Automatic Leaf Health Monitoring with an IoT Camera System based on Computer Vision and Segmentation for Disease Detection

RICARDO YAURI, ANTERO CASTRO, RAFAEL ESPINO
Facultad de Ingeniería,
Universidad Tecnológica del Perú,
Lima,
PERÚ

Abstract: - Manual identification of diseases in crops is costly and subjective, driving the need for automated systems for accurate detection in the field. This requires the use of technologies based on the integration of IoT and deep learning models to improve the assessment capacity of crop health and leaf disease, with continuous monitoring. The literature review highlights technological solutions that include weed and disease detection using artificial intelligence and autonomous systems, as well as semantic segmentation algorithms to locate diseases in field images whose processes can be improved with systems based on microcontrollers and sensors. This research implements a leaf health monitoring system using IoT and AI technologies, with the development of an IoT device with a camera, the configuration of an MQTT broker in NODE-Red, and the implementation of a script in Python for leaf instance segmentation and image display. As a result, it is highlighted that image analysis, with the Python tool, allowed obtaining valuable information for precision agriculture, while the visualization or messaging interface allows health monitoring and management of crops. In conclusion, the System adequately performs image capture, processing, and transmission, being a contributes to precision agriculture solutions, considering that this can be improved with the integration of more complex deep learning algorithms to increase precision.

Key-Words: - Computer vision, Segmentation, ESP32CAM, leaf health, Precision agriculture, IoT, Node-RED.

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1 Introduction

Currently, processes related to the area of smart agriculture are integrating technologies such as the Internet of Things (IoT) and Deep Learning Models (DLMs) to develop solutions that help determine the health status of crops, [1], [2] and level. of leaf disease in the fields efficiently, thus improving the quality of agricultural production, [3], [4]. On the other hand, the growth of industrialization and urbanization has led to a decrease in agricultural land worldwide, which makes it important to use advanced techniques that optimize resource consumption compared to traditional agricultural systems, [5], [6]. For this reason, continuous monitoring is necessary to detect the evolution of crop leaf diseases by performing their early classification, which is essential to promote healthy agricultural production, determine the appropriate use of water, and control weeds and diseases, as well as decision-making, [7], [8].

The traditional identification of crop diseases through visual inspection is complex because it consumes human resources that have a degree of subjectivity and inaccuracy, making manual monitoring a process that demands significant effort, [3], [9]. On the other hand, the automated detection of diseases using sensors is a contribution to monitoring which is strengthened by taking images in the field, where one of the challenges is determining the precise location of the diseased areas on the leaves of the crops through image segmentation, [7], [10], [11]. Furthermore, there is a problem in simultaneously monitoring numerous parameters and diagnosing plants, which makes it necessary to use assistance systems in a smart agriculture that integrate IoT, [12], and AI, [4], [5] technologies, to recognize how environmental variables affect crops, plants, and diseases, [8], [13], Although technologies strengthen new plant cultivation and breeding practices, they could be expensive and require highly skilled labor, making their adoption by small farmers difficult, [6], [14], [15].

2 Literature Review

In the literature review, research is identified that overcomes technological problems by integrating techniques for object detection, artificial intelligence and autonomous systems aimed at identifying weeds, [1], [16], [17] through devices that incorporate automatic identification technologies, [18], [19], adaptation of machine learning models for execution on devices with limited resources, [20], [21] and use of data obtained by IoT sensors and UAVs (Unmanned Aerial Vehicle), [22]. On the other hand, in the case of field images, segmentation algorithms are integrated for disease localization, [3], [10], along with the development of techniques using images with complex backgrounds and Generative Adversarial Neural Networks (GAN), [11]. The integration of the aforementioned technologies allows automatically detecting anomalous patterns in real time, improving agricultural management, [9], [23], where it is common to use systems based on ESP32 microcontrollers, temperature and humidity sensors, [24]. Among the important limitations of the reviewed literature is its application in controlled environments, which reduces its usefulness in real conditions. In addition, the adaptation of models for devices with limited resources sacrifices precision, and the use of GANs implies a high computational demand. On the other hand, traditional IoT sensors and UAVs present latency problems and energy inefficiency for image acquisition and analysis, so this work focuses on analyzing these deficiencies.

