Surveillance of insect pests in corn crops: monitoring and counting using electronic traps

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Abstract

Insect-pest management in corn cultivation is essential to increase crop yields, reduce production costs and contribute to food security. Integrated pest management in agriculture uses the new technologies of Agriculture 4.0. This article shows an intelligent platform for *Spodoptera Frugiperda* monitoring in the maize crop with the site-specific conditions of the Colombian Orinoquía. This system uses models based on artificial intelligence immersed in embedded devices that make up a wireless network of electronic traps and a Web application. The system architecture design, image preprocessing algorithms and definition of deep learning models for recognition and counting of insects caught in the traps are specified. The results show that the insect counting based on convolutional neural networks allowed detection accuracy of 97% concerning other insect types trapped in the traps. These results show the robustness of the electronic traps and their usefulness for infestation map generation.

Keywords: Deep learning, electronic, internet of things, pheromone, *Spodoptera Frugiperda*, trap.

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1. Introduction

Insects represent one of the largest biomasses of terrestrial animals, and within this category, they are the most diverse group [1]. Globally, agriculture is affected by crop pests, and their impacts on ecosystems can be either positive or negative, as in the case of pollinators and those that are vectors of infectious diseases [2]. In Spain, specifically in the Murcia region, pest-related losses amounted to approximately 120 million euros in 2020 [3]. Similarly, in 2020, an alert was issued in the eastern plains of Colombia regarding a locust plague that attacked sugar cane, corn, and rice crops, resulting in difficult-to-calculate losses for livestock farmers and agricultural producers [4].

Due to the diversity of existing agents that influence crop production throughout their development, the damages they cause are often complex to evaluate in social and economic terms [5]. Regarding the problem of pest insect control, it is necessary to implement methods that utilize current technologies to monitor and define infestation hotspots, making it more cost-effective by avoiding the application of inputs, especially chemicals. This is achieved by applying the corresponding inputs in the right place, quantity, and timing to prevent pest proliferation in cultivated plots.

In small crop production in Chilean greenhouses, pest control represents a high cost, further reducing profit margins. In some cases, the price can amount to USD 1759 per hectare for controlling whiteflies and tomato moths, applying inputs weekly, and USD 980 per hectare in a carnation crop for red spider mite management [6].

Integrated Pest Management (IPM) is an ecological tool for pest control and monitoring in crops that aims to help farmers make decisions for pest management. Through IPM, the goal is to reduce the frequency and amount of inputs applied to the crop without affecting production, while being environmentally friendly [7].

Electronic trap networks for insects aim to assist in defining infestation hotspots of pest insect populations in a crop or cultivated region, allowing the use of current digital agriculture technologies. Traps with instrumentation systems can determine the number of trapped insects and wirelessly transmit this information to a central station. These devices provide estimates of insect presence that can be associated with infestation beginnings and population dynamics. Additionally, they are used to assess the effectiveness of insecticide treatment following treatment application for control purposes. On the other hand, electronic traps collect data at defined time intervals, allowing tracking of insect responses to pheromones [8].

From the references used in this work, two research branches emerge regarding electronic traps for integrated pest management. The first uses electronic devices such as optical counters in combination with pheromones [9,10]. The second branch uses image processing acquired by digital cameras [11,12,13]. Optical counters utilize a trap funnel and interrupt infrared light flow between an emitter and receiver. Fluctuation of light causes a shadow on the receiver by the insect falling through the funnel, which converts into an electric pulse used for insect counting [8].

Electronic trap networks for insects recognize programs for pest detection, delimitation, suppression, and eradication. Examples of their application are evident in the United States Department of Food and Agriculture – USDA, which operates networks of around 63,000 traps, with 30,000 for the detection of *Ceratitis Capitata* [14].

Internet of Things (IoT) technologies are used for detection, monitoring, control, and action activities, and are useful in electronic traps development. IoT devices must have interfaces for transmitting information with other devices through specific communication protocols [15]. User interactions with the system are enhanced with software applications, particularly in terms of visualizing data obtained in trap monitoring [16].

