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Research Article

Gun Detection in CCTV Images using HAAR-Like Features

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Abstract: Automated video-based surveillance is an important area of research to assist the security personnel to detect the incident of any abnormal events in the surroundings. The objective of this paper is to develop a framework for automatic gun detection using closed-circuit television (CCTV) images. The methodology presented in this paper involves the development of a framework for automatic gun detection using closed-circuit television (CCTV) images, with the aim of enhancing the surveillance of crime and improving human security. The proposed approach consists of a dataset of CCTV images containing instances of guns, as well as non-gun images for comparison. These images would be used to train the proposed algorithm to recognize and identify guns in future CCTV images. The proposed framework is designed for an indoor environment and uses Haar-like features for gun detection. The proposed system involves the installation of CCTV cameras in a suitable corner of an indoor environment for surveillance. The CCTV cameras capture the scene and the frames of the scene are compared with a predefined dataset for automatic gun detection. The proposed approach draws a bounding box and raises an alarm if it detects a gun in a frame extracted from a captured scene. This provides a visual indication of the presence of a gun, making it easier for relevant authorities to quickly identify and respond to the threat. The proposed system shows promising results in real-time applications and about 90% accuracy has been achieved.

Keywords: Gun Detection, CCTV, Security, Video-based Surveillance, Haar-like Features, Support Vector Machine.

1. INTRODUCTION

Over the last two decades, the situation of the whole world becomes very difficult in terms of security due to terrorist attacks on public and private organizations such as universities, colleges and schools. Several methods have been taken to reduce security threats such as security alarm implementations, detection of grievous objects, and deployment of security guards and metal detectors. But these methods cannot work well because of the complex nature of anti-security threats and can be counteracted or deceived very easily. Now technology is used to deal with robbery and terrorist attacks with advanced computer vision systems. Closed-circuit television (CCTV) based security systems consist of cameras installed at different locations. With the help of these cameras, the locations of physical objects are detected and monitored. CCTV-based system record the scenes based on various visual information which greatly help in the investigation.

Although CCTV-based security systems play an important role in crime control and investigation, however, the system needs continuous monitoring from the human operator which sometimes becomes very difficult. Due to the advancement in technology, security threats are now automatically detected and alarms are generated accordingly. CCTV footages are automatically monitored for this purpose by applying various computer algorithms. These algorithms detect various types of human security threats [1]. The commonly detected threats are the detection of weapons, gunshots and suspected humans like thieves and terrorists [2]. These methods automatically generate an alarm when the above parameters are detected.

Automatic gun detection is indeed an important area of research and development that has the potential to contribute significantly to crime prevention efforts [3]. Automatic gun detection refers to the use of technology, such as computer vision algorithms and machine learning techniques,

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to identify the presence of firearms in images or video footage [4]. This technology can be used in various settings, such as airports, schools, and public spaces, to detect the presence of firearms and alert security personnel or law enforcement officers.

The use of automatic gun detection technology can help prevent violent crimes and save lives [5]. For example, if a firearm is detected in a school or public place, security personnel can respond quickly to remove the threat and prevent a potential mass shooting. Similarly, if a firearm is detected at an airport or border crossing, law enforcement officers can take appropriate action to prevent smuggling or other illegal activities.

Gun detection in CCTV images using Haar-like features is a computer vision technology that can automatically detect the presence of guns in indoor environments from CCTV camera footage [6]. Haar-like features are image features that describe the local intensity patterns of an image and are commonly used in object detection applications [7].

