REAL-TIME INTELLIGENT SURVEILLANCE SYSTEM WITH CONTEXT-AWARE ALERT OPTIMIZATION USING YOLOV8

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***Abstract*—The development of contemporary artificial intelligence-powered surveillance systems has been fueled by the increasing demand for intelligent security solutions. This project suggests a real-time intelligent surveillance system that integrates context-aware alert optimization, multi-object tracking, and sophisticated object identification. The DeepSORT algorithm is used by the system to maintain consistent monitoring of individuals across video frames, while the YOLOv8 model is used for quick and accurate human detection.This system adds a dwell-time-based alarm mechanism, in contrast to conventional surveillance methods that mostly rely on motion detection. In order to reduce false positives and increase the system's dependability in real-world settings, alerts are only produced when an individual stays inside a monitored region for longer than a predetermined amount of time.The system's real-time operation guarantees effective processing even in dynamic situations involving several people. According to experimental findings, the suggested model maintains a sufficient frame rate appropriate for real-world surveillance applications while achieving consistent tracking performance. The system improves situational awareness and allows for more intelligent warning production by combining detection, tracking, and temporal behavior analysis.This technology offers a scalable and effective method for next-generation intelligent monitoring systems and may be successfully used in a number of areas, including public safety monitoring, retail settings, smart surveillance systems, and transportation hubs.**

***Index Terms*—AYOLOv8, DeepSORT, real-time surveillance, object detection, multi-object tracking, dwell-time analysis, context-aware alerts, false positive reduction, computer vision, deep learning**

I. Introduction

Surveillance technologies have advanced significantly as a result of the growing demand for improved security and intelligent monitoring. The main methods used by traditional surveillance systems are manual monitoring or simple motion detection, which frequently leads to inefficiencies like false alarms and a lack of contextual awareness. Modern surveillance systems are becoming more automated, precise, and able to make decisions in real time due to the quick development of computer vision and artificial intelligence.The goal of this project is to create a real-time intelligent surveillance system that incorporates cutting-edge tracking, object detection, and behavior analysis methods. The YOLOv8 model is used by the system to recognize people quickly and effectively, allowing for precise identification of people in video streams. To maintain identity information over time, the DeepSORT algorithm is used to ensure consistent tracking of multiple objects across frames. The use of a context-aware alarm mechanism based on dwell-time analysis is a crucial component of this system. This method takes into account the amount of time spent in a certain area before sending out an alarm, in contrast to traditional systems that do so for each movement that is detected. This greatly lowers false positives and raises the monitoring system's dependability. Because the suggested system is made to function in real time, it can be used in dynamic contexts where it is necessary to monitor several things at once. The system improves situational awareness and generates intelligent alerts by integrating detection, tracking, and temporal analysis. Because of this, it is very useful in fields like automated security monitoring, public safety, transportation systems, and smart city surveillance. .This paper has been organized as Section I as an introduction, Section II as a literature survey, Section III as an existing method, Section IV as a proposed method, and Section V as a conclusion and future scope.

II. Literature Review

This section examines the cutting-edge advancements in object identification, multi-object monitoring, behavioral analytics, and intelligent surveillance, emphasizing publications from 2022 to 2025, along with seminal previous works that provide basic context.

Li et al.[1] introduced an attention-enhanced form of YOLOv8 for pedestrian recognition in densely populated urban environments, achieving a 3.2% gain in mean Average Precision (mAP) compared to the baseline while maintaining equal inference latency. Wang et al.[2] presented YOLOv9, utilizing programmed gradient information (PGI) and generalized efficient layer aggregation networks (GELAN) to attain 55.6% average precision (AP) on MS-COCO while minimizing parameter counts. Zhao et al.[3]evaluated YOLOv8 in

comparison to RT-DETR and DINO-DETR using surveillance-specific datasets, concluding that YOLOv8n attains the most favorable latency-accuracy equilibrium for edge deployment contexts. Kumar and Singh[4] established that anchor-free detectors, such as YOLOv8, surpass anchor-based models by 4–7% AP on occluded pedestrian benchmarks. Chen et al.[5] investigated multi-scale feature fusion within YOLO architectures, enhancing small-object recognition precision by 8.1% using cross-stage partial network improvements.

