iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: II Month of publication: February 2026

DOI: https://doi.org/10.22214/ijraset.2026.77184

Agri Sentinel AI: Revolutionizing Smart Agriculture with Real-Time Disease Detection and Advisory Systems

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Abstract: Agriculture remains the backbone of many developing economies, yet it is increasingly threatened by plant diseases, insect infestations, and animal intrusions that lead to significant yield losses and economic instability for farmers. Conventional crop monitoring still depends largely on manual field visits and occasional expert supervision. This approach is labour intensive, slow, and unsuitable for continuous large-scale surveillance. In the early stages, symptoms of diseases such as rust, blight, or bacterial infections are often faint and easily overlooked, allowing problems to spread before any action is taken. To resolve these issues, this work introduces Agri Sentinel AI, an intelligent, real-time agricultural monitoring system that combines deep learning, computer vision, and Internet of Things (IoT) technologies. Low cost ESP32 camera modules are installed across the field to continuously capture live images of crops. These image streams are processed by YOLO-based object detection models capable of identifying plant diseases, pest activity, and animal intrusions under diverse environmental conditions. When a potential threat is spotted, the system produces labelled images highlighting detected areas and confidence levels, and links each detection to an integrated agricultural knowledge base. This knowledge base provides detailed disease descriptions, prevention strategies, and recommended treatments. The relevant information, along with the annotated image, is immediately delivered to farmers via Telegram alerts, enabling quick, informed responses. Field experiments conducted in real agricultural environments indicate that the system is accurate, scalable, and affordable, ensuring its suitability for smart farming and precision agriculture.
Keywords: Smart Farming, Identification of Plant Diseases, Pest Monitoring, YOLO, IoT, ESP32 Camera, Edge Computing, Real-Time Monitoring, Precision Farming.

I. INTRODUCTION

Last monsoon In recent years, we have repeatedly observed farmers in nearby rural areas struggling to identify crop diseases until visible damage had already spread across large portions of their fields. Yellow leaves, unusual spots, and wilting plants were often noticed only after the damage had already affected the harvest. By that point, it was usually too late to prevent yield loss. In many cases, farmers had to rely on guesswork or wait for experts to visit the field, which often led to overuse of pesticides and higher production costs.

These experiences highlight a persistent problem: even though agriculture has advanced in machinery and irrigation, monitoring crop health still depends largely on manual field inspections. Some existing tools try to improve this, such as periodic surveys or mobile apps that ask farmers to take and upload photos of their crops. However, these methods cannot provide continuous monitoring and quickly become impractical on large farms.

Real-world conditions make this challenge even more difficult. Unpredictable lighting, changing weather patterns, and a shortage of agricultural experts in rural areas all contribute to delays in correctly identifying crop problems. As a result, diseases and pest infestations are often missed during their early stages the very stage where intervention is most effective and least costly.

Faced with these challenges, we explored whether modern automation and artificial intelligence could provide a more reliable and scalable solution for farmers. The goal was simple: build a system that monitors crops continuously, detects potential threats as they appear, and alerts farmers immediately without requiring them to walk through fields or constantly check their devices.

To realize this idea, we combined deep learning–based object detection with low-cost Internet of Things hardware. The aim was to develop a system that performs well technically while remaining affordable for small and medium-scale farmers. This effort led to the creation of Agri Sentinel AI.

The proposed system is a real-time crop monitoring platform that integrates YOLO based detection models for fast and accurate threat identification, ESP32 camera modules for continuous image capture, and automated advisory notifications delivered via Telegram. Together, these components help farmers make quicker, better-informed decisions and move toward more precise and sustainable agricultural practices.

II. LITERATURE SURVEY

In recent years, many researchers have focused on using deep learning techniques to detect plant diseases. Early work in this area mainly used convolutional neural network (CNN) classifiers. These networks were trained on leaf images that were manually collected from fields or controlled environments.

