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CRACK MONITORING IN CONCRETE STRUCTURES USING ACOUSTIC EMISSION AND MACHINE LEARNING TECHNIQUES

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Abstract. Structural integrity assessment of concrete infrastructures is increasingly reliant on non-destructive testing (NDT) techniques capable of delivering real-time, in-situ information about damage evolution. Among these, Acoustic Emission (AE) stands out as a passive monitoring method that captures stress-induced ultrasonic wave emissions generated by internal material changes, such as microcracking. AE offers a unique advantage: it allows volumetric, continuous monitoring of structural elements without invasive procedures.

However, a critical challenge in AE-based monitoring is the vast volume of signal data generated during structural loading, which complicates manual interpretation and reduces the practicality of the technique in operational settings. To address this, Machine Learning (ML) methods have been introduced to support automated signal classification and pattern recognition.

In this work, we present experimental results from reinforced concrete beams subjected to four-point bending until failure under controlled conditions. AE signals were continuously recorded using a sensor array, and parameters such as amplitude, energy, and duration were extracted. These signals were then analyzed through a trained Multilayer Perceptron (MLP) neural network model to classify AE events into “cracking” and “non-cracking” categories. The approach was specifically designed to enhance real-time interpretation of AE data in structural applications.

The results show a strong correlation between AE signal characteristics and the evolution of damage in concrete elements. The ML approach significantly enhanced the detection accuracy, enabling automated, real-time identification of crack initiation and propagation. These findings highlight the combined power of AE and AI for effective structural health monitoring and early warning systems in aging concrete infrastructure.

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1 INTRODUCTION

Reinforced concrete (RC) is the most widely used construction material worldwide due to its durability, versatility, and relatively low cost. However, its performance can be critically affected by cracking, which may compromise integrity, durability, and service life. Traditional crack detection relies primarily on visual inspection, which is subjective and limited, especially for large infrastructures or inaccessible areas (see Figure 1).

Structural failures in concrete infrastructures pose significant risks to safety, serviceability, and economic costs. Recent catastrophic events, such as the collapse of the Polcevera Viaduct in Genoa, Italy, or the Champlain Towers South in the USA, highlight the vulnerability of aging structures and the limitations of periodic visual inspection. These examples emphasize the need for continuous and objective monitoring techniques capable of detecting early signs of structural distress. Structural Health Monitoring (SHM) provides such capability, enabling continuous evaluation of structural integrity and delivering data to support maintenance and repair decisions. In particular, cracking in concrete is often the earliest indicator of deterioration, making its early detection especially critical in high-risk facilities such as nuclear power plants.

AE monitors ultrasonic-frequency elastic waves generated within a material when it undergoes stress changes, such as micro-cracking, crack propagation, or friction between crack surfaces, allowing the detection of damage processes as they develop. Unlike active methods (e.g., ultrasound), AE is passive: sensors placed at the surface detect naturally occurring elastic waves without introducing external signals, allowing continuous monitoring in real time. AE can provide information about the location, magnitude, and evolution of damage, as well as the type of cracking mechanism involved. The main challenge of AE lies in the large volume of signals generated (Figure 2), which can include noise from environmental or mechanical sources. Therefore, robust data processing and automated analysis are essential to extract meaningful structural information.

Machine Learning (ML) has emerged as a powerful tool to address these challenges. By uncovering patterns and relationships in Acoustic Emission (AE) data, ML models can classify events, distinguish between crack mechanisms, and enhance real-time monitoring capabilities.

In this study, we present an application of Multilayer Perceptron (MLP) neural networks for AE-based crack detection in reinforced concrete beams under controlled laboratory loading conditions. The MLP model is trained to identify AE signal patterns associated with crack development, offering a computationally efficient and reliable approach for automated SHM.

