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Research Article

Post-Earthquake Bridge Damage Assessment Using Machine Learning (ML) and Artificial Intelligence (AI): A Systematic Literature Review

Ainil Mardhiyah[1]
[1] Study Program Road and Bridge Design and Planning Engineering, Politeknik Negeri Medan, Medan, Indonesia

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Abstract

Bridges are critical infrastructure highly vulnerable to earthquake-induced damage, posing serious risks to transportation continuity and public safety. Traditional methods, such as visual inspection, remain in use; however, they are limited in efficiency, scalability, and accuracy. This highlights the urgent need for more advanced approaches. Machine Learning (ML) and Artificial Intelligence (AI) have emerged as promising alternatives for assessing post-earthquake bridge damage. However, existing studies often lack a systematic synthesis of methodological trends, rely on limited or unstandardized datasets, and insufficiently address real-world implementation challenges. This study conducts a Systematic Literature Review (SLR) to critically examine the application of ML/AI in post-earthquake bridge damage assessment, focusing on methodological trends, commonly used datasets, and implementation challenges. Relevant journal articles published between 2019 and 2025 were selected through structured keyword strategies and filtered based on publication type, relevance, and journal quality (Q1-Q4). The findings indicate that Random Forest (RF) and Convolutional Neural Networks (CNN) are among the most widely applied ML methods, owing to their strengths in classification and visual data analysis. Frequently used datasets include bridge damage records from California, shake table test time-series data, and sensor-based monitoring data. Persistent challenges include data heterogeneity, limited availability of real-time datasets, and the interpretability of ML models. The novelty of this study lies in providing a consolidated synthesis of current research, bridging methodological gaps, and highlighting implementation challenges. Future research should focus on developing real-time datasets, establishing robust model validation frameworks, and enhancing the interpretability of ML techniques to strengthen disaster risk mitigation and improve bridge resilience.

Keywords: *Machine Learning, Artificial Intelligence, Bridge, Earthquake, Post-Earthquake*

1. INTRODUCTION

As vital infrastructure, bridges play an important role in connecting roads, overcoming physical barriers, and ensuring the smooth flow of transportation of goods and the mobility of people [1]. Bridge failure or loss of function can cause major disruptions to transportation networks and the economy, which have far-reaching impacts on various sectors. In addition, bridges also serve as key pathways for evacuation and logistics distribution, especially in emergency situations, such as natural disasters or conflicts, further emphasizing their critical role and reliability [2].

Bridges are vulnerable to multiple hazards, particularly earthquakes, which can severely affect their stability and structural integrity. One of the most critical damage is the collision between bridge segments at expansion joints, which may cause deck dislodgement [3]. In addition, abutments failures and large relative displacements between decks and piers, often due to vertical seismic acceleration, can create unusual stress conditions [4]. To improve resilience against such threats, technologies such as Bridge Management Systems (BMS) and AI-based Structural Health Monitoring (SHM) have been introduced to enhance predictive maintenance and decision-making [5].

Traditional methods for evaluating bridge damage, such as visual inspection and manual analysis, have several limitations. These include being labor-intensive, time-consuming, and often incapable of detecting hidden or internal damage. Consequently, their accuracy and scalability remain limited [6], [7].

*Corresponding author: ainilmardhiyah@polmed.ac.id

In response, Machine Learning (ML) and Artificial Intelligence (AI) offer innovative approaches for rapid and reliable post-earthquake damage assessment. For instance, Support Vector Machines (SVM) and Random Forest (RF) have demonstrated high accuracy in damage classification [8], [9], while Artificial Neural Networks (ANN) are effective in modelling complex nonlinear relationships, enabling faster and more adaptive fault detection [10].

Despite these advances, three key research gaps remain: (1) the absence of a systematic synthesis of ML/AI methodologies for post-earthquake bridge assessment, (2) reliance on limited and non-standardized datasets, and (3) insufficient exploration of practical implementation challenges in real-world scenarios. To address these gaps, this study conducts a Systematic Literature Review (SLR) to identify ML/AI methods applied in post-earthquake bridge damage assessment, evaluate the datasets commonly used, and analyze the main challenges associated with ML/AI integration. The novelty of this study lies in its comprehensive synthesis of methodologies, datasets, and challenges, providing insights that can guide the development of more robust, efficient, and scalable approaches for improving bridge resilience against seismic events.

