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Enabled Deep Learning Framework For Smart Mango Farming

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Abstract:

The rapid advancement of Artificial Intelligence (AI) and Internet of Things (IoT) technologies has enabled the development of intelligent systems for modern agriculture. This project presents an integrated solution for automated mango grading and environmental monitoring using deep learning and IoT-based control mechanisms.The system employs a YOLOv5-based object detection model to identify and classify mangoes into three categories: ripe, medium ripe, and unripe. A live video stream from a webcam is processed in real time using computer vision techniques, allowing accurate detection and counting of mangoes. The trained model, deployed in ONNX format, ensures efficient and fast inference suitable for real-time applications.The detection results, including the count of each mango category, are transmitted to an ESP32 microcontroller through serial communication. The ESP32 acts as a central IoT node, integrating multiple environmental sensors such as DHT11 (temperature and humidity), soil moisture sensor, and LDR (light intensity sensor). These sensors continuously monitor the surrounding conditions to support smart agricultural decision-making.The system is further integrated with the Blynk platform, enabling remote monitoring and control through a smartphone interface. Real-time data, including mango grading results and environmental parameters, are displayed on the mobile application. Additionally, automation features are implemented using relay modules to control devices such as a water pump and lighting system based on sensor thresholds and user input.An LCD display is also incorporated for local visualization of sensor data, ensuring accessibility even without internet connectivity. The system operates efficiently with minimal human intervention, reducing manual labor and improving grading accuracy. Furthermore, it provides scalability for integration into larger agricultural or industrial environments.

Overall, the proposed system demonstrates a cost-effective, reliable, and intelligent approach to fruit grading and smart farming, combining AI-driven decision-making with IoT-enabled monitoring and automation. This solution has the potential to significantly enhance productivity, reduce post-harvest losses, and support precision agriculture practices.

Index Terms—YOLO, ESP32, IOT, Embedded systems

I. INTRODUCTION

Agriculture plays a vital role in the economy, especially in countries like India, where a large portion of the population depends on farming for livelihood. Among various agricultural products, mango is one of the most widely cultivated and commercially important fruits. However, post-harvest processes such as sorting and grading of mangoes are still largely performed manually. Traditional grading methods rely on human observation to determine ripeness based on color, texture, and size. These methods are not only time-consuming but also inconsistent, leading to errors, reduced quality control, and economic losses.With the emergence of advanced technologies such as **Artificial Intelligence (AI)** and the **Internet of Things (IoT)**, there is a growing opportunity to transform conventional agricultural practices into smart and automated systems. AI, particularly deep learning techniques like object detection, enables machines to analyze visual data with high accuracy. Models such as YOLOv5 have proven highly effective for real-time object detection tasks, making them suitable for applications like fruit classification and grading.

At the same time, IoT technologies allow seamless connectivity between devices, sensors, and cloud platforms. Microcontrollers such as the ESP32 enable real-time data acquisition and communication, while platforms like Blynk provide user-friendly interfaces for monitoring and controlling systems remotely. By integrating AI with IoT, it becomes possible to develop intelligent agricultural solutions that not only automate tasks but also provide actionable insights.

This project focuses on developing an **AI and IoT-based mango grading and monitoring system**. The system utilizes a deep learning model to detect and classify mangoes into different ripeness stages—ripe, medium ripe, and unripe—using live video input. The detection results are then transmitted to an IoT-enabled microcontroller, which simultaneously monitors environmental parameters such as temperature, humidity, soil moisture, and light intensity. These parameters are crucial in determining crop health and optimizing agricultural practices.In addition to monitoring, the system incorporates automation features such as controlling irrigation and lighting using relay modules. The integration with a mobile application allows farmers or users to access real-time data, receive alerts, and control devices from anywhere. This reduces dependency on manual supervision and enhances operational efficiency.The proposed system aims to address key challenges in agriculture, including labor shortages, inconsistent grading, and lack of real-time monitoring. By leveraging AI for accurate fruit classification and IoT for smart control and connectivity, the system provides a scalable and cost-effective solution for modern farming. It represents a significant step toward **precision agriculture**, where data-driven decisions improve productivity, quality, and sustainability.

