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Article

Mobile application for the identification of the fall armyworm (*Spodoptera frugiperda*) in Maize (*Zea mays*) cultivation using image processing techniques in the Central Region of Veracruz: A systematic literature review

Aplicación móvil para la identificación del gusano cogollero (*Spodoptera frugiperda*) en el cultivo de maíz (*Zea mays*), mediante técnicas de procesamiento de imágenes en la región central de Veracruz: Una revisión sistemática de literatura

Antonio-De la Luz, Luis Fernando[a] & Ralero-De la Mora, Manuel Prisciliano[b]

[a] ROR Instituto Tecnológico Superior de Xalapa • 0009-0003-4863-845X • 2027396
[b] ROR Instituto Tecnológico Superior de Xalapa • 0000-0003-1278-508X • 203824

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* ✉ [antoniodelaluzlf@gmail.com]

Abstract

Global population growth has intensified pressure on food security, making the optimization of agricultural productivity essential. In this context, constant monitoring and early detection of pests and diseases are key to preventing crop losses. This study presents a Systematic Literature Review (SLR) on the use of computer vision and digital image processing in plant health diagnostics. The analysis focuses on the identification of the fall armyworm (Spodoptera frugiperda) in maize (Zea mays), a pest with high incidence in the central region of Veracruz. The review compares applied strategies and techniques, including image types, dataset sizes, machine learning algorithms, and the performance achieved in proposed systems. The findings of this SLR provide a solid foundation for the development of a mobile application aimed at delivering accurate and efficient agricultural diagnostics, supporting timely decision-making and contributing to improved crop management and yield.

Objectives	Methodology	Contribution
Develop a computational tool based on image processing techniques for the early and accurate detection of damages caused by Spodoptera frugiperda (fall armyworm) in maize (Zea mays) crops, in order to support timely decision-making by farmers and contribute to optimizing crop yield in the central region of Veracruz.	The methodology used in this project is based on the principles established by Kitchenham for conducting a Systematic Literature Review (SLR) and on a structured approach for the development of computer vision systems. The key stages of the process are as follows: 1. Systematic Literature Review (SLR) 2. Computer Vision • Image Acquisition • Image Preprocessing • Image Segmentation • Feature Extraction • Classification 3. Evaluation Using Machine Learning Metrics 4. Improvement Process	This work contributes to the field of precision agriculture by providing a systematic review of computer vision techniques applied to maize pest detection, particularly Spodoptera frugiperda. It proposes a structured methodology for developing an image-based diagnostic tool, integrating image acquisition, preprocessing, segmentation, and classification. Additionally, the study outlines the design of a user-friendly application aimed at assisting farmers in early pest detection and informed decision-making, with the potential to improve crop management and yield in the central region of Veracruz.

Agricultural pests, Computer vision, Maize (*Zea mays*)

Resumen

El crecimiento poblacional ha intensificado la presión sobre la seguridad alimentaria, haciendo indispensable optimizar la productividad agrícola. En este contexto, el monitoreo constante y la detección temprana de plagas y enfermedades son claves para evitar pérdidas en los cultivos. Este trabajo presenta una Revisión Sistemática de Literatura (RSL) sobre el uso de visión por computadora y procesamiento digital de imágenes en el diagnóstico fitosanitario. El análisis se centra en la identificación del gusano cogollero (Spodoptera frugiperda) en el maíz (Zea mays), plaga de alta incidencia en la región central de Veracruz. La revisión compara enfoques y técnicas aplicadas, como el tipo de imagen, el tamaño de los datasets, los algoritmos de Machine Learning empleados y el desempeño alcanzado en los sistemas propuestos. Los hallazgos de esta RSL proporcionan una base sólida para el desarrollo de una aplicación móvil orientada a un diagnóstico agrícola preciso y eficiente.

