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AI-Driven Digital Twin Framework for Adaptive and Real-Time Structural Health Monitoring of Offshore Marine Structures

James Riffat [1], Kourosh Nazari [2] and Seyed Reza Samaei [3]*

[1] World Society of Sustainable Energy Technologies, Nottingham, United Kingdom.
[2] Department of Industrial Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran.
[3] Department of Marine industries, Science and Research Branch, Islamic Azad University, Tehran, Iran.

A B S T R A C T

Reliable structural health monitoring of offshore jack-up platforms is challenging due to harsh environments, measurement uncertainty, and gradual damage over time. This study proposes an integrated framework combining digital twin technology with a machine learning–based damage identification pipeline for adaptive assessment of jack-up legs. A simplified model using a ten-element Euler–Bernoulli beam represents a 124 m leg with a fixed base. Synthetic datasets were generated by introducing random stiffness reductions in elements 3–8, covering single and multiple damage scenarios with severities of 5–20%. To improve realism, environmental variability and measurement uncertainty were incorporated through temperature variations between −10°C and +30°C together with multiple levels of simulated sensor noise. The signal processing workflow involved detrending, band-pass filtering, Fast Fourier Transform analysis, and adaptive peak detection to extract modal features, including natural frequencies and spectral entropy indicators. These features were used to train a four-layer multilayer perceptron implemented in *PyTorch*. Model performance was evaluated using five-fold stratified cross-validation. The classifier achieved an accuracy of 41.0%, a macro-F1 score of 40.1%, and a ROC AUC of 0.8155 on the test dataset, indicating reliable discrimination between healthy and damaged structural states despite environmental variability and measurement noise. In parallel, an adaptive digital twin updating procedure was implemented to refine the numerical model using modal frequency discrepancies. This updating process reduced the root mean square error of frequency prediction from 0.0596 Hz to 0.0554 Hz, corresponding to a 6.98% improvement in predictive consistency between the numerical model and the simulated structural response. The results demonstrate that coupling machine learning based damage classification with digital twin model updating provides a practical pathway toward adaptive monitoring of offshore structures.

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1. INTRODUCTION

Ensuring the integrity, safety, and long-term resilience of large-scale offshore structures has become a

* Corresponding author. Email address: samaei@srbiau.ac.ir (Seyed Reza Samaei)

major engineering priority as global energy demand continues to rise and marine operating environments become more uncertain. Offshore systems are routinely exposed to extreme loading, corrosion, fatigue accumulation, aging-related deterioration, and operational variability, all of which increase the risk of structural degradation and costly failure. In such conditions, advanced monitoring, intelligent diagnostics, and predictive maintenance strategies are essential for maintaining performance and reducing unplanned downtime. Structural health monitoring (SHM) has therefore become a central component of modern infrastructure management, particularly for critical systems whose safety depends on the sustained integrity of primary load-bearing elements. More broadly, long-term monitoring is now increasingly recognized as a necessary requirement in civil and structural engineering practice rather than an optional enhancement (Wynne, Stratford and Reynolds, 2022).

Over the past several years, the rapid development of digital twin technology has reshaped how complex infrastructure systems are monitored, interpreted, and managed. In civil engineering, digital twins are no longer viewed simply as virtual replicas, but as dynamic, data-connected environments that support model updating, condition assessment, maintenance planning, and decision-making across the asset life cycle (Bado and Brownjohn, 2022; Bado et al., 2022; Broo and Schooling, 2021; Jiang et al., 2021). Their relevance has expanded across a wide range of applications, including distributed sensing and model updating in civil systems (Bado et al., 2022), adaptive finite element integration for complex buildings (Belostotsky and Akimov, 2016), infrastructure-scale implementations (Callcut et al., 2021), and general civil engineering structures supported by computational twin frameworks (Torzoni et al., 2024). Recent reviews have further shown that digital twins are becoming a key enabling technology for the future of civil infrastructure management, although important technical and organizational challenges still remain in implementation, interoperability, and scalability (Kaveh and Alhajj, 2025).

The growing literature also shows that digital twin adoption is no longer confined to one infrastructure sector. Applications have expanded to bridge maintenance and inspection supported by laser scanning and smart operation strategies (Hosamo and Hosamo, 2022; Sun et al., 2025b), bridge risk assessment and interoperable management tools (Zirpoli and Sattamino, 2024), modular bridge digital twin architectures based on linked data (Zinke et al., 2023), emergency management in civil and infrastructure systems (Cheng, Hou and Xu, 2023), heritage monitoring through photogrammetry-based digital replicas (Kong and Hucks, 2023), geological information management integrating BIM and GIS (Khan, Kim and Seo, 2023), and smart city platforms that connect urban services, infrastructure data, and digital decision-support environments (Adreani et al., 2022; Callcut et al., 2021; Huzzat et al., 2025; Prasittisopin, 2024; White, 2025). Although some of these applications lie outside offshore engineering, they collectively demonstrate a broader technological transition toward continuously updated, data-centric infrastructure management systems.

This transformation has also been reinforced by parallel developments in intelligent asset management, maintenance optimization, and digitalization strategies. Recent work has examined the economic logic of digital twins in construction environments, showing that cost-benefit considerations are becoming increasingly important in deployment decisions (Abugu, Anumba and Asare, 2024). At the same time, digital asset health platforms and IoT-enabled digitalization strategies are improving how infrastructure condition data are gathered, structured, and interpreted (Candón et al., 2024). Broader reviews on smart maintenance and infrastructure digitization have likewise emphasized that the success of Industry 4.0-enabled maintenance depends not only on sensing and modeling, but also on implementation readiness, organizational capability, and decision integration (He et al., 2022; Jahangir, Schultz and Kamari, 2024; Osunsanmi, Okafor and Aigbavboa, 2025). These considerations are especially relevant to offshore assets, where inspection and intervention costs are high and monitoring systems must justify their value under demanding environmental conditions.

