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Scorpion Detection and Classification Systems Based on Computer Vision as a Prevention Tool

Francisco Luis Giambelluca, Grupo de Control Aplicado (GCA), Instituto LEICI (CONICET-UNLP), Argentina

Jorge Rafael Osio, Grupo de Control Aplicado (GCA), Instituto LEICI (CONICET-UNLP), Argentina & TICAPPS, Universidad Nacional Arturo Jauretche, Argentina

Luis Giambelluca, CEPAVE (CONICET-UNLP-CCT), CICBA, Argentina

Marcelo Cappelletti, Grupo de Control Aplicado (GCA), Instituto LEICI (CONICET-UNLP), Argentina & TICAPPS, Universidad Nacional Arturo Jauretche, Argentina*

ABSTRACT

In this paper, automatic and real-time systems were developed to detect and classify two different genera of scorpions using computer vision and deep learning techniques, with the purpose of providing a prevention tool. The images of scorpions were obtained from an arachnology laboratory in Argentina. YOLO (you only look once) and MobileNet models were implemented. The data augmentation technique was applied to significantly increase the amount of training data. High accuracy and recall values have been achieved for both models, which guarantees that they can early and successfully detect scorpions. In addition, the MobileNet model has shown to have excellent performance to detect scorpions within an uncontrolled environment, to carry out multiple detections, and to recognize their danger in case of accidents. Finally, a comparison has been made with other different machine learning-based models used to identify scorpions.

KEYWORDS

Augmentation, Automatic System, Classification, Confusion Matrix, Deep Learning, Detection, MobileNet, Prevention Tool, Real-Time System, Scorpions, YOLO

1. INTRODUCTION

Scorpions are invertebrates of the phylum Arthropoda and class Arachnida, which also includes spiders, opilions, mites, solifuge, pseudoscorpions among others. All species of scorpions have the ability to inoculate venom with the tail stinger, and some of them even with the possibility of killing a human. For this reason, due to the high dangerousness, scorpions have been studied for a long time and is still a major subject of interest for health care (Abushama 1964; Ahmadi et al. 2020; Gaffin et al. 2012; Gopalakrishnakone et al. 2015; Kladt et al. 2007; Petricevich 2010).

Scorpions are nocturnal animals with negative phototropism. They can be found sheltered during the day, in natural environments, under rocks or inside holes, although some species can also be domiciliary, which remain hidden in the daytime and roam at night. Usually, the scorpion bites happen accidentally, which is due to the ignorance of the presence of these arachnids.

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*Corresponding Author

These arachnids inhabit all continents except Antarctica, living in a wide variety of environments, preferably in warm areas. Some of the dangerous species worldwide belong to the Buthidae family, which with 95 genera and 1259 species, it is the largest of the scorpion families (Rein 2021). This family is widespread around the world and many of their genera are dangerous for humans. In South America the genus Tityus has some species that can cause death (Borges 2013; Kaltsas et al. 2008; Mullen and Sissom 2018).

Argentina has about 60 species of scorpions belonging to two families, the Bothriuridae with the largest number of genera (*Bothriurus*, *Timogenes*, *Brachistosternus*, *Orobothriurus*, *Vachonia*, *Phoniocercus* and *Mauryius*), and the Buthidae family with three genera (*Tityus*, *Zabius* and *Ananteris*) (de Roodt et al. 2019; Ojanguren Affilastro 2005). Only one genus (*Tityus*) is considered of sanitary importance, since they cause accidents every year, and some can be fatal, especially in children and elderly. This genus has several highly dangerous species, such as *Tityus confluence*, *Tityus serrulatus*¸ *Tityus bahiensis* and *Tityus carrilloi* (known until now as *Tityus trivittatus*) (Affilastro et al. 2021). Other species of this genus can cause great pain with their bites, although they do not register fatal accidents.

Specifically, two species of *Tityus* (*Tityus confluence* and *Tityus carrilloi*) and one species of *Bothriurus* (*Bothriurus bonariensis*) coexist in La Plata city (Argentina) (L. A. Giambelluca et al. 2021). The two species of *Tityus* are of sanitary importance whereas *Bothriurus bonariensis* is not dangerous for humans. These different species of scorpions can not only increase their population but can also conquer new areas. In recent years, the number of consultations made at the CEPAVE Arachnology Laboratory (CONICET-UNLP- Assoc. CICPBA) in La Plata city have increased substantially, which is due to the increase in the appearance of scorpions in different areas of this city. The query species are mainly *Bothriurus bonariensis* and *Tityus carrilloi* (L. Giambelluca et al. 2018).

Figure 1 shows pictures of two species of scorpions: *Tityus* and *Bothriurus.* Although both arachnids have many similarities, they also have some differences, especially concerning their morphology, in the shape of their tails and pedipalp. The difference in dangerousness between these species makes it necessary to identify them correctly, in order to avoid determination errors in case of accidents, and thus proceed according to the dangerousness of the scorpion. In the event that a person has been bitten by a species dangerous to humans, early, fast and accurate detection and identification of the different types of scorpions, by people unrelated to the subject, can help save lives.