In corn cultivation, one of the most damaging insects is the fall armyworm, *Spodoptera frugiperda* (J.E. Smith, 1797). It is a lepidopteran insect of the *Noctuidae* family and has feeding habits that make it a migratory, polyphagous, and destructive pest of crops in the Western Hemisphere [17]. The fall armyworm causes damage in the early stages of cultivation; the larvae chew the epidermis on the underside of the leaf, creating translucent windows. Subsequently, in the third stage, they start consuming the entire leaf, resulting in irregular holes appearing on the leaves (Figure 1). Finally, they will move on to eat the fruit, causing the corn to lose its commercial value [18].

Figure 1. Fall Armyworm and *Spodoptera Frugiperda* Moth.

Source: FAO [18].

This document presents the development of a system for monitoring the population density of *Spodoptera Frugiperda* in maize crops, consisting of a network of electronic traps for the fall armyworm. The system is developed to identify infestation hotspots, thereby enabling agronomists or producers to make more informed decisions regarding the definition of management sites or zones where inputs should be applied, employing concepts of site-specific management.

The proposed system aims to address some challenges of using electronic traps, particularly the application of IoT and deep learning for autonomous system development for counting insect pests. Secondly, its potential as a tool for preventive biological management can be applied before *Spodoptera Frugiperda* becomes a pest and causes economic damage.

2. Materials and Methods

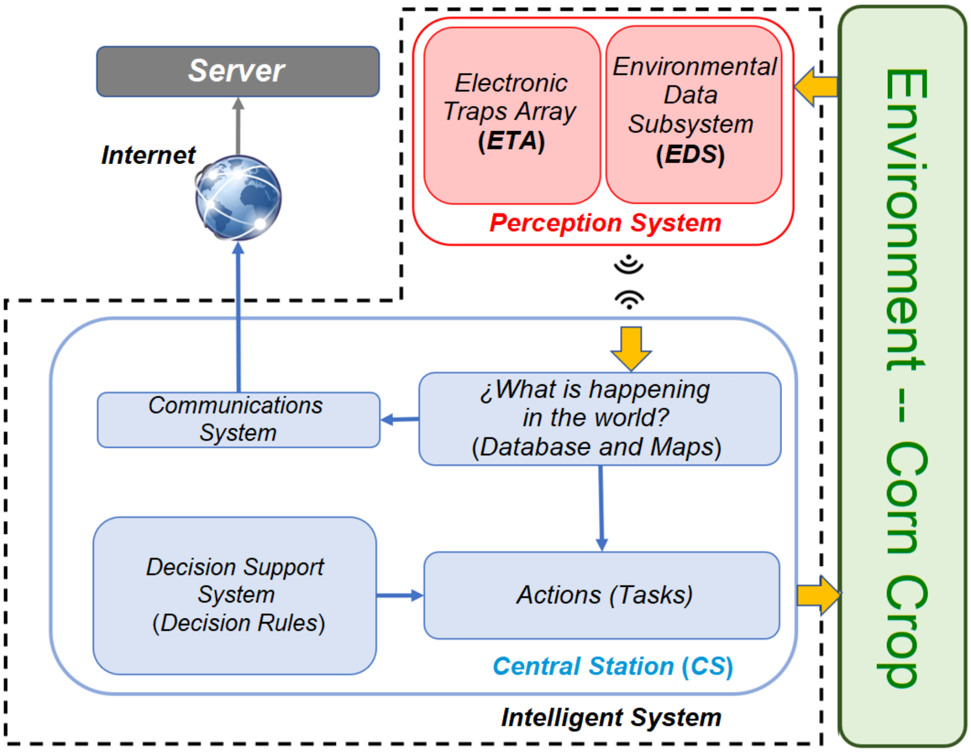
This study was conducted at the Libertad Research Center of the Colombian Agricultural Research Corporation - AGROSAVIA, located in Villavicencio municipality, at kilometer 17 of the road leading to Puerto López, in the Meta department, Colombia. The experimental cultivation area is located in AGROSAVIA at a latitude of approximately 4°03'31" north and a longitude of around 73°27'58" west. The region has an average annual precipitation of 2,933 mm and an average temperature of about 26°C [19].

The Libertad Research Center covers an area of 1,332 hectares and encompasses various agroecological zones. These areas include humid alluvial valleys and soils characterized by acidity and low fertility, which are classified as oxisols for agricultural purposes. The landscape of this region is characterized by the presence of high, medium, and low terraces, typical of the Colombian Piedmont subregion. Within the framework of this study, maize is the crop planted in the research area.

