SMART MONITORING AND OPTIMIZATION METHODS FOR PEST DAMAGE IN MAIZE CROPS

Andrei Chiriloaie-Palade, Raluca-Gabriela Georgescu, Teodoru Andrei, Valentin-Marius Ciontu, Daniel Jaloba*

Research and Development Institute for Plant Protection
*correspondence address
Research and Development Institute for Plant Protection Bucharest
Bd. Ion Ionescu de la Brad no. 8, CP 013813, Bucharest, Romania
E-mail: chiriloaie.andrei@icdpp.ro

Abstract. To ensure both the quantity and quality of maize crops, vigilant pest monitoring is indispensable. Identifying and controlling pests effectively is paramount in mitigating agricultural losses and upholding food security. Various methods, from conventional field observations to sophisticated intelligent monitoring systems, are currently employed to manage pests in maize fields. However, traditional surveillance methods have inherent drawbacks, such as the need for frequent visual inspections and the inability to deliver real-time comprehensive data. Consequently, there's a rising demand for intelligent solutions that can enhance accuracy and efficiency in pest monitoring on maize farms.

Keywords: *pests, maize, monitoring systems*

INTRODUCTION

Agriculture has a long history of using a variety of approaches and strategies for pest management in order to prevent and control the losses that these organisms cause. Using traps and other pest-capturing tools, along with visual observations, are traditional methods of pest monitoring in maize crops. A variety of intelligent monitoring technologies have been developed and applied in agriculture in recent years. These technologies use machine learning algorithms, sophisticated sensors, and image processing techniques to effectively and precisely identify and detect pests. Depending on the needs and unique circumstances of maize crops, there are numerous intelligent pest monitoring options on the market, each with unique benefits and drawbacks (Vadlamudi, 2019).

By observing the presence and/or variation of pest populations in the field, monitoring adult insects using traps is thought to be a standard practice in integrated pest management (IPM) and early warning detection, helping to optimize control or eradication operations. The gathered information has allowed for the integration of the temporal and spatial variability of sampled pest populations in the field, as well as the provision of advice and cautions to farmers and other agricultural sector stakeholders. Traps, often including attractants, are powerful tools to attract and capture specimens of the target pest. Sometimes, these traps are species-specific, but they usually require trained personnel to discriminate between target species and similar ones that may be captured. In many standard IPM programs, especially in perennial crops, different types of traps are used for monitoring and controlling specific insect species, deployed in a grid pattern in fields, checked and maintained manually through periodic visits by human operators (Sciarretta & Calabrese, 2019).

Manual counting of the insects that are captured is a standard procedure for monitoring. For the majority of insects, surveillance of trap sites is usually done once a week, occasionally twice. Every time, the collection and analysis of data is delayed because inspectors have to go to the field trap, count the insects in each device, record the data on paper, then come back to the office, enter the data into a spreadsheet, and process it before sending it to the end users. By using a handheld device to enter data directly into the field and connect it to a server that stores the data automatically, this process has been partially shortened. On the other hand, there is a delay in the assessment of trap results that impacts the decision-making time (Böckmann, 2021).

A number of factors, including cost, ease of implementation, accuracy, and efficiency, must be taken into account when choosing the best intelligent pest monitoring system for maize crops. The selected intelligent monitoring system uses machine learning algorithms, sophisticated sensors, and image processing methods to identify and locate pests instantly. In order to effectively execute the intelligent monitoring solution in maize crops, considerations need to be made for things like sensor placement strategy, communication network connectivity, and integration with current agricultural systems.