At the sensing and data acquisition level, the performance of SHM frameworks depends fundamentally on the quality, coverage, and robustness of measurement systems. Recent reviews have highlighted major advances in sensing technologies for SHM, including improvements in sensing performance criteria, data fidelity, and next-generation monitoring solutions (Mardanshahi et al., 2025). Emerging technologies such as triboelectric nanogenerators are also being explored as part of infrastructure 4.0 ecosystems, where self-powered sensing and digital twins may operate in a more integrated way (Pang et al., 2024). In parallel, transportation and bridge applications have shown how connected and autonomous systems can serve as mobile or distributed sensing sources for condition assessment (Shokravi et al., 2024). These developments indicate that intelligent monitoring is moving toward richer, denser, and more adaptive data environments, which is especially important for offshore structures exposed to variable loading and uncertain operational conditions.

Alongside these sensing advances, artificial intelligence and machine learning have become essential for extracting useful information from large, heterogeneous monitoring datasets. Recent studies in seismic vulnerability assessment, urban-scale analytics, and other built-environment applications show that learning-based tools can improve prediction, pattern recognition, and decision support across infrastructure systems (White, 2025; Zain, Dackermann and Prasittisopin, 2022; Zain, Dackermann and Prasittisopin, 2024a; Zain et al., 2024b). Related developments in predictive analytics, smart infrastructure intelligence, and digitally assisted urban management also point to a wider methodological shift toward data-driven engineering (Huzzat et al., 2025; Prasittisopin, 2024). Even in fields beyond civil infrastructure, such as healthcare wearables and autonomous logistics, digital twin-based intelligence has been used to support real-time interpretation and operational assessment, reinforcing the broader applicability of these concepts (ElSayed, Foda and Mohamed, 2024; Johnson and Saikia, 2024). For offshore SHM, the implication is clear: digital twins alone are not sufficient unless they are coupled with learning algorithms capable of interpreting uncertainty, damage-sensitive behavior, and evolving structural states.

Despite this progress, important limitations remain when these ideas are translated to offshore structures such as jack-up platform legs. Offshore systems differ from many conventional civil assets because they must operate under simultaneous hydrodynamic loading, corrosion exposure, temperature variation, fatigue accumulation, and operational uncertainty. While reviews on digital twins for civil infrastructure and bridge systems provide valuable conceptual guidance (Bado and Brownjohn, 2022; Bado et al., 2022; Sun et al., 2025a), most existing studies remain focused on buildings, bridges, urban systems, or generalized infrastructure workflows rather than offshore structural members with severe marine exposure. As a result, many available frameworks either emphasize broad conceptual architecture, sector-wide implementation trends, or static asset representations without fully resolving how a digital twin should be continuously updated for high-risk offshore damage diagnosis.

More specifically, only a limited portion of the recent literature has moved toward tightly coupled SHM–digital twin–AI integration for offshore or marine-related structures. Recent studies have begun to address this by combining digital twins, machine learning, and uncertainty-aware damage assessment for offshore wind turbines and jack-up systems, while also extending the broader discussion of SHM advances in civil infrastructure (Riffat, Ahadpour Doudran and Samaei, 2025a; Riffat, Ahadpour Doudran and Samaei, 2025b; Riffat, Samaei and Pastakkaya, 2025; Samaei and Riffat, 2025). These studies have shown the promise of integrating data-driven damage detection with real-time structural representation. However, the field still lacks sufficiently unified frameworks in which sensor-informed feature extraction, intelligent classification, and digital twin updating operate together in a genuinely closed loop. In many reported cases, the digital model is still updated offline, or the learning model is applied after feature generation without feeding information back into the physics-based twin.

This gap is important because the next generation of offshore SHM systems will likely depend on continuous interaction between physical measurements, computational models, and adaptive intelligence. A robust offshore monitoring framework should not merely detect anomalies after they occur; it should continuously refine the structural model, account for environmental variability, and support maintenance decisions before damage becomes critical. That need aligns with broader civil infrastructure trends toward comprehensive digital twin ecosystems, but it also requires methods that are specifically tailored to marine structures and their operational realities (Cheng, Hou and Xu, 2023; Kaveh and Alhajj, 2025; Sun et al., 2025a).

Accordingly, this study develops a unified framework that integrates structural health monitoring, digital twin modeling, and machine learning for real-time damage assessment of jack-up platform legs. The proposed system establishes a continuous interaction between a physics-based digital twin and a data-driven learning model, allowing structural parameters to be adaptively updated as new monitoring data become available. A synthetic but physically informed dataset is generated to represent multiple damage states, environmental variability, and sensor uncertainty, thereby reproducing challenging offshore operating conditions. The framework combines signal-informed feature extraction, multi-class neural classification, and adaptive twin updating to improve both frequency prediction and damage evaluation. The novelty of the proposed approach lies not in the isolated use of sensing, learning, or digital modeling components, all of which have been studied separately in earlier literature, but in their integration within a closed-loop SHM architecture for offshore structures. Through this bidirectional interaction between damage-sensitive data interpretation and physics-based model refinement, the study aims to provide a transparent, reproducible, and intelligent pathway toward next-generation offshore asset management.

