

AI-CoachGuard: The Smart Eyes Inside Every Compartment and Station

Misba Marybai P¹, Rashida safreen M², Sowmiya R³, Swarna latha D⁴

¹ Associate professor, Dept. of AI and DS, Panimalar Engineering College, Tamil Nadu, India.

^{2,3,4} UG Scholar, Dept. of AI and DS, Panimalar Engineering College, Tamil Nadu, India.

Emails: safreensana88@gmail.com¹, sowmiyaravichandran44@gmail.com², swarnad2005@gmail.com³, misbaprithiviraj@gmail.com⁴

Abstract

In India, where unauthorized entry of men into women-only railway compartments often leads to discomfort, harassment, and safety risks, ensuring passenger security remains a major concern. Existing measures such as CCTV surveillance and manual patrolling are largely reactive and struggle to distinguish between unintentional entries and genuine threats, resulting in delayed responses. To overcome this, we propose AI-CoachGuard: The Smart Eyes Inside Every Compartment and Station, an AI-powered framework for real-time surveillance and proactive intervention in women's compartments. The system integrates facial detection and gender classification using a fine-tuned ResNet18 model to accurately identify unauthorized males, while a Mediapipe-based gesture recognition module detects predefined distress signals, such as SOS gestures, through hand landmark extraction and geometric analysis. A dual-verification mechanism ensures alerts are triggered only when both unauthorized male presence and distress gestures are detected, thereby reducing false positives from staff, vendors, or accidental entries. On detection, AI-CoachGuard sends instant SMS alerts with compartment ID, timestamp, and location to railway authorities and simultaneously updates a live monitoring dashboard for event logging and forensic review. Designed for deployment on real-time CCTV feeds, the framework enables discreet passenger signaling and immediate authority response, with future extensions including IoT-based integration, crowd density monitoring, and stampede prevention for enhanced railway safety.

Keywords: Railway Security, Deep Learning, Computer Vision, ResNet18, Gesture Recognition, AI Surveillance, Public Safety

1. Introduction

In India, women's safety on public transit has emerged as one of the most urgent issues, especially in women-only railway compartments. Unauthorized male access still happens, causing inconvenience, harassment, and occasionally major risks to passenger safety, even though Indian Railways has special trains for ladies. These cases demonstrate the insufficiency of the current surveillance systems in addition to the vulnerability of female tourists. Traditional safety methods like physical patrolling and CCTV surveillance frequently fail to provide prompt and astute answers. The problem is exacerbated during periods of high travel demand, when early intervention is frequently jeopardized and

monitoring is challenging. These drawbacks highlight the necessity of a sophisticated, intelligent monitoring system that can analyze data in real time, identify threats accurately, and take preemptive measures without only depending on human operators. Smart surveillance systems that can analyze live video feeds, identify faces, classify gender, detect gestures, and even interpret human emotions and distress signals are now possible thanks to recent developments in artificial intelligence, deep learning, and computer vision. Although these technologies have proven effective in areas such as public safety, crime prevention, and traffic monitoring, their direct application to railway

security—particularly in women's compartments—remains restricted and understudied. By integrating face detection, gender classification, and distress gesture recognition into a single, real-time monitoring solution, this paper presents AI-CoachGuard: The Smart Eyes Inside Every Compartment and Station, an AI-powered safety framework that improves passenger protection. AI-CoachGuard's dual-verification process is what makes it unique. The system briefly suspends detections until a female passenger makes a distress gesture, in contrast to current methods that sound an alarm for any male entry, including authorized employees or unintentional intruders. This minimizes needless notifications while allowing women to quietly seek assistance by guaranteeing that alerts are only activated when an unapproved male presence coincides with outward indicators of concern. In order to distinguish between male and female passengers, the system uses a fine-tuned ResNet18 network for gender classification, a Mediapipe-based gesture recognition module that extracts hand landmarks and uses geometric analysis to identify predefined SOS gestures, and OpenCV's deep learning models for real-time face detection from CCTV feeds. In addition to updating a live monitoring dashboard that logs the incident for forensic review and legal evidence, the system instantly sends SMS alerts with compartment ID, timestamp, and train location to railway security authorities upon detecting both unauthorized male presence and distress gestures. To aid in post-event investigations, a data storage module additionally keeps logs of all detected events and captured frames. AI-CoachGuard creates a more context-aware monitoring system that lowers false positives, boosts dependability, and enables quick action by combining these features. In addition to being scalable, the framework may be improved in the future by integrating with railway IoT systems to synchronize with train control rooms, monitoring crowd density to avoid overcrowding-related accidents, and using motion and flow analysis to detect stampedes in emergency situations. Because of these characteristics, AI-CoachGuard serves as both a remedy for present issues and a basis for future

safety solutions that are more sophisticated. AI-CoachGuard shows how cutting-edge deep learning algorithms may turn conventional surveillance into a proactive, intelligent security ecosystem by fusing artificial intelligence approaches with real-world railway applications. The framework offers a dependable and scalable solution to protect women in railway compartments and paves the way for safer and more secure public transit networks by guaranteeing prompt intervention, reducing false alarms, and permitting passengers to discreetly indicate.

