Multi-Modal Deep Learning-Based Seismic Damage Identification for Nuclear Power Plant Structures

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1. Introduction

Damage identification is critically important for infrastructure systems subjected to seismic excitations, particularly Nuclear Power Plant (NPP) structures. Accurate and rapid detection of structural damage following ground motion is essential for post-earthquake decision-making and operational continuity. In this study, a multi-modal one-dimensional convolutional neural network (CNN) framework is proposed to detect and localize floor-level damage in NPP auxiliary buildings. The model integrates heterogeneous data sources, including structural response measurements such as floor acceleration, ground motion records, and modal features extracted via Time Domain Decomposition, to achieve high-fidelity damage prediction. The proposed methodology is evaluated using various input configurations and validated through both numerical simulations and hybrid simulation experiments of an NPP auxiliary building. The results demonstrate that the proposed framework enables accurate and efficient damage detection, highlighting its potential for probabilistic post-earthquake damage assessment of NPP structures.

2. Proposed Model and Results

2.1 Multi modal deep learning architecture

A 1-D CNN model was adopted due to its capability to extract spatial and temporal features from structural response signals [2]. The convolutional kernels learn discriminative patterns that distinguish damaged states from the undamaged state. To effectively incorporate diverse data types, multi-modal architecture was constructed to integrate multiple sources of information, including floor responses, modal features, and ground motion characteristics.

As illustrated in Figure 1, different input modalities are processed and fused within the network to improve robustness and classification accuracy. Specifically, each input modality is first processed through an independent convolutional branch to extract modality-specific features. The extracted feature maps are then concatenated in a fusion layer and passed through fully connected layers for final classification of structural damage states. This architecture allows effective integration of heterogeneous information while preserving the physical characteristics of each modality.

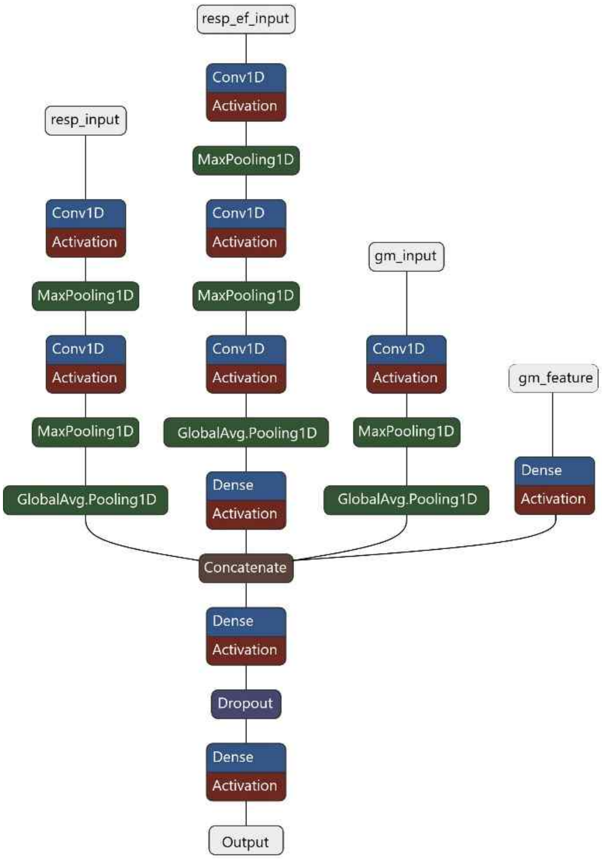

Figure 1. Proposed multi-modal 1D-CNN architecture.

2.2 Feature extraction

Directly utilizing raw seismic response time-series as inputs can lead to initial training instability due to high-dimensionality of data. Therefore, relying solely on raw response data may limit model generalization. To address this issue, the Time Domain Decomposition (TDD)-based [1,3,4] extracted features were designed as a modular input component, enabling the model to incorporate as a multi-modal scheme during the training and evaluation process. Structural damage leads to changes in stiffness, which in turn modifies the natural period. TDD applies band-pass filtering and singular value decomposition to response signals to isolate modal components. From this process, first-mode modal coordinates are obtained and used as physics-based features for model training. These features can provide direct information about structural dynamic characteristics and enhance damage sensitivity. These modal features are incorporated as complementary inputs to the CNN, enabling the model to capture physically interpretable changes in structural behavior that may not be evident from raw response signals alone.

2.3 Numerical validation

The proposed deep learning architecture was applied to a 7-story lumped mass model (LMM), which was designed to replicate the dynamic behavior of an APR-1400 NPP auxiliary building finite element (FE) model provided by the Korea Atomic Energy Research Institute, for computational efficiency. The model was rigorously calibrated to ensure a normalized root mean squared error of less than 5% across all floors relative to the original FE model. Damage states were defined in terms of 10~15% of stiffness degradation at each floor. A total of eight structural states were considered, including one undamaged state and seven single-floor damage scenarios.