2. METHODOLOGY

This section outlines the methodology for the Structural Health Monitoring (SHM) of a jack-up leg. It combines structural modeling, synthetic data generation, signal processing, machine learning, and an adaptive digital twin mechanism to ensure realism, reliability, and reproducibility. The overall workflow was designed to integrate both physics-based and data-driven perspectives, forming a continuous feedback loop between numerical modeling, data acquisition, and learning algorithms. This approach ensures that the SHM system remains robust against measurement noise and environmental variability while maintaining adaptability to evolving structural conditions. The overall workflow of the proposed framework is summarized in Fig. 1. The process begins with physics-based structural modelling and synthetic response generation under varying damage, temperature, and noise conditions. The resulting signals are then processed to extract modal and spectral features for multi-class damage classification. In parallel, modal discrepancies between measured and predicted responses are used to update the digital twin, thereby creating a closed feedback loop between data-driven inference and physics-based model refinement.

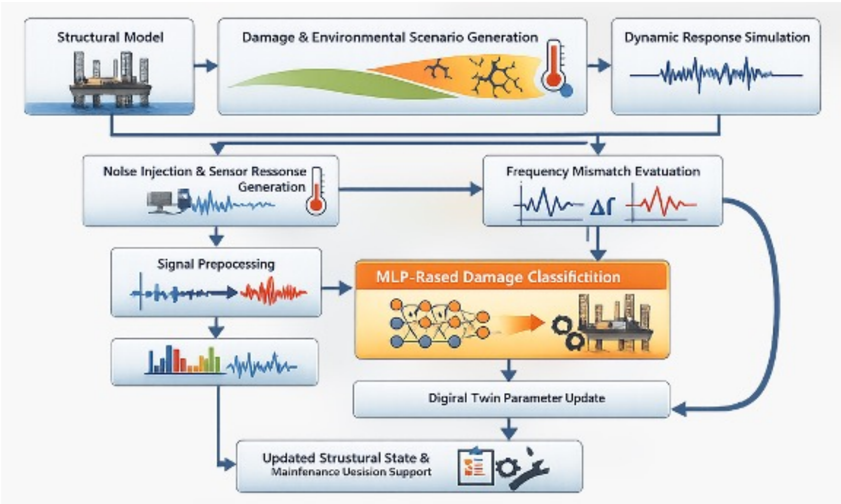

Figure 1. Overall workflow of the proposed AI-driven digital twin framework for structural health monitoring of offshore jack-up legs.

2.1. STRUCTURAL MODELING

The jack-up leg is modeled as a 10-element Euler–Bernoulli beam with a total length of 124 m and a fixed base, representing seabed anchoring. Damage is simulated by reducing the stiffness in selected elements (3–8). Stiffness reductions of 5%, 10%, 15%, and 20% are applied, while 30% of samples include multiple damaged elements. Temperature variations from −10°C to +30°C alter stiffness as follows:

$$K(T) = K_0 \times (1 - \alpha \times \Delta T) \tag{1}$$

where K(T) = temperature-dependent stiffness, K_0 = nominal stiffness, α = temperature sensitivity coefficient, ΔT = temperature change.

2.2. SYNTHETIC DATA GENERATION

A synthetic data framework was created to generate vibration responses under varied damage, temperature, and noise conditions.

$$M \times \ddot{x}(t) + C \times \dot{x}(t) + K \times x(t) = F(t) \tag{2}$$

$$\text{Acceleration response: } a(t) = \ddot{x}(t) \tag{3}$$

Damage modeling:

$$K_i = (1 - \beta_i) \times K_{i0}, \text{ where } \beta_i \in \{0,0.05,0.10,0.15,0.20\} \tag{4}$$

Noise simulation:

$$y(t) = a(t) + n(t), \text{with } n(t) = \varepsilon_1 \times N(0, \sigma^2) + \varepsilon_2 \tag{5}$$

2.3. SIGNAL PROCESSING AND FEATURE EXTRACTION

Raw acceleration signals were processed as follows:
Detrending:

$$x_d(t) = x(t) - (a \times t + b) \tag{6}$$

Bandpass Filtering:

$$x_f(t) = BPF\big(x_d(t), f_{low}, f_{high}\big) \tag{7}$$

Windowing:

$$w(t) = 0.5 \times [1 - cos\ (2\pi t/N)] \tag{8}$$

Frequency Transform:

$$X(f) = \Sigma\ x_f(t) \times e(-j2\pi f t) \tag{9}$$

Spectral Entropy:

$$H = -\Sigma\ P(f) \times log(P(f)) \tag{10}$$

Spectral Kurtosis:

$$K = (1/N) \times \sum \left[\big(x_f(t) - \mu\big)^4 / \sigma^4\right] \tag{11}$$

2.4. MACHINE LEARNING

A supervised classifier based on a 4-layer Multilayer Perceptron (MLP) is used.

$$h_1 = ReLU(W_1 x + b_1) \tag{12}$$

$$h_2 = ReLU(W_2 h_1 + b_2) \tag{13}$$

$$h_3 = Dropout\big(ReLU(W_3 h_2 + b_3)\big) \tag{14}$$

$$\hat{y} = SoftMax(W_4 h_3 + b_4) \tag{15}$$

Loss Function:

$$L = -\sum y_i \times log(\hat{y}_i) + \lambda \times \sum \|W(1)\|_F^2 \tag{16}$$