Overall, this project demonstrates how the convergence of AI and IoT can revolutionize traditional agricultural practices, making them more efficient, reliable, and intelligent

II. .RELATED WORK

Castillo-Israel et al. [1] conducted a comprehensive study on the storage quality of fresh-cut Philippine Carabao mangoes by applying 1-Methylcyclopropene (1-MCP) treatment. Their research primarily focused on post-harvest handling and preservation, where they demonstrated that 1-MCP effectively delays the ripening process by inhibiting ethylene production. This results in extended shelf life and improved texture and color retention. Although the study does not involve automation or computer vision, it provides a strong foundation for understanding quality parameters such as freshness, firmness, and color, which are critical for developing automated grading systems.

Lu and Sang [2] proposed an image processing-based approach for detecting citrus fruits in natural environments. Their work addressed key challenges such as varying illumination, shadows, and occlusion caused by leaves and branches. By applying segmentation and feature extraction techniques, they improved detection accuracy under uncontrolled outdoor conditions. This research is significant because it highlights the complexity of real-world agricultural environments and the need for robust detection algorithms that can adapt to such variability.

He et al. [3] introduced a fruit recognition system for green litchi using an improved Linear Discriminant Analysis (LDA) classifier. Their method focused on distinguishing fruits from complex backgrounds with similar color distributions. By enhancing the LDA classifier, they achieved better class separability and improved recognition accuracy. This study demonstrates the effectiveness of classical machine learning techniques in agricultural applications, especially when computational resources are limited.

Padmanabula et al. [4] developed a stacked YOLOv3 model to improve object detection performance. Their approach combines multiple YOLO layers to enhance feature extraction, particularly for small and overlapping objects. This is highly relevant for fruit detection, where fruits often appear in clusters. The stacked architecture increases detection precision and recall, making it suitable for real-time applications in smart agriculture systems.

Raka et al. [5] explored an innovative approach to fruit sorting by using thermal imaging. Instead of relying solely on visible features such as color and size, their system analyzed temperature distribution to determine fruit ripeness and taste quality. This method introduces an additional dimension to fruit grading, showing that combining multiple sensing techniques can lead to more accurate and reliable classification systems.

Lawal [6] proposed a modified YOLOv3 framework specifically for tomato detection. By optimizing network parameters and improving feature extraction, the model achieved higher detection accuracy and faster processing speed. This research highlights the importance of customizing deep learning models for specific agricultural tasks and demonstrates the potential of YOLO-based systems for real-time deployment.

Lin et al. [7] introduced Feature Pyramid Networks (FPN), a significant advancement in object detection architectures. FPN improves multi-scale feature representation, allowing models to detect objects of different sizes effectively. This is particularly important in fruit detection, where fruits may vary in size due to growth stages or camera distance. The integration of FPN into detection frameworks has become a standard practice in modern computer vision systems.

Shi et al. [8] proposed a real-time mango detection system using an optimized YOLO network with pruning techniques. Their method reduces the computational complexity of the model while maintaining high detection accuracy. This makes the system suitable for deployment on embedded devices such as edge processors and IoT-based agricultural systems. Their work directly contributes to efficient and scalable mango detection solutions.

Legaspi et al. [9] utilized YOLO-based models to detect agricultural pests such as whiteflies and fruit flies. Their research demonstrated that deep learning models are not limited to fruit detection but can also be extended to pest monitoring, which is crucial for crop health management. This highlights the versatility and adaptability of YOLO architectures in precision agriculture.

Lawal [10] further reinforced the effectiveness of YOLOv3-based detection systems by demonstrating improved robustness and accuracy in agricultural environments. The study emphasized the importance of dataset quality and model tuning in achieving reliable detection performance.

Balbin et al. [11] developed an image processing-based system for profiling and sorting mangoes based on morphological features such as size, shape, and color. Their work focused on grading fruits according to predefined standards, providing a structured approach to quality assessment. This study forms a direct foundation for automated mango grading systems and bridges the gap between traditional methods and modern AI-based approaches.