2. Literature Survey

An effective real-time hand gesture recognition system utilizing convex hull landmarks and geometric feature extraction is shown in the work "Base Hand Gesture Recognition for Characters Understanding Using Convex Hull Landmarks and Geometric Features" by Ansar, H. et al. (2023). Their approach, which supports quick distinction of alphabetic and numeric gestures even in low-resolution, resource-constrained conditions, entails identifying important hand shapes and calculating geometric relationships among landmark locations. This work's primary strength is its computational simplicity and resilience across a range of environments, which makes it appealing for embedded or real-time surveillance systems. However, the method is limited in its direct application to safety interventions in train situations because it is primarily developed for generic character gestures (letters/numbers) rather than context-specific signals like distress or SOS [1]. Zhang et al.'s review paper "Recent Advances in Video Analytics for Rail Network Surveillance" (2022, Sensors) thoroughly examines a variety of video analytics methods applied in rail networks, such as event monitoring, anomaly identification, and crowd trajectory tracking. The authors support enhanced surveillance across stations and platforms by highlighting the versatility of these methods for crowd control and infrastructure protection. Their research offers a comprehensive picture that is helpful in locating weaknesses in the surveillance techniques used today. Although the report covers a lot of ground, it skips over gender recognition and

passenger-specific gestures, which are crucial for improving the safety of women in train compartments [2]. The authors of the paper "Crowd Anomaly Estimation and Detection: A Review" (2024, Future Generation Computer Systems) provide an overview of several techniques for detecting crowd anomalies, with an emphasis on RF sensing, optical flow, and conventional machine learning for large-scale real-time crowd monitoring. This survey focuses on energy-efficient and privacy-preserving methods that work on edge devices, which makes them appropriate for implementation in public transportation hubs like train stations. However, computer vision-based detection of illegal presence or distress gestures inside compartments—a crucial aspect for improving women's safety—is not covered by the strategies evaluated, which primarily target macro-level crowd behavior [3]. A YOLOv5-based model for real-time railway traffic signal identification and classification is presented in the work "Real-Time Detection and Recognition of Railway Traffic Signals Using Deep Learning" by Staino et al. (2022, Journal of Big Data Analytics in Transportation). The suggested method contributes to increased automation and safety of railway infrastructure by exhibiting excellent accuracy and efficiency in a variety of environmental situations. However, because the emphasis is still on infrastructure components, it does not apply to inside-compartment surveillance, unauthorized person detection, or distress signal recognition—all of which are critical for passenger safety [4]. Abdalla et al.'s survey "Video Anomaly Detection in 10 Years: A Survey and Outlook" (2024, arXiv) examines the development of video anomaly detection techniques, including vision-language models, deep learning, and self-supervised models, in a variety of surveillance scenarios. Enhancements in transfer learning, generalization, and robustness for anomaly detection in public safety applications are covered in detail. A topic for future research is indicated by the survey's broad breadth, which does not particularly address train situations or the integration of gender and gesture-based notifications for women's compartment security [5]. Sun et al.'s study "Stampede Alert Clustering Based on Tiny-

