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Advancements in AI for Seismic Performance Assessment and Vulnerability Prediction in RC Buildings

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ABSTRACT

The seismic performance assessment of reinforced concrete (RC) buildings has gained significant importance due to increasing earthquake frequency and aging infrastructure. Traditional analytical methods, like nonlinear time history analysis, are computationally intensive, making them impractical for large-scale applications. Artificial intelligence (AI) models, particularly machine learning (ML) and deep learning, offer scalable, data-driven solutions. These AI techniques enhance seismic vulnerability predictions, surpassing traditional methods like Rapid Visual Screening (RVS). Furthermore, AI has enabled advancements in structural control systems, improving seismic mitigation. AI-based approaches, including hybrid models and reinforcement learning, have demonstrated promising results, improving prediction accuracy and overall performance.

Keywords: *Seismic Performance, Reinforced Concrete, Machine Learning, Vulnerability Prediction, Seismic Mitigation.*

I. INTRODUCTION

The seismic performance assessment of reinforced concrete (RC) buildings has become a critical area of research in structural engineering due to the increasing frequency of earthquakes and the large-scale vulnerability of aging infrastructure worldwide. Traditional analytical methods, such as nonlinear time history analysis and incremental dynamic analysis (IDA), although accurate, are computationally expensive and often impractical for large urban building inventories. This limitation has led to the integration of artificial intelligence (AI)-based predictive models, which offer faster, data-driven, and scalable solutions for seismic risk evaluation and decision-making in civil infrastructure systems. Recent advancements indicate that machine learning (ML) and deep learning techniques significantly enhance the accuracy of seismic vulnerability prediction compared to conventional Rapid Visual Screening (RVS) methods. For instance, Varolgüneş and Karaşin (2026) demonstrated that traditional RVS techniques like RBTY-2019, FEMA-P154, and IITK-GSDMA have limitations in capturing local structural behaviour. To overcome this, an Artificial Neural Network (ANN) model was developed using post-earthquake damage data from the 2003 Bingol earthquake. The ANN achieved a regression coefficient above 0.90, highlighting superior predictive performance. Similarly, Yilmaz et al. (2025) developed a hybrid AI framework combining structural, geometric, and seismic parameters, achieving 77% internal and 83% external accuracy, outperforming traditional RVS methods. In addition to predictive modelling, AI has been applied to structural control systems for seismic mitigation. Kurucu et al. (2026) introduced a deep reinforcement learning (DRL)-based control strategy for semi-active friction dampers, demonstrating up to 63.7% improvement in seismic performance compared to rule-based systems. This reflects a shift from passive assessment to active adaptive structural control using AI-based optimization techniques. Further, Gondaliya et al. (2024) and Kazemi et al. (2023) explored ensemble machine learning and neural network-based frameworks for seismic vulnerability prediction using Monte Carlo simulations and incremental dynamic analysis datasets. Their results revealed prediction accuracies between 87% and 95%, confirming the robustness of stacked and deep learning models in capturing nonlinear structural behaviour. From a fragility assessment perspective, Rasheed et al. (2022) showed that Artificial Neural Networks (ANNs) outperform Gene Expression Programming (GEP) in predicting global drift responses, achieving an R^2 value of 0.938. Meanwhile, Harirchian et al. (2020) emphasized the applicability of Support Vector Machines (SVM) for classifying building performance under seismic hazards across multiple international datasets, reinforcing the generalizability of ML approaches. Complementary advancements in digital engineering have also influenced seismic assessment methodologies. Musella et al. (2021) integrated Building Information Modelling (BIM) with AI-based image recognition systems for automated damage detection, enabling efficient post-earthquake assessment workflows. Additionally, Tarfan et al. (2019) highlighted improvements in seismic resilience through retrofitting strategies, although their study relied more on numerical modelling rather than AI.

