International Operational Modal Analysis Conference
11th International Operational Modal Analysis Conference
20 - 23 May 2025 | Rennes, France

Feasibility study of utilising modal-based features for finite element model-informed artificial neural network-based damage identification

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ABSTRACT

The rapid advancement of digital technologies has revolutionized industrial maintenance practices, with predictive maintenance emerging as a proactive and cost-effective strategy. The conventional machine learning (ML) model for damage identification is trained by data collected from sensors, where majority of the data is collected when the structure is in undamaged condition. Due to the scarcity of damaged condition data, the extrapolation capacity of conventional ML model is questionable, especially dealing with new unseen damages. Furthermore, it is not practical to create new damages on the physical structure just for data collection purposes. This research explores the feasibility of utilising modal-based features in a hybrid digital twin damage identification scheme by integrating physics-based finite element (FE) model and ML model, in which artificial neural network (ANN) is used. A lab-scale plate-like structure supported at 4 corners is used as the test rig, with damage simulated by loosening support fasteners. Modal data collected from the test rig by Impact-Synchronous Modal Analysis (ISMA) is processed and used for ML training, with high severity damage treated as unseen damage intentionally left out. The ML model failed to identify the unseen damage. A correlated high-fidelity FE model of the test rig is developed, where the natural frequency error is less than 6% and the modal assurance criterion (MAC) is greater than 0.95 for the first 3 modes when undamaged. The FE model created synthetic high severity damage (unseen damage) data generated to train a new FE model-informed ML model. Validation accuracy of the FE model-informed ML model is 100.00%. When tested with real high severity damage (unseen damage) data, the FE model-informed ML model predict accurately the damage location and damage severity for all the damage cases. By utilising modal-based features and integrating FE and ML models, the FE model-informed ML model showcases enhanced accuracy in predicting unseen damages.

Keywords: Finite element analysis, hybrid digital twin, modal analysis, structural damage identification, structural health monitoring

1. INTRODUCTION

Structural health monitoring (SHM) is essential for ensuring the safety and performance of critical infrastructure, such as bridges, buildings, and aircraft. Damage identification, a core objective of SHM, involves detecting, locating, and quantifying structural anomalies.

Modal-based features are preferred for damage identification schemes, due to its robustness against operating environment and strong correlation with structural health. Modal-based features, such as waveform chain code (WCC) analysis feature of principal component analysis-frequency response function (PCA-FRF) [1], and features derived from mode shape [2, 3], are sensitive to structural changes and offer a compact representation of system dynamics. Impact Synchronous Modal Analysis (ISMA) is particularly useful for modal data acquisition due to its robustness to operating conditions [4].

Recent advances in sensor technology and computational methods have opened new avenues for applying machine learning (ML) techniques to enhance the accuracy and robustness of damage identification systems [5, 6].

One significant challenge in developing ML-based damage identification systems is the scarcity of data representing structures in damaged conditions. Real-world structures are typically maintained to remain in healthy states, and experimental data from controlled damage scenarios are often difficult, expensive, or impractical to obtain. Studies have shown that the majority of available datasets for SHM focus on undamaged or healthy conditions, while data from damaged states remain limited [7]. This imbalance is particularly problematic for large-scale civil or aerospace structures, where intentional damage experiments are rare due to cost, ethical, and operational constraints.

On the other hand, Finite Element (FE) models are widely used in structural analysis to simulate the dynamic behaviour of systems under various conditions [8]. These models provide high-fidelity representations of structural responses, which are critical for understanding the relationship between damage and measurable outputs. However, directly utilising FE model in real-time SHM applications is often computationally prohibitive due to their complexity [9].

This paper explores the feasibility of addressing the problems mentioned above by utilising modal-based features in a hybrid digital twin damage identification scheme by integrating physics-based FE model and ML model, in which artificial neural network (ANN) is used. By integrating the physics-informed FE model with the ML model, the FE model-informed ML model can be trained on simulated damage scenarios, effectively compensating for the lack of extensive real-world damage data.

The proposed approach is investigated through a comprehensive feasibility study, which examines the capability of modal-based features to encode damage information and evaluates the performance of ML models trained on these features. The study addresses critical questions regarding the integration of FE method and ML. The findings are expected to inform the development of efficient and scalable SHM systems that combine the strengths of FE method and ML for real-world applications.

2. METHODS

2.1. Modal data acquisition

A lab-scale plate-like structure test rig with supports at the 4 edges is used for experimentation, see Figure 1.

