Unsupervised ML for managing accidents safety for Railway stations

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Abstract:

Railway stations are among the busiest transportation hubs, and ensuring safety within these areas is a critical challenge. Traditional safety mechanisms rely on human supervision or rule-based systems, which are often insufficient to detect anomalies or predict potential accidents. This project proposes the use of **Unsupervised Machine Learning (ML)** techniques to enhance accident prevention and safety management at railway stations. By analyzing surveillance footage, sensor data, and human movement patterns, unsupervised algorithms such as clustering and anomaly detection can automatically identify unusual behaviors or safety threats—like trespassing, overcrowding, or unattended objects—without requiring labeled data. This intelligent, scalable solution supports real-time monitoring and early warning mechanisms, improving overall safety and reducing the risk of accidents.

I.INTRODUCTION

Railway stations witness heavy daily foot traffic, diverse passenger behaviors, and complex operational workflows, making them vulnerable to accidents such as falls, track trespassing, and crowd surges. Ensuring passenger safety in such dynamic environments requires continuous monitoring and rapid decision-making.While supervised learning systems depend on annotated datasets, acquiring large volumes of labeled safety-related data is time-consuming and impractical in real-world railway operations. Unsupervised machine learning, which identifies hidden patterns and anomalies in unlabelled data, offers a powerful alternative. Techniques like clustering, Principal Component Analysis (PCA), and Isolation Forests can detect unusual activity, equipment malfunctions, or crowd patterns, allowing preemptive safety measures. Integrating these models with real-time video analytics, IoT sensors, and cloud-based dashboards can transform how railway safety is monitored and managed.

II.LITERATURE SURVEY

1. Wang et al. (2020) applied unsupervised learning to video surveillance for crowd behavior detection. Their work showed how K-Means and Gaussian Mixture Models could identify abnormal patterns in densely populated environments.
2. Xu & Yung (2018) focused on anomaly detection using autoencoders in public transit surveillance. Their model detected unusual human behavior with high accuracy and low false positives.
3. Chakraborty et al. (2019) developed a railway safety system using vibration and smoke sensors integrated with a rule-based decision system. They highlighted the limitations of static rule systems.
4. Jia et al. (2021) explored unsupervised deep learning models for visual anomaly detection in railway track monitoring. Their research demonstrated the power of self-learning models in identifying subtle threats.
5. Zhou et al. (2022) applied DBSCAN and PCA to detect crowd congestion at metro stations, concluding that unsupervised models can detect bottlenecks more effectively than threshold-based systems.
6. Zhang et al. (2020) investigated using Isolation Forests for safety anomaly detection in transport systems, showcasing better performance compared to statistical outlier methods.
7. Li et al. (2019) proposed the use of clustering algorithms to predict station-level risks based on footfall and time-of-day patterns.
8. Kumar & Sharma (2021) integrated IoT and unsupervised ML for proactive hazard alerts in Indian railway stations.
9. Liu et al. (2020) tested autoencoder-based anomaly detectors on real-world CCTV footage and achieved high recall in detecting crowd surges.
10. Sato & Tanaka (2017) worked on early detection of suspicious packages using ML models trained on movement patterns of luggage.
11. Tripathi et al. (2021) reviewed safety monitoring systems in Indian railways and emphasized the potential of AI for predictive risk management.
12. Rajput et al. (2022) developed a scalable edge-computing ML system for real-time accident detection in public transit.
13. Bhattacharya & Sinha (2018) reviewed global trends in intelligent transport safety systems and endorsed AI-based monitoring in railway environments.
14. Gupta et al. (2022) implemented a hybrid

unsupervised ML and rule-based engine to identify security breaches in metro stations.

15. World Bank (2020) emphasized smart infrastructure investments in public safety and highlighted ML-based surveillance systems in transportation networks as a key strategy.

III.EXISTING SYSTEM

Currently, most railway stations rely on manual monitoring using CCTV cameras and patrolling staff. Surveillance footage is observed in control rooms, often leading to missed incidents due to human error or fatigue. Some modern systems use rule-based motion detectors or crowd control alarms, but they lack adaptability and intelligence to handle complex scenarios like early-stage crowd buildup, unusual motion, or unattended baggage. In addition, existing systems are reactive rather than proactive, providing alerts only after an event has occurred. There is minimal use of advanced data analytics or AI in public railway safety systems.

IV.PROPOSED SYSTEM

The proposed system employs Unsupervised Machine Learning models to identify anomalies and safety risks at railway stations in real time. Input is collected from CCTV cameras, footfall sensors, and environmental detectors (e.g., smoke or vibration). The data is analyzed using algorithms like **K-Means Clustering**, **DBSCAN**, and **Autoencoders** to establish baseline behaviors and detect deviations. For example, if a person enters restricted zones, or an object is left unattended, the system recognizes it as an anomaly and sends alerts to station control staff. These models continuously learn from new patterns, making the system adaptive. Integration with a **dashboard interface** allows administrators to monitor alerts, heatmaps, and incident logs. The solution is scalable, efficient, and reduces dependence on human monitoring while enhancing the speed and accuracy of accident prevention.

V.SYSTEM ARCHITECTURE

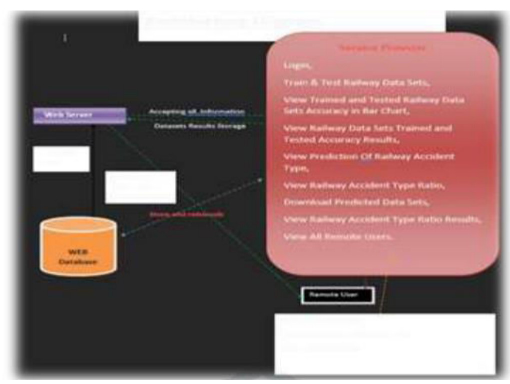

Fig 5.1 System Architecture

The proposed system architecture integrates IoT sensors, CCTV cameras, data preprocessing units, and unsupervised ML models into a real-time safety and anomaly detection system for railway stations. It emphasizes modularity, scalability, and real-time response, leveraging edge and cloud computing infrastructure.

VI.IMPLEMENTATION

Fig 6.1 User Login

Fig6.2 :User login

Fig 6.3 Results

VII.CONCLUSION

The proposed Unsupervised ML-Based Accident Safety System for Railway Stations addresses the critical limitations of traditional safety management by introducing intelligence, automation, and adaptability. Using algorithms capable of identifying anomalies without the need for pre-labeled datasets makes the system highly efficient and scalable across diverse station environments. It offers a real-time, proactive approach to preventing accidents, detecting threats, and managing crowds—while significantly reducing human monitoring overhead.

The solution not only strengthens surveillance capabilities but also aligns with the future vision of smart and safe transportation infrastructure. As unsupervised learning techniques continue to evolve, their integration into public safety systems can redefine how cities and transportation authorities protect passengers and ensure seamless transit operations**.**

VIII.FUTURE SCOPE

Integration with smart IoT sensors: To enhance anomaly detection by including real-time environmental data (vibrations, smoke, temperature).Deployment of Edge AI: For local and faster real-time processing near CCTV installations, reducing server load.Scalable deployment across railway networks: Integrate with national smart railway programs for wider safety enforcement.

Data fusion from multiple sources: Combine footfall, video, and social data for comprehensive predictive safety models.

Integration with emergency response

systems: Automated incident alerts to fire stations, ambulances, and control rooms.

Multilingual voice alerts & mobile notifications: To instantly inform passengers of safety threats or station evacuation procedures.

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