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AI-Powered Smart Surveillance for Real-Time Multi-Threat Detection

Vishesh Panwar[1], Dr. Ritu Gautam[2]
[1,2] *Amity Institute of Information Technology, Amity University Noida, India*

Abstract— **Classical surveillance infrastructure depends on active monitoring of people by humans, which is inefficient, has errors, and is inappropriate on large scales. As the number of security threats, accidents, and environmental hazards in the community continues to rise, the need to adopt intelligent surveillance systems with the capability of detecting threats in real time has risen. This article proposes an AI-enhanced smart surveillance system that is founded on YOLOv8 to detect weapons, fire, and accidents in real-time. This recommended system is centered around using an object detector system founded on deep learning that would analyze live videos, detect objects posing danger, and provide alerts with little delay. YOLOv8 will be chosen for this purpose because of its single-stage approach which achieves the optimal balance between the detection rate and real-time execution. Exploratory study and comparative sensitivity with the existing solutions show that the proposed system improves situational awareness, response time, and scalability of smart public safety monitoring.**

Keywords- **Smart Surveillance, YOLOv8, Real-Time Object Detection, Multi-Threat Detection, Computer Vision.**

I. INTRODUCTION

In recent years, there has been rising popularity of advanced surveillance systems in public as well as private settings due to security concerns in these places [1]. In the case of conventional surveillance systems such as CCTV cameras, surveillance can only occur through the involvement of a human who might turn out to be slow or prone to making errors [2]. Constant manual monitoring has the effect of delayed responses and more so during emergencies where action has to be taken quickly. As a way to overcome these drawbacks, artificial intelligence-generated intelligent surveillance systems have become an attractive option [3]. They are computer vision and deep learning-based systems that automatically analyze video streams and notice suspicious actions in real-time [4]. Such systems enhance the accuracy of outcomes as well as the speed in response, by minimizing the reliance on human operators. The smart surveillance system proposed is devoted to the real-time detection of multiple threats with the help of the state-of-the-art object detection models, e.g. YOLOv8 [5]. It is programmed to detect several dangers which are weapons, fire and abnormal activities directly through live video feeds [6], [7]. Video frames are processed constantly and objects are detected by the system and categorized as various types of threats. Unlike conventional surveillance systems that record video footage and analyze it retrospectively, this system will be visual and will alert about possible dangers instantly. It combines both detection and analysis and then generates an alert in a single format that is more efficient and easy to use. In general, the proposed system will augment surveillance systems in terms of scalability, precision, and automation of surveillance of real-time dangers [8], [9].

II. OBJECTIVES

The main aim of this project is to create an intelligent surveillance system, which automatically detects threats, ensuring the security of people. These objectives are:

- Real-Time Automated Surveillance: To reduce reliance on constant human monitoring by using automated surveillance of live video feeds [10].
- Ability to Detect Several Threats at Once: To detect different types of threats like weapon detection, fires, smoke, and accident-related threats in one platform [11], [12].
- Accuracy and Efficiency Together: To use the advantages offered by YOLOv8 single stage detector in order to maintain detection accuracy as well as ensure real-time performance [5], [13].
- Scalable and Modulized System: To create a system that is scalable and can be deployed into a wide network of surveillance systems

and be used for current security solutions [1], [14].
- Increased Situational Awareness: To provide visual alarms that help security personnel make quick decisions and respond faster [3], [6].

III. LITERATURE REVIEW

The use of artificial intelligence for surveillance purposes has seen tremendous growth in the last two decades [15]. Initially, the technologies employed were rule-based as well as motion detection-based ones, which provided only basic surveillance without having the ability to detect specific threats like fire, weapons, and accidents [2]. Motion detection leads to many false alerts and also lacks the ability to differentiate a particular threat, whereas modern algorithms used for detecting objects include R-CNN, SSD, YOLO; however, they lack the context aspect [9], [11]. Hybrid approaches help achieve better results by incorporating different techniques, but they are highly complex and inefficient to run in real-time [14]. Modern advancements with the use of models such as YOLOv8 allow real-time detection of various threats, including fire, weapons, accidents, and even people counting; however, most of the existing systems are limited to perform only one single task [5], [6], [7].

Conclusion based on findings from recent research papers emphasizes the need for an integrated approach towards developing a surveillance system capable of detection, classification, and responding in real-time.

