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Article

IDENTIFICATION OF GREEN LEAFHOPPERS (CICADELLIDAE) IN VINEYARDS THROUGH AN AUTOMATIC IMAGE ACQUISITION SYSTEM FROM YELLOW STICKY TRAPS ASSOCIATED WITH DEEP-LEARNING

IDENTIFICAÇÃO DE CIGARRINHAS VERDES (CICADELLIDAE) EM VINHAS ATRAVÉS DE UM SISTEMA AUTOMÁTICO DE AQUISIÇÃO DE IMAGENS DE ARMADILHAS AMARELAS ADESIVAS ASSOCIADO A UM ALGORITMO DE *DEEP-LEARNING*

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SUMMARY

This work presents an innovative approach to expedite the identification process of green leafhoppers by combining a deep-learning algorithm with an automatic camera system that captured high-resolution images from yellow sticky traps. Identifying and monitoring agricultural insects are crucial for implementing effective pest management strategies. Conventional insect identification and counting methods can be time-consuming and labor-intensive, urging the need for efficient and accurate automated solutions. The deep learning algorithm based on convolutional neural networks (CNNs) learn discriminators from a diverse set of green leafhopper images. The model's architecture was optimized to handle variations in lighting conditions, angles, and orientations commonly found in field settings. To assess the algorithm's efficacy, the test images were also evaluated by human curation and results accounted for in terms of false positives and false negatives. The results demonstrated the algorithm's capability to accurately identify green leafhopper species, improving the speed of identification compared to conventional methods while maintaining a high level of precision (80%), and a harmonic mean of the precision and recall (F1) of 0.85. The combination of a deep learning algorithm and real-time data acquisition allows a fast decision-making by technicians and researchers, supporting the implementation of pest management strategies, and demonstrates the promising potential for specific and sustainable pest monitoring, contributing to the progress of precision farming practices.

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RESUMO

Este trabalho apresenta uma abordagem inovadora para agilizar a identificação de cigarrinhas verdes, combinando um algoritmo de *deep-learning* com um sistema automatizado que captou imagens de alta resolução de armadilhas amarelas adesivas. A monitorização e identificação de insetos agrícolas são cruciais para a implementação de estratégias eficazes de gestão de pragas. Os métodos convencionais de identificação e contagem de insetos podem ser demorados e árduos, exigindo soluções automatizadas eficientes e precisas. Os métodos de *deep-learning* baseados em redes neuronais convolucionais (CNNs) aprendem caraterísticas discriminativas associadas ao complexo de espécies de cigarrinhas verdes através de um processo de treino, recorrendo a um conjunto diversificado de imagens dos insetos. A arquitetura do modelo foi otimizada para variações nas condições de iluminação, ângulos e orientações comumente encontradas no campo. A eficácia do algoritmo foi avaliada sobre um conjunto extenso de imagens-teste, em que um especialista humano identificou as ocorrências, para se proceder posteriormente à contabilização de falsos positivos e falsos negativos detetados. Os resultados demonstraram a capacidade do algoritmo para identificar com precisão espécies de cigarrinhas verdes, melhorando a velocidade de identificação em comparação com métodos tradicionais, mantendo um alto nível de precisão (80%) e um F1=0,85. A combinação de um algoritmo de *deep-learning* e a aquisição de dados em tempo real permite uma rápida tomada de decisão, apoiando a implementação de estratégias de gestão de pragas, e demonstra um potencial promissor para a monitorização sustentável de pragas específicas, contribuindo para o progresso de práticas agrícolas de precisão.

Keywords: Automatic traps, pest monitoring, cicadellids, *Vitis vinifera*.
Palavras-chave: Armadilhas automáticas, monitorização de pragas, cicadelídeos, *Vitis vinifera*.

INTRODUCTION

For centuries, vineyards have flourished in the border regions of the Mediterranean basin (Fátas-Cabeza, 2002). Nowadays, they are a major fruit crop in Europe, covering an area of about 3.2 million ha, corresponding to 2.0% of utilized agricultural land (Eurostat, 2024). In Portugal, in 2022, the crop was grown on 191,170 ha. The country ranks 10th among the world's largest wine producers, with a total of 6.7 million hL (IVV, 2022).

