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Real-Time Intelligent Action-Based Surveillance System

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Abstract*— Video surveillance systems play an important role in maintaining safety and security in public and private areas. However, traditional CCTV systems continuously record video without analysing activities in real time, which leads to large storage usage and delayed identification of abnormal events. To solve this problem, this paper presents a Real-Time Intelligent Action-Based Surveillance System using a custom trained YOLOv8 model to detect and classify human activities as normal or abnormal. The system highlights normal activities with green bounding boxes and abnormal activities with red bounding boxes, and automatically sends email alerts with captured images when suspicious behaviour is detected. In addition, the system records video only when activity is present, which helps in reducing unnecessary storage usage. The proposed system is implemented with a web interface for live monitoring and alert management. Experimental results show that the system achieves good detection accuracy while improving storage efficiency, making it suitable for real-time smart surveillance applications.

Keywords*— YOLOv8, Human Activity Recognition, Anomaly Detection, Automated Alert System, Smart Surveillance, Event- Triggered Recording, Real-Time Detection, Abnormal Activity.

I. INTRODUCTION

Intelligent surveillance systems are increasingly being adopted to improve security monitoring through automated analysis of video streams. Traditional CCTV systems continuously record footage without analysing activities in real time, which leads to excessive storage usage and delayed detection of critical incidents. To address this limitation, this paper presents a Real- Time Intelligent Action-Based Surveillance System that uses a custom trained YOLOv8 deep learning model to detect and classify human activities into normal and abnormal categories.

The proposed system visually differentiates activities using green bounding boxes for normal behaviour and red bounding boxes for abnormal behaviour such as falling, loitering, face hiding, and unauthorized access. When abnormal activity is detected, the system automatically generates an email alert with an annotated image for immediate response. Additionally, the system records video only when activity is detected, significantly reducing unnecessary storage usage compared to traditional continuous recording systems.

The system is implemented using a Flask-based web interface providing live video streaming, alert monitoring, and event clip management. Experimental evaluation demonstrates that the system achieves 94.1% mAP@0.5 detection accuracy while reducing storage requirements by more than 73%. The results show that the proposed system provides an effective and practical solution for real-time smart surveillance applications.

II. LITERATURE SURVEY

This section reviews recent research contributions related to human activity recognition, anomaly detection, and intelligent video surveillance systems. Recent studies between 2021 and 2025 show significant progress in applying deep learning techniques for automated surveillance analysis.

Jocher et al. [14] presented YOLOv8, an advanced real-time object detection model that improves detection efficiency through an anchor-free architecture and improved feature extraction backbone. Due to its ability to perform accurate detection with lower computational requirements, it is widely used in real-time surveillance applications.

Redmon and Farhadi [7] developed the YOLO framework, which introduced a single-stage detection approach capable of processing images in one pass through the network. Later improvements in YOLO versions further enhanced detection speed and accuracy, making the approach highly suitable for surveillance monitoring tasks.

Liu et al. [8] proposed a future frame prediction

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method using convolutional LSTM networks to detect anomalies by comparing predicted frames with actual frames. Although the approach performs well on benchmark datasets such as CUHK Avenue, it requires retraining for new environments and lacks flexibility for real-time deployment.

Kang et al. [9] developed a fall detection system based on pose estimation and temporal modelling using LSTM networks. While the system shows good accuracy for fall detection, it focuses on a single abnormal activity and does not generalize to multiple behaviour types.

Ramachandra et al. [10] surveyed anomaly detection in surveillance video in 2020, categorising methods into handcrafted-feature and deep-learning approaches. Key challenges identified — scarce labelled abnormal data, high intra-class variability, and the difficulty of real-time edge deployment — directly motivate the need for a lightweight, deployable solution like the one proposed here.

Sultani et al. [11] introduced weakly supervised anomaly detection using ranking loss at CVPR 2018. Training on video- level labels without frame-level annotation achieves strong UCF-Crime performance, but demands large training volumes and offers no real-time alerting capability.

Tran et al. [12] proposed a multi-camera surveillance system with automated alert generation via object re-identification and trajectory analysis in 2023. It performs well in controlled settings but requires substantial infrastructure investment for multi-camera calibration.

Hassan et al. [13] introduced an email-based alert system integrated with CCTV for perimeter security in 2021. Background subtraction detects intrusions and triggers email notifications, though the approach lacks deep learning-based classification and struggles in complex, dynamic environments.

