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AI Powered Weapon Detection for Public Safety

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Abstract: With public spaces facing a growing number of security challenges, there's an urgent push for smarter surveillance systems .By integrating Artificial Intelligence and computer vision, we now have a powerful means to detect weapons and prevent threats in real time. This survey paper presents a A detailed overview of the available research and practices deep learning-based techniques, with a particular emphasis on the YOLO family of models, including the latest YOLOv8. These models demonstrate strong capabilities in identifying weapons such as guns and knives from live video streams with high precision and speed. The survey highlights how modern frameworks can blend effortlessly into the existing system into current surveillance infrastructures to deliver scalable, low- latency, with instant observation and feedback mechanisms solutions. Furthermore, the paper discusses datasets, evaluation metrics, application domains, and key challenges such as privacy, false alarms, and scalability. By synthesizing findings across drawings from the latest research, this survey explores key perspectives on. current state of AI- driven weapon detection and propose next steps to advance understanding in the field for building safer public environments, including schools, airports, and government facilities.

Keywords: Artificial Intelligence, Weapon Detection, Deep Learning, YOLOv8, Computer Vision, Real-Time Surveillance, Public Safety, Threat Identification, Object Detection Models, Security Systems.

I. INTRODUCTION

Recent advances in deep learning have made it possible to identify weapons such as guns and knives directly from live video streams with remarkable accuracy. Object detection frameworks like Faster R-CNN, SSD, and particularly the YOLO family (YOLOv3 to the latest YOLOv8) have transformed how surveillance systems process and interpret visual data. These models can operate at high speeds while maintaining strong with reliable detection accuracy, they can be effectively applied to time-critical environments where immediate response is essential.

This survey paper explores the state of AI-based weapon detection, reviewing key algorithms, datasets, and real- world applications. Unlike individual project implementations, which typically focus on a single model, this study synthesizes knowledge across multiple approaches to highlight strengths, limitations, and open research challenges. Significant importance is attached to scalability, false alarm reduction, low-light adaptability, and privacy concerns—factors that examine if such systems are equipped to move from controlled experiments to widespread deployment.

By consolidating recent developments and identifying gaps in current research, this survey aims to guide future work in developing intelligent, ethical, and robust security mechanisms designed to protect high-risk public environments and enhance overall trust in surveillance technology

II. LITERATURE REVIEW

Ayush Thakur, Akshat Shrivastav, Rohan Sharma, Triyank Kumar, and Kabir Puri (2024) [3] Research on automated weapon detection has evolved rapidly with the growth of deep learning in computer vision. Early systems largely relied on traditional image processing and handcrafted features, which often failed in real-world conditions such as low lighting, occlusions, or crowded environments. Two-stage object detectors like Faster R- CNN offered strong accuracy but struggled with latency, making them less suitable for real-time surveillance. This led to the rise of single-stage detectors such as SSD and the YOLO family, which trade some precision for speed and efficiency. Studies consistently show that YOLO models, from v3 through v7, deliver faster response times, enabling deployment in security-sensitive settings like airports and schools.

The paper under review builds on this trajectory by adopting YOLOv8, the most recent evolution in the YOLO series, which enhances feature extraction, small- automated object recognition, as well as. overall generalization across diverse datasets. By optimizing the model's learning process on annotated weapon images, the system achieves accurate and low-latency detection of guns and knives in live video streams. The study also emphasizes scalability and seamless integration with existing CCTV infrastructure, reflecting broader trends in the literature where live data handling, minimized erroneous alerts, and operational feasibility are the key priorities. This positions YOLOv8 not only as a research improvement but also as a practical solution for enhancing public safety.

