An intelligent system for detecting Mediterranean fruit fly [Medfly; *Ceratitis capitata* (Wiedemann)]

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Abstract

Nowadays, the most critical agriculture-related problem is the harm caused to fruit, vegetable, nut, and flower crops by harmful pests, particularly the Mediterranean fruit fly, *Ceratitis capitata,* named Medfly. Medfly's existence in agricultural fields must be monitored systematically for effective combat against it. Special traps are utilised in the field to catch Medflies which will reveal their presence and applying pesticides at the right time will help reduce their population. A technologically supported automated remote monitoring system should eliminate frequent site visits as a more economical solution. This paper develops a deep learning system that can detect Medfly images on a picture and count their numbers. A particular trap equipped with an integrated camera that can take photos of the sticky band where Medflies are caught daily is utilised. Obtained pictures are then transmitted by an electronic circuit containing a SIM card to the central server where the object detection algorithm runs.

This study employs a faster region-based convolutional neural network (Faster R-CNN) model in identifying trapped Medflies. When Medflies or other insects stick on the trap's sticky band, they spend extraordinary effort trying to release themselves in a panic until they die. Therefore, their shape is badly distorted as their bodies, wings, and legs are buckled. The challenge is that the deep learning system should detect these Medflies of distorted shape with high accuracy. Therefore, it is crucial to utilise pictures containing trapped Medfly images with distorted shapes for training and validation.

In this paper, the success rate in identifying Medflies when other insects are also present is approximately 94%, achieved by the deep learning system training process, owing to the considerable amount of purpose-specific photographic data. This rate may be seen as quite favourable when compared to the success rates provided in the literature.

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The Centre for Invasive Species and Ecosystem Health at the University of Georgia granted written permission to our image usage request number 178344 to freely utilise their 96 Medfly pictures throughout this study (University of Georgia Centre for Invasive Species and Ecosystem Health, 2020); Ismail Uzun from Nokia Corporation in Germany.

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Introduction

One of the most crucial agricultural problems nowadays is the harm caused by harmful pests, particularly the Mediterranean fruit fly, *Ceratitis capitata*, from now on referred to as Medfly. The Medfly can harm more than 260 kinds of cultivated and wild fruits (USDA NASS, 2012). This means Medfly, which exists in most tropical and subtropical areas, threatens virtually all kinds of crops. Moreover, since it can also tolerate cooler climates, it has spread more than any other fruit fly species. All these unfortunate facts grant the Medfly the ability to become one of the world's most economically important fly species (Cohen *et al*., 2007; The University of Arizona, 2021).

To minimise the economic losses caused by Medfly, its population must be taken under control. However, this is not an easy task because Medfly emergence is unpredictable and somewhat dependent on local weather conditions. Female Medflies can lay eggs for a short duration of about five days after their birth (Fruitfly Africa, 2021). They inject up to 20 eggs at a time under the skin of ripening fruits. After several days, larvae emerge and start feeding on the fruit and defecating inside. These activities are more than enough to make the fruits rot.

Moreover, Medfly can give up to 7-8 offspring per year in the Mediterranean region (Sorhocam, 2021a). Without any control mechanism, Medfly could damage up to 100% of a crop (Cohen *et al*., 2007). For these reasons, Medfly's existence in agricultural fields must be monitored. Technological supported systems are critically needed to enable automated remote monitoring. Even though such systems are rarely available today, hundreds of millions of people struggling to survive through small-scale farming cannot afford to buy them. Two typical views of adult Medflies are presented in Figure 1.

The Ministry of Agriculture and Forestry in the Republic of Turkey publicly emphasises the importance of the fight against Medfly and encourages scientists, institutions, and firms to work on more effective and economical technological solutions. Accordingly, authorised Medfly experts who work for the following institutions (Ministry of Agriculture and Forestry, 2019) are contacted throughout this study: i) Ministry of Agriculture and Forestry in the Republic of Turkey (T.C. Tarım ve Orman Bakanlığı); ii) Agricultural Protection Research Institute (Zirai Mücadele Araştırma Enstitüsü), Bornova, İzmir, Turkey; iii) Biological Control Research Institute (Biyolojik Mücadele Araştırma Enstitüsü), Adana, Turkey; iv) Horticultural Research Institute (Bahçe Kültürleri Araştırma Enstitüsü), Alata, Mersin, Turkey.

