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Vibration Classification Of Intact And Cracked Brick Materials Using Fast Fourier Transform–Extreme Learning Machine For Structural Damage Early Detection

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Abstract

Structural damage in buildings is often initiated by small cracks in lightweight brick elements, which, if undetected, may compromise structural safety. This study developed a vibration-based classification system using the ADXL345 accelerometer, Fast Fourier Transform (FFT), and Extreme Learning Machine (ELM) for early detection of such damage. Vibration data were collected along three axes (X, Y, and Z) with excitation frequencies ranging from 10–50 Hz. FFT analysis revealed clear distinctions between intact and cracked bricks, where cracked samples exhibited higher amplitudes and multiple resonance peaks. These frequency-domain features were then processed by ELM classifier. ELM achieved high computational efficiency and demonstrated strong predictive capability, correctly classifying 7,855 intact and 4,548 cracked samples. However, it also produced 1,879 false positives and 5,100 false negatives, resulting in an RMSE of 0.548. While the model proved more accurate in identifying intact bricks, its sensitivity to crack detection remains a challenge. Overall, FFT–ELM framework shows promising potential as a fast, non-destructive, and scalable approach for structural health monitoring, with further refinements needed to improve detection accuracy of damaged materials.

Keywords : *Classification, Crack, ELM, FFT, and vibration*

1. INTRODUCTION

Structural integrity is a crucial aspect in the design and maintenance of buildings. Cracks in structural components such as walls and foundations often serve as early indicators of deeper mechanical failures, potentially compromising the safety and performance of buildings if left undetected [1]. The degradation of structural materials commonly results from repetitive loading, encompassing dead loads, live loads, and dynamic loads such as human activity, vibrations from equipment, or external environmental impacts [2], [3]. These loads may cause fatigue in materials such as lightweight bricks, initiating small cracks that eventually evolve into major structural weaknesses [4], [5]. Lightweight bricks are increasingly used in modern construction due to their low weight, ease of installation, and thermal insulation efficiency. However, their mechanical behaviour differs from conventional bricks, making them more susceptible to damage under stress conditions, especially vibration [6], [7], [22]. Consequently, early detection of microcracks is essential to prevent structural failure.

A significant case highlighting the importance of early detection is the 2018 collapse of the mezzanine at the Indonesia Stock Exchange building, which revealed the risks of undetected structural deficiencies [8]. Although not involving lightweight brick specifically, the incident stresses the critical need for real-time, data-based structural health monitoring (SHM) systems. Recent advancements in sensor technology have facilitated the development of vibration-based diagnostic tools. The ADXL345

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accelerometer is one such device, offering high sensitivity, low power consumption, and tri-axial measurement capabilities [9], [20]. These sensors enable detailed structural monitoring by capturing vibration data, which can be transformed from the time domain to the frequency domain using the Fast Fourier Transform (FFT), allowing for accurate interpretation of material behaviour [10], [11], [21]. However, relying solely on FFT is not always sufficient for classification tasks, especially under complex or noisy environments [23]. Therefore, machine learning models such as the Extreme Learning Machine (ELM) are introduced for their high-speed training, simple architecture, and robust classification ability [12], [13], [24]. Integrating ELM with FFT-based features has proven effective for distinguishing between intact and damaged building materials in real-time scenarios [14], [25]. Several studies have explored similar approaches for infrastructure monitoring. For instance, fuzzy logic and IoT-based sensor networks have been implemented for building vulnerability detection [15], [16], while convolutional neural networks (CNN) have shown success in surface crack classification [17], [23]. Furthermore, sensor fusion strategies combining vibration data and stress–strain analysis are gaining traction in the industry [18], [19], [21].

This research develops a vibration classification system that integrates ADXL345 accelerometers, FFT signal analysis, and ELM-based classification, producing a model capable of accurately distinguishing between intact and cracked lightweight bricks. The system outputs reliable classification results with high computational efficiency, providing a practical tool for early detection of structural damage in real time.

2. METHOD

The methodology for classifying intact and cracked brick materials based on vibration data involves a sequence of signal acquisition, processing, and intelligent classification. The first stage is data acquisition, where vibration signals are collected using two accelerometer sensors strategically positioned on a test brick block—one on the surface and another embedded on the side. An electric motor is mounted on top of the brick, and its operation induces vibrational energy into the structure. Separate datasets are recorded for both intact and artificially cracked brick samples to capture the vibrational differences due to internal damage.