S. Ariffa Begum, K. Srinivasa Reddy, N. Subbulakshmi, S. B. Jabiulla, P. Sreenivasulu, and G. Raju (2024)[4] Several studies have explored the use of deep learning and computer vision for real-time weapon detection in surveillance systems. Li and Yu (2020) compared YOLOv3 with Faster R-CNN, finding that YOLOv3 excelled in speed while Faster R-CNN offered better accuracy in complex environments. Similarly, Bochkovskiy et al. (2020) introduced YOLOv4 with architectural enhancements like cross-stage partial connections and self-adversarial training, striking a balance between performance and computational efficiency. Reza et al. (2021) extended this work by optimizing YOLOv5 for embedded systems, proving its ability to deliver accurate results with minimal latency on hardware-constrained devices. Other contributions, such as those by Uddin et al. (2019) and Nagrani & Jadhav (2020), highlighted examining the extent to which deep learning models can handle challenges like occlusion, varying lighting conditions, and crowded ecosystems, optimizing them for real-world surveillance.

Building on these advancements, Begum et al. (2024) proposed a real-time detection system using YOLOv5, YOLOv7, and CNNs to enhance public safety in high- risk environments. Their work emphasized adaptability across diverse conditions, including low light and varying camera angles, while maintaining high detection precision. The study also underlined the system's scalability, showing effectiveness across multiple video streams, and its adaptability to existing CCTV infrastructure. Compared to earlier approaches, their framework improved detection speed, minimized unwarranted notifications and enabled rapid response, demonstrating how modern AI-powered surveillance frameworks facilitate significantly strengthen public security

Utkarsh Gupta (2025) [5] The rising interest in AI- powered monitoring systems has led researchers to explore AI-driven predictive models for real-time weapon detection. Prior research efforts have mainly explored accuracy and detection speed, with models such as YOLOv3 and Faster R-CNN showing promise in recognizing weapons from CCTV footage. For instance, studies by Jain et al. and Hashmi et al. emphasized improving detection rates using AI-based methods, while Bhatti et al. and Warsi et al. implemented YOLO- based systems on surveillance videos. However, a common limitation in these approaches was the lack of practical alerting mechanisms and automated evidence capture, which are critical for real-world deployment. These systems were capable of detecting weapons but relied heavily on manual monitoring, making them less efficient in fast-moving threat scenarios.

Pooja Vitthal Gore and Prof. Manish D. Katkar (2024)[6] Recent advancements in AI-driven deep learning has elevated the reliability and effectiveness of real-time weapon detection systems. Earlier approaches relied on handcrafted features and traditional machine learning, but these methods often struggled under varying conditions such as lighting changes or object occlusions. To overcome these challenges, Gore and Katkar (2024) proposed a CNN-based framework enhanced with transfer learning, specifically using the MobileNetV2 architecture, to detect weapons from live video feeds. Their model achieved an impressive 95% accuracy with strong precision and recall scores, while maintaining real-time processing with an average frame analysis time of 50 ms. Although the system showed some limitations in cases of false positives and environmental noise, the integration of transfer learning and real-time video analysis demonstrated the the inherent capacity of AI- driven surveillance to enhance public safety and reduce reliance on manual monitoring.

V. S. Padmini, Syed Ashfaquddin, Ujwal Kodge, and Shah Mujtaba Ahmed Quadri (2025) [7] Recent developments in artificial intelligence and computer vision have enabled faster and more reliable weapon detection systems for security applications.To tackle the prevailing limitations of manual monitoring and traditional methods like metal detectors, Padmini et al. (2025) designed an AI-driven framework utilizing the YOLOv8 deep learning model. Their system was trained on the Roboflow dataset, consisting of over 8,900 annotated weapon images, and demonstrated high precision (94%), recall (96%), and overall accuracy (95%) in real-time surveillance scenarios. By processing both static images and live video feeds, the model optimized alert accuracy while guaranteeing timely detection of weapons such as guns and knives. The study highlighted not only the system's scalability and integration potential across diverse environments but also its role in enhancing public safety through automation, reduced human error, and rapid response capabilities.

