International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 07, July 2026)

Recent Advances in Artificial Intelligence for Seismic Analysis and Damage Prediction in RCC Structures: A Comprehensive Review

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Abstract— **Earthquakes are among the most destructive natural hazards, causing significant damage to Reinforced Cement Concrete (RCC) structures and resulting in substantial economic losses and safety concerns. Accurate seismic analysis and damage prediction are essential for improving structural resilience and supporting effective disaster management. Conventional seismic assessment methods, including linear static, nonlinear pushover, and nonlinear time-history analyses, are reliable but often computationally intensive and time-consuming, limiting their use in rapid post-earthquake assessment and real-time monitoring.**

Recent advances in Artificial Intelligence (AI), particularly Machine Learning (ML), Deep Learning (DL), and Computer Vision (CV), have transformed earthquake engineering by enabling rapid seismic response prediction, automated damage detection, and intelligent Structural Health Monitoring (SHM). This review summarizes recent developments in AI-based seismic analysis and damage prediction for RCC structures by examining published research from 2015 to 2026. Major AI techniques, including Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Support Vector Machines (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Graph Neural Networks (GNN), and Physics-Informed Neural Networks (PINNs), are discussed with respect to their applications, advantages, and limitations.

The review also highlights AI applications in seismic response prediction, crack detection, structural damage classification, seismic fragility assessment, Digital Twin technology, and IoT-based structural health monitoring. Furthermore, current research gaps related to data availability, model interpretability, and real-world implementation are identified. Finally, future research directions, including explainable AI, hybrid physics–AI models, multimodal learning, and intelligent monitoring systems, are discussed. Overall, this review demonstrates that AI has significant potential to improve the accuracy, efficiency, and reliability of seismic analysis and damage prediction, contributing to the development of safer and more resilient RCC infrastructure.

Keywords— **Artificial Intelligence; Machine Learning; Reinforced Cement Concrete (RCC); Seismic Analysis; Damage Prediction.**

I. INTRODUCTION

Earthquakes are among the most devastating natural disasters, causing significant loss of life, economic damage, and structural failures worldwide. Reinforced Cement Concrete (RCC) structures constitute the majority of residential, commercial, and industrial buildings due to their high strength, durability, and cost-effectiveness. However, these structures remain vulnerable to seismic forces, particularly when subjected to strong ground motions or when they have been inadequately designed, constructed, or maintained. Accurate seismic analysis and early damage prediction are therefore essential for ensuring structural safety, minimizing repair costs, and improving disaster resilience.

Traditional seismic assessment methods, including linear static analysis, response spectrum analysis, nonlinear pushover analysis, and nonlinear time-history analysis, have been widely employed to evaluate the seismic performance of RCC structures. Although these techniques provide reliable engineering insights, they often require substantial computational resources, accurate material characterization, and expert interpretation. Furthermore, conventional numerical methods may not be suitable for rapid post-earthquake damage assessment or real-time monitoring of large-scale infrastructure.

Recent advancements in Artificial Intelligence (AI) have significantly transformed the field of structural engineering by introducing intelligent, data-driven approaches for seismic analysis and damage prediction. AI techniques can process large volumes of structural and sensor data, identify complex nonlinear relationships, and provide rapid predictions with high accuracy. Machine Learning (ML), Deep Learning (DL), Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), Gradient Boosting algorithms, and Computer Vision (CV) have emerged as powerful tools for structural damage identification, seismic response prediction, crack detection, and structural health monitoring.

Machine Learning algorithms are increasingly being used to estimate important seismic response parameters such as maximum displacement, inter-storey drift ratio, base shear, acceleration, and residual deformation.

These models are capable of learning from historical earthquake records, finite element simulations, and experimental datasets, enabling faster prediction compared to conventional numerical simulations. Deep Learning architectures, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have demonstrated remarkable performance in analyzing vibration signals, structural images, and time-series data for automated damage detection and condition assessment.

Computer Vision has become another important application of AI in earthquake engineering. High-resolution images captured using drones, smartphones, and unmanned aerial vehicles (UAVs) can be processed using deep learning models to identify cracks, concrete spalling, exposed reinforcement, and other structural defects without requiring direct human inspection. This technology has significantly improved the efficiency and safety of post-earthquake damage assessment while reducing inspection time and operational costs.