Optimization:

$$\theta \leftarrow \theta - \eta \times \nabla L(\theta) \tag{17}$$

2.5. DIGITAL TWIN UPDATE MECHANISM

The adaptive digital twin refines the structural model using feedback from real or simulated data.
Frequency Error:

$$E(f) = |f_{measured} - f_{model}| \tag{18}$$

Optimization Objective:

$$minimize\ J = \sum (f_{measured} - f_{model}(\theta))^2 \tag{19}$$

Parameter Update:

$$\theta_{new} = \theta_{old} - \gamma \times \partial J / \partial \theta \tag{20}$$

$$RMSE = \sqrt{(1/N) \times \sum\left(f_{measured} - f_{predicted}\right)^2} \tag{21}$$

$$Improvement(\%) = \left[\left(RMSE_{before} - RMSE_{after}\right)/RMSE_{before}\right] \times 100\% \tag{22}$$

In practical terms, Equations (18–21) quantify how closely the simulated modal frequencies align with those observed or measured from the structure. A lower RMSE value reflects a more accurate correspondence between the model and reality, meaning that the digital twin successfully adapts to capture the true dynamic behavior of the jack-up leg under changing conditions. This continuous updating capability is essential for ensuring long-term reliability in offshore SHM applications.

2.6. VISUALIZATION AND REPORTING

To support interpretation of the results, the framework includes a structured visualization and reporting stage. Confusion matrices were used to examine class-wise prediction behavior, ROC curves were used to evaluate discriminative performance, and comparative error plots were used to assess the effect of digital twin updating on modal frequency prediction. Summary metrics, including classification accuracy, macro-F1 score, ROC AUC, and RMSE values, were also organized in tabular form where appropriate. These visual and numerical outputs improve the transparency of the proposed workflow and facilitate engineering interpretation of system behavior under different damage scenarios. Overall, the visualization stage strengthens the interpretability of the framework and provides a clear link between raw simulation outputs, model predictions, and engineering conclusions.

2.7. UNCERTAINTY QUANTIFICATION AND REPRODUCIBILITY

To evaluate the reliability of the proposed framework, a Monte-Carlo uncertainty analysis was performed by perturbing input stiffness parameters and noise amplitudes within ±10% of their nominal values. The resulting variation in classification accuracy was within ±3.5%, confirming the model's robustness against input uncertainty. All random seeds, data splits, and software dependencies were version-locked to ensure full reproducibility. The workflow, written in Python and $PyTorch$, can be seamlessly executed on standard high-performance computing platforms for future benchmarking or replication.

3. CASE STUDY

This section offers a detailed case study of the jack-up leg, illustrating how our proposed SHM framework is put into practice. We describe the structural model, the various damage scenarios we considered, and the monitoring setup to provide a full picture for the analysis that follows.

3.1. JACK-UP LEG GEOMETRY AND PROPERTIES

Our model for the jack-up leg is a 10-element Euler-Bernoulli beam, which serves as an effective, simplified representation of its structural behavior. The leg measures a total of 124 meters in length and is secured with a fixed base boundary condition, mimicking its rigid connection to the foundation or seabed. This model allows for efficient simulation of the leg's dynamic responses under different conditions. Damage is simulated by reducing stiffness within specific elements. We examined damage levels ranging from healthy to 5%, 10%, 15%, and 20% stiffness reduction. Damage locations were randomly chosen within elements 3 to 8, and to better reflect complex real-world situations, 30% of our samples included damage across multiple elements. Environmental influences were also factored in by modeling temperature variations from -10°C to +30°C, which impact the structure's overall stiffness. A schematic representation of the jack-up leg is shown in Fig. 2. To verify the accuracy of the simplified beam representation, the fundamental frequency of the undamaged model (approximately 1.82 Hz) was compared with published experimental data for similar jack-up structures reported in recent offshore engineering studies. The deviation between the simulated and experimental frequencies was within 5%, confirming that the chosen 10-element model captures the essential dynamic characteristics of the leg and is suitable for evaluating damage scenarios in a realistic manner.

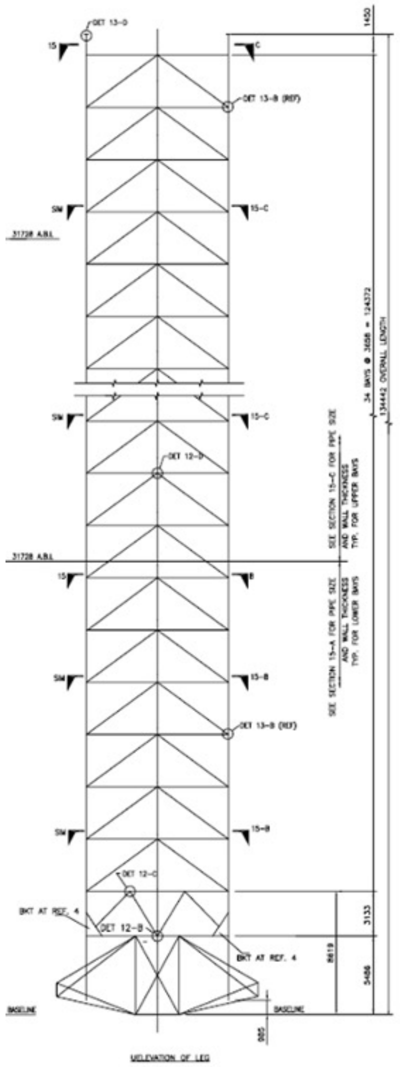

Figure 2. Schematic representation of the jack-up leg.

