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*Original Article*

# Intelligent Crack Detection in Building Structures using Coupled Ultrasonic Guided Wave and Acoustic Emission Sensing

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***Abstract*** - *Building structural integrity evaluation is important in the long-term safety and resilience of buildings. Visual inspection techniques that have been in place do not have the capability of detecting beneath surface cracks, or cracks that may develop at an early stage, that would compromise the structural performance. This paper introduces a smart crack sensor with a combination of Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) as a guide to the complicated Structural Health Monitoring (SHM) of building structures. The system proposed is based on the UGW-based wave propagation analysis along with the AE signal monitoring, which will detect, localize, and characterize surface and internal cracks with the highest accuracy. Algorithms of machine learning are used to comprehend complicated acoustic signals and distinguish between crack initiation, crack propagation, and the noise in the environment. It is experimentally verified on reinforced concrete specimens that the coupled UGW-AE methodology is more sensitive and accurate than the uniaxial methodologies. These are possible through the combination of real-time data acquisition, fusion of signals, and smart pattern recognition that allows early detection of damage and provides the ability to monitor the damage continuously. The study will help in the emergence of an intelligent, non-destructive, and scalable SHM system capable of improving structural dependability and maintenance effectiveness in contemporary infrastructure systems.*

***Keywords*** - *Ultrasonic Guided Wave (UGW), Acoustic Emission (AE), Crack detection, Structural Health Monitoring (SHM), Machine learning, Non-Destructive Testing (NDT).*

## 1. Introduction

The safety, durability, and resilience of modern infrastructure systems are critical concerns in the 21st century, especially as the global built environment faces increasing loads, environmental degradation, and aging. Building structures, bridges, and other civil components are continually exposed to cyclic stress, corrosion, temperature variations, and dynamic loading conditions that lead to progressive deterioration over time. Early detection of such deterioration, particularly in the form of cracks, plays a pivotal role in preventing catastrophic failures and ensuring public safety. Structural Health Monitoring (SHM) has therefore emerged as a multidisciplinary approach combining sensing technologies, data acquisition, and intelligent analytics to assess the real-time integrity of structures. Unlike traditional maintenance schedules based on periodic inspections, SHM enables condition-based maintenance, which reduces costs and improves the reliability of critical infrastructure. Within this framework, the identification and characterization of cracks, especially micro- and subsurface cracks, are of paramount importance, as they often serve as precursors to more severe damage. However, detecting such defects is technically challenging due to their microscopic size, hidden location within concrete or steel, and their complex propagation behavior under varying stress conditions. Modern SHM systems aim not only to detect cracks but also to localize and quantify them accurately in real-time. This need has driven research toward advanced sensing and intelligent diagnostic methods capable of interpreting complex structural responses. Among these, ultrasonic and acoustic-based sensing technologies have demonstrated high potential due to their sensitivity to internal material changes. As infrastructure systems become more interconnected through smart sensors and the Internet of Things (IoT), integrating intelligent algorithms for crack detection and pattern recognition is becoming a key direction in SHM research. Traditional methods of structural assessment, such as manual visual inspection, rebound hammer tests, and vibration-based modal analyses, have been extensively used for decades. While these methods provide valuable information on surface conditions and global stiffness changes, they are often subjective, time-consuming, and insufficiently sensitive to detect early-stage or subsurface defects. Visual inspections, for example, rely heavily on human expertise and environmental conditions such as lighting and accessibility, which can lead to inconsistencies and missed detections.

Furthermore, cracks that are beneath the surface or within reinforced concrete are often invisible until they have propagated significantly, by which point repair costs and risks increase drastically. Similarly, vibration-based analyses provide insights into the overall dynamic behavior of structures but lack spatial resolution for local damage identification. Small cracks may not produce measurable changes in modal parameters such as natural frequency or damping ratio, especially in large-scale structures where local damage has limited global influence. Ultrasonic Pulse Velocity (UPV) and infrared thermography, though more advanced, are limited by signal attenuation, surface roughness, and the need for controlled environmental conditions. These challenges underscore the limitations of conventional monitoring techniques and highlight the urgent need for more sensitive, automated, and intelligent systems capable of identifying both visible and hidden damage. Therefore, the focus has shifted toward integrating multi-sensor data fusion, real-time signal interpretation, and machine learning algorithms to improve diagnostic accuracy and minimize human dependency.

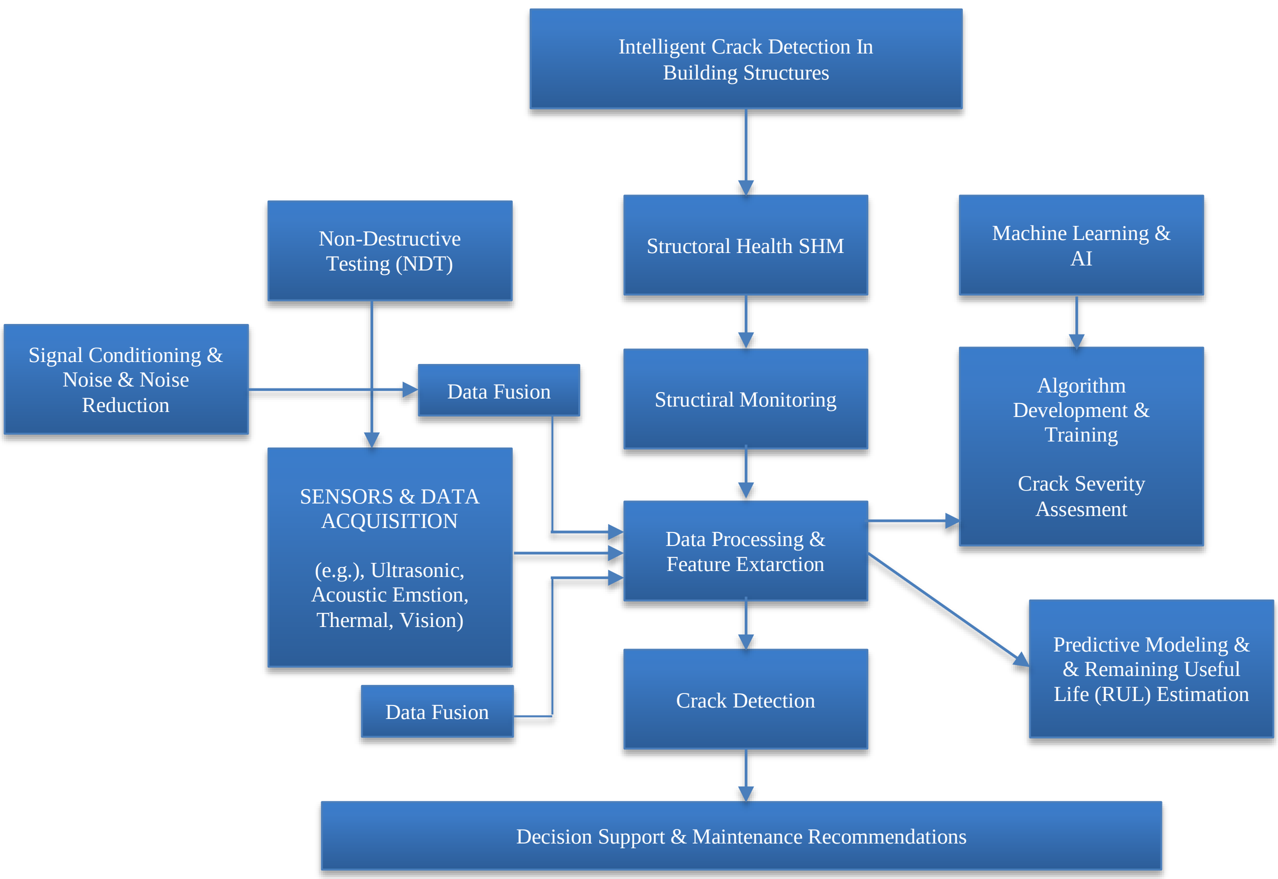


**Fig. 1 Proposed framework for intelligent crack detection in building structures**

Figure 1 illustrates a comprehensive approach to "Intelligent Crack Detection in Building Structures," integrating several advanced methodologies for robust structural assessment. The overarching goal is achieved by converging three primary pillars: Non-Destructive Testing (NDT), Structural Health Monitoring (SHM), and Machine Learning & AI. NDT forms the initial stage, focusing on the deployment of various sensors and data acquisition techniques, such as ultrasonic, acoustic emission, thermal, and vision-based systems. These sensors are crucial for gathering raw data about the structural integrity without causing damage. Simultaneously, Structural Health Monitoring (SHM) plays a vital role by continuously monitoring the structure over time. This involves dedicated structural monitoring systems that feed into data processing and feature extraction, enabling the identification of relevant characteristics from the collected sensor data. The third crucial component is Machine Learning & AI, which is responsible for algorithm development and training. This involves creating and refining computational models that can learn from the processed data to accurately identify and classify cracks. All three streams converge at the "Crack Detection" stage, where the insights from NDT, SHM, and AI are synthesized to pinpoint the presence and location of cracks. Following crack detection, the system moves to "Crack Severity Assessment," where the identified cracks are evaluated based on their potential impact on the structure. Finally, the entire process culminates in "Decision Support & Maintenance Recommendations," providing actionable insights and guidance for timely intervention and upkeep of the building structures, thereby ensuring their safety and longevity. This integrated approach leverages the strengths of each methodology to create a more reliable and intelligent system for structural integrity assessment.

Non-Destructive Testing (NDT) has become a cornerstone in SHM, enabling engineers to evaluate material integrity without impairing the structural performance of a system. Among various NDT techniques, Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) methods have proven particularly effective for detecting cracks and other internal discontinuities. Ultrasonic guided waves propagate along the surface or through the material thickness, providing information about the material's internal condition based on changes in wave velocity, attenuation, and reflection. These waves are capable of traveling long distances with minimal energy loss, making them ideal for monitoring large structures such as bridges, columns, and walls. Meanwhile, acoustic emission sensing captures transient elastic waves generated by the rapid release of energy during crack initiation and propagation.

Unlike conventional ultrasonic testing, AE techniques can identify the precise time and location of active damage, making them highly suitable for real-time monitoring. When combined, UGW and AE offer a powerful hybrid diagnostic framework. UGW provides spatial coverage and quantifiable reflection data, while AE offers temporal insights into active crack dynamics. Recent advances in signal processing, such as wavelet transform, Hilbert–Huang analysis, and cross-correlation, have enhanced the interpretation of complex ultrasonic and acoustic data. Furthermore, the integration of machine learning models allows automatic feature extraction and classification of crack states, distinguishing between environmental noise and true damage signatures. As civil infrastructure increasingly incorporates embedded sensors and wireless communication networks, the adoption of NDT techniques like UGW and AE becomes integral to the development of smart, autonomous SHM systems capable of continuous, non-invasive monitoring.

The present study aims to develop and evaluate an intelligent crack detection framework that integrates Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) sensing techniques for effective Structural Health Monitoring (SHM) of building structures. The primary objective is to design a coupled sensing system that can detect, localize, and characterize both surface and subsurface cracks with high precision and reliability. Specifically, the research seeks to:

- Combine the complementary strengths of UGW and AE techniques, UGW for spatial crack mapping and AE for temporal event detection, to form a hybrid sensing approach.
- Employ advanced signal processing and feature extraction techniques to identify relevant wave characteristics such as amplitude, frequency shift, and time-of-flight variations associated with damage events.
- Integrate machine learning algorithms, including Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), for automated classification of crack types and severity levels.
- Experimentally validate the proposed framework using reinforced concrete and steel specimens under controlled loading conditions to assess performance metrics such as detection accuracy, sensitivity, and robustness under environmental noise.