Camera-equipped traps, consisting of hardware like trap structures, cameras, data transmission modems, and batteries, along with software components such as image analysis algorithms, are tailored for various pest species, with trap designs and bait choices crucial for optimal image capture and pest identification. Automated traps with data transmission systems enable remote monitoring, reducing the need for frequent field visits, while interconnected networks enhance surveillance capabilities. Continuous power supply is ensured through efficient battery systems and optimization strategies. These traps represent a significant advancement in pest management, enhancing efficiency and effectiveness in agriculture and forestry (Preti, 2020)

Recent studies have focused on using convolutional neural networks (CNNs) and machine learning techniques for pest identification and classification. Various CNN architectures, such as Deep Convolutional Neural Networks (DCNNs) like AlexNet and VGG16, have been trained with insect images to achieve high accuracy in pest detection. IoT frameworks are deemed suitable for remote trap monitoring, while DL frameworks excel in insect identification from images. Integrating DL and IoT frameworks can create a comprehensive remote insect trap monitoring and detection system targeting different pests, offering a promising approach for future pest management practices (Ramalingam, 2020).

MATERIALS AND METHODS

This literature review examines recent advancements and trends in the Intelligent Insect Trap System field by analyzing relevant sources such as journal articles, research papers, and books published in English or French. One focus is on detecting pests that frequently infest maize crops, such as those from the Noctuidae family. Haq et al., (2023) proposed a method involving a deep convolutional neural network (DCNN) trained on an agricultural pest dataset. They collected 5500 images, with 2750 images specifically gathered from Shandong, China, depicting maize crops and pest-infested leaves at various growth stages and weather conditions. The study evaluated the performance of different deep learning models, focusing on metrics like training/testing accuracy, loss and recall. While fewer studies have focused on maize crops specifically, insights from research on other crops like tomatoes and paddy fields can inform the development of tailored monitoring solutions for maize cultivation.

In the field of pest management, Preti et al., (2020) implemented a pioneering approach by employing a smart trap system. When designing traps for insect monitoring, several factors must be considered to ensure their effectiveness and practicality. Trap design should prioritize proven designs while also validating new ones. The trap shape and opening size significantly impact capture efficiency, emphasizing the importance of preserving effective designs and validating new ones. Additionally, trap structure must be robust, waterproof, and compact to protect electronic components and minimize the trap's overall size. Consideration of the distance between the camera lens and insect level is essential to ensure proper focus.

Trap color selection is critical, as it affects both insect attraction and the temperature of electronic components. Materials and colors should be chosen to prevent overheating from sunlight exposure without impacting capture rates. Bait type and killing mechanisms should be tailored to specific species to minimize non-target captures and ensure accurate data collection. Dry traps are preferable for high accuracy in insect recognition, though liquid traps can also be used when appropriate. Electronic components must be miniaturized, low-maintenance, and cost-effective to reduce trap size and enable large-scale production. Cameras should have high resolution and low power consumption, with adequate illumination for capturing clear images under varying conditions. Incorporating weather sensors improves data reliability, while remote data transmission via cellular networks ensures real-time monitoring.

Power units should be durable and sustainable, with options for solar support to extend operational life. Access to captured images should be easy and remote, allowing for timely analysis. Image recognition algorithms can aid in automatic data analysis, though human validation is essential due to potential errors. Cost-effectiveness is crucial for widespread adoption, considering material, assembly, and maintenance costs.

Integrating camera traps with remote sensing enhances monitoring capabilities, especially in forestry and quarantine pest detection. Environmental sustainability, user-friendliness, and adaptability to different pest species are also vital considerations. Automatic traps offer several advantages over traditional methods, including higher temporal and spatial resolution, reduced labor costs, and real-time data access, making them valuable tools for insect pest management.

In the context of quarantine pests, camera-based monitoring proves effective in detecting invasive species in high-risk areas such as international ports and airports. It enables frequent inspections without the need for human intervention, ensuring quick reactions in case of detection. Moreover, camera-based monitoring can support eradication programs of invasive species by providing real-time data on pest presence and distribution.

Comparatively, camera-equipped traps offer several advantages over traditional on-site trap checks. They provide higher sampling frequency and spatial resolution, allowing for more accurate and timely data collection. Additionally, they reduce labor costs and logistical challenges associated with frequent field visits. Real-time data transmission facilitates instant alerts and lowers the likelihood of human-biased information.

