Acoustic Emission-based Damage Detection and Classification in Steel Frame Structure Using Wavelet Transform and Random Forest

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Abstract

This research proposes a unique approach for detecting damage locations and identifying damage kinds. This method is beneficial for discovering and categorizing internal structural faults that vision-based approaches cannot locate. Construction-related vibrations in a steel frame structure can be used as a source for acoustic emission. Sensor devices detect the stress waves produced by structure collapse, and spectrum analysis using wavelet transform of such data is valuable in pinpointing the location of the damage. The collected characteristics from these signals are input into the most effective RF (Random Forest) classifier, which are used to categories damage types like cracks and bolt loosening. When compared to previous damage localization approaches, the findings show that the proposed strategy is more efficient and has a higher classification accuracy.

Keywords

acoustic emission, spectrum analysis, wavelet transform, Random Forest classifier, integrity monitoring, damage localization

1 Introduction

Civil, mechanical, and aerospace engineers have long been attracted by Structural health monitoring (SHM) and vibration-dependent structural degradation diagnosis. One of the key aims of SHM applications has always been to identify damage at an early stage [1]. Acoustic emission (AE) has been a well-known SHM strategy that is extensively utilized for non-destructive damage monitoring in a variety of industrial applications [2] in which the acoustic (elastic) waves are released from solids when their internal structure undergoes irreversible modifications. Fracture initiation and propagation, fracture opening and closure, displacement, merging, and phase transformation are all plausible drivers of internal structural modifications in monolithic materials [3]. The AE Approach is an appealing solution for SHM structures such as concrete [4] and steel bridges. It is gaining popularity; acoustic emission monitoring is most likely the most basic physical concept among the several Non-destructive tests (NDT).

The favorable characteristics of AE include its great sensitivity to crack propagation, ability to determine the source, passive nature, and ability to do real-time monitoring. Good SHM requires effective data processing, which is connected to three important monitoring goals: correctly recognizing the source of damage, detecting and separating signals from AE source materials, and quantifying the AE source's amount of damage for severity evaluation [5]. Infrastructure is outfitted with AE sensors to identify the commencement of damages in real-time. The positioning of the AE sensor becomes critical for detecting a breach within a structure. Inserting sensors in a structure that enable real-time damage monitoring is expensive. Consequently, the count of sensors employed for structural health monitoring should be kept low for economic reasons [6].

Steel frame structures, generally mixed with steel or wholly constructed of steel, have been used to develop civil structures and diverse structural components. Ensured steel frame durability is inextricably tied to structural safety and longevity. Surface defects in steel produced by physical strain, and environmental fluctuations, including chemical reactions, diminish its aesthetics, effectiveness, and lifetime [7]. Steel products come in a diversity of shapes and sizes, comprising slabs, plates, and hot/cold strips [8]. External stress may cause fatigue as well as structural deterioration.

In contrast, repetitive external or cyclic stresses introduced to a steel element create fatigue or fractures, leading to structural deterioration and tragic occurrences, including loss of life and properties. Surface defects of different types may form in these products. However, no classification criteria for these disorders have been provided [9].

To detect degradation on the exterior of large-scale steel structures, several SHMs have been employed. Sensor-dependent technologies utilize a diversity of sensors and extensive data processing operations [10]. Relying solely on a high number of variables, identifying damage from structural images with machine learning algorithms requires stringent attribute selection procedures. To solve these issues, computer vision algorithms have been created. Mobile manipulator imaging systems, hybrid image segmentation approaches, and edge diagnostic tools are common condition monitoring approaches. Computer vision solutions were utilized to examine spatiotemporal vehicle load distribution patterns in long-span steel structures, whereas vision-based technologies cannot identify interior flaws in massive civil constructions [11]. The novelty and complexity of noise filtering under AE control stem from the fact that noise and useable signals generally have almost identical frequency ranges, necessitating signal identification and classification algorithms to distinguish useful signals from interference. A classifier is built such that the signals representing the AE activity of faults are allocated to one class, and the sounds are assigned to another or many classes [12].

As a result, a mechanism for efficiently processing data from several sources must be developed. Machine learning (ML) approaches enable data-driven learning and may predict structural deterioration based on existing knowledge [13]. Furthermore, artificial neural networks (ANNs) have been widely used to detect degradation in arches, steel frames, and steel bridges [14], in which a wavelet transform (WT) is used to decompose data at various scales to extract features or to assess the outcomes of time-frequency decomposition during signal processing [15] and that encourages non-stationary signals to be empirically validated, which is also a very clear mathematical theory-dependent strategy for signal analysis. It is feasible to extract even little local signal perturbations from the overall response of a structure utilizing multi-resolution decomposition/analysis (MRA), which demands a vast amount of data.

In addition, if wavelet analysis is employed to locate the damage, it is adequate to analyze the data received from the damaged structure before comparing it to the signals from the unaffected system. The method's main advantage is that the entire structural response signal is rarely available in real trials, and the numerical model may not have accurately depicted reality [4]. When dealing with transient non-stationary data, this wavelet transform outperforms other transformations. Wavelet analysis provides excellent frequency resolution on the low-frequency side of a signal but extremely poor frequency resolution on the high-frequency side, compensating for Fourier's limitations. According to the literature, the mother wavelet acts as an adaptive window that adjusts the resolution, including both time and frequency [16] and the other wavelet, such as the Morlet wavelet, seems to be another complex, non-adaptive wavelet which extracts simultaneously amplified as well as unamplified signals. Energy and Shannon entropy variables, as well as other parameters, are used to improve neural network performance [17], where Shannon entropy quantifies the energy distribution among wavelet coefficients; the integration of wavelet, as well as Shannon entropy, seems highly helpful in identifying the best wavelet for extracting signal characteristics [18].

Han et al. [19] proposed a convolutional neural network to categorize the flow of AE data. The neural network's input receives an AE signal spectrogram. Based on a certain time-frequency pattern in the signal, the neural network assigns AE signals to faults. The authors perform a comparative classifier assessment to identify the best classifier. Weak classifiers (decision trees) are joined in a Random Forest to create a stronger classifier. It produces a group of trees and the ultimate categorization, which was determined by letting the trees vote on their preferred class. A tree is built on the fresh training set by employing random feature selection. If a tree is not pruned, it will reach its full potential. Random Forests with dual randomness are less susceptible to overfitting and have higher accuracy and generalization capabilities. Eventually, the Random Forest allows diverse trees to vote for the highly preferred class. A Random Forest outperforms choice trees in terms of categorization accuracy [20]. Nguyen et al. [21]; developed machine learning (ML) models for the first-ever, to the authors' knowledge, quick seismic damage-state evaluation of steel moment frames. A graphical user interface was designed based on the existing RF model to provide engineers easy access. This work marks a milestone in the development of machine learning's application to the quick evaluation of building structure damage.

