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Original Article

Autonomous Visual Pest Detection System with ESP32-CAM, Zonal Classification, and Notification via Telegram for Agriculture

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Abstract - *This article presents the design and implementation of an autonomous system for visual pest detection using an ESP32-CAM. Electronic modifications are also made to a drone to enable this system, ensuring that it is fully automatic, delimiting the drone's monitoring path, including wireless communication and artificial vision for pest assessment using captured images. The system captures images of the crop at monitoring points defined by the zonal classification of areas where a subsequent harvest will take place, generating a heat map of infestation points. Upon detection of the presence of possible pests, the system will save monitoring images to a microSD card when no network is available and will send captures of the assessment with a critical percentage of the pest when it has a Wi-Fi connection from the ESP32, as well as notifications via TELEGRAM and the location of the critical zonal classification point using a GPS module. This study focuses on corn cultivation, as it is a widely harvested product in areas of Peru such as Arequipa, using low-cost components, providing farmers with real-time alerts to improve response and efficiency by 70% in agronomic decision-making, improving productivity by 21% of total production, and reducing pesticide use. It is adaptable to any environment in the current agricultural industry. It can also be used for other crops such as grapes, avocados, asparagus, rice, etc.*

Keywords - *Autonomous Pest Detection, ESP32-CAM, Precision Agriculture, Drone-based Monitoring, Smart Farming.*

1. Introduction

In regions with high crop demand, such as Arequipa, which focuses on corn cultivation, pests are one of the main factors limiting productivity, generating economic losses of up to 30% of total production. The lack of continuous monitoring and reliance on manual inspections lead to late diagnoses, which increase the indiscriminate use of pesticides, high production costs, and time lost in evaluating different pests such as the fall armyworm (Spodoptera frugiperda), the corn stalk borer (Diatraea saccharalis), cutworm (Agrotis ipsilon), and aphids (Rhopalosiphum spp.), which represent constant threats that require early detection and targeted control.

In response to this problem, this article presents the design and implementation of an autonomous visual pest detection system, using an ESP32-CAM integrated into a control PCB that modifies the flight directions and functions of a drone for automatic operations. The system performs scheduled flights over areas delimited and classified by crop zones using a GPS module, capturing images that are evaluated with artificial vision to identify the corresponding pests.

The purpose of the system is to provide a low-cost solution, improve response time, adapt to different environments, improve detection efficiency by 70%, increase crop productivity by approximately 21%, and reduce environmental impact by minimizing excessive pesticide use. Although this study focuses on corn cultivation, the proposed methodology can be used for other crops such as grapes, avocados, asparagus, and rice, contributing to the strengthening of precision agriculture in Peru. This article presents related work in Section 2, the methodology in Section 3, the development of the system in Section 4, the tests and results in Section 5, and finally, the conclusions in Section 6.

2. Related Works

Currently, pest detection systems using drones are relatively expensive, and it does not have different applications to serve more industries, with limitations in software and hardware, relatively high costs in terms of crop monitoring, pesticide waste, and [1] where pests have traditionally been controlled through the manual application of pesticides, posing serious health risks, with nearly one million cases reported annually according to the WHO. To overcome these limitations, the use of customized agricultural drones (UAVs) is proposed, which allows for the precise application of pesticides and fertilizers, reduces risks for farmers, and improves crop management efficiency. Equipped with advanced cameras and sensors, UAVs enable real-time monitoring, early disease detection, and optimization of irrigation and fertilization. This technological integration represents a transformative change in agriculture, contributing to higher yields, environmental sustainability, and reduced operating costs.

Similarly, [2] evaluates commercial drones equipped with RTK-GNSS technology, which can accurately estimate plant height in agricultural environments without the need for Ground Control Points (GCPs) or manual estimates. To this end, the performance of the RTK-GNSS method without GCP or manual control was compared with two traditional approaches for sizing triticale, corn, and soybean crops. The results showed that the use of RTK-GNSS achieves accuracy in crop dimensions according to its positioning and offers reliable performance compared to conventional methods, with high determination indices and low crop height estimation errors. Therefore, this study confirms that drones with RTK-GNSS are a reliable, efficient, and lower-cost alternative for measuring crop height, significantly reducing the time, effort, and labor required for field work in agricultural research and production. Also in [3], where the use of drones for agricultural remote sensing for crop monitoring, growth estimation, and production efficiency is achieved through an aerial system that combines automatic operations, multispectral and thermal image acquisition, and evaluates current crop conditions, such as health, dimensions, and projected production estimates. The results of the study confirm that the system allows for reliable identification of crop health, differentiation between high- and low-yield areas using Normalized Difference Vegetation Index (NDVI), and evaluation of proper growth with adequate crop sizing. Similarly, this system incorporates autonomous landing without GPS when required or when operating in a complex environment. The study confirms that the system integrated into the drones is a scalable and accurate solution for agriculture, which aims to improve sustainability and decision-making in agricultural production.