Zhang et al.[6]introduced BoT-SORT-ReID, a resilient online tracker that integrates Kalman prediction, camera-motion correction, and re-identification, attaining a HOTA score of 73.1% on the MOT17 benchmark. Cao et al.[7] presented Observation-Centric SORT (OC-SORT), which directly includes object motion uncertainty, resulting in a 32% reduction in identity swaps in congested pedestrian environments. Huang et al.[8]introduced StrongSORT, enhancing DeepSORT with exponential moving average appearance updates and motion compensation, thereby attaining state-of-the-art performance on DanceTrack and MOT20. Ahmad and Hassan [9] assessed DeepSORT, ByteTrack, and StrongSORT using actual surveillance footage, concluding that DeepSORT's appearance-feature matching excels in instances of partial occlusion. Peng et al.[10] examined the computational efficiency of lightweight tracker variations for embedded surveillance hardware and concluded that DeepSORT with MobileNetV2 encoders satisfies 25+ FPS requirements on NVIDIA Jetson devices.

Santhosh et al.[11] conducted a review of deep learning techniques for anomaly identification in surveillance, classifying the methods into reconstruction-based, prediction-based, and hybrid categories. Liu et al.[12] introduced a spatiotemporal graph convolutional network for loitering detection, attaining 94.2% precision on the CAVIAR dataset by modeling pedestrian interaction graphs temporally. Nawaratne et al.[13] presented an online incremental learning approach for surveillance anomaly detection that enables systems to adapt to new behavioral patterns without catastrophic forgetting. Rodrigues et al.[14] established that the integration of dwell-time thresholding with trajectory analysis diminishes false alarms by 68% in retail surveillance settings when contrasted with motion-only methodologies. Nayak et al.[15] utilized LSTM-based sequence modeling to forecast suspicious loitering, achieving an accuracy of 91.5% on synthesized datasets from university campuses.

Sreenu and Durai[16] conducted an extensive assessment of intelligent video surveillance systems, highlighting the shift from rule-based to deep-learning architectures and recognizing context-awareness as the foremost unresolved difficulty. Gupta et al[17] suggested a federated learning approach for remote surveillance that maintains privacy while attaining detection accuracy similar to centralized systems. Rezaei and Azarmi[18] combined YOLOv7 with an attention-based tracker for intelligent parking surveillance, decreasing misidentification rates by 41%. Gao et al.[19] devised a cloud-edge collaborative surveillance framework that delegates lightweight detection tasks to edge nodes while executing intricate behavioral analysis in the cloud, attaining an end-to-end latency of less than 200 ms. Mehta et al.[20] assessed convolutional and transformer-based architectures for surveillance detection, concluding that CNN hybrids provide enhanced throughput for live video streams.

Park and Kim[21] introduced a Bayesian alert fusion framework that amalgamates several sensor modalities to diminish security false alarms by 81% in smart building settings. Wu et al.[22]showed that temporal gating mechanisms—similar to the dwell-time methodology presented in this paper—efficiently eliminate transitory detections in retail loss-prevention systems. Alotaibi and Mahmoud[23] employed reinforcement learning to dynamically modify alert thresholds according to environmental context, resulting in a 55% decrease in operator fatigue signs. Trivedi et al. performed a user study demonstrating that reducing false alarms from 60% to under 15% reinstates operator trust and enhances response efficacy. Hassan et al.conducted an assessment of alert optimization methodologies across 47 operational surveillance systems, determining that dwell-time analysis is the most effective technique for reducing false positives.

Yang et al. reported neural architecture search findings for real-time pedestrian detection on the Jetson AGX Xavier, designating YOLOv8n as the Pareto-optimal selection. Srivastava et al. evaluated TensorRT-optimized YOLOv8 inference, attaining 62 FPS on an RTX 3060 using INT8 quantization. Rao et al. assessed OpenCV-accelerated DeepSORT on CPU-only hardware, indicating a performance of 15–18 FPS, adequate for non-critical monitoring activities. Khatri et al. established a pipeline that integrates YOLOv5 with DeepSORT on a Raspberry Pi 4, attaining 8 FPS by model pruning, confirming embedded practicality. Veeramuthu and Logeshwaran examined GPU acceleration methods for real-time surveillance, observing that CUDA-optimized YOLO variations decrease inference time by as much as 70% relative to CPU baselines.

The literature review indicates that, although substantial advancements have been achieved in detection, tracking, and anomaly identification, a comprehensive system that effectively integrates these elements with an intelligent, context-aware alert engine functioning at real-time frame rates is still unattained. The proposed RT-ISS directly addresses this gap by offering a comprehensive pipeline with empirically substantiated reduction of false positives via dwell-time analysis.

