SHM of RC Bridge Girder for Damage Identification and Localization Using Machine Learning

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ABSTRACT

Structural Health Monitoring (SHM) is essential for ensuring the safety of reinforced concrete (RC) bridge girders, which are key components of transportation infrastructure. Traditional methods like visual inspection and non-destructive evaluation can be expensive and may not cover all areas, making it hard to detect and localize damage comprehensively. This study uses Finite Element (FE) modelling in Abaqus software to create detailed computer models of scaled down RC bridge girder (as a RC beam) and simulate different localized shear crack scenarios through smear crack modelling to extract time history output with respect to acceleration data. These generated synthetic datasets are then used to train a multi-layer perceptron (MLP) based machine learning architecture for damage detection and localization. The MLP model is designed to automatically learn complex, non-linear relationships from a wide range of statistical, frequency domain, and wavelet features extracted from the acceleration data. This approach offers a cost-effective way to monitor bridges by reducing the need for extensive sensors and manual inspection, potentially improving safety and reduce maintenance costs. However, further validation with lab tested data and then scaling it to real-world data is needed to confirm its effectiveness.

Keywords: Structural Health Monitoring (SHM), Damage Localization, Finite Element (FE), RC Bridge Girder, Multi-Layer Perceptron (MLP)

1. INTRODUCTION

Bridges are vital components of a country's infrastructure, facilitating transportation and economic activities across the nation. However, many of these structures are aging and require systematic monitoring to ensure safety and longevity. The Indian Bridge Management System (IBMS) has inventoried over 169,528 bridge structures, with more than 200 exceeding 75 years of age. Notably,

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IBMS has identified 147 bridges as critically distressed, necessitating immediate rehabilitation or reconstruction efforts [1]. The Indian Railways' bridge inventory reveals that 44% of in-service bridges are over 100 years old, 62% exceed 80 years, and 75% are over 60 years old [2]. This aging infrastructure underscores the urgency for effective SHM systems to prevent potential failures and ensure public safety. Similar concerns exist in across all the other nations, where aging infrastructure requires innovative monitoring solutions.

SHM has therefore emerged as a critical discipline aimed at detecting damage early, localizing defects accurately, and informing timely maintenance decisions to prevent catastrophic failures [3,4]. Traditional inspection techniques, such as visual assessment and non-destructive evaluation (NDE) methods offer valuable information on surface conditions and material properties. However, these approaches often involve significant labour, can be cost-prohibitive for large-scale deployment, and may fail to detect sub-surface or distributed damage phenomena comprehensively [5,6]. To overcome these limitations, computational modelling using FE software like in this case Abaqus has been employed to simulate RC components under a loading scenario. Smear crack models capture diffuse cracking patterns characteristic of reinforced concrete subjected to flexural and shear stresses, enabling the extraction of dynamic response data that correlate with damage states.

Recent advances in machine learning have enabled automated feature extraction and sequence analysis for structural health monitoring (SHM). This study employs a multilayer perceptron (MLP) model trained on statistical, frequency-domain, and wavelet features derived from simulated acceleration time-history data [7–9]. The MLP effectively captures complex non-linear relationships between features and damage states, offering accurate classification and regression for crack detection and localization [10,11]. This scalable, cost-effective approach reduces reliance on manual inspection while maintaining high detection accuracy. Future work will focus on validating the model under real-world conditions and integrating it into practical SHM workflows for bridge maintenance [12].

2. GIRDER DESIGN AND SCALE-DOWN

A 200mm-thick RC slab is assumed to rest on three 12m-long bridge girders with a cross-sectional dimension of 800mm x 1200mm. M25 grade concrete and Fe415 grade steel were used. The beams were designed for wheel point loading (Class A) using Indian Road Congress (IRC) and Indian Standard (IS) regulations. A typical concrete mix design for beams (as bridge girder representation) was obtained with a slump of 75 mm and a 0.45 water–cement ratio.

