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(Review Article)

Review on artificial intelligence application in structural earthquake engineering

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Abstract

Artificial Intelligence (AI) has brought a transformative shift to seismic engineering during past decade, enabling engineers to address complex challenges with unprecedented precision and efficiency. By leveraging machine learning (ML) and deep learning (DL) technologies, researchers are redefining seismic analysis, structural response prediction, and damage assessment. AI-driven methods such as artificial neural networks (ANNs) and convolutional neural networks (CNNs) have proven highly effective in analyzing seismic data and predicting structural performance during earthquakes. These tools process vast datasets collected from global seismic networks, facilitating real-time monitoring and more accurate damage assessments. They predict structural responses with remarkable precision, optimize designs for resilience, and better prepare for natural forces Furthermore, advancements like physics-informed neural networks (PiNNs) integrate engineering principles with AI, providing models that are both reliable and interpretable. This paper reviews the advancements of AI application in earthquake engineering during the past decade (Open Access Articles), current challenges and future directions.

Keywords: Artificial Intelligence (AI); Machine Learning (ML); Structural Engineering; Seismic Engineering; AI algorithms

1. Introduction

Incorporating artificial intelligence (AI) and machine learning (ML) in structural engineering has opened new avenues for optimizing materials, design, and maintenance processes. Within this domain, advanced computational techniques are being employed to address complex challenges such as material property predictions, structural health monitoring, and sustainable construction. For example, Ben Seghier et al. [1] utilized hybrid artificial neural networks (ANNs) and genetic expression programming (GEP) to predict the bond strength of corroded steel reinforcement with high accuracy (96%) based on 218 data points. Similarly, Gorphade et al. [2] applied a combination of genetic algorithms (GA) and ANN to predict the workability and strength of high-performance concrete using 324 data points. In another study, Naseri et al. [3] explored the use of various algorithms, including water cycle, soccer league competition, GA, ANN, and support vector machines (SVM), to optimize concrete mixtures for compressive strength and sustainability metrics such as CO2 emissions and resource efficiency.

Artificial intelligence (AI) refers to computational methods designed to replicate human cognitive functions such as reasoning, decision-making, classification, and interpretation (Ertel, 2017 [11]; Neapolitan and Jiang, 2018[12]; Salehi and Burgueño [13], 2018; Shehab et al., 2020 [14]). This interdisciplinary field draws from mathematics, computer science, biology, neurology, and engineering, providing solutions to complex problems that traditional methods often cannot address (Nti et al., 2021[15]). Unlike conventional software, AI excels in processing incomplete or uncertain

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data, allowing it to infer patterns and make predictions. Consequently, AI is now widely applied in domains such as education, healthcare, transportation, and structural engineering (Shehab et al., 2020[014]; Zhang et al., 2021[16]).

Supervised learning techniques, a subset of ML, are widely utilized for predictive tasks in structural engineering. These methods rely on labeled data to train models for regression (continuous variable prediction) or classification (categorical variable prediction). On the other hand, unsupervised learning methods, which do not require labeled datasets, have been used to identify patterns and clusters in structural data. Algorithms such as k-means clustering, association rules, auto-encoders, and principal component analysis (PCA) are frequently employed to enhance data interpretation and computational efficiency (Bertolini et al., 2021 [4]; Meng et al., 2020 [5]).

Optimization is another key area where ML has proven invaluable in structural engineering. Yepes et al. [006] developed cognitive methods leveraging multi-objective optimization for reinforced concrete beams, highlighting the potential for reducing lifecycle costs and improving durability. Garcia-Segura et al. [6] employed modified harmonic search algorithms combined with ANN to optimize post-tensioned concrete bridges under corrosion conditions, achieving designs with extended corrosion resistance. Similarly, Chatterjee et al. [7] demonstrated the efficacy of multi-objective genetic algorithms in refining neural network models for structural failure classification.

seismic analysis and earthquake engineering in the field of structural engineering has witnessed a remarkable transformation in recent years through the integration of artificial intelligence (AI) technologies (Liu, T) [8]. Traditional approaches to seismic analysis, while foundational, have been limited by their computational intensity and inability to process vast amounts of real-time data effectively. The emergence of AI and machine learning has revolutionized how engineers approach seismic analysis, offering unprecedented capabilities in pattern recognition, predictive modeling, and real-time structural health monitoring (Chen, S) [9]. The development of foundation models like SeisLM has demonstrated the potential of AI to learn complex seismic waveform patterns from extensive datasets, enabling more accurate event detection and phase-picking capabilities. These advancements have particularly benefited from the exponential growth in seismic data collection, with networks of thousands of stations worldwide contributing to an ever-expanding repository of seismic recordings.