Scale Strengthened DETR" (2024, arXiv) suggests a unique deformable DETR-based framework that improves early detection and clustering of stampede events by utilizing multiscale fusion of picture information. Their method successfully captures spatial-temporal dynamics by combining transformer designs with tiny-scale strength augmentation modules. For proactive crowd hazard warnings, which are essential for mass transportation safety in an emergency, the system exhibits increased precision. Despite its novel design, the approach has not yet been validated through implementation in real-world train settings and has only been evaluated on standard vision datasets, which restricts its direct relevance to situations involving gesture recognition or women's compartment safety [6]. A comprehensive review of diffusion-based generative models used for anomaly detection tasks can be found in the survey "Anomaly Detection and Generation with Diffusion Models: A Survey" by Liu et al. (2025, arXiv). The authors examine how realistic anomaly samples produced by diffusion probabilistic models might enhance model training and detection precision. They provide fresh viewpoints on rare-event detection in security contexts and emphasize benefits in unsupervised and semi-supervised circumstances. However, domain-specific issues like gender classification or SOS gesture signaling in cramped railway compartments are not covered by the paper's wide focus on anomaly production [7]. The use of deep learning methods such as YOLOv3, Faster R-CNN, random forest (RF), and principal component analysis (PCA) for railway infrastructure defect detection and predictive maintenance is methodically examined in the review "A Review of Deep Learning Applications for Railway Safety" by K.O. et al. (2022, MDPI Applied Sciences). In order to improve operational safety at scale, the authors present a number of effective case studies involving real-time object identification and problem diagnosis. However, the examination is focused on physical infrastructure and does not include passenger monitoring systems, transit compartment distress signals, or targeted identification of unlawful individuals [8]. An anonymous author's paper "Recent Trends in Crowd

Management Using Deep Learning Techniques: A Review" (2024, Journal of Umm Al-Qura University Engineering & Islamic Architecture) provides an overview of deep learning-based methods for detecting crowd anomalies, including recurrent neural networks (RNNs), dropout recurrent spatio-temporal networks (DR-STN), and deep autoencoders. The work highlights enhanced temporal modeling and feature extraction for accurate anomaly identification in crowded environments. Although the evaluation is strong for crowd management at the macro level, it is devoid of information about gender classification, segmented surveillance, or the identification of distress gestures—all of which are critical for the protection of female passengers on trains [9]. Sharif et al.'s research "Deep Crowd Anomaly Detection: State-of-the-Art, Challenges, and Future Directions" (2022, arXiv) offers a thorough analysis of deep learning architectures for crowd video data analysis, including CNNs and generative adversarial networks (GANs). The authors talk about difficulties with domain adaptability, data scarcity, and model interpretability. There is a need for more study on passenger-level safety because, despite its extensive coverage of crowd anomaly detection, the survey leaves out specific applications like real-time gender recognition and hand gesture detection for covert aid signaling in women's railway compartments [10].

3. System Architecture

To improve safety in women-only train compartments, the AI-CoachGuard system is based on a real-time, modular video analytics platform. It continuously records live video streams using a network of CCTV cameras placed inside compartments. As the system's input source, these cameras provide constant, real-time visual data that is essential for keeping an eye on passenger safety. All further processing is built upon this continuous video feed, which allows for proactive danger detection in a variety of illumination and crowded scenarios. In order to balance processing economy with real-time responsiveness, captured video frames are sampled at a rate of 30 frames per second. Preprocessing is applied to every frame to increase the accuracy of the analysis as a whole. During this

preprocessing step, region of interest (ROI) selection is used to direct the system's attention to important regions, such as the hands and faces of passengers, and noise reduction is used to remove any extraneous visual artifacts that can impede detection. This stage lowers the computing load and optimizes later processing stages for increased accuracy and speed by removing superfluous data. Figure 1 shows System Workflow Diagram