The integration of Internet of Things (IoT) devices with AI-based Structural Health Monitoring (SHM) systems has further enhanced the capability of continuously monitoring the condition of RCC structures. Sensors such as accelerometers, strain gauges, displacement transducers, and fiber-optic sensors generate real-time structural response data, which can be analyzed using intelligent algorithms to detect anomalies, estimate damage severity, and predict potential structural failures. Such systems support predictive maintenance and enable engineers to make timely decisions regarding repair, retrofitting, or evacuation.

Another emerging trend is the integration of AI with finite element analysis and digital twin technology. Hybrid AI–Finite Element (AI–FE) models combine the physical accuracy of numerical simulations with the computational efficiency of machine learning models, allowing rapid seismic performance assessment without performing computationally expensive nonlinear analyses for every scenario. Digital twins further enhance this capability by creating virtual replicas of physical structures that are continuously updated using sensor data, enabling real-time monitoring and decision-making throughout the structure's lifecycle.

Despite these advancements, several challenges remain in the practical implementation of AI for seismic engineering. Many AI models require large, high-quality datasets for training, while earthquake data are often limited and highly variable across different geographical regions.

Model interpretability, uncertainty quantification, transferability between different structural systems, and the lack of standardized benchmark datasets continue to hinder widespread adoption in engineering practice. Moreover, integrating AI models into existing structural design codes and regulatory frameworks remains an ongoing challenge.

In recent years, research has increasingly focused on developing explainable AI models, physics-informed machine learning algorithms, graph neural networks, transformer-based architectures, and multimodal learning techniques that improve prediction accuracy while maintaining engineering interpretability. These innovations have opened new opportunities for intelligent seismic analysis, automated damage assessment, and resilient infrastructure management.

The primary objective of this review paper is to present a comprehensive overview of recent advances in Artificial Intelligence for seismic analysis and damage prediction in Reinforced Cement Concrete (RCC) structures. The paper reviews the major AI techniques used in earthquake engineering, discusses their applications in seismic response prediction, structural health monitoring, crack detection, and damage classification, compares their advantages and limitations, identifies existing research gaps, and highlights future research directions for developing more reliable, interpretable, and intelligent seismic assessment systems. By synthesizing current developments, this review aims to provide researchers, engineers, and practitioners with valuable insights into the rapidly evolving role of Artificial Intelligence in enhancing the safety, resilience, and sustainability of RCC structures under seismic loading.

II. Literature Review

Abeysuriya et al. (2026) conducted a systematic review of deep learning methods for image-based post-earthquake structural damage assessment. The research evaluated CNN, U-Net, YOLO, Mask R-CNN, and Vision Transformer models for crack detection, damage segmentation, and severity classification. The findings indicated that computer vision techniques achieve high detection accuracy and significantly reduce post-earthquake inspection time. The authors recommended developing larger benchmark datasets for improving model reliability [1].

G. Bustamante et al. (2025) performed a systematic review of machine learning models for improving early earthquake detection in urban environments.

The review assessed multiple supervised learning algorithms for seismic event classification and early warning systems. The findings showed that machine learning enhances prediction accuracy and supports more effective disaster preparedness, although better temporal validation strategies are required for reliable deployment [6].

Hu et al. (2025) reviewed recent progress in machine learning for earthquake engineering with emphasis on seismic performance evaluation and design optimization. The study investigated supervised learning, ensemble learning, and deep learning techniques applied to nonlinear seismic analysis, fragility assessment, and surrogate modeling. The review reported that machine learning substantially improves prediction efficiency while reducing computational time, making it suitable for rapid structural assessment. However, the authors identified data scarcity, feature engineering, and model generalization as major research challenges [7].

Li et al. (2025) reviewed the application of Artificial Intelligence in the study of anthropogenic earthquakes induced by mining, hydraulic fracturing, geothermal energy extraction, and reservoir operations. The review focused on AI-based seismic event detection, clustering, source identification, and hazard forecasting using deep learning and ensemble learning techniques. The study concluded that AI enhances seismic monitoring and supports more effective hazard management while emphasizing the importance of integrating geophysical knowledge with data-driven models [9].

Moghadamnejad et al. (2025) reviewed machine learning and deep learning algorithms for earthquake prediction. The study compared ANN, CNN, LSTM, Random Forest, XGBoost, and hybrid models based on prediction accuracy, robustness, and computational performance. The review concluded that hybrid deep learning architectures generally outperform conventional statistical methods, but uncertainty estimation and model explainability remain important research challenges [14].

