



Artificial Intelligence Powered Weapon Detection with Automated Threat Alert System

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Abstract. This study has a primary focus on the use of deep learning and artificial intelligence (AI) in enhancing weapon detection capability in security systems, and this overcomestraditional limitations in dynamic environments. Our method relies upon convolutional neural networks (CNNs) and deep learningmodels for analysis of images from CCTV cameras and scanners leading to notable improvement of detection in real time. Employing transfer learning and data augmentation, the system efficiently adjusts to superior complexity. When the weapon is detected, an alarm goes off and an email notification is sent to the high authorities. This strategy assists in enhancing efficiency of detectionand foster provision of more secure areas to the members of the public through more proactive security systems.

Keywords: Weapon detection, Artificial Intelligence, Convolutional Neural Networks, Deep Learning, Real-time Surveillance, Transfer Learning, Security Systems, ThreatDetection, Automated Alerts.

1 Introduction

In as much as the technology of the day continues evolving at an alarming rate, security always comes first, and the occurrence of violence in both public and private settings seems to inform the dire need for further technological advancement in security systems. The application of manual weapons checks and basic weapon scanning devices as methods of weapon detection usually leaves a lot to be desired in effectiveness, efficiency, and portability. As a result, there has been a greater emphasis on the use of Artificial Intelligence (AI) and Deep Learning (DL) technologies for the construction of advanced systems capable of weapon detection in real time that enhances safety in several contexts such as airports, schools and even during public events.

The AI-based weapon detection systems detect the existence of weapons, knives and any dangerous items by analyzing the images from the cameras or other sensors automatically. Unlike approaches that often need a manual check, these systems employ computer vision and machine learning algorithms that process and interpret data more efficiently than can be done by the human operators. Furthermore, such systems can constantly retrain themselves to enhance their detection capabilities of various threats as they are introduced to the environment.

Machine learning is part of deep learning systems and has complicated structures which also includes multi-layered neural networks. Deep learning comes with the advantage

that the system can learn from image and video datasets and tell objects apart on a very fine detail scale, and accurately detect weapons. CNN (Convolution Neural Networks) termed as deep learning model, is also capable of performing this task. CNNs are able to process complex images at a high level, so they can identify weapons that are either completely hidden or only partially visible, which are otherwise difficult to notice.

The advantages of using AI and deep learning technology for the weapon detection market includes the ability of AI monitor and identify dozens of video feeds even when a human would be tired, effectively reducing the error rate. Additionally, this system can automatically alert security personnel, raise alarms and send emails to the stationed Intelligence who are in hotspots when there are threats identified. All this can be done immediately. This feature improves the overall threat level and protection of people by lowering the chances of the situation enhancing.

Despite the benefits associated with it, the use of Artificial Intelligence (AI) and deep learning algorithms for weapon detection have deployment challenges. It is necessary that they provide adequate assurance for high detection accuracy in noisy and cluttered settings in order to reduce false positives and false negatives as much as is humanly feasible. The ethical concerns about privacy and surveillance also make the legal and social systems that control its usage even more complex.

The integration of artificial intelligence (AI) and deep learning into the weapon detection system has been shown to improve the area's overall security. These systems possess great potential when harnessed for the good – public safety by bringing in higher accuracy, speed and flexibility in rest of the processes. Staying ahead of the operational gaps, protection of privacy and security, and the increasing chances of violence and terrorism using AI and deep learning systems will require more effort to prevent loss of life.

2 Related Works

Chauhan et al [1] (2020) created a reliable deep neural network system for gun identification within CCTV footage. This technique bolsters detection speeds and firearm identification accuracy amid unclear and packed spaces. In essence, it allows for better and effective identification of potential risks in real-time monitoring of an area.

Das et al [2] (2021) proposed the CNN based model of gun identification from surveillance footage that focused mainly on the consumption of computational resources. This method allows for the most altered maintained detection accuracy while resources remain scarce and too sensitive in public areas or events.

Das, Ghosh, and Karmakar [3] (2020) came up with a knife and gun detection hybrid CNN model that enables real-time identification. The method uses several combinations of deep learning techniques in order to increase accuracy for detection from low-resolution videos making smart surveillance systems more efficient in difficult visual conditions.