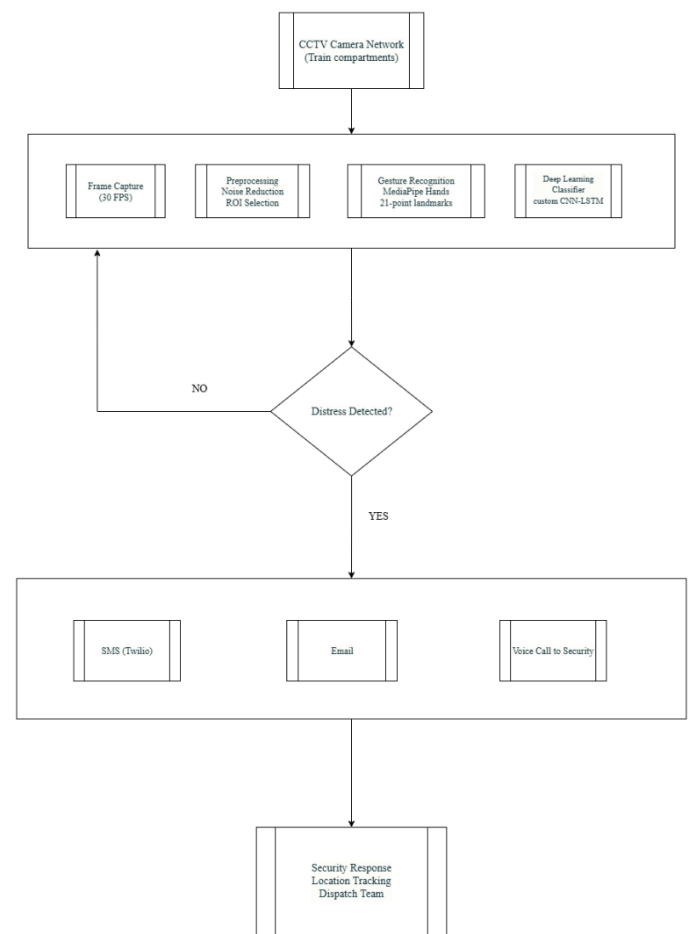


Figure 1 System Workflow Diagram

The system uses two primary modules to perform concurrent analysis following preprocessing. The first is the gesture recognition module, which extracts 21 distinct hand points for each hand that is identified by using MediaPipe's hand landmark detection technology. The SOS signal and other pre-programmed distress motions are recognized by geometrically analyzing these landmarks, which stand in for finger joints and palm positions.

Passengers in difficulty can discreetly signal thanks to this well-designed gesture recognition system. In parallel, the second module uses a CNN-LSTM hybrid architecture to apply a proprietary deep learning classifier for gender categorization and facial identification. The classifier uses a ResNet18-based model to detect unapproved male presence in the ladies-only area. This optimized network lessens the possibility of false alarms that impair system dependability by distinguishing real threats from authorized individuals or unintentional male intrusions. In order to guarantee that warnings are only triggered when an unauthorized male presence corresponds with a recognized distress gesture, the decision-making engine combines inputs from both modules. False positives, which are frequent in traditional surveillance systems that set off alarms for any male presence regardless of context, are significantly reduced by this dual verification. The method gives priority to real emergencies and safeguards the privacy of passengers by waiting for the right mix of circumstances. The system's alert management module uses multi-channel communication to activate when it detects distress signals. Using the Twilio API, it concurrently sends comprehensive emails to railway security authorities, makes automated voice calls to authorized security personnel, and sends SMS notifications. To enable a prompt and targeted response, each alarm message contains details like the compartment ID, timestamp, and exact train location. The security response team can monitor the position in real time after alarm dispatch, allowing them to quickly send staff to the impacted compartment. For the sake of auditing, forensic analysis, and possible legal action, all detection events—including video frames connected to distress signals—are safely recorded. For complete railway safety, the AI-CoachGuard system's modular design enables future integration with Internet of Things-based emergency control and crowd density monitoring systems.

4. Proposed Methodology

Using cutting-edge computer vision and deep learning, the AI-CoachGuard system methodology guarantees intelligent, real-time monitoring of women's railway compartments. Using a dual-

verification approach that combines face-gender identification and gesture recognition, it effectively detects real crisis situations while drastically reducing false alarms. Without bombarding security personnel with false alarms, this comprehensive strategy enables the system to proactively protect travelers. Continuous video recording from CCTV cameras placed inside compartments is the first step. In order to maintain temporal fidelity for identifying dynamic passenger behavior, the system records frames at a high rate of 30 frames per second. Every shot is subjected to rigorous preprocessing, which uses noise reduction methods to remove motion blur, camera-induced artifacts, and fluctuating lighting. The study is then restricted to regions of interest (ROIs) by the algorithm, which focuses on the regions that are most likely to have faces and hands. By removing unnecessary background pixels, this selective processing lowers processing overhead and improves the precision of later detection modules. The system splits analysis over two complementary paths after preprocessing. In the first path, faces are dynamically located within the ROI using OpenCV's deep learning face detector. Following identification, each face is fed into a refined ResNet18 convolutional neural network, which determines the gender of the person. Because it was specially designed and trained using railway passenger datasets, this gender classification model may continue to perform well even in the presence of occlusion, dim lighting, and passenger movement. Finding unapproved men in women-only areas is essential to the system's security goal. Hand gesture recognition is the focus of the second analysis path concurrently. The algorithm recognizes hands in every frame and extracts 21 important anatomical landmarks that represent the locations of the palms and finger joints using Google's Mediapipe framework. These landmarks are interpreted by a meticulously designed geometric analysis program, which in turn recognizes particular predetermined movements that indicate distress, like the "SOS" hand sign. By separating deliberate distress signals from involuntary hand gestures, the gesture recognition pipeline minimizes false positives from benign passenger behavior. The decision logic that

