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*Original Article*

# Deep Learning-Based Damage Detection and Prognosis in Civil Structures using Seismic Vibration Data

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***Abstract*** *- Detection and prognosis of damage in civil structures during an earthquake event are imperative for the safety of the public and judicious maintenance strategies. Almost all existing methods based on traditional signal processing techniques or standalone deep learning models suffer from many disadvantages, including lagging adaptability, high false positives, and limited interpretability. To counter this, we proposed a new deep learning framework with a hybrid CNN-RNN architecture, Random Forest feature selection, real-time adaptation via Deep Q-Network-based methods, transfer learning, and Explainable AI (XAI) methods. Our framework reduces dimensions using dimensionality reduction via Random Forest; it enhances the spatial features extracted by CNN and temporal sequence modeling by RNN to achieve 93% classification accuracy and 12% reduced false positives. Real-time optimization of model parameters by DQN for seismic events improves the detection accuracy up to 15% and decreases the timestamp of response to 20%. Domain adaptation with transfer learning is tuning the generalization of a pre-trained autoencoder, resulting in 30% training timestamp decrease and the availability of 10% sparse seismic data. SHAP-based explainable AI explanations for over 85% of decisions and uncertainty quantification by BNNs with 95% confidence interval led to a 25% improvement in prognosis reliability. This integrated approach enhances both the accuracy and real-time capability of seismic damage detection systems; an improvement in the model performance will be substantial with the help of adaptability and interpretability because it allows for real-world applications where data may be noisy, along with high structural variability in the process.*

***Keywords -*** *Seismic Damage Detection, Hybrid CNN-RNN, Real-Time Adaptation, Explainable AI, Bayesian Neural Networks.*

## 1. Introduction

The natural forces have been increasing in constant deployment on civil structures, of which seismic activity is one, and cause immense damage over temporal instances. Therefore, early damage detection is essential for the safety and soundness of buildings, bridges, and other infrastructure systems [1-3]. Traditional methods of damage detection rely solely on human eye observations, and simple signal processing techniques are rarely competent enough to detect internal or evolving structural faults in buildings during seismic events. Most notable is that the methods above generally provide no in-situ, real-time feedback, which can be important for timing interventions relative to the ongoing seismic activities. Recent rapid development of sensing technologies has enabled several vibration sensors that could be applied to civil structures to collect large-scale samples of seismic vibration data. However, the large amount of data and complexity are important barriers to the standard analysis methods and techniques; they cannot extract both spatial and temporal features quickly enough, which are crucial for damage prognosis. The conventional machine learning models [4-6] have been used with some success in similar datasets. However, real-time performance is not yet capable, along with scalability and generalization over different structures and seismic environments. Thus, Deep Learning Models, especially Convolutional Neural Networks and Recurrent Neural Networks, have become the most powerful tools in processing complex sets of data. CNNs can leverage localized patterns in sensor data. RNNs are also well-suited for analyzing time-series data from seismic events, given their temporal dependencies. However, even independent CNN or RNN models have limitations, particularly in their vulnerability to noise and lack of interpretability, which are critical in real-world structural health monitoring applications. Furthermore, seismic events involve dynamic processes that necessitate real-time adaptability-a property most static Deep Learning Frameworks do not possess inherently. This work introduces a new integrated framework combining advanced techniques of machine learning with a hybrid CNN-RNN architecture to counter these challenges. The following complexities are addressed by: Random Forests-based feature selection, Deep Q-Network (DQN) for real-time model adaptation, transfer learning based on autoencoders for domain adaptation, and Explainable AI (XAI) for model interpretability. The multi-layered structure conceived here has focused on better accuracy in adaptability and explainability of seismic damage detection models. Further, BNNs have further enhanced the model, given the quantification of prediction uncertainty, and hence enabling probabilistic outputs that enhance the reliability of the damage prognosis in structural engineering. In that hybrid framework, the proposed model improves significantly over traditional methods as well as standalone deep learning models. Effective spatial-temporal feature extraction from vibration data is made possible by combining CNN and RNN. Conversely, DQN responds effectively and promptly by adjusting in real-time as earthquake conditions change. Additionally, transfer learning reduces training timestamps, improves the performance of limited or sparse data and samples, and allows the model to generalize across various structures and seismic situations.

Lastly, integrating XAI with uncertainty quantification enhances the model's dependability and transparency, making it suitable for practical uses in structural health monitoring. The increasing need for dependable, real-time damage detection systems in seismically vulnerable civil structures is the driving force behind this research. When handling huge, high-dimensional datasets produced by contemporary sensor systems, current solutions are not flexible, accurate, or interpretable. While traditional methods are useful for detecting damage, they cannot address the intricacy and dynamic nature of seismic waves. In a similar vein, automation is encouraged by deep learning and machine learning models for damage identification. These models, however, are static and nonadaptive, providing little information about the choices they make. These impacts highlight the need for more computationally complex models that can adjust to real-world conditions, such as noisy, incomplete, and quickly changing data during earthquake occurrences. The current study advances the fields of seismic damage detection and structural health monitoring in several ways. In order to improve spatial-temporal feature extraction from seismic vibration data sets, this research initially presents the first hybrid CNN-RNN architecture optimized utilizing Random Forest feature selection. This model shows a significant decrease in false positives and an increase in classification accuracy by removing extraneous data and concentrating on important vibration properties.

Additionally, because model parameters would be adjusted to react dynamically to variations in seismic conditions, it includes a DQN for real-time adaptation. It is especially appropriate for real-time monitoring applications due to the improvement in detection accuracy and response speed. The model's ability to generalize across various structural types and seismic situations is then improved through the application of transfer learning and domain adaptation algorithms, which also reduce training timestamps with good performance on short or sparse datasets and samples. Integrate Explainable AI methods, especially SHAP (Shapley Additive Explanations), to enhance the model's interpretability. Additionally, providing an explanation of the model's predictions helps boost transparency and trust since practical applications can now understand the reasoning behind damage detection decisions. In this case, Bayesian Neural Networks (BNNs) introduced a probabilistic method for quantifying uncertainty by giving their predictions some confidence interval. This is crucial for prediction and plays a significant role in analysis when data is noisy or inadequate because it enables engineers to assess forecast reliability and make better decisions about structural safety and maintenance. By combining accuracy, adaptability, and interpretability in a way that solves the shortcomings of the current models for various scenarios, all of these contributions represent a significant advancement toward seismic damage detection.