Objetivos	Metodología	Contribución
Desarrollar una herramienta computacional basada en técnicas de procesamiento de imágenes para la detección temprana y precisa de daños ocasionados por *Spodoptera frugiperda* (gusano cogollero) en cultivos de maíz (*Zea mays*), con el fin de facilitar la toma de decisiones oportunas por parte de los productores agrícolas para contribuir a la optimización del rendimiento de las cosechas en la región central de Veracruz.	La metodología utilizada en este proyecto se basa en los principios establecidos por Kitchenham para la revisión sistemática de la literatura (RSL) y en un enfoque estructurado para el desarrollo de sistemas basados en visión computacional. A continuación las etapas clave del proceso: 1. Revisión Sistemática de la Literatura (RSL) 2. Visión Computacional • Adquisición de la Imagen • Preprocesamiento de imagenes • Segmentación de imágenes • Extracción de Características • Clasificación 3. Evaluación mediante Métricas de Aprendizaje Automático 4. Proceso de Mejora	Este trabajo aporta al campo de la agricultura de precisión al ofrecer una revisión sistemática de las técnicas de visión por computadora aplicadas a la detección de plagas en maíz, en particular Spodoptera frugiperda. Se propone una metodología estructurada para el desarrollo de una herramienta de diagnóstico basada en imágenes, que integra adquisición, preprocesamiento, segmentación y clasificación de imágenes. Además, se plantea el diseño de una aplicación amigable para el usuario, orientada a apoyar a los productores en la detección temprana de plagas y en la toma de decisiones informadas, con el potencial de mejorar el manejo de cultivos y el rendimiento agrícola en la región central de Veracruz.

Plagas agricolas, Visión computacional, Maíz (*Zea mays*)

Area: Development of strategic leading-edge technologies and open innovation for social transformation

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Introduction

Agriculture is one of the essential economic activities for any country, as it guarantees the subsistence of the population through the production of raw materials destined for food generation. The implementation of technology in the agricultural sector has increased over the years, with the intention of creating new opportunities for the industry and improving its performance. In the 1980s, the concept of Precision Agriculture (PA) emerged, which revolutionized traditional farming by incorporating a more detailed approach adapted to the specific needs of crops and their environment.

Traditional agriculture has operated under the assumption that farmland is homogeneous, applying inputs uniformly without considering internal variations in soil and environmental conditions. In contrast, Precision Agriculture (PA) has transformed this perspective by using advanced technologies to analyze differences in the field and in crop development. Thanks to this information, it is possible to optimize the use of fertilizers, water, and other agricultural inputs, thereby improving efficiency and reducing costs. Originally focused on nutrient dosage, PA has evolved with the incorporation of sensors, satellite systems, and agricultural automation, allowing for more detailed control of field conditions and facilitating real-time decision-making.

The accelerated growth of the world's population poses a significant challenge to food security. The Food and Agriculture Organization of the United Nations (FAO) estimates that by 2050, the demand for food will increase by 60%, requiring greater efficiency in agricultural production. In the face of this challenge, the implementation of continuous monitoring systems becomes essential to maximize crop productivity and prevent losses derived from adverse factors such as pests, diseases, and unforeseen climatic changes.

Several factors influence agricultural performance, ranging from seed quality to crop management. However, one of the main problems producer's faces is the damage caused by pests, which can significantly reduce yields and compromise production stability.

Proper management of these risks requires not only the implementation of control strategies but also the ability to promptly detect the presence of organisms that may affect crops.

This study addresses the impact of early pest detection on maize production, analysing innovative methodologies based on computer vision for its identification and monitoring. Recent studies employing machine learning algorithms for pest classification and prediction will be reviewed, evaluating their accuracy and the relationship between dataset quality and the effectiveness of the models in identifying threats.

Methodology

This study conducted a systematic literature review (SLR), following the methodology established by Kitchenham in 2004. The main objective was to identify computer vision techniques applied to crop analysis, with a particular focus on maize due to its importance in the context of the project. However, the review was not limited exclusively to this crop, which allowed for the examination of research related to other agricultural products and broadened the perspective on advances in this field. This strategy made it possible to compare different approaches and assess their effectiveness in detecting crop-related issues.

The methodological process began with the formulation of key research questions to guide the analysis. Table 1 presents these questions, organized in a way that facilitates the collection and systematization of data obtained from the studies reviewed.