[12]H. M. I. Salehin and his co-authors developed an advanced IoT-based smart baby monitoring system integrated with face recognition technology to improve infant safety and remote supervision. The system utilizes IoT-enabled cameras and sensors to continuously monitor the baby’s activities, such as movement, sleeping patterns, and environmental conditions. A key contribution of this work is the incorporation of facial recognition algorithms that can identify authorized caregivers and detect unknown individuals in real time. When an unfamiliar face or abnormal condition is detected, the system

immediately sends alerts to parents or guardians through connected devices. This research demonstrates the effectiveness of combining IoT with artificial intelligence for real-time monitoring, automation, and security. Although the application focuses on healthcare, the techniques used—such as real-time image acquisition, object detection, and automated alert generation—are highly relevant to agricultural automation systems, including fruit grading, where similar image processing and monitoring mechanisms are required.

[13]M. S. Farooq and colleagues presented a comprehensive survey on the role of the Internet of Things (IoT) in agriculture, emphasizing its importance in enabling smart farming practices. The study explores how IoT devices such as sensors, drones, and automated systems are used to collect real-time data related to soil moisture, temperature, humidity, and crop health. This data is then processed using cloud computing and data analytics to support intelligent decision-making. The authors highlight several applications, including precision irrigation, pest control, crop monitoring, and livestock management, all of which contribute to improved productivity and resource optimization. Additionally, the paper discusses challenges such as high implementation costs, data security concerns, lack of standardization, and connectivity issues in rural areas. This work is significant because it provides a strong conceptual and technological foundation for integrating IoT into agricultural systems. It is particularly relevant to fruit grading systems, where sensor data and automated monitoring can be combined with image processing techniques to enhance quality assessment and operational efficiency.

[14]M. H. Widianto and co-authors conducted a systematic review of the latest trends in artificial intelligence (AI) applications for smart farming, focusing on improving crop yield and agricultural efficiency. The study examines various AI techniques, including machine learning, deep learning, and computer vision, and their applications in agriculture. It highlights the use of convolutional neural networks (CNNs) for image-based tasks such as fruit detection, classification, and disease identification. The authors also discuss other AI models used for yield prediction, soil analysis, and automated harvesting systems. One of the key findings of this review is that deep learning models significantly outperform traditional methods in terms of accuracy and scalability when dealing with large and complex agricultural datasets. Furthermore, the paper emphasizes the integration of AI with IoT systems to create intelligent, automated farming environments capable of real-time decision-making. This research is highly relevant to fruit grading systems, as it supports the use of advanced AI models like YOLO and ResNet for accurate fruit classification, defect detection, and quality evaluation

III. Proposed System

To address the above challenges, this project proposes an integrated system that combines **AI-based mango detection** with **IoT-based monitoring and automation**.

The proposed system consists of two main modules:

1. AI-Based Mango Detection Module

Uses webcam input to capture real-time images
Applies YOLOv5 model for object detection
Classifies mangoes into:
Ripe
Medium ripe
Unripe
Counts and labels detected mangoes

2. IoT-Based Monitoring and Control Module

Uses ESP32 as the central controller
Receives mango detection data via serial communication

Reads sensor data:
Temperature and humidity (DHT11)
Soil moisture
Light intensity (LDR)
Displays data:
On LCD (local display)
On mobile app via Blynk

Expected Outcome
Improved accuracy in mango grading
Reduced labor and time
Efficient resource utilization
Smart farming solution with real-time insights

IV. IMPLEMENTATION

The implementation of the proposed system involves the integration of **Artificial Intelligence (AI)** for mango detection and **Internet of Things (IoT)** for monitoring and automation. The system is divided into two major parts: the **AI-based detection module** and the **ESP32-based IoT module**, which communicate through serial communication.

1. AI-Based Mango Detection Implementation

The mango detection system is developed using **Python** and computer vision libraries such as OpenCV and NumPy. A deep learning model based on
YOLOv5 is trained to detect and classify mangoes into three categories:

- Ripe mango
- Medium ripe mango
- Unripe mango

Steps Involved:

Step 1: Model Preparation
The trained YOLOv5 model is converted into **ONNX format (best.onnx)** for faster inference.
Class labels are stored in a file (coco.names).

