



AI-Enabled Structural Vibration Prediction for Enhanced Stealth Performance

Harish Kumar Kuppili¹, Kuda Nageswara Rao²

Master of Technology in AI&ML, Department of Computer Science and Systems Engineering, Andhra University,
Visakhapatnam, Andhra Pradesh, India¹

Professor, Department of Computer Science and Systems Engineering, Andhra University, Visakhapatnam,
Andhra Pradesh, India²

Abstract: Increasing engineering complexity and the need for dependable structural health monitoring have created a demand for accurate and computationally efficient vibration-prediction methods. Conventional approaches—including physics-based models, extensive experimental testing across operating conditions, and computationally intensive simulations—can be difficult to apply when structures and service environments vary widely and decisions must be made under uncertainty. This study presents an AI-based framework for predicting structural vibration responses using regression algorithms. Five approaches—artificial neural network (ANN), k-nearest neighbours (KNN), decision tree (DT), gradient boosting regression (GBR), and random forest regression (RFR)—were evaluated using historical and simulated data representing material characteristics, stiffened geometries, and applied loading conditions. The comparison indicates that ensemble methods, particularly RFR and GBR, provide stronger predictive accuracy and generalisation than the other evaluated models. GBR delivered the best test performance, while RFR achieved a closely comparable result. ANN could represent nonlinear relationships but required additional computational effort and tuning, whereas KNN and DT were more sensitive to variation in the data. The findings indicate that AI-based regression can support faster preliminary assessment, reduce design-cycle time, and contribute to structural monitoring. This work demonstrates the potential of ensemble learning as a scalable approach to vibration prediction and as a foundation for data-driven infrastructure monitoring, proactive maintenance, anomaly detection, and improved structural safety.

Keywords: Artificial intelligence, vibration prediction, structural health monitoring, predictive models, data-driven methods, machine learning.

I. INTRODUCTION

Machine learning and deep learning are increasingly being used to develop predictive models for structural vibration. Over the past decade, research has expanded into intelligent methods that can estimate dynamic responses with improved accuracy and reduced computational cost. Common approaches include conventional machine-learning algorithms such as random forests, support vector machines, and decision trees; artificial neural networks; ensemble methods; and physics-informed techniques. These methods address growing requirements in structural health monitoring (SHM) and damage recognition and prediction (DRP). Their development has been supported by the increasing availability of experimental datasets generated through modal analysis and impact-hammer testing [1], [2]. Such data enable more effective model training and encourage further optimisation through hyperparameter selection and architectural refinement.

Impact-hammer testing combined with random-forest prediction has been used to estimate the dynamic characteristics of different structural systems, including magnetorheological elastomers [2]. Physics-informed methods have also gained attention. Neural modal ordinary differential equations, for example, combine physical modelling with neural differential equations to represent high-dimensional structures under continuous monitoring [3]. Artificial neural networks have been applied to detect damage in composite beams from vibration-response data, enabling the identification of structural anomalies [4]. Non-destructive vibration testing has also been combined with ANN models to estimate the modulus of elasticity of bamboo-wood composites [5]. Ensemble learning has been used to predict aircraft vibration environments and represent complex dynamic behaviour [6], while physics-informed Gaussian processes have supported stochastic stiffness and response estimation for Timoshenko beams with quantified uncertainty [7].

Hybrid data-physics deep-learning methods have been proposed for impact-force identification, combining mechanistic models with data-driven techniques [8]. Neural extended Kalman filters integrate state-space models and neural-network architectures to learn and predict structural dynamics [9]. Frequency-response functions (FRFs) have been used with



support vector machines, decision trees, and related algorithms for structural damage identification [10]. Hybrid intelligence systems combining ANNs and vibration-based methods have likewise been investigated [11]. Other studies have developed optimised multilayer perceptrons for real-time vibration forecasting under non-stationary conditions, including deployment on resource-constrained hardware [12], and physics-informed Gaussian-process regression for estimating modal parameters of lattice towers under changing environmental conditions [13]. Sparse adaptive Bayesian filters have provided a basis for reconstructing unknown excitation forces from measured responses [14], while distance-assisted graph neural networks have used sensor-location relationships to reconstruct and localise impact forces [15].

