

Development of an IoT-Based Chili Ripeness Detection System Using Raspberry PI

Juwita Mohd Sultan^{1*}, Sanjeev Kanakan¹, Darmawaty Mohd Ali², Wan Haszerila Wan Hassan¹, Azdiana Md Yusop¹, Zahariah Manap¹, Vigneswara Rao a/l Gannapathy¹ & Garik Markarian³

^{1*}Centre for Telecommunication Research and Innovation (CeTRI), Fakulti Teknologi dan Kejuruteraan Elektronik dan Komputer, Universiti Teknikal Malaysia Melaka. Jalan Hang Tuah Jaya, Durian Tunggal, 76100 Melaka, Malaysia

²School of Electrical Engineering, College of Engineering, UiTM Shah Alam, 40450 Shah Alam, Selangor, Malaysia.

³School of Computing & Communications, Lancaster University, United Kingdom.

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ABSTRACT

As a result of the rapid development of the Internet of Things (IoT) and computer vision technologies, agricultural systems nowadays may be more developed in the aspects of automation and intelligent detection. Proper ripeness grade selection is critical to attain the optimal quality, market value, and agricultural output in chilli plantations. Farmers typically inspect the maturity stages visually, but it suffers from inconsistent, time-consuming, and weather-dependent result. Hence, this project will develop an intelligent system for chilli ripeness detection by integrating Web Camera module and Raspberry Pi controller to minimize the human intervention to monitor the ripeness stage. The procedure involves capturing real-time images of the chili fruits and classifying them into green stage, changing stage, and ripe stage by colour and visual characteristics. Real-time image data will be analyzed by Raspberry Pi and wirelessly transmitted to cloud storage and made available for remote monitoring through WiFi connectivity and signal processing. Additional sensors including TCS34725 colour sensor, DHT22 temperature and humidity sensor, and BH1750 light sensor are added into the system to optimize the detection accuracy and reliability especially in an agricultural field environment. This project would contribute to the agricultural efficiency and promote smart farm implementation in Malaysia by providing a low-cost, accurate ripeness detection tool to farmers.

Index Terms- Internet of Things (IoT), Computer Vision, Artificial Intelligence (AI), Chilli Ripeness Detection, Raspberry Pi, Smart Agriculture, Image Processing.

INTRODUCTION

Agriculture plays a vital role in Malaysia's economy, with chili cultivation acting as a cornerstone of the local food industry. However, the traditional harvesting process faces critical challenges that hinder agricultural efficiency. Currently, farmers rely heavily on manual visual inspections to determine fruit ripeness. This method is subjective and easily compromised by fluctuating lighting and weather conditions, frequently resulting in poor harvest timing that diminishes crop quality, flavor, and market value. Furthermore, existing automated monitoring systems are often too expensive and complex for small farm operations. A significant gap exists for an affordable Internet of Things framework capable of correlating crucial environmental parameters, such as temperature, humidity, and ambient light, directly with the ripening process to help farmers make informed decisions driven by data.

To resolve these challenges, this project introduces an economical and autonomous smart farming system that merges environmental telemetry with advanced computer vision. By replacing unreliable manual checks with a multiple sensor setup and artificial intelligence powered visual analysis, the system provides accurate and live insights into crop maturity. All gathered data is transmitted wirelessly to a centralized cloud hosted dashboard.

This allows farmers to monitor their crops remotely, receive automated harvest alerts, and optimize their yield, thereby supporting Malaysia's broader modernization toward Agriculture 4.0.

The primary objective of this project is to develop this intelligent, automated maturity monitoring system. Specifically, the project aims to:

- To develop an automated 2-axis (X-Y) mechanical gantry system capable of positioning a camera across multiple chili plant bays based on user-defined web parameters.
- To implement an optimized AI-based vision model (YOLOv8 via ONNX) on a Raspberry Pi for the real-time detection and 4-stage classification of chili ripeness.
- To design a comprehensive IoT web dashboard for live environmental telemetry, remote gantry execution, and automated cloud-based data logging.

LITREATURE REVIEW

This section reviews current literature on the integration of Internet of Things and computer vision in precision agriculture. It examines deep learning methodologies for crop maturity assessment on embedded systems and identifies the live monitoring limitations this project aims to resolve.