Jahangir et al. [22]; proposed vibration responses from time-domain modal testing of prestressed concrete slabs are used to try to detect defects. Chencho et al. [23]; described the

invention and use of the extremely randomized tree (ERT) as a multi-output regression model in decision tree-based ensemble approach for quantifying structural damage to civil engineering structures. Jahangir et al. [24]; determined the sites damage in RC beams, suggest a wavelet-based damage index. It should be noted that the suggested damage detection approach has just one limitation: the border effect and finding damage areas close to boundaries. The structural element would be suspended in order to reduce boundaries' effects on the collected modal data in order to get around this constraint, as described in the specifics of the modal tests. To overcome this limitation, Guo et al. [25] investigated its uniqueness, the excitation angle of the ground motion was treated as a random variable with a uniform distribution. To improve the seismic performance of double-deck structures, the top beam's distance from its limit device can be properly adjusted, or double-layer limit devices can be installed. Daneshvar et al. [26]; introduced Tools for locating and quantifying damage that are effective and dependable. Arokiaprakash and Selvan [27] Developed a unique learning-based artificial neural network model to forecast the column's axial compression strength. Concrete-filled steel tubular (CFST) columns can withstand axial compression.

A simple and robust acoustic emission-based integrity evaluation approach for identifying AE crack signals and monitoring the structural health of steel-framed facilities is presented in the paper. In this research, a supervised learning mechanism was used to classify acoustic emission signals from diverse damages to a steel frame construction. It is also cost-effective and technically feasible for identifying internal defects in massive steel-framed structures.

The main contribution of the research is described below:

1. Damage localization with Acoustic Emission (AE) is proposed, which identifies the external damage and localizes the internal damage of the steel frame structure.
2. This is a sensitive diagnostic technique for structural health monitoring that allows early detection of cracks (SHM) and bolt loosening.
3. The use of machine learning to classify the image data can considerably simplify data processing and reduce time consumption.
4. The results have been compared with the existing Artificial intelligence-based model.

The following is how this document is structured: The review of the literature for numerous studies is summarized in Section 2, The experimental setup is given in Section 3, the proposed innovative methodology is outlined in Section 4, the findings of the proposed method are given in Section 5, conclusion is given in Section 6, and the references for this work are supplied in the following section.

2 Literature survey

Acoustic emission is indeed a non-destructive approach for assessing the technical state of industrial facilities that are extensively and effectively utilized. Some research works related to the damage localization of steel structures are given below.

Barat et al. [28] developed a CNN-based approach for separating important signals from noise in a flow of acoustic wave data. Noise filtering in AE control is unusual in that noise, and useable signals generally share the same frequency range, necessitating signal identification and classification methods to distinguish useful signals from noise. The classifier is set up such that signals indicating fault AE activity are allocated to one class, while noises are assigned to another or several classes. A convolutional system was trained to categorize acoustic emission signals with 95% accuracy. Convolutional neural networks may significantly speed up data processing by categorizing auditory signals.

Hasni et al. [29] provide two deep learning techniques for localizing AE sources inside metallic plates using geometric characteristics, including rivet-connected stiffeners. Specifically, an auto encoder layer, as well as a convolutional neural network, have been employed. The target is either to manipulate both reflection and reverb patterns of AE waveforms and their dispersive and multimodal features to localize their origins with a single sensor. Fatigue fractures were experimentally modeled through Hsu–Nielsen pencil lead break examinations to train, validate, and test the deep learning networks. These pencil lead breaks were made on the surface of the plate and all around the edges. As per the data, this deep learning network can be trained to track AE signals back to their origins. Ebrahimkhanlou and Salamone [30] created an automated methodology for analyzing bolt looseness relying on a mask and a region-dependent convolutional neural network by tagging the flaw to each picture pixel, retrieving annotated categorization sorts, positions, and geometrical information. The automated bolt looseness monitoring was performed using a simple truss structure with bolted joints. The experimental findings demonstrated that the suggested detection technique relying on Mask R-CNN distinguished the categories (i.e., tight or loose), marked the bolt sites using bounding boxes, and recovered the region of interest from the pixel level background.

Yuan et al. [31] demonstrated a CNN-dependent damage identification system for high-speed real-time bridge inspections. Lower the count of variables to be altered to reduce the count of outcomes acquired throughout the upgrading process to boost testing speed. When trained and tested with three independent data sets constructed with three damage severities, the approach can predict the damage location with an accuracy of 87.3 % when such damage intensity in the bridge is severe. As per the findings, deep learning provides a method for overcoming the problems associated with traditional damage localization methodologies.

Teng et al. [32] have used a CNN model to develop a new efficient approach for recognizing structural collapse from real-time vibration (CNN). The FEA of a steel structure being employed to produce training samples for CNN and the efficacy of the suggested diagnosis approach is evaluated by feeding experimental findings into the CNN. The findings show that the CNN trained with FEA information has a detection rate of 94 % for numerically induced defects and 90 % for defects within an actual steel frame. It is demonstrated that the CNN has a tremendous identification impact for both single and multiple damages.

Lee et al. [33] created a new computer vision model for detecting deterioration in small-scale steel constructions. Decoding the active perceptron ensures the effectiveness of the DL model. that may be used to classify steel bar deterioration. Grad-CAM becomes a strategy for displaying active perceptron by making a heat map that can categorize steel bar degradation. The Grad-CAM visualizations' active neurons offer information about the damaged and undamaged regions of the steel bars. As a result, this visualization approach was utilized to verify the model's efficacy.

Li and Jing [34] suggested a novel second-order output spectrum (SOOS)-dependent solution with just a local tuning strategy to precisely detect simultaneous bolt-loosening difficulties in complicated systems using only a simple sensor chain. A more comprehensive multi-degree-of-freedom (MDOF) framework incorporates general non-linear restoring forces caused by faults, inherently existent material or non-linear border effects to construct the innovative SOOS-dependent damage predictor, and a particular local tuning approach structures is examined. Numerical as well as experimental findings suggest that this novel SOOS-dependent local tuning strategy could provide extra detailed, sensitive, as well as trustworthy data about fault positions and can also be used to precisely localize innumerable bolt loosening flaws in complex structures, even though underlying substance or boundary nonlinearities exist.

Zhao et al. [35] suggested a genuine non-linear ultrasonic approach based on vibroacoustic modulating for quantitatively monitoring early bolt looseness utilizing piezo ceramic transducers. In addition to recognizing early bolt looseness, they significantly contributed by replacing the shaker, normally employed in a vibroacoustic modulation approach, with factory affixed and low-cost lead zirconate titanate patches. When two distinct frequency input waveforms, notably raised probing wave and the low-frequency pumping wave, were stimulated in the vibroacoustic modulator, the high-frequency probing wave gets manipulated by either the low-frequency pumping wave to generate sidebands in regards to bolt looseness. These experiment findings revealed that the lead zirconate titanate enabled vibroacoustic modulation approach is dependable and simple for determining bolt looseness. Furthermore, low-frequency amplitudes for actuating voltage must be chosen within an acceptable limit. This demonstrates that the vibroacoustic modulation approach works better at monitoring earlier bolt looseness.