These methods produced promising results and were able to distinguish between healthy and diseased plants with good accuracy. However, they had a major limitation: they were designed for one-time classification tasks rather than continuous, real-time monitoring in actual farm conditions.As the field evolved, newer studies began exploring object detection approaches, particularly YOLO and similar frameworks. These methods offered two important advantages: they could process images much faster, and they could pinpoint exactly where on a leaf or plant the disease symptoms appeared.This was a step forward from simple classification. However, despite these improvements, most of these detection systems were put to the test only inside laboratories or greenhouses where conditions stayed mostly stable. Previous studies often overlooked the effects of deploying these systems such technology outdoors, where sunlight shifts throughout the day, backgrounds are messy with weeds and soil, and weather can change without warning.

At the same time, a separate group of researchers began pairing Internet of Things gadgets with camera setups to keep an eye on crops from a distance. These arrangements could gather helpful information about field conditions. A major drawback was that almost all of them sent their images off to cloud servers for processing. This meant that farmers needed a reliable, steady internet connection something that many rural and remote farming communities simply do not have. Even when connectivity was available, the time spent uploading images and waiting for results slowed the process, making it harder to identify problems quickly.

Another limitation of previous work is that most projects focused only on plant diseases. They gave little or no attention to insect pests or wandering animals, both of which can damage crops in a matter of hours if not managed.

All of these shortcomings the lack of affordable solutions, the absence of true real-time monitoring, and the failure to cover the full range of threats farmers face highlighted a clear need for a better system.

This need led us to develop Agri Sentinel AI. Our goal was to combine edge-based YOLO detection, cameras connected via IoT technology, and automatic alerts with practical guidance into a single, easy-to-use system that performs effectively under real farming conditions.

III. PROBLEM STATEMENT

Diseases that affect crops, insects that feed on plants, and animals that wander into fields create major challenges for farmers. These issues directly reduce the harvest and, in turn, the income farmers rely on to support their families.

When plant diseases first appear, the early signs are often so subtle that a farmer walking through the field might not notice anything unusual. Leaves may look slightly off, or small spots can blend in with natural variations. By the time the damage becomes visible to the naked eye, the disease has usually spread from plant to plant, affecting a large portion of the field. At this stage, saving the crops becomes much more difficult, and sometimes impossible.

Insects and roaming animals pose similar problems. A swarm of pests or a group of hungry animals can destroy a section of crops in just a few hours. This often happens after dark, when no one is around to intervene. Farmers may wake up to find their hard work ruined overnight.

When these problems are discovered too late, farmers often respond by applying large amounts of pesticides in an attempt to stop the outbreak. This reaction increases costs for chemicals and labor. Beyond the financial impact, excessive pesticide use contaminates the soil and can run into nearby streams and wells, causing long-term harm to the land and water resources communities depend on.

The traditional way farmers monitor their crops has not changed much over the years. They walk the fields, examine leaves closely, and rely on their experience to notice anything unusual. Sometimes, they call in outside experts for a closer look. While this hands-on approach has worked for generations, it is exhausting, time-consuming, and impractical for large fields or during bad weather. Finding skilled specialists is particularly difficult in remote areas far from cities or agricultural universities.

Some newer tools have tried to help, but they come with limitations. Certain apps ask farmers to take photos of their plants and send them for analysis. While this seems simple, busy farmers often forget or skip this step amid other responsibilities. Other systems require fast, reliable internet or expensive equipment that small family farms cannot afford.

Considering all these challenges, it is clear that farmers need a different solution. They require a monitoring system that operates automatically, detects problems as soon as they appear, and is affordable to use. Such a system must monitor for diseased plants, pests, and unwanted animals continuously. Equally important, it should notify farmers with clear alerts and practical advice, enabling them to act quickly and prevent minor issues from turning into major crop losses.

IV. PROPOSED SYSTEM

Our solution places ESP32 camera units throughout the farm, where they continuously capture images of the crops without interruption. These images are sent to YOLO-based detection models trained to identify diseased plants, crawling insects, and animals wandering through the fields.

As soon as a potential threat is detected in an image, the system immediately sends a Telegram alert to the farmer’s phone.