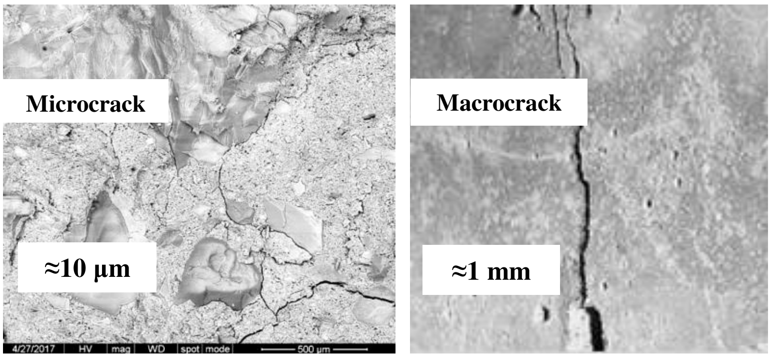

Figure 1: Typical cracks in reinforced concrete beams.

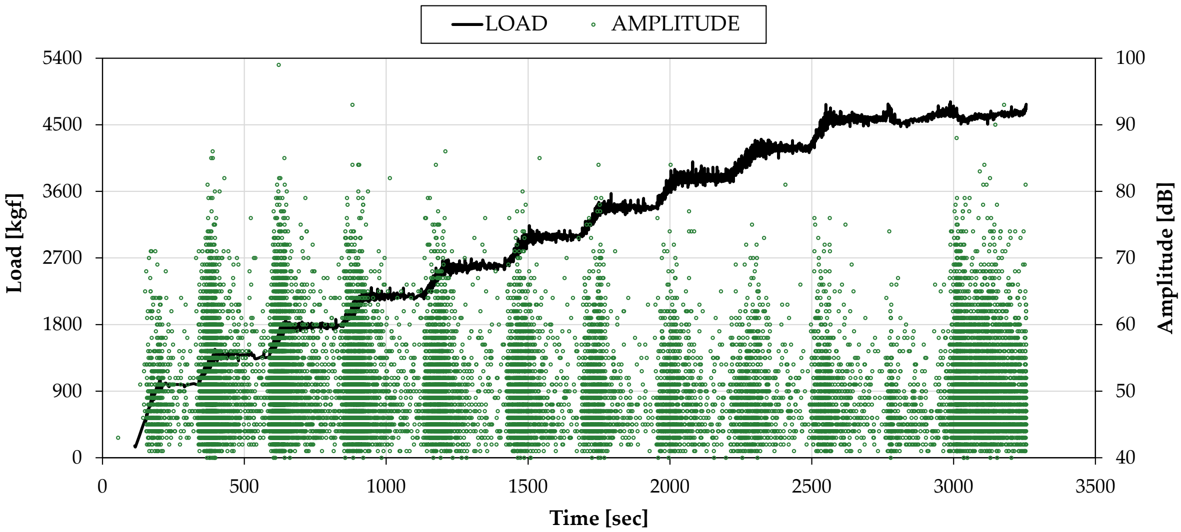

Figure 2: Diagram illustrating AE generation in reinforced concrete under stepped-loading and detection by surface-mounted sensors.

2 BACKGROUND

AE has proven effective as a passive, NDT method for monitoring ultrasonic elastic waves generated by internal events, such as crack formation and propagation, in concrete under stress. Our previous studies highlighted the potential of AE to monitor damage processes in fiber-reinforced concretes and complex loading scenarios. For instance, AE parameters have been successfully employed to track crack initiation and propagation in beams under cyclic loading (Xargay et al., 2021), as well as to characterize the mechanical response of self-compacting high-strength fiber-reinforced concrete after exposure to elevated temperatures (Xargay et al., 2018). These contributions support the usefulness of AE for assessing both load-induced and thermally induced degradation in cementitious composites.

However, the large volumes of data generated present challenges in processing and interpretation. To overcome these limitations, the application of AE techniques combined with ML for crack detection in RC structures has gained significant attention in recent years.