In [4], the need to transform current agriculture is sought in order to address problems or deficiencies in productivity, sustainability, and proper control of inputs and resources in the face of population growth and current climate change, focusing on current limitations such as water scarcity, soil degradation, increased costs, and lack of information regarding current technologies that have comprehensive solutions to meet the need. The study proposes the use of technologies such as drones, remote sensing, GPS, robotics, and the Internet of Things (IoT) to optimize resources, improve decision-making, and reduce environmental impact. This technology is presented as a change aimed at increasing productivity, sustainability, and profitability in the agricultural sector. Similarly, [5] presents a comprehensive vision of agriculture to analyze the appropriate use of technologies to transform traditional farming practices, highlighting the integration of robotics, drones, remote sensing, artificial intelligence, and IoT, allowing for the optimization of crop cultivation, improvement of water management, and increased production efficiency through detected variables. The benefits and limitations of these technologies are shown in countries with little information and adaptation of these systems, emphasizing the need for research, development, infrastructure, and technical training to take full advantage of smart agriculture as a key tool for addressing challenges such as climate change, resource scarcity, and health. For [6], the aim is to evaluate, through a study, the correct distribution of pesticide spraying with a fiber optic-based detection probe, specifically in the dispersion of droplets during spraying operations with drones. The aim is to address one of the main barriers to the adaptability of drones in current agriculture, the control and quantification of inputs such as pesticides. It is demonstrated that the sensor used is capable of reliably detecting the presence of microdroplets at considerable distances according to the position of the drone, using spectral parameters related to current conventional methods. According to this study, it is confirmed that the technique used offers an effective and reliable tool for improving environmental control, safety, and the efficiency of spraying operations with technologies using drones for the precision agronomy industry.

Likewise, considering a previous application in [7], the choice of the most suitable spraying drone for the agricultural company Semberija was evaluated using a structured process or system for multi-criteria decision-making based on the opinions of specialists in the field. To this end, eight drone models were evaluated considering ten technical and operational evaluation criteria, with the aim of selecting the best alternative to suit the needs of modern agriculture. The methods applied infer a method of bonderization and hierarchy of criteria to obtain a reliable and objective selection, considering that the evaluation identifies the DJI Agras T30 as the most optimal for these needs, thus demonstrating that this study presents multi-criteria approaches that constitute an effective tool for the adoption of new technological strategies for the agricultural sector. Likewise, [8] evaluates and selects drones for smart agricultural applications that must operate in regions such as Posavina, in northern Bosnia and Herzegovina, analyzing eight drones costing less than €2,000 that offer a balance of reliable technical performance, ease of use, and cost. The results confirm that control accuracy, flight autonomy, and ease of operation are very relevant. The analysis of the operation of these drones shows viable and effective solutions for smart agriculture, validating the use of drones as technological tools for productivity and decision-making in small and medium-sized farms. According to studies with artificial systems, [9] shows the use of drones for monitoring cherry trees with artificial intelligence to improve the efficiency and effectiveness of pesticide and fertilizer spraying, increasing agricultural production and reducing agricultural inputs in the face of growing food demand, evaluating object detection models with YOLO, and applying image processing techniques to increase the accuracy of identifying the tree to be cultivated. It has been demonstrated that the integration of the artificial vision model allows the system to spray cherry trees efficiently and selectively, achieving a significant reduction in the consumption of these inputs, confirming that the use of agricultural drones with artificial intelligence is an effective and sustainable solution for agriculture in terms of precision, aimed at maximizing productivity and minimizing the environmental impact of chemical use.

Regarding the selection and correct use of sensors, [10] shows that the analysis of the quality and reliability of the data acquired by the sensors mounted on drones reveals reliable radiometric and geometric distortions for the evaluation of surfaces and images. Radiometric correction at terrestrial points achieves high levels of spectral and spatial accuracy, meeting the objective for industrial agricultural applications in this case. The study validates that the proper application of processing techniques with these sensors enhances the use of drones as reliable tools for monitoring crop health and agricultural management within the respective framework of technological applications for smart agriculture.

According to input management, [11] shows the correct rational use of water based on an irrigation system that improves water efficiency and productivity. The system integrates the use of drones and IoT technologies to overcome the limitations of traditional irrigation systems and adaptability to climatic conditions that damage the soil and crops. The use of IoT sensors and automatic learning algorithms in drones allows for thermal and multispectral monitoring for necessary irrigation planning. This approach contributes significantly to reducing operating costs, increasing crop yields, and promoting the rational and sustainable use of water, positioning itself as an effective solution for agriculture.

3. Methodology

This article presents the design and implementation of an autonomous system for pest detection using artificial vision integrated into an ESP32. Monitoring is carried out by a drone, communication and data transmission via TELEGRAM, as well as the classification of areas to generate a heat map of critical areas and local alerts.