The methodologies found in the research are aimed at using architectures based on convolutional neural networks (CNN), Multi-Model Fusion Networks (MMF-Net) to classify diseases of corn leaves in the field of precision agriculture, [1], [7], or tomato crops [5]. Other articles describe the use of cameras integrated into embedded systems such as CanopyCAM, which can continuously and accurately monitor canopy cover in crops, using image processing algorithms and IoT technology, followed by field tests and comparison. Of the results with conventional methods, [4], [8], [25], [26]. On the other hand, some research integrates the use of IoT systems that use semantic segmentation methods to identify diseased parts in leaf crops, and compare their performance with other methods [27], using various methods such as FCN-8s, SegNet, DeepLabv3, and U-Net, evaluating performance, [1], [3].

The research results show that the proposed systems, such as MMF-Net, CanopyCAM, and AI-SHES with IoT, allow the classification and detection of diseases in agricultural crops with an accuracy greater than 90%, [5], [7], [8]. Furthermore, it is mentioned that future research should focus on optimizing image processing algorithms for greater accuracy under different lighting and environmental conditions, [1], [3], [8]. Furthermore, continued exploration is required to further improve the accuracy and efficiency of these proposed systems, as well as their implementation and validation in real agricultural environments, [4], [5], [7].

Therefore, we have the following research question: How can a leaf health monitoring system be implemented by integrating IoT and AI technologies for disease detection? To answer the question, the objective is to develop an automated system to monitor the health of leaves using an IoT device with an integrated camera, using computer vision and segmentation techniques to detect diseases. For this, it is necessary to carry out the following activities: Design an IoT device with a camera based on the ESP32CAM module, configure an MQTT (Message Queuing Telemetry Transport) broker in NODE-Red to store the captured images, implement a Python script to process the images and perform the segmentation of the leaves to determine the percentage of area affected by diseases and visualize the images in the NODE-Red graphical interface. Furthermore, the motivation of the proposal is aimed at having an automated and low-cost process to contribute to the productivity and quality of crops that can be used by farmers and people interested in more effective management.

The value of the research is in the integration of IoT communication technologies based on MQTT and image instance segmentation processes to detect the evolution of diseased areas on the leaves. The paper is organized into 5 sections as follows: Section 1 presents the introduction, section 2 with the methodological process, and section 3 shows the results. The paper ends with section 4 of the discussions and section 5 of conclusions.

3 Methodology

The proposed system uses the camera integrated into the IoT device to acquire images, which are then transmitted to a centralizing processing and management team, which identifies the diseased regions and calculates the affected percentage. These images are sent via instant messaging service applications for manual monitoring (Figure 1). Finally, the results are visualized in a graphical interface integrating image segmentation processing techniques with deep learning.

The prototype is scalable to broad and diverse agricultural environments thanks to its implementation through a web API, which allows integration of multiple IoT devices for real-time monitoring. Its model based on instance segmentation can adapt to different crops with minimal adjustments, optimizing large-scale analysis and generating customized agricultural strategies to detect diseases in varied conditions.

3.1 Architecture

The components and techniques that make up the system correspond to the determination of the architecture. The proposed system is composed of:

a) an IoT device with an integrated camera for the periodic sending of images obtained in the field.

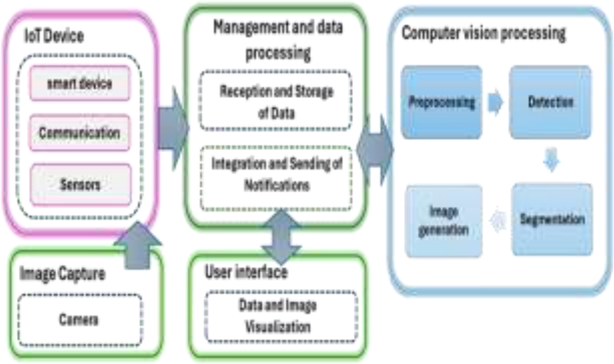

Fig. 1: Scheme for the system proposal

b) The data management system implemented with the Node-Red software platform and an image reception service using the MQTT protocol and a communication broker called Mosquitto.

c) A Python script, which is executed to process the received images applying semantic segmentation model (IFast) and is trained in the Roboflow Web tool using the COCO (Common Objects in Context) checkpoint, which allows identifying the diseased regions and calculating the affected percentage.

d) Display and messaging interface for monitoring using Node-RED and sending messages via Telegram. These integrated components are seen in Figure 2, improving the accuracy and efficiency of disease detection.

3.2 IoT Device for Image Capture

The main component of the system hardware is the IoT device composed of the ESP32-CAM module, which is a low-power consumption device that integrates a camera. The integration of the ESP32-CAM with the OV2640 camera allows images to be captured at a resolution of 1600x1200 pixels and supports various formats such as JPEG and BMP.