Step 2: Video Capture
A webcam is used to capture real-time video frames using OpenCV:
cap = cv2.VideoCapture(0)

Step 3: Image Preprocessing
Frames are resized and converted into a blob format suitable for the model:
blob = cv2.dnn.blobFromImage(image, 1/255.0, (640, 640))

Step 4: Object Detection
The model processes the image and outputs bounding boxes, class IDs, and confidence scores.

Step 5: Post-Processing
Non-Maximum Suppression (NMS) is applied to remove duplicate detections.
Bounding boxes and labels are drawn on the frame.

Step 6: Counting and Classification
The number of mangoes in each category is counted:
ripe_count += 1
medium_ripe_count += 1
unripe_count += 1

Step 7: Serial Communication
The detection results are sent to ESP32 via serial communication:
msg = f"MR:{medium_ripe_count} R:{ripe_count} UR:{unripe_count} Total:{total}\n"
ser.write(msg.encode())

Step 8: Web Streaming
A Flask server is used to stream the processed video to a web interface.

MATHEMATICAL MODEL

The proposed system combines **computer vision-based classification** and **sensor-based decision-making**. The mathematical model represents both AI detection and IoT automation processes.

1. Input Definition

Let:

- I = Input image/frame captured from camera
- S_t = Temperature sensor value
- S_h = Humidity sensor value
- S_m = Soil moisture value
- S_l = Light intensity value

2. AI-Based Mango Detection Model

The system uses YOLOv5 for object detection.

Detection Function:

$$D(I) = \{(c_i, b_i, p_i)\}_{i=1}^{n}$$

Where:

- c_i = class label (ripe, medium ripe, unripe)
- b_i = bounding box
- p_i = confidence score
- n = number of detected mangoes

3. Classification Mapping

Each detected mango is classified as:

$$c_i \in \{R, MR, UR\}$$

Where:

- R = Ripe
- MR = Medium Ripe
- UR = Unripe

4.Sensor-Based Decision Model

Soil Moisture Control (Pump)

Soil Moisture Control (Pump)

$$P = \begin{cases} 1, & S_m > T_m \\ 0, & S_m \le T_m \end{cases}$$

Where:

- $P = 1 \rightarrow$ Pump ON
- $P = 0 \rightarrow$ Pump OFF
- T_m = Soil moisture threshold

5. Light Control System

$$L = \begin{cases} 1, & S_l > T_l \\ 0, & S_l \le T_l \end{cases}$$

Where:

- $L = 1 \rightarrow$ Light ON
- $L = 0 \rightarrow$ Light OFF
- T_l = Light threshold

6. System Output Function

The system output can be represented as:

$$O = \{N_R, N_{MR}, N_{UR}, S_t, S_h, S_m, S_l, P, L\}$$

Where:

- Mango classification results
- Sensor readings
- Control states (pump & light)

7. Data Transmission Model

$$M = f(N_R, N_{MR}, N_{UR})$$

Example:

```
MR:2 R:5 UR:3 Total:10
```

8. Overall System Function

$$System(I, S) \rightarrow (Detection, Monitoring, Control)$$

Where:

- Input = Image + Sensor data
- Output = Classification + Automation + Display

2. IoT-Based ESP32 Implementation

The IoT module is implemented using the
ESP32 microcontroller, which acts as the central processing unit for sensor data, automation, and cloud communication.

Steps Involved:

Step 1: Wi-Fi and Blynk Setup

ESP32 connects to Wi-Fi and the
Blynk platform:
Blynk.begin(auth, ssid, pass);

Step 2: Sensor Integration

Temperature & Humidity (DHT11)

```
float temperature = dht.readTemperature();
float humidity = dht.readHumidity();
```

Soil Moisture Sensor

```
int soilMoisture = analogRead(SOIL_PIN);
```

Light Sensor (LDR)

```
int ldrValue = analogRead(LDR_PIN);
```

Step 3: Serial Data Reception

ESP32 reads mango detection data sent from Python:

```
readString_data = Serial.readString();
```

Step 4: Data Processing

Mango counts and sensor values are processed and prepared for display.

