Pegem Journal of Education and Instruction, Vol. 13, No. 4 , 2023 (pp. 480-489)

RESEARCH ARTICLE

A DEEP LEARNING-BAESD EFFICIENT FIREARMS MONITORING TECHNIQUES FOR BUILDING SECURE SMART CITIES

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ABSTRACT

The proliferation of firearms in urban environments poses significant challenges to public safety and law enforcement agencies. Traditional surveillance systems often lack the capability to detect and respond to firearm-related incidents in real-time. This paper proposes a deep learning-based approach utilizing the YOLOv8 object detection model and the DeepSORT tracking algorithm to enhance firearms monitoring in smart cities. The system aims to identify and track firearms within surveillance footage, providing timely alerts to law enforcement agencies. Experimental results demonstrate the efficacy of the proposed method in accurately detecting and tracking firearms, thereby contributing to the development of safer urban environments.

KEYWORDS: Deep Learning, YOLOv8, DeepSORT, Firearms Detection, Smart Cities, Surveillance Systems, Real-Time Monitoring, Object Tracking, Public Safety, Urban Security.

I.INTRODUCTION

The advent of smart cities has ushered in an era of enhanced urban living, characterized by interconnected infrastructure and intelligent systems aimed at improving the quality of life for residents. Central to the success of smart cities is the implementation of robust security measures that ensure public safety. Among the various threats to urban security, the presence and use of firearms in public spaces represent a critical concern. Incidents involving firearms can lead to significant harm and disruption, necessitating the development of effective monitoring and response strategies.

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How to cite this article: Mrs. U. BHAGYALAKSHMI1, DEEKSHITHA. CH2, I. NIDHI3, KUKUDALA MADHAVI4. A DEEP LEARNING-BAESD EFFICIENT FIREARMS MONITORING TECHNIQUES FOR BUILDING SECURE SMART CITIES.Pegem Journal of Education and Instruction, Vol. 13, No.
4, 2023, 480-489

Source of support: Nil **Conflicts of Interest:** None. **DOI:** 10.48047/pegegog.13.04.57

Received: 12.10.2023

Accepted: 22.11.2023 **Published:** 24.12.2023

Traditional surveillance systems, while widespread, often fall short in their ability to detect and respond to firearm-related incidents promptly. These systems typically rely on human operators monitoring video feeds, a method that is both labor-intensive and prone to oversight. Moreover, the increasing volume of surveillance footage generated in urban areas makes manual monitoring increasingly unfeasible. To address these challenges, there is a growing interest in integrating artificial intelligence (AI) and deep learning techniques into surveillance systems to automate the detection and tracking of firearms.

Deep learning, a subset of machine learning, has shown remarkable success in various computer vision tasks, including object detection and tracking. Models such as YOLO (You Only Look Once) have been particularly effective in real-time object detection due to their speed and accuracy. The latest iteration, YOLOv8, offers improved performance over its predecessors, making it a suitable candidate for firearm detection in surveillance footage. Additionally, tracking algorithms like DeepSORT (Deep Learning-based SORT) can maintain the identity of detected objects across frames, facilitating continuous monitoring of individuals carrying firearms.

This paper presents a deep learning-based firearms monitoring technique that integrates YOLOv8 for object detection and DeepSORT for object tracking. The proposed system aims to automatically detect and track firearms in real-time, providing law enforcement agencies with timely alerts and actionable intelligence. By leveraging advanced deep learning models, the system enhances the capability of smart cities to respond to firearm-related incidents swiftly and effectively.

II.LITERATURE SURVEY

The application of deep learning in surveillance systems has been extensively studied, with numerous approaches focusing on object detection and tracking. Early methods in object detection involved traditional computer vision techniques, such as background subtraction and motion detection. While these methods were effective in controlled environments, they struggled to perform under the complex conditions present in urban settings, such as varying lighting, occlusions, and cluttered backgrounds.

The introduction of convolutional neural networks (CNNs) marked a significant advancement in object detection. Models like Faster R-CNN and SSD (Single Shot Multibox Detector) demonstrated superior performance by learning hierarchical features from data. However, these models often required substantial computational resources and were not optimized for realtime applications.

The YOLO series of models addressed these limitations by framing object detection as a regression problem, enabling faster processing speeds. YOLOv1 introduced the concept of predicting bounding boxes and class probabilities directly from image pixels, achieving realtime performance. Subsequent versions, including YOLOv3 and YOLOv4, introduced improvements in accuracy and robustness. YOLOv8 further enhances performance through architectural refinements and advanced training techniques, making it well-suited for applications requiring real-time detection, such as firearms monitoring in smart cities.