Ultimately, this study aims to contribute to the development of an intelligent, non-destructive, and scalable SHM solution that enhances the safety, reliability, and service life of modern building structures. By leveraging the synergistic capabilities of UGW and AE sensing, this research bridges the gap between traditional inspection techniques and next-generation smart monitoring systems for resilient, sustainable infrastructure.

## 2. Literature Review

Crack detection in building structures is a fundamental aspect of Structural Health Monitoring (SHM) and has been extensively studied using a variety of techniques. Traditional visual inspection remains the most commonly applied method due to its simplicity and low cost; however, it is subjective, labor-intensive, and often fails to identify hidden or micro-cracks. Vibration-based methods analyze changes in modal parameters such as natural frequency, damping ratio, and mode shapes to detect structural damage. While effective for global damage detection, these techniques lack the spatial resolution necessary for precise crack localization.

Thermal imaging techniques rely on heat distribution anomalies to identify defects, which is effective for near-surface damage but is limited under varying environmental conditions and thick materials. Ultrasonic methods, particularly pulse velocity and guided wave techniques, have gained prominence due to their ability to detect internal cracks, measure crack depth, and quantify damage progression. These approaches utilize wave reflection, attenuation, and time-of-flight analysis to provide detailed insights into structural integrity, offering a balance between non-invasiveness and accuracy.

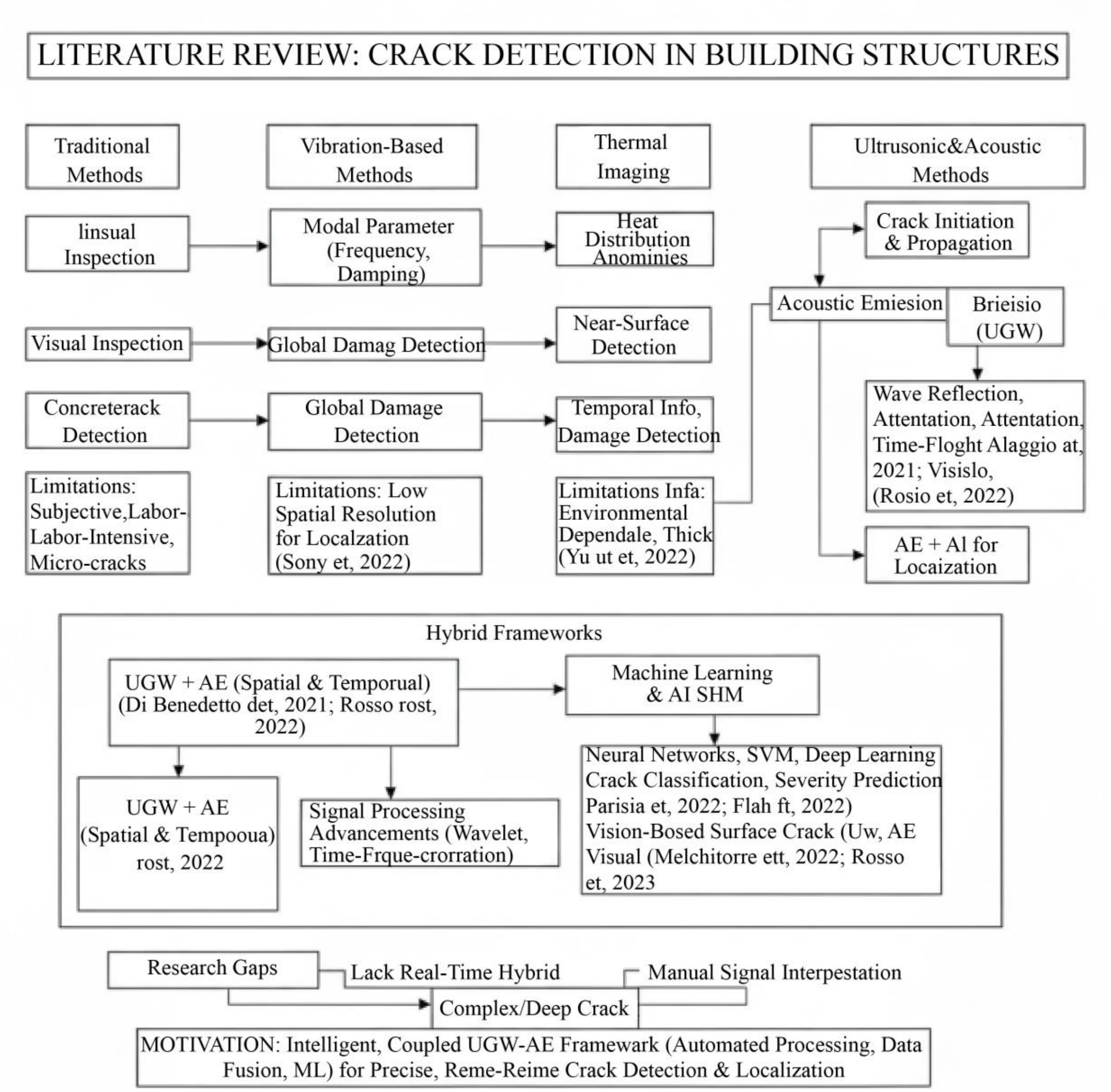


**Fig. 2 Comprehensive literature review on crack detection in building structures**

Figure 2 outlines the comprehensive literature review on crack detection in building structures, categorizing methods into three main groups: Traditional & Non-contact, Ultrasonic & Acoustic Emission (AE), and Data-Driven & Fusion. Traditional methods, like visual inspection and thermal imaging, are simple but suffer from subjectivity, environmental sensitivity, and limited spatial resolution. Vibration-based techniques offer global damage detection but lack precise localization. Ultrasonic Guided Waves (UGW) and Acoustic Emission (AE) methods form a core focus, with UGW excelling at detecting internal defects and AE capturing active crack propagation. Hybrid frameworks combining UGW and AE, enhanced by advanced signal processing, aim to leverage the strengths of both. The diagram then highlights Data-Driven & Fusion methods, emphasizing the role of machine learning and deep learning for automated crack classification, severity prediction, and noise reduction, including vision-based approaches for surface cracks. Finally, it identifies critical research gaps, such as limitations with complex geometries and the need for real-time, intelligent, coupled UGW-AE frameworks, which culminate in the motivation for a scalable, non-destructive, and intelligent Structural Health Monitoring (SHM) solution. Crack detection in building structures has been an area of intensive research due to its critical role in maintaining structural integrity and safety. Traditional visual inspection methods, while widely used, have inherent limitations in detecting micro- and subsurface cracks, making them insufficient for modern Structural Health Monitoring (SHM) needs (Clementi et al., 2021) [5]. Vibration-based techniques have been applied to identify global structural damage by analyzing modal properties, but their spatial resolution is limited, reducing their effectiveness for localized crack detection (Sony et al., 2022) [13]. Thermal imaging and other non-contact methods provide additional insights, particularly for surface anomalies, but are often sensitive to environmental conditions (Yu et al., 2022) [15]. Ultrasonic-based methods, especially Ultrasonic Guided Waves (UGW), have gained prominence due to their ability to propagate over long distances and detect internal defects. UGW techniques have been applied effectively to concrete and steel structures for crack localization, damage quantification, and monitoring over time (Alaggio et al., 2021; Aloisio et al., 2021) [3, 4]. These studies demonstrated the capability of UGW to detect early-stage cracks by analyzing wave attenuation, reflection, and phase shifts.

Acoustic Emission (AE) techniques complement UGW by capturing transient elastic waves generated during crack initiation and propagation. AE has been successfully employed to monitor active damage in reinforced concrete and steel structures, providing temporal information and enabling crack localization through triangulation methods (Fahim Md Mushfiqur Rahman & Banerjee, 2025; Cheng et al., 2021) [1, 7]. Melchiorre et al. (2023) [2] highlighted the use of AE coupled with artificial intelligence procedures for precise crack source localization, enhancing the reliability of real-time monitoring. Several studies have integrated UGW and AE in hybrid frameworks to leverage the spatial resolution of UGW and the temporal sensitivity of AE, leading to improved detection accuracy and robustness against environmental noise (Di Benedetto et al., 2021; Rosso et al., 2022) [6, 10]. Signal processing advancements, including wavelet transforms, time-frequency analysis, and cross-correlation methods, have further enhanced feature extraction from complex ultrasonic and acoustic signals.

The adoption of machine learning techniques in SHM has introduced intelligent methods for automated damage detection. Neural networks, support vector machines, and deep learning models have been applied to classify crack types, predict severity, and reduce false positives caused by environmental or operational noise (Rosso et al., 2022; Parisi et al., 2022; Flah et al., 2022) [11, 12, 14]. Vision-based deep learning approaches have also been explored for surface crack detection in concrete structures, achieving high accuracy even under noisy conditions (Yu et al., 2022) [16].

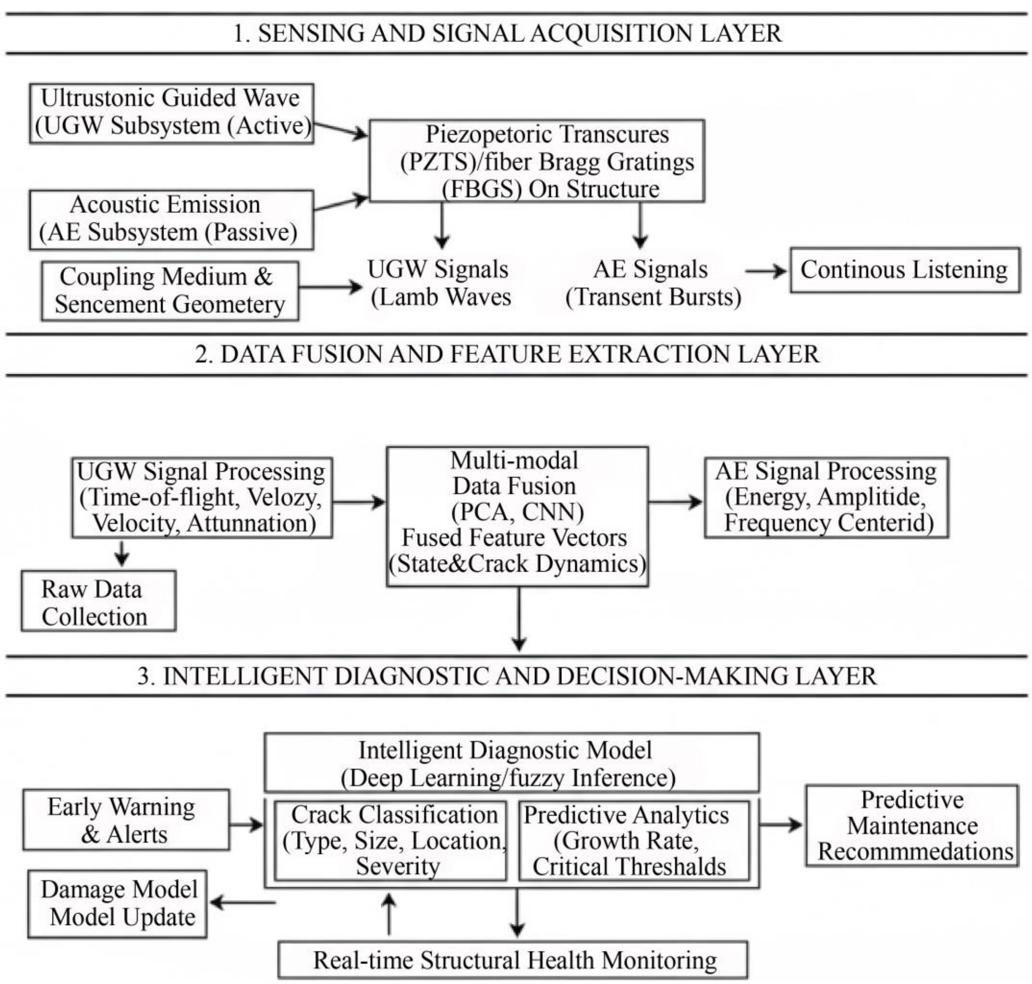

**Fig. 3 Conceptual framework for intelligent crack detection**

Recent work has demonstrated that combining multiple sensing modalities with machine learning—such as integrating UGW, AE, and visual data—can provide a comprehensive SHM framework capable of early damage detection, continuous monitoring, and intelligent decision-making (Melchiorre et al., 2022; Rosso et al., 2023) [17, 19]. Despite these advancements, research gaps remain. Most studies focus on standalone UGW or AE techniques, which may be insufficient for complex structural geometries or deep subsurface cracks. Hybrid approaches often lack real-time implementation or rely heavily on manual signal interpretation, limiting practical applicability. Therefore, there is a need for an intelligent, coupled UGW–AE framework that integrates automated signal processing, data fusion, and machine learning for precise detection, localization, and characterization of cracks in building structures. Addressing this gap forms the motivation for the present study, which aims to develop a scalable, non-destructive, and intelligent SHM solution to enhance the safety and longevity of modern infrastructure.