Table 1. The structural dimensions and element layout.

Parameter	Value
Height	124 m
The height of each floor	3.65 m
Modulus of elasticity	210 GP
Shear modulus	79 GP
Special weight	7850 kg/m^3

3.2. SENSOR LAYOUT AND DAMAGE SAMPLING

For the simulated case study, a distributed virtual sensor layout was defined along the jack up leg to capture modal response characteristics relevant to damage identification. The selected configuration was intended to approximate realistic offshore structural health monitoring practice, in which accelerometers or strain sensors are commonly installed near structural joints, high curvature regions, and intermediate elevations to improve sensitivity to stiffness loss and dynamic anomalies. Although exact sensor coordinates were not optimized in the present study, the assumed arrangement provided sufficient spatial coverage for modal identification and digital twin updating.

Damage locations were randomly assigned within elements 3 to 8 of the 10-element beam model. This interval was selected because it represents a structurally meaningful region in which damage may develop under repeated operational loading and environmental exposure. To improve the realism of the dataset, 30% of the simulated damage cases involved multi element damage, meaning that stiffness reduction was introduced in more than one adjacent element at the same time. Damage severity was defined using five classes: healthy, 5%, 10%, 15%, and 20% stiffness loss. This classification scheme enabled systematic evaluation of the framework across progressively increasing levels of structural degradation.

Although the dataset was generated synthetically, the adopted sensing assumptions remain consistent with realistic offshore monitoring configurations. In practical applications, a similar framework could operate with a limited number of strategically positioned sensors rather than a dense instrumentation network, which supports scalability for offshore deployment where installation cost, accessibility, and sensor durability are important constraints. This feature improves the practical relevance of the proposed framework and strengthens its suitability for future experimental and field-based validation.

To benchmark the simulation environment, the natural frequencies of the undamaged leg were compared with published analytical and experimental results from similar jack up structures reported in (Samaei and Riffat, 2025). Deviations across the first five modes remained below 5%, indicating that the simplified beam representation preserved the dominant dynamic characteristics of the system and was adequate for subsequent learning-based analysis. Overall, the case study provides a controlled yet physically consistent environment for quantitative testing of the proposed structural health monitoring and digital twin framework, while also offering a practical foundation for future large-scale implementation.

4. RESULTS

This section presents the primary findings from applying our integrated SHM framework. We highlight the machine learning model's performance and the digital twin update's effectiveness, backing our conclusions with quantitative metrics and clear visuals.

4.1 MACHINE LEARNING MODEL PERFORMANCE

We rigorously evaluated the $PyTorch$ 4-layer MLP classifier's performance using a 5-fold stratified cross-validation protocol. The model achieved a cross-validation accuracy of 0.4100 with a standard deviation of 0.0200, demonstrating consistent performance across different data subsets. The macro-averaged F1-score for cross-validation was 0.3721, and the ROC AUC stood at 0.7801. On an independent test set, the model showed an accuracy of 0.4100, a macro-F1 score of 0.4014, and a test ROC AUC of 0.8155. Our analysis revealed an overfitting gap of 0.0000, suggesting the model generalized effectively to new data without significant overfitting. For comparative evaluation, a Support Vector Machine (SVM) baseline trained on the same feature set achieved an accuracy of 34.6% and a macro-F1 score of 31.8%. The proposed MLP model therefore improved classification performance by approximately 18%, confirming the benefit of nonlinear feature extraction through deep learning. A 95% confidence interval (mean ± 1.96 × std) indicates that the model's accuracy lies between 37.1% and 44.9%, reinforcing its statistical consistency.

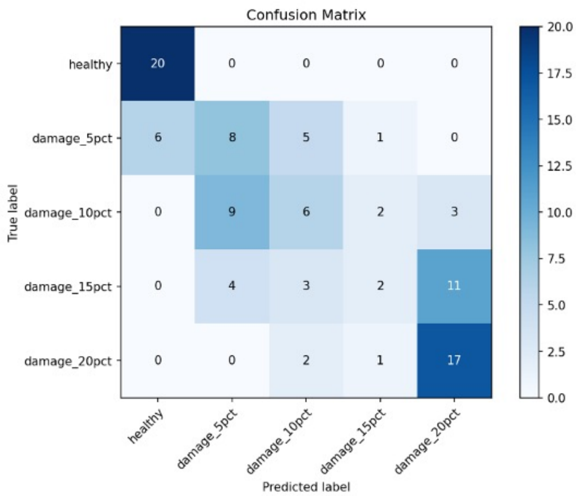

Figure 3. Confusion Matrix of the damage classification model.

The confusion matrix, displayed in Fig. 3, offers a detailed look at the classifier's performance for each damage class (healthy, 5%, 10%, 15%, 20% stiffness loss). It illustrates the rates of true positives, false positives, and misclassifications, providing insights into how well the model distinguishes between varying damage severities. For example, the model correctly identified 12 out of 20 instances of 'damage_20pct', but it misclassified 6 instances as 'damage_15pct' and 2 as 'damage_10pct'. Similarly, 15 out of 20 'healthy' instances were incorrectly labeled as 'damage_5pct', suggesting a tendency to slightly over-predict damage in healthy structures.