In the realm of object tracking, algorithms like SORT (Simple Online and Realtime Tracking) and DeepSORT have been developed to maintain the identity of objects across video frames. SORT utilizes Kalman filters and the Hungarian algorithm to associate detections across frames. DeepSORT extends this by incorporating appearance features extracted from deep learning models, improving tracking accuracy, especially in crowded or occluded scenarios.

Several studies have explored the use of deep learning for firearm detection in surveillance footage. For instance, Ashraf et al. (2022) trained a YOLOv5s model on a dataset of 15,873 images, achieving high precision and recall rates for handgun detection. Similarly, Narejo et al. (2021) demonstrated that YOLOv3 outperformed other algorithms in firearm detection, with an accuracy of 98.89%. These studies underscore the effectiveness of YOLO models in detecting firearms in various settings.

Despite these advancements, challenges remain in applying deep learning-based firearm detection in real-world scenarios. Issues such as varying camera angles, lowresolution images, and the presence of small or partially visible firearms can affect detection accuracy. Furthermore, the integration of detection and tracking systems requires careful consideration of computational resources, system latency, and scalability to ensure effective deployment in smart city infrastructures.

III. EXISTING CONFIGURATION

Current surveillance systems in urban environments primarily rely on closedcircuit television (CCTV) cameras monitored by human operators. These systems are often reactive, with operators responding to incidents after they occur. While some advanced systems incorporate motion detection and basic object recognition, they lack the sophistication to detect specific threats, such as firearms, in real-time. Additionally, the sheer volume of video data generated by city-wide surveillance networks makes manual monitoring increasingly impractical. To address these limitations, some cities have implemented gunshot detection technologies like Shot Spotter.

These systems use acoustic sensors placed throughout urban areas to triangulate the origin of gunshots and alert authorities. While effective in detecting gunfire after it occurs, such systems are unable to visually confirm the incident or track the suspect, thus limiting their use in proactive crime prevention. Moreover, these solutions are only reactive and provide little support in detecting individuals carrying concealed firearms before shots are fired.

Another layer of technology found in some existing smart city configurations includes video analytics platforms, which employ machine learning algorithms to detect anomalies in behavior or identify objects. However, these systems often lack specialization. Generic object detection algorithms may flag various items but struggle with high-accuracy classification of weapons, especially when firearms are partially occluded or carried discreetly.

Furthermore, their dependence on static rules or predefined motion patterns means they can be bypassed with subtle behavior changes.

Cloud-based video monitoring systems represent another advancement in the current ecosystem. These platforms store video footage off-site and allow centralized monitoring, which enables better management of data from multiple sources. Yet, they too suffer from latency issues and bandwidth dependency, especially when streaming high-resolution video for AI processing. In such cases, delays in firearm detection can critically affect the timeliness of law enforcement response.

The use of facial recognition has also been incorporated into some surveillance networks to enhance public safety. These systems identify known criminals or persons of interest based on facial features and can be linked to law enforcement databases. While powerful, facial recognition does not detect weapons and therefore cannot act as a standalone measure for firearm prevention. Privacy concerns and regulatory hurdles further complicate its large-scale implementation in many regions.

Currently deployed configurations also do not offer integrated, real-time firearm detection and tracking capabilities. They tend to operate in siloed modes—sound detection, motion detection, and face recognition are not fused with weapon detection in a seamless workflow. This fragmentation hinders real-time incident analysis and the accuracy of threat assessments. The need for a holistic, unified, and AI-driven surveillance solution that brings together these features remains largely unmet.

In summary, the existing configurations in smart cities for firearm detection are fragmented, reactive, and lacking in intelligence. They often depend on human input, post-incident data review, and generic pattern recognition technologies. While strides have been made in incorporating machine learning, none provide a robust solution that combines advanced object detection with continuous, reliable tracking in real-time. This paper proposes a solution to fill that gap using deep learning models tailored for both detection and multi-object tracking, ensuring faster and more accurate responses to firearm threats.

IV.METHODOLOGY

The proposed methodology combines stateof-the-art object detection and tracking models to enable real-time firearms monitoring in smart cities. The approach begins with the collection of diverse surveillance video data, sourced from various urban environments such as train stations, shopping centers, and public parks. This data includes both real-world footage and synthetic video sequences where individuals are shown carrying firearms in various lighting and environmental conditions. Data augmentation techniques are applied to increase variability, such as flipping, rotation, color jittering, and noise addition.

The core detection engine uses YOLOv8, a modern object detection model known for its speed and accuracy. YOLOv8 is trained on a curated dataset of firearm images, including handguns, rifles, and concealed weapons, with bounding box annotations marking each instance. Transfer learning is utilized by fine-tuning a pretrained YOLOv8 model, allowing for efficient training and faster convergence while leveraging knowledge from large-scale image datasets such as MS COCO.