The oldest methods of scorpion detection include rock rolling, burrowing detection, peeling loose back of tree and pitfall trap, which are dangerous, time consuming and invasive (Hadley and Williams 1968; Shehab et al. 2011). Other methods of detection use different biological characteristics of scorpions such as vibration signals or the fluorescent property of scorpions (Aibinu et al. 2014; Gaffin et al. 2012).

Figure 1. Pictures of Tityus (left) and Bothriurus (right)

In recent years, artificial intelligence (AI) techniques, such as machine learning (ML), deep learning (DL) and computer vision (CV), are becoming useful as alternative approaches to conventional techniques. They have been used to solve complex problems in different areas such as: medicine, security, tourism, finance, robotics, soil analysis, climate analysis, among others. In particular, ML uses different algorithms capable of learning from input data (training stage) to improve, describe data and predict outcomes (Alpaydin 2016; Jordan and Mitchell 2015). DL is a subset of ML, inspired by the biological behavior of the human brain, that uses neural network architectures with several layers to know the relationship between the input characteristics (Chollet 2018; Goodfellow et al. 2016). On the other hand, computer vision is a set of computer techniques developed in order to interpret and process digital images, and to imitate (and even improve) the human vision system (Davies 2017). Aiming to improve their performance, deep learning techniques have begun to be used in the field of computer vision, for example, to detect, recognize and classify objects (Cui et al. 2020; Dairi et al. 2018; Ghosh et al. 2020; Y. Sun et al. 2017; Wu et al. 2020), to face recognition (Tripathi 2017), to analyze textures (Andrearczyk and Whelan 2016), to arm fracture detection (Guan et al. 2020), and to study prostate cancer (Li et al. 2014), among other applications. Specifically, regarding the detection and classification of scorpions, a previous work has recently shown the comparison between three different models based on ML algorithms, which are used to discriminate between two genera of scorpions (F. L. Giambelluca et al. 2020). They are the local binary-pattern histogram (LBPH) algorithm and deep neural networks with transfer learning (DNN with TL) and data augmentation (DNN with TL and DA) approaches. In the last two cases, a pre-trained VGG-16 model was used.

In order to improve the results obtained with these models, in this work, the development of two systems of automatic detection and classification of scorpions in real time using different deep learning models is presented. On the one hand, object detection was implemented with two models, based on the shape features of the scorpions, which were compared with each other. Both models, known as YOLO (You Only Look Once (Redmon et al. 2016)) and MobileNet (Howard et al. 2017) with TensorFlow platform, are based on deep convolutional neural networks (Zhou 2020) for real-time object detection. On the other hand, the MobileNet model with TensorFlow was also used for image classification in order to identify between two genera of scorpions, such as *Tityus* and *Bothriurus*. In particular, we have used the fourth version of YOLO (*YOLOv4*) for object detection (Bochkovskiy et al. 2020), and the second version of MobileNet (*MobileNetV2*) (Sandler et al. 2018) for object detection and image classification systems.

The contributions in this paper are:

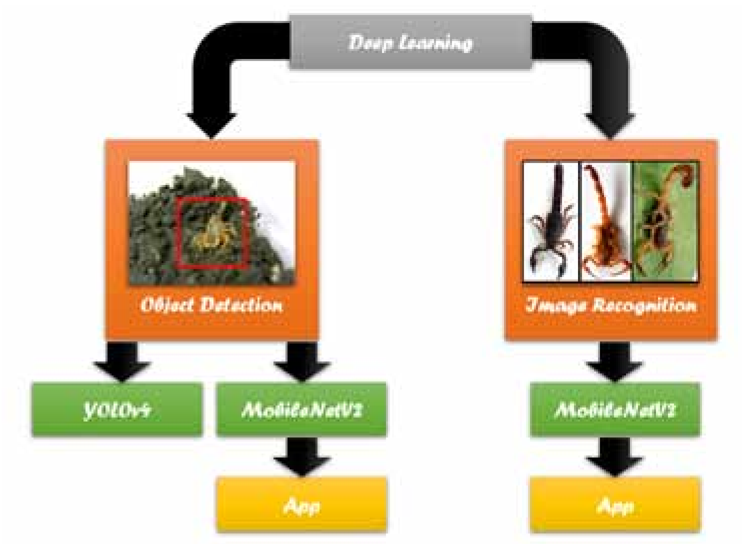
- Fully automatic systems were developed to warn and alert in real-time about the potential presence and danger of scorpions found in La Plata city (Argentina).
- Scorpions are early, quickly and accurately detected and classified in a non-invasive and safe way, by using deep learning methods. Two techniques, YOLOv4 and MobileNetV2, are compared using different criteria.
- The systems developed have an excellent responsiveness to detect scorpions within an uncontrolled environment, to carry out multiple detections and to identify between dangerous and non-dangerous scorpions.
- Both systems were implemented as a mobile application, with the advantage of the portability and readily available to the population, which can be used as a effective prevention tool to minimize scorpion stings and to help reduce the harm they can cause to populations exposed to these arachnids, especially the most vulnerable sectors to the venom of a scorpion, such as hypertensive, cardiac or diabetic people, but also children and the elderly.