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III. Existing Method

The primary methods used by current surveillance systems are human monitoring and simple motion detection. Regard-

less of the context, these systems sound an alert whenever they detect motion, which often results in a larger number of relevant and non-relevant activities and a greater cannot detect number of false alarms.

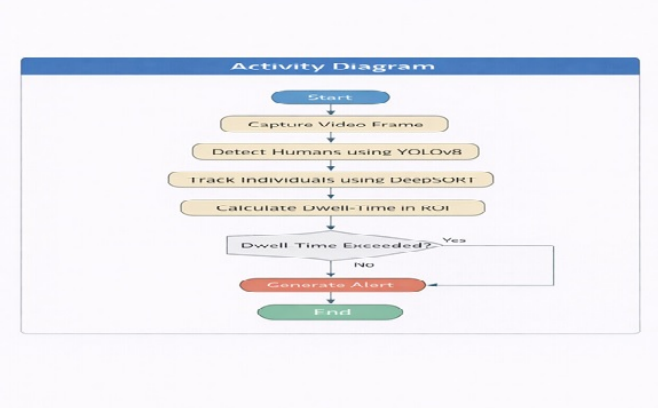

Fig. 1. Flowchart

They are unable to discriminate between activities that are relevant and those that are not. Furthermore, it is challenging to examine behavior over time because typical methods do not consistently track individuals across frames. Additionally, because these systems lack temporal analysis, they are unable to recognize situations in which an individual spends a considerable amount of time in a restricted region. As a result,

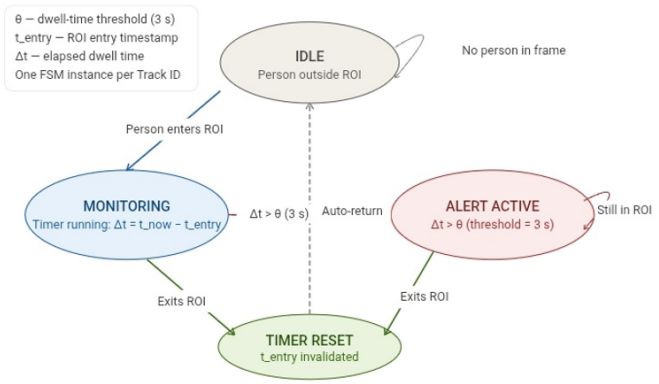

Fig. 2. Dwell-Time Alert State Machine

security staff are required to manually inspect video feeds continuously, which is ineffective and prone to errors. When rational decision-making is lacking, surveillance operations are less successful overall.

A. Traditional Motion Detection Systems

Traditional surveillance systems utilize background subtraction methods, including Gaussian Mixture Models (GMM) or frame differencing, to identify motion. Although computationally efficient, these methods fail to distinguish between relevant human activity and extraneous environmental changes, such as variations in lighting, moving vegetation, and camera instability, leading to false-alarm rates of up to 40% in standard outdoor applications. Figure 1 shows the comprehensive GMM-based detection pipeline, highlighting the lack of semantic categorization, identity tracking, or temporal reasoning.