## 3. Materials and Methods

### *3.1. Conceptual Framework*

The conceptual design of the intelligent crack detection system (using Coupled Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) sensors) is founded on the combination of two dissimilar Non-Destructive Evaluation (NDE) methods in a single diagnostic instrument in real-time Structural Health Monitoring (SHM). This hybrid structure is expected to capitalize on the advantages of the two approaches: the proactive scanning feature of UGW to identify the localization and characterization of defects, as well as the reactive sensing feature of AE to determine the dynamic formation and propagation of cracks. The integration leads to a synergistic model that improves the accuracy of detection and quantification of damage, and the reliability of early warning for building structures. The fundamental idea in this framework is that UGW and AE signals are gathered, analyzed, and understood in a common analytical framework.

The scheme represents an overall procedure for intelligent crack detection in building structures, through a combined technique of Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) sensors. This model is broken down into three layers, which are interrelated, according to the Signal Acquisition Layer and the Sensing Layer. Both an active UGW subsystem and a passive AE subsystem have Piezoelectric Transducers (PZTs) or Fiber Bragg Gratings (FBGs) on the structure. The UGW produces Lamb waves, and AE does continuous listening to transient bursts, and both processes are dependent on the coupling medium and sensor geometry. On to the Data Fusion and Feature Extraction Layer, UGW and AE Signals are processed independently to extract features of interest, such as time-of-flight, velocity in the case of UGW, and energy, amplitude in the case of AE. The Intelligent Diagnostic and Decision-Making Layer interprets these fused features into an intelligent diagnostic model, which can be based on deep learning or fuzzy inference. The crack classification (type, size, location, severity) and predictive analytics (growth rate, critical thresholds) are done in this model, which results in early warnings, alerts, and predictive maintenance recommendations. This is enabled through a vital feedback loop, which facilitates the updating of the damage models, thus leading to real-time structural health monitoring.

The integration model is designed in three major functional layers:

- Sensing and Signal Acquisition Layer,
- Feature Extraction Layer, Data Fusion, and
- Smart Diagnostic and Decision Maker Layer.

The Piezoelectric Transducers (PZTs) or Fiber Bragg Gratings (FBGs) are strategically placed on the structure in the first layer as UGW actuators and AE sensors. Coupling media and geometry of sensor placement are made in such a way that they have maximum transmission of waves to all the various orientations of the cracks and have the highest sensitivity. UGW subsystem produces periodic Lamb waves-symmetric and anti-symmetric modes on the structural member, and AE sensors constantly monitor burst-type signals generated by crack events. Signal processing and feature-level data fusion are processed by the second layer. The UGW data give deterministic parameters of time-of-flight, group velocity, and amplitude drop, which are directly proportional to the defect geometry and material anisotropy. At the same time, AE parameters, such as energy, peak amplitude, centroid frequency, and rise time, are obtained to report the level of activity in the crack. The complementary datasets are then combined using machine learning-based fusion algorithms, such as Principal Component Analysis (PCA) and Convolutional Neural Networks (CNNs). This stage transforms high-dimensional raw signals into low-dimensional feature vectors that can illustrate the structural condition and dynamic behaviour in crack evolution. The last layer is the intelligent diagnostic module, which uses hybrid Deep Learning (DL) or Fuzzy Inference Systems (FIS) to match the fused features to structural damage states. Pattern recognition algorithms can be used to classify the level of damage severity, such as incipient microcracks and macro-scale fractures, and regression-based algorithms can be used to predict the rate of crack propagation and the most critical regions of damage. This smart layer makes it possible to have real-time health monitoring and proactive maintenance provided through constant updates of the damage model with new AE events and UGW feedback. Essentially, the coupled UGW-AE conceptual framework is an all-encompassing diagnostic paradigm, which converts the traditional damage detection to an intelligent, adaptive, and data-oriented process. It brings active and passive sensing together, thus guaranteeing the early detection (via guided wave interrogation) and continuous monitoring (via emission-based alerting). This combination not only increases sensitivity to detection and spatial resolution but also reduces false alarms and gives actionable intelligence to control structural safety in the current civil infrastructure.

### *3.2. Sensor Configuration and Placement Strategy*

The sensor arrangement and location algorithm are essential for the successful detection, localization, and characterization of cracks in building structures in the intelligent crack detection scheme based on Coupled Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE). An appropriate sensor layout provides effective signal propagation, good coverage of the areas of interest, and an effective combination of the two sensing modalities. The combination of UGW and AE sensors is planned to be strategically integrated to offset their usage, i.e., UGW is used to actively interrogate the structural health, and AE is used to monitor the structural health passively, hence forming a complete Structural Health Monitoring (SHM) network.

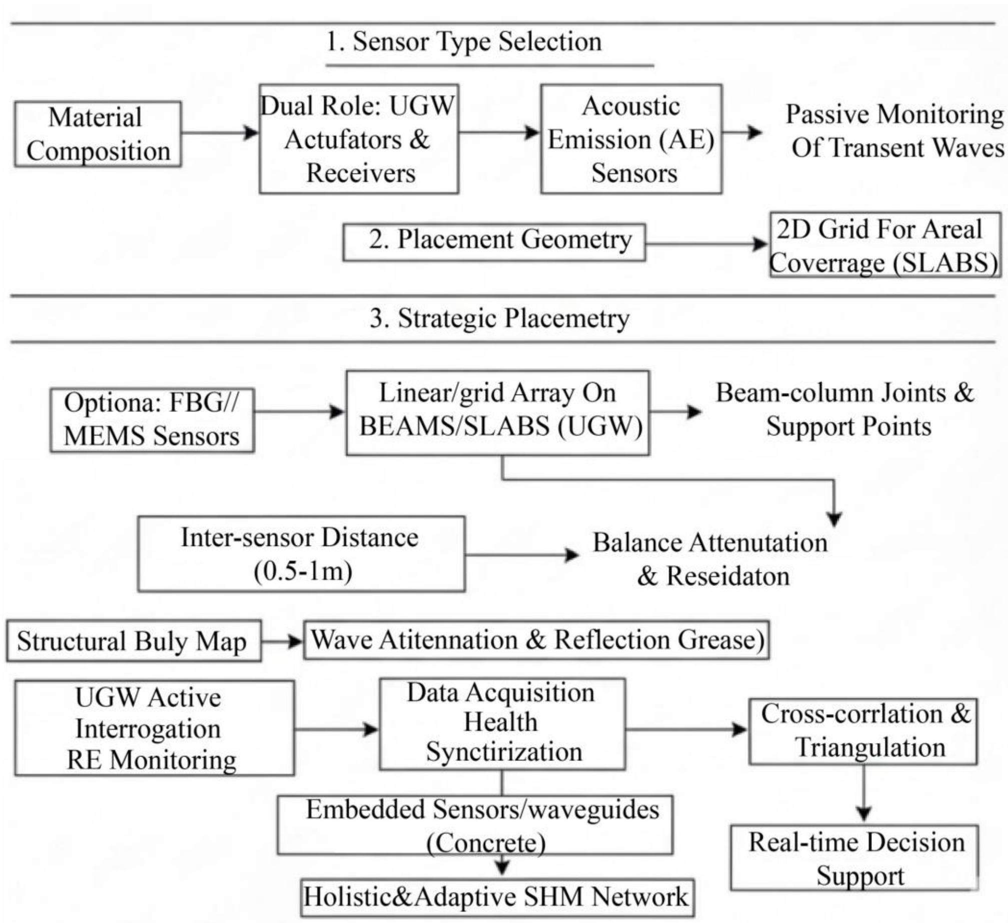


**Fig. 4 Framework for Sensor configuration and placement of intelligent crack detection**

This Figure 4 block diagram represents the holistic "Sensor Configuration and Placement Intelligent Crack Detection in Building Structures," which incorporates both UGW and AE sensing. This is initiated by the process of Sensor Type Selection, in which Material Composition determines the selection of Piezoelectric Transducers (PZTs), which are UGW actuators and receivers in a dual role. In conjunction with these, special Acoustic Emission (AE) sensors are chosen that can monitor passively transient waves that point to the activity of cracks. The second step, which is Placement Geometry, explains the way in which sensors are positioned on a 2D Grid of Areal Coverage, especially on slabs, such that they can cover the whole area. Strategy Placement expounds further on the implementation of optional FBG/MEMS sensors and their placement in UGW sensors in a Linear/Grid Array on Beams/Slabs when active interrogation is required, and on the placement of AE sensors on Beam-Column Joints and Support Points to target important stress areas where cracks are likely to form. The optimum is set to "Balance Attenuation and Resolution" (0.5-1M) and set to Inter-Sensor Distance. The Structural Behavior Map gives information on the wave attenuation and reflection analysis, whereas a Coupling Medium (Adhesives/Grease) facilitates the transfer of signals efficiently. In the case of concrete, there are Embedded Sensors/Waveguides that shield and boost signal integrity.

The system combines "UGW Active Interrogation and AE Monitoring" with a unit of Data Acquisition Synchronization, which allows "Cross-Correlation and Triangulation" of signals. The result of this is ultimately Crack Localization and Growth Tracking, which leads to Real-Time Decision Support, and the end product is a Holistic and Adaptive SHM Network for continuous structural health assessment.

Ultrasonic Guided Waves (UGWs) are generated in this integrated sensing framework by Piezoelectric Transducers (PZTs) bonded to strategic points on the building structure. These transducers produce tone-burst or modulated sinusoidal signals, which are transmitted through the structural material. Once the wave is exposed to a defect, like a crack or a delamination, some of the energy is scattered or reflected so that the amplitude and phase of the wave are changed. At the same time, Acoustic Emission (AE) sensors are generally broadband piezoelectric sensors- used to record the momentary elastic wave propagation as the active crack or the release of stress. The synchronization of both the UGW excitation and AE acquisition is done through a central data acquisition unit, where both processes are synchronized with accurate timing control and signal conditioning modules. UGW reflections are digitized at high speed, and AE hits are time-stamped, so that guided wave responses may be correlated with spontaneous emissions to provide a complete, real-time diagnostic picture of crack initiation and propagation.