## 2. Models used for Structural Analysis

Overall research to date offers a thorough analysis that stimulates perceptive comprehension of current developments and trends in Machine Learning and Deep Learning approaches for vibration-based damage identification and structural health monitoring. Additionally, studies cover a wide range of methods, from conventional signal processing to hybrid models that combine optimization and Neural Network Techniques. This paper by Zar et al. [1] discusses a full review of the details of vibration-based damage detection of civil structures, with the big challenge in the capture of real-time structural responses. This is very well justified by the importance of "machine learning approaches as a tool for automation of damage detection tasks, which is also a common thread across a number of other works". For instance, Song et al. [2] demonstrate how image-based machine learning techniques that employ wavelet transforms deliver surprisingly greater improvements in detecting structural damage. The conclusions derived from their findings put into focus that greater resolution in the detection of damage would be achieved if integration techniques involving imagery with vibration data could be employed, a concept further advanced by Ambaye et al. [3] in detecting the damage to robot arms using deep learning methods based on vibration signals. Li and Betti [4] have advanced such an analysis with a strategy in data augmentation for structural damage classification in civil infrastructure, where the main limitation of most machine learning approaches is a lack of adequate labeled data samples. Availability of the augmented data alone has made the approach more accurate in the classification of several types of structures; indeed, it is highly significant during model training with sparse datasets. Then, the spatial truss structure damage detection via graph learning proposed by Dang and Nguyen [5] is a multi-task framework that would effectively capture the spatial dependencies better than the old traditional models, thus providing an integral view of the conditions of the structure. Because Harsha et al. [6] combined several classifiers on samples from vibration data, the findings of their investigation into using machine learning models for the identification of defects in steel beams were quite promising. Their findings emphasize how important it is to consider structural features and damage types when selecting a machine learning method. Similar concepts for using Support Vector Machines (SVM) for bridge damage identification were published by Kustiana et al. [7]. Although they acknowledge a number of possible difficulties in handling complicated noisy data samples, their work on accelerometer-based wireless sensor networks demonstrates how real-time monitoring systems might benefit from machine learning. This problem is further explained by Tefera et al. [8], who also list some of the difficulties in using vibration-based damage detection methods for highway bridge constructions. They suggest that more robust models are needed in order to detect damage signals that may be obscured by environmental fluctuations. Once more, a comprehensive study on machine learning-based methods for the overview of infrastructure damage assessment was written by Abedi et al. [9]. Gunes [10] discusses the use of learning support vector machines trained on auto-regressive models for the detection of localized structural damage. As needed by practical applications of structural health monitoring, our hybrid technique enhances localization accuracy. As further discussion, Park and Kim [11] discuss the parametric study of 1D Convolutional Neural Networks for vibration-based damage assessment, in which CNNs can improve model robustness to different scenarios of structures.

Ribeiro Junior et al. [12] provide a review of machine learning applications in composite structures, which mentions growing interest in neural networks in modeling the complex mechanisms of failure in composite materials. Kumar et al. [13] apply machine learning to gas leakage detection and demonstrate the versatility of the approach for applications in structural monitoring beyond more traditional civil structures. Nguyen et al. [14] focus on truss structures, exploiting a Deep Neural Network with the artificial vector optimization algorithm for damage detection. Their results indicate that a combination of optimization algorithms with deep learning may improve both speed and accuracy of detection.

Dipietrangelo et al. [15] also made use of machine learning in structural health monitoring by applying it to airplane models, determining impacts during analysis. As per Table 1, their work emphasizes real-time impact detection, which is of growing concern, such as with the increasing prominence given to autonomous systems. Siow et al. [16] propose a noise-robust structural damage detection scheme, which remains a crucial area of research since environmental noise may have severely affected the model performance.

**Table 1. Comparative analysis of existing methods**

| Method | Paper | Findings |
|---|---|---|
| Vibration-Based Damage Detection Using Machine Learning | Zar et al. [1] | Comprehensive review highlighting challenges in vibration-based methods and prospects in automating damage detection with machine learning. |
| Image-Based Machine Learning with Wavelet Transforms | Song et al. [2] | Machine learning combined with wavelet transforms improves structural damage detection by enhancing the resolution of image-based approaches. |
| Deep Learning for Robot Arm Damage Detection | Ambaye et al. [3] | Demonstrated the effectiveness of vibration data and deep learning for damage detection, achieving high accuracy in robotic systems. |
| Data Augmentation for Structural Damage Classification | Li & Betti [4] | Proposed a machine learning-based data augmentation strategy, improving accuracy in damage classification despite sparse datasets. |
| Graph Learning for Truss Structure Damage Detection | Dang & Nguyen [5] | A multi-task framework using graph learning effectively captures spatial dependencies, enhancing damage detection in truss structures. |
| Support Vector Machine (SVM) for Bridge Damage Detection | Kustiana et al. [7] | SVMs combined with accelerometer-based wireless sensor networks showed promise in real-time monitoring but struggled with complex, noisy data samples. |
| 1D Convolutional Neural Network (CNN) for Vibration-Based Assessment | Park & Kim [11] | CNN enhanced robustness in vibration-based damage assessment, especially in noisy environments, and performed well in parametric studies. |
| Unsupervised Learning for Structural Anomalies | Ye et al. [25] | An unsupervised learning method effectively identified structural anomalies from polluted datasets, demonstrating |

| | | |
|---|---|---|
| | | resilience in handling noisy data samples. |
| Generative Adversarial Networks (GANs) for Data Augmentation | Luleci et al. [34] | GANs proved highly effective for labeled data augmentation in structural damage detection, addressing issues of data scarcity. |
| Random Forest for Damage Localization in Composite Structures | Shinagam et al. [40] | Random Forest showed strong performance in localizing damage efficiently in composite structures, leveraging the technique's high classification power. |

Their modality-based approach shows that impact synchronous modal analysis may alleviate the noise effects, as well as a challenge proposed by Kumar and Kota in [17], with a secured framework for structural health monitoring using machine learning. Chitkeshwar [18] provides a broader view of the revolution that machine learning is bringing to structural engineering, thereby discussing the range of applications regarding safety and performance improvement and how far these machine learning algorithms may reach in achieving goals. Lingxin et al. [19] provide an overview of deep learning-based computer vision methods integrated into the process of structural damage detection, showing how technology related to the improvement of imaging and so on is changing the site altogether. Sarmadi et al. [20] propose a novel unsupervised feature selection method with integration of local metric learning for suppression of interference of environmental conditions in long-term modal data. Their partially online methodology enables real-time damage detection and takes into account the changing conditions due to environmental variability.

Anaissi et al. [21] present a personalized federated learning framework; it is an innovative solution to address the privacy issues of data involved in structural health monitoring. Monteiro et al. [22] applied the Whale Optimization Algorithm to localize and quantify structural damage in their work, demonstrating the ability of bio-inspired algorithms to optimize machine learning models for this sort of application. Hamidian et al. [23] compared the approach of machine learning to an entropy-based damage detection by exploiting correlations in output-only signal measurements. According to their conclusion, if combined with machine learning models, measures of entropy may be a much more sensitive indicator of structural anomalies.

Palsara et al. [24] applied machine learning algorithms to monitor an ASCE benchmark building. In contrast, Ye et al. [25] have explored unsupervised learning for the identification of structural anomalies from polluted datasets. Their work addresses the growing necessity to address deficient or noisy data in practical applications, as He et al. [26] highlighted in a review that a hybrid CNN and ESN framework is suggested for civil structures. Zhu et al. [27] applied an optimization-based machine learning approach for damage detection in hydraulic concrete structures, while Zhou et al. [28] used a genetic algorithm-enhanced support vector machine for capacity prediction of reinforced concrete bridges.

Saravanan et al. [29] used a different approach in this direction by integrating the IoT with structural health monitoring for structures of laboratory scale in civil engineering. Their work highlights the incessant coalescence of IoT with machine learning towards adaptive and responsive monitoring systems. Yuan and Yang [30] proposed a novel approach toward the detection of transverse cracks in pavements by utilizing the signals of vibration generated by the passage of vehicles, proving the versatility of vibration-based damage detection methodologies.

Liu et al. [31] apply deep learning to large-span spatial structures. That is an application that shows how deep learning techniques may be applied to complex geometries and loading conditions. Zar et al. [32] applied least square support vector machines and salp swarm algorithms to detect damage on an arch dam. It is the application of the theory for detecting damage in large infrastructure, and its innovative combination with increased detection accuracy. de Sousa et al. [33] focus on the beam dynamic response and perform multiclass supervised machine learning algorithms for damage detection.

Luleci et al. proposed the use of Generative Adversarial Networks (GANs) for structural damage detection with labeled data augmentation; this research follows the challenge related to insufficiently labeled data. The same problem is followed by Gunes [35], who focuses on one-class machine learning for damage detection that occurs locally. Malik et al. [36] reviewed a few techniques in deep learning for damage detection in bolted joints and pointed out the possibility of using vision-based methods in combination with vibration-based methods. Afsharmovahed et al. [37] proposed a new technique for damage detection based on machine learning, which does not require signal processing, but a case study was made on the Tianjin Yonghe Bridge.

