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Robust Human Target Detection and Aquisitions

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Abstract: In recent years, the rise of security threats in public and private spaces has emphasized the need for intelligent surveillance systems. This research presents a real-time AI-based threat detection model that identifies potential hazards such as guns, knives, and masks using a customized YOLOv8 architecture integrated with OpenCV. The system is designed to differentiate threatening and non-threatening objects across 27 classes, providing immediate alerts through a web-based dashboard and voice notifications. The application, built using Flask, JavaScript, and SQLite, offers a live camera feed and automated logging of detected threats with time and date. Achieving an accuracy of 90% and high frame-rate inference, the system demonstrates strong potential for real-world deployment in smart surveillance, ensuring rapid and automated responses to life-threatening events.

Keywords: *Object Detection, Computer Vision, Real Time Surveillance, Threat Identification, Deep Learning.*

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I. INTRODUCTION

Traditional surveillance systems rely heavily on manual monitoring, which is time-consuming and prone to human error. With the advancement of deep learning and computer vision technologies, automated object detection models have gained prominence for enhancing situational awareness.

This research focuses on developing a real-time, intelligent monitoring system capable of identifying dangerous objects such as guns, knives, and masks, while also detecting general objects like people, bags, and glasses. The integration of a YOLOv8-based detection model with a Flask web application ensures instant accessibility for authorized users through a live dashboard. The system not only provides visual cues through bounding boxes—red for threats and green for safe objects—but also auditory alerts to ensure immediate action by the admin. By storing event logs in an integrated database, it also supports post-incident analysis and investigation.

II. LITERATURE REVIEW

Recent advancements in multi-object tracking (MOT) have significantly improved the accuracy and efficiency of human target detection systems. One notable approach is BoT-SORT, a state-of-the-art multi-object tracker that effectively combines motion and appearance features with camera motion compensation and an enhanced Kalman filter. It has achieved top-tier results on the MOT17 and MOT20 benchmarks, with metrics such as 80.5 MOTA, 80.2 IDF1, and 65.0 HOTA, demonstrating its robust tracking capabilities in crowded scenes [1].

Transformers have also been introduced into the visual tracking domain to exploit temporal dependencies across frames. A Siamese-based tracking pipeline with separate encoder and decoder branches has been proposed to improve object search and target template enhancement. This method showed improved performance on standard tracking benchmarks, highlighting the advantages of temporal context modeling [2].

A deep learning framework utilizing stereo vision for person tracking has also been presented. This approach employs a regression-based tracker alongside head-based detection and a PID controller for real-time performance on mobile robots. The use of stereo cameras enables spatial depth understanding, improving tracking reliability in dynamic environments [3].

SiamFC++, a fully convolutional Siamese network, integrates classification and state estimation branches within a single tracking model. Following a set of practical design

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principles, this tracker achieves high accuracy on datasets such as OTB2015, VOT2018, LaSOT, GOT-10k, and TrackingNet. SiamFC++ operates at over 90 frames per second (FPS), making it suitable for real-time applications [4].

Another effective solution for real-time human tracking combines MobileNet-v2 with the Single Shot MultiBox Detector (SSD) for initial detection, followed by a particle filter for tracking. This system maintains performance across varying lighting, clothing, and complex backgrounds, demonstrating high robustness under real-world conditions [5].

Furthermore, a stereo vision-based tracking system using block matching algorithms and color histogram comparison has been developed for mobile robots. This system maintains real-time performance and can reliably follow a specific individual even in the presence of similar background colors, making it suitable for assistive robotic applications [6].

III. METHODOLOGY/EXPERIMENTAL

The system architecture comprises five main modules: Dataset Preparation, Model Training, Detection & Classification, Alert Mechanism, and Web Dashboard Integration.

➢ *Dataset Preparation*

A custom dataset of 1,000+ images was created, covering 100+ classes, including both every day and threatening objects. The dataset was automatedly ensuring high annotation accuracy. Data augmentation techniques such as flipping, rotation, and brightness adjustment were applied to increase model robustness and generalization.