Morizet et al. [36] introduced a unique method for classifying acoustic emission (AE) data derived during corrosion tests, even when contained in a noisy background. Synthetic data has been used in a detailed study that contrasts Random Forests (RF) with the k-Nearest Neighbor (k-NN) approach to verify such a novel technique. Furthermore, these alter-class matrices (ACM) are offered a novel assessment tool for simulating varying uncertainties on tagged information for the categorization process. Subsequently, real-world noises accompanying crevice corrosion tests were performed via pre-processing those signals, incorporating wavelet noise removal, thus producing a comprehensive set of characteristics as feed to that same RF technique. To fulfil the aim, RF-CAM software was developed. The findings show that this approach is exceptionally effective for ground truth data and very appealing for real data, particularly dependability, performance, and speed, all of which are important requirements inside the chemical sector.

Guo et al. [37] developed a fiber optic sensing-based approach for monitoring track slab deformation and an adaptive random-forest model-based technique for recognizing track slab displacement. High-speed railways (HSRs) are now being established all around the globe due to their features such as high speed, travel convenience, very low vibration, and noise. Ballast less track slab is indeed an important component of the HSR, as well as its state has a direct impact on the train's safety. As train operation time grows, track slabs develop faults such as buckling,

arching, and a layer detaching fault. The findings demonstrate that vibration signals originating from train vibration, railway slab displacement, sounds, and ambient vibration can indeed be reliably recorded by track-side surveillance. The suggested intelligent method can efficiently detect track slab deformation, with a detection rate of 96.09 percent. This research proposes innovative tracking slab deformation tracking and intelligent recognition algorithms.

Ye et al. [38] presented a multiple-variable categorization framework that links the valve-internal-leakage acoustic emission signal (VILAES) properties and the leakage rates under varied pressure by integrating time and frequency domains features and also the random-forest approach. The initial stage in utilizing acoustic-emission technology to discover leakage within a valve is to model the VILAES computationally. The analysis reveals that when the leakage rate increases, so do the five VILAES features. The Random Forest offers a multi-variable categorization system to estimate if the valve leakage was little, moderate, or extreme. To forecast the ultimate result, the Random Forest employs many decision trees. It demonstrates that depending on time properties with Random Forest, the modelling technique has a shorter operation time and improved accuracy.

Even though numerous studies have employed acoustic emission for damage localization, classifying distinct types of failures in a steel frame structure with a single sensor remains a difficult problem. Only image-based algorithms have been established for fault classification; this method cannot use for the early detection of faults that occur within structures, such as internal cracks. A machine learning-based acoustic emission is proposed to fill this research gap in steel frame structures. This proposed method is appropriate for detecting failures in a steel frame structure and for classifying such failures utilizing acoustic emission signals collected from a sensor device attached to the structure.

3 Experimental setup for collecting the data
In the experimental study, 0.5 mm pencil leads were broken to create AE signal sources, Hsu and Breckenridge [39]. Pencil-lead break (PLB) is a long-recognized as a reliable artificial AE source.

The experimental program setup comprises of a prototype steel frame, an AE acquisition system, a mechanical pencil, and a broadband AE transducer as receiver [6]. The AE transducer (Model: R15D, "Physical Acoustics Corporation") serves as the receiver and is a broadband

type sensor with a comparatively flat response between 20 kHz and 1 MHz. On the beam members and beam-column junction members, receivers have been attached. On a steel frame that has been stripped and fixed supports, acoustic emission tests have been performed. The frame is 300 mm X 300 mm and 900 mm in height. Fig. 1 illustrates the placement of sensors on the subsequent nodes (outer faces the beams). PLB has been carried out on the subsequent nodes as seen in Fig. 1.

The prototype model is a single-bay, three-story frame that has undergone independent testing on each floor. Fig. 2 depicts the experimental configuration. The AE sensor/transducer was installed at one node at a time (i.e., 1, 2, 3, and so on) to record the responses resulting from damage that was simulated using PBL at the other nodes. The Fast
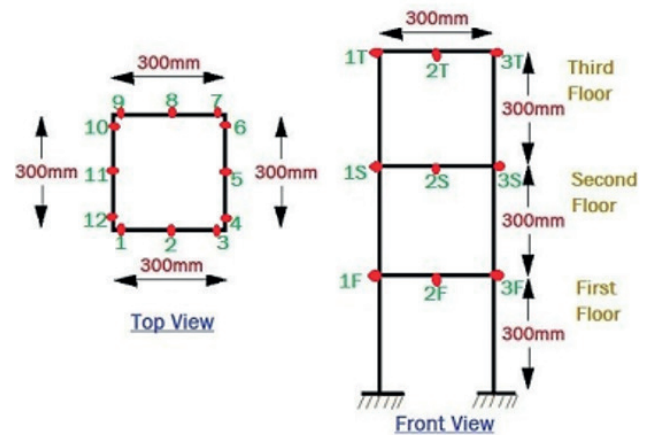

Fig. 1 Steel frame structure with nodal points

Fig. 2 Test setup

Fourier Transform (FFT) is used in a MATLAB program to convert the time-domain answers so generated using the AE system into the frequency domain.

The experiment was run to determine where the sensors should be mounted on the frame; separately, the positions of the beams and columns were examined for this. The ideal placement on beams is determined by studies that involve installing a sensor at the center of the beams (Node 2) on the first level and performing PLB at the beam-column junction (Node 1), with the AE response recorded appropriately. Now that the PLB position is fixed (i.e., at Node 1), the first floor's answer at each node is recorded. The responses of the other nodes are recorded by putting the sensors on each node, accordingly, while retaining the PLB placement at Node 2 (i.e., the center of the beam). Similar to this, all nodes are covered by altering the PLB position one at a time, and AE data is captured sequentially for each site. In this manner, the AE event data from each node for the first floor have been acquired in order to analyze the variance of AE event response with source location distance. The second level and third floor likewise go through the same procedure. Data for investigation of the key sensor placement on the beams are so reported.

By installing a sensor at the beam-column junction on the second level (Node 13) and performing PLB at the beam-column joint on the first floor (Node 1), tests are conducted to determine the optimal position on columns. The AE response is then recorded in accordance with the results. The response at all nodes of the second floor and third floor, respectively, is recorded while maintaining the PLB position fixed (i.e., at Node 1).

The responses of the other nodes of the second floor and third floor are recorded by putting the sensors on each node, with the PLB placement remaining at Node 3 (i.e., the beam-column junction). Similar to this, all the nodes on the beam-column junction and beam center are covered by moving the PLB position one at a time, and AE data for each floor location and AE event data are captured successively. In this manner, information for analyzing the ideal sensor placement on the columns is noted.

The time-dependent ae responses from the experimental work performed for beams and columns independently for each level were used for analysis. Later, the fast Fourier transform (fft) function in Matlab is used to convert the time domain data into the frequency domain. Fig. 3 depicts a steel frame with a sensor location at Node 2's first level and a plb position at Node 1's.

Fig. 3 Test Frame with sensor mounted at 2F

4 Acoustic emission-based damage detection and classification in steel frame structure using wavelet transform and random forest

A structural health monitoring (SHM) technology evaluates and analyses a building's structural fitness. It has been extensively implemented in a diversity of engineering fields owing to its capacity to respond to unfavorable structural changes, boost durability and longevity, and effectively govern the life cycle of infrastructures. Acoustic emission (AE) has been a well-known SHM method adopted during non - destructive degradation evaluation in various industrial applications. It is beneficial in detecting damage to civil constructions such as bridges, reinforced structural concrete, steel frames, plate-like structures, etc. Additionally, rivets, welding sites, or bolted connections link the elements of an aeronautic, automotive, or civil engineering construction. The steel frame bolted joints are prone to self-loosening and breaking when the structure is subjected to shocks. Numerous research studies have examined the damage localization of steel frame structures utilizing many neural networks for picture categorization; however, these networks cannot identify damage deep within a material.