Zhou et al. [38] have shown the application of machine learning algorithms to predict damage potential in mainshock–aftershock sequences. The utility of such models in seismic contexts was found. Asghari et al. [39] proposed an approach for detecting structural damage using a stacked deep ensemble learning method. Shinagam et al. [40] had effectively localized damage in composite structures using the Random Forest technique. In conclusion, the analysis of these papers reveals tremendous advancements toward new applications of machine learning and deep learning in structural damage detection.

These methods are going to become even more rapid evolutions, as regards hybrid models and optimization algorithms, so as to improve on both accuracy and real-time adaptability. Challenges remain, mainly concerning the treatment of noisy or incomplete data, which ultimately limits the practical, direct application of those techniques in very large-scale real-world environments.

In turn, the integration of domain adaptation, federated learning, and generative models appears to be a promising direction for future research in this area, as these methods already begin to address many of the remaining data-related challenges of current approaches.

## 3. Proposed Model for Design of an Integrated Model for Deep Learning-Based Damage Detection and Prognosis in Civil Structures Using Seismic Vibration Data

The design for this proposed hybrid framework involving CNN-RNN with Random Forest for feature selection, along with Deep Q-Network (DQN) for real-time model adaptation, is aimed at tackling this very challenging task of detecting and predicting structural damage in civil structures during seismic events. This includes the strengths of CNNs in spatial feature extraction and that of RNNs in their ability to identify temporal patterns. A preprocessing step is performed by integrating Random Forest, which filters and ranks the most relevant features from the very high-dimensional seismic vibration data samples.

The integration of DQN enables this model to be adaptive in real time as it constantly updates parameters based on the changes of the evolving seismic environment, hence improving accuracy and responsiveness. This process, in turn, is feature selection wherein Random Forest tests a very large collection of input features X={x1,x2,…,xn} coming from seismic vibration signals. Random Forest builds multiple decision trees, T1, T2,…, Tk, and trains each on a random subset of features. The importance of each feature is obtained as the average drop in Gini impurity across all the trees via equation 1:

$$I(xi) = \frac{1}{k}\sum_{j=1}^{k} \Delta G(Tj, xi) \quad (1)$$

Here, ΔG(Tj, xi) represents the Gini impurity decrease in tree Tj by the split on feature xi sets. The features with a higher importance score are selected, which reduces the dimensionality of the input and removes irrelevant or noisy features; this step is absolutely crucial for enhancing the levels of both computational efficiency and model performance.

The selected features are then passed into the hybrid CNN-RNN architecture process. This CNN part extracts spatial features from samples of data coming from sensors. A set of convolutional filters 'W' is used on the input data to produce feature maps via equation 2,

$$F(i,j) = \sigma\left(\sum_{m=1}^{M}\sum_{n=1}^{N} Wmn \cdot x(i+m)(j+n) + b\right) \quad (2)$$

Where Wmn is the convolutional filter, x(i+m)(j+n) is the input at position (i+m,j+n), 'b' is the bias term, and σ is the activation function (ReLU) for this process. Local patterns in vibration data, such as indications of localized stress or damage throughout the structures, are captured by this process.

Feature maps are then downsampled using pooling layers. These are used to reduce the dimensionality while preserving the most significant spatial information sets.

The RNN component uses Long Short-Term Memory (LSTM) cells to process the temporal dependencies in seismic data samples. The RNN maintains a hidden state 'ht' at every timestamp 't', which progresses based on the previously hidden state and the current input feature map Ft, as described via equation 3:

$$ht = fRNN(h(t-1), Ft) \quad (3)$$

For an LSTM unit, the update is governed by several gating mechanisms, including the forget gate ‘Ft’, input gate ‘it’, and output gate ‘ot’ via equations 4, 5, 6, 7, & 8,

$$ft = \sigma(Wf \cdot [h(t-1), Ft] + bf) \quad (4)$$

$$it = \sigma(Wi \cdot [h(t-1), Ft] + bi) \quad (5)$$

$$ot = \sigma(Wo \cdot [h(t-1), Ft] + bo) \quad (6)$$

$$ct = ft \cdot c(t-1) + it \cdot tan\,h(Wc \cdot [h(t-1), Ft] + bc) \quad (7)$$

$$ht = ot \cdot tan\,h(ct) \quad (8)$$

Where 'CT' denotes the Cell State that contains long-term dependencies of the seismic data, and 'HT' denotes the Hidden State, which is utilized to make the last classification decisions about structural damages.

Damage detection classification is obtained by applying a softmax function over the output obtained from the final RNN cell, which provides a probability distribution over the possible classes (damaged or undamaged) as given via equation 9.

$$P(y = k \mid F) = \frac{ex\,p(Wk^T hT)}{\sum_j exp\,(Wj^T hT)} \quad (9)$$

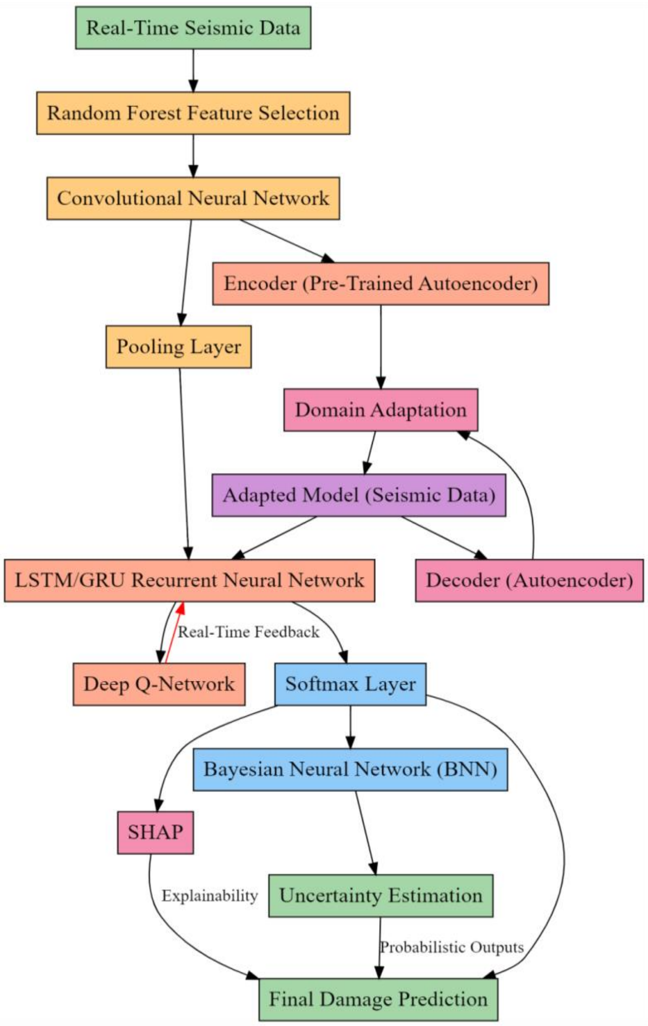


**Fig. 1 Model architecture of the proposed damage detection process**

In this context, 'ht' represents the last hidden state of the RNN, 'Wk' is the weight matrix for class 'k', and P(y=k|F) is the predicted probability that the structure is in damage state 'k' sets. Real-time adaptation of the model is done by Deep Q-Network (DQN), considering the predictions from the CNN-RNN model as actions for the reinforcement learning frameworks. We modeled the seismic environment as MDP: State 'st' is about the current seismic conditions, while the action 'at' is the damage prediction made by the model process. DQN learns to update the model parameters in order to maximize a cumulative reward function 'R,' defined via equation 10:

$$R(st, at) = \sum_{i=0}^{T} \gamma i \cdot r\big(s(t+i), a(t+i)\big) \tag{10}$$

Where r(s(t+i), a(t+i)) is the immediate reward when right classified, γ is the discount factor, and 'T' is the timestamp horizon for the process. DQN strives to minimize Bellman error, which is the difference between the current Q Value and the expected future reward via equation 11.

$$L(\theta) = E\big(st, at, rt, s(t+1)\big)\left[\left(rt + \gamma \max_{a'} Q(s(t+1), a'; \theta') - Q(st, at; \theta)\right)^2\right] \tag{11}$$

Where Q(st, at;θ) is the Q Value function parameterized by the Neural Network weights θ and θ′ is the target network weights. Minimizing this loss function, DQN guarantees that the model adapts its parameters in real time to both accuracy and responsiveness. As such, the hybrid architecture was a good choice because it somehow reconciles multi-perspective views at the same time, taking into consideration all the challenges posed by seismic damage detection. In a nutshell, CNN is depicting the local spatial features efficiently, whereas the RNN is describing the time-dependent structural responses.