Box 1

Table 1
Research Questions

General Question	Specific Question
1. In what context are they applied?	1. What is the crop under study?
	2. What is being detected?
	3. What is the scope of detection?
	4. What type of image feeds the system?
2. What methods and techniques are used in system development?	5. Methods and techniques in the system
	6. With what technologies was it developed?
3. How is the proposal validated?	7. What is the dataset size used?

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	8. What type of test or experiment is conducted?
	9. Where was it evaluated?
	10. What results were obtained?
	11. What open issues were identified?
4. What does the study contribute to my work?	12. What did the authors do?
	13. What aspect can I address in my work?
	14. How could it be useful for me?

Subsequently, the search protocol was designed, consisting of 1) Selection of digital libraries, 2) Selection of keywords, and 3) Specification of the search string.

Digital libraries: IEEEXplore, ACM, Springer Link, SCIELO, and Google Scholar.

To construct the search strings, it was necessary to select the most relevant keywords and their synonyms. The selected terms are shown in Table 2.

Box 2

Table 2
Keywords and Synonyms

Keyword (Spanish)	English	Synonyms
Plagas	Plague	Infestation, Swarm, Blight, Scourge
Enfermedades	Diseases	Infections, Pathologies, Afflictions
Maíz	Corn	Maize crop, Corn-plant, Corn leaves
Visión artificial	Artificial vision	Artificial intelligence techniques, Automatic detection, Image analysis
Agricultura de precisión	Precision agriculture	Digital Agricultural System
Datos	Dataset	

Using these terms, search strings were built to test across the different databases, as shown in Table 3.

Box 3

Table 3
Search Strings Used

Cadenas	
1	“Diseases” OR “infections” OR “pathogens” AND “Corn” OR “maize crop” OR “corn-plant” AND “artificial vision” OR “artificial intelligence techniques” OR “automatic detection” OR “image analysis” AND “precision agriculture” OR “digital agricultural system” AND “dataset”
2	“Plague” OR “gusano cogollero” AND “Corn” OR “maize” AND “artificial vision” OR “artificial intelligence techniques” OR “image analysis” AND “precision agriculture” AND “dataset”
3	“corn” OR “maize” OR “crop” AND "plague" OR "gusano cogollero" AND "detection" OR “artificial vision” AND “dataset”

The article search process began with the formulation of the first search string, which yielded many results, many of which could be discarded based on their titles. From this initial exploration, the most frequently used English terms were identified, and some synonyms were discarded to optimize the search. This refinement led to the creation of a second search string, which was also evaluated. At this stage, more synonyms were removed due to the excessive number of results obtained.

During searches in databases such as Springer Link, it was observed that the order of terms influenced the results. For this reason, the sequence of key terms such as corn, maize, and crop was adjusted, prioritizing the most relevant. As a result of these modifications, a third search string was generated and applied across all the previously mentioned digital libraries.

The next step in the methodology consisted of defining selection and quality criteria for the articles. To optimize results, specific exclusion criteria were established. First, publication date was considered, restricting articles to the period between 2021 and the current year, in order to ensure the review of recent and updated information. Second, only articles published in scientific journals were included, while other types of publications were excluded.

Thanks to these criteria, the number of articles obtained from the third search string was significantly reduced. A first review was then carried out based on reading the abstracts.

At this stage, articles were selected that met the following requirements: the use of artificial vision techniques for image processing, the implementation of machine learning or deep learning for detection and classification, the mention of dataset size used for system training, and the presentation of metrics to evaluate model performance, including the achieved accuracy rate.

In a second review, a more superficial reading of the selected articles was performed, focusing on results and conclusions. Additionally, accessibility to the documents was also a key factor in the final selection. After completing this process, 30 scientific articles were obtained, which were analyzed in the Results section.