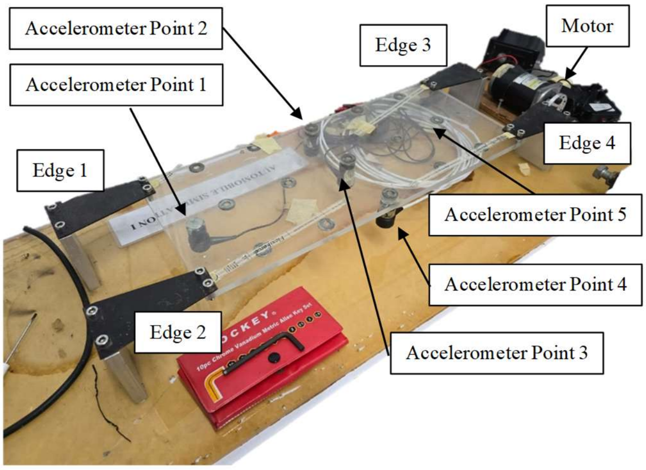


Figure 1. Test rig setup.

Damage is created on the test rig by loosening of screws on the 4 edges. The damage severity is grouped into 4 classes, i.e. undamaged (UD), low severity damage (LD), medium severity damage (MD) and high severity damage (HD). Different combinations of damage location and damage severity are created as listed in Table 1.

Table 1. Damage location and damage severity combinations by varying screw tightness at different edges.

Damage Location	Damage Severity	Force Sensor Reading (N) / Description	Class Abbreviation
N/A	UD	150 N	UD
Edge 1	LD	113 N, 78 N, 38 N	LD-1
Edge 1	MD	0 N / both screws loosened and not removed; 1 screw loosened, and the other is removed	MD-1
Edge 1	HD	0 N / both screws removed	HD-1
Edge 2	LD	113 N, 78 N, 38 N	LD-2
Edge 2	MD	0 N / both screws loosened and not removed; 1 screw loosened, and the other is removed	MD-2
Edge 2	HD	0 N / both screws removed	HD-2
Edge 3	LD	113 N, 78 N, 38 N	LD-3
Edge 3	MD	0 N / both screws loosened and not removed; 1 screw loosened, and the other is removed	MD-3
Edge 3	HD	0 N / both screws removed	HD-3
Edge 4	LD	113 N, 78 N, 38 N	LD-4
Edge 4	MD	0 N / both screws loosened and not removed; 1 screw loosened, and the other is removed	MD-4
Edge 4	HD	0 N / both screws removed	HD-4

With the motor in operation, the vertical-axis accelerance at the 5 accelerometer points are acquired via ISMA, which suppressed the noise due to the operating motor. The FRFs are collected for all damage classes.

2.2. ML and physics-based model development

In ML-based model development phase, it is essential that suitable features are selected for the ML model training, with the aim of condensing the large set of FRF data to a smaller set of data, while retaining information required for damage identification. Since this work focuses up to Level 3 damage identification [10], which includes damage detection, damage localisation and damage severity assessment, the features used for ML training shall show qualities sensitive towards damage location and damage severity. This work utilises FRF peak amplitude and WCC feature computed from PCA-FRF as training features due to their sensitivity towards different damage locations and severity respectively. The ML model for damage identification is built by means of ANN using only UD, LD and MD data, while HD data is intentionally left out to be treated as unseen damage data.

In physics-based model development phase, a high-fidelity FE model in UD state is developed and correlated to the actual test rig by optimising the properties of the FE model by direct optimisation of material properties, to minimise natural frequency errors and maximise the Modal Assurance Criterion (MAC) for the first 3 modes.

Moving towards the hybrid digital twin (HDT) model development phase, synthetic HD data is simulated on the FE model at the 4 edges. The FRFs produced is processed, i.e., peak amplitude and WCC feature and used as additional data for the ML model training. The trained model is then tested with unseen damages, i.e., real HD data. The full flow of this study is as decipted in Figure 2.

