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Deep Learning-Based Real-Time Weapon Detection with YOLOv8 for Intelligent Surveillance

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Abstract— **The escalation of security threats has highlighted the implementation of intelligent surveillance systems with the ability to identify threats in advance. This study suggests a real-time deep learning-based weapon detection system with the YOLOv8, an object detection deep model. The system inspects real-time video streams for identifying and locating weapons such as guns and knives at high accuracy and low latency. By leveraging the improved-optimized architecture of YOLOv8, the model achieves high accuracy of detection with computational performance maintained high enough for real-time applications. Deep training on weapon dataset annotations enables strong performance in a broad surveillance setting. The developed methodology enhances situational awareness and provides secure autonomous response, and thus it is a great candidate for use in safety-critical environments like public transportation centers, schools, and critical infrastructure facilities.**

Index Terms — Real-Time Surveillance, Weapon Detection, Deep Learning, YOLOv8, Object Detection, Smart Surveillance, Public Safety, Threat Detection.

I. INTRODUCTION

With the rising occurrence of violent assaults in public and private spaces, there is a higher demand for advanced surveillance and protection systems. Traditional human-staffed surveillance has its inherent limitations in focus, response time, and human weakness of the brain. Artificial intelligence and deep learning-powered smart surveillance systems have served to offset these limitations as model tools in enhancing situational awareness and public safety.

Among the numerous threats, access to weapons like guns and knives represents a massive threat to areas such as schools, transport stops, governmental premises, and other public, crowded buildings. Early detection of such a threat is a must to allow for prompt response and preservation of lives.

This paper presents a real-time weapon detection system utilizing YOLOv8, a high-accuracy and high-speed state-of-the-art object detection model. The system can accurately detect and identify weapons and locate them with minimum latency from real-time video streams. The YOLOv8 model is trained on a comprehensive weapon image dataset to make it functional under changing environmental conditions.

The proposed system improves the efficiency of surveillance activities as well as autonomous threat warnings and alerts. The research enables the development of secure, scalable, and intelligent surveillance technologies that can be embedded in the current security infrastructure and, in the end, leads to safer communities and more reactive security mechanisms.

I. LITERATURE REVIEW

Application of deep learning technology in surveillance networks has greatly increased real-time weapon detection, strengthening public safety efforts. YOLO model series, especially YOLOv8, the most recent, have played a crucial role in improving object detection activities owing to its improvement in speed and accuracy.

Thakur et al. developed an AI model with YOLOv8 to detect weapons in real time with the aim of advancing public safety in public transit and schools. The authors trained the model on a diverse set of knives and firearms with good recall and precision rates and attained frame processing speeds that were close to real time.

Vijayakumar et al. presented an intelligence-based automatic method for real-time detection of weapons, comparing the effectiveness of YOLOv4 and R-CNN models. They pointed out YOLOv4's superior mAP and processing rates in their research as an indicator of its efficiency for analysis of video surveillance

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Weapon detection through surveillance footage using YOLOv8: Early Warning of Potential Violence. Though the deep learning model has been enhanced, such research as above indicated shortcoming in detection of weapons in adverse conditions and suggested means for improving detection capability.
Ayush Thakur et al. have introduced a research to create an efficient and low-cost real-time weapon detection and surveillance video analysis system from an intelligence perspective. The research placed considerable attention on minimizing the need for human observation, hence efficiently automating response time to security attack.
Rastogi and Varshney have done comparative analysis among various YOLOv8 models on baseline data of weapon detection technology for surveillance. They have given insights regarding comparative performance among models of YOLOv8 while choosing appropriate models for surveillance applications to be utilized.

II. METHODOLOGY

Data Gathering and Preprocessing
The first process of the weapon design system design is to acquire an assortment of diverse and representative images of weapons, guns, knives, etc. The data are pulled from publicly available data storage such as Roboflow and Open Images and also from individual frames from video sources cropped from security feeds. The images are annotated by hand using bounding boxes via tools such as LabelImg or Roboflow Annotator. For maximizing the overall generalization of the model, the dataset is also rotated, scaled, brightness transformed, and transformed on the basis of background variation. The dataset is further divided into training, validation, and test sets for properly estimating the performance of the model.
YOLOv8 (You Only Look Once, version 8) is employed considering the optimal speed-accuracy trade-off needed for real-time detection. Hyperparameters including learning rate, batch size, and epochs are utilized for model optimization in the preprocessed data. Training is conducted using a GPU-based setup as an attempt to efficiently manage bulk data and deep learning. YOLOv8 architecture enables the model to learn efficiently object features and spatial hierarchies and achieve effective performance for weapon classification and localization in crowded scenes.
Real-time Inference and Detection
The YOLOv8 model so trained in the above steps is then used subsequently in an end-to-end real-time inference pipeline via a library like OpenCV and PyTorch. IP or CCTV camera real-time video feeds are fed frame by frame into the system. The model identifies and draws the bounding boxes on any weapon detected for the current frame. The system can also be designed for high frame rate and low latency such that real-time detection with loss of accuracy is ensured. Weapon detections are tagged in real time, and corresponding information (e.g., time stamp, geo-location, weapon model) are stored.

