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Security in smart cities using YOLOv8 to detect lethal weapons

Ederson Rodriguez-Rosas, Aron Castillo-Turpo, Kevin Acuña-Condori, Ernesto Paiva-Peredo
Department of Electronic Engineering, Faculty of Engineering, Universidad Tecnológica del Perú, Lima, Peru

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ABSTRACT

The increase in the illegal use of lethal weapons at a global level has reached worrying figures, resulting in an increase in assaults and armed robberies. Based on the above, closed circuit television (CCTV) surveillance systems emerge as an alternative solution. Therefore, the use of artificial intelligence is explored in order to detect the presence of lethal weapons in images accurately. In this study, a convolutional neural network model YOLOv8 is trained. A database including 4104 images with the presence of lethal weapons is generated. The Google Colab platform is used for the training phase, since it provides us with a free graphic processing unit (GPU), and the YOLOv8x and YOLOv8n models are used for comparison. The results indicate an advantage when using the YOLOv8 models, and when comparing them with similar models already proposed in the studied literature, we can conclude that our model stands out with an accuracy of 89.56% in the detection of lethal weapons. In conclusion, we were able to obtain a model capable of detecting lethal weapons in CCTV images, in addition to being able to be used in applications that require real-time detection.

Corresponding Author:

Ernesto Paiva-Peredo
Department of Electronic Engineering, Faculty of Engineering, Universidad Tecnológica del Perú
125 Natalio Sanchez Street, Santa Beatriz Urbanization, Cercado de Lima, Lima, Peru
Email: C22395@utp.edu.pe

1. INTRODUCTION

Globally, there are more than 1,013 million firearms in the world and more than 85% of them are in the hands of civilians [1]. Consequently, the use of firearms causes up to 1,000 deaths per day, along with more than 250,000 armed incidents per year [2]. This reality highlights the importance of the use of closed circuit television (CCTV) systems for the early identification of lethal weapons (firearms and sharp weapons) in images [3]–[9]. In this way, it is possible to combat crimes such as assaults and robberies, which are carried out with armed hands [5], [10]. In this context, the detection of crimes by images based on artificial intelligence arises, due to its high precision, anticipation and adaptability in the detection of objects [6], [11].

Currently, the use of artificial intelligence, for the identification of violence scenarios such as crimes involving the presence of lethal weapons, is in constant expansion. Therefore, algorithms based on an artificial neural network and the moving picture experts group 7 (MPEG-7) descriptor are proposed to classify frames of a CCTV transmission, in which results of 94% and 95%, respectively, are obtained [4], [12]. It is relevant to note that both models exhibit a low rate of positive incorrect detections, but miss a considerable amount of negative incorrect detections. However, among the most outstanding approaches is the application of convolutional neural networks (CNN) [9], [10], [13]. Therefore, a network based on visual geometry group-16 (VGG-16) and another on VGG were configured, which have an efficiency of 93% and 86%, respectively [10], [13]. It is important to note that both models use the VGG extractor, which does not allow optimal performance when locating the presence of lethal weapons in the images. In this sense, for the identification of a crime scene it is important to detect lethal weapons, for this purpose, CNNs are usually used [3], [14]. For example, the method called flow gated network, which combines the advantages of three-dimensional convolutional neural networks (3D-CNN) and optical flow, resulting in an accuracy of 87.25% [3]. It is worth mentioning that 3D-CNNs require a higher computational load with respect to CNNs [3].

