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WeaponVision: Real-Time AI Surveillance System

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Abstract: In recent years, the rise in violent incidents involving firearms and sharp weapons in public spaces has increased the demand for intelligent surveillance systems capable of identifying threats in real time. Traditional CCTV monitoring systems depend heavily on human operators, which often leads to delayed response, fatigue, and missed detections. This paper presents "SafeVision: AI-Based Real-Time Weapon Detection System," an intelligent surveillance framework that utilizes Artificial Intelligence (AI), Deep Learning, and Computer Vision techniques for automatic weapon detection from live CCTV or webcam feeds. The proposed system employs the YOLOv8 object detection algorithm to identify weapons such as guns, pistols, rifles, and knives with high accuracy and low latency. The system processes video frames in real time and immediately generates alerts whenever a weapon is detected. A Flask-based web interface is integrated to provide live monitoring, detection visualization, and alert notifications. The system improves surveillance efficiency, minimizes human dependency, and enhances public safety by enabling rapid threat response. Experimental analysis demonstrates that the proposed system achieves efficient detection performance under different environmental conditions. The proposed framework can be deployed in public areas such as airports, railway stations, shopping malls, schools, and government organizations to strengthen modern surveillance infrastructure.
Keywords: Artificial Intelligence, Weapon Detection, Computer Vision, YOLOv8, Real-Time Surveillance, Flask, CCTV Monitoring, Deep Learning, Object Detection, Public Safety.

I. INTRODUCTION

In today's rapidly evolving world, ensuring public safety has become one of the most critical challenges for modern societies. The increasing number of violent incidents involving firearms, knives, and other lethal weapons in public areas has created the need for intelligent surveillance and early threat detection systems. Conventional CCTV monitoring systems rely heavily on human operators who continuously observe multiple video feeds for identifying potential threats. This manual monitoring process is time-consuming, prone to fatigue, and often results in delayed responses during emergencies. To overcome these limitations, "SafeVision: AI-Based Real-Time Weapon Detection System" has been designed as an intelligent and automated solution using Artificial Intelligence (AI) and Computer Vision technologies. The system utilizes the YOLOv8 deep learning model for detecting weapons such as pistols, rifles, and knives from live surveillance video streams. Once a weapon is detected, the system instantly generates alerts and displays detection results through a Flask-based web dashboard.Unlike traditional systems that only record events for post-incident analysis, the proposed system focuses on proactive real-time detection and prevention. The system can process continuous video streams from CCTV cameras or webcams and identify dangerous objects with high accuracy and low latency. Bounding boxes and confidence scores are displayed on detected objects, helping security personnel respond quickly and efficiently.

The integration of AI, deep learning, and web technologies makes SafeVision suitable for deployment in airports, railway stations, educational institutions, shopping malls, and government buildings. The system improves surveillance efficiency, reduces dependency on human monitoring, and enhances public safety through intelligent automated threat detection.

II. LITERATURE SURVEY

In recent years, researchers have focused extensively on AI-based surveillance systems and weapon detection techniques to improve public safety and reduce criminal activities. Various deep learning models, computer vision techniques, and intelligent monitoring systems have been proposed for detecting weapons in real-time environments. The paper "Weapon Detection in Real-Time CCTV Videos Using Deep Learning" proposed a surveillance framework using YOLO-based object detection models for detecting firearms in live CCTV footage. The research demonstrated high detection accuracy and faster response time through real-time monitoring systems. Another research paper titled "Anchor-Free Weapon Detection for X-Ray Baggage Security Images" introduced advanced object detection architectures for detecting weapons without predefined anchor boxes. The proposed approach improved detection speed and achieved better localization accuracy compared to traditional methods.