Another disadvantage of the current techniques is that noise problems remain unsolved. At the same time, they can detect both fractures and bolt loosening in steel frame structures by employing a novel self-powered strain coupled acceleration sensor for such applications. To address this research gap, this work presents a novel approach

based on AE structural monitoring techniques that can detect both internal and external damage to the steel frame design. The flow diagram of the proposed damage identification and classification method is given in Fig. 4.

The overall purposes of this work's systemic acoustic emission (AE) evaluation are to primarily focus on the component of fault type identification and classification. Several studies have focused on damage localization and image-based failure classification. The proposed method is based on the acoustic emission technique. On the other hand, it focuses on damage localization in the early stages and categorizes the two most common steel structural problems, including bolt loosening and crack development. The upcoming sections briefly explain the pre-processing of the input signal before applying the wavelet transform to detect the damages.

4.1 Pre-processing

In this paper, elastic waves formed during a steel frame structure design are used as a source of damage or load. Because of the apparent great sensitivity of acoustic emission, sensor locations do not need to be changed or cleaned. As a result of these factors, acoustic emission was frequently employed as a non-destructive approach in many sectors, including industrial and bioengineering. It is simply an elastic wave produced by a rapid reconfiguration of stresses inside a material. Because structure resonance has less impact on AE signals, those will be much more attentive to early fault activity.

Damage occurs in the steel frame structure during the creation of a steel frame construction, resulting in structural failures such as fractures and bolt loosening owing to vibrations. These oscillations are referred to collectively as the AE source. The AE sensors convert the stress

waves into this type of electrical signal. The AE signals produced during vibration are faint and may be obscured by background noise (except near yield and at fracture). It is possible to magnify these faint AE signals by superimposing acoustic waves. External acoustic wave injection activates some of the possibly subcritical AE sources, contributing to an increase in AE energy.

The noise captured during acoustic emission (AE) testing is quite diverse. Noise could be induced by a mixture of physical sources, notably sensor noise, measurement route imperfections, and technology noise in the testing item. The noise in the signal waveform might be substantially different. They can be stochastic or deterministic, stationary or non-stationary, wide-band or narrow-band, with high and low noise conveniently suppressed via frequency or median filtering. Furthermore, to identify AE impulses against a background of static white noise, we adopt a filtering technique depending on a discrete wavelet transform. Further, filtering noise with waveforms comparable to AE signals is very difficult in which the wavelet-filtering may be conducted more successfully over a longer period. The dispersion of stochastic noise, whose value influences the threshold value, is more accurately calculated as the supervision duration increases.

Furthermore, the adaptive wavelet-thresholding process may be implemented for lengthy supervision times. This approach presupposes that the examined signal is represented as different length segments. The length and quantity of segmentation intervals are chosen with consideration for the signal shape to offer the highest ratio of signal energy to noise after filtering. A sensor is put on the beam-column junction of a steel frame structure for increased efficiency. The final pre-processed signal has been processed using wavelet transform to extract the features, and that detail has been explained in the next section.
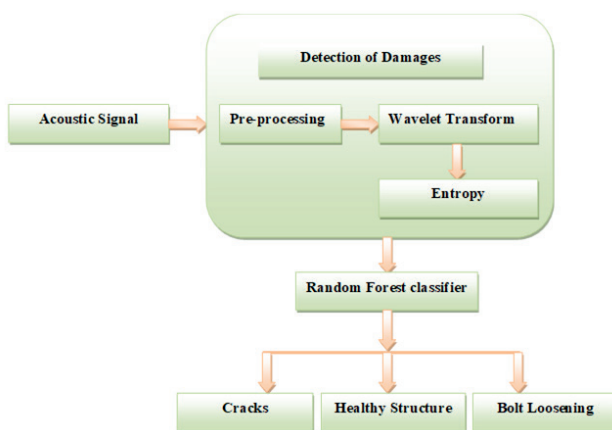
4.2 Transformation

Following signal pre-processing, the feature extraction stage entails extracting the signal's best features. The wavelet transform (WT) is a well-known technique for extracting essential characteristics from stochastic waveforms. The WT utilizes a time-frequency representation rather than defining a waveform using simply time or only frequency representation. Because of the properties of wavelets and the freedom in picking wavelets, wavelet signal processing is useful for extracting unique signal features. The wavelet transform (WT) determines the frequency spectrum as a function of time by employing

Fig. 4 Flow diagram of proposed method

small waveform segments or wavelets as the basis functions. A wavelet is a wave-like vibration whose amplitude starts at zero, rises, and afterwards falls back to zero. Wavelets come in various shapes and sizes, and the one chosen depends on the characteristic to be retrieved from the signal. To be utilized with digital signals, they must first be turned into wavelet filters with only a finite sequence of distinct points. Wavelets can also be merged with sections of a known signal using a "reverse, shift, multiply and integrate" process called convolution to obtain information from an unknown signal. The signal spectrum describes the amplitude and phase characteristics of a signal regarding frequency.

In spectrum analysis, power spectral density is an effective tool. A Power Spectral Density (PSD) is a metric that relates a signal's power level to its frequency. A PSD is frequently employed to illustrate wide-band random signals. The spectral resolution of the signal utilized to digitize has been employed to normalize the PSD's amplitude. Because of its computing efficiency and simplicity of understanding, the Power Spectral Density (PSD) has been the most extensively utilized orthogonal representation of signals. Likewise, the signal is supposed to be stationary; nevertheless, the PSD is frequently utilized with transient events whose duration is large compared to their spectral contents. The Wavelet transform may be used to sparsely represent signals, record transient characteristics, and analyze signals at numerous resolutions. The wavelet transform can capture transitory information exactly since wavelets are variable in shape and have a limited duration. The wavelet transform is also used to overcome the resolution problem during short-term Fourier transformations. Wavelet-based transformation is mostly utilized for temporal frequency analysis, which would be the study's major goal of identifying abrupt changes enabling signal classification. The Continuous Wavelet Transform is used to compute the wavelet coefficients of the signals (CWT).