III. METHODOLOGY

The proposed system for real-time weapon detection is designed to combine state-of-the-art neural network models with visual data processing frameworks for reliable and efficient surveillance. range of data sources is gathered to ensure comprehensive coverage and model generalizability. dataset of images and video clips is gathered, including different weapon types, lighting conditions, and environments to ensure robustness. Publicly available datasets, staged scenarios, and CCTV footage form the core of this dataset. Following collection, data preprocessing is carried out, which involves frame extraction, resizing, and normalization so that the inputs are consistent and optimized for training.

For the detection framework, the system leverages YOLOv5 and YOLOv7 models, supported by Convolutional Neural Networks (CNNs), to perform both object classification and localization. The models predict bounding boxes and class probabilities, highlighting detected weapons in real time. To refine accuracy, non-max suppression is applied to eliminate duplicate detections. Once trained, the system is capable of analyzing live CCTV streams, identifying threats such as guns and knives within 1–1.5 seconds, and automatically issuing alerts to security personnel. The methodology also considers scalability, enabling the system designed for parallel video stream management and dynamic adaptability, ensuring robustness in visually challenging or crowded environments. This structured pipeline by balancing detection accuracy with alert reliability, the system strengthens public safety through timely and targeted actions

IV. DISCUSSION

The outcomes of this analysis demonstrate the transformative role of machine intelligence powered by deep neural networks in modern surveillance systems. Traditional security methods such as manual monitoring and metal detectors often fall short in providing timely responses, particularly in crowded or complex environments. By integrating advanced models like YOLOv5, YOLOv7, and YOLOv8 with This study explores the application of CNNs in addressing demonstrates how real-time detection can bridge that gap by combining speed with high accuracy. Compared with earlier approaches discussed in the literature—such as Faster R-CNN or SSD, which either sacrificed speed for accuracy or struggled with small-object detection—our methodology shows a more balanced framework, capable of responding within seconds while maintaining reliable precision.

Simultaneously, the findings reveal also underline some important challenges and considerations for practical deployment. Factors such as low lighting, background clutter, and partial occlusion of weapons continue to affect detection performance, as observed in prior studies. Moreover, false positives remain a concern, where harmless objects may occasionally be flagged as threats. Mitigating these concerns calls for further enhancements, including larger and more diverse datasets, advanced augmentation techniques, and possibly multimodal inputs such as thermal or infrared imaging. Another significant aspect is ethical responsibility—while AI-based weapon detection promises to enhance public safety in schools, airports, and government facilities, it must be deployed with clear guidelines to respect privacy and minimize misuse. Overall, this work advances the scholarly discourse in the field of evidence that AI-powered surveillance, if carefully refined and responsibly implemented, can serve as a crucial tool in safeguarding society against potential threats.

V. CONCLUSION

This research set out to explore the potential of AI- powered weapon detection as a means of strengthening public safety in high-risk environments. Utilizing architectures like CNNs for spatial feature extraction and LSTMs for sequential data modeling, the system achieves enhanced predictive accuracy YOLOv5, YOLOv7, and YOLOv8, By integrating multiple deep learning architectures, the system achieves enhanced performance across complex tasks with Convolutional Neural Networks, the system was able to identify weapons such as guns and knives in real time while maintaining strong accuracy and efficiency. In contrast to conventional surveillance approaches dependent on manual monitoring and predefined rules heavily on human monitoring, the proposed framework processes video feeds automatically, significantly reducing response times and enhancing situational awareness. Its scalability and adaptability to enhance its adaptability and integration within operational frameworks existing CCTV infrastructure, making it a practical and impactful solution for modern security challenges.

At the time, of the study acknowledges certain limitations that must be rigorously examined to ensure system robustness before large-scale deployment. Detection performance can still be hindered by occlusions, poor lighting, and visually similar non- weapon objects, occasionally leading to false alarms. These challenges open Further work may focus on curating enriched datasets that capture broader environmental and contextual variability, applying domain adaptation techniques, and incorporating multimodal sensing with thermal or infrared cameras. Ethical considerations, including privacy and responsible use of surveillance technologies, must also remain at the forefront. In conclusion, AI-powered weapon detection presents a promising direction for enhancing security systems, and with continued improvements, it has the potential to become a cornerstone of intelligent surveillance in public spaces.