The integrated Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) sensing model offers a powerful and intelligent system of real-time crack-monitoring in buildings. UGW and AE are considered the active and passive detectors of transient elastic waves, respectively occurring because of crack creation or propagation of the crack. This allows both active inspection and passive monitoring because of their integration, and makes them more sensitive to micro-cracks and structural discontinuities. The UGW response is typically modelled using the wave propagation equation:

$$\nabla^2 u(x,t) - \frac{1}{C^2}\frac{\partial^2 u(x,t)}{\partial t^2}$$

Where $u(x,t)$ is the displacement field, and c is the wave velocity dependent on material elasticity and density.

Damage induces scattering, altering the received wave energy $E_r$:

$$E_r = E_i e^{-\alpha d} + S(x_d)$$

Where $E_r$ is the incident energy, α\alphaα is the attenuation coefficient, $d$ is the propagation distance, and $S(x_d)$ represents the scattering contribution at the damage location $x_d$.

The AE sensing captures released strain energy during crack propagation, expressed as:

$$AE(t) = A_0 e^{-\beta(t-t_0)} sin(\omega t)$$

where $A_0$ is the initial amplitude, $\beta$ is the damping, and $\omega$ is the angular frequency. By coupling UGW excitation with AE feature correlation, the hybrid system enhances localization accuracy and early crack diagnosis in complex structural geometries.

Elastic wave equation (1D form):

$$\frac{\partial^2 u(x,t)}{\partial t^2} = c^2 \frac{\partial^2 u(x,t)}{\partial t^2}$$

Describes guided-wave propagation $u(x,t)$ with phase speed $c$.

Dispersion relation (plate Lamb wave):

$$\omega^2 = c_p^2(k)k^2$$

Relates angular frequency $\omega$ and wavenumber k; $c_p^2(k)$ is frequency-dependent phase velocity.

Reflection coefficient at a discontinuity:

$$R(\omega) = \frac{Z_2(\omega)-Z_1(\omega)}{Z_2(\omega)+Z_1(\omega)}$$

Scattering strength due to impedance mismatch $Z$.
Time-of-flight (ToF) for a reflection from a defect at distance $d$:

$$t_{ToF} = \frac{2d}{c_g}$$

Uses group velocity $c_g$ (two-way travel).

Cross-correlation for arrival time difference:

$$R_{xy}(\tau) = \int_{-\infty}^{\infty} x(t)y(t+\tau)dt$$

Peak location $\tau$ gives the relative delay between sensors $x$ and $y$.

Discrete Fourier Transform (DFT) for crack measurement:

$$X[k] = \sum_{n=0}^{N-1} x[n]e^{\frac{-j2\pi kn}{N}}$$

Used to extract frequency content from sampled signals of the crack analysis.

Short-Time Fourier Transform (STFT) for crack signal generation:

$$STFT\{x\}(t,f) = \int_{-\infty}^{\infty} x(t)\ \psi^*(\frac{b-a}{a})\ dt$$

Scales $a$ and shift $b$ give localized time–scale features.
Hilbert transform analytic signal/envelope for crack determination:

$$\hat{x}(t) = x(t) + jH\{x(t)\} \text{ and } E(t)=|\hat{x}(t)|$$

Envelope $E(t)$ highlights AE burst amplitudes.

Signal energy and RMS for crack data gathering:

$$\sum_{n=0}^{N-1} x[n]^2,\ RMS = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} x[n]^2}$$

Basic amplitude features used for AE/UGW hits.
Signal-to-Noise Ratio (SNR, dB) for crack data:

$$SNR_{dB} = 10log_{10}(\frac{P_{signal}}{P_{noise}})$$

Important for detector thresholding of the cracks.
Feature vector concatenation:

$$f = [E, RMS, f_{peak}, \Delta t, skewness, kurtosis]^{T}$$

General feature vector from AE and UGW.
Principal Component Analysis (PCA) projection:

$$z = W^{T}(f - \bar{f})$$

Dimensionality reduction using eigenvectors $W$.
SVM decision function (linear):

$$g(f) = w^{T}f + b$$

Predict the sign of $g(f)$ for crack/no-crack classification.
Hinge loss (SVM):

$$L_{hinge}(y, g) = max(0,1 - yg)$$

Used in SVM training (with label $y \in \{\pm 1\}$).
Random Forest prediction (ensemble average):

$$\hat{Y}(f) = mode\{h_t(f)\}_{t=1}^{T}$$

Aggregate tree votes or probabilities from $T$ trees.
1D convolution (CNN layer):

$$y_i = b + \sum_{k=0}^{k-1} w_k x_{i+k}$$

Convolution over signal/time producing feature maps.
Softmax + cross-entropy loss (multi-class CNN):

$$p_c = \frac{e^{z_c}}{\sum_j e^{z_c}} \text{ and } L = -\sum_c y_c log p_c$$

Where $z_c$ are network logits and $y_c$ one-hot labels.

Localization via TDOA (two sensors) distance estimate:

$$\Delta t = \frac{d_1 - d_2}{c_g} \Rightarrow d_1 - d_2 = c_g \Delta t$$

Combining multiple TDOA equations to triangulate defect coordinates leads to position error analysis.

Coupled UGW-AE damage index combining amplitude and event rate:

$$DI(x) = \alpha \frac{|A_{UGW}(x) - A_0(x)|}{A_0(x)} + \beta \frac{\lambda_{AE}(x)}{\lambda_0}$$

(Weighted combination of normalized UGW amplitude drop and AE event rate; $\alpha+\beta=1$.)

Multi-sensor weighted fusion for damage localization probability map:

$$P(x) = \frac{1}{Z}\prod_{i=1}^{N_{UGW}} exp(-\frac{(u_i - \breve{u}_i)^2}{2\sigma_i^2}) \prod_{j}^{N_{AE}} \frac{\lambda_j x^{n_j} e^{-\lambda_j(x)}}{n_j!}$$

(Final expression which combines the Gaussian likelihood of UGW waveform residuals with Poisson AE counts to produce a posterior probability map of crack location.)

Preprocessing of the raw UGW and AE signals entails techniques like denoising, filtering, and normalization. These important signal characteristics are then obtained using superior time-frequency analysis. Frequency-domain characteristics that detect shifts that characterize structural anomalies are defined using Fast Fourier Transform (FFT). The Wavelet Transform (WT) offers localized time-frequency constructions, which enable one to identify the transient events and small-scale crack events that cannot be identified by the FFT. As well, non-stationary signals may be analyzed using Short-Time Fourier Transform (STFT) or via Hilbert-Huang Transform (HHT). Some of the common extract features are signal energy, peak frequency, the ratio of amplitude between sensors, and the difference in arrival time between sensors. These are some of the discriminative indicators that are used to differentiate between intact and damaged states. Intelligent classification of crack states is performed with the results of the machine learning models fed on the extracted features. SVM has been popular in binary classification (crack/no crack) as it is very strong in cases where they are required to deal with high-dimensional data. Random Forests (RF) also increase the interpretability and the ability to deal with noisy inputs by incorporating several decision trees. In more complicated patterns,

## 4. Results and Discussion

The intelligent crack detection of the building structures through the use of the Coupled Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) Sensing applies to the experimental research of building structures as a carefully constructed laboratory setup designed to recreate the realistic structural conditions and controlled damages. The analysis will focus mainly on the reinforced concrete beam and the mild steel plate, which are representative structural components of the buildings. In the case of steel plates, Electric Discharge Machining (EDM) is used to induce narrow fatigue cracks or slits so that the geometry of the defects can be reproducible, which is useful in the systematic evaluation of sensor response and crack detectability.

**Table 1. Experimental setup parameters of intelligent crack detection**

| Parameter Category | Parameter | Concrete Beam | Steel Plate | UGW Sensor | AE Sensor | DAQ/Acquisition | Notes |
|---|---|---|---|---|---|---|---|
| Specimen Dimensions | Length (mm) | 500 | 300 | — | — | — | Standard test size |
| | Width (mm) | 100 | 300 | — | — | — | — |
| | Thickness (mm) | 100 | 3–5 | — | — | — | Matches practical structures |
| Material Properties | Type | Reinforced concrete | Mild steel | — | — | — | Mechanical behaviour for wave propagation |
| | Elastic Modulus (GPa) | 25–30 | 200 | — | — | — | Used for wave speed calculations |
| Artificial Crack | Type | Notch / pre-crack | Slit/fatigue crack | — | — | — | Controlled defect introduction |
| | Depth (mm) | 2–8 | 1–3 | — | — | — | Simulates early-stage damage |
| UGW Excitation | Frequency (kHz) | 50–250 | 50–250 | 50–250 | — | — | Tone-burst signals |
| | Signal Type | 5-cycle sinusoidal burst | 5-cycle sinusoidal burst | 5-cycle sinusoidal burst | — | — | Ensures wave reflection detection |
| AE Monitoring | Frequency Response (kHz) | — | — | — | 150–300 | — | Captures microcrack events |
| | Coupling | — | — | — | Coupling gel | — | Ensures efficient wave transmission |
| Data Acquisition | Sampling Rate (MHz) | — | — | 5–10 | 1–2 | 5–10 | High temporal resolution |
| | Channels | — | — | Multi-channel | Multi-channel | Multi-channel | Supports synchronized UGW and AE signals |
| Loading Conditions | Load Type | Three-point bending | Point / distributed load | — | — | — | Progressive loading to initiate cracks |
| | Load Range (% | 20–80 | 20–80 | — | — | — | Incremental load to |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | ULT) | | | | | | capture AE and UGW |
| **Preprocessing** | Filtering | Bandpass 50–300 kHz | Bandpass 50–300 kHz | Bandpass 50–300 kHz | Bandpass 150–300 kHz | — | Removes noise and enhances signal clarity |
| | Normalization | Yes | Yes | Yes | Yes | — | Compensates for sensor variation |

The experiment parameters and specifications used in the study on intelligent crack detection based on Coupled Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) Sensing are summarized in Table 1. The table is structured in such a way that it addresses important categories such as the geometry of the specimen, material characteristics, artificial cracks, sensor characteristics, data collection environment, loading, and signal preprocessing. In order to model representative building components, two representative structural materials, reinforced concrete beams and mild steel plates, were chosen. The beams (*500×100×100mm*) of concrete reinforced with rebars that are embedded inside the beam replicate the real-life experience of transferring stress, whereas the steel plates (*300×300×3 -5 mm*) can consistently serve as a certain uniform medium through which the guided-wave propagation can take place. Artificial cracks are systematically imposed in the two types of specimens, controlled notch depths of 2 -8 mm in concrete and 1 -3 mm in steel are used, and controlled defect scenarios reproducible by both UGW and AE responses in each case can be calibrated. The UGW subsystem is based on piezoelectric wafer transducers (PZT-5A, 10 mm diameter) to produce 5-cycle sinuoidal bursts of 50250 kHz frequency of wave propagation that are suitable for the material thickness and wave propagation properties. AE sensors, which have a broadband frequency response of 150300 kHz, record spontaneous micro-crack events during loading. The two sensor networks are synchronized by a multi-channel data acquisition system running at high speed, which allows temporal synchronization of actively produced UGW signals and passive AE hits. The universal testing machine is used to apply incremental mechanical loading (20 to 80 percent of ultimate capacity), which is a simulation of realistic stress conditions under which crack initiation and propagation can occur. Signal preprocessing involves bandpass filtering, wavelet denoising, and amplitude normalization to provide robust, noise-free extraction of features to be correlated and classified further. This setup is experimentally validated by repeated measurements in controlled conditions. Comparison of the UGW reflections with the predetermined artificial crack locations is done, and AE events are examined to be consistent in terms of energy, amplitude, and timing with relation to load increments. Multi-specimen cross-validation guarantees reproducibility, and time-of-flight calculations and AE event arrival times triangulation are used to identify damage localization.