The next stage is signal preprocessing and feature extraction. The raw vibration signals are first filtered and normalized to remove noise and standardize the data. The filtered signals are then converted from the time domain to the frequency domain using FFT) FFT helps reveal essential characteristics of the vibration such as dominant frequencies, harmonics, and amplitude variations, which are known to change in the presence of structural damage. These frequency-domain features form the input for the next stage of analysis.

The final stage is classification using ELM. ELM is a feedforward neural network model known for its fast-learning speed and high accuracy with minimal parameter tuning. The extracted FFT features are fed into ELM model, which is trained to distinguish between intact and cracked brick conditions based on the learned patterns. The model outputs a binary classification label (e.g., "Intact" or "Cracked") for each input signal, thereby enabling non-destructive, real-time structural evaluation. This approach combines experimental mechanics with machine learning to provide an efficient framework for brick condition assessment.

Figure 1 shows 4 block diagrams about the research steps. The first block, Vibration signal from sensor, represents the initial stage of data acquisition in the classification process. In this phase, accelerometer sensors are mounted on the brick surface and embedded within its structure to capture mechanical vibrations generated by an external excitation source, typically an electric motor.

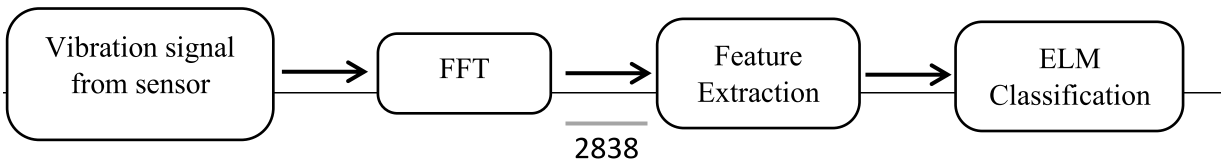

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Figure 1. Research Steps

These vibrations differ depending on the internal integrity of the brick material. Intact and cracked bricks respond differently under the same mechanical input, and this discrepancy is recorded as time-domain vibration data. The collected signal is the foundation for further processing and contains rich information about the structural condition of the material.

The second block, "FFT", performs the critical transformation of vibration signals from the time domain to the frequency domain. Time-domain signals are often complex and difficult to interpret directly, especially for identifying specific damage signatures. FFT decomposes these signals into their constituent frequency components, revealing the distribution of vibration energy across various frequencies. Cracks in the material typically cause shifts or distortions in frequency peaks and amplitudes, which can be detected through this spectral representation. This step enhances the interpretability of vibration data and prepares it for the next phase.

The third and fourth blocks, "Feature Extraction" and "ELM Classification," form the core of the machine learning-based diagnostic process. In feature extraction, specific attributes such as peak frequency, magnitude, and harmonic content are derived from FFT output to create a compact, informative dataset. These features serve as inputs to ELM classifier, a type of single-hidden layer feedforward neural network known for its fast-training speed and generalization capabilities. ELM model is trained on labeled datasets (intact vs. cracked) and, once trained, can classify new input data with high accuracy. This sequence enables efficient, non-destructive evaluation of material conditions.