The remainder of this paper is organized as follows: Section 2 introduces the proposed object detection and image classification systems in detail. In Section 3, the results obtained are presented and discussed. Finally, Section 4 presents the conclusions of this study.

2. PROPOSED APPROACH

Figure 2 shows a flowchart of the proposed methodology in this paper, which involves the development of two systems, for the detection and recognition of scorpions. Two deep learning tools, such as Yolov4 and MobilenNetv2, have been used in the study. Also, using the built-in tools, both systems were implemented as a mobile application (App), which was developed from the Tensorflow repository.

Figure 2. Schematic flowchart of the systems studied in this work



We have selected the YOLOV4 and MobileNetV2 models, as they have shown great performance in terms of accuracy and real-time processing speed (Kurdthongmee 2020; Redmon and Farhadi 2017). In future, we will try to implement other alternatives with possible better performance, such as Inception, ResNet, R-FCN, among others (Jung et al. 2017; Singh et al. 2018; Szegedy et al. 2016).

The analysis has been carried out using a primary dataset obtained from the database belonging to the CEPAVE Arachnology Laboratory. A selection of the best images was made. Also, the authors have added new images, which were obtained by photographing all the specimens of the scorpion collection of the aforementioned Laboratory.

In the object detection systems, a total of 612 images of scorpions (positive images) of very good quality and sharpness were considered. To reduce the false positive rate, that is, detection in the absence of the target, 197 images without scorpions (negative images) were added. Additionally, Roboflow (Alexandrova et al. 2015) was used to increase the dataset size, reaching a total of 1937 images, which were randomly assigned to training, validation, and test datasets in a 70:20:10 ratio, respectively. Since the training process involves the training and validation stages, there is a 77:23 relationship, which is very close to the "Pareto principle" of 80:20 rule (Sanders 1987).

The dataset for the training purpose was exported using the TFRecord format, and a link was generated to be able to use it directly from Google Colaboratory. The data augmentation technique was applied to significantly increase the amount of training data in order to prevent overfitting and enhance the generalization ability of the model (Goodfellow et al. 2016; Han et al. 2018; Liu et al. 2018). In this paper, image-transformation operations, such as flip (horizontal and vertical), rotation by ± 45 and ± 90 degrees, tilt (± 45 degrees), $\pm 48\%$ saturation, $\pm 25\%$ exposure, blur (1.75pX) and noise (5%) have been used.

In order to validate and better understand the scope of the trained models, confusion matrix were implemented to classify the results and evaluate the performance of these models from the following four metrics: accuracy (A), precision (P), recall (R), and $F_{measure}$ (F1). Equations (1), (2), (3) and (4) are used to calculate these metrics (Arisholm et al. 2010; Sucithra B. and Gladston 2020):

$$A = \frac{\left(TP + TN\right)}{\left(TP + TN + FP + FN\right)} \tag{1}$$

$$P = \frac{TP}{\left(TP + FP\right)} \tag{2}$$

$$R = \frac{TP}{\left(TP + FN\right)} \tag{3}$$

$$F_{measure} = 2.\frac{P.R}{\left(P + R\right)} \tag{4}$$

where TP, TN, FP and FN denote true positives, true negatives, false positives and false negatives, respectively.

In both object detection systems, the presence of the scorpion in the image was considered as a true positive case (TP). Then, the worst situation occurs when the system fails to detect the scorpion, which can put the health of vulnerable people in danger. That is, in the case of absence of detection when the effective presence of a scorpion was omitted (case of false negative (FN)). Therefore, since R increases when FN decreases, recall is the metric of greatest interest in the developed detection systems.

The receiver operating characteristic (ROC) curve (Vuk and Curk 2006) was also used to examine the behavior of the binary model when the detection threshold is changed. Only the TPs and FPs are necessary to graph the ROC curve, in which the TP rate (sensitivity) is plotted against the FP rate (1-specificity). Every point in a ROC space corresponds to a given instance of the confusion matrix and represents a relative trade-off between TP and FP. The higher the values of TP with respect to FP, the better the trained model will be. The optimal model corresponds to the point located in the upper left corner of the ROC space, with coordinates (0,1). which represents 100% sensitivity (no false negatives) and 100% specificity (no false positives).

On the other hand, the image classification system was implemented using the MobileNetV2 model from the web environment "teachable machine" (Carney et al. 2020) provided by Google. The dataset was divided by genus in three categories: *Tityus* with 105 images, *Bothriurus* with 113 images, and "None" (for the absence of a scorpion) with 60 images. Roboflow was used to increase the dataset, reaching a total of 315, 339, and 180 images, respectively, for each category.

For both object detection and image classification systems, applications for smartphones were developed. Today, these devices have the necessary computing capacity for such activities, with the advantage of the portability of the systems. These applications can be used for help tool for emergency services, biological research, and civil use, among others. Both smartphone applications developed in this paper were implemented in the TensorFlow Lite model, which was obtained by making the corresponding transformations to the trained models. Also, the developed systems in this work are easily scalable to other genera and species of scorpions to extend the region where these applications can be used.