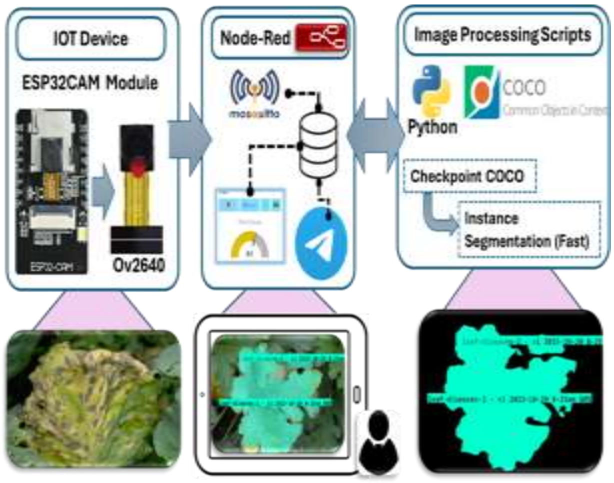

Fig. 2: Architecture of the proposed system

Configuration and communication with the camera are conducted with the I2C communication protocol (inter circuit communication). After capturing the image, it is sent to the ESP32 using the DVP digital interface, synchronizing with the HSYNC pins (to determine the start of a new image line) and the PCLK (which provides the clock signal to transmit the pixels). Finally, the ESP32 performs preprocessing before displaying the image (Figure 3).

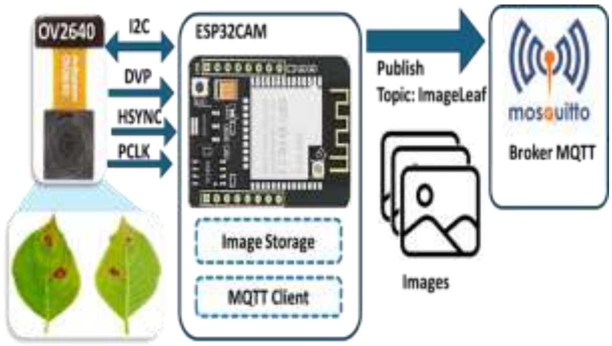

Fig. 3: ESP32CAM IoT Device

The device control algorithm initializes the I2C communication protocol with the camera and sets the Wi-Fi communication type to client mode. Then the access credentials to the HiveMQ MQTT Broker, [28] and the publication topic that has the name generated for the project called: “esp32cam/pic”. The camera captures images using the Jpeg format and then a timer runs the streaming function. Captured images are encrypted before being published to an MQTT server. Finally, mechanisms are used to manage errors and reconnect with the MQTT Broker in case of transmission failures (Figure 4).

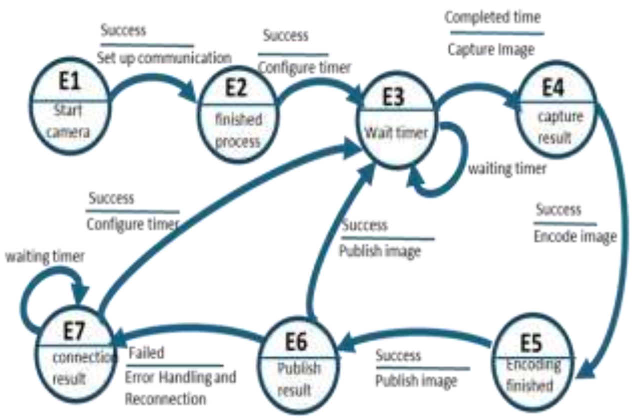

Fig. 4: State diagram of the capture and transmission algorithm

3.3 Segmentation Model for Leaf Disease

To use the segmentation model, it is necessary to conduct a series of processes to identify the areas affected by diseases on the leaves. The steps to implement this technique are as follows:

- Instance segmentation: To develop the disease detection model in plant leaves, the instance segmentation technique was used, which differentiates between classes of objects and objects within each class. This technique first performs object detection to find all bounding boxes in an image. Semantic segmentation is then applied within each rectangle that classifies each pixel into a class. In this way, it is possible to differentiate elements and their limits by detecting the areas affected by diseases on the leaves (Figure 5).