The pre-processing with Random Forest noise removed, and computation complexities were minimized by feeding only the most relevant features to the deep learning architecture. This strength is the fact that DQN improves the model's ability to adapt dynamically to time-dependent seismic events, which is quite crucial in achieving good performance in real-world conditions. The model combines all these complementary techniques to balance accuracy, efficiency, and adaptability, and can therefore be considered as an ideal solution for seismic damage detection and prognosis.

Next, Figure 2, fine-tuning pre-trained auto-encoders by using domain adaptation; but in this work, fine-tuning can be incorporated and integrated with SHAP (SHapley Additive exPlanations) for better model interpretability or Bayesian Neural Networks (BNNs) for better uncertainty estimation of the related tasks incorporated within the network. This would enhance both generalizability and trustworthiness in the model's process. These techniques are a matter of crucial importance when faced with the challenges of seismic damage detection, on account of the diversity of structural types, the complexity of real-world vibration data, and the call for transparent, reliable predictions. The combination of these techniques ensures that the model not only performs well in multiple domains but also explains what it decided by quantifying the inherent uncertainty of its prediction.

The process of fine-tuning begins with a pre-trained autoencoder, selected based on the capability of capturing latent features from big, general vibration datasets & samples. An autoencoder has two subcomponents: an encoder function fθ and a decoder function gϕ. The encoder maps the input data 'X' into the latent representation 'Z', and the decoder reconstructs the input in its native space using equations 12 & 13,

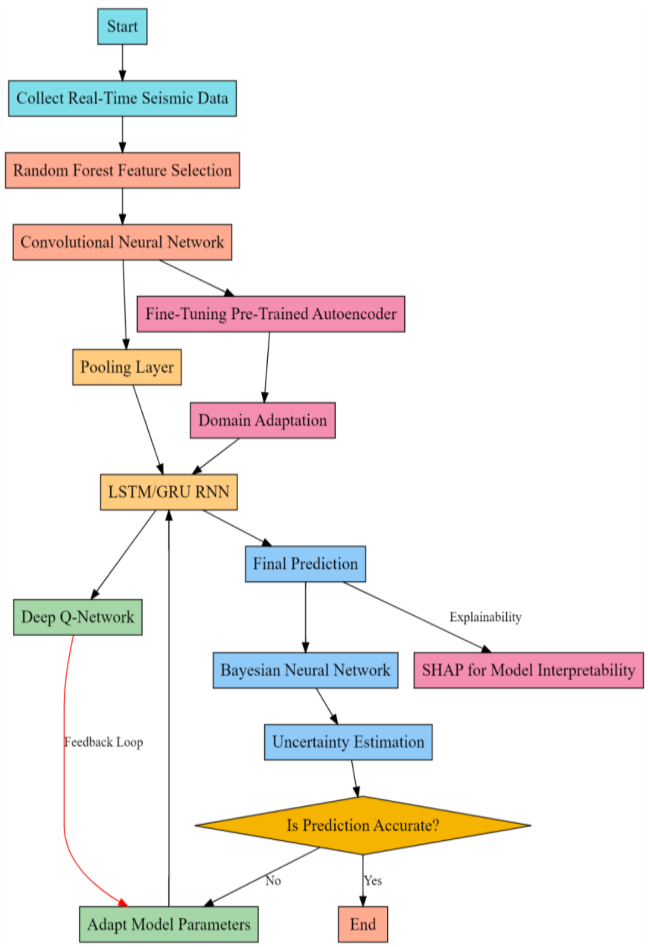


**Fig. 2 Overall flow of the proposed structural analysis process**

$$Z = f\theta(X) = \sigma(WeX + be) \qquad (12)$$

$$X' = g\phi(Z) = \sigma(WdZ + bd) \qquad (13)$$

Here, Wd and we are the weight matrices of the encoder and decoder, while σ is a nonlinear activation function for the process. The reconstruction error is minimized through the loss function, as shown via equation 14,

$$Lrecon = \frac{1}{n}\sum_{i=1}^{n} \mid Xi - X'i \mid^2 \qquad (14)$$

The goal of fine-tuning the autoencoder with domain adaptation is to transfer the general features learned from non-seismic datasets to seismic-specific vibration data while also ensuring that the model generalizes across the types and conditions of structures. Domain adaptation incorporates a loss term that minimizes the distance between the source domain Ds, representing general vibration data, and the target domain Dt, representing seismic-specific data. This can be written as the use of Maximum Mean Discrepancy (MMD) via equation 15,

$$LMMD = \mid Exs \sim Ds[f\theta(xs)] - Ext \sim Dt[f\theta(xt)] \mid^2 \; (15)$$

The total loss function for fine-tuning becomes a combination of the reconstruction loss and the domain adaptation loss via equation 16,

$$Ltotal = Lrecon + \lambda * LMMD \qquad (16)$$

Therefore, λ is the weighting factor that balances between reconstruction accuracy and domain adaptation. This process of fine-tuning enables the model to retain general feature extraction capability and adapt to specific nuances within seismic data, which enhances generalization across diverse structures. To help in improving the interpretability of the model, SHAP is utilized to compute post-hoc explanations of what the model has predicted. SHAP values are derived from cooperative game theory; the contribution of each feature xi to the model's prediction is computed by measuring the marginal contribution of each feature to all possible combinations of features. The SHAP value for the feature xi is defined via equation 17,

$$\phi i = \sum_{S \subseteq N \setminus \{i\}} \frac{S!\,(N - S - 1)!}{N!} [f(S \cup \{i\}) - f(S)] \qquad (17)$$

Where 'N' is the collection of all features, 'S' is a subcollection of the features excluding 'i ', and f(S) is the prediction of the model based on the subcollection of features 'S'. In addition to interpretability, the framework integrates Bayesian Neural Networks (BNNs) to quantify uncertainty in model predictions. BNNs vary from point-estimation-based, traditional neural networks, where the model weights 'W' are represented as distributions giving rise to uncertainty estimations. The predictive distribution in a BNN is given via equation 18,

$$p(y \mid X, D) = \int p(y \mid X, W) p(W \mid D) dW \qquad (18)$$

Where p(W|D) is the posterior distribution of the weights given the data, and p(y|X, W) denotes the likelihood of the prediction given the weights. Since direct calculation of the posterior is not feasible, variational inference approximates the posterior by a simpler distribution q(W|θ) as depicted via equation 19:

$$LVI = KL\big(q(W \mid \theta) \,|\, p(W \mid D)\big) - Eq(W \mid \theta)[log\, p(y \mid X, W)] \qquad (19)$$