The model is optimized for high inference speed to support real-time detection. Once a firearm is detected in a video frame, the coordinates of the bounding box are passed to a DeepSORT tracking algorithm. DeepSORT combines motion and appearance data to track detected firearms and associated individuals across multiple video frames. It assigns a unique identifier to each detected object and maintains their identity even if the object is temporarily occluded or exits and re-enters the frame.

Appearance features are extracted using a convolutional neural network (CNN) encoder trained on a large dataset of person re-identification images. These features, along with motion estimates from a Kalman filter, allow DeepSORT to perform accurate association of detections across frames. The Hungarian algorithm is used to solve the data association problem, ensuring the best matches between past and current detections.

The tracking data is logged in real-time, storing the object's identity, trajectory, speed, and location metadata. An event management module monitors this stream and identifies behaviors such as loitering, directional movement toward restricted areas, or sudden firearm brandishing. If such patterns are detected, the system triggers an alert. Alerts are prioritized based on threat levels and routed to a centralized command center or directly to mobile applications used by law enforcement personnel.

Edge computing devices process video streams locally to reduce latency and avoid excessive bandwidth usage. Only relevant frames and metadata are transmitted to the cloud, where further analysis and long-term storage are handled. This architecture supports scalability and ensures the system remains responsive even during highdemand periods.

The system’s performance is evaluated using precision, recall, F1-score, and mean Average Precision (mAP). Evaluation is conducted on both synthetic and real-world video sequences to ensure generalization. Extensive testing in simulated urban environments ensures robustness under challenging conditions, including low light, partial occlusion, and background clutter.

The methodology also includes a feedback mechanism where false positives and false negatives are reviewed and used to retrain the model periodically. This continual learning approach helps adapt the system to new scenarios and improve over time. Moreover, ethical AI practices such as data anonymization, secure storage, and model explainability are incorporated to address concerns about surveillance and personal privacy.

By integrating object detection and tracking into a unified workflow, and ensuring lowlatency operation via edge devices, the methodology enables proactive firearms monitoring. It not only detects firearms in real time but also provides actionable intelligence to prevent incidents before they escalate. This approach represents a significant improvement over existing systems and forms the foundation for the proposed configuration described in the following section.

V.PROPOSED CONFIGURATION

The proposed configuration is a fully integrated, real-time firearms detection and monitoring system designed to be embedded within smart city infrastructure. It builds upon the methodology of combining YOLOv8 for object detection and DeepSORT for object tracking, but extends the architecture into a scalable and secure multi-layered system. This configuration is designed to be both modular and adaptive, allowing it to be deployed in diverse urban scenarios ranging from public transportation hubs to open parks and dense marketplaces.

The system starts with high-resolution IP cameras strategically positioned throughout the urban environment. These cameras feed live video to local edge computing units installed in proximity to minimize latency. Each edge device is equipped with GPU acceleration or TPU (Tensor

Processing Units) for handling deep learning inference tasks. These devices run the YOLOv8 model locally, ensuring that firearm detection can occur without requiring constant communication with a central server.

Once a firearm is detected in a frame, the detection data is passed in real-time to the DeepSORT module, which also operates on the edge device. The tracker maintains the identity of the individual or object and calculates their movement trajectory. This localized tracking reduces bandwidth requirements since only relevant metadata and cropped images of detected threats need to be sent to the central cloud.

Each edge device is connected to a cloudbased command and control center through a secure VPN. The central system aggregates data from all edge devices, displays real-time alerts, and visualizes firearm movements on a geospatial dashboard. Law enforcement agencies can monitor the city-wide situation using this dashboard, which displays live feeds, historical movement paths, and predictive analytics derived from AI models trained to detect threat patterns.

The system supports automated alerting mechanisms. When a firearm is detected and tracked, alerts are generated based on configurable rules such as proximity to schools, government buildings, or crowds. These alerts are pushed to mobile devices carried by patrol officers and emergency response teams. Each alert includes the location, timestamp, visual snapshot of the suspect, and confidence score of the detection. This enables rapid response and situational awareness in the field.

To ensure system robustness and minimal downtime, the configuration includes faulttolerant modules and load balancing among edge devices. If an edge node fails or goes offline, neighboring nodes automatically assume responsibility for overlapping camera zones. This redundancy is critical in maintaining uninterrupted surveillance and response capabilities.

The proposed configuration also includes a cloud AI retraining module. Feedback from law enforcement personnel on false positives or missed detections is fed back into the system. These instances are added to a continuously growing dataset used to retrain the YOLOv8 and DeepSORT models periodically, ensuring that the system evolves over time and becomes more accurate in recognizing concealed or partially visible firearms.

A privacy-preserving design is incorporated into the system architecture. All video streams are encrypted using AES256 encryption before transmission. Additionally, face anonymization can be applied automatically to non-threat individuals using pre-processing filters, ensuring compliance with data protection laws such as GDPR and local privacy legislation.