Study [1] integrated YOLOv8 and fuzzy logic to evaluate chili harvest readiness based on color and shape. Although the model demonstrated high accuracy [5], testing was restricted to a laboratory setting without live Internet of Things connectivity, highlighting the necessity for integration with microcontrollers such as the ESP32 CAM.

Study [2] proposed a Convolutional Neural Network model utilizing TensorFlow to classify chili ripening stages in real time using RGB images. While it achieved rapid and accurate inference on embedded devices, it lacked telemetry data transmission, a capability this project introduces using a Raspberry Pi.

Study [3] demonstrated decentralized computing by employing an ESP32 CAM to capture tomato images for remote grading. However, the system relied heavily on a stable internet connection and omitted local image preprocessing, validating the approach of this project to utilize a Raspberry Pi for localized processing.

Study [4] successfully executed an optimized YOLOv8 model on a Raspberry Pi for tomato ripeness detection, demonstrating that high performance artificial intelligence can operate on economical hardware. Because the system was not evaluated under outdoor lighting variations, this project will assess model reliability in a natural agricultural environment.

Study [6] engineered a mobile robotic framework utilizing a Raspberry Pi to identify pests on chili plant leaves. While effective as an economical embedded vision system, the research focused exclusively on pest detection rather than fruit maturity, a paradigm this project adapts for classifying ripening stages.

Study [7] applied YOLOv7 to accurately detect chili fruits across fluctuating lighting conditions. While proficient at rapid object recognition, the study did not classify ripeness stages or operate within an Internet of Things ecosystem, a limitation this current research addresses.

Study [8] utilized classical machine learning algorithms, specifically Support Vector Machine and Random Forest, to classify chili ripeness using shape, color, and texture features. This methodology achieved high accuracy solely under controlled lighting and underperforms outdoors, reinforcing the necessity for modern deep learning architectures to manage varied environments.

Study [9] implemented YOLOv5 to detect various chili varieties with remarkable accuracy. However, its substantial computational requirements render it impractical for lightweight Internet of Things devices, emphasizing the need for optimized models deployed on hardware like the Raspberry Pi.

METHODOLOGY

Project Flowchart

The chili ripening detection project operates through two independent subsystems working simultaneously. The Raspberry Pi system initializes environmental sensors and a camera to capture live images of the crops. It utilizes the YOLOv8 algorithm to analyze these images and classify fruit ripeness, instantly triggering alerts and sending mobile notifications to a dashboard when a fully mature chili is identified. Concurrently, a wireless ESP32 microcontroller continuously monitors soil moisture levels. It autonomously manages the irrigation process by activating a water pump whenever the soil becomes too dry and turning it off once optimal moisture is restored. Together, these components deliver a highly efficient smart farming solution that seamlessly combines visual ripeness detection with automated crop watering.

