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RAILEYE : AI Driven Real Time Crowd SafetyAnalytics for RailwayStations Using Cctv Surveillance

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Abstract—Overcrowding in railway stations, particularly in densely populated urban and semi-urban areas, poses significant safety hazards, including stampedes, theft, service disruptions, and accidents near platforms and tracks. Traditional surveillance systems, which depend primarily on manual observation of CCTV footage, are constrained by human limitations such as delayed response times, observational fatigue, and susceptibility to error. These methods are often insufficient for real-time crowd management, especially in high-footfall environments.

This project introduces an AI-based system for real-time crowd monitoring and safety analysis in railway stations. Utilizing deep learning models like YOLOv8 for object detection and DeepSORT[1] for individual tracking, the system generates zone-specific crowd heatmaps and congestion forecasts. It identifies early indicators of hazardous conditions, such as crowd accumulation, extended dwell durations, and congestion in critical areas like entrances, escalators, and boarding platforms. The system enables predictive alerting, visual analytics, and automated risk classification, facilitating timely intervention by station authorities. Its scalable and cost-efficient architecture supports large-scale deployment, enhancing public safety, operational reliability, and the overall commuter experience, in line with the development of AI-enabled smart infrastructure in modern transit systems.

Keywords—Railway station safety, crowd monitoring, deep learning, YOLOv8, DeepSORT, spatiotemporal analysis, anomaly detection, computer vision, real-time surveillance, smart infrastructure, congestion forecasting, pedestrian tracking.

I. INTRODUCTION

In recent years, the volume of passengers in public transport systems, especially in countries like India, has significantly increased. Railway stations, being one of the most widely used modes of transportation, frequently witness heavy footfall during peak hours, holidays, and special events. While most stations are equipped with CCTV surveillance systems, their role is largely passive merely recording events for later review. The lack of real-time analytics and decision support tools results in missed opportunities for preventing hazardous situations likestampedes, overcrowding near platform edges, long queues, or sudden crowd surges during train arrivals or delays.

Traditional surveillance systems rely heavily on human operators to interpret video feeds. This manual process is not only time-consuming and inefficient but also susceptible to fatigue, distractions, and human error, especially when monitoring multiple cameras. These limitations create a critical need for intelligent, automated systems that can assist station authorities in proactively managing crowds and ensuring public safety.

With the advancements in Artificial Intelligence (AI), Computer Vision (CV), and Deep Learning (DL), there is a growing opportunity to enhance public safety through intelligent video surveillance. Recent research shows promising results in applying models like YOLO (You Only Look Once), DeepSORT (Simple Online and Realtime Tracking)[1][7] , and Transformer-based neural networks for object detection[4], crowd tracking, and anomaly prediction.

The proposed project, RailEye is an AI-based surveillance system that monitors live CCTV feeds, tracks individuals, analyzes crowd behavior, and predicts unsafe crowd formations. It generates heatmaps and sends alerts to help station authorities take timely action.

II. RELATED WORK

Research on crowd monitoring and safety analytics has advanced significantly with the rise of computer vision and deep learning, yet many traditional surveillance systems still rely on manual observation.

Early computer vision studies on crowd analysis focused on handcrafted features and simple motion patterns. These conventional methods lacked robustness in real-world environments, especially in dense crowds with frequent occlusions. Later works using techniques such as optical flow and social force models improved motion understanding but struggled with real-time performance in complex public spaces like railway stations.

With the emergence of deep learning, object detection frameworks such as YOLO gained popularity due to their ability to detect people at high speed. Redmon et al. introduced the YOLO family, marking a major shift toward fast single-shot detection. The more recent YOLOv7 and YOLOv8 architectures significantly improved accuracy and efficiency, making them suitable for real-time applications. However, detection alone is insufficient for crowd analytics in dynamic environments. To maintain identity across frames, researchers have employed multi-object tracking (MOT) algorithms such as DeepSORT, which integrates appearance embeddings with Kalman filtering for robust long-term tracking. Studies by Wojke et al. demonstrated that coupling deep feature extractors with traditional temporal filtering can greatly reduce identity switches, even in crowded scenes.

