ARTIFICIAL INTELLIGENCE APPLICATIONS IN ROAD AND RAIL TRANSPORT RISK MANAGEMENT: BETWEEN INNOVATION AND NECESSITY

MARIAN PUIE[1,*]

ABSTRACT – Artificial Intelligence Applications in Road and Rail Transport Risk Management: Between Innovation and Necessity. Natural and anthropogenic hazards severely threaten transport infrastructures. This review explores AI's role in enhancing risk detection, prediction, and response for road and rail. This review synthesizes advances in object detection, machine learning, and geospatial integration. Five global case studies demonstrate AI in early warning, structural monitoring, and predictive maintenance, enhancing transport system safety and resilience.

Key words: artificial intelligence, transport infrastructure, risk management, object detection, GIS, remote sensing, predictive maintenance, early warning systems.

1. INTRODUCTION

In recent years, road and rail infrastructures have become increasingly exposed to natural and anthropogenic hazards. Events such as floods, landslides, rockfalls, snowstorms, and extreme weather are causing significant disruptions to transport networks, especially in mountainous and riverine regions. At the same time, human-induced risks, ranging from accidents and structural failures to poor maintenance, continue to generate severe socio-economic impacts. Traditional risk management approaches often rely on static models and reactive strategies, which may not provide the adaptability and speed needed in a changing risk landscape (Li et al., 2016).

The rise of Artificial Intelligence (AI) offers new opportunities for improving the safety and resilience of transport systems. Through real-time data processing, pattern recognition, predictive analytics, and autonomous systems, AI technologies can help anticipate, detect, and respond to hazard events more effectively. From traffic monitoring with computer vision algorithms to predictive maintenance of railway infrastructure, AI has begun to reshape the way risk is understood and managed (Haydari & Yilmaz, 2020).

This paper provides a comprehensive review of AI applications in road and rail transport, with an emphasis on their role in hazard detection and risk mitigation.

[1] *Bucharest University, Simion Mehedinți Doctoral School, Faculty of Geography, 010041, Bucharest, Romania, e-mail: marian.puie@s.unibuc.ro, https://orcid.org/0000-0002-5026-1466*

The objective is to outline the main technological developments, identify best practices, and highlight the potential for integration with geospatial analysis tools such as GIS and remote sensing. Moreover, the paper aims to assess the current challenges and future directions for AI implementation in transport-related risk management, particularly in Eastern Europe and other regions facing digital and infrastructural limitations (Russell & Norvig, 2020).

2. THEORETICAL BACKGROUND: ARTIFICIAL INTELLIGENCE IN RISK MANAGEMENT FOR TRANSPORT SYSTEMS

Artificial Intelligence (AI) refers to the ability of machines and computer systems to simulate human intelligence processes, including learning, reasoning, and problem-solving. In the context of risk management, AI supports a shift from reactive approaches to proactive and predictive strategies. This shift is particularly important for transport systems, where early identification of risks can prevent accidents, reduce costs, and save lives.

Several AI subfields contribute to transportation risk analysis:

Machine Learning (ML) algorithms are trained on historical data to detect patterns and forecast risk-prone situations (e.g., predicting landslides or identifying accident hotspots).

Computer Vision techniques, often based on Convolutional Neural Networks (CNNs), are used to analyze video feeds or satellite imagery for detecting vehicles, hazards, or infrastructure damage (Russell & Norvig, 2020).

Natural Language Processing (NLP) allows the extraction of real-time data from textual sources such as traffic reports, news feeds, or social media, contributing to rapid hazard identification.

Reinforcement Learning is applied in traffic control systems or autonomous vehicles to adaptively respond to dynamic conditions (Haydari & Yilmaz, 2020).

Geospatial AI (GeoAI) integrates AI with GIS and remote sensing, enabling the spatial analysis of risks such as floods, snow, or slope instability, often with the support of Sentinel or LiDAR data (VoPham et al., 2018).

AI's ability to process large datasets from heterogeneous sources such as weather sensors, GPS, surveillance cameras, satellite imagery, or social platforms makes it a crucial tool in modern risk management frameworks.