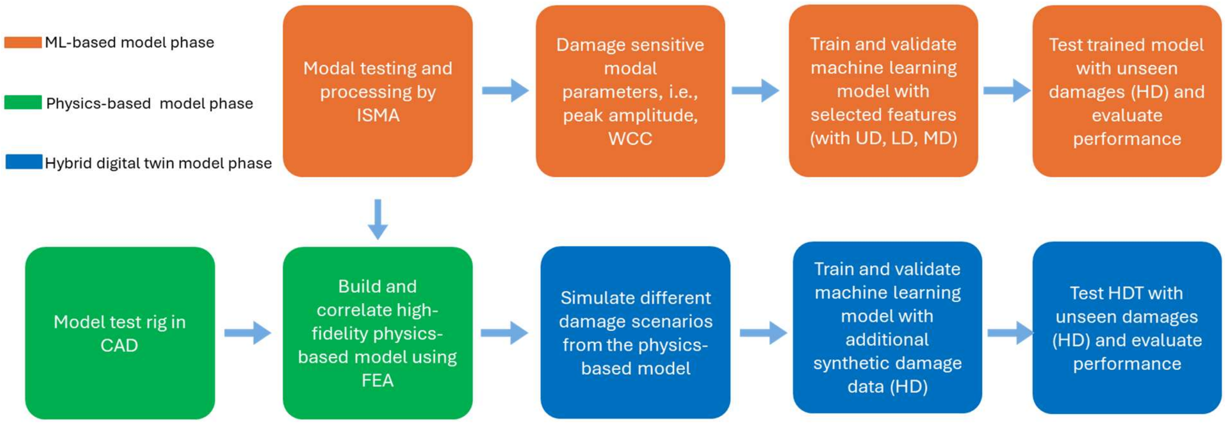


Figure 2. Research flowchart.

3. RESULTS AND DISCUSSIONS

3.1. Data processing and ML model development

3.1.1. ML training features

From the FRFs, the first peak amplitude is extracted. The normalised first peak amplitude at measurement points 1, 2, 4, and 5 is depicted in Figure 3. When damage occurs at Edge 1 and 3, measurement point 2 has the greatest normalised peak amplitude; when damage occurs at Edge 2 and 4, measurement point 3 has the greatest normalised peak amplitude. When damage occurs at Edge 1 and 2, measurement point 5 has the lowest normalised peak amplitude; when damage occurs at Edge 3 and 4, point 1 has the lowest normalised peak amplitude. Focusing on measurement point 1 and 5, there is an increasing trend of normalised peak amplitude at the measurement point nearer to the damaged edge with increasing damage severity. Similarly, focusing on measurement point 2 and 4, there is a decreasing trend of normalised peak amplitude at the measurement point farther from the damaged edge with increasing damage severity. This aligns with other research, where a structure has higher mode 1 peak amplitude near the damaged location [1, 6, 11]. There is a clear correlation between damage location (Edges 1 – 4) and peak amplitude for measurement points 1, 2, 4, and 5. Hence the peak amplitudes are used as ML training features due to its sensitivity towards damage location.