Further advancements incorporated spatiotemporal analysis for predicting crowd density and movement. Transformer-based models and LSTM networks have been explored to forecast crowd flow, enabling proactive safety measures. Recent studies in crowd counting and density estimation, using methods like CSRNet and P2PNet, provided high accuracy but were often computationally expensive and unsuitable for real-time CCTV deployment. Research combining heatmap-based density estimation with detection-and-track pipelines showed promise, yet most works either focused only on counting or only on tracking, without integrating predictive intelligence..

Existing literature also highlights limitations related to deployment in railway stations, where lighting variations, camera vibrations, and dense footfall patterns introduce challenges. Several studies addressed crowd monitoring in stadiums, public events, or malls, but applications specifically targeting the unique operational environment of railway stations remain limited. Very few works offer an end-to-end system that combines real-time detection, multi-object tracking, density heatmap generation, and predictive analytics.

The present research fills this gap by integrating YOLOv8 for high-speed person detection, DeepSORT for identity tracking, and an LSTM-based prediction model to forecast crowd surges. Unlike prior work that focuses solely on detection or counting, RailEye introduces a unified framework capable of real-time crowd monitoring, early crowd-surge prediction, and automated alert generation. This holistic approach aims to support railway authorities in ensuring passenger safety, preventing overcrowding events, and enabling timely intervention during peak operational hours.

III. LITERATURE SURVEY

Existing research in AI-driven surveillance, pedestrian tracking, and crowd analytics has advanced significantly in recent years, particularly with the adoption of deep learning models such as YOLO, DeepSORT, and Transformer-based architectures. However, most studies focus either on crowd detection, behavior analysis, or spatiotemporal prediction in isolation, leaving a notable gap in fully integrated real-time safety systems for railway environments.

Liu et al. proposed a spatiotemporal congestion-risk perception framework combining YOLOv8-based pedestrian detection with lightweight multi-object tracking and geographic mapping. Their method effectively graded congestion levels using density and deceleration metrics, though it lacked multitask behavior understanding in complex public spaces. Similarly, Chen et al. introduced Dense-stream YOLOv8n, a lightweight model enhanced with DensityNet and distillation, demonstrating real-time crowd monitoring capabilities; however, the system struggled with extreme occlusion and poor lighting conditions.

In another direction, Dorai et al. utilized YOLOv8 for headcount estimation and suspicious activity detection in real-time surveillance environments. Their approach was effective in controlled settings but faced performance degradation in low-quality CCTV feeds and culturally diverse action patterns. Complementing these detection-based works, Qaraqe et al. integrated Swin Transformer networks with optical flow to classify crowd behavior across four violence and density categories, though temporal motion artifacts in online videos occasionally reduced accuracy.

3D ConvNet models have also been explored, as shown by Elmezain et al., who combined 3D convolutional networks with multi-SVM classifiers to detect 11 types of crowd behaviors in highly dense environments. While effective, the system suffered from misclassifications in visually similar flow patterns and high computational cost for deeper temporal kernels. Ilić further highlighted the practical integration of AI-based computer vision in railway station surveillance using YOLOv8 and difference-detection techniques, but noted that long-distance detection and diverse real-world scenarios remained challenging.

Recent studies have additionally focused on multi-camera fusion and spatiotemporal mobility estimation. Wong and Law proposed a framework that fuses CCTV data with urban spatial information using YOLO-based detectors and DeepSORT tracking to generate mobility graphs and congestion forecasts through GCN-GRU models. However, the requirement for manual floorplan alignment limited automation. Similarly, Zhu et al. designed an AI-aided rail transit analytics system using YOLO and DeepSORT for head detection, flow estimation, and crowd dynamics tracking but identified reduced accuracy under prolonged occlusion.

Group-based behavior understanding has also emerged as a relevant domain. Shen et al. introduced Group-MOT integrated with dynamic risk mapping for safe path planning in crowded pedestrian environments. Despite promising results, the system required careful parameter tuning and showed reduced performance in highly dense settings.

Overall, the literature demonstrates substantial progress in video-based crowd detection, tracking, and behavioral analytics using deep neural networks. Yet, few studies provide a holistic, real-time, railway-station-focused safety system that integrates detection, multi-object tracking, heatmap generation, predictive modeling, and automated alerts within a single operational framework.

The present work addresses this gap by developing RailEye, a unified AI-driven crowd safety system that combines real-time YOLOv8 detection, DeepSORT tracking, spatiotemporal heatmap generation, and LSTM-based crowd prediction to support proactive safety interventions in railway stations.

