# USE OF COMPUTER VISION FOR INSECT RECOGNITION

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**Abstract**: The use of technologies such as computer vision has been a trend in agriculture. This technology can reduce the effort and time to obtain data about crops, improving production, crop health and bringing more sustainable practices. This article presents a literature review, among the topics covered, the article includes algorithms and computational techniques, including Convolutional Neural Networks (CNNs), YOLO (You Only Look Once) and Support Vector Machines (SVMs). These techniques are used in conjunction with various image processing techniques to detect and classify insects. Machine learning techniques have been shown to be effective in classifying insects based on characteristics such as color, size and position. Different datasets, such as IP102, Pest24, Xie1, Xie2 and Wang, were used to train and evaluate these algorithms. This article concludes the effectiveness of deep learning algorithms, particularly YOLOv5 and Faster R-CNN, in insect detection and classification, suggesting a promising future for automated insect monitoring.

**Keywords:** Computer Vision, Insects, Agriculture.

## 1. INTRODUCTION

The use of computer vision and deep learning technologies enables the detection and classification of insects in agriculture. Insect control is necessary to reduce crop losses and improve agricultural productivity [1]. Traditional insect monitoring methods are slow [2], and the Internet of Things (IoT), deep learning, and computer vision offer opportunities to automate insect detection and support precision farming practices [3, 4, 5, 6].

Convolutional neural networks (CNNs), specifically architectures such as Mask R-CNN, have shown promising results in detecting insects in images, even in complex overlapping scenarios [7]. These techniques enable automated insect identification and counting, eliminating potential manual errors and accelerating monitoring efforts [3, 7].

Research highlights the importance of data selection and augmentation techniques for building robust insect detection models [8, 9]. Strategies such as HSV Mosaic and Mixup can improve model performance when dealing with variations in imaging conditions and insect appearance [9]. Furthermore, researchers are exploring lightweight deep learning models for efficient deployment on devices with limited computational resources, making them suitable for real-time agricultural applications [10, 11].

The integration of IoT and blockchain with these insect detection systems will enable real-time tracking, predictive analysis, and decision-making [6]. This paper presents a review of the state-of-the-art inherent in the use of computer vision and deep learning technologies in insect detection and classification in agriculture.

## 2. LITERATURE REVIEW

Early and accurate insect detection is necessary to maintain crop health, optimize yields, and promote sustainable agricultural practices. Accurate insect identification enables targeted interventions, minimizing crop damage, reducing reliance on pesticides and their associated negative impacts, and contributing to environmental sustainability.

Technology-based insect monitoring approaches offer promising tools for accurate detection and identification, enabling more efficient and sustainable insect management practices.

## 2.1 Insect detection for crop health and yield

Early insect detection is necessary to protect crop health and maximize yield [12, 13, 9, 14]. It allows the implementation of control strategies, avoiding widespread infestations that can lead to production losses [13, 9]. Accurate identification of insects, differentiating them from beneficial species, is used to optimize insect management [8, 15].

Insect pests are a major cause of crop yield and quality loss [12, 9]. They can damage plants directly by feeding on them or indirectly by transmitting bacterial, viral, or fungal diseases [12]. Pests and pathogens have been estimated to cause crop losses ranging from 10% to 28% for wheat, 25% to 41% for rice, 20% to 41% for corn, 8% to 21% for potatoes, and 11% to 32% for soybeans [12]. Insect monitoring is part of agricultural production management, impacting agricultural development, grain production, and farmers' income [8].

Early insect detection allows timely interventions, preventing insects from establishing themselves and causing damage to crops [12, 13]. This reduces the need for more aggressive control measures, such as extensive use of pesticides [12, 13]. Insect identification, distinguishing harmful from beneficial species, allows targeted use of pesticides [14, 15, 16], minimizing negative effects on beneficial insects, preserving biodiversity and reducing environmental impact [14, 13, 17].

Traditional insect detection methods rely heavily on visual identification by experts, which can be a time-consuming and laborious process prone to errors, especially when working with large numbers of samples and diverse insect species [14, 15, 7, 18, 8]. Automating the insect detection and identification process with advanced technologies such as computer vision and machine learning offers a solution to overcome the limitations of manual methods [13, 14, 8, 15, 12, 19, 20, 3, 21, 22].

Figure 1. Excerpt from the "Guide to Identifying Natural Enemies in Vegetable Crops".