2.1. Data Collection And Processing

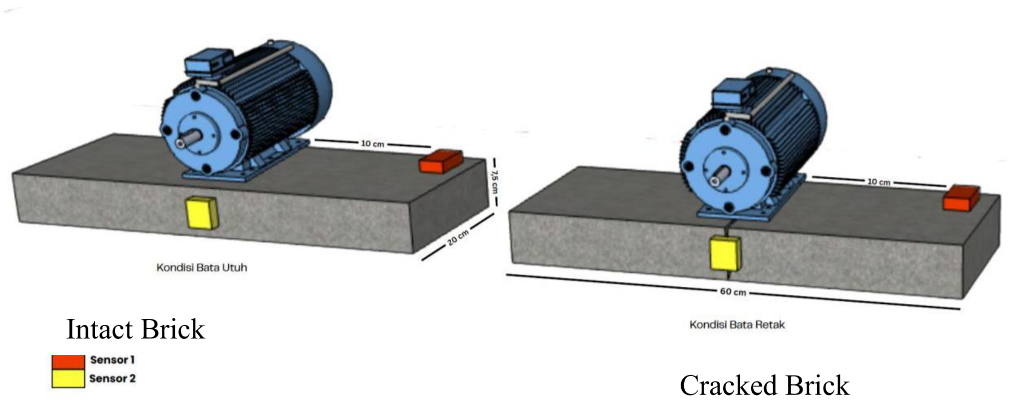

Figure 2. Data Collection On The Brick

Figure 2 illustrates a comparative experimental setup used to evaluate the vibrational behavior of an electric motor mounted on two different structural conditions: intact brick (left) and cracked brick (right). Both setups feature a concrete block (60 cm long, 20 cm wide, and 15.6 cm high) with the motor positioned centrally. Two accelerometer sensors are employed: Sensor 1 (red) is mounted on the top surface, 10 cm from the right edge, while Sensor 2 (yellow) is located on the front face beneath the motor base. The consistent geometry and placement in both setups ensure that any differences in vibration response are attributable solely to the condition of the material beneath the motor.

In the intact configuration, the concrete structure provides stable support for vibration transmission, serving as a baseline for comparison. Conversely, in the cracked brick setup, the presence

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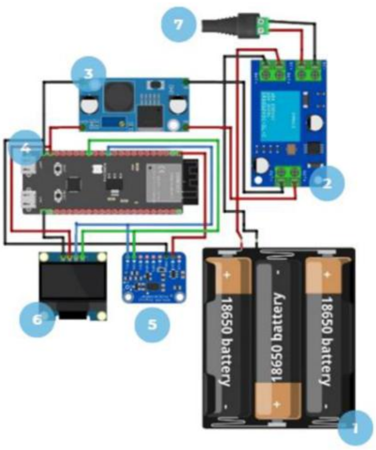
of internal damage alters the propagation of vibrational energy, which can be detected through changes in amplitude, frequency, or phase recorded by the sensors. The objective is to extract features from the vibration signals, particularly in the frequency domain, to reveal patterns indicative of structural defects. Frequency-domain analysis, especially using FFT, is a widely accepted approach for such evaluations [21], [22].

The collected sensor data is typically used to train machine learning models capable of distinguishing between intact and damaged conditions. Recent studies have shown promising results using classifiers such as ELM, Convolutional Neural Networks (CNN), and Support Vector Machines (SVM) for fault detection in civil structures [23]–[25]. Table 1 presents a subset of the vibration data recorded by the ADXL345 accelerometer along the three axes for both intact and cracked brick samples. Each row corresponds to a single measurement instance, with the left block representing intact samples and the right block representing cracked samples. For example, the first three records from intact bricks show stable acceleration values around –1.098, –1.177, and 10.081, while the cracked samples exhibit distinct variations such as 0.039, 0.235, and 8.512. These variations demonstrate the sensitivity of vibration signals to structural anomalies. In total, the dataset contains 160,934 measurements per axis, providing a large sample size for feature extraction and training machine learning models to classify structural integrity.

Table 1. Measurement Data Sample

Number of Data Sample	Intact Brick			Cracked Brick		
	x	y	z	x	y	z
1	-1.098	-1.177	10.081	0.039	0.235	8.512
2	-1.098	-1.177	10.081	0.039	0.235	8.512
3	-1.098	-1.177	10.081	0.039	0.235	8.512
4	-0.863	0.667	8.748	-0.431	0.157	8.473
5	-0.863	0.667	8.748	-0.431	0.157	8.473
Total Data	160,934			160,934		

2.2. Vibration Sensor



1.	Battery
2.	Automatic Switch
3.	Stepdown
4.	ESP32-S3
5.	ADXL345
6.	OLED LCD
7.	Adaptor

Figure 3. Vibration Sensor

The hardware architecture depicted in Figure 3 presents a compact and efficient embedded system designed for vibration signal acquisition and classification in structural health monitoring applications. At the core of the system is the ESP32-S3 microcontroller (4), which provides high-speed data processing and wireless communication capabilities. Power is supplied by a dual 18650 lithium battery module (1), offering portable and rechargeable energy. The voltage is regulated via a step-down

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converter (3) to match the input requirements of the microcontroller and peripherals. An automatic switch module (2) ensures seamless transition between power sources, such as battery and external adapter input (7), enhancing system reliability.