Further work has explored ANN-based damage detection using experimentally measured FRFs and mode-shape curvature [16], vibration-based rail-stress measurement through modelling and field testing [17], and machine-learning-based health monitoring of high-performance fibre-reinforced concrete communication towers [18]. Regression algorithms, including random forests and gradient boosting, have been applied to identify multiple forms of damage in lattice-core sandwich composites [19]. Neural-network arrays with branch-pruning optimisation have been investigated for damage detection in seismically excited buildings [20]. Machine learning has also supported time-domain model reduction for structural mechanical responses [21], force reconstruction and state estimation in structural dynamics [22], time-series-based damage detection in civil structures [23], and identification of void damage in post-installed rebar-reinforced slab tracks using impact-hammer tests and deep-learning classifiers [24].

Recent applications include simulation-assisted dynamic analysis of 3-D printers using deep-learning prediction [25], experimental validation of machine-learning surrogate models for finite-element applications [26], wavelet-energy features for identifying structural changes [27], and condition monitoring of mechanical systems by integrating multibody-dynamics models with machine-learning algorithms [28]. Building on this body of work, the present study compares regression approaches for predicting the acceleration response of a constrained-layer-damped (CLD) beam. The objective is to identify a model that can capture the nonlinear, frequency-dependent response while offering useful generalisation to unseen data.

II. METHODOLOGY

Figure 1 presents the proposed hybrid experimental and artificial-intelligence workflow for structural vibration analysis. The framework is intended to improve analysis efficiency while reducing the time and cost associated with repeated testing. The process begins with selecting appropriate specimen materials, preparing the surfaces, checking dimensional accuracy, and defining boundary conditions that approximate the intended structural configuration. These steps are essential for producing reliable and representative experimental data.

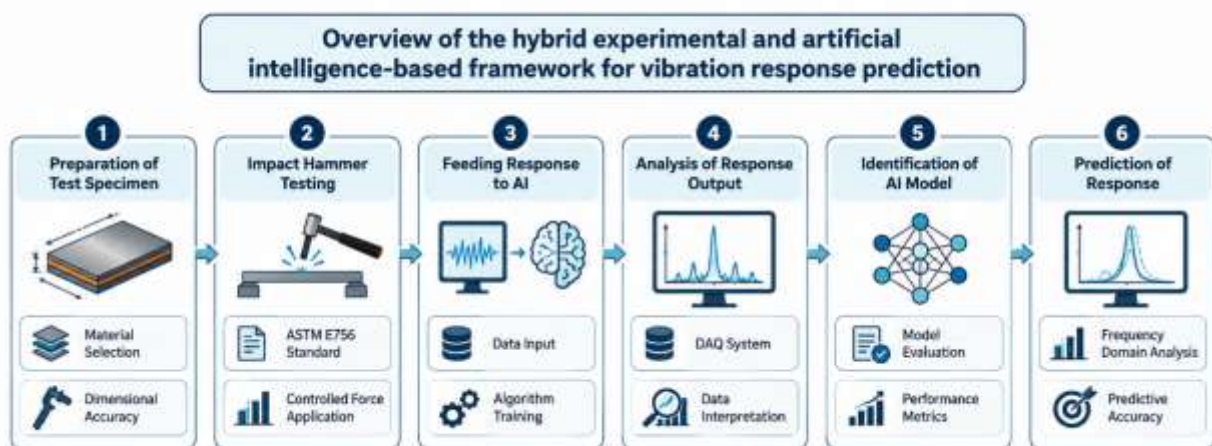


Figure 1. Overview of the hybrid experimental and artificial intelligence-based framework for vibration response Prediction

After specimen preparation, impact-hammer testing is conducted with reference to ASTM E756, which describes methods for determining damping and vibration properties using mechanical excitation. An instrumented hammer delivers a controlled impact to excite the structure; where fitted, its force transducer measures the input force. Accelerometers positioned at selected points record the resulting response in the time domain. The sensor outputs are passed to a data-acquisition (DAQ) system, which digitises and records the signals at the required sampling rate.