In the literature, several approaches are available for gun detection. For example, Kumar *et al*. [4] have proposed a method for gun detection using Harris Interest Point Detector (HIPD). In this method, color-based segmentation is used to remove unrelated objects from the image by applying a k-mean clustering algorithm in their system. In the segmented image, HIPD and Fast Retina Key point (FREAK) help in locating the gun in the scene. Signal detection frameworks with psychophysical experiments are used for weapons detection by Darker *et al*. [8]. The goal of their work is to increase the effectiveness of the system by detecting firearms that are carried into public places. In the work of Xue *et al*. [9] various image fusion methods are used for concealed weapons detection. Another method proposed by Darker *et al*. [10] for weapons detection. Their method is the combination of two approaches: The first approach is the use of psychological techniques, and the visual cues used by CCTV operators for the detection of potential gun crime in real-time CCTV footage are made clear. The latest Digital Image Processing (DIP) algorithms and these extracted cues are combined in the second approach for object detection, motion tracking and machine learning. Image processing and sensors-based technologies are used for the automatic detection and recognition of concealed weapons in the method developed by Prof *et al*. [11]. The fuzzy K-NN approach is used in the work of Roomi *et al*. [12]. In this approach, an image is converted into binary form by selecting the threshold as a mean of the two peaks of the bimodal histogram. To collect the object of interest the region of every object is ordered and the mean value is calculated which is set to a threshold value. The shape feature algorithm is implemented after object boundary extraction. Some sensors technologies are listed in the work proposed by Khajone *et al*. [13] which are used for Concealed Weapons Detection applications such as imaging sensors, recent advancement in Millimeter Wave (MMW) sensor technology that led to video rate (30 frames per second) and Passive Millimeter Wave (MMW). The detailed information of every object that is being monitored cannot provide by MMW alone.

Therefore, camera sensor fusion methodologies by means of MMW and IR or MMW and EO cameras are required to enhance the practical values of passive MMW in order to get information from various sensors that led to an effective Concealed Weapons Detection System. Concealed threats can be detected in high-security areas by using active mm-wave [14]. Metal and non-metal threats like handguns, knives, explosives or any concealed anomalous object can be detected by using this technology. It is not possible to monitor a huge amount of cameras with a human operator, therefore, implementing an image-understanding system instead of the human operator and alerting them if potentially dangerous situations occur is the best solution [15]. Another work was done by Dever *et al*. [16] for armed robbery detection. To classify the point of the arms and identify the classic hold-up position of armed robbery they examine the skeleton of the medial lines of the silhouette. Their proposed method contains four steps: Silhouette extraction, Skeleton segmentation, Segment identification and arm analysis. Another work was proposed by Andrzej *et al*. [17] for the visual detection of knives in a security application. The base of their work is on the Active Appearance Model (AAM) which is a statistical framework of shape and pixel intensities (texture) through the object. The arrangement of shape and texture is term as ‘appearance’ and the use of an algorithm that fits the shape texture model in a new image is term as 'active'. Regions of interest are manually labelled in the training phase which is supposed to be the milestone for defining their shape. Richard *et al*. [18] attempt three different approaches for concealed weapon detection. In the first approach, edge detection is used with pattern matching to specify the presence of concealed weapons. Daubechie wavelet is used in the second approach and Scale Invariant Feature Transform (SIFT) is used in the third approach. Lowe *et al*. [19] developed a system in which distinctive invariant features are extracted from images. These features are used for dependable matching among various views of an object or scene. Low-level image and video processing techniques are presented in the work of Foresti *et al*. [20] which are required to implement a modern visual-based surveillance system. Another work by Veena *et al*. [21] proposed a system for gun-type classification by implementing edge detection and SUSAN (Smallest Uni value Segment Assimilating Nucleus) low-level image processing. Michal *et al*. [22] proposed and benchmark an algorithm which is able to detect an individual that carries concealed weapons and alert the CCTV operator. Dee *et al*. [23] present an overview of behavior analysis and event detection systems within computer vision for surveillance. Spirito *et al*. [24] developed a system for the automatic detection of risky actions for underground surveillance using automatic video sequence processing techniques. In another work presented by Lee *et al*. [25] they found a video clip which is mostly different in terms of similarity measures from another type of video. The similarity matrix is calculated by using difference or chamfer difference as the similarity measure of features in different clips without searching the key-frames and finally, N-cut clustering is applied for abnormal event detection in video. In the work of Hung *et al*. [26] analyzed robbery events for suspicious object detection. First, background subtraction is used to detect foreground objects, and then every moveable object is tracked and obtains its route. Then suspicious object transferring condition between two persons is analyzed by using a robbery event analysis system. Ismail *et al*. [27] proposed a method for real-time monitoring of individuals and their activities. Their system works on monocular grey-scale video imagery and is applicable in outdoor environments. They employ a combination of shape analysis and tracking to locate people and their parts to create a model of people's appearance so that they can be tracked through interactions such as occlusion.