3. CASE STUDIES: RELEVANT APPLICATIONS OF AI IN ROAD AND RAIL TRANSPORT RISK MANAGEMENT

3.1. AI-Driven Landslide Prediction and Early Warning for Mountain Roads (Taiwan)

Mountainous regions, like those in Taiwan, are highly vulnerable to landslides, which can block roads, cause accidents, and isolate communities. Traditional monitoring methods are often reactive. This study presents a cutting-edge method based on artificial intelligence for predicting the displacement of deep-seated landslides in Taiwan's Lushan area. The authors integrate Convolutional Neural Networks (CNNs) with a novel optimization algorithm (Age of Exploration-Inspired Optimizer) to analyze a multitude of geo-morphological, geological, hydrological, and pluviometric factors (Fig. 1). The goal is to improve the accuracy of predictions for ground movements, providing a crucial tool for more efficient early warning systems and proactive management of geological risks that can impact transport infrastructure, thereby preventing disasters (Fig. 2), (Chou et al., 2025).

$$x_{i,d}(t+1) = x_{i,d}(t) + \alpha \cdot \left(\mathrm{Meanvl}_d(t) - x_{i,d}(t)\right) \times \mathrm{rand}(0,1) \times R,$$

$$\mathrm{Meanvl}_d(t) = \frac{x_{1,d}(t) + x_{2,d}(t) + \ldots + x_{n_{\mathrm{Pop}},d}(t)}{n_{\mathrm{Pop}}},$$

Eq. 1. "Explorers Follow General Trends" Strategy in Exploration-Inspired Optimization (Source: Chou et al., 2025).

$$x_{i,d}(t+1) = x_{i,d}(t) + \left(\mathrm{Best}_d(t) - x_{i,d}(t)\right) \times \mathrm{rand}(0,1) \times R,$$

Eq. 2. "Explorers Follow the Best One" Strategy in Exploration-Inspired Optimization (Source: Chou et al., 2025).

3.2. AI-Driven Real-time Road Accident Risk Prediction Using Spatiotemporal Trajectories (Urban Areas)

Road accidents represent a major anthropogenic risk with significant socio-economic and human consequences, where emergency response time is crucial. This paper presents an innovative deep learning approach for real-time traffic accident risk prediction using spatiotemporal features of vehicle trajectories in urban environments. The model integrates Convolutional Neural Networks (CNN) for spatial feature extraction (e.g., vehicle speed, acceleration, lane-changing distance), Long Short-Term Memory (LSTM) for capturing temporal dependencies in trajectories, and Graph Neural Networks (GNN) for effectively modeling the complex spatial structure of traffic networks (Fig. 3). This combined deep learning framework significantly enhances prediction accuracy and offers a robust technical approach for intelligent traffic management and real-time accident warning systems, ultimately contributing to public safety (Li & Chen, 2025).

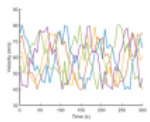

Fig 1. Vehicle speed time series curves.

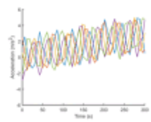

Fig 2. Acceleration time series curves.

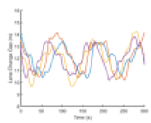

Fig 3. Change lane spacing time series...

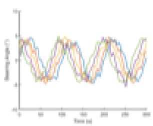

Fig 4. Steering angle time series curve.

Fig. 1–4. "Time series of the main features of vehicle trajectories": speed, acceleration, lane change distance, and steering angle (Source: Li & Chen, 2025).

3.3. AI-Enhanced Structural Health Monitoring of Bridges (Hong Kong-Zhuhai-Macau Bridge)

The structural integrity of bridges is critical for transportation safety, as failures can lead to major disasters. Manual monitoring is costly and may miss incipient problems. This study focuses on developing a dynamic warning method, based on the statistical ARIMA (Autoregressive Integrated Moving Average) model, for Structural Health Monitoring (SHM) of the immersed tunnel of the Hong Kong–Zhuhai–Macau Bridge (HZMB) (Fig. 5). By analyzing data from structural sensors, the model identifies abnormal deviations from the structure's normal behavior, indicating potential incipient failures or degradations. This approach allows for early warnings in case of anomalies, crucial for prevention of structural collapse or major damages and for optimizing maintenance of a critical transport infrastructure (Chen et al., 2022).