The digitised signals are processed using the Fast Fourier Transform (FFT) to convert the time-domain measurements into the frequency domain. The resulting data are used to identify key dynamic characteristics, including natural frequencies, mode shapes, damping ratios, and frequency-response functions. These characteristics provide insight into structural dynamics, resonance behaviour, and energy-dissipation capacity under dynamic loading. Instead of repeating physical tests for every combination of loading and boundary conditions, extracted response features can be used to train machine-learning models such as neural networks and tree-based or distance-based regressors. Once trained and validated, the model can act as a virtual testing aid for estimating responses in cases not directly tested, subject to the representativeness of the training data and the validation range.

B. Impact-Hammer Testing

In the constrained-layer-damping arrangement shown in Fig. 2, the base beam is the primary structure and undergoes flexural deformation. A viscoelastic material (VEM) is bonded to the base and dissipates mechanical energy by converting part of it into heat. A rigid constraining layer is placed over the viscoelastic material to induce cyclic shear deformation during vibration. This three-layer configuration can provide greater damping than a free-layer treatment because the polymer is forced to deform in shear between the base and the constraining layer. The resulting energy dissipation increases the loss factor and can reduce resonant response over the relevant frequency range.

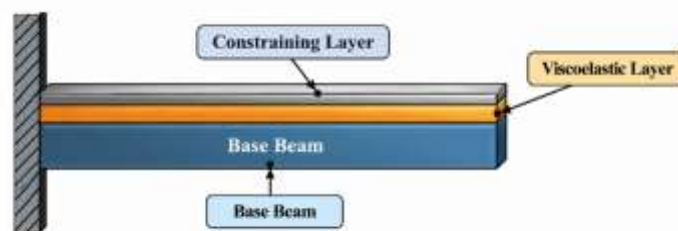


Fig. 2. Cantilever Setup of CLD for Impact Hammer Testing

Figure 3 illustrates the modal-test arrangement used for the CLD beam. The beam is secured to a fixture to reproduce the intended boundary condition and minimise unwanted movement. An instrumented impact hammer applies a short-duration force to the beam, producing a transient response. A piezoelectric accelerometer mounted on the beam converts its mechanical motion into an electrical signal. The hammer input and accelerometer output are recorded simultaneously by the DAQ system. The measured signals are then analysed in the frequency domain to estimate natural frequencies, damping ratios, mode shapes, and FRFs. These quantities help characterise the structure's dynamic response and assess the effectiveness of the damping treatment. Results are commonly presented as FRF curves or acceleration-versus-frequency plots.

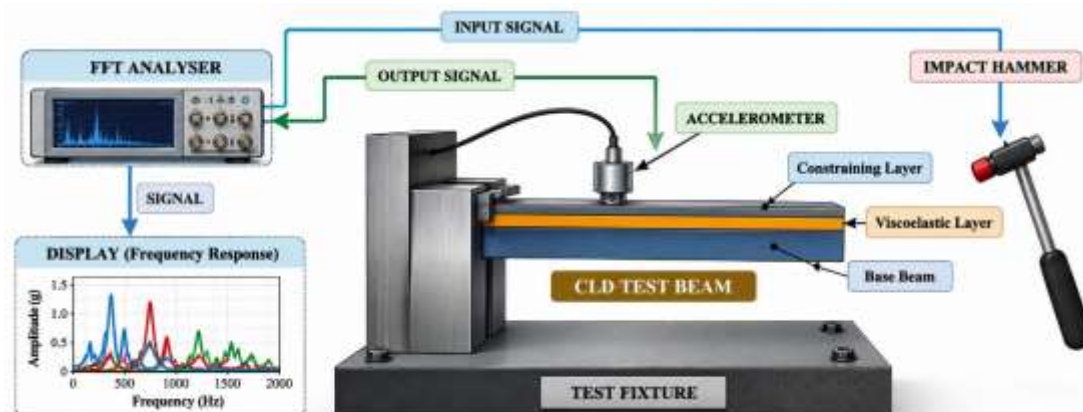


Fig. 3: Experimental Setup for Impact Hammer testing

Impact-hammer testing is widely used to identify the dynamic properties of beams and other structural components. The DAQ system converts the measured input and output channels into digital signals. A frequency-response function is obtained from the relationship between the response spectrum and the applied-force spectrum. FRFs are valuable for estimating modal properties, assessing structural integrity, and validating numerical models, including finite-element analysis (FEA).