1) Data acquisition**:** Collects images from all the cameras.
2) Intelligent processing**:** Analyzes the images using detection models to identify potential issues.
3) Alert and advisory: Combines annotated images with easy-to-follow guidance and delivers them to farmers instantly.

A. System Architecture

The system architecture of Agri Sentinel AI is designed as a layered framework that enables continuous real-time agricultural monitoring. ESP32 camera modules form the data acquisition layer, capturing live visual information from the field. The processing layer consists of YOLO-based deep learning models deployed on edge or local processing units, where captured images are analyzed to detect plant diseases, insect infestations, and animal intrusions. The alert and advisory layer integrates an agricultural knowledge base with the Telegram messaging platform to deliver annotated images and actionable recommendations to farmers. These components work together to ensure low-latency detection, minimal network dependency, and timely decision support.

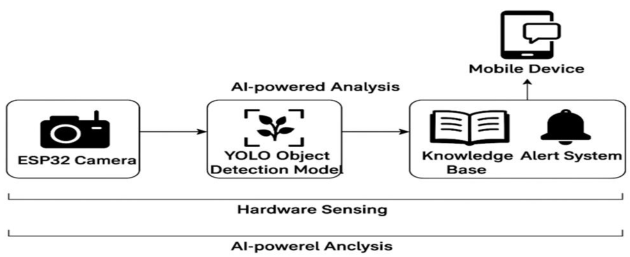

Figure 1: System Architecture of an AI-Powered Plant Health Monitoring System

B. Algorithms

The system operates by continuously capturing live images from ESP32 camera modules deployed across the agricultural field. Every image frame captured by the cameras goes through initial preprocessing before being fed into a YOLO-based deep learning model for instant analysis. The model scans each image for signs of plant diseases, insect pests, and animal presence by recognizing specific visual patterns and drawing bounding boxes around detected objects, along with confidence scores indicating how certain the detection is.Once a potential threat is identified, the system marks up the image with these detection boxes and pulls relevant guidance from a built-in agricultural knowledge base. This guidance includes details about the detected problem and suggests preventive steps or treatments. The marked image and the advisory message are then pushed directly to the farmer via Telegram, allowing them to take quick action.This entire cycle repeats without stopping, providing round-the-clock surveillance and helping catch agricultural problems at the earliest possible stage.

C. Data Flow Diagram

The flow of data in our system begins with ESP32 camera modules constantly capturing live images from the farm. Images captured by the cameras are sent to the processing unit, where they are cleaned and sharpened before any analysis begins. Once ready, the images are processed by the YOLO-based detection model, which quickly identifies signs of plant disease, insect activity, and wandering animals. For each detected issue, the model provides the type of threat, its confidence level, and the exact location within the image.

When a potential problem is detected, the system consults its built-in agricultural knowledge base to retrieve practical guidance. It then combines the annotated image with clear, actionable suggestions and sends everything to the farmer via Telegram. This cycle runs continuously, monitoring the fields around the clock and identifying problems early, before they turn into costly damage.

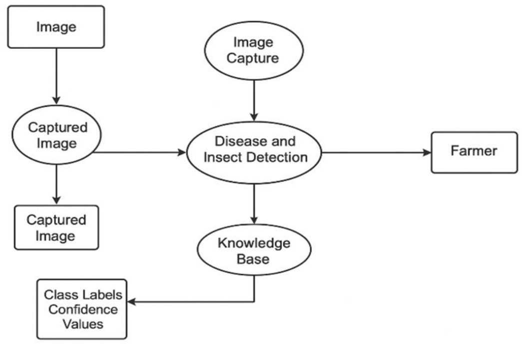

Figure 2: Data Flow of the Smart Crop Health Monitoring System

D. Use Case Diagram

The use case diagram of the proposed system illustrates the interaction between the farmer and the Agri Sentinel AI system. Farmers are at the center of this system as the main users, receiving alerts and practical guidance whenever a problem is detected. ESP32 camera modules placed throughout the farm continuously capture images, keeping watch over every part of the field.