➢ *Model Training*

The model was trained using the YOLOv8n framework, known for its high inference speed and precision. Training was performed on a GPU-based system in VS Code and later extended to cloud-based training for scalability.

- Epochs: 500
- Batch Size: 64
- Image size:640*640
- Accuracy: 90% (mAP-based estimation) The model achieved strong detection consistency even under low-light and varying environmental conditions.

➢ *Real-Time Detection*

Using OpenCV, the live camera feed was processed to detect objects frame-by-frame.

- Red bounding boxes indicated threat objects (knife, gun, mask).
- Green bounding boxes represented non-threat objects such as people, glasses, and bags. The detection system maintained real-time inference at high FPS, enabling continuous monitoring without lag.

➢ *Alert System*

A dual alert mechanism was developed:

- Visual Alerts: Threats highlighted in red bounding boxes within the live feed.
- Auditory Alerts: Implemented using Python’s pyttsx3 text-to-speech library, generating repetitive voice alerts until manually stopped by the admin.

➢ *Web Dashboard & Backend*

The Flask-based backend served the trained model and managed the live feed through JavaScript (AJAX) integration for seamless updates.

- *The SQLite Database Logged:*

✓ Object detected
✓ Date and time of detection
✓ Threat classification (threat / non-threat) The dashboard displayed the live feed, alert history, detection count, and threat timeline, providing a complete situational overview for administrators.