First, in the field of CNNs, YOLO is one of the most widely used to identify objects in the frames of a real-time video sequence [8]. For this reason, a YOLOv3 model was trained, with the purpose of identifying the presence of firearms in images [2], [15], [16]. This model is fused with recurrent convolutional neural networks (R-CNN), through which it achieves a performance of 94.23% [15]. It should be noted that the model uses the open source database ”kaggle”, this generates a limited management in the quality and variety of the training data to the network. It is also important to consider that the R-CNN does not work in real time [15]. Also, models for weapon detection are proposed by applying YOLOv5 [1], [8], [17], [18]. The model exhibits the ability to identify lethal weapons, achieving a mAP of 52.92%. It also exhibits an inference rate of 61 frames per second (FPS) [8]. In addition, the database applied to the training of the network, is deficient based on the variety. Also, an efficiency of 93% image accuracy was obtained by combining YOLOv5 and faster R-CNN, using a database of 3000 guns [1].

On the other hand, for the recognition of firearms in images by means of deep learning, the fusion between posture estimation and object detection is being used [5], [6]. Therefore, an algorithm is designed to define the pose of each person in a frame, in order to obtain the position of the hands and create a bounding box where the object detector is applied [5], [6]. The model uses Open Pose to estimate the posture and vision transformer (ViT) to detect the weapon [5]. It is important to point out that the efficiency relies on the pose estimator, if it fails, there will be no detection process [5], [6]. To achieve an early detection of firearms, it is essential to consider that these are not always carried in the hands, since there are varieties of weapons that can be carried on the chest or hanging from the shoulders.

Given the need for more efficient systems for the detection of dangerous objects, whether firearms or knives. A YOLOv8 CNN is trained using a cloud computing infrastructure to reduce the computational burden [19]. In addition, a diverse dataset is generated that includes a wide range of lethal weapons, such as shotguns, pistols, knives, machetes, among others. To augment the training data, synthesis techniques are employed, this increases the database and gives better learning versatility to the CNN [3], [5].

2. METHODOLOGY

Today, the number of crimes involving lethal weapons (firearms and knives) has risen exponentially [1], [4]. Measures have been taken to address this problem, such as the installation of CCTV systems. However, these systems only accumulate the data, and do not work it through video inspection or object detection algorithms [7], [9], [12]. Therefore, a neural network capable of detecting lethal weapons in real time is trained, in order to provide greater accuracy, versatility and reduction of false positives. After conducting a comparative analysis of various object detection techniques that rely on deep learning, such as YOLO, single-shot multibox detector (SSD) and the fastest R-CNN. It is determined that YOLO excels in achieving an optimal trade-off between mean average precision (mAP) and inference speed, for real-time predictions [8], [11], [18].

Finally, YOLOv8 is defined as the CNN to be trained, because it is the most recent iteration in a sequence of algorithms created by Open AI researchers for object detection and tracking. To our knowledge, this is the first work investigating the use of YOLOv8 in identifying deadly weapons in images. The research is divided into three stages, the first one covers the obtaining of the database, the second stage corresponds to the data augmentation together with the etiquedata and the third stage the training of the CNN YOLOv8, obtained from ultralytics.

2.1. Data acquisition

In this stage, the collection of 3104 images is performed, proportionally 1554 images with the presence of firearms and 1550 images with the presence of white weapon. Considering the importance of the variety of data for a good training, we considered images of the different types of firearms and knives that exist [9], [10]. A collage of the collected images is presented in Figure 1. It is relevant to note that the dataset was obtained from three sources, in order to have variety in the origin of the images. From Kaggle dataset 1040 images were extracted, from Youtube 931 images were collected and from Google 1133 images were collected. The acquisition process in the sources used is explained as follows.

Figure 1. Collage of collected images

2.1.1. Google images

A Google extension called ”download all images” was used. This tool allows us to download all the images that have been visually loaded, and gives us a file in rar format, where all the images are in jpg format [2]. In this way, we searched for images using keywords such as: people with knives, assaults with knives, people with axes, people with firearms, assault with firearms.

2.1.2. YouTube

Additionally, the YouTube platform was used for the collection of images with the presence of a sharp weapon, in this platform we can find videos of CCTV [3]. A flowchart is presented in Figure 2, of the procedure of obtaining images from a video. Initially, we explored the YouTube platform using a series of keywords related to violent acts, such as real knife fights, knife-wielding assailant, and other similar terms. Subsequently, we used the online video converter program that automatically downloads the videos from the obtained links. After completing this process, we extract images every 5 seconds, all at a speed of 30 FPS.