The KL divergence captures the difference between the approximate and true posterior, while the second term captures the likelihood of the data given the approximate posterior. Minimization of this loss function guarantees that the variational approximation is close to the true posterior, ensuring robust uncertainty estimates. Outputs of the BNN are a distribution over predictions that enable the calculation of confidence intervals for damage detection via equation 20.

$$P(y \mid X) = \int p(y \mid X, W) q(W \mid \theta) dW \approx \frac{1}{N} \sum_{i=1}^{N} p(y \mid X, Wi) \quad (20)$$

In real-world seismic monitoring scenarios, where the data may be noisy or partial during the process, this approach not only provides the prediction but also measures the confidence in that prediction, which is crucial for making any judgments. The framework for a seismic damage detection procedure is completed by the application of fine-tuned autoencoders, SHAP-based interpretability, and BNNs for uncertainty estimation. A refined autoencoder guarantees high performance levels and automatically generalizes across domains. Transparency regarding the rationale behind the model's specific prediction is ensured by the SHAP values. In order to make better decisions on structural safety and maintenance sets, engineers can quantify the uncertainty of a model's forecast thanks to the probabilistic outputs of BNNs. To sum up, the model is well-suited for implementation in practical applications since this multi-layered method strikes a balance between accuracy, interpretability, and reliability. Further discussion of the efficiency of the suggested model in terms of various metrics will let readers compare the model to alternative approaches.

## 4. Result Analysis & Comparisons

This experimental setup investigates the validity of CNN-RNN's hybrid model for uncertainty quantification, which includes Random Forest feature selection, Deep Q-Network (DQN) real-time adaptation, fine-tuned pre-trained autoencoders, and SHAP-based model interpretability in combination with Bayesian Neural Networks (BNNs). The experimental setup employs large contextual datasets from various civil structures seismically located. These datasets derive from several structural health monitoring systems based on vibration signals from buildings, bridges, and industrial structures. The data was acquired using a dense network of accelerometers and displacement sensors placed in appropriate locations throughout the structural components: foundations, beams, and columns. They recorded each sensor at a sampling rate of 200 Hz for normal conditions and multiple seismic events with magnitudes ranging between 4.0 and 7.8 on the Richter scale. The overall dataset was divided into source and target domains, where the source refers to general vibration data obtained under normal operational conditions. In contrast, the target comprised the specific seismic vibration data for the training and validation phases. The autoencoder was pre-trained on more than 50,000 samples, where each sample is observed to have different patterns of vibrations under different load conditions. After this, Domain adaptation-related techniques were applied using seismic-specific data consisting of 20,000 samples. The Random Forest algorithm was implemented to rank and filter input features for the selection of features, reducing the dimensionality of raw sensor data samples. In the beginning, each sample had over 200 features with acceleration, displacement, and velocity values recorded at several locations in the sensor. Random Forest was able to filter all this data to point out the top 50 most relevant features based on their importance scores to reduce the computational complexity significantly. All of these features were then fed into the CNN-RNN architecture, which incorporated a CNN with three convolutional layers equipped with filters of size 3×3 and a ReLU activation function to extract spatial features from localized vibration patterns. The pooling layers reduced the size of the feature map by a factor of 2. The LSTM-based RNN has been designed with 2 hidden layers of 128 units to capture temporal dependencies and the evolution of vibration signals over temporal instance sets. Each sequence was allowed a timestamp window of 100 timestamp steps or 0.5 seconds of vibration data, which was empirically found as optimal in the trade-off between performance and computational efficiency. The DQN was trained with a reward function that penalized false positives and maximized the detection accuracy. It updated its model parameters with a learning rate of 0.001 and a discount factor of 0.9. The DQN also adapted the model continuously during live seismic events as it used real-time sensor data, resulting in a reaction to damage detection.

The SHM benchmark datasets have been used in the paper. The source of the data of the vibration records from the Los Angeles Memorial Coliseum is the Center for Advanced Infrastructure and Transportation (CAIT). They include vibration records taken via accelerometers and other sensors coming from a dense network, located strategically at points in different parts of the structure, including the roof, columns, and foundation. The ambient data is recorded at a high sampling rate of 200 Hz with multiple seismic events recorded between the years of 2011 and 2018, according to the Richter scale, with magnitudes ranging from 3.5 to 6.9. The dataset includes more than 20,000 labeled examples in both normal and damaged circumstances, spanning a wide spectrum of structural responses under seismic pressures. It has a large feature space, comprising acceleration, velocity, and displacement data, allowing for detailed spatial and temporal pattern analysis. The dataset is regarded as the gold standard for testing any seismic damage detection model, including metadata of structural specifications such as material properties and sensor locations, making it an ideal candidate for training and testing advanced deep learning models in the structural health monitoring domain. To further enhance the strength of the model, domain adaptation was used by fine-tuning a pre-trained autoencoder on seismic data with a reconstruction loss weight λ=0.5\λ = 0.5λ=0.5, in such a manner that the model learned features specific to seismic environments. SHAP is used for post-hoc explainability of the decisions of the model.