The resulting design is geometrically scaled down by a factor of 0.25 from the original. Tensile reinforcement consists of three 12mm diameter rebars, while two 8mm diameter rebars serve as hanging bars to hold the stirrups. The final scaled-down dimensions and layout of the beam along with the reinforcement representing the behaviour of RC bridge girder is as shown in the Figure 1.

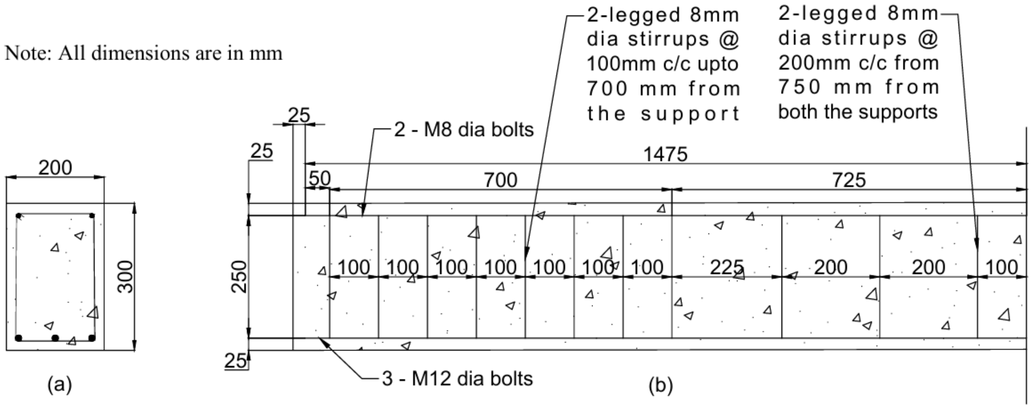


Figure 1. (a) Cross-Section and (b) Longitudinal Section of RC beam girder

3. ABAQUS MODELLING

The designed scaled-down RC bridge girder is modelled in a FE software, ABAQUS with a simply supported condition. An impact load is applied at the centre of the beam that would generate time history output as acceleration from 5 positions at the bottom of the beam. The considered 5 positions are L/6, L/3, L/2, 2L/3, 5L/6, where L is considered the scaled-down support to support length. The support condition obtained here was pin-pin at the bottom considered at 160mm from each end of the beam.

The material properties of concrete and steel used are as given in **Table I**. Note that the table values are to be converted to one consistent system of units to actually use in the ABAQUS. The Concrete Damage Plasticity (CDP) properties were also used as input parameter in the concrete material as generated by a tool - CDP Generator [13]. The interface of the tool is shown in Figure 2 and the values generated by it is used in ABAQUS.

The steel reinforcement (embedded region) was embedded in the concrete beam (host region) with a Constraint 'Embedded Region'. The Mesh Control – 'Hex-Sweep' with Element type of 20-node quadratic brick, reduced integration, i.e., C3D20R. The Mesh global seed size of 50 was obtained. Refer to Figure 2 for rendered view of the model in ABAQUS software.

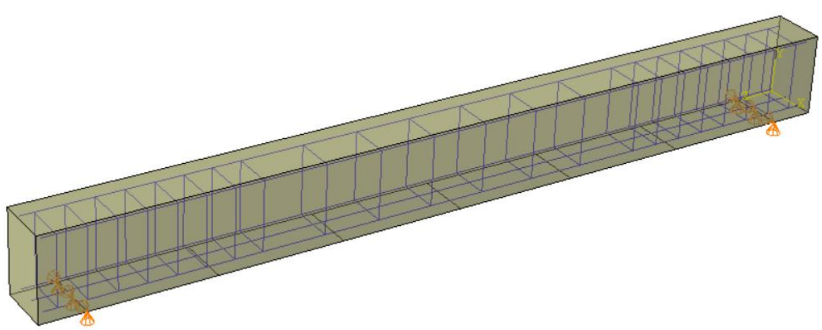
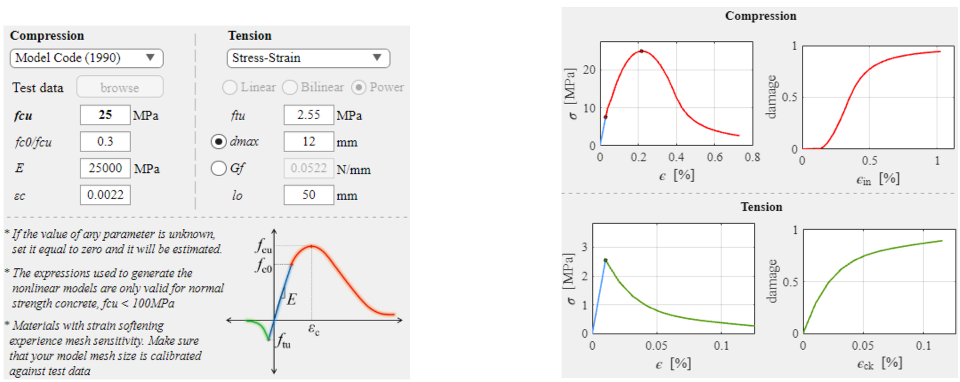