The system consists of three main blocks: evaluation using computer vision, with a drone modified for the task; the second block consists of the evaluation of images captured and stored for the subsequent generation of a heat map with infestation points; and the third block consists of notification via TELEGRAM to the farmer in charge to focus on the critical points detected. The system has the following features and conditions:

- Integration of a PCB for drone control and flight modifications
- Artificial vision and image capture for pest assessment.
- Heat map and accurate alerts using GPS locations generated by the drone.
- The system does not rely on a network for pest assessment.
- Sending of critical images and notifications via TELEGRAM when located at the starting point with WiFi connectivity.
- Delimited areas for autonomous drone flight.
- Low implementation and modification costs compared to relatively expensive pest monitoring systems.
- Image storage via microSD for later download.

Table 1. Components to be used

TYPE	MODEL	QUANTITY
PCB control	PCB CDA V1.0	1
Drone PCB control	PCB CDD V1.0	1
GPS module	GPS Neo M8N	1
PLT module	Module platform	1
Microcontroller	ESP32	1
Limit switch sensor	10T85U	1
Camera	OV2640	1
SD card	16GB	1
MicroSD module	74LVC125A	1
Accelerometer	MPU9250	1
Lora module	SX1278	1
Battery	Lipo 4S-5Ah	1

The development of this autonomous system for pest detection using computer vision, focused on corn crops, is organized into four main design stages: hardware, software, flight planning, and processing. For the hardware design, the aerial platform that will contain the drone is manufactured, with the respective modifications in Autodesk Autocad 3D software. Likewise, the control PCB is made in EAGLE 9.6 software, integrating sensors such as GPS Neo M8N, MPU9250 accelerometer, Lora SX1278 module, 16GB MicroSD 74LVC125A storage, and the use of the WIFI module integrated into the ESP32 microcontroller for data transmission to the cloud when connectivity is available, and functions such as data sending. Sensors such as GPS geolocation modules are also included to record GPS Neo M8N monitoring coordinates, MPU9250 accelerometer to verify correct flight monitoring in the drone, Lora SX1278 module to issue alerts without connectivity when km distances are reached and to be able to locate the drone by means of an audible alert if it is damaged or crashed, with an emergency recovery option to return it to its starting point on its platform.

In terms of software development, autonomous flight control is achieved through delimitations depending on the growth of the crop to be monitored, allowing periodic flights without manual intervention, thanks to a programmed daily or weekly timer configuration. The artificial vision is based on Edge Impulse models, programming the operating logic in the Arduino IDE, as well as the storage of images captured and selected by the artificial vision, which will be saved on a 74LVC125A microSD card, in order to detect a critical pest situation and send a notification via TELEGRAM to the farmer. Similarly, critical images can be evaluated via the network, and each image captured can be evaluated from a computer from the 16GB SD card. In terms of flight planning, the crop is delimited, and corn plots are divided according to their growth, respecting the respective dimensions of 80cm between crops and 50cm between corn in this case. It can also be programmed for a specific type of crop, such as grapes, avocados, asparagus, etc. The monitoring route, the drone executes detection trajectories as low as possible, depending on the exponential growth height of each cultivated plant, with an additional 20 cm offset depending on the current height of each type of plant to be cultivated. Likewise, the flight frequency can be programmed by day according to the location of the land and the stages of cultivation. In terms of processing and analysis of results, the detection heat map is generated with critical areas detected by infestation, only visible with network connectivity using the ESP32's WiFi connection. Notification via TELEGRAM is carried out once the processing has been evaluated across the entire field, highlighting the location via GPS coordinates with reference images captured and stored on the MicroSD card. Finally, to understand the implementation of this system, a flowchart of the processes has been developed (see Figure 1).

