AI Integrated Smart Irrigation and Plant Disease Detection using Raspberry Pi Camera

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ABSTRACT

Water is very important in farming because it is becoming scarcer. This study suggests a Smart Irrigation System that is powered by AI. This system uses Artificial Intelligence, the Internet of Things, and satellite technology to monitor farming activities and resources. This system will use many distributed IoT devices that will monitor the various soil and environmental conditions. DHT11 will monitor the moisture and temperature, and other sensors will monitor rain, NPK nutrients, and PIR. These sensors will use LoRa technology to cover large fields and monitor soil and environmental conditions. These sensors will be used to relay data, stream sensor data, and process data in real time. This data will be used to capture and analyze satellite and camera imagery. This monitoring will help to pinpoint and analyze stress, diseased crops, pests, animals, and other problems. Seasonal and predictive machine learning models will analyze weather data to create irrigation schedules. Smart Irrigation uses sensors to monitor the irrigation levels of crops and in turns manage the irrigation system. Energy and water diversion will be controlled by the smart irrigation system to conserve resources. Farmers can get alerts and system controls through a web-based system. They will have access to real-time data, as well as historical and predictive reports. Experimental assessment shows better irrigation and water savings as well as additional crop yields over the standard method. The proposed framework provides a scalable, affordable, and climate-smart solution for smart farming, aiding in data-driven agricultural management, and promoting sustainability in the long term.

Keywords

Smart irrigation, Precision agriculture, IoT sensors, Artificial intelligence, LoRa communication, Computer vision, Sustainable farming.

1. INTRODUCTION

Modern agriculture is still facing large problems regarding the lack of available water and the inefficient systems used to water crops; this is especially true in areas that rely on rain seasonally. Some of the problems created by the practice of inefficient irrigation include increased operational costs, lower crop yield, and unnecessary water waste. A long-term solution to these problems is smart irrigation systems that utilize AI (artificial intelligence), the Internet of Things (IoT), and remote sensing technologies.

The AI smart irrigation system that will be discussed in this paper can make autonomous decisions about crop irrigation systems by using real-time analysis of the environment and utilizing predictive analytics. Various disconnected soil moisture sensors, DHT11 temperature and humidity sensors, rain sensors, nutrient sensors, and PIR sensors are used to gather data about the fields. The irrigation system can be controlled over large areas of fields using very little power, thanks to long range (LoRa) communication.

The system can integrate predicted weather models, as well as utilizing crop health and stress detection. Camera data can be analyzed in the same way to find and sustain environmental factors on the crop, as well as locate and sustain the presence of pests and diseases. From the information that is gathered, the system can adjust irrigation schedules to better utilize water. The web-based user dashboard allows farmers to access the system's data to monitor system parameters in real-time; the system will also provide notifications, store data, and offer controllable features, including switching the system to manual operation. Overall, this system is designed to help make positive changes to the way we utilize available resources.

2. LITERATURE SURVEY

KS, Syam Kishor, and colleagues [1] developed one of the first and most detailed IoT-enabled frameworks for real-time prediction of crop-growing potential based on the analysis of soil fertility. The system uses cloud-based analytics with several types of soil sensors (pH, moisture, nitrogen, phosphorus, and potassium) to assess crop growing potential. The authors found continuous monitoring to be superior to periodic monitoring, emphasizing that real-time data delivery yields superior decision-making compared to past, present, and future data streams. The authors applied machine learning (ML) classifiers and correlated soil nutrients with crop types to predict crop yield more accurately compared to conventional yield prediction methods. Within the modular IoT frameworks, scalability and economic accessibility for smallholders are the most advantageous features of the system. Although the system is built using static ML models, meaning the system cannot adjust to changes in the environment, overall, the work demonstrated the successful fusion of predictive agriculture and sensing technologies.

Senthil Kumar Swami Durai and others [2] embraced the concept of smart agriculture further by integrating machine learning and deep learning techniques into crop management. Their framework used Random Forest and Support Vector Machine supervised learning algorithms and deep neural networks for yield forecasting. The authors noted that deep learning models can identify and capture complex hidden relationships and interactions among soil metrics, temperature, humidity, and rainfall, which traditional ML methods do not address. Their comparative analyses revealed that deep models usually outperform traditional ML methods, provided they are trained with a large enough dataset. This study articulated that agricultural datasets are distinct in that they can benefit from deep learning's hierarchical feature representation. Additionally, they developed automated advisory systems to optimize and schedule irrigation and recommend fertilizers. Although deep learning models are more predictive, the power and computational demands may be too much for low-spec edge computing devices. Therefore, this study emphasizes the importance of finding a compromise between predictive accuracy and power consumption in IoT.