Latest studies have explored various ML strategies to improve the analysis of AE signals. Barbosh et al. (2024) demonstrated automated crack identification in concrete structures by coupling AE with deep learning models, highlighting the potential for real-time structural monitoring. Similarly, Inderyas et al. (2024) proposed a deep learning-based filtering model for AE signals in RC elements, improving the reliability of crack detection and reducing false positives. Deep convolutional neural networks have also been widely applied to AE and image-based crack detection. Siracusano et al. (2019) exploited statistical event descriptors from AE signals to automatically classify cracks, while Yang et al. (2021) and Kumar and Ghosh (2020) used convolutional architectures for rapid identification of crack patterns in concrete specimens, demonstrating high accuracy and robustness across different experimental setups. The integration of AE with AI techniques extends beyond detection to localization and characterization of cracks. Boschetti et al. (2023) implemented an AI-based procedure for AE signal analysis to locate crack sources in concrete structures, and Zhang and Choi (2025) proposed a transfer learning framework for AE source localization in RC components, enabling adaptation across different structural geometries and sensor layouts. Carpinteri and Lacidogna (2022) provided a comprehensive review of ML-based AE methods, summarizing advances in feature extraction, signal classification, and predictive modeling. Further, Tonelli and Tulliani (2023) demonstrated the identification of crack patterns in cementitious materials based on AE signal clustering, offering insights into the types of micro- and macro-cracks that develop under varying load conditions. Singh and Chandra Kishen (2021) applied ML-based AE techniques for corrosion detection in RC, indicating the versatility of AE monitoring when combined with AI-driven data analysis.

In summary, the combination of AE and ML provides a powerful tool for SHM of RC structures, enabling early detection, classification, and localization of cracks. These approaches significantly enhance the reliability and scalability of SHM systems, particularly in complex or critical infrastructures where traditional inspection methods are limited.

3 METHODOLOGY

The methodology of this study combines experimental testing, AE monitoring, and ML to detect cracks in RC beams under controlled laboratory conditions.

3.1 Experimental Setup

Reinforced concrete beams (120 × 300 mm cross-section, 210 cm length) were prepared using normal strength concrete mix design (compressive strength 35 MPa). Beams were reinforced with steel bars according to conventional structural design practices (see Figure 3).

The beams were subjected to four-point bending tests using a hydraulic testing machine to simulate controlled load conditions. The loading protocol consisted of incremental cycles, increasing the applied load until failure. Each cycle included a rising branch, a constant maximum load stage, and a descending branch. This approach allowed the recording of AE signals corresponding to crack initiation, propagation, closing and ultimate failure.

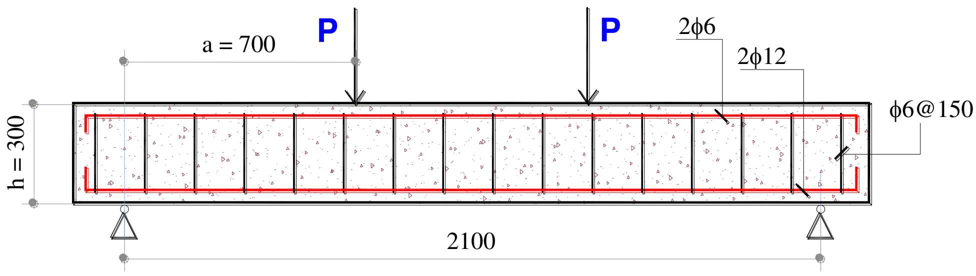

Figure 3: Four-point bending test setup for RC beam.

3.2 Acoustic Emission Monitoring

This paper presents the analysis of one beam from the experimental campaign, as shown in Figure 3. Four AE sensors were attached along the beam surface at critical locations, focusing on regions where high tensile or shear stresses and crack development were expected (Figure 4). AE signals were continuously recorded during the entire loading process.