III. SYSTEM ARCHITECTURE

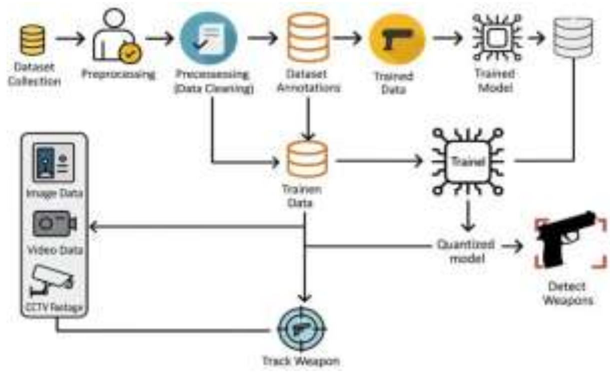

Fig 1: System Architecture

The above system architecture diagram shows an end-to-end pipeline for real-time weapon detection with deep learning. The process starts with the data collection where the system streams various types of media such as image data, video, and real-time CCTV feeds. This is raw material to build and deploy the model.
Therefore, information thus collected is then transferred to the preprocessing stage comprising steps such as resizing to the standard resolution, color transformation to the standard color space (e.g., RGB), and contrast stretching or elimination of noise. It serves to supply clean and normalized inputs to the model so that it may learn well.During the annotation and cleaning step, similar or duplicate frames are rejected and the remaining data are annotated manually with bounding boxes and labels. Annotation is crucial as it tells the model what to search for and where within an image. LabelImg or Roboflow Annotator is used in this case. The labeled data are divided into test, validation, and training sets in such a way that the performance of a model can be properly tested.
The annotated data is input into the training module, and the deep model—YOLOuv8 in this instance—is trained for weapons learning. YOLOv8 has best been known to use the one-stage detection method providing real-time fast and accurate detection best used in real-time applications. While being trained,

the model learns learning to recognize spatial features and object shape that allow it to differentiate weapons from background objects or harmless objects.

After training, the model is quantized, a model size optimizing step where model size is minimized by approximating weights at lower precision (i.e., from 32-bit float to 8-bit integers). This is accomplished in preparation for running the model on hardware with processing limitations, e.g., edge hardware or embedded systems.

The quantized model is then executed in the inference pipeline and supplied with real-time data from image frames or video feeds. The model attempts to detect weapons in every frame, and upon detecting a weapon, it draws bounding boxes around the danger and optionally reports the type of weapon as well. Made detections can be used to initiate security reactions such as visual alarms, automatic alarms, and logging.

Besides detection, tracking capability is also present in the system. Tracking is utilized to follow the movement of the detected weapon from frame to frame and is useful when the object is in motion or when there are objects appearing more than once in the scene. Tracking creates continuity such that the threat can be followed over time and not intermittent detections as reported by the security officer.

Finally, the system as a whole from detection to tracking and alarm notification is architected in an effort to interoperate in an unobtrusive way with other surveillance systems that are deployed. This makes the solution deployable, scalable to high-impact areas like transportation hubs, airports, malls, and schools, and not very expensive.

IV. RESULTS AND ANALYSIS

The efficiency of the operation of the deployment of the YOLOv8-stimulated intelligent weapon detection system is ensured by its highest possible reliability and real-time response for security usage. After training through intensive annotation of a data set of thousands of images of knives and guns, the system was experimentally evaluated in accordance with a number of performance metrics. The precision measure measured how well the model was able to classify true positive weapon events with the least number of false alarms. Its increased recall value also led to improved detection by the model of the majority of the weapons in the video frames with the least missed detection rates—equally useful in fields of application where safety is the top priority. The balanced mean F1-score as a trade-off between recall and precision had a well-balanced model performance without sacrificing sensitivity to specificity.