The continuous wavelet transform (CWT) has been utilized to split data into frequency bands & subsequently get the local temporal data via correlated resolutions. This continuous wavelet transform (CWT) may offer an over-complete description of acoustic emission signals by repeatedly altering and scaling the wavelet parameters. The following integral describes the continuous wavelet transform of a time series $f(t)$.

$$Wf(a,b) = \int_{-\infty}^{\infty} f(t) \overline{\psi_{a,b}}(t) dt \tag{1}$$

Here $f(t)$ seems to be the time domain tracking signal; $\psi(t)$ denotes the analytical wavelet, and $\overline{\psi(t)}$ denotes the complex conjugation of $\psi(t)$. The function $f(t)$ corresponds to the space of quantifiable, square-integral one-dimensional functions L2 (R) and is an acceptable fundamental wavelet only if the following conditions are satisfied:

$$\int_{0}^{\infty} \frac{|\psi(\omega)|^2}{\omega} d\omega < \infty , \tag{2}$$

where $\psi(\omega)$ is the Fourier transform of function (t):

Where $\psi(\omega)$ seems to be the Fourier transform of the function $\psi(t)$:

$$\psi(\omega) = \int_{-\infty}^{\infty} \psi(t) e^{-i\omega t} dt . \tag{3}$$

The wavelet function's average value is zero, as indicated by the relationship:

$$\int_{-\infty}^{\infty} \psi(t) dt = 0 . \tag{4}$$

Signal decomposition is accomplished by duplicating the wavelet function that describes the wavelet group. They were computed by scaling as well as translating the function $f(t)$ as follows:

Duplicates of the wavelet function that describe the wavelet

$$\psi_{a,b} = 1/\sqrt{|a|} . \psi((t-b)/a) . \tag{5}$$

When t is indeed a time point, a has been a scaling parameter, while b is just a time-domain wavelet shift. The parameters a and b from the real number sets were real numbers (a, b R) and a 0, respectively. The number (a, $b \in$ R) and $a \neq 0$. The number $|a|^{-1/2}$ would be a normalization factor that ensures constant wavelet energy regardless of scale, implying that the norm $\|\psi_{a,b}\| = \|\psi\| = 1$.

On the other hand, the Discrete wavelet transform decomposes a given signal into many sets. By entering $a = 1/2^j$ and $b/2^j (k, j \in C)$ into Eq. (5), the wavelet family has been developed:

$$\psi_{j,k}(t) = 2^{(j/2)} . \psi(2^j . t - k) , \tag{6}$$

where j and k are indeed the scales as well as translation parameters.

The Mallat pyramid algorithm may be utilized to do multi-resolution analysis on the discrete signal $f_j(t)$.

$$f_J = S_J + D_J + \ldots + D_n + \ldots D_{1,n} = J - j \tag{7}$$

Every element of the signal representation Eq. (7) corresponds to a certain frequency range that offers information at distinct degrees of decomposition $j = 1, …, J$.

The discrete parameter J specifies the level of multi-resolution assessment, where S_J has been the signal approximation, D_n, S_n were details as well as rough sections at distinct decomposition levels, while D_1 has been the most comprehensive description of the signal. The function f_J must be approximated by $N = 2\,J$ discrete values to meet the DWT dyadic constraints.

In 1D space, the Mexican hat wavelet comprises the following shape:

$$\psi(x) = \left(1 - x^2\right)e^{-x^2/2}. \tag{8}$$

It is simply the Gaussian's second derivative.

The Mexican hat function in 2D space,

$$\psi(x) = \left(2 - |x|^2\right)e^{\left(\frac{-1}{2}|x|^2\right)}. \tag{9}$$

The function's strong slope, as well as oscillating properties, allow us to identify the signal.

As a result, the Mexican hat is often used as a mother wavelet to identify patch and gap events in this article. In this research, the Mexican hat mother wavelet is used to depict waveforms better. The Wavelets can readily handle abnormal signals that cannot be handled in the time-frequency plane.

To find out the variation or disorders in the generated waveforms, Shannon's entropy is a frequently used measure indicating signal disorder or the amount of data that may be gathered from observations from disordered systems. Shannon entropy is a standard term of entropy defined by Claude Shannon.

$$S = -c\sum_{i=1}^{n} P_i \log_2 P_i, \tag{10}$$

where P_i has been the probability of an event occurring x_i is an element of the event (feature) X that can have values $\{x_i, …, x_n\}$, and c would be an arbitrary positive constant term that specifies the units. The logarithm base is 2, and the entropy gets measured in bits. If we set c to $1/\log(2)$, we can also see that Shannon's entropy S is non-negative; hence the probabilities should be 1.

In the interpretation and analysis of AE data, Shannon's entropy has been successfully utilized as an indicator of uncertainty. Shannon's entropy was proven to quantitatively describe the energy distribution of wavelet representations of AE signals, allowing the optimal wavelet to be chosen and the signal attributes to be defined.

The energy of the signals m amount of wavelet coefficients at every resolution scale n expressed as

$$Energy(n) = \sum_{i=1}^{m} \left|C_i(n)\right|^2. \tag{11}$$

The Shannon entropy, which assesses the uncertainties of signal wavelet coefficients, is calculated as follows:

$$Entropy_{sh}(n) = -\sum_{i=1}^{m} P_i \log P_i, \tag{12}$$

where P_i denotes the probability distribution of each wavelet coefficient's energy with $\sum_{i=1}^{m} P_i = 1$, defined by

$$P_i = \frac{\left|C_i(n)\right|^2}{Energy(n)}. \tag{13}$$

The damage locations can be identified using the continuous wavelet transform. The distance between the sensors and the source provides information about the location of the failure in a steel frame structure. The use of novel parameters such as energy and Shannon entropy and existing features such as peak frequency, standard deviation, amplitude, signal intensity, and mean values can improve the accuracy of a damage localization approach and the classifier's performance.

The time-frequency attributes of acoustic emission signals were depicted utilizing a scalogram depending on the wavelet transform. The x-axis indicated the time, the y-axis indicated the scale, and the frequency coefficient values were represented by altering the color. The spectrogram of wavelets is termed a scalogram, and it may be used to determine impulse frequency response. From this, we can determine the location of the failures of the structure. These scalograms were sent into the Random Forest classifier as input for further classification of the faults in the steel frame structure.

4.3 Random Forest classification

The CWT was used to identify the feature for the damages existing in the steel structure. The output of the wavelet transform has been converted into scalogram images to identify the damages in the steel frame structure accurately. It was supplied to RF to categorize the sorts of damages in the steel structure, such as fracture and bolt loosening. Numerous research works based on machine learning have been offered to identify the damages. Still, the model's accuracy remains a challenge when classifying the various damages in the steel frame construction and the explanation below.

Regression and classification problems may be accomplished using the RF approach, which makes use of an ensemble of decision trees. The algorithm chooses a certain amount of characteristics at random when creating trees. In essence, this stops multiple decision-making identical feature-dependent trees in trees. Repeat the procedure up until a group of regression. It creates trees, each trained on a different subset of data that was chosen at random. This led to randomness makes up for the flaws of each individual tree.

From Table 1, a few key parameters may be adjusted to change how well an RF model performs; some studies claim that changing RF parameters from their default values has a considerable advantage. [40]

In theory, the forest should contain as many trees as feasible, but in reality, performance plateaus after a few hundred trees. A lower value will increase the likelihood of selecting features with small effects, which in turn could lead to improved performance in situations where such a feature would be masked. In general, increasing the number of features considered in splitting a node will improve performance as each node will now have a higher number of options to consider. The minimal size of terminal nodes is represented by the parameter min samples leaf. Lesser trees result from smaller numbers, whereas trees with smaller leaf sizes are more susceptible to data noise.