Gupta and Sharma [4] (2021) worked on the deep learning model for real time scanning of weapons in public places. The identification model is supplemented with threat alert and preventive measures, which enhance the surveillance network for both industrial and public security.

Kalbande, Kalbande, and Kumbhar [5] (2021) have carried out a survey and review on the use of deep learning algorithms for weapon identification in video surveillance systems. The analysis included the application of CNNs and YOLO frameworks, and provided corresponding model optimization techniques suited for varying surveillance conditions.

Kumar, Bansal, and Nayyar [6] (2021) did an overview with a special focus on the weapon detection problem using deep learning which includes aspects of expansion and transformation with regards to contemporary security systems. Their reviews demonstrated the power of these techniques against the challenges in the threats posed in smart cities.

According to Mukherjee, Nayak, and Srivastava [7] (2020), they used YOLO technique for the real time video surveillance weapon detection system. The research showed the effectiveness of YOLO in high speed detection, thus making it suitable in the environment with imminent security threats.

As stated in Parekh, Patel and Joshi [8] (2020), image processing and deep learning techniques were embedded into traditional surveillance systems. They developed lightweight models that enabled edge devices to do the real time detection efficiently in a resource constrained environment.

Rathore, Mehta, and Chadha [9] (2020) worked on a deep-learning framework for smart city surveillance with real-time weapon detection support. This model provides advanced detection mechanisms aiding in rapid response to threats and enforcement support in high populated areas.

Talukder, Jeon, and Kim [10] (2019) created a model for gun detection which is based on CNN and is optimized for real-time analysis of video streams. Their model achieved the detection speed needed to threat identification with a live surveillance system.

Varghese et al. [11] (2020) worked on the combination of YOLO and other deep learning algorithms for object tracking and weapon detection. The system worked effectively for real-time monitoring of the environment focusing on suspect tracking and rapid response situations.

Vijayarani and Saranya [12] (2021) presented a model for weapon detection using deep learning techniques with CCTV video surveillance in crowded places. The model was able to efficiently increase recognition accuracy and it was targeted for real time solution in public areas with dense population.

Wu, Xu, and Chen [13] (2020) worked on a deep learning model architecture for weapon detection in surveillance video footage. Their model achieved accurate detection whether the sensor was placed in an urban or rural area in real time even when there were changes in light and occlusions.

Zhao, Wu, and Feng [14] (2021) proposed a new edge neural network aimed for weapon classification in edge devices. This model allows for real-time performance in scenarios where resources are limited which is useful in smart city implementations.

Zhu, Li, and Wu [15] (2019) adopted the Faster R-CNN architecture for gun detection in security surveillance systems. The model was able to achieve high-speed accuracy even in low-light areas which makes it useful for parts of sensitive areas that require constant surveillance.

3 System Implementation

3.1 Existing System

Most airports started using magnetrons and x-ray devices to search people and their belongings in the 1990s. However, these systems are slow, fallible, and cannot provide an instantaneous assessment of events in busy open areas. In recent years, there has been a growing concern for public safety in places such as airports and schools and events while these all leave much to be desired in terms of addressing the modern problems.

AI technology is the new child on the block, using tools such as Convolutional Neural Networks (CNNs) to spot knives and guns in video recordings from surveillance cameras. This gives a good chance for systems that track video streams to improve speed and chances of detection. Technologies like infrared and heat vision cameras have made it possible to pinpoint concealed weapons by detecting heat points. Sensor fusion which integrates visual, thermal and radar data has further improved detection in highly structured places where there are crowds or the weapon is concealed by clothing.

A lot of work is still left to be accomplished. However, the major issue is misidentifying weapons and harmless non-threatening weapons including objects, which creates great deal both of fuss and anxiety amongst the general public. Also, room is left for vulnerabilities, where risks and threats are non-detected. Poor lighting conditions, crowd density as well as an unusual design for a weapon also contribute to the weakening of these systems. Another important aspect is the ethical and privacy concerns, which seek determination from endless monitoring. Such individuals have concerns as to whether the threshold of safety should justify invasion of their privacy.