3. RESULTS AND DISCUSSION

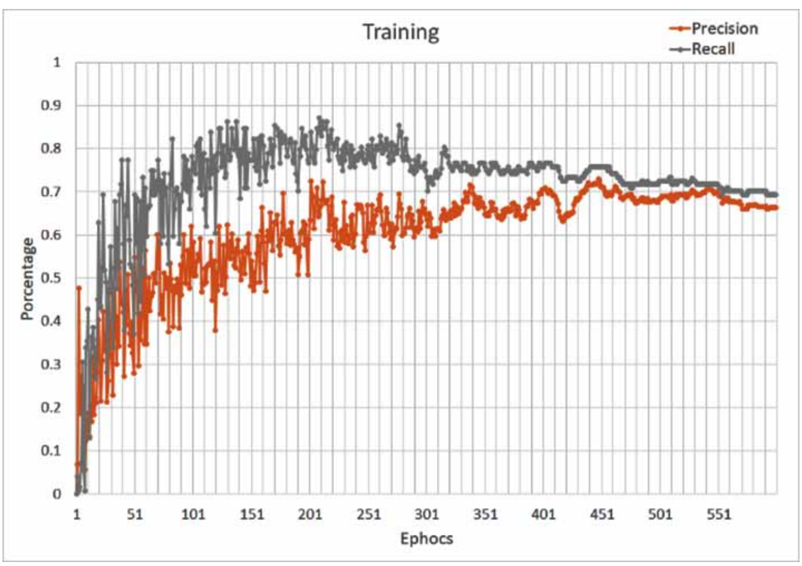
3.1. Object Detection

The performance of both object detection systems developed in this work, using the YOLOv4 and MobileNetV2 models, were evaluated and compared in terms of the evaluation metrics and computational complexity. The models were evaluated from 81 images of the dataset, which were not used in the previous training processes. These images were randomly selected through the Roboflow.

In YOLOv4 detection system, the "Scaled-YOLOv4" (Wang et al. 2020) was used for the training and testing phases, which provides the necessary tools. The images used for the training process have a size of 416x416 pixels, the batch size was set to 16, and the network was trained for 600 epochs. The calculations were run in the free access web development environment "Google Colaboratory". A Tesla T4 GPU with 15GB allocated memory was used. The processing time for training was close to 8 hours. Compared to other similar systems, this system is increasingly used for its high speed and efficiency.

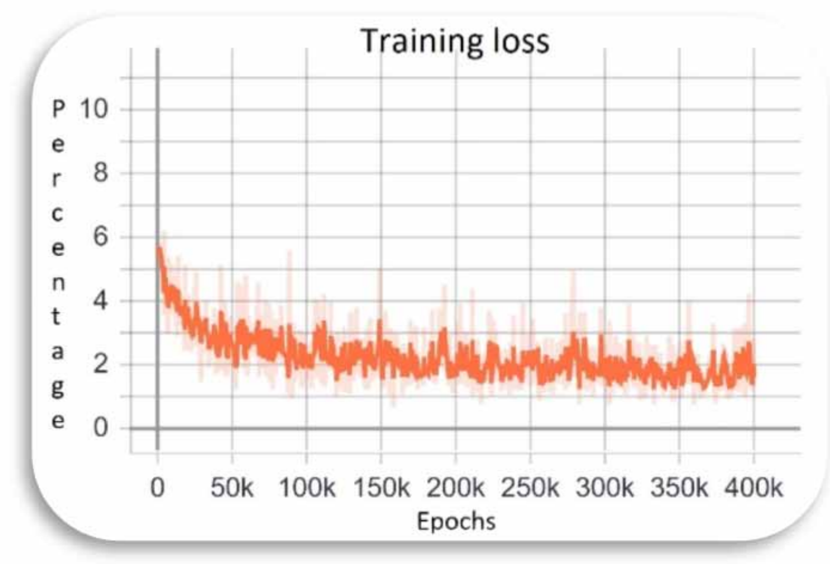
The evolution of the precision and recall metrics during training can be observed in Figure 3. Both metrics are saturated at a value close to 70%, which ensures a complete training with the dataset used, and without overtraining. It can also be seen that recall is always above precision, which is ideal for our system that demands a low rate of FN.

Figure 3. Precision and recall as a function of epochs for the YOLOv4 model



On the other hand, the TensorFlow Lite model was used in MobileNetV2, in order to run this detection system on a smartphone. Also, the transfer learning technique (G. Sun et al. 2018) was adopted for the training phase, in which the MobileNetV2 pre-trained model was used with a batch size of 12, 100 steps per epoch and a total of 400000 epochs. The processing time for training was close to four days. The training loss as a function of the number of epochs is shown in Figure 4.

Figure 4. Training loss as a function of epochs for the MobileNetV2 model



Scorpion detections using the YOLOv4 (left picture) and the MobileNetV2 (right picture) models are shown in Figure 5. A high accuracy in the detection of the scorpion (99.93%) can be seen for the MobileNetV2 model.

Figure 5. Scorpion detections with YOLOv4 (left) and with MobileNetV2 (right) models

The confusion matrices obtained during the testing for the YOLOv4 and MobileNetV2 models are shown in Figure 6 and Figure 7, respectively, where the vertical axes correspond to the true data and the horizontal axes correspond to the predictions of the models.