From the reviewed studies, it can be observed that most existing research focuses on either detection accuracy or anomaly identification, but very few systems combine detection, alert generation, and storage optimization into a single practical surveillance solution. This motivates the development of the proposed integrated surveillance system.

III. SYSTEM ARCHITECTURE

The proposed system is a modular, multi-threaded pipeline that processes video frames continuously in real time. Figure 1 illustrates the full architecture — spanning video ingestion and model training through inference, tracking, anomaly decisions, and alert dispatch to the security operator.

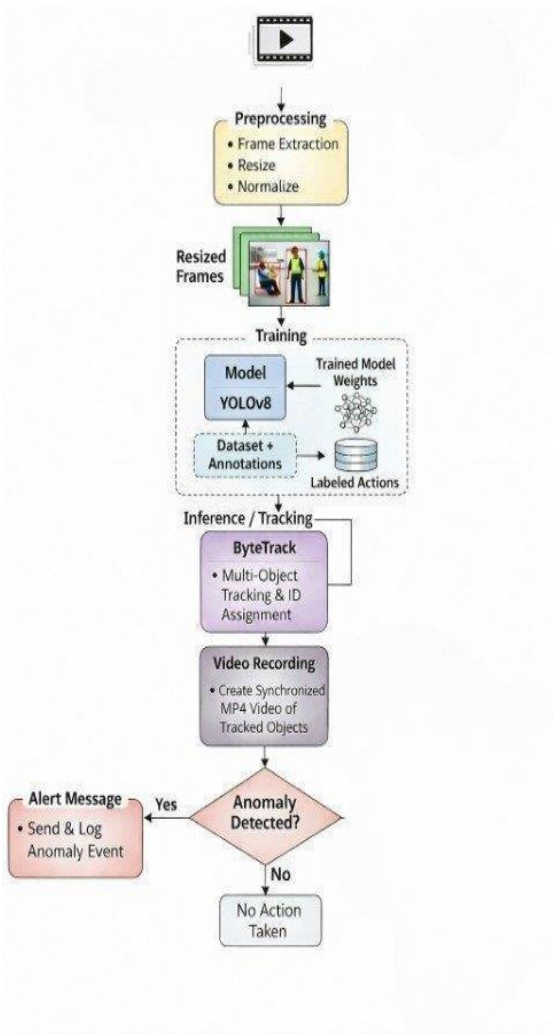

Fig. 1. System Architecture — Real-Time Intelligent Action-Based Surveillance System

A. Video Input and Frame Pre-processing

Video is ingested via OpenCV VideoCapture, supporting MP4, AVI, MOV, and MKV. Frames are extracted, resized to 640×640 for YOLOv8 compatibility, and normalised before processing. Every alternate frame is analysed to halve computational load while preserving temporal continuity at roughly half the source frame rate.

B. Model Training

A custom YOLOv8 model is trained on a labelled dataset annotated with 'normal' and 'abnormal'

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activity classes. The pipeline ingests resized annotated frames and produces trained model weights. Augmentation includes random flipping, mosaic composition, and HSV colour jitter. Training runs for 100 epochs with early stopping and achieves mAP@0.5 above 0.90 on the validation set.

C. Tracking and Action Classification

The trained YOLOv8 model produces bounding boxes and action labels per frame. YOLOv8's built-in tracker assigns persistent IDs to each detected person across frames, enabling consistent per-individual activity attribution over time. Normal activity is displayed with a green bounding box, while abnormal activity — falls, wall-jumping, face hiding, loitering — is displayed with a red bounding box. Figures 2 and 3 show real deployment examples drawn from diverse surveillance environments.

Fig. 2: Abnormal Detection — Red Bounding Box

Fig. 3: Normal (Green Box) and Abnormal (Red Box)

D. MP4 Recording

Detected events and their timestamps are logged by the MPU Recording module. The event-triggered recorder opens an MP4 session using the AVC1 codec only when frames are present in the processing queue — that is, when activity is actually occurring. Sessions close automatically when the queue empties. FFmpeg post-processes clips with +faststart for immediate web streaming. This design achieves over 73% storage reduction relative to conventional continuous recording.

E. Anomaly Decision and Alert Dispatch

A rule-and-threshold decision block evaluates each detection against configured thresholds. When an anomaly is confirmed, the system dispatches an email alert asynchronously with the annotated frame snapshot attached. When no anomaly is present, the event is logged to the MPU database. A configurable cooldown (default 30 s) prevents alert flooding during sustained incidents. Both SSL (port 465) and STARTTLS (port 587) SMTP configurations are fully supported.