IV. METHODOLOGY

The methodology of this research focuses on developing an integrated AI-driven computational framework for real-time crowd detection, tracking, density estimation, and predictive crowd risk analysis inside railway stations. The system is designed to intake CCTV surveillance streams, analyze pedestrian movement patterns using deep learning models (YOLOv8 + DeepSORT), generate spatial crowd density heatmaps, and forecast hazardous crowd buildup using LSTM-based temporal prediction. The overall pipeline follows a modular, scalable design suitable for real-world deployment across large public transit infrastructures.

1) Data Collection : The dataset used in this research consists of CCTV-based crowd video sequences collected from railway-station–like environments to support realistic crowd analysis and anomaly detection. The proposed system is designed to process live CCTV/IP camera feeds, offline recorded videos, and synthetic crowd video data generated for controlled experimental evaluation. The video frames range from 480p to 1080p resolution with an average frame rate of 15–30 FPS, enabling detailed and high-frequency monitoring of crowd behavior. To ensure robustness and real-world applicability, the dataset incorporates various challenging conditions, including low-light environments, occlusions, dense crowd formations, irregular pedestrian movement, multiple camera viewpoints, motion blur, and rapid movement patterns. These variations help evaluate the system’s performance under diverse and complex surveillance scenarios commonly observed in public transportation areas.
2) Data Preprocessing : Raw CCTV frames are standardized through resolution normalization and RGB conversion to ensure consistent inputs for YOLOv8 detection. Low-confidence and overlapping detections are removed using confidence filtering and non-maximum suppression, followed by normalization of bounding boxes for camera-independent processing. DeepSORT-generated tracks are temporally smoothed using exponential averaging to reduce jitter and improve stability in dense crowds. Outlier detections, frame drops, and short-term occlusions are corrected using interpolation and temporal holding. Heatmap points are generated by mapping normalized bounding box centers onto a fixed spatial grid with Gaussian smoothing. Finally, crowd count sequences are normalized and windowed to form clean time-series inputs for the LSTM-based early prediction model.
3) Feature Engineering : Feature engineering in this system focuses on extracting meaningful spatial–temporal attributes from real-time CCTV surveillance data. Person detections from YOLOv8 are converted into structured descriptors such as centroid coordinates, bounding box dimensions, and aspect ratios. DeepSORT tracking contributes motion-specific features including velocity, direction, and trajectory smoothness for each unique individual. These features help differentiate stationary, slow-moving, and fast-moving crowd behaviors in dense environments. Additionally, localized density estimation is performed by dividing the frame into grid cells and computing per-cell person counts for heatmap generation.Temporal modeling is strengthened through the extraction of sequential patterns from crowd-flow variations over time. Rolling statistics such as moving averages, variance, and short-term fluctuations are computed from the live crowd count stream to capture abnormal surges. These time-series features are combined into fixed-length sequences and supplied to the LSTM model for predictive analytics.

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The LSTM forecasts upcoming threshold exceedance by learning patterns in density buildup and movement directionality. Finally, fused spatial and temporal features enable accurate detection and early prediction of risky crowd conditions in railway stations.

4) Model Training : The model training stage is a crucial component of the RailEYE system, ensuring accurate person detection, robust multi-object tracking, and reliable temporal crowd forecasting. The training pipeline integrates three key modules—YOLOv8 detector, DeepSORT tracker, and an LSTM-based prediction model—each trained or fine-tuned to handle the unique characteristics of crowded railway-station environments.