The following AE parameters were extracted for each event: amplitude, rise time, duration, counts, energy and mean frequency, among others. These features characterize the AE signals of the loading process and material response and provide critical information for ML-based classification.

To reduce noise and ensure data quality, the pre-processing procedure included signal filtering and thresholding to remove spurious events caused by external or non-relevant sources. After pre-processing, 73,895 significant AE events were obtained for model training and validation.

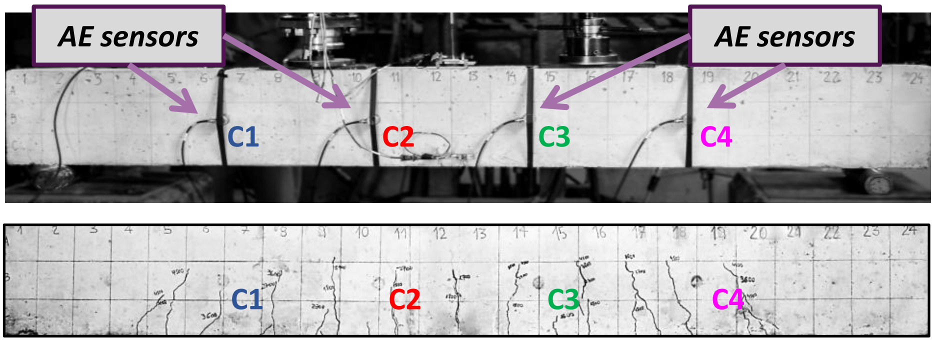

Figure 4: RC beam with AE sensors placement and final cracking pattern.

3.3 Multilayer Perceptron Neural Network

A MLP neural network was implemented to classify AE signals into two categories: cracking and non-cracking. The MLP architecture consisted of one input layer, two hidden layers, and one output layer (Figure 5).

The model training process included:

- Forward propagation: AE feature vectors were passed through the network layers.
- Error calculation: The difference between predicted and actual labels was computed.
- Backpropagation: Weights and biases were updated using gradient descent to minimize classification error.
- Iteration: The process was repeated until convergence.

Seventy percent of the AE dataset was used for training, while the remaining thirty percent was reserved for testing. Performance metrics included accuracy, precision, recall, and F1-score.

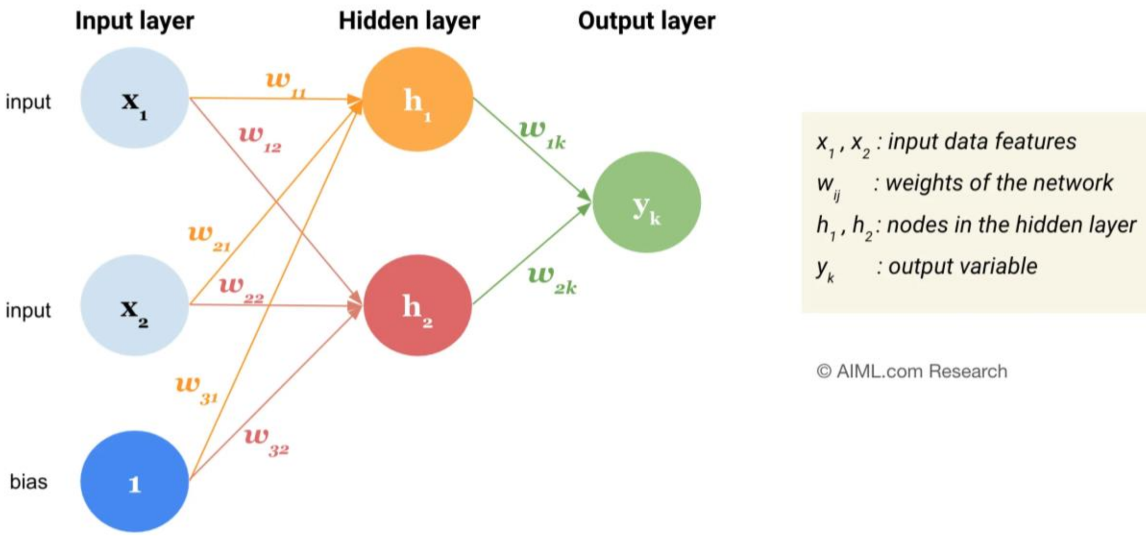

Figure 5: Schematic example of MLP neural network architecture. Source: AIML.com Research.