2.1. Intelligent Detection and Mapping System for Insect-Pest Population

Figure 2 illustrates the architecture of the intelligent system for detecting and mapping the population density of insect pests in crops using machine learning and IoT techniques, proposed in this research.

Figure 2. Architecture of the intelligent system.



Source: Authors.

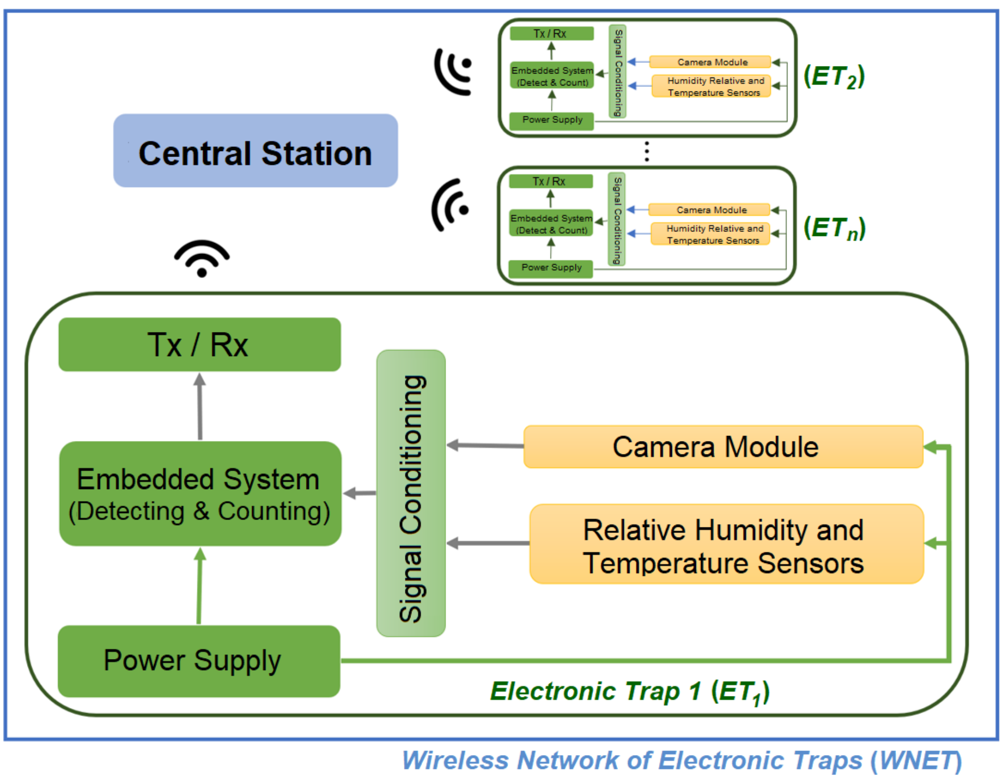
The intelligent system acquires environmental data using the perception or sensing system. The perception system employs an Electronic Traps Array – ETA and an Environmental Data Subsystem – EDS. The intelligent system can determine the insect population in the crop by receiving data from the perception system, storing it in a database, and mapping its spatial distribution in the field. Based on the infestation map obtained, agronomic engineers or experts in integrated pest management decide on actions or activities.

The design and construction of the intelligent system imply that various elements are integrated and interconnected. This section provides an overview of the system's structure and the essential hardware and software requirements necessary to ensure its proper functioning. First, the requirements and technical specifications that the components of the perception system must meet are detailed. Subsequently, the underlying reasoning algorithms that enable precise and efficient insect counting are presented.

2.2. Perception Subsystem: Hardware Components.

The hardware design requirements for the perception system have been developed using low-cost electronic components that offer the advantage of modularity and replicability. This system consists of sensor nodes interconnected through a mesh wireless network linking all nodes to a Central Station – CS, as illustrated in Figure 3. Each sensor node is powered by a rechargeable 12V battery and equipped with a 10W solar panel for operation.

Figure 3. The architecture of the electronic trap array.



Source: Authors.

To fulfill the role of the central station for each sensor node, a RaspberryPi® ZeroW is employed. Communication between these nodes is facilitated through the use of XBee® RF modules (Digi

International, Minnetonka, Minn.), operating under the ZigBee® wireless communication protocol. Regarding ZigBee® specifications, a 2.4 GHz operating frequency and an effective range of 3200 meters are highlighted. The installation of a 6 dBi omnidirectional antenna, offers significant signal gain.