The following information is obtained from the abovementioned Medfly experts:

> New technological solutions are desperately needed to enable effective combat against harmful pests that cause severe loss to crop and decrease the exportation income of the country. The most important pests are reported to be the Mediterranean fruit fly (*Ceratitis capitata*) on the top, olive fly (*Bactrocera oleae*), and apple butterfly (*Cydia pomonella*), its common name being codling moth. We often get the news that Medfly has negatively affected the international trade of fruits and vegetables. The abovementioned experts urge and encourage the formation of an intelligent system for detecting and monitoring harmful pests, especially Medfly, to effectively fight against them. Such a system would help to optimise insecticide application as well. Ministry experts state that many farmers currently apply pesticides more often than required because of Medflies' fear of harm since they do not have a warning system for pests. Medflies may appear on different dates each year, depending on local weather conditions. Excessive application of pesticides has many drawbacks: more cost, more harm to humans who eat the fruits due to chemical remnants, more harm to nature since insecticides could kill beneficial creatures (like bees, ladybugs, *etc*.) together with harmful ones, and also pollute groundwater (Remboski *et al*., 2018). Thus, the optimisation of pesticides is an extremely critical issue in the fight against Medfly and pests in general.

Special traps similar to the one in Figure 2A are utilised in the field to catch Medflies, monitor their existence, and decrease their population by giving pesticides at the right time.

Integrated pest management aims to control the number of pests to keep the harm caused to crops tolerable. For monitoring the population of pests, the most commonly used technique relies on placing special traps in the field and carrying out frequent visits to the field to observe each trap visually. However, this is a costly and non-efficient way of monitoring since it has to be carried out by human operators (Remboski *et al*., 2018; Hong *et al*., 2020). Thus, a technological solution is needed for automating the following 2 main actions in order to eliminate the need for site visits to check for Medflies caught in the traps: i) detect and count the number of Medflies caught inside the special traps placed in the field and report this number on a daily basis; ii) change or roll the sticky catching tape inside the trap whenever necessary (once per month on average).

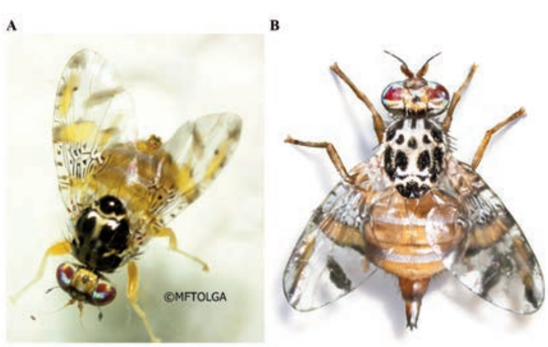

Figure 1. Two typical views of adult Medflies: A) Male Medfly (courtesy of M. F. Tolga); B) female Medfly has ovipositor needle at its back (SEDQ Healthy Crops S.L., 2020).

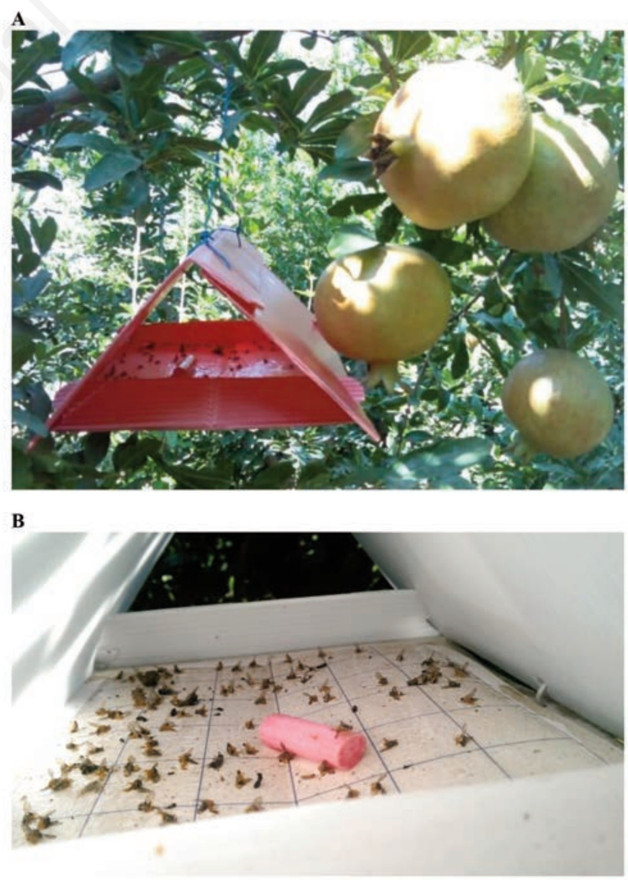

Figure 2. A) View of a Delta trap utilised to attract and catch Medfly (Sorhocam, 2021b); B) sample picture of trapped Medflies used in intelligent system training (picture extracted from a video courtesy of M. F. Tolga).