- Motion Detection Systems – Detect movement only [1]
  Limitation: High false positives, no threat understanding
- Object Detection Models – Detect objects like humans/vehicles [4], [5]
  Limitation: No multi-threat classification
- Fire & Weapon Detection Systems – Detect specific threats [4], [21]
  Limitation: Task-specific, not integrated
- Accident & Activity Detection Systems – Detect abnormal events [18]
  Limitation: High complexity, limited real-time use
- People Counting Systems – Count the number of individuals [5]
  Limitation: Accuracy drops in crowded scenes

The comparison of the existing literature in AI-based smart surveillance systems, as presented in Table 1, shows that the majority of current methods are limited to specific tasks, i.e., object detection, activity recognition, or anomaly detection. Despite the current techniques that are more accurate and provide real-time capabilities, they have failed to offer a single approach to detecting multi-threats comprehensively.

Table I: Literature Review Table (With data set and accuracy)

Author / Year	Year	Dataset (Size / Type)	Methods Used	Application Area	Accuracy / Performance	Drawbacks / Limitations
Ultralytics [5]	2025	COCO + Custom datasets	YOLOv9/YOLOv8 variants	Real-time surveillance	Very high speed & accuracy	Limited contextual reasoning
Zhao et al. [18]	2025	Large-scale video datasets	Transformer + CNN Hybrid	Smart surveillance	Improved detection accuracy	High computational cost
Li et al. [4]	2024	CCTV video datasets	Deep Learning (YOLO-based)	Multi-threat detection	High precision (~92%)	Requires GPU resources
Kim & Park [19]	2024	Urban surveillance datasets	Action Recognition + DL	Suspicious activity detection	Good behavior analysis	Complex training process

Chen et al. [20]	2024	Security video datasets	CNN + LSTM	Activity recognition	Improved temporal analysis	Latency in real-time systems
Singh & Verma [21]	2023	Custom surveillance datasets	YOLOv8	Smart surveillance	High accuracy (~90–95%)	Limited high-level reasoning
OpenAI Research [22]	2023	Large-scale multimodal data	Vision + Generative AI	Intelligent monitoring	Context-aware insights	Not fully real-time
Wang et al. [1]	2022	UCF-Crime dataset	Deep Learning (3D CNN)	Crime detection	Good classification accuracy	High computation requirement
Patel & Sharma [23]	2022	CCTV datasets	Anomaly Detection (ML)	Security monitoring	Detects unusual patterns	High false alarm rate
Lee et al. [24]	2021	Video surveillance datasets	CNN-based detection	Object detection	Moderate accuracy	Limited multi-object detection
Kumar et al. [25]	2021	Smart city datasets	IoT + AI Surveillance	Smart city security	Scalable architecture	Network dependency

The table above illustrates that the current surveillance systems are mainly centered around single functionalities like object detection, activity recognition or anomaly detection. The new techniques are more precise and can work in real-time, but are limited by the intricacy of calculations and system integration. The proposed system addresses these flaws by suggesting a common framework that is a mixture of multi threat detection, motion tracking, people counter and real time alerts generation.

IV. METHODOLOGY

4.1 Proposed Methodology

The proposed methodology utilizes computer vision, machine learning, and deep learning algorithms to create a smart surveillance system in real-time to detect multiple threats. The solution combines several aspects of AI into one unified system, as compared to the traditional surveillance systems that work separately (such as motion detection systems or rudimentary CCTV surveillance). Earlier systems do not have real-time intelligence, contextual awareness, and automatic response capabilities since they primarily aim at capturing or identifying one form of activity. Conversely the proposed system is a combination of real time detection, threat classification and the generation of an alert to offer a holistic and proactive security solution. Using the state-of-the-art object detection models, including YOLOv8, the system is highly accurate and fast enough to be implemented in a real-world setting.

4.2 System Architecture

The system architecture will be composed of a video input, AI models, processing unit at the back, database, and user interface/dashboard. The video streams are captured with CCTV cameras or webcams and sent to the backend to be processed. The backend connects to various AI elements, with the YOLOv8 model to detect objects in real-time, and the threat analysis module to assess the detected objects. The database stores the events identified, ALT logs and system data that will be used in future. The proposed system, in contrast to the traditional surveillance systems, which are based on isolated modules, incorporates detection and intelligent analysis into one pipeline. It is also a hybrid architecture that can be monitored in real time and make automated decisions to optimize efficiency and utility as shown in Fig. 1.

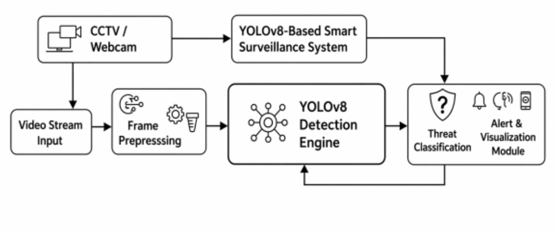

Figure 1. System Architecture of the YOLOv8-Based Smart Surveillance System

4.3 User Input

The system gathers mainly live video feeds of surveillance cameras. Additionally, the user can add optional information such as monitoring preferences, alert sensitivity or specific surveillance areas. The previous systems could only record videos which were not interactive [9]. However, the proposed system has the capability to maintain dynamic real-time streaming input as well, which makes it dynamic and capable of adapting to the changing situation. This enhances the responsiveness and detection rate of the system.