This research introduces an anchor-free deep learning approach for detecting weapons—such as knives and guns—in X-ray baggage images used in security screening. Traditional anchor-based object detection models require predefined bounding boxes, which limit flexibility and increase computational complexity. The authors present six anchor-free architectures (e.g., YOLOx, CenterNet, ExtremeNet) that eliminate anchor dependency, thus improving generalization and processing speed. Experiments show that YOLOx, with the CSPDarknet53 backbone, achieves an impressive 0.905 mean average precision (mAP), outperforming anchor-based detectors like Faster-RCNN and YOLOv5. The findings underscore the benefits of anchor-free networks in achieving high accuracy and efficiency, which can be extended to battlefield target detection and autonomous threat identification systems.

This paper presents a real-time surveillance system for weapon detection using advanced deep learning models. The framework leverages CNN-based architectures such as YOLOv3 and YOLOv4 to detect firearms in live CCTV footage. The researchers construct a comprehensive dataset combining internet images, YouTube videos, and publicly available firearm databases to train the model effectively. Among tested algorithms, YOLOv4 delivers the highest F1-score of 91% and mean average precision (mAP) of 91.73%, outperforming other models in both accuracy and speed. The study demonstrates the potential of real-time vision-based weapon recognition systems in improving situational awareness and automatic threat response for security and defense applications.

Several researchers have also focused on lightweight object detection models such as YOLO-G and improved YOLOv8 architectures for detecting military targets and weapons in complex environments. These systems achieved better performance in crowded scenes and low-light conditions. Although existing systems provide weapon detection capabilities, many systems suffer from issues such as low detection speed, limited scalability, delayed alert generation, and poor real-time performance. To overcome these limitations, the proposed SafeVision system integrates YOLOv8-based weapon detection, Flask-based dashboard visualization, real-time alert generation, and scalable surveillance architecture into a single intelligent security platform.

This research introduces a novel approach to handgun detection by combining human pose estimation with weapon appearance features. Unlike existing models that rely solely on visual weapon cues, this method leverages human skeletal keypoints to identify the likelihood of a person carrying or using a firearm, even when partially obscured. The model integrates two subnetworks—one for pose-based input and another for visual features—and fuses their outputs for improved accuracy. Experiments conducted on surveillance datasets show significant improvements in detecting hidden or occluded handguns. The paper contributes to enhancing the interpretability and robustness of detection systems, which can also inform threat posture recognition in defense contexts.

III. PROBLEM STATEMENT

The increasing number of violent incidents involving weapons in public spaces has highlighted major limitations in existing surveillance systems. Traditional CCTV monitoring systems depend completely on human operators for identifying suspicious activities. Monitoring multiple camera feeds continuously often leads to fatigue, delayed response, and missed detections during critical situations. Existing surveillance systems are mainly passive in nature, as they record footage for post-event analysis instead of providing real-time threat detection. Conventional approaches also struggle in detecting small or partially visible weapons under challenging conditions such as low lighting, crowded environments, and object occlusion.

IV. PROPOSED SYSTEM

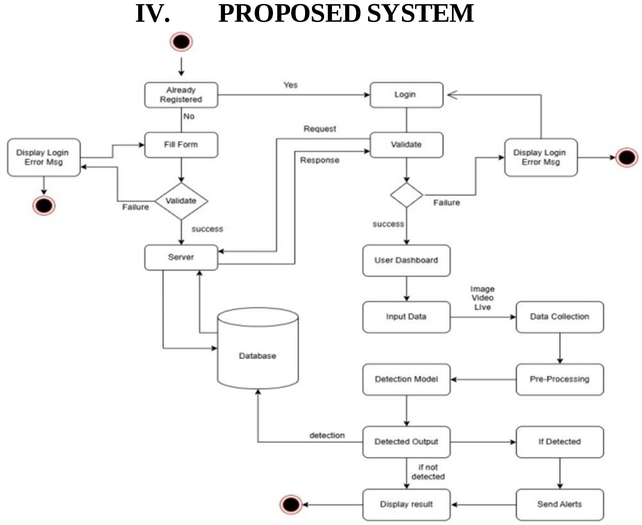

Fig 1. System Architecture

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In this fig. 1 shows the system architecture .The proposed system “SafeVision” is an AI-based real-time weapon detection platform designed for intelligent surveillance and public safety monitoring. The architecture of the system consists of multiple modules including video acquisition, preprocessing, object detection, alert generation, and result visualization.