Each image is sent to a YOLO-based detection model, which analyzes it to identify diseased plants, insect activity, or animals that have entered the crops. As soon as the model detects an issue, it marks the affected areas and retrieves practical advice from its agricultural knowledge base.

All of this information is then sent to the farmer via Telegram within seconds, allowing them to take action immediately. From the moment the camera captures the image to the notification on the farmer's phone, the entire process operates automatically without any manual effort.

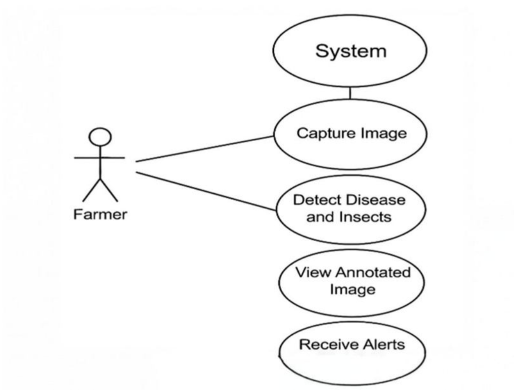

Figure 3: Use Case Diagram of Agri-Vision AI

V. METHODOLOGY

The methodology of the proposed *Agri Sentinel AI* system describes the systematic approach adopted to achieve real-time crop disease, pest, and animal intrusion detection using artificial intelligence and IoT technologies. The system integrates live image acquisition, deep learning–based object detection, knowledge-driven advisory support, and instant farmer notifications. This structured methodology ensures continuous monitoring, early threat identification, and timely intervention, thereby reducing crop losses and improving agricultural productivity.

A. Image Acquisition and System Initialization

The system begins by initializing the ESP32 camera modules or local webcams and loading the trained YOLO object detection model. Cameras are strategically deployed in the agricultural field to continuously capture live images of crops. This stage ensures uninterrupted data acquisition and prepares the system for real-time monitoring operations.

B. Real-Time Detection and Frame Processing

Each captured frame is processed by the YOLO-based object detection model to identify plant diseases, insect infestations, or animal intrusions. Detected objects are localized using bounding boxes and confidence scores. If no relevant object is detected, the system continues capturing the next frame.

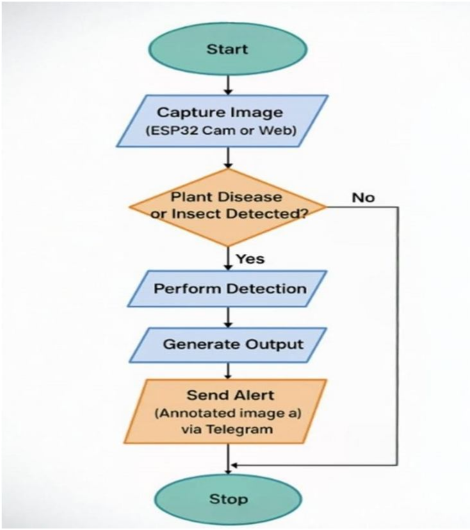

Figure 4: Flowchart of the Automated Pest and Pathogen Identification Process

C. Knowledge Mapping and Validation

Once a valid detection is confirmed, the detected class is mapped to the agricultural knowledge base. This module retrieves disease descriptions, preventive measures, recommended treatments, and recovery timelines. A cooldown validation mechanism is applied to avoid repetitive alerts for the same event within a short duration.

D. Alert Generation and Communication

After validation, the system generates an alert containing the annotated image and advisory information. This alert is transmitted to the farmer via the Telegram Bot API in real time.