Each sensor node is integrated with a Raspberry Pi® V2 (RPI-CAM-V2) second-generation camera module with a fixed-focus lens. This camera is based on a Sony Exmor IMX219 sensor, capable of capturing images up to 1080P30 and 8MP photographs on the Raspberry Pi® board, powered by a 2A source (Spectrum Technologies, Inc., Aurora, IL, USA). The core of the system was developed using a Raspberry-Pi® W Zero.

2.3. Central Station - Hardware Components.

The main component of the Central Station – CS module is a Raspberry Pi® 3 model B. This central station is responsible for collecting data from sensor nodes and then transmitting it to a web server where it is mapped and monitored. Additionally, the CS also stores the data in an internal database. To carry out these tasks, the software is based on Python™ 3 and the Qt5 graphical interface library.

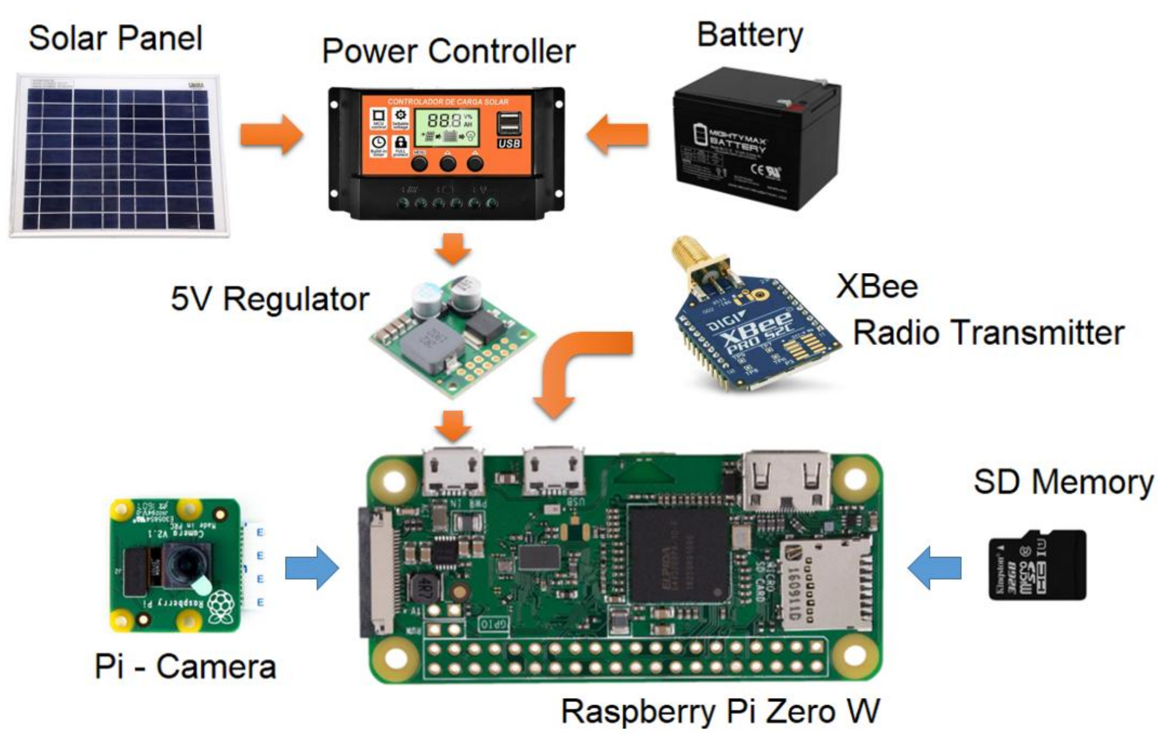
2.4. Detection and Insect Counting Subsystem.

Two approaches have been incorporated into the integrated pest management system to detect and count insects. The first is based on image processing, covering various stages involving image acquisition, enhancement, restoration, color processing, morphological processing, segmentation, representation, description, and object recognition. The second approach relies on deep learning techniques to detect and count the insects. In this paper, the study focuses on describing the second method. The results of the comparison between these two approaches will be presented in future publications, providing a more comprehensive overview of the strategies used in the system.

