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A DEEP LEARNING BASED DAMAGE ESTIMATION MODEL INCORPORATING HYBRID AE DATA FOR MONITORING REINFORCED CONCRETE STRUCTURES

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Abstract

The reinforced concrete structures require constant monitoring to ensure their durability and safety of the structures. Thus, it is of great importance to monitor and identify the damage in structures. From non-destructive testing methods, acoustic Emission (AE) is a well-known method used to locate cracks, and damages and provide information about the performance of the material or a structure. This study aimed to determine the damage progress within a reinforced concrete beam by incorporating all AE datasets in a hybrid deep neural network. For this, a hybrid AE dataset consisting of three damage states of AE activities obtained from a four-point bending test of a reinforced concrete beam was developed. For the development of the hybrid model, a 1-dimensional convolutional network and a 2-dimensional convolutional network were combined and all AE data containing AE parameters, 1D waveforms, and scalograms extracted from continuous wavelet transform (CWT) were used to train the model and validated against a testing dataset. From the results, it was found that the model was trained well enough with a large amount of hybrid AE dataset, and the performance accuracy in training and testing was found 97.6% and 95% respectively, leading to the conclusion that the hybrid model has the potential to predict damages in reinforced concrete with great confidence.

Keywords: Reinforced concrete, acoustic emission, deep learning, hybrid model, damage identification

1 Introduction

In the field of structural health monitoring (SHM), promising the resilience and safety of reinforced concrete structures is critical. These reinforced concrete structures are commonly bridges, buildings, and dams, which require constant monitoring to ensure their durability and safety. The ability to appropriately evaluate and predict damage in these structures helps in performing preventative maintenance, which plays an important role in avoiding potential catastrophic events. Thus, it is of great importance to monitor and identify the damage in structures to take the essential precautions against major catastrophic events.
Acoustic Emission (AE), one of the structural health monitoring methods used for this purpose, is a promising technique to capture acoustic signals emitted during the initiation and propagation of cracks in concrete [1, 2]. AE method provides both parametric and waveform analysis, which are further used to monitor the damage, location, size, and type of cracks in a material [3, 4]. By using the AE parameters and waveforms recorded by the AE sensors, the damage characteristics of a material can be identified. In literature many studies have been done on the estimation and classification of damages with AE technique by incorporating machine learning and deep learning models, however, most of them are based on a single net-

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work. In the study [5], the investigation was done on crack detection and structural damage in concrete specimens through the classification of acoustic emission signals from flexural and shear tests. Utilizing a Support Vector Machine (SVM), the authors found that classification performance was influenced by the distance between the crack source and the sensor, with processing data individually from sensors leading to higher success rates. In [6], the authors applied advanced pattern recognition techniques to the collected AE data to identify failure mechanisms in CFRP-reinforced RC beams. Principal component analysis (PCA), an unsupervised k-means clustering method was applied to automatically cluster and separate the AE patterns. Both multilayer perceptron (MLP) and support vector machine (SVM) training algorithms were applied to the AE data and found that the performance accuracy of the SVM algorithm was comparatively higher than the MPL algorithm. In [7] authors used the AE method to monitor the mechanical behavior of different polymer concrete specimens subjected to quasi-static three-point bending tests. AlexNet algorithm was applied and the result showed that damage classification can be performed by applying deep learning and clustering methods for AE data obtained from concrete specimens. Similarly in [8], a study was done to estimate the damage status of the RC beam exposed to three-point loading using acoustic emission by developing a pattern recognition damage detection model. Estimation capability results of the model show that data-driven data was more successful than using the raw AE dataset in estimating the damage level. In a recent study [9], authors combined deep neural networks with bidirectional long short-term memory (Bi-LSTM) and advanced statistical analysis to develop a classification tool for tensile, shear, and mixed modes resulting from AE events, specifically cracks. Using cube samples of different grades, they achieved a 92% accuracy in AE signal classification by selecting appropriate event descriptors (EDs) as inputs to the deep neural network.
From the literature, there is a lack of intention towards using the hybrid AE data in machine learning or deep learning models. This study aimed to determine the damage progress within a reinforced concrete beam by incorporating all AE dataset in a deep learning model. For this, damage patterns identified in the load-deformation test consisted of thousands of AE signals containing damage characteristics that was used to build training and validation datasets. Within this scope, a deep learning based hybrid model was used to enhance the accuracy and efficiency of damage detection from recorded activities of AE in a reinforced concrete beam.