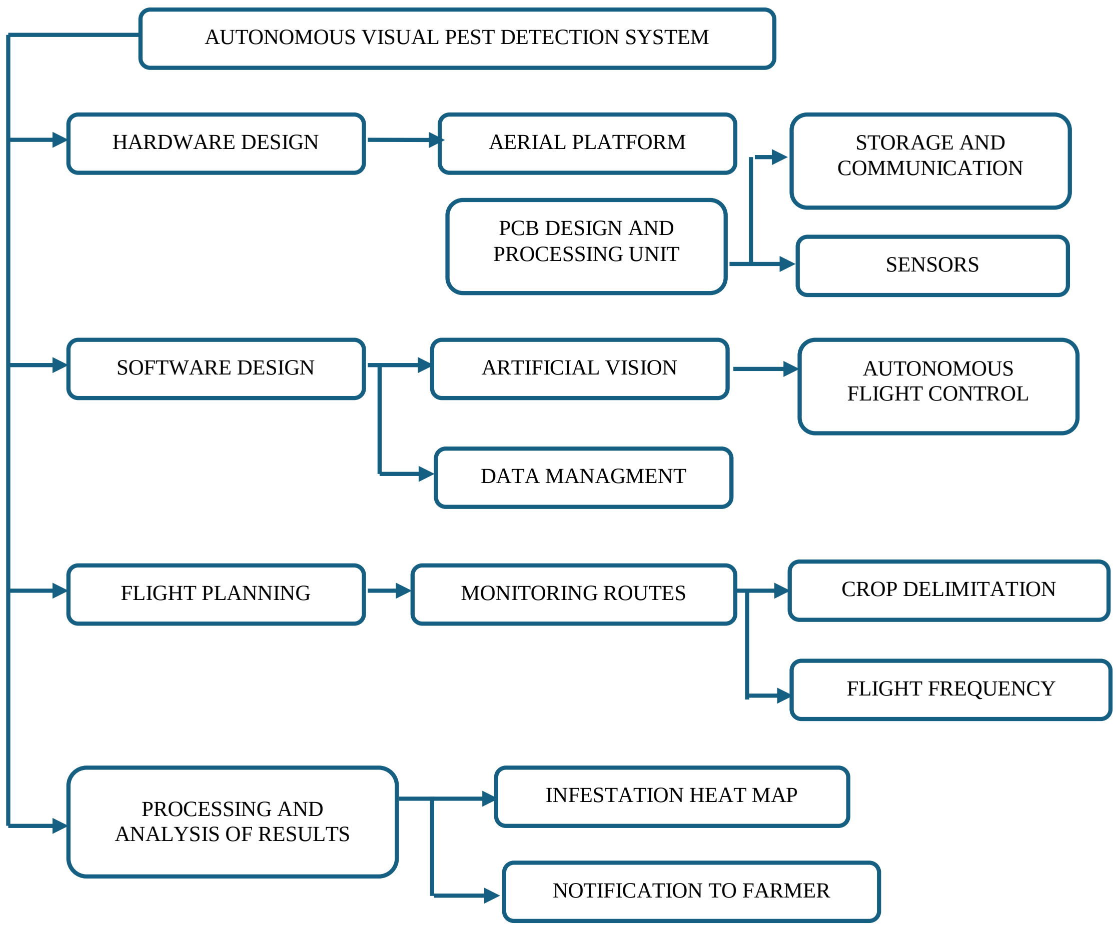


Fig. 1 System flow diagram

4. Developed System

The hardware design of this system is based on the structure of the platform responsible for supporting the drone and indicating the starting point of the route to the field, as well as the design of the processing PCB, which captures positioning data with the Neo M8N GPS via the Lora SX1278 module from the drone. This structure detects the drone's position from its departure to its return through limit switches incorporated between the platform and the drone. The initial communication data will be received by the PLT module, which, with its built-in right display, will show values such as the drone's current position with GPS coordinates, data communication such as capture performed, and battery status. The left display will show voltage values for charging the drone, and the encoder can be used to modify crop types, which are height, classification, such as corn, grapes, avocados, asparagus, etc., as well as monitoring programming, whether daily, every three days, or weekly. (See Figure 2).

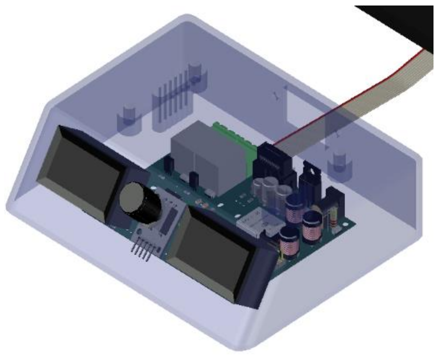


Fig. 2 PLT module

As for the design of the CDA V.1 PCB, it is powered by 12VDC through a PLUG connector. The electronic card reduces the voltage to 5V linearly through the built-in 7805 and adjustable voltages of 3.3V, each with the integrated LM2597, respectively. This card is responsible for receiving the corresponding data from the GPS module built into the drone, such as location based on coordinates that will be shown on the PLT module display.There are two relays at the output, one of which will be used to connect a drone positioning alarm, which turns on when the drone is about to take off and when it returns after its scheduled monitoring routine, while the other enables charging for the drone and likewise disables it, in order to protect the battery by completely canceling the charging cycle of its internal batteries (see Figure 3). The modifications to the drone were made to its control, which was configured according to the programming and movement condition given by the CDD V1.0 PCB card, according to the coordinates occupied by the Neo M8N GPS module, and the movement condition of the MPU9250 accelerometer. It should be noted that the CDA V1.0 PCB card will be the master that controls the other card mentioned, since all control programming regarding crop type, change, climate, and coordinates is configured on that card. Communication between the two will be carried out through the Lora module to verify a correct link and not depend on Wi-Fi, since at the end of its route, this card will establish a stable network connection and upload the data to the cloud, respectively. Part of the initial power supply circuit for modifying the drone's control circuit is shown (see Figure 4).