Table 1 shows the values of accuracy, precision, recall and $F_{measure}$ calculated using equations (1)–(4), respectively, for both models considered in this study. These results show that both object

Figure 6. YOLOv4 confusion matrix

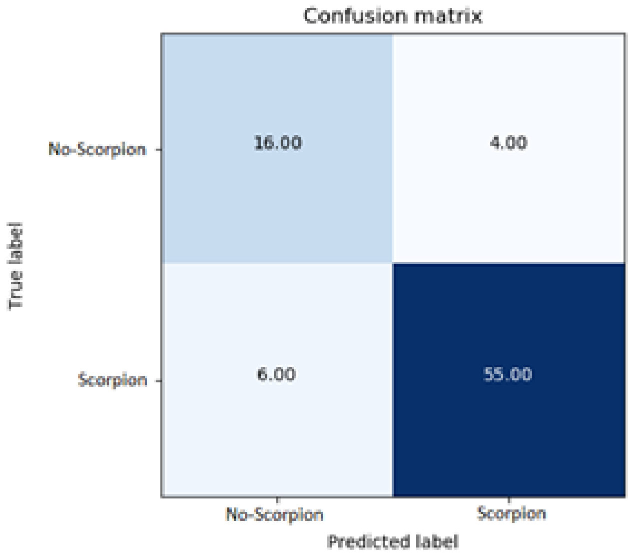


Figure 7. MobileNetV2 confusion matrix

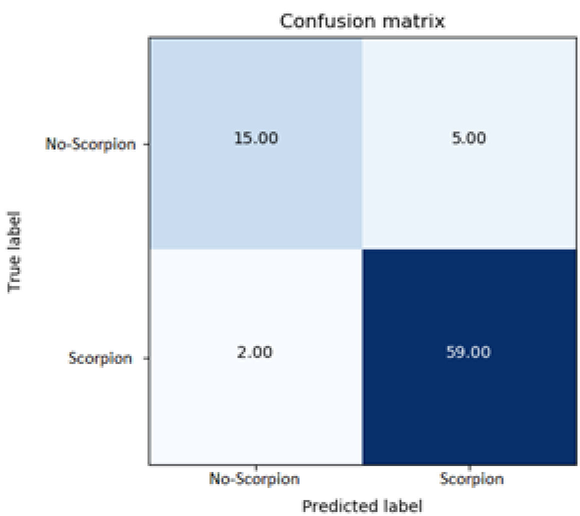


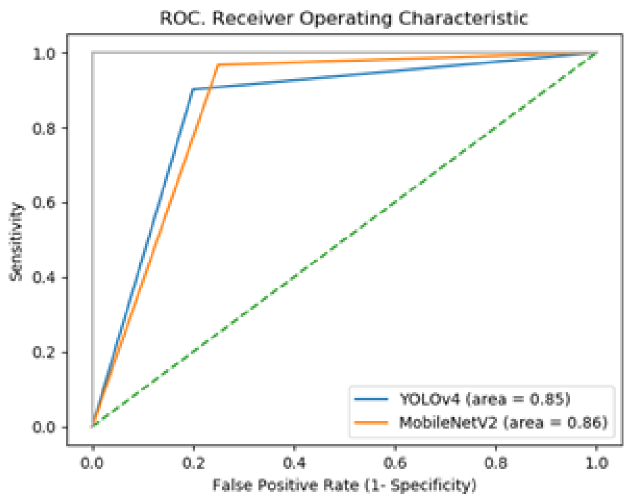
Table 1. Metrics for the two detection models under study

Method	Accuracy (A)	Precision (P)	Recall (R)	$F_{measure}$
YOLOv4	0.88	0.93	0.90	0.92
MobileNetV2	0.91	0.92	0.97	0.94

detection systems are able to successfully detect scorpions. Furthermore, the high values of recall obtained indicate that there are very low values of false negatives, which is essential as prevention tool. In particular, the recall of the MobileNetV2 model (0.97) is greater than that obtained by the YOLOv4 model (0.90), which implies that the MobileNetV2 model performs better as scorpion detection system.

The ROC curves for both detection systems are shown in Figure 8. It can be seen in this figure that the areas under the ROC curves for the YOLOv4 and MobileNetV2 models are very similar, with area of 85% and 86%, respectively, which implies a very good sensitivity and specificity relationship.

Figure 8. Comparative ROC curves for the two detection models under study



From the results obtained, it has been found that the MobileNetV2 method has better performance than YOLOv4 method for the detection of scorpions. Although the MobileNetV2 method requires a greater number of epochs and a longer training time, the comparison between both methods is valid, because both systems were trained until their saturation without overtraining.

The MobileNetV2 method has also demonstrated an excellent ability to correctly detect scorpions within an uncontrolled environment, that is, under changing lighting conditions with multiple positions not present in the original dataset, and with various objects that make detection difficult, as shown in Figure 9. It can be seen in this figure that despite the presence of the wires, and of darker and brighter areas, this system detects the scorpion correctly, and does not erroneously detect another object.

Additionally, the MobileNetV2 method also has an excellent responsiveness to carry out multiple detections continuously without problems, as shown in Figure 10. In this image, it can be observed the presence of three scorpions of two different genera, which were all properly detected as expected.