The integration of deep learning architectures, including convolutional neural networks (CNNs), recurrent networks, and generative adversarial networks (GANs), has enabled more sophisticated approaches to analyzing structural responses to seismic events. Recent developments in physics-informed neural networks have further enhanced our ability to incorporate fundamental physical principles into AI models, leading to more reliable and interpretable results (Morocco Solidarity Hackathon) [10].

However, significant challenges remain, including the need for more robust validation methods, the integration of domain expertise with AI capabilities, and the development of more efficient computational approaches. The field continues to evolve rapidly, with new methodologies emerging that combine traditional engineering principles with cutting-edge AI technologies. This synthesis of approaches promises to enhance our understanding of seismic phenomena and improve our ability to design and maintain resilient structures.

As we move forward, the focus increasingly shifts toward developing more sophisticated AI models that can handle the complexity of seismic analysis while maintaining computational efficiency and reliability. This review examines the current state of AI applications in seismic analysis, highlighting both the achievements and challenges that define this rapidly evolving field. Collectively, these studies emphasize the transformative impact of AI and ML on structural engineering. This review explores practical application of artificial intelligence in seismic engineering.

AI's widespread adoption has raised concerns about the transparency and accountability of its decision-making processes, particularly in critical areas like defense, finance, and healthcare. This has led to the emergence of Explainable Artificial Intelligence (XAI), a field focused on making AI systems more interpretable and reliable. By elucidating how decisions are made, XAI helps establish trust, facilitates verification, and enables continuous model improvement (Minh et al., 2022[17]; Vassiliades et al., 2021[18]; Wells and Bednarz, 2021[019]). Moreover, XAI offers human designers' insights into previously unexplored scenarios, fostering more reliable human-machine collaboration.

The application of AI in structural engineering has expanded significantly since 2014, driven by advancements in computational technology and the increasing availability of data. Machine learning (ML) and deep learning (DL) play pivotal roles in this growth, while techniques like expert systems, fuzzy logic, and genetic algorithms, though important, have seen a comparatively stable rate of usage over time. ML and DL, in particular, have revolutionized fields such as structural health monitoring, material optimization, and predictive modeling, making them indispensable in modern structural engineering.

Soft computing, often considered synonymous with computational intelligence (CI), extends AI's ability to handle complex and uncertain problems. Techniques such as neural networks, fuzzy logic, and evolutionary algorithms are integral to soft computing, enabling solutions to nonlinear and ambiguous challenges. Unlike conventional models, which often require clearly defined parameters, soft computing excels in approximating solutions where uncertainties dominate.

AI intersects significantly with big data and data mining, where large and diverse datasets offer new opportunities for insights. Data mining focuses on discovering unknown properties and trends in datasets, while big data addresses challenges involving the volume, velocity, and variety of data types. ML utilizes these datasets to create predictive models, while deep learning refines this process by enabling learning from unstructured and unlabeled data. This has made DL particularly effective in applications like image recognition, structural health monitoring, and topology optimization.

Research on AI applications in structural engineering has grown steadily, with methods such as pattern recognition, ML, and neural networks showing substantial advancements over the last decade. Fig. 1 illustrates the relationship between various intelligent computational techniques. Some methods, like evolutionary computation and expert systems, have maintained a steady application rate, and there has been a marked increase in the use of ML and DL, including convolutional neural networks (CNNs). These developments reflect the growing recognition of AI's transformative potential in addressing structural engineering challenges, paving the way for more efficient, resilient, and sustainable solutions.

