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Artificial Intelligence and Machine Learning for Resilient Transportation Infrastructure

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Abstract

The escalating frequency and severity of natural hazards - such as earthquakes, floods, and landslides - present critical challenges to the resilience and reliability of transportation infrastructure. Conventional methods for resilience assessment and disaster response often lack the real-time adaptability and predictive capabilities required to address dynamic and complex hazard scenarios. In this evolving landscape, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative technologies, offering advanced analytical capabilities to enhance the robustness, responsiveness, and post-disaster recovery of critical transportation systems. This review provides a comprehensive and structured synthesis of contemporary AI/ML approaches deployed across the disaster management cycle. Particular emphasis is placed on their application in structural health monitoring, predictive modeling of infrastructure failure, risk and vulnerability assessment, and real-time emergency response. A critical evaluation of key AI/ML algorithms - including Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory networks, Support Vector Machines, Random Forests, and Extreme Gradient Boosting - is presented, highlighting their respective strengths, limitations, and domain-specific applicability. The paper also explores essential aspects of data-driven modeling, including data acquisition strategies, preprocessing techniques, and the integration of diverse data sources such as satellite imagery, unmanned aerial vehicle systems, and ground-based sensor networks. Despite significant advancements in the accuracy, efficiency, and scalability of AI/ML applications, several challenges persist - particularly concerning data availability, model transparency, and the seamless integration of intelligent systems with existing infrastructure frameworks. By identifying these critical gaps, the review outlines key research directions aimed at developing intelligent, adaptive, and interpretable AI-based frameworks for resilience assessment.

Categories: AI applications, Soft Computing, Disaster Recovery and Business Continuity
Keywords: transportation infrastructure, resilience assessment, disaster response, cnn, rnn, risk mapping, emergency management, infrastructure vulnerability, predictive modeling

Introduction And Background

Transportation infrastructure is a foundational pillar of social and economic development, enabling the efficient movement of people, goods, and services, supporting commerce, facilitating emergency response, and ensuring access to essential resources. In recent decades, the increasing frequency and severity of both natural disasters - such as storms, floods, and earthquakes and human-induced threats - including cyberattacks and accidents - have underscored the growing need for resilient transportation systems. To ensure operational continuity during and after such disruptive events, infrastructure must possess the capacity to absorb shocks, adapt to changing conditions, and recover swiftly without halting critical functions [1]. The rising incidence of climate-related disasters highlights the vulnerabilities inherent in existing transportation networks. High-impact events such as the 2011 Tōhoku earthquake in Japan, the 2015 Chennai floods in India, and Hurricane Harvey in the United States have caused extensive damage to transportation assets including roads, bridges, and transit systems - resulting in significant economic losses and human hardship [2]. These events emphasize the multifaceted nature of resilience, which encompasses system stability, redundancy, adaptability, recovery rate, and inter-system coordination [3]. Comprehensive resilience planning in transportation must therefore address both physical infrastructure (e.g., roads, bridges, tunnels) and operational systems (e.g., traffic control, logistics, and emergency management). A key priority is the ability to rapidly restore essential services post-disaster, minimizing downtime to support emergency evacuation, relief operations, and societal recovery [4]. Enhancing transport resilience is also essential for advancing disaster risk reduction goals and achieving sustainable development targets [5], particularly in the context of climate change and rapid urbanization, which amplify exposure and vulnerability to hazards. Traditional resilience assessment in transportation infrastructure relies on three main approaches: topological, feature-based, and performance-based. Topological methods analyze network structure and connectivity (e.g., redundancy, centrality), identifying vulnerabilities but overlooking dynamic factors like traffic flow. Feature-based methods assess resilience using attributes such as the “4 Rs” (Robustness, Redundancy, Resourcefulness, Rapidity), offering

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comprehensive yet often qualitative and subjective evaluations. Performance-based methods quantify resilience by tracking system performance (e.g., travel time, traffic flow) during disruption and recovery, with the "Resilience Triangle" as a key example. Though more accurate, this approach is highly data-intensive and challenging to implement. Traditional resilience assessment methods often rely on static models and historical data, which are insufficient for capturing the dynamic, complex, and nonlinear nature of modern crises. In contrast, recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have enabled the development of data-driven tools that support real-time monitoring, predictive analytics, and decision-making under uncertainty. The integration of AI/ML into resilience frameworks is reshaping how transportation systems are evaluated, designed, and managed [6]. These technologies shift the paradigm from reactive recovery to proactive risk mitigation and adaptive system design. Investing in resilient infrastructure reduces direct economic losses, ensures the continuity of essential services, enhances community safety, and fosters long-term adaptability. As transportation networks become increasingly digitalized and interconnected, leveraging AI-driven resilience assessment will be critical for building intelligent and future-ready infrastructure systems [7]. Figure *1* illustrates a comprehensive framework depicting the systematic integration of AI/ML technologies into transportation systems to address resilience challenges effectively.

FIGURE 1: Flowchart showing the integration of AI/ML tools in the transportation engineering

AI, Artificial Intelligence; ML, Machine Learning

Role of AI/ML in disaster mitigation

AI and ML play a pivotal role in disaster mitigation by enabling data-driven, scalable, and adaptive solutions. These technologies enhance system performance and responsiveness, particularly in scenarios where traditional risk assessment methods fall short - such as during large-scale, complex, and rapidly evolving catastrophes in transportation engineering. AI and ML enable improved forecasting, real-time monitoring, early warning generation, damage detection, and rapid decision-making processes [8]. One of the most significant contributions of AI/ML lies in the development of early warning systems and hazard prediction models. By analyzing historical data from meteorological, hydrological, and seismic sources, machine learning techniques can enhance the accuracy and timeliness of predicting natural disasters such as earthquakes, floods, and landslides. Algorithms such as Random Forest and Long Short-Term Memory