Sarangi et al. [3] focused on enhancing control of agricultural processes by evaluating soil fertility. The study suggested the first use of artificial intelligence (AI) in agricultural control systems to assist the decision-making process on nutrient management. Unlike prior research, which mainly centered on prediction, this research focused on control systems where sensor-mediated feedback drives direct control of actuator systems, such as in the case of pumps and nutrient dispensers. The authors used a regression approach in which models of soil fertility were continuously updated in accordance with incoming soil data. The dynamic control approach reduced the sustainability challenge of the overuse of fertilizers. Their contribution illustrates the shift from systems that solely monitor to fully closed-loop control systems in automated agriculture. Nonetheless, their work was confined to small experimental testbeds and, therefore, the need for large-scale testing remains.

Afzal et al. [4] researched irrigation control using an adaptive watering system supported by IoT and ARIMA soil moisture forecasting. Their research incorporated time-series forecasting methodologies, which meant irrigation scheduling could be done more proactively. Rather than reactive watering based on threshold violations, this predictive approach conserved watering and optimally sustained moisture. The use of ARIMA models in an IoT environment provided an example of how traditional statistical methodologies continue to be integrated with modern artificial intelligence methodologies. Their research concluded that it was possible to sustain the health of crops while using less water. However, ARIMA models tend to fail when it comes to forecasting and modeling abrupt and non-linear environmental changes, which makes for an opportunity for blended models, which consist of both traditional statistical methodologies and machine learning methodologies.

Laskar et al. [5] investigated the possibility of embedding smart systems into farm tools to help improve soil fertility and crop productivity. The authors detailed mechanization fused with smart sensing and how tractors, seeders, and sprayers outfitted with IoT devices can collect data in real time. This method pushes the boundaries of smart agriculture from the use of stationary sensor nodes to mobile sensing devices that can survey entire fields. The system created precision agriculture by spatially mapping field fertility and supporting practices such as variable-rate fertilization. The authors improved the operational efficiency and decreased the manual labor of IoT-integrated farming tools. Still, there is the downside of the high costs of outfitting farming tools with smart devices, which can affect smallholder farmers.

Khaliq et al. [6] proposed an AI-integrated framework that combines soil analysis, irrigation management, and crop-fertilizer recommendations. Their research presented an integrated approach where sensor data is processed by AI frameworks to optimize several agricultural inputs simultaneously. Instead of analyzing soil and irrigation as two different problems, they created multi-task learning algorithms to generate interdependent solutions. Their research showed that balanced management of water and optimum nutrient levels synergistically improved crop yields. The solution also combined cloud computing for advanced analytics and edge nodes for real-time analytics. This architecture illustrates the effective use of distributed intelligence in agriculture. However, reliance on consistent internet connectivity may impede implementation in isolated rural locations.

Luo et al. [7] offered a data management review integrating AIoT technologies applied to smart farming. Along with the assimilation of the different data acquisition, processing, and storage techniques, the authors stress the management of scalable architectures capable of monitoring large volumes of data during the farming cycle. They discussed issues such as data variety, latency, the interoperability of different systems, and data pipeline security. More than anything, the authors pointed out that data management is as vital as predictive modeling; data pipelines need to be present for the sensing systems to provide operational insights. This review laid the groundwork for the consideration of edge computing and federated learning in the agricultural IoT domain.

Dutta et al. [8] broadened the bounds of farming beyond the soil with their consideration of IoT-based precision farming in soilless agriculture. Their work illustrated that even in systems of hydroponics and aeroponics, IoT-enabled monitoring of nutrient solutions, pH, and other environmental factors is beneficial. This study focused on the sustainability aspect and argued that with controlled environment agriculture, land and water usage could be optimized, also highlighting the globally critical issue of food security. With the incorporation of sensors and automation, they accomplished and optimized precise nutrient dosing and growth. Their findings confirmed that the bounds of IoT-driven agriculture extend beyond remote and open fields to also encompass urban and indoor farming.