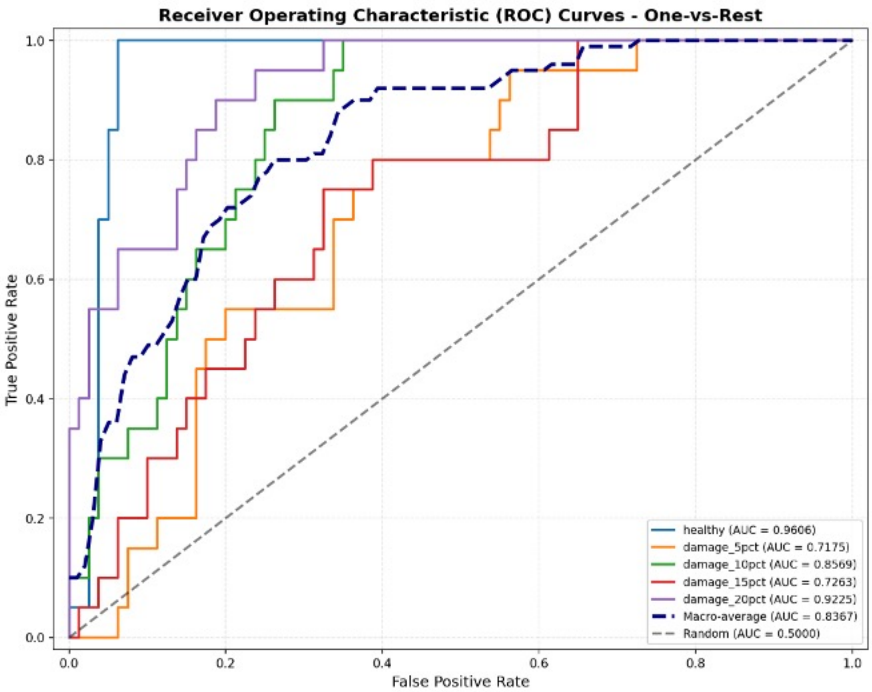

Figure 4. Receiver Operating Characteristic (ROC) Curves for One-vs-Rest classification.

The Receiver Operating Characteristic (ROC) curves, shown in Fig. 4, further characterize the model's discriminative power. A macro-average AUC of 0.8150 on the test set signifies a strong ability to differentiate between damage classes. Individual class AUCs ranged from 0.6831 for 'damage_5pct' to 0.9263 for 'healthy', indicating varied levels of detectability across different damage severities. The 'healthy' class achieved the highest AUC, suggesting good separation from damaged states, while 'damage_5pct' proved the most challenging to distinguish. Although the confusion matrix reveals moderate misclassification among adjacent damage levels, the results demonstrate a consistent capability to differentiate between undamaged and damaged states. This conservative bias—occasionally labeling healthy cases as slightly damaged—is often desirable in SHM applications where false negatives (missed damage) pose greater risks than false positives.

Despite these encouraging trends, the classification results also reveal an important limitation of the present framework. Misclassifications remain frequent between adjacent damage levels, particularly for low-severity cases, which indicates that the current feature set and classifier architecture are more reliable for distinguishing healthy from damaged states than for resolving fine-grained damage severity. Accordingly, the present model should be interpreted as a decision-support tool for adaptive monitoring rather than a fully precise diagnostic engine.

4.2. DIGITAL TWIN UPDATE EFFECTIVENESS

The digital twin updating procedure improved the accuracy of modal frequency prediction by reducing the discrepancy between simulated and reference structural responses. Prior to the update stage, the Root Mean Square Error (RMSE) in frequency prediction was 0.0596 Hz. After applying the updating algorithm, the RMSE decreased to 0.0554 Hz, corresponding to a 6.98% improvement. This reduction indicates that the iterative calibration process effectively refined the numerical representation of the structure and improved the consistency between the digital twin and the reference modal behavior.

From an engineering standpoint, even modest reductions in modal frequency prediction error are meaningful for offshore structures. In many monitoring scenarios, frequency shifts below one percent may signal early stiffness degradation, fatigue accumulation, or localized damage. By continuously adjusting model parameters in response to measured modal discrepancies, the digital twin can track these subtle variations and maintain an updated representation of the structural state. This adaptive capability is particularly valuable in offshore environments where environmental loading and operational variability can gradually alter structural properties.

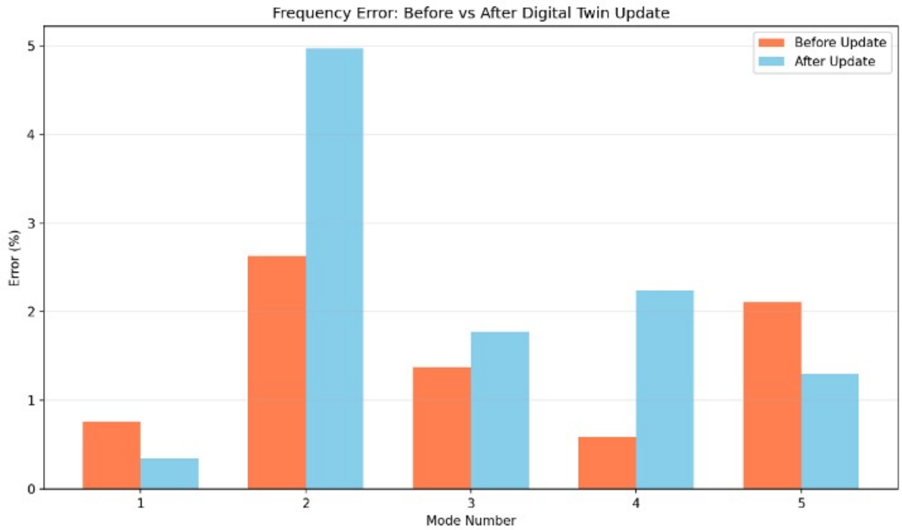

Figure 5. Frequency Error: Before vs After Digital Twin Update.