(LSTM) networks [9,10] have demonstrated strong performance in forecasting seismic events, flood levels, and rainfall patterns in real time. These predictive capabilities enable preemptive actions - such as road closures, route reconfiguration, and pre-positioning of emergency resources - thereby enhancing safety and reducing the risk to human life and infrastructure. AI also offers transformative capabilities in post-disaster damage assessment. For instance, computer vision techniques powered by deep learning - particularly Convolutional Neural Networks (CNNs) - can efficiently process and classify imagery from Unmanned Aerial Vehicles (UAVs) and satellite platforms to detect structural damage such as cracks, deformations, and settlements. This capability significantly accelerates Structural Health Monitoring (SHM) processes, allowing for large-scale, rapid, and accurate assessments that would be impractical through manual inspection alone [11]. In emergency contexts, timely situational awareness is essential for informed decision-making and coordinated response efforts. In addition to damage detection and early warning, AI/ML techniques have also been instrumental in optimizing emergency logistics. Techniques such as reinforcement learning and genetic algorithms [12] can dynamically determine optimal routes for emergency response vehicles, manage the distribution of relief supplies, and facilitate the safe evacuation of populations. These models are capable of adapting to real-time data such as traffic conditions, road closures, and hazard propagation, making them highly effective in fast-changing disaster scenarios. Moreover, AI-based decision-support systems can simulate and evaluate various intervention strategies, enhancing the robustness of contingency planning and improving overall response efficiency. Furthermore, AI-powered data fusion and anomaly detection techniques enable the integration of heterogeneous data sources to identify potential threats. These sources may include weather forecasts, traffic sensor data, social media activity, and infrastructure performance metrics. Natural language processing methods, for example, have proven effective in extracting actionable insights from unstructured data streams such as Twitter feeds, helping authorities gauge public sentiment, identify high-impact zones, and prioritize response measures [13]. Despite these advancements, the deployment of AI and ML in disaster mitigation still faces several challenges. These include issues related to data quality and availability, model interpretability, generalizability across different geographies, and interoperability with existing infrastructure systems [14-17]. However, recent innovations - such as Explainable AI (XAI), edge computing, and transfer learning - are progressively addressing these barriers and improving the practical applicability of AI/ML in disaster risk reduction. In summary, AI and ML technologies are indispensable across all phases of disaster management. However, their most impactful applications lie in the domains of disaster preparedness and mitigation, where they facilitate faster, more flexible, and more accurate decision-making. Their integration into transportation networks not only enhances infrastructure longevity but also enables a strategic shift from reactive recovery to proactive risk reduction. Figure *2* presents the resilience performance curve, which conceptually illustrates how a transportation system responds to and recovers from a disruptive event. The horizontal axis represents time, divided into pre-event, post-event, and long-term phases, while the vertical axis indicates system performance or level of service. Prior to the disruption, resilience is reflected in the system's robustness and preparedness. Once the event occurs, performance declines, with the magnitude of the drop signifying the severity of the impact. During the event, absorption capacity influences how much functionality can be retained. The recovery phase then demonstrates how quickly and effectively the system regains its original or near-original performance level. The comparison between the resilient and non-resilient trajectories highlights that resilient systems experience a smaller loss of functionality and a faster recovery, whereas non-resilient systems face deeper declines and slower restoration. This curve thus provides an intuitive visualization of resilience by capturing the dynamics of system performance before, during, and after disruption.

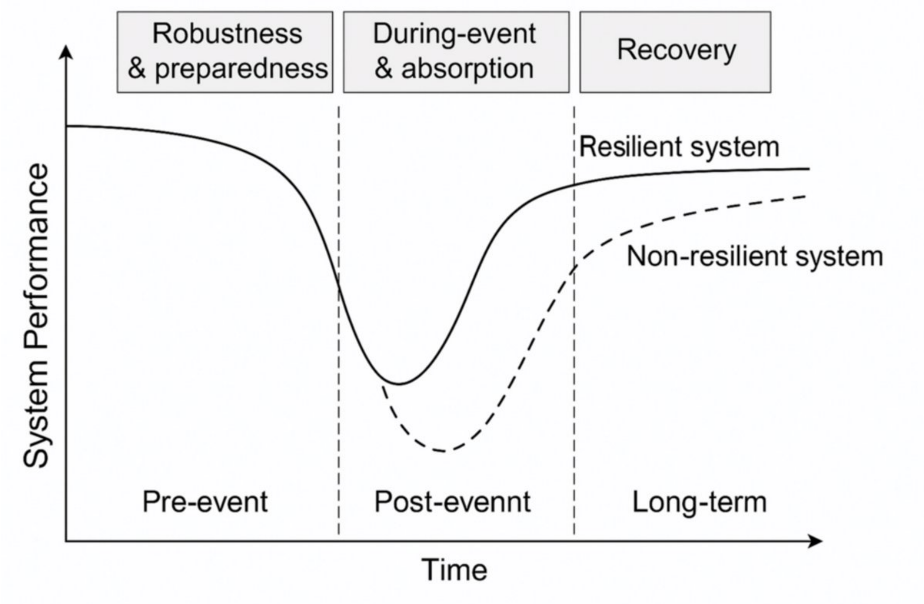

FIGURE 2: Conceptual resilience performance curve showing system functionality before, during, and after a disruptive event

Objectives and scope of the review

This review aims to address the growing vulnerability of transportation infrastructure to climate-induced and natural disasters by advocating a shift from traditional, deterministic resilience assessment methods toward intelligent, data-driven frameworks. It synthesizes recent advances in AI and ML for enhancing the resilience of transport networks, focusing on predictive analytics, real-time monitoring, damage detection, and adaptive emergency response. The review systematically categorizes state-of-the-art AI/ML techniques - ranging from supervised and unsupervised learning to deep learning architectures - and evaluates their effectiveness in hazard prediction, SHM, and post-disaster recovery, with a focus on highways and bridge systems. It also examines the integration of remote sensing, Internet of Things (IoT), big data, and geospatial analytics to improve model performance. By presenting real-world applications, case studies, and hybrid modeling approaches, the study highlights the practical relevance of AI-driven resilience metrics while excluding purely theoretical or non-transport-focused works unless transferable. This review is intended to guide researchers, infrastructure planners, and policymakers in leveraging AI/ML technologies to develop autonomous, interpretable, and future-ready transport systems that support smart city development and sustainable infrastructure planning.

Review

Review methodology

The literature review followed a systematic and structured process to ensure comprehensive coverage of relevant studies while maintaining methodological rigor. The process was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses framework and consisted of three primary stages: identification, screening, and eligibility assessment, culminating in the final inclusion of studies.

Identification - The initial search was conducted across two leading bibliographic databases, Scopus and Web of Science, selected for their extensive indexing of peer-reviewed publications in engineering, transportation, and disaster resilience domains. The search period spanned from January 2010 to June 2025, and the search strategy combined key terms relating to AI, ML, resilience, and transportation infrastructure. Keywords used in searching databases were as follows: ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("resilient transportation" OR "transport infrastructure" OR "disaster response"). This search retrieved a total of 3,041 records (Scopus: 1,742; Web of Science: 1,299). All search results were exported in CSV format, including metadata such as titles, authors, abstracts, keywords, publication years, and DOIs.