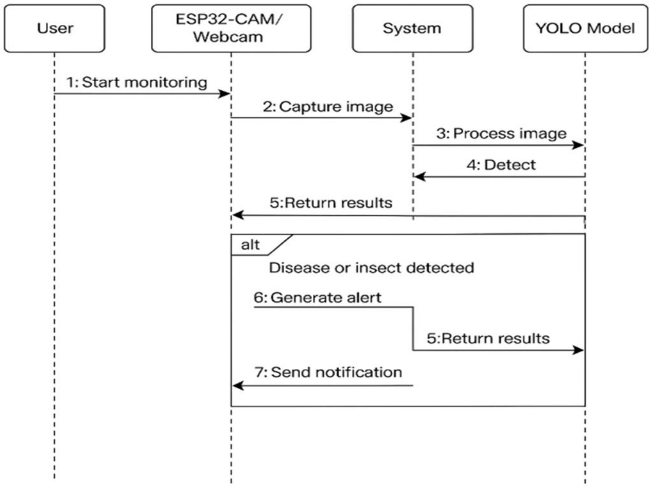

Figure 5: Sequence Diagram of the Agri Sentinel AI Monitoring Event

E. Continuous Monitoring and Feedback Loop

Following alert delivery, the system resumes continuous monitoring by capturing new frames and repeating the detection cycle. This closed-loop operation ensures uninterrupted surveillance and timely detection of emerging crop health issues, enabling proactive and efficient farm management.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue II Feb 2026- Available at www.ijraset.com

VI. SYSTEM IMPLEMENTATION

A. Implementation Overview

The proposed intelligent plant disease and insect detection system is implemented as a real-time agricultural monitoring solution by integrating IoT devices, deep learning models, and communication services. ESP32 camera modules and webcams are used to continuously capture live images of crops from the field. These images are transmitted wirelessly to the processing unit, where a YOLO-based deep learning model analyzes each frame to detect plant diseases and insect infestations. The system is designed to operate automatically with minimal human involvement, ensuring smooth data flow, low latency, and reliable performance even under challenging field conditions such as poor lighting, moving leaves, and network fluctuations. Optimization techniques and error-handling mechanisms are incorporated to support long-term, uninterrupted operation.

B. Module Level Operation

The system is organized into three main modules: input, processing, and output. The input module collects image frames from ESP32 cameras or webcams placed around the farm and performs a quick quality check on each frame before passing it along.Once approved, the images enter the processing module, where the YOLO model analyzes each frame to detect potential problems. The system filters out unclear or low-confidence detections and connects confirmed threats to a knowledge base containing disease descriptions and treatment recommendations.A built-in cooldown timer prevents the system from sending repeated alerts about the same ongoing issue.The output module organizes the information and delivers clear, actionable warnings to farmers via Telegram. Each alert includes an annotated image highlighting the detected problem areas, along with simple suggestions for the next steps.Dividing the system into these modules ensures accurate detection, fast notifications, and practical advice, giving farmers the support they need to manage crop health without being overwhelmed by technical complexity