Aldhahri et al. [9] studied the use of analytics for prediction in urban farming and resource management. They worked in smart city farming, where optimized management of space and resources is critical. They developed predictive models to optimize the use of water, energy, and fertilizer without an operational compromise. Their findings show that urban farming, when integrated with the Internet of Things and analytics, offers a promising solution for food security. The carbon footprint and other sustainability measures noted in the study suggest that their approach could benefit the environment.

Gunasekaran et al. [10] used machine learning and deep learning algorithms to create a crop and real-time soil fertility prediction system. Of the different ensemble methods they used, the authors cited the greatest accuracy in comparison to ensemble and stand-alone methods. The authors focused on the usability and interpretability of the system and proposed the use of dashboards to assist farmers in receiving information that is actionable, rather than simply raw information. The authors suggest that their dashboards, along with other visualization tools, help to simplify complex analytics. The foundational studies pose the basic principles of smart and IoT-based agriculture, which include automated controls, resource management, predictive analytics, and real-time data. The initial research primarily focused on the development of sensor networks. The next generation of smart agriculture sensor networks incorporated AI to help with complex decision-making. The literature demonstrates a distinct transition from observation to predictive and prescriptive agriculture. Despite the advances, the literature does still identify boundaries with regards to computation and connectivity that create barriers to cost and scalability. Solving these problems will help in the adoption of the techniques.

3. METHODOLOGY

The system includes integrated AI, IoT sensors, communication modules, TRANSMIT, and RECEIVE units. The system contains many kinds of sensors. Soil moisture sensors, DHT11 sensors (for temperature & humidity), rain sensors, PIR sensors, and NPK sensors. Data processing and AI execution is done on Raspberry Pi 4B. Long-range data transmission is done via LoRa modules. Disease & crop monitoring is done via Pi Camera. The system is powered by solar panels, a battery, and a DC-DC buck converter. The system consists of a relay-controlled irrigation motor, buzzer notifications, an OLED display, and a web dashboard.