Figure 2. Video frame acquisition process

2.1.3. Kaggle dataset Online

The Kaggle platform hosts a wide range of datasets. These datasets can be used for machine learning [17], [20], [21]. For the detection of lethal weapons, this online database was used to extract images whose content contains any type of firearms or sharp weapons [15]. The justification for using Kaggle is the presence of images obtained from a CCTV system, in addition to the variety of images presented by [15], [22].

2.2. Increased data and labeling

In order to increase the number of images collected, which were 3104, and also to improve the variety of the database in terms of tonalities and visualization perspective, we propose the application of data augmentation techniques [3], [5]. These techniques allow us to identify patterns in our data by performing various transformations on the images, such as flipping, rotating, scaling, converting to black and white, among others [14]. In this study we chose to change the image to gray tone and invert it horizontally. Figure 3 shows the algorithm performed in the MATLAB environment, where a group of 500 images selected from the group of images initially collected were loaded and the rgb2gray and fliplr commands were applied. Through this technique we were able to increase 1000 more images and obtain a dataset of 4104 images with the presence of lethal weapons.

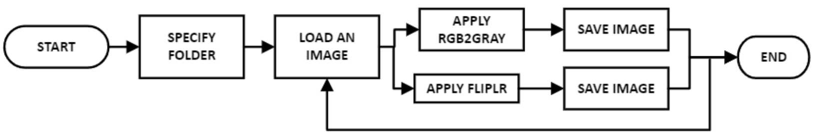


Figure 3. Data augmentation process

On the other hand, the images are tagged in the Makesense online platform. For this purpose, two tags ”Firearm” and ”White weapon” were created. These labels provide the neural network with information about the exact location of the object to be identified, so that the network learns to recognize patterns and relevant features in the area limited by the label. Finally, the images are divided into two groups, 4104 for training and 892 for validation. Figure 4 shows a group of labeled images.

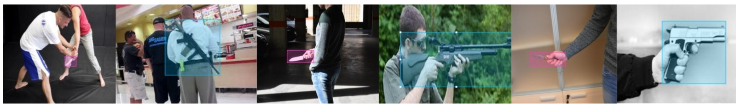


Figure 4. Collage of labeled images

2.3. Deep learning model YOLOv8

YOLO algorithms in computer vision are recognized for their high accuracy and small model sizes, making them easy to use for both developers and machine learning experts [18]. The latest version, YOLOv8, is used in a variety of applications, including object detection, image classification and segmentation [23]. Ultralytics has developed YOLOv8 as an evolution of YOLOv5, incorporating architectural improvements. A distinguishing feature of YOLOv8 is that it does not use anchors; instead, it explicitly estimates the center of objects, leading to a reduction in the number of predictions and speeding up the non-maximum suppression (NMS) process [18]. YOLOv8 is broken down into five models, YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x, each with variations in accuracy and speed [11], [18], [23].

For this study, the YOLOv8x model is used, due to the results obtained in each parameter presented in the table. Also, it is important to make a comparison between the YOLOv8x and YOLOv8n model, because a wide difference is observed in the results using a COCO dataset. But we do not know their behaviors when trained with our lethal weapon database [23].

2.4. YOLOv8 training

For training and validation of YOLOv8, we use Google Colab, a free cloud runtime environment, this platform, provides us with a free online GPU [17]. Using a GPU significantly speeds up both the rendering process and the compile time. When working with a large data set that is not limited only to numerical values, there is an improvement in performance when running numerous steps [17].