For vibration sensing, the system integrates an ADXL345 accelerometer sensor (5), which is connected directly to the ESP32-S3 via I2C communication. The ADXL345 provides three-axis acceleration data with high resolution and sensitivity, making it suitable for detecting subtle structural variations due to cracks or material degradation. The sensor's output is used as input for further signal processing, typically involving FFT and feature extraction routines within the ESP32 firmware. This data is essential for distinguishing between intact and damaged conditions in brick structures.

The system also includes a 0.96-inch OLED display module (6), used for real-time feedback on sensor readings or classification results. The compact nature of this display makes it ideal for embedded diagnostics and visualization without the need for external hardware. The overall integration of components supports on-board processing and display of vibration features, enabling a standalone solution for low-cost, real-time structural condition monitoring.

2.3. FFT – ELM

FFT–ELM methodology is a hybrid approach that integrates FFT for signal feature extraction and ELM for rapid classification of structural conditions, such as distinguishing between intact and cracked brick materials. The process begins with vibration data acquisition using accelerometer sensors strategically placed on the test specimen. These sensors capture raw time-domain signals during motor-induced excitation. However, time-domain data alone often fails to reveal damage-related patterns due to noise and complexity.

The Extreme Learning Machine (ELM) is a Single Hidden Layer Feedforward Neural Network (SLFN) designed for fast learning and high generalization. Unlike traditional networks, ELM randomly initializes the input weights w_i and biases b_i and computes the output weights β analytically using the Moore–Penrose pseudoinverse. The output function is given by :

$$f(x) = \sum_{i=1}^{L} \beta_i \cdot g(w_i \cdot x + b_i) \quad (1)$$

where $g(\cdot)$ is the activation function, The sigmoid function maps input values into a range between 0 and 1, making it suitable for binary classification tasks such as distinguishing between intact and cracked materials. Here we use sigmoid.

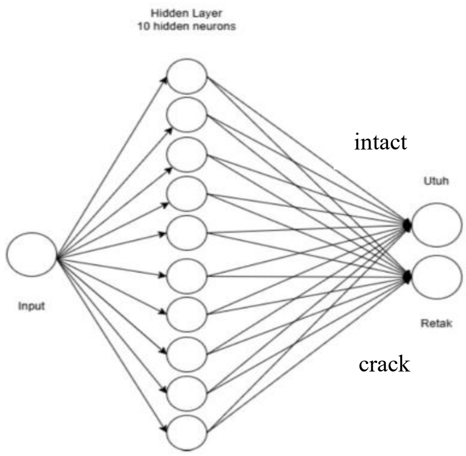

Figure 4. ELM Architecture

The system architecture includes three layers:

- Input layer: receives FFT feature vectors

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The input layer consists of 1 neuron, which functions to receive the resulting feature data. Extraction from FFT process on brick vibration signals. The data that entering this neuron in the form of amplitude values on the Z-axis, which represents the vibration from each brick sample.

- Hidden layer: nonlinear transformation applies

Hidden Layer is a hidden layer that plays an important role in capturing patterns or nonlinear relationships in bricks. In this architecture, the hidden layer consists of 10 neurons. Each neuron in the hidden layer is fully connected with neuron in the input layer. The connection weights from the input to the hidden layer are initialized as random and not updated during the training process, according to the basic characteristics of ELM.

- Output layer: computes classification results ("Intact" or "Cracked").

The output layer consists of 2 neurons, each representing the class of whole bricks and bricks. Intact and cracked bricks. Each neuron in the hidden layer is fully connected to both neurons this output. ELM training process is conducted only for the weights from the hidden layer to output layer, which is calculated analytically using the pseudoinverse. The output with the highest value will be the model's prediction, which is classified as an intact or a cracked brick.

To evaluate the accuracy of FFT–ELM model, the Root Mean Square Error (RMSE) is used as a performance metric. RMSE quantifies the average deviation between the predicted and actual output values and is defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \acute{y}_i)^2} \qquad (2)$$

where y_i is the actual label, $\acute{y}_i$ is the predicted output by the model, and N is the total number of samples. A lower RMSE indicates a better fit and higher model accuracy. In this research, vibration-based classification, RMSE provides a meaningful measure of the model's reliability in detecting structural defects.