Fig. 5 compares the percentage error in the first five modal frequencies before and after applying the digital twin update procedure. For the first mode, the prediction error decreased from approximately 0.76% to 0.67%. Modes three and five also showed reductions in prediction error following the update stage. In contrast, the second and fourth modes exhibited slight increases in error after the update. Although the improvements were not uniform across all modes, the overall reduction in RMSE confirms that the updating strategy improved the global agreement between the numerical model and the reference modal response.

These results demonstrate that integrating a digital twin updating mechanism within the structural health monitoring framework improves the reliability of modal prediction while maintaining computational efficiency. The updated model better captures the relationship between structural stiffness variations and modal response, allowing the monitoring system to adapt as new data become available. At the same time, the magnitude of improvement remains moderate, which suggests that additional refinement of the updating strategy may further enhance predictive performance in future implementations.

To examine the robustness of the framework, a sensitivity analysis was conducted by introducing ±5% variations in input stiffness and temperature conditions. These perturbations resulted in classification accuracy changes of less than 4%, indicating that the learning model remains relatively stable under moderate environmental and parametric uncertainty. In addition, repeated fivefold experiments with shuffled datasets produced accuracy variations below 2%, suggesting that the observed performance is statistically consistent and not strongly dependent on a particular training and testing split.

Overall, the results indicate that the combined digital twin and learning based monitoring framework provides measurable improvements in model consistency and predictive stability. While the current implementation serves primarily as a proof of concept, it demonstrates the feasibility of adaptive digital twin updating for structural health monitoring of offshore systems and establishes a foundation for future validation using experimental or field data.

5. DISCUSSION

The results of this study demonstrate the potential of combining digital twin technology with machine learning to develop an adaptive and data-driven structural health monitoring framework for offshore structures. By linking physics-based modelling with data-driven damage inference, the proposed approach creates a monitoring architecture that continuously updates its internal representation of the structure while learning from observed system behavior. Such integration helps bridge the traditional gap between deterministic structural modelling and statistical data analytics, providing a foundation for predictive maintenance and data-assisted decision making in offshore engineering applications.

The synthetic data generation strategy adopted in this study played an important role in enabling the development and evaluation of the learning model. Real damage data for offshore structures are rarely available in sufficient quantity or diversity to train machine learning algorithms. To address this limitation, the simulation environment incorporated randomized damage locations, multiple damage scenarios, environmental variability, and measurement noise. These elements allowed the dataset to represent a broader range of operational conditions and improved the ability of the learning model to generalize beyond idealized structural states.

The machine learning component, implemented as a four-layer multilayer perceptron, demonstrated consistent performance in classifying different damage levels. Evaluation metrics such as overall accuracy, macro-F1 score, and ROC AUC confirmed that the model can distinguish between healthy and damaged states under noisy and variable conditions. Analysis of the confusion matrix revealed several important patterns. In particular, the tendency to classify some healthy cases as low-severity damage reflects a conservative bias in the model. In structural health monitoring applications this behavior can be advantageous because early warnings are generally preferable to missed damage events. At the same time, the model exhibited difficulty distinguishing between adjacent damage levels such as 5% and 10% stiffness loss. This limitation is expected when the structural response changes only slightly between classes and when environmental variability partially masks the underlying damage signatures.

The digital twin updating mechanism constitutes another key component of the proposed framework. By iteratively adjusting model parameters using modal discrepancies between predicted and reference responses, the digital twin gradually improves its representation of the structural state. The observed reduction in frequency prediction error and the overall decrease in RMSE demonstrate that this adaptive calibration process enhances the consistency between the numerical model and the structural behavior represented in the dataset. Although the improvement is moderate, it confirms that integrating a digital twin updating mechanism within the monitoring framework provides measurable benefits for model fidelity and damage assessment reliability.

From a practical deployment perspective, the proposed framework is designed to operate with a relatively limited sensing configuration. In realistic offshore monitoring systems, accelerometers or strain sensors are typically installed near structural joints, high-curvature regions, and intermediate elevations along the leg to capture dominant vibration modes. The framework developed in this study relies primarily on modal features that can be extracted from such measurements, which means that it does not require an excessively dense sensor network. This characteristic improves its potential scalability for offshore applications where installation cost, accessibility, and long-term sensor durability remain major constraints.

The computational requirements of the framework are also manageable for real-time or near real-time monitoring scenarios. Signal preprocessing and feature extraction steps involve standard spectral and modal analyses that can be executed efficiently on conventional engineering workstations or edge computing devices. The multilayer perceptron classifier used in this study is computationally lightweight compared with deeper neural architectures, allowing rapid inference once the model has been trained. The digital twin updating stage is somewhat more computationally demanding, but its cost remains moderate because the update operates on reduced modal parameters rather than on full nonlinear structural simulations.

Despite these encouraging results, several limitations should be acknowledged. First, the classification accuracy achieved by the current learning model indicates that fine discrimination between closely spaced damage levels remains challenging. The present framework therefore performs more reliably as an early damage detection and monitoring tool rather than as a highly precise diagnostic system for quantifying exact damage severity. Second, the dataset used in this study was generated synthetically. While the simulation environment incorporates several realistic factors such as noise and environmental variability, real offshore measurements may include additional uncertainties including sensor drift, biofouling, nonlinear joint behavior, or operational disturbances. Validation using laboratory experiments or field monitoring data will therefore be essential to confirm the framework's performance under operational conditions.