The previously created database is uploaded to the Google Colab environment in ”rar” format, in addition to a dot yaml file, where the paths of each of the two folders of the training and validation database are found, also in this file the number of items to detect in this case firearms and sharp weapons is defined. Then, the training is started by importing the ultralytics libraries and defining the YOLO version and model to be used. Finally, the training parameters are defined, such as the number of epochs to be trained, the batch size to be used and the size of the images to be processed. It should be noted that for the study a comparison between two versions of YOLOv8 will be made, using YOLOv8n and YOLOv8x, due to the high margin of results in each of its metrics obtained in the test performed by ultralytics.

2.5. Evaluation metrics

These are very important parameters to measure the performance of the model in terms of accuracy and speed. This paper uses accuracy, detection rate, false detection rate and mAP as metrics to evaluate the performance of the algorithm. Accuracy measures the ratio of correct detections to the total number of correct detections [24]–[26]. While the recall parameter measures the ratio between the positive objects that have been detected and the total number of positive objects [23]–[25], [27]. Finally, the mAP is widely used because it provides information about the accuracy of all classes of objects present in the database [25], [27], [28].

3. RESULTS AND DISCUSSION

The training results of both YOLOv8 models are very close when observing their evaluation metrics. Regarding the performance of the proposed YOLOv8x model for the detection of lethal weapons we obtained a mAP of 87.8% and a mAP50-95 of 63.47%. In the identification of firearms we obtained a mAP of 88.7%, and in the identification of sharp weapons a mAP of 86.8%, training the network for 50 epochs and with a batch size of 16. The results of the evaluation metrics are shown in Figure 5.

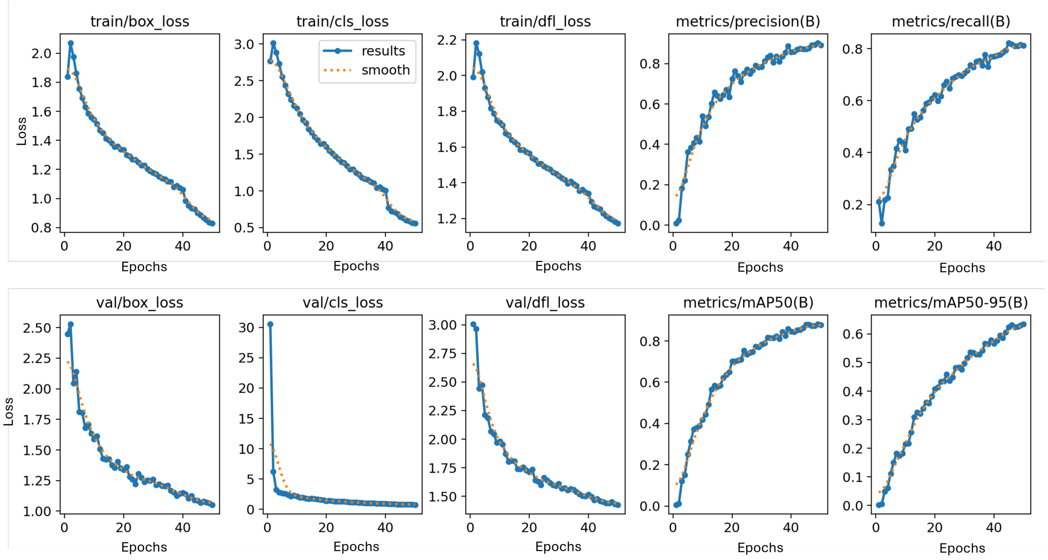


Figure 5. YOLOv8x model results

On the other hand, the results of the YOLOv8n model with the same training parameters were very similar to the previous one. Because a mAP50 of 89.59% and a mAP50-95 of 63.26% were obtained in the detection of lethal weapons. This allows us to conclude that the YOLOv8n model has a better performance in the detection of lethal weapons, this is observed when analyzing each evaluation metric in Figure 6.