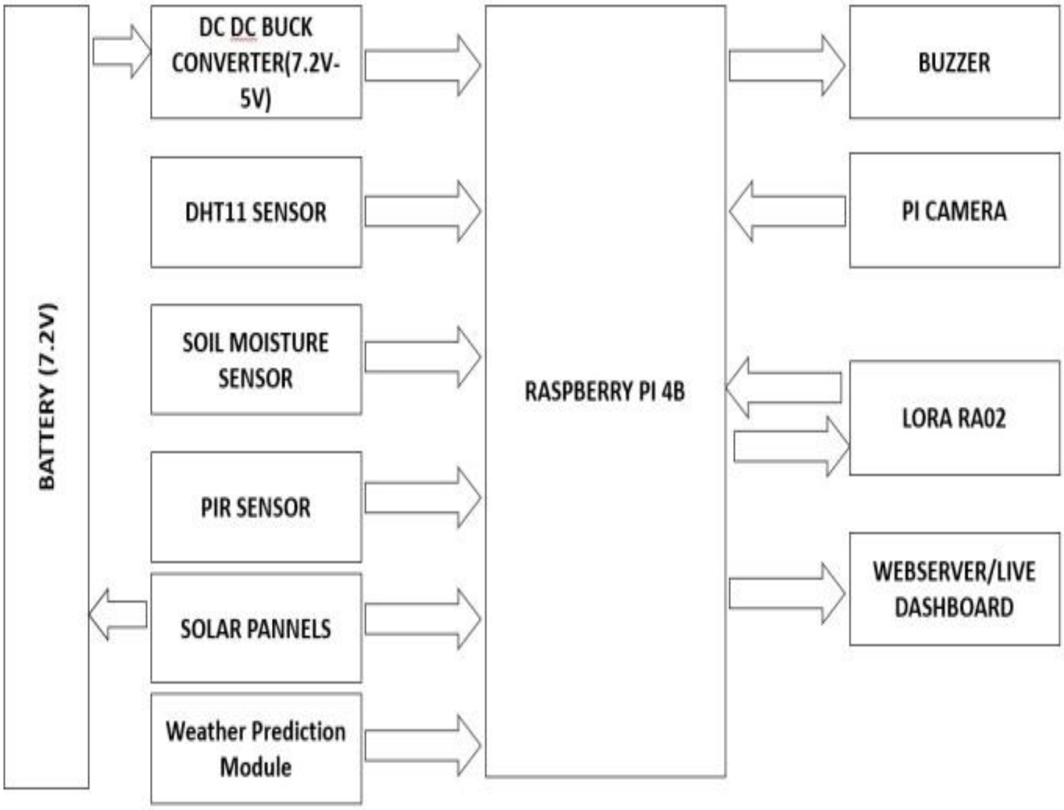

Fig 1: System Architecture

Figure 2 illustrates the flow of a Smart Agri AI transmitter unit. The process begins with the activation of the sensors (soil, temperature, humidity, PIR, and camera), as well as the LoRa communication device. In parallel, the system begins environmental sensing, weather forecasting, motion tracking, and disease monitoring. The unit continuously evaluates the variables present in the field and uses LoRa communication to transmit data packets of the variables (soil condition, temperature, humidity, weather prediction, and disease status). In the event of motion detection, the camera captures the motion and sends an alert. Furthermore, in disease detection, the system requests a leaf image, which is analyzed with a TensorFlow Lite model and the results are presented in a web dashboard

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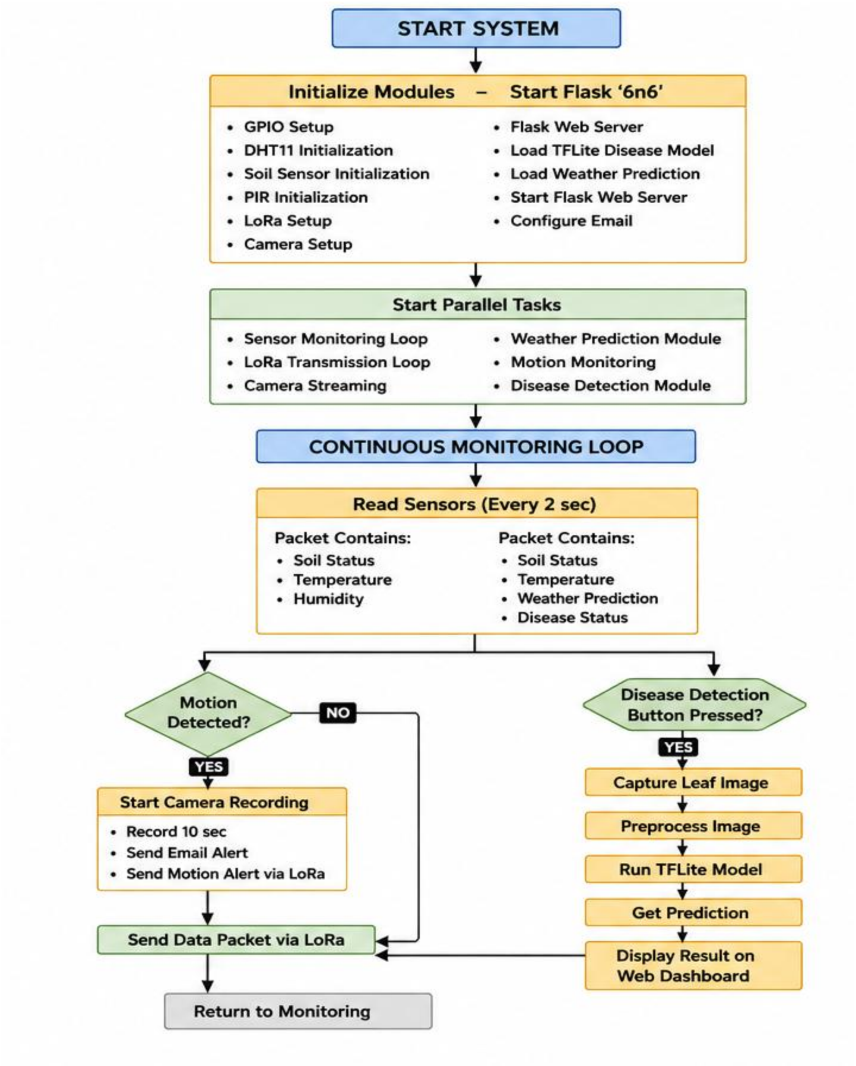