The intelligent system within this study has been designed to detect trapped Medflies using machine learning approaches. Machine learning explores the study and construction of algorithms that can learn from training data and then can make predictions based on learned data (Kashinathan *et al*., 2020; Espinoza *et al*., 2016; Akbas *et al*., 2019; Xie *et al*., 2018; Patricio and Rieder, 2018). Faster R-CNN has been utilised as an image processing and selecting tool to detect Medflies caught in special traps. CNNs perform much better on images than classic neural networks because they take advantage of the local spatial coherence of images (Ren *et al*., 2016). This means that adjacent pixels are meaningful together. Furthermore, convolution and pooling reduce the size and number of operations needed; this way, considerable speed enhancement is achieved. Faster R-CNN is a deep convolutional network developed by Microsoft that has lately gained wide use in object detection. It appears to the user as an end-to-end unified single network that can quickly and accurately predict various objects' locations. Faster R-CNN operates much faster than traditional algorithms like selective search, *etc*., owing to its ability to generate region proposals through its region proposal network, named shortly RPN (Gad, 2020). RPN has been introduced within the faster R-CNN object detection framework to overcome the run time bottleneck of the previous state-of-art object detection networks (Galdames *et al*., 2018). It can generate region proposals to be inspected by the faster R-CNN detection model. This is the key feature that reduces detection duration (Ren *et al*., 2016). As explained in detail in upcoming sections, favourable results have been achieved in terms of accuracy of detection and the economy of practical application in the field.

Goldshtein *et al*. (2017) state that the drawbacks of the traditional monitoring based on weekly site visits to count trapped medflies manually have resulted in a suboptimal spraying frequency in citrus orchards. This problem on one side and the scarcity of sensors for insect monitoring on the other side motivated them to contribute to the efforts to develop an automatic trap for remote insect monitoring, particularly for Medfly. The authors designed a new cylinder-shaped trap and created optical sensors to detect and count trapped Medflies. From this article, it is understood that scientific work on automatic Medfly monitoring traps is a matter of recent years since they emphasise that they developed the first automatic trap to their knowledge for Medfly monitoring in 2017. Furthermore, they conducted field tests in commercial citrus orchards over five different periods between 2013 and 2015 to determine the accuracy of their system based on optical sensors. They state that their work resulted in an accuracy range between 88% and 100% and concluded that daily monitoring using automatic traps holds promise for reducing insecticide applications.

Hong *et al*. (2020) developed models that detect three species of pest moths in pheromone trap images using deep learning object detection methods to monitor pests' presence and abundance and protect plants. For this purpose, they used a combination of meta-architectures such as faster R-CNN, region-based fully convolutional network, single shot multi-box detector, and feature extractors such as Alexnet, Mobilenet, Inception, and ResNet. The faster R-CNN ResNet 101 detector exhibited the highest accuracy of 90.25% among the seven combinations they used.

Bekker *et al*. (2019) used machine learning to identify the geographical drivers of *Ceratitis capitata* trap catch in an agricultural landscape. Their machine learning-based models produced classification accuracies of up to 80%.

Apolo *et al*. (2020) utilised faster R-CNN in their model they set for fruit detection. Furthermore, they indicate they obtained an average standard error of just 6.59% between visual counting and their model's fruit detection during their study, which can be considered promising.

This study aims to design and develop an intelligent system that detects the existence of Medfly to give timely warnings to farmers, cultivators, and fruit orchard owners. The machine learning system utilised provides the following advantages: i) check the existence of Medfly daily. This way, it provides the opportunity to report its existing occurrences on time (by email, SMS, *etc*.); ii) help effective and timely fighting against MedFly; iii) help optimise pesticide usage, and this way grow more food for less cost, less harm to human beings, and less harm to the beneficial species in nature.