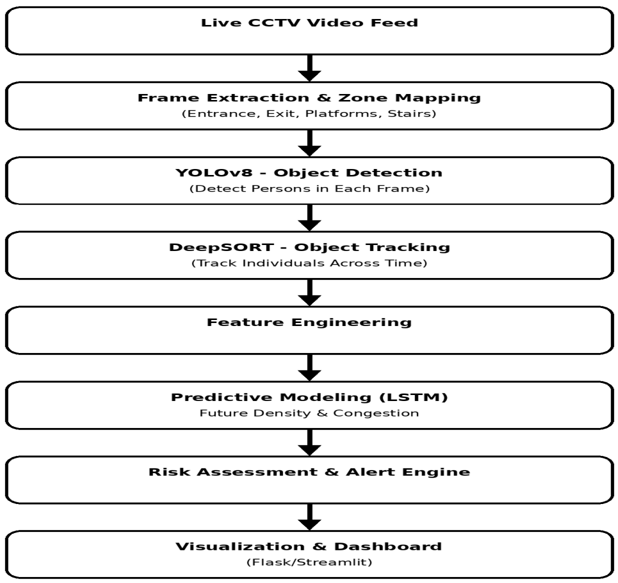

Fig. 4.1Basic Workflow of RailEye

V. SYSTEM ARCHITECTURE

The RailEYE system is designed as a modular, AI-driven architecture that integrates computer vision, machine learning, and predictive analytics for real-time railway crowd monitoring. The architecture ensures low-latency detection, accurate tracking, and proactive crowd prediction using YOLOv8, DeepSORT, and LSTM models Data Ingestion Module.

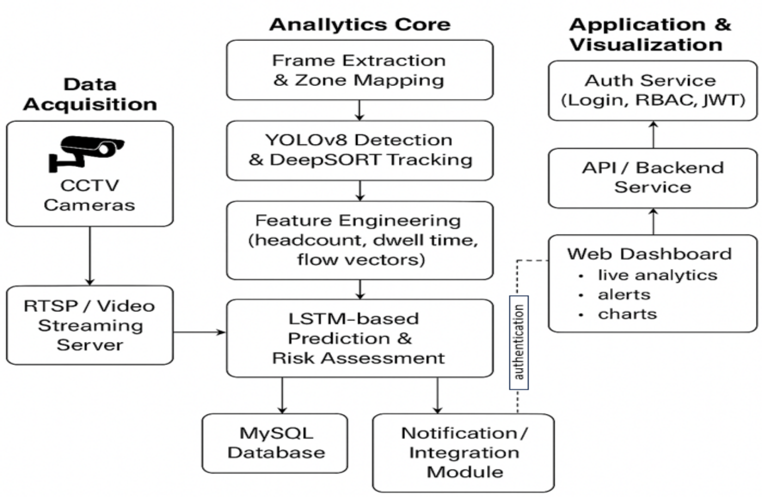

Fig. 5.1Architecture Diagram

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VI. OBJECTIVES

The core goal of RailEYE is to provide an AI-driven intelligent crowd monitoring and predictive surveillance system for railway stations that enhances passenger safety, improves crowd management, and enables proactive incident prevention through real-time video analytics. By combining computer vision, deep learning, multi-object tracking, and predictive analytics, the platform aims to assist railway authorities in identifying overcrowding situations, monitoring passenger movement patterns, and generating timely alerts for high-risk zones. In particular, the objectives include:

1) To develop a real-time computer vision framework using advanced deep learning models such as YOLOv8 for accurate detection of individuals and crowd density estimation from CCTV surveillance feeds across railway station premises.
2) To implement multi-object tracking mechanisms such as DeepSORT that continuously track individual movement trajectories across video frames, enabling behavioural analysis, movement flow estimation, and crowd pattern recognition over time.
3) Integrating predictive analytics and spatiotemporal forecasting models, including LSTM-based architectures, for anticipating crowd buildup, congestion trends, and potential risk zones several minutes before critical situations arise.
4) Generating dynamic visual heatmaps, anomaly indicators, and automated alert mechanisms that assist station authorities in identifying overcrowded areas, unusual movement behaviour, and emergency-prone regions in real time.
5) Design and implement an interactive dashboard that provides railway authorities with centralized monitoring capabilities, including live CCTV feeds, crowd statistics, predictive insights, alert notifications, and graphical visualizations of station activity.
6) Adopt a modular multi-layer system architecture separating video acquisition, AI processing, analytics, and visualization components, thereby ensuring scalability, maintainability, and easier future integration with smart railway infrastructure systems.
7) Optimize deep learning inference performance using techniques such as model compression, pruning, and efficient frame processing so that the system can operate effectively on resource-constrained edge devices and real-time surveillance environments.
8) Conduct performance evaluation and pilot testing using real or simulated railway station datasets in order to measure detection accuracy, tracking efficiency, prediction reliability, and overall system effectiveness in improving crowd safety and operational management.

VII. RESULTS

The RAILEYE platform successfully demonstrated its capability to provide intelligent real-time crowd monitoring and predictive safety analytics for railway stations. During experimental evaluation using live CCTV feeds and recorded surveillance datasets, the system exhibited accurate pedestrian detection, stable multi-object tracking, and efficient crowd-density estimation under varying environmental conditions. The generated analytics, heatmaps, and congestion forecasts proved highly useful for proactive crowd management and safety monitoring.