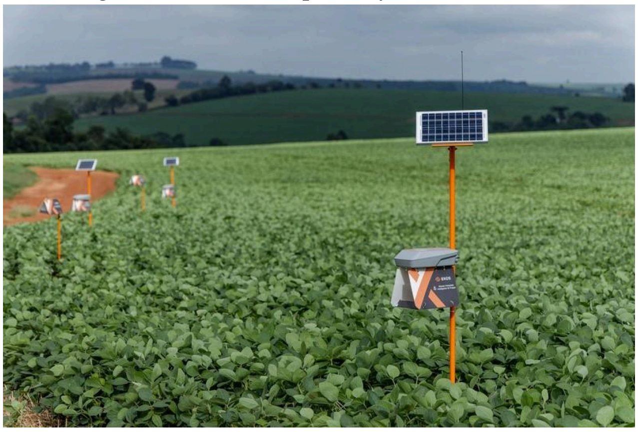
Source: Embrapa, 2019.

Embrapa (2019) presented a guide for identifying natural enemies in vegetable crops" (Figure 1), bringing together images and information on predators and parasitoids used in integrated pest management. Focused on biological control, the objective was to train producers and technicians in the recognition of beneficial species, such as beetles, wasps and mites, essential for reducing the use of pesticides and increasing agricultural sustainability. The publication is part of a project aimed at implementing good practices in vegetable cultivation in the Federal District, promoting training, reducing spraying and producing healthier foods.

## 2.2 Computer Vision in Agriculture

Computer vision can be used to identify and monitor insect pests in real time using camera trap images (Figure 2) [23, 24]. One way to set up the camera trap system involves ten cameras on a green roof with several species of Sedum plants, collecting time-lapse images during the day to detect and identify visiting insects [24].

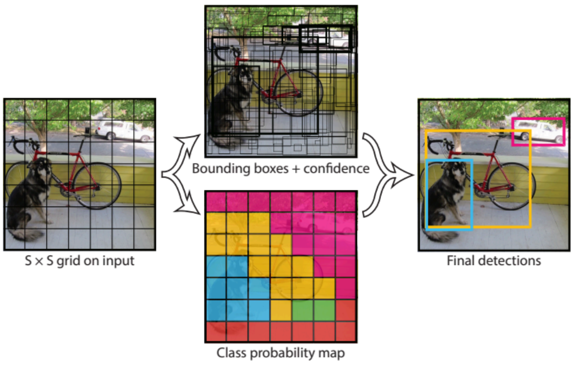
Figure 2. Camera Trap in Soybean Plantation.



Source: O presente rural, 2023.

Deep learning algorithms, such as YOLO v.5 (Figure 3), can be trained to detect and classify different insect species in images [24]. YOLO works by detecting objects in images in real time, through a convolutional neural network that divides the image into regions and predicts bounding boxes and classes simultaneously, using a fast and efficient approach [43].

Figure 3. YOLO v.5 operating characteristics.




Source: Lapix, 2018.

Camera-equipped drones can capture aerial images of agricultural fields, which can be analyzed using computer vision algorithms to monitor crop health, identify areas affected by diseases or nutrient deficiencies, and estimate yield [25]. It can be used to detect plant diseases at early stages by analyzing images of leaves, stems, or fruits [26, 25, 27].

Furthermore, it allows the automated measurement of plant characteristics, such as height, leaf area and biomass, from images [26]. Robots equipped with computer vision systems can identify and spray herbicides selectively on weeds, reducing herbicide use and environmental impact [26, 25]. Computer vision can be used to monitor water levels in crops and optimize irrigation systems [25]. It can also help optimize the use of resources, such as water, fertilizers and pesticides, by analyzing images of crops and soil [25].

Real-time insect tracking systems use computer vision and deep learning to study insect behavior, movement, and interactions [28]. The Fast Lock-On (FLO) system uses insect-attached retroreflectors and high-speed cameras to capture high-resolution videos of insects in flight [28]. Detecting small objects, such as insects, in images or videos presents unique challenges [23]. Deep learning models are prone to false positives when identifying complex background elements as the object of interest [23]. Approaches such as ClusterNet utilize a two-stage deep network with a wide receptive field and are proposed for small object detection [23].