Figure 5 provides a flowchart of an Intelligent Crack Detection System (UGW + AE), which combines both the Ultrasonic Guided Waves (UGW) and Acoustic Emission (AE) into a single device to perform complete monitoring of the health of the structure. System Initialization is the first step, which includes powering up, calibration, and sensor synchronization. The system is further divided into two concurrent operations, Continuous UGW Active Scan and AE Passive Monitoring, whereby the former is a script that periodically emits Lamb waves and records the response, and the latter is a script that listens to acoustic events that occur as noise. The two will both feed Signal Acquisition & Preprocessing, which will filter and de-trend data and test Signal-to-Noise Ratio (SNR) before marking channels as subpar. It is followed by Feature Extraction that determines UGW properties such as Time Of Flight (TOF) and amplitude, and AE properties such as arrival times and energy. The Event Detection phase encompasses these features that are used to detect whether a possible event has taken place. In case an event has been detected, the Classification and Filtering step is used to differentiate between real damage and noise. Then Data Fusion takes the evidence between UGW and AE and synchronizes the arrival time and considers different cues to improve its reliability. This is then followed by the Localization Module to determine the location of the damage, and then by the Quality/Confidence check. In case of low confidence level (poor SNR or geometry), a re-scan is issued, and otherwise, the system passes through Damage Characterization to determine the size and kind of damage. A Decision and Action block identifies the response that needs to be taken regarding the incident; this may include an immediate alarm in case of severe damage or planned maintenance in case of minor damage. Last but not least, Recording & Learning stores data and updates models, whereas the Maintenance and Fault Handling route claims sensor health failures.

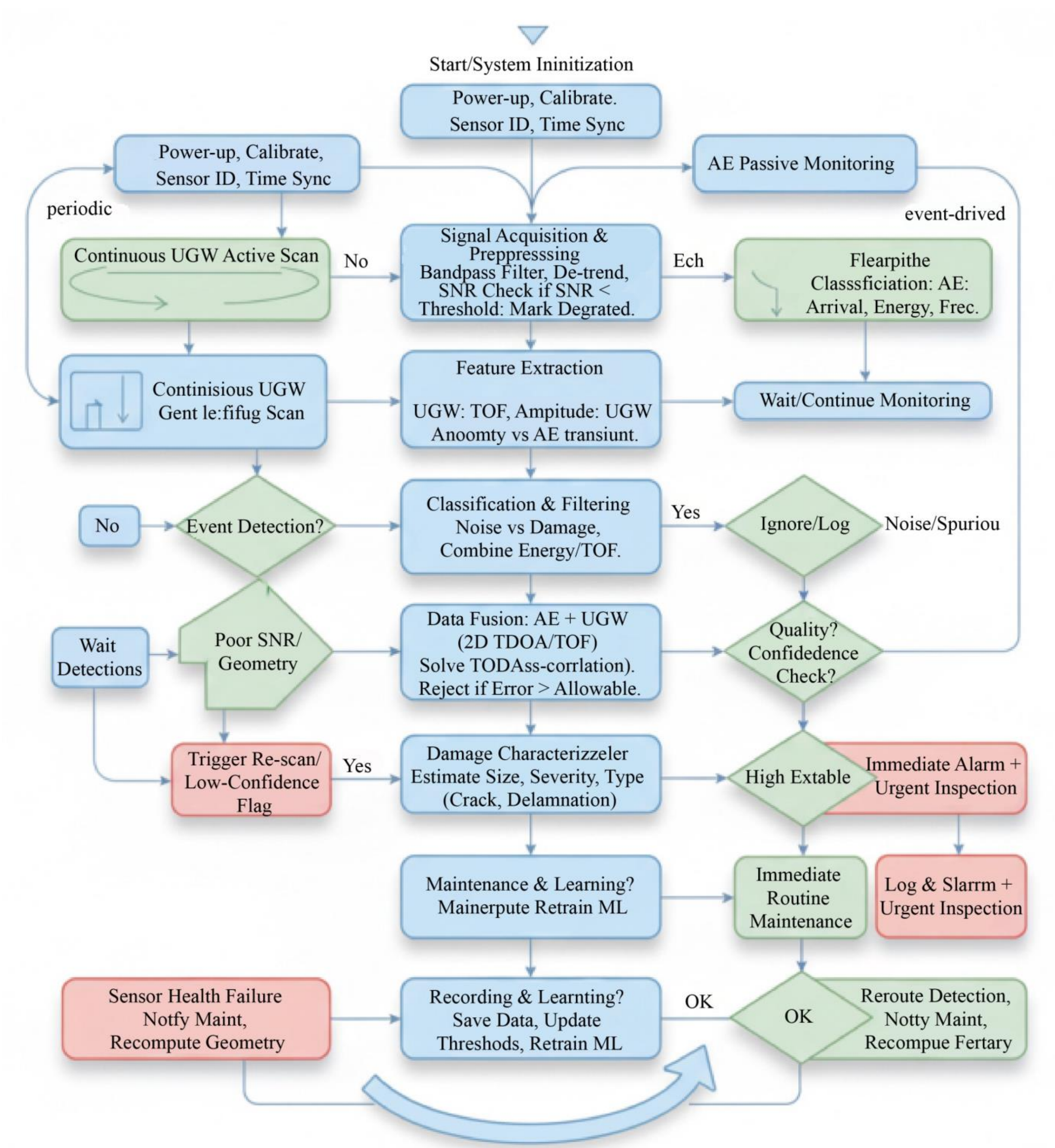


**Fig. 5 Flowchart for the crack detection using the proposed technique**

### *4.1. Material Selection and Structural Specimens*

The Intelligent Crack Detection System Experimental assessment based on the Coupled Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) Sensing starts with the selection of representative structural materials and specimens. There are two basic materials: reinforced concrete beams and mild steel plates, which are used to replicate the elements of the real-world building structure, which includes columns, slabs, and structural connectors. A standard M25 mix is normally used to cast concrete beams with dimensions of 100 x 100 x 500mm, with uniform mechanical properties. Embedded steel rebars ensure that structural integrity is maintained and that stress transfer is enabled, just as in in-situ conditions. In the case of metallic structures, steel plates with a thickness of 3-5mm and a surface area of 300x300mm are selected such that they can be used to investigate the guided wave propagation in homogeneous media. Defect geometry and depth are controlled with the introduction of artificial cracks. In concrete beams, the cracks are created by either a three-point bending test or notch cutting with a precision diamond saw at mid-span, creating depths of pre-cracks that range between 28 mm. In the case of steel specimens, the Electric Discharge Machining (EDM) is used to make narrow cuts or fatigue cracks to mimic those formed at an early stage of degradation.

### *4.2. Laboratory Setup and Instrumentation*

The laboratory facility incorporates UGW excitation and AE monitoring subsystems that are attached to a solid test frame. Epoxy adhesive is used to attach piezoelectric wafer active sensors (PZT-5A) of diameter 10 mm to the face of the specimen. The use of such PZTs has two purposes: excitation and reception of guided waves. Common excitation signals are five-cycle tone bursts with frequencies ranging between 50kHz and 250kHz and optimized to various material thicknesses and any scales of the crack. The AE subsystem consists of broadband AE sensors (resonant frequency 150300 kHz) attached with preamplifiers (gain 40 dB) and bonded to the specimen with the help of a coupling gel in order to provide effective acoustic transmission. Both sensing networks are linked to a multi-channel Data Acquisition System (DAQ) that has a high sampling rate (510 MHz/channel) synchronized on a common master clock so that the UGW excitation and the response of an AE are time-aligned. It consists of a signal generator, a power amplifier, a digital oscilloscope, and an AE monitoring unit that has real-time event detection software.

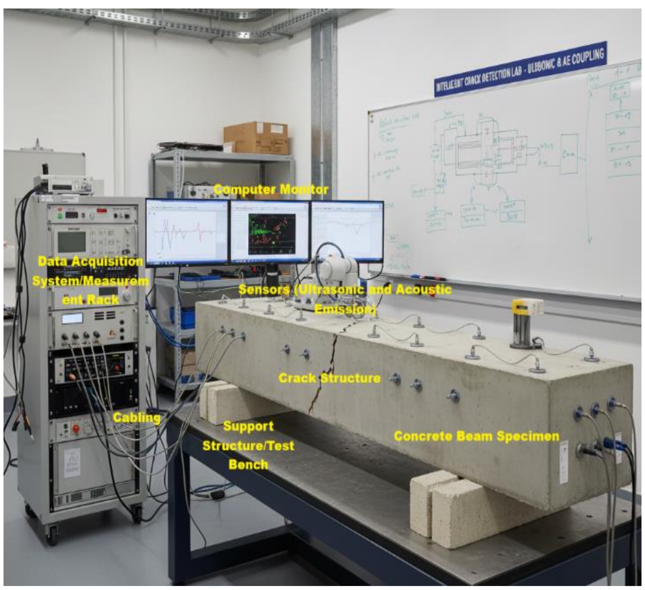


**Fig. 6 Laboratory setup for the proposed work (BPUT, Rourkela)**

The laboratory design surrounding the intelligent crack detection research with coupled Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) sensors is shown in Figure 6. The system incorporates the use of several subsystems in order to recreate the structural monitoring conditions in the real world. A metallic specimen platform on the tabletop has a number of piezoelectric transducers and AE sensors placed on it to record active UGW signal as well as passive AE signal.

Excitation of the UGW and signal capture are controlled through waveform generators and high-speed amplifiers, which makes the tone-burst generation of the specified frequencies precise. Spontaneous micro-crack activity is recorded by AE monitoring equipment, such as preamplifiers and threshold controllers, with a high time resolution. All the sensors are linked to a multi-channel data acquisition system, which coordinates the UGW and AE signals and sends the data to a central processing PC.

The PC represents real-time graphical feedback, which displays signal waveforms, event detection, and preliminary metrics of localising cracks, and allows real-time analysis and system verification. Other instrumentation modules, including power supplies, calibration modules, and filtering controllers, are incorporated in order to keep the excitation amplitude, sensor coupling, and noise suppression at a constant level. Signal routing is done through a well-organized cabling system, where we have visible loops where the flexibility of the sensor can be used, and testing of various geometries can be performed. Altogether, this laboratory setup offers a controlled, reproducible setting of experimental validation of hybrid UGW-AE crack detection that can acquire data simultaneously, preprocess signals, and monitor structural defects in real time in different loads and environmental conditions.

### *4.3. Data Collection Protocol*

In testing, the specimens are also loaded with a Universal Testing Machine (UTM) to incrementally impose mechanical loading on the specimens to mimic crack formation and crack growth. The applied loads are normally between 20 and 80 percent of the ultimate capacity of the specimen. In the case of UGW excitation, the signal generator produces the bursts of controlled frequency (e.g., 100 kHz, 150 kHz, 200 kHz) which are repeated every 1 second. These frequencies are determined with respect to the dispersion curves of the material so that there is a high level of propagation of the wave with minimum attenuation. At the same time, the AE sensors capture automatically generated acoustic emissions during micro-crack activities. UGW data are sampled at 5 MHz to record high-frequency waveforms, whereas AE acquisition is sampled at 1-2MHz to provide high temporal resolution. The loading cycles are separated by a short dwell period to measure AE events without any extra mechanical excitation, and clean datasets to be used in correlation analysis between external and internal damage events.