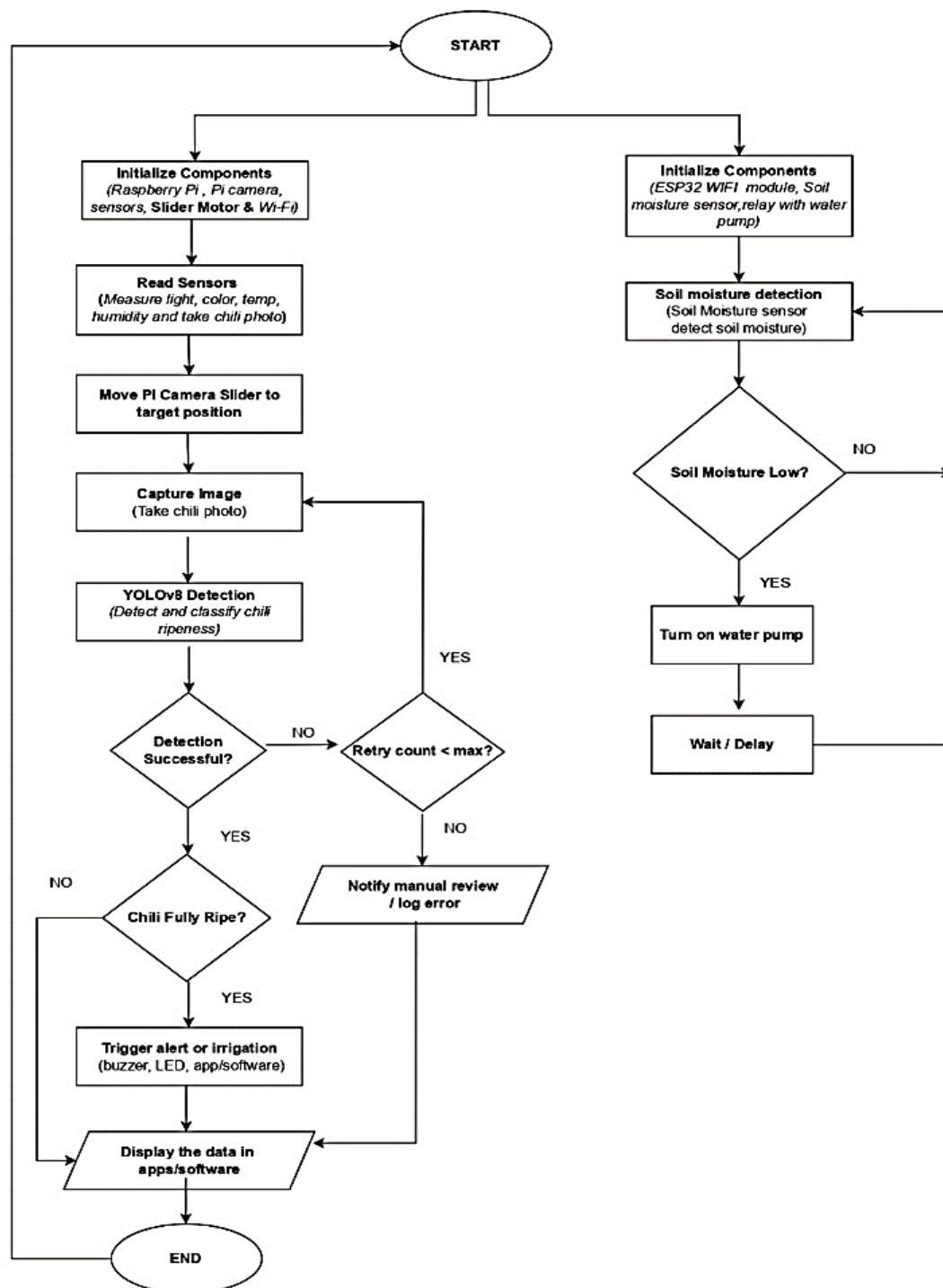


Fig 1 Flowchart of overall system process

Project Cost Analysis

No.	Item	Unit	Unit Price (RM)	Total Amount (RM)
1	Raspberry Pi 3 Model B 1GB	1	252.13	252.13
2	ESP 32 Wi-Fi module	1	23.9	23.9
3	Web Cam	1	15	15
4	DHT 22	1	15.5	15.5
5	TCS34725 color sensor	1	14.5	14.5
6	BH1750 light Intensity sensor	1	15	15
7	Soil moisture sensor	2	5	10
8	Water pump	2	5.8	11.6
9	Relay	1	10	10
10	Lithium battery	1	15.9	15.9
11	LED	2	1	2
12	TMC2290 Motor Driver	1	4.9	4.9
13	Nema 17 stepper motor	2	20	40
14	Buzzer	1	2	2
15	Battery 3.3V	2	10	20
Estimated Total		20		452.43

Table 1.1: Cost Estimation for System Development

Effective cost management ensures this smart farming system remains financially accessible for users. As detailed in table above, the total hardware cost for the project is RM 452.43. This budget covers all essential components, including the Raspberry Pi 3 Model B, ESP32 microcontroller, webcam, motion drivers, sensors, and actuators.

Block Diagram

The system architecture is powered by a lithium battery and consists of three main sections: input, central processing, and output. The input unit collects data using a Web Cam for visual ripeness assessment, alongside sensors that monitor color, temperature, humidity, light, and soil moisture. A Raspberry Pi 3 Model B serves as the central processing unit, utilizing machine learning algorithms to evaluate the crop status using the collected data. An ESP32 WiFi module manages all wireless communication, transmitting the processed information to the output unit. The output unit then activates a buzzer and LED for local alerts, triggers a water pump for automated irrigation, and delivers live updates directly to a smartphone.