Qing [29] describes a system using two 12MP digital cameras placed above and below a glass plate with four black light sources to attract and capture images of insects. Muppala and Guruviah [22] mention the use of a Canon CCD digital camera with an LDR illumination module to capture images of insects in a darkroom. An array of 200 LEDs was used to focus light on the plate surface for uniform reflections of light from the insect. Muppala and Guruviah [22] and Popescu et.al. [13] discussed the use of drones (Figure 4) to capture aerial images for insect detection.

Figure 4. Quadcopters developed at the Intelligent Systems and Modeling Laboratory.

Source: Romani *et al.,* 2024.

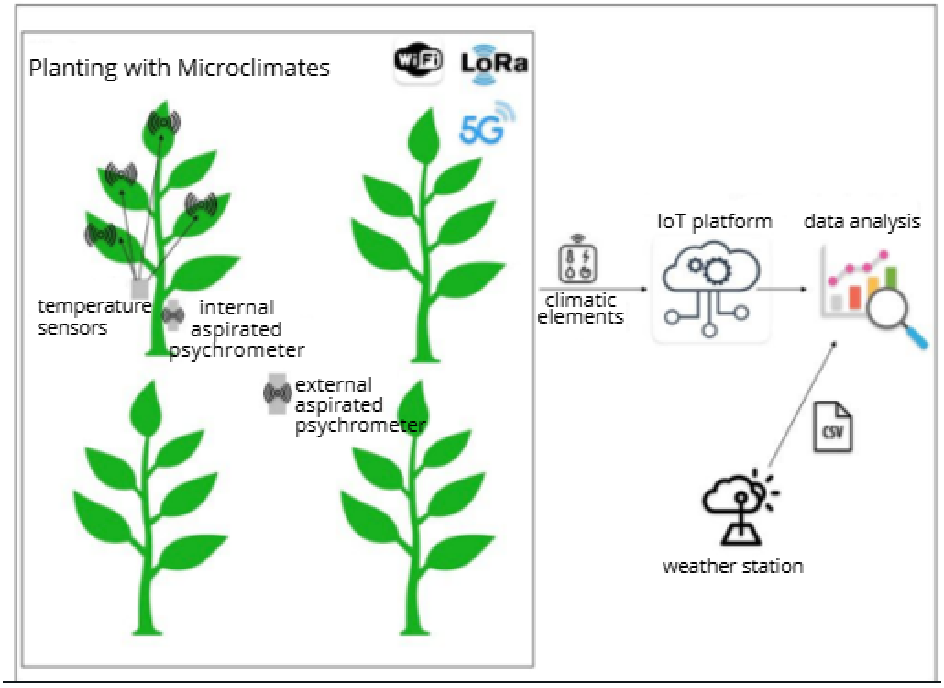
They also describe an experiment conducted with an 18MP Canon EOS M digital camera, used on a horizontal mobile agricultural robot, controlled by LabVIEW software, to capture images of strawberry flowers. Another system was assembled with 6 cameras to capture images of psyllid pests, which fall on a plate attached to a mobile vehicle with a beating unit, to shake the branches of citrus trees. The use of a 12MP digital camera and a 1.3MP multispectral camera, mounted on a quadcopter UAV, to capture aerial images of sunflower fields was described.

Rasheed [30] describes a computer vision-based multispectral pest detection algorithm using multispectral images as input, providing information on different textural and morphological characteristics, as well as visible information such as size, shape, orientation, color, and wing patterns for each insect. The use of NIR (near-infrared) images in the 700–1500 nm range and soft X-ray images between 0.1 nm and 10 nm to detect invertebrates is mentioned [30].

One study used a horizontal mobile agricultural robot, controlled by LabVIEW software, equipped with a digital camera to capture images of strawberry flowers and detect pests [22]. Some studies used IoT-based platforms and systems (Figure 5) for insect detection [3, 17, 31, 5]. Cardoso [5] described an IoT network combined with intelligent Computer Vision techniques to improve insect monitoring, using low-cost cameras to capture images of pest traps and send them to the cloud.

Figure 5 shows the structure of the system for analyzing plant microclimate, where each microclimate attracts a specific species or family of insects. The collection of climate elements is performed using temperature and humidity sensors, strategically positioned at different points of the plant and field. The data collected by the sensors is sent to an IoT platform in the cloud for analysis and permanent storage. In addition to the sensors collecting plant microclimate data, climate data from the meteorological station closest to the plantation is collected for analysis [46].