Green leafhoppers (GL) (Hemiptera, Auchenorrhyncha, Cicadellidae) are major pests of vineyard (Afonso *et al*., 2023). In Portugal, the first reference to GL as vineyard pests dates back to 1980 in the Alentejo region (Coelho, 1983). Later, during the 1990s, the species complex spread and affected the Douro and Dão regions (Raposo and Amaro, 2003), particularly *Empoasca vitis* (Göthe). *Jacobiasca lybica* (Bergevin & Zanon) was first identified in 1989 (Quartau *et al.*, 1989), and it was considered the main GL species responsible for yield losses in vineyards from the southern region.

The feeding process of GL on leaves triggers typical symptoms known as hopperburn, leading to direct or indirect damage, including lower assimilate production, lower sugar accumulation in grapes, and lower vine reserves (Rebelo, 1993), resulting in considerable losses in production and income, as well as significant increase in control costs (Backus *et al.*, 2005).

GL are very similar in their external morphology, and specific identification is only possible by analysing the male genitalia microscopically (Quartau and Rebelo, 1992; Rebelo, 1993).

Effective monitoring systems for risk assessment and decision-making are needed in Integrated Pest Management (IPM) of GL. Monitoring systems of GL populations include visual observation of leaves to detect symptoms or nymphs' presence, and sampling with yellow sticky traps, aspirators, and entomological nets (Félix and Cavaco, 2009). However, these procedures are usually time-consuming, in fieldwork, insect counting, and identification, depending on trained manpower.

Automatic remote monitoring constitutes an innovative and highly efficient technology for pest monitoring, which has registered increasing developments in the last 20 years (Preti *et al.,* 2021). However, such technology was not applied yet in GL monitoring. Remote monitoring, coupled with automatic image acquisition systems and identification, presents a promising avenue for GL sampling. This integration of technology holds the potential to revolutionize the way vineyards are monitored, offering real-time data acquisition and analysis. Nevertheless, a decision support tool based on mobile-acquired sticky trap images was recently developed for GL (Gonçalves *et al,* 2022; Rosado *et al.*, 2022).

This article addresses the gap in current research by presenting a comprehensive study using an automatic image acquisition system from yellow sticky traps, coupled with a deep-learning algorithm based on convolutional neural networks (CNNs), to provide an efficient and accurate solution for remote monitoring of GL in vineyards. The main objectives of this study included evaluating the performance of the proposed system, assessing its feasibility for large-scale implementation, and contributing to the improvement of digital viticulture practices.

MATERIALS AND METHODS

Study site and sampling period

Sampling was carried out between May and September 2023 in two grapevine plots of ‘Touriga Nacional’ grapevine variety (one managed in organic production system and the other in integrated production system) at Colinas do Douro, a 450 ha farm with about 160 ha of vineyards, located at Vale das Eiras, Escalhão, in the SE of the Dermarcated Region of Douro and integrated in the Natural Park of Douro Internacional.

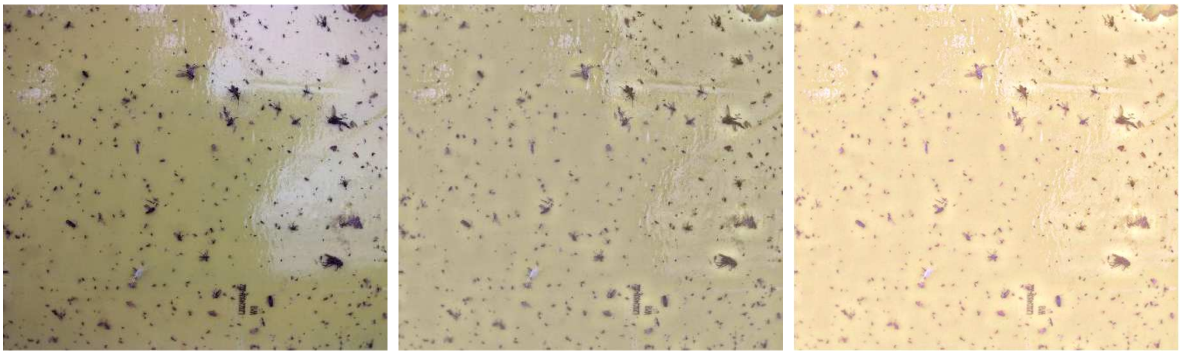
Sampling and image acquisition system

Leafhopper sampling was conducted using yellow sticky traps. Two iSCOUT®COLOR TRAPS were installed, one per grapevine plot. This remote monitoring system is a self-sufficient device, powered by a solar panel and a battery, and integrating a camera, a modem, and a yellow sticky trap (Figure 1). The incorporated camera takes high-resolution pictures of the sticky trap and the images are sent via GPRS to the FieldClimate platform, which are then visible on the web. The sticky plates were substituted every 3-4 weeks, during the sampling period, depending on the level of insect captures, as well as on logistical constraints. The collected plates were kept in the laboratory for insect identification. Each trap was photographed daily, but only a sample of 20 images was analyzed for this study, of which 15 images that captured all trapped GL were used. In the end of each exposure period, the captures in a trap correspond to the accumulated number of insects captured during that period. Therefore, the image of the trap on day n shows the total number of insects captured between day 1 and day n.