Finally, this system was used to detect pseudoscorpions, also known as false scorpions, which are arachnids with the general appearance of scorpions except that they have no tails. Figure 11 shows that the MobileNetV2 method mistakenly detects the pseudoscorpion as a scorpion, with 90% certainty. However, this error is more than acceptable and understandable because the trained model has never seen pseudoscorpions before.

Figure 9. Scorpion detection using MobileNetV2 method within an uncontrolled environment

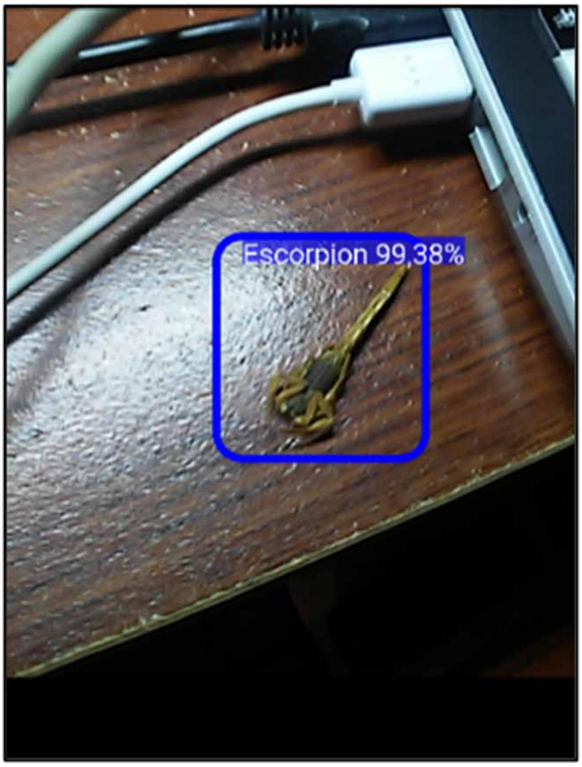


Figure 10. Detection of three scorpions using MobileNetV2 method

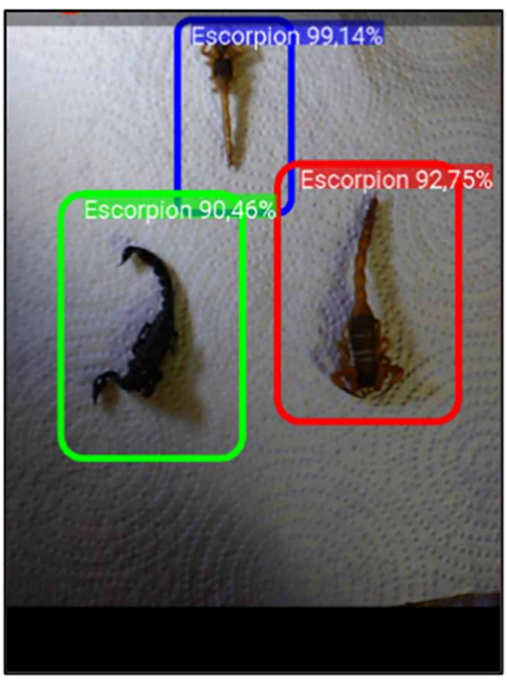


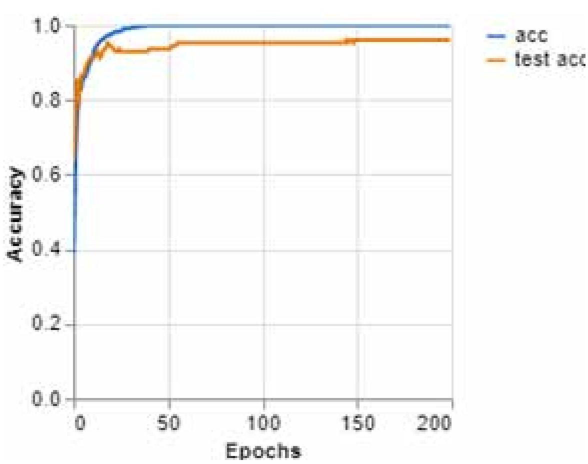
Figure 11. Pseudo-scorpion detection as real scorpion using MobileNetV2 method

3.2. Image Classification

The image classification system was developed in order to distinguish between scorpions of dangerous and non-dangerous species for people. Specifically, this system consists of a classifier that discriminates between three classes: dangerous scorpion (*Tityus*), non-dangerous scorpion (*Bothriurus*), and the absence of both (an environment without the close presence of scorpions).

Teachable Machine was used for the training stage, which is based on the MobileNetV2 pre-trained model. The training consisted of 200 epochs, with a batch size of 512, and a learning rate of 0.001. This learning rate value is very close to 1.66×10^{-3}, which was found as the optimal learning rate of the MobileNet-V2 model (Ziouzios et al. 2020). Values too large can cause divergence in training process, whereas a too small learning rate can cause overfitting. The training and test accuracy is presented in Figure 12. During this training, the expected improvement in accuracy was achieved, with a strong correlation between the training and its validation. It can also be seen that both curves are saturated at a value higher than 90%, so our system is not undertrained or overtrained.