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➢ *Block Diagram*

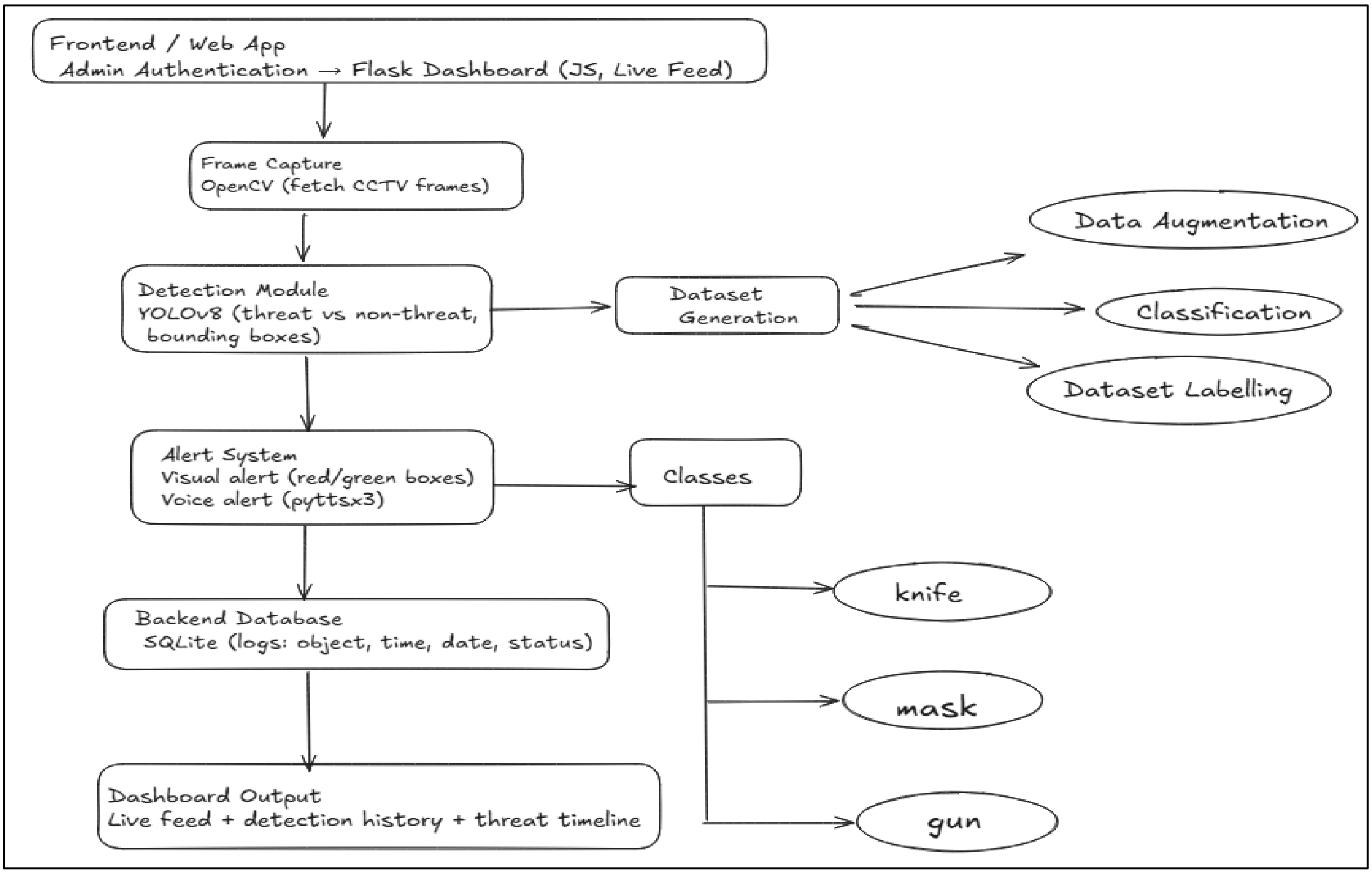

Fig 1 Block Diagram

➢ *Pseudo Code*

The system was evaluated under diverse lighting and environmental conditions to verify its detection accuracy, performance, and response time. Testing confirmed that the model achieved an overall detection accuracy of 90%, maintaining stable performance across various backgrounds. The average processing speed was observed at high FPS, allowing real-time frame updates. The threat detection component was particularly responsive, raising alerts within a fraction of a second after object identification.

✓ Initialize YOLOv8 model
✓ Start camera feed using OpenCV

- While camera is active:

✓ Capture frame
✓ Detect objects using YOLOv8 inference

- For each detected object:

- If object in ['knife', 'gun', 'mask']:

✓ Draw red bounding box
✓ Trigger voice alert using pyttsx3
✓ Log detection (object, time, date, threat status)

- Else:

✓ Draw green bounding box
✓ Display frame on dashboard (Flask interface) Testing confirmed smooth performance even during multiple object detections, proving the system's reliability for real-world deployment.

IV. RESULTS AND DISCUSSIONS

The proposed system demonstrated high efficiency and low latency, making it suitable for real-time surveillance.

➢ *Key Outcomes Include:*

- Detection Accuracy: 90%
- Average Inference Speed: High FPS real-time detection
- Classes Detected: 100+
- Threat Detection Response Time: <1 second
- Database Logging: Automated with time-stamped entries

A hypothetical confusion matrix indicated minimal false positives for major threat classes due to effective dataset balancing and augmentation. The YOLOv8n model outperformed traditional CNN approaches in both detection speed and recall rate.

The web-based interface allowed remote monitoring and control, reducing the dependency on manual supervision.

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The continuous voice alert ensured that no critical incident went unnoticed.

➤ *Math*

Mathematical concepts from Geometry, Linear Algebra, Calculus, and Probability are applied in this project. The main concepts include:

- Mean, Mode, Median – Used for analyzing various user data.
- Bounding Coordinates and Area – Used to create frames around detected objects.
- Matrices and Vectors – Used for image processing, such as transformations (translation, rotation, scaling) within frames.
- Probability Distributions – Used in machine learning for modeling predictions and classification.

➤ *Units*

The project uses units such as seconds, area, distance, frame rate, resolution, weight, and power consumption. Their usage is as follows:

- Seconds – Used for measuring time and processing speed.
- Frame Rate – Used to track the speed at which frames are displayed.
- Distance – Measures the distance between the webcam and the object.
- Area – Used for creating bounding boxes around detected objects.
- Resolution, Weight, and Power Consumption – Monitored to ensure efficiency and proper operation of the system.