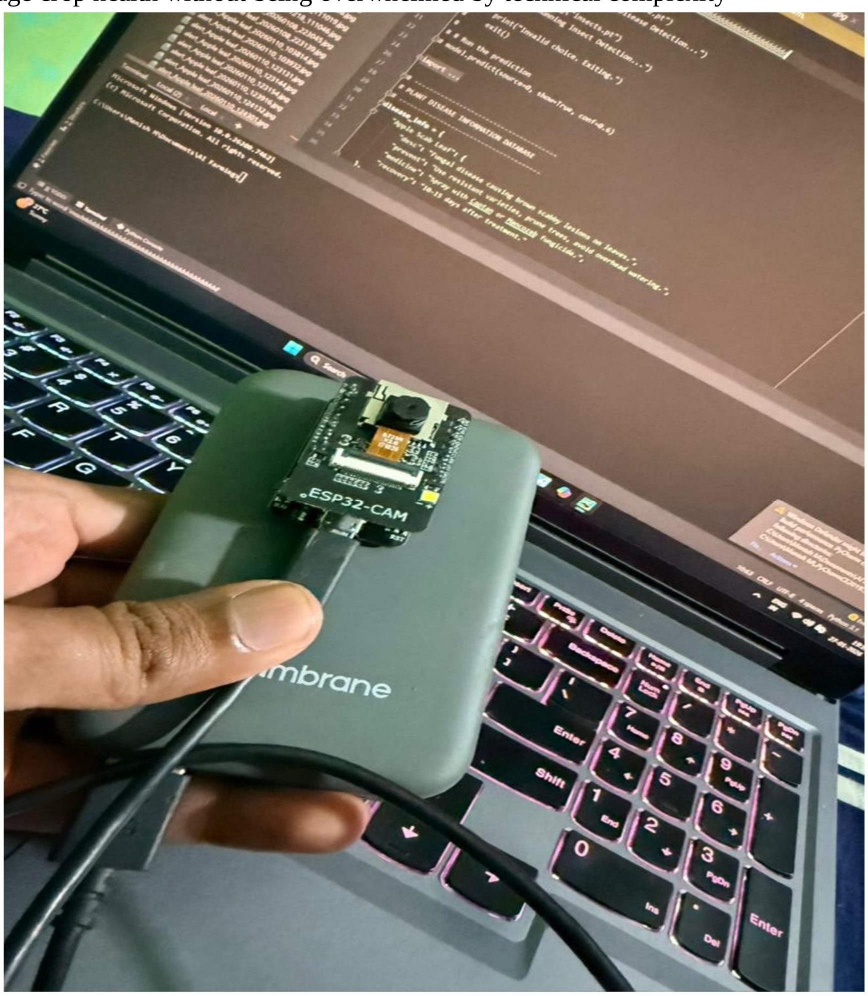

Figure 6: Experimental Setup Showing ESP32-CAM–Based Crop Image Acquisition for AI Analysis

Figure 7:ESP32 CAM Module Integrated with Real-Time Plant Disease Detection System

VII. RESULTS AND DISCUSSION

The implemented intelligent plant disease and insect detection system successfully demonstrated reliable real-time performance under both laboratory and simulated field conditions. The ESP32-CAM modules were able to continuously capture and transmit live crop images with stable connectivity, while the YOLO-based detection model accurately identified plant diseases and insect infestations with minimal delay. The system produced clear bounding boxes and confidence scores, enabling precise localization of affected regions. Alert messages, along with annotated images and recommended treatment information, were delivered promptly to farmers through the Telegram platform. Overall, the results confirm that the proposed system is efficient, responsive, and suitable for practical agricultural monitoring, helping farmers take timely preventive actions and reduce potential crop losses.