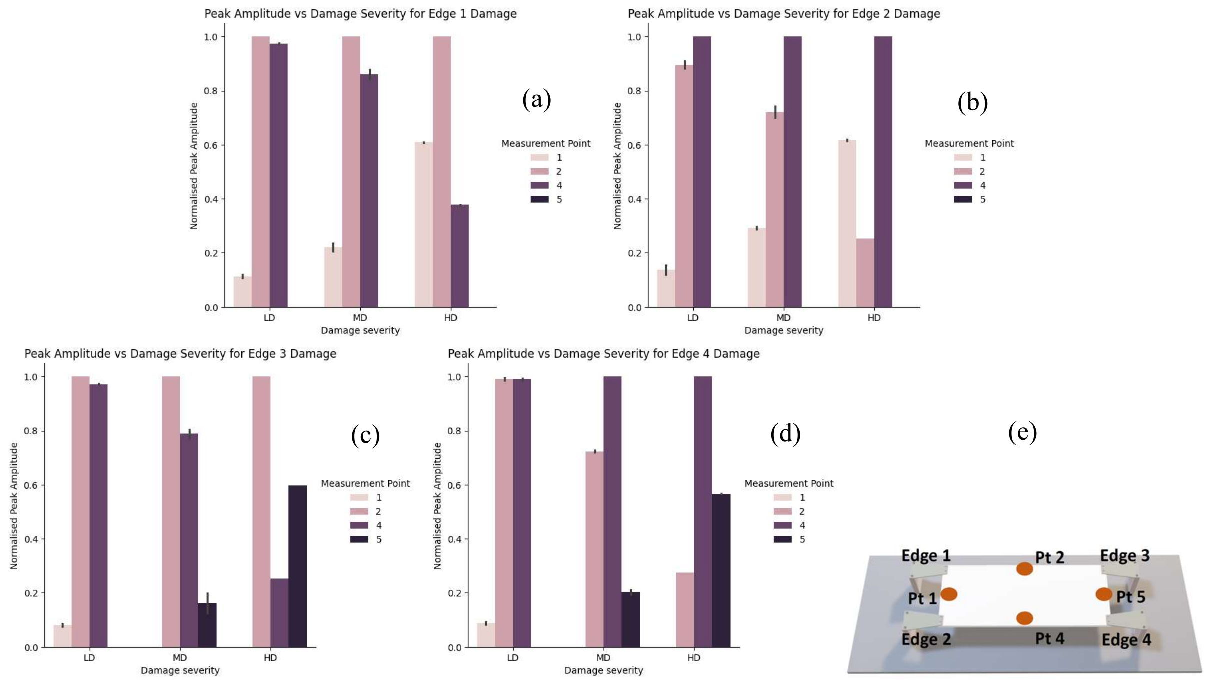


Figure 3. Normalised peak amplitude against damage severity for damage at: (a) Edge 1, (b) Edge 2, (c) Edge 3, (d) Edge 4. (d) Location of measurement point and damaged edge.

PCA-FRFs depicted in Figure 4(a) are computed by only taking the first principal component (PC1) for each set of FRF data for all damage scenarios. Taking 1 set of UD data as benchmark, WCC feature for frequency band 10Hz – 25Hz, corresponding to mode 1, is computed from the PCA-FRFs, which is denoted by a_{s1}. It is evident that a_{s1} has strong correlation with damage severity, as shown in Figure 4(b).

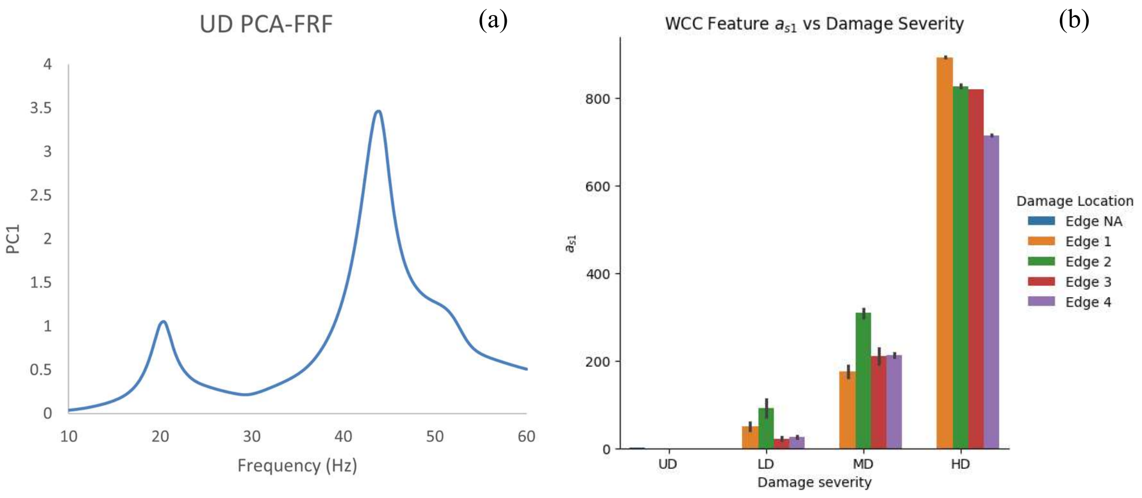
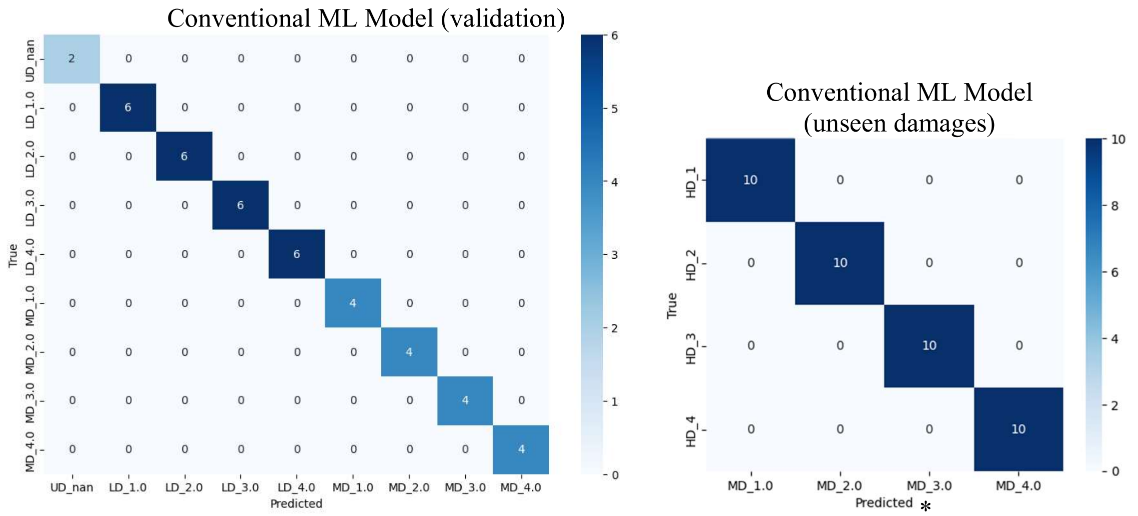