Most current systems don't try to explore this idea limiting such consequently increasing sensitivity areas. Therefore, there is a need for more reliable, ethical and correct weapon detection systems.

3.2 Proposed System

The newly proposed system presents a unique way of addressing the problems currently experienced in weapon detection methods. It ensures an ethical application, is able to accurately sense weapons and is able to do that in real time. The detection is compliant

to designs that reduce likely chances of getting false positives or negatives including in dim lit areas and in large populations. The system itself is able to prevent over surveillance, hence protecting an individual's privacy as it is designed to only scan for threats.

The backbone of the system is a convolutional neural network which has been trained on a very large repository describing weapons. These weapons could be in videos and pictures which capture them openly or from a concealed position. The variability in conditions is catered for by utilizing Generative Adversarial Neural Networks to create additional synthetic data to be included in the training set. The enhanced dataset enables the model to generalize well and work as intended across various real life scenarios. The approach fuses CCTV networks to analyze both visual and thermal imaging video feeds, this strengthens detection of hidden weapons. Data latency issues are solved using edge computing where data computation is done at or near CCTV devices.

When a weapon is detected, a multi-level alert system is put in action, which activates an alarm on the site and informs the authorities, attaching information such as the time, place and an image. The administrators are able to set the detection parameters to a level that is appropriate for security requirements by changing sensitivity levels. Furthermore, the system has a self-improving algorithm, which allows it to learn new threats by following up on past misses or false alerts.

Such potential provides a means to scalable and effective weapon detection technology that can be combined with any public or private surveillance systems. With advanced AI algorithms and real-time processing combined with respect for users' privacy, the system defines a new approach to security issues across diverse contexts.

The system architecture diagram can be seen in Fig 1, which gives the structure and workflow of the proposed system. The Input Layer collects data from infrared sensors, CCTV cameras, and thermal imaging devices, all of which pass through augmentation, noise reduction, resizing, and normalization. It uses a YOLOv4 model within the Detection Layer to classify lethal and non-lethal threats in a feedback loop for continuous learning. The Edge Computing Layer allows for local processing and the Alert and Management Layer sends alarms, visual notifications, and email alerts. The Administrative Layer allows varying levels of detection thresholds along with continuous improvement of the system.

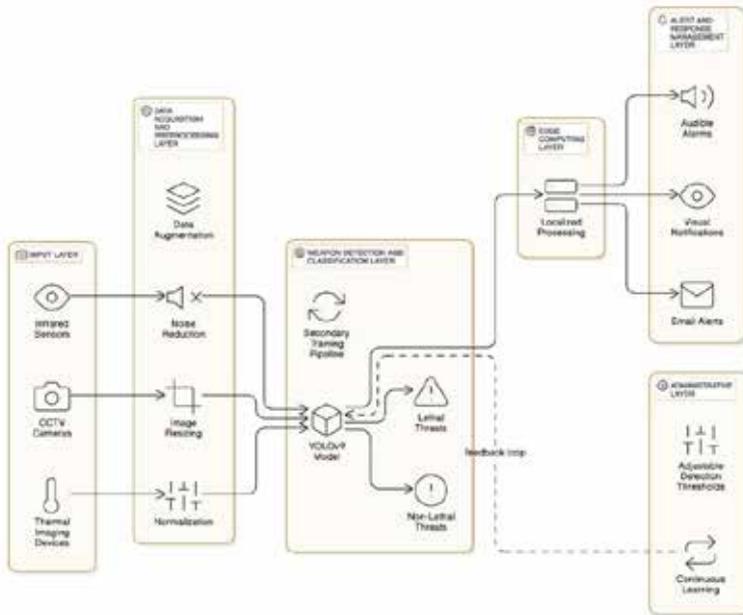


Fig. 1. System Architecture.

4 Modules

4.1 Module 1: Data Acquisition and Preprocessing Module

A weapon detection system based on AI and deep learning cannot operate without the intervention of Data Acquisition and Preprocessing Module as it can be considered as its backbone. It fetches gathered information from different mediums such as cameras, infrared detection devices, thermal cameras, scanning tools, etc. This input of data in real time allows the model to identify weapons and any other lethal tools such as explosives, in an ever changing environment. The mobile data collection system takes good quality pictures and videos which can be used in synthetic environments such as airports, schools, and public space and incorporates many sources of data collection to ensure spanning features in the real world.