2 Method

2.1 Acoustic Emission

Acoustic Emission (AE) is one of the non-destructive Testing (NDT) method used to locate cracks, damages and provide information about the performance of the material or a structure. Fundamentally, AE is based on the concept of propagation of energy in the form of elastic waves released from damage or cracks in a material under stress [10]. These waveforms are detectable by piezometer sensors that convert the mechanical waves into electrical signals and start processing the voltage-time graph as shown in Figure 1. Following these signals are processed by a preamplifier, filters and power amplifier in the processing stage to record and display AE data on the computer.

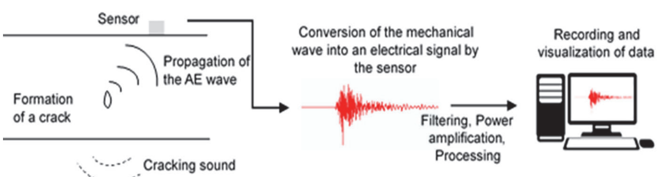

Figure 1 Generation of the AE event, detection and signal transformation of the elastic wave by the sensor

The resulting signal is known as the AE signal, and by further processing and analysing it with mainly two types of analysis; parametric and waveform-based analysis, various information about the damage can be obtained. In the parameter-based approach, signal characteristic parameters such as amplitude, duration, rise time, count energy, etc. are utilized to evaluate the nature and classification of damage. Whereas in waveform-based analysis the source localization and source discrimination of the damage can be estimated in a material [11].

2.2 Wavelet analysis on acoustic emission signals:

Wavelet analysis plays an effective role in investigating signals in the time-frequency domain. It allows better localization compared to conventional Fourier Transforms. It provides enhanced time-frequency resolutions, denoising of the signals and pattern by revealing distinct features. By employing wavelet analysis, transient and non-stationary variations can be captured within the AE signals helping to understand and monitor material behaviour.
Wavelet analysis has two basic types: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). The CWT is the process of assembling a continuous wavelet function with the signal at different scales and positions. While DWT integrates subsampling, resulting in a signal analysis with several resolutions. In this study, CWT analysis was utilized on AE signals to acquire scalograms along the entire length of the signals so that distinct features of the indicative damages can be captured.

3 Experimental set-up

A large-scale reinforced concrete beam with dimension of 2000 mm*150 mm*250 mm was produced to examine the damage condition of the test beam. The beam was manufactured according to C50 design strength and mix design (with a water/cement ratio of 0.6) is given in Table 1.

Table 1 Mix design for C50 reinforced concrete beam (kg/m^3)

Cement	Aggregate [mm]			Water	Admixture
	0-3	5-15	16-25		
385	855	455	-	160	2.2

Besides this, the beam was designed for shear failure containing four ø20 mm S420 longitudinal rebars in total and ø8 mm stirrups placed at 65 mm intervals along one-half of the beam. The beam was tested under four-point-bending test and in total 8 AE sensors of 150 kHz were placed on the surface of the test beam by silicon grease. The load was applied monotonically from the midpoint of the beam through a hydraulic pump at a rate of approximately 30N/s and AE activities amplified with 40 dB gain by pre-amplifiers were acquired on an 8-channel DiSP AE system. The complete experimental setup including arrangement of the AE sensors and loading setup is shown in Figure 2.

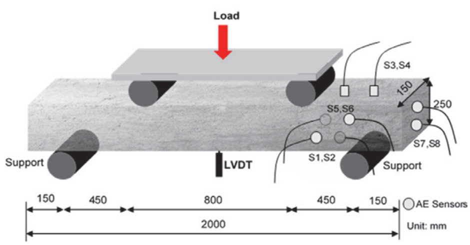

Figure 2 Loading and AE set-up of the test beam

3.1 Experimental test results:

After the successful testing, large shear cracks were observed on the beam as shown in Figure 3. Afterward, a relationship was established between the AE parameters and the mechanical load-time curve to investigate the mechanical behavior of the beam and its AE activities in proportion limit, yield point, and ultimate loading point. In Figure 4. and Figure 5., AE hits(a hit is a signal captured by a sensor) and AE energy (a measured area under the rectified signal envelope) can be seen plotted against the load-time curve respectively.