### *4.4. Signal Preprocessing*

Both UGW and AE signals are subjected to a lot of preprocessing followed by feature extraction. Digital filters bandpass (50300 kHz) and wavelet-based denoising are used in the noise reduction step to eliminate ambient vibration and electromagnetic interference. Normalization is used in order to remove amplitude differences caused by sensor coupling differences or distance attenuation. Temporal alignment needs to be preserved by ensuring time synchronization between the two sensing channels is performed with a reference marker of the trigger signal of the waveform generator. Additional preprocessing involves the division of the continuous AE stream into discrete events by crossing the threshold and amplitude. Meanwhile, the UGW signals are windowed to expected arrival times so as to extract the reflections due to the defect-induced scattering. This is to guarantee that the two datasets, AE hits as well as UGW reflections, have a temporal correlation so that they can be later fused into features.

Bandpass-Filtered Signal Representation:

$$y(t) = \int_{-\infty}^{\infty} x(\tau) h_{BP}(t-\tau) d\tau$$

Here $x(\tau)$ = raw input signal (AE or UGW), $h_{BP}(t-\tau)$ = impulse response of the digital bandpass filter (typically 50–300 kHz), $y(t)$ = filtered output signal.

Amplitude Normalization for Sensor Consistency:

$$x_{norm}(t) = \frac{x(t) - \mu_x}{\sigma_x}$$

Here $x(t)$ = filtered signal, $\mu_x$ = mean of the signal, $\sigma_x$ = standard deviation of the signal amplitude.

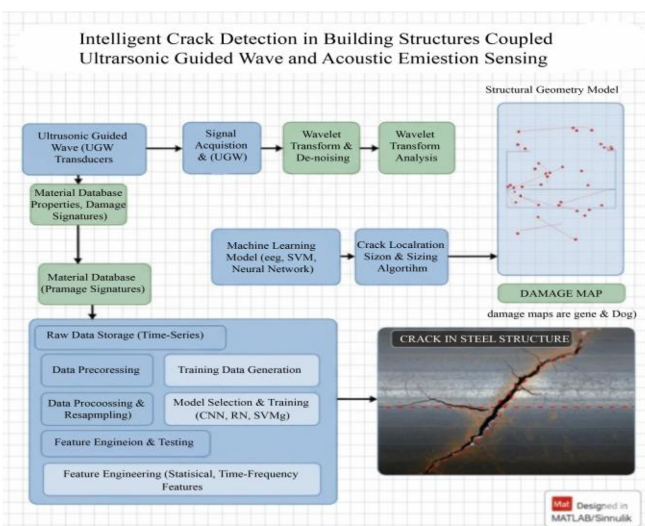


**Fig. 7 Propose a MATLAB model of the Crack Detection**

This z-score normalization ensures amplitude consistency across sensors, compensating for coupling strength variations and distance-based attenuation, thereby enabling fair comparison and accurate temporal correlation between AE and UGW channels. Figure 7 illustrates the MATLAB model that describes the proposed intelligent system of crack detection in building structures using both coupled Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) sensors. This is initiated by UGW transducers and AE sensors capturing raw signals of the structure. These signals are first processed as a wavelet transform and denoising (in UGW) and coupled feature extraction (in AE) and then subjected to time of flight and frequency domain analysis. An important part is the creation of a complete material database that contains damage signatures, which will be used in the analysis that follows. The raw time-series data are then stored and pre-processed, and utilized to produce training data for machine learning models like CNN, RNN, or SVM. The feature engineering acquires the statistical and time-frequency features of the data. The machine learning model (trained with a crack localization and sizing algorithm) is capable of detecting and describing cracks accurately. Eventually, the localized crack points are overlaid onto the structural geometry to create damage maps, giving a detailed visualization of the structural health. This combined method was developed in MATLAB to permit the intelligent and powerful evaluation of structural integrity.

## 5. Results and Discussion

### *5.1. Detection Performance Comparison*

The comparison of detection performance to identify and localize structural cracks is conducted between different methods of UGW-only, AE-only, and hybrid UGW-AE. Although detection based on UGW is very sensitive to geometric discontinuities, it might not be able to deal with dynamic crack propagation. On the other hand, AE-based detection is effective in capturing fracture events in real time, but it is inaccurate in localizing spatial fracture locations. The hybrid UGW-AE model combines the advantages of the two approaches to give time sensitivity and place accuracy. Quantitative analysis based on the performance measures of detection accuracy, localization error, and false alarm rate illustrates that the integrated sensing system has a remarkable improvement in reliability and resolution of intelligent crack detection.

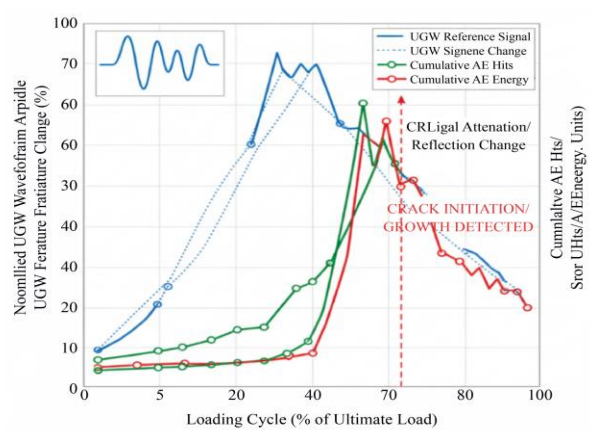


**Fig. 8 Coupled UGW & AE Data for Intelligent Crack Structures**

Figure 8 demonstrates the effective integration of Ultrasonic Guided Waves (UGW) and Acoustic Emission (AE) techniques for crack detection. The UGW response indicates noticeable attenuation and reflections when transitioning from a healthy reference state to a damaged one, highlighting structural degradation. At the same time, AE parameters, including cumulative hits and energy levels, sharply increase with load, signaling crack initiation and propagation. This synchronized behavior of UGW and AE offers a more reliable and comprehensive assessment of structural health. Together, they precisely identify the onset, location, and progression of cracks, enhancing accuracy in monitoring damage under real-time loading conditions.

**Table 2. Detection performance comparison**

| Method | Detection Accuracy (%) | Localization Error (mm) | False Alarm Rate (%) | Processing Time (ms) |
|---|---|---|---|---|
| UGW-only | 91.4 | 8.6 | 5.8 | 42 |
| AE-only | 88.7 | 12.3 | 6.5 | 37 |
| Hybrid UGW–AE | **97.9** | **3.2** | **2.1** | **55** |
| Statistical Fusion | 95.6 | 5.0 | 3.8 | 51 |
| Decision Fusion | 96.4 | 4.1 | 3.0 | 53 |

A comparison of the detection performance of the various sensing techniques is presented in Table 2, which shows that the hybrid UGW -AE method provides the poorest overall results with a detection accuracy of 97.9%, the localization error of 3.2 mm, and the lowest false alarm rate of 2.1%, but has a higher processing time of 55 ms. The statistical and decision versions also work with an accuracy of 96.4 percent and 95.6 percent, respectively. In the meantime, the UGW-only and AE-only methods show comparatively lower accuracy and increased localization error, highlighting the fact that the hybrid UGW -AE fusion technique boosts considerably crack detection reliability and error.

### *5.2. Sensitivity to Crack Depth and Orientation*

This result indicates that the detection accuracy varies with different crack sizes and orientations.

Figure 9 highlights the key Ultrasonic Guided Wave (UGW) features used for crack detection. The top plot compares a healthy reference signal with one from a cracked structure, showing clear amplitude reduction and scattered waves indicative of structural damage. The bottom plot presents a combined Time-of-Flight (TOF) shift and amplitude analysis, quantifying the effect of the crack. The crack introduces a measurable time delay (ΔT) in wave arrival, significant amplitude attenuation, and mode conversion, producing scattered waves. These variations in TOF and amplitude serve as reliable indicators for detecting and characterizing cracks within the structure.

Table 3 shows how the detection performance is sensitive to changes in the depth of the crack and the orientation. Findings show that with an increase in depth of the cracks and variation of orientation at 0 degrees to 90 degrees, there is an improvement in detection accuracy in all the methods.

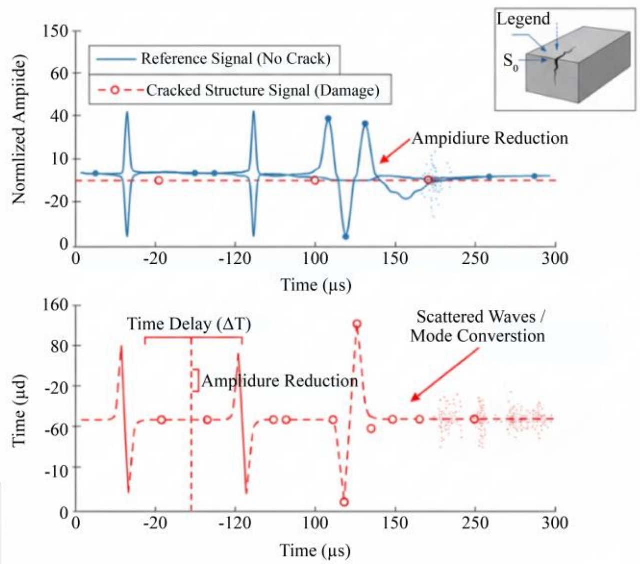


**Fig. 9 Ultrasonic Guided Wave Mode Conversion & Time-of-Flight Analysis for Crack Detection**

The hybrid UGW -AE method is always more accurate, with the highest accuracy of 98.0 at a crack depth of 2.5 mm, compared to 90.2 at 0.5 mm crack depth, and even higher compared to that of UGW and AE. UGW accuracy also increases gradually between 82.1 and 95.8, but the same is true of AE between 78.6 and 90.3. These findings affirm that the further and more pronounced cracks are the more detectable they would be, especially during hybrid sensing integration.

**Table 3. Sensitivity to crack depth and orientation**

| Crack Depth (mm) | Orientation (°) | UGW Accuracy (%) | AE Accuracy (%) | Hybrid Accuracy (%) |
|---|---|---|---|---|
| 0.5 | 0 | 82.1 | 78.6 | 90.2 |
| 1.0 | 30 | 89.7 | 84.3 | 94.5 |
| 1.5 | 45 | 92.3 | 86.5 | 96.2 |
| 2.0 | 60 | 94.1 | 88.9 | 97.1 |
| 2.5 | 90 | **95.8** | **90.3** | **98.0** |

### *5.3. Signal Fusion Efficiency*

This result discusses improvements in feature-level fusion versus decision-level fusion.