Figure 12. Training and test accuracy of the image classification system



Regarding the loss function, Figure 13 shows the expected decrease during training, reaching values close to 0% and 20% for the training and validation phases, respectively.

As can be seen in Figure 12 and Figure 13, the training was achieved with acceptable accuracy and loss in order to obtain an appropriate image classification. The behavior of this system was evaluated from 126 images (15% of the dataset), which were not used in the previous training processes.

As has been previously mentioned, this image classification system is a classifier that discriminates between three classes: dangerous scorpion (*Tityus*), non-dangerous scorpion (*Bothriurus*), and the absence of both. Figure 14 shows the confusion matrix of 3x3 obtained during the testing, where it is possible to observe the low rate of error that is obtained in the classification process. Table 2 shows the values of accuracy, precision, recall and $F_{measure}$. These results show that our model is able to successfully discriminate between the three classes. Since the main interest of the developed classification system is to provide a prevention tool, it is essential to guarantee the correct classification of the genus *Tityus* due to its dangerousness. This condition is satisfactorily fulfilled by the proposed system.

Figure 13. Training and test loss of the image classification system

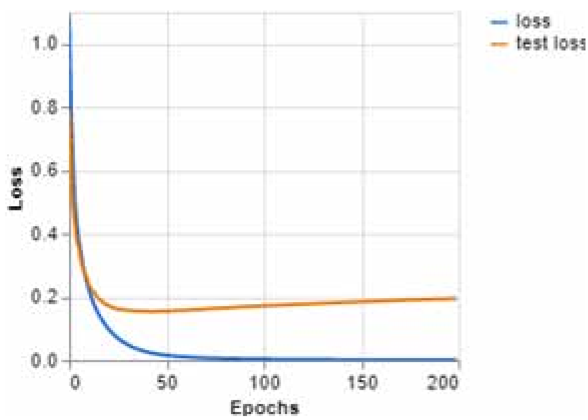


Figure 14. Confusion matrix of the image classification system

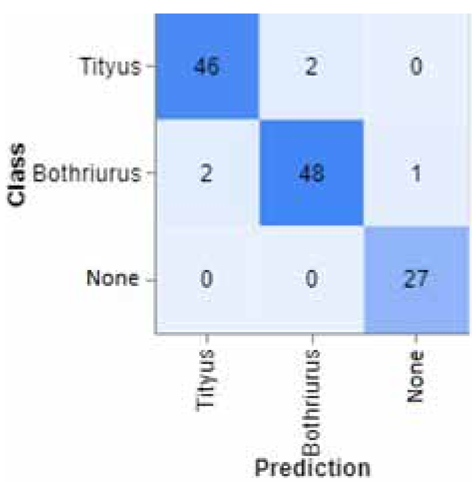


Table 2. Metrics for the three classes considered in the image classification system

Class	**Accuracy** (*A*)	**Precision** (*P*)	**Recall** (*R*)	$\mathbf{F}_{measure}$
Tityus	0.97	0.96	0.96	0.96
Bothriurus	0.96	0.96	0.94	0.95
None	0.99	1.00	0.96	0.98

The ROC curve is shown in Figure 15, which indicates the very good performance of this classification system.

Considering only the images corresponding to the two genera of scorpions (*Bothriurus* and *Tityus*), it is possible to compare our results with those presented in Giambelluca 2020 for three different machine learning approaches (F. L. Giambelluca et al. 2020). Table 3 summarizes the results of the four metrics considered in this paper. These results show that the MobileNetV2 method is clearly more efficient than the others to discriminate between dangerous scorpion (*Tityus*) and non-dangerous scorpion (*Bothriurus*).

Figure 16 shows the correct recognition and classification of non-dangerous (*Bothriurus*) and dangerous (*Tityus*) genera of scorpions, using the MobileNetV2 model. For example, in the right picture, this system reports that the displayed object is classified as a dangerous scorpion ("peligroso" in Spanish). Therefore, a functional system was developed to warn and alert in real-time about the potential presence and danger of the scorpions.