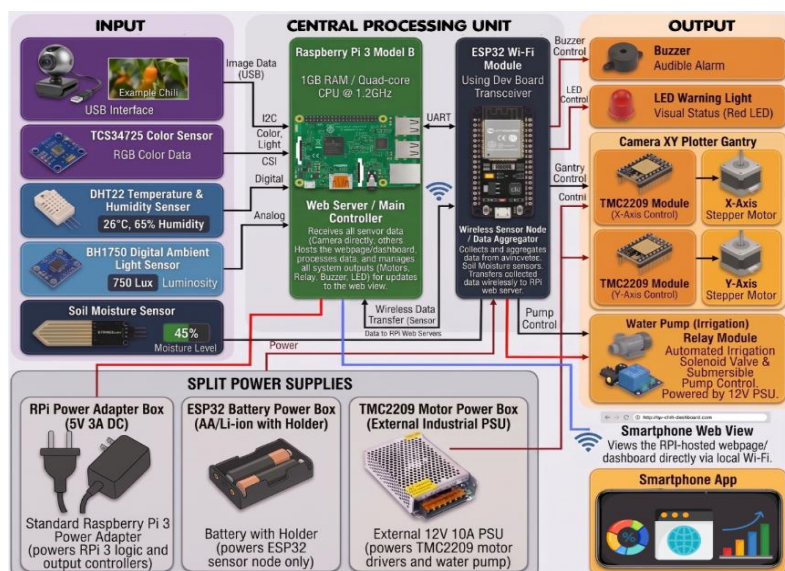


Fig.2 The block diagram of project

Circuit Design

Circuit design utilizes dual controller architecture to maximize efficiency and prevent processing delays. A Raspberry Pi 3 Model B serves as the primary processor, exclusively handling intensive image data from the Web Camera for the YOLOv8 visual ripeness detection. Operating simultaneously, an ESP32 WROOM microcontroller manages all-time environmental sensing and hardware automation. The ESP32 continuously collects data from soil moisture, temperature, humidity, light, and color sensors. Using these readings, it controls a relay to activate a 12V water pump for automatic irrigation, drives the mechanical watering arm, and operates status LEDs and a buzzer for user alerts. A single 12V lithium battery powers the entire system, supplying direct energy to the heavy-duty motors and regulated power to the microcontrollers and sensors.

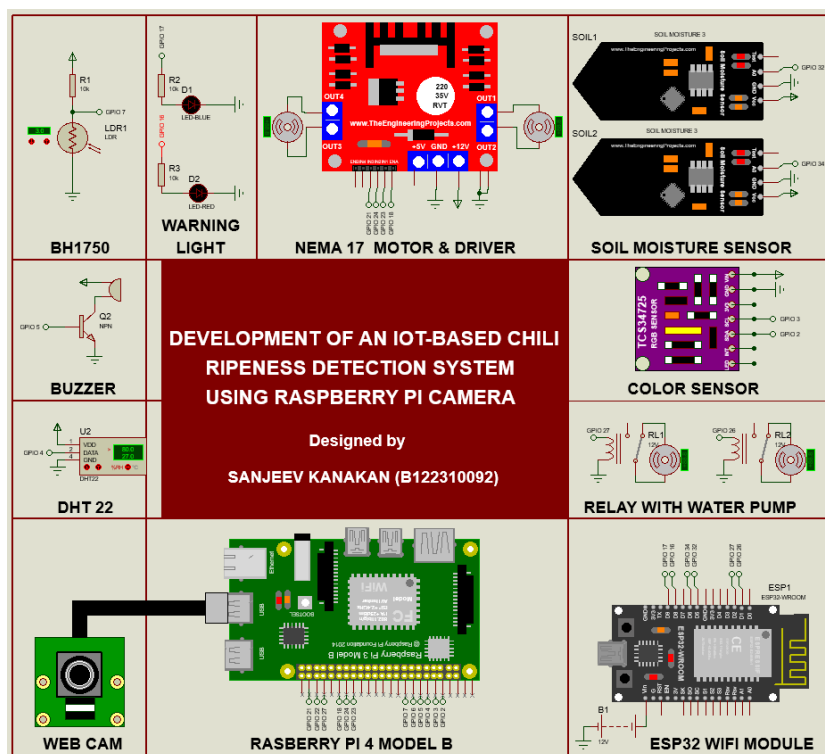


Fig.3 Circuit design of project

Hardware Prototype

The hardware prototype combines mechatronics, artificial intelligence visual detection, and microclimate control into an automated precision agriculture platform. A camera mounted on a two-axis gantry moves across plant bays to record video of the crops. This footage is processed in real time using OpenCV and a YOLOv8 model, which overlays visual bounding boxes onto the live stream to assess chili ripeness. Simultaneously, an ESP32 microcontroller manages automated irrigation by activating a water pump when soil moisture falls below 45 percent and deactivating it at 70 percent. All visual classification results and sensor telemetry are streamed directly to an online dashboard for remote monitoring and decision making.