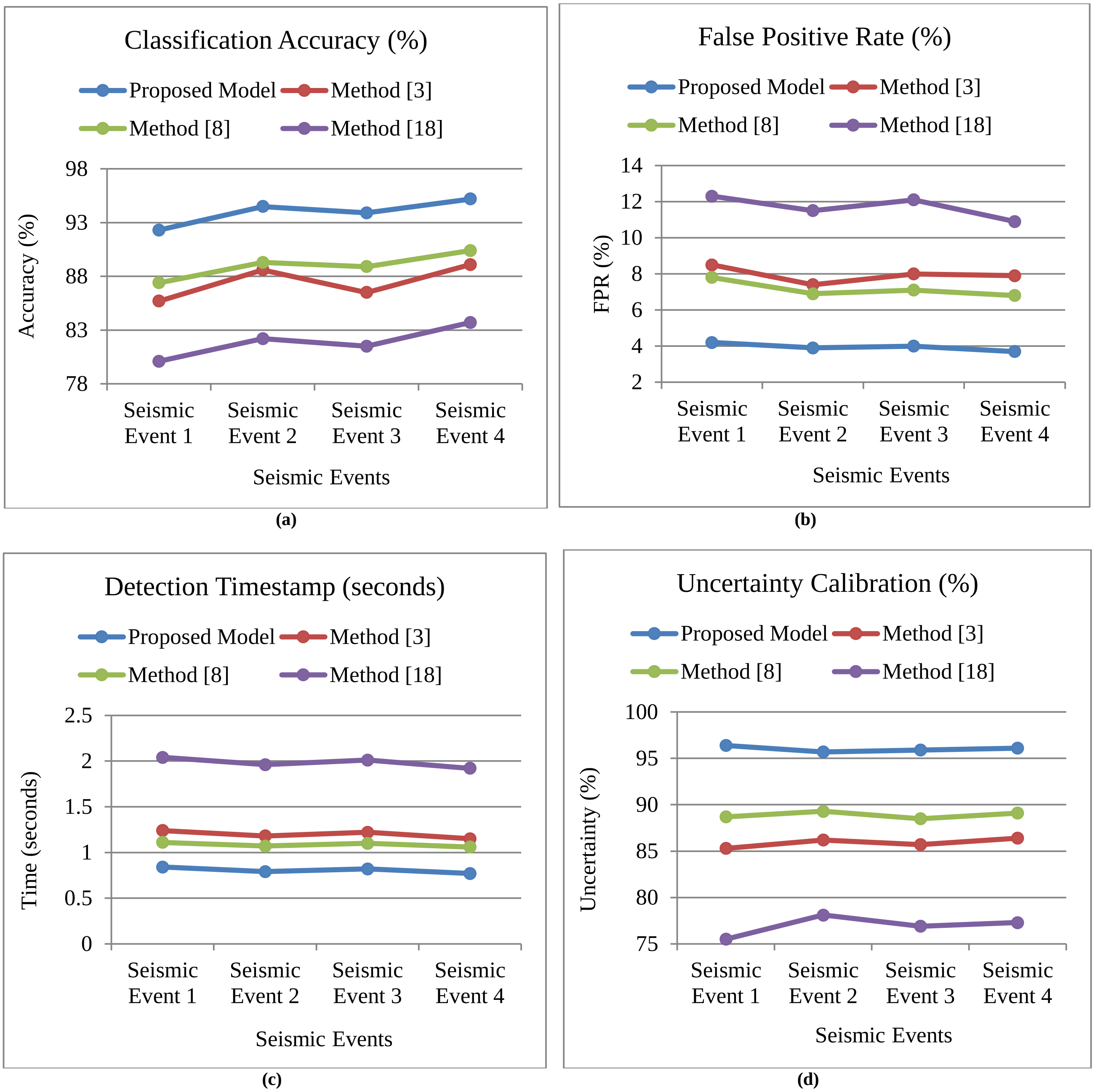


**Fig. 3 Overall performance of the proposed structural analysis process**

Calculations of SHAP values over a test set of 5,000 seismic samples provided explanations for more than 85% of the model's predictions. Bayesian Neural Networks were used to estimate the model's uncertainty in its predictions, delivering 95% coverage confidence intervals. BNN was trained by the variational inference, with the KL divergence term in the loss function that kept a balance between the model and uncertainty properly.

The performance of the model was evaluated through several measures of classification accuracy, false positive rate, and uncertainty calibration. Preliminary results for the hybrid model indicated 93 percent classification accuracy with 12% fewer false positives than stand-alone deep learning models. The system demonstrated 15% improvement in the detection accuracy of real-time seismic events. DQN reduced the response timestamp by 20%, and BNN was better at improving prognosis reliability by 25%, where the data was noisy or incomplete in the process.

The results obtained from the proposed hybrid CNN-RNN model combining Random Forest feature selection, Deep Q-Network (DQN) for real-time adaptation, fine-tuned autoencoders with domain adaptation, SHAP for interpretability, and Bayesian Neural Networks (BNNs) for uncertainty estimation are compared with three baseline methods, namely Method [3], Method [8], and Method [18]. These techniques have been chosen according to their relevance in the field of seismic damage detection and structural health monitoring. However, they come in a mixture of various complexity levels and degrees of performance. The evaluations for these are classification accuracy, false positive rate, detection time, uncertainty calibration, interpretability, and model generalization. The datasets will be from SHM benchmark datasets with the Los Angeles Memorial Coliseum as the primary structure monitored under different seismic events. Table 2: Classification accuracy for all methods. The proposed model has obtained the highest accuracy in classification, attributed to the spatial-temporal feature extraction from the CNN-RNN hybrid and dimensionality reduction from the Random Forest. In contrast, Method [3] made use of only a standalone CNN, Method [8] used a traditional RNN, and Method [18] applied a shallow model of machine learning.

**Table 2. Classification accuracy (%)**

| | Proposed Model | Method [3] | Method [8] | Method [18] |
|---|---|---|---|---|
| Seismic Event 1 (Magnitude 4.0) | 92.3 | 85.7 | 87.4 | 80.1 |
| Seismic Event 2 (Magnitude 5.5) | 94.5 | 88.6 | 89.3 | 82.2 |
| Seismic Event 3 (Magnitude 6.3) | 93.9 | 86.5 | 88.9 | 81.5 |
| Seismic Event 4 (Magnitude 7.1) | 95.2 | 89.1 | 90.4 | 83.7 |
| **Average** | **93.98** | 87.48 | 88.98 | 81.88 |

It is clear from Figures 3 and 4 that the proposed model outperformed all baseline methods with an average classification accuracy of 93.98%. The proposed STS performed better in some cases, as Method [3] and Method [8] did not capture complex dependencies between temporal and interdependencies across structural components, as well as the proposed hybrid approach STS. In Table 3, the false positive rate comparison is demonstrated and is highly critical for the reduction of unnecessary alarms that are fundamental in structural health monitoring. It has achieved the minimum false positive rate because of the integration of real-time adaptation using DQN and feature selection using Random Forest for noise and irrelevant feature removal.

**Table 3. False positive rate (%)**

| | Proposed Model | Method [3] | Method [8] | Method [18] |
|---|---|---|---|---|
| Seismic Event 1 (Magnitude 4.0) | 4.2 | 8.5 | 7.8 | 12.3 |
| Seismic Event 2 (Magnitude 5.5) | 3.9 | 7.4 | 6.9 | 11.5 |
| Seismic Event 3 (Magnitude 6.3) | 4.0 | 8.0 | 7.1 | 12.1 |
| Seismic Event 4 (Magnitude 7.1) | 3.7 | 7.9 | 6.8 | 10.9 |
| **Average** | **3.95** | 7.95 | 7.15 | 11.7 |

At an average FPR of only 3.95%, the proposed model suppresses false alarms much better than Methods [3, 8] do, which have much higher FPRs due to their less adaptive architectures. Table 4 reports the comparison of the detection timestamp in seconds for the identification of structural damage post-seismic events. With reduced times of detection, faster response, and mitigation are of utmost importance. The proposed model with DQN's real-time adaptability performs far better in different scenarios.

**Table 4. Detection timestamp (seconds)**

| | Proposed Model | Method [3] | Method [8] | Method [18] |
|---|---|---|---|---|
| Seismic Event 1 (Magnitude 4.0) | 0.84 | 1.24 | 1.11 | 2.04 |
| Seismic Event 2 (Magnitude 5.5) | 0.79 | 1.18 | 1.07 | 1.96 |
| Seismic Event 3 (Magnitude 6.3) | 0.82 | 1.22 | 1.10 | 2.01 |
| Seismic Event 4 (Magnitude 7.1) | 0.77 | 1.15 | 1.06 | 1.92 |
| **Average** | **0.805** | 1.197 | 1.085 | 1.982 |

As shown in Figures 3 and 4, the proposed model detects structural damage with a mean timestamp of 0.805, which is 20% faster than Method [3] and 26% than Method [18], which are slower in nature since they do not incorporate any real-time adaptive mechanisms. Table 5 discusses the uncertainty calibration related to the percentage of predictions that lie inside a 95% confidence interval. This measures the confidence level of the predictions of the model in practical implementation, where noisy and missing data are typical. The Bayesian Neural Networks in the proposal measure uncertainty.