Screening - The first screening step involved removal of duplicate records, which reduced the dataset to 2,367 unique entries. Subsequent filtering applied subject-area restrictions to retain only studies relevant to transportation infrastructure resilience, followed by a language filter to exclude non-English publications. After these filters, records underwent a title and abstract review to eliminate works outside the scope (e.g., unrelated sectors, purely theoretical discussions without AI/ML application). This stage reduced the dataset to 180 articles for full-text examination.

Eligibility - Each of the 180 full-text articles was assessed for methodological depth, relevance to the review objectives, and the presence of empirical data, case studies, and technical frameworks integrating AI/ML for resilience assessment or disaster response in transportation systems. Studies were excluded if they lacked full-text availability, were outside the transportation domain, or did not incorporate AI/ML methodologies. This process resulted in 32 eligible articles from database sources.

Final Inclusion - An additional four studies were identified through manual methods, including backward and forward citation searches and consultation of authoritative reports not indexed in Scopus or Web of Science. These additions brought the final number of studies included in the review to 36. The complete selection process is visually summarized in Figure 3.

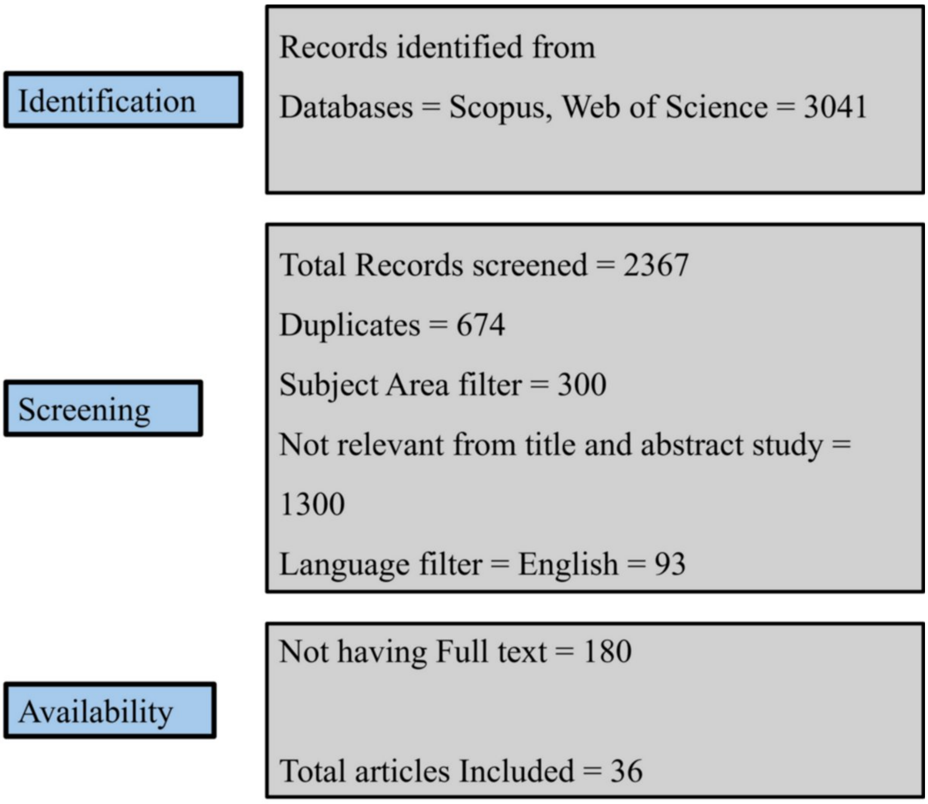

FIGURE 3: PRISMA flow diagram illustrating the literature search and selection process

PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Fundamentals of resilience in transportation infrastructure

Resilience and robustness are often used interchangeably in transportation infrastructure discussions, yet they represent distinct system attributes under stress or disruption. Robustness refers to the inherent strength of an asset to resist known or anticipated stresses - such as extreme loads or environmental hazards - without significant degradation in performance. For instance, a robust bridge may withstand seismic shaking or flooding due to specific structural design features [18]. Resilience, however, is broader and more dynamic, focusing on the ability of the system to absorb shocks, adapt to evolving conditions, and recover rapidly to a functional or even improved state. While robustness emphasizes physical durability, resilience incorporates adaptability, flexibility, and learning capacity. Detailed comparison between robustness and resilience is presented in Table 1 from previous literature [19]. In practice, resilience in transportation systems manifests through adaptive response mechanisms such as AI-enabled real-time monitoring, predictive modeling, rapid post-event damage assessment, and intelligent rerouting strategies. Unlike the static nature of robustness, resilience relies on active processes, including feedback loops, real-time decision-making, and continuous system evolution. Integrating AI and ML into resilience planning enables infrastructure to transition from merely withstanding disruptions to actively managing and accelerating recovery. This integration supports dynamic risk assessment, operational flexibility, and sustained service continuity - critical factors in maintaining long-term infrastructure sustainability [19].

Feature	Robustness	Resilience
Definition	Ability to resist disruption	Ability to absorb, adapt, and recover from disruption
System behavior	Static, strength-based	Dynamic, performance- and time-based
Response to shock	Minimal performance loss	Rapid recovery and adaptive response
Design strategy	Overdesign, redundancy	Flexibility, learning, adaptive capacity
Focus	Pre-event	Pre-, during, and post-event
AI/ML role	Limited (e.g., stress prediction)	High (e.g., monitoring, forecasting, adaptive control)

TABLE 1: Comparison between robustness and resilience

Source: [19]

AI, Artificial Intelligence; ML, Machine Learning

Measurements for Resilience

To develop effective resilience strategies, it is essential to quantify resilience using measurable, data-driven indicators. Resilience metrics evaluate the ability of transportation infrastructure to absorb shocks, maintain critical functions, and recover over time. One widely recognized conceptual model is the resilience triangle, which represents system functionality over time; smaller areas under the curve indicate faster and more efficient recovery [20]. Temporal indicators such as Time to Recovery, Time to Minimal Functioning, and Rate of Recovery provide quantitative measures of restoration speed and efficiency. Complementary metrics - like the Redundancy Index (measuring alternative routes or modes), Robustness Coefficient (evaluating resistance to performance degradation), and Functionality Loss Ratio (quantifying initial service loss) - help assess both immediate and long-term system performance [21]. These metrics offer a framework for benchmarking resilience and guiding investment in adaptive capacity. Building on these performance measures, resilience can be quantified using time-based mathematical models. A common approach defines the Resilience index (R) as:

$$R = \frac{1}{T}\int_0^T Q(t)\,dt \qquad (1)$$

where,

R: Resilience index

Q(*t*): Quality or performance function at time $t\,(0 \leq Q\,(t) \leq 1)$

T: Total time considered for system recovery

Emerging computational methods - such as agent-based modeling, system dynamics, and network theory - extend these measures by simulating how interconnected infrastructure components behave under different hazard scenarios. When combined with big data sources (e.g., traffic sensors, satellite imagery, remote sensing), these methods enable risk-informed decision-making. AI and ML enhance this process by providing predictive capabilities and adaptive analytics, allowing resilience metrics to be updated in real time.