The system first captures video input from CCTV cameras or webcams. Each frame is processed and passed through preprocessing operations before being analyzed using the YOLOv8 object detection model. The model detects weapons such as guns, knives, and rifles and generates bounding boxes along with confidence scores.

Whenever a weapon is detected, the system automatically generates alert notifications and displays the results on the Flask-based web dashboard. Detection logs are stored in the database for future analysis and monitoring purposes.

The proposed system provides several advantages such as:

- Real-time weapon detection
- Faster emergency response
- Improved surveillance automation
- Reduced human dependency
- Scalable multi-camera support
- High detection accuracy using deep learning

V. EXISTING SYSTEM

Existing surveillance systems mainly focus on video recording and manual monitoring. Some systems use traditional image processing techniques for object detection, while others provide AI-based monitoring solutions with limited functionalities.

Most existing systems face issues such as:

1) Dependency on continuous human observation
2) Delayed threat identification
3) Poor performance in crowded scenes
4) Low real-time detection speed
5) Lack of automated alert generation
6) Limited scalability and adaptability

To overcome these limitations, the proposed SafeVision system integrates deep learning-based weapon detection, real-time alert mechanisms, Flask dashboard visualization, and intelligent surveillance automation into a unified platform.

Parameters	Existing Systems	Proposed System (SupportHive)
Detection Method	Manual Monitoring	AI-Based Detection
Alert Generation	Limited	Real-Time Alerts system
Accuracy	Moderate	High Accuracy
Processing Speed	Slow	Real-Time Processing
Scalability	Limited	Multi-Camera Support
User Interface	Basic	Interactive Dashboard
Automation	Partial	Fully Automated
Threat Response	Delayed	Immediate Response

TABLE 1. Comparison Table of Existing Vs Proposed System

The table 1 presents a comparative analysis between traditional surveillance systems and the proposed SafeVision system. Existing systems mainly depend on manual monitoring and provide limited automation, delayed threat response, and low scalability. In contrast, the proposed system utilizes Artificial Intelligence and YOLOv8-based deep learning techniques for real-time weapon detection and automated alert generation. The proposed platform offers high detection accuracy, faster processing speed, interactive dashboard visualization, multi-camera support, and fully automated surveillance capabilities. These improvements enhance monitoring efficiency and strengthen public safety infrastructure.

VI. MATERIALS AND METHODS

The proposed system, "SafeVision: AI-Based Real-Time Weapon Detection System", is developed using advanced Artificial Intelligence, Deep Learning, and Computer Vision technologies to provide an intelligent and automated surveillance solution. The system is designed to detect weapons such as guns, pistols, rifles, and knives in real-time from CCTV cameras or webcam feeds. The complete architecture integrates video processing, object detection, alert generation, database management, and dashboard visualization modules to ensure efficient monitoring and rapid response during emergency situations.

A. Software Requirements

1) Python – Python is used as the primary programming language because of its simplicity, flexibility, and extensive support for Artificial Intelligence and Computer Vision libraries.
2) YOLOv8– YOLOv8 is the core deep learning model used for real-time object detection.
3) OpenCV– OpenCV (Open Source Computer Vision Library) is used for image and video processing tasks.
4) Flask Framework – Flask is used for developing the web-based dashboard interface.
5) HTML, CSS, and JavaScript – Frontend technologies such as HTML, CSS, and JavaScript are used for designing the interactive user interface and dashboard pages. These technologies improve usability and user experience.
6) SQLite / MySQL Database– The system stores detection logs, timestamps, alert records, and user details in the database