Results

From the 30 scientific articles selected in the systematic review, relevant data were extracted to address the formulated research questions. The applications of computer vision techniques and the main findings are summarized below:

1) In what context are they applied?

a. Crop under study

Maize is the primary focus of numerous studies due to its economic and nutritional importance. Recent research has developed mobile applications and computer vision-based systems to identify diseases in this crop, improving accuracy and speed in detection. Figure 1 illustrates the articles grouped by crop type.

Box 4

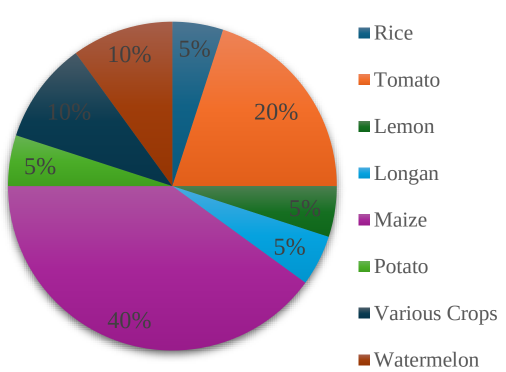

Figure 1
Crop of study in each article

b. What is being detected?

Computer vision-based systems are employed to identify a wide range of pests and diseases in maize plants. Given the variety of crops and pests analysed, most approaches focus on detection for pest control and behavioral analysis. Based on the keywords disease and pest, results showed that maize is particularly threatened by the fall armyworm (Spodoptera frugiperda), as highlighted in [Bravo Reyna, 2023; Nazareno González, 2024]. Among the reviewed studies, pest detection accounted for 68%, combined pest and disease detection for 12%, and disease-only detection for 20%.

Pests

Pests represent one of the most significant factors in reducing crop productivity and harvest quality. Among the main pests detected, the fall armyworm (Spodoptera frugiperda) stands out as a widely studied insect in maize cultivation in Mexico and Ecuador [Bravo Reyna, 2023; García, 2021; Aguilar García, 2022; Nazareno González, 2024]. Classification techniques such as KNN and CNN achieved accuracies exceeding 98%. This pest causes severe foliar damage, reduces photosynthetic capacity, and consequently affects crop yield.

Other important pests include Aphis frangulae Kalt. in watermelon in Peru [Ferreñán Piscoya, 2020], the citrus leaf miner (Phyllocnistis citrella) in lemon in Mexico [Carranza Rosales, 2020], Bemisia tabaci and Prodiplosis longifila in tomato [Rivera García, 2019; León León *et al*., 2024], as well as yellow stem borer and white butterfly in rice in Ecuador [Vivar Callirgos, 2020]. In multi-crop studies, Turkish research [Gaikwad, Pawar, & More, 2022] identified pests affecting apricot and cherry using KNN, SVM, and ELM, reaching 97.86% accuracy.

The overall impact of pests translates into significant reductions in agricultural output due to physical plant deterioration, reduced photosynthesis, and loss of productive tissues, compromising both the quantity and quality of harvests.

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Diseases

Plant diseases caused by bacteria, fungi, and viruses pose another critical threat to agricultural productivity. In maize, Cercospora leaf spot, Common Rust, and Northern Leaf Blight have been widely studied in India and Indonesia [Panigrahi, Sahoo, & Das, 2020; Kusumo, Heryana, Mahendra, & Pardede, 2018] using CNN and SVM classifiers, achieving accuracy rates up to 98.78%.

In Mexico, several studies have focused on the analysis and understanding of maize leaf damage caused by diseases or pests, contributing to the characterization and automated identification of such damage. For instance, [Guzmán Aguirre, 2020] developed an artificial vision system based on deep learning techniques for the identification of foliar diseases in maize, demonstrating the effectiveness of convolutional neural networks for accurate disease classification. Similarly, [Baca Gutiérrez, 2020] designed a monitoring system using OpenCV and Raspberry Pi for the detection of pests and diseases in maize crops, highlighting the potential of low-cost embedded systems for real-time field analysis and precision agriculture.

In China, maize studies [Liu *et al*., 2020; Fu, Zhang, Dong, & Wang, 2022] employed SVM combined with PCA and multispectral image processing (RGB-HSI), obtaining precision, recall, and F1-scores above 90%. Similarly, maize blights (ML Blight, TL Blight, BL&S Blight) were documented in India [Haque & Marwaha, 2022] with accuracies near 96%.