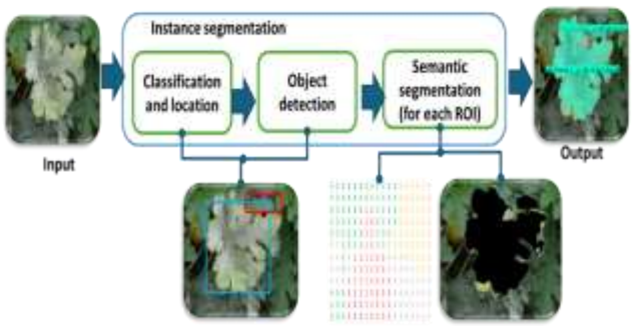

Fig. 5: Instance segmentation

- Use of Roboflow: To implement the model, the Roboflow platform was used, which has a set of images of diseased leaves already labeled with the affected areas. Then, these images are used to generate the instance segmentation model, using the Roboflow 3.0 model type (machine learning framework version) and the COCO checkpoint that allows efficient learning from the pre-existing data set (Figure 6). This model will be accessible through a web communication API for the inference process.

  To deploy the instance segmentation model to detect disease-affected areas on leaves, a process was followed that guarantees accuracy and reproducibility. The Roboflow platform was key in the implementation, working with a set of previously labeled images, where the affected areas were already delimited and there is a pre-created model accessible with a web API KEY. The model already existing on the platform has an average accuracy (mAP) of 92%, showing a high capacity to detect and segment affected areas even in images with complex backgrounds. For inference, the model was deployed in a web API, which facilitates its integration into IoT systems and its real-time use in agricultural applications.

- Python script for segmentation: it is used to import the model, which integrates image processing, segmentation, and confidence percentage. This script reads the images stored by the Node-RED application. Processing is performed using an HTTP client to make inferences through the RoboFlow API. Then, for each prediction, a polygon is drawn over the image, and class and confidence labels are added. Finally, the image is stored with a detailed analysis of the affected areas, performing the process every 15 seconds (Figure 7).

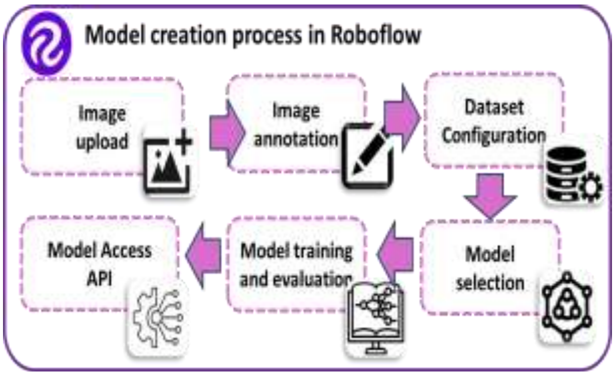

Fig. 6: Model creation process with RoboFlow

3.4 IoT Data Management and Processing Platform

The components necessary for data management and image processing include the MQTT broker HiveMQ and Node-RED software. In addition, connection services with the instant messaging platform Telegram are used to send the processed image. The activities in this stage are the following:

- Node-RED is responsible for receiving the images and data sent from the ESP32CAM module through the MQTT broker. Subsequently, this data is stored on the hard drive.

- Visualization of the original and processed images in the NODE-Red graphical interface, which facilitates making informed decisions about plant management.
- Integration and sending of notifications using Telegram by detecting an information request command “/annotated” (Figure 8).