B. Hardware Requirements

1) Processor – Intel i5 or higher
2) RAM – Minimum 8 GB
3) GPU – NVIDIA GTX 1650 or higher GPU
4) Camera – CCTV cameras or webcams
5) Storage – 20 GB free space minimum

VII. EXPERIMENTAL RESULT

The proposed system "SafeVision" was tested using multiple surveillance scenarios to evaluate its detection accuracy, real-time performance, and alert generation capabilities. The system successfully detected weapons such as pistols, rifles, and knives from live webcam and CCTV video streams. The YOLOv8 model processed each frame efficiently and displayed detection results with bounding boxes and confidence scores on the Flask dashboard. The system achieved fast response time and generated instant alerts whenever suspicious weapons were detected. The proposed platform demonstrated reliable performance even in crowded environments and different lighting conditions. The integration of Flask dashboard and OpenCV visualization improved monitoring efficiency and provided a user-friendly interface for security personnel.

The following experimental modules were successfully implemented:

1) Real-time CCTV weapon detection
2) Webcam-based live surveillance
3) Bounding box visualization
4) Confidence score display
5) Alert generation mechanism
6) Detection logging and monitoring
7) Multi-weapon detection capability
8) Low-latency real-time video processing
9) Automated threat notification system
10) Detection performance under low-light conditions

Parameters	Results
Weapon Detection Accuracy	High Accuracy
Detection Speed	Real-Time Processing
Alert Generation	Successfully Implemented
Dashboard Visualization	Interactive
Bounding Box Detection	Accurate
Multi-Camera Support	Available
System Latency	Low
User Interface	User-friendly and interactive
Detection Logging	Functional
Overall System Performance	Efficient

TABLE 2. Performance Analysis of the Proposed System

The table 2 presents the performance evaluation results of the proposed SafeVision system under different surveillance conditions. The experimental analysis demonstrates that the system achieves high weapon detection accuracy with efficient real-time processing and low system latency. The alert generation mechanism, dashboard visualization, bounding box detection, and detection logging modules were successfully implemented and functioned effectively. The results confirm that the proposed system provides reliable, scalable, and intelligent surveillance performance suitable for real-time security applications in public environments.

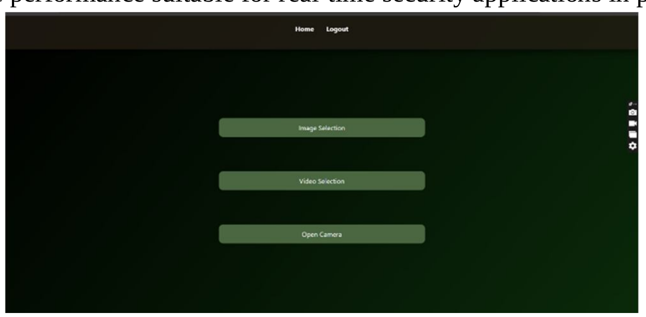

Fig 2. Predict page

In this fig. 2 shows The Predict Page. It allows users to upload live CCTV footage or webcam video for real-time weapon detection. The system processes the input using the YOLOv8 deep learning model and identifies weapons such as guns and knives with high accuracy. Detected objects are highlighted using bounding boxes along with confidence scores. The page provides fast and intelligent surveillance monitoring through an interactive Flask-based interface.

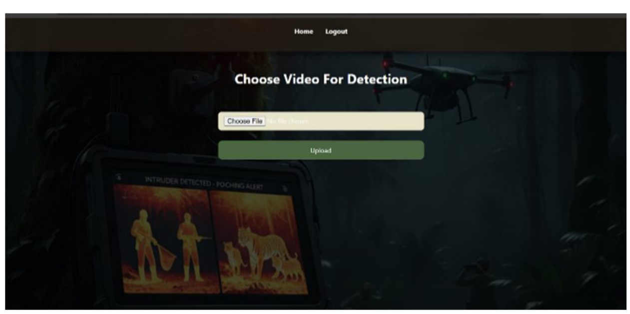

Fig 3. video upload page

In this fig. 3 shows The Video Upload Page. It allows users to upload recorded CCTV or surveillance videos for weapon detection analysis. The system processes each video frame using the YOLOv8 model to identify weapons such as guns, pistols, and knives. Detected objects are highlighted with bounding boxes and confidence scores for better visualization. The page provides an efficient and user-friendly interface for intelligent video-based surveillance monitoring.

