or multiple rovers.
- **Data-driven Decision Support:** Cloud-based analytics help in predicting pest trends and improving farm management.

CHAPTER – 5
DESIGN & IMPLEMENTATION TECHNIQUES

5.1 Hardware Design

The hardware design of the AI-Based Smart Pest Detection and Advisory Rover focuses on modular integration of sensors, actuators, and processing units. The core components include the Raspberry Pi 4, which acts as the main processing and communication hub, and an Arduino Uno, which manages low-level sensor operations.
The rover is equipped with multiple sensors — DHT22 (temperature and humidity), LDR (light intensity), GPS (location tracking), Ultrasonic sensors (obstacle avoidance), and a Bio-acoustic microphone (sound-based pest activity detection). The camera module (1080p, 30 fps) captures crop images and transmits them to the Raspberry Pi for preprocessing.
Power is supplied via a rechargeable Li-ion battery with solar charging support for field sustainability. Motor driver circuits enable smooth rover movement, and Wi-Fi/Bluetooth modules support IoT communication.
The design ensures that each component operates efficiently within low power constraints and can be easily maintained or replaced.

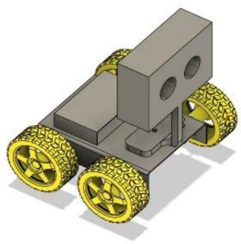

FIGURE 5.1: 3D Model of the Pest Detection Rover

5.2 Software Design

The software architecture integrates **embedded control logic**, **AI-based pest detection**, and **cloud-based IoT communication**.
The Arduino firmware collects raw sensor readings and sends them to the Raspberry Pi using serial communication. The Raspberry Pi runs Python scripts for:

- Sensor data acquisition and logging,

- Image capture and preprocessing,
- Communication with the IoT cloud via MQTT/HTTP, and
- Running the **YOLOv11 AI model** for pest detection.

The web dashboard, developed using **Flask/Django** (backend) and **HTML, CSS, JavaScript** (frontend), retrieves processed data from the cloud and presents pest detection results, environmental metrics, and pesticide recommendations.

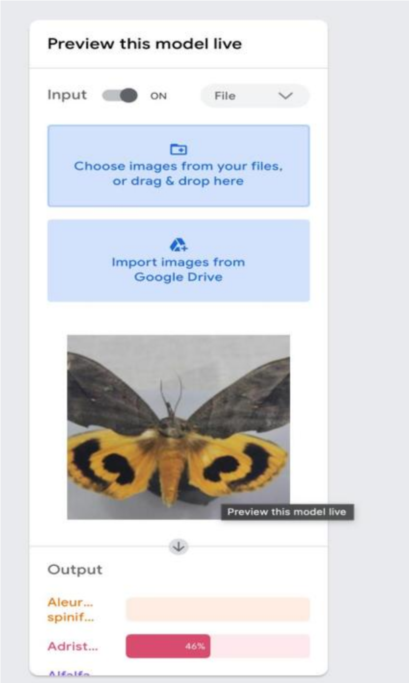

FIGURE 5.2: Live Pest Detection Model Interface Preview

5.3 Integration of Hardware and Software

The integration phase serves as the backbone of the system, bridging the physical components (hardware) and digital intelligence (software). In this stage, seamless communication is established between sensors, the processing unit, the AI detection model, and the user interface. The system operates in real-time, ensuring accurate data flow and coordination across all subsystems.

The Arduino microcontroller is responsible for gathering data from multiple sensors such as temperature (DHT22), humidity, LDR, GPS, and bio-acoustic sensors. This raw data is transmitted via serial communication or IoT protocol (such as MQTT or HTTP) to the Raspberry Pi, which functions as the central processing hub. The Raspberry Pi synchronizes the environmental readings with live image data captured from the high-resolution camera module mounted on the rover.

The YOLOv11 AI model, deployed either locally on the Raspberry Pi or hosted on the cloud server, processes these images to detect and classify pest species. Once detection is completed, the processed data and classification results are uploaded to the IoT Cloud Database, which acts as a central repository for storage and further analysis.

