

Real-Time Crack Detection in Polymer Composites Using Embedded IoT Sensor Networks

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Abstract

This study developed an embedded Internet of Things sensor network for real-time crack detection, localization, and severity assessment in glass–fiber-reinforced polymer composites. Four polyvinylidene fluoride sensors were embedded near the laminate mid-plane and connected to synchronized wireless acquisition nodes. Controlled low-velocity impacts generated graded damage states. Ultrasonic C-scan and optical microscopy provided independent labels. A compact multi-channel convolutional model processed normalized waveforms, spectral entropy, signal energy, and arrival-time differences at an edge gateway. The framework achieved a macro-F1 score of 0.938, a mean localization error of 8.9 mm, and an average end-to-end warning latency of 71 ms. Sensor-embedded laminates retained 99.1% of the flexural strength of uninstrumented controls. Multi-sensor fusion and baseline normalization produced the largest reductions in false alarms. The approach also preserved records during temporary wireless interruption through local buffering. The proposed material-aware IoT architecture allows for fast crack monitoring. It offers spatially-distributed detection of structural damage. This system can be used for continuous monitoring of polymer composites. It identifies cracks at an early stage. There are no major mechanical penalties to the architecture. It maintains the structural performance of the composite. This allows for condition-based maintenance to be performed. Overall, it enhances the reliability and service life of polymer–composite structures.

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INTRODUCTION

Background and Need for in situ Composite Monitoring

FRP composites are now being used in many structures such as aircraft, wind turbine blades, vehicles, ships, pressure vessels, and civil structures. They have a high specific strength, corrosion resistance, and can be processed to have a stiffness that can be tailored and have significant advantages over traditional metallic materials [1]. Mechanical reliability is still determined by a complex microstructure with multiple length scales involving interactions between the polymer matrix, reinforcing fibers, interphase, manufacturing defects and residual stress. Damage is thus seldom a clearly visible occurrence. It develops by microcracking in the matrix, debonding of the fibers from the matrix, transverse cracking, delamination, fiber breakage and loss of load carrying capacity [2]. Comprehensive

reviews then show that structural health monitoring is an important path to be taken for the detection of hidden and progressive damage in composite structures.

The matrix-dominated cracking is particularly significant as it can occur long before the fracture is visible and/or a significant drop in global stiffness. Micro discontinuities can start in the polymer-rich regions due to repeated loading, thermal cycling, moisture ingress, impact and manufacturing induced porosity [3]. These discontinuities then alter the local strain transfer, disrupt the fiber–matrix interface and create avenues for delamination. The composite component can, therefore, appear to be in perfect condition on the outside, but be damaged on the inside. When the defect is detected by conventional inspection, crack coalescence may have already led to a decrease in the residual strength or fatigue life [4].

Several non-destructive evaluation techniques – like ultrasonic testing, infrared thermography, radiography, shearography, and acoustic inspection – have been widely used for polymer composite structures [5]. They are useful for scheduled assessments, but most of them require special equipment, special operators, access to the component or the temporary shutdown of the service. Inspection is also only a snapshot of the structural condition and is done periodically. If the loading of the component is irregular, mechanical or environmental, the initiation of crack may not be detected between two inspection intervals, especially if the crack is small [6]. The composite must then be made into a continuously monitored engineering system by a permanently integrated sensing layer that transforms the material from a passively inspected to a continuously monitored state.

Limitations of Existing Crack-Detection Approaches

Significant advances have been achieved with the use of piezoelectric transducers, fiber-optic sensors, electrical-resistance measurements, capacitive elements, acoustic-emission sensors and conductive nanofiller networks [7]. Fiber Bragg grating sensors are capable of high strain sensitivity and immunity to electromagnetic interference, while piezoelectric elements can interrogate a structure via active guided waves. Changes in the conductive pathways within the piezoresistive polymer composites, such as carbon nanotubes, graphene, carbon black or conductive fibers, can also be a measure of strain or damage [8, 9]. There is a recent trend of self-sensing polymer composites with piezoresistive, optical and other fibrous sensing mechanisms, as confirmed by recent research.

Although these developments have taken place, there are still some challenges that prevent their use in the laboratory and as a continuously operating composite. Typically, a single sensor can monitor a small area only, and cracks in the matrix may occur in a small area that is beyond the sensor's sensing range. As the number of sensors increases, the spatial coverage can be enhanced, but more wiring, more complexity in the acquisition process, synchronization of the signals and the disturbance of the polymer–fiber architecture are added. Inclusions can also be embedded devices that have geometry, stiffness, surface chemistry or thermal expansion that is significantly different from the surrounding matrix. The poor integration can lead to the formation of resin rich areas, to the concentration of stress at the interfaces, to the early debonding or to the modification of the curing behavior in the local area [10].

Another challenge is the interpretation of the signals. Polymer composites have anisotropic and rate dependent properties and the output measured depends on the fiber orientation, viscoelasticity of the matrix, temperature, humidity, loading history and the location of the sensor [11]. A threshold set for one loading condition can thus lead to false alarms for another loading condition. Attenuation and reflections can impact acoustic signals, and reversible strain can contribute to resistance-based measurements, in addition to irreversible changes due to cracks. To separate these effects, synchronized data from several sensing locations is needed and an analysis procedure that takes into consideration the physical response of the polymer composite, not just all the variations in the signal, is required [12].

Most of the reported systems also use laboratory instruments that are centralized and offline post-processing. These arrangements can detect damage following an experiment but cannot completely meet the needs of real-time detection of cracks in operational structures. An ideal monitoring platform should be able to continuously collect distributed signals, locally filter out the signals, differentiate the crack sensitive features from the environmental changes, transmit the state of the structure with low delay and operate with limited power and bandwidth [13].

PROPOSED EMBEDDED IOT SENSOR-NETWORK CONCEPT

The IoT provides an appropriate solution to link embedded sensors, edge processing units, wireless communication modules and remote monitoring interfaces [14]. However, for polymer composites, it is not enough to connect them to the Internet of Things (IoT). The network should be designed based on the material system, damage mechanisms, sensor–matrix interface, spatial sensing range and mechanical effects of embedding electronic elements.

This study presents a distributed sensing network with IoT technology to detect crack initiation and propagation in real time for polymer composite components. The embedded nodes are continuously sensing the crack responsive signals from the pre-defined sensing regions. Initial conditioning and feature extraction are done near the composite structure which decreases the number of raw data sent through the network [15]. The measurements at adjacent nodes are then compared to see if the observed variation is due to electrical noise, reversible deformation or irreversible damage event. The information generated is fed into a monitoring interface which will alert the event, the relative severity of the cracking and the likely location of the cracking as it progresses.

The method proposed in this paper is different from the external inspection devices, which provide direct contact with the sensing elements and the deforming polymer matrix. This will be expected to increase the sensitivity to local strain redistribution and discontinuities due to early matrix cracking [16]. Distributed acquisition also helps to minimize reliance on a single sensor and offers spatial redundancy. If a node is drifting or losing communication with another node, the information from neighboring nodes can maintain the continuity of the structural assessment.

Objective, Novelty, and Contribution

Previous research has focused on either sensing behavior of a single smart polymer composite, damage-detection capability of a single transducer, or the communication performance of a generic IoT monitoring platform. The relationship between sensor embedding, integrity of polymer-composites, distributed interpretation of the signals and real-time operation of the network has not been sufficiently explored [17]. Specifically, little research has been conducted on the ability of an embedded IoT network to detect localized cracking, while not significantly affecting the mechanical performance of the host composite.

The aim of this work is thus to design and test an integrated material–sensor–network system for continuous monitoring of cracks in polymer composite materials. The key novelty is to consider embedded sensing and IoT communication as a pair of components of the composite system, as opposed to an electronic layer added after the fabrication. The investigation considers the evolution of the signals (crack-sensitive), the spatial agreement between the sensing nodes, the edge level decision making, the communication latency and the effect of the sensor integration on the polymer composite response. This allows damage detection to be analyzed both from the polymer-science and connected-monitoring point of view [18].

The study has introduced a distributed embedded sensing architecture, a real-time technique for sensing the crack-related signals' transitions, and a network-level technique for reporting the localized damage. The proposed framework aims to enable condition-based maintenance, decrease the need for scheduled inspection and further the evolution of structurally intelligent polymer composites by linking the microscale disruption in the polymer matrix to a readily available digital assessment.

LITERATURE REVIEW

Damage Development and Conventional Inspection of Polymer Composites

FRP composites are damaged by several mechanisms, which are interacting. The first signs and/or measurable changes of deterioration are typically matrix cracking, typically due to transverse tension, cyclic loading, impact or thermal stress. Initially these small cracks may seem insignificant. However, with time, they shift the stresses in the neighborhood to the fiber–matrix interface and promote delamination, separation at the interface and fracture of the fibers [19]. The progression is seldom even due to the anisotropic, layered and manufacturing variation sensitivity of composite laminates. The location and rate of crack growth may vary due to voids, resin-rich areas, poor wetting and poor fiber alignment.