II. RESEARCH BACKGROUND

Varolgüneş and Karaşin (2026) examined the rapid assessment of existing reinforced concrete (RC) buildings for seismic risk mitigation, particularly in the highly active seismic region of Bingol, Türkiye. The study compared the local performance of three Rapid Visual Screening (RVS) methods, namely RBTY-2019, FEMA-P154, and IITK-GSDMA, by using verified post-earthquake damage data from the 2003 Bingol Earthquake (SERU-2003). It was reported that traditional RVS approaches showed certain limitations in accurately reflecting local structural behaviour. Therefore, an Artificial Neural Network (ANN) model was developed and trained on the same dataset to predict building damage levels based on structural deficiency parameters. The ANN was found to achieve a regression coefficient above 0.90 and complete consistency in test predictions, indicating superior accuracy and adaptability. Additionally, a Local Scaling Function (LSF) was proposed to convert RBTY-2019 scores into empirical damage states. The study emphasized that locally trained AI-integrated RVS frameworks could significantly improve urban seismic risk prioritization and disaster management planning.

Kurucu et al. (2026) investigated the seismic protection of multi-story buildings through the application of semi-active friction dampers (SAFDs), whose friction force could be adaptively adjusted according to structural response. The study highlighted that the energy dissipation efficiency of SAFDs largely depended on the adopted control strategy, while the nonlinear and complex behaviour of such systems made optimal control difficult. To address this issue, the authors proposed an intelligent control framework based on deep reinforcement learning (DRL) for real-time seismic response mitigation. A numerical case study was conducted to evaluate the proposed method against three alternative approaches, namely constant-force friction dampers calibrated heuristically, friction dampers optimized through a Genetic Algorithm, and SAFDs controlled by a rule-based strategy. The findings indicated that the DRL-based controller produced superior seismic performance, with improvements of up to 63.7% over the rule-based method. The study’s major contribution was the formulation of a Markov Decision Process and reward-design framework for adaptive friction control.

Yilmaz et al. (2025) had developed an artificial intelligence-based framework to predict both the risk level and damage level of reinforced concrete structures through classification and proportioning techniques. The study had aimed to identify buildings requiring preventive intervention before earthquakes and those needing immediate repair or demolition afterward. A normalized risk index had been calculated by dividing the risky story count by the total number of stories, allowing fair comparison across buildings of different sizes. The dataset had comprised 100 earthquake-affected buildings in Türkiye and 782 buildings with detailed seismic analyses. Thirteen structural, seismic, and geometric parameters had been incorporated. Rapid visual screening (RVS) methods had been employed for structural assessment, while machine learning models had enhanced predictive efficiency and accuracy. Pearson-correlation-based feature analysis and Random Oversampling had improved model balance. The ensemble of four models had achieved 77% accuracy and 83% external accuracy, outperforming traditional RVS (68%) while significantly reducing computation time.

Gondaliya et al. (2024) examined the growing role of artificial intelligence in structural engineering and reported that recent AI advancements had significantly improved safety, efficiency, and cost-effectiveness in the design, construction, and maintenance of infrastructure. Their study investigated a machine learning-based framework for estimating the seismic vulnerability of reinforced concrete (RC) building frames. A probabilistic approach was adopted to simulate the response of a four-story RC building frame under epistemic uncertainty. The dataset was generated through a Monte Carlo method, which supported the development of predictive machine learning models for structural damage assessment. The problem was formulated in both regression and classification forms. For classification, a feed-forward artificial neural network was employed, and the optimal hidden-layer neuron configuration was determined for improved prediction. For regression, LASSO regression, random forest, and gradient boosting were integrated using stacking generalization. The findings indicated that the stacked model achieved lower variance and high predictive accuracy, with damage forecasting performance ranging from 87% to 95%.

Kazemi et al. (2023) investigated the challenge of predicting seismic responses of reinforced concrete moment-resisting frames (RC MRFs), acknowledging that the complex and unpredictable nature of earthquakes prevented the use of a single universal predictive formula. The study aimed to implement widely recognized machine learning techniques in Python to develop a prediction model for seismic response and performance assessment. For this purpose, 92,400 training data points were generated through Incremental Dynamic Analyses (IDAs) on 165 RC MRFs ranging from two to twelve stories, with varying bay lengths and near-fault seismic excitations. Key structural features were incorporated into the datasets for model training and testing. The findings indicated that improved machine learning algorithms achieved higher R^2 values in estimating maximum interstory drift ratio (IDRmax). In particular, enhanced artificial neural networks and extreme gradient boosting models effectively estimated median IDA curves, supporting seismic limit-state capacity assessment. A graphical user interface was also introduced to reduce computational effort and facilitate practical application.