Random Forest generates a highly accurate classifier for many data sets among the most accurate learning algorithms. On large databases, it performs well and can handle tens of thousands of input parameters without deleting any of them. The Random Forest seems to be a form of supervised learning. The "forest" generates an ensemble of decision trees, which are frequently trained utilizing the "bagging" method. This bagging strategy primarily focuses on merging many learning models to enhance the final output.

Rather than relying on a single decision tree, the Random Forest aggregates forecast from each tree and then anticipates the final output depending on the majority vote of projections. Since this Random Forest aggregates several trees to predict the category of the dataset, certain decision trees might forecast the correct output while others may not. But, since all of the trees have been joined, they correctly forecast the outcome. As a consequence, two assumptions for a better Random Forest classifier were just as follows:

The dataset's feature variables must have genuine values so that the classifier can predict actual outcomes instead of guesses.

The forecasts of each tree will have very low correlations.

The Random Forest typically works in two stages: the first is to build the Random Forest by mingling M decision trees, and the second should be to generate forecasts for every tree formed in the first phase. The Random Forest categorization algorithm is described in Algorithm 1.

Fig. 5 depicts the structure of the Random Forest classifier for the proposed approach.

Table 1 Summarizes the most common hyperparameters of the RF model

Parameter	Meaning	Value
n_estimations	The number of estimators in the Random Forest	382
max_features	max number of features considered for splitting a node	sqrt
max_depth	max number of levels in each decision tree	none
min_samples_split	min number of data points placed in a node before the node is split	2
min_samples_leaf	min number of data points allowed in a leaf node	1
bootstrap	method for sampling data points. True = bootstrap samples	true

Algorithm 1 Damage Classification in the steel frame structure using Random Forest classifier

Input: Scalogram image of the transformed AE signal from steel frame Structure
Output: Damage Classification.
1. Choose N data points at random from the training set.
2. Create the decision trees corresponding with the chosen subsets.
3. Choose the value K for the number of decision trees built.
4. Repeat steps 1 and 2.
5. Compute the prediction of each decision tree for new data points, then allocate those new data points towards the class that has the most votes.
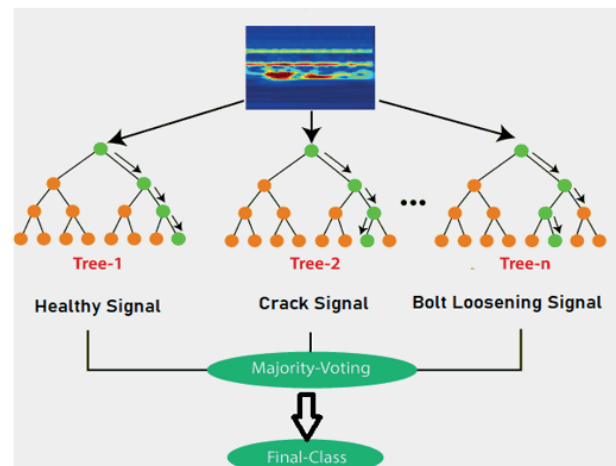

Fig. 5 Random Forest categorization structure

Multiple decision trees are used in the ensemble learning technique known as Random Forest (RF) [41]. Decision tree models are trained to operate independently of one another, and when their output is combined, the forecast with the most votes wins [42–44].

The following are the stages to making a Random Forest:

1. Randomization of sample size: Assume that T is the original dataset, and N samples make up T. The bootstrapping approach involves creating a new subset by selecting N samples at random from the original dataset T with replacement. These N samples in the new subgroup might include samples that have been taken several times or never before. Equation may be used to determine the likelihood that a sample has never been taken Eq. (14). Eq. (15) may be used to determine the probability's upper limit.

$$h(N) = \left(1 - \frac{1}{N}\right)^N \tag{14}$$

$$\lim_{N \to \infty} \left(1 - \frac{1}{N}\right)^N = 0.368 \tag{15}$$

Nearly 36.8% of the data in the original data set might not be included in the new subset, according to Eq. (16).

$$N_{hidden} \leq 2N_{input} + 1, \tag{16}$$

where N_{hidden} is the number of neurons in the hidden layers and N_{input} is the number of input variables. Out-of-bag (OOB) data, which refers to this unselected data, can be used to evaluate how well the decision tree generalized.

2. Feature randomization: Assume that there are n characteristics for each sample in the new subgroup. The decision tree receives randomly chosen t characteristics ($n \leq t$). Each feature's information content is calculated, and the feature with the greatest capacity for categorization is chosen for node branching. According to Genuer et al. [45], the connection between n and t should be as follows:

$$t \approx \sqrt{n}. \tag{17}$$

3. Construct a decision tree: Steps (1) and (2) can be repeated m times to get m subsets that contain t characteristics in each sample. Every subset is then given its own decision tree. To put it another way, m decision trees are built.

4. Create the Random Forest: A Random Forest is created using the m trees. The decision trees in the Random Forest produce their own outcomes for categorization. The total number of votes determines the final outcome.

This research uses RF methods to detect the kind of failures in a steel frame structure using scalogram images of the damage identified signals using wavelet transform as inputs. The primary parameters analyzed in the RF-based machine learning process include meaning, amplitude, signal intensity, peak frequency, kurtosis, standard deviation, energy, and entropy. In this research, the mean and standard deviation of signals describe the distinction between the healthy and faulty aspects of the steel frame structure. These characteristic values will be higher for erroneous signals and lower for healthy signals. The feature parameters will vary in response to changes in signal behavior.

Every AE scalogram picture gets run down each tree in the Forest during the testing stage, yielding T votes. For defect categorization, the majority voting rule was utilized. A defined AE signal scalogram picture is allocated to a certain category if more than 70% of the total count of trees is voted explicitly for that class under this criterion. If more than 70% of the trees voted for crack, the picture would be categorized as crack failure; if more than 50% voted for bolt loosening, the image would be classified as bolt loosening failure.

Consequently, using a Random Forest classifier to identify steel frame structure failure is a novel method that has never been tried previously and can handle many input variables while being relatively unaffected by overfitting. Using the majority voting method with this classifier, we may obtain exact damage identification and the kind of failure.

5 Result and discussion
This section includes a full overview of the implementation outcomes and the effectiveness of our proposed approach.

Tool:	MATLAB 2018a
OS:	Windows 10 (64 bit)
Processor:	Intel premium
RAM:	8 GB RAM

The sequential data from the experimental results have been converted into signals for further processing. Acoustic emission testing was performed on a bare steel frame having fixed supports. This frame is 300 mm by 300 mm and stands 900 mm tall.

5.1 Performance evaluation
The illustrated performance matrices of the proposed model are shown below.

The Acoustic sensors record the signals that emerge during small cracking or bolt loosening problems. Fig. 6 depicts a graphical depiction of the acoustic emission signal, including damages present in the steel frame structure.

Fig. 7 shows a Scalogram representation of the Acoustic Emission signal constructed for better viewing.

Fig. 8 depicts the graphical representation of this reconstructed signal, where the input signal is rebuilt to determine the original continuous signal from a sequence of evenly spaced samples.

Fig. 9 depicts the Different Scale estimates of the input signals such as meantime, mean frequency, Time duration, Frequency, and Amplitude. It indicates that the variations are strong and weak at a specific level.