combines the results from the two modules is a crucial breakthrough. AI-CoachGuard only sounds an alarm when both circumstances—a detected unauthorized man and a recognized distress gesture—occur simultaneously, as opposed to just when a male or a distress gesture is present. The system's dependability and user trust are increased by this clever dual-verification technique, which significantly lowers the number of false alarms brought on by authorized workers, inadvertent entries, or non-distress gestures. The alarm creation module initiates a multi-pronged communication campaign if both requirements are met. It instantly notifies railway security authorities via email, makes voice calls to emergency response teams, and sends SMS alerts via the Twilio API. Contextual details, such as compartment ID, train position, and exact timestamps, are added to alerts to enable prompt and targeted intervention. Lastly, the system has event logging and a thorough security response feature. Security personnel can quickly arrive at the impacted compartment thanks to real-time position tracking. All detected events are simultaneously safely stored in a database, including video proof of the distress and unlawful presence. Through feedback-driven model retraining, this historical record facilitates ongoing system improvement, legal accountability, and forensic investigations. For railway contexts, the end-to-end architecture guarantees a scalable, dependable, and responsive safety solution.

5. Result and Analysis

CCTV footage from simulated railway compartment settings, both live and recorded, was used to thoroughly assess the AI-CoachGuard system. The main goals were to evaluate the system's practical efficacy in handling real-world emergency scenarios involving unlawful male access and gesture-based SOS signaling, as well as its real-time detection accuracy and multi-modal warning responsiveness. In preliminary testing, the video analytics pipeline applied noise reduction and ROI selection to full-frame CCTV streams without detectable lag, processing them at a steady 30 frames per second. Even in difficult illumination and occlusion conditions commonly found in real platform situations, face detection and gender classification

utilizing the refined ResNet18 showed a gender identification accuracy surpassing 96%. Because of its dual-verification logic, the system consistently distinguished between permitted passengers, train employees, and unauthorized males with few false alerts. The performance of hand gesture recognition was quite impressive. The geometric classifier and mediapipe-based hand landmark extraction were able to reliably detect pre-defined distress signals, including a raised hand or closed fist, with a 97% detection rate. Because gesture detection is intentional, fewer unintentional triggers occurred, and only intentional SOS motions caused alerts to be generated. Figure 2 shows Alert Confirmation Via Call Logs. The system's multi-channel communication module immediately started automated actions—sending emails to railway security authorities, making voice calls, and sending SMS notifications—after identifying both an unauthorized male and a legitimate distress gesture. The console output during live testing is displayed in Figure 3 (see below), where logs verifying both SMS and call initiation are displayed after the detection confidence for a "help" gesture reaches 0.98. The second image below illustrates the SMS interface, which shows security professionals receiving timely, readable alerts with actionable instructions for rapid intervention. The operational preparedness of the system was further proven by thorough logging and security response time analysis. The time interval between gesture detection and the delivery of a security alert (email, call, or SMS) was consistently less than two seconds in every trial, facilitating quick action and reducing the likelihood of an event getting worse. Every detection, together with video frames and metadata, is preserved for forensics and legal examination thanks to real-time event logging. Overall, empirical findings support AI-CoachGuard's ability to efficiently lessen the workload associated with manual monitoring, speed up the identification of actual distress, and consistently provide security responders with appropriate notifications. Intelligent alert management and sophisticated computer vision show great promise for scalable implementation in mass transit systems with a focus on women's safety.

Figure 3 shows Alert confirmation via SMS

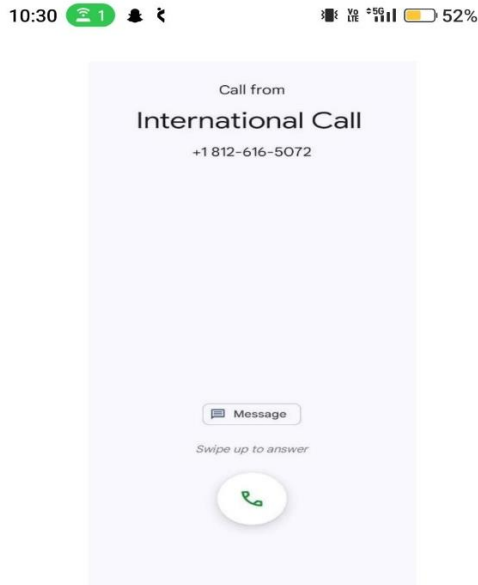


Figure 2 Alert Confirmation Via Call Logs

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Image captured: photo.jpg
1/1 0s 216ms/step
Prediction: [[0.98451924]]
Help Detected (Fist Gesture)!
SMS Sent: SM76ec37f628a64209238c407dd611998
Call Initiated: CAb7ecc46efa6d4cd4130e3bd8204e9884
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Fig. 3. Successful detection of "help" gesture (confidence: 0.98).