2. METHODOLOGY

This study employs a Systematic Literature Review (SLR) following the PRISMA protocol, aiming to identify methodological trends, datasets, and key challenges in applying Machine Learning (ML) and Artificial Intelligence (AI) for post-earthquake bridge damage assessment. The review was conducted in four systematic stages: (1) Identification, (2) Screening, (3) Eligibility, and (4) Inclusion. In the identification stage, literature was collected using the Publish or Perish application and Scopus database (2019-2025). The search strategy combined three sets of keywords: (1) main criteria (focused on bridge damage detection using ML/AI), (2) supporting criteria (datasets and methods), and (3) additional criteria (overview and future perspectives). Each criterion used at least five structured keywords.

Duplicates were removed, and non-journal publications (conference papers, books, editorials) were excluded in the screening stage. Abstracts were then examined to ensure relevance, specifically whether the study addressed bridge damage, applied ML/AI, and aligned with the research objectives. In the eligibility stage, only full-text journal articles were considered. Review and bibliometric studies were excluded to ensure focus on empirical, experimental, or simulation-based research. Journal quality was also considered: Q1 and Q2 were prioritized, while Q3 and Q4 were included only if they provided significant contributions.

And in the inclusion stage, articles passing all criteria were analyzed in detail. Information extracted included (i) ML/AI methods applied (e.g., Random Forest, Convolutional Neural Networks, Artificial Neural Networks), (ii) datasets used (source, type, and application), and (iii) implementation challenges and solutions proposed. The flow of article identification, screening, eligibility testing, and inclusion is presented in Figure 1, the PRISMA flow diagram of the study selection process.

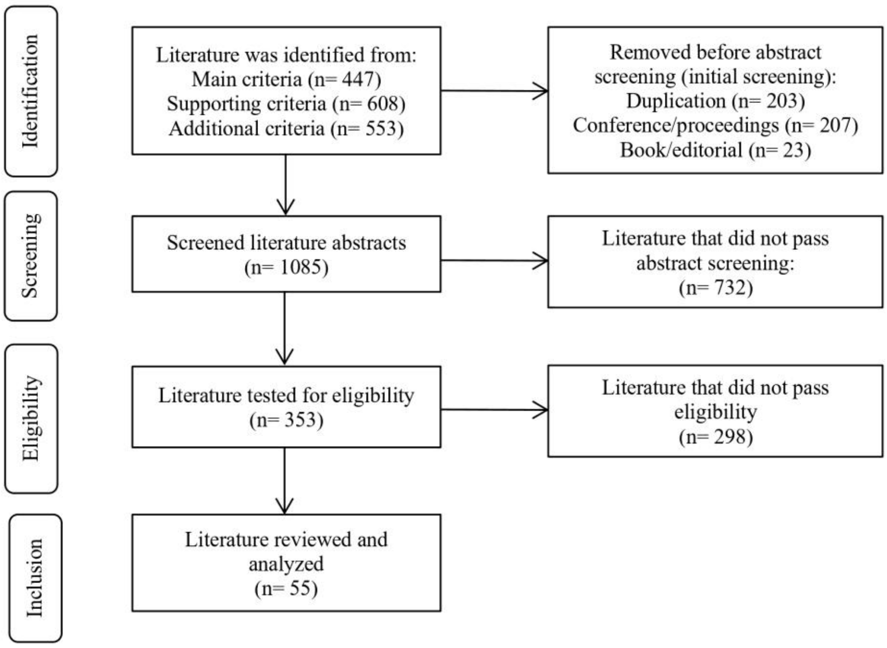

Figure 1. PRISMA flow diagram

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In addition to the PRIMA-based selection process, the review also considered the distribution of studies across different publication years and research domains. This allows not only a methodological synthesis but also the identification of emerging patterns in how ML/AI techniques are being adapted to earthquake engineering problems. Such contextual mapping strengthens the robustness of the review, ensuring that the selected literature represents both methodological rigor and disciplinary relevance.

Finally, the selected articles were synthesized to address three research questions: (1) Which ML/AI methods are most applied in post-earthquake bridge damage assessment? (2) What datasets are available and commonly used? (3) What are the main challenges and solutions in implementing ML/AI in this field? This structured approach ensures a comprehensive and transparent review while directly addressing the identified research gaps.

3. RESULTS AND DISCUSSION

This study began with the identification of literature obtained using the Publish or Perish application and Scopus database. Tables 1 and 2 show that the literature was searched using three categories of criteria: main, supporting, and additional. Before screening, duplicates and non-journal publications were removed, leaving a refined set of 55 journal articles. Publication trends indicate a steady increase in studies from 2019 to 2025, with a particularly sharp growth in 2022 and 2024, see Figure 2. This reflects the growing academic and practical interest in integrating ML/AI with earthquake engineering.