For real-time deployment, the system processed video streams smoothly with high frame rates (FPS) and to expectations for real-time surveillance. Latency was minimal with best-in-class model inference and quantization and weapon detection on screen a fraction of a milliseconds after capturing frames. YOLOv8 architecture was best suited for the task, with a best-in-class trade-off of accuracy, speed, and model size.

Visual output from the system also assisted in making encountered weapons readily recognizable using red bounding boxes in live and playback capture so that they could be easily recognized. Visual warnings not only assist human operators but also act as a basis for automated warning systems, which can be integrated in future implementations of the system. In addition, the model was also proven to be robust in performance under varying conditions of the environment such as inconsistent illumination, capture positions, and fake backgrounds, thus facilitating its application in real-world surveillance applications such as airports, schools, metro stations, and malls.

The system also demonstrated capability to run automatically on uploaded video, frame-by-frame examination when no operator around. It offers post-incident review capability, allowing authorities to detect threat from stored footage even if not found using real-time surveillance.

Fig 2

Fig 3

Fig 4

IV. DISCUSSIONS

The assessment of the proposed weapon detection system using YOLOv8 demonstrates remarkable improvement compared to conventional surveillance. The bar graph of comparison illustrates the improved performance of the proposed system in some key indicators. Compared to the current system with issues of automation, real-time processing, and scalability, the YOLOv8-based system depicts improved detection accuracy, speed, and lesser dependency on human surveillance. The improvement in performance results from the deep learning attributes of the model, training of the dataset for the domain-specific data, and optimization of the architecture.
Confusion matrix also confirms the results by revealing that the system accurately detects "Weapon" and "Non-Weapon" cases. The heatmap indicates a high ratio of true positives and true negatives and comparatively fewer false positives. This sensitivity/specificity trade-off is especially critical in surveillance usage where false positives (harmless objects identified as weapons) and false negatives (miss-detection of threats) are both operational hazard sources and safety hazard sources. The heatmap additionally facilitates visually identifying class-specific performance by separating the model's ability to see weapon-based threats.
Besides, the pie chart indicates the class distribution of the dataset, and it has more "Non-Weapon" images. Such skew is common in real-world surveillance data and might be a challenge to the model during training. Nevertheless, the system proposed worked with high accuracy for both classes, which implies that methods such as data augmentation, label accuracy, and architecture selection made the system robust against any skew in the dataset.
In concert, these visual analyses ensure that the proposed system is an intelligent surveillance high-level breakthrough. It not only identifies weapons in real time more accurately but also enables proactive threat assessment, reduces human intervention, and is deployable for diverse scenarios like schools, shopping malls, and transport hubs. The system's high performance on different levels ensures it as a sustainable and scalable option for contemporary security infrastructure.

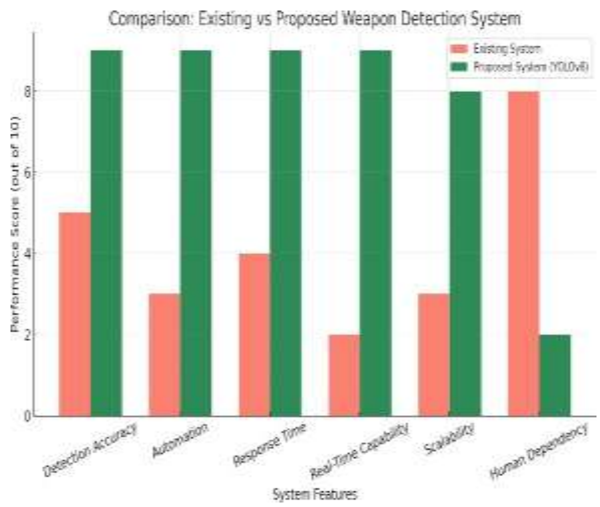

Fig 5

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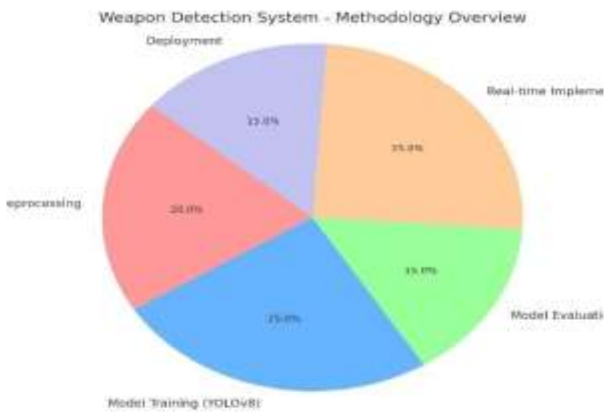