Figure 1. iSCOUT®COLOR TRAP: general perspective (left); camera and yellow sticky trap (right).

Dataset and Methodology

The dataset included 15 images of 2748 x 3664 pixels, obtained through FieldClimate platform, that were pre-processed in a Matlab (nd) environment to attenuate the gradient in the background with a modified homomorphic filter and all histograms were matched to one reference image (Figure 2). The large image size was not supported by the available hardware; these images were divided into 916 x 916 non-overlapping tiles, and the dataset was restrained to focused tiles.



a b c

Figure 2. The evolution of an image with the preprocessing: a) original image; b) after homomorphic filter; and c) histogram match.

The objects of interest were detected and counted in the images with a deep-learning algorithm released in July 2022 called YOLO v7 (Redmon *et al*., 2016), that is publicly available in a GitHub repository (GitHub, nd). To use YOLO v7 on any new data set, a training stage is needed: the objects of interest intended to be detected should be identified in a representative subset of images (Figure 3), that will allow the algorithm to define discriminative features.

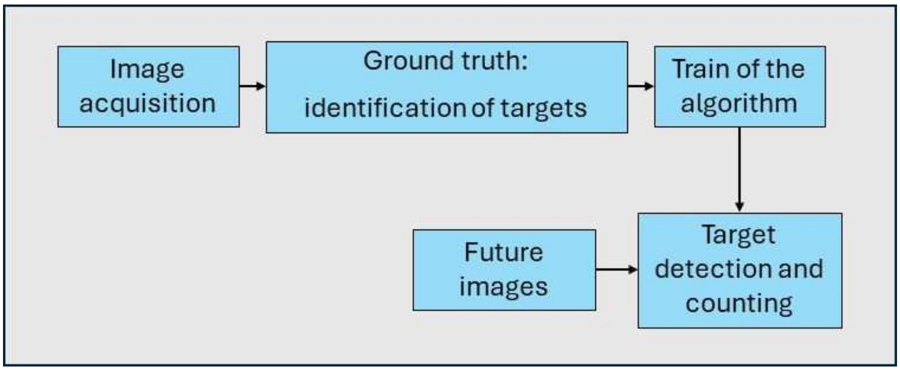


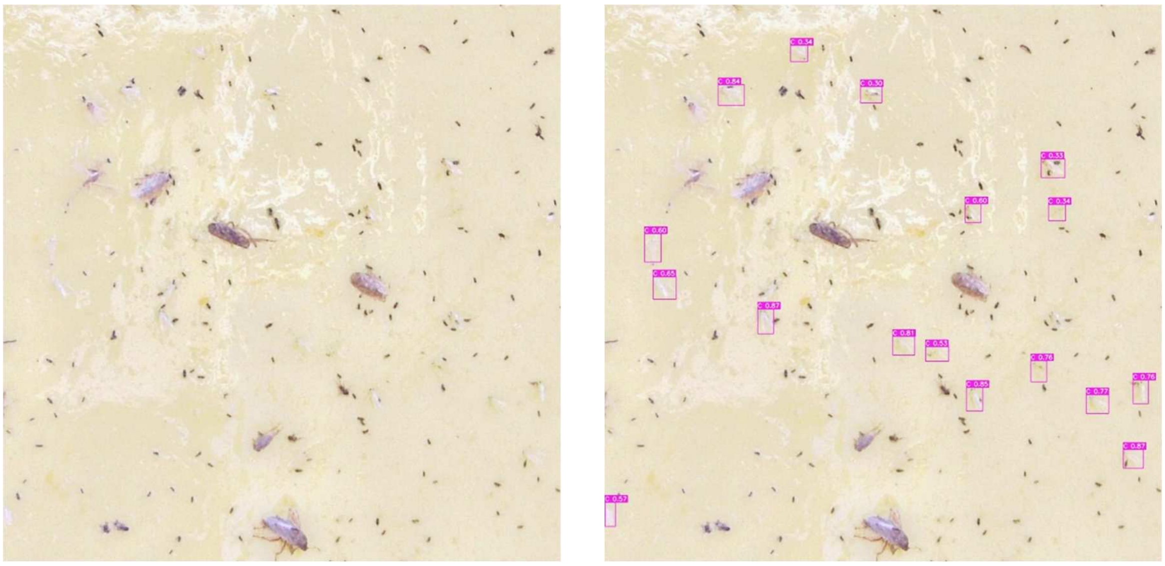
Figure 3. Fluxogram describing the procedure: i) all the targets are manually identified in a subset of images; ii) the set of annotated images is divided for training and validation of the algorithm, that will proceed in several iterations (750 in the present case); iii) the resulting weights define a new model that can be applied to any image with the same characteristics, detecting and counting the targets to which it is trained.

