Video surveillance system based on artificial vision and fog computing for the detection of lethal weapons

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ABSTRACT

Citizen insecurity in underdeveloped third world countries is aggravated by poor management of arms control and illegal trafficking, which requires information technology solutions in intelligent video surveillance systems for the detection of lethal weapons. The literature review highlights the need for an intelligent video surveillance system to combat high crime, using fog computing, which processes data in real time for the detection of weapons and other crimes. Furthermore, at an international level, solutions based on artificial intelligence and deep learning are being implemented for object recognition and weapons detection. Therefore, this paper describes the design of an intelligent video surveillance system based on artificial vision, fog and edge computing to detect lethal weapons in domestic environments, performing weapon classification and data transmission to police centers. The intelligent video surveillance system allows detecting lethal weapons and operates in three stages: an edge node with a Raspberry Pi 4; a detection algorithm based on a convolutional neural network with YOLOv5; and streaming tagged images to a security unit via WhatsApp. The main conclusion is that the system achieved a precision greater than 0.85 and a quick and efficient response in sending alerts, representing a scalable and effective solution against home burglary.

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1. INTRODUCTION

Currently, one of the problems that afflicts Peruvian society is citizen insecurity, which seeks to combat with solutions that are not efficient [1], [2]. Citizen insecurity is aggravated by the poor management of arms control, attributed to factors such as corruption in public administration and poor surveillance of the illegal importation of weapons [3], [4]. Although in Latin America most countries prohibit civilians from possessing certain small arms, illegal trafficking persists, generating insecurity, and an increase in homicides [5], [6]. Therefore, one of the solutions is the use of artificial intelligence for the recognition and detection of images in video cameras, which serve specialized police investigation centers for rapid action against criminal acts [7], [8].

In this context, the internet of things (IoT) is a trend to connect objects to the internet and its integration with intelligent video surveillance systems appears as a modern solution to combat crime in third world countries [9], [10]. Smart video surveillance systems with IoT connected to the cloud face challenges in resource and bandwidth consumption, which can be optimized through fog computing, which processes data locally and improves network efficiency due to its proximity to data sources [11], [12]. Furthermore, one of the most widely used deep learning algorithms for object recognition in video is the convolutional neural network (CNN), which is trained with a database of firearm images [13], [14].

The literature review describes how the high crime rates that affect society, such as hitmen, extortion and robbery in various cities in Peru, make it necessary to implement an intelligent video surveillance system that uses advanced technology [15], [16]. These elevated levels of crime especially affect developing countries, where corruption and institutional weakness increase violence and theft. Some articles describe how violent crimes try to be reduced based on interventions at different levels [17], [18], which increase due to the existing poverty in developing countries [19]. On the other hand, research shows that there are high rates of car thefts for which it is necessary to track and recover stolen vehicles in cities like Lima [20], [21]. Internationally, solutions based on artificial intelligence are being implemented for object recognition in video cameras [22], [23]. Furthermore, some research describes a deep learning-based system that analyzes closed circuit television (CCTV) recordings to detect weapons in real time [24]. An example is the EU-funded SURVANT system, which uses machine learning to filter data and detect crime patterns using video surveillance cameras [25], [26].

Due to this, the research question is posed: "How to detect lethal weapons in a domestic environment in the city of Lima?" This question will be answered by fulfilling the objective of designing an intelligent video surveillance system based on artificial vision, computational fog and edge layers for the detection of lethal weapons in a domestic environment in Lima. The specific objectives focus on: design of the edge node stage, development of the CNN model, and reporting the crime to police centers.

2. METHOD

The smart video surveillance system uses fog and edge computing technologies to detect lethal weapons in home environments, in three stages. The first stage involves using an edge node with a Raspberry Pi 4, connected to a computer via virtual network computing (VNC) viewer, monitoring the environment with a camera. The second stage employs a detection algorithm based on a CNN on a laptop, accurately labeling firearms or knives. The algorithm is trained with an image database using YOLOv5 and tools such as Makesense.AI and Google Colab. The third stage involves sending tagged images to a remote security unit via WhatsApp, using Node.js and the Twilio API (Figure 1).