Table 1. Criteria for literature identification

Criteria	Focus	Keyword
Main	Specific topic	1. Bridge damage detection using machine learning 2. Post-earthquake structural assessment with AI 3. Structural damage identification in bridge after earthquake 4. Earthquake-induced damage detection in bridges 5. Machine learning for bridge
Supporters	Dataset and method	1. Earthquake datasets for structural damage detection 2. Sensor-based structural health monitoring for bridges 3. Image processing for bridge damage detection 4. Finite element situation for bridge damage assessment 5. Remote sensing in post-earthquake damage evaluation
Additional	Overview and other perspectives	1. Challenges in applying AI for structural engineering 2. Machine learning applications in earthquake-engineering 3. AI in civil engineering 4. Bridge damage detection 5. Future trends in post-earthquake assessment technologies

Table 2. Number of literature found based on keywords

Keywords	Scopus
Bridge damage detection using machine learning	200
Post-earthquake structural assessment with AI	9
Structural damage identification in bridge after earthquake	18
Earthquake-induced damage detection in bridges	45
Machine learning for bridge damage assessment	175
Earthquake datasets for structural damage detection	113
Sensor-based structural health monitoring for bridges	200
Image processing for bridge damage detection	143
Finite element situation for bridge damage assessment	135
Remote sensing in post-earthquake damage evaluation	17
Challenges in applying AI for structural engineering	3
Machine learning applications in earthquake-engineering	149
AI in civil engineering	200
Bridge damage detection	200
Future trends in post-earthquake assessment technologies	1

The synthesis revealed that eight ML/AI methods are most frequently applied: Random Forest (RF), Artificial Neural Networks (ANN), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Extreme Gradient Boosting (XGBoost), Gaussian Process Regression (GPR), K-Nearest Neighbors (KNN), and Decision Trees (DT), that can be seen in Table 3. Among these, RF and ANN

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dominate due to their scalability and robustness. RF is widely used for rapid classification with high computational efficiency, while ANN is favored for probabilistic prediction of damage with strong accuracy. CNNs, although fewer in number, have been increasingly adopted in recent years because of their capability in handling visual and time-series data.

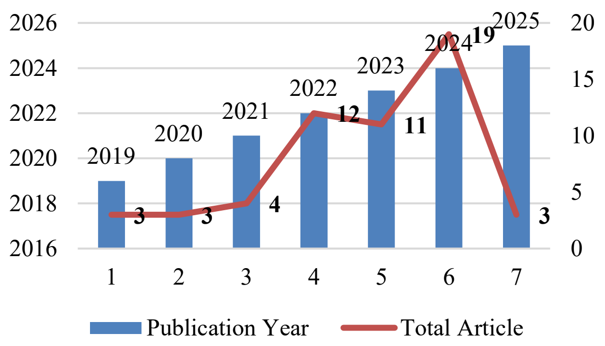

Figure 2. Trends in the publication of scientific articles (journal articles) related to the application of ML/AI in post-earthquake bridge damage assessment from 2019 to the first month of 2025

Table 4 summarizes the most common datasets: California bridge damage records, shake table experimental time series, sensor-based monitoring data, Probabilistic Seismic Demand Models (PSDMs), and experimental pier column data. California datasets are widely adopted because of their comprehensive coverage and availability, while shake table data provide controlled experimental insights. However, the scarcity of real-time, large-scale datasets remains a critical limitation.

Table 3. Most frequently used Machine Learning (ML) and Artificial Intelligence (AI) methods

Method	Author	Total Article
Random Forest (RF)	[8], [11], [12], [13], [14], [15], [16]	7
Artificial Neural Networks (ANN)	[11], [12], [14], [16], [17], [18], [19]	7
Support Vector Machine (SVM)	[9], [11], [13], [15], [20], [21]	6
Convolutional Neural Networks (CNN)	[16], [22], [23], [24], [25], [26]	6
Extreme Gradient Boosting (XGBoosting)	[14], [16], [27], [28]	4
Gaussian Process Regression (GPR)	[14], [29], [30], [31]	4
K-Nearest Neighbor (KNN)	[9], [11], [13], [14]	4
Decision Tree (DT)	[9], [13], [14]	3

Table 4. Most used datasets

Dataset	Author	Total Article
Data on Bridge Damage in California	[8], [11], [13], [16]	4
Time-Series Data of Shake Table Test	[22], [25], [32]	3
Data Probabilistic Seismic Demand Models (PSDMs)	[18], [19], [33]	3
Monitoring Data from Bridge Sensor	[31], [34]	2
Experiment Dataset on Pier Column	[18], [35]	2

Another important observation related to the geographical concentration of datasets. Most studies rely heavily on case studies from the United States, particularly California, while limited contributions are found from regions with high seismic activity in Asia, South America, or the Middle East. This imbalance highlights a potential source of bias, as ML/AI models trained on localized datasets may not fully capture the structural diversity and construction practices in other seismic regions. Addressing this imbalance through more globally distributed datasets would enhance the generalizability of ML/AI applications for bridge damage assessment.