➤ *Helpful Hints*

Fig 2 Helpful Hints

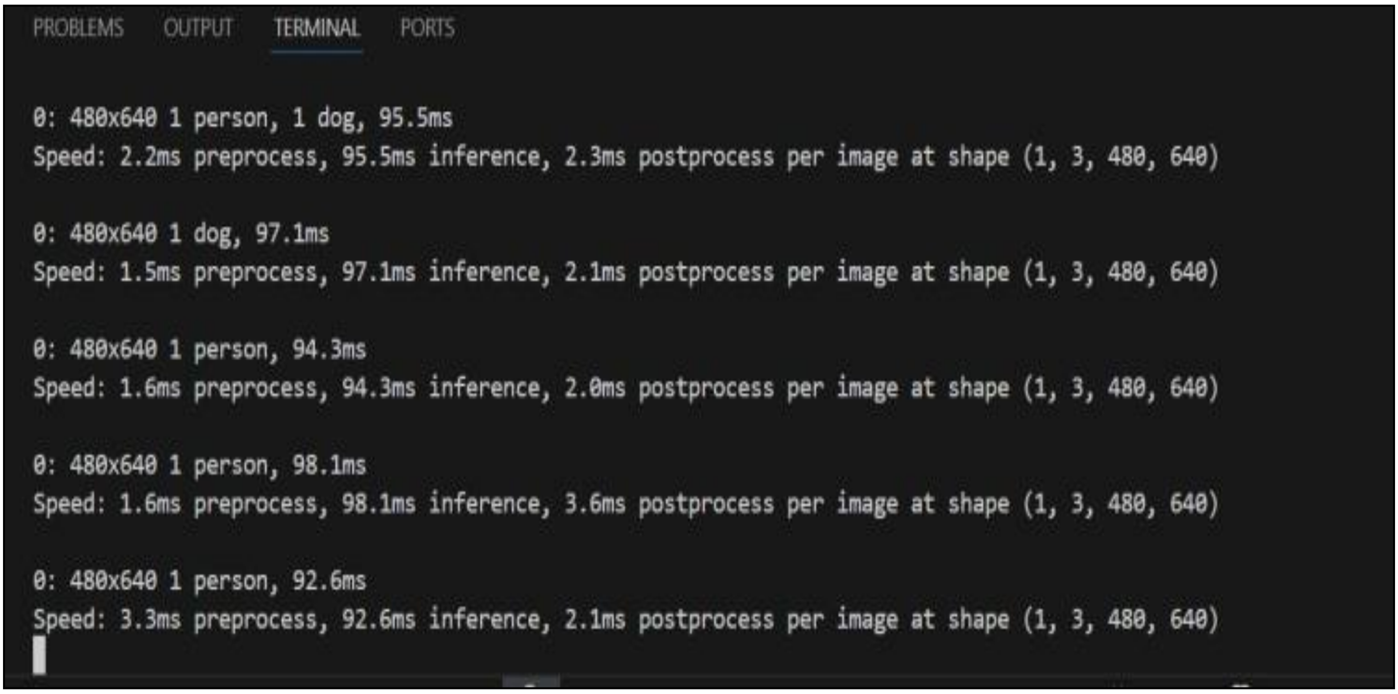

Fig 3 Terminal

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V. FUTURE SCOPE

➢ *The Project Can be Further Enhanced by Integrating:*

- CCTV and multi-camera network systems for large-scale surveillance coverage.
- Cloud-based multi-camera monitoring for distributed security management.
- AI-driven automated incident reporting and mobile alert notifications to enhance field response.
- Deployment on Jetson Orin Nano or Raspberry Pi for edge-based processing, enabling cost-efficient on-site intelligence.

VI. CONCLUSION

This research demonstrates a robust, real-time AI-based threat detection and alert system leveraging YOLOv8 and Flask for intelligent surveillance. The model effectively distinguishes between general and threatening objects, providing instant voice and visual alerts to minimize response time.

The system's scalability, automation, and efficiency mark a significant step toward smart security infrastructure, capable of reducing manual workload and ensuring public safety through proactive detection and response mechanisms.

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