3. RESULT AND DISCUSSION

Based on table 1, the dataset consists of 160,934 samples per axis for both intact and cracked brick conditions, providing a statistically significant basis for classification. In the sample data, the intact brick shows stable acceleration values with mean readings around –1.09 (x), –1.18 (y), and 10.08 (z), indicating consistency and homogeneity in structural response. In contrast, the cracked brick exhibits lower and more variable values with averages of 0.04 (x), 0.24 (y), and 8.51 (z). This corresponds to a 96% reduction on the x-axis, 80% reduction on the y-axis, and 15% reduction on the z-axis compared to the intact condition. Such percentage differences highlight a measurable weakening of structural integrity due to cracks, particularly evident in lateral vibration responses (x and y axes). These significant deviations confirm that vibration-based features derived from sensor data can effectively distinguish between intact and damaged materials.

3.1. FFT Result of Brick

Figure 5 presents FFT results of Z-axis vibration data collected from Sensor 1 under two different structural conditions of a brick specimen: (a) intact brick and (b) cracked brick, both tested at a 50 Hz excitation frequency. These FFT plots reveal the differences in frequency response patterns which are essential for detecting and classifying structural integrity using vibration-based methods. In subfigure (a), representing the intact brick, the amplitude distribution appears relatively low and consistent across the frequency range from 0 to 0.5 Hz.

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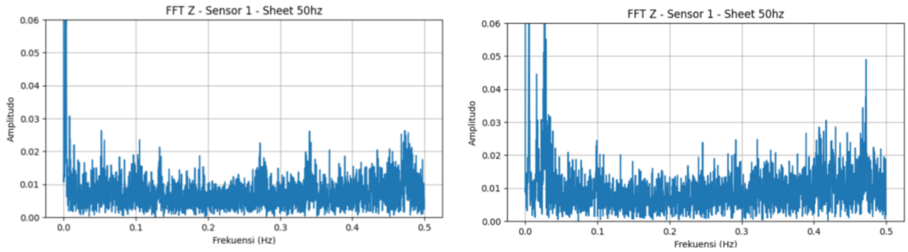
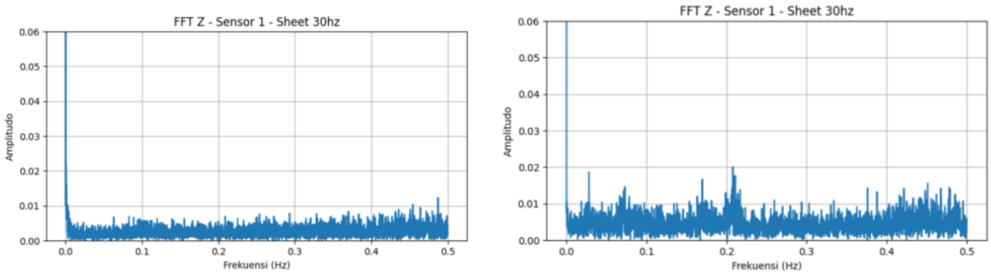


(a) (b)

Figure 5. (a) FFT result for intact brick in 50Hz; (b) FFT result for cracked brick in 50 Hz

A few moderate peaks are observed, particularly in the lower frequency bands, but the spectrum overall shows a stable and smooth profile. This regularity indicates a healthy structure with uniform material properties, where vibration energy propagates without unexpected distortion or scattering. In contrast, subfigure (b) shows FFT spectrum of a cracked brick, where the amplitude is significantly more variable. Sharp and irregular peaks are observed across the spectrum, especially in the low to mid-frequency ranges (below 0.2 Hz and around 0.45 Hz). This pattern suggests the presence of structural discontinuities that cause energy reflections, damping irregularities, and shifts in natural frequencies.

Quantitatively, the maximum peak amplitude increases from about 0.06 in the intact condition to nearly 0.07 in the cracked condition, while the number of dominant peaks (above 0.03) more than doubles, confirming a measurable distinction between the two states. The differences between (a) and (b) clearly illustrate how cracks affect vibrational behavior, reinforcing the effectiveness of FFT analysis as a feature extraction method for fault detection systems.