Step 5: Cloud Communication

Data is sent to Blynk mobile app:

```
Blynk.virtualWrite(V2, temperature);
Blynk.virtualWrite(V3, humidity);
Blynk.virtualWrite(V4, readString_data);
```

Step 6: Relay Control (Automation)

Water Pump Control

Activated based on soil moisture level:

```
if (soilMoisture > threshold) {
   digitalWrite(RELAY_PUMP, LOW);
}
```

Light Control

Activated based on light intensity:

```
if (ldrValue > threshold) {
   digitalWrite(RELAY_LIGHT, LOW);
}
```

Step 7: LCD Display

Displays sensor data locally:

```
lcd.print("Temp: ");
lcd.print(temperature);
```

Step 8: Mobile Control

Users can manually control pump and light using Blynk buttons (V0, V1).

3. System Integration

The integration between AI and IoT modules is achieved through **serial communication**:

Python (YOLO Detection)
↓
Serial Communication (USB)
↓
ESP32 (Processing + IoT)

- Python sends mango data
- ESP32 receives and processes it

- Data is displayed on:
  - LCD
  - Blynk app

4. Workflow Summary

Camera → AI Detection → Mango Classification
↓
Serial Data Transfer
↓
ESP32
↓
Sensors Reading → Decision Making
↓
Relay Control + Blynk Update + LCD Display

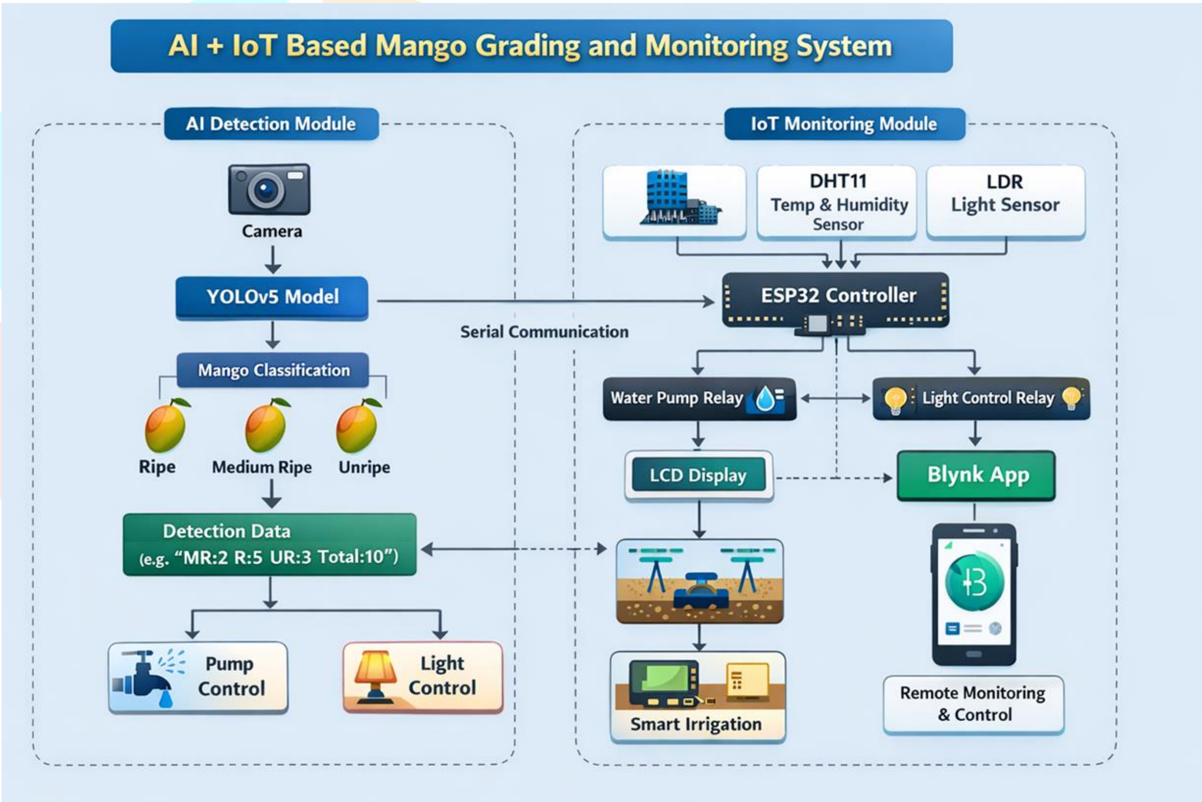

Fig1. Architectural Diagram

Block diagram represents the complete workflow of the **AI-based mango grading and IoT monitoring system**, showing how data flows from input to output and control.