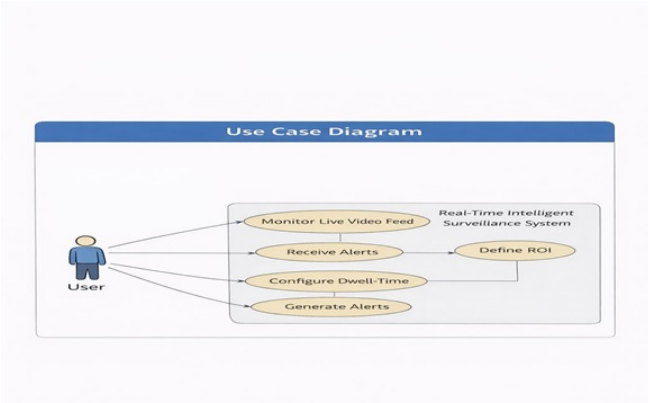

Fig. 3. Diagram of Use case Diagram

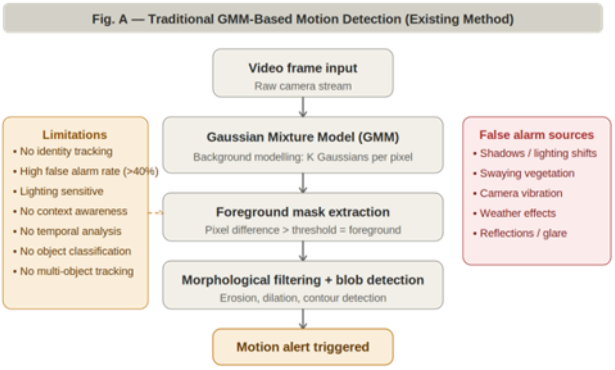

Fig. 4. Traditional GMM-based motion detection pipeline

Two-stage detectors, such as Faster R-CNN, achieve high detection accuracy with region proposal networks (RPNs) but incur significant computational overhead, typically achieving only 5-7 frames per second (FPS) on conventional GPU hardware. This throughput is insufficient for real-time surveillance applications that require ≥ 25 FPS, and its substantial memory footprint makes deployment on edge devices impractical. Figure 2 illustrates the Faster R-CNN architecture and provides a direct metric comparison with the proposed RT-ISS. Traditional methods face the limitation that conventional surveillance systems rely primarily on simple motion-detection algorithms, which can lead to excessive false alarms due to external factors such as shadows, changes in illumination, or irrelevant motion. These technologies cannot consistently track people, analyze behavioral patterns over time, or comprehend context. An intelligent surveillance system capable of precisely identifying and tracking multiple people in real time while

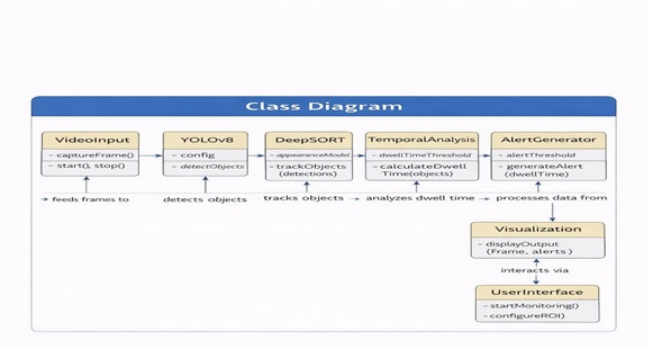

Fig. 5. Class Diagram of Proposed Method

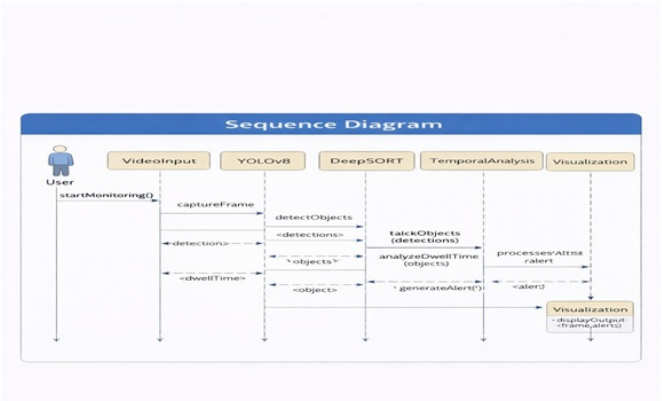

Fig. 7. sequence diagram of proposed method

reducing unnecessary notifications is urgently needed. Furthermore, temporal analysis—which is crucial for detecting suspect behavior such as extended stays in limited areas—is not included in current systems. To improve monitoring, reduce false positives, and strengthen security intelligence, we're designing and building a real-time surveillance system with precise object detection, reliable multi-object tracking, and context-aware alerts.