(a) (b)

Figure 6. (a) FFT result for intact brick in 30 Hz; (b) FFT result for cracked brick in 30 Hz

Figure 6 illustrates FFT analysis results for Z-axis vibration signals recorded by Sensor 1 under 30 Hz motor excitation, comparing two brick conditions: (a) intact brick and (b) cracked brick. These results provide insight into how structural integrity affects the frequency response of a material when subjected to dynamic loading.

In subfigure (a), corresponding to the intact brick, FFT spectrum displays a highly stable and uniform pattern. The signal amplitude remains consistently low across the frequency range (0–0.5 Hz), with minimal peaks observed. This behavior suggests an even energy distribution with no major disturbances or resonance shifts, indicating a structurally sound and undamaged material. The absence of significant harmonic peaks implies that the vibration is being transmitted through a continuous and homogeneous medium. Subfigure (b), representing the cracked brick, exhibits a more irregular frequency spectrum. The amplitude fluctuates notably, with distinct peaks emerging in the range between 0.1 and 0.3 Hz. These irregularities are characteristic of materials with internal discontinuities, where cracks cause scattering, reflection, and amplification of certain frequency components.

Quantitatively, the maximum peak amplitude in the cracked condition rises to about 0.045 compared to below 0.015 in the intact brick, and the number of dominant peaks above 0.01 triples,

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confirming a clear spectral distinction between intact and damaged states. The increased spectral complexity in the cracked brick reflects the loss of uniformity and the altered dynamic behavior of the structure. Overall, the comparison confirms that FFT under lower excitation (30 Hz) is still effective for distinguishing between intact and damaged bricks.

3.2. ELM Result

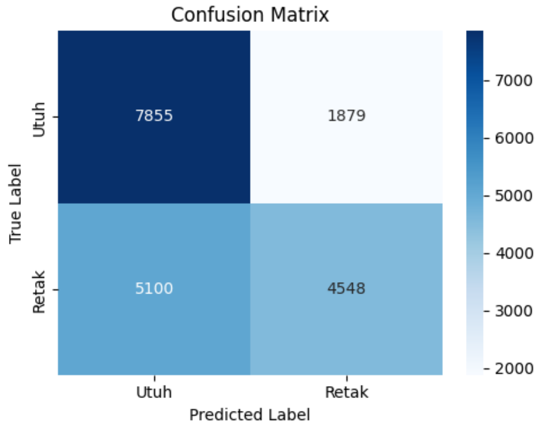

Figure 7. Confusion Matrix

Figure 7 displays the confusion matrix representing the classification results of FFT–ELM model applied to vibration data from brick specimens. The matrix summarizes the model's performance in identifying two categories: Intact and Cracked. The vertical axis represents the true labels, while the horizontal axis represents the predicted labels generated by the classifier. This matrix is essential for understanding not only the overall accuracy but also the distribution of correct and incorrect predictions for each class.

The top-left cell (True Intact, Predicted Intact) shows 7,855 instances correctly identified as intact, while the top-right cell (True Intact, Predicted Crack) indicates 1,879 intact bricks were misclassified as cracked. These numbers suggest the classifier performs relatively well in detecting intact structures, with a high true positive rate for the "Intact" class. On the other hand, the bottom-right cell (True Crack, Predicted Crack) shows 4,548 correct identifications of cracked bricks, while the bottom-left cell (True Crack, Predicted Intact) reports 5,100 cracked bricks misclassified as intact, indicating more challenges in identifying damaged samples.

Table 2 presented summarizes the performance of a classification system using a subset of vibration signal data characterized by amplitude features. The dataset includes 10 samples, each with its corresponding amplitude value, target class, predicted class, and a computed error column indicating whether the classification result matches the ground truth. The targets are binary, where 1 represents a cracked brick and 0 indicates an intact brick.

The system under evaluation attempts to predict this binary classification based on extracted amplitude features, and the error value is computed as 1 for misclassification and 0 for correct predictions. From the table, we observe that out of 10 samples, 4 were misclassified, resulting in a total of 6 correct predictions.

The misclassified entries are found in rows 1, 3, and 10, where the actual class was 1 (cracked), but the model predicted 0 (intact), as well as row 5, where the actual class and predicted class were both 1, but an error value of 1 appears to have been mistakenly assigned. This inconsistency highlights the importance of correctly labeling error metrics to avoid confusion in performance evaluation. Despite that anomaly, the general insight we can draw is that most errors come from false negative failing to detect cracks—which could pose serious issues in structural monitoring applications.