In short, the need for site visits for a complete agricultural yield season is to be eliminated by automating the sticky tape change. The abovementioned ministry experts report that the sticky tape starts losing its stickiness within a month, so it needs to be replaced. Moreover, if many flies are caught, the sticky tape should be replaced for effective monitoring and counting afterwards. Having this information in mind, our intelligent system is designed in such a way to address these issues. The special trap for this purpose contains a sticky band on a rollbar mechanism. This band can be rolled automatically by a command the system gives whenever necessary.

Figure 3. A and B) Medfly labelling and annotation in a picture used for intelligent system training (raw pictures extracted from videos courtesy of M. F. Tolga).

Materials and methods

Acquisition of pictures used for intelligent system training and validation

In our case, 722 pictures were used to train the intelligent system, while 150 others were used as a validation set. Most of these pictures contain multiple Medfly images (the sources of these pictures are mentioned in the *Acknowledgements* and *References* sections). It is important to note that regular Medfly pictures commonly available in the literature did not yield satisfactory results in training the system because the machine learning system is expected to detect trapped and wrapped Medflies in unusual shapes. Note that caught Medflies become buckled up during their struggle to release themselves from the sticky band, so the shape of trapped Medflies is usually distorted. Therefore, it is crucial to train the intelligent system with pictures of trapped Medflies like the ones in Figure 2B to increase the accuracy. All the acquired pictures are used for system training and validation. The critical issue that helped us to achieve qualified training is that many pictures have been extracted from videos related to the fight against Medfly. We acquired these valuable videos from the Internet.

Dataset labelling and annotation

Data labelling is used to identify raw data (images, videos, text, *etc*.) by attaching descriptive labels so that a machine learning model can utilise this information for learning (Amazon Web Services, 2021).

In this work, the free source 'LabelImg' program specialised in image labelling for machine learning has been utilised for labelling Medfly images in our training and validation dataset. LabelImg is a graphical image annotation tool that labels object bounding boxes in images (Github Inc, 2021). Each Medfly image in our pictures is marked manually by the operator by placing a rectangle around it and is annotated as 'Medfly,' as shown in Figure 3, sample cases 1 and 2. Note that only Medfly images are labelled in this study, *i.e*., images that do not represent a Medfly are not labelled because we are only interested in counting the number of Medflies. We are not interested in counting any other species. Most of the pictures used for intelligent system training and validation in this study contain multiple Medfly images.

Sample cases 1 and 2 are two pictures among the dataset used in intelligent system training and validation. Please note that each Medfly image in the dataset pictures has been marked (enclosed in a rectangle) and named 'Medfly.'

Particulars of the deep learning system

Tensorflow software library for machine learning tool is utilised in this study for convenience. Tensorflow is an open-source library for machine learning and deep neural networks research developed by Google Brain Team within Google's Machine Intelligence research organisation. It is flexible and general enough to be used in various applications (Umruh, 2017). For object detection, we used faster R-CNN as an image processing tool. Python has been used together with Tensorflow as the underlying programming language. The architecture of the intelligent system constructed for Medfly detection is given in Figure 4. Note that a blue star has marked each Medfly image in the output picture, and the total number of Medflies detected is printed as an output.

Mean average precision (mAP) is a commonly used accuracy measuring metric in object detection algorithms like faster R-CNN. It is calculated by estimating the area under the curve of the precision-recall relationship (Padilla *et al*., 2020; Hong *et al*., 2020; Jonathan, 2018). Tensorflow object detection API has an integrated feature to determine the mAP of the intelligent system by using the validation data set. This study determined the mAP based on an intersection over the union threshold of 0.5. The output is presented in Figure 5. As stated before, most of the pictures in our training and validation sets contain multiple Medfly images labelled and annotated manually; thus, the 150 pictures we used as a validation set contain several hundred Medfly images in total, which is a sufficient quantity for measuring the accuracy of our intelligent system.