Other examples include gray mold, canker, and leaf spot in tomato in Korea [Fuentes, Yoon, Kim, & Park, 2017] using Faster R-CNN and ResNet, and powdery mildew, late blight, and anthracnose in India [Ngugia, Abelwahab, & Abo-Zahhad, 2020] with CNN models, surpassing 95% accuracy.

Diseases reduce productivity mainly by inhibiting vegetative growth, reducing photosynthetic efficiency, inducing necrosis, and lowering fruit or grain quality. Early detection and integrated disease management are therefore essential to mitigate adverse effects.

c. Scope of detection

In this study, scope is defined as the number of pest or disease classes that a system can identify. Some research [Fina *et al*., 2013] also included classes such as healthy leaves or abiotic stress, though these were not considered here. Results showed that 43% of studies detected three classes, while 36% detected only one.

A trend toward broader class coverage was observed: before 2018, most studies identified only one class [Bravo Reyna, 2023; Nazareno González, 2024; Ferreñán Piscoya, 2020; León *et al*., 2023; Fu *et al*., 2022; León León *et al*., 2024; Villasana-Montes *et al*., 2023; García Amaro, 2022; Vivar Callirgos, 2020; Carranza Rosales, 2020; Miranda, Gerardo, & Tanguilig III, 2014; Gondal & Khan, 2015; Rivera García, 2019; Chen *et al*., 2020], while more recent works reported higher coverage, such as seven classes [Ngugia, Abelwahab, & Abo-Zahhad, 2020], eight classes [Fina *et al*., 2013; Gaikwad, Pawar, & More, 2022], nine classes in Korea [Fuentes *et al*., 2017], and twelve classes in tomato disease detection in China [Liu & Wang, 2020].

Box 5

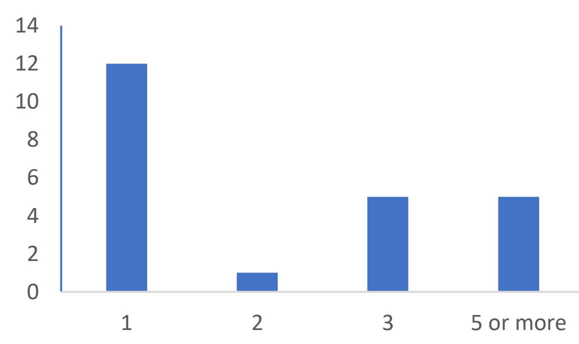

Figure 2
Number of diseases detected in the articles

d. What type of images feed the system?

Image acquisition and type are fundamental for successful pest and disease detection, since color, texture, and shape features are key indicators. The RGB model is the most widely used due to its ability to capture significant foliar changes. For instance, CNN-based detection of fall armyworm in maize reached 98.78% accuracy [Nazareno González, 2024].

Similar approaches for Cercospora leaf spot, Common Rust, and Northern Leaf Blight reported accuracies of 98.78% and 98.06% [Panigrahi, Sahoo, & Das, 2020; Morales Sosa, 2022].

Other studies applied ORB and SURF for aphid detection in watermelon [Ferreñán Piscoya, 2020] or traditional classifiers such as SVM, Decision Trees, Random Forest, and Naive Bayes on RGB images [Kusumo, Heryana, Mahendra, & Pardede, 2018; Liu *et al*., 2020], with variable accuracy between 76% and 92.64%.

The HSV color model was also explored, offering robustness against illumination changes. For example, pest detection in tomato achieved 94.65% and 90.80% accuracy [García Amaro, 2022; Rivera García, 2019]. Hyperspectral imaging (HIS) was another approach, yielding precision, recall, and F1 above 96% [Fu *et al*., 2022], though its cost remains a limitation.

Overall, CNN-based methods consistently outperformed traditional approaches across crops such as maize, tomato, watermelon, and potato.

2) What methods and techniques are used to develop the systems?