4 RESULTS

4.1 AE Signal Analysis

During the four-point bending test, AE signals were continuously recorded, capturing the evolution of damage in the reinforced concrete beam. Figure 6 shows the temporal distribution of AE events from one representative channel during a full loading cycle.

Meanwhile, evolution of AE cumulated events across different channels is displayed in Figure 7. Most AE events occurred during the loading rising branch of each cycle and constant maximum load stage, consistent with the initiation and propagation of cracks. Signals in the descending branch were limited, corresponding to structural relaxation and minor frictional events.

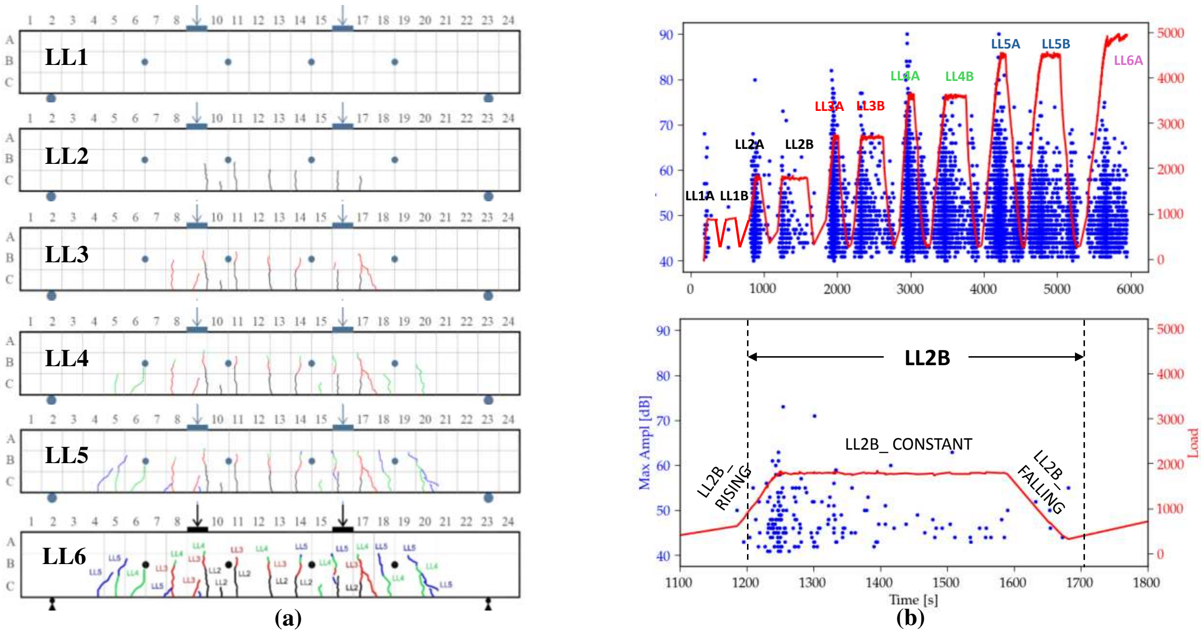

Figure 6: (a) Evolution of the cracking pattern with load levels (LL#), as observed through visual inspection. (b) Loading procedure (top) represented by the red line, with two repetitions (A and B) at each load level, and corresponding AE event amplitudes; (bottom) detail for LL2 cycle B, showing correlation with the applied load.