Typical Hazards Affecting Transportation Infrastructure

Quantifying resilience is only meaningful when the potential threats to transportation systems are clearly understood. Hazards - both natural and anthropogenic - are the primary stressors that test a system's robustness and resilience. Identifying these hazards, along with their region-specific characteristics, is essential for developing AI/ML-based models that can anticipate risks, guide disaster response, and inform adaptive infrastructure planning. Seismic events such as earthquakes can cause severe structural damage through ground shaking, liquefaction, and fault ruptures, often resulting in bridge collapse, pavement cracking, and traffic network disruptions [22]. Flooding, whether from river overflow, storm surges, or urban flash floods, can erode bridge foundations, submerge roadways, destabilize embankments, and degrade pavement surfaces. AI-powered flood forecasting models now integrate hydrological, meteorological, and sensor data to provide early warnings and proactive management strategies [23]. Landslides, frequently triggered by intense rainfall or seismic activity in hilly or mountainous terrain, can block transport corridors and damage retaining structures. Machine learning models that process topographic, soil, and weather data have advanced landslide susceptibility mapping [24]. Cyclones and storms exert damaging forces through high winds, heavy rainfall, and coastal erosion, affecting coastal roads, bridges, and port infrastructure. In colder climates, snowstorms and avalanches obstruct transportation routes, increase accident risk, and accelerate infrastructure wear; AI-based road condition prediction models now help optimize snow clearance operations. Wildfires, though less direct in structural impact, can force extended road closures, reduce visibility, and damage roadside assets. The integration of multi-hazard datasets-including satellite imagery, meteorological records, Light Detection and Ranging (LiDAR) surveys, and geospatial maps-into AI/ML workflows enables more accurate and region-specific resilience assessments. Table *2* summarizes commonly used AI/ML algorithms for hazard-specific resilience applications, highlighting their advantages and limitations in real-world deployment.

Hazard	Impacts on infrastructure	AI/ML applications
Earthquakes	Structural collapse, bridge failure	SHM, fragility modeling, damage classification
Floods	Roadway submersion, embankment erosion	Real-time flood mapping, traffic rerouting
Landslides	Road blockage, slope failure	Predictive modeling, early warning systems
Cyclones	Wind-induced failures, debris on roads	UAV-based assessment, emergency logistics
Tsunamis	Coastal road destruction, bridge scour	Risk zoning, post-event UAV mapping
Wildfires	Pavement damage, reduced visibility	Satellite-based fire spread prediction

TABLE 2: Common hazards affecting transportation infrastructure

AI, Artificial Intelligence; ML, Machine Learning; SHM, Structural Health Monitoring; UAV, Unmanned Aerial Vehicle

Overview of AI and ML techniques

Effectively addressing the diverse hazards impacting transportation infrastructure requires analytical tools capable of processing large, heterogeneous datasets and identifying complex, non-linear relationships. AI and ML provide such capabilities, offering predictive and adaptive solutions that complement and, in some cases, surpass traditional engineering models. While conventional hazard analysis often relies on predefined equations and static thresholds, AI/ML methods can dynamically learn patterns from historical and real-time data, enabling more accurate risk forecasting, damage detection, and recovery planning. AI and ML techniques can be broadly classified into supervised learning, unsupervised learning, and deep learning, each suited to specific resilience-related applications. Supervised learning relies on labeled datasets to establish explicit mappings between inputs and outputs, making it ideal for classification (e.g., damage severity) and regression (e.g., recovery time estimation) tasks [25]. Popular algorithms in this category include Support Vector Machines (SVMs), Random Forests (RFs), and Gradient Boosting Machines, chosen for their predictive accuracy and adaptability to structured engineering data. In contrast, unsupervised learning is designed to uncover hidden patterns within unlabeled datasets. Techniques such as Principal Component Analysis, k-means clustering, and Self-Organizing Maps have proven valuable for anomaly detection, clustering assets based on vulnerability, and identifying latent risk factors without prior labeling [26]. Deep learning, a subset of machine learning, leverages multi-layered neural networks to automatically extract high-level features from raw inputs, including images, videos, and sequential sensor readings. CNNs excel in spatial feature extraction for image-based damage detection, while RNNs and LSTM models are optimized for temporal data, enabling accurate trend prediction in hazards such as floods or landslides [27]. Selecting an appropriate AI/ML approach depends on multiple factors, including data availability, task complexity, and computational resources. Table *3* provides a comparative overview of hazards, their impacts on transportation infrastructure, and the AI/ML techniques most frequently applied to their mitigation. This structured mapping not only highlights the strengths of different algorithms but also underscores the importance of aligning computational tools with the specific characteristics of each hazard scenario.

Algorithm	Type	Applications in resilience/Disaster response	Advantages	Limitations
SVM	Supervised	Classification of damage zones, risk levels	High accuracy, effective in small datasets	Limited interpretability
Random Forest	Supervised	Infrastructure failure prediction, vulnerability mapping	Robust to overfitting, interpretable	Requires feature engineering
CNN	Deep Learning	Image/video-based damage detection	Excellent spatial feature learning	Data-hungry, black-box nature
RNN/LSTM	Deep Learning	Time-series analysis for traffic, sensor data, recovery	Captures temporal dependencies	Prone to vanishing gradients
XGBoost	Ensemble Learning	Risk scoring, damage classification, recovery prediction	High performance, handles missing data	Can be complex to tune
K-Means	Unsupervised	Clustering affected regions, resource allocation	Simple, fast clustering	Sensitive to initialization

TABLE 3: Summary of AI/ML algorithms in resilience and disaster applications

AI, Artificial Intelligence; CNN, Convolutional Neural Network; LSTM, Long Short-Term Memory; ML, Machine Learning; RNN, Recurrent Neural Network; SVM, Support Vector Machine; XGBoost, Extreme Gradient Boosting

Key Algorithms Used in Transportation Resilience Applications

Building on the learning paradigms outlined in the previous section, specific AI/ML algorithms have emerged as particularly effective in transportation resilience research. Their selection depends on the nature of the task, the type of data involved, and the required balance between accuracy, interpretability, and computational efficiency. SVM is widely used for binary classification problems such as crack detection or pavement distress categorization. Its robustness in handling high-dimensional datasets and small sample sizes makes it especially suitable for scenarios where labeled data are limited [28]. RF, an ensemble method based on decision trees, is valued for its predictive accuracy and resilience to overfitting. RF has been successfully applied to landslide susceptibility mapping, flood risk analysis, and post-disaster infrastructure classification. A key component of RF is the Gini Impurity metric, which measures the quality of splits during tree construction:

$$G(t) = 1 - \sum_{i=1}^{K} p_i^2 \qquad (2)$$

This capability to evaluate variable importance helps decision-makers understand which factors most influence infrastructure vulnerability [29].