For the CLD beam considered in this work, the steel beam dimensions are reported as 220 mm × 20 mm, with viscoelastic damping material bonded using a strong adhesive such as Araldite epoxy. The total beam thickness is 5 mm, comprising a 2 mm base layer, a 2 mm viscoelastic layer, and a 1 mm constraining layer. The beam is configured as a cantilever and divided into sections for modal analysis. Impacts are applied at selected locations, while accelerometers are placed near the free end to measure the response. This arrangement is suitable for studying damping because the viscoelastic layers dissipate energy during deformation. To improve repeatability, each test case is generally repeated five to ten times. The measured acceleration commonly exhibits an initial impact followed by decaying oscillations associated with the beam's natural modes and damping.

The time-domain response of a single-degree-of-freedom system subjected to an impulse can be expressed as:

$$x(t) = A e^{(-\zeta\omega_n t)} \cos(\omega^d t + \phi) \quad (1)$$

where A is the initial amplitude, ζ is the damping ratio, ω_n is the undamped natural frequency, ω^d is the damped natural frequency, and ϕ is the phase angle. The measured response is transformed to the frequency domain using the Fast Fourier Transform (FFT) to examine the frequency response. The relationship between damped and undamped natural frequencies is:

$$\omega^d = \omega_n \sqrt{1 - \zeta^2} \quad (2)$$

Impact-hammer testing, CLD materials, and modern signal-processing methods together provide a practical approach for investigating structural dynamics. The technique is economical, non-destructive, and suitable for characterising vibration behaviour under representative service conditions. The resulting experimental data can also train AI models to estimate structural responses under new conditions, potentially reducing the need for additional physical tests. Combining experimental mechanics and AI can therefore streamline design, testing, and validation in civil, automotive, aerospace, and machinery applications.

III. RESULTS AND DISCUSSION

A. Acceleration Response of a CLD Beam

Table I presents selected frequency–acceleration values for the CLD beam and illustrates how the measured response varies with excitation frequency. The DAQ data cover the 0–5000 Hz range, with 2000 data points reported for the spectrum. The maximum listed acceleration is approximately 0.1708 mm/s² at 62.5 Hz, indicating a prominent resonant response near this frequency. Acceleration rises rapidly as the frequency approaches the peak and then decreases at higher frequencies. This trend is consistent with a damped structural response in which energy is dissipated after resonance, limiting sustained oscillation.

The structure was excited using an instrumented impact hammer, but only the accelerometer response signals were supplied to the machine-learning models. The hammer struck the free end of the cantilever, and vibration responses across 0–5000 Hz were recorded in the time domain. Although the impact force could have been measured directly, it was not included as a model input; therefore, the learning framework relies on response-only data. The measured damping ratio was 0.091.

Table I. Selected frequency-versus-acceleration values for the CLD beam.

Frequency (Hz)	Acceleration (mm/s ²)
0.0	0.001396
12.5	0.002732
25.0	0.004852
37.5	0.022128
50.0	0.143919
62.5	0.170848
112.5	0.002410
125.0	0.002384
137.5	0.002446
150.0	0.002711
5000.0	0.001101



B. Machine-Learning Prediction Accuracy for the CLD Beam

The results in Tables II and III show that ensemble regression methods—particularly Gradient Boosting Regression (GBR) and Random Forest Regression (RFR)—predicted the nonlinear acceleration response more accurately than the other evaluated methods. With a training-to-test split of 70:30, GBR achieved the strongest test performance, with an R^2 value of 0.9060 and an RMSE of 0.0225. RFR produced a closely comparable test R^2 of 0.9038 and an RMSE of 0.0228. By comparison, polynomial regression of degree three and ANN regression performed poorly, with test R^2 values below 0.11, suggesting that these configurations did not adequately represent the measured response.