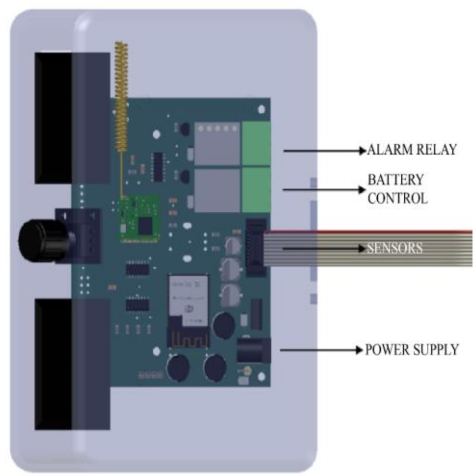


Fig. 3 CDA V.1 card functions

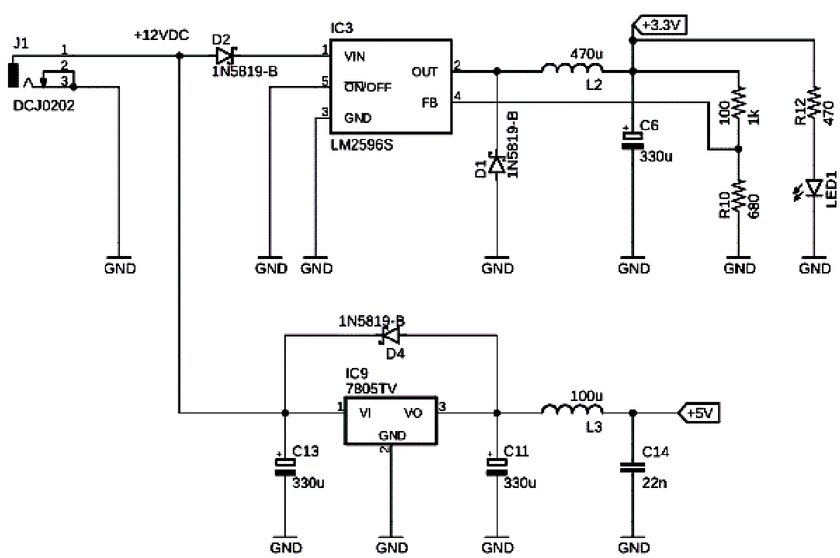


Fig. 4 Regulated power supply in DRON

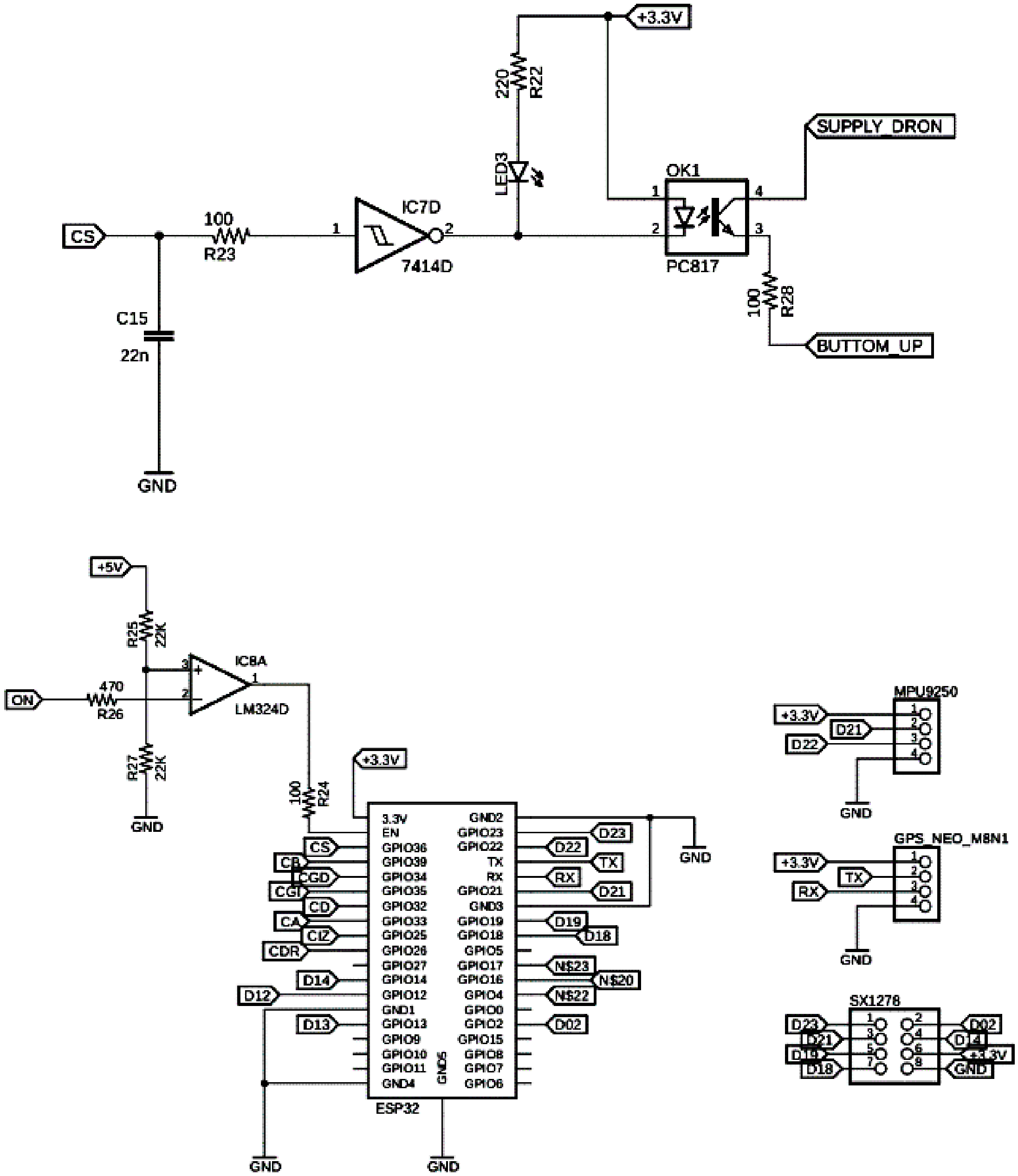


Fig. 5 DRON control circuit

In terms of its digital logic, a simple control will be used, which consists of modifying a button for turning the motors on and off, stabilization, and a joystick for height and rotation movements, referring to button presses as if it were a manual control (see Figure 5). In this case, the input is the coordinate signal from the Neo M8N GPS and the enabling of the platform where the drone is located, obtaining a discrete reading of 5V in terms of its initial position from the limit switches. The ESP32 on the CDD V1.0 PCB card is responsible for receiving the signal to indicate the takeoff or rest of the drone. Likewise, the flight coordinates are given directly to the control card when calibrating the drone manually using coordinates through the NEO M8N GPS module and signals sent to the CDA V.1 PCB card using Lora communication with the SX1278 module.

To better understand how communication between the CDD and CDA control boards works, 3D simulations are used to represent each part of the control system, as well as the area of terrain to be covered according to the coordinates, using maximum values based on calibrations with the respective