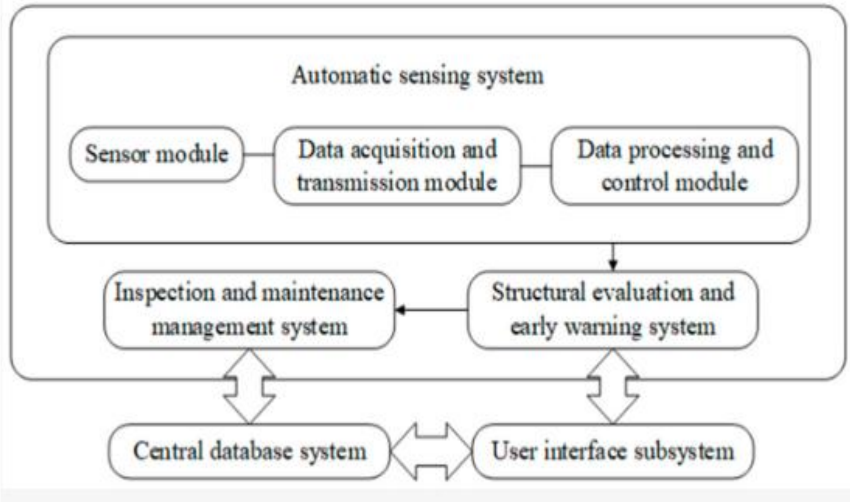

Fig. 5. "SHM system of the HZMB" (Source: Chen et al., 2022).

3.4. AI-Powered Predictive Maintenance for High-Speed Rail Networks

The safety and reliability of railway networks depend crucially on the condition of infrastructure and rolling stock, as failures can lead to derailments or collisions. This paper provides a comprehensive review of advanced maintenance technologies for high-speed train traction systems, including approaches that underpin AI-powered predictive maintenance. It highlights the evolution towards Condition-Based Maintenance (CBM) and Prognostic and Health Monitoring (PHM) technologies, which leverage intelligent algorithms to predict potential equipment failures (Fig. 6). Specifically, the review discusses the maintenance system of Japan's Shinkansen network, detailing how data from various sensors is increasingly utilized for real-time condition monitoring, analysis, and prediction of component aging trends. This proactive, data-driven approach aims to significantly reduce maintenance costs, improve operational efficiency, and enhance the exceptional safety and reliability standards of railway systems by moving away from reactive or time-based maintenance (Xu et al., 2021).

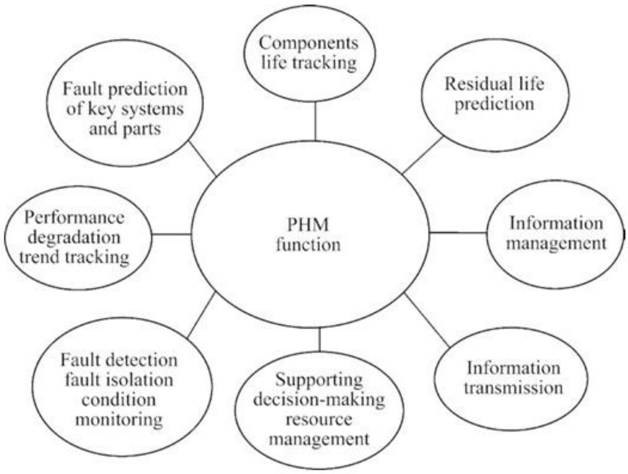

Fig. 6. "Prognostic and Health Monitoring (PHM) technology and application scope" (Source: Xu et al., 2021).

3.5. AI-Enhanced Flood Early Warning and Management

Floods pose a significant risk to transport infrastructure, leading to route blockages and substantial damage, making the need for early warning systems increasingly urgent. This study presents an innovative flood early warning system (FEWS) developed for estuarine areas, exemplified by its implementation in the Douro River Estuary in northern Portugal (Fig. 7). The system combines Artificial Intelligence (specifically, deep learning with Long Short-Term Memory - LSTM neural networks) with process-based hydrodynamic models.

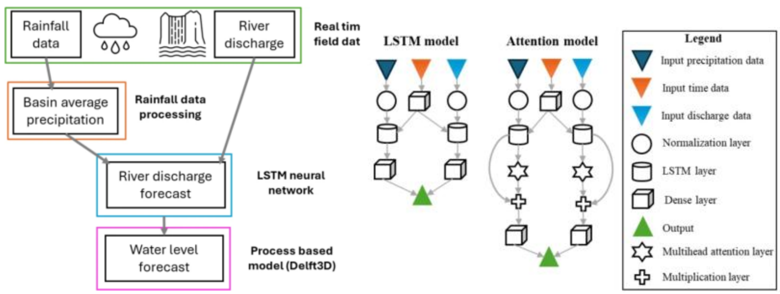

Fig. 7. "Flood Early Warning Systems (FEWS) framework (left)" and "model implementation architecture (right) " (Source: Weber de Melo et al., 2025).