Fig.4 Final hardware prototype

Dashboard Overview

The UTeM SmartAgroNics dashboard centralizes data collection, hardware control, and live monitoring into a single interface. It simultaneously manages high-speed computer vision processing, environmental sensor telemetry, and gantry movement without lag. To ensure accuracy, the system filters visual data to minimize false alarms and automatically logs timestamped images of ripe crops into an Evidence Gallery. The dashboard also provides real-time alerts for critical events by checking system data every two seconds. For detailed analysis, users can click on sensor telemetry cards to view interactive charts displaying a 24-hour history of system performance.

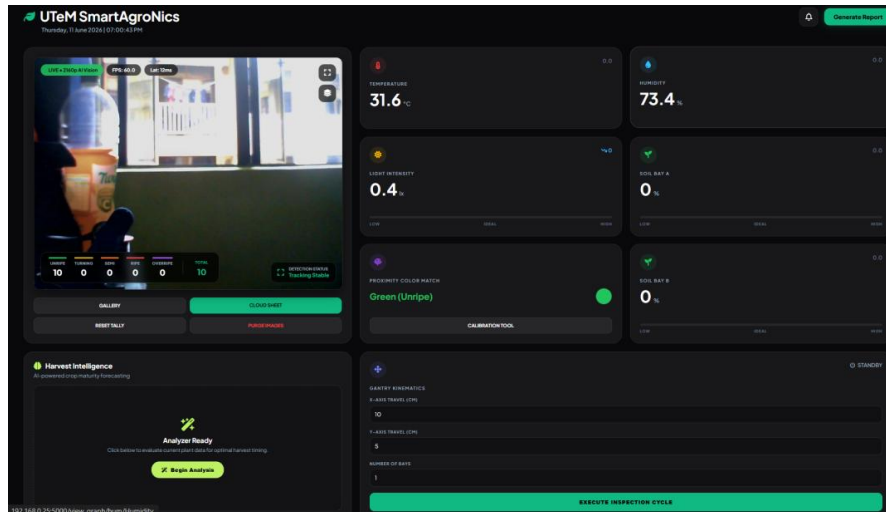


Fig.5 UTeM SmartAgroNics dashboard

RESULTS AND DISCUSSION

Image Processing Result

The AI vision system is fully integrated into the custom web dashboard to process live video from the mechatronic gantry. The image processing pipeline reliably detects and counts multiple chillies in real time, successfully overcoming real-world challenges like overlapping leaves and uneven lighting. It accurately generates bounding boxes and streams the live counting data directly to the user interface for continuous automated monitoring.

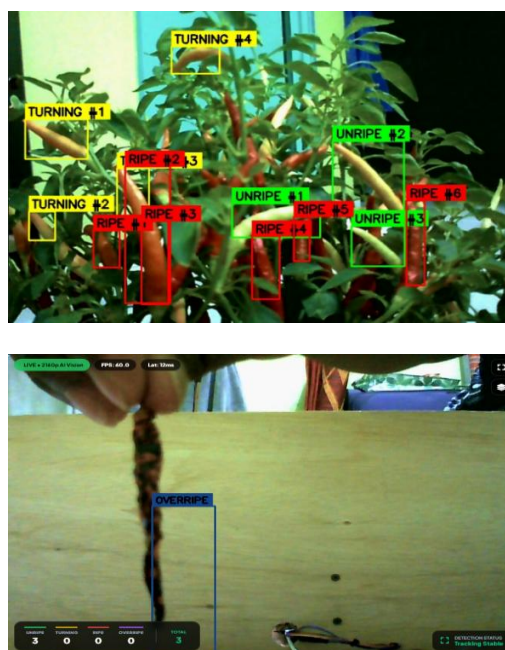


Fig.6 Chili detection result

Temperature Vs Time Graph

The Temperature versus Time graph plots the local system conditions from 06:40 AM until 14:08 PM. The temperature remains mostly constant during the morning and early afternoon with only small natural changes. Just before 14:08 PM, the data shows a sudden and sharp increase. This continuous recording demonstrates the high sensitivity of the sensor, allowing the system to accurately detect rapid physical changes like trapped heat or direct sunlight.