Figure 2. Modelled girder in ABAQUS software

TABLE I. PROPERTIES CONSIDERED TO INPUT IN ABAQUS

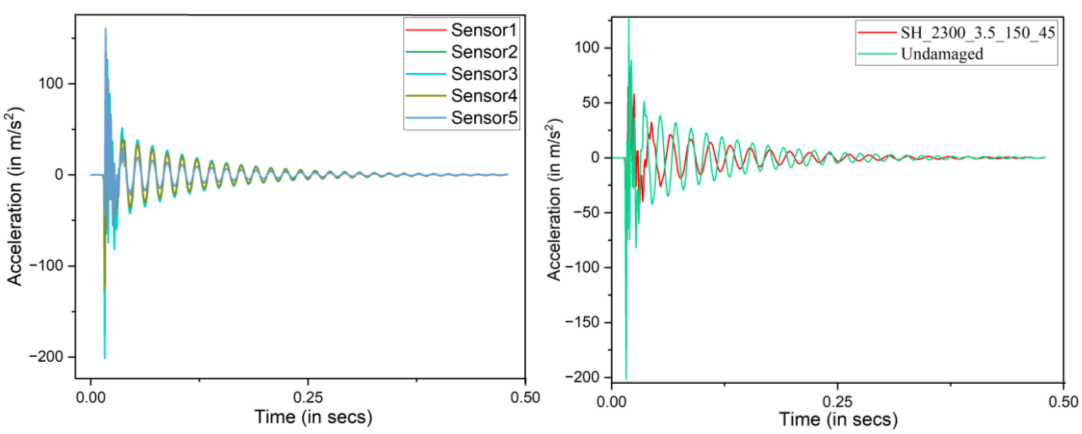
Parameters	**Values with Units**
Concrete Properties	
Density	25 kN/m^3
Young's Modulus	25 GPa
Poisson's Ratio	0.15
Steel Properties (For Rebars)	
Density	7850 kg/m^3
Young's Modulus	210 GPa
Poisson's Ratio	0.27
Yield Stress	415 MPa
Plastic Strain	0



(a) (b)

Figure 3. (a) Input parameters of CDP Generator and (b) Plot window of CDP Generator

A Python script was executed to run ABAQUS in a loop and simulate various smear crack scenarios using input parameters such as crack type (can refer to an undamaged condition, or a shear crack, both abbreviated as UD/SH, respectively), crack location, crack width, crack depth, and crack inclination. The generated responses from five sensor locations are saved in local disk and then pushed to python interpreter to train and test the dataset to detect and localize the damage.



(a) (b)

Figure 4. Acceleration vs Time response of (a) one of the undamaged cases for all the 5 sensors (b) damaged at SH_2300_3.5_150_45

The acceleration vs time response of one of the undamaged cases for all the 5 sensors is as shown in Figure 4 (a). As the beam is symmetrical and so the position of sensors, therefore, the responses of Sensor 1 with Sensor 5 and Sensor 2 with Sensor 4 looks overlapped.