For visual damage detection, CNNs have become the dominant deep learning architecture, excelling at spatial feature extraction from UAV or satellite imagery [30]. CNNs can identify fine-grained structural anomalies, such as pavement cracks or bridge joint displacements, with high precision [31]. In contrast, when time-series data are critical - such as monitoring bridge vibrations, slope stability, or water levels - RNNs and LSTM models provide superior performance by capturing temporal dependencies:

$$h_t = \sigma(W_{xh}\, x_t + W_{hh}\, h_{t-1} + b_h) \qquad (3)$$

where,

x_t: Input at time

h_t: Hidden state

W_{xh}, W_{hh}: Weight matrices

b_h: Bias

σ: Activation function (e.g., tanh, ReLU)

Beyond these, XGBoost offers high computational efficiency and predictive accuracy for structured tabular data, making it well-suited for tasks such as damage severity estimation and hazard classification [32]. The choice of algorithm ultimately depends on aligning computational strengths with the nature of the resilience challenge. For example, image-rich datasets favor CNNs, while time-series sensor data may require LSTMs or hybrid models that integrate both spatial and temporal learning [33]. Figure *4* illustrate how these algorithms fit within broader AI/ML-based resilience assessment frameworks.

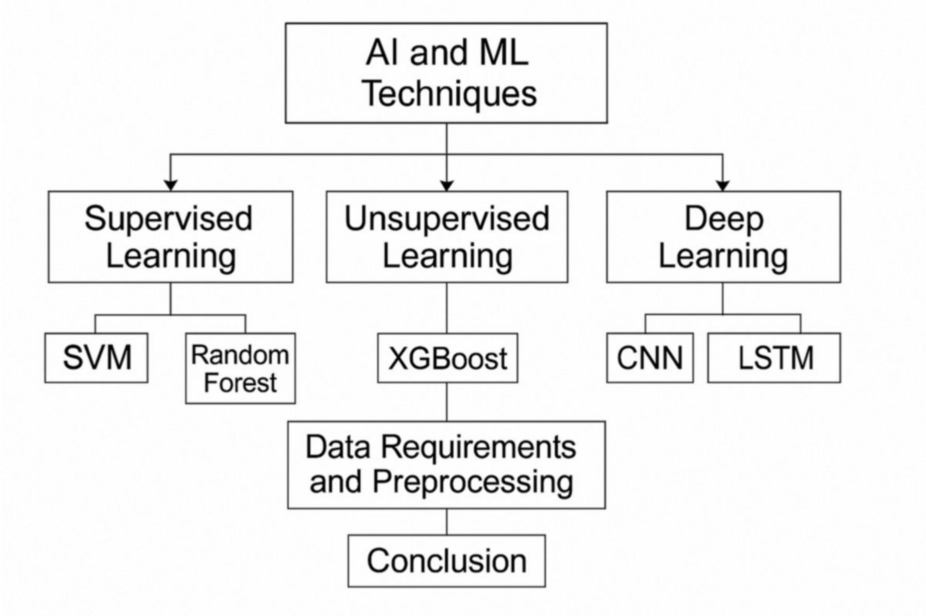

FIGURE 4: Classification of AI/ML techniques applied in transportation engineering

AI, Artificial Intelligence; CNN, Convolutional Neural Network; LSTM, Long Short-Term Memory; ML, Machine Learning; SVM, Support Vector Machine

Data Requirements and Preprocessing

The effectiveness of any AI/ML algorithm described in the previous section is fundamentally dependent on the quality, volume, and organization of its input data. In transportation resilience applications, data sources are highly diverse, ranging from structured datasets - such as sensor measurements, traffic flow logs, meteorological records, and historical hazard inventories - to unstructured inputs like UAV imagery, satellite photographs, LiDAR point clouds, and even social media reports. Spatiotemporal datasets, including GIS layers, flood inundation maps, and continuous monitoring from accelerometers or strain gauges, are particularly valuable for hazard forecasting and post-event assessment. Before these datasets can be used effectively, robust data preprocessing is required to ensure accuracy and model readiness. This process typically involves 1) data cleaning to remove noise, correct errors, and handle missing values; 2) outlier detection to prevent anomalous entries from skewing model performance; 3) feature normalization or scaling to improve convergence in optimization algorithms; and 4) feature selection/extraction using statistical tests or dimensionality reduction methods such as Principal Component Analysis to retain the most relevant information. For supervised learning tasks, high-quality labeling is critical. Damage classification, for example, may require manual annotation of image datasets or semi-automated methods to expedite labeling. In image-based applications, data augmentation - including rotation, flipping, and scaling - can enhance generalization and reduce overfitting.

AI/ML in Resilience Assessment

Once high-quality, well-preprocessed datasets are available, AI and ML techniques can be deployed to assess the resilience of transportation infrastructure under both routine operational conditions and extreme hazard scenarios. Traditional approaches - such as periodic inspections, deterministic modeling, and manual interpretation of monitoring data - often face limitations in scalability, timeliness, and adaptability. In contrast, AI/ML systems offer real-time analytics, predictive modeling, and adaptive decision-making capabilities, enabling continuous performance monitoring and proactive risk management as shown in Figure *5*. By integrating sensor networks, geospatial datasets, and historical hazard records, AI/ML-driven resilience assessment frameworks can address three core objectives: monitoring current infrastructure health, forecasting potential failures, and mapping risk/vulnerability.

Each objective leverages different classes of algorithms and data types, ensuring that the analytical approach matches the resilience need. The following subsections detail key AI/ML applications across these domains, starting with SHM for real-time detection of performance degradation, moving into predictive modeling for forecasting failure and deterioration, and concluding with risk and vulnerability mapping for spatial hazard assessment. This structured progression reflects how AI/ML tools can be applied across the lifecycle of hazard management-from prevention and preparedness to response and recovery.