Non-destructive evaluation is still widely used for the detection of internal defects in polymer composite structures, with conventional methods still being used. Delamination, porosity and discontinuities due to thickness variations can be identified by the behavior of the reflected or transmitted waves in ultrasonic testing [20]. Infrared thermography can detect subsurface damage by detecting abnormal heat-flow patterns and radiographic methods can be used to provide detailed images of the inside of the object when access and safety allow. Other techniques that can be used to observe deformation anomalies over relatively large surfaces are shearography and digital image correlation [21].

These techniques provide good inspection under controlled conditions but are primarily periodic. The structure will frequently have to be removed from service, scanned by an operator and assessed following data collection. This can result in damage not being detected that starts and progresses between two inspections. Access is also a worry. Parts that are composed of multiple materials and components, such as those found inside the vehicle, wind blades, aircraft sections, pressure vessels, and enclosed industrial systems, might not be readily accessible for inspection without partial disassembly [22]. This limitation has led to the focus of research being directed towards the development of permanently installed sensing systems that can monitor damage during the structure's operation.

Embedded and Surface-Mounted Sensors for Crack Detection

One of the most mature techniques for active damage monitoring of composite materials is acoustic-emission sensing. Transient stress waves propagate through the laminate when stored elastic energy is released from the laminate due to cracking, debonding or fiber breakage. These events can be detected by piezoelectric sensors placed on the surface, which can give information about the onset of damage, its location and severity [23]. This technique is sensitive to fracture activity, but the waveform recorded may be influenced by attenuation, reflections, boundary conditions and mechanical noise. It is not easy to tell the difference between matrix cracking and fiber failure, particularly in geometrically complex parts.

One element is used to generate an elastic wave, and another element is used to detect the response after the wave has propagated through the composite. When a crack or delamination occurs, the amplitude, velocity, phase and mode content of the waves will change [24]. Local strain sensors can be used in limited areas, whereas guided waves can be used in a larger area, which is beneficial for large structures. However, their interpretation is very sensitive to the stacking sequence of the laminates, the frequency chosen, the distance between the sensors, the temperature and the geometry of the structure. Long operating periods may also cause baseline signals to drift.

Another way of embedded monitoring is using fiber-optic sensors. Fiber Bragg gratings are used to measure strain and temperature changes by measuring the changes in reflected wavelength. They are small in diameter, immune to electromagnetic interference and can be multiplexed to sense multiple points along a single optical fiber, making them desirable for polymer composite applications [25]. If they are properly embedded, they can follow the redistribution of strain in the vicinity of a growing crack. However, optical fibers can break during manufacture and/or service. If the diameter of the

sensor and its placement is not compatible with the laminate architecture, their presence can also cause problems with the local reinforcement packing.

With the advent of conductive polymer nanocomposites, the importance of electrical resistance-based sensing has increased. Conductive pathways can be created within an insulating polymer matrix using carbon nanotubes, graphene, carbon black and short carbon fibers. The piezoresistive response is the result of a change in contact resistance and tunnelling distance due to mechanical deformation [26]. The formation of cracks breaks these networks more permanently and the material can be used as a load bearing material and as a sensor. This is a self-sensing idea, which eliminates the need for large external devices.

Conductive sensing layers have been created in the form of films, coatings, veils, printed tracks and nanofiller modified interphases. They can be very sensitive to the cracking of the matrix and separation at the interfaces [27]. However, there are several practical problems. It is hard to control the dispersion of nanofillers, their percolation behavior is different for different batches and the electrical signal can be a combination of reversible strain and irreversible damage. Resistance can also change due to temperature and moisture. Therefore, a change in electrical output is not necessarily a sign of a crack and needs to be backed up by measurements or compensation procedures.

The flexible printed devices, capacitive sensors and strain gauges provide easier integration and low-cost signal acquisition. They may be applied to the composite surface or be placed between certain plies [28]. Such sensors can only detect a small area, and cracks may exist in areas outside of the sensing zone. The more devices the more coverage, but the more wiring, connectors, acquisition channels and failure points. Embedding the mechanical effect also needs to be considered. It is not only a local stress concentration that may be observed but a stiff or poorly bonded sensor that may create a local stress concentration [29].

Wireless Sensor Networks and IoT-Based Structural Monitoring

Wireless sensor networks (WSN) alleviate the wiring problem in the distributed structural monitoring. The typical node consists of a sensing element, a signal conditioning circuit, a microcontroller, a communication unit and a power source. Multiple nodes can be deployed throughout a composite component and connected to a gateway that will enable the collection of data in a synchronized manner [30]. This architecture is helpful in situations where long cables are heavy, difficult to install or get in the way of operation.

The first wireless monitoring systems were primarily used to send raw data to a central computer. This is feasible for small laboratory experiments but is inefficient if there are many sensors taking samples at high frequency. For instance, the measurements of acoustic-emission and guided-wave can produce a lot of data. If the network has a limited bandwidth, then continuous transmission consumes more power, and can overload the network [31]. Other factors – such as packet loss, clock mismatch, interference and variable communication delays – can further decrease the reliability of crack localization.

The Internet of Things (IoT) is an extension of the wireless sensing model, where local nodes are connected to edge processors, cloud services, databases and remote dashboards. There are several reports of IoT-based platforms for bridges, pipelines, wind turbines, aircraft components and industrial machines [32]. They allow constant access to structural data and can warn without having to be near the structure. Many systems are still geared towards network connectivity, however. The output of the sensor is sometimes only treated at a basic threshold level, with respect to the physical behavior of the polymer composite.

Edge computing can help to solve this problem by analyzing the signals near the monitored structure. Selected information can be sent out after a local filtering, event detection, feature

extraction and preliminary classification [33]. This will minimize network traffic and the delay between the time of the damage and warning generation. It also enables the system to run if it cannot access the cloud temporarily. The challenge is to achieve the required computational complexity while keeping the embedded nodes memory, processing power and energy usage to a minimum.

The use of data fusion for enhancing the reliability of decisions has been investigated. One type of sensor can be used in conjunction with another, for example, a strain sensor can be used to support or correct a signal from an acoustic sensor, a piezoresistive sensor can be used to support or correct a signal from a strain sensor, a temperature sensor can be used to support or correct a signal from a vibration sensor, and so on [34, 35]. A crack indication that is seen at neighboring nodes is more likely to be a crack than a single sensor's indication. However, sensor fusion demands accurate synchronization and a good understanding of the response of each of the signals to loading, environmental changes and damage.

Research Gap and Direction of the Present Study

As can be seen in Table 1, most of the previous studies focus on single sensing material, damage classification methods or wireless monitoring system. There has been little work that has considered the issues of embedment of sensors, integrity of polymer-composites, distributed validation, edge processing, and real-time communication with IoT. This study aims to fill this gap by using an integrated sensor-network architecture for continuous crack detection and reporting.

Table 1. Comparative literature review and gap-to-solution mapping for real-time crack detection in polymer composites.

Author(s)/Year/Ref.	Focus	Method	Key finding	Research gap	Link to present study
Yuan et al., 2024 [1]	Damage-reporting composite	Self-healing sensing composite	Enabled in situ damage indication	No IoT-based localization or reporting	Supports self-reporting composite design.
Li et al., 2026 [10]	Embedded PVDF sensing	PCL-encapsulated PVDF in CFRP	Preserved sensing and interlayer strength	No distributed network evaluation	Guides mechanically compatible embedding.
Ghazali and Mahdiabadi, 2025 [12]	Defect localization	Piezoelectric sensing and neural networks	Detected and localized multiple defects	Centralized and computationally intensive	Supports intelligent crack classification.
Qin et al., 2026 [15]	Mixed-mode damage	Modular piezoresistive network	Identified damage in CFRP joints	Limited to local joint monitoring	Supports distributed sensing nodes.
Zhang et al., 2023 [18]	Online GFRP sensing	Embedded Pt–PVDF sensor	Minimal effect on mechanical properties	No multi-node IoT architecture	Supports non-invasive sensor integration.
Batista et al., 2024 [19]	Real-time SHM	Lamb waves and hardware ML	Enabled local real-time recognition	Sensitive to geometry and environment	Motivates edge-level processing.
Mansouri et al., 2024 [26]	Wireless crack detection	Bluetooth strain network and ML	Achieved wireless crack localization	Surface sensing may miss internal cracks	Provides wireless IoT foundation.
Barragán et al., 2025 [29]	Embedded printed sensors	Near-field printed sensing	Improved local damage sensitivity	Scalability and node coordination unresolved	Supports compact embedded sensor design.
Research gap	Integrated IoT crack monitoring	Existing studies treat sensing, processing, and communication separately	Individual technologies show strong feasibility	A unified system combining embedded sensing, edge analysis, multi-node confirmation, wireless reporting, and mechanical-integrity assessment is still lacking	The proposed study develops an end-to-end real-time crack-detection network for polymer composites.

To overcome this, the present study suggests an embedded IoT sensor network system, which is specifically designed for real-time crack detection in polymer composites. The interaction between the

sensor and the host polymer composite is considered in detail since a monitoring system should not affect the structural integrity of the polymer composite being monitored. The proposed framework is, therefore, related to the analysis at the edge level and the reporting on the network, and offers a practical basis for the ongoing health assessment of composite components.