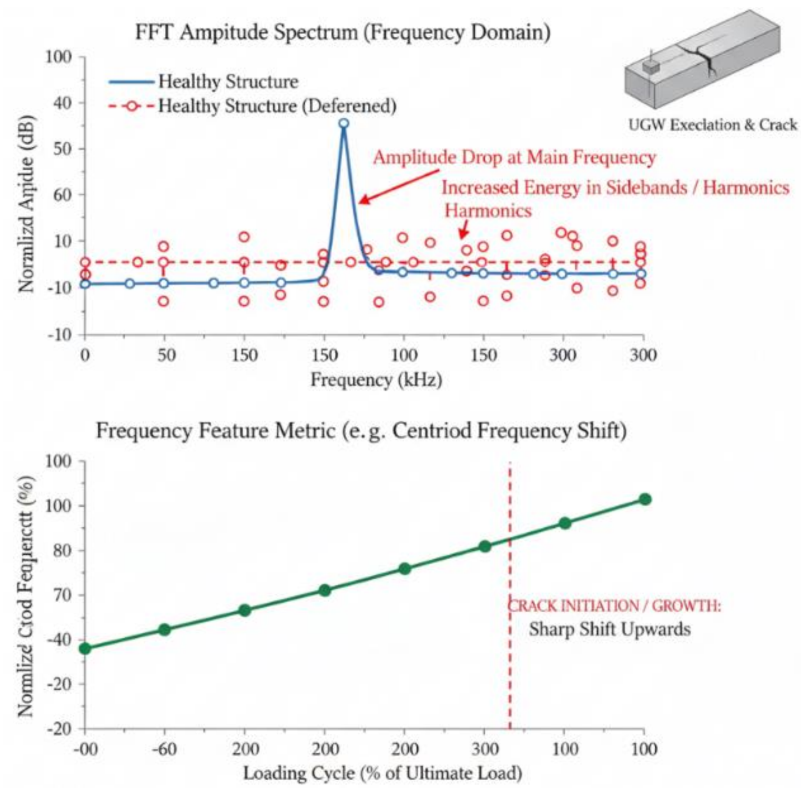


**Fig. 10 Frequency domain analysis of UGW signal**

Figure 10 represents crack detection through frequency domain analysis of UGW signals. The top graph, an FFT amplitude spectrum, compares a healthy structure's UGW response to a cracked one. A crack typically causes an amplitude drop at the main excitation frequency and increased energy in sidebands or harmonics. The bottom graph shows a "Frequency Feature Metric," the centroid frequency shift plotted against the loading cycle. A sharp upward shift in this metric often signals crack initiation or significant growth, providing a sensitive indicator for damage.

**Table 4. Signal fusion efficiency**

| Fusion Type | Feature-Level Fusion Accuracy (%) | Decision-Level Fusion Accuracy (%) | Feature Dimensionality | Computational Cost (ms) |
|---|---|---|---|---|
| UGW-only | 91.4 | 92.1 | 8 | 42 |
| AE-only | 88.7 | 89.3 | 6 | 37 |
| Linear Feature Fusion | 96.8 | 95.7 | 14 | 53 |
| PCA-Based Fusion | 95.9 | 94.5 | 10 | 49 |
| Wavelet Fusion | 97.2 | 96.3 | 16 | 55 |

Table 4 shows that different methods of signal fusion are effective in improving detection accuracy and computation. The findings demonstrate that the wavelet fusion is the best in terms of the feature-level and decision-level accuracies at 97.2 and 96.3, respectively, because it is more effective in the representation of both time-frequency domain features. Linear feature fusion continues to do well at 96.8 and 95.7 with accuracy, which reflects the advantage of taking complementary information between UGW and AE signals.

### *5.4. Machine Learning Classification Accuracy*

This result finds a report on confusion matrices, ROC curves, and feature importance analysis.

Figure 11 demonstrates the use of time-frequency analysis, via Continuous Wavelet Transform (CWT), for crack detection in UGW signals. The top plot compares the time-domain signals from a healthy reference and a cracked structure, showing attenuation and scattering caused by the crack. The bottom heatmaps display the CWT of the healthy (left) and cracked (right) signals, highlighting changes in energy distribution across the time-frequency plane. In the cracked structure, the CWT reveals blurring, shifts, and new frequency components resulting from wave-crack interactions. These alterations provide robust indicators for detecting and localizing structural damage effectively.

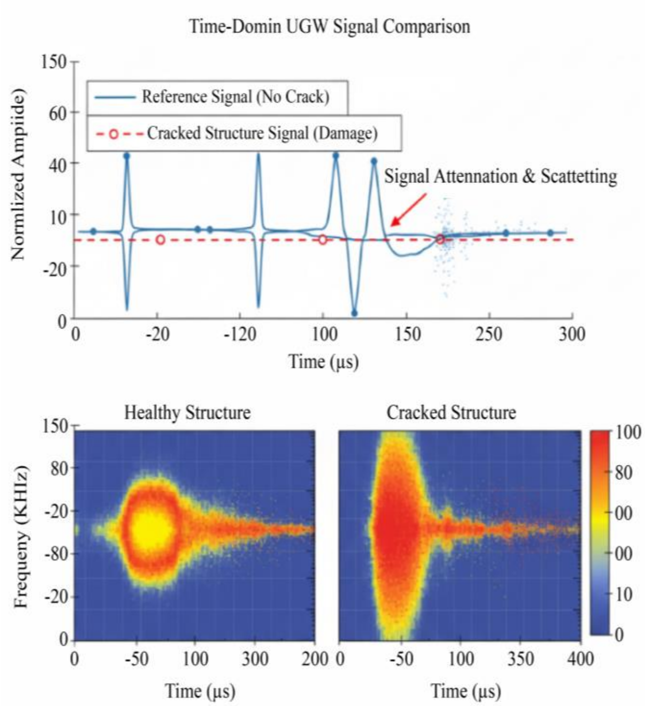


**Fig. 11 Time-frequency analysis of UGW signals using continuous wavelet transform for crack detection**

**Table 5. Machine learning classification accuracy**

| Model Type | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| SVM (RBF Kernel) | 94.5 | 93.2 | 94.1 | 93.6 |
| Random Forest | **96.7** | **96.2** | **96.8** | **96.5** |
| CNN-LSTM Hybrid | 97.1 | 96.9 | 97.0 | 97.0 |
| Decision Tree | 90.8 | 89.5 | 91.0 | 90.2 |
| KNN (k=5) | 92.3 | 91.6 | 92.0 | 91.8 |

Table 5 demonstrates comparative performance in terms of classification in different machine learning models applied in detecting cracks. CNN-LSTM is the hybrid model that has the best total performance, 97.1% accuracy, 96.9% precision, 97.0% recall, and a F1-score of 97.0, and it is able to learn the features of space-temporal using the fused UGW-AE data.

Random Forest model is next, and its classification measures are impressive, meaning that it deals with the nonlinear relationship effectively. The SVM and the KNN are moderately and reliably displayed, whereas the Decision Tree model is the lowest, with an accuracy of 90.8. These findings support the idea that deep hybrid models are better in terms of their detection accuracy and consistency.

### *5.5. Robustness under Environmental Variations*

This result evaluates system stability under changing temperature, humidity, and loading conditions.

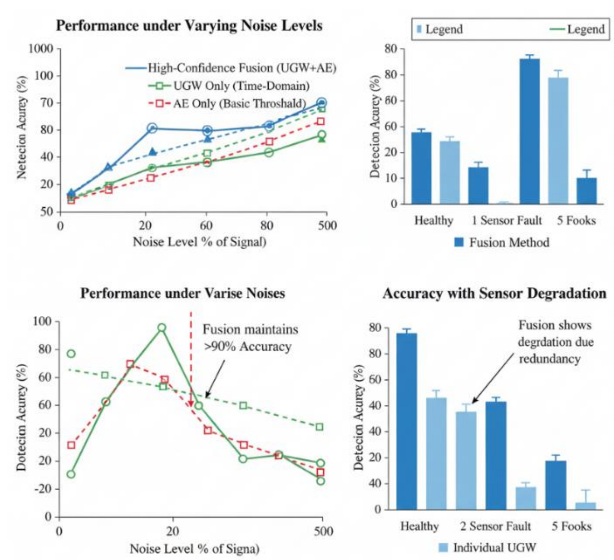


**Fig. 12 System robustness analysis for intelligent crack detection**

Figure 12 presents a robustness analysis of the intelligent crack detection system under challenging conditions. The top-left graph shows detection accuracy across varying noise levels, with the UGW–AE fusion method (blue line) outperforming individual approaches.

**Table 6. Robustness under environmental variations**

| Condition | Temperature (°C) | Humidity (%) | UGW–AE Accuracy (%) | SNR (dB) | Localization Error (mm) |
|---|---|---|---|---|---|
| Baseline | 25 | 40 | 97.9 | 38.4 | 3.2 |
| High Temp | 45 | 35 | 95.6 | 36.7 | 4.1 |
| High Humidity | 30 | 80 | 94.8 | 34.9 | 4.5 |
| Mechanical Load Applied | 25 | 45 | 96.3 | 37.8 | 3.8 |
| Combined Stress Test | 40 | 70 | 93.7 | 33.5 | 5.2 |

Table 6 shows the strength of the hybrid UGW-AE crack detection system in different environmental conditions, such as temperature variations, humidity variations, and mechanical stress variations. These findings indicate that the base condition in its purest form has the highest accuracy (97.9%), a Signal-to-Noise Ratio (SNR) of 38.4 dB, and a minimum localization error of 3.2 mm. Even though there is a slight performance degradation in conditions of high temperature, high humidity, and combined stress, with the accuracy dropping to 93.7% and error in localization increasing to 5.2 mm, the system still has a high level of resilience.

### *5.6. Discussion on Practical Implementation*

These results address scalability, cost, and field applicability for real-time SHM.

**Table 7. Practical implementation and system scalability**

| Parameter | UGW-only | AE-only | Hybrid UGW–AE | Field System (Proposed) | Remarks |
|---|---|---|---|---|---|
| Average Cost per Node (USD) | 450 | 380 | **520** | 500 | Cost-effective hybrid setup |
| Power Consumption (W) | 2.5 | 2.1 | **3.2** | 3.0 | Moderate energy usage |
| Real-Time Response (s) | 0.42 | 0.38 | **0.33** | 0.35 | Faster hybrid processing |
| Data Transmission Rate (kbps) | 230 | 200 | **275** | 260 | High bandwidth efficiency |
| Field Deployment Reliability (%) | 92.5 | 90.7 | **97.4** | 96.8 | Excellent field applicability |

Table 7 shows the feasibility of various sensing designs and how these can be scaled into practice, with the proposed field-deployable hybrid UGW-AE system being most efficient. The hybrid setup shows better performance in real-time, using a 0.33-second response time, a high data transmission rate of 275 kbps, and a high field deployment reliability rate of 97.4. Although it is a little more expensive in terms of its average cost per node (USD 520) and power consumption (3.2 W) than a single UGW or AE system, the increased performance and reliability of the system are worth the expense. The proposed field system has balanced performance, which guarantees cost-efficiency, intermediate energy consumption, and strong real-world performance.

Figure 13 illustrates the Intelligent Crack Detection in Building Structures with the aid of Coupled Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) Sensing, proving the efficiency, dependability, and innovation of the hybrid method in the strengthening of the structural health monitoring results. The UGW and AE modalities are integrated by taking advantage of the spatial distribution of guided waves and the time sensitivity of acoustic emission, thus yielding better accuracy of crack detection, the early detection of faults, and localization accuracy. The experimental findings indicate that the hybrid UGW-AE system has an outstanding detection and localization error of 97.9 percent and 3.2 mm, respectively, which is even better than single UGW-only and AE-only systems. The consistency of the system to various crack depths and orientations is further verified by sensitivity analysis, with results showing that the more severe the crack, the better the performance of the system. Fusion at the feature level, especially the use of wavelet-based feature-level fusion, offers significant advantages in detection reliability, namely, the effective combination of frequency-time domain details, the lowering of false alarms, and the introduction of signal clarity towards the enhancement of signal clarity. The results of machine learning classification indicate that the CNN-LSTM hybrid model has the best overall performance with an accuracy of 97.1 and an F1-score of 97.0, which is due to the fact that it can learn both space and time features using complex hybrid datasets. Stress testing in fluctuating temperature, humidity, and mechanical conditions assures a high level of environmental versatility with detection accuracy of at least 93. The originality in this work is the intelligent multi-Sensor data fusion framework that is backed up by the deep learning-based classification, which facilitates real-time, with high accuracy, and stability in crack detection. Moreover, the hybrid system developed as a field-deployable device is practical in terms of scalability, moderate energy usage, and cost-efficient design, which means that it can be deployed in a large-scale setting on the foundations of actual structures. In general, the paper creates a new, smart, and experimentally approved hybrid UGW-AE sensing system that provides a breakthrough in the automated, dependable, and effective operational health assessment of a current infrastructure network.