3. Results and Discussion

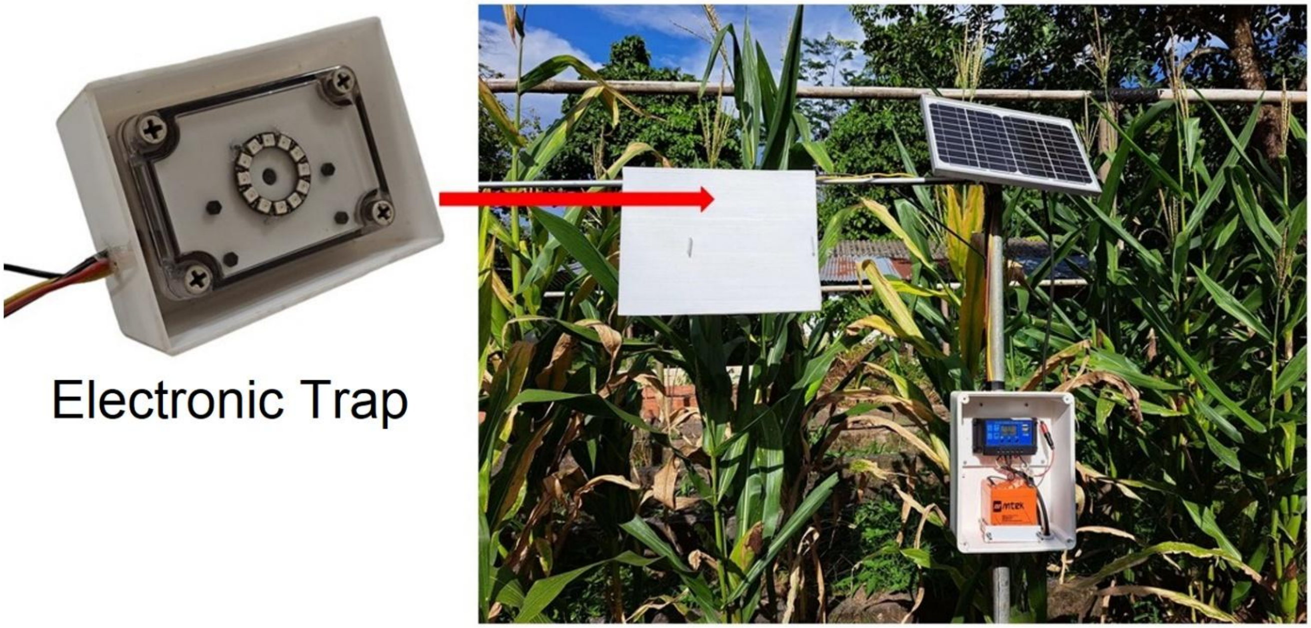
This paper presents the progress of a project developed in the FarmTechnology Research Seedbed, at the University of Los Llanos, aimed at creating an electronic trap for detecting the fall armyworm (*Spodoptera Frugiperda*) in maize crops. This work shows advances in the implementation and study of deep learning models for the detection of the examined insect species. Figure 4 presents a scheme detailing the electronic components used in the electronic trap. Figure 5 illustrates the implementation of the electronic trap that allows the periodic collection of digital images of insects trapped in the trap. The box containing all the electronic components of the trap is shown, with protection against environmental conditions such as temperature changes, humidity, dust, and rain. The power supply system, based on the solar panel, regulator, and battery, is also appreciated. The system also integrates the XBee™ transceiver, which uses the ZigBee® protocol.

Figure 4. Electronic trap components for fall armyworm detection.



Source: Authors.

Figure 5. Trap implementation for insects.



Source: Authors

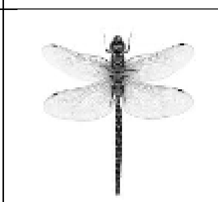
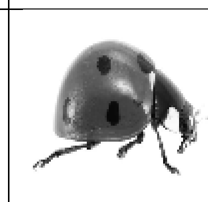
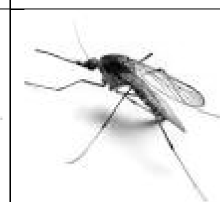
The algorithms applied to process and condition training images were developed in Python™ 3 and the OpenCV2 library. Figure 6 shows the captured image of the moths trapped in the adhesive paper.

Figure 6. Captured image detecting trapped insects on adhesive paper.

Source: Authors.