Fig. 10 illustrates the PSD estimation of the signals from the different scales, indicating which frequencies have substantial fluctuations and mild variations.

Fig. 11 depicts the scalogram pictures of the linear frequency, independent of the amplitude of the oscillations in the signal generated by the sensor utilizing acoustic emission, with the minimum frequency set to 30 Hz and the highest frequency set to 350 Hz to detect cracks in the steel structure.

Fig. 12 depicts a scalogram image of the non-linear frequency of the sensor signal, which is dependent on the amplitude of the oscillations, with the minimum frequency being 30 Hz and the highest frequency being 350 Hz.

Fig. 13 depicts a scalogram image of the signal's normalized scaling, in which the values are shifted and rescaled for the highest and minimum values of the feature, respectively.

Fig. 14 shows a Scalogram depiction of Overlaps between Scales Image in which the fluctuations of the signal may be discovered.
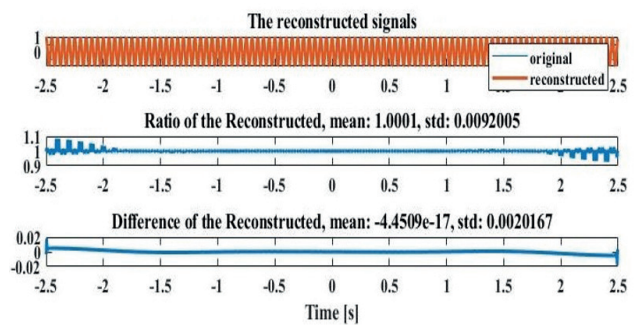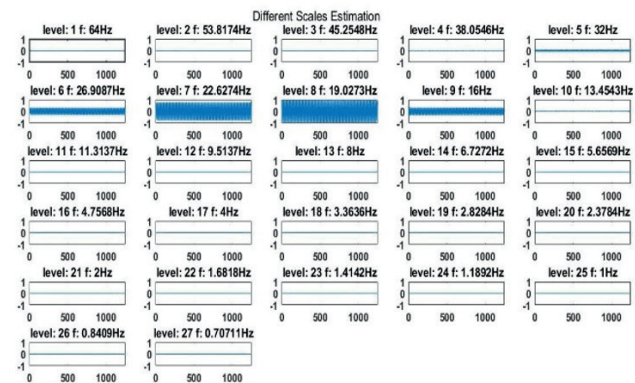

Fig. 8 Reconstructed signal
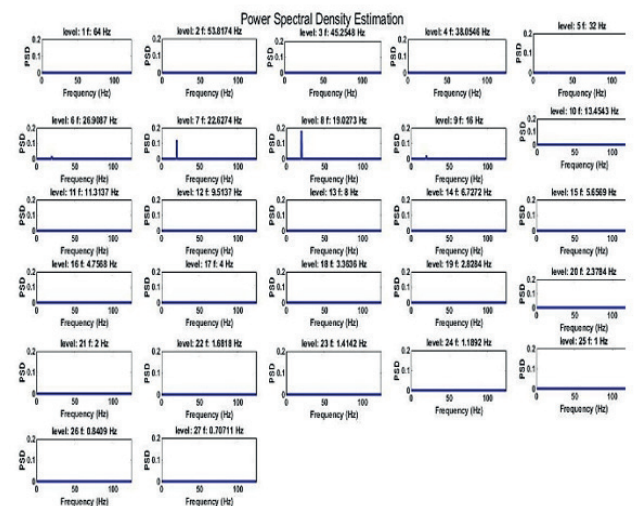

Fig. 9 Different scale estimation

Fig. 6 Generated acoustic emission signal
X-axis- Amplitude (Milli volts), Y-Axis- time (Micro Seconds)

Fig. 7 Scalogram representation of the input signal

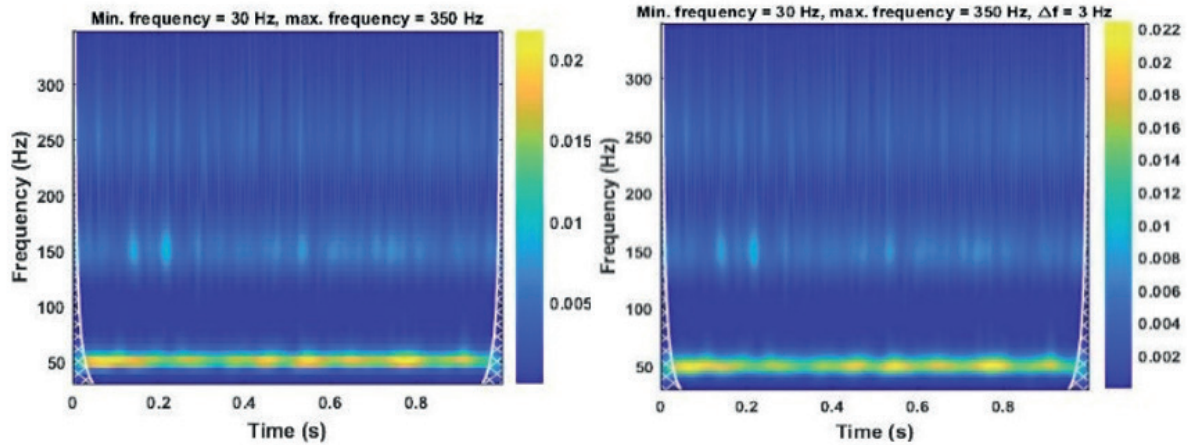**Fig. 10** Power spectral density estimation

Fig. 11 Scalogram of linear frequency signal
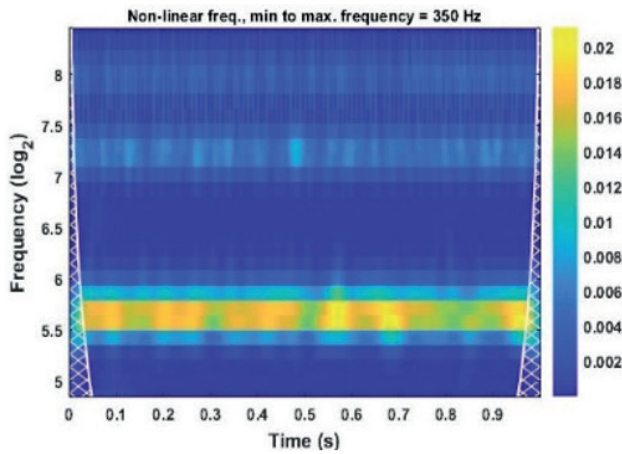

Fig. 12 Scalogram image of the non-linear frequency signal
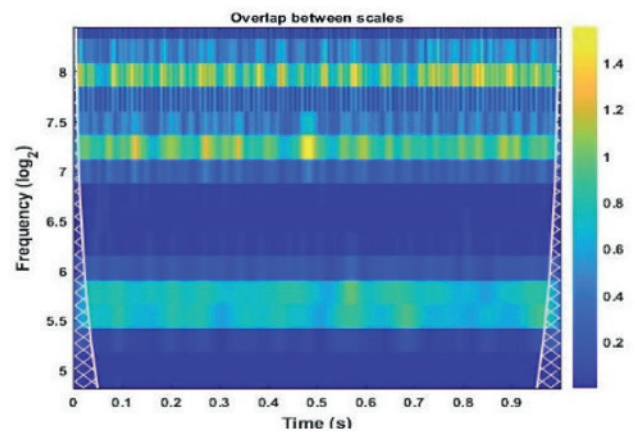