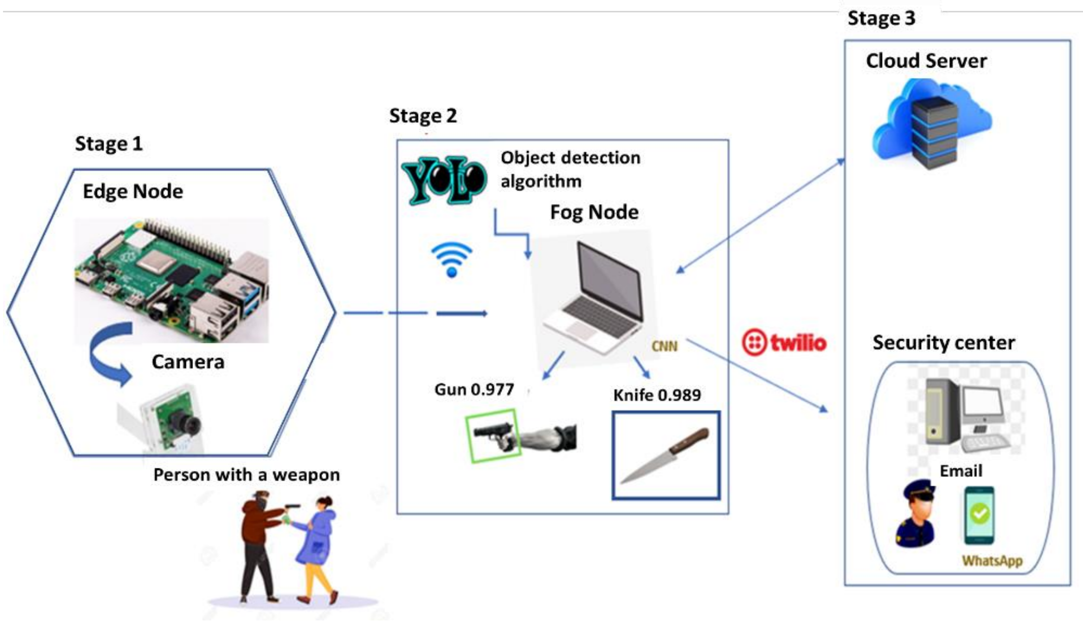


Figure 1. Stages of the intelligent video surveillance system

2.1. Edge node

The first phase of the intelligent video surveillance system involves the use of a Raspberry Pi 4 board, with a camera that is the image sensor, configured for remote connection via Wi-Fi with a computer. VNC viewer software is used to control the Raspberry Pi and the camera remotely. The detection of armed people is conducted by sending the images to the computer which functions as a fog node. To configure the edge node, the Raspberry Pi is considered, on which the Raspbian operating system is installed (Figure 2).

