International Journal for Modern Trends in Science and Technology
Volume 10, Issue 04, pages 359-364.
ISSN: 2455-3778 online
Available online at: http://www.ijmtst.com/vol10issue04.html
DOI: https://doi.org/10.46501/IJMTST1004055

Advanced Weapon Detection: Integrating AI Capabilities with Amazon Rekognition

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To Cite this Article
V.Prem Kumar , Mediboyina Chandra Mouli, Ganta Durga Prasad, Mullapudi Pavani Kumari, Pothuraju Vineel, Chodavarapu Pavan Raj, Advanced Weapon Detection: Integrating AI Capabilities with Amazon Rekognition, International Journal for Modern Trends in Science and Technology, 2024, 10(04), pages. 359-364. https://doi.org/10.46501/IJMTST1004055

Article Info
Received: 06 April 2024; Accepted: 18 April 2024; Published: 26 April 2024.

ABSTRACT

Security and safety are highly valued in today's world. A nation's ability to provide a safe and secure environment for travellers and investors determines how strong its economy will be. Even if closed-circuit television (CCTV) cameras are used to monitor and survey actions like robberies, human oversight and engagement are still necessary. We require technology that is capable of automatically identifying these unlawful actions. Real-time weapon detection is still a significant difficulty even with the use of improved CCTV cameras, high-performance processing gear, and sophisticated deep learning algorithms. The task becomes more complicated when one considers angle fluctuations and occlusions brought about by the weapon bearer and others in its vicinity. The goal of this project is to use CCTV video as a source to create a secure environment. Use to identify potentially dangerous weaponry the cutting-edge, publicly available deep learning algorithms. Using the weapon class as our starting point class and the relevant confused items inclusion concept, we performed binary classification with the purpose of decreasing the number of false positives and erroneous negatives. Because no pre-existing dataset for an actual situation existed, we created one using our own camera, manually collected images from the internet, obtained data from YouTube CCTV footage, and accessed data from the World Wide Web Movies Firearms databases (IMFDB) at imfdb.org and the University of Granada GitHub repositories. There are two approaches used: sliding window categorization and region proposal/object detection. The algorithms used are VGG16, Inception-V3, Inception-ResnetV2, SSDMobileNetV1, Faster-RCNN Inception-ResnetV2 (FRIRv2), YOLOv3, and YOLOv4. These full methods were examined in terms of precision and recall, which matter more when performing object detection than accuracy. Among all the algorithms, Yolov4 stands out the most, providing an F1-score of 91% and mean average accuracy that is 91.73% greater than previously attained.

Keywords: Gun detection, deep learning, object detection, artificial intelligence, computer vision