The web dashboard retrieves this information from the cloud and visualizes it in a user-friendly format. It displays pest type, location coordinates, time stamps, and environmental conditions. In case of unusual pest activity, the system can generate automated alerts or notifications to assist farmers in early intervention.

This end-to-end integration ensures that every module—from hardware sensors to AI analytics and the dashboard—operates in perfect synchronization. It results in a fully automated, intelligent pest monitoring network that bridges on-field sensing with real-time decision-making.

5.4 Implementation Techniques

The implementation phase involves programming, testing, and optimizing all system modules.

The AI model was implemented using Python and PyTorch, where the YOLOv11 algorithm was trained on a pest image dataset for accurate detection. The Arduino IDE was used to code sensor operations, while Raspberry Pi scripts managed communication and local processing.

For IoT connectivity, the system uses MQTT or HTTP for cloud uploads. The database stores pest detection logs, and the dashboard retrieves these in real time for farmers. The implementation emphasizes modularity allowing updates or replacements of sensors, models, or interfaces without redesigning the full system.

Key techniques include:

- **Edge AI processing for faster local detection.**
- **Real-time IoT communication for continuous monitoring.**
- **Adaptive learning feedback** from farmers to improve model accuracy.

CHAPTER – 6

MODULE DESCRIPTION

6.1 CAMERA MODULE

The camera module is the primary vision sensor of the system, responsible for capturing high-resolution images or real-time video of crop fields. The module, mounted on the rover, continuously monitors the field area for pest presence. Using the Raspberry Pi Camera Module or USB HD Camera, it collects clear visual data even in variable lighting conditions.

Captured frames are processed either locally or sent to the cloud for AI-based pest detection. The camera supports high frame rate (30–60 fps) and HD resolution (720p–1080p), ensuring accurate detection of small pests and insect activity. Integration with the IoT system allows real-time transmission of image data through Wi-Fi or MQTT protocols.

6.2 SENSOR MODULE

The sensor module acts as the environmental intelligence unit of the system. It consists of multiple sensors that collect contextual data essential for pest behavior analysis:

- **DHT22 Sensor** – Measures temperature and humidity.
- **LDR Sensor** – Detects light intensity and helps adjust camera exposure.
- **GPS Module** – Tracks the exact location of pest detections.
- **Bio-Acoustic Sensor (Microphone)** – Captures wingbeat frequencies of flying pests.

All sensors are connected to the Arduino microcontroller, which preprocesses the signals and sends them to the Raspberry Pi for synchronization with image data. This fusion of sensory and visual data improves pest identification accuracy and environmental mapping.

6.3 AI DETECTION MODULE (YOLOV11)

The AI Detection Module is the brain of the system. It utilizes the **YOLOv11** deep learning model for real-time pest recognition and classification. The model is trained on a diverse dataset of pest images to identify species such as aphids, beetles, caterpillars, and locusts.

When an image is received from the camera, YOLOv11 processes it using convolutional neural networks (CNNs) to detect pests with bounding boxes and confidence scores. The results are either displayed on the dashboard or stored in the IoT Cloud. This AI-driven approach eliminates manual observation and ensures fast, accurate detection under real-world conditions.

6.4 IOT AND CLOUD MODULE

The IoT and Cloud module ensures real-time communication, data storage, and analytics. Data from the rover (sensor readings, images, and pest detections) is transmitted to the IoT Cloud Platform using Wi-Fi or LoRa protocols. Platforms like ThingSpeak, Firebase, or AWS IoT Core can be used for data management.

The cloud acts as both a data repository and processing hub, enabling remote access, scalability, and secure storage. It also facilitates bidirectional communication — the cloud can send control commands to the rover if needed. Additionally, the cloud hosts the database and supports dashboard visualization through an API or web server.

6.5 DASHBOARD AND WEB INTERFACE MODULE

The dashboard serves as the user interaction platform, displaying processed pest data, environmental conditions, and system alerts in real-time. Built using HTML, CSS, JavaScript, and IoT integration APIs, it provides a visual summary of detections and system performance.