In Table 5, five recurring challenges were identified: (1) complexity of heterogeneous data, (2) limited validation under real conditions, (3) lack of model interpretability, (4) scarcity of real-time datasets, and (5) dependency on difficult-to-measure parameters. The most critical barriers are model validation and real-time dataset availability, which directly hinder field implementation. Mitigation strategies such as UAV-based sensors, ensemble techniques (e.g., RF), and interpretability tools (e.g., SHAP) have been applied but require further development.

Overall, this review highlights that ML.AI methods can significantly enhance the accuracy and speed of post-earthquake bridge assessments, but no single method can be considered universally superior. For example, RF is fast and interpretable but less effective with high-dimensional visual data; CNN excels with image and time-series data but requires large datasets and high computational resources; ANN achieves strong accuracy but suffers from black-box issues; SVM performs well on smaller datasets but lacks scalability.

These findings reveal a clear research gap: the need for standardized, real-time datasets and rigorous model validation in field conditions. Addressing these gaps will enable the development of more reliable and interpretable ML/AI tools for earthquake resilience.

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Table 5. Main challenges and solutions in applying ML and AI for post-earthquake bridge damage assessment

Dataset	Author	Total Article	Solution
Large and heterogeneous data complexity	[8], [11], [13], [16]	4	Using ensemble techniques such as Random Forest to handle the complexity of large datasets.
Validation of model data in real conditions	[22], [27], [33]	3	Use of a combination of simulated and experimental datasets to approximate real-world conditions.
Difficulty understanding black-box model results	[13], [14], [36]	3	Model interpretability techniques such as SHAP and visualization of prediction results were used to explain the model results.
Lack of real-time and specific datasets	[12], [31], [34]	3	Real-time sensor-based datasets from UAVs and smartphones are used to increase data availability.
Model dependency on parameters that are difficult to determine	[15], [29], [37]	3	Bayesian Network and Gaussian Process are used to reduce dependency on manual parameters.

4. CONCLUSION

This study presents a systematic literature review (SLR) on the application of Machine Learning (ML) and Artificial Intelligence (AI) in post-earthquake bridge damage assessment. It identifies trends of key methodologies, commonly used datasets, and major challenges in the practical implementation.

The review highlights that Random Forest (RF) and Artificial Neural Networks (ANN) are the most widely applied methods due to their scalability and robustness, while Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) are also increasingly adopted for smaller datasets and image-based data, respectively. Other methods, such as Extreme Gradient Boosting (XGBoost), Gaussian Process Regression (GPR), K-Nearest Neighbors (KNN), and Decision Trees (DT), complement these approaches by offering alternative solutions for different data and computational contexts.

Regarding datasets, the most frequently used include California post-earthquake bridge damage records, shake table experimental data, sensor-based monitoring data, probabilistic seismic demand models (PSDMs), and pier column experimental datasets. While these sources provide valuable insights, the lack of standardized and real-time datasets remains a critical limitation.

Five recurring challenges were identified: heterogeneous data complexity, limited validation under field conditions, model interpretability issues, scarcity of real-time data, and reliance on hard-to-measure parameters. Among these, validation in real-world scenarios and dataset scarcity are the most pressing barriers to practical adoption. The novelty of this study lies in its comprehensive synthesis of ML/AI methodologies, datasets, and challenges, bridging fragmented findings across the literature into an integrated perspective.

Limitations of this study include (1) reliance on published journal articles only, which may overlook gray literature or recent conference work, and (2) potential language and database restrictions, as only English-language studies from Scopus were included. Future research should prioritize (1) developing standardized and real-time datasets, (2) conducting field-based validation of ML/AI models, and (3) designing interpretable models that balance accuracy with transparency for engineering decision-making.

Beyond methodological and technical contributions, this review underscores the critical role of data accessibility and interdisciplinary collaboration. Future progress in ML/AI-based earthquake damage assessment will depend not only on algorithmic advancements but also on the establishment of open-access data repositories, standardized reporting practices, and stronger collaboration between computer scientists, structural engineers, and disaster management agencies. Such collaborative frameworks will ensure that ML/AI tools are not only scientifically sound but also practically implementable in disaster preparedness and response.

In conclusion, this review provides a structured foundation for advancing reliable, interpretable, and scalable ML/AI solutions to enhance post-earthquake bridge damage assessment, thereby supporting more resilient infrastructure and disaster risk mitigation strategies.

DECLARATION OF COMPETING INTEREST

The authors declare no conflicts of interest.

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