Another approach, spearheaded by Sciarreta & Calabrese (2019), introduces innovative methods in insect trapping and monitoring, complementing existing technologies with cutting-edge solutions. Automated devices for insect trapping encompass a broad spectrum of technologies, ranging from bioacoustic sensors to image-based systems, meticulously crafted to target diverse insect species across various environments. For instance, sensors were initially deployed in passive grain probe traps, revolutionizing the continuous monitoring of stored-grain beetles. Modified automatic pheromone traps have proven effective in monitoring notorious pests. Innovative approaches include multi-funnel traps equipped with cameras for early detection of wood-boring beetles, and automatic traps utilizing rollers and electric arcs for counting small-bodied insects. Traps baited with sex pheromones have been developed for Lepidoptera monitoring, employing optical sensors and light emitting diodes (LEDs) for moth detection. Some systems utilize location-aware wireless sensor networks for real-time monitoring, transmitting data to remote servers for decision support systems. Validation of these systems involves comparing captured flies counted remotely with those manually checked in the field, ensuring reliability (Jiang et al., 2008; Deqin et al., 2016).

Overall, these automated devices, ranging from infrared sensors to optoelectronic systems, offer efficient and accurate solutions for insect trapping and monitoring across various agro-ecosystems, aiding in pest management and control applications.

The system proposed by Ramalingam et al., (2020) combines Internet of Things (IoT) and deep learning (DL) for remote trap monitoring and insect detection. In the four-layer IoT framework, comprising the perception layer, transport layer, processing layer, and application layer, smart wireless cameras and sticky insect trap sheets are utilized at the perception layer. These cameras, with low power requirements, continuously monitor insects and send trap images to the processing layer via the transport layer, which utilizes WiFi communication and TCP/IP protocol.

At the processing layer, high-speed computing devices execute the DL framework for insect identification. A deep learning-based object detection algorithm is employed, specifically Faster Region-based Convolutional Neural Networks (RCNN) RestNet 50, which consists of ResNet 50, Regional Proposal Network (RPN), and Fast RCNN modules. ResNet 50 acts as a feature extractor, generating feature maps for insect detection. RPN utilizes anchor boxes to generate bounding boxes for objects, while Fast RCNN performs object classification and bounding box regression. The application layer delivers trap status information to end-users through web-based GUI and mobile applications. A mobile application can be developed for insect monitoring. Overall, this system offers an integrated approach to remote insect trap monitoring and insect detection, leveraging IoT and DL technologies for efficient and accurate pest management (Ramalingam et al., 2020).

RESULTS AND DISCUSSIONS

Research indicates that intelligent trap systems are effective in detecting and identifying different pest species. New methods like infrared sensors and deep learning algorithms provide efficient solutions for trapping and monitoring insects. The study conducted by Lima et al., (2020) makes significant contributions to the field of automatic monitoring of lepidopteran pest species, offering new perspectives and solutions for the efficient management of these harmful organisms in agriculture.

Their research targets several moth and butterfly species, notorious for causing substantial crop yield reductions worldwide. These pests lay abundant eggs, and their voracious larval stages cause direct defoliation, resulting in significant losses. Despite traditional surveillance methods relying on delta traps with pheromone lures, automatic detection and identification models encounter challenges due to insects varied poses on sticky traps.

In order to get beyond these obstacles, a machine learning algorithm was created that has the ability to successfully recognize eyespot patterns in a variety of butterfly species. They used a combination of shape, color, texture, and numerical features to identify moths from pictures. Furthermore, they suggested using a pyramidal stacked de-noising auto-encoder (IpSDAE) to build a deep neural network that could identify moths with a genus-level accuracy of 98.13%. Compared to local visual inspection using modified traps with mobile phone cameras, their automated model for monitoring the codling moth achieved up to 100% efficacy (Silveira & Monteiro, 2009).