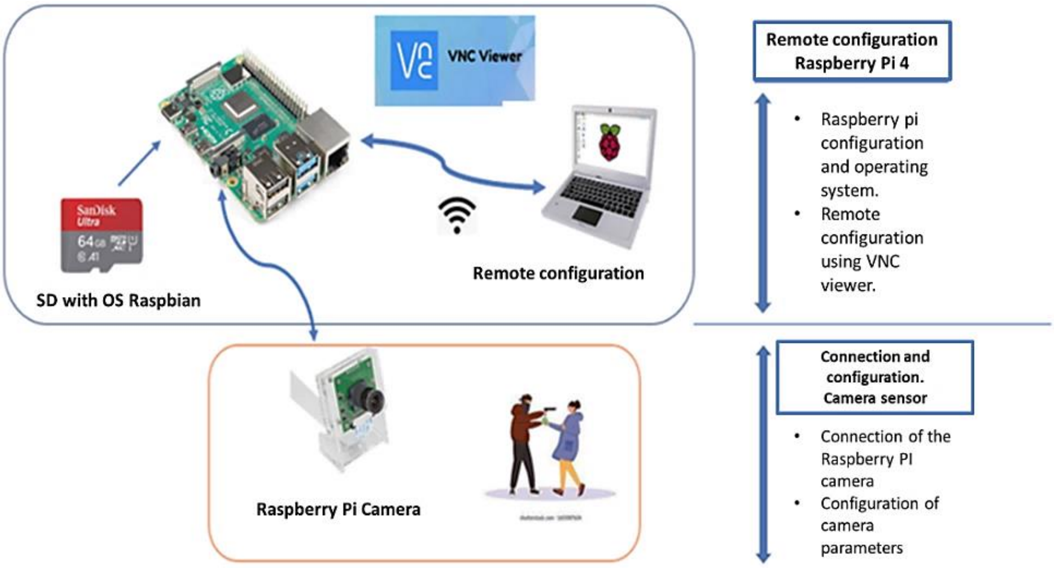


Figure 2. Edge node stage description

2.2. Convolutional neural network model on the fog node

The second phase consists of image classification in the fog node, using a computer and an object detection algorithm trained with images of guns and knives. A database of gun images is collected, labeled with Makesense.AI, and the CNN is built using YOLOv5 and PyCharm. Google Colab is used to initially train the neural network with YOLOv5. Finally, the algorithm is executed in PyCharm to start detecting the objects (Figure 3).

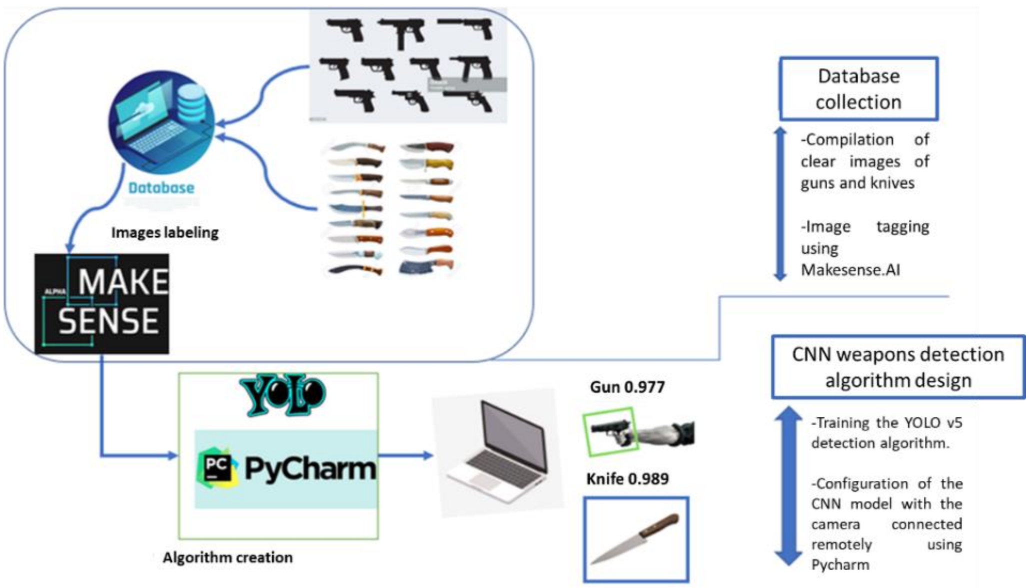


Figure 3. Description of the fog node classification stage

For the development of the gun and knife detection algorithm, the cross-industry standard process for data mining (CRISP-DM) data science methodology is followed, which allows the file to be exported

(Figure 4). The development of the algorithm is divided into: establishing the objectives of the detection algorithm, detailing the accuracy required to detect firearms and knives (Figure 4(a)). In the next stage, a set of proportional images of guns and knives is selected and cleaned, removing non-useful images and obtaining label files using MakeSense.AI. In the final stage, the resulting model with the extension "*.pt" is generated, using Google Colab and YOLOv5 XLarge to train the CNN as seen in Figure 4(b).

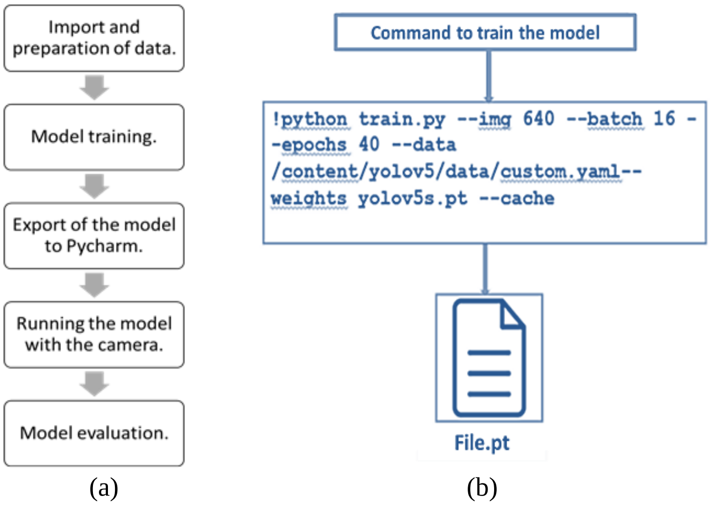


Figure 4. Implementation of the neural network using (a) a flowchart and (b) commands for model training