Users can view pest locations, sensor readings, and image outputs through a secure login interface. Graphs, maps, and tables present data clearly, while notifications alert users of pest outbreaks. The dashboard ensures that all insights from the AI model and IoT sensors are easily accessible to farmers or researchers from any connected device.

CHAPTER – 7

TESTING & RESULTS

7.1 HARDWARE TESTING

The hardware testing phase ensured that all electronic components and sensors functioned correctly under field conditions. Each module, including the camera, sensors (DHT22, LDR, GPS, and microphone), Arduino, and Raspberry Pi, was individually verified for accuracy, power stability, and communication response. Voltage and current tests confirmed that the hardware operated within safe limits using solar and Li-ion power sources. The sensor readings were compared with calibrated reference instruments to validate their accuracy. The rover’s mobility and camera alignment were tested to ensure proper field coverage and stable image capture.

During testing, sensors showed minimal deviation from reference readings, and the camera captured clear pest images up to two meters under varying light conditions. The Wi-Fi module maintained a stable connection during continuous operation, ensuring reliable data transmission.

Additional field trials were conducted in varying light and weather conditions to evaluate real-world robustness. The rover successfully navigated uneven terrain using ultrasonic sensors for obstacle detection. The DHT22 and LDR sensors provided consistent readings across temperature fluctuations and varying daylight exposure, confirming environmental stability. This ensured that the rover’s sensing and imaging subsystems were reliable for continuous agricultural field operation.

7.2 SOFTWARE TESTING

Software testing focused on verifying the YOLOv11 AI detection model, IoT communication scripts, and dashboard interface. The AI model was tested using a validation dataset containing multiple pest species captured under different environmental conditions. Performance metrics such as accuracy, precision, recall, and inference time were analyzed to ensure robustness and reliability.

The IoT communication layer was tested to verify the smooth transfer of image and sensor data between the Raspberry Pi and the cloud database without packet loss. The web dashboard was evaluated for responsiveness, display accuracy, and compatibility across different browsers and devices. The YOLOv11 model achieved an average detection accuracy above 92%, with a response latency of approximately 1.8 seconds per frame, demonstrating high performance and efficiency in real-time pest detection.

Furthermore, functional testing verified that alerts and notifications triggered correctly based on threshold values of pest presence or environmental parameters. Stress testing was also performed to evaluate the software's performance during multiple simultaneous data uploads. The results confirmed that the system maintained stable functionality even under high-load scenarios, demonstrating its scalability for larger agricultural deployments.

7.3 INTEGRATION TESTING

Integration testing validated the seamless operation between hardware and software modules, ensuring consistent communication and data flow from the field rover to the cloud and dashboard. The synchronization of environmental data and pest images was tested to confirm that both datasets aligned correctly for accurate analysis.

The system was observed to maintain consistent performance even during extended operation, with real-time updates appearing on the dashboard immediately after AI processing. The integration between the hardware sensors, AI detection module, and the IoT cloud ensured uninterrupted functioning and efficient data management, confirming that all components worked cohesively to deliver accurate pest detection and reporting.

Extended field integration tests confirmed that even when one module temporarily disconnected due to network fluctuations, automatic reconnection mechanisms in the IoT framework restored communication without user intervention. This demonstrated system resilience and reliability in real agricultural environments, ensuring that farmers receive uninterrupted insights from the system in real-time.

7.4 RESULT ANALYSIS

The overall system performance demonstrated that the AI-based Smart Pest Detection and Advisory Rover effectively identified pest infestations with high precision and minimal false detections. The combination of real-time IoT communication, edge data acquisition, and cloud-based AI processing significantly enhanced the speed and reliability of pest detection compared to manual observation.

The system achieved a detection accuracy of over 92%, response time of less than two seconds per frame, and reliable IoT data transmission exceeding 99%. These results indicate that the proposed system can serve as an efficient and sustainable solution for precision agriculture, enabling farmers to make informed decisions and reduce pesticide misuse.