Furthermore, artificial neural networks (ANNs) played a crucial role in developing species identification models. Lima et al. combined ANNs with morphological features and support vector machines (SVM) to achieve high efficacy (93%) across various insect orders. Another model combined ANNs with binary patterns for butterfly identification and proposed a method based on color and texture features. The use of texture descriptors, especially the gray-level co-occurrence matrix (GLCM), aided in identifying Lepidoptera species, achieving 96.3% accuracy for 19 species in the Pieridae family.

The model based on texture Gabor filter and extreme machine learning achieved 97% accuracy in identifying five butterfly species. Additionally, deep convolutional neural networks and deep learning techniques identified multiple Lepidoptera, Coleoptera, and Orthoptera species with accuracy ranging from 95% to 97%.

Additionally, studies by Liu et al. (2019) and Wang et al. (2019) developed mobile robot cars with cameras for real-time Pyralidae species identification, achieving 95% accuracy. Their two-step recognition procedure, including color space evaluation and object contour recognition, outperformed the support vector machine method with 94.3% accuracy. Commercial solutions by EFOS, incorporating funnel-style bucket traps and cloud-based image processing, effectively identified larger moth species such as *Spodoptera* spp., *Autographa gamma* (Linnaeus, 1758), and *Helicoverpa armigera* (Hübner, 1808).

Results obtained from the study conducted by Welsh et al. in 2022 revealed the successful implementation and performance of a smart trap system designed to detect insects using an optoelectronic sensor configuration. The system, comprising infrared emitters and photodiode receivers, effectively detected disruptions in the emitted light, translating them into measurable voltage changes through a trans-impedance amplifier. To combat interference from ambient light, particularly sunlight, a novel differentiator-based analogue front end was devised, demonstrating cost-effectiveness and power efficiency.

Upon detection, the sensor output was efficiently processed by an STM32 microcontroller, employing pulse width modulation (PWM) and band-pass sampling techniques to discern relevant signal peaks, thereby minimizing false positives. Notably, the microcontroller operated in a power-saving sleep mode until insect presence was detected, showcasing energy conservation measures. The traps architectural design, characterized by a rectangular layout of emitters and receivers, effectively minimized amplitude distortion, with the integration of high-intensity emitters further enhancing signal quality. Housed within a 3D-printed trap, the sensor electronics were discreetly concealed to emulate the appearance of a standard delta-type trap, thereby deterring potential theft or vandalism.

Data transmission was facilitated by a Particle Boron cellular networking module, enabling seamless wireless relay of insect detection events to an InfluxDB database. This streamlined data acquisition process eliminated the need for on-board storage, enhancing operational efficiency. Experimental trials, both in controlled laboratory settings and real-world field conditions, underscored the systems efficacy in detecting target insect species. Moreover, advanced data processing techniques employed in the study revealed complex behavioral patterns exhibited by moths within the traps. Video analysis elucidated a spectrum of entry behaviors, including direct flight, external perching, and walking ingress. Notably, spectral analysis of detected events provided unique patterns conducive to species identification, contributing to a deeper understanding of insect behavior in trap surveillance applications.

Despite the evident advantages, implementing smart pest monitoring in agriculture may face various challenges, such as high costs, technological complexity, and resistance to change.

To overcome these challenges, it is important to develop appropriate solutions and strategies, such as cost reduction, simplification of technologies, and active involvement of the agricultural community.
Future research in the field of smart pest monitoring should focus on the development and implementation of innovative technologies and solutions that enable more precise and efficient detection and identification of pests in corn crops.