There are some limitations in the existing work; some approaches used special types of sensors which are too expensive while others have complex methodologies and complex feature types. Some of the approaches are not real-time and have a lengthy process of feature calculations. In the proposed work we have used a HAAR-like feature for gun detection which is a simple, accurate and fast calculation process.

This paper presents an automatic system for gun detection in a real-time scene using computer vision techniques. The proposed gun detection system uses CCTV images to read frames, process them, and identify the presence of a gun. The system's speed and efficiency make it a suitable solution for indoor environments where the need for quick action may be critical to preventing security threats. By detecting guns in real-time, the system can alert security personnel to the presence of a potential threat and help to decrease the response time in the event of an incident.

2. PROPOSED ALGORITHM

A schematic diagram of the proposed methodology for gun detection in a real-time indoor environment is shown in Figure 1. In the proposed algorithm, first, the algorithm calculates the HAAR-like features of the current frame. Then these features are compared with reference features of the existing data set. If the features are matched with reference features, then a gun is detected in the frame otherwise the frame is ignored and the next frame is read out.

The proposed methodology for automatic gun detection in a real environment consists of two phases i.e., the training phase and the testing phase.

2.1 Training Phase

In this phase, the system is trained for gun detection and consists of the following steps: First positive frames are selected from the dataset which contains the gun. Then the frames are pre-processed and the region of interest (Gun) is selected from the frames. After selecting the region of interest, HAAR Like

Table 1. Summary of the state-of-the-art approaches

Reference	Work based on	True positive rate	True negative rate	False positive rate	Accuracy	Comments
[2]	HIP Detector	83.07%	-	8.33%	84.26%	Uses color based segmentation
[14]	3D radar imaging technique					Complex configuration of T/R pairs of antennas
[17]	AAM				92.5%	Corner detection
[12]	Use fuzzy K-NN Approach					Implementation of shape context descriptor and Zernike moments
[25]	Clustering based on N-CUT					Implementation of N-cut algorithm for clustering
[29]	HOG Features	81.14%	96%	4%	88.57%	Complex methodology of features calculation
[8]	Sensors Technology					Complex conversion process of analogue output of a CCTV camera to a digital signal and transformation of digital signal to computer via fire wire
[21]	Edge detection					Implementation of Canny Edge detector and SUSAN corner detection
Proposed work	HAAR Like Features	91%	87%	12.50%	95%	Simple method for feature calculations

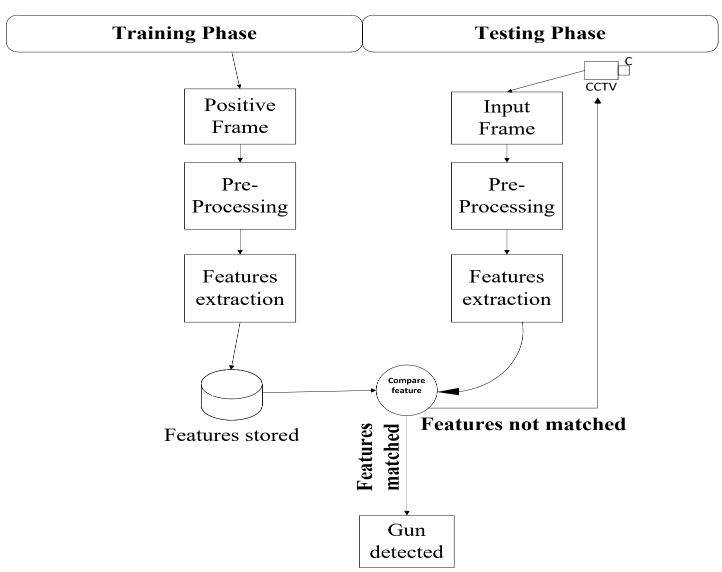

Fig.1. Schematic diagram of the proposed methodology for gun detection in real time indoor environment