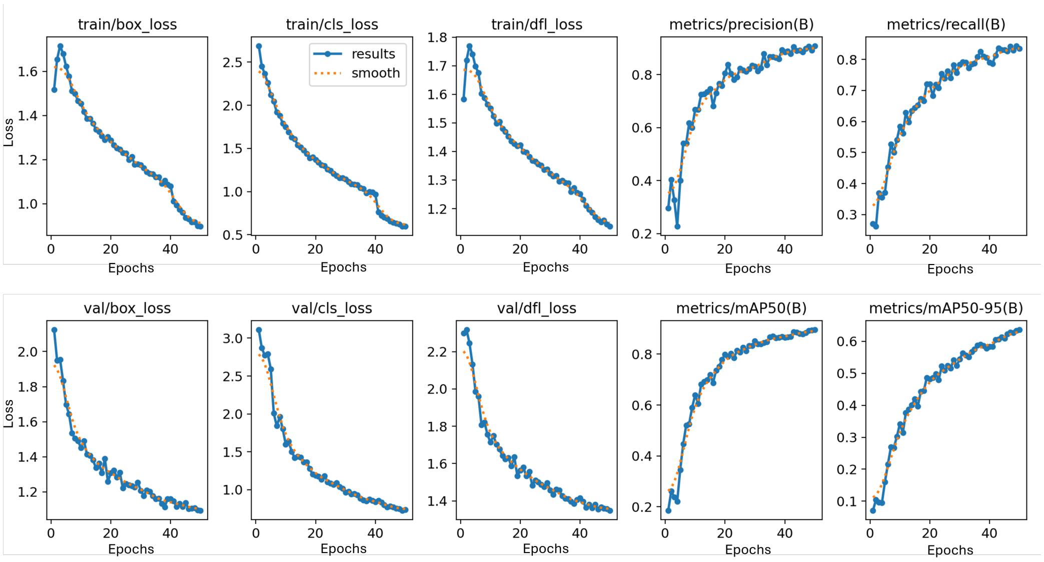
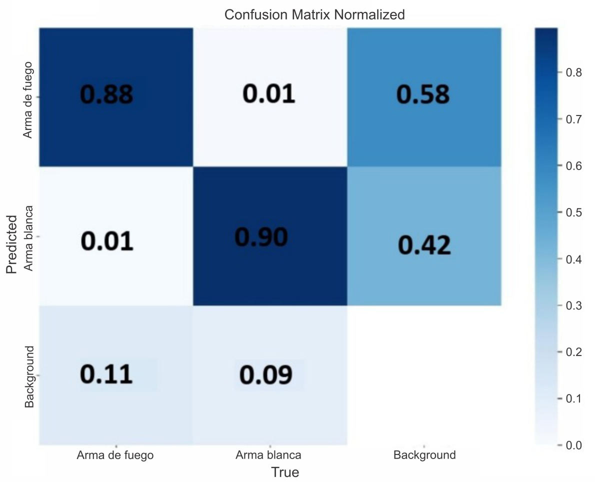


Figure 6. YOLOv8n model results

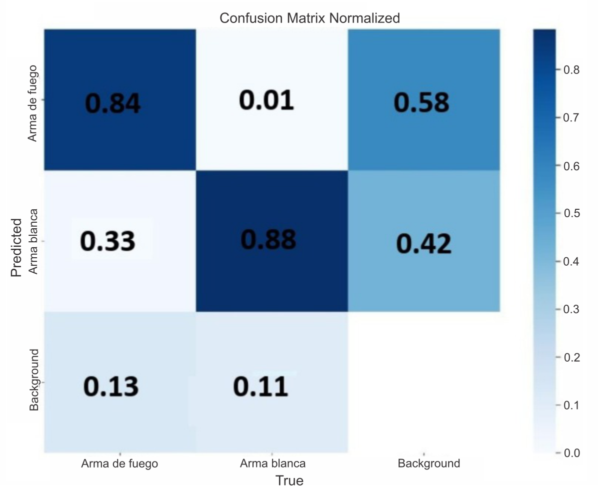
Our YOLOv8n network demonstrates superior performance compared to existing methods in the literature. The flow gated network, which combines 3D-CNN and optical flow for violence scene detection, achieved a mAP of 87.25% [3]. In comparison, our YOLOv8n model achieved a higher mAP of 89.59%, with lower computational requirements. Additionally, while a YOLOv3 and R-CNN hybrid model for firearm detection reported a mAP of 85% [15], it is not suitable for real-time use due to its slower speed. Our YOLOv8n model, with a mAP of 89.59%, supports real-time operation, making it ideal for early weapon detection. Furthermore, it outperforms a YOLOv5 model designed to detect lethal weapons, which achieved a mAP of 52.92% [8], thanks to our more diverse training dataset.