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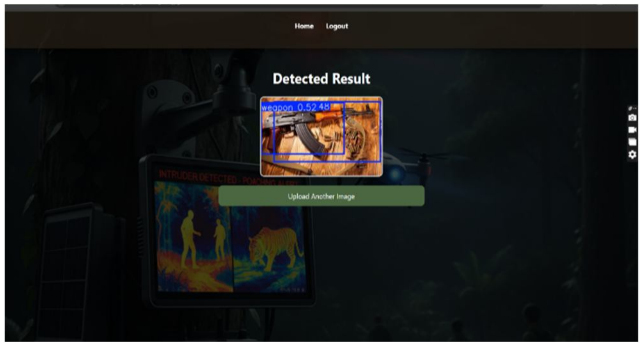

Fig 4. Detection page

In this fig. 4 shows The real-time weapon detection module processes live CCTV or webcam feeds using the YOLOv8 deep learning model. The system successfully identifies weapons such as guns and knives and highlights detected objects using colored bounding boxes and labels.

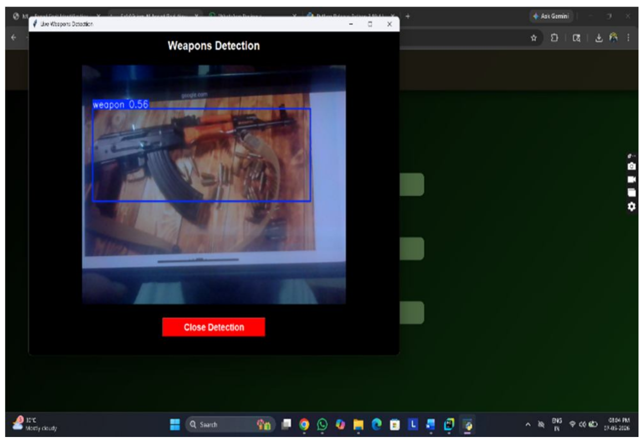

Fig 5. Detection page

In this fig. 5 shows Whenever a weapon is detected, the system instantly generates visual and audio alerts to notify security personnel. The alert mechanism reduces response time and improves public safety by enabling quick action during emergency situations.

VIII. MATHEMATICAL MODEL

The mathematical model of the SafeVision system represents the relationship between surveillance input, object detection, and alert generation. The model explains how video frames are processed through the YOLOv8 detection pipeline for identifying suspicious weapons

A. Mathematical Representation

Let,

- *U*= Set of users
- V = Video input frames
- F = Extracted video frames
- D = YOLOv8 detection model
- W = Detected weapon objects
- C = Confidence score
- A = Alert notifications
- R = Detection results

B. Input Function

- V = {v1, v2, v3, … vn}
- Frame Extraction:
- F(V) → Extracted Frames
- Detection Function:
- D(F) → W
- Confidence Function:
- C(W) → Confidence Score
- Alert Function:
- A(W) → Alert Generated
- Output:
- R = {Bounding Boxes, Labels, Alerts, Confidence Scores}
- B. Time Complexity
- The detection process depends on the number of video frames processed by the YOLOv8 model.
- Time Complexity:
  - O(n)
  - Where n represents the number of frames processed.