1. INTRODUCTION

The primary reason for the rise in crime rates worldwide is the growing usage of handguns during violent incidents. A nation has to maintain control of its law-and-order situation in order to advance. An atmosphere that is tranquil and secure is necessary for both attracting investors and generating money from the tourist sector. Gun violence is a major contributing factor to crime rates in many regions of the world. It mostly consists of nations where owning a weapon is allowed. These days, the entire globe is a community, and what we say and write affects other individuals. The harm is done even if the news they were told was manufactured and included no reality; it just needs to become viral in a matter of hours thanks to social media and the media in general. Hate speech has the power to drive individuals insane because people are becoming more depressed and less able to manage their rage. Individuals are susceptible to brainwashing, and psychological research indicates that in such circumstances, a person carrying a firearm may become delusional and engage in violent behaviour. There have been many incidents in recent years involving the use of deadly weapons in public areas. Commencing with the assaults on a few mosques in New Zealand the previous year, the assailant strikes the Christchurch AL-Noor Mosque at 1:40 pm on a Friday during prayer, murdering about forty-four defenseless and unarmed worshipers. Seven further individuals were killed in an incident that occurred on the same day at 1:55 PM, barely fifteen minutes later [1]. There have also been instances of active shooters in the USA and later in Europe. The most notable incidents were the 37-victim Columbine High School massacre in the United States, the 179-victim attack on Uotya Island by Andreas Broeivik in Norway, and the 23-victim Charlie Hebdo publication attack. The UNODC released statistics that show how many gun-related crimes there are per 0.1 million inhabitants in each country: 1.6 in Belgium, 4.7 in the US, and 21.5 in Mexico [2]. CCTV cameras are thought to be one of the most crucial security component needs as they help to solve this issue. [3] These days, CCTVs are placed in every public area and are mostly utilized for crime prevention, safety, and other detection-based security measures. The most significant evidence in courts is CCTV footage. When law enforcement officials get to the site of a crime, they take the video recording with them [4]. When comparing the surveillance systems of other nations, we find that the United Kingdom has around 4.5 million cameras in use. Around 2010, there were 50,000 cameras installed in Sweden. Using just 450 cameras, the Polish authorities was able to drastically cut down on drug charges by 60% and street fights by 40% in Poznan [5]. With 170 million cameras spread across the country, China boasts the largest surveillance system in the world. By 2020, an additional 400 million cameras are scheduled to be connected, resulting in a threefold expansion of the system. Chinese authorities used its robust CCTV camera network and face recognition technology to locate and detain BBC reporter John Sudworth in only seven minutes, putting the offender behind bars [6]. Even if surveillance cameras were deployed in the past, using them for security reasons was not a reliable or simple process. In order to keep an eye on displays, a person must always be present. The CCTV operator has ten hours to watch twenty to twenty-five screens. He needs to watch out for, recognize, and take action against any circumstance that can endanger people or property. The person's ability to focus on each screen is progressively worse as the number of screens rises. The individual in charge of the screens cannot possibly pay the same amount of attention all the time [7]. Installing video surveillance systems with the capacity to automatically identify firearms and sound an alarm to notify operators or security personnel is the solution to the aforementioned issue. Though similar research frequently investigates hidden weapons detection (CWD), mostly utilizing X-rays or millimetre wave pictures applying typical machine learning approaches, there is not a lot of work done on methods for weapon identification in surveillance cameras [8],[12]. Convolutional neural networks (CNNs), which are a kind of deep learning, have produced ground-breaking breakthroughs in object identification and classification in recent years. In terms of grouping, detection, and localization—three classic image processing problems it has produced the best results to date When comparing the surveillance systems of other nations, we find that the United Kingdom has around 4.5 million cameras in use. Around 2010, there were 50,000 cameras installed in Sweden.

2. LITERATURE SURVEY

Real-time object recognition and categorization became a challenge following significant advancements in deep learning models, processing hardware, and CCTV technology. There has been very little prior research in this area, and the majority of that research focused on the detection of hidden weapons (CWD). Beginning with hidden weapon detection (CWD), which was based on imaging methods including millimetre-wave and infrared imaging, it was utilized for luggage inspection and other safety concerns at airports prior to its application in weapon detection [8]. For the purpose of finding undetected weapons at airports and other secure sites within the body, Sheen et al. proposed the CWD approach, which depends on a three-dimensional millimetre wave imaging technology. A CWD method was proposed by Z. Xue et al. based on a fusion-based multi-scale decomposition methodology that integrates colour visual images with infrared (IR) images. In order to emphasize the concealed armament of the target picture, R. Blum et al. proposed a CWD approach based on the integration of visual and IR or mm wave pictures utilizing a multi-resolution mosaic methodology. Image fusion was proposed as a CWD approach by E. M. Upadhyay et al. When there was a picture of the scene above and under an exposed region, they employed IR imaging and visual fusion to find hidden weaponry. Their approach involved applying a homomorphic filter on infrared and visible images taken under various exposure circumstances.

Various combinations of extractors and detectors are used in current approaches to achieve high accuracy. Simple techniques like intensity descriptors, boundary detection, and pattern matching are employed, as are more complex ones like cascade classifiers with boosting. Although CWD had been effective in certain situations, it had several drawbacks. Non-metallic firearms cannot be identified by these technologies since they are dependent on metal detection. Because they had to be used in conjunction with conveyor belts and X-ray scanners and were inaccurate because they responded to any metallic item, they were expensive to use in many places. Health hazards and financial costs prevented these techniques from being used in practice. Moreover, acoustic gunshot detection was prevented by video-based weapon detection, which may be used in conjunction with it for implementation.

3. SYSTEM ANALYSIS

A. EXISTING SYSTEM

Hidden weapon detection (CWD) relied on imaging modalities including millimeter-wave and infrared imaging for luggage control and other security objectives at airports before being used to weapon detection [8]. Based on three-dimensional millimeter wave imaging technology, Sheen et al. presented the CWD approach for locating hidden weapons at airports and other secure places within the body [13]. A CWD solution was proposed by Z. Xue et al. [14] that combines color visual and infrared (IR) data using a fusion-based multi-scale decomposition mechanism. Using a multi-resolution mosaic technique of the target picture, R. Blum et al. devised a CWD technique to highlight an undetected weapon by merging a photo with an infrared or millimeter wave picture.