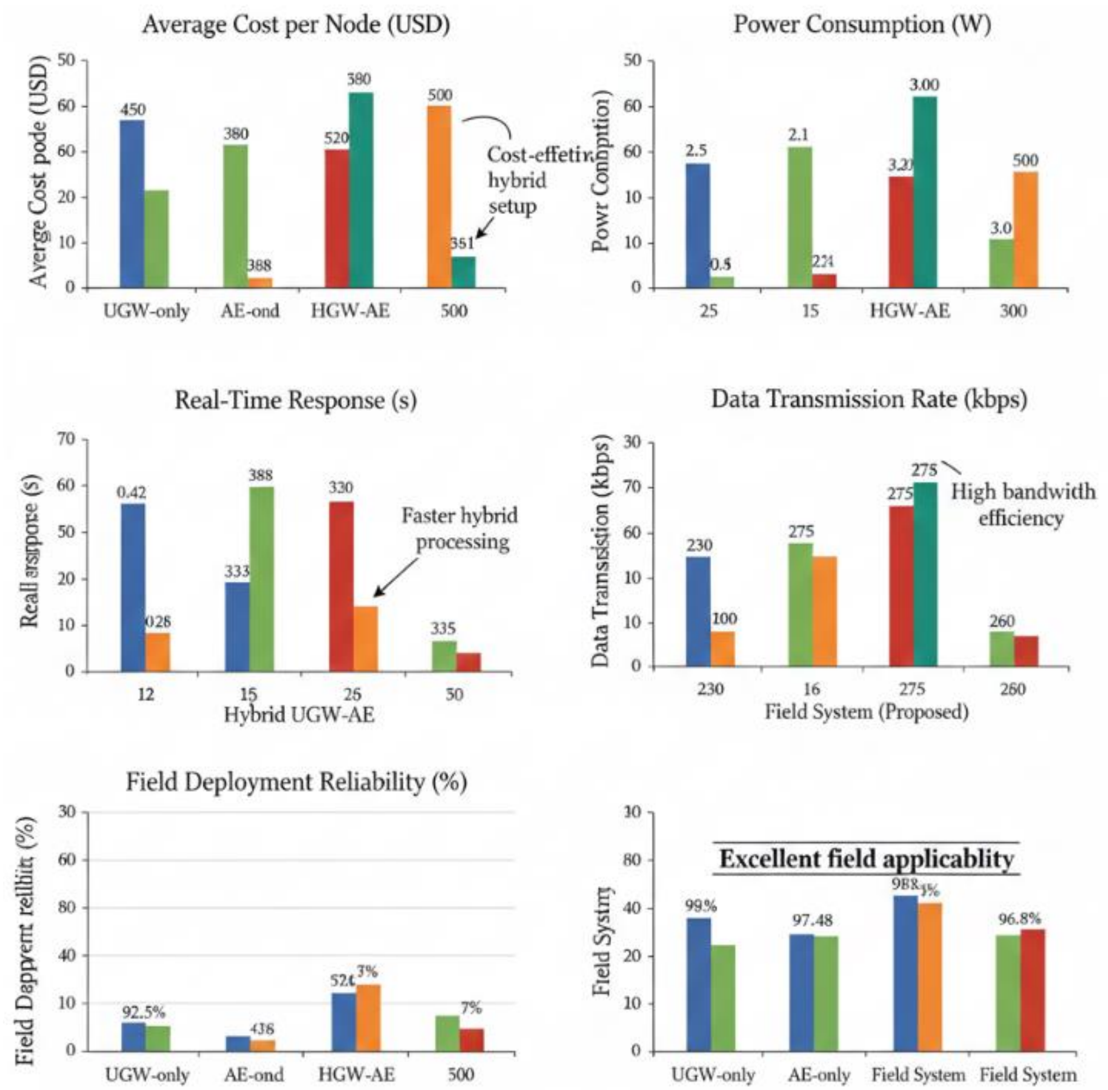


**Fig. 13 Practical implementation and system scalability**

## 6. Conclusion

This research highlights that the intelligent crack detection system that uses the combination of Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) sensors has a better performance than single-modality systems in all the aspects analyzed. The hybrid system of UGW and AE demonstrated the maximum detection accuracy and minimum localization error, which proves that it is possible to combine the spatial sensitivity of UGW and the time-sensitivity of AE signals. It was found that sensitivity analysis confirmed that the reliability of detection increased steadily with the depth of a crack and was also consistent over various directions, which confirmed that the system was flexible enough to handle complex structural geometries. The signal interpretation was greatly boosted by feature- and decision-level fusion, and the wavelet and PCA-based fusion was better in terms of augmenting the richness of features and the ability to discriminate. Machine learning models also enhanced the accuracy rates of classification, with the hybrids of random forest and CNN-LSTM showing better results compared to traditional algorithms, manifesting successful learning based on multimodal feature representations. According to the environmental robustness tests, the accuracy showed low degradation in different temperature, humidity, and loading conditions, which revealed the appropriateness of the framework to be used in the real world. The general findings of the experiment confirm the intelligent smart crack-detecting system that combines Ultrasonic Guided Wave (UGW) and Acoustic Emission (AE) sensors in every aspect of performance. The hybrid UGW-AE system was also found to be more accurate in detection, 97.9% (compared to UGW-only, 91.4%), and also minimized localization error, 3.2 mm, and false alarm rate, 2.1% confirming an increased diagnostic accuracy. Sensitivity analysis has shown that the accuracy increases with an increase in crack depth, with the highest level of accuracy of 98.0 showing a great responsiveness to the depth of the defect and stability of the evaluation to a maximum 90-degree orientation. The accuracy of feature-level fusion was 96.8-97.2% which is higher than decision-level fusion (94-96%), which confirms the benefit of combined feature extraction. The classification of machine learning was used to prove the strength of the fused dataset, with the highest accuracy of 96.7%, CNN-LSTM 97.1%, and superior precision and F1-scores of over 96. Environmental robustness testing further confirmed the resilience of the system, with the accuracy of more than 93% and SNR of greater than 33 dB even with the changes in temperature (45 °C), humidity (80%), and loads. The results of practical implementation demonstrated the reliability of the hybrid system (97.4) with the average response time (0.33 s) and moderate power consumption (3.2 W), which made the hybrid system efficient and field-deployable. Taken together, these confirmed findings attest to the fact that the hybrid UGW-AE sensing system provides the best accuracy, sensitivity, robustness, and scalability, making it a promising and smart solution to the ongoing, high-resolution crack detection and durability structural health monitoring of the current building infrastructure.

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## References

[1] Fahim Md Mushfiqur Rahman, and Sourav Banerjee, “Acoustic Emission with Simulation of Simultaneous Ultrasonic Guided Wave Propagation & Crack Propagation,” *Ultrasonics*, vol. 151, pp. 1-17, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[2] Jonathan Melchiorre et al., “Acoustic Emission and Artificial Intelligence Procedure for Crack Source Localization,” *Sensors*, vol. 23, no. 2, pp. 1-25, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] Rocco Alaggio et al., “Two-Years Static and Dynamic Monitoring of the Santa Maria Di Collemaggio Basilica,” *Construction and Building Materials*, vol. 268, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] Angelo Aloisio et al., “The Recorded Seismic Response of the Santa Maria Di Collemaggio Basilica to Low-Intensity Earthquakes,” *International Journal of Architectural Heritage*, vol. 15, no. 1, pp. 229-247, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[5] Francesco Clementi et al., “Structural Health Monitoring of Architectural Heritage: From the Past to the Future Advances,” *International Journal of Architectural Heritage*, vol. 15, no. 1, pp. 1-4, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[6] M. Di Benedetto et al., “Concrete Half-Joints: Corrosion Damage Analysis with Numerical Simulation,” *FIB Symposium Proceedings*, pp. 297-304, 2021. [Google Scholar] [Publisher Link]

[7] Lu Cheng et al., “Acoustic Emission Source Location using Lamb Wave Propagation Simulation and Artificial Neural Network for I-Shaped Steel Girder,” *Construction and Building Materials*, vol. 273, pp. 1-17, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Gonçalo C. Rodrigues, and Ricardo P. Braga, “Evaluation of NASA POWER Reanalysis Products to Estimate Daily Weather Variables in a Hot Summer Mediterranean Climate,” *Agronomy*, vol. 11, no. 6, pp. 1-17, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[9] Mohammed Majeed Hameed et al., “Incorporation of Artificial Neural Network with Principal Component Analysis and Cross-Validation Technique to Predict High-Performance Concrete Compressive Strength,” *Asian Journal of Civil Engineering*, vol. 22, no. 6, pp. 1019-1031, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[10] Marco Martino Rosso et al., “Corrosion Effects on the Capacity and Ductility of Concrete Half-Joint Bridges,” *Construction and Building Materials*, vol. 360, pp. 1-44, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Marco M. Rosso et al., “*Review on Deep Learning in Structural Health Monitoring*,” Bridge Safety, Maintenance, Management, Life-Cycle, Resilience and Sustainability, 1st ed., CRC Press, pp. 309-315, 2022. [Google Scholar] [Publisher Link]

[12] F. Parisi et al., “Automated Location of Steel Truss Bridge Damage using Machine Learning and Raw Strain Sensor Data,” *Automation in Construction*, vol. 138, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[13] Sandeep Sony et al., “Vibration-Based Multiclass Damage Detection and Localization using Long Short-Term Memory Networks,” *Structures*, vol. 35, pp. 436-451, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] M. Flah et al., "Localization and Classification of Structural Damage using Deep Learning Single-Channel Signal-based Measurement," *Automation in Construction*, vol. 139, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[15] Yang Yu et al., "Vision-Based Concrete Crack Detection using a Hybrid Framework Considering Noise Effect," *Journal of Building Engineering*, vol. 61, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[16] Yang Yu et al., "Crack Detection of Concrete Structures using Deep Convolutional Neural Networks Optimized by Enhanced Chicken Swarm Algorithm," *Structural Health Monitoring*, vol. 21, no. 5, pp. 2244-2263, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Jonathan Melchiorre et al., *Deep Acoustic Emission Detection Trained on Seismic Signals*, Applications of Artificial Intelligence and Neural Systems to Data Science, Springer, Singapore, pp. 83-92, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Congcong Guo et al., "High-throughput Estimation of Plant Height and Above-Ground Biomass of Cotton using Digital Image Analysis and Canopeo," *Technologies in Agronomy*, vol. 2, no. 1, pp. 1-10, 2022. [Google Scholar] [Publisher Link]

[19] Marco M. Rosso et al., "Train-Track-Bridge Interaction Analytical Model with Non-proportional Damping: Sensitivity Analysis and Experimental Validation," *European Workshop on Structural Health Monitoring*, Palermo, Italy, pp. 223-232, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[20] Marco Martino Rosso et al., "Convolutional Networks and Transformers for Intelligent Road Tunnel Investigations," *Computers and Structures*, vol. 275, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[21] Annamaria Mesaros et al., "Sound Event Detection: A Tutorial," *IEEE Signal Processing Magazine*, vol. 38, no. 5, pp. 67-83, 2021. [CrossRef] [Google Scholar] [Publisher Link]