boards. First, the initial location of the drone is determined for a subsequent departure (see Figure 6). This programming will be configured by the user so that they can monitor the crop at regular intervals.

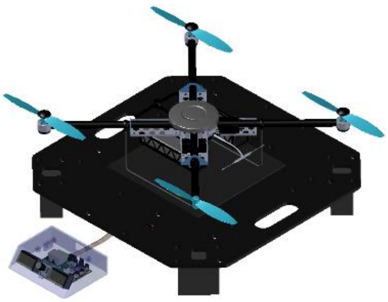


Fig. 6 Drone starting point

Next, the drone is activated remotely via Lora from the CDA card, with movement coordination signals provided by the CDD card using coordinates sent from the GPS module, with a maximum range of 5 km to prevent the Lora module from losing efficiency in terms of response time. The first step is to evaluate the crop. For this application, a stem at 65% growth is used to assess healthy conditions and inspect for pests such as the stem borer (Diatraea saccharalis) and the cutworm (Agrotis ipsilon), which are the most critical for this crop, depending on the area and its location. The drone will be positioned from the highest point configured on the CDA card and then descend to a minimum configured height. It will begin the inspection by evaluating with the artificial vision in the ESP32-CAM, capturing images according to the conditions set in its programming. A notification will be sent whenever the network is near the drone. In general, it should perform its routine without a WiFi connection, so that when it returns to the initial platform, it can upload photos to the cloud (see Figure 7).