Rasheed et al. (2022) investigated the seismic vulnerability of school buildings in Muzaffarabad district, located in seismic zone-4 of Pakistan, a region historically prone to large earthquakes that had caused extensive infrastructure collapse and significant loss of life. They highlighted the critical need for seismic assessment of infrastructure, which could be performed using fragility analysis. In their study, fragility curves were initially developed through incremental dynamic analysis (IDA), though they noted that this numerical approach was computationally intensive and costly. To overcome these limitations, they employed soft computing techniques, specifically Artificial Neural Networks (ANN) and Gene Expression Programming (GEP), as alternative methods for predicting seismic performance. The optimized feedforward backpropagation ANN model [5-25-1] was trained with 70% of the data, validated with 15%, and tested with the remaining 15%. GEP was similarly utilized. Comparative analysis based on the coefficient of determination (R^2) indicated that the ANN model more accurately predicted global drift values ($R^2 = 0.938$) than the GEP model ($R^2 = 0.87$).

Musella et al. (2021) investigated the integration of digital technologies, specifically Building Information Modelling (BIM) and artificial intelligence, in the detection, assessment, and digitalization of damage in existing buildings. The study aimed to demonstrate the potential and realized benefits of combining structural-assessment methods with automated digitization of hazard-induced damage. To achieve this, the authors employed an image-based recognition approach linked with BIM classification, applied to on-site visual-damage data. Their methodology was further extended to existing masonry and concrete structures, allowing the researchers to explore new opportunities for accelerating the processes of assessment, design, and management of seismic repair and retrofit interventions. The study concluded that the use of image-acquired data, integrated with BIM and AI, could significantly enhance the efficiency and accuracy of structural evaluation and post-damage management, highlighting the value of combining computational tools with traditional engineering practices in building preservation and hazard mitigation.

Harirchian et al. (2020) highlighted that, although preventing seismic disturbances and their associated physical, social, and economic impacts was practically impossible, advances in computational science and numerical modelling had enabled prediction of earthquake severity, understanding of potential outcomes, and preparation for post-disaster management. They noted that many buildings in developed metropolitan areas were old, still in use, and often constructed before national seismic codes or construction regulations were established. Consequently, risk reduction was considered essential through developing alternative strategies and designing models to improve existing structural performance. These models were reported to classify risks and potential casualties from earthquakes, facilitating emergency preparedness. Recognizing structures vulnerable to seismic vibrations and prioritizing them for retrofitting was emphasized. Given the impracticality of detailed structural analysis for every building due to computational and financial constraints, the study advocated Rapid Visual Screening (RVS) as a simple, reliable, and accurate primary assessment method. They examined damage classification using Machine Learning, training and testing a Support Vector Machine (SVM) model on datasets from Ecuador, Haiti, Nepal, and South Korea, which successfully categorized building performance under seismic hazards.

Tarfan et al. (2019) investigated the probabilistic seismic performance of non-ductile reinforced concrete (RC) structures retrofitted with pre-tensioned aramid fiber reinforced polymers (AFRP). They considered three RC buildings of varying heights (4-, 6-, and 8-stories), which were originally designed according to outdated construction practices. The poorly detailed columns in each model were retrofitted using pre-tensioned AFRP belts. Numerical finite element models were developed in OpenSees, employing concentrated plastic hinge models to capture the shear weakness of the original columns and the degradation of beams’ stiffness and strength. Incremental dynamic and nonlinear static analyses were conducted to assess structural performance at both global and component levels. Structural responses were evaluated through fragility curves, mean annual frequency of collapse, and collapse margin ratios. Statistical analyses further provided median inter-story drift distributions, member ductility, and dissipated energy under multiple seismic hazard levels. Their findings suggested that pre-tensioned AFRP retrofitting enhanced global ductility, reduced collapse probability, mitigated weak story formation, and improved column-level performance under near-collapse conditions.