Fig 2: Flowchart of TX

Figure 3 shows the process of the smart irrigation system on the receiver end. Upon initialization of the Wi-Fi, Blynk, LoRa, Relay, OLED, and Flow sensor components, the system will connect to a weather API and receive data from the transmitter. From this point, the system will operate in either automatic or manual mode. In automatic mode, the system will make irrigation decisions autonomously based on the readings from the soil moisture sensor, the weather API, and the flow sensor. In manual mode the user can open the motor via the Blynk app (with the option to set a timer for the motor to be closed). There are flow monitoring and other safety features present in the system, while the status of the system is continuously updated on the OLED display

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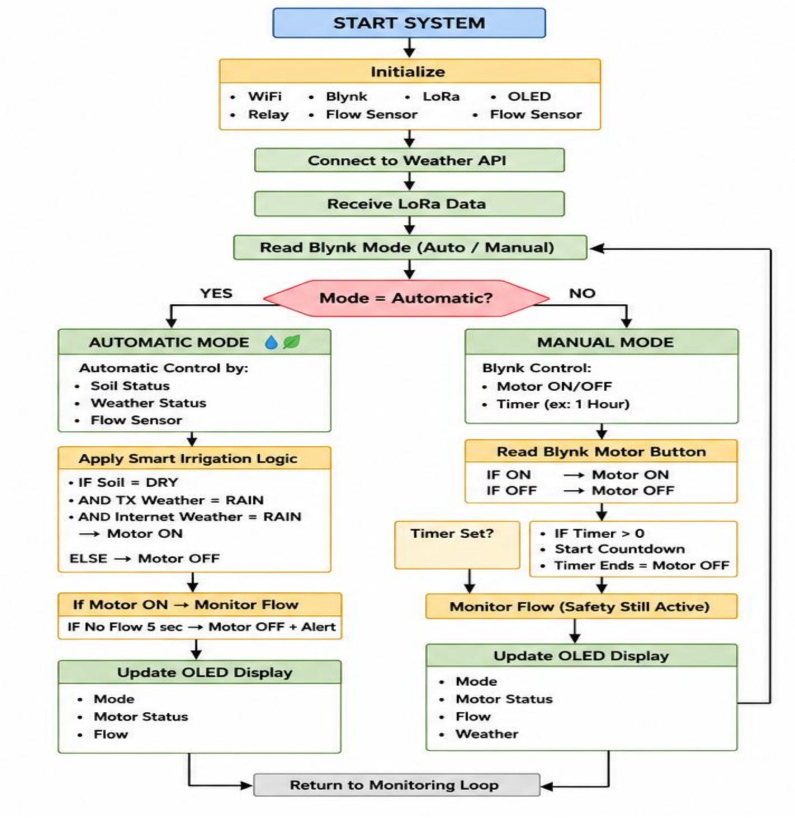


Fig 3: Receiver Flow Chart

Figure 4 provides a representation of the hardware architecture of the receiver system. Here, the ESP32 is the primary controller that manages inputs from the weather prediction module, water flow sensor, and the LoRa (long range) receiver. The ESP32, in turn, commands the relay to activate the motor pump. The OLED display shows the system's status in real-time; meanwhile, cloud services, such as Blynk and Thing Speak, facilitate the system's remote monitoring and control, as well as provide access to the system from mobile and desktop applications

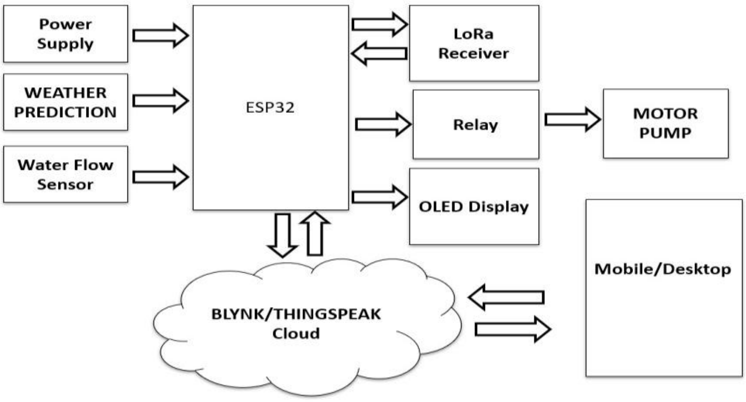


Fig 4: Receiver Block Diagram

A. **Data Acquisition and Monitoring:** Sensors continuously collect environmental parameters such as soil moisture, temperature, humidity, and weather conditions at regular intervals. The data is transmitted through LoRa to the receiver module and cloud server for processing and storage.