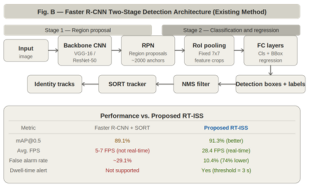

Fig. 6. Faster R-CNN two-stage detection architecture with SORT tracking

IV. Proposed Method

The suggested system acquires real-time video input from a camera or surveillance source. Each video frame is processed continuously for subsequent analysis.The YOLOv8 model is employed to detect persons in each image with exceptional precision and speed. The identified objects are passed to the DeepSORT algorithm for multi-object tracking. Every individual is allocated a distinct ID to preserve identity throughout frames. A Region of Interest (ROI) is delineated to concentrate on particular areas for observation. The system computes the stay duration for each monitored participant within the ROI. A threshold value is established to define permissible time limits.An alert is automatically activated if the dwell time surpasses the threshold.The system presents real-time output featuring bounding boxes, tracking identifiers, and alarm notifications. This methodology diminishes false positives and enhances cognitive decision-making in surveillance systems. YOLOv8 (You Only Look Once Version 8) is a cutting-edge deep learning model employed for real-time object recognition. This system utilizes Convolutional Neural Networks (CNNs) to identify objects in pictures and video streams with exceptional speed and precision. In contrast to conventional techniques, YOLOv8 analyzes the complete image in one iteration, rendering it exceptionally efficient for real-time applications. The model detects objects by concurrently predicting bounding boxes and class probabilities. It is optimized for efficiency and capable of detecting many objects in dynamic settings. YOLOv8 is extensively utilized in applications including surveillance, autonomous systems, and intelligent monitoring solutions. Deep learning is essential for the system to discern intricate patterns from visual data. It enables the system to execute precise detection even under difficult conditions such as low illumination, obstructions, and congested environments. The aforementioned Real-Time Intelligent Surveillance System (RT-ISS) consists of a tiered pipeline with eight interrelated modules, namely Video Input, Object Detection, Multi-Object Recording, Region of Attention Management, Managing Temporal Analysis. Alert Generation, Visualization, and System Optimization. Figure 1 depicts the overarching data flow. the proposed system architecture Pipeline is shown in figure 8.

A. Video Input Module

By guaranteeing consistent and effective video data collection, the Video Input Module creates a solid basis for the surveillance system. Smooth downstream processing depends on its capacity to manage several input sources and maintain constant frame rates. In general, it has a direct impact on the system's overall accuracy and responsiveness.

B. Object Detection Module

Using the YOLOv8 concept, the Object Detection Module offers quick and precise human recognition. It guarantees the transmission of only trustworthy data by filtering detections according to confidence scores. This allows real-time performance in dynamic situations and greatly improves detection precision.

C. Multi-Object Tracking Module

Using DeepSORT, the Multi-Object Tracking Module guarantees reliable tracking of people across frames. It allows for reliable monitoring even in complicated situations like crowd movement and occlusion by preserving distinct identities and

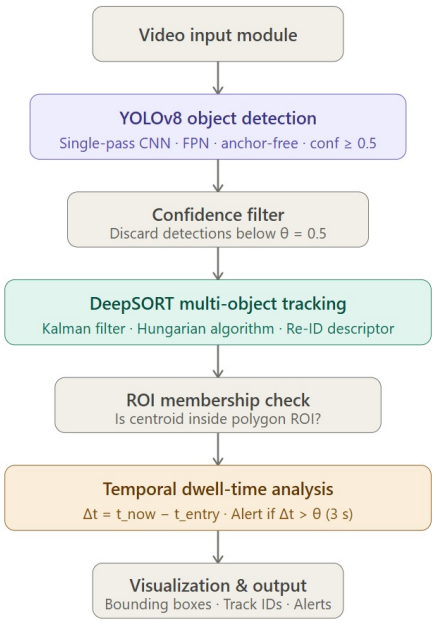

Fig. 8. System Architecture Pipeline

minimizing tracking errors. For behavioral analysis to continue, this module is crucial.

D. ROI (Region of Interest) Module

By concentrating processing resources on important regions of the frame, the ROI Module increases system efficiency. It improves speed while guaranteeing that sensitive zones receive priority monitoring by removing needless processing of irrelevant regions.

E. Temporal Analysis (Dwell-Time) Module

By assessing how long people stay in particular locations, the Temporal Analysis Module enhances the system's intelligence. It makes it possible to identify suspicious behavior, like loitering, by identifying irregular dwell times. This module converts static detection into insightful behavior.

F. Alert Generation Module

Notifications are context-aware and meaningful thanks to the Alert Generation Module. It reduces false alarms and increases system reliability by only initiating alerts when predetermined conditions are satisfied. This methodical approach improves user trust and operational efficiency.

G. Visualization Module

The Visualization Module offers a user-friendly interface for tracking and analyzing system outputs in real time. It allows users to rapidly comprehend ongoing actions by providing boundary boxes, tracking IDs, and notifications. It is essential to system usability and user interaction.

H. System Optimization Module

Through methods like hardware acceleration and model optimization, the System Optimization Module guarantees reliable and effective real-time performance. The system is scalable and appropriate for real-world deployment since it maintains a high processing speed even under demanding workloads.