The manual identification of the targets can be achieved online, for instance with MakeSenseAI (nd) in three steps, consisting in: i) upload the subset of images for training the algorithm; ii) identify the objects of interest in each image using the tools available on the graphic interface; iii) download the annotations in a YOLO compatible format, in the form of text files.

YOLO v7 and its precedent versions have the possibility of transfer learning, which consists of reusing an already trained network as a base for a new problem. Since simple features such as edges, shapes or contrasts are common to many objects in detection problems, a trained network can be used to implement a new problem, with a set of initial weights well established from training on very large datasets, such as Common Objects in Context (COCO), which was trained with more than 200,000 annotated images. The new discriminators will tune the detector according to the details of the new training dataset, defining the last layers of the convolutional neural network (CNN), while the basics are defined by the first layers previously trained.

The new GL detection model uses the e6e model from YOLO v7 as base and training with augmented data, changing a few hyperparameters from the default values, namely the amounts of rotation to 0.75 degrees, and the change in scale to 0.2. Translation, shear and perspective were kept to zero. The annotation of 33 images of a subset of 120 tiles (916 x 916 pixels, 24-bit depth) with one class of objects of interest was done online (MakeSenseAI, nd). Of these tiles, 22 were used for training and 11 for validation of the algorithm, respecting the recommended ratio of 1:2 between validation and training images.

The training was done once, and took two hours nineteen minutes for 750 iterations in a laptop equipped with dual Core Intel i7-10750H processor, 16 GB SDRAM, and a graphic unity NVIDIA GeForce RTX 2060 Max-Q 6GB. The resulting weights defining the new model can be used to detect the same objects of interest on any similar image (Figure 4), with a processing time around 0.2 s for each image.



a   b

Figure 4. Example of an image (a) and the detections made by the model with the respective confidence associated with each identification (b

To evaluate the performance of the model considered the best, with the hyperparameters mentioned above, the remaining 87 tiles were processed using a confidence threshold of 0.30, meaning that the model is at least 30% confident that each object detected is similar to the ones used in the training stage. The results were compared to those obtained by a human expert, identifying false detections (false positives) and failed detections (false negatives). The results were quantified in terms of the usual metrics Precision and Recall; the first one is defined as the percentage of objects correctly classified among all the objects detected by the model as in Equation

Precision = True Positives/(True Positives + False Positives) **Eq. 1**

Recall refers to the percentage of positives correctly identified among all occurrences of real positives (Equation 2).

Recall = True Positives/(True Positives + False Negatives) **Eq. 2**

The F1 score is a combined measure of the accuracy of a model in a data set, computed as the harmonic mean of the accuracy and recall of the results (Equation 3).

F1 = 2 x (Precision x Recall) / (Precision + Recall) **Eq. 3**

The resulting F1 score is in the range [0, 1], the value 1 indicating perfect precision and recall, and a zero-value revealing that either precision or recall are zero.

Species identification

Samples of GL specimens were collected from 20 traps, during the sampling period, to determine the most common GL species captured, based on the microscopic study of male genitalia (Le Quesne, 1983). The pygofer was dissected from the insect and placed in boiling KOH solution 10% (w/v) for approximately 2 min. Then, the pygofer was washed and mounted in glycerine on glass slides. Species identification was carried out following Ribaut (1936), Biedermann and Niedringhraus (2009), Dmitriev *et al.* (2022), and Evangelou *et al.* (2023).