features are calculated from the region of interest and are stored in a database for comparison of input frames.

2.2 Testing Phase

In this phase detection of the gun is done from input frames in the following steps: First, the input frame is read from the CCTV camera and then the input frame is preprocessed and HAAR Like features are extracted from the input frames which are explained in the next section. Then these features are compared with the existing features. If the features match then the gun will be detected from the frame otherwise the frame will be discarded and the next frame will be read from the CCTV stream.

2.3 Haar-Like Features

The proposed system uses a HAAR-like feature for gun detection which can be obtained by the product of an image and some HAAR-like templates.

More precisely, let *I* denote an image and *P* denote a pattern respectively with the same size N X N. The feature value f can be calculated for HAAR-like features which have k rectangles as.

$$f = \sum_{j=1}^{k} w(j).u(j) \qquad (1)$$

The mean intensity of the pixel in image *I* surrounded by j^{-th} rectangle is supposed to $u(j)$. The rectangle mean is referring to u and the weight assigned to the j^{th} rectangle is represented by $w(j)$ in the above equation.

Usually, to satisfy the following equation, the weight given to the rectangles of HAAR-like features is set to default numbers.

$$\sum_{j=1}^{k} w(j) = 0 \qquad (2)$$

For example, in Figure 2(a) default weights 1 and -1 are assigned to the rectangles of HAAR-like features. In Figure 2(c) default weights 1, -2, and 1 are assigned to the rectangles of HAAR-like features.

HAAR-like features provide a very attractive trade-off between speed of evaluation and accuracy which is the main cause of the popularity of HAAR-like features.

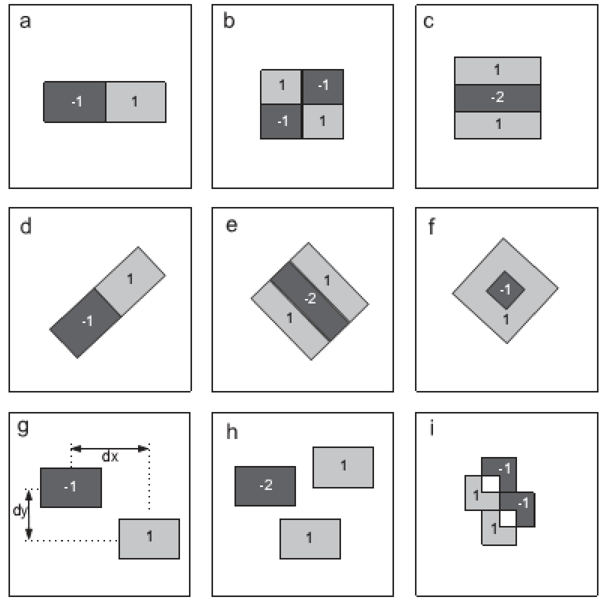

Fig. 2. HAAR-like features are presented with the default weights given to its rectangles. Fig (a) and (b) presented HAAR-like features introduced by Papageogiou et al. [28], Fig (c) presented a HAAR-like feature with three rectangles proposed by Viola and Jones [29]. Fig (d-f) presented Leinhardt's rotated feature. Fig (g) and (h) presented Li et al. [30] disjoint HAAR-like features and Fig (i) presented Voila and Jones [31] diagonal feature proposed to get diagonal arrangements of the object's visualization.