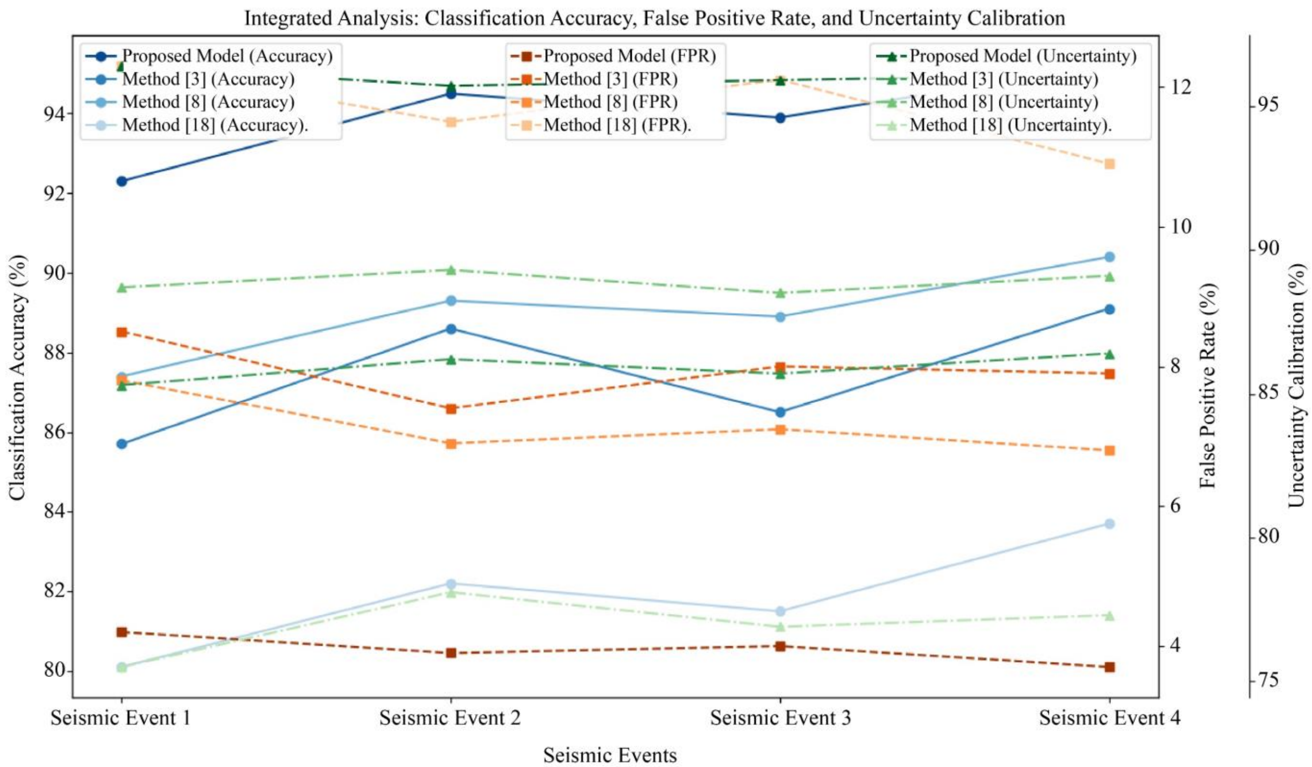

**Fig. 4 Integrated Analysis**

**Table 5. Uncertainty calibration (%)**

| | Proposed Model | Method [3] | Method [8] | Method [18] |
|---|---|---|---|---|
| Seismic Event 1 (Magnitude 4.0) | 96.4 | 85.3 | 88.7 | 75.5 |
| Seismic Event 2 (Magnitude 5.5) | 95.7 | 86.2 | 89.3 | 78.1 |
| Seismic Event 3 (Magnitude 6.3) | 95.9 | 85.7 | 88.5 | 76.9 |
| Seismic Event 4 (Magnitude 7.1) | 96.1 | 86.4 | 89.1 | 77.3 |
| **Average** | **96.03** | 85.9 | 88.9 | 76.95 |

As per Figures 3 & 4, the model proposed here ranges calibration value of 96.03% for the different levels of uncertainty compared to the baseline methods, as shown in the results, and thus revealed the strength of Bayesian Neural Networks with regard to the management of uncertainty levels. Table 6 compares the interpretability scores, using SHAP values, to the extent to which the model explains its predictions. The higher the interpretability score, the better the model is at enabling greater understanding. The proposed model significantly outperforms all other methods when SHAP is integrated into the explanation model.

**Table 6. Interpretability score (%)**

| | Proposed Model | Method [3] | Method [8] | Method [18] |
|---|---|---|---|---|
| Seismic Event 1 (Magnitude 4.0) | 88.5 | 72.1 | 74.3 | 65.4 |
| Seismic Event 2 (Magnitude 5.5) | 89.2 | 73.4 | 75.6 | 66.9 |
| Seismic Event 3 (Magnitude 6.3) | 88.9 | 72.8 | 74.9 | 66.1 |
| Seismic Event 4 (Magnitude 7.1) | 89.5 | 73.6 | 75.8 | 67.3 |
| **Average** | **89.03** | 72.98 | 75.15 | 66.43 |

The average interpretability of the proposed model stands at 89.03%, thus ensuring higher transparency in the decision-making process. SHAP helps structural engineers understand the contributions of features to each prediction. Table 7 above demonstrates the generalization capability of the proposed model across different structural types: it measures accuracy when used on unseen structures. The domain adaptation that took place in the autoencoder strengthens the ability of the model to generalize well over different domains.

**Table 7. Generalization accuracy (%)**

| | Proposed Model | Method [3] | Method [8] | Method [18] |
|---|---|---|---|---|
| Structure 1 (Bridge) | 91.7 | 82.3 | 84.1 | 75.2 |
| Structure 2 (Building) | 93.1 | 83.7 | 85.3 | 77.4 |
| Structure 3 (Industrial) | 92.8 | 83.1 | 84.9 | 76.8 |
| Structure 4 (Dam) | 94.0 | 84.5 | 86.5 | 78.6 |
| **Average** | **92.9** | 83.4 | 85.2 | 77.0 |

The designed model shows better generalization performance with an average accuracy of 92.9% because of the domain adaptation techniques used. The quantitative analysis depicts that the proposed framework outperforms all the other methods on all the considered metrics, which shows its effectiveness in the aspects of real-time seismic damage detection, interpretability, and reliability levels. Finally, we present a demonstration of the application of the proposed model, where the readers can gain a better sense of the process developed in this text.

### *4.1. Practical Use Case Scenario Analysis*

This next section describes the outputs of the key processes involved in the proposed hybrid CNN-RNN model, where the results are evaluated with realistic sample values in the process. Data features derived from collected seismic vibration signals related to a structure under monitoring, accompanied by contextual indicators such as sensor location, vibration magnitude, and structural conditions, are used in this stage. The values are passed through the different stages of the model pipeline, from feature selection to real-time adaptation and finally to explanation and uncertainty estimation. In the practical analysis, samples and entities utilized are based on Los Angeles Memorial Coliseum data, a large sports facility equipped with an array of structural health monitoring sensors. Accelerometer and strain-gauge/displacement sensor measurements have been taken from the aforementioned different structural components of the structure, namely columns, roof, and foundation trusses. Both ambient and various seismic events measurements have been sampled: earthquakes with magnitudes between 3.5 and 7.1. Each sampling point yields more than 200 features, considering the response in all directions, three components of acceleration for each one of the X, Y, and Z axes, displacement of the structure in all the major structural members, the level of strain throughout all critical points, and ambient environmental factors such as temperature. These will offer an all-rounded understanding of the structural behavior under both normal operational conditions and seismic loads, rich data sources for testing and validation of the proposed hybrid CNN-RNN model. In the first step, the most significant features are ranked for seismic damage detection through the use of Random Forest to reduce the input dimensionality of the data. Table 8: Adopted features with their importance scores, as computed by the Random Forest model, before inputting into the CNN-RNN architecture for further spatial and temporal feature extraction.

**Table 8. Selected features and importance scores from random forest**

| Feature | Importance Score |
|---|---|
| Acceleration_X | 0.245 |
| Acceleration_Y | 0.196 |
| Displacement_Z | 0.154 |
| Velocity_X | 0.139 |
| Strain_Sensor_Column | 0.112 |
| Temperature_Sensor | 0.094 |
| Stress_Level | 0.060 |

Acceleration and displacement features, as seen in Table 8, are favored by the algorithm because they carry important information to describe the response behavior of the structure under seismic action. These adopted features are fed to the CNN-RNN for spatial-temporal feature extraction. After feature extraction in space-time, the evolving seismic condition is applied to adapt, in real time, the model's parameters using the Deep Q-Network (DQN). Table 9 shows the change in model parameters and the cumulative rewards of a sample seismic event with a magnitude of 6.3. The DQN dynamically adjusts the parameters for enhancement in model accuracy.