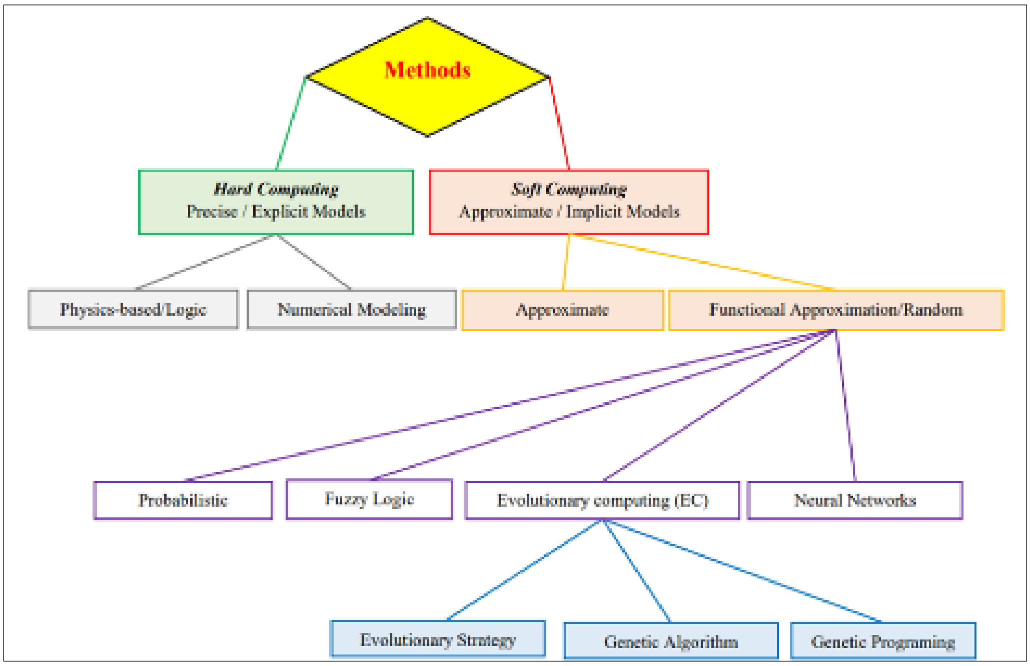

Figure 1 Computational Methodologies [20]

2. Recent Advancements of AI in Earthquake Engineering

Machine learning techniques have also advanced the prediction and analysis of structural responses under earthquake conditions, focusing on drifts, deflections, strength, natural frequencies, and hysteresis behaviors. Nguyen et al. [27] employed ANN and XGBoost to model the drift of steel moment frames under seismic loading, while Hwang et al. [28] compared several ML algorithms, including Random Forest (RF), Decision Trees (DT), k-Nearest Neighbors (kNN), Naive Bayes (NB), RA1, RA5, AdaBoost, and XGBoost, for predicting the drift of RC frames. Boosting algorithms like AdaBoost and XGBoost consistently outperformed other models in handling complex, high-dimensional datasets with reduced overfitting. Charalampakis et al. [29] and Somala et al. [30] examined the natural frequency of masonry-infilled RC structures using both ANN and RF as well as other ML approaches, again finding that boosting methods achieved superior predictive accuracy. Studies by Mangalathu and Burton [33] used an LSTM-based DL approach to evaluate seismic damage in thousands of buildings with high accuracy. Zhang et al. [34] further investigated RC special moment frames using classification and regression tree (CART) and RF, reporting high rates of successful damage classification

The field of seismic analysis has witnessed remarkable transformations through the integration of artificial intelligence (AI) methods, particularly in recent years. This advancement has been primarily driven by the availability of extensive datasets, significant improvements in computational capabilities, and the evolution of sophisticated algorithmic techniques in network architecture and training methodologies (Xie, Y) [21]. Deep Learning (DL) has emerged as a cornerstone in this context, demonstrating exceptional capabilities in extracting meaningful features from raw seismic data. Its power lies in creating efficient representations of complex input spaces through statistical training against large datasets, leading to groundbreaking applications across various aspects of seismic analysis, from signal processing to structural response prediction (Xie, Y) [21]. Hwang et al. [35] applied algorithms including AdaBoost and Extreme Gradient Boosting Trees (ExGBT) to classify collapse statuses of RC buildings under earthquake ground motions, outperforming traditional methods. Morfidis and Kostinakis [42] also used ANNs to analyze seismic performance, identifying real-time damage states under 65 ground motions. Luo and Paal [36] employed SVM for shear resistance prediction in RC columns, contributing to more accurate and robust seismic design strategies.