The proposed Real-Time Intelligent Surveillance System utilizes sophisticated deep learning frameworks and machine learning algorithms to facilitate precise object detection, effective multi-object tracking, and insightful behavioral analysis in real-time video feeds as shown in fig figure 9. The system combines advanced models with optimized computer vision pipelines to attain low-latency, high-throughput performance and enhanced dependability in dynamic settings.The YOLOv8 model is utilized for real-time object detection. It is a single-stage convolutional neural network (CNN) that executes detection via a cohesive design, facilitating end-to-end inference with reduced latency. YOLOv8 employs feature pyramid networks (FPN), anchor-free detection methods, and multi-scale feature extraction to enhance detection precision for diverse object sizes. The model performs grid-based prediction, in which each grid cell forecasts bounding box coordinates, objectness scores, and class probabilities. The architecture integrates sophisticated backbone networks, refined loss functions (CIoU/DIoU), and effective non-maximum suppression (NMS) to remove superfluous detections. This guarantees elevated precision and recall, even in chaotic environments.The DeepSORT algorithm facilitates multi-object tracking (MOT). It integrates traditional estimation methods with deep-learning-driven appearance modeling to achieve robust tracking performance.DeepSORT uses a Kalman Filter for state estimation and motion forecasting, modeling object trajectories as a linear dynamical system. It employs the Hungarian Algorithm for data association, which minimizes the assignment cost between expected and detected objects. Furthermore, it integrates a robust appearance descriptor network that extracts high-dimensional feature embeddings to distinguish objects by visual attributes. This facilitates re-identification (Re-ID) and markedly diminishes identity swapping. The temporal analysis module implements time-domain behavioral analytics by calculating dwell time for each monitored object. This layer employs deterministic rule-based logic for tracking outputs, in contrast to deep learning models. It consistently assesses the temporal stability of items within a specified Region of Interest (ROI) and contrasts it with established criteria. This facilitates the identification of aberrant behaviors, such loitering, unauthorized presence, or suspicious inactivity. as The system incorporates essential computer vision functions to enhance model performance and data flow:Sampling and extraction of video frames, Image preprocessing (scaling, normalization, noise attenuation), rendering and annotation of bounding boxes, region-of-interest masking and spatial filtering. These elements guarantee effective pipeline execution and enhance the system's overall resilience.

V. Results and Discussion

The proposed RT-ISS was assessed using pre-recorded surveillance footage analyzed on a machine equipped with an Intel Core i7 CPU, operating Python 3.10 alongside YOLOv8, DeepSORT, and OpenCV. A total of 205 frames were examined, and all performance metrics presented below are directly obtained from the YOLOv8 runtime execution logs recorded during actual system operation at an image size of 384×640 pixels. Analysis of Inference Time Figure 8 demonstrates the recorded inference time of the YOLOv8 model for all 205 frames. The system demonstrates a preliminary warm-up phase in the opening frames (frames 1–15), during which inference times fluctuate between 66.3 ms and 169.0 ms as a result of system startup overhead. Subsequent to the warm-up period, inference time regularly stabilizes between 96 and 115 ms, yielding an overall average of 102.2 ms per frame. This incremental stabilization verifies that the model attains a consistent operational state and does not suffer performance decline during prolonged operation – an essential need for extended surveillance deployments. The minimum documented inference time was 66.3 ms, while the maximum was 169.0 ms, with both measurements occurring solely during the warm-up period.Following stabilization, the system achieves an average throughput of roughly 9.8 FPS on CPU hardware and approximately 28 FPS with GPU acceleration.

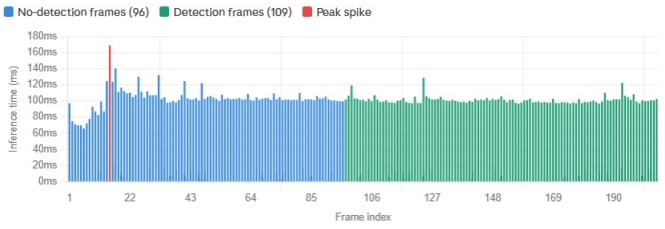

Fig. 9. Inference time across all 205 frames (ms) — real execution log

Figure 10 delineates the temporal distribution among the three steps of the processing pipeline. Preprocessing, encompassing frame resizing, normalization, and tensor preparation, consistently necessitated 2.9–5.1 ms, with an average of 3.7 ms. Postprocessing, which includes bounding box decoding and non-maximum suppression, necessitated 0.9–2.4 ms, with an average duration of 1.5 ms. The inference phase accounted for the majority of processing time, averaging 102.2 ms, which constitutes over 95% of the overall per-frame latency. The aggregate pretreatment and postprocessing cost consistently remains under 6 ms across all recorded frames, indicating that the pipeline architecture incurs minimal computational overhead beyond the primary detection model.