C. Space Complexity

- Space complexity depends on model parameters and frame storage.
- Space Complexity:
- O(n)

D. Flow Chart

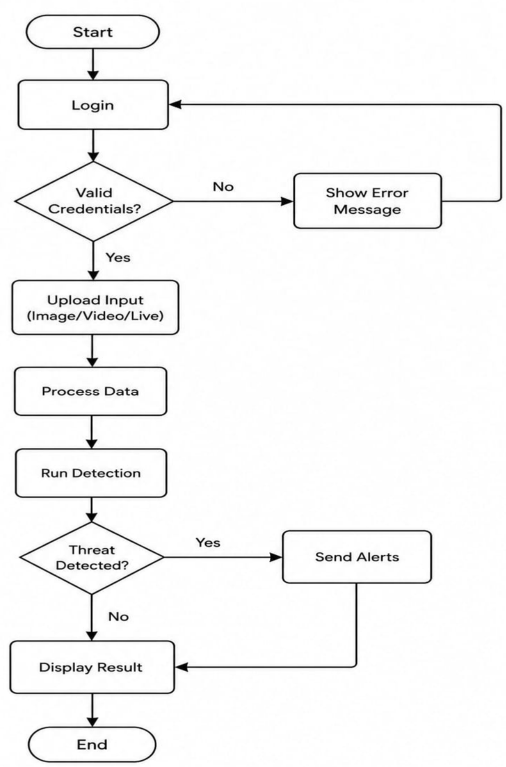

Fig 6. Flow chart

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In this fig. 6 shows The flowchart. It represents the complete working process of the SafeVision weapon detection system. It starts with user registration or login and validates the user credentials. After successful login, the user provides input in the form of image, video, or live camera stream. The system collects and preprocesses the input data before passing it to the YOLOv8 detection model. If a weapon is detected, the system displays the result, stores detection details in the database, and sends real-time alerts. If no weapon is detected, the system simply displays the result without generating alerts.

IX. SIMULATION RESULT

The simulation of “SafeVision” was performed to analyse the overall working performance and weapon detection capability of the proposed system in real-time surveillance environments. The system successfully handled live video processing, object detection, alert generation, and dashboard visualization in a smooth and efficient manner.

The YOLOv8 deep learning model accurately detected weapons such as pistols, rifles, and knives from CCTV and webcam feeds under different environmental conditions. The detection results were displayed with bounding boxes and confidence scores through the Flask-based dashboard interface. The system generated instant alerts whenever suspicious weapons were detected, thereby improving emergency response time and surveillance efficiency.

The proposed system maintained stable performance in crowded environments, varying lighting conditions, and continuous video monitoring scenarios. The integration of AI-based object detection and real-time alert mechanisms significantly reduced dependency on manual surveillance systems.

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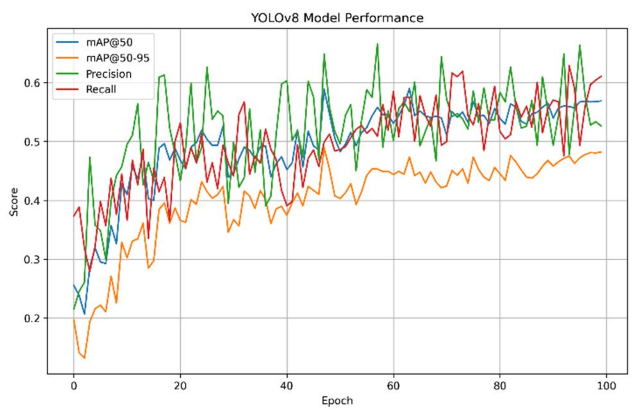

Fig 7. Model Performance

In this fig. 7 shows The graph represents the performance of the YOLOv8 model during training across different epochs. It shows evaluation metrics including mAP@50, mAP@50–95, Precision, and Recall. The increasing trend of these values indicates continuous improvement in the model’s detection capability and learning performance. The final results demonstrate stable convergence with good accuracy, precision, and reliable object detection performance.