Figure 5. IoT Plant Microclimate Analysis System.




Source: Adapted from Mendes et al., 2021.

Cesaro Jr [7] describes the use of the Mask R-CNN algorithm for insect detection and segmentation in digital images. Mask R-CNN is based on Faster R-CNN and includes an additional layer for segmentation of each identified object, using instance segmentation techniques. There are reports of the use of CNNs for insect detection and classification [1, 13, 32, 18, 8, 33], using YOLO v.3, a CNN-based model used to classify and label insects [17].

SVM was used for insect classification and insect detection [22, 15, 16, 34, 11] and YOLO for insect detection [5, 18, 15, 16, 11]. The algorithms KNN (K-Nearest Neighbors), Naive Bayes, Faster R-CNN, SSD (Single Shot MultiBox Detector), R-FCN (Region-based Fully Convolutional Network), SegNet, U-Net, DeepLab v3 and deep learning-based algorithms [22, 30, 1, 35, 33, 15, 16, 21] were used. Table 1 presents some advantages of the reviewed articles, while Table 2 highlights some disadvantages.

Table 1. Advantages of using computer vision in insect recognition.

| Advantages | Description |
|---|---|
| Task automation. | The combination of computer vision and the Internet of Things enables real-time insect monitoring. Sensors installed in the field can capture images and send them for processing, generating immediate alerts about the presence of insects and assisting in decision-making for crop management. |

| Advantages | Description |
|---|---|
| Big data analysis | Automated computer vision systems can operate continuously, generating a large volume of data on the presence and behavior of insects. This large amount of data allows for accurate and detailed analyses of insect population dynamics, aiding in the development of effective control strategies. |
| Early detection and increased productivity | Early detection of pests, made possible by the use of computer vision, allows for effective and environmentally friendly control measures to be taken. This helps to minimize losses in agricultural production and reduce the use of pesticides. |
| Cost reduction | Automation provided by computer vision can lead to reduced costs for specialized labor and pesticide use. |

Source: The authors.

Table 2. Disadvantages of using computer vision in insect recognition.

| Disadvantages | Description |
|---|---|
| Need for large data sets | Computer vision models, especially those based on deep learning, require large datasets for training, including images of different stages of insect development, in different lighting conditions and positions. Lack of sufficient and diverse data can lead to inaccurate results and detection errors, such as false positives and false negatives. |
| Difficulty of detection in real conditions | The performance of computer vision models can be affected by factors such as variations in lighting, presence of debris, insect overlap, similarity between species, and image quality. These factors can lead to errors in insect identification and counting. |
| Implementation costs | The implementation of computer vision systems for insect detection can have a high initial cost, especially in relation to the acquisition of hardware, software and model development. |
| Energy and connectivity dependency | The operation of real-time computer vision systems depends on the availability of power and connectivity in the growing area. The lack of adequate infrastructure may limit the application of the technology in some areas. |

Source: The authors.

## 2.3 Advances in Computer Vision in Agriculture

Bjerne [36] describes a system for monitoring insects and flowers in natural environments using time-lapse cameras and deep learning. The system is divided into three main steps:

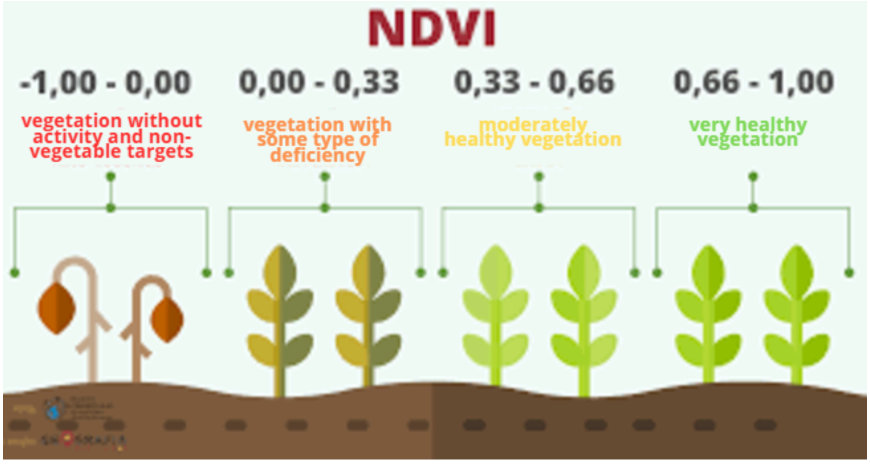
- Arthropod Detection: A YOLO v.5 model, pre-trained on the COCO dataset, is used to detect arthropods in images. The use of motion-enhanced images has been shown to improve model performance, especially on time-lapse images not included in the training and validation datasets [36]. The accuracy of the YOLO v.5 algorithm without motion-enhanced data was 93.3%, while the algorithm with motion-enhanced data achieved 89.0% accuracy [36].
- Detection Filtering: To reduce false positives, especially detections of plant parts that could be confused with arthropods, the system employs "stationary" and "matching" filters [36]. The stationary filter removes detections that occur