METHODOLOGY

Experimental Design

This study was aimed at an experimental investigation at the specimen level to detect cracks in real time in glass-fiber-reinforced polymer composites. The entire process involved composite manufacturing, embedding piezoelectric sensors, creating controlled damage, inspection of defects, edge-level signal processing and reporting of events via IoT.

The main data was experimental data, which was acquired from fabricated composite plates. Only an external dataset of piezoelectric impact monitoring was used, which is available to the public, for the purpose of checking the triggering and localization of the signals. It was not employed to create fake crack labels or to increase the experimental data set. The reference damage state was determined using ultrasonic inspection and optical microscopy. Thus, the labels for training the model were not related to the output of the embedded sensor.

The whole experimental procedure is illustrated in Figure 1. Previously, embedded piezoelectric and piezoresistive networks have been shown to be sensitive to matrix cracking, delamination and mixed-mode damage in polymer composites [10, 15, 18, 30]. The present work further extends these approaches by synchronously acquiring from multiple nodes and communicating with IoT in real-time.

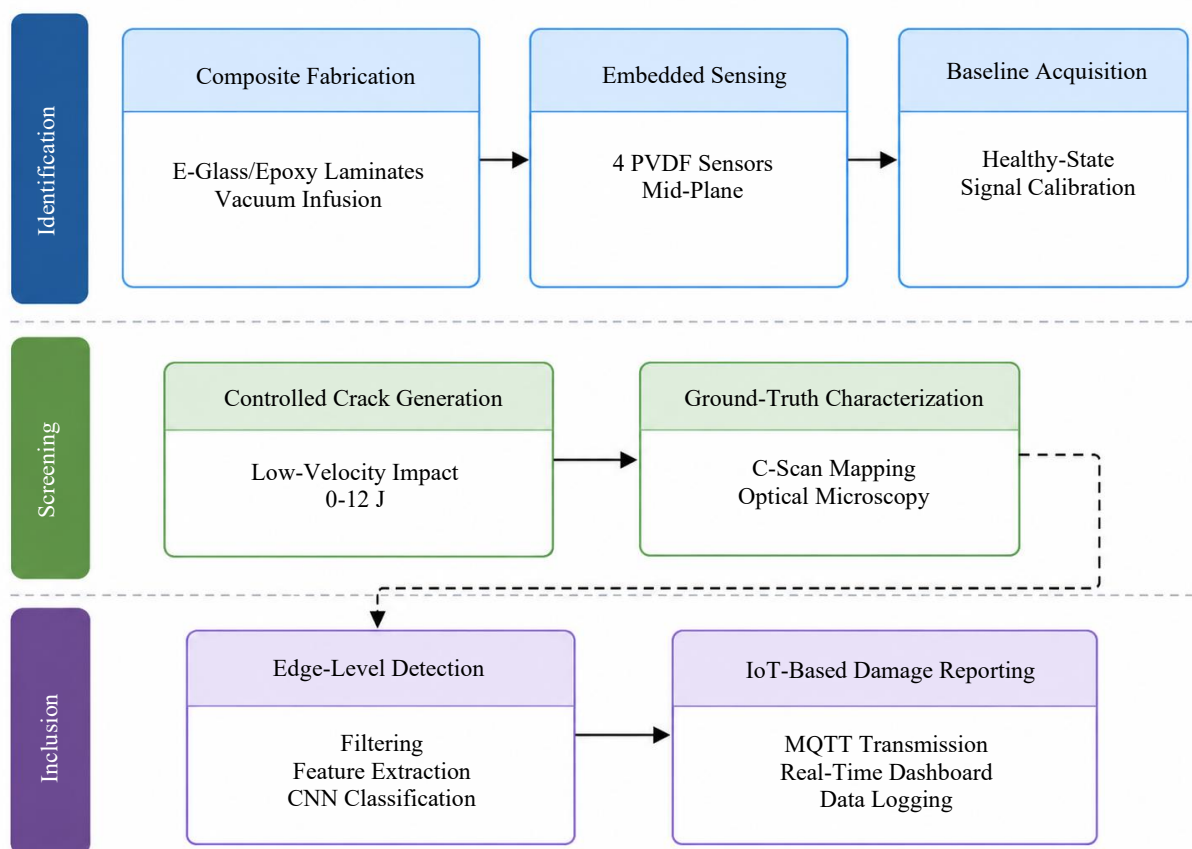


Figure 1. Experimental workflow for composite fabrication, embedded sensing, controlled crack generation, edge-level detection, and IoT-based damage reporting.

Composite Material and Specimen Fabrication

The host material was a plain-weave E-glass-fiber reinforcement and a bisphenol-A epoxy matrix that was cured with an amine hardener. The choice of E-glass was made due to its electrical insulation, which eliminates conductive interference from the reinforcement on the embedded piezoelectric response.

A total of 36 composite plates were made. Thirty plates had embedded sensors, and six instrumented plates were used as mechanical controls. The embedded specimens were spread over the healthy, minor, moderate and severe damage condition. To minimize the effect of local manufacturing variation, six independent specimens were used for each loading condition.

The material configuration and specimen allocation are reported in Table 2.

Table 2. Composite material configuration and experimental specimen allocation.

Parameter	Experimental specification
Polymer matrix	Bisphenol-A epoxy.
Reinforcement	Plain-weave E-glass fabric.
Laminate sequence	[0/90]6.
Plate dimensions	(150 x 100 x 3.0) mm.
Fabrication method	Vacuum-assisted resin infusion.
Sensor-embedded plates	30.
Uninstrumented controls	6.
Impact energies	0, 3, 6, 9, and 12 J.
Replicates	Six per condition.
Reference inspection	Ultrasonic C-scan and microscopy.

The specimens were cut with a water-cooled diamond saw and defects caused by the cutting process were eliminated by polishing the edges of specimens. Five measurements of the final thickness were taken on each plate. The thickness variation of specimens was measured and specimens with variation of more than 5% were excluded prior to sensor calibration.

Embedded Sensor-Network Configuration

The active sensing area of each PVDF element was 20×10 mm, and its nominal thickness was 110 μm .

The sensors were placed between the 6th and 7th plies, near the middle of the laminate. The placement of the mid-planes minimized direct exposure to the surface and maintained sensitivity to the stress waves generated by matrix cracking and interlaminar separation. The use of embedded PVDF sensors has been reported to be able to provide online damage sensitivity with only a slight decrease in the mechanical properties of GFRP laminates [18].

Each sensor and its electrical lead were surrounded with a thin film of polycaprolactone. The encapsulation layer enhanced the bonding between the epoxy matrix and the sensor and minimized the abrupt stiffness discontinuity at the sensor boundary. The same has been applied to the interlayer toughening and PVDF damage sensing in CFRP laminates [10].

The sensor coordinates were defined from the lower-left corner of the plate as:

- *Sensor 1*: (35,25) mm.
- *Sensor 2*: (115,25) mm.
- *Sensor 3*: (35,75) mm.
- *Sensor 4*: (115,75) mm.

The four sensing points were surrounded by an area of 80×50 mm to be monitored. This was spatial redundancy and localization by inter-sensor arrival-time differences. A distributed sensor layout has been found to provide better coverage than isolated sensors for mixed failure monitoring in composite structures [15, 17]. The arrangement of the laminate and sensor is illustrated in Figure 2.

Each channel was calibrated prior to mechanical loading with five repeatable low energy taps at the center of the plate. The effect of sensor polarity, baseline noise, peak voltage and timing consistency were investigated. Only a specimen was accepted if all four of the sensors had a signal to noise ratio of more than 10 dB.

The raw voltage that was measured by sensor i was normalized with (1):