Figure 4 (b), suggests compared acceleration vs time responses of undamaged and SH_2300_3.5_150_45 (i.e. shear crack at crack location 2300mm, crack width 3.5mm, crack depth 150mm, and crack inclination of 45°. It can be clearly observed that there is reduction in amplitude of shear crack scenario when compared with undamaged scenario. Additionally, the observed change in frequency is noteworthy, as it highlights increase in time period, which implies a reduction in stiffness of the beam.

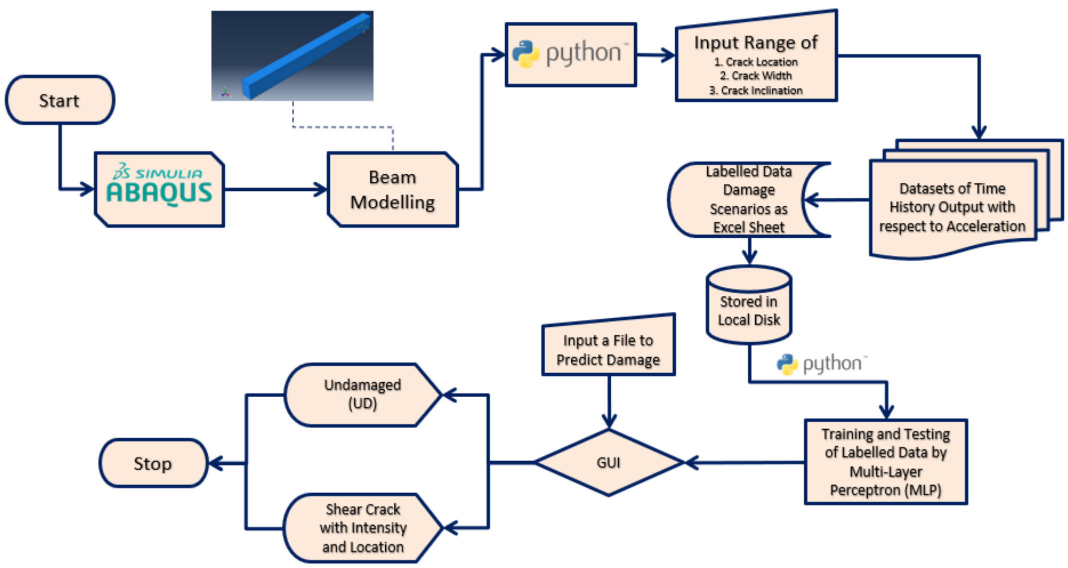


Figure 5. A flowchart of MLP based damage detection algorithm

4. EMPLOYED MACHINE LEARNING FRAMEWORK

4.1. FEATURE EXTRACTION AND DATA PREPARATION

The system first processes acceleration data from five sensors, extracting a comprehensive set of 235 features through multi-domain feature engineering. For each sensor, 41 features are computed including: (a) ten basic statistcal features (mean, standard deviation, peak values, kurtosis, skewness, RMS, crest factor, peak-to-peak amplitude, variance, and zero-crossing rate), (b) three frequency-domain features (spectral centroid, spectral bandwidth, and spectral rolloff), (c) six dominant frequency features (top three dominant frequencies and their corresponding magnitudes), (d) Fifteen wavelet-based features from 5-level Daubechies 4 (db4) wavelet decomposition providing mean, standard deviation, and energy for each decomposition level, and (e) Seven comparison features computed against an undamaged reference signal (maximum correlation, correlation lag, natural frequency, frequency change, Modal Assurance Criterion, Frequency Response Function magnitude, and coherence). Additionally, 30 cross-sensor features are extracted from the 10 sensor pairs, capturing cross-correlation, phase differences, and amplitude ratios between sensors.