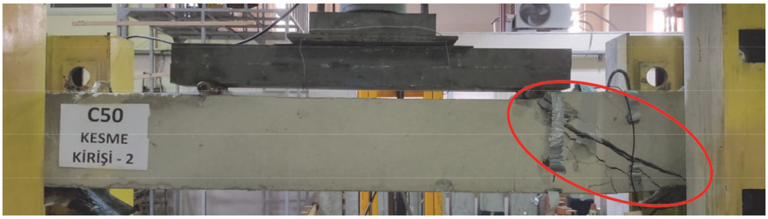

Figure 3 Development of shear cracks in the beam

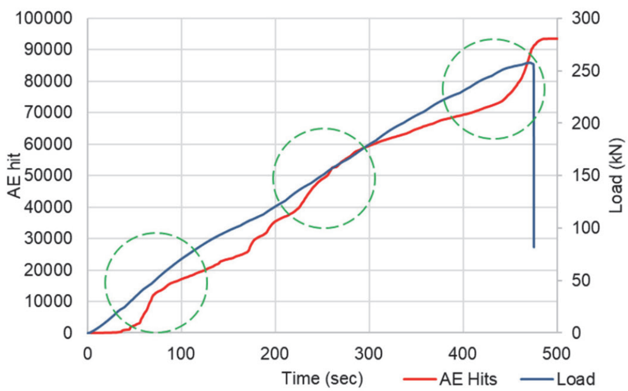

Figure 4 Relationship between AE hits and load

It was observed that at the beginning of the test, when the beam was within the proportional limit, AE hits with lower AE energies were recorded. As the duration reached 200-300 seconds, the beam exhibited a significant increase in both the number of AE hits and their energies, indicating the development of cracks. Around the ultimate loading point at 480 seconds, massive AE hits and energies were recorded. Within this context, three damage classes—Class 1, Class 2, and Class 3—were identified for the hybrid model.

3.2 Extraction:

AE data acquired from the test was preliminarily pre-processed by filtering AE signals through the threshold and Swansong-II filter. The threshold limit was set to 40dB to eliminate low amplitude signals while Swansong-II filter limits [14] were employed to remove noise-induced signals. These AE signals comprise demonstrative data of elastic waveforms and AE features. In this study, common AE features known as; amplitude, rise time, duration, energy, AE hits, etc., time domain waveforms, and time-frequency domain scalograms were used to build a hybrid AE dataset for a deep learning network as shown in Figure 6. To acquire scalograms, continuous wavelet transform (CWT) integrating Morlet wavelet was utilized on AE signals.

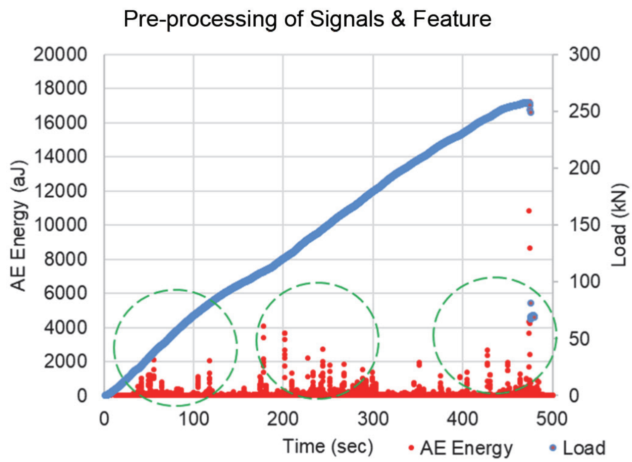

Figure 5 Relationship of AE energy and load

4 Hybrid deep neural network:

In the field of artificial intelligence, the primary focus of research is on improving the training of effective artificial or deep neural networks. Traditionally, in artificial neural networks, this can be achieved by training multi-layered perceptrons. However, when there is a large number of data, the classical algorithms struggle to achieve performance accuracy.

In recent years, there has been an increasing change toward the development of hybrid approaches that leverage the training of diverse networks at the same time. For instance, in this study, the one-dimensional convolutional neural network (1DCNN) was used for learning time dependencies in the time domain while the convolutional neural network (CNN) was used for processing images using designed convolutional filters. The typical architecture of the hybrid model is shown in Figure 6.