Additionally, the comparative analysis against traditional pest monitoring methods revealed a substantial reduction in inspection time and resource wastage. The AI-integrated system not only improved the detection rate but also provided farmers with instant advisory outputs through the dashboard. This intelligent automation demonstrates strong potential for large-scale deployment in modern smart farming practices.

CHAPTER – 8

CONCLUSION & FUTURE SCOPE

8.1 CONCLUSION

The AI-Based Smart Pest Detection and Advisory Rover successfully demonstrates how Artificial Intelligence (AI), Internet of Things (IoT), and robotics can be integrated to create an intelligent, automated, and eco-friendly pest monitoring system for modern agriculture. By utilizing a mobile rover equipped with high-resolution imaging, environmental sensors, and a Raspberry Pi 4 controller, the system efficiently collects field data and transmits it to the cloud for processing. The embedded YOLOv11 deep-learning model accurately identifies pest species from real-time crop images, achieving high precision in pest recognition.

This intelligent framework eliminates the need for manual pest inspection, reduces the misuse of pesticides, and provides farmers with actionable insights through a web-based advisory dashboard. The project proves that combining AI-driven analytics, IoT-enabled data flow, and robotic mobility can revolutionize pest management practices by ensuring faster detection, improved accuracy, and minimal environmental impact.

Overall, the system contributes to precision agriculture by promoting sustainable farming methods, enhancing crop protection efficiency, and optimizing resource usage. It stands as a practical, scalable, and cost-effective solution that empowers farmers with real-time decision support and fosters data-driven agricultural innovation.

8.2 FUTURE SCOPE

Although the current system performs effectively for pest detection and advisory functions, several improvements can be made to enhance scalability and usability. Future versions can integrate **autonomous navigation with GPS-based path planning**, enabling the rover to cover larger field areas without manual control. Incorporating **drone-based aerial imaging** can further expand detection coverage and accuracy.

The use of **multispectral or hyperspectral cameras** can help identify crop diseases and nutrient deficiencies alongside pest activity. Additionally, integrating **machine-learning models for predictive analysis** could forecast potential pest outbreaks based on environmental and historical data. The system can also be enhanced with **mobile-app integration** for real-time farmer alerts, multilingual voice assistance, and cloud analytics dashboards for large-scale farm monitoring.

In the long term, this project can evolve into a **fully automated smart agriculture ecosystem**, where AI-based pest detection, irrigation management, and crop health analytics operate in harmony. Such innovations would not only boost productivity but also contribute to sustainable and climate-resilient farming practices worldwide.

CHAPTER – 9

COST ESTIMATION

S.No	Name of the componets	Rate	Quantity	Total
1.	Raspberry Pi 4 (8gb or 4gb)	7499/-	1	7499/-
2.	Arduino Uno	600/-	1	589/-
3.	Aluminum 4WD robotic chassis	2000/-	1	2000/-
4.	100–300 RPM 12V DC gear motors	1199/-/-	4	1199/-
5.	BTS7960 motor driver	699/-	2	699/-
6.	Rubber wheels	800/-	4	800/-
7.	Micro SD Card	700/-	1	700/-
8.	12V Li-ion	2000/-	1	2000/-
9.	LM2596 module	200/-	1	200/-
10.	Solar panel	1200/-	1	1200/-
11.	Camera module	4999/-	1	4999/-
12.	SG90(2X)	150/-	2	300/-
13.	Camera mount	300/-	1	300/-
14.	MAX4466 mic module	450/-	1	450/-
15.	HC-SR04	100/-	3	300/-
16.	DHT22	250/-	1	250/-
17.	LDR module	80/-	1	80/-
18.	NEO-6M GPS module	850/-	1	850/-
19.	Jumper Wires (M/F, M/M)	150/-	1	150/-
20.	Breadboard	150/-	1	150/-
21.	Nuts + Bolts + Spacers	250/-	1	250/-
22.	Cooling Fan for Pi	300/-	1	300/-
23.	Body Cover	450/-	1	450/-
24.	AI module	2000/-	1	2000/-
	Total:			**27,715/-**

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