DISADVANTAGES OF THE EXISTING SYSTEM

Limited Dataset:

The creation of a dataset by combining various sources might lead to biases or insufficient representation of real-world scenarios. The limitations of the dataset could affect the model's generalization to diverse situations.

Complex Real-world Scenarios:

Real-world scenarios are often complex, with variations in lighting conditions, camera angles, and occlusions. The existing system may struggle to perform consistently in such challenging environments.

False Positives and False Negatives:

Despite efforts to reduce false positives and false negatives, the system might still produce inaccurate results. Addressing these errors is crucial, especially in security applications, as false positives can lead to unnecessary interventions, while false negatives pose a security risk.

Real-time Processing Challenges:

Achieving real-time processing for CCTV videos with high accuracy is a demanding task. The existing system may face challenges in meeting the real-time requirements, especially when dealing with high-resolution video streams.

B. PROPOSED SYSTEM

The proposed system aims to address the limitations inherent in the existing "Weapon Detection in Real-Time CCTV Videos Using Deep Learning." To enhance the system's performance, the proposed approach focuses on several key aspects. First, there will be a concerted effort to curate a more diverse and extensive dataset, incorporating a wider range of real-world scenarios, camera angles, and lighting conditions. This will help mitigate biases and improve the model's generalization capabilities. Additionally, the system will undergo refinement to better handle complex situations, such as occlusions and variations in object appearances. Advanced algorithms with improved robustness against adversarial attacks will be explored to bolster the system's security.

The proposed system also emphasizes the importance of real-time processing, seeking optimizations in model architectures and leveraging parallel processing to meet stringent video streaming requirements. An increased emphasis on privacy preservation will be incorporated, ensuring that the system adheres to privacy norms and regulations. Moreover, the scalability of the system will be a priority, enabling its deployment across a broader network of CCTV cameras, making it suitable for large-scale surveillance applications. Ongoing advancements in deep learning and computer vision will be closely monitored to ensure that the proposed system remains adaptable to emerging, more effective algorithms. Through these enhancements, the proposed system aims to provide a more robust, efficient, and scalable solution for real-time weapon detection in CCTV videos, thereby contributing to a safer and more secure environment.

ADVANTAGES OF THE PROPOSED SYSTEM

Improved Generalization:

By incorporating a diverse and extensive dataset, the proposed system enhances the model's ability to generalize to various real-world scenarios. This results in increased accuracy and reliability in detecting weapons across different environments, lighting conditions, and camera angles.

Enhanced Real-Time Processing:

The system focuses on optimizing model architectures and leveraging parallel processing to meet the demands of real-time video streaming. This improvement ensures timely detection of weapons, addressing the challenges associated with processing high-resolution CCTV video feeds efficiently.

Increased Robustness and Security:

The proposed system explores advanced algorithms with improved robustness against adversarial attacks. This enhancement enhances the system's security, making it more resilient to potential manipulations and ensuring reliable weapon detection even in the face of intentional disruptions.

Scalability for Large-Scale Deployments:

The system prioritizes scalability, enabling its deployment across a broader network of CCTV cameras. This scalability is crucial for applications in smart cities or other large-scale surveillance scenarios, where multiple cameras need to be monitored simultaneously.

Privacy Preservation:

The proposed system places a strong emphasis on privacy preservation, ensuring compliance with privacy norms and regulations. This feature is essential in maintaining a balance between security measures and individual privacy rights, making the system more socially and ethically responsible.

4. SYSTEM DESIGN

SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture.

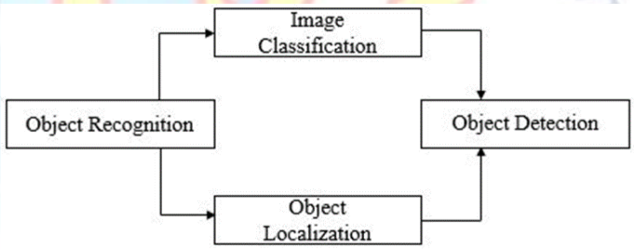

Fig 1. Methodology followed for proposed model

5. SYSTEM IMPLEMENTATION

MODULES

Data Collection and Preprocessing:

This module involves the collection of a diverse dataset from various sources, including weapon photos, internet images, YouTube CCTV videos, GitHub repositories, and data from academic institutions. The collected data is then preprocessed to clean and organize it, ensuring compatibility with the deep learning models.

Model Training and Selection:

The system incorporates multiple deep learning algorithms such as VGG16, Inception-V3, Inception-ResnetV2, SSDMobileNetV1, FRIRv2, YOLOv3, and YOLOv4. This module is responsible for training these models on the prepared dataset, fine-tuning hyperparameters, and selecting the best-performing model based on evaluation metrics such as precision, recall, and F1-score.