B. **AI and Prediction Modules:**
Weather prediction using machine learning models. Crop disease detection using TFLite image classification. Irrigation scheduling using soil and environmental analysis.

C. **Control Modes:**
Automatic Mode:
The automatic mode operates the motor based on factors such as soil dryness, local weather prediction, and internet weather API, and water availability.
Manual Mode
User control through mobile applications with ON/OFF, timer, and override options.

D. **Decision Logic**
The system evaluates sensor data and prediction outputs to decide irrigation timing. Safety

mechanisms such as flow detection prevent motor damage during dry-run conditions. Data is uploaded to the cloud for visualization and analytics.

Algorithm 1:

```
TX SIDE ALGORITHM

Step 1: Start system.
    • Initialize all sensors and modules.
    • Load AI models.
Step 2: Start web server.
    • Enter continuous loop.
    • Every 2 seconds:
Step 3: Read soil moisture.
    • Read temperature.
    • Read humidity.
Step 4: Predict weather.
    • Send data via LoRa.
    • If PIR detects motion:
    • Start recording.
    • Save video.
    • Send email.
    • Send alert via LoRa.
    • If disease detection is requested:
Step 5: Capture image.
    • Run TFLite model.
    • Send disease result.
Step 6: Repeat indefinitely.

START RX SYSTEM

Step 1: Initialize
    • WiFi
    • Blynk
    • LoRa
    • OLED
    • Relay
    • Flow Sensor
Step 2: Connect to Weather API
Step 3: Receive LoRa Data
Read Blynk Mode (Auto / Manual)
MODE DECISION BLOCK
IF MODE = AUTOMATIC
Step 4: Apply Smart Irrigation Logic
IF Soil = DRY
AND TX Weather ≠ RAIN
AND Internet Weather ≠ RAIN
Motor ON
ELSE
Motor OFF
If Motor ON → Monitor Flow
IF No flow 5 sec → Motor OFF + Alert
IF MODE = MANUAL
Step 5: Read Blynk Motor Button
IF ON:
Motor ON
IF OFF:
Motor OFF
Timer Set?
IF Timer > 0:
Step 6: Start countdown
When timer ends:
Motor OFF
Step 7: Monitor Flow (Safety Still Active)
If no water → Motor OFF
Update OLED Display
Step 8: Show:
    • Mode
    • Motor Status
    • Flow
    • Weather
Step 9: Upload Data to Cloud
Repeat Loop
```

4. RESULTS

The first tests of the proposed system showed better efficiency of irrigation and better conservation of water against irrigation methods that are already available. The proposed system had constant monitoring that allowed accurate understanding of the moisture level of the soil and the surrounding environment. This allowed better optimization of irrigation practices.

With the use of AI for forecasting of the available moisture and consequent rainfall, irrigation practices were not required to alter. Also, the AI and disease recognition system through imaging detects crop problems at an early enough stage to take control of the issue. The use of LoRa technology for data transmission proved to guide and control the crop growing technology over large and less power consuming agricultural areas.

The control of irrigation practices through technology reduced participation from farmers and less water was provided to the crops and as a result, over-watering of the crops was avoided. The farmers also had monitoring of the system in real time and received changes to the system as well as predictive reports through the dashboard that was available on the web. The first tests of the technology showed.

To deepen the assessment, the proposed system was validated under different conditions—different types of soil (sandy, loamy, clay), different weather types (dry, humid, rainy), different crop types, different historical weather data, and different environments. To assess the reliability of the AI-based irrigation model, historical data and environmentally simulated data were used. Compared to the rule-based system and the irrigation system, this proposed system analyzed the crop health and irrigation system, saving approximately 25 to 35 % more water. This system was also able to provide continuous, stable irrigation and crop health data, despite presenting an intermittent channel. These features of the system are especially important from the perspective of irrigation system designers and agricultural engineers, as they allow the system to be adapted to different agricultural practices.