One of the earliest implementations of AI in seismic analysis involved the use of Artificial Neural Networks (ANNs) for seismic data denoising (Harsuko, R) [22]. As computational resources became more accessible and data availability increased, researchers developed more sophisticated approaches. The introduction of Generative Adversarial Networks (GANs) and U-Net convolutional neural networks marked a significant advancement in seismic image processing and analysis, proving particularly effective in handling complex seismic data patterns and extracting relevant features for structural analysis (Harsuko, R) [22]. Long-Short Term Memory (LSTM) networks have also made substantial contributions, especially to the temporal aspects of seismic analysis. These networks excel in processing time-series data, making them valuable for seismic signal analysis and prediction. An innovative application combined "You Only Look Once" (YOLO) architecture with LSTM networks to develop automated picking systems for seismic events (Harsuko, R) [22].

Physics-informed Machine Learning (PiML) has further bridged the gap between traditional physics-based methods and pure data-driven approaches by incorporating physical laws and constraints into the learning process, thereby improving both accuracy and reliability in seismic response predictions. Recent developments have seen the emergence of SeisGPT, a specialized implementation of transformer-based models that adapts the power of large language models to meet the specific requirements of seismic data processing. SeisGPT has demonstrated promising results in understanding complex seismic patterns and generating accurate predictions of structural responses.

The integration of these AI methods has revolutionized earthquake-related research and applications, leading to significant improvements in ground motion prediction, structural response assessment, and damage detection (Morocco Solidarity Hackathon) [10]. By enabling the processing of large-scale seismic datasets, these advancements contribute to more accurate and efficient predictions, ultimately helping inform earthquake preparedness and response strategies. Looking forward, the field continues to evolve with the development of more sophisticated AI architectures and hybrid approaches that combine traditional physics-based methods with advanced AI techniques. This integration is a crucial step toward more reliable and comprehensive analysis methods in seismic engineering.

Real-world applications underscore this progress. A 30-week real-time earthquake forecasting study in China demonstrated the practical effectiveness of AI-based approaches in seismic prediction and analysis (Morocco Solidarity Hackathon) [10]. These outcomes highlight AI's potential to transform seismic engineering practice and improve structural safety in seismically active regions. The application of AI in earthquake engineering has significantly advanced the understanding and assessment of seismic damage to structures; machine learning (ML) and deep learning (DL) approaches have become indispensable tools for predicting structural responses to earthquakes, improving resilience, and guiding design modifications.

Deep learning has revolutionized seismic analysis through various neural network architectures, each bringing unique capabilities to structural engineering applications (Zhang, R) [23]. Convolutional Neural Networks (CNNs) have emerged as powerful tools for processing ground motion records and structural response patterns, with architectures like U-Net (Xie, Y) [21] enabling detailed analysis of waveforms and damage states. Recurrent Neural Networks (RNNs), particularly LSTM variants (Xie, Y) [21], have proven invaluable in processing sequential seismic data, capturing both short-term and long-term patterns for more accurate structural behavior predictions. Generative Adversarial Networks (GANs) further address the challenge of limited real-world data by generating realistic ground motion scenarios and synthetic training sets. Recent efforts combine multiple network types—such as CNN-LSTM hybrid models—to provide comprehensive spatial and temporal analyses of seismic responses, which has proven especially useful in real-time damage assessment and structural health monitoring (Zhang, R) [23].

Seismic engineering, confronted with the complexities of earthquake-induced structural damage, has increasingly integrated AI-based methodologies to enhance predictive and diagnostic capabilities. Arsalan [26] employed artificial neural networks (ANN) to analyze earthquake resistance factors in RC structures, achieving 92%–99% accuracy and identifying key parameters like shear wall ratio and short column formation. Pattern recognition (PR) techniques have further propelled this domain; Zhang et al. [224,25] combined PR with support vector regression (SVR) for nonlinear parameter identification in vibration data, while Lautour et al. [26] used ANNs to model seismic-induced damage in RC frames, revealing correlations between ground motion and structural characteristics. Elwood et al. [18] illustrated how fuzzy classifiers effectively detect damage in post-earthquake scenarios, using real-world data for robust pattern recognition and diagnostics. Table below presents recent application of AI in earthquake engineering.