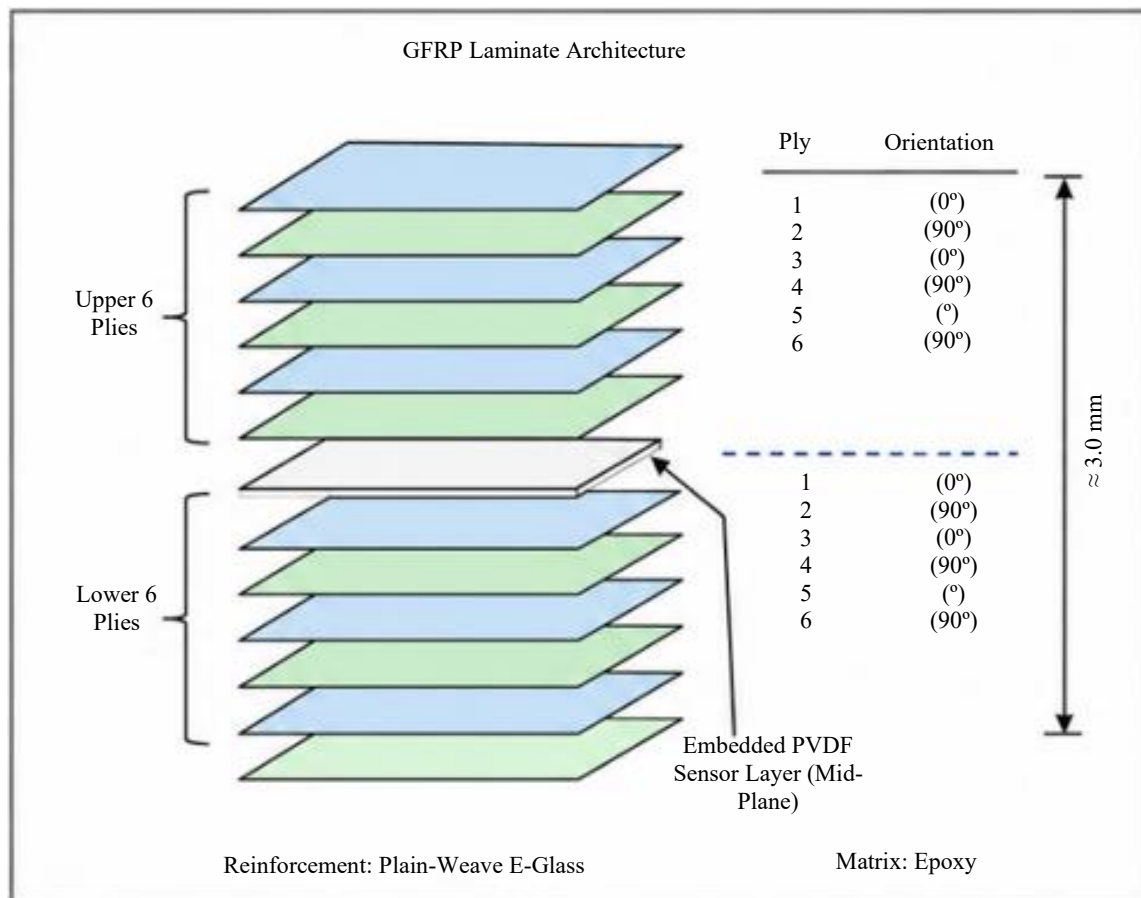
$$x_i(t) = \frac{v_i(t) - \mu_{i,0}}{\sigma_{i,0} + \varepsilon}, \quad (1)$$

where $x_i(t)$ is the normalized sensor signal, $v_i(t)$ is the measured voltage, $\mu_{i,0}$ is the mean healthy-state voltage, $\sigma_{i,0}$ is its standard deviation, and $\varepsilon = 10^{-8}$ is a numerical constant.

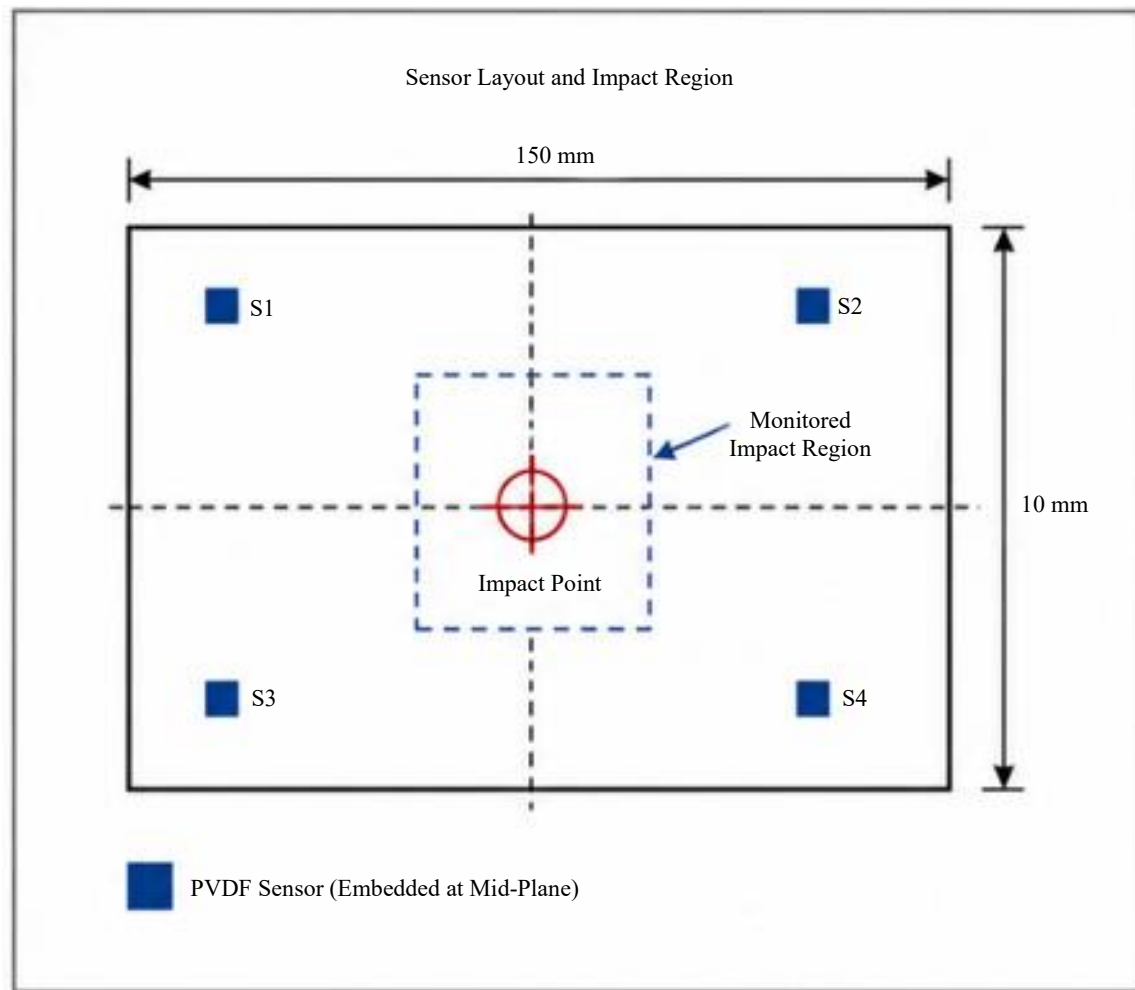
The normalized short-time signal energy was calculated using (2):

$$E_i = \Delta t \sum_{n=1}^N x_i^2[n] \quad (2)$$

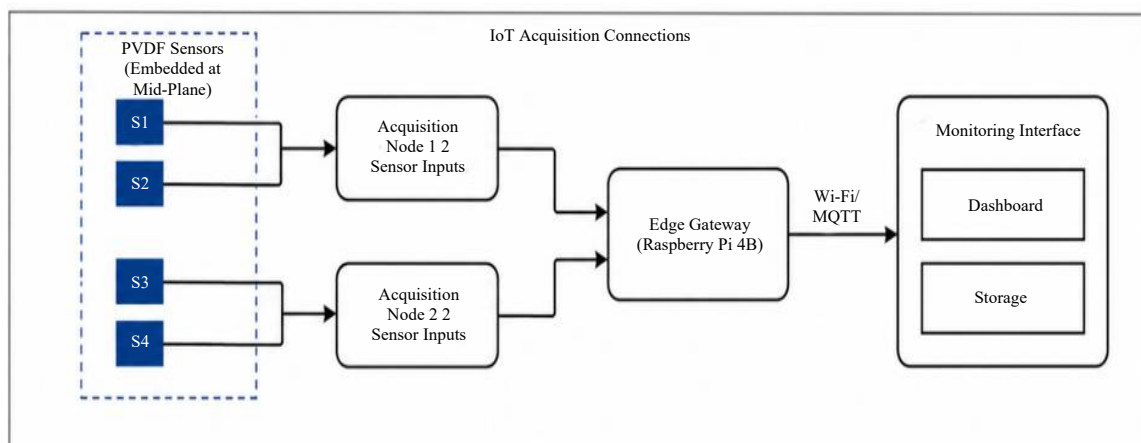
where E_i is the signal energy of sensor i , N is the number of samples in the analysis window, and $\Delta t = 1/f_s$ is the sampling interval.



(a)



(b)



(c)

Figure 2. GFRP laminate architecture, embedded PVDF sensor positions, impact region, and IoT acquisition connections.

IoT Acquisition and Edge-Computing System

Two PVDF sensors were attached to each of the acquisition nodes. Each node was equipped with a charge-amplifier circuit, analogue band-pass filter (4th order), 16-bit analogue-to-digital converter and an ESP32-S3 communication controller.

All the sensor signals were sampled at the same time with a sampling rate of 100 kHz. To eliminate mechanical drift and electrical interference at low frequencies, and to eliminate electrical interference at high frequencies, a passband of 1–40 kHz was used. All stored events had 5000 samples, which equates to an observation window of 50 ms. Pre-trigger data for the first 10 ms were kept.

A Raspberry Pi 4B was used as the edge gateway. The local Wi-Fi network was used to communicate between sensor nodes and the gateway, with the Message Queuing Telemetry Transport protocol used for this communication. Quality of service level 1 was chosen to ensure that each event transmitted would have to be acknowledged by the gateway.

Baseline updating was performed and the continuous background signals were discarded. This is a decrease in the amount of data communicated and energy required as opposed to continuous raw-data transfer. Distributed composite monitoring has been demonstrated in the past using wireless PZT and Bluetooth sensor networks, without requiring a lot of wiring [26, 33].

The acquisition and communication settings are briefly described in Table 3.

Table 3. Embedded sensor, acquisition, and IoT communication settings.