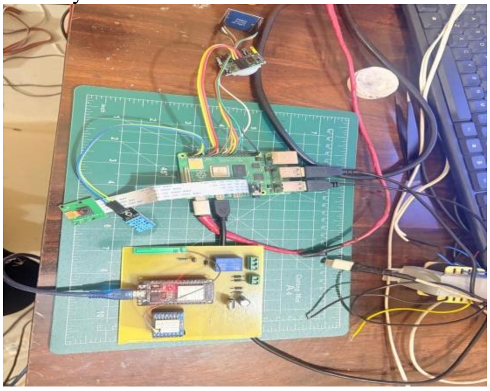


Fig 5: Hardware Setup

This figure 5 hardware setup on a cutting mat with a Raspberry Pi and various sensors and modules connected via jumper wires. A camera ribbon cable is attached, and there are visible power and USB clips. This setup is likely for an internet of . things (IoT) or smart ag prototype and is still in the developmental stages.

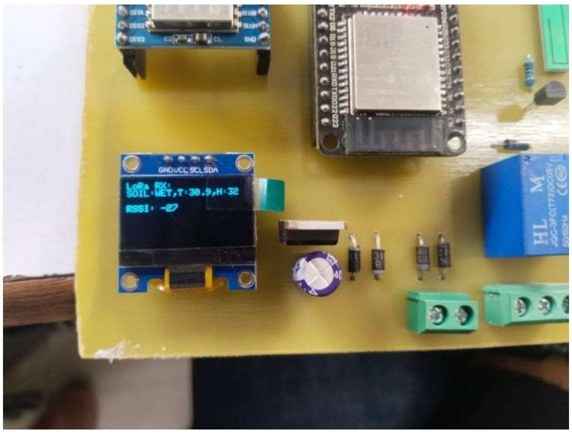
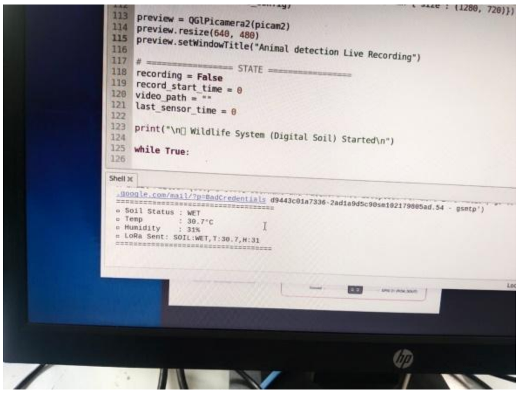


Fig 6: A Customs PCB which includes an ESP32 microcontroller

This figure 6 showcases a custom PCB which includes an ESP32 microcontroller and an OLED display that shows soil and environmental readings. It also includes a relay module, some capacitors, diodes, and some terminal connectors. From the look of the board, it has been made for the purpose of monitoring and control, most probably in an automated soil or irrigation system.



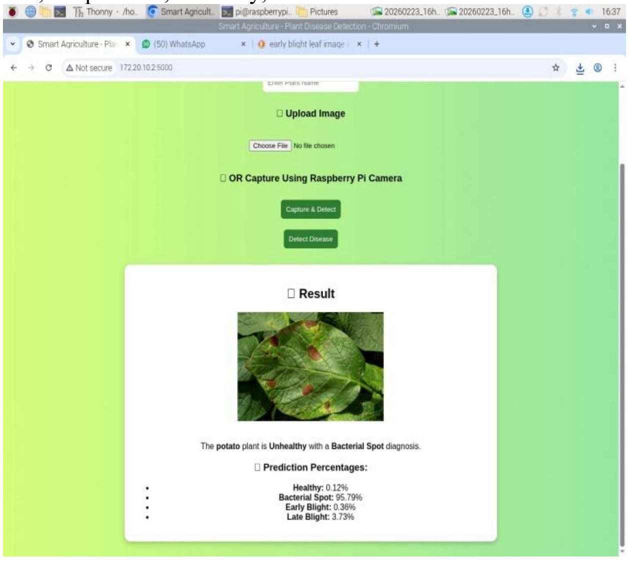
```
preview = QGlPicamera2(picam2)
preview.resize(640, 480)
preview.setWindowTitle("Animal detection Live Recording")
# ================ STATE ================
recording = False
record_start_time = 0
video_path = ""
last_sensor_time = 0

print("\n Wildlife System (Digital Soil) Started\n")
while True:
```

```
.google.com/mail/?p=BadCredentials d9443c01a7336-2ad1a9d5c90sm102179805ad.54 - gsmtp')
===================================
▫ Soil Status : WET
▫ Temp        : 30.7°C
▫ Humidity    : 31%
▫ LoRa Sent: SOIL:WET,T:30.7,H:31
===================================
```