Machine learning approaches were subdivided as follows [Mahesh, 2018]:

Supervised learning: Has been widely used for the detection of pests and diseases in agricultural crops. Within this type of learning, methods such as SVM, KNN, Artificial Neural Networks (ANN), and Random Forests (RF) are commonly applied.

For example, in [Kusumo, Heryana, Mahendra, & Pardede, 2018], in Indonesia, SVM, Decision Trees (DT), Random Forests (RF), and Naive Bayes (NB) were compared for the detection of three maize diseases: C. Rust, G-Leaf Spot, and N Leaf Blight, with SVM achieving the highest accuracy (88%). This level of accuracy may have been influenced by the dataset size, as 3,823 images were used.

A similar situation is observed in [Liu *et al*., 2020], where in China, SVM was used in combination with PCA to detect three maize diseases (G-Leaf Spot, C. Rust, C. Big Spot), reaching an accuracy of up to 92.64%. In comparison, in [Morales Sosa, 2022], an accuracy of 98.06% was achieved in the identification of three diseases (Cercospora, Common Rust, Northern Leaf Blight) using CNN, indicating that techniques based on deep neural networks outperform traditional supervised classifiers when adequate image data are available.

In other studies such as [Bravo Reyna, 2023; Carranza Rosales, 2020], the KNN algorithm was applied for the detection of pests such as the fall armyworm in maize and the citrus leaf miner in lemon, respectively. Although precision metrics were not reported, the choice of KNN suggests a practical approach when working with limited datasets.

Unsupervised learning: Has also been incorporated into the detection process, primarily as a preprocessing technique or for dimensionality reduction. In [Liu *et al*., 2020], the use of Principal Component Analysis (PCA) allowed for improved classification with SVM in the detection of maize diseases, contributing to achieving high accuracy in the classification of the three diseases evaluated. Although PCA does not directly function as a final classifier, its implementation has proven to be useful in enhancing the effectiveness of supervised algorithms.

Neural networks: CNNs achieved 98% accuracy in pest detection in Mexican crops [Villasana-Montes *et al*., 2023].

Deep learning: CNNs remain the most robust, reaching 98.78% for fall armyworm in maize [Nazareno González, 2024] and >96% for RGB-HSI maize infections [Fu *et al*., 2022]. Advanced architectures (Faster R-CNN, SSD, R-FCN with VGG16, ResNet, ResNeXt) were tested in tomato, and hybrid methods (KNN, SVM, ELM, CNN) reached 97.86% and 95.67% accuracy in Turkey and India [Gaikwad, Pawar, & More, 2022; Ngugia, Abelwahab, & Abo-Zahhad, 2020]. IoT-integrated YOLOv3 with LSTM achieved 90% precision for Tessaratoma papillosa in longan in Taiwan [Chen *et al*., 2020].

3) How is the proposal validated?

Validation relies heavily on dataset size and experimental design. Larger datasets (>1000 images) consistently yielded higher accuracy. Out of 30 articles, 15 reported exact dataset sizes. Figure 3 summarizes the ranges.

Box 6

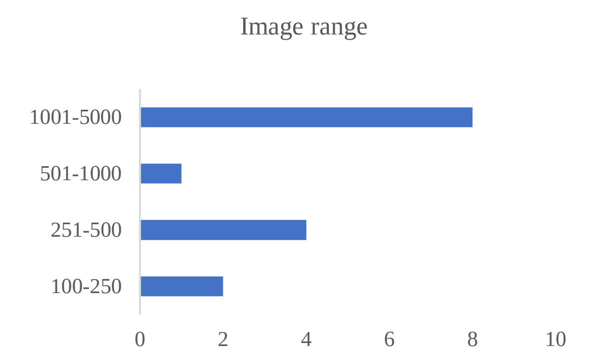

Figure 3
Image dataset ranges in the reviewed studies

Maize was among the most studied crops, with fall armyworm and diseases like Cercospora leaf spot, Common Rust, and Leaf Blight being the primary focus. CNN-based models achieved up to 98.78% accuracy [Nazareno González, 2024; Aguilar García, 2022], while traditional classifiers such as SVM, RF, and NB reached 76–92.64% [Panigrahi, Sahoo, & Das, 2020; Morales Sosa, 2022; Kusumo, Heryana, Mahendra, & Pardede, 2018; Liu *et al*., 2020].