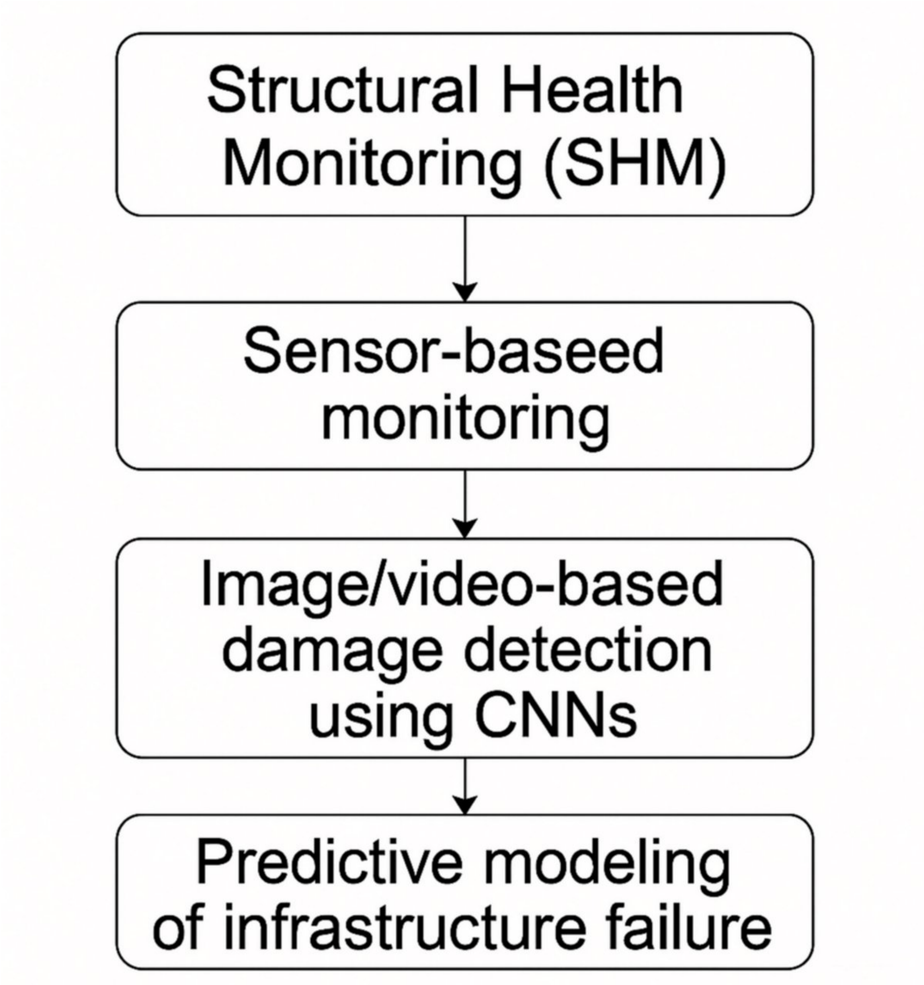

FIGURE 5: AI/ML-based resilience assessment framework

AI, Artificial Intelligence; CNNs, Convolutional Neural Networks; ML, Machine Learning

Structural Health Monitoring

SHM forms the foundation of AI/ML-enabled resilience assessment, providing continuous or periodic measurements of critical performance indicators such as strain, displacement, acceleration, temperature, and vibration frequency. These data streams - collected through embedded or surface-mounted sensors - serve as early warning signals for potential performance degradation or structural failure. AI and ML enhance SHM by enabling automated anomaly detection and damage classification, reducing the reliance on manual inspection. SVMs and RFs have been widely applied to classify structural states, particularly for bridges and pavements, using inputs such as strain gauge readings or acoustic emission data [34]. For sequential sensor data, Recurrent Neural Networks (RNNs) and LSTM architectures are especially effective in identifying both gradual deterioration trends and sudden deviations from normal behavior [35]. These temporal models allow engineers to differentiate between routine operational variations and early indicators of failure. Recent advances in edge computing have made it possible to deploy lightweight ML models directly on sensor nodes. This distributed approach enables local anomaly detection without the need for constant cloud connectivity, accelerating decision-making and improving system autonomy during emergencies [36].

Image/video-based damage detection using CNNs: While sensor-based monitoring provides valuable quantitative data on internal structural performance, visual inspection remains indispensable for detecting surface-level defects such as cracks, spalling, corrosion, and joint displacement. Advances in imaging technology - ranging from UAVs and ground-based high-resolution cameras to satellite imagery - have made large-scale, repeatable visual assessments increasingly feasible. However, manual interpretation of these images is time-consuming, subjective, and prone to inconsistency. CNNs have transformed visual damage detection by automating feature extraction and classification directly from raw imagery. In transportation resilience applications, CNNs have been successfully deployed to identify and quantify pavement cracking, bridge joint misalignments, and post-earthquake structural deformations [37]. Enhanced techniques such as transfer learning allow pre-trained models to adapt to new datasets with minimal labeled samples, while data augmentation improves model generalization under diverse environmental conditions. Beyond simple classification, advanced CNN architectures incorporating semantic segmentation (e.g., U-Net, DeepLab) enable pixel-level localization of defects, providing precise measurements of damage extent and severity. This fine-grained output supports targeted maintenance, faster recovery planning, and integration into broader resilience assessment frameworks [38].

Predictive Modeling of Infrastructure Failure

While visual and sensor-based assessments provide a snapshot of current structural health, predictive modeling extends resilience planning by estimating how infrastructure will perform in the future - both under routine operational conditions and during extreme hazard events. These models enable proactive maintenance, risk mitigation, and optimized resource allocation before failures occur. Traditional physics-based prediction approaches require detailed structural parameters and predefined relationships between loads, materials, and deterioration mechanisms. In contrast, AI/ML models can infer complex, non-linear patterns directly from historical performance records, operational data, and environmental variables, even when complete structural specifications are unavailable. Algorithms such as Gradient Boosting Machines, XGBoost, and Artificial Neural Networks have demonstrated high predictive accuracy in estimating indicators like Pavement Condition Index, bridge deterioration rates, and the probability of scour formation during floods [39]. These models handle multidimensional datasets effectively, incorporating variables such as traffic load, weather patterns, material properties, and hazard exposure. By integrating historical disaster data, predictive models can also estimate the likelihood, extent, and timing of damage under hazard-specific scenarios (e.g., landslides, floods, earthquakes). Ensemble approaches that combine environmental, structural, and operational datasets tend to produce more generalizable predictions, accommodating a wide range of asset types and geographic contexts [40].