Figure 4. (a) Sample PCA-FRF, UD, (b) WCC feature a_{s1} (10Hz – 25Hz).

3.1.2. ML model development

Having selected features which are sensitive to damage location and severity, in the form of peak amplitudes and WCC feature, the ML model for damage identification is built with 4 layers neural network (1 input layer, 2 hidden layers and 1 output layer), with each hidden layer consisting of 64 neurons. The conventional ML model is only trained with 80% of the UD, LD and MD data, where the remaining 20% is used for validation. The conventional ML model showcases satisfying validation accuracy of 100% when tested with the 'seen damages'. However, the conventional ML model has 0% accuracy when tested with unseen damages (HD data), since it has never been trained with HD data. Figure 5 shows the confusion matrix of the conventional ML model when tested with seen damages and unseen damages.



*Note: All prediction for unseen damages is MD.

Figure 5. Conventional ML model confusion matrix, tested with seen damages (left), unseen damages (right).

3.2. FE Model Development

UD FE model is created, with 5mm mesh size and hex elements. Screws are modelled as beam elements with pretension applied. The bottom surface of the 4 pillars is set as fixed support.

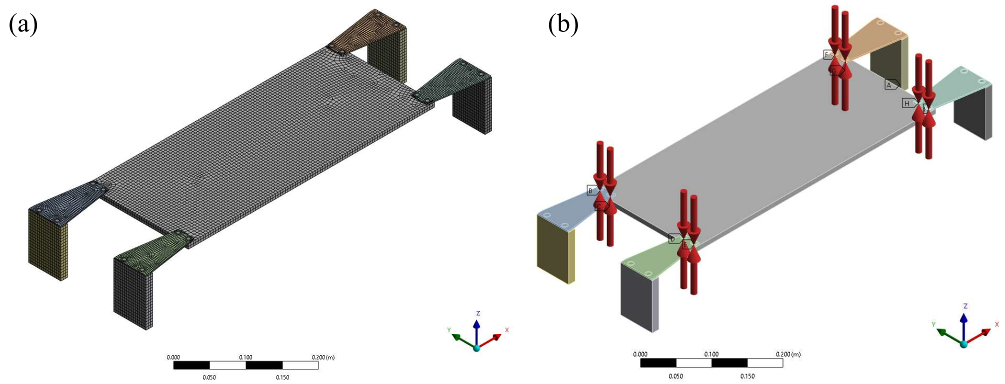
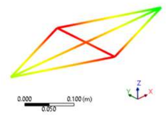
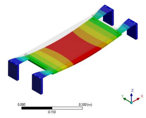
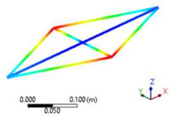
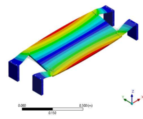
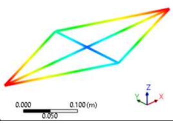
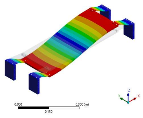


Figure 6. (a) FE model mesh, (b) FE model screws modelled as beam elements with pretension.

The correlated UD FE model has natural frequency error within 6%, MAC greater than 0.95 for the first 3 modes, which is satisfactory (Table 2). This correlated FE model will be utilised as source of synthetic HD data creation, as detailed in the next section.

Table 2. Comparison of modal parameters of actual test rig and FE model.