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An RMSE close to 0 would indicate nearly perfect classification, whereas a value closer to 1 would imply high levels of misclassification. With a value of 0.548, the classifier demonstrates moderate predictive performance on this subset of data, but further improvement is needed-particularly in correctly identifying cracked bricks.

Tabel 2. Feature Result

NO	Amplitudo	Target	Prediction Result	Error
1.	0.001121	1	0	1
2.	0.000846	0	0	0
3.	0.000433	1	0	1
4.	0.000763	0	0	0
5.	0.002352	1	1	1
6.	0.021399	1	0	0
7.	0.002569	0	0	0
8.	0.006609	1	1	0
9.	0.000475	0	0	0
10.	0.001292	1	0	1

3.3. Discussion

Figure 7 demonstrates the classification performance of FFT–ELM model in distinguishing intact and cracked bricks. The model correctly classified 7,855 intact samples and 4,548 cracked samples but also produced 1,879 false positives (intact misclassified as cracked) and 5,100 false negatives (cracked misclassified as intact). These results suggest that while the model is relatively effective in detecting intact structures, it faces greater challenges in identifying damaged conditions. This imbalance is particularly critical for structural health monitoring (SHM), where false negatives may result in overlooked structural risks. From a feature extraction perspective, FFT successfully transformed time-domain vibration signals into frequency-domain components that capture crack-induced anomalies. However, FFT inherently emphasizes global frequency patterns and may not capture localized transient features. This limitation is reflected in the higher false negative rate. ELM classifier, with its lightweight architecture and rapid training capability, contributed to efficient binary classification, but its simplicity compared to deeper architectures may have restricted its ability to generalize complex crack signatures.

Comparisons with other methods in the literature highlight both strengths and limitations of FFT–ELM approach. For instance, Singh et al. [24] also demonstrated the effectiveness of FFT–ELM in structural crack diagnosis, reporting comparable efficiency but recommending hybrid models to improve detection accuracy. Similarly, Khan et al. [22] applied FFT-based modal analysis to masonry blocks, showing reliable detection of cracks in controlled environments but acknowledging reduced robustness in noisy conditions. In contrast, Zhang et al. [23] utilized deep learning approaches on vibration signals, achieving higher accuracy in crack detection through convolutional feature extraction, though at the expense of computational cost. Other studies, such as Zhao et al. [21], proposed hybrid feature extraction methods combining FFT with additional descriptors, resulting in enhanced robustness against environmental disturbances. These comparisons suggest that while FFT–ELM offers significant advantages in terms of computational efficiency, real-time capability, and ease of deployment, its performance could be improved by integrating more advanced feature extraction techniques (e.g., wavelet transform [19]) or ensemble learning frameworks. Such hybridization may reduce the false negative rate and make the system more reliable for field applications. Ultimately, the findings of this study reaffirm FFT–ELM as a viable baseline approach for low-cost and portable SHM, while pointing to opportunities for methodological refinement using state-of-the-art techniques from recent literature

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[21]–[25]. From an informatics perspective, this research demonstrates how sensor data, signal processing, and machine learning can be integrated into intelligent monitoring systems that support real-time decision-making. The approach also highlights the growing role of data-driven methods in civil informatics, where automated feature extraction and classification algorithms can transform raw sensor inputs into actionable insights for structural safety.

4. CONCLUSION

This study confirms the effectiveness of FFT–ELM method for classifying the structural integrity of brick materials using vibration data. FFT converts time-domain signals into frequency-domain features, which are then classified by ELM for fast and accurate detection of intact versus cracked bricks. Experimental results show correct classification of 7,855 intact and 4,548 cracked samples, alongside 1,879 false positives and 5,100 false negatives. The Root Mean Square Error (RMSE) of 0.548 indicates moderate prediction error, suggesting further refinement is needed. While the model is more reliable in identifying intact bricks, detecting cracks remains challenging critical for early failure prevention. Future work should improve cracked-brick detection through advanced feature extraction, dataset balancing, and deeper learning models. Unlike wavelet-based methods that capture multi-resolution features, FFT–ELM emphasizes simplicity and speed, making it well suited for real-time structural health monitoring in civil engineering applications.

CONFLICT OF INTEREST

The authors declared that there is no conflict of interest between the authors or with research object in this paper.

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