Image pre-processing

This study pre-processed training images by the channel mean subtraction method to improve the system's detection accuracy. The main idea is to make the network less sensitive to differ backgrounds and lighting conditions. First, the per-channel mean is calculated by taking the average of the pixels of all images in the training set. Then, the calculated per-channel mean is subtracted from each image to form the pre-processed new images for train-

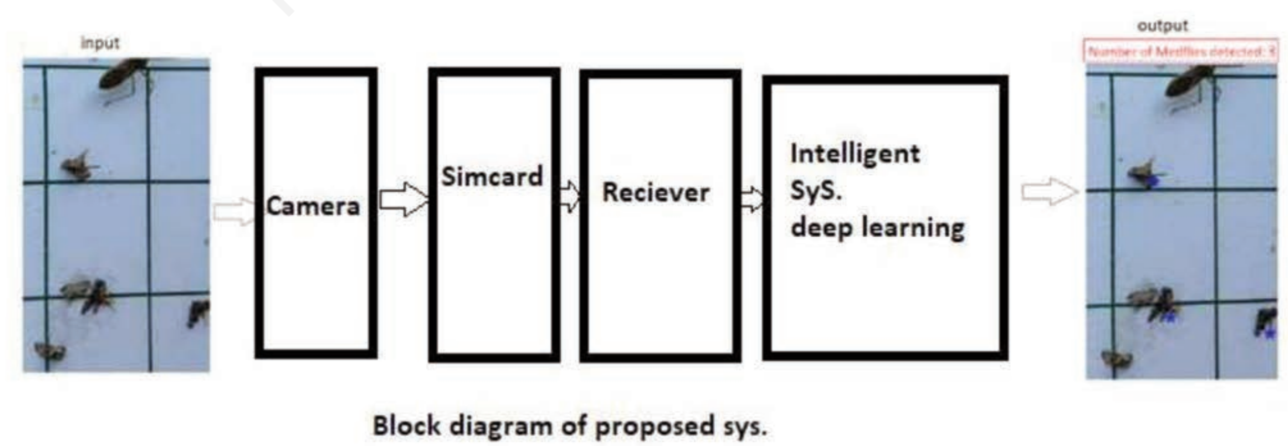

Figure 4. Intelligent system architecture for Medfly detection.

ing the intelligent system. Subtracting the dataset mean from each image aims to ‘centre’ the data around zero mean for each channel (R, G, B). This action decreases the amount of data to be processed and, in this way, enables the network to learn faster. In addition, a ‘mean image’ can be calculated from the training set, which is then subtracted from the training, validation, and testing sets to make the network less sensitive to differ backgrounds and lighting conditions (Stackoverflow, 2016, 2017).

The training process

This study developed an intelligent system that can detect Medflies caught in special traps. When flies or insects stick on the trap’s sticky band, they spend extraordinary effort trying to release themselves in a panic until they die. Therefore, their shape is badly distorted; their body, wings, and legs are wrapped. The challenge here is that the intelligent system needs to be able to detect these Medflies of distorted shape with high accuracy. To achieve that, it is crucial to utilise pictures containing trapped Medfly images that have distorted shapes for intelligent system training and validation. Unfortunately, it is impossible to find such pictures in the literature because everybody who aims to publish them tries to catch Medfly photos of the best look. In other words, no one publishes photos of Medflies with distorted shapes.

For this reason, initial trials of intelligent system training carried out by using pictures that contain Medfly images in suitable shapes did not accommodate the desired high performance in detecting trapped Medflies that have distorted shapes as the accuracy level remained slightly below 80%. Thus, pictures of trapped Medfly images are desperately needed. Even though pictures of trapped and wrapped Medflies are rarely available in the literature, fortunately, we obtained many videos available on the Internet regarding the combat against Medfly in which trapped Medflies are displayed quite often. This opportunity has been taken for granted to extract hundreds of useful Medfly pictures that contain trapped Medfly images with distorted shapes to form training and validation datasets utilised in this study. One of the issues was that many of the trapped Medfly pictures extracted from videos had low resolution simply because the videos were old. Luckily, the outcome proved that there was no need to worry because extremely high accuracy rates have been achieved in detecting trapped Medfly images. The impact of this fact on our e-trap design will be explained further.

722 pictures have been used to train the Intelligent System, while 150 others were used as a validation set. Some of these pictures contain multiple Medfly images, so it can be stated that the intelligent system has been trained with around 2000 different Medfly images. A preliminary training was prolonged up to 100K

Figure 5. A) Determining the minimum loss by training the system 100K steps; B) optimising the intelligent system training process and determining the optimum mean average precision (mAP).