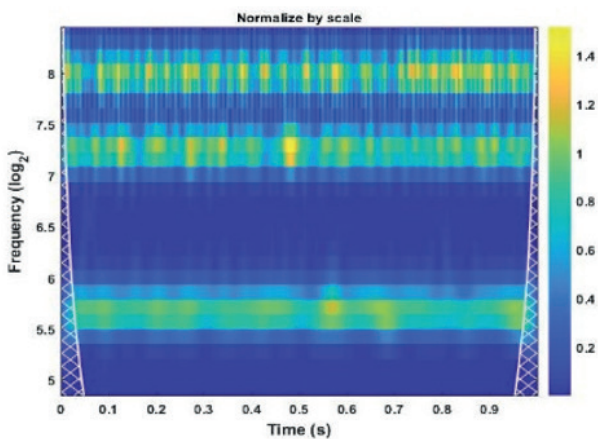**Fig. 14** Scalogram image of the overlaps between scales

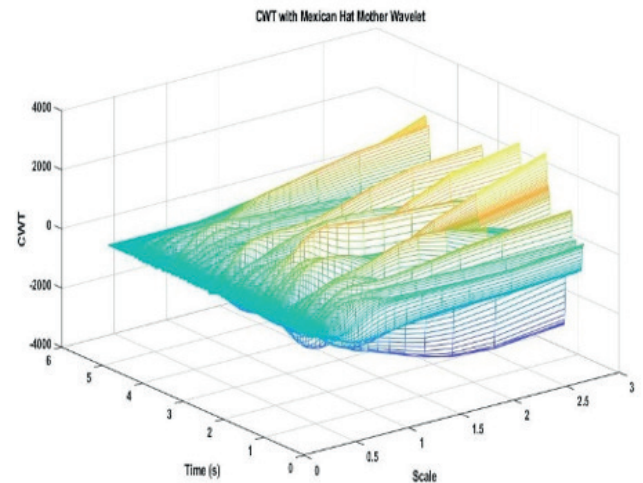**Fig. 13** Scalogram image of the normalized signal

Fig. 15 3D representation of the Mexican hat continuous wavelet transform

Fig. 15 illustrates a three-dimensional depiction of the Mexican hat CWT, utilized to discover signal discontinuities in steel frame structures.

The signal difference identifies the problem in the steel frame construction. Each structural fault has a unique amplitude and peak frequency. The RF classifier determines whether the problem is a fracture or a bolt loosening based on the provided reference and the training process.

The difference has been identified using the given input signal's energy and peak amplitude features.

Fig. 16 depicts the graphical depiction of crack localization, whereas Fig. 17 depicts the graphical representation of bolt loosening fault localization. It trains the signals to depend on the scalograms of the test signals.
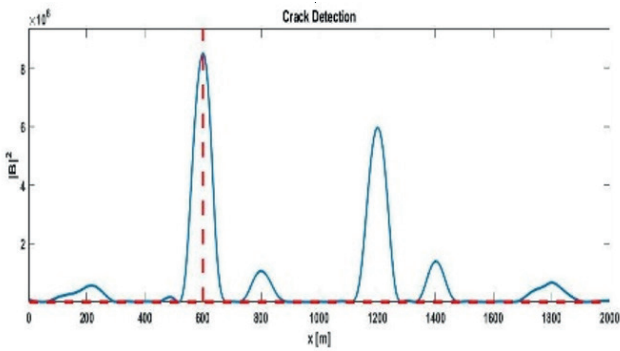
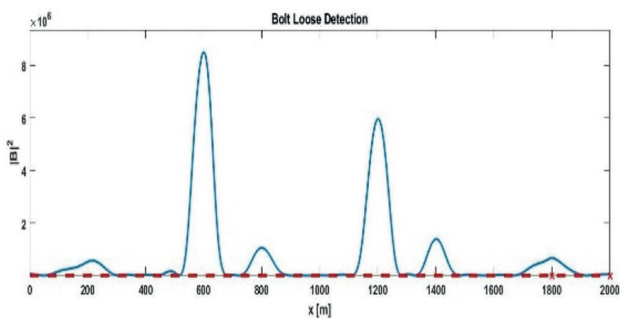**Fig. 16** Crack localization in the steel frame structure

Fig. 17 Bolt loosening localization in the steel frame structure

5.2 Comparison evaluation

The following section discusses the findings of the proposed model's comparison with the existing models. Some of the existing damage classification algorithms and their categorization accuracy are depicted in Table 2.

Fig. 18 depicts the accuracy of the proposed methodology. This graph illustrates that the proposed approach beats other existing fault categorization approaches in terms of categorization accuracy. This proposed strategy had an accuracy of 99.7%, whereas the other methods had an accuracy of 99.7% and 97%, respectively.

Table 2 Comparison of categorization accuracies for damage detection with the existing models

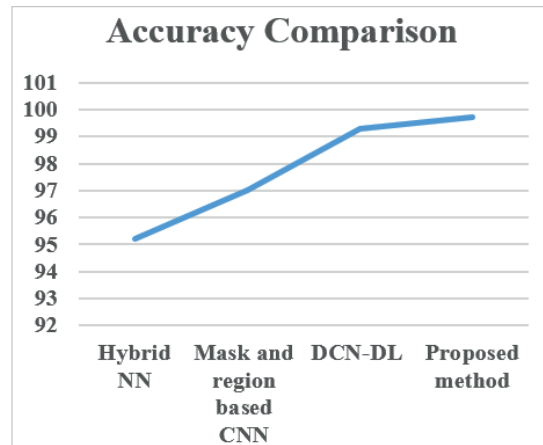| Methods	Classification accuracy (%)
Hybrid NN [2]	95.2%
Mask and region-based CNN [5]	97%
DCN-DL [7]	99.3%.
Proposed method	99.7%

Fig. 18 Comparison of the proposed method

Consequently, the proposed method detects faults in the steel frame structure, such as bolt loosening and internal cracks, using wavelet transforms and then classifies the kind of detection using an RF classifier. Based on the data shown above, we can infer that the suggested framework performs better in damage detection and categorization.

6 Conclusions

- The certainty of building ageing and degradation and the subsequent structural failures have created a demand for early prediction of impending structural damage so that preventative actions can be performed.
- To identify the location and the intensity of damage is indeed a critical stage in the structural health monitoring (SHM) operation.
- In this research, a novel approach for early failure identification is provided. We can prevent significant accidents caused by structure collapses by detecting failures.
- This proposed approach is useful for monitoring the steel frame structure and identifying the defect based on signal changes in a shorter amount of time and effort.
- Using an effective random forest classifier, the defects are categorized as crack or bolt loosening in this technique. According to the data, this classifier has a classification accuracy of 99.7%, which is greater than other current approaches.

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