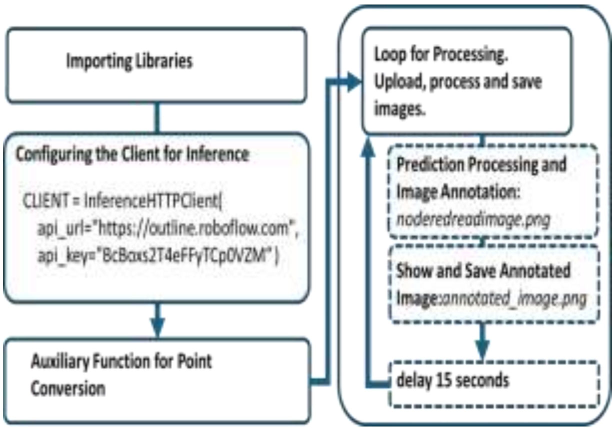

Fig. 7: Python script to import the model

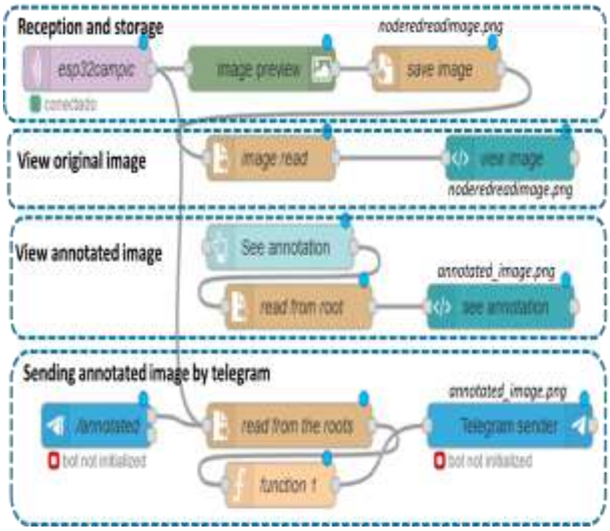

Fig. 8: Program by node flow in Node-RED

4 Results

The model is already available on the Roboflow platform, however, for future implementations, a proprietary segmentation model can be developed to optimize the adaptation of the system to other scenarios. On the other hand, although exhaustive evaluations of metrics such as processing time and hardware performance were not conducted, this is because the main objective is to build a prototype that would demonstrate the technical viability of the system.

The ESP32 IoT device was installed on a tripod mechanical structure which is protected by an IP65 protection box for external environments and then placed in a field environment for pilot testing. In this case, it powered up and began capturing images of a bush and transmitting them over Wi-Fi using the MQTT protocol (Figure 9).

The Python script was evaluated by generating images representing: the image of the bush, the image with the detected regions of disease highlighted in black, and a third image showing the confidence data about the detected diseased areas (Figure 10).

The working Node-RED application is shown in Figure 11. This shows previous images received in the node streams. In addition, a screenshot of the Node-RED GUI visual interface is observed that shows both the original image received and the segmented image with the detected disease.

Fig. 9: Pilot test of the IoT Device

Fig. 10: Images of diseased leaves detected in python

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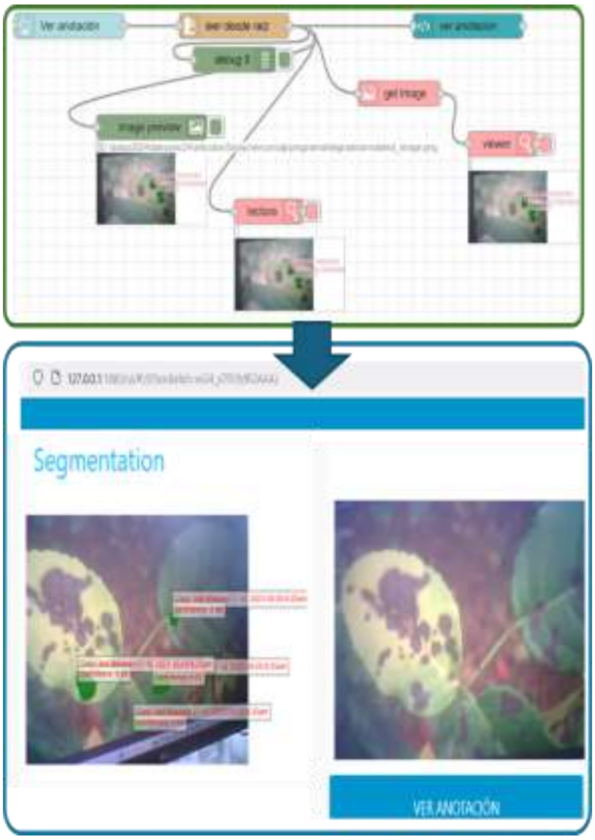
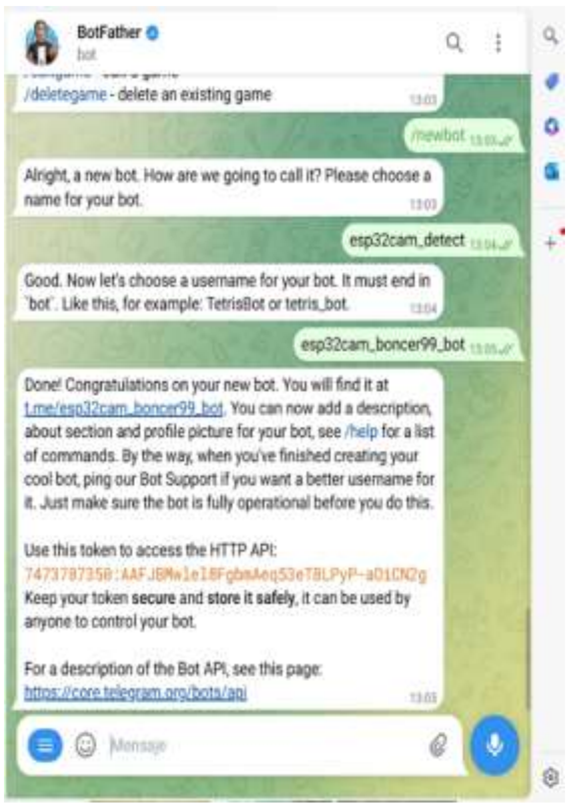