4.2. MULTI-LAYER PERCEPTRON (MLP)

The development of MLP neural networks in SHM has taken them from basic pattern recognition to complex damage detection systems. The move to MLP architectures was a big step forward because researchers realized that they could better capture complex relationships between structural response data and damage parameters through multiple hidden layers and activation functions. Early tests showed that a lot of ML methods could differenciate between damaged and undamaged structures with more than 90% accuracy [15,16]. However, modern uses have shown that MLP works, with recent studies showing that it does an excellent job of finding damage on cable-stayed bridges, with over 90% accuracy in classification tasks [17]. The proposed MLP model aims to achieve more than 95% accuracy on the simulated dataset, however, the same would

5. RESULTS AND DISCUSSION

The MLP based damage detection system demonstrated exceptional performance in identifying and quantifying shear damage in RC bridge girders. The system successfully processed 357 shear case scenarios with variation of input parameters over a range through Abaqus software and 178 undamaged synthetic datasets.

Here, two separate cases were generated: Case-(a) first an undamaged case was weaved to generate numerous cases through python code with variation in small amplitude scaling, minimal random noise of ±2% (gaussian white noise), minimal baseline shift and subtle frequency modulation in the response to balance the training without hampering shear cases. Case-(b) Similar variations were also applied to generate shear cases keeping the Case-(a) as it is.

a) The MLP architecture, configured with three hidden layers using ReLU activation function, achieved exceptional performance across all evaluation metrics. The training accuracy reached 98.65% while validation accuracy stabilized at 95% for the dataset for Case-(a). Whereas, the training accuracy reached 99% while validation accuracy stabilized at 95% for the dataset with Case-(b). Interestingly, both the cases successfully distinguish between undamaged and shear damage cases with high precision.

b) Refering to Figure 6, the confusion matrix demonstrates perfect seperation between UD and SH cases, all 357/1071 SH samples for Case-(a)/Case-(b) were precisely classified, and likewise, all 178 UD samples were correctly identified, yielding no false positives or false negatives.