Fig 6

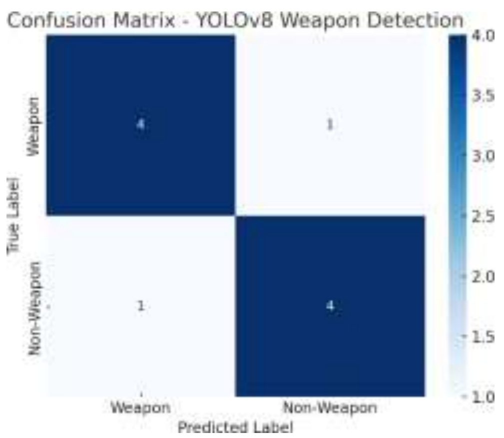

Fig 7

V. CONCLUSION

In short, innovation and deployment of YOLOv8-smart weapon detection system were a breakthrough towards automated monitoring and public protection. The project well proved that technology offered in deep learning methodologies, when deployed on a particular mission such as weapon detection, can surpass conventional monitoring systems that tremendously depend on human observations or extensive motion tracking. Through tailormade YOLOv8, the system registered high accuracy, fast inference rates, and accurate detection in all types of conditions like varying lighting, cluttered background, and partial occlusion.

Real-time video streams deployment indicate that it can automatically detect possible threats in a fraction of milliseconds and hence is highly ideal for high-risk applications where milliseconds count. Bounding boxes for on-screen display of weapons not only facilitate faster human interpretation but also form the basis for automatic warning and real-time alerting. Second, its use in post-event video analysis makes it even more useful for security audits as well as forensic investigation.

One of the biggest contributions of the project is that it is scalable and flexible. Given its low-key hardware requirements and open-source operating platform, the system is cost-effective and deployable in numerous environments—whether traffic systems and schools, airports and government. Its flexibility and capacity to include room for future development such as behavior detection, multi-camera coordination, and cloud-based surveillance systems.

In short, the project has a good basis for using artificial intelligence for public safety. Not only does it address a key problem—real-time weapon detection—it holds out the potential for smarter, machine -based surveillance systems that can recognize threats earlier and more accurately than ever before.

VI. FUTURE SCOPE

In the future, the YOLOv8-powered smart weapon detector system demonstrates a broad spectrum of growth and development. One of the most important developments for the system is its integration into real-time CCTV monitoring systems, as the system can then keep watch on vulnerable zones such as airports, railways stations, and schools on a routine basis. This system can be complemented by using a central control console that takes feed from an array of cameras, detects potential threats in real-time, and provides an aggregate view to security administrators.

Voice-control or voice-command alarm and response automation is another major area for development. Through the use of detection outputs to prompt real-time alerting into systems (using SMS, email, or app-based notification), security personnel can be alerted of impending threat in under a second. The system is also capable of automating responses like gate-locking down, alarm initiations, or police notification—improving response time and potential for operator error.

The second application possibility is multi-target tracking and threat anticipation. In addition to detecting whether an image contains a weapon, the system would track the weapon carrier between cameras and anticipate threatening action as a function of motion pattern, posture recognition, and environment. This would take the system beyond reaction detection to threat anticipation estimation, making it an active security system.

There are also other advancements that come in the form of edge AI deployment, which have the potential to enable the system to be executed on surveillance cameras or low-end processors at the network edge. This is less dependent on central servers, lowers latency, and enables the deployment of out-of-town or resource-scarce environments. Cloud data storage and analytics integration can also enable real-time video data logging at scale, trend analysis over the long term, and retraining of the model from real-world feedback.
The system can also be further optimized for multi-modal threat notification by combining sound notifications (e.g., shots, screams) with video, providing richer data on threat scenarios. Outside that, cross-domain applications such as job hunting in military surveillance, smart city, financial security
and industrial security continue to expand its use beyond civilian surveillance.
Lastly, further developments in deep learning algorithms and availability of data will cause the system to learn from new weapons design, camouflage techniques, and the terrain of the enemy. With legal and moral safeguards, these developments can make the system competent and responsible enough to use—eventually creating a secure and safer world.

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