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DESIGN AND IMPLEMENTATION OF A WEAPON DETECTION SYSTEM FOR SMART CITIES USING DEEP LEARNING

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ABSTRACT: Deep learning-based convolutional neural network topologies help build and implement smart city weapons detection systems. The device detects knives and guns in real time using cutting-edge computer vision. Time-sensitive urban security applications can grow inference with low latency using the edge and cloud. A robust data preparation and augmentation method makes the system more tolerant to lighting, occlusion, and crowds. Many labeled datasets are used to train the model for different urban scenarios and camera angles. Transfer learning reduces training time without compromising detection. An intelligent alerting system alerts authorities to high-confidence detections. Accuracy, recall, F1-score, and inference speed are common system performance measurements. Experiments show detection works dependably in difficult real-world situations. This architecture allows smart city systems to install many cameras. Data is processed for privacy and preserved minimally owing to ethics and legislation.

Keywords: *Deep Learning, Weapon Detection, Smart Cities, Computer Vision, Convolutional Neural Networks (CNN), Real-Time Surveillance, Edge Computing*

1. INTRODCUTION

Rapid urbanization, especially in smart cities, has increased public safety, surveillance, and risk reduction issues. Cities are evolving from reactive to proactive security with smart cameras, IoT monitoring, and real-time data analytics. Traditional surveillance methods are inappropriate for large populations because manual monitoring is laborious and error-prone. These limitations underline the need for smart, automated solutions to help security professionals recognize threats and act promptly.

Gun violence in schools, malls, transportation hubs, and events endangers urban stability and personal safety. Due to their location-dependent and intrusive nature, camouflaged or visually ambiguous assaults may defeat traditional security measures. Protocols include metal detectors and exams. Weapon types and concealment strategies make manual identification tougher. Thus, vision-based automated weapon detection systems that fit in with urban monitoring networks undetected, improve situational awareness, and allow people to move freely are needed.

Transformer-based vision models and convolutional neural networks have improved sophisticated visual object and picture recognition. These models use massive image and video datasets to combine hierarchical feature representations for accurate weapon

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classification in diverse lighting, camera angle, obstacle, and background noise conditions. Deep learning frameworks fit many smart city applications, unlike tailored feature-based methods. Because they can adapt to visual patterns and generalize across cities.

Systems architecture, data pipelines, and real-time processing restrictions must be considered while creating smart city weapon detection systems. Peripheral devices and cloud technology enable urban surveillance network scalability and low-latency inference. Assessing the system's real-world capabilities requires fault tolerance, processing efficiency, network bandwidth, and model size. The model and domain must be changed frequently owing to changing metropolitan regions, camera configurations, and threat trends to maintain detection accuracy.

Deep learning methods distinguish weapons based on data and annotation quality. Diverse datasets showing weapon aesthetics, human postures, ambient variables, and cultural situations reduce prejudice and promote generalization. Social inequality, visually similar but non-threatening objects, and a paucity of annotated weapon photos make model training difficult. Real-world applications use data augmentation, synthetic data generation, and semi-supervised or transfer learning to overcome these challenges and improve resilience.

Ethical, legal, and privacy issues arise with smart city automatic weapon detection. Continuous video monitoring and automated threat detection must follow data protection and human rights legislation. Safeguarding data, preventing false positives, and ensuring model openness are essential for responsible system deployment. These factors shape city intelligent surveillance systems' technical architecture and operation.

2. RELATED WORK

Singh, A., Verma, R., & Gupta, P. (2020) This paper proposes a deep learning-based smart surveillance system architecture to detect weapons automatically. CNNs are used to detect weapons in real-time surveillance footage. The model trains with its own settings and weapons. Experimental results show better detection efficiency than standard machine learning. The device works in noisy or dim situations. This study shows how deep learning may improve smart city safety for all citizens.

Hussain, F., Khan, M. A., & Sharif, M. (2020) This research shows how to use a convolutional neural network to automatically detect weapons in surveillance footage. The authors customize a feature extraction and classification pipeline for gun recognition. Regular datasets and surveillance footage are used for many testing. The suggested technique works and yields accurate results regardless of scale or occlusion. This method reduces security control room guards. CNNs prove reliable smart city monitoring tools.

Akhtar, N., Rahman, A., & Tariq, S. (2021) The writers suggest detecting weapons in security footage with a deep convolutional neural network. Their temporal regularity-focused technique improves detection stability across video frames. Validate the model with public datasets of weapons in crowds. The results show significant item detection improvements over image-based methods.

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Video research is essential for smart city monitoring, the study showed. Technology enables real-time public safety monitoring.