Mode	Natural Frequency			MAC
	Data from Actual Test Rig [Hz]	FE Model [Hz]	Error [%]	
1	20.11 	21.17 	5.27	0.99
2	43.11 	43.12 	0.02	0.99
3	51.82 	50.34 	2.86	0.98

3.3. FE-informed ML Model

HD is simulated on the FE model at the 4 edges by suppressing the beam elements at the corresponding edges. The FRFs produced by simulating HD conditions using the FE model as shown in Figure 7 is used as additional data for the ML model training, which is now known as a FE model-informed ML model. It uses the same training features and neural network architecture as in 3.1. The FE model-informed ML model showcases satisfying validation accuracy of 100.00% when tested. When tested with real HD data (unseen damage), the FE model-informed ML model correctly predicted all samples, having 100% accuracy (Figure 8).

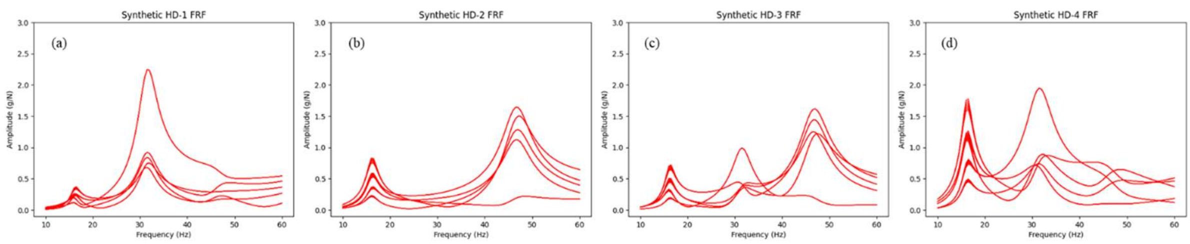


Figure 7. Synthetic FRFs for HD at: (a) Edge 1, (b) Edge 2, (c) Edge 3, (d) Edge 4.

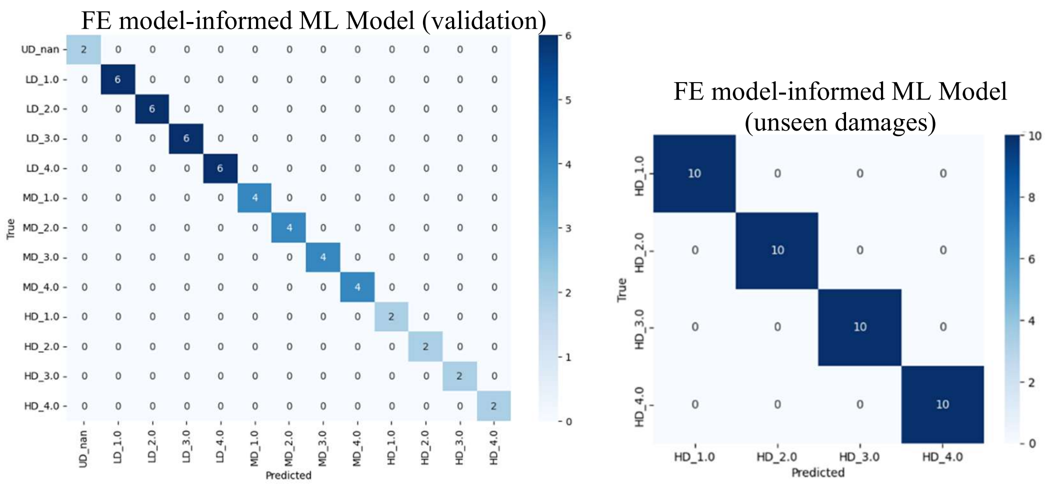


Figure 8. FE model-informed ML model confusion matrix, tested with seen damages (left), unseen damages (right).

4. CONCLUSION

This work demonstrates that modal-based features, namely the WCC feature and peak amplitude, exhibit high sensitivity for assessing damage severity and facilitating damage localization with both the conventional ML model and FE model-informed ML model have 100% validation accuracy. By incorporating synthetic data generated from FE model for ML training using ANN, the FE model-informed ML framework demonstrates enhanced accuracy in unseen damage identification compared to conventional ML models that rely solely on available data. This approach effectively addresses the lack of extensive real-world damage data, thereby improving the reliability of ML models in damage identification applications. Considering the current work covers up until prediction of damage severity and damage location, it is suggested that future work shall include remaining useful life prediction, as well as structural analysis on the damaged structure to assist user to make maintenance decision.

ACKNOWLEDGEMENTS

The financing support given by the Malaysian Ministry of Higher Education through Fundamental Research Grant Scheme (No. FRGS/1/2022/TK10/UM/02/29) is gratefully appreciated. Also, special thanks to Advanced Shock and Vibration Research (ASVR) Group of Universiti Malaya.

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