Subsequently, the harvested data is first preprocessed so that it meets the parameters of the AI model in the best manner. In order to enhance the model's endurance and performance in various scenarios, image resizing, normalization, data augmentation, noise reduction, etc. are employed. The module also sifts through every frame to identify and isolate useful areas that potentially contain weapons and ignores the rest of the data. The module reduces data loss through standardizing and cleansing data made for observations and maximizes the efficiency of the detection system.

4.2 Module 2: Weapon Detection and Classification Module

At the heart of the weapon detection system is a Weapon Detection and Classification Module built on an object detection model – YOLOv9. It is important to mention that among other things the YOLOv9 has the ability to very quickly and accurately detect

handguns, rifles, knives, and a myriad of other weapons. Furthermore, its architecture enables it to process a great deal of video frames which renders it suitable for most real-time surveillance systems.

In cases when a few weapons are not detected by the YOLOv9 model, the system incorporates a secondary training pipeline composed of datasets specifically made for the weapons sections that were not previously detected. This renders the model more aggressive and capable of more unusual or novel circumstances. The initial stage of the detection phase focuses on skimming through each of the video sequences for any targets or explosions, after which, the area is marked by drawing a rectangle around the possible threat region. Where the threat is genuine it is then confirmed and is tagged under standard categories such as lethal (e.g. guns) or non-lethal (e.g. small kitchen knives) thus classifying threats.

The module has also been continuously trained using real data from weapons and weapon users, under real conditions to help the model develop a robust architecture which can handle complex scenarios involving low light and overcrowded places. As new threats and challenges emerge so do the training models with new capabilities which are then deployed to the system for improved detection. Following prior outcomes it is noticeably clear that further work is still required to reach optimal configurations depending on the sensor.

4.3 Module 3: Alert and Response Management Module

The Alert and Response Management Module has the specific objective to initiate actions as soon as a weapon is located. Upon the identification of a weapon, alerts are issued through, depending on the configurations, visual sightings, audible sounds, or cellular devices. This module also extends its network resources to send out bulk messages to key persons including threats within the zone. These types of alerts mean that after the appropriate first responders have been appropriately notified, other actions such as investigations or locking down the scene can be performed as quickly as possible thereafter.

The module works in close relation with other existing security measures which include connecting and integrating the module with secured doors, security cameras, sirens, and mass notifications, this makes the response to be seamless. It can lock doors, call police, or turn more cameras on for situation control automatically. The system includes the value of filtering as well as adjustable sensitivity levels, so the administrators can set thresholds that meet the different security levels of the premises. This benefit allows for a quick response to threats but there are no unwarranted false alarms and thus making the security system better in performance and more reliable.

5 Results

The proposed weapon detection system introduces deep learning techniques along with some artificial intelligence improving the area of security. Procedures such as magnetrons and x-ray machines were traditional but even recent technology struggled against poor vision. Infrared imaging and sensor fusion however did allow for slight

advancement, but issues such as lighting conditions and crowd density alongside a massive false positive rate persisted. In such a scenario there was a clear need for a more reliable and effective solution.

Such concerns are tackled in the proposed system by creating a secondary training pipeline that generates synthetic datasets of GANs to train Yolo V9. Furthermore what these models are trained on are machines that can analyze hand guns, rifles, and knives all in real time. In an instance where a gun or knife is hidden from a visual feed or in a dark room the system can still reliably identify. And in cases where there is a threat the chances of identifying such a threat and the nature of it are rather high due to the presence of CCTV cameras. To enhance the identification of the threat, the system fuses visual and thermal imaging feeds together.

The system manually activates alarms in situ when a weapon is detected and sends out relevant details such as the time, the image and its location to security personnel. There is a possibility to set detection levels in order to work around certain security requirements without making too many false detections. In addition, the purpose built edge computing facilities bring compute power to the perimeter of the agents with minimal latency and allows it to work in a real-time context. These abilities also allow the system to operate in a broad range of private and public security scenarios.