The user interface maintains a real-time surveillance-oriented design philosophy. The dashboard displays live CCTV streams, active crowd count, tracking IDs, congestion indicators, prediction graphs, and alert notifications within a unified monitoring environment. The system provides dedicated visualization panels for real-time person detection, crowd-density heatmaps, predictive analytics, and threshold-based alert generationdemonstrating the framework’s ability to support intelligent crowd surveillance and rapid decision-making in railway stations.

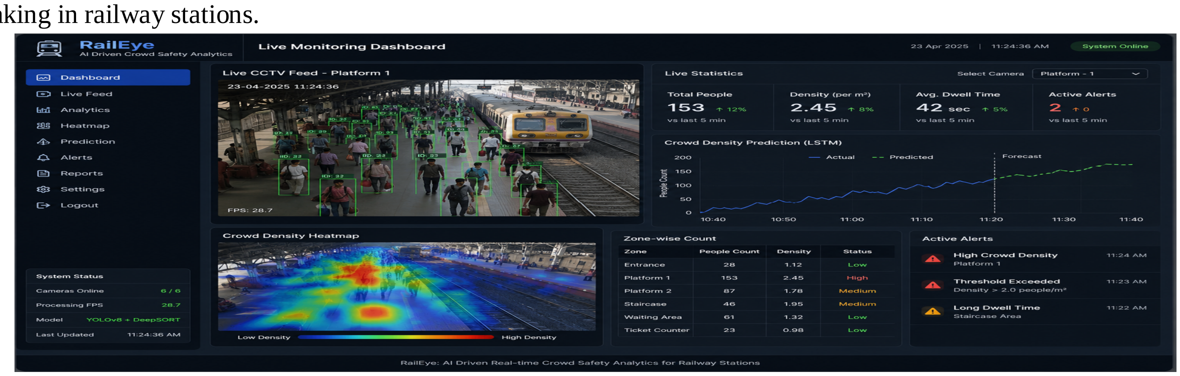

Fig. 7.1: Real-time RAILEYE dashboard showing CCTV monitoring, crowd analytics, and detection interface.

The integration of YOLOv8 and DeepSORT enabled accurate real-time pedestrian detection and continuous tracking across video frames. The system successfully maintained unique tracking identities even during moderate crowd congestion and partial occlusion scenarios. Bounding-box visualization and trajectory tracking allowed efficient monitoring of passenger movement patterns across different station zones.

Fig. 7.2: Live Person Detection and Tracking

The predictive analytics module generated dynamic crowd-density forecasting graphs using historical pedestrian movement data processed through the LSTM model. The forecasting system effectively identified increasing congestion trends and potential threshold exceedance conditions before critical overcrowding occurred, enabling proactive safety intervention.

Fig. 7.3: LSTM-based crowd-density prediction and congestion forecasting graph.

The heatmap generation module successfully visualized spatial crowd-density distribution within monitored station regions. High-density zones such as staircases, waiting areas, platform entrances, and ticket counters were highlighted dynamically, allowing security personnel to identify potentially hazardous regions quickly and improve crowd-control efficiency.