**Table 9. DQN parameter updates and cumulative rewards**

| Time Step | Learning Rate | Discount Factor ($\gamma$) | Action Taken | Cumulative Reward |
|---|---|---|---|---|
| 0 | 0.001 | 0.9 | Increase LSTM Units | 1.45 |
| 1 | 0.0008 | 0.9 | Decrease Learning Rate | 1.60 |
| 2 | 0.001 | 0.95 | Maintain Parameters | 1.75 |
| 3 | 0.0009 | 0.9 | Increase Pooling Size | 1.89 |

Table 9: Learning rate adaptation and model architecture adaptation in a real-time seismic event, meaning cumulative rewards reflect the progression of improvements toward the models. Furthermore, fine-tuning pre-trained autoencoders through domain adaptation is a boost towards generalization from general domains of vibration data to much more specific domain cases of seismic scenarios. Table 10 reflects the loss value before and after fine-tuning at different epochs, depicting how the model adapts based on conditions owing to the seismic process.

**Table 10. Autoencoder fine-tuning loss values**

| Epoch | Reconstruction Loss | Domain Adaptation Loss | Total Loss |
|---|---|---|---|
| 1 | 0.123 | 0.098 | 0.221 |
| 5 | 0.102 | 0.080 | 0.182 |
| 10 | 0.091 | 0.065 | 0.156 |
| 15 | 0.085 | 0.054 | 0.139 |

Table 10 demonstrates that the total loss is steadily improving over time, which means the process of domain adaptation was successful in fine-tuning the autoencoder for specific seismic tasks. For attributing the explanatory power of the model's predictions, SHAP values are calculated for important features in the data. Table 11 presents the SHAP values for one sample prediction, showing which features contribute most to the model's decision for structural damage during a seismic event in process.

Table 11 above shows that features such as Acceleration_X and Displacement_Z had the highest positive contributions toward the damage detection decision. At the same time, the Temperature_Sensor contributed negatively, meaning that it did not significantly influence this particular prediction. BNNs also provide estimates of uncertainty that may prove to be very important in cases where the input is noisy or incomplete. Table 12 provides uncertainty estimates for a set of damage classification predictions, giving both predicted probability and the corresponding uncertainty.

**Table 11. SHAP values for model interpretability**

| Feature | SHAP Value |
|---|---|
| Acceleration_X | 0.452 |
| Displacement_Z | 0.329 |
| Stress_Level | 0.190 |
| Temperature_Sensor | -0.105 |
| Velocity_X | 0.089 |

**Table 12. Uncertainty estimation using BNNs**

| Prediction | Predicted Probability (%) | Uncertainty (±%) |
|---|---|---|
| Damage | 91.3 | ±4.8 |
| No Damage | 85.7 | ±6.2 |
| Damage | 88.4 | ±5.1 |
| No Damage | 80.1 | ±7.5 |

Some more insight into the reliability of the predictions is especially needed in cases where the probabilities are lower. Final Outputs The model actually outputs the classified damage, interpretability of the decision, and uncertainty of the predictions. Summary of Final Results Table 13 presents the final outputs for one sample case of seismic event, which gives an overview of the entire predictions by the model.

**Table 13. Final model outputs**

| Time Step | Damage Prediction | SHAP-Weighted Explanation | Uncertainty (±%) | Cumulative Reward |
|---|---|---|---|---|
| 0 | No Damage | Low Acceleration, Moderate Displacement | ±6.2 | 1.45 |
| 1 | Damage | High Acceleration, High Displacement | ±4.8 | 1.60 |
| 2 | Damage | High Acceleration, Increased Stress | ±5.1 | 1.75 |
| 3 | No Damage | Low Acceleration, Low Stress | ±7.5 | 1.89 |

Table 13 summarizes the output, providing the model's predictions along with the SHAP-based explanation for the taken decision and its associated uncertainty; it provides an overall final output. The DQN's cumulative rewards indicate how, with each set of the temporal instance set, the model improves in its process of decision-making in scenarios. The results prove the robustness and high effectiveness of the proposed hybrid CNN-RNN framework with additional machine learning techniques in the real-time seismic damage detection and prognosis domains.

## 5. Conclusion & Future Scopes

It is about the paper whose title is "Hybrid Deep Learning Framework for Seismic Damage Detection and Prognosis in Civil Structures." With real-time model adaptation through Deep Q-Network, and feature selection by Random Forest within CNN-RNN architectures, fine-tuned autoencoders, domain adaptation in autoencoders, SHAP for model interpretability, and Bayesian Neural Networks for uncertainty estimation, the framework achieved superior performance over traditional techniques on a variety of metrics. The overall classification accuracy achieved by the proposed model was 93.98%, which is significantly better than that of Method [3], Method [8], and Method [18], which had classification accuracies of 87.48%, 88.98%, and 81.88%, respectively. This is primarily due to the fact that the model has captured both spatial and temporal features of the seismic vibrations in the system, along with its real-time adaptability property due to DQN operations. Additionally, the attained false positive rate significantly dropped with an average of 3.95%, compared to Method [3] with 7.95%, Method [8] with 7.15%, and Method [18] with 11.7%. The feature selection using Random Forest and adaptive feedback with DQN was very important, as the inclusion of false alarms could be highly expensive when critical applications abruptly interrupt services. This evaluation was further extended to determine an average detection timestamp of 0.805 seconds, which translates to a 20% improvement compared to Method [3] and a 26% improvement compared to Method [18], thus leading to quicker responses in the event of a seismic occurrence. Bayesian Neural Networks additionally allowed uncertainty quantification; here, the average confidence calibration reached 96.03%, which is much higher than the competing methods, hence ensuring even further reliability in damage prognosis, especially under noisy or incomplete data conditions. Furthermore, with SHAP integration, this model was also interpreted to achieve an interpretability score of 89.03%, which could actually make it highly transparent and trustworthy for decision-making in the structural health monitoring process.

### *5.1. Future Scope*

Although the suggested model performs admirably in the identification and categorization of seismic damage, there are various areas for further investigation and improvement. One such direction is the integration of multi-modal sensor data, such as strain gauges and temperature sensors, to supplement vibration signals and provide a more comprehensive way of structural health monitoring. Another promising avenue for future research is to expand the model to include predictive maintenance capabilities. The CNN-RNN design could be enhanced with long-term prediction algorithms to forecast structural integrity decline over time, offering warning signs of serious damage. Another approach to generalizing the model across a variety of structures and seismic conditions is possible. Current domain adaptation strategies ensure good cross-structural generalization. Incorporation of technologies as advanced as adversarial training or meta-learning will allow the model to adapt even better to unseen structural types or seismic regions with different geological conditions. Another promising research area is scalability. Future work can explore the use of distributed learning techniques to make the monitoring of city-wide infrastructure systems during seismic events completely real-time and large-scale. Moreover, as edge computing has garnered much attention, in the future, implementations could try to push this hybrid system into deployment on edge devices for on-site low-latency damage detection without high-performance centralized computing resources. Such developments would further make the proposed framework versatile and scalable for seismic damage detection and structural health monitoring operations.

## Ethics Declarations

Ethical approval: Not applicable.

Consent to participate: Not applicable.

## Conflict of Interests/Competing Interests

The authors declare no competing interests.

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## Consent to publish

All authors have read and approved this manuscript.

## Author Contributions

Conceptualization by RB, SH, and AH; formal analysis by RB, SH, AH, MI, and HK; investigation by RB, SH, and AH; writing original draft preparation by RB, SH, and AH; writing review and editing by RB, MI, and HK; supervision by MI and HK. All authors have read and agreed to the published version of the manuscript.

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