RESULTS AND DISCUSSION

Leafhopper species

Two species of GL were identified: *Empoasca solani* (Curtis) and *J. lybica*, with an asynchronous distribution. *E. solani* appears earlier in the spring and the first months of summer, being gradually replaced by *J. lybica*, which reaches its peak by mid-summer and early autumn, as also recorded by Quartau and Rebelo (1992) and Rebelo (1993). This distribution pattern may help reduce competition between the two species.

E. vitis was unexpectedly not identified, especially during the spring season. This may be due of having only two traps, one per grapevine plot. Additionally, the specimens collected in May were only females, making specific identification unfeasible.

Recently, Xu *et al.* (2021) published a phylogeny and reclassification of the complex and diverse tribe Empoascini, which included a subdivision of the genus *Empoasca* Walsh. Other experts in Auchenorrhyncha (Nickel, 2022; Evangelou *et al.*, 2023) have adopted these changes. According to their reclassification, the species found in this study formerly placed in the genus *Empoasca* as *E. solani*, has been renamed. Xu *et al.* (2021) now refer to it as *Hebata* (*Signatasca*) *solani*, and Nickel (2022) as *Hebata* (*Signatasca*) *pteridis* (Dahlbom). Additionally, *J. lybica* has retained its original genus.

Despite the taxonomic changes, which are primarily based on molecular analyses, the genitalic characteristics of the male are sufficient to categorize systematically a Typhlocybinae individual as belonging to *H. solani/pteridis* or *J. lybica* (Evangelou *et al.*, 2023). Moreover, the damage they cause in vineyards is very similar.

Algorithm assessment

The model built had a precision of 79.8%, recall of 90.4%, and consequently an F1=0.85, when evaluated over the test dataset of 87 tiles. A human operator was able to identify 188 GL on these tiles, and the model was able to correctly identify 90.4%, with a confidence level of 30%, failing to detect 9.6%. The erroneous detections were mainly related with other Auchenorrhyncha and small Diptera. The main reasons for keeping the confidence level at 0.30 were: i) to ensure that some already degraded insects were included in the detections, since each trap remained in place for about one month; and simultaneously ii) to keep the number of erroneous detections low. Any change in the confidence level is reflected in the number of detections, as shown in Figure 5.

a b c

Figure 5. Example of the evolution of the number of GL detections in the same image with different confidence thresholds: a) 0.25; b) 0.55; and c) 0.75.

The stability of the algorithm can be seen in the small changes in the number of detections as the confidence threshold increases. An example from one image in the test dataset shows the number of detections as the confidence threshold goes from 0.15 to 0.80 in steps of 0.05 (Figure 6): within the range [0.20, 0.60], the average number of detections is 19.7, with a standard deviation of 1.0.

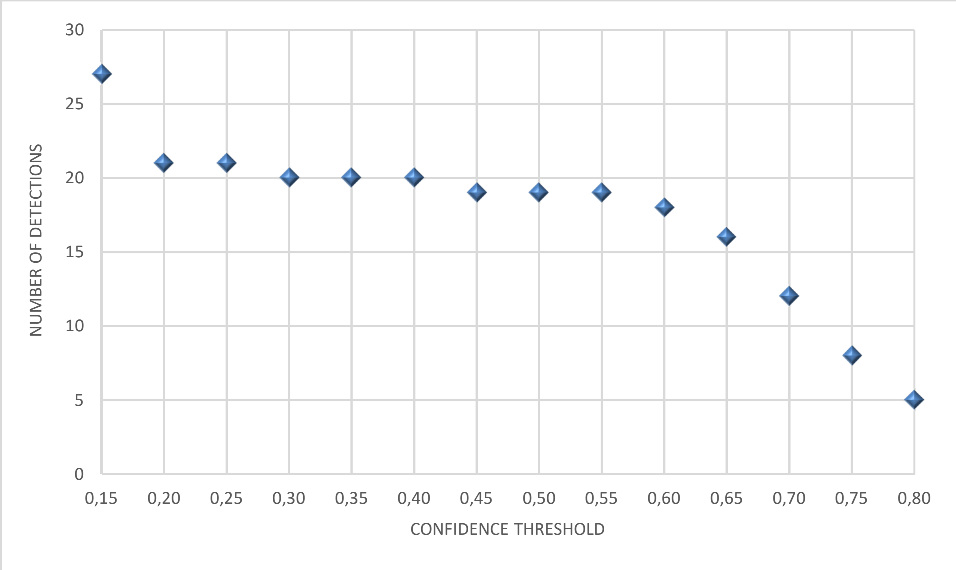


Figure 6. The value for the confidence threshold presents good stability within the range [0.2, 0.6], showing the robustness of the algorithm: in this range, the mean number of detections is 19.7, with standard deviation of 1.0.