Table II. Training-set performance of regression algorithms

Method	RMSE	R^2 Score
Polynomial Regression (degree 3)	0.053902	0.154333
ANN Regression	0.055730	0.095993
Random Forest Regression	0.007373	0.984175
Gradient Boosting Regression	0.007875	0.981950
KNN Regression	0.018316	0.902349

Table III. Test-set performance of regression algorithms

Method	RMSE	R^2 Score
Polynomial Regression (degree 3)	0.069350	0.107167
ANN Regression	0.069694	0.098302
Random Forest Regression	0.022769	0.903757
Gradient Boosting Regression	0.022506	0.905971
KNN Regression	0.032608	0.802607

A comparison of training and test results suggests some overfitting in the non-parametric models. RFR and GBR achieved training R^2 values close to 0.98, declining to approximately 0.90 on the test data. KNN also declined, from a training R^2 of 0.9023 to a test R^2 of 0.8026. These differences indicate that the flexible models may have learned some noise in the training samples alongside the underlying viscoelastic response. Nevertheless, GBR retained the best balance between fit and generalisation among the evaluated approaches and was therefore the preferred model for this analysis.

C. Prediction of Acceleration Response Using Gradient Boosting Regression

Figure 5 compares the experimental acceleration response (Leq5) with the predictions generated by the Gradient Boosting Regression model over the 0–5000 Hz frequency range. The predicted curve has a step-like profile, reflecting the tree-based ensemble structure, which divides the input space into regions with approximately constant predictions rather than fitting one continuous smooth function. Despite this characteristic, GBR captures important features of the nonlinear response, including the locations of major resonant peaks and anti-resonant valleys.

A small reduction in predicted amplitude is visible at high-response regions, particularly around the primary resonance near 400 Hz, where the model slightly underestimates the peak. This behaviour is consistent with averaging within the terminal tree nodes. Overall, the predicted response follows the measured frequency-dependent pattern reasonably well, in agreement with the test R^2 of approximately 0.906. The results suggest that GBR can learn useful relationships in the vibration data while maintaining acceptable performance on observations withheld from training.

IV. CONCLUSION

This study evaluated machine-learning methods for predicting the nonlinear acceleration response of a constrained-layer-damped beam. Five regression algorithms were compared, and the main findings are summarised below.

1) Performance of tree-based ensemble methods: Tree-based ensembles provided the strongest performance for modelling the response of the CLD sandwich structure. Gradient Boosting Regression achieved the highest test R^2 (0.9060) and the lowest test RMSE (0.0225), while Random Forest Regression performed almost as well, with a test R^2 of 0.9038. These results indicate that ensemble models can represent nonlinear relationships in the measured vibration response without requiring a full, computationally expensive FEA model for every prediction.



2) Limitations of conventional models: Polynomial regression (degree three) and the evaluated ANN configuration showed limited generalisation, with test R^2 values below 0.11. In this application, polynomial fitting was insufficiently flexible to capture rapid frequency-response variations, while the ANN configuration did not learn the relevant response patterns effectively under the selected modelling conditions.

3) Physical consistency and generalisation: Although the ensemble models showed some loss of performance between training and test data, their test R^2 values remained around 0.90. The spectral response predicted by GBR reproduced the principal resonant peaks and anti-resonant valleys over the 0–5000 Hz range. This agreement suggests that the model captured important response characteristics, although further validation across additional specimens and operating conditions is needed before broader deployment.

4) Practical application: The prediction accuracy achieved by GBR indicates its potential as a surrogate model for CLD design and optimisation. Using a trained regressor alongside, or as a rapid approximation to selected parts of, an FEA workflow may reduce computational effort when analysing complex damping treatments. Its suitability for engineering use should be confirmed through further validation and explicit assessment of prediction uncertainty.

FUTURE RESEARCH DIRECTIONS

Future work will examine how temperature influences the vibration response of the system and assess damping performance using learning models that account for temperature-dependent material properties. Additional datasets will be developed to include both mechanical and thermal responses as model inputs. The objective is to train models capable of predicting system behaviour across a broader range of operating conditions while accounting for ambient-temperature effects.