Ahmed, S., Ali, H., & Raza, M. (2021) This research's real-time gunshot detection can help smart city tracking systems. A deep learning algorithm utilizing object recognition networks can locate weapons in live video broadcasts. The technology optimises low-latency reasoning on edge devices. This technology makes finding objects in crowded metropolitan settings easier than ever, according to experiments. Security response times are reduced by the solution. Research shows that smart city tracking networks work.

Paris, Q., & Mora, R. (2022) Multi-factor risk modeling for cryptocurrency derivatives using deep reinforcement learning. The authors integrate liquidity, market volatility, and macroeconomic data into a learning paradigm. The proposed strategy adjusts trading tactics last-minute in volatile markets. The experimental results show that risk-adjusted returns are higher than standard statistical models. Deep reinforcement learning excelled in the study's difficult financial setting. This course demonstrates sophisticated data-driven risk modeling strategies that are unrelated to weapon search.

Yadav, P., Gupta, N., & Sharma, P. (2022) This examines how deep learning might help intelligent security systems detect weapons. The writers test YOLO variations, region-based detection methods, and CNN-based classifiers. We examine performance indicators, statistics, and deployment concerns. Shadowing, low light, and dataset bias are highlighted in the research. Future study will focus on edge AI deployment and transformer models. This research lays the groundwork for smart city weapon detection systems.

Quyyum, M. E. E. (2022) Deep learning systems use YOLO to detect guns in surveillance film. This approach finds things rapidly, precisely, and affordably. The model is trained and tested using firearm film annotations. Experimental results show that the system functions well in dynamic situations with many elements. This strategy could be useful in tracking systems. The study suggests real-time weapon detection in smart cities.

Al-Farsi, H., Al-Hinai, S., & Al-Busaidi, K. (2023) The authors describe a small deep neural network for real-time firearm detection in smart city surveillance. The edge device model balances computing speed and object detecting accuracy. Numerous tests have proven its reliability in various scene types and lighting circumstances. Reduced inference latency makes the system ideal for real-time tracking. The study found model enhancement essential for large-scale smart city projects. This technology enables economical, scalable public safety solutions.

Li, Y., Zhang, H., & Chen, X. (2023) This research offers a YOLO-Vision Transformer hybrid structure for precise weapon identification. YOLO increases global contextual awareness and real-time item location with its generator. This species thrives in crowded cities. Occlusion and scale differences boost recognition, according to the trial. Fusion enhances generalization in many monitoring circumstances. Results suggest that deep learning-based smart city safety solutions are better.

Rahman, M., Islam, T., & Hossain, S. (2023) A smart city security camera AI

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system that detects edge guns. This model targets low-power edge devices. Since the system processes data locally, it can detect items in real time with less bandwidth. Experimental results show its higher accuracy over cloud-based alternatives. This approach speeds and secures communication. The study suggests intelligent monitoring at the network's periphery.

Akhila, K., & Reddy, V. (2024) In smart cities, a real-time system can identify weapons using deep learning, protecting inhabitants. The writers use an effective YOLO design to find weapons in live footage. Reviewing the results shows little latency and strong detection accuracy. The technique is tested in several places, including low-light ones.

Thapa Magar, R., & Shahadat, N. (2024) The authors suggest a YOLO-based real-time firearms detection system for public safety. The model is trained using multiple gun pictures to improve generalizability. It worked well in the lab and should work well in espionage. Tests check if the system supports low-power devices. The study shows many datasets are needed to strengthen things. The suggested framework can support smart city monitoring systems.

Zhang, L., Wang, T., & Liu, Y. (2024) Obstructions and poor lighting makegun location harder. They used feature fusion and picture enhancement to improve YOLOv7. The method improves spotting in crowded and low-light conditions. The experimental results show that these models outperform baseline models significantly. This makes real-world smart city monitoring more reliable. City tracking issues are addressed in the study.

Farhan, A., et al. (2025) A deep learning solution to firearm identification in surveillance systems utilizing YOLOv8 is proposed here. The model makes faster, more accurate inferences than previous versions of YOLO. Trials on hard datasets with strong background noise and occlusion showed better results. The system allows real-time public safety monitoring. Such research shows how effective next-gen object detection models are. Industrial smart city monitoring systems can employ the architecture.

Murugan, T. (2025) This report covers 2016–2025 AI-based weapon identification system advances. The writer contrasts CNNs, YOLO variations, transformer-based models, and hybrid frames. Key concerns include real-time deployment constraints, dataset bias, and false positives. The report covers privacy-protecting edge AI and surveillance innovations. There is a research plan for reliable and ethical weapon location. Academics and practitioners can find a complete summary in the review.