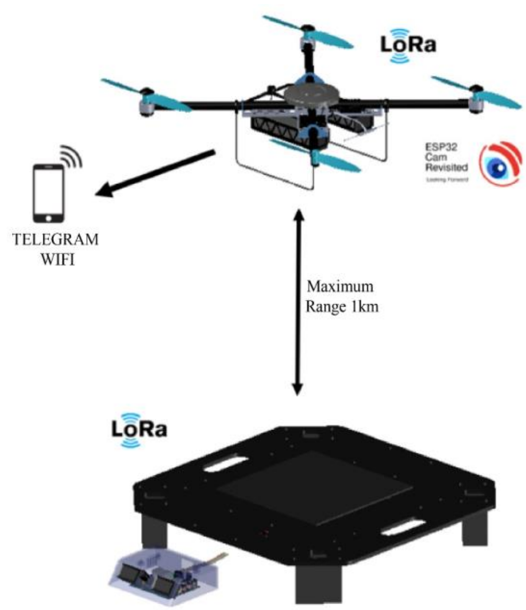
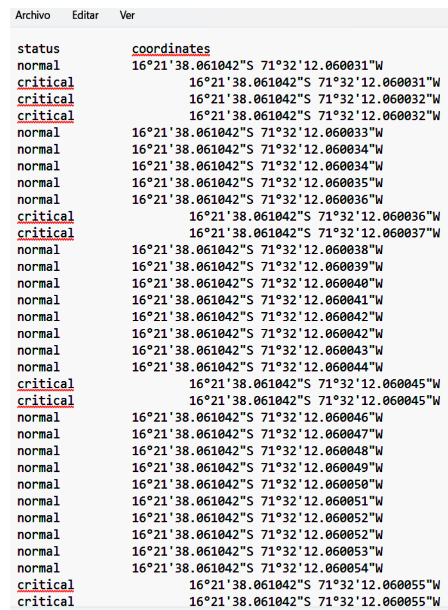


Fig. 7 Communication in the field

Likewise, the heat map is generated based on the critical coordinates detected by the artificial vision system and stored on the SD card of the CDD card (see Figure 8). Alert notifications will consist of pest detection evaluated by the system's artificial vision, in addition to generating a message with the exact coordinates of the location considered a critical alert. Regarding the drone's battery performance, the system will send an alert via message, and the battery charge sensing circuit in the drone will perform its emergency routine, returning the drone when its battery is below the limit of 10.5V. Also, if the drone experiences problems due to the accelerometer sensing instability in flight due to wind, dust, etc., it will send an audible alert on the CDA V.1 PCB card and a text message via TELEGRAM indicating turbulence or instability on the ground, emergency stop.



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status	coordinates
normal	16°21'38.061042"S 71°32'12.060031"W
critical	16°21'38.061042"S 71°32'12.060031"W
critical	16°21'38.061042"S 71°32'12.060032"W
critical	16°21'38.061042"S 71°32'12.060032"W
normal	16°21'38.061042"S 71°32'12.060033"W
normal	16°21'38.061042"S 71°32'12.060034"W
normal	16°21'38.061042"S 71°32'12.060034"W
normal	16°21'38.061042"S 71°32'12.060035"W
normal	16°21'38.061042"S 71°32'12.060036"W
critical	16°21'38.061042"S 71°32'12.060036"W
critical	16°21'38.061042"S 71°32'12.060037"W
normal	16°21'38.061042"S 71°32'12.060038"W
normal	16°21'38.061042"S 71°32'12.060039"W
normal	16°21'38.061042"S 71°32'12.060040"W
normal	16°21'38.061042"S 71°32'12.060041"W
normal	16°21'38.061042"S 71°32'12.060042"W
normal	16°21'38.061042"S 71°32'12.060042"W
normal	16°21'38.061042"S 71°32'12.060043"W
normal	16°21'38.061042"S 71°32'12.060044"W
critical	16°21'38.061042"S 71°32'12.060045"W
critical	16°21'38.061042"S 71°32'12.060045"W
normal	16°21'38.061042"S 71°32'12.060046"W
normal	16°21'38.061042"S 71°32'12.060047"W
normal	16°21'38.061042"S 71°32'12.060048"W
normal	16°21'38.061042"S 71°32'12.060049"W
normal	16°21'38.061042"S 71°32'12.060050"W
normal	16°21'38.061042"S 71°32'12.060051"W
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normal	16°21'38.061042"S 71°32'12.060054"W
critical	16°21'38.061042"S 71°32'12.060055"W
critical	16°21'38.061042"S 71°32'12.060055"W

Fig. 8 Generation of red dots for critical pests

The drone's volatility range is also configured for the type of crop. In this case, it refers to corn crops that are 20 cm taller than the current height. The reference depends on the growth of the leaves, stems, or fruits, as this can change depending on the crop selected (see Figure 9).

Fig. 9 Additional height range for corn

The respective tests were carried out in terms of reviewing and evaluating the monitoring performed with the autonomous system, since Edge Impulse was used for computer vision models, which supports grayscale (black and white) images in order not to overload the processing of the ESP32 microcontroller for the evaluation of results, confirming that these are as accurate and fast as an average farmer could perform (see Figure 10).