Three Input layers were assembled as; the first input layer with 1D AE signals having 2048 voltage points, the second input layer with 18 AE parameters, and third input layer of RGB (Red Green Blue) images compatible with AlexNet. In each network, 2 convolution layers followed by ReLU activation function, normalization, and max. pooling layers were connected to the concatenation layer. In the final stage, fully connected layers followed by the softmax function were used to classify the damage classes in the output layer. In total 60000 AE signals, divided into 75% (45000 AE signals,15000 from each class) for training and 25% (15000 AE signals, 5000 from each class) for testing used in the model and the performance of the model was evaluated using performance metrics.

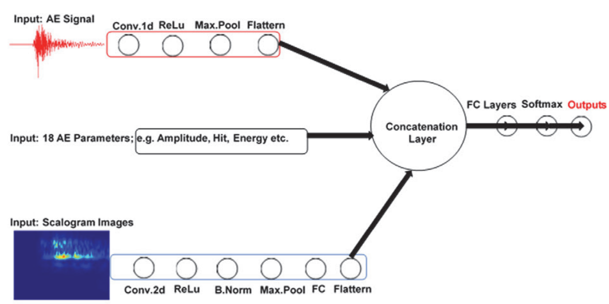

Figure 6 Representation of a typical hybrid model

5 Hybrid model results

While training the hybrid model, a batch size of 256 with a learning rate of 0.01 and 25 epochs were considered and validated in a training session. To observe the damage outcomes in each damage class, performance matrices like accuracy, macro precision, macro recall, macro specificity, and macro F1-score were calculated as tabulated in Table 2. and the number of AE observations correctly predicted against true class was acquired using confusion matrix as shown in Figure 7.

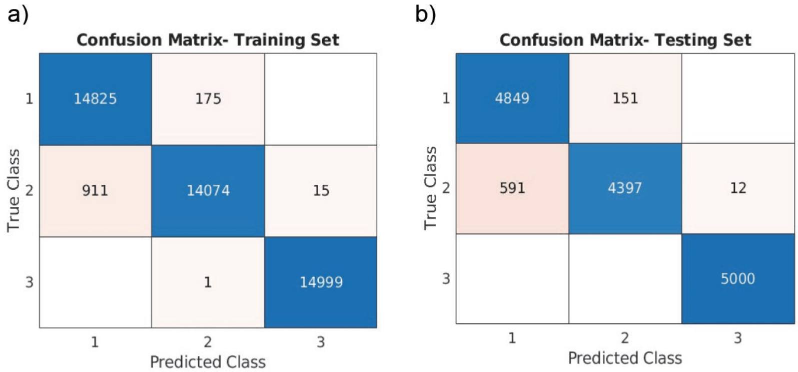

Figure 7 Confusion matrix of a) training; b) testing dataset

Table 2 Results of performance matrices in hybrid model

Type of Dataset	Accuracy	Macro Precision	Macro Recall	Macro Specificity	Macro F1-Score
Training	97.6%	97.6%	97.6%	96.6%	97.5%
Testing	95%	95.2%	95%	97.5%	95%

Figure 7 illustrates that in training, 14825 AE observations were correctly predicted against true observations in class1. Similarly, in class2, out of 15000 AE observations, 14074 observations were correctly predicted and in class3, 14999 AE observations were accurately predicted. Similarly, in testing, 4849, 4397, and 5000 observations were correctly predicted against true observations in class1, class2, and class3 respectively. In class3, no false positive or false negative observations were found. This indicates that, at the ultimate loading point, AE activities representing major cracks with the collapse of the beam exhibit a more distinctive behaviour compared to the minor and moderate cracks in class1 and class2, respectively. The accuracy of the hybrid model during training was found around 97.6% with an initial training loss of 1.2 to 0.2 while on the testing dataset accuracy of 95% was achieved successfully validating in predicting damages accurately.
On the other hand, the precision, recall, specificity, and F1-score values were calculated using the true positive, true negative, false positive, and false negative observations of each class, and their average values were found above 95% in both training and testing. This is evident that the model was excellent in classifying the damages of each class.

6 Conclusions

In this study, a hybrid AE dataset consisting of three damage states of AE activities obtained from the four-point-bending test of a reinforced concrete beam was incorporated to develop and test a hybrid deep neural network. The hybrid AE dataset contained AE parameters, 1D waveforms and scalograms were trained and validated using the performance matrices. From the results, it was found that the model was trained well enough with a large amount of hybrid AE dataset. Consequently, the model was tested and demonstrated a testing accuracy of 95%, leading to the conclusion that the hybrid model has the potential to predict damage status in reinforced concrete with confidence.

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