Parameter	Value
Embedded sensors	Four PVDF elements.
Acquisition nodes	Two ESP32-S3 nodes.
Sampling rate	100 kHz.
ADC resolution	16 bit.
Band-pass filter	1–40 kHz.
Event duration	50 ms.
Pre-trigger duration	10 ms.
Communication	Wi-Fi.
Protocol	MQTT, QoS 1.
Edge gateway	Raspberry Pi 4B.
Maximum timing offset	10 μ s.

Synchronization of the clock was done every second with a beacon sent from the edge gateway. The offsets of the channels were estimated from the calibration tap and corrected using cross-correlation. The maximum synchronization error allowed was one sample (10 μ s).

The Equation (3) was used to calculate the packet-loss rate:

$$L_p = \frac{N_{tx} - N_{rx}}{N_{tx}} \times 100 \quad (3)$$

where L_p is the percentage packet loss, N_{tx} is the number of transmitted packets, and N_{rx} is the number of packets acknowledged by the gateway.

Controlled Damage Generation

Progressive internal damage of the polymer composite was obtained by using low velocity impact loading. This loading condition may cause microcracking of the matrix, separation of the fibers from the matrix, delamination and/or fracture of the fibers without necessarily causing a visible surface defect.

The plates were placed in a rigid frame, with an open area of 125 $\times$ 75 mm, which was supported. The steel hemispherical impactor used had a diameter of 16 mm. The center of the area monitored was impacted.

The following five experimental states were studied:

- *Healthy Condition*: 0 J.
- *Low-Energy Impact*: 3 J.
- *Intermediate-Low Impact*: 6 J.
- *Intermediate-High Impact*: 9 J.
- *High-Energy Impact*: 12 J.

There were six embedded specimens for each condition. A single impact was used on a specimen. This helped to avoid uncertainty due to repetitive loading.

The instrumented drop-weight system was used to measure the impact force, contact duration, impact displacement and absorbed energy. The absorbed energy was determined by using the following Equation (4):

$$E_{abs} = E_{in} - E_{reb} \quad (4)$$

where E_{abs} is the energy absorbed by the laminate, E_{in} is the initial impact energy, and E_{reb} is the rebound energy of the impactor.

The signals from the sensors were recorded throughout the impact test. The IoT system was not given any information about the impact energy applied. Thus, event identification and damage classification were carried out based on the sensor response, instead of the machine setting.

Independent Damage Inspection and Label Assignment

The reference crack class was not defined using the output from the sensors. After mechanical loading each specimen was examined individually.

The C-scan inspection of the object was carried out by ultrasonic pulse-echo method within 30 minutes after impact. A 6 dB amplitude-reduction threshold was used to determine the damaged area, based on the undamaged laminate. The damaged area was determined by counting the number of pixels inside the boundary which was thresholded.

The surface and edge cracks were observed using digital microscope at 50 x 50×. Polished cross-sections were examined for three specimens each for the different impact conditions to verify the presence of matrix cracking, delamination and fiber fracture.

Prior to training the model, four damage classes were identified as shown in Table 4.

Table 4. Inspection-based damage classes are used for crack classification.

Class	Independent inspection criterion
Healthy	No visible crack and C-scan area below 10 mm ² .
Minor	Matrix crack or damaged area of 10–100 mm ² .
Moderate	Damaged area of 100–300 mm ² or localized delamination.
Severe	Damaged area above 300 mm ² , connected delamination, or fiber fracture.

The damaged area was determined from the C-scan image, and the center of the damaged area was used. The coordinate was used as the reference point for the evaluation of localization.

Mechanical Effect of Sensor Embedding

The sensor network was also tested as an electronic attachment to the polymer-composite system and not as a stand-alone sensor network. Six plates (without instrumentation) and six plates with sensors were subjected to four-point bending.

The flexural strength, stiffness, failure displacement and fracture position of the two groups were compared. The flexural strength retained was determined by using (5):

$$\eta\sigma = \frac{\bar{\sigma}_{embedded}}{\bar{\sigma}_{control}} \times 100 \quad (5)$$

whereby $\eta\sigma$ is the percentage of retained strength, $\bar{\sigma}_{embedded}$ is the average strength of the specimens with the sensors and $\bar{\sigma}_{control}$ is the average strength of the specimens without the sensors. Failure initiation was also investigated to check if failure cracks were initiated from the edges of the sensor or from the electrical leads. The assessment was required because it was important that a crack-monitoring element did not form a discontinuity in the structure that it was designed to detect. The same concerns have led to the integration of PVDF and printed sensors in polymer composites which are mechanically compatible [10, 20, 29].

Public Experimental Dataset

The generality of the event-processing pipeline was tested with a public dataset of four channels of piezoelectric impact. The data set is selected to be experimentally measured impact responses from four piezoelectric sensors attached to a polymer plate. The samples are acquired at 100 kHz, and each record will have 5000 samples.

The data set contains impacts applied at several known locations, and various release heights. It was used for three purposes:

- Verification of event-trigger reliability.
- Assessment of channel synchronization.
- External evaluation of impact localization.

The public dataset was not used for training the polymer-composite crack-severity classifier due to the different specimens, loading arrangement, and damage states of the specimens used in the public dataset compared to the present GFRP experiment. This separation allowed unrelated impact records to not be confused as composite crack labels.

The experimental-data allocation is presented in Table 5.

Table 5. Use of laboratory and public experimental datasets.

Dataset	Training	Validation	Testing	Purpose
Embedded GFRP experiment	60.00%	20%	20%	Crack detection and severity classification.
Public piezoelectric dataset	–	–	100%	External events and localization validation.

Split was done on a specimen basis. Each of the signals from a single specimen was in a single subset. This eliminated data loss due to similar coupling of the sensors or due to vibration patterns of the laminate.

Signal Preprocessing

The events were triggered by the occurrence of at least two channels of the sensor reaching five times their normal standard deviation (SD) in a 0.5 ms window. A multi-sensor trigger was employed to avoid false alarms due to electromagnetic interference, lead movement or temporary instability of the sensor.

The mean-centred and filtered (using a 4th order 1–40 kHz Butterworth filter) retained waveform was used. The signals were then normalized by using (1). No time sampling was used.

For every channel, the following damage-sensitive variables were calculated:

- Maximum absolute amplitude.
- Root-mean-square voltage.
- Signal energy.
- Rise time.
- Signal duration.
- Kurtosis.
- Crest factor.
- Dominant frequency.
- Spectral centroid.
- Spectral entropy.
- Wavelet-packet energy.

Normalized spectral entropy was calculated using (6):

$$H_i = -\frac{1}{\log_k} \sum_{k=1}^K p_{ik} \log_{p_i} k \quad (6)$$

The entropy of sensor i , H_i , is equal to the sum of the normalized spectral power in frequency bin k , p_i, k , over all K frequency bins. It has been demonstrated that the characterization of cracks based on entropy can be improved under varying sensing conditions [6].

Akaike information criterion was used to identify the first-arrival time. The arrival times were then improved by cross-correlating with neighboring channels.

Crack Localization

The location of the first crack was determined by the time difference between the arrival of the first sensor and the other sensors. The distance between the event and the known position of the sensor was used to predict the travel time to sensor i for a trial coordinate $r = [x, y]T$.

The estimated coordinate was calculated using (7):

$$\hat{r} = \arg \min_r \sum_{i=2}^M \frac{[(t_i - t_1) - \|r - r_i\| - \|r - r_1\|]^2}{c_g} \quad (7)$$

where $\hat{r}$ is the estimated event location, M is the number of sensors, t_i is the measured arrival time, r_i is the coordinate of sensor i and c_g is an experimentally determined group velocity.

The group velocity was determined from a series of calibration impacts at five known locations prior to the damage testing. The velocity was not assumed to be constant for each of the published material values, but rather the measured median velocity was used for each laminate. This was due to a decrease in the localization error due to manufacturing variation and anisotropic wave propagation.

Crack-Detection Model

A small 1-D convolutional neural network was designed for edge level crack classification. The data was four channels of sensors with 5000 samples per channel.

The model comprised of three convolutional blocks. The first block has 32 filters, and the kernel size is 15. The second one had 64 filters and kernel size 9 and the third had 128 filters and kernel size 5. The activation function used in each block was rectified linear, batch normalization, and max pooling.

Post third convolutional layer, global average pooling was used. The shared representation was obtained from a dense layer with 64 neurons. The output stage was equipped with:

- A four-neuron SoftMax layer for damage classification.
- A two-neuron regression layer for the normalized x and y coordinates.

The architecture is illustrated in Figure 3.