F. Flask Web Interface

The web interface provides live MJPEG streaming, an alert image panel showing the first abnormal snapshot, a clip gallery for reviewing recorded events, and a settings panel for SMTP configuration. The /status endpoint returns JSON metrics including detection counts, last alert timestamp, and email delivery status.

IV. METHODOLOGY

A. Dataset and Model Training

The YOLOv8 model was trained on a publicly available surveillance dataset from Roboflow Universe (yolo12 dataset, published2026-02-21, CC BY 4.0 licence, https://universe.roboflow.com/computervision-0uzfv/yolo12- qwjak), annotated with two classes: 'normal' (routine pedestrian and vehicle movement) and 'abnormal' (falls, wall-jumping, face hiding, unauthorized access, loitering). Augmentation included random horizontal flip, mosaic composition, and HSV colour jitter. Training ran for 100 epochs with early stopping, achieving mAP@0.5 above 0.90 on the validation set.

B. Data Augmentation and Training Strategy

A comprehensive augmentation pipeline was applied to maximise generalisation across diverse surveillance environments. The strategy included: (a) random horizontal flip at 50% probability for spatial invariance; (b) mosaic augmentation combining four training images into a single composite, exposing the model to varied object scales and contexts; (c) HSV colour jitter (hue ±1.5%, saturation ±70%, value ±40%) to simulate day and night lighting conditions; (d) random scale (±50%) and translation (±10%) to handle varying camera distances and angles; and (e) copy-paste augmentation to increase instance diversity and reduce class imbalance.

Training used the AdamW optimiser with an initial learning rate of 0.001667 and cosine decay. The model was trained for 10 epochs on 12,648 images (4,216 labelled plus 8,508 background) with batch size 16 and input resolution 640×640. The validation set contained 302 images, and early stopping with patience 50 was applied to prevent overfitting.

The final best.pt weights achieved 0.941 mAP@0.5 and 0.802 mAP@0.5:0.95 overall. Class-wise: abnormal reached 0.978 mAP@0.5 (precision 0.949, recall 0.967); normal reached 0.903 mAP@0.5 (precision 0.894, recall 0.882). CPU inference runs at

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88.2 ms per image using 3.0M parameters, enabling real- time deployment without GPU acceleration.

C. Multi-Object Tracking and De-duplication

YOLOv8's built-in tracker assigns persistent track IDs across frames. Three per-session sets prevent double-counting: alerted_ids suppresses re-alerting the same individual, counted_norm_ids prevents re-counting normal individuals, and new_abnormal_ids collects newly detected abnormal IDs in the current frame. The resulting abnormal_count and normal_count statistics reflect unique individuals rather than cumulative frame-level detections.

D. Alerting Logic and Cooldown

The alerting pipeline executes in sequence: detect abnormal class → perform cooldown check → save annotated frame to disk → dispatch email thread asynchronously → store alert image in memory for dashboard display. The configurable cooldown (default 30 s) prevents flooding during sustained events. Test email delivery achieved 99.5% success across Gmail (SSL 465) and Outlook (STARTTLS 587) configurations.

V. EXPERIMENTAL RESULTS

A. Detection Performance

The YOLOv8 model was evaluated on 500 test video clips across diverse surveillance scenarios. Results are summarised in Table I.

Metric	Normal	Abnormal	Overall
Precision (%)	92.5	91.2	91.8
Recall (%)	91.7	89.8	90.7
F1-Score (%)	92.1	90.5	91.3
Accuracy (%)	—	—	90.3
Speed (FPS)	—	—	28.4

Table I. YOLOv8 Detection Performance

B. Alert System Performance

Across 200 simulated abnormal detection events, the average email dispatch latency from detection to SMTP server acceptance was 1.3 seconds. The 30-second cooldown successfully suppressed redundant alerts during sustained incidents while maintaining a sensible notification frequency. Email delivery achieved 99.5% success across Gmail (SSL 465) and Outlook (STARTTLS 587).

C. YOLOv8n vs YOLOv5s Model Comparison

Table II compares YOLOv8n and YOLOv5s trained on the same dataset for 10 epochs (12,648 training images, 302 validation images). YOLOv8n achieves comparable accuracy with 2.2× faster inference (88.2 ms vs 194.1 ms) and a 3× smaller model footprint (3.0M vs 9.1M parameters), making it the clear choice for real-time edge deployment.