The automatic identification of GL based on deep learning models was only recently investigated in vineyards (Gonçalves *et al.,* 2022). However, in this case, mobile devices were used for image acquisition from yellow sticky traps in the field. Gonçalves *et al.* (2022) compared five different deep learning models suitable to run locally on mobile devices, and concluded that the SSD ResNet50 model was the most suitable, presenting a precision, recall, and F1 score of 56%, 73% and 64%, respectively. In the present study, a different image acquisition system was used for the first time, consisted by high-resolution pictures remotely sent via GPRS to a web platform, combined with a deep learning algorithm based on convolutional neural networks. This automatic identification system showed a better performance (accuracy, precision, recall, and F1 score of 80%, 90%, 85%, respectively), in comparison to the best model studied by Gonçalves *et al.* (2022). Nevertheless, it should be considered the two algorithms were developed for different systems of image acquisition, i.e., field image acquisition with mobile devices, in Gonçalves *et al.* (2022), and remote image acquisition by camera-equipped traps, in the present study. Furthermore, the apparently different levels of performance could have been influence by the different number of images used to evaluate the performance of the algorithms in the two studies (a higher number was used by Gonçalves *et al.*, 2022).

The application of this new technology might improve the cost effectiveness of GL monitoring systems for decision making in IPM in vineyards. Nevertheless, it should be further evaluated in different climatic conditions, insect numbers and farm management systems, for a more complete assessment of its cost effectiveness, in comparison to the conventional trap´s monitoring system. According to Preti *et al.* (2021), the use of automatic traps in remote monitoring systems has several benefits compared to the conventional traps : 1) Field visits are only required to empty traps or replace lures, saving time and money; 2) On-site checking of empty traps is unnecessary, further saving resources; 3) Fewer personnel are needed, as one operator can manage a high number of traps spread over a wide area; 4) High sampling frequency allows for detailed temporal resolution, with the potential for multiple pictures per day; 5) Traps can be easily deployed over a large territory, providing high spatial resolution; 6) Accurate records can be maintained even by non-expert operators when combined with reliable automatic identification and counting systems; 7) Increased data flow, potentially including automatic counting and identification, enables real-time alerts and reduces the risk of human bias in information; 8) Although the initial trap cost may be higher, the long-term savings in manpower make it cheaper overall; 9) Enables the creation of real-time or regularly updated online monitoring systems covering large areas, connecting captured data with environmental, biological, and human variables to implement Decision Support Systems (DSS).

However, the automatic traps tested for GL present challenges compared to remote monitoring systems based on automatic pheromone traps. Unlike pheromone traps, these traps (e.g., yellow sticky traps) are non-specific and attract various insect species, including Diptera, Hymenoptera, and Thysanoptera. This lack of specificity can hinder the identification performance of the monitoring system and may require more frequent field trap replacements due to insect saturation of trap surface. Furthermore, the cost effectiveness analysis should also consider different scenarios, including farm size and number of traps needed for reliable estimate of GL population level.

With the imaging system already installed and accessible online, a standard laptop running the algorithm will allow an immediate reaction when the number of detections exceeds a critical threshold previously established for the species.

Application to new species of interest will require a new training stage and a new dedicated model. As yellow sticky traps are not selective, capturing many different insects, they could be also used to simultaneously estimate de abundance and diversity of pest natural enemies in vineyards, and thus evaluate actual situation on the potential for conservation biological control. Future developments on the automatic identification of predators and parasitoids of major grapevine pests would be an important contribution to support a monitoring system with that purpose.

CONCLUSIONS

GL are major vineyard pests in many grape-producing countries, including Portugal. Pest management strategies for a sustainable control of these insects are dependent on efficient DSS. In the present work, an automatic image acquisition system was developed and evaluated, coupled with a deep-learning algorithm based on CNNs, for remote monitoring of GL in vineyards. The results showed that the new algorithm successfully identified GL specimens in images obtained from automatic traps, evidencing a very good performance. This is a significant achievement, providing a technological solution for remote monitoring of GL populations with automatic insect identification, which will contribute to improve the efficiency of pest management decision making in vineyards. The possibility of applying the same approach to the identification and monitoring of biocontrol agents of vineyard pests, using the same yellow sticky traps, simultaneously with GL monitoring, should be considered in future developments of the model.

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