Fig 7: Output Computer terminal

Figure 7 displays a Python program in a computer terminal for a digital soil or wildlife monitoring system. The console shows live sensor readings including soil state, temperature, humidity, and LoRa data that indicate the system's successful data capture and system boot.



☐ **Upload Image**

☐ **OR Capture Using Raspberry Pi Camera**

☐ **Result**

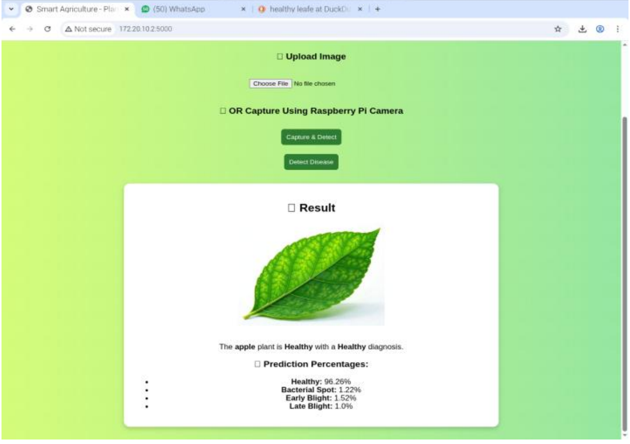
The **potato** plant is **Unhealthy** with a **Bacterial Spot** diagnosis.

☐ **Prediction Percentages:**

- **Healthy:** 0.12%
- **Bacterial Spot:** 95.79%
- **Early Blight:** 0.36%
- **Late Blight:** 3.73%

Fig 8: Detecting Plant Diseases

Figure 8, a web application shows a system for detecting plant diseases using an image of a potato leaf. The results indicate that the plant is unhealthy, diagnosed with bacterial spots, and includes prediction percentages for various disease classes that reflect the model's level of confidence.



☐ **Upload Image**

☐ **OR Capture Using Raspberry Pi Camera**

☐ **Result**

The **apple** plant is **Healthy** with a **Healthy** diagnosis.

☐ **Prediction Percentages:**

- **Healthy:** 96.26%
- **Bacterial Spot:** 1.22%
- **Early Blight:** 1.52%
- **Late Blight:** 1.0%

Fig 9: Apple leaf classified

This example prediction on the web interface shows an apple leaf classified as healthy. The model shows high confidence in the healthy category and low probabilities for any of the disease classes, suggesting that the model has correctly identified a healthy plant sample.

5. CONCLUSION

The smart irrigation system uses IoT sensors, machine learning, and long-range communication technologies. The system seeks to address modern challenges of agriculture. It helps conserve water and improve productivity by intelligently scheduling irrigation. It has autonomous control, but it can be operated manually to address the needs of varied farming conditions. The system has been shown to maintain nice levels of soil moisture and reduce water waste. The smart irrigation system has also been integrated with image processing to help with disease detection to monitor crops. In the future, this research could be expanded to include satellite- based remote sensing for real-time, large-scale farm monitoring and analysis. Improved prediction for irrigation and crop health analysis will be an achievable result of deep learning with numerical analysis and Convolutional Neural Networks (CNN) and Long Shorts and Term memories (LSTM) models. Edge AI optimization will allow the system to be implemented in low-power devices in rural areas. The system’s adaptability for changing crops and region models across different agricultural environments will be improved. The system will be able to share cross- border concerns and data at an international level with the integration of smart government agricultural platforms, and the ease of use for farmers will be significantly improved with the latest in mobile technology in their own languages.

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