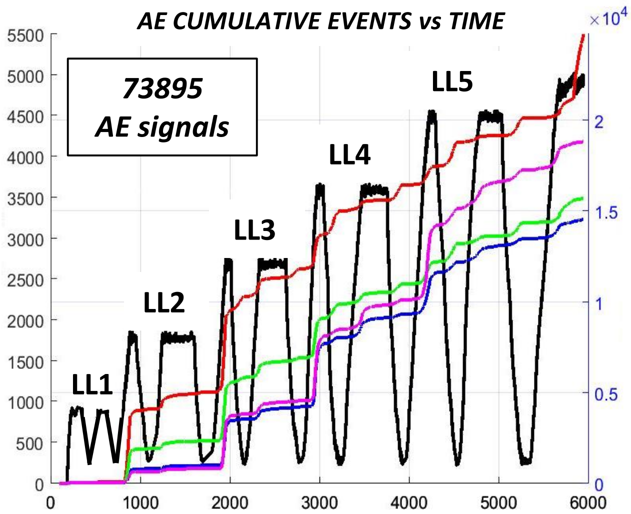

Figure 7: Temporal evolution (in sec) of cumulative AE events across different channels during the complete loading procedure, with the applied load (in kgf) shown as a black line.

The extracted AE parameters exhibited clear trends correlating with load increase. High-amplitude and high-energy events were associated with macrocracking, while lower amplitude events corresponded to microcracking (Figure 8). These trends confirm the suitability of AE monitoring to detect and characterize cracking in real time.

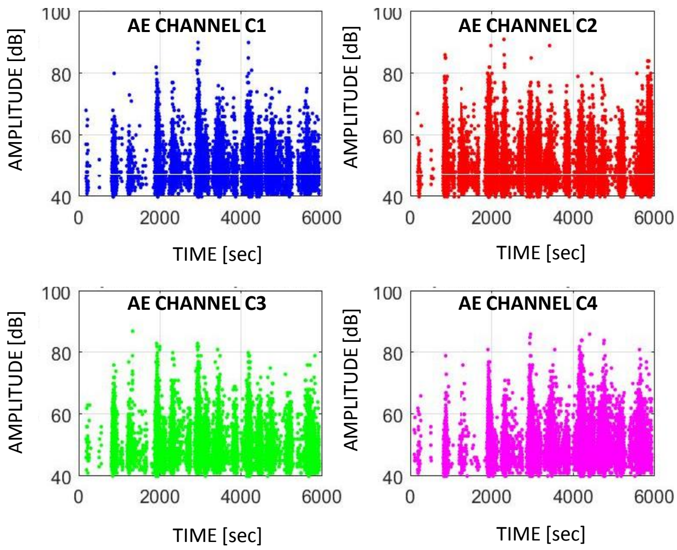

Figure 8: Scatter plot of AE amplitude vs. applied load, highlighting cracking events.

4.2 MLP Model Performance

As outlined previously, the MLP neural network was trained to classify AE signals into cracking and non-cracking events. Training and testing were conducted using 70% and 30% of the dataset, respectively. The model achieved high predictive performance, as summarized in Figure 9.

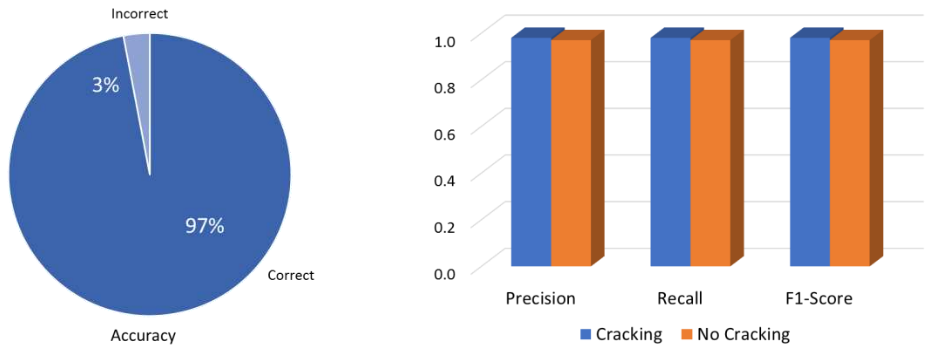

Figure 9: Performance metrics: Accuracy (left) and Precision, Recall and F1-score (right).