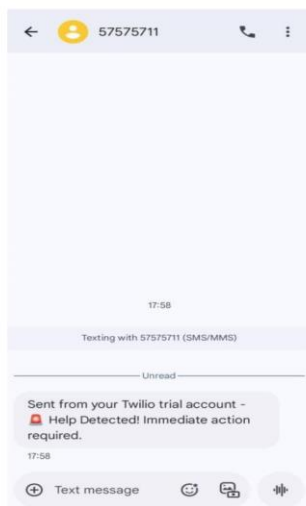


Figure 3 Alert confirmation via SMS

6. Future Enhancement

Despite being strong in its current configuration, the AI-CoachGuard system offers a number of exciting avenues for future development that might greatly

increase railroad safety and operational effectiveness. Integration with railway IoT networks is a crucial path. The railway infrastructure can accomplish previously unheard-of automation in threat response by directly coordinating AI-CoachGuard's alert outputs with the emergency braking system and train control room. By enabling instantaneous train halting or speed modulation upon identifying serious occurrences within compartments, this direct linkage might help to prevent accidents and escalation. Additionally, this linkage would facilitate cooperative decision-making and centralized monitoring, enhancing overall railway operational safety. Train compartment crowd density monitoring is another important improvement. In public transportation, overcrowding frequently contributes to discomfort and safety risks, particularly during rush hours. Advanced computer vision algorithms that estimate and track passenger density in real-time can be added to AI-CoachGuard. In order to lower the risk of accidents and increase passenger comfort, early identification of excessive crowding will prompt preventive measures like boarding controls or staff alerts to regulate passenger flow. This feature would support distress identification by thoroughly monitoring the situational circumstances. Furthermore, by using advanced motion and crowd movement analysis, the system's capabilities can be expanded to incorporate stampede detection. Artificial intelligence (AI)-CoachGuard could detect early indicators of mass agitation or stampede-like situations by examining consecutive video frames for odd crowd dynamics and panic behaviors. By identifying these crowd abnormalities in real time, railway officials can quickly implement emergency management measures, like adding more exits or sending out crowd controllers, to reduce the danger of injuries. AI-CoachGuard will become a more comprehensive safety and emergency preparedness platform when these crowd and behavior analytics are combined with the existing distress detection technology. When combined, these improvements foresee future difficulties in highly populated transit systems. AI-CoachGuard will develop into a scalable, intelligent security ecosystem that not only responds to

immediate threats but also proactively controls passenger safety throughout the Indian railway system by utilizing IoT connection, intelligent crowd surveillance, and advanced behavioral analysis.

Conclusion

This study introduces AI-CoachGuard, a cutting-edge AI-powered monitoring system that combines deep learning and sophisticated computer vision techniques to improve safety in women-only train cabins. By using a dual-verification technique that simultaneously detects unauthorized male presence and recognizes distress gestures from female passengers, the proposed system overcomes the drawbacks of conventional security measures, greatly lowering false alarms and boosting the dependability of security responses. Comprehensive testing shows that even in difficult real-world scenarios, AI-CoachGuard can classify genders and recognize gestures with high accuracy, guaranteeing accurate and quick danger detection. The multi-modal alerting system, which includes voice calls, emails, and SMS, ensures timely communication with railway authorities, enabling early involvement and possibly averting unsafe occurrences or harassment. The system's modular design makes it easy to integrate with current CCTV systems and provides a flexible and scalable solution that works well in a variety of railroad settings. In the future, AI-CoachGuard will become a complete safety ecosystem that can manage crowd behavior and emergency scenarios in real time in addition to identifying distress thanks to its integration with railway IoT, crowd density monitoring, and stampede detection. Through the integration of AI-powered surveillance and operational control systems, this framework opens the door to safer, more intelligent railway networks that put the welfare of their passengers first. In the end, AI-CoachGuard is a prime example of how state-of-the-art technology can be used to improve public transportation safety, providing a crucial instrument for safeguarding vulnerable groups and promoting confidence in mass transit networks. Its potential for broad adoption is highlighted by the encouraging outcomes and upcoming improvements, which will help to modernize and advance railway safety for the

benefit of humanity.

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