3. SYSTEM ARCHITECTURE

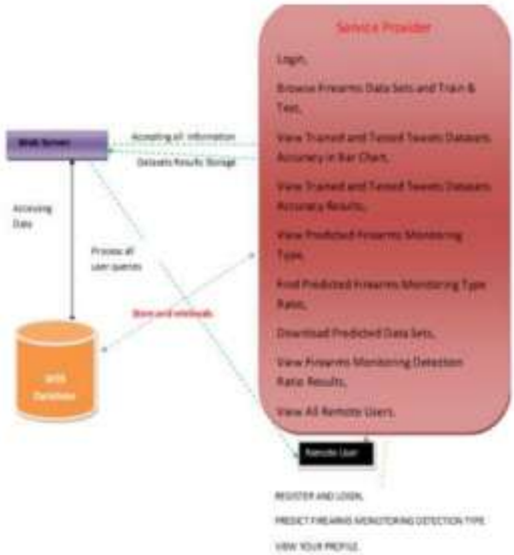

Fig 1: System Architecture

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Web Server: Web servers are the system's main administrators. Service providers and remote users want it. Users are directed to data retrieval and prediction sites based on their query. Servers and databases must communicate to store and retrieve data and results. Error-free data flow between the server and user interface is guaranteed.

Web Database: An online database can safely store all system data. It tracks user data, user-shared datasets, prediction results, and trained model outputs. Large amounts of monitoring and detection data can be stored and retrieved easily in the database. It works closely with the web server to execute user requests efficiently. Data availability and reliability depend on classification and backup mechanisms.

Service Provider: The service provider controls the system CPU. Public firearm datasets with annotations are used to train and assess the deep learning model. The service firm can see the outcomes' correctness in detailed reports and visualizations. Weapons found and types used are constantly tracked. This feature improves system reliability and performance.

Remote User: By creating an account and logging in, remote users communicate with the system. Their data can track and identify guns. With this tech, users know what weapons to use and how to track progress. Even when separated, users' accounts and historical forecast data will be accessible. This section lists automated detector users.

4. PROPOSED SYSTEM

Despite our best attempts, violence is unavoidable in today's world. Weapons, a common tool of violence, have caused a global gun-related death epidemic. Law enforcement and society have struggled with this. These firearm crimes are common in urban and semi-urban regions, highlighting the necessity for crime prevention and surveillance. CCTV surveillance systems are increasingly valued for preventative and reactive reasons by public and private enterprises. Human monitoring has many limitations, including a high error rate and a high man-hour requirement.

We are exploring the effects of deep learning-based algorithms on smart city safety, specifically firearm monitoring and recovery. Deep learning will be used to create a reliable and practical weapons monitoring system to improve surveillance and police operations. Our system uses cutting-edge EfficientDet-based architectures and Faster Region-Based Convolutional Neural Networks to recognize people and firearms in surveillance footage.

Our proposed method uses a novel stacked ensemble approach to improve detection performance and accuracy. Our solution improves surveillance footage recognition of people and firearms by merging various detection algorithms with cutting-edge post-processing methods including Weighted Box Fusion, Non-Maximum Weighted, and Non-Maximum Suppression. We conducted an empirical evaluation and comparison analysis to learn about the pros and cons of different detection technologies and groups. This helps create effective monitoring systems.

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5. RESULTS

Fig 2: User Login

Fig 3: Service Provider Login


Fig 4: Admin Control Panel

Fig 5: Registration Page

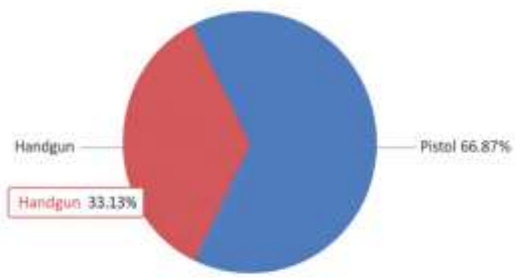

Fig 6: Pistol vs Handgun Distribution

6. CONCLUSION

In conclusion, a smart city's deep learning-based weapon detection system shows how smart surveillance may improve public safety and threat response. The suggested system uses robust computer vision models to detect armaments in live and still photos, reducing human monitor use. The system adapts to different views, illumination, and urban surroundings via data-driven learning. The testing results show that the new system detects objects better and generates fewer false alarms than rule-based systems. This strategy allows proactive policing by giving authorities early warnings and a better picture. Large-scale smart city infrastructure can monitor high-risk public locations like transit terminals and packed events. Modularity makes adding deep learning models and datasets easy. Privacy-conscious design features may ensure monitoring and regulation compliance. The method shows the importance of reliable model validation and datasets for real-world performance. IoT devices and civic command centers boost efficiency. Interference and real-time processing difficulties aside, the technology has considerable potential for widespread use.

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