REFERENCES

- [1] A. Khatir, R. Capozucca, et al., “Advancing structural integrity prediction with optimized neural network and vibration analysis,” 2024.
- [2] P. Shenoy, N. Kamath, et al., “Experimental modal analysis using impact hammer testing with random forest-based prediction of magnetorheological elastomer dynamics,” 2024.
- [3] S. Bhattacharya, V. Balakrishnan, et al., “Neural modal ODEs: Integrating physics-based modeling with neural ODEs for modeling high dimensional monitored structures,” 2022.
- [4] P. A. Reis, K. M. K. Iwasaki, et al., “Damage detection of composite beams using vibration response and artificial neural networks,” 2021.
- [5] G. You, B. Wang, et al., “The prediction of MOE of bamboo-wood composites by ANN models based on the non-destructive vibration testing,” 2022.
- [6] S. Février, L. Mathelin, et al., “Data-driven model to predict aircraft vibration environment,” 2023.
- [7] G. R. Tondo, S. Rau, et al., “Stochastic stiffness identification and response estimation of Timoshenko beams via physics-informed Gaussian processes,” 2023.
- [8] J. Zhou, Y. Cai, et al., “Data-physics hybrid-driven deep learning method for impact force identification,” 2024.
- [9] W. Liu, Z. Lai, et al., “Neural extended Kalman filters for learning and predicting dynamics of structural systems,” 2023.
- [10] D. V. Ruiz, B. L. Poncetti, et al., “Structural damage identification through machine learning approaches using FRFs,” 2024.
- [11] S. J. S. Hakim, M. J. Irwan, et al., “Structural damage identification employing hybrid intelligence using artificial neural networks and vibration-based methods,” 2022.
- [12] I. Singh, P. Conrad, et al., “Real-time forecasting of vibrations with non-stationarities,” 2022.
- [13] S. Møller, C. Jonscher, et al., “Investigations towards physics-informed Gaussian process regression for the estimation of modal parameters of a lattice tower under environmental conditions,” 2023.
- [14] J.-B. Ghibaudo, M. Aucejo, et al., “A sparse adaptive Bayesian filter for input estimation problems,” 2022.
- [15] C. Huang, C. Tao, et al., “Impact force reconstruction and localization using distance-assisted graph neural network,” 2023.
- [16] S. Gupta and S. Das, “Damage detection using experimentally obtained frequency response data with an application of artificial neural network-based improved mode shape curvature,” 2023.
- [17] M. Belding, A. Enshaiean, et al., “Vibration-based approach to measure rail stress: Modeling and first field test,” 2022.
- [18] S. J. Saleem, F. Hejazi, et al., “Health monitoring of ultra high fiber performance reinforced concrete communication tower using machine learning algorithms,” 2023.



- [19] M. Avarzamani, M. Ghazali, et al., “Multiple damage detection in sandwich composite structures with lattice core using regression-based machine learning techniques,” 2024.
- [20] J.-Y. Chou, C.-M. Chang, et al., “Damage detection of seismically excited buildings using neural network arrays with branch pruning optimization,” 2025.
- [21] X. Yan, X. Guo, et al., “Model reduction of structural mechanical response in the time domain,” 2025.
- [22] S. Hao, “Advanced machine learning approaches for force reconstruction and state estimation in structural dynamics,” 2024.
- [23] B. Güneş and O. Güneş, “Time series analysis methodology for damage detection in civil structures,” 2023.
- [24] Z. Chen, X. Cai, et al., “Void damage identification in post-installed rebar reinforced slab tracks via impact hammer tests and deep learning,” 2025.
- [25] R. Behera and T.-C. Chan, “Dynamic analysis of 3D printer through simulation, experimental validation, and deep learning-based prediction,” 2025.
- [26] S. Arunachalam, M. Chierichetti, et al., “Experimental validation of surrogate machine learning models for finite elements applications,” 2025.
- [27] Springer, “Experimental study on identification of structural changes using wavelet energy features,” 2022.
- [28] J. Koutsoupakis, D. Giagopoulos, et al., “AI-based condition monitoring on mechanical systems using multibody dynamics models,” 2023.