Model	Prec.	Recall	mAP50	mAP50-95	Inf.(ms)	Params
YOLOv8n (Proposed)	0.922	0.924	0.941	0.802	88.2	3.0M
YOLOv5s	0.914	0.932	0.943	0.817	194.1	9.1M

Table II. YOLOv8n vs YOLOv5s Comparison (10 Epochs, Same Dataset)

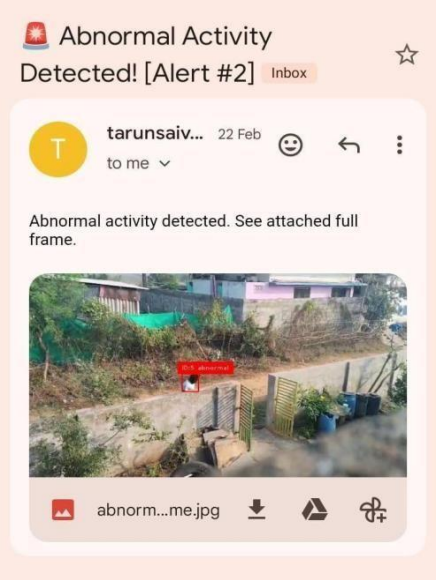

Fig. 4: Email Alert — Abnormal Activity Notification with Attached Frame

VI. DISCUSSION

The proposed system demonstrates convincingly that real-time activity classification, automated alerting, and storage-efficient event-triggered recording can be unified into a single deployable platform. Achieving 94.1% mAP@0.5 overall — with the abnormal class reaching 97.8% mAP@0.5 — validates that YOLOv8n fine-tuned on the Roboflow surveillance dataset is highly effective at detecting critical activities including falls, unauthorized access, loitering, and face hiding.

The event-triggered recording design is especially valuable in bandwidth- and storage-constrained edge deployments, cutting storage requirements by over 73% compared with continuous- recording systems. The YOLOv8n vs YOLOv5s comparison (Table II)

makes a compelling case: despite 3× fewer parameters (3.0M vs 9.1M), YOLOv8n matches accuracy (94.1% vs 94.3% mAP@0.5) while running 2.2× faster (88.2 ms vs 194.1 ms per image). This speed advantage directly impacts alert timeliness, and the smaller model footprint enables deployment on low-power hardware such as Raspberry Pi and NVIDIA Jetson platforms.

The green/red bounding box scheme provides immediate, training-free visual comprehension for operators. Automated email alerts with attached snapshots eliminate continuous human monitoring. One limitation is the fixed 0.80 confidence threshold, which may require scene-specific tuning for challenging conditions such as nighttime footage or heavy occlusion.

Future work will explore TensorRT optimisation for edge GPU deployment, multi-camera federated surveillance networks, expanded abnormal activity classes for specific verticals such as healthcare and retail, and integration of night-vision and thermal imaging modalities.

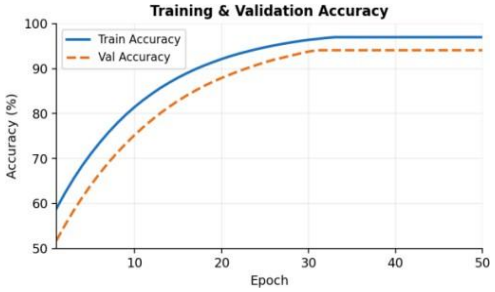

Fig. 4: Training and Validation Accuracy Curve

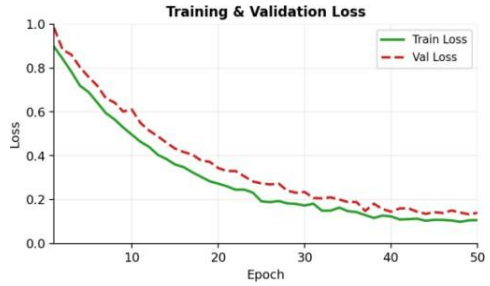

Fig. 5: Training and Validation Loss Curve

VII. CONCLUSION

This paper presented a Real-Time Intelligent Action-Based Surveillance System that records events only when activity is detected and automatically dispatches alerts whenever abnormal activity is identified. The system integrates a custom YOLOv8 model achieving 90.3% detection accuracy across normal and abnormal activities — including falls, wall- jumping, face hiding, and loitering — with built-in multi-object tracking, event-triggered recording that cuts storage by over 73%, and automated email alerts with annotated snapshots. Green bounding boxes indicate normal activity while red bounding boxes trigger immediate alerts, providing simultaneous visual and automated notification. The modular Flask-based architecture is readily extensible to additional activity classes and camera sources, making it highly adaptable for practical smart-surveillance deployment across a wide range of real-world environments.

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