2.3.1 Integral Image

Integral image representation helps in the fast computation of HAAR-like features. It is the use of summed area table. Crow in 1984 introduced this concept which is used mostly in computer graphics.

The integral image can be defined as:

$$jj(m,n) = \sum_{m' \leq m, n' \leq n} j(m',n') \qquad (3)$$

Where $jj(m,n)$ is the integral image and $j(m',n')$ is the intensity of the original image. The integral image can be calculated in only one pass using the following recurrences.

$$s(m,n) = s(m,n-1) + j(m,n) \qquad (4)$$
$$jj(m,n) = jj(m-1,n) + s(m,n) \qquad (5)$$

Where $s(m,n)$ is the collective sum of row with the following cases:

$s(m,-1)=0$ And $jj(-1,n)=0$ with the integral image, constant time is required to calculate each feature. Four memory references are required to calculate the sum of any rectangle.

The integral image calculation is shown in Figure 3.

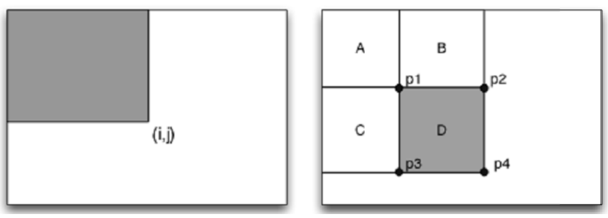

Fig. 3. Rectangle feature calculation and integral image. $k(i,j)$ = Sum of image intensities in shaded area

$$D = k(p4) + k(p1) - k(p2) - k(p3)$$

Moreover, rectangles which share corners are used by HAAR-like feature, the total amount of memory references required to calculate a feature can further be decreased.

For example, two, three and four rectangle features need only six, eight and nine memory references respectively.

2.4 Pseudo Code of the Proposed Algorithm

Step.1 CF=read frame
Step.2 Calculate HAAR-like feature of the current frame
Step. 3 Compare these features with pre-defined features
If (current frame features = predefined features)
Step.4 A Gun exists and detected
B CF=read next frame
C Go to step.2
Else
Step.5 A Ignore this frame
B CF=read next frame
Step.6 Go to step 2

In step. 1& step. 2 the algorithm read one frame from CCTV footage and assign this frame to the variable CF (Current Frame). The system then extracts HAAR like features from this frame. In step.3 comparison of the extracted features were initiated with predefined features on which the system was trained. In step.4, if the current frame features are matched with predefined features, then the gun is detected in the current frame and the algorithm read the next frame in step.4 (b) from the CCTV footage and that process is repeated continuously. If this condition is not matched then the algorithms ignore/discard that frame and read the next frame for the next operation.

The initial point of the proposed system was to select the best feature type. Therefore, we select HAAR like features for our proposed system because these features are mostly used for object detection, fast evaluation speed and simple method of calculations. In the proposed system, we have used our own created data set due to unavailability of standard datasets on Internet. For the dataset, we have recorded two video clips. Then we have extracted positive and negative frames from recorded videos with some background images.

Positive frames are those frames in which the gun is present and negative frames are those frames which do not contain guns. Using this dataset, we trained the HAAR cascade classifier to detect the gun in the video. A lot of miss detections occurred using the HAAR cascade classifier due to its weak classification. Therefore, we have used Support Vector Machine (SVM) for further classification of the detected region selected by the HAAR cascade classifier. We have trained the SVM classifier by extracting the HAAR-like features from the gun and background images and then classifying the selected region of the HAAR cascade on the trained SVM classifier. This classifier performs a strong classification to ensure that the detected region is a gun.

3. RESULTS

To evaluate the performance of the proposed method, it was tested in different sessions with various conditions. For Example, different angles of the gun and occlusion (if the object of interest is hidden by another object) etc. were used. There are multiple images with various scaling and angles in the dataset and these images are used to test the trained classifier.