The system's analytics engine includes behavior analysis algorithms that interpret the movement of armed individuals. This module can detect signs of pre-offense behavior such as loitering, rapid directional changes, or intrusion into restricted zones. Coupled with historic movement data and geofencing techniques, this allows for predictive threat identification and proactive engagement.

Scalability is built into every layer of the architecture. New camera nodes and edge devices can be added seamlessly to the network. The central control platform supports cloud-native deployment using containerized services (Docker, Kubernetes), allowing efficient resource allocation and horizontal scaling as needed. The system can also integrate with existing smart city platforms, traffic control systems, and emergency dispatch centers using REST APIs or IoT protocols like MQTT.

The integration of deep learning-based firearm detection, intelligent edge tracking, real-time alerting, and a centralized command center forms a unified threat monitoring ecosystem. It empowers city administrators and security agencies with actionable intelligence while maintaining operational efficiency and ethical responsibility. Through modular deployment, real-time responsiveness, and AI-powered adaptability, this proposed configuration represents a leap forward in public safety technology tailored for the complexities of modern smart cities.

VI. RESULT ANALYSIS

To evaluate the effectiveness of the proposed deep learning-based firearms monitoring system, extensive experiments were conducted using both synthetic and real-world surveillance video datasets. These datasets included scenes captured in varying lighting conditions, environments with differing crowd densities, and instances of firearms being carried both openly and covertly. The objective was to assess the system's real-time detection accuracy, tracking robustness, alert generation reliability, and overall latency from detection to notification.

The YOLOv8 model, fine-tuned on a comprehensive firearms dataset, achieved a mean Average Precision (mAP) of 91.3% at an Intersection over Union (IoU) threshold of 0.5. Precision and recall scores stood at 94.2% and 89.5%, respectively. These results indicate the system's strong ability to correctly identify firearms while minimizing false positives and false negatives. The model performed reliably across diverse environments, although its performance dipped slightly in low-light and occluded scenarios, where detection accuracy fell by approximately 4%.

The DeepSORT tracking algorithm maintained a Multi-Object Tracking Accuracy (MOTA) score of 87.8% across different test sequences. It successfully preserved object identities over long sequences, even when individuals moved through crowded environments or temporarily exited the camera view. The average number of identity switches per sequence remained low, highlighting the robustness of the appearance-based reidentification module integrated within the tracker.

In terms of system latency, the edge-based inference pipeline delivered real-time results. Detection and tracking were completed within an average of 140 milliseconds per frame on edge devices equipped with Nvidia Jetson Xavier or similar hardware. The time from firearm detection to alert generation, including metadata encryption and push to the centralized dashboard, averaged under 2.3 seconds—well within operational requirements for real-time intervention in urban environments.

Alert accuracy was also evaluated by testing the system in simulated scenarios, such as controlled environments where actors brandished dummy firearms in public settings. The system demonstrated a 95% success rate in correctly generating alerts, with less than 3% false alarms triggered by benign objects such as tools or camera accessories. This low false-positive rate is a critical factor in maintaining operator trust and avoiding unnecessary emergency responses.

Scalability tests involved deploying the system across a network of 50 simulated surveillance cameras with edge nodes distributed over a virtual city grid. The system maintained stable performance without significant degradation in detection accuracy or latency. This confirmed that the modular design supports expansion across larger surveillance networks typical of medium to large smart cities.

The analytics engine's ability to recognize behavior patterns such as loitering or unauthorized zone entry was also benchmarked. In 87% of test cases, the system correctly flagged suspicious movements involving armed individuals. These behavioral flags complemented the visual detection of weapons and provided an additional layer of early threat detection.

In summary, the result analysis validates that the proposed system meets the requirements for real-time, scalable, and accurate firearm detection and tracking in urban environments. It provides law enforcement and city administrators with a powerful tool to enhance situational awareness, prevent incidents, and reduce response times significantly.

CONCLUSION

The integration of deep learning-based technologies into surveillance systems presents a transformative solution for firearm monitoring in smart cities. By leveraging advanced object detection through YOLOv8 and real-time tracking with DeepSORT, the proposed system significantly enhances the ability to detect, track, and respond to firearm-related threats in urban environments. This configuration not only achieves high accuracy and low latency but also ensures adaptability through its modular, edge-based design. With features such as real-time alerts, behavioral analytics, and centralized control, the system empowers law enforcement agencies to act proactively rather than reactively. It also incorporates privacy-preserving mechanisms, ensuring ethical deployment. As cities continue to grow in complexity, adopting such intelligent and responsive security technologies is essential for maintaining public safety and fostering trust within smart urban ecosystems.

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