Figure 15. ROC curve of the image classification system

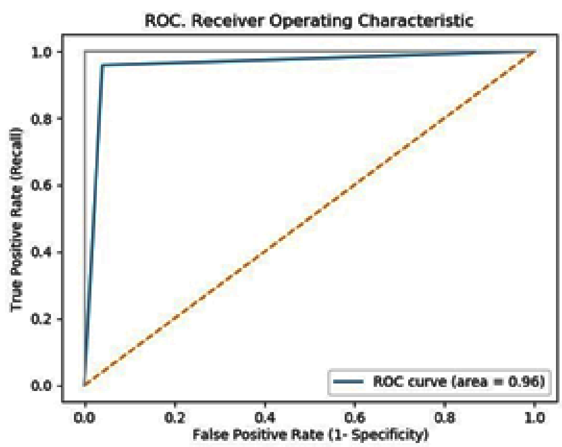
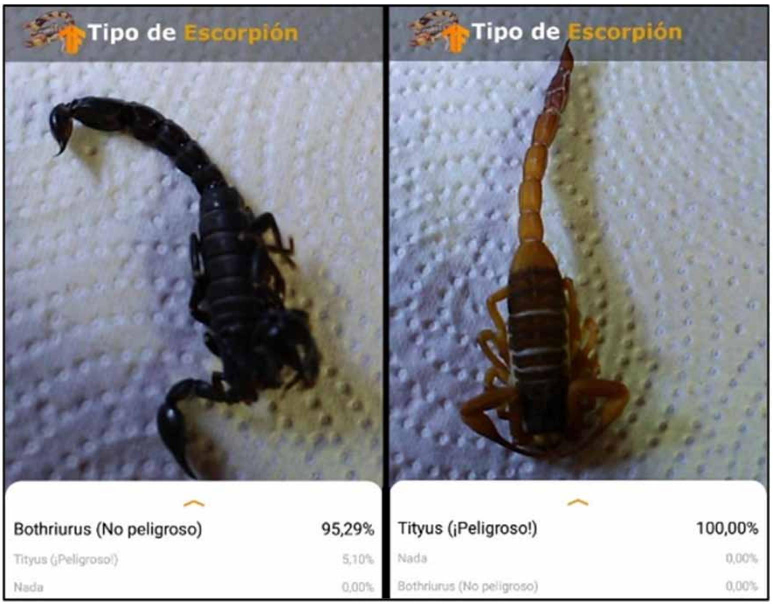


Table 3. Comparison of metrics between different machine learning approaches

Method	**Accuracy** (*A*)	**Precision** (*P*)	**Recall** (*R*)	$\mathbf{F}_{measure}$
LBPH	0.65	0.78	0.63	0.70
DNN with TL	0.78	0.77	0.93	0.84
DNN with TL and DA	0.78	0.79	0.89	0.84
MobileNetV2	0.96	0.96	0.96	0.96

Figure 16. Example of the correct classification of the two genera of scorpions: Bothriurus (left image) and Tityus (right image)



4. CONCLUSION

Automatic and real-time systems capable of detecting and identifying scorpions were proposed in this work, using computer vision and deep learning techniques. YOLOv4 and MobileNetV2 models were used and compared for object detection process, which provide high accuracy values of 88% and 91%, and high recall values of 90% and 97%, respectively. Although both object detection methods can successfully detect scorpions, the performance of the MobileNetV2 method was better than that of the YOLOv4 method. Additionally, the MobileNetV2 method also has an excellent responsiveness to detect scorpions within an uncontrolled environment, to carry out multiple detections and to identify between dangerous and non-dangerous scorpions.

Both systems were implemented as a mobile application, with the advantage of the portability and readily available to the population, which can be used as a effective prevention tool to minimize scorpion stings and to help reduce the harm they can cause to populations exposed to these arachnids, especially the most vulnerable sectors to the venom of a scorpion, such as hypertensive, cardiac or diabetic people, but also children and the elderly.

We have used well-known models to solve the proposed problem, achieving good results. These models have never been previously used for the detection and classification of scorpions. The next step of this research is to implement other alternatives with possible better performance, such as Inception, ResNet, R-FCN, among others.

The systems presented in this work were originally designed to provide a solution to a local problem in La Plata city (Argentina), such as the continuous increase in the appearance of scorpions in different areas of this city, more precisely, of the three scorpion species chosen for the study (*Tityus confluence*, *Tityus carrilloi* and *Bothriurus bonariensis*). In future, we will try to incorporate more genera and species of scorpions to extend the region where these systems can be used.

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Francisco L. Giambelluca was born in La Plata, Buenos Aires, Argentina in 1994. He received the Electronic Engineer degree in 2018 from the National University of La Plata (UNLP), Argentina. He is currently a PhD Student at the Group of Control Applications (GCA) of the Institute of Research in Electronics, Control and Signal Processing at the Faculty of Engineering, UNLP and the National Research Council (CONICET), Argentina. His main research focuses on the detection and classification of scorpions using different techniques of machine learning and computer vision.

Jorge Osio was born in Salliqueló, Buenos Aires, Argentina, in 1979. He received the Electronic Engineer degree in 2007 and the MS degree in 2018, both from National University of La Plata (UNLP), Argentina. Currently he is Associated Professor at the Faculty of Engineering, UNLP and at the Arturo Jauretche National University (UNAJ). His main research interests are in Internet of Things and computer vision applications.

Luis A. Giambelluca was born in La Plata, Buenos Aires, Argentina in 1965. He is graduate in Biology in National University of La Plata (UNLP). He currently works in CEPAVE (CONICET- UNLP Asoc. CICBA) and researchs in arachnids. He wrote more of 23 papers, three books and he participated in more of 50 seminars, talks and courses. He also participated in more of 50 presentations to Conferences.

Marcelo Cappelletti was born in Godoy Cruz, Mendoza, Argentina, in 1974. He received the Electronic Engineer degree in 2002 and the PhD degree in 2009, both from National University of La Plata (UNLP), Argentina. Currently he is Associated Professor at the Faculty of Engineering, UNLP and at the Arturo Jauretche National University (UNAJ) and he is Associated Researcher of the National Research Council of Argentina (CONICET). His main research interests are in (1) the study of photovoltaic devices, including perovskite solar cells, and (2) the study of real systems using machine learning approaches.