Table 1 AI Application in Earthquake Engineering

Application	AI Algorithm(s)	Reference
Predict energy dissipated in steel reinforcing bars in reinforced concrete members	ANN	Abdalla and Hawileh [37]
Assessing post-earthquake structural safety	CART, RF	Zhang and Burton [38]
Classification of building damages from textural document	Long short-term memory (LSTM)	Mangalathu and Burton [40]
Predicting the seismic response and structural collapse	MLR, ridge regression, DT, RF, AdaBoost, ExGBT, Naıve Bayes, (NB), KNN	Hwang et al. [40]
Quantification of seismic behavior of RC buildings	Locally weighted least squares support vector machines for regression (LWLS-SVMR), coupled simulated annealing, (CSA), Grid search (GS)	Luo and Paal [36]
Predicting seismic damage state	ANN	Morfidis and Kostinakis [42]
Predicting the seismic response of structures	CNN	Oh et al. [43]
Predicting the fundamental period of vibration of infilled frame reinforced concrete structures	Artificial bee colony (ABC)	Asteris [44]
Detecting damage in reinforced concrete frames	DT	Su and He [45]
Predicting damage of steel frame structures	ANN	Liu and Zhang [46]

3. Real-time Prediction Systems

Real-time seismic response prediction systems represent a crucial application of deep learning in structural engineering. These systems have evolved significantly, with frameworks like SeisGPT leading the way in providing rapid, accurate predictions of structural responses during seismic events. The implementation of these systems typically involves a combination of deep learning architectures and high-performance computing infrastructure to deliver real-time predictions (Woollam, J) [47].

Modern real-time prediction systems utilize advanced preprocessing techniques and optimized neural network architectures to minimize computational overhead while maintaining high accuracy. The integration of Parametric Exponential Linear Units (PELU) and dropout layers has significantly improved the robustness and efficiency of these systems (Zhang, R) [23]. These architectural improvements have enabled faster processing of seismic data streams while maintaining high prediction accuracy.

Recent developments in real-time systems have focused on reducing latency and improving scalability. The implementation of distributed computing frameworks, coupled with optimized deep learning models, has enabled these systems to process multiple data streams simultaneously. This capability is particularly crucial for monitoring large-scale structural systems or multiple structures across seismic regions (Liu, T) [8].

The effectiveness of real-time prediction systems has been enhanced through the integration of cloud computing and edge computing technologies. These advancements have enabled more efficient distribution of computational loads and reduced response times in critical situations. The implementation of automated model updating mechanisms ensures that these systems maintain their accuracy over time, adapting to new seismic data and structural conditions (Woollam, J) [47].

The latest generation of real-time prediction systems incorporates uncertainty quantification methods, providing not just predictions but also confidence intervals for their estimates. This feature is particularly valuable for decision-making during seismic events, allowing engineers and emergency responders to make more informed choices based on the reliability of predictions. The continuous improvement in deep learning frameworks and computing infrastructure suggests that future real-time prediction systems will offer even greater accuracy and reduced latency, further enhancing their utility in seismic structural analysis and emergency response scenarios.

4. Observations From Past Research:

- This review has illuminated the significant strides made in applying artificial intelligence to seismic analysis of structures over the past decade. The evolution of AI applications in this field has demonstrated remarkable progress, particularly in the development and implementation of various machine learning techniques. From the early applications of genetic programming in 2009 to the recent advancements in deep neural networks, the field has witnessed a continuous refinement of methodologies and approaches (Chen, S) [9].

- The analysis reveals that artificial neural networks (ANNs) have emerged as particularly effective tools, consistently achieving accuracy rates above 90% in seismic response predictions (Sun, Y) [48]. The integration of physics-informed neural networks has further enhanced the reliability of these AI-driven approaches, bridging the gap between traditional analytical methods and modern computational techniques.

- Looking forward, several recommendations emerge for advancing AI applications in seismic analysis. First, there is a need for greater integration of uncertainty quantification in AI models, particularly for critical infrastructure applications. Second, the development of hybrid approaches that combine physics-based modeling with data-driven techniques shows promise for improving prediction accuracy while maintaining physical consistency. Third, efforts should be directed toward creating standardized benchmarking datasets and evaluation metrics to facilitate meaningful comparisons between different AI approaches.

- The field would benefit from increased collaboration between structural engineers, seismologists, and AI researchers to address these challenges. Additionally, future research should focus on improving the interpretability of AI models, particularly for complex deep learning architectures, to enhance their acceptance in practical engineering applications. The successful implementation of these recommendations will require continued investment in both computational resources and experimental validation, ultimately leading to more resilient structural design and more effective seismic risk mitigation strategies.