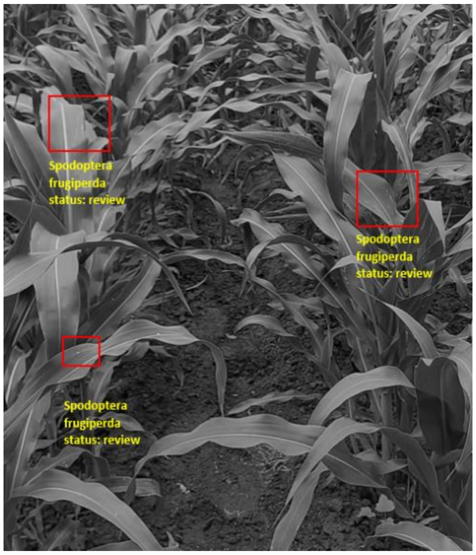

Fig. 10 Field monitoring and evaluation

These tests were carried out in the Chilina Valley, located in Arequipa, Peru. This field has an area of 75 x 30 m, with a warm environment due to its proximity to a river (see Figure 11). In addition, comparisons were made between an experienced farmer and the autonomous monitoring system in terms of time and efficiency in pest selection, increase in crop productivity, post-heat map evaluations of infestation points, measurement range, and coverage between LoRa modules, and remote alerts via messages.

Fig. 11 Corn crop and evaluation site

5. Tests and Results

Following the implementation and evaluation of this corn crop, results were compiled in terms of time and efficiency in crop monitoring for the early detection of pests that could affect or proliferate throughout the field, causing a total loss of the crop. This comparison was made between an experienced farmer using the developed system, obtaining a 70% improvement in terms of decision-making and scheduled monitoring, and a farmer who only prioritizes inspection when the crop is fertilized.

Real data is considered for the evaluation of 4 hours per week for 2 inspections per week for the experienced farmer, and 1 hour and 12 minutes for the system to perform the evaluation and generate the heat map of infestation points.

Field Size	Agricultor	Autonomous System
75 x 30 m	4h/2 x week	1h 12min/2 x week

Based on these hours calculated in real time, there is an approximate difference of 2h 48 min between the two inspections carried out. In addition, generating the report and the infestation heat map by the system would considerably increase the time in terms of efficiency and crop field assessment. Using the approximate time, a 70% improvement in weekly crop monitoring would be achieved. Furthermore, to calculate its efficiency, the crop area of 2250 m² is used; considering that the evaluation is carried out twice a week, the following is obtained:

$$\text{Efficiency\%} = \left(\frac{time_{manual} - time_{system}}{time_{manual}}\right)$$

$$\text{Efficiency\%} = \left(\frac{4 - 1.2}{4}\right) * 100 = 70\%$$

Because the production of this corn crop is affected each year by common environmental pests, an empirical estimate is made using data collected over the 15-day evaluation period of the equipment's operation, using a total of approximately 3 hours and 20 minutes of this system. The respective care was taken, reducing the cost of purchasing pesticides and their misuse. The improvement is estimated at a 30% reduction in pests after these corn monitoring evaluations, already at a stage close to harvest, together with an efficiency of 70%, obtaining:

$$\text{Productivity} = 0.7 * 0.3 * 100 = 21\%$$

On the other hand, the transmission of data and location between the drone and the receiver module, coming from their CDA and CDD electronic cards, respectively, takes into account the response time as the drone moves further away. It should also be noted that the drone's coverage was a maximum of 1 km; therefore, this system must be limited to a maximum communication range of 1 km. In addition, the antenna design for the Lora SX1278 module requires amplification because it gains or increases latency (see Figure 12).

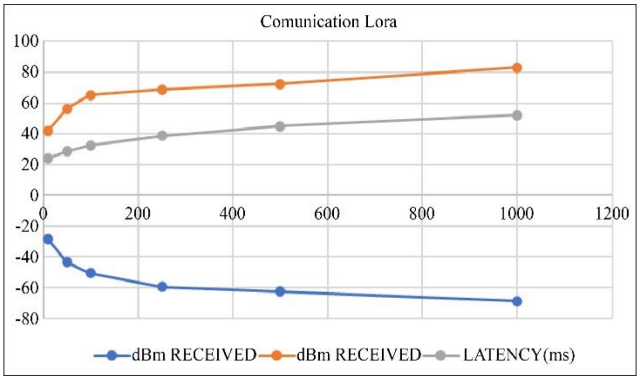

Fig. 12 Lora communication between CDA and CDD cards

6. Conclusion

This study presents the development of an autonomous visual pest detection system for corn crops using an ESP32-CAM, Edge Impulse computer vision models for image classification, and an SX1278 LoRa communication module that enables data transmission in hard-to-reach fields. The integration of computer vision into a drone modified to perform programmed flight routines ensures automatic, zone-based monitoring to generate heat maps that identify critical areas of infestation.

Furthermore, the use of low-cost hardware and the ability to operate in environments with low connectivity using LoRa make the system accessible and scalable to different crops and regions.

In conclusion, this system is a viable and sustainable solution for agriculture, promoting more efficient time management and a positive impact on agricultural competitiveness, providing an innovative approach that can be replicated in different production scenarios in the agro-industrial sector.

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