3.1. Confusion matrix

The confusion matrix is a critical tool for evaluating the performance of classification models. Figure 7 presents the confusion matrices for the YOLOv8n and YOLOv8x models, enabling a comparative analysis of their performance. In Figure 7(a), the confusion matrix for the YOLOv8n model is displayed, illustrating the classification errors and the distribution of predicted versus actual labels. Figure 7(b) shows the confusion matrix for the YOLOv8x model, providing a similar analysis and facilitating a comparison with the YOLOv8n model.



(a)



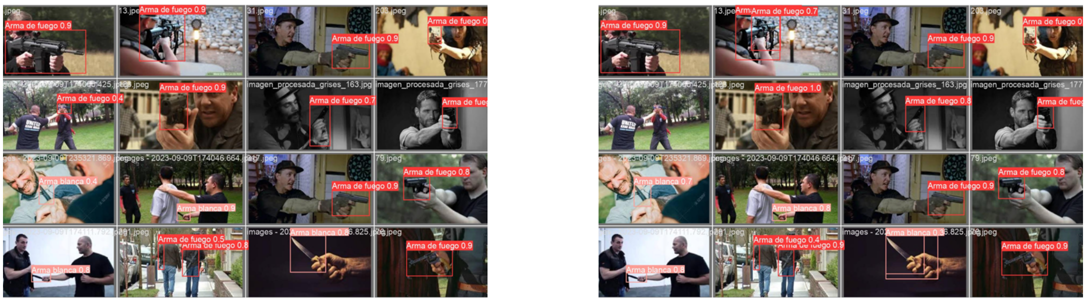
(b)

Figure 7. Matrix of confusion for (a) the YOLOv8n model and (b) the YOLOv8x model

3.2. Prediction

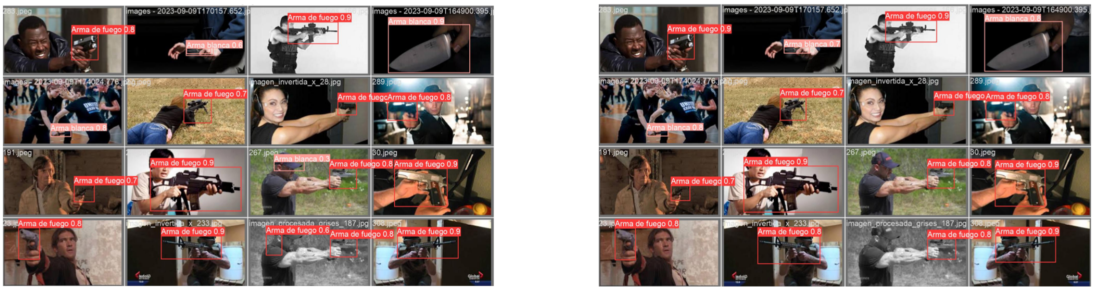
The prediction results of YOLOv8n and YOLOv8x models are depicted in Figures 8 and 9. Figure 8 includes the prediction results for a batch of 16 images using both models. In Figure 8(a), the predictions of the YOLOv8n model are shown, detailing how the model performs on the given images. Figure 8(b) presents the prediction results of the YOLOv8x model for the same batch of images, allowing for a direct comparison with the YOLOv8n model.