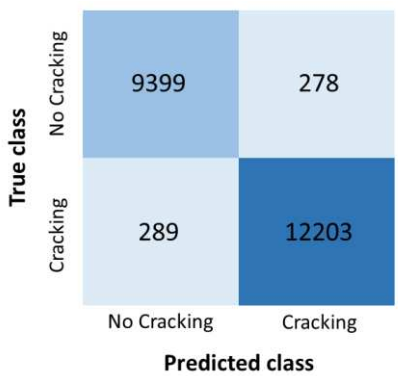

Figure 10: Confusion matrix of MLP classification results.

In Figure 10, the confusion matrix shows that false positives and false negatives were minimal, indicating that the model effectively distinguished cracking from non-cracking AE events. These results demonstrate the MLP's capability to handle large volumes of AE data while maintaining high accuracy, offering a practical approach for automated SHM.

5 DISCUSSION

The combination of AE monitoring and MLP classification enables real-time detection of crack initiation and propagation in reinforced concrete beams. The strong correlation observed between AE parameters and structural damage confirms that AE signals contain sufficient information to characterize cracking processes. The proposed methodology offers several advantages over conventional NDT approaches. Continuous monitoring through AE sensors allows damage detection without interrupting structural operation, while automated analysis based on MLP reduces the reliance on manual interpretation and enhances both the speed and reliability of decision-making. The method also demonstrates high sensitivity, as even microcracking events can be detected, providing an early warning of potential failure. These findings are consistent with previous studies demonstrating the feasibility of applying ML to AE signal classification—such as the use of convolutional neural network for crack detection in concrete—and further highlight the potential for scaling this approach to larger structures and real-world applications. Nonetheless, certain limitations remain. These include the requirement for high-quality AE data and the need to optimize sensor placement in structures with complex geometries.

6 CONCLUSIONS

In this study, a full-scale reinforced concrete beam was tested under controlled laboratory loading and continuously monitored using AE. The recorded signals were parameterized and processed through a MLP neural network specifically developed and trained to classify AE events into cracking and non-cracking categories. The dataset was split into 70% for training and 30% for validation, ensuring robust model evaluation.

This work demonstrates the successful integration of AE monitoring and ML techniques for structural health assessment. The main findings are as follows:

- AE monitoring effectively captured crack initiation and propagation, providing real-time insight into the structural behavior of reinforced concrete.
- The MLP neural network achieved high accuracy (> 98%) in distinguishing cracking from non-cracking events, with Precision, Recall, and F1-Score all exceeding 97%.
- AE parameters showed strong correlation with applied load, confirming their potential as qualitative indicators of structural integrity.
- The combined AE/ML methodology enables continuous, non-invasive, and automated monitoring, offering early warning of potential failures not easily detected by visual inspection or periodic NDT methods.

7 FUTURE WORK

Several avenues for further research are proposed:

- Applying the AE/ML methodology to larger and more geometrically complex structures, such as bridges or nuclear containment elements, to validate scalability and robustness.
- Combining AE monitoring with other non-destructive evaluation methods (e.g., ultrasonic pulse velocity) to enhance damage detection accuracy and localization.

- Developing fully automated SHM systems capable of providing real-time alerts and integrating predictive analytics for proactive maintenance.
- Investigating optimal sensor layouts and exploring more advanced neural network architectures, such as deep learning models, to improve classification performance in field conditions.

In summary, the integration of AE and AI-based analysis represents a promising approach for structural health monitoring, providing early detection of damage, improving safety, and supporting data-driven decision-making in civil infrastructure management.

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