in the same position in successive images, while the matching filter eliminates detections when there is no noticeable difference in the last three images [36].

- Taxonomic Classification: After detection and filtering, the detected arthropods are classified into different taxonomic levels (order, family, genus) using an EfficientNetB4 Algorithm [36]. The algorithm achieved an average F1 score of 0.81 on a dataset with 19 arthropod classes [36].

Rhodes [27] explored the use of remote sensing to study insects [27]. Despite challenges, such as the small size of insects relative to data resolution, he highlighted advances in sensors, platforms, and algorithms that allow the collection of relevant ecological data. Vegetation indices, such as NDVI (Figure 6), are used to map insect habitats and food resources. LiDAR and SfM data allow the three-dimensional characterization of habitat structure.

Figure 6. NDVI values established in the bibliography for vegetation.




Source: Adapted from EOS, 2019.

Microclimate models can be fed with remotely sensed data, such as surface temperature, water content and vegetation structure, to understand how insects experience environmental conditions. Satellite imagery is used to monitor the extent and brightness of light pollution, which affects insect behaviour and physiology.

Signs of insect feeding, such as defoliation and nest structures, can be detected using multispectral and SAR imaging. Radar, LiDAR and harmonic radar are used to detect and track insects in flight, providing information on migration, behavior and population dynamics.

Several image processing techniques have been described and used for insect detection and classification, and can be grouped into two main categories: preprocessing techniques and segmentation and feature extraction techniques [27]. In preprocessing, color transformation converts images from one color space to another, such as RGB, and is useful for segmentation by highlighting specific features of the target, facilitating its separation from the background.

Techniques such as rotation, normalization, and resizing adjust the orientation, size, and scale of the image, preparing the data for processing and analysis. Additionally, noise reduction and contrast enhancement eliminate imperfections and highlight differences between areas of the image, improving quality for subsequent steps.

In segmentation and feature extraction, after preprocessing, areas of interest are segmented, dividing the image into relevant parts, such as tree canopies, diseased areas or spaces between canopies. Next, feature extraction occurs, where distinct characteristics are obtained from the segmented areas, allowing the differentiation of targets, such as insects, from the background. These steps, together, enable efficient and accurate analysis for the proposed purposes.

When it comes to feature extraction techniques, features can be divided into four forms [37]: (i) Morphology: Shape, size, texture, and structure of the target; (ii) Visual Texture: Visual patterns within the segmented area; (iii) Spatial Context: Position and spatial arrangement of the target relative to the environment; and (iv) Spectral Information: Spectral characteristics of the target, such as reflectance at different wavelengths.

The use of Deep Learning (DL) as a powerful approach to extract complex structural information from raw images is highlighted. In contrast to traditional image processing techniques, algorithms can automatically learn relevant features from the data, without requiring manual extraction.

The use of DL and computer vision techniques to detect and classify insects in images is addressed, mainly in the context of precision agriculture. Specific methodologies include the implementation of Mask R-CNN, used to detect and segment multiple insects in a single image, even in cases of partial overlap [7].

The Faster R-CNN approach was used, together with the Inception-ResNet-v2 feature extractor for object classification, on a yellow sticky trap dataset [16]. A DL approach includes a channel spatial attention module, a region proposal network, and a position-sensitive score map (PSSM) for multiple insect class detection [13].

The use of a variety of CNN architectures, including ResNet50, GoogleNet and DenseNet201, for insect classification includes the application of transfer learning techniques, from public databases [13].