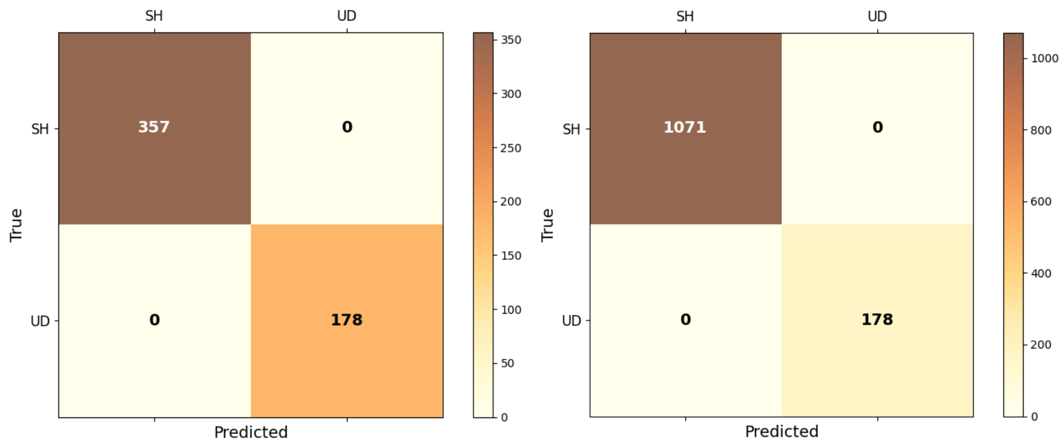


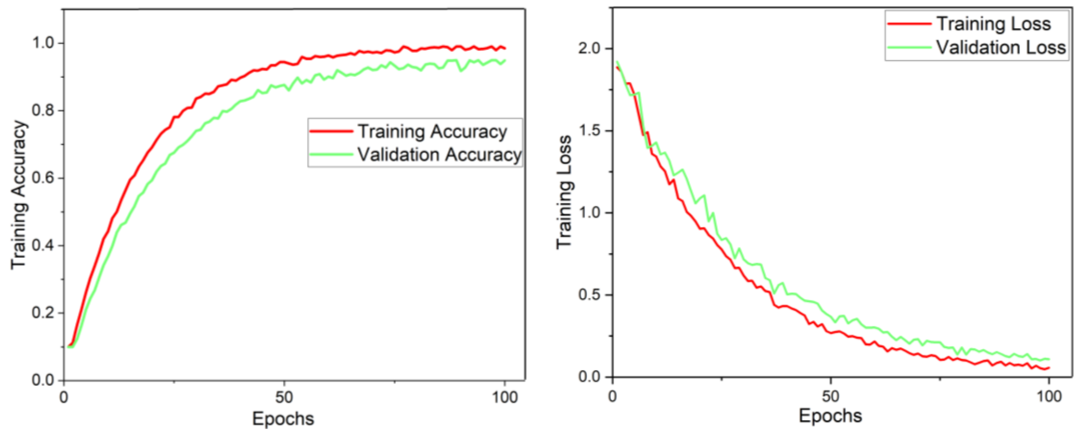
Figure 6. Confusion Matrix depicting True Vs Predicted UD and Shear Cases

c) The 4 separate MLP regressors for damage parameter quantification demonstrated robust prediction capabilities across all damage characterisitcs for Case-(b). Crack location and width prediction achieved mean confidence levels of more than 95% with effective localization within ±15mm and crack width within ±5mm accuracy range. Crack depth and crack inclination prediction achieved precision with confidence level of over 92%. Three cases were tested for prediction and ML's confidence level that can be referred from TABLE II.

TABLE II. ACTUAL VS PREDICTED DAMAGE PARAMETERS BY MLP ALGORITHM

Cases	**Parameters**	**Actual**	**Predicted**	**%Error**	**% of ML's Confidence**
1	Crack Location (in mm)	2000	1996	0.2	97.2
	Crack Width (in mm)	4.0	3.95	1.25	96.1
	Crack Depth (in mm)	250	252.1	0.84	97.0
	Crack Inclination (in °)	40	40	0	95.1
2	Crack Location (in mm)	2200	2207.8	0.35	97.5
	Crack Width (in mm)	3.0	3.05	1.67	95.5
	Crack Depth (in mm)	225	228.9	1.73	96.7
	Crack Inclination (in °)	35	35.2	0.57	94.7
3	Crack Location (in mm)	2400	2421	0.88	97.6
	Crack Width (in mm)	3.5	3.46	1.14	96.4
	Crack Depth (in mm)	150	153.2	2.13	94.4
	Crack Inclination (in °)	45	44.2	1.78	93.8

d) The MLP classifier converged rapidly, with both training and validation accuracy rising sharply during the first 30 epochs and gradually plateauing by epoch 60. The training and validation loss curves exhibit exponential decay from an initial loss near 1.9 down to below 0.1 by the end of 100 epochs, with minimal divergence between the two curves. The learning curves for which can be seen from Figure 7.



(a) (b)

Figure 7. (a) Accuracy Learning Curve and (b) Loss Learning Curve

6. CONCLUSION

The study demonstrates that a deep MLP model, trained on comprehensive acceleration-based feature extracted from Abaqus FE simulations of RC bridge girder shear cracks, can achieve near-perfect classification of damage type. The high convergence speed, strong validating accuracy of 95% on unseen data relating to damage parameter detection, and zero misclassification highlight the potential of simulation-driven datasets combined with advanced feature engineering for SHM applications. The results further indicate that the implemented MLP model demonstrates strong predictive performance, achieving a margin of error of less than 5% in estimating crack parameters. In addition, the percentage confidence of the algorithm in predicting the crack parameters is more than 90% as discussed in the previous section of the paper. Future work will focus on validating the approach with laboratory-collected dataset and extend the framework to flexural and mixed-mode damage scenarios, thereby paving the way for cost-effective, scalable bridge monitoring solutions.