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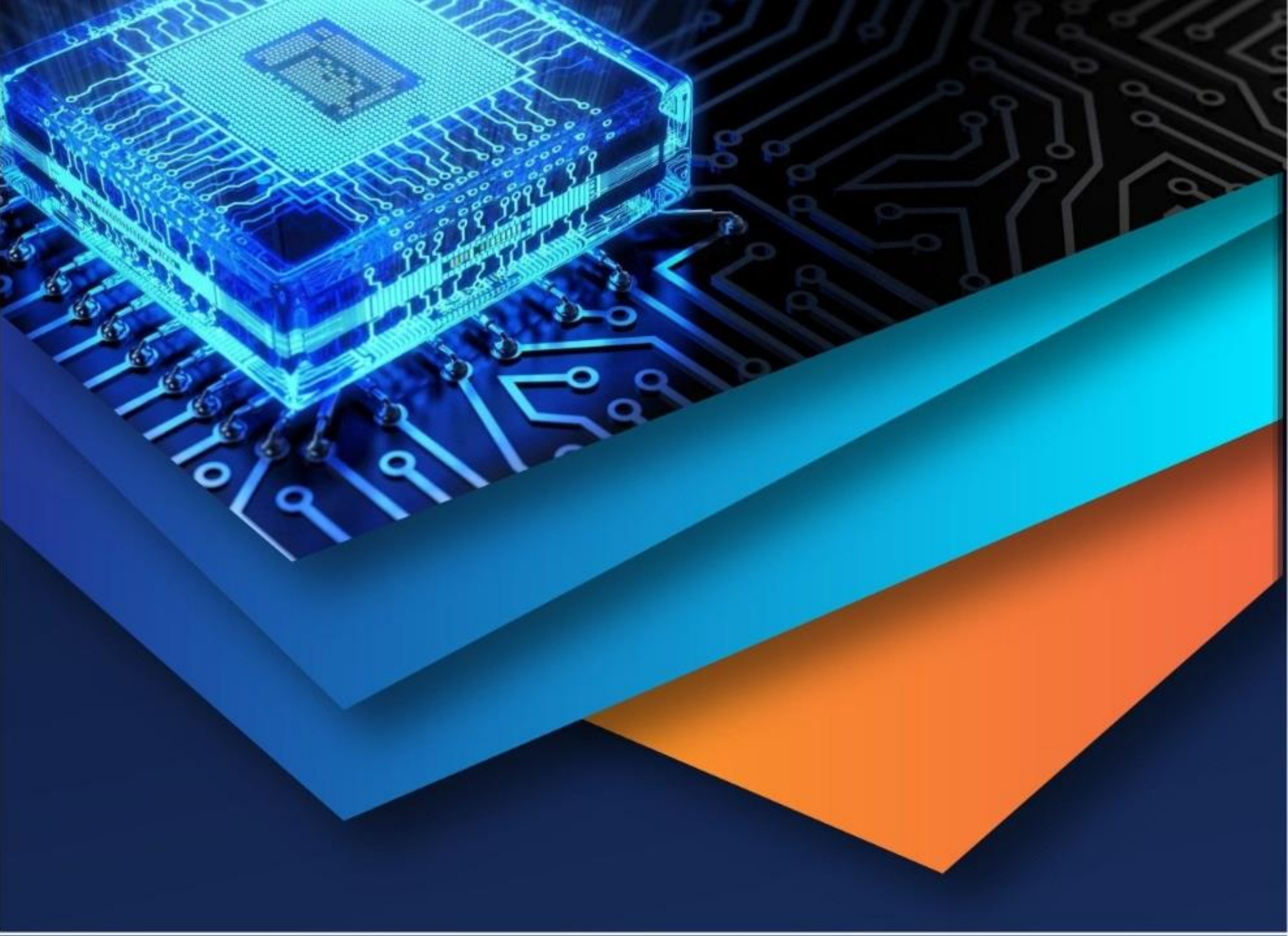

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