CONCLUSIONS

Smart pest monitoring in maize crops is a promising method for managing agricultural losses due to pests. This technology can improve pest management practices and optimize maize crop yields. Smart sensor traps detect and count moths, providing real-time alerts for automated biosecurity surveillance. Manual trap inspections can be targeted based on trap activity, improving efficiency. Behavioral recordings from traps could aid in species identification, enhancing population modeling and prediction accuracy. Improved trap design, such as optimizing power consumption, could enhance performance and longevity. Smart sensor traps reduce labor costs and carbon emissions, and their integration with machine learning models could further enhance species identification accuracy. Automatic trap systems, such as image recognition, infrared sensors, and audio traps, offer potential for integrated pest management, providing real-time information about pest infestation risk and aiding in population dynamics studies.

REFERENCES

DEQIN, X., QIUMEI, Y., JUNQIAN, F., XIAOHUI, D., JIANZHAO, F., YAOWEN, Y., & YONGYUE, L., (2016). A multi-target trapping and tracking algorithm for Bactrocera Dorsalis based on cost model. *Computers and Electronics in Agriculture*, 123, 224-231.

HAMZAVI, F.(2017). Proposing Intelligent Insect Trap System for Their Recognition and Classification. *American Journal of Engineering Research* (AJER), 6, 199–201. www.ajer.org

HAQ, S. I. U., RAZA, A., LAN, Y., & WANG, S. (2023). Identification of Pest Attack on Corn Crops Using Machine Learning Techniques. *Engineering Proceedings*, 56(1), 183.

JIANG, J. A., TSENG, C. L., LU, F. M., YANG, E. C., WU, Z. S., CHEN, C. P., LIAO, C. S. (2008). A GSM-based remote wireless automatic monitoring system for field information: A case study for ecological monitoring of the oriental fruit fly, Bactrocera dorsalis (Hendel). *Computers and electronics in agriculture*, 62(2), 243-259.

LIMA, M. C. F., DE ALMEIDA LEANDRO, M. E. D., VALERO, C., CORONEL, L. C. P., & BAZZO, C. O. G. (2020). Automatic detection and monitoring of insect pests - A review. *Agriculture*, 10(5), 161.

LIU, B., HU, Z., ZHAO, Y., BAI, Y., & WANG, Y. (2019). Recognition of pyralidae insects using intelligent monitoring autonomous robot vehicle in natural farm scene. arXiv preprint arXiv:1903.10827.

PRETI, M., VERHEGGEN, F., & ANGELI, S. (2021). Insect pest monitoring with camera-equipped traps: strengths and limitations. *Journal of Pest Science,* (Vol. 94, Issue 2, pp. 203–217). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/s10340-020-01309-4.

RAMALINGAM, B., MOHAN, R. E., POOKKUTTATH, S., GÓMEZ, B. F., SAIRAM BORUSU, C. S. C., TENG, T. W., & TAMILSELVAM, Y. K. (2020). Remote insects trap monitoring system using deep learning framework and iot. *Sensors*, 20(18), 1–17. https://doi.org/10.3390/s20185280.

SCIARRETTA, A., & CALABRESE, P. (2019). Development of Automated Devices for the Monitoring of Insect Pests. *Current Agriculture Research Journal*, 7(1), 19–25. https://doi.org/10.12944/carj.7.1.03.

SILVEIRA, M., & MONTEIRO, A. (2009). Automatic recognition and measurement of butterfly eyespot patterns. *Biosystems,* 95(2), 130-136.

VADLAMUDI, S. (2019). How artificial intelligence improves agricultural productivity and sustainability: A global thematic analysis. *Asia Pacific Journal of Energy and Environment*, 6(2), 91-100.

WELSH, T. J., BENTALL, D., KWON, C., & MAS, F. (2022). Automated surveillance of lepidopteran pests with smart optoelectronic sensor traps. *Sustainability*, 14(15), 9577.

ZHAO, Y., WANG, Y., WANG, J., HU, Z., LIN, F., & XU, M. (2019). GMM and DRLSE based detection and segmentation of pests: a case study. *Proceedings of the 2019 4th International Conference on Multimedia Systems and Signal Processing* (pp. 62-66).