For the initial study of machine learning algorithms and models for the detection and counting of *Spodoptera*, a Convolutional Neural Network – CNN model was evaluated to identify different types of insects. The insects used for this purpose were labeled as follows: butterflies (1), dragonflies (2), grasshoppers (3), ladybugs (4), mosquitoes (5), and *Spodoptera* (6). The insect data were taken in the laboratory and also acquired from *https://www.kaggle.com/datasets/hammaadali/insects-recognition*. The data augmentation procedure used image rotations of 90 degrees, except for *Spodoptera*, which used rotations of 10 degrees. Each image was also flipped, and new rotations were performed. The number of images utilized for CNN training is presented in Table 1.

Table 1. Quantity of images used for CNN training.

Butterflies	**Dragonflies**	**Grasshoppers**	**Ladybugs**	**Mosquitoes**	**Spodoptera**
					
3596	4144	3840	3456	2760	3612

Source: Authors.

The characteristics in the neural network employed consisted of the layers shown in Table 2.

Table 2. Layers of the implemented convolutional neural network.

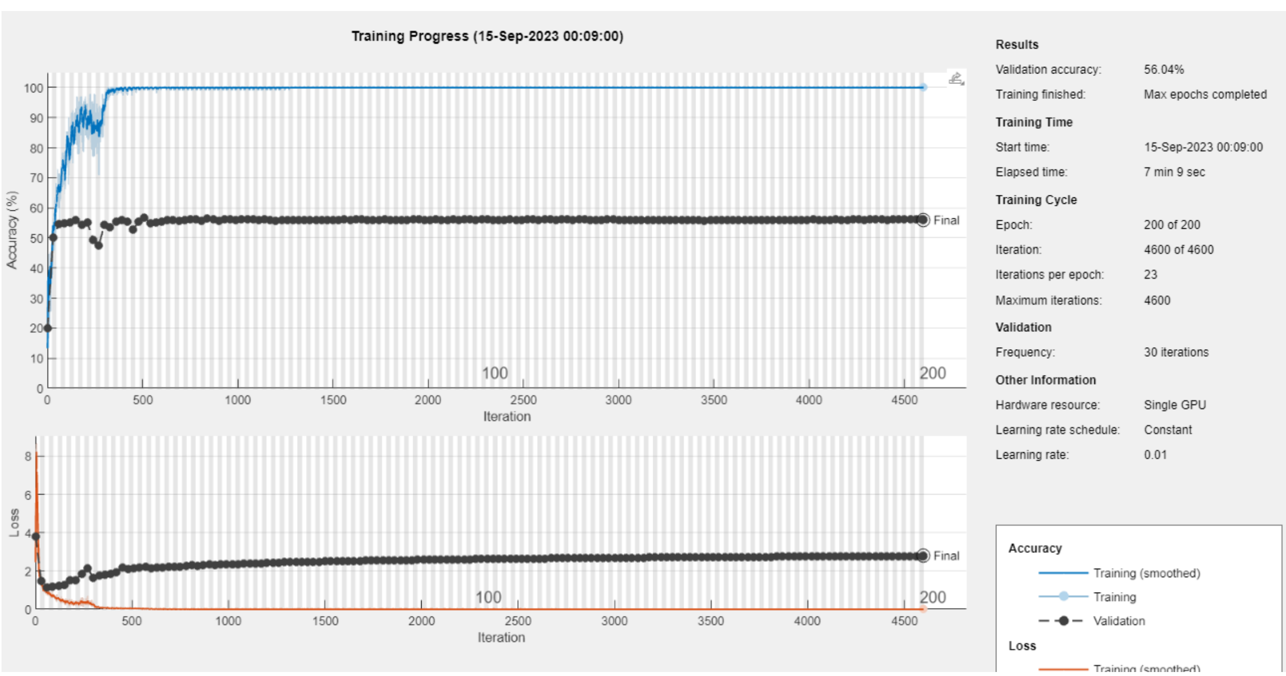
Number	***Layer Type***
1	convolution2dLayer
2	batchNormalizationLayer
3	reluLayer
4	maxPooling2dLayer
5	convolution2dLayer
6	batchNormalizationLayer
7	reluLayer
8	maxPooling2dLayer
9	convolution2dLayer
10	batchNormalizationLayer
11	reluLayer
12	fullyConnectedLayer

Number	Layer Type
13	softmaxLayer
14	classificationLayer];

Source: Authors

The results of implementing the Convolutional Neural Network in MATLAB® are depicted in Figures 7 and 8. Figure 7 displays the precision and error graph during the training and validation stages of the learning algorithm. It can be observed that while the training curve ascends to 100%, the validation data does not exhibit appropriate behavior. This suggests that the neural network is not learning correctly from the number of image samples used. Possible reasons for this behavior include insufficient data preprocessing before inputting them into the training algorithm, inadequate data for proper learning, or the type of convolutional neural network model utilized. Despite this situation, the confusion matrix demonstrates a favorable performance for this study, with *Spodoptera* detection yielding better results than the detection of other insects (Figure 8).