- Artificial intelligence (AI) has significantly expanded the capabilities of structural engineering, particularly in seismic. In earthquake engineering, machine learning (ML) and deep learning (DL) algorithms have enhanced the accuracy of damage assessments, facilitated real-time monitoring, and guided adaptive design strategies. Diverse methods—ranging from artificial neural networks (ANNs) to boosting algorithms—have demonstrated strong predictive performance for drifts, deflections, strength, and other key parameters, ultimately improving resilience against seismic hazards.

- Collectively, the studies underscore AI's growing importance in advancing knowledge, streamlining analyses, and promoting sustainable, resilient structural systems. Despite challenges such as data quality, interpretability, and computational demands, ongoing research and interdisciplinary collaboration are likely to refine these AI methodologies. As the field continues to integrate advanced computing techniques with domain-specific insights, AI is poised to play an increasingly critical role in shaping the future of seismic.

5. Conclusion

The application of artificial intelligence in seismic analysis of structures has shown remarkable progress, yet several significant challenges and limitations need to be addressed for its widespread adoption and reliability. One of the primary challenges lies in data availability and quality. While seismic events generate vast amounts of data, the collection, processing, and standardization of this information remain complex tasks. The inherent variability in structural responses, ground motion characteristics, and environmental conditions creates challenges in developing comprehensive datasets that can effectively train AI models.

Model reliability and generalization present another crucial challenge. Current AI models often perform well on specific datasets but may struggle when confronted with new, unseen scenarios. This limitation becomes particularly critical in seismic analysis, where the consequences of incorrect predictions could be catastrophic. The integration of physics-based constraints and domain knowledge into AI frameworks requires careful consideration to ensure the models remain both accurate and physically meaningful.

Computational efficiency continues to be a significant concern, especially when dealing with large-scale structural systems. The real-time analysis requirements for early warning systems and rapid post-earthquake assessment demand efficient algorithms that can process and analyze data quickly without compromising accuracy. The balance between model complexity and computational resources needs careful optimization.

Looking toward future directions, several promising avenues emerge for addressing these challenges. The development of hybrid approaches that combine traditional numerical methods with AI techniques shows potential for improving model reliability while maintaining computational efficiency. These hybrid models can leverage the strengths of both approaches, using physics-based understanding to guide and constrain AI predictions.

Data augmentation and synthetic data generation techniques offer solutions to the data scarcity problem. Advanced generative models can create realistic seismic scenarios, helping to expand training datasets while maintaining physical consistency. However, the validation of such synthetic data requires careful consideration of path effects and spatial correlations between different stations and sources.

The integration of uncertainty quantification in AI models represents another crucial direction. Future research should focus on developing frameworks that not only provide predictions but also quantify the associated uncertainties. This becomes particularly important in risk assessment and decision-making processes for structural safety.

The advancement of explainable AI (XAI) techniques specific to structural engineering applications presents another important research direction. Understanding how AI models arrive at their predictions is crucial for building trust among practitioners and ensuring safe implementation in critical applications.

Scientific machine learning (SciML) shows promising potential in addressing the unique challenges of geoscience applications, including seismic analysis. The field's ability to handle sparse direct measurements, unbalanced data distribution, and inevitable noise makes it particularly relevant for advancing structural engineering applications.

Future developments should also focus on creating standardized benchmarks and evaluation metrics specific to seismic analysis applications. This standardization would facilitate fair comparison between different approaches and help establish best practices in the field. The organization of workshops and data competitions could accelerate progress by bringing together experts from both geophysics and machine learning communities.

The integration of real-time monitoring systems with AI-based analysis tools represents another promising direction. Such integration could enable more effective early warning systems and rapid post-earthquake assessment capabilities. However, this requires addressing challenges related to data transmission, processing speed, and reliability under emergency conditions.

As we move forward, the focus should be on developing more robust and reliable AI systems that can handle the complexities of seismic analysis while maintaining practical applicability. This includes improving the interpretability of AI models, enhancing their generalization capabilities, and ensuring their reliability under various operating conditions. The continued collaboration between structural engineering experts and AI researchers will be crucial in advancing these developments and addressing the current limitations in the field.

Future orientation in machine learning and deep learning encompasses a range of applications, for predicting earthquake-induced structural damage, demonstrating the value of handling complex, high-dimensional data while reducing reliance on extensive experimentation.

Transparency and explainability are essential to foster trust in AI-driven decisions within structural engineering, where safety is paramount. Interpretable models enable stakeholders to validate and embrace AI solutions more confidently.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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