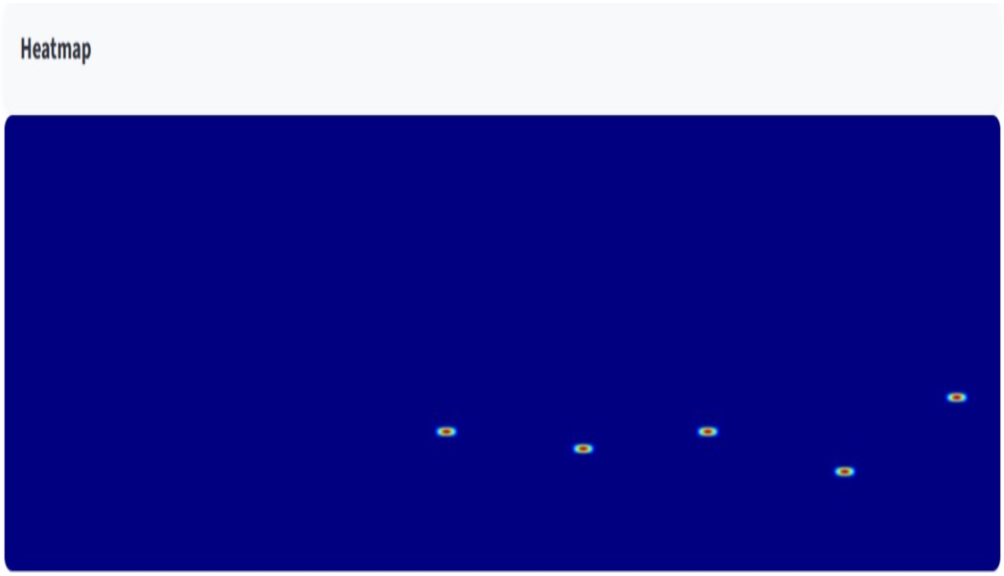

Fig. 7.4: Heatmap visualization representing crowd-density concentration in monitored railway-station zones.

The RAILEYE system was evaluated under multiple real-world and simulated railway-station crowd conditions using live CCTV feeds and recorded surveillance datasets.

The experiments were conducted in environments involving dense pedestrian movement, partial occlusion, low-light conditions, and irregular crowd flow patterns to analyze the effectiveness of real-time crowd monitoring and predictive safety analytics. The integration of YOLOv8 and DeepSORT enabled accurate pedestrian detection and stable multi-object tracking across consecutive frames, while the system successfully maintained identity continuity even in moderately crowded scenarios.

Quantitative observations showed that the proposed framework effectively identified crowd-density buildup and congestion-prone regions within monitored station zones. The LSTM-based prediction module generated real-time forecasting graphs capable of identifying increasing congestion trends before critical threshold exceedance occurred. Additionally, the generated heatmaps dynamically highlighted high-density areas such as staircases, waiting zones, platform entrances, and ticket counters, allowing surveillance operators to quickly identify risk-prone regions and improve crowd-management efficiency. The centralized monitoring interface further provided live CCTV visualization, active crowd count, prediction analytics, and automated alert notifications for abnormal crowd behavior.

System performance remained stable during continuous surveillance operations. The YOLOv8 detection model achieved low-latency inference with strong detection accuracy, while DeepSORT minimized identity-switching issues and maintained smooth trajectory tracking across frames. Optimized frame processing and GPU utilization enabled real-time execution with acceptable computational overhead. The modular system architecture also supports scalability for integration with multiple CCTV feeds across large railway infrastructures, making the framework suitable for deployment in smart transportation systems.

Certain limitations were observed during experimentation. Detection accuracy slightly decreased under severe occlusion and extremely dense crowd conditions where multiple individuals overlapped heavily. Low-resolution CCTV footage occasionally affected long-distance pedestrian tracking consistency, and the predictive analytics module requires larger temporal datasets for improving long-term forecasting accuracy. Future enhancements may include multi-camera fusion, edge-computing deployment, transformer-based crowd behavior analysis, and anomaly-detection mechanisms for panic movement or aggressive crowd behavior. Overall, the results validate that RAILEYE effectively transforms conventional CCTV surveillance into an intelligent AI-driven crowd safety analytics system capable of proactive monitoring and real-time railway crowd management.

VIII. CONCLUSION

This research presents the development of RAILEYE, an AI-driven real-time crowd safety analytics system designed for large-scale public environments, specifically railway stations. The proposed framework integrates state-of-the-art computer vision techniques—YOLOv8 for person detection and DeepSORT for identity tracking—with an LSTM-based temporal prediction model to ensure proactive crowd management. By processing live CCTV streams with reduced latency and high accuracy, the system enables continuous crowd monitoring, dynamic population estimation, and identification of high-risk congestion zones. This approach demonstrates how advanced video analytics can enhance public safety and support real-time decision-making in complex transportation hubs.

The integration of detection, tracking, and forecasting modules bridges the gap between conventional CCTV monitoring and intelligent automated surveillance. The system not only provides precise real-time crowd counts but also predicts potential threshold exceedances before they occur, allowing authorities to intervene early and prevent hazardous conditions. The incorporation of heatmap visualization, alert mechanisms, and temporal behaviormodeling significantly enhances situational awareness and operational efficiency for crowd control teams. Through its modular architecture, RAILEYE establishes a scalable and adaptive framework capable of functioning effectively across diverse station layouts and camera configurations.