In watermelon, pests (Aphis frangulae Kalt.) and diseases such as late blight and virosis were studied [Ferreñán Piscoya, 2020; Atencio Florez, 2021]. Potato infestation by Premnotrypes vorax in Peru was detected with CNN at 95.12% accuracy [León *et al*., 2023]. Tomato studies addressed pests (Prodiplosis longifila, Bemisia tabaci) and diseases, employing CNN and hybrid deep models with high performance (>90%) [León León *et al*., 2024; Rivera García, 2019; Fuentes *et al*., 2017 ; Nasiri, 2020].

Rice pests in Ecuador [Vivar Callirgos, 2020], citrus leaf miner in Mexico [Carranza Rosales, 2020], and multiple pests/diseases in Turkey and India [Gaikwad, Pawar, & More, 2022; Ngugia, Abelwahab, & Abo-Zahhad, 2020] showed accuracies up to 97.86%. Longan pest detection in Taiwan reached 90% using YOLOv3 with LSTM [Chen *et al*., 2020].

Box 7

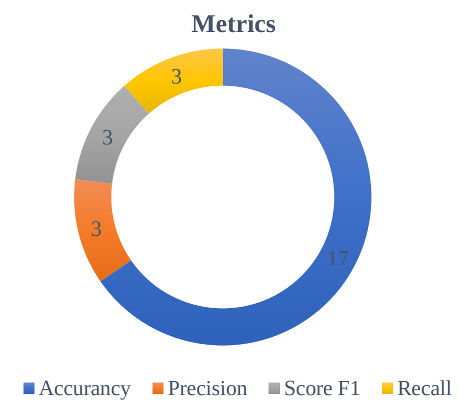

Figure 4
Evaluation metrics used in the reviewed articles

Accuracy was the most frequently reported metric, with comparative ranges grouped in 5% intervals. These results highlight the effectiveness of computer vision and deep learning in pest and disease detection across multiple crops.

Conclusions

Several variables can influence the performance of a classification algorithm. One of the most critical factors is the appropriate selection and extraction of features from digital images, as this process is essential to ensure an accurate representation of visual information. Given its importance, conducting a detailed analysis at this stage is crucial before advancing in model development.

Another determining factor is the size of the dataset used to train the algorithm. Machine learning models require large volumes of data to generalize effectively and make accurate decisions across different scenarios. An insufficient or poorly represented dataset can significantly compromise the model's ability to classify new samples with precision.

Finally, the choice of the classification algorithm also plays a key role in the results obtained. Over the years, advancements in artificial intelligence have led to increasingly sophisticated models, reaching accuracy levels close to 100%. Convolutional neural networks (CNNs) have evolved into architectures with more than 100 layers, aiming to improve the accuracy of image classification.

However, as these models continue to be optimized, a fundamental question arises: Are we truly approaching the development of infallible classification systems? Is it merely a matter of time before artificial intelligence achieves perfection in this domain?

Declarations

Conflict of interest

The authors declare no conflict of interest. They have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Author contribution

Luis Fernando Antonio de la Luz: Conceptualization, methodology, writing.

Manuel Prisciliano Ralero De La Mora: Supervision, critical review.

Availability of data and materials

The data are available in the sources cited throughout the manuscript.

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Abbreviations

AIoT	Artificial Intelligence of Things
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
DT	Decision Tree
ELM	Extreme Learning Machine
HSI	Hyperspectral Imaging
HSV	Hue, Saturation and Valor
IoT	Internet of Things
KNN	K-Nearest Neighbors
NB	Naive Bayes
PCA	Principal Component Analysis
RGB	Red Green Blue
RNN	Recurrent Neural Network
RF	Random Forest
SVM	Support Vector Machine
YOLO	You Only Look Once

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Antecedents

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Basics

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