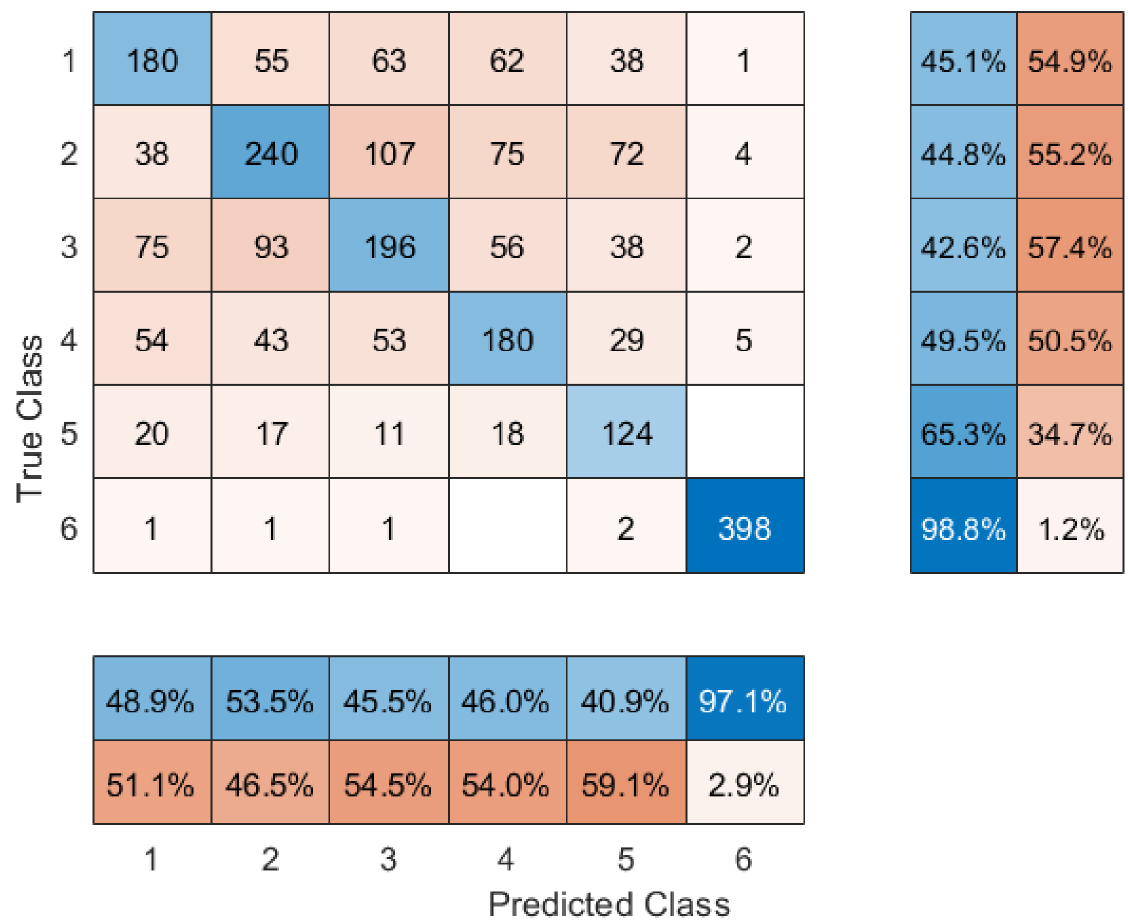
Figure 7. Training and validation of the CNN for insect detection and counting.



Source: Authors.

In Figure 8, the rows of the confusion matrix refer to the actual classes, representing different types of insects: (1) Butterfly, (2) Dragonfly, (3) Grasshopper, (4) Ladybug, (5) Mosquito, (6) *Spodoptera*. The columns represent the predicted classes, and the main diagonal of the matrix is known as True Positives – TP, indicating the number of elements correctly predicted for each class. Elements above the main diagonal are False Negatives – FN, indicating elements incorrectly predicted not to belong to the corresponding class when they do. Elements below the main diagonal are False Positives – FP, representing elements incorrectly predicted to belong to the corresponding class when they do not.