The AI component forecasts river discharge at the fluvial boundary using streamflow and rainfall data, while the process-based model simulates water levels and flood extent within the estuary. This hybrid approach enables accurate and timely predictions, offering lead times of up to 36 hours. Such predictive capability is vital for transport authorities, allowing for the proactive closure of affected routes (road and rail) and better planning of emergency response, significantly enhancing the resilience of critical infrastructure to hydrological disasters (Weber de Melo et al., 2025).

4. CHALLENGES AND OPPORTUNITIES IN EASTERN EUROPE

Eastern Europe presents a unique set of challenges and opportunities for implementing AI-driven risk management in road and rail transport. The region's diverse topography, varying climate conditions, and infrastructure legacy require tailored approaches that consider local environmental and socioeconomic factors (Gawlak et al., 2025).

Challenges include:

Limited availability and accessibility of high-resolution spatial data and sensor networks in some rural or mountainous areas.

Insufficient integration of AI tools with existing GIS and transport management systems due to infrastructural or financial constraints.

Lack of trained personnel specialized in AI, GIS, and remote sensing, which hinders widespread adoption.

Regulatory and policy frameworks that may lag behind technological advances.

Opportunities are:

Growing investments in digital infrastructure and the European Union's support for smart transport initiatives.

Potential for cross-border collaboration in hazard monitoring and data sharing, especially in transnational corridors.

Increasing availability of open-access satellite data (e.g., Sentinel missions) enabling cost-effective remote sensing analyses.

Development of educational and training programs to build expertise in AI and geospatial technologies (Al-Maamari, 2025).

Addressing these challenges through capacity building, funding, and institutional collaboration could transform Eastern Europe into a regional leader in innovative transport risk management systems, enhancing safety and resilience (Ghaffarian et al., 2023).

5. INTEGRATION WITH GIS AND REMOTE SENSING

The integration of Artificial Intelligence (AI) with Geographic Information Systems (GIS) and remote sensing technologies has significantly enhanced the capacity for risk monitoring, prediction, and management in road and rail transport. GIS provides the spatial framework to visualize, analyze, and interpret hazard data, while remote sensing offers timely and comprehensive earth observation data, crucial for detecting changes in terrain, vegetation, and infrastructure conditions (Zhang & Kovacs, 2012).

AI algorithms such as machine learning and deep learning can process large volumes of remote sensing data (e.g., satellite imagery, LiDAR, UAV photogrammetry) to identify patterns indicative of potential hazards, floods, landslides, rockfalls, or avalanches, that threaten transport networks (Johnson et al., 2022). For example, satellite Synthetic Aperture Radar (SAR) data can detect ground displacement related to landslides, which when combined with AI classification techniques, enables early warning for infrastructure at risk (Clarke & Obrien, 2016).

Moreover, GIS platforms allow for overlaying AI-derived hazard maps with transport infrastructure layers to assess vulnerability and exposure, facilitating targeted interventions and maintenance prioritization (Zhang et al., 2025). This multidisciplinary approach supports comprehensive risk management and resilience planning, especially in geographically complex and hazard-prone areas.

CONCLUSIONS

This review highlights the growing role of Artificial Intelligence in enhancing risk assessment and management in road and rail transport, supported by integration with GIS and remote sensing technologies. Real-world case studies demonstrate successful applications ranging from flood and rockfall monitoring to traffic management and predictive maintenance, underscoring AI’s potential to improve safety and operational efficiency.

For Eastern Europe, embracing these technologies presents an opportunity to address existing vulnerabilities in transport infrastructure through proactive hazard detection and mitigation. However, realizing this potential requires overcoming data accessibility barriers, investing in human capital, and fostering inter-institutional cooperation.

Future research should focus on developing adaptable AI models that incorporate local geographic and climatic variables, optimizing the integration with geospatial platforms, and expanding real-time monitoring capabilities. Moreover, ethical considerations and data privacy must be integrated into system designs to ensure societal acceptance and sustainability.

In conclusion, AI-driven transport risk management, coupled with advanced geospatial technologies, represents a promising frontier for safeguarding critical infrastructure and improving resilience against natural and anthropogenic hazards.

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