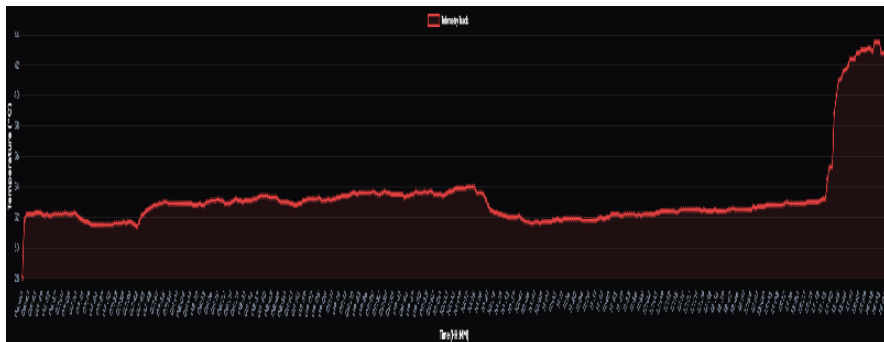


Fig.7 Temperature monitoring graph

Humidity Vs Time Graph

The humidity versus time graph records local moisture from 06:40 AM to 14:08 PM. The data shows early morning fluctuations, followed by a stable period, and then a sharp drop just before 14:08 PM. This continuous tracking proves the sensor can accurately detect rapid environmental changes minute by minute.

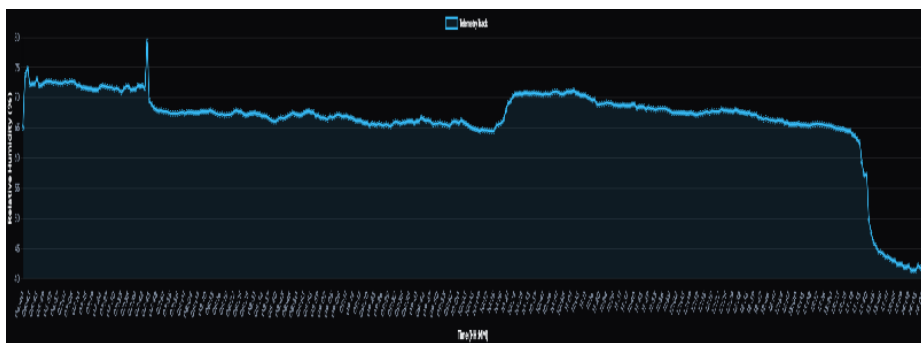


Fig. 8 Humidity monitoring graph

Light Intensity Vs Time Graph

The Light Intensity versus Time graph records local light levels in lux from 06:40 AM to 14:08 PM. The morning readings remain low and steady, followed by natural fluctuations as daylight increases. Just before 14:08 PM, the data shows a sudden and drastic spike in light intensity. This continuous tracking proves the sensor can accurately detect rapid environmental light changes minute by minute.

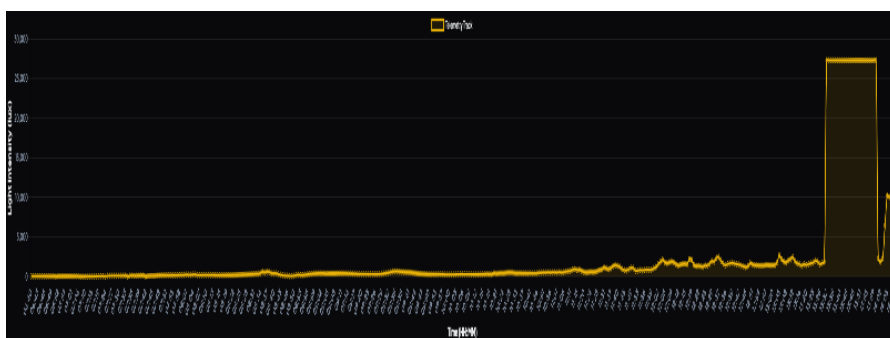


Fig. 9 Light intensity monitoring graph

Soil Moisture Vs Time Graph

The Soil Moisture versus Time graph shown records saturation levels from 06:40 AM to 14:08 PM. Initially, the moisture settles between 46% and 50%. Just after 07:40 AM, the reading drops to approximately 20%, falling below the automated threshold of 45%. This dry condition triggers the water pump, causing a sudden vertical jump in the data. The moisture reaches a 100% saturation peak and stays completely steady for the remainder of the recorded period. This demonstrates that the automated control system can effectively monitor soil conditions minute by minute and instantly execute physical interventions.