The classifier detects the gun, the detector draws a bounding box around the gun if it exists in the scene. We conduct two recordings for the precise estimation of algorithm performance. The gun was not visible for the whole duration of the recording however the subject was holding a gun in hand in the first recording. The gun was occluded by certain objects or it was not in the coverage of the camera for a period of time. The subject did not hold any gun in hand but was empty-handed or take some casual items in hand in the second recording. To validate the performance of the cascade classifier we use evaluation metrics. This is discussed in the next section.

3.1 Evaluation Metrics

True positive (TP)

Gun exists in the frame and is detected.

1. $Tp = Gd \div (Gn + Gd)$

Gd=Frames in which gun exist and is detected

Gn=Frames in which gun exist but not detected

False positive (FP)

Gun is not existed in the frame and is detected

2. $Fp = {\sim}Gd \div ({\sim}Gd + {\sim}Gn)$

~Gd=Frames in which gun is not exist and is detected

~Gn=Frames in which gun is not exist and not detected.

True negative (TN)

Gun does not exist in the frame and nothing is detected.

3. $Tn = {\sim}Gn \div ({\sim}Gn + {\sim}Gd)$

~Gn= Frames in which the gun is not existed and is not detected

~Gd= Frames in which the gun is not existed and is detected

False negative (FN)

Gun exist in the frame but it is not detected

4. $Fn = Gn \div (Gn + Gd)$

Gd=Frames in which gun exist and is detected

Gn=Frames in which gun exist but not detected

Precision (P)

In relation to all instances, the rate of correctly detected gun instances is measured by precision.

5. $P = Tp \div (Tp + Fp)$

Accuracy (Acc)

In relation to all instances, the overall rate of the correctly detected gun is measured by the accuracy.

6. $Acc = (Tp + Tn) \div (Tp + Fp + Tn + Fn)$

Figure 4 shows some sample images from a data set in which some are positive frames and some are negative frames.

The experimental results of the cascade classifier are shown in Figure 5. As shown in the Figure, the bounding box around the gun ensures the detection of the gun in all test images. Similarly,

Figure 6(a) show an example input image of individuals carrying firearm from the dataset that is being analyzed. Figure 6 (b) shows the output of the proposed gun detection algorithm applied to the input image. The output image includes a bounding box around the detected gun in the input image. This is achieved using the proposed method, where the algorithm searches for specific features or patterns that are characteristic of guns and then locates and highlights these areas in the input image.

The purpose of presenting this information is to demonstrate the effectiveness of the proposed algorithm in accurately detecting guns in CCTV images, which can aid law enforcement agencies in preventing and solving crimes involving firearms.

In Table 2 we present the experimental results. In the initial stage of experiments, the system creates too many false alarms in the whole sequence of frames which makes the system unusable in a real scenario. To solve this problem, we increase the number of frames and did strong classification to reduce these false alarms. As a result, we noted a significant improvement in the accuracy and achieved an excellent result for the proposed system. Although the system misses some detection of the gun but does not generate too many false alarms for negative frames.

Table 3 shows a summary of the dataset used for training or testing the algorithm. It includes the total number of frames collected for the dataset. The number of frames containing guns (positive frames) and the number of frames without guns (negative frames). The number of images used for positive and negative frames.

Table 2. Experimental results of the proposed method

Evaluation metrics	Values
True Positive (TP)	91%
False Positive (FP)	12.5%
True Negative (TN)	87%
False Negative (FN)	8%
Precision (P)	98%
Accuracy (ACC)	95%

Table 3. Frames and number of images used in the experiments

Frames	No. of images
Positive frames	1100
Negative frames	1300
Total frames	2400

4. DISCUSSION

The proposed system uses HAAR-like features. HAAR-like features are rectangular patterns that are used to detect edges, lines, and other visual features in an image [32]. These features are calculated by comparing the pixel values in different regions of an image. A gun has a unique interest point which can be easily detected as a corner i.e., Barrel and Trigger guard therefore, this was the fact which is used in the proposed system. To use HAAR-like features for gun detection in CCTV images, we have trained the proposed algorithm to recognize the specific patterns associated with guns. This would involve collecting a large dataset of images containing guns and images without guns, and then using the HAAR-like features to train the algorithm to distinguish between the two. Once the proposed algorithm has been trained, it can be used to analyze new CCTV images in real-time to detect the presence of guns. If a gun is detected, the system could trigger an alarm or alert security personnel.