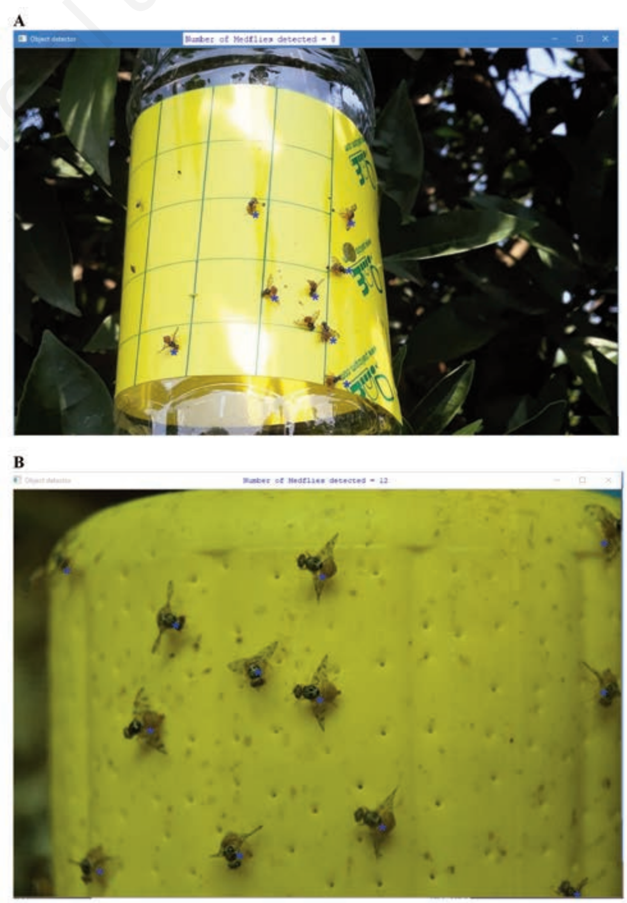

Figure 6. Trapped Medflies detected by the intelligent system, and the count is printed on the top: A) raw picture from Picbear (2020); B) number of Medflies detected.

steps, aiming to determine the optimum number of training steps. As it can be seen in Figure 5A, the optimum number of steps has been determined to be 14.73K steps because the loss starts to increase afterwards. Note that the mAP reaches its optimum value at minimum loss. The meaning of the loss starting to increase after its minimum is that the system does not learn anymore and starts overfitting. Therefore, a new training process of 14.73K steps has been carried out to determine the optimum outcome. At that point, the mAP reaches a value as high as 94.05%, as can be seen in Figure 5B.

Results

Standard Tensorflow object detector output places rectangles around each detected image and places the name of the detected object together with the calculated detection probability. If there are many Medfly images in the input image, it can be challenging to distinguish among the dense rectangles and texts placed in the output. Since pests usually exist in large numbers in nature, this will be the case most of the time. Within this study, the programme's source code has been modified specifically to eliminate this problem. The intelligent system has enabled the system to behave in the following way: when the intelligent system processes a picture containing one or more Medfly images, the object detector places a blue star on each detected Medfly image and prints the total number of detected Medflies in written form. Figures 6-8 show the outputs of different pictures containing multiple images. 722 pictures containing one or multiple Medfly images have been used to train the intelligent system, while 150 others were used as a validation set. As a result of the training, the overall detection accuracy of the intelligent system has been determined to be as high as 94,05%. Surprisingly, the contribution of pre-processing the training images by the channel mean subtraction has been only 1.5%. The reason can be justified as follows:

Applying the channel mean subtraction method could only make such an insignificant improvement because the accuracy without it is already relatively high anyway, making it difficult for any pre-processing method to assure a significant increase in the accuracy. It is worth mentioning the following interesting case among the outcomes of validation set processing. In Figure 8B, the black rectangle is the label placed manually around the existing Medfly image in the picture, while the green rectangles are placed by the intelligent system after testing for validation purposes. Please note that there are 2 green rectangles placed by the intelligent system, the big one around the Medfly and the other small one around the shadow of the Medfly. Surprisingly, the intelligent system proves to be so sensitive that it can even detect the Medfly's