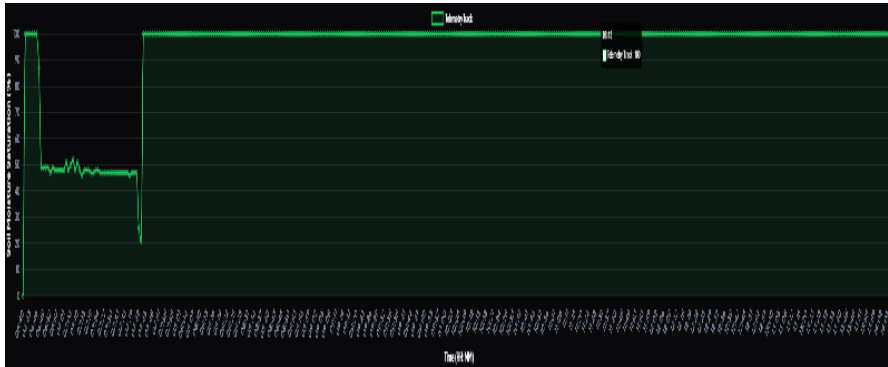


Fig. 10 Soil moisture monitoring graph

Harvest Intelligence (AI Suggestion)

The graphic displays the final data output screen of the Harvest Intelligence subsystem. It summarizes real-time sensor and AI data, showing a temperature of 31.8°C, 0.0% soil saturation, and a crop count of 1 ripe and 1207 overripe chillies. Based on these readings, the system assesses the crop state as ideal and confirms the optimal harvest window has been reached. It then provides automated management advice, instructing the operator to harvest mature chillies immediately and to increase watering by above 40% to protect any unripe plants. This output demonstrates the system's ability to turn raw data into clear, actionable agricultural decisions.

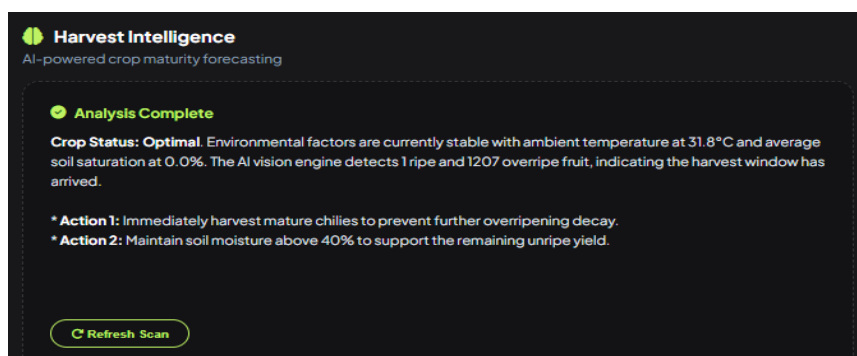


Fig. 11 Dashboard AI suggestion

FUTURE WORKS

To commercialize this prototype, future upgrades must focus on expanding the training dataset to improve outdoor accuracy across various chilli species. Additionally, physical scalability can be achieved by integrating autonomous mobile robots (AMRs) and solar power for off-grid operations. Finally, optimizing the AI for edge computing and adding predictive analytics will create a comprehensive decision-support platform for harvest forecasting.

CONCLUSION

This project successfully delivered a cost-effective, IoT-based chili ripeness detection system that provides a reliable, automated alternative to subjective manual harvesting. By integrating dual-controller architecture

(Raspberry Pi and ESP32), environmental sensors, and a highly accurate YOLOv8 machine learning model, the prototype effectively monitors agricultural conditions and classifies chili ripeness in real-time. Ultimately, the system proves that combining computer vision with automated environmental sensing is a highly practical and efficient solution for smart agriculture.

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