2.3. Tagged image transmission

During the stage of sending tagged images, the police crime prevention center is alerted to take preventive actions. Figure 5 shows the classified image, with the detection of the weapon in question, and it is sent to a cell phone number through WhatsApp using Twilio and Node.js. In addition, a descriptive message is attached so that the police center can act proactively.

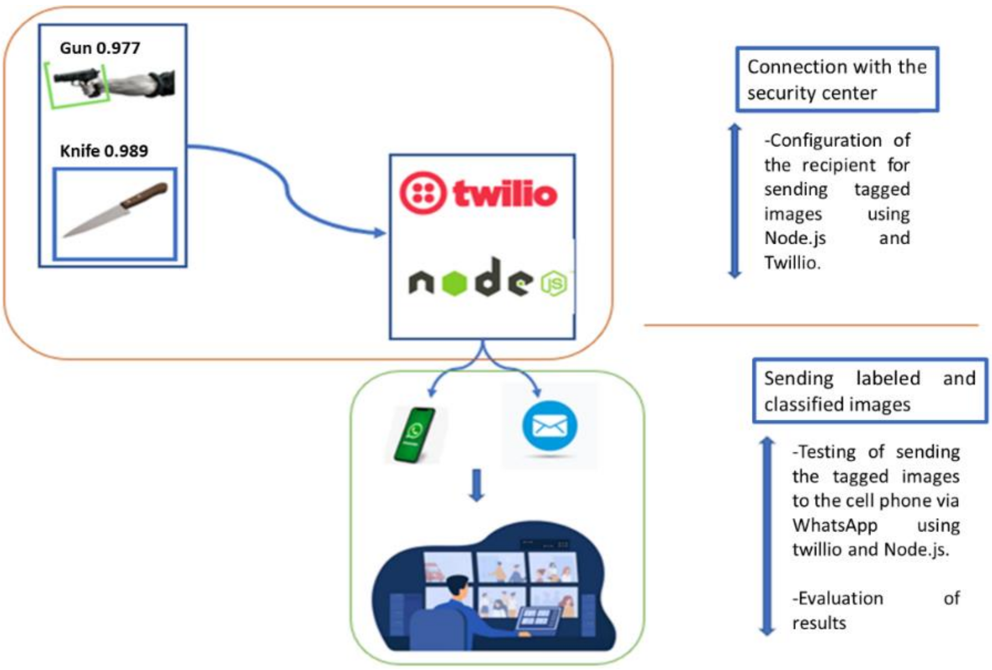


Figure 5. Image transmission stage

To send alerts through WhatsApp, the Visual Studio, and Node.js tool is used, and the creation of a Twilio account is used, activating the Sandbox option by sending a specific message to the Twilio number. In Visual Studio, the Express, and Twilio packages are installed to develop the chatbot responsible for sending messages. Program configuration includes writing the Twilio ID and secret code (Algorithm 1), creating the instance, specifying the recipient number, and the message.

Algorithm 1. App.js code

Instruction

```
const TWILIO_ID = 'ac900629ae0f917d44937b997b30ad2130'
const TWILIO_SK = 'a3ab7d3d3d34c6d774a8195c0c7ecd76'
const client = require('twilio')(TWILIO_ID, TWILIO_SK);
client.messages
     .create({
        from: 'whatsapp:+51155238885',
        body: 'Hola mundo',
        to: 'whatsapp:+51043768431'
      })
     .then(message =>console.log(message.sid));
```

3. RESULTS AND DISCUSSION

A Raspberry Pi with the training of the neural network is deployment and the results are presented in the case of a person holding a knife, holding a gun, and holding both objects simultaneously. The model ".pt" file is loaded and libraries such as OpenCV (Cv2) and pandas are used in the PyCharm development environment. Detection evaluations of different weapons were carried out as shown in Figure 6. The evaluation scenarios were in the presence of weapons such as knives (Figure 6(a)) and a firearm or pistol (Figure 6(b)). The performance analysis was carried out in different lighting conditions and camera angles, which allowed the robustness of the algorithm to be evaluated, verifying that the system maintains high precision in detecting weapons even demonstrating its effectiveness and applicability in various environments.