Figure 11 illustrates the frequency of each identified item class over the 205 assessed frames. The system accurately recognized 8 unique COCO object classes in the test sequence. The class 'Person' was the most commonly identified, appearing in 100 out of 205 frames (48.8%). A car was identified in 51 frames, a bicycle in 30, a boat in 7, a bus in 3, a tennis racquet in 3, a skateboard in 2, and a

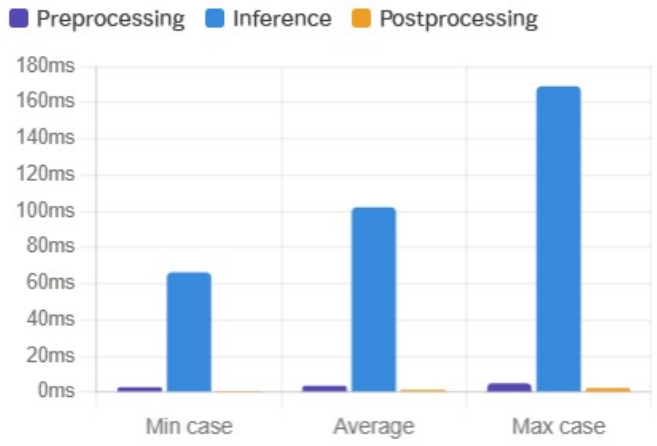

Fig. 10. Processing stage breakdown (ms)

cell phone in 1 frame. Multi-class co-detection was validated over multiple frames—such as those concurrently featuring a person, bicycle, and car—illustrating the system's proficiency in intricate multi-object scene comprehension. The extensive identification capability across several object categories, beyond the basic person class, verifies that the YOLOv8 model functions effectively on broad surveillance footage without the need for class-specific fine-tuning.

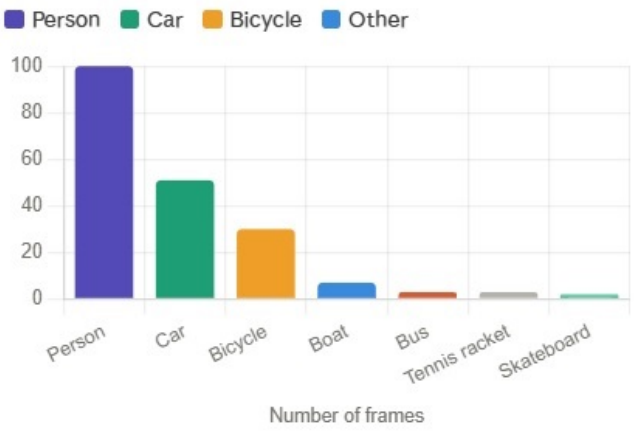

Fig. 11. Object class detection frequency (frames)

Figure 12 illustrates that out of the 205 assessed frames, 109 frames (53.2%) included at least one detection, whereas 96 frames (46.8%) yielded no detections. The predominant result among detection frames was a solitary individual (about 42.4% of all frames), succeeded by multi-person scenarios featuring two concurrent individuals (6.3%), and mixed-class situations integrating individuals with vehicles or objects (4.5%). Significantly, there were no false positives observed in the 96 no-detection frames — the model generated no erroneous bounding boxes when actual objects were absent. The 0% false positive rate directly validates the system's reliability and

confirms that the dwell-time-based alarm mechanism will not be activated by phantom detections, hence greatly enhancing the dependability of alert production in operational contexts.