Structural responses for both damaged and undamaged states were obtained using 200 synthetic ground motions, which match the design spectrum of Ulsan with a return period of 500 years, reflecting the specific site conditions of the NPP. The model was trained and tested using the simulated dataset. To evaluate the contribution of each input modality, incremental input configurations were considered. Starting from displacement responses only, additional features were progressively incorporated. The test accuracy and loss results are summarized in Table 1.

Table 1. Test results for the numerical model. Resp., r.ef., gm., gm.ef indicate displacement responses, extracted features (modal coordinate), ground motion, and features of ground motion. Loss is calculated based on cross entropy

	Accuracy (%)	Loss
Only resp.	60.0	0.4891
Resp., r.ef.	95.8	0.1747
Resp., r.ef., gm	96.9	0.1516
Resp., r.ef., gm, gm.ef	96.9	0.2108

The results demonstrate that as more information is incorporated into the input, the model achieves more accurate and stable damage detection performance, indicating that complementary structural and seismic features contribute to improved discriminative capability.

2.4 Real data application

The proposed framework was validated using hybrid simulation data, in which the first floor of the LMM model representing the NPP auxiliary building was replaced with a reinforced concrete shear wall physical substructure to capture complex nonlinear behavior, as illustrated in Figure 2. Due to the limited size of the hybrid simulation dataset, consisting of 81 response samples, and its imbalanced nature, a transfer learning strategy combined with a two-stage hierarchical classification framework was adopted.

Fig. 2. Hybrid simulation model of NPP auxiliary building. Among seven stories, where the first story is set as an experimental substructure.

In the hybrid simulation dataset, damage cases are predominantly concentrated on the first floor (Class 1), which can bias the model toward over-predicting first-floor damage. To address this issue, a two-stage hierarchical framework was introduced. In the first stage, a binary classifier determines whether the damage corresponds to the first floor (Class 1) or not. In the second stage, only the samples classified as non-Class 1 are further processed by a multi-class classifier to predict the remaining damage locations. This hierarchical approach mitigates class imbalance effects while improving overall classification reliability.

For model training, a transfer learning procedure was employed due to the scarcity of experimental data. The model was first trained on the numerical dataset using both structural response and ground motion inputs, and then fine-tuned on the hybrid simulation dataset using the proposed two-stage framework. This approach allows the model to retain generalized damage-sensitive features learned from numerical data while adapting to the characteristics of real measurements.

Table 2 presents the validation and test results for the hybrid simulation dataset. The proposed framework achieved an accuracy of 0.78 for the validation dataset and 0.80 for the test dataset. These results demonstrate that the proposed two-stage framework, combined with transfer learning, provides stable and reliable performance despite the limited and imbalanced dataset.

To further evaluate the effectiveness of the proposed approach, comparative studies were conducted as summarized in Table 3. When ground motion information was excluded from the input, the validation accuracy decreased significantly from 0.78 to 0.56, indicating the importance of incorporating seismic excitation characteristics. In addition, when transfer learning was not applied, the validation accuracy dropped to 0.00 and the test accuracy decreased to 0.60, highlighting the critical role of knowledge transfer from numerical simulations to experimental data.

Overall, the results confirm that the proposed framework, which integrates multi-modal inputs, transfer learning, and a two-stage hierarchical classification strategy, achieves the best performance among the considered approaches and is particularly effective under data-scarce and imbalanced conditions.

Table 2. Validation and test results for the hybrid simulation dataset. The number i denotes damage at the i-th floor, and 0 represents the undamaged state. The table presents target and predicted damage classes, along with the corresponding classification accuracy.

	Validation dataset	Predicted
Target	[1, 4, 1, 7, 0, 2, 5, 6, 3]	[4, 5, 1, 1, 1, 1, 0, 1, 1, 1]
Predicted	[6, 4, 1 ,7 ,0, 4, 5, 6, 3]	[4, 5, 1, 1, 1, 1, 3, 1, 1, 6]
Accuracy	0.78	0.8

Table 3. Comparison of classification accuracy between the proposed framework and baseline models without ground motion input and without transfer learning for the hybrid simulation dataset.

	Proposed	w/o ground motion	w/o transfer learning
Validation accuracy	0.78	0.56	0.00
Test accuracy	0.80	0.80	0.60

3. Conclusions

This study proposed a multi-modal 1-D CNN-based damage detection framework for NPP structures subjected to seismic excitation. By integrating structural responses, ground motion information, and modal coordinates extracted through Time Domain Decomposition, the proposed model effectively combines data-driven learning with physics-informed features to enhance damage sensitivity and robustness.

Numerical validation results demonstrate that incorporating multi-modal inputs significantly improves classification performance, while experimental validation using hybrid simulation data confirms the applicability of the proposed approach under data-scarce conditions. In particular, the integration of transfer learning and a two-stage hierarchical classification framework enables stable and reliable damage identification despite limited and imbalanced experimental data.

Comparative results further show that both ground motion input and transfer learning play critical roles in improving model performance, highlighting the importance of incorporating seismic characteristics and knowledge transfer from numerical simulations.

Overall, the proposed framework provides a practical and effective approach for rapid damage detection and localization, and has strong potential for application in probabilistic post-earthquake damage assessment of NPP structures.

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