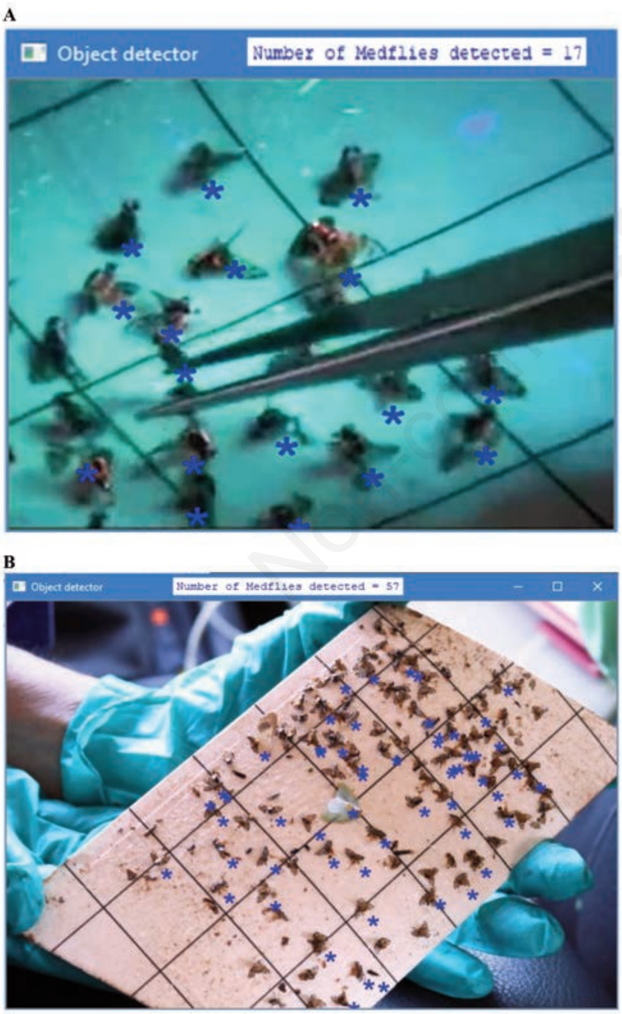

Figure 7. A) Trapped Medflies detected by the intelligent system, and the count is printed on the top: A) raw picture from (ZF, 2010); B) raw picture from (Eliza W., 2017).

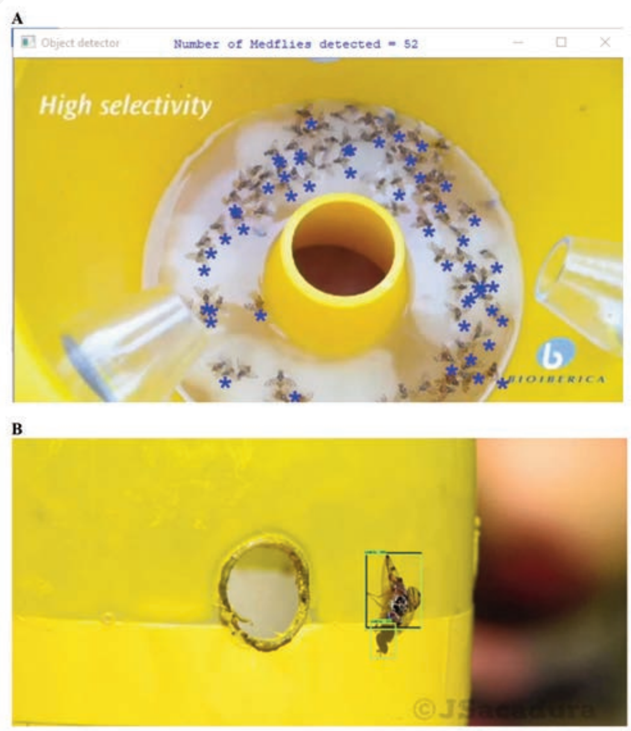

Figure 8. A) Trapped Medflies detected by the intelligent system, and the count is printed on the top (raw picture from Estres vegetal, 2020); B) a surprising result: the intelligent system detects the shadow of a Medfly and gives the count of Medflies in this picture as 2 (raw picture from JSacadura, 2020).

shadow. Moreover, the intelligent system places calculated possibilities as 99% for the Medfly itself and 61% for its shadow.

Discussion and conclusions

In the literature, there are numerous investigations on automatic remote insect monitoring. This is because traditional monitoring involving manned site visits is not economical, has big obstacles in today's conditions and complicates large-scale operations in the field (Ding *et al*., 2016; Li *et al*., 2021; Sun *et al*., 2018). Thus, its elimination has become a prioritised goal for many scientists worldwide. Some scientists utilise sensors for insect monitoring (Goldshtein *et al*., 2017; Moraes *et al*., 2019; Rustia *et al*., 2020). However, the scarcity of such purpose-specific sensors for insect monitoring, in addition to the recent developments in deep learning, has turned the trend towards systems based on deep learning in the last several years (Wenyong *et al*., 2021).