(a) (b)

Figure 6. Testing for (a) the knife detection and (b) the gun detection event

Once the training of the neural network is completed, the results are presented in the case of a person holding a knife, holding a gun, and holding both objects simultaneously. The ".pt" model file is loaded and libraries such as OpenCV (Cv2) are used. Figure 7 demonstrates that multiple object detection is performed adequately with a classification and precision greater than 0.85, locating each class using the pandas detection function "detect.pandas().xyxy[0]", obtaining the 4 coordinates per class (Table 1).

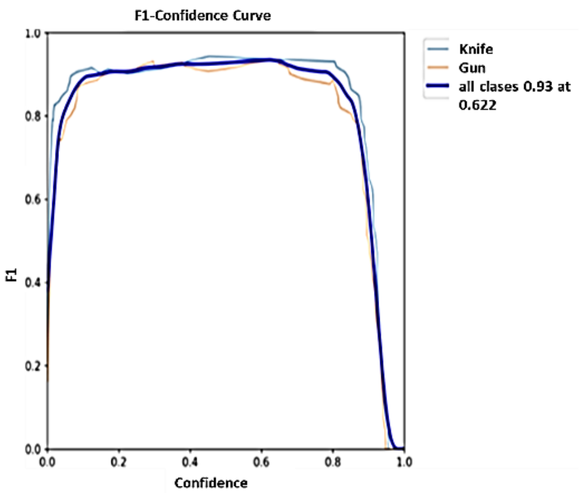
Figure 7. Execution of the model with two objects and a pandas function

Table 1. Result of pandas detection function "detect.pandas().xyxy[0]"

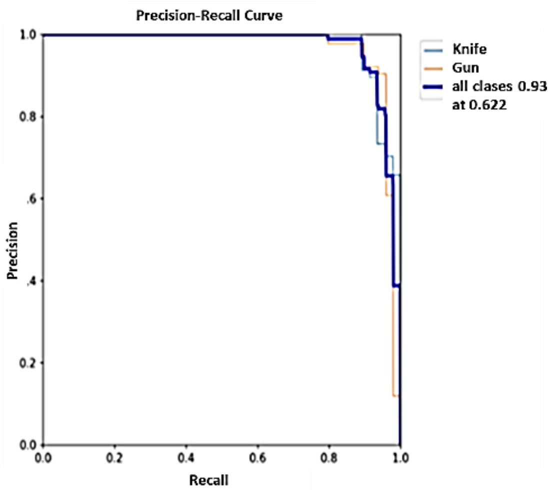
Line	xmin	Ymin	Xmax	Ymax	Confidence	Class	name
0	98.4756	283.5674	291.6845	466.3645	0.87345	0	Gun
1	429.3577	178.4752	515.7943	479.5732	0.89334	1	knife

Figure 8 shows some evaluation metrics used to validate the operation of the system. The F1 curve is seen in Figure 8(a), where the optimal value that balances precision and recall is approximately 0.601. On the other hand, the precision-recall (PR) curve evaluates the classification capacity of the algorithm, considering a curve that is close to the upper right corner as a perfect classifier (Figure 8(b)). Figure 9 shows the progression of precision values obtained for the detection model. In the case of Figure 9(a) it is observed that there is a continuous increase of the function, reaching its maximum point of 0.9676 at step 37 of the horizontal axis for the case of the detection of knives, while for the detection of guns, a value is observed that is close to 0.85 (Figure 9(b)).

The stage of sending images and alerts through WhatsApp to a registered number is presented, with the aim of notifying the resident when the presence of a lethal weapon is detected. Figure 10 illustrates the alert message transmitted via WhatsApp when running the algorithm developed with Node.js and Visual Studio Code, along with the image of the detected weapon.