Real-Time Detection Integration:

The selected deep learning model is integrated into a real-time CCTV video stream. This module may involve implementing either sliding window/classification or region proposal/object detection techniques to achieve real-time detection of weapons. Special attention is given to optimizing processing speed and accuracy for efficient deployment.

Performance Evaluation and Optimization:

This module focuses on evaluating the system's performance using metrics like precision, recall, and F1-score. Based on the results, the system is fine-tuned and optimized to address any identified shortcomings. Continuous monitoring and improvement ensure the system remains effective in detecting weapons across diverse scenarios.

Privacy and Ethical Considerations:

This module addresses privacy concerns and ethical considerations associated with the surveillance system. It involves implementing measures to preserve privacy, such as anonymization techniques and adherence to legal regulations. Striking a balance between security and individual privacy rights is crucial, and this module ensures the system's responsible use.

6. RESULTS AND DISCUSSION

We have identified guns in low-resolution, low-light real-time CCTV broadcasts at a frame rate of one frame per second. The majority of previous work focused on high-quality image and video detection; as a result, since those models were trained on high-quality datasets, it is not feasible to recognize a low-quality item in real-time. After training and testing models on the datasets listed in Table 1, the results are analyzed. The methodology section provides a description of how the outcomes of various techniques are assessed. Since handguns and revolvers account for 97% of the weapons used in robberies, our primary problem statement is real-time detection. Various dataset findings for the sliding window and region proposal approaches have been assessed here.

Dataset 1 contains 1732 images distributed between two classes of pistol and not-pistol with 750 and 982 images in each class respectively. Experimentation on dataset-1 has

Sr.No	Algorithms	Precision	Recall	F1-score
1	VGG16	71%	66.66%	69.09%
2	Inceptionv3	74.11%	96.18%	83.71%
3	Inception-ResNetV2	79.24%	89.54%	84.07%

Fig 2. Algorithms Test results

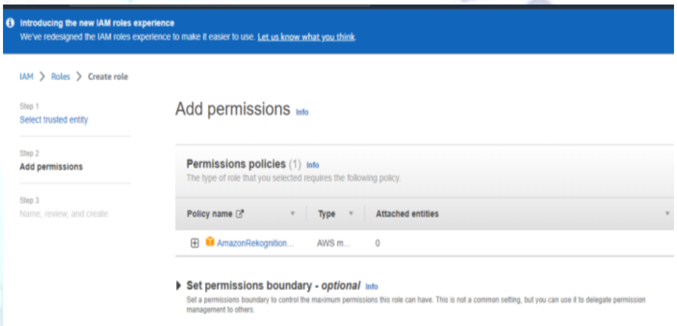

Fig 3. Amazon Rekognition Configuration

***Fig 4.* Weapon Detection.**

7. CONCLUSION AD FUTURE WORK

This study has proposed a revolutionary automatic weapon identification system in real-time for both monitoring and control applications. For the protection and betterment of mankind, this endeavour will undoubtedly contribute to the improvement of security and law and order, particularly for those nations that have suffered greatly as a result of these violent acts. Since security and safety are the main concerns of investors and visitors, this will have a favourable effect on the economy.

Our goal has been to identify weapons in real-time CCTV footage while minimizing false positives and negatives. We created a fresh training database for the real-time situation, trained it, and assessed it using the most recent, cutting-edge deep learning models in order to achieve high accuracy and recall utilizing two methods: region proposal/object detection and sliding window/classification the most advanced Yolov4, who was trained on our recently acquired database, had the most fruitful outcomes since he provided very few erroneous positive and negative values. On every kind of picture and video, it produced a 91.73% mean average accuracy (mAP), a 91% F1-score, and an almost 99% confidence score. It meets the requirements for an automated real-time weapon detector, so to speak. Based on the data, we were able to obtain the greatest mean average accuracy (mAP) F1- score when compared to previous real-time scenario study.

Future efforts will focus on further lowering false positives and negatives because there is still room for improvement. In the future, we could also try to add more classes or objects, but improving precision and recall is the main goal for now.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

References

[1] (2019). Christchurch Cathedral Shootings. Reached on July 10, 2019. [Online]. The page https://en.wikipedia.org/wiki/Christchurch_mosque_shootings is accessible.

[2] (2019). Worldwide Research on Murder. Reached on July 10, 2019. [Online]. The global study on homicide may be seen at https://www.unodc.org/unodc/en/data-and-analysis.html.