$$\min_{\mathbf{w}, b, \boldsymbol{\xi}} \quad \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i \qquad (4)$$

$$\text{subject to:} \quad y_i\big(\mathbf{w}\cdot\mathbf{x}_i + b\big) \geq 1 - \xi_i, \quad i = 1, 2, \ldots, n$$

$$\xi_i \geq 0, \quad i = 1, 2, \ldots, n$$

where,

w: Weight vector

b: Bias

C: Regularization parameter

ξ: Slack variable

y_i: True label

x_i: Feature vector

Risk and Vulnerability Mapping

Predictive modeling identifies where and when infrastructure may fail, but translating these insights into actionable resilience strategies requires a spatial perspective. Risk and vulnerability mapping provides this by integrating predictive outputs with geospatial data to visualize hazard exposure, asset susceptibility, and potential impacts. These maps support decision-makers in prioritizing interventions, allocating resources, and planning emergency responses with greater precision. AI/ML approaches to risk mapping typically combine multiple data layers, including topography, soil classification, land use, hazard frequency, infrastructure condition, and traffic density. Supervised learning algorithms such as RF, Naïve Bayes, and Logistic Regression are frequently applied when labeled hazard impact data are available, enabling the classification of regions into distinct risk categories [41]. In cases where labeled data are scarce, unsupervised learning methods like Self-Organizing Maps and k-means clustering are used to detect spatial patterns and group assets with similar vulnerability profiles. Advances in open-source platforms such as QGIS and Google Earth Engine have made it easier to integrate AI/ML models into large-scale, automated mapping workflows. These systems can ingest continuous data streams from IoT sensors, UAV surveys, and satellite monitoring to produce near-real-time risk maps [42]. Furthermore, the adoption of XAI techniques - such as SHAP values - enables planners to understand which variables most influence model outputs, increasing transparency and stakeholder trust. A simplified formulation often used in vulnerability mapping is given in below Equation 5:

$$Risk \doteq H \times V \times E \tag{5}$$

where H represents hazard intensity, V denotes vulnerability, and E reflects exposure in terms of asset value or population.

While risk and vulnerability mapping strengthen preparedness and mitigation strategies, the disaster response phase requires rapid, data-driven decision-making to minimize disruption and safeguard human life. In such high-stakes situations, AI and ML technologies play a critical role by integrating real-time data streams, predicting evolving hazard conditions, and optimizing resource deployment under dynamically changing circumstances [43]. These capabilities build on the predictive and geospatial assessment frameworks discussed earlier, but their application in disaster response is distinguished by stringent time constraints and the need for operational adaptability. One of the most crucial tasks following a disaster is the rapid assessment of damage to transportation infrastructure [44]. High-resolution imagery acquired from satellites and UAVs can be processed using CNNs and advanced semantic segmentation models, such as U-Net, DeepLab, and Mask R-CNN, to automatically detect damaged assets across large geographic areas [45]. By comparing pre- and post-event imagery, these systems enable precise change detection, identifying structural deformations, collapsed sections, and debris-blocked roads. When coupled with auxiliary geospatial datasets - such as OpenStreetMap layers or LiDAR-derived elevation models - AI-driven damage detection workflows can produce accessibility maps within hours, greatly enhancing the coordination of rescue and relief operations. Beyond damage identification, AI/ML also optimizes emergency mobility and evacuation planning [46]. Graph-based deep learning and reinforcement learning techniques are increasingly used to model transportation networks as dynamic graphs, where edge weights adapt in real time to reflect changes in travel time, hazard severity, and route accessibility. These systems can continuously recalculate optimal evacuation paths as disaster conditions evolve, while multi-objective optimization approaches help balance competing priorities such as minimizing evacuation time and ensuring safety for vulnerable populations. Effective evacuation planning further requires a nuanced understanding of human behavior under stress. AI-enhanced agent-based modeling can simulate individual and group decision-making by incorporating demographic profiles, historical evacuation patterns, and real-time behavioral data, including sentiment analysis from social media [47]. Complementary to this, Deep Reinforcement Learning enables adaptive evacuation strategies that automatically adjust traffic flows, shelter assignments, and resource allocation in response to rapidly shifting hazard scenarios, offering significant advantages in multi-hazard events where conditions can change without warning. In the post-disaster recovery phase, AI-enabled Decision Support Systems integrate multi-source datasets - including damage assessments, economic loss estimates, and stakeholder-defined recovery priorities - to guide strategic repair scheduling and optimal resource allocation [48]. Machine learning models such as RF, Bayesian Networks, and ensemble learning frameworks can forecast recovery timelines for different asset types, ranging from individual road sections to complex bridge networks. Modern Decision Support System platforms often combine GIS-enabled dashboards for spatial visualization with collaborative cloud-based planning tools for multi-agency coordination. NLP modules further enhance these systems by rapidly extracting actionable insights from post-event reports, ensuring that recovery efforts are transparent, evidence-based, and responsive to community needs.

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i) \tag{6}$$

y_i: True label

y_i: Predicted probability of class

n: Number of classes

Results of the systematic review

The systematically reviewed literature has been consolidated in Table *4*, which maps widely adopted AI/ML algorithms to their respective application areas in transportation resilience. The reported performance metrics are included to provide an evidence-based comparison of model effectiveness.

CNNs dominate image-based applications such as UAV and satellite-driven post-disaster damage detection, consistently achieving accuracies between 85% and 95%, and in some cases enabling pixel-level defect localization through semantic segmentation [49,50]. LSTM networks demonstrate superior performance in temporal forecasting tasks - such as traffic flow, flood levels, and recovery trajectories - reporting RMSE values ranging from 0.12 to 0.25 across multiple case studies [51,52]. RF are widely applied in landslide susceptibility mapping, flood vulnerability assessment, and infrastructure classification, yielding AUC values of 0.82-0.90 and offering interpretability through feature importance analysis [53]. Extreme Gradient Boosting (XGBoost) provides high computational efficiency and strong predictive accuracy for structured datasets, achieving R^2 scores up to 0.92 in recovery prediction and damage severity classification [54]. SVMs, although less dominant in recent years, continue to be used for binary classification tasks such as crack detection and damage state categorization, demonstrating high precision on small datasets. Together, these results illustrate that algorithm choice is closely tied to the nature of the resilience task: CNNs for spatial feature extraction, LSTMs for temporal dynamics, ensemble methods (RF, XGBoost) for risk mapping and recovery forecasting, and SVMs for targeted classification. Importantly, these algorithmic outcomes directly support resilience metrics such as functionality loss ratio, time to recovery, and rate of recovery, thereby bridging technical model performance with practical resilience assessment.