1. Input Layer (Image Acquisition)

- Camera / Webcam
- Captures real-time images or video of mangoes.
- Acts as the **primary input source** for the system.
- The quality of detection depends on lighting and camera resolution.
- Output: Raw image frames

2. AI Processing Layer

YOLOv5 Detection Model

- Uses YOLOv5
- Performs:
- Object detection
- Classification

Classification Output:

- Ripe mango
- Medium ripe mango
- Unripe mango

The model:

- Draws bounding boxes
- Assigns labels
- Calculates confidence

Output:

- MR:2 R:5 UR:3

3. Data Processing Layer (Python System)

- Processes detection results
- Counts number of mangoes in each category
- Displays results on screen (OpenCV window)
- Streams video using Flask (web interface)

Serial Communication

- Sends processed data to microcontroller:
- MR:2 R:5 UR:3 Total:10
- This is the **bridge between AI and IoT**

4. IoT Controller Layer

- ESP32 Microcontroller
- Central controller of the system
- Receives data from Python via USB serial
- Using ESP32, it:
- Processes mango data
- Reads sensor values
- Controls relays
- Sends data to cloud

5. Sensor Layer (Environmental Monitoring)

- **DHT11 Sensor**
  Measures temperature and humidity
- **Soil Moisture Sensor**
  Detects soil dryness or wetness
- **LDR Sensor**
  Measures light intensity
- **Output:**
  Real-time environmental data

6. Control Layer (Automation)

- Relay Module
- Controls electrical devices:
- Water Pump
  Activated when soil is dry
- Light
  Activated when environment is dark
- Enables **automatic decision-making**

7. Output Display Layer

- LCD Display (Local Output)
  Shows:
  - Temperature
  - Humidity
  - Soil moisture
  - Light intensity
  - Useful when internet is not available
- Mobile App (Remote Monitoring)
  Using Blynk:
  Displays:
    - Mango grading results
    - Sensor values
  Allows:
    Manual control of pump and light

8. Cloud / IoT Communication Layer

- ESP32 connects to WiFi
- Sends data to Blynk server
  Enables:
  - Remote access
  - Notifications
  - Real-time monitoring
  -

V. Result Analysis

The proposed **AI + IoT Based Mango Grading and Monitoring System** was successfully implemented and tested under real-time conditions. The system integrates computer vision, embedded systems, and IoT technologies to achieve automated mango classification and environmental monitoring.

1. Mango Detection Results

The AI model based on
YOLOv5
successfully detected and classified mangoes into three categories:

- Ripe mango
- Medium ripe mango
- Unripe mango

Observations:

- Accurate detection with clear bounding boxes
- Real-time classification achieved
- Multiple mangoes detected simultaneously
  Sample Output:

MR:2 R:5 UR:3 Total:10

2. Real-Time Performance

- The system processed video frames continuously using OpenCV
- Achieved real-time performance (~10–25 FPS depending on hardware)
- Detection results were displayed instantly

3. Serial Communication

- Data was successfully transmitted from Python (AI system) to ESP32
- Format used:
  MR:x R:y UR:z Total:n
- Communication was stable and reliable

4. Sensor Monitoring Results

The ESP32 system continuously monitored environmental conditions:

- Temperature and Humidity (DHT11)
- Soil Moisture
- Light Intensity (LDR)

Observations:

- Accurate sensor readings obtained
- Real-time updates every few seconds
- Values displayed on LCD and mobile app

5. Automation Results

Water Pump Control

- Automatically turned ON when soil moisture was low
- Turned OFF when sufficient moisture was detected