[3] W. Desman, in the Research and Evaluation Branch of the Community, Contract, and Aboriginal Policing Services Directorate, "CCTV: Literature review and bibliography." Royal Canadian Mounted, Ottawa, Ontario, Canada, 2003.

[4] J. Ratcliffe, "Video surveillance of public places," US Department of Justice, Office of Community Oriented Policing Services, Washington, DC, USA, Technical Report No. 4, 2006.

[5] "Automated detection of firearms and knives in a CCTV image," by M. Grega, A. Matila's, P. Guzik, and M. Leszczuk, Sensors vol. 16, no. 1, p. 47, Jan. 2016.

[6] (2019). The BBC Reporter Was Captured by China's CCTV Surveillance Network in Just 7 Minutes. Reached on July 15, 2019. [Online] Available: https://techcrunch.com/2017/12/13/china-cctv-bbc-reporter/

[7] K. MacLennan-Brown, J. Gattuso, and N. Cohen. 2009 Manual of Operational Requirements for CCTV. Home Office Scientific Development Branch, St Albans, U.K., 2009.

[8] Pattern Recognit., vol. 46, no. 9, pp. 2420–2436, Sep. 2013, G. Flitton, T. P. Breckon, and N. Megherbi, "A comparison of 3D interest point descriptors with application to airport baggage object detection in complex CT imagery."

[9] "Automatic image analysis process for the detection of concealed weapons," R. Gesick, C. Sarita, and C.-C. Hung, Proc. 5th Annu. Workshop Cyber Secure. Inf. Intel. Res. Cyber Secure. Inf. Complexities Strategies (CSIIRW), 2009

[10] A computer vision-based framework for visual gun identification using the Harris interest point detector, R. K. Tiwari and G. K. Verma, Procedia Compute. Sci., vol. 54, pp. 703–712, Aug. 2015.

[11] A computer vision-based framework for visual gun identification using SURF, by R. K. Tiwari and G. K. Verma, in Proceedings of the Int. Conf. on Electron., Signals, Common. Optim. (EESCO), Jan. 2015, pp. 1–5.

[12] In Proc. IEEE Int. Conf. Image. Syst. Techn. (IST), Sep. 2015, pp. 1-4, Z. Xiao, X. Lu, J. Yan, L. Wu, and L. Ren, "Automatic detection of concealed pistols using passive millimeter wave imaging."

[13] "Three-dimensional millimeter-wave imaging for concealed weapon detection," by D. M. Sheen, D. L. Mcmakin, and T. E. Hall, IEEE Trans. Micro. Theory Techn., vol. 49, no. 9, pp. 1581–1592, Sep. 2001

[14] Fusion of visual and infrared pictures for hidden weapon detection, Z. Xue, R. S. Blum, and Y. Li, Proc. 5th Int. Conf. Inf. Fusion, vol. 2, Jul. 2002, pp. 1198–1205.

[15] Multisensory hidden weapon detection by employing a multiresolution mosaic technique, R. Blum, Z. Xue, Z. Liu, and D. S. Forsyth, Proc. IEEE 60th Veh. Technol. Conf. (VTC-Fall), vol. 7, Sep. 2004, pp. 4597–4601.

[16] "Exposure fusion for concealed weapon detection," by E. M. Upadhyay and N. K. Rana, in Proceedings of the 2nd International Conference on Devices, Circuits and Systems (ICDCS), March 2014, pp. 1–6.

[17] R. Maher, "Acoustic gunshot recordings: modeling and signal processing," in Proceedings of the IEEE 12th Digit. Signal Process. Workshop (4th IEEE Signal Process. Educ. Workshop), September 2006, pp. 257–261.

[18] "Evaluation of gunshot detection algorithms," A. Chacon-Rodriguez, P. Julian, L. Castro, P. Alvarado, and N. Hernandez, IEEE Trans. Circuits Syst. I, Reg. Papers, vol. 58, no. 2, pp. 363–373, Feb. 2011.

[19] (2019). Video Surveillance: A History, From Edison to the Internet. Reached on June 13, 2019. [Online]. Accessible at https://www.business2community.com/tech-gadgets/ahistory-of-video-surveillance-from-edison-to-internet-0578308

[20] (2019). IFSEC Global | Security and Fire News and Resources - Infographic: The Evolution of Video Surveillance. Reached: September 15, 2019. [Online]. The infographic "History of Video Surveillance" is accessible at https://www.ifsecglobal.com/video-surveillance/