AI/ML algorithm	Application area	Reported metrics	Typical values	References
CNN	Damage detection (UAV/satellite images)	Accuracy, F1-score	85–95% accuracy	[49,50]
LSTM	Flood/traffic prediction	RMSE, MAE	RMSE = 0.12–0.25	[51,52]
RF	Landslide susceptibility, vulnerability mapping	AUC, Precision-Recall	AUC = 0.82–0.90	[53]
XGBoost	Damage classification, recovery forecasting	R^2, Accuracy	R^2 = 0.78–0.92	[54]

TABLE 4: Summary of AI/ML algorithms applied in transportation resilience studies

AI, Artificial Intelligence; AUC, Area Under the Curve; CNN, Convolutional Neural Network; LSTM, Long Short-Term Memory; MAE, Mean Absolute Error; ML, Machine Learning; RF, Random Forest; RMSE, Root Mean Squared Error; UAV, Unmanned Aerial Vehicle; XGBoost, Extreme Gradient Boosting

Challenges and limitations

While AI and ML hold significant promise in enhancing the resilience and responsiveness of transportation networks, several critical challenges - spanning technical, operational, and ethical domains - must be addressed to ensure their effective, reliable, and equitable deployment in real-world disaster scenarios. The performance of AI/ML models is heavily dependent on the availability of diverse, high-quality datasets. However, data scarcity remains a major obstacle, particularly in low-resource regions and for rare but high-impact events like tsunamis or earthquakes. SHM systems often suffer from incomplete or noisy data due to sensor malfunctions, connectivity issues, or environmental disruptions. Furthermore, the limited availability of labeled datasets hinders supervised learning, especially for damage detection, failure prediction, and hazard classification. The unpredictability of disasters means that existing data may not capture the full range of possible risk scenarios, infrastructure types, or socio-economic conditions. To address these gaps, researchers increasingly employ techniques such as transfer learning, data augmentation, and synthetic data generation. However, these methods may compromise generalizability and introduce overfitting risks. The lack of standardized data formats and open-access repositories further impedes collaborative model development and replication. Many high-performing AI models - especially deep learning architectures like CNNs, LSTMs, and ensemble methods such as XGBoost - lack interpretability, which limits their use in safety-critical domains like disaster response and infrastructure risk assessment. Model opacity undermines stakeholder trust and complicates accountability, especially during high-stakes decision-making. XAI techniques, such as SHapley Additive Explanations, Local Interpretable Model-Agnostic Explanations, and counterfactual analysis, have emerged to improve model transparency. However, their adoption in civil infrastructure applications remains limited. Post-disaster evaluations and real-time emergency planning require clear rationale behind model outputs to ensure fairness, detect model flaws, and support informed decisions under uncertainty. Incorporating AI/ML into aging transportation infrastructure presents substantial technical and financial barriers. Many existing systems lack the hardware foundation - such as distributed sensors, IoT connectivity, or edge computing capabilities - required for real-time AI-driven monitoring and decision-making. Retrofitting legacy assets with smart sensors or UAV-compatible nodes can be costly, particularly in low-income regions. Interfacing AI modules with existing platforms like GIS, traffic management systems, or emergency databases also poses compatibility challenges. To overcome these issues, low-cost solutions such as crowdsourced data, GPS traces, smartphone sensors, and social media inputs are being explored to supplement traditional sensing infrastructure. AI applications in disaster management raise important ethical and regulatory concerns. Bias in training data can lead to inequitable outcomes, such as disproportionate false alarms or resource misallocation in vulnerable communities. Privacy concerns also arise when location data, social media activity, or real-time monitoring is used for situational awareness. Regulatory frameworks such as the General Data Protection Regulation must be adhered to during AI system development. Additionally, the absence of comprehensive legal standards for AI-based resilience planning creates ambiguity around liability and accountability in cases of system failure. Addressing these challenges requires institutional reform, cross-sector collaboration, inclusive data practices, and integration of AI ethics into engineering education.

Conclusions

The systematic review revealed that CNNs consistently achieve 85-95% accuracy in post-disaster damage detection, while LSTM networks demonstrate strong predictive performance in temporal recovery and hazard forecasting with RMSE values between 0.12 and 0.25. Ensemble methods such as Random Forests and XGBoost report high accuracy and interpretability in vulnerability mapping and recovery forecasting (area under the curve up to 0.90; R^2 up to 0.92). These findings confirm that algorithm selection is strongly application-dependent, with CNNs most effective for spatial feature extraction, LSTMs for temporal dynamics, and ensemble methods for structured risk data. Importantly, the performance of these algorithms directly supports resilience metrics such as functionality loss ratio, time to recovery, and rate of recovery, thereby strengthening the link between AI/ML techniques and resilience measurement. This evidence-based synthesis underscores the growing potential of AI/ML to transform transportation resilience assessment, while highlighting the need for standardized metrics, high-quality datasets, and integrated frameworks to ensure robust and scalable applications in future research. In light of accelerating climate change and rapid urbanization, there is an urgent need for transportation systems that can withstand and adapt to the increasing frequency and severity of natural disasters. According to the World Bank, global losses from such events amount to approximately $300 billion annually, with over 60% attributed to transportation and other critical infrastructure. AI and ML have emerged as transformative tools in this domain, enabling proactive disaster forecasting, real-time monitoring, rapid response, and data-driven resilience planning. This study highlights the growing shift toward adaptive, data-centric approaches in resilience engineering, contrasting the reactive nature of robust systems with the self-healing capabilities of resilient ones. AI techniques such as CNNs for damage detection, RNNs for traffic flow prediction, and XGBoost for hazard classification demonstrate significant potential in assessing and enhancing infrastructure resilience. Empirical evidence shows that ML models can outperform traditional statistical methods by 25-40% in infrastructure failure prediction. Furthermore, the integration of deep learning with UAV and satellite imagery enables damage detection with up to 90% accuracy, substantially improving situational awareness for emergency responders. AI-driven traffic optimization algorithms have also reduced evacuation and logistics delays by up to 30%. Despite these advances, several challenges persist - particularly regarding data availability and quality, model interpretability, and integration with legacy systems. To realize the full potential of AI/ML in real-world disaster resilience applications, clear implementation guidelines, standardized data formats, and XAI models are essential. Moreover, stronger interdisciplinary collaboration among policymakers, emergency managers, transportation engineers, and data scientists is critical to ensure these technologies are applied responsibly, equitably, and effectively.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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