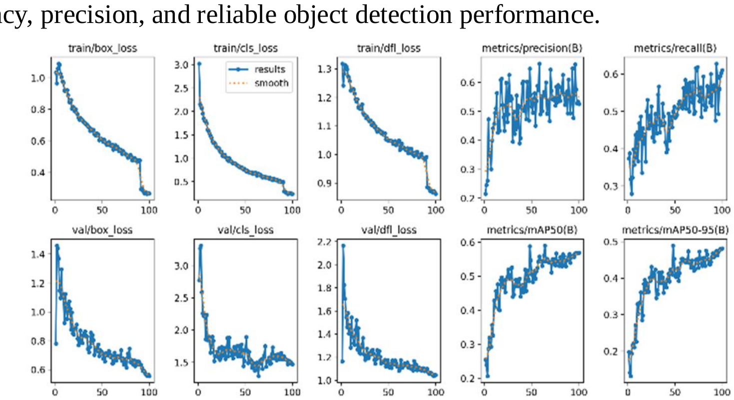

Fig 8. Accuracy Graph

In this fig. 8 shows The training and validation performance graphs illustrate the learning progress of the YOLOv8 model during training. The train and validation loss values (Box Loss, Classification Loss, and DFL Loss) continuously decrease, indicating improved model optimization and reduced prediction errors. Precision, Recall, mAP@50, and mAP@50–95 show an increasing trend across epochs, demonstrating enhanced detection accuracy and object localization performance. The final results confirm that the model achieved stable convergence with effective and reliable weapon detection capability.

X. CONCLUSION

In recent years, the increasing number of violent incidents involving firearms and dangerous weapons in public spaces has highlighted the importance of intelligent surveillance and real-time threat detection systems. Traditional CCTV surveillance systems mainly depend on continuous human monitoring, which often leads to delayed responses, reduced efficiency, and missed detections due to fatigue and human limitations. Therefore, there is a growing need for automated and AI-powered security systems capable of detecting suspicious activities accurately and instantly. The proposed system, "SafeVision: AI-Based Real-Time Weapon Detection System," successfully demonstrates the application of Artificial Intelligence, Deep Learning, and Computer Vision technologies in modern surveillance systems. The system utilizes the YOLOv8 object detection model for identifying dangerous weapons such as pistols, rifles, and knives from live CCTV and webcam video feeds with high accuracy and low latency. The integration of OpenCV and Flask technologies enables smooth real-time video processing, dashboard visualization, and intelligent alert generation. The proposed system effectively reduces dependency on manual monitoring by automatically detecting suspicious weapons and generating instant alerts whenever a threat is identified. Bounding boxes and confidence scores displayed on the dashboard improve surveillance visualization and help security personnel respond quickly during emergency situations. The implementation of a logging mechanism also allows storage of detection records for future analysis, monitoring, and investigation purposes. The experimental and simulation results prove that the system performs efficiently under different environmental conditions such as crowded areas, low-light environments, and continuous video surveillance scenarios. The YOLOv8 deep learning model provides fast and accurate detection performance, making the system suitable for real-time public security applications. The modular architecture of the system also ensures scalability and adaptability for deployment across multiple surveillance environments such as airports, railway stations, educational institutions, shopping malls, banks, and government organizations. Furthermore, the integration of AI-driven surveillance technologies helps improve public safety by enabling proactive threat detection instead of traditional post-incident monitoring approaches. The system minimizes response time during emergencies and enhances overall situational awareness through intelligent automated monitoring mechanisms. Overall, the SafeVision system presents an efficient, scalable, and intelligent surveillance solution capable of improving modern public security infrastructure. The project demonstrates how Artificial Intelligence and Deep Learning technologies can transform conventional surveillance systems into smart automated security platforms for preventing dangerous incidents and ensuring safer environments and multi-camera coordination for further improving accuracy, scalability, and real-time threat analysis capabilities.