Light Control

- Turned ON in low light conditions
- Turned OFF in bright conditions

6. IoT (Blynk) Monitoring

Using
Blynk:

- Mango detection data displayed in real-time
- Sensor values updated continuously
- Manual control of pump and light achieved

Features Verified:

- Remote monitoring
- Button-based control
- Data visualization

7. LCD Display Output

- Local display showed:
  - Temperature
  - Humidity
  - Soil moisture
  - Light intensity
  - Useful for offline monitoring

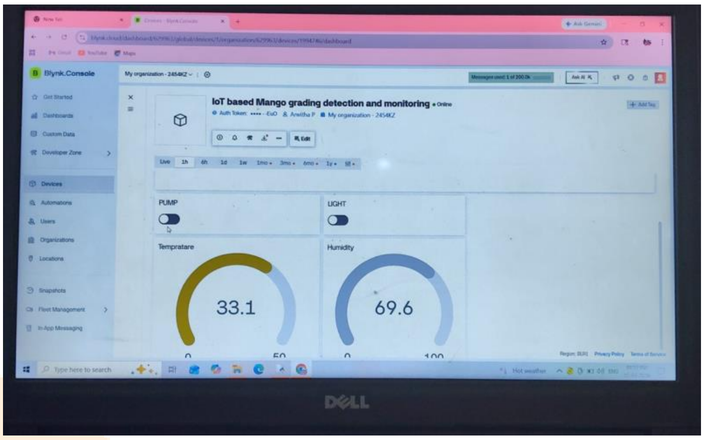

Fig2. Blynk IoT platform with sensor data

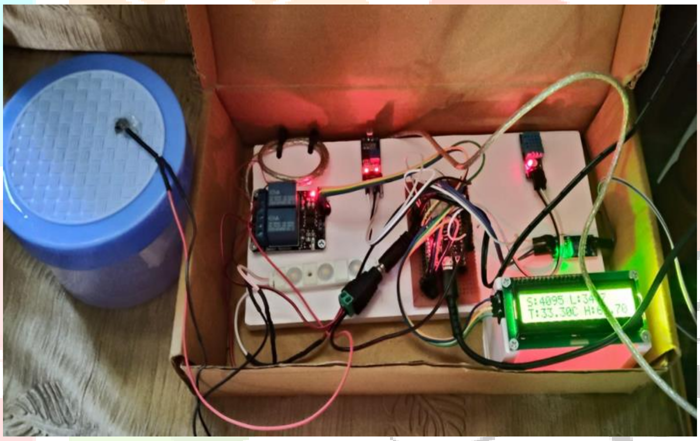

Fig3. IoT hardware integration circuit with sensor

VI. Conclusion

The AI + IoT Based Mango Grading and Monitoring System was successfully designed and implemented, demonstrating the effective integration of Artificial Intelligence and Internet of Things technologies for smart agriculture applications. The system utilizes a deep learning model based on YOLOv5 to accurately detect and classify mangoes into ripe, medium ripe, and unripe categories in real time.The integration of theESP32 microcontroller enabled efficient processing of sensor data and seamless communication between the AI module and IoT components. Environmental parameters such as temperature, humidity, soil moisture, and light intensity were continuously monitored using appropriate sensors, providing valuable insights into farm conditions.The system also implemented automation features, including water pump and lighting control, which operated based on predefined threshold conditions. This ensured optimal resource utilization and reduced the need for manual intervention. Furthermore, the integration with theBlynk platform allowed users to monitor system data remotely and control devices in real time through a user-friendly interface.The experimental results demonstrated that the system performs efficiently with reliable communication, accurate detection, and effective automation. The real-time processing capability and seamless interaction between components make the system suitable for practical deployment in agricultural environments.

Overall, the proposed system provides a cost-effective, scalable, and intelligent solution for automated fruit grading and smart farm monitoring. It significantly reduces human effort, improves accuracy, and enhances decision-making through data-driven insights. This project highlights the potential of combining AI and IoT to transform traditional agricultural practices into modern, efficient, and sustainable systems.

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