Figure 9 further illustrates the prediction performance of both models. Figure 9(a) highlights an instance where the YOLOv8n model misidentifies a white weapon as a person's cap, providing insight into the model's limitations. In contrast, Figure 9(b) shows the YOLOv8x model's ability to correctly identify the white weapon with high accuracy, even when only a partial view of the weapon is visible. This comparison underscores the YOLOv8x model's superior detection capabilities in specific scenarios.



(a) (b)

Figure 8. Prediction results of the (a) YOLOv8n model and (b) YOLOv8x model



(a) (b)

Figure 9. Detection performance comparison of the (a) YOLOv8n mislabels a weapon and (b) YOLOv8x labels it correctly

4. CONCLUSION

In this study, we developed and evaluated a YOLOv8 network specialized in the detection of lethal weapons, covering both firearms and edged weapons. The results obtained were exceptional, with a performance rate of 89.56%. This figure validates the effectiveness of our approach and highlights the model's ability to accurately identify potential threats. In addition, we note that our YOLOv8n model exhibits superiority in certain aspects compared to YOLOv8x, especially in terms of accuracy. However, it is essential to emphasize that the prediction results do not allow us to state with certainty a general superiority, indicating the need for more detailed analyses in future research. Our research work provides a trained network with the ability to be implemented in real time in any CCTV system that has the necessary computational parameters, as would be the case in a smart city. Also, we believe that our proposed model could enhance its performance by training with a more diverse database. It is worth noting the importance of the size of the images used in the training, since YOLOv8 operates with a recommended size of 640 pixels for image.

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BIOGRAPHIES OF AUTHORS

Ederson Rodriguez-Rosas is student as an electronic engineer from the Universidad Tecnológica del Perú. His learning interests include industrial process automation, machine learning, and neural networks. He currently holds the position of intern in the TEC operations area, which is focused on the management of technological projects in the field of electronic security, which consist of the implementation of CCTV systems, access control, fire and intrusion detection. He can be contacted at email: U18302561@utp.edu.pe.

Aron Castillo-Turpo is student as an electronic engineer from the Universidad Tecnológica del Perú. His learning interests include data communication networks, as well as control and automation. He currently holds the position of supervisor in the telecommunications area at Claro, which is focused on quality control and large-scale fiber optic projects, which consists of offering and providing telecommunications services with the highest quality. Coverage and innovation that meet people's needs. He can be contacted at email: U18205726@utp.edu.pe.

Kevin Acuña-Condori received his B.Eng. degree in electrical engineering from Universidad Nacional Mayor de San Marcos, Perú, in 2015. He was awarded the CONCYTEC scholarship in 2015 for his master's studies, which he completed in mechatronic engineering from the Pontifical Catholic University of Peru, Lima, in 2017. Currently, he serves as a lecturer in electronic design, digital systems, control and automation, digital image processing, artificial intelligence, and robotics at the Universidad Tecnologica del Perú since 2017 and Pontifical Catholic University of Peru since 2018. As a researcher at Universidad Tecnológica del Peru, he has authored publications in bioengineering, artificial intelligence, and control. His research interests include bioengineering, artificial intelligence, brain-computer interface, and neuroprosthetics. He can be contacted at email: C17419@utp.edu.pe.

Ernesto Paiva-Peredo is graduated as an electrical mechanical engineer from the Universidad de Piura in Peru in 2013. He pursued further studies and obtained a master's degree in electrical mechanical engineering with a specialization in automation and optimization, which was supported by CONCYTEC and awarded by the Universidad de Piura in 2016. During his academic journey, he served as a research assistant at the Department of Technology and Innovation (DTI) at SUPSI. Presently, he holds the position of a Professor-Researcher at the Universidad Tecnológica del Perú. He can be contacted at email: C22395@utp.edu.pe.