Figure 8. Confusion matrix that evaluates the classification model of detected insects.



Source: Authors.

Alongside the confusion matrix in Figure 8, the precision and recall percentages for each class are displayed, highlighting the achievement of 98.8% precision with 1.2% recall for the

Spodoptera class, which exhibits the highest recognition accuracy. The second-highest recognition class (Mosquito) achieved 65.3% precision and 34.7% recall, while the classes with the lowest recognition were Grasshopper and Dragonfly, with precision rates of 42.6% and 44.8%, and recall rates of 57.4% and 55.2%, respectively.

At the bottom of the confusion matrix in Figure 8, the overall accuracy percentage of the algorithm is presented, representing the weighted average of precision and recall for all classes. *Spodoptera* emerges as the class with the highest recognition, with 97.1% precision and 1.2% recall, while the class with the lowest recognition is Mosquito, with 40.9% precision and 59.1% recall.

4. Discussion

The results obtained from the development of electronic traps for counting *Spodoptera Frugiperda* in corn crops, as well as the implementation of the hardware and its performance in the field, have been satisfactory. One of the limitations identified in the design of this trap prototype is that transmission distances reach up to 3000 meters in line of sight when using XBee™ devices with high-gain antennas. In large crops located far from areas with internet access, this could pose an inconvenience for proper data acquisition.

Regarding the insect detection and counting software, an algorithm based on digital image processing was also developed, which will be compared with the results obtained using the deep learning algorithm. The convolutional neural network studied in this project showed advantages in detecting *Spodoptera* compared to other insect classes detected, as demonstrated in the analysis of the confusion matrix obtained. This ensures the model's reliability in detecting insects, distinguishing them from others with an accuracy exceeding 97%. The results highlight the advantages of deep learning for achieving this classification, although further studies with a larger amount of data are needed to obtain even better results.

The proposed research process must continue, evaluating other types of convolutional neural networks. For this purpose, the following activities are proposed as future work: selecting two additional deep learning models, defining the most important hyperparameters, and generating a grid search algorithm to find the best solution. Once the best model is found, the algorithm must be implemented so that the Raspberry Pi® Zero W of the electronic trap can use the detection model and thus count how many insects were captured with the camera.

5. Conclusions

The results of this study present a comprehensive perspective for automatic pest management in the fall armyworm moths detection in corn crops, utilizing a system based on image capture through an electronic trap. These electronic traps represent innovative systems that enable effective monitoring of pest populations, incorporating a camera as an independent subsystem for image acquisition. Data collection on insect density and evaluation of the number of moths provide valuable information that can be used by farmers and agronomists for planning and implementing pest control measures more effectively, through remote information access.

This work details the technical specifications of the electronic acquisition and communication system used in comprehensive pest detection. Furthermore, this study underscores the feasibility of employing convolutional neural networks in detecting *Spodoptera Frugiperda* using electronic traps. However, it is important to note that further research and development are still required to refine these approaches and achieve even more precise and reliable results.

Regarding the impact on the agricultural sector and food security, this work has the potential to revolutionize integrated pest management by providing farmers and agronomy professionals with a precise and efficient tool for early detection, monitoring, and control of pests. Significant improvements can be achieved in this regard, such as reducing pesticide use, increasing agricultural productivity, environmental sustainability, and resource conservation.

Acknowledgments

This research was funded by Universidad de Los Llanos (DGI) – Colombia, through the project: Intelligent System for Detection and Mapping of Pest Insect Population Density in Agricultural Crops using Machine Learning and IoT Techniques (C09-F02-007-2021 FCBI). A.F. Jiménez expresses gratitude to the Department of Boyacá and Minciencias – Colombia for the support through the scholarship program No. 733 - 2015 for the Doctorate at Universidad Nacional de Colombia and to Universidad de Los Llanos, Villavicencio, Colombia. The authors extend their gratitude to Andrés Javier Peña Quiñones and Elsa Judith Guevara from the Center for Research La Libertad Colombian Agricultural Research Corporation – AGROSAVIA, Villavicencio, Colombia.

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