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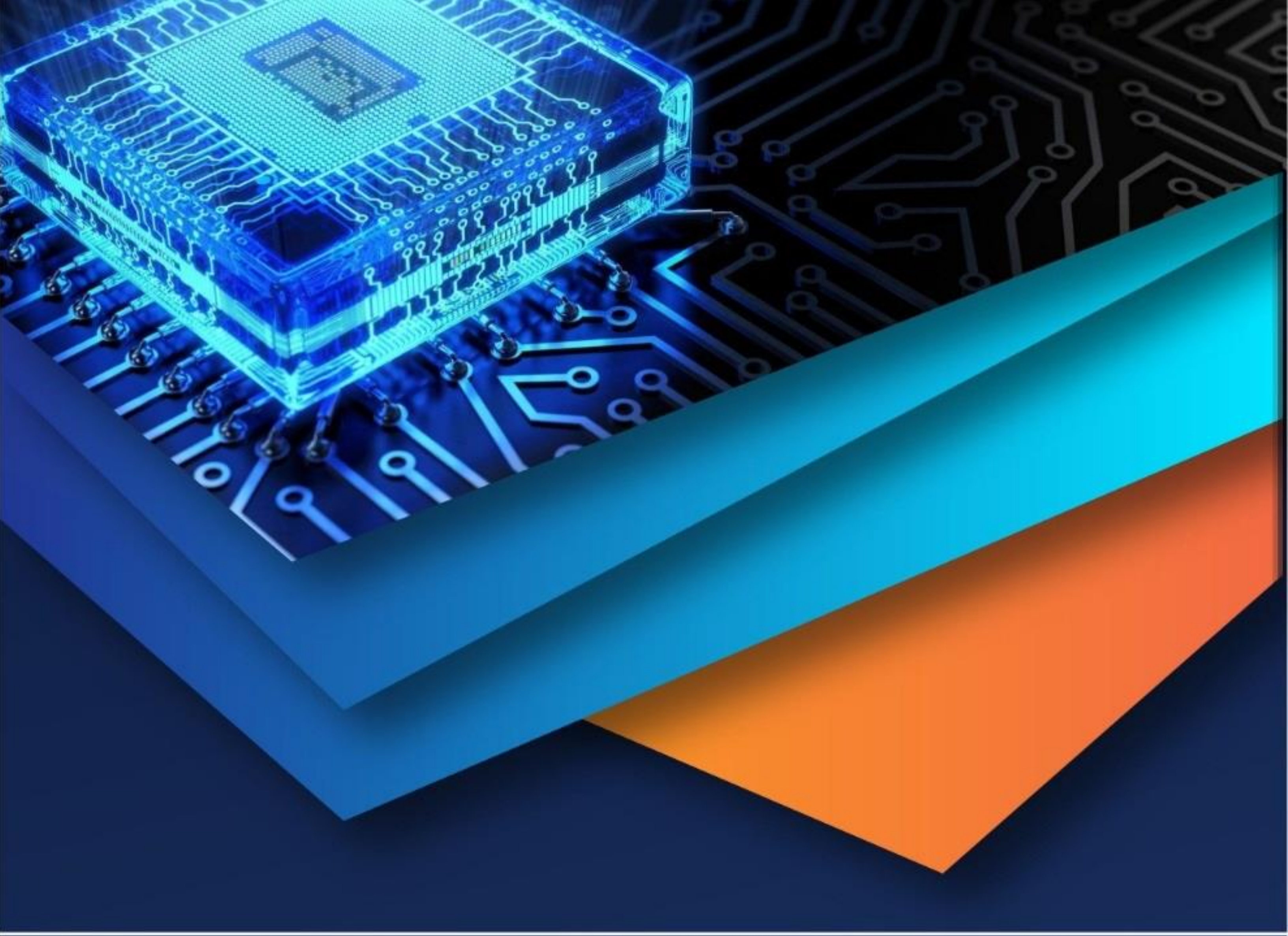

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