It is worth noting that while HAAR-like features can be effective for object detection, their performance can be affected by factors such as lighting conditions, image quality, and the size and orientation of the object being detected [33]. Therefore, it is important to carefully design and test any system that uses HAAR-like features for gun detection to ensure that it is accurate and reliable.

The proposed system can efficiently and accurately work in an indoor environment where the scene is clearly visible. In the outdoor environment, the system cannot properly detect the gun due to the presence of other objects in the scene. In an outdoor environment, the speed and accuracy of

Fig 4. Some samples from training and testing datasets.

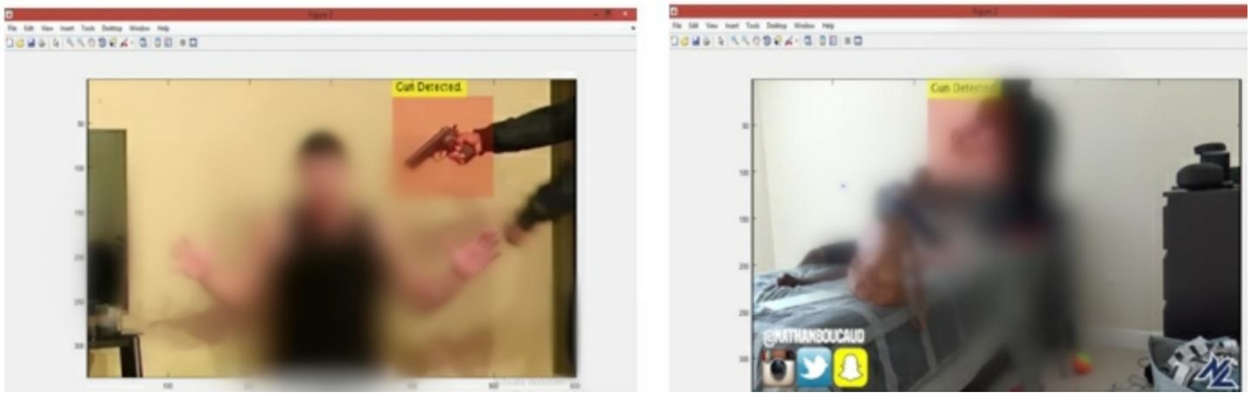

Fig 5. Results of the cascade classifier

(a) (b)

Fig 6. (a) Input image (b) output image

the proposed system will compromise efficiency and accuracy while searching for the gun. The performance of the proposed system is also affected when a sudden illumination change occurs in the scene or the scene is not clearly visible.

5. CONCLUSION

A comprehensive approach to indoor security that includes alarms, surveillance, access control, and staff training can help to create a safer and more secure environment for individuals inside the building. In this work, an automated system for gun detection has been presented. Unlike the existing methods, the proposed method detect gun without background subtraction and foreground detection. The proposed method always tries to detect only the gun in the whole scene. HAAR cascade classifier makes it possible to detect the gun in real time. Our proposed method also searches for the gun in an expected size. In the proposed method, only pistol and shotgun is detected in the current video. The proposed automatic gunshot detection system can provide important benefits for security and safety in indoor environments. By quickly detecting gunshots and immediately alerting authorities or security personnel, response times can be improved and potential harm to individuals in the area can be minimized. However, the proposed method cannot differentiate between the other types of guns. In future work, the focus will be to differentiate between other types of guns and to detect gun of any size. Moreover, future work also includes determining whether the gun is real or not.

6. ACKNOWLEDGMENTS

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7. CONFLICT OF INTEREST

The authors declare no conflict of interest.

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