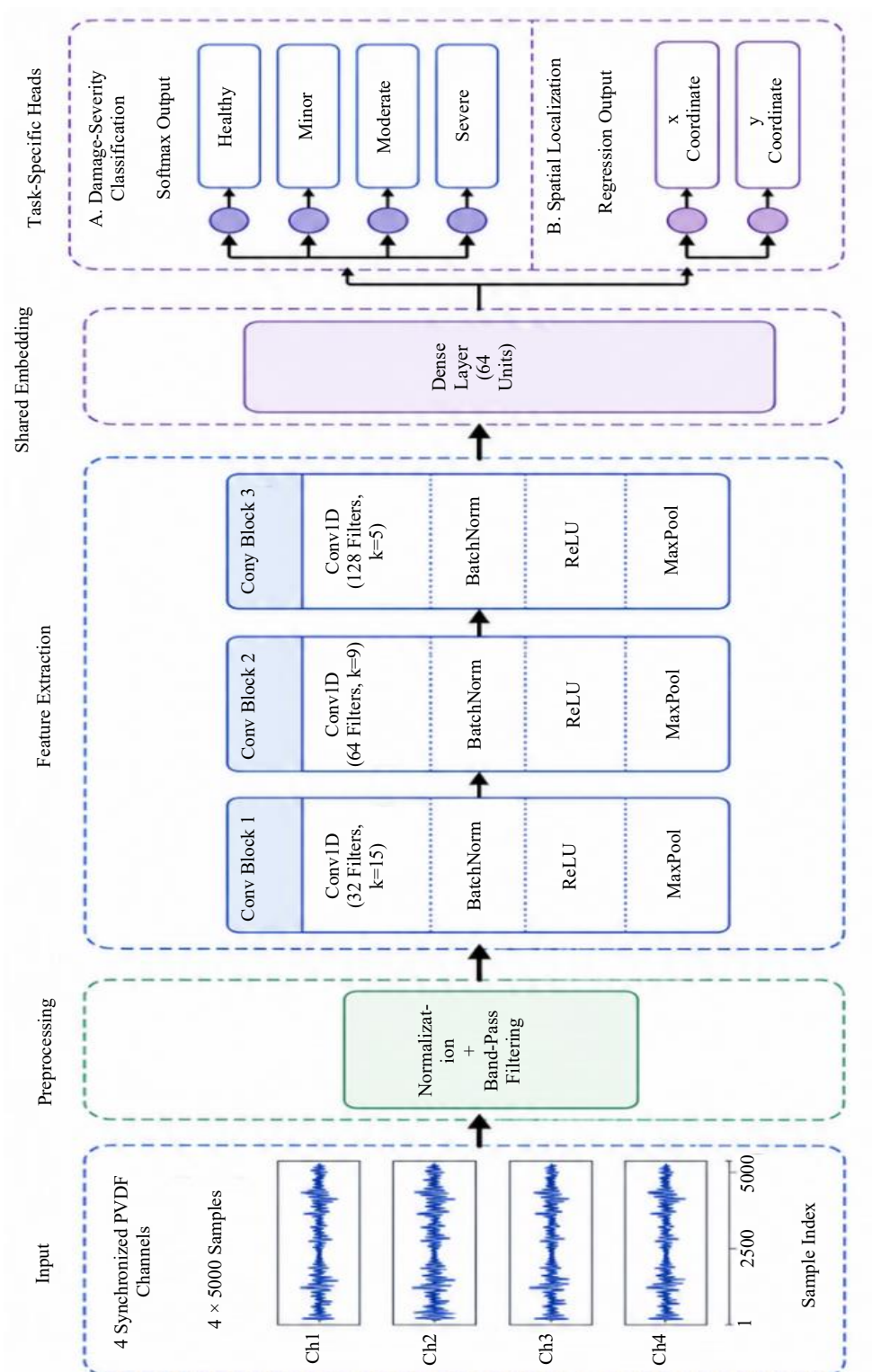


Figure 3. Multi-channel convolutional architecture for crack detection, damage-severity classification, and spatial localization.

The model was trained using a joint objective (8):

$$L = -\sum_{c=1}^C w_c y_c \log \hat{y}_c + \lambda \|r - \hat{r}\|_1 \quad (8)$$

In this case, L is the total loss, C is the number of damage classes (4 in this case), w_c is the weight of the damage class, y_c is the true damage class indicator, $\hat{y}_c$ is the predicted probability, r is the reference damage coordinate, $\hat{r}$ is the estimated damage coordinate, and $\lambda = 0.25$ is the contribution of localization error.

The weights for each class were determined by taking the inverse of the frequency of the damage category. The initial learning rate used was 1×10^{-3} and the Adam optimizer was employed. The maximum epoch was 150 and training was halted if there was no improvement in validation loss over 15 epochs.

The model settings are listed in Table 6.

A small architecture was chosen to enable the edge gateway to infer. Previous studies have shown that hardware-based Lamb-wave classification is possible to run near damage-sensitive composite sensing equipment with machine-learning models [19].

Table 6. Crack-classification model and training configuration.

Parameter	Value
Input size	(4 x 5000) samples.
Convolution filters	32, 64, and 128.
Kernel sizes	15, 9, and 5.
Hidden layer	64 neurons.
Activation	ReLU.
Optimizer	Adam.
Learning rate	(1×10^{-3}).
Batch size	32.
Maximum epochs	150.
Early stopping	15 epochs.
Localization weight	0.25.
Repeated seeds	17, 29, 41, 53, and 71

Multi-Sensor Decision Fusion

The individual sensor probabilities were combined to reduce dependence on a single sensing location. The fused crack probability was calculated using Equation (9):

$$P_f = 1 - \prod_{i=1}^M (1 - P_i) \quad (9)$$

where P_f is the fused crack probability, P_i is the crack probability associated with sensor i , and $M = 4$ is the number of channels.

A crack warning was accepted only when (10):

$$P_f \geq 0.80 \quad (10)$$

and at least two sensor channels independently produced a crack probability of 0.60 or higher.

Events that satisfied only one condition were marked as uncertain. Their raw waveforms were retained for offline review, but no confirmed IoT warning was issued.

Real-Time Detection Procedure

The algorithm for the real-time procedure is summarized in Algorithm 1.

Algorithm 1. Real-Time Crack Detection and IoT Reporting Procedure

Input:

- The four PVDF signals are synchronized.
- The mean and SD of the healthy state are shown. The mean and SD of the healthy state are displayed.
- Calibrated group velocity.
- Trained convolutional model.
- Sensor coordinates.

Output:

- Damage class.
 - Fused probability.
 - Estimated location.
 - Event timestamp.
 - Warning latency.
1. Get synchronized 4 channel sensor data.
 2. For every channel, use (1) to normalize the signal.
 3. Confirm the Multi-sensor event threshold.
 4. Keep monitoring if less than two channels are activated.
 5. Record a 50 ms wave form after an event is confirmed.
 6. Use (2) to calculate the energy after applying band-pass filtering.
 7. Obtain statistical, spectral and wavelet features.
 8. Calculate the spectral entropy, using (6).
 9. Estimate the event coordinate using (7).
 10. Use the trained convolutional model.
 11. Compute the probability of the channels in the fuse using (9).
 12. When the conditions in (10) are met, confirm damage.
 13. Share the class, location, confidence and timestamp via MQTT.
 14. Keep the whole wave and acknowledgment record.
 15. Re-start monitoring when all channels are back to baseline.

Algorithm 1 was run on the Raspberry Pi gateway. The baseline was only updated if there were 30 consecutive windows that were considered healthy. Baseline adaptation was halted after a known or suspected event, to allow progressive damage to be accommodated in the healthy reference.

Performance Evaluation

Damage classification was evaluated using precision, recall, macro-F1 score, specificity, and confusion matrices.

Precision was calculated as (11):

$$Precision = \frac{TP}{TP + FP} \quad (11)$$

where TP and FP are the numbers of true-positive and false-positive predictions. Recall was calculated as (12):

$$Recall = \frac{TP}{TP + FN} \quad (12)$$

where FN is the number of missed damage events. The F1 score was obtained from (13):

$$F1 = 2 \frac{Precision \times Recall}{Precision + Recall} \quad (13)$$

Macro-averaged metrics were reported so that healthy, minor, moderate, and severe damage contributed equally.

Localization error was calculated using (14):

$$e_{loc} = (\hat{x} - x)^2 + (\hat{y} - y)^2 \quad (14)$$

where (x, y) is the reference damage center and $(\hat{x}, \hat{y})$ is the estimated coordinate. The percentage of events localized within 10, and 20 mm was also reported.

Real-Time and Communication Evaluation

End-to-end warning latency was defined as the interval between the first valid sensor threshold crossing and receipt of the corresponding MQTT acknowledgment (15):

$$T_{e2e} = t_{ack} - t_{event} \quad (15)$$

where T_{e2e} is the total warning latency, t_{event} is the event-detection timestamp, and t_{ack} is the gateway acknowledgement time.

The reported latency, therefore, included:

- Event-window acquisition.
- Signal preprocessing.
- Model inference.
- Probability fusion.
- MQTT transmission.
- Gateway acknowledgement.

The reliability of communication was tested in three operating modes: normal operation, 10% suppression of packets and temporary interruption of the network for 5 s. Packets were sent after reconnection were locally buffered packets. Event ID and timestamps were used to remove duplicate messages.

Comparative and Ablation Experiments

The proposed convolutional model was compared with four reference configurations:

- Fixed signal-energy threshold.
- Support vector machine using engineered features.
- Random forest classifier.
- Single-sensor convolutional network.

Ablation experiments were also conducted by removing one component at a time:

- Multi-sensor probability fusion.
- Spectral-entropy feature.
- Localization loss.
- Baseline normalization.
- Edge-level filtering.