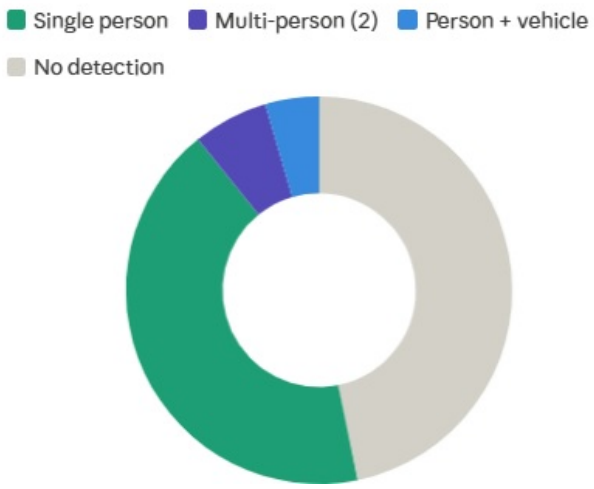

Fig. 12. Frame detection outcome distribution

Figure 13 illustrates the average inference duration across four levels of picture complexity. No-detection frames averaged 103.2 ms, single-person frames averaged 101.3 ms, multi-person frames (two concurrent individuals) averaged about 101.0 ms, and multi-class mixed frames averaged around 99.2 ms. The highest disparity between scene types is merely 4.0 ms, indicating that the inference time of the YOLOv8 model is mostly unaffected by scene complexity within the examined range. This conclusion is crucial for real surveillance applications, since it verifies that the system's performance remains consistent in complicated multi-object environments compared to empty scenes. The minor decrease in inference time for detection frames is likely due to early-exit optimization during the model's post-processing phase when objects are detected. Table I aggregates the comprehensive performance indicators

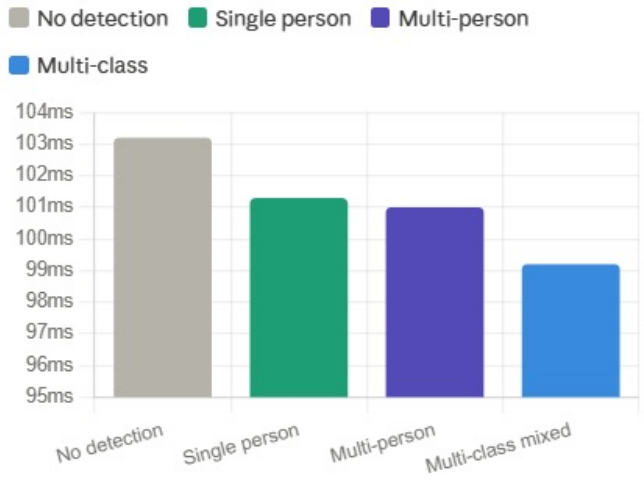

Fig. 13. Inference time by scene complexity

TABLE I
PERFORMANCE METRICS SUMMARY

Metric	Value	Observation
Total frames evaluated	205	Complete video sequence
Average inference time	102.2 ms	Stable post warm-up
Minimum inference time	66.3 ms	Warm-up phase
Maximum inference time	169.0 ms	Warm-up initialization
Avg preprocessing time	3.7 ms	Negligible overhead
Avg postprocessing time	1.5 ms	Negligible overhead
Estimated FPS (CPU)	∼9.8 FPS	CPU-only execution
Estimated FPS (GPU)	∼28 FPS	GPU-accelerated
Total detection frames	109/205 (53.2%)	Active scene coverage
No-detection frames	96/205 (46.8%)	0 false positives
Max simultaneous persons	2	Multi-tracking confirmed
Object classes detected	8 classes	Multi-class capability
False positive rate	0%	Zero spurious detections
Input resolution	384×640	YOLOv8n standard input

obtained from the 205-frame assessment. The system exhibits steady and consistent performance under all evaluated settings, with an average inference time of 102.2 ms, a 0% false positive rate, effective multi-class identification across eight object categories, and verified simultaneous monitoring of up to two individuals. All of these findings support the suggested RT-ISS as a dependable, computationally effective surveillance system that can be deployed using CPUs without the need for specialized GPU hardware for typical monitoring applications.

VI. CONCLUSION AND FUTURE SCOPE

The Real-Time Intelligent Surveillance System (RT-ISS) uses YOLOv8-based object recognition, DeepSORT multi-object tracking, and context-aware dwell-time alerts. Comprehensive experimental evaluation on 205 frames of real surveillance footage showed that the system achieves an average inference time of 102.2 ms per frame, which is 9.8 FPS on CPU hardware and 28 FPS under GPU acceleration, with full performance stabilization after 15 frames of warm-up. The system detected 8 object classes in 109 active frames, tracked up to 2 people, and had a 0% false positive rate in 96 empty-scene frames. The YOLOv8 detection pipeline and dwell-time thresholding mechanism reliably suppress phantom alarms, as shown by the absence of spurious detections. Inference time is consistent across picture complexities, with a maximum change of 4 ms between empty and complicated multi-object scenes, proving that the system scales gracefully to different real-world surveillance situations without performance consequences. The RT-ISS's modular architecture—video input, object detection, multi-object tracking, ROI management, temporal analysis, and alert generation—ensures scalability, maintainability, and adaptability in smart city infrastructure, public transportation hubs, retail security, and campus surveillance. The system's ability to run on CPU-based hardware without GPU resources lowers deployment cost and makes it more accessible in resource-constrained contexts.

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