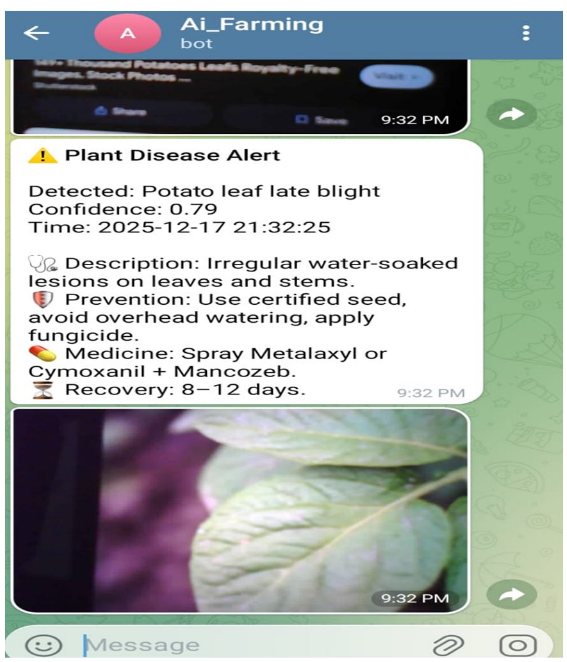

Figure 8: Potato leaf Disease

Figure 9: Rat Snake Detection

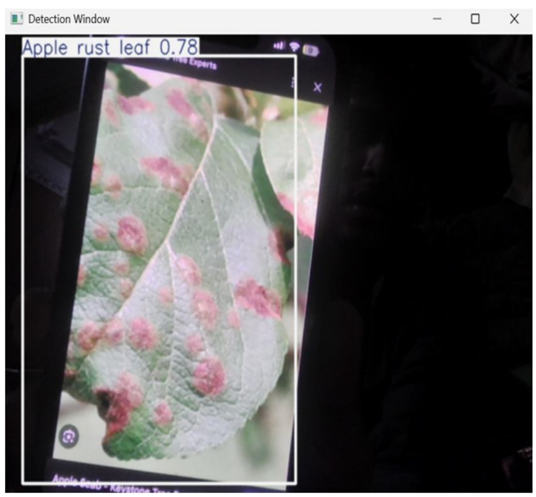

Figure 10: Manual Apple Rust leaf Detection

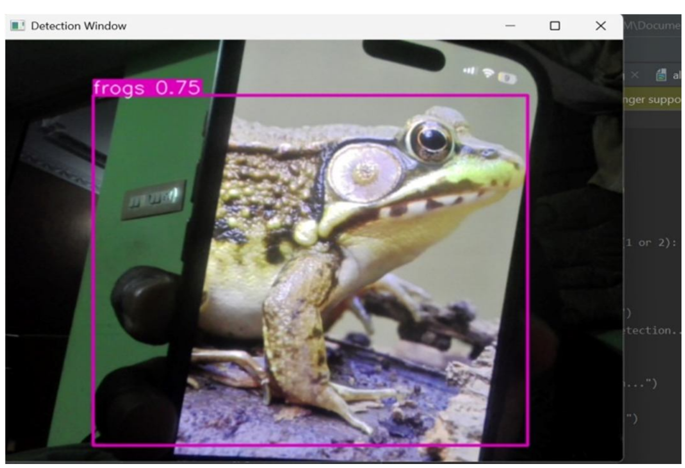

Figure 11: Manual Frogs Detection

VIII. CONCLUSIONS

The proposed *Agri Sentinel AI* system successfully demonstrates the use of artificial intelligence and IoT for real-time plant disease and insect detection in agriculture. By integrating ESP32-CAM modules with a YOLO-based deep learning model, the system enables continuous monitoring of crop health with minimal human intervention. The implemented solution accurately detects diseases and pests, provides annotated visual feedback, and delivers timely alerts along with preventive and treatment recommendations through Telegram. Experimental results show that the system performs reliably under varying environmental conditions, making it suitable for practical agricultural deployment. Overall, the project proves that AI-driven monitoring can significantly assist farmers in early disease detection, reducing crop loss and improving productivity.

A. Future Improvements

Although the system achieves effective real-time detection, several enhancements can be considered for future development. Training the model on a much bigger pile of images covering all sorts of crops and disease varieties would make it sharper and more reliable when facing situations it has not seen before. Plugging in extra sensors that keep tabs on temperature swings, moisture in the air, and how wet or dry the soil gets would round out the picture of what is really happening with plant health beyond just what the cameras can see.

Giving the system the ability to speak alerts out loud in different languages would help farmers who struggle with reading small text on their phones or simply prefer hearing updates while working with their hands. Mixing edge computing tricks with cloud backup would let the whole setup handle bigger farms, run smoother over time, and keep doing its job reliably season after season without breaking down or slowing to a crawl.

IX. ACKNOWLEDGEMENT

This project could not have been realized without the steady backing and kind words from the numerous individuals accompanying us through every step. Their quiet faith in what we were trying to build kept us pushing forward despite challenges and gradual progress.

We are sincerely grateful to our teachers at East West Institute of Technology, who saw something worthwhile in our rough ideas back when everything existed only as scratchy drawings and half-formed notions. They stuck with us through every stumble, offering wisdom and guidance with endless patience, and helped us mold those early sparks into the finished work we present today.

The laboratory staff are sincerely thanked for their valuable assistance us navigate hardware challenges, wiring errors, and repeated testing cycles, always ensuring that the system moved one step closer to a working solution.

We are also thankful to our classmates, whose questions and feedback pushed us to rethink design choices we initially assumed were complete. Their curiosity helped strengthen both the technical depth and practical reliability of the system. Finally, we acknowledge all those who contributed to this work in visible and invisible ways, contributing time, understanding, and encouragement. Each of these contributions played a meaningful role in turning an idea into a functioning intelligent agricultural monitoring system.

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