Kunnath (2018) highlighted that performance-based seismic engineering had driven an increased adoption of nonlinear tools for evaluating the seismic response of structures. The study provided an overview of various modelling techniques applicable to the analysis of reinforced concrete (RC) structures under seismic loads, emphasizing simplified approaches. It was indicated that both element models and constitutive models commonly employed in nonlinear RC analysis had been systematically summarized. The research discussed general modelling considerations that needed to be accounted for when conducting nonlinear seismic analyses. Additionally, Kunnath presented a sample simulation of a multistory RC frame subjected to lateral and seismic loads, illustrating how different modelling choices could influence the predicted structural response. The study suggested that careful selection of modelling strategies was essential to capture the nonlinear behaviour accurately while maintaining computational efficiency. Overall, the work contributed to a better understanding of practical and simplified approaches in performance-based seismic evaluations of RC structures.

III. KEY FINDINGS FROM STUDY

Author (Year)	Methodology	Key Focus	Major Findings
Varolgüneş & Karaşin (2026)	ANN + RVS comparison	Seismic damage prediction	ANN achieved >0.90 accuracy, outperforming RVS methods
Kurucu et al. (2026)	Deep Reinforcement Learning	Seismic control using dampers	DRL improved performance by 63.7%
Yilmaz et al. (2025)	Ensemble ML + feature engineering	Risk classification	77–83% accuracy, better than traditional RVS
Gondaliya et al. (2024)	Stacking ML models	RC vulnerability prediction	87–95% predictive accuracy
Kazemi et al. (2023)	ANN + XGBoost + IDA dataset	Seismic response prediction	High R^2 values for drift prediction
Rasheed et al. (2022)	ANN vs GEP	Fragility curves	ANN outperformed GEP (R^2 = 0.938)
Musella et al. (2021)	BIM + AI image recognition	Damage digitalization	Faster seismic damage assessment
Harirchian et al. (2020)	SVM classification	Rapid seismic screening	Effective multi-country classification
Tarfan et al. (2019)	FEM + fragility analysis	Retrofitting RC buildings	Improved ductility and reduced collapse
Kunnath (2018)	Nonlinear modeling review	RC seismic simulation	Emphasized importance of modeling accuracy

IV. CONCLUSION

The reviewed literature clearly demonstrates that artificial intelligence-based predictive models have significantly transformed seismic performance assessment of reinforced concrete buildings. Traditional methods such as Rapid Visual Screening (RVS) and nonlinear dynamic simulations, although reliable, are limited by computational complexity, lack of scalability, and inability to incorporate large multidimensional datasets effectively. AI-based approaches, particularly Artificial Neural Networks (ANN), ensemble learning, and deep reinforcement learning, have shown superior performance in predicting structural damage, seismic vulnerability, and response behaviour with higher accuracy and reduced computational time. Studies such as Varolgüneş and Karaşin (2026) and Yilmaz et al. (2025) confirm that machine learning models consistently outperform conventional RVS techniques in real-world seismic datasets. Similarly, reinforcement learning-based adaptive control systems, as proposed by Kurucu et al. (2026), highlight the potential of AI not only in prediction but also in active seismic mitigation strategies. Furthermore, hybrid approaches combining physics-based simulations with AI models, as seen in Kazemi et al. (2023) and Gondaliya et al. (2024), provide more robust and generalized solutions for seismic performance evaluation. Overall, AI-driven seismic assessment frameworks offer a promising pathway toward smart, resilient, and data-driven infrastructure systems. However, challenges remain in terms of data quality, model interpretability, and integration into existing engineering design codes.

V. FUTURE SCOPE

- Development of hybrid physics-informed AI models combining structural mechanics with deep learning.
- Integration of real-time sensor data (IoT) for continuous structural health monitoring.
- Improved explainable AI (XAI) models for better interpretability in engineering decisions.
- Expansion of datasets across diverse seismic zones for better generalization.
- Implementation of AI-based early warning and automated retrofit decision systems.
- Use of digital twin technology for real-time seismic performance simulation.
- Optimization of computational efficiency for large-scale urban seismic risk mapping.
- Development of standardized AI frameworks for integration into building codes and regulations.

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