Different versions of the YOLO Algorithm, including YOLO v. 2 to v. 5, have been used for insect detection and classification [13, 11, 12]. YOLOX was used as a foundation, implementing improvements to deal with forest pest detection, addressing challenges such as small datasets and limited imaging resources [32]. Also, the Pest-YOLO approach was used, combining deep image mining and multi-feature fusion for real-time pest detection [14].

To overcome the limitations of small datasets, they have employed dataset augmentation techniques, such as geometric transformations, to artificially increase the size of training datasets [7, 11, 14]. In addition to camera images, some studies have explored the use of ultrasonic sensors and lasers to measure tree canopy parameters and support precision spraying [37]. To improve detection accuracy, they have used multi-network-based systems, such as custom ensembles combining multiple CNN architectures or optimization variants [13].

## 2.4. Databases

The databases used in the experiments, providing information on their application and relevance, were highlighted. The IP102 database contains images of 102 common insect classes, totaling about 72,222 images. It is updated and maintained by entomology experts and covers a wide range of insect orders [13]. IP102 was used to evaluate an improved YOLOX algorithm, examining the impact of various augmentation components on its detection accuracy [32].

The Pest24 dataset, containing images of agricultural pests, was used to evaluate the performance of Pest-YOLO. Although the number of images or classes in Pest24 was not specified, it was observed that Pest-YOLO outperformed other methods in terms of speed and accuracy [14].

The Xie1 and Xie2 datasets were used to create larger datasets or to test and train architectures. Xie2, known as D0, contains 4,508 RGB images of 40 insect classes with a resolution of 200 x 200 pixels. Due to its smaller size, image augmentation techniques were used in the dataset [13].

The Wang dataset, with nine insect classes in 225 images (25 images per class), was used to evaluate machine learning techniques for insect classification and detection in field crops. The researchers split the dataset into a 70–30% training–testing ratio [34].

In addition to these databases, [5, 16] used proprietary datasets or datasets constructed by combining multiple sources. A dataset of yellow sticky trap images was used, with labeling for greater accuracy.

Focusing on insect detection in coffee plantations [3], one research used a custom dataset of coffee beetle images, not making the dataset publicly available. [15] developed a system to monitor insect pests in soybean crops, using a proprietary dataset of images collected from the field, not providing details about the dataset.

[38] used smartphones to capture images of insects to identify bee families at the genus level, successfully in almost three-quarters of cases. However, the identification of flies proved to be challenging, highlighting the need for optimization for this category.

## 3. RESULTS

The study demonstrated that deep learning algorithms, particularly YOLO v.5 and Faster R-CNN, are effective for the detection and classification of various insect species. These state-of-the-art algorithms exhibited remarkable improvements in both accuracy and processing speed when compared to traditional pest monitoring methods, which often rely on manual identification and are time-consuming and prone to human error.

To further enhance the detection capabilities of these algorithms, the research incorporated a range of advanced image processing techniques. These techniques played a crucial role in accurately identifying insects by analyzing their distinguishing characteristics, including color patterns, body size, wing structure, and spatial positioning within the images. This approach ensured a higher degree of precision in insect classification, even in complex or cluttered environments.

The research utilized several datasets to train and evaluate the machine learning models, including IP102, Pest24, Xie1, Xie2, and Wang. These datasets presented variability in insect species, habitats, and imaging conditions, supporting the development of models applicable to real-world scenarios with varying environmental and biological conditions. Building on this foundation, the study demonstrates the significant potential of automated insect monitoring systems to revolutionize modern agricultural practices. By integrating advanced computer vision techniques with state-of-the-art machine learning algorithms, these systems offer a robust solution for real-time pest population monitoring. This integration allows for the continuous collection and analysis of data, providing precise and actionable insights into pest dynamics.

The capabilities enable farmers and agronomists to implement timely and targeted interventions, effectively mitigating the impact of pest infestations. Additionally, these technologies contribute to reducing the excessive use of chemical pesticides, promoting more sustainable and environmentally friendly agricultural practices while enhancing crop productivity and safeguarding food security. Beyond improving pest management, the implementation of such automated systems has the potential to significantly reduce the labor and time traditionally required for pest monitoring and management.

This shift not only streamlines the pest management process but also allows farmers to allocate their resources and attention to other critical aspects of crop cultivation and production. Ultimately, the adoption of these technologies could lead to improved crop yields, reduced use of pesticides, and a more environmentally friendly approach to farming, benefiting both the agricultural sector and the ecosystem as a whole.