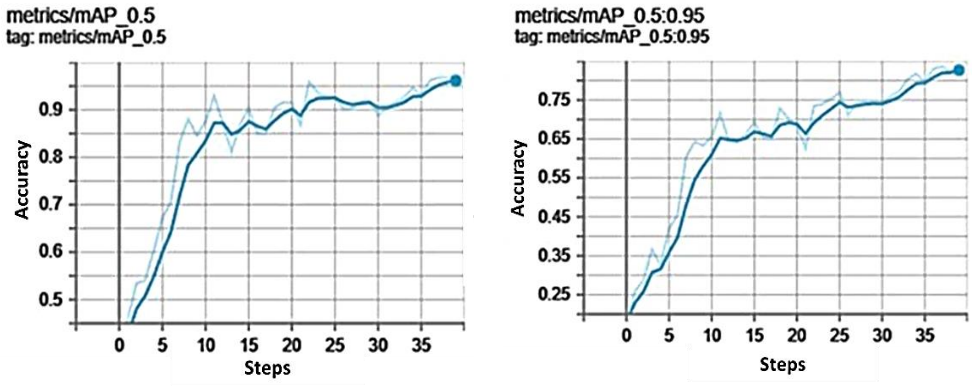


(a)



(b)

Figure 8. Metric related to (a) the F1-score curve and (b) the PR curve



(a) (b)

Figure 9. Accuracy for (a) knife detection and (b) gun detection

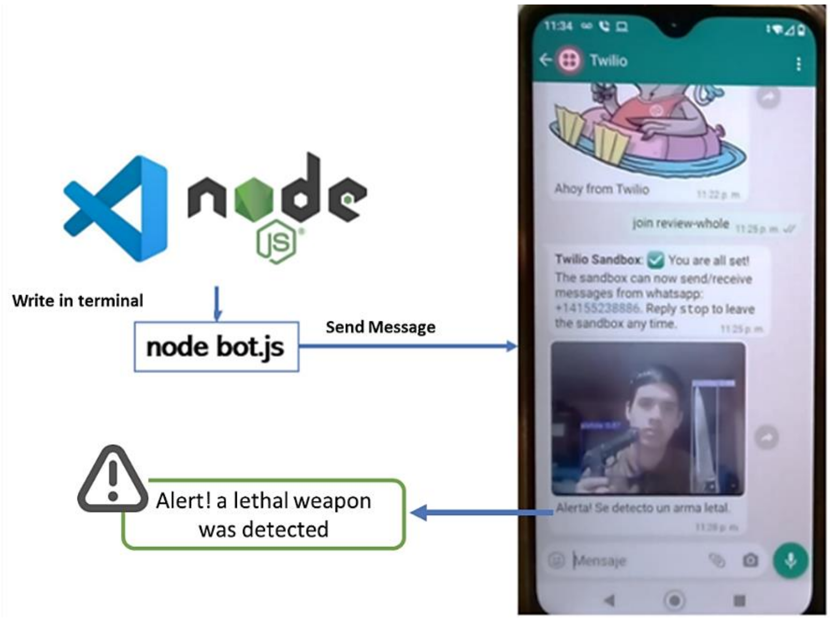


Figure 10. Evaluate sending images to WhatsApp using Twilio

4. CONCLUSION

An intelligent video surveillance system was created using fog computing for the detection of lethal weapons, integrating a prototype with a camera sensor connected to a computer network, running the detection algorithm based on YOLOv5, and sending the images via Twilio and No-de.js. The performance of the model was evaluated using precision metrics with TensorFlow and F1 and PR curves, obtaining favorable results with a precision greater than 0.85. Sending images and alerts via WhatsApp was conducted efficiently and quickly. This implementation, based on fog and edge computing, offers an agile response to events, representing a scalable solution aligned with the leading technologies in the international market to combat home burglary.

Three key stages were designed for the operation of the system: that of the edge node, the detection edge node, object detection, and sending labeled images. In the first stage, a Raspberry Pi 4 board with a camera sensor was integrated. In the stage of sending tagged images, a sending bot was created using Twilio and Node.js libraries, activating the Sandbox and configuring the alert message and the image for transmission to a WhatsApp number, concluding in an effective solution against home theft in its implementation.

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