Fig. 11: GUI with the original leaf image and detected diseased section



(a)

(b)

Fig. 12: Telegram app for (a) chatbot setup and (b) status response

Figure 12 demonstrates the operation of communication with the Telegram instant messaging application. This application receives images of the detected diseased region when the user sends a command. For this, a chatbot, created with BotFather in Telegram, was used to automate this process, allowing users to send a specific command (/annotated) and receive the processed image.

5 Discussion

The integration of the IoT device into the mechanical structure shows the practical application of image transmission to a computer vision stage, intended for monitoring and analyzing vegetation in natural environments. The ESP32CAM module is integrated with remote applications efficiently using the MQTT protocol for high-resolution image transmissions of the bush. This allows this data to be processed in real-time to segment and classify different elements within the framework with a confidence level assigned to each class.

Running the Python script demonstrates the system's ability to identify and highlight disease-affected areas. This script analyzes the captured images, segments the diseased areas, and overlays the confidence information on the original image, providing a clear and detailed visualization of the health status of the shrub. This result is crucial for applications in precision agriculture, allowing farmers to make informed decisions about crop management.

The operation of the GUI highlights the efficient integration between the IoT device and the Node-RED platform, facilitating the visualization and analysis in real-time of images of diseased leaves and their evolution. The connection with the Telegram application shows the effectiveness of using the disease detection system, providing an accessible and easy-to-use tool for monitoring. Automation through chatbots improves response capacity and decision-making.

The proposed solution is distinguished from other methods described in the literature because while some have developed systems such as MMF-Net, CanopyCAM, or GAN-based models for disease segmentation and detection, these present challenges in real environments due to their high computational demand, lack of adaptation to uncontrolled conditions and latency problems. The developed prototype uses an IoT device integrated into a structure for external environments and optimized to transmit images using the MQTT protocol. Although the prototype does not yet include exhaustive evaluations of processing time and hardware performance, its modular design can be scaled for future optimizations.

Hardware optimizations have been left as future work to consolidate the solution in operational environments and ensure its maximum efficiency. This planning allows current efforts to focus on the initial validation of the approach and to progressively move towards comprehensive improvements.

6 Conclusion

In this research, an automated system was developed to monitor the health of leaves, demonstrating its proper integration of an IoT camera module with the ESP32CAM, using computer vision and segmentation techniques to detect diseases. The implementation of the IoT device, the MQTT broker in Node-RED, and the Python script were properly integrated for the capture, processing, and real-time visualization of images, contributing to precision agriculture solutions.

The construction of the prototype demonstrated the technical feasibility of the system for disease detection in leaves, but the integration of additional environmental data (such as humidity and temperature), models such as transformers, native mobile interfaces, or extensive field testing would have diverted the focus to complex aspects that are outside the initial scope of the project. These activities are considered as future research to optimize, validate, and scale up the system in real environments and improve its accessibility.

The IoT module allows the automatic capture of images in the field, with the use of the MQTT protocol being an appropriate form of transmission. In the case of using Node-RED with MQTT, the storage and management of the images captured by the ESP32CAM module was facilitated, showing the system's ability to manage and provide information in agriculture.

The use of Python allows for a flexible and simple stage for identifying areas affected by diseases on leaves using segmentation services in the cloud, overlaying trusted information. In addition, its proper functioning with the Node-RED platform was demonstrated by writing and reading images. Connecting the system with the Telegram application is an effective way to automate the monitoring process, as it is conducted at the user's request but can easily be updated to become automatic.

As future improvements, more complex deep learning algorithms can be integrated to increase the accuracy of detecting disease types. Additionally, the integration of additional sensors, such as soil moisture and temperature, provides a more complete analysis of environmental conditions and their impact on plant health through multimodal analysis. It would also be beneficial to develop a friendlier user interface to make it easier for farmers to use the system. Finally, testing is suggested in different agricultural environments to validate the robustness of the system.

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Conflict of Interest

The authors have no conflicts of interest to declare.