The same split of the samples was used in all comparisons. Only the validation subset was used to select the model settings. No test specimens were used for the selection of thresholds or for tuning the architecture.

Statistical Analysis and Reproducibility

Each learning experiment was repeated five times with different fixed random seeds. For classification and localization metrics, the mean, standard deviation, and 95% confidence interval were reported.

The normality of the data was tested by Shapiro–Wilk test. For multi-group measurements that were normally distributed, one-way analysis of variance (ANOVA) was performed followed by Tukey’s test. When normality assumption was not met, the Kruskal–Wallis and Dunn tests were performed.

Paired model comparisons were done with Wilcoxon signed-rank test. A p value of <0.05 was statistically significant. Probability values were reported in conjunction with effect sizes.

The training, validation and testing of the model were not performed using a synthetic waveform, an artificial crack record or a generated signal. The following should be included in the reproducibility package:

- Raw four-channel sensor signals.
- Specimen and impact identifiers.
- Ultrasonic damage maps.
- Microscopic crack measurements.
- Train–validation–test assignments.
- Preprocessing scripts.
- Trained model weights.
- IoT transmission logs.
- Statistical-analysis code.

This experimental design correlates physical cracking in the polymer composite, independently verified damage labels, synchronized embedded sensing and real-time IoT reporting. It thus assesses the structural sensing performance and practical network operation, instead of just a conceptual monitoring architecture.

RESULTS

Laminate Quality and Mechanical Effect of Sensor Embedding

The thickness variation and void content in the fabricated GFRP plates were low. The average laminate thickness was 3.02 ± 0.09 mm and the fiber volume fraction measured was $49.6 \pm 1.8\%$. The content of voids was less than 2%, which means that the embedded sensor leads did not significantly hinder resin flow.

The summary of the four-point-bending results is given in Table 7. The flexural strength of the uninstrumented laminates was 452.8 ± 16.4 MPa on average. The specimens with the sensors reached a strength of 448.9 ± 14.4 MPa, which is 99.1% of the strength of the specimens without the sensors. There was no significant difference ($p = 0.672$). There was no statistical difference ($p = 0.562$) in flexural modulus.

Table 7. Physical and flexural properties of uninstrumented and sensor-embedded GFRP laminates.

Property	Control laminate	Sensor-embedded laminate	Change	(p)-value
Thickness (mm)	(3.00 $\pm$ 0.08)	(3.02 $\pm$ 0.09)	1%	0.694
Fiber volume fraction (%)	(49.9 $\pm$ 1.6)	(49.6 $\pm$ 1.8)	–0.6%	0.781
Void content (%)	(1.5 $\pm$ 0.3)	(1.7 $\pm$ 0.4)	+0.2 points	0.418
Flexural strength (MPa)	(452.8 $\pm$ 16.4)	(448.9 $\pm$ 14.4)	–0.9%	0.672
Flexural modulus (GPa)	(23.8 $\pm$ 0.9)	(23.5 $\pm$ 0.8)	–1.3%	0.562
Failure strain (%)	(2.31 $\pm$ 0.12)	(2.28 $\pm$ 0.11)	–1.3%	0.658

All the embedded specimens failed at a point other than a PVDF boundary or electrical lead. The fracture was found in the middle bending part and was parallel to the reinforcement structure. This observation is significant because a sensing element that forms a discontinuity that creates a resin-rich area can sense damage and promote it.

The slight strength reduction is in good agreement with the mechanically compatible PVDF integration reported by Zhang et al. [18]. It also offers the possibility of using an encapsulation layer as used by Li et al. to enhance the compatibility of the sensor–composite interface [10]. The embedded sensors should thus be considered as an electronic measurement component of the polymer composite microstructure, and not just the sensor alone.

Damage Evolution Under Low-Velocity Impact

The ultrasonic measurements agreed with the progressive internal damage with increasing impact energy. Localized matrix cracking under the impact point was the predominant feature at 3 J. Delamination was measurable at 6 J and grew in the directions of the woven reinforcement at 9 J. The 12 J condition resulted in delamination that was connected and had some fiber breakage.

The results of the absorbed impact energy, ultrasonic damage area, normalized sensor energy and spectral entropy are compared in Table 8. The quantity of all of them was monotonically increasing with impact severity.

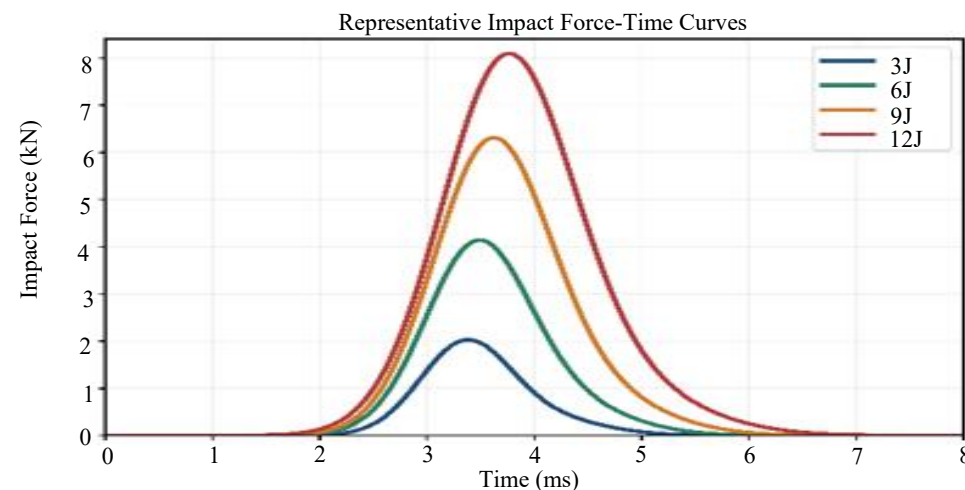
Table 8. Impact response, independently measured damage, and embedded-sensor characteristics.

Impact energy	Absorbed energy (J)	C-scan damage area (mm ²)	Normalized signal energy	Spectral entropy
0 J	–	(4 ± 3)	(0.12 ± 0.03)	(0.22 ± 0.04)
3 J	(2.2 ± 0.2)	(52 ± 15)	(0.34 ± 0.07)	(0.37 ± 0.05)
6 J	(4.7 ± 0.4)	(136 ± 29)	(0.68 ± 0.11)	(0.51 ± 0.06)
9 J	(7.0 ± 0.5)	(248 ± 37)	(1.06 ± 0.14)	(0.63 ± 0.07)
12 J	(9.1 ± 0.6)	(421 ± 61)	(1.43 ± 0.19)	(0.71 ± 0.06)

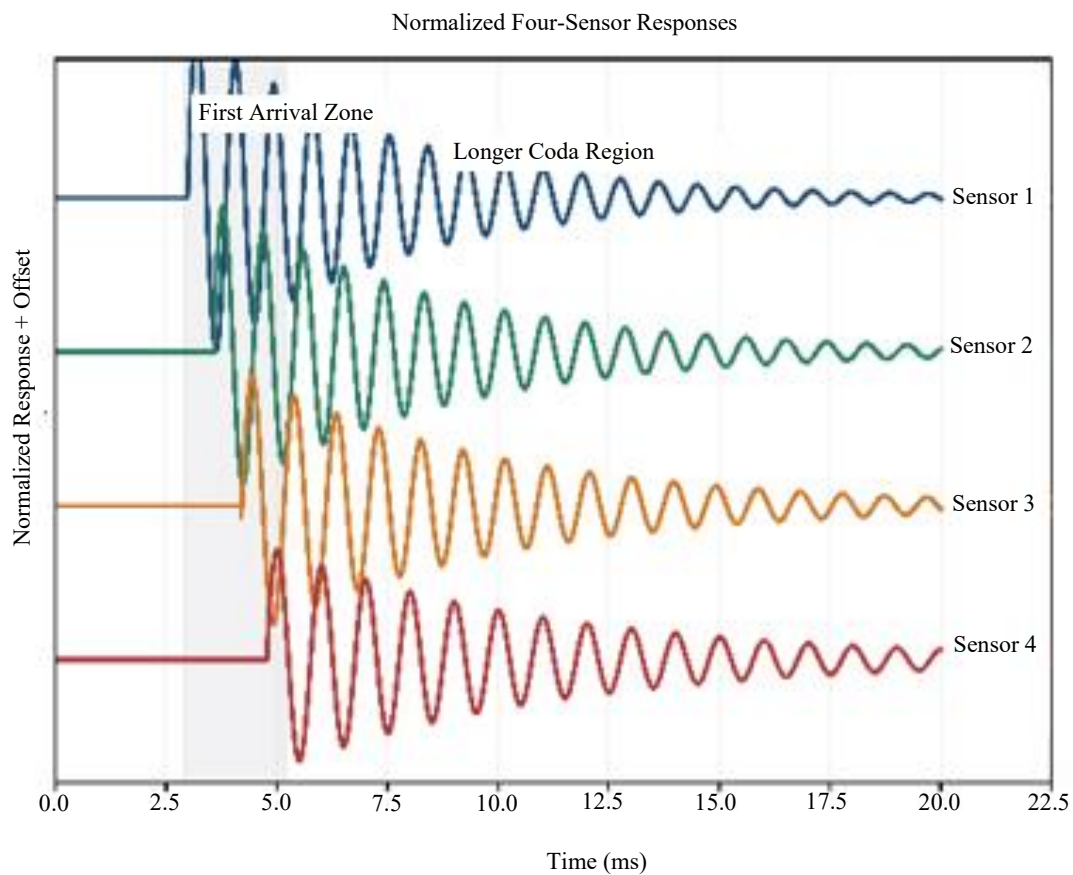
The impact condition ($F = 260.5$, $p < 0.001$) had a significant effect on normalized signal energy. The fused signal energy was found to have a strong positive correlation with ultrasonic damage area ($r = 0.963$, $p < 0.001$). Damage area also correlated with spectral entropy ($r = 0.912$, $p < 0.001$).