Navarro-Rodríguez et al. (2025) conducted a systematic review on machine learning techniques for early earthquake magnitude estimation. The research evaluated deep neural networks, convolutional neural networks, random forests, and gradient boosting algorithms for earthquake detection, phase identification, and magnitude estimation. The findings demonstrated that machine learning significantly improves the speed and accuracy of earthquake early warning systems compared with conventional statistical methods. The study also emphasized the importance of standardized datasets for improving model robustness [15].

Rosales Huamani et al. (2025) presented a systematic review of machine learning applications in earthquake studies. The review analyzed studies involving earthquake prediction, seismic hazard mapping, ground motion estimation, and structural damage assessment. Various algorithms, including ANN, SVM, Random Forest, and deep learning models, were compared based on prediction accuracy and computational efficiency. The authors concluded that machine learning provides significant improvements in seismic data interpretation but requires better validation using real-world earthquake events [16].

Zhang et al. (2025) presented a cross-disciplinary review integrating Artificial Intelligence with geophysical knowledge for earthquake forecasting. The study discussed deep learning, multimodal data fusion, and physics-informed AI for processing seismic, geochemical, and geodetic observations. The review concluded that combining physical principles with AI models can improve forecasting performance while reducing false alarms and enhancing model reliability [21].

Zhou S. et al. (2025) compiled a collection of studies on machine learning applications in seismology. The work highlighted the use of deep neural networks, random forests, support vector machines, and transformer-based models for earthquake detection, seismic phase picking, signal classification, and hazard assessment. The collection emphasized handling large-scale seismic datasets and improving model generalization across different regions. The findings confirmed that AI significantly enhances the efficiency and precision of seismic data analysis compared with conventional techniques [22].

Kumar et al. (2024) developed a machine learning-based approach for assessing seismic vulnerability in reinforced concrete educational buildings. The research focused on predicting structural damage levels using supervised learning models such as artificial neural networks and decision trees trained on parameters like building height, stiffness, material strength, and ground motion intensity. The methodology involved dataset preparation from simulated and real seismic responses. Empirical insights revealed that ML models outperform conventional empirical and code-based approaches in prediction accuracy. Results confirm that AI-based vulnerability assessment enables faster, data-driven evaluation of RCC structures, aiding engineers in retrofit and design decisions [8].

Marano G. C. et al. (2024) proposed an AI-based approach for estimating subsurface seismic velocity models using earthquake waveform data. The research focused on training neural networks to predict P-wave and S-wave velocities without relying on iterative inversion techniques.

International Journal of Recent Development in Engineering and Technology
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The methodology reduced computational complexity while maintaining accuracy. Empirical findings show that AI models achieve results comparable to traditional geophysical inversion methods but with faster processing time. Results confirm that machine learning offers an efficient alternative for seismic subsurface characterization [12].

Xie (2024) provided a comprehensive review of deep learning applications in earthquake engineering. The study examined Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Graph Neural Networks (GNN), Autoencoders, and Generative Adversarial Networks (GANs) for structural damage detection, seismic demand prediction, ground motion analysis, and community resilience assessment. The review demonstrated that deep learning substantially improves prediction accuracy through automatic feature extraction while reducing human intervention [20].

Malekloo et al. (2022) reviewed machine learning applications in Structural Health Monitoring (SHM). The study investigated AI-based vibration analysis, sensor data interpretation, anomaly detection, and predictive maintenance of civil infrastructure. The review highlighted that integrating machine learning with wireless sensor networks and IoT technologies enables continuous monitoring and early detection of structural deterioration, thereby improving infrastructure safety [11].

Woollam et al. (2021) introduced **SeisBench**, an open-source framework for machine learning in seismology. The framework standardizes benchmark datasets and machine learning models for earthquake detection, seismic phase picking, and ground motion prediction. The study demonstrated that standardized datasets and reproducible workflows facilitate fair comparison of algorithms and accelerate the development of AI applications in seismology [18].

Xie et al. (2020) presented a comprehensive review of machine learning applications in earthquake engineering. The study focused on the use of Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and Deep Learning models for seismic response prediction, structural damage assessment, fragility analysis, and reliability evaluation. The review highlighted that machine learning algorithms efficiently capture nonlinear structural behavior while significantly reducing computational costs associated with traditional finite element analysis. The authors concluded that AI has considerable potential to improve seismic risk assessment, although challenges related to data availability, model interpretability, and uncertainty quantification remain [19].