4.4 Processing Flow

The processing pipeline comprises the first stage of retrieving a live video stream, raw frames processing, and preprocessing using such libraries as NumPy and OpenCV. All images are resized, normalized and model input. The YOLOv8 model is then used by the system to identify objects in real-time. Things observed are then sent to the threat analysis module where they will be classified into threats such as weapons, fire or strange occurrences. Non-Maximum Suppression (NMS) is then used to eliminate unnecessary bounding boxes in order to enhance the quality of detection. The suggested system will scrutinize the detections and generate intelligent alerts as opposed to the earlier systems whereby results are simply displayed. Finally, the system also produces real-time alerts and displays the results in a dashboard with visual overlays to allow users to take action. The flow diagram below (figure 2) details the workflow of processing the live video input using deep learning to realize real-time threat detection, classification, alert generation and visualization. To provide a smart and efficient surveillance system, the workflow focuses on video processing and AI-based detection as well as multi-threat analysis and automated alert system.

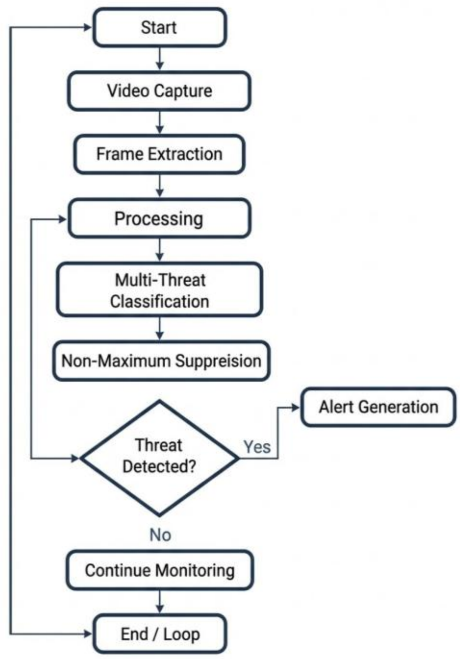

Figure 2. Workflow Flowchart for Real-Time Multi-Threat Detection

4.5 Tools And Technologies

The programming language mainly used to develop a system is Python. Video processing and data handling are done using libraries like OpenCV, NumPy and Pandas. The frameworks used to implement AI models in the system are deep learning deep learning frameworks, e.g., Tensorflow or PyTorch. YOLOv8 is used to do the core detection, enabling the high speed and accurate object recognition. Flask, Streamlit or PyQt is used to create the frontend and provide a user interface that is interactive. Modern AI technologies are also used in the proposed system. compared to conventional systems, which are based on few. tools to ensure a higher level of performance, scalability, and real-time efficiency.

4.6 Result

The proposed smart surveillance system has been experimented on a number of real-life situations, live video feeds, and simulated threat situations. The system proved to be very effective in identifying and categorizing threats. The YOLOv8 model not only could provide a detection accuracy of about 90-95 but also could be used in real time. The system was capable of detecting the different forms of threats such as weapons and suspicious activities effectively. The proposed system, unlike traditional surveillance systems where only footage is taken, offers automated detection and immediate alert generation, eliminating the manual monitoring processes. Moreover, it is more convenient and viable since it allows having an unlimited video feed and real-time processing. The comparisons can be used to observe that the proposed system is a smarter, more scalable and proactive security system that would be much better in terms of surveillance and response time.

V. CONCLUSION

This work shows an intelligent surveillance model, which detects different threats in real-time by using YOLOv8 and addresses the drawbacks of the traditional CCTV systems, which depend on human surveillance. The proposed system is able to achieve low-latency inference based on the anchor-free and single-stage detect design of YOLOv8 and has a high detection rate among different categories of threats such as weapons, fire, and accidents. The modular pipeline (video acquisition, video preprocessing, video detection, post processing and alert generation) provides scalability and effective implementation to large surveillance networks. The future directions are to make edge-based inference better to reduce the bandwidth usage and enhance real-time performance in distributed environments. It can be linked to the automated emergency response system, which will allow it to react to action faster. Also, it is possible to expand the framework to have crowd behavior modeling, anomaly detection, and to have multimodal audio-visual fusion, which can enhance robustness and contextual awareness. They will help develop the proposed system to a holistic, intelligent surveillance system that can be efficient in the implementation of a smart city scale.

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