REFERENCES

1. Indian Bridge Management System (IBMS) | Ministry of Road Transport & Highways, Government of India. (n.d.). Retrieved June 20, 2025, from https://morth.nic.in/hi/node/2686

2. Welcome to Rail Bridge. (n.d.). Retrieved June 20, 2025, from https://railbridges.com/site/resources

3. Ahmed, A., & Urs, N. (2022). Structural Health Monitoring of an Old RC Bridge. 9(7). https://doi.org/10.17148/IARJSET.2022.9753

4. He, Z., Li, W., Salehi, H., Zhang, H., Zhou, H., & Jiao, P. (2022). Integrated structural health monitoring in bridge engineering. Automation in Construction, 136, 104168. https://doi.org/10.1016/j.autcon.2022.104168

5. Morcous, G. (2006). Discussion of "Bridge Management and Nondestructive Evaluation" by Kevin L. Rens, Carnot L. Nogueira, and David J. Transue. Journal of Performance of Constructed Facilities, 20(3), 300–301. https://doi.org/10.1061/(ASCE)0887-3828(2006)20:3(300)

6. Hesse, A. A., Atadero, R. A., & Ozbek, M. E. (2017). Using Expert Opinion to Quantify Uncertainty in and Cost of Using Nondestructive Evaluation on Bridges. Advances in Civil Engineering, 2017(1), 7925193. https://doi.org/10.1155/2017/7925193

7. Buckley, T., Ghosh, B., & Pakrashi, V. (2023). A Feature Extraction & Selection Benchmark for Structural Health Monitoring. Structural Health Monitoring, 22(3), 2082–2127. https://doi.org/10.1177/14759217221111141

8. Entezami, A., Sarmadi, H., Behkamal, B., & Mariani, S. (2020). Big Data Analytics and Structural Health Monitoring: A Statistical Pattern Recognition-Based Approach. Sensors, 20(8), 2328. https://doi.org/10.3390/s20082328

9. Wu, J., El Naggar, M. H., & Wang, K. (2023). Pile Damage Detection Using Machine Learning with the Multipoint Traveling Wave Decomposition Method. Sensors, 23(19), 8308. https://doi.org/10.3390/s23198308

10. Ayman Ahmed Seleemah. (2012). A multilayer perceptron for predicting the ultimate shear strength of reinforced concrete beams. Journal of Civil Engineering and Construction Technology, 3(2). https://doi.org/10.5897/JCECT11.098

11. Azimi, M., Eslamlou, A., & Pekcan, G. (2020). Data-Driven Structural Health Monitoring and Damage Detection through Deep Learning: State-of-the-Art Review. Sensors, 20(10), 2778. https://doi.org/10.3390/s20102778

12. Hanif, M. U., Ibrahim, Z., Ghaedi, K., Javanmardi, A., & Rehman, S. K. (2018). Finite Element Simulation of Damage In RC Beams. Journal of Civil Engineering, Science and Technology, 9(1), 50–57. https://doi.org/10.33736/jcest.883.2018

13. Elkady, A. (2023). ABAQUS_CDP_Generator: A tool for generating concrete damage parameters for ABAQUS [Computer software]. Zenodo. https://doi.org/10.5281/zenodo.7755926

14. Skarżyński, Ł., & Tejchman, J. (2021). Investigations on fracture in reinforced concrete beams in 3-point bending using continuous micro-CT scanning. Construction and Building Materials, 284, 122796. https://doi.org/10.1016/j.conbuildmat.2021.122796

15. Malekloo, A., Ozer, E., AlHamaydeh, M., & Girolami, M. (2022). Machine learning and structural health monitoring overview with emerging technology and high-dimensional data source highlights. Structural Health Monitoring, 21(4), 1906–1955. https://doi.org/10.1177/14759217211036880

16. Teng, Z., Teng, S., Zhang, J., Chen, G., & Cui, F. (2020). Structural Damage Detection Based on Real-Time Vibration Signal and Convolutional Neural Network. Applied Sciences, 10(14), 4720. https://doi.org/10.3390/app10144720

17. Pham, V.-T., Jang, Y., Park, J.-W., Kim, D.-J., & Kim, S.-E. (2022). Cable damage identification of cable-stayed bridge using multi-layer perceptron and graph neural network. Steel and Composite Structures, 44(2), 241–254. https://doi.org/10.12989/SCS.2022.44.2.241