Table 3. Comparative Table of Deep Learning Algorithms for Insect Recognition

| Aspect | YOLOv5 | Faster R-CNN | Mask R-CNN |
|---|---|---|---|
| **Type** | Object Detection | Object Detection | Object Detection + Instance Segmentation |
| **Speed** | High (real-time detection) | Moderate (slower than YOLO) | Moderate (slower than YOLO) |
| **Accuracy** | High (good for real-time applications) | Better for complex scenes | Very High (best for detailed segmentation) |
| **Complexity** | Less complex, easier to implement | More complex, requires more resources | Most complex, requires significant resources |
| **Use Case** | Ideal for real-time insect detection | Suitable for detailed analysis and counting | Best for scenarios needing precise segmentation |
| **Training Data Requirements** | Requires diverse datasets for robustness | Requires large annotated datasets | Requires large annotated datasets with masks |
| **Implementation** | Easier to deploy on edge devices | More suited for server-side processing | More suited for server-side processing |
| **Applications** | Pest detection in real-time | Insect counting and classification | Detailed insect analysis and segmentation |

Source: The authors.

The Table 3 provides a comprehensive overview of the various approaches and technologies employed in the detection and classification of insects in agricultural environments. The análise highlights the diversity of methods utilized, including deep learning algorithms like YOLO and Faster R-CNN, alongside image processing techniques. This variety is a positive indication, as it suggests that the research is exploring multiple avenues to address the issue of insect detection. However, it is essential to assess the relative effectiveness of each method under different field conditions.

While many studies demonstrate promising results in controlled environments, practical application in real-world field conditions may present significant challenges. The table should include data on the robustness and accuracy of the models across diverse scenarios, such as different crop types, climatic conditions, and lighting variations. The absence of data on field performance may limit the applicability of the proposed solutions.

Analyzing the datasets used to train the models is crucial. The table could indicate whether the datasets are sufficiently large and diverse to ensure that the models can identify a wide range of insects in different contexts. A lack of dataset diversity could introduce bias into the models, resulting in low accuracy in situations not represented in the training data.

The table could showcase how different technologies, such as IoT and sensors, are being integrated into insect detection systems. This integration is fundamental for developing precision agriculture solutions. However, it is necessary to evaluate the feasibility and costs associated with implementing these technologies on a large scale.

A critical aspect to consider is the environmental impact of the proposed solutions. The table may not adequately address how insect detection technologies can contribute to more sustainable agricultural practices, such as reducing pesticide use. The analysis should include considerations on how these technologies can promote the health of the agricultural ecosystem.

## 4. CONCLUSION AND FUTURE RESEARCH PERSPECTIVES

In conclusion, this study highlights the effectiveness of deep learning algorithms, particularly YOLO v.5 and Faster R-CNN, in the detection and classification of insects. The combination of these technologies with advanced image processing techniques not only enhances the accuracy and efficiency of monitoring systems but also offers a viable solution to the challenges faced in modern agriculture. The ability to perform real-time monitoring can transform agricultural practices, allowing for quicker and more targeted interventions, resulting in more sustainable and effective pest management.

However, there are several areas that warrant attention in future research. Firstly, the expansion and diversification of datasets used for training are crucial. While datasets such as IP102 and Pest24 have been valuable, including images from different environmental conditions, lighting, and capture angles can further increase the robustness of the models. Additionally, real-time data collection in field environments can help create more adaptable and accurate models.

Another future research perspective is the exploration of continuous learning and transfer learning techniques. These approaches can enable models to adapt and improve continuously with new data, reducing the need for complete retraining and increasing system efficiency over time.

Furthermore, integrating multiple data sources, such as ultrasonic sensors and weather data, can enrich analysis and real-time decision-making. Combining visual data with environmental information can provide a more holistic understanding of pest dynamics and their interactions with the agricultural ecosystem.

Finally, research on the implementation of automated monitoring systems at scale, including the integration of drones and IoT devices, holds immense potential for advancing precision agriculture. By leveraging automation and connectivity, these technologies can enhance efficiency while enabling the sustainable management of natural resources. The prospects for future research in this domain are promising, with the potential to drive significant innovations in pest detection and management, ultimately contributing to smarter, more efficient, and environmentally sustainable agricultural practices.

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