As explained in detail in the *Introduction* section, Goldshtein *et al*. (2017) state that their system based on optical sensors specifically designed for detecting and counting trapped Medflies resulted in an accuracy range between 88% and 100% and concluded that daily monitoring using automatic traps holds promise for reducing insecticide applications.

Hong *et al*. (2020) used deep learning object detection methods to monitor pests and compared the performance of combinations of meta-architectures such as faster R-CNN, region-based fully convolutional network, single shot multi-box detector, together with some feature extractors. They achieved the highest accuracy of 90.25% with a faster R-CNN ResNet 101 detector.

Bekker *et al*. (2019) used machine learning techniques to identify the geographical drivers of *Ceratitis capitata* trap catch in an agricultural landscape and produced up to 80% classification accuracies. Apolo *et al*. (2020) utilised faster R-CNN in their model they set for fruit detection. They indicate they obtained an average standard error of just 6.59% between visual counting and their model's fruit detection during their study.

In this paper, the success rate in identifying Medflies when other insects are also present in the trap is 94.05%. This is achieved by our deep learning system training process, which considers the considerable amount of purpose-specific photographic data. Analysing the above findings, we can conclude that our overall success rate is comparable to those given in the literature.

Now that an intelligent system that can detect trapped Medfly images within a picture and give their count has been made available, it is not difficult to construct a special trap containing a webcam and an electronic circuit containing a SIM card. The webcam is stationed in the top section of the trap, adjusted to view the sticky band. A relatively simple battery is sufficient because the webcam will be activated only once per day for a short period by the electronic control circuit to take a picture of the sticky band in the trap and transfer the picture to the central server over the integrated sim card. Medflies in the pictures must be detected and counted in the central server. The system is to be adjusted to take the picture once daily in daylight; thus, no additional lighting is required. The sticky band within the trap is rarely rolled over (once per month), so this action does not consume too much energy either. For all these reasons, a relatively simple battery is enough for the trap, *i.e*., there is no need for stationing solar panels *etc*. The battery in the trap needs to be charged or replaced once per year.

Another important aspect is the selection of the camera. An essential criterion of design is the selection of inexpensive elements for achieving a low-cost pest monitoring system not only in the construction phase but also later in the operation and maintenance phase. Having a quick look at webcams available in World markets, it is not difficult to see that the cheapest low-end webcams are well enough to take pictures of a resolution as high as 1280×720 pixels. Noting that most of the trapped Medfly pictures extracted from videos related to the subject of combat against Medfly to be used in intelligent system training and validation in this study have lower resolutions than that of a lower-end webcam, presumably because these videos are old. This is very good news because the intelligent system can detect Medflies with such high accuracy by trained, validated, and tested by images of lower resolution than today's low-end webcam resolution rates. Therefore, owing to the surprisingly high sensitivity of our intelligent system, it can be concluded that a cheap low-end webcam is well suited to be selected to be used in our equipped trap design.

The intelligent system developed in this study, together with the integrated special e-trap whose particulars are explained in detail, could open a new horizon in the fight not only against Medfly but also against all kinds of flies owing to the following advantages: i) *wide usage capability* - even though the intelligent system has been trained to detect Medfly, it can be trained to detect any desired flies as it is flexible to be configured and trained to detect multiple flies simultaneously; ii) *economic aspect* - it is important to note that very few fully automated intelligent pest monitoring systems are commercially available in the world today. Many villagers and those who do small-scale farming cannot afford to buy them because they are known to be still quite expensive. Extraordinary economic advantages can be provided to cultivators, farmers, and fruit orchard owners if this system is used commercially. This would constitute a life-preserving effect on millions of poor villagers in the world who are trying to survive by doing small-scale farming and thus cannot afford to buy commercially available intelligent pest monitoring systems.

In this model, the farmer or end-user does not have to purchase the server side where the intelligent system runs. It is enough to buy the equipped trap only. An intelligent system can serve end users within a central server maintained by the company or institution to sell the traps.

Lastly, as a further future study, the intelligent system described here can be configured and trained to detect multiple pests simultaneously.

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