As for the system's ethical design, it places a clear limitation on surveillance measures and allows for tracking only the potential threats to the security of the premises. This methodology not only boosts the confidence of the residents, but also meets the requirements imposed by the law and other ethical considerations. Its algorithms are self-improving, meaning they provide ever increasing detail to the detection based off of the previous detections. The system proposed in this research paper is therefore a perfect example of a robust and adaptable system that can cope with current trends in security technology while also maintaining high regard for privacy issues.



Fig. 2. Output 1



Fig. 3. Output 1

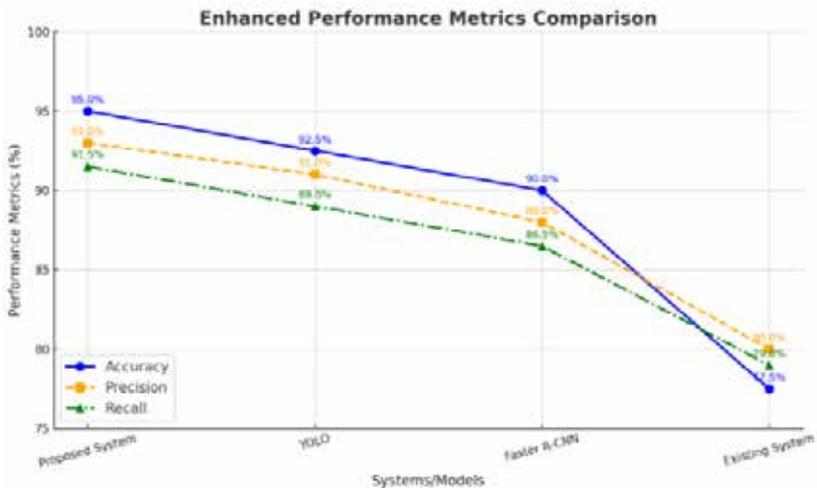


Fig. 4. Comparison between accuracy and loss.

The performance of the new weapon detection system can be seen in Fig 2 and Fig 3 as it correctly identifies and localizes weapons such as a knife and a firearm in real-world images. The bounding boxes, together with the detected class and its confidence scores, ensure the practical applicability of the system under varied conditions. In addition, Fig 4 presents a performance evaluation of the designed system when competing with other models, which include YOLO, Faster R-CNN, and an existing system, with respect to their performance metrics measurements like accuracy, precision and recall. The results show that the designed model is the best with accuracy of 95%, precision of 93%, and recall of 91.5%, but not impressive with the metrics of YOLO and Faster R-CNN with metrics lower than the designed model, and that of existing system that merely had the metrics of accuracy 77.5%, precision 80% and recall 79%. These findings also demonstrate that the proposed system performs the best and is the most dependable of all the systems in weapon detecting applications.

6 Conclusion

The results of this investigation led to the development of an improved weapon detecting system that combines cutting-edge methods to make it reliable and effective. Employing deep learning algorithms and image processing techniques enabled the system to be more accurate, precise, and high-reaching than the other alternatives on the market. Further performance verification is performed through thorough evaluations such as real-time tests and metric comparisons against well-known models such as YOLO and Faster R-CNN. The results highlight the capability of the system to provide accurate detection within the shortest time possible “This is crucial in preventing unauthorized activities and managing risk in various critical locations”.

Moreover, the effectiveness of this system meets the intended objectives as scrutinized using detailed performance and efficiency metrics analysis, as I was able to outperform the set solutions. Real-world datasets make this possible, while modular design makes it easy to meet changing industrial demands. The lack of detection efficacy is also an indicator that it has the potential to address critical issues found within the public safety, law enforcement and defence sectors.

So, this research not only advances the field of weapon detection by addressing weaknesses in current systems but also contributes to future work in this area. Adding more advanced features, such as multi-class object detection or connecting the system to IoT-based security systems, could make the system even more efficient. However, possibly the most important aspect of this work is that it tackles the gap between times advances in theory become useful in practice, thus enabling the design of better and more reliable security measures of prevention and protection and ultimately enhancing public safety and the welfare of the society at large.

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Findings and conclusions are based on unbiased data analyses carried out with no influence from outside sources or individual conflicts that stood to compromise the integrity of this study.

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