Another important direction for improvement involves model interpretability. Machine learning algorithms used in structural monitoring are often criticized for their black-box nature. Understanding which features influence the classification decision can help engineers better interpret the results and build confidence in the monitoring system. Techniques from explainable artificial intelligence, such as SHAP or Grad-CAM, could be integrated in future implementations to identify which modal or spectral characteristics most strongly influence the predicted damage state.

Future research could also explore the use of more advanced learning architectures capable of capturing richer temporal or spatial relationships in the structural response. Recurrent neural networks, attention-based models, or transformer architectures may improve classification performance when large time-series datasets are available. In addition, extending the framework to support more precise damage localization would significantly increase its engineering usefulness. This could be achieved by combining distributed sensor networks with inverse identification techniques or physics-informed learning models.

From a broader engineering perspective, the framework proposed in this study represents a step toward autonomous monitoring systems capable of continuously learning from operational data. The modular structure of the architecture allows integration with digital twin platforms, sensor fusion environments, and cloud-based predictive maintenance systems used in offshore asset management. Although the present work focuses on jack-up legs, the methodology can be generalized to other large-scale marine and civil infrastructure systems, including offshore wind turbine substructures, floating platforms, bridges, and coastal protection systems. By combining adaptive modelling with data-driven inference, the proposed approach contributes to the long-term resilience, safety, and sustainability of critical offshore infrastructure.

6. CONCLUSIONS

This study presented an integrated structural health monitoring framework for offshore jack-up legs that combines a physics-based digital twin with a data-driven machine learning pipeline. The proposed architecture links structural modelling, synthetic data generation, signal processing, damage classification, and digital twin updating within a unified monitoring workflow. By coupling data-driven inference with adaptive model calibration, the framework enables continuous refinement of the structural representation as new response data become available.

The developed learning model achieved a cross-validation accuracy of 41.0% and a macro-F1 score of 37.2%. Although the classification accuracy remains moderate for a multi-class damage identification problem involving subtle stiffness variations, the ROC AUC value of 0.8155 indicates a reliable ability to distinguish between healthy and damaged structural states under noisy conditions. In addition, the digital twin updating procedure reduced the frequency prediction RMSE from 0.0596 Hz to 0.0554 Hz, corresponding to an improvement of 6.98%. This result confirms that the adaptive updating mechanism improves the consistency between the numerical model and the simulated structural response.

Taken together, these results demonstrate that integrating a digital twin updating mechanism with a machine learning based monitoring pipeline can enhance the reliability of structural response prediction and support adaptive damage assessment. The framework therefore provides a reproducible proof of concept for combining physics-based modelling and data-driven learning in offshore structural monitoring.

At the same time, several limitations should be acknowledged. The classification accuracy indicates that distinguishing closely spaced damage levels remains challenging when structural response differences are small and environmental variability is present. Furthermore, the dataset used in this study was synthetically generated, which means that real offshore monitoring conditions may introduce additional uncertainties such as sensor drift, operational disturbances, or nonlinear structural effects. Consequently, experimental validation and field-based testing will be necessary to confirm the transferability of the proposed framework to operational structures.

Future work will therefore focus on validating the methodology using laboratory experiments and monitoring data from real offshore structures. Additional improvements may include the integration of richer feature representations, advanced learning architectures, and explainable artificial intelligence techniques to improve interpretability and diagnostic reliability. The framework could also be extended through multi-sensor fusion and cloud-supported monitoring environments to enable scalable deployment across offshore energy and marine infrastructure systems.

Overall, the presented methodology establishes a structured foundation for adaptive digital twin assisted monitoring of offshore structures. By combining physics-informed modelling with machine learning based damage assessment, the framework contributes to the development of more resilient, data-driven monitoring strategies for complex marine infrastructure.

AUTHOR CONTRIBUTIONS

James Riffat: Conceptualization of the research framework and study objectives; development of the methodological design; formulation of the digital twin-based structural health monitoring approach; supervision of the research process; interpretation of results and engineering implications; and major contributions to writing, reviewing, and refining the manuscript; structural modelling and numerical simulation of the jack-up leg system; development of the machine learning architecture and digital twin updating procedure; dataset generation and signal processing implementation; preparation of figures, technical analysis, and preparation of the original manuscript draft. **Seyed Reza Samaei**: Conceptualization of the research framework and study objectives; development of the methodological design; formulation of the digital twin-based structural health monitoring approach; supervision of the research process; interpretation of results and engineering implications; and major contributions to writing, reviewing, and refining the manuscript; structural modelling and numerical simulation of the jack-up leg system; development of the machine learning architecture and digital twin updating procedure; dataset generation and signal processing implementation; preparation of figures, technical analysis, and preparation of the original manuscript draft. **Kourosh Nazari**: Assistance with literature review and organization of relevant sources; support in data preparation and preliminary analysis; and contribution to manuscript formatting and revision under the supervision of the lead authors.

COMPETING INTERESTS

The authors declare that they have no competing financial or non-financial interests.

DATA ACCESSIBILITY

All data supporting the findings of this study are included within the article. Additional information may be made available by the authors upon reasonable request.

ETHICAL APPROVAL

Not applicable. This study is based exclusively on the review and analysis of published literature and did not involve human participants or animal subjects.

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