III. Research Gaps

Although the reviewed studies demonstrate that Artificial Intelligence (AI) has significantly improved seismic analysis, earthquake prediction, and damage assessment of Reinforced Cement Concrete (RCC) structures, several critical research gaps remain. Most existing studies have been developed and validated using simulated datasets or region-specific earthquake records, limiting their applicability across diverse seismic zones and structural configurations. The availability of large-scale, standardized, and high-quality benchmark datasets for RCC structures subjected to real earthquake events is still inadequate, which restricts the robustness and generalization capability of machine learning and deep learning models (Xie et al., 2020; Hu et al., 2025; Rosales Huamaní et al., 2025). Furthermore, many AI models function as "black-box" systems, providing limited interpretability and uncertainty quantification, making engineers hesitant to rely on them for critical structural safety decisions. Existing research also places greater emphasis on earthquake detection and seismic signal analysis than on comprehensive damage prediction and lifecycle performance assessment of RCC buildings (Li et al., 2025; Zhou & Jia, 2025; Zhang et al., 2025).

Another major gap is the limited integration of AI with physics-based numerical models, Building Information Modeling (BIM), Digital Twin technology, and real-time Structural Health Monitoring (SHM) systems for continuous seismic performance evaluation. Most current studies focus on single AI algorithms under controlled laboratory conditions, whereas hybrid frameworks combining machine learning, finite element analysis, computer vision, IoT, and sensor networks remain relatively unexplored. Additionally, there is insufficient research on transfer learning, multimodal data fusion, explainable AI (XAI), federated learning, and physics-informed machine learning for improving model reliability under varying structural and environmental conditions. Few studies have evaluated the practical implementation of AI models within existing seismic design codes and engineering standards or assessed their performance using real-time post-earthquake inspection data. Addressing these limitations through standardized datasets, interpretable AI models, hybrid computational frameworks, and large-scale field validation will significantly enhance the reliability and practical adoption of AI-based seismic analysis and damage prediction systems for RCC structures (Malekloo et al., 2022; Thai, 2022; Kumar et al., 2024; Abeysuriya et al., 2026; Moghadamnejad et al., 2026).

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IV. Future Research Directions

Future research should focus on developing hybrid AI models that combine machine learning, deep learning, finite element analysis, and physics-informed approaches to improve the accuracy and reliability of seismic analysis for RCC structures. The creation of large, standardized earthquake and structural damage datasets, along with the adoption of Explainable AI (XAI) and Physics-Informed Neural Networks (PINNs), will enhance model transparency and engineering applicability. Furthermore, integrating AI with Digital Twin, Building Information Modeling (BIM), Internet of Things (IoT), and Structural Health Monitoring (SHM) systems can enable real-time monitoring and rapid post-earthquake damage assessment (Xie et al., 2020; Hu et al., 2025; Malekloo et al., 2022).

Additionally, future studies should emphasize real-world validation, transfer learning, multimodal data fusion, and uncertainty quantification to improve the robustness and generalization of AI models across different seismic regions and structural systems. Incorporating emerging technologies such as Graph Neural Networks (GNNs), Vision Transformers (ViTs), and edge AI can further enhance intelligent seismic monitoring and support the practical implementation of AI in earthquake-resistant design and resilient infrastructure management (Abeysuriya et al., 2026; Kumar et al., 2024; Zhang et al., 2025).

V. Conclusions

Artificial Intelligence (AI) has emerged as a powerful tool for improving seismic analysis and damage prediction in Reinforced Cement Concrete (RCC) structures. Machine learning, deep learning, and computer vision techniques have demonstrated significant potential for accurately predicting seismic responses, detecting structural damage, and enabling real-time structural health monitoring. Compared with conventional methods, AI-based approaches offer faster analysis, higher computational efficiency, and improved decision-making capabilities.

Despite these advancements, challenges such as limited high-quality datasets, model interpretability, and real-world validation remain. Future research should focus on developing hybrid AI frameworks, standardized datasets, and explainable models integrated with Digital Twin, IoT, and Structural Health Monitoring systems. These developments will enhance the reliability and practical implementation of AI, contributing to safer, more resilient, and sustainable RCC structures in earthquake-prone regions.

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