In the future, this work can be extended by integrating multi-camera fusion for 3D crowd localization, reinforcement learning for adaptive thresholding, and edgecomputing deployment to further reduce processing delays. Incorporating behavioral analysis models—such as anomaly detection for panic, sudden motion, or aggressive activity— can broaden system capabilities. RAILEYE demonstrates the potential of AI-powered surveillance to transform public safety infrastructure, providing a foundation for nextgeneration smart transportation systems that prioritize passenger safety, operational resilience, and intelligent automation..

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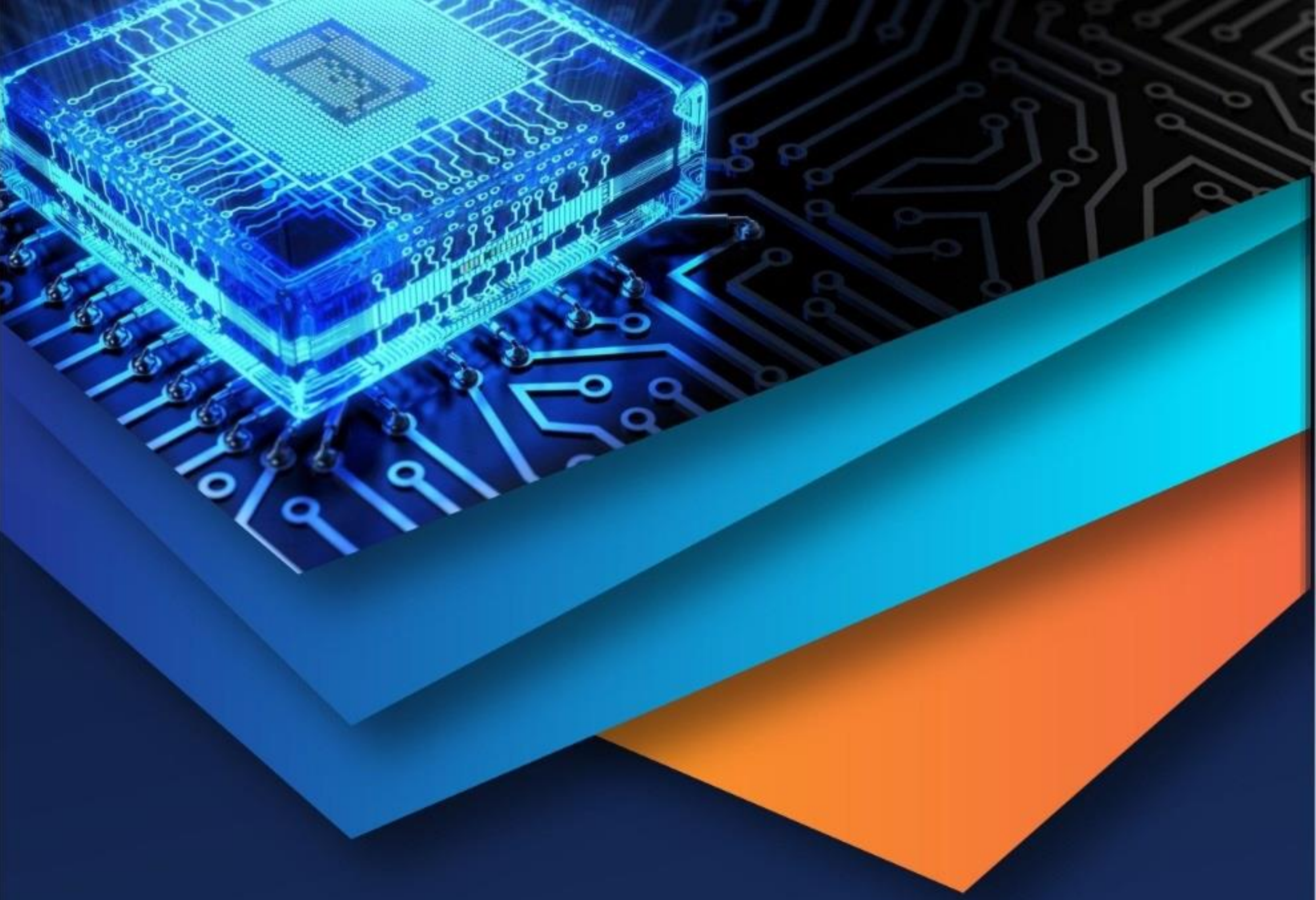

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