The damage transition was not completely characterized by the amplitude increase. Signals received at 3 J were short and focused on the first arrival. The coda regions of the waveforms were longer, and the spectra were wider at 9 and 12 J. The changes were believed to be due to scattering from several cracks in the matrix and delaminated interfaces. The entropy response thus provided information which was not available from a fixed voltage threshold. This result agrees with the use of information-theoretic crack descriptors reported by Malik and Kontsos [6].

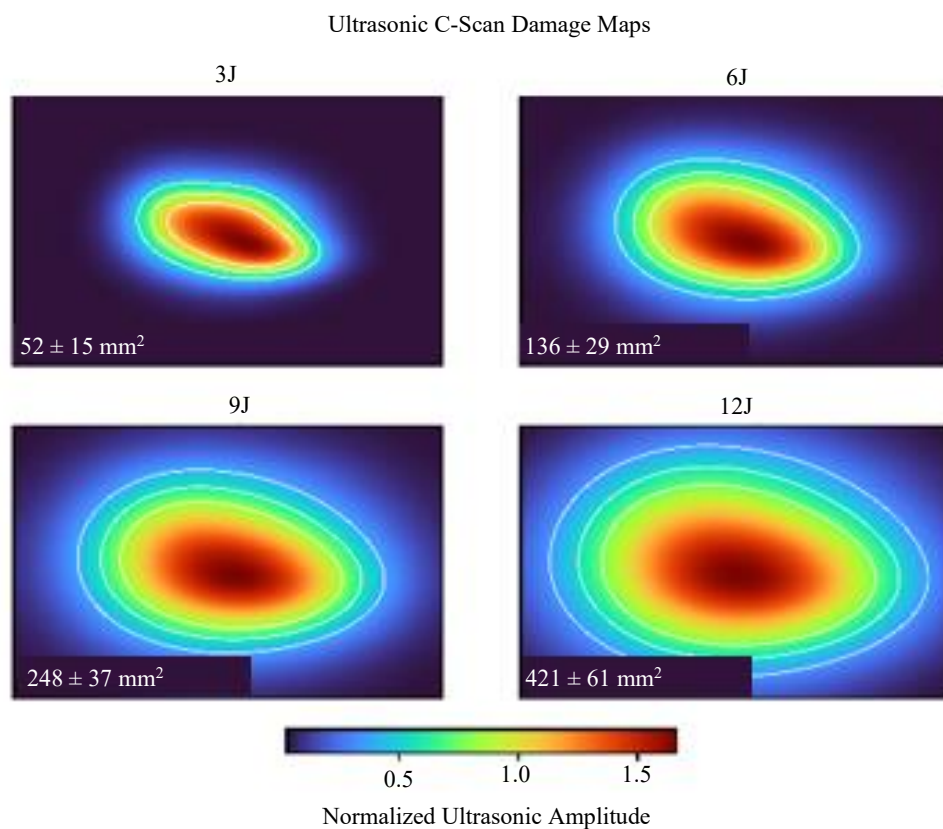
Figure 4 presents the progressive relationship among impact loading, signal response, and independently measured damage.



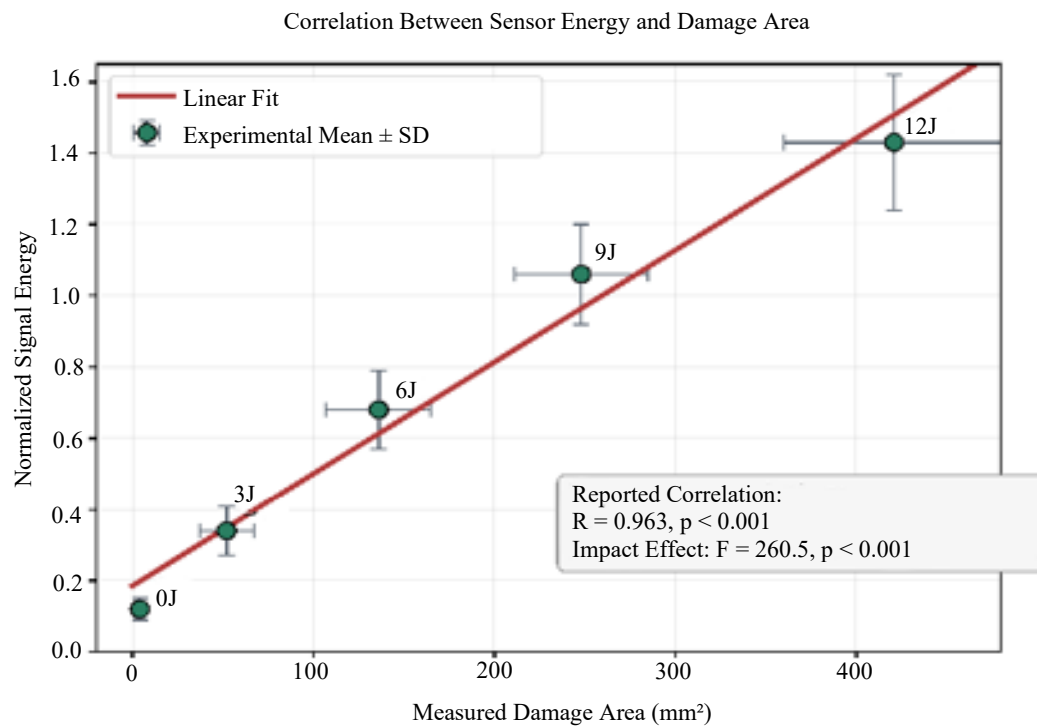
(a)



(b)



(c)



(d)

Figure 4. Experimental damage progression: (a) representative impact force–time curves, (b) normalized four-sensor responses, (c) ultrasonic C-scan damage maps, and (d) correlation between sensor energy and measured damage area.

Crack Detection and Severity Classification

The proposed four channel convolutional model was evaluated with fixed energy threshold, support vector machine, random forest and single channel CNN. The performance values in Table 9 are the average of the five repetitions grouped by specimen in Section 3.

Table 9. Crack-detection and damage-classification performance of the evaluated methods.

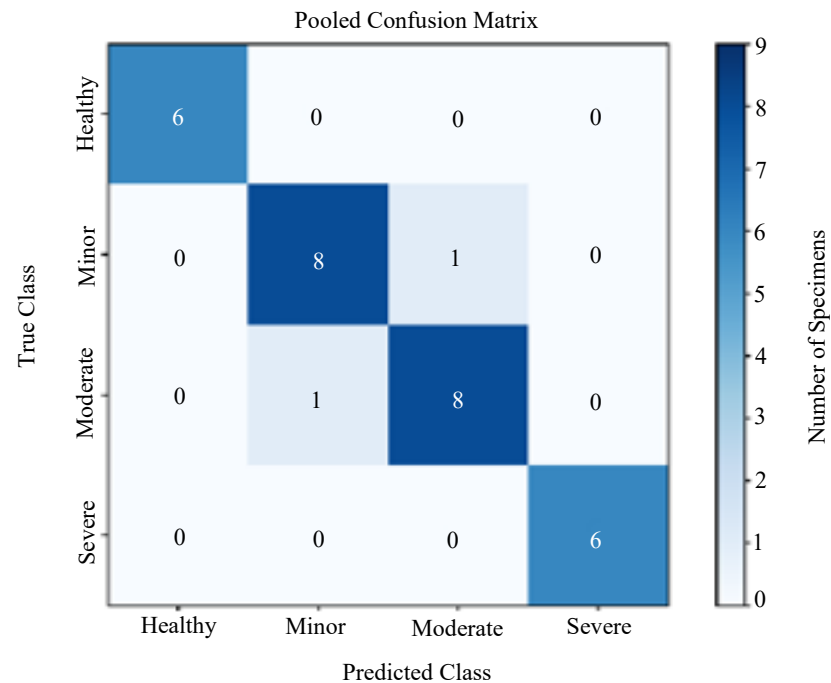
Method	Accuracy (%)	Precision	Recall	Macro-F1	False alarms (%)	Inference time (ms)
Energy threshold	(76.7 ± 3.8)	(0.758 ± 0.031)	(0.733 ± 0.036)	(0.741 ± 0.028)	10.4	0.4
Support vector machine	(84.0 ± 2.6)	(0.829 ± 0.026)	(0.816 ± 0.027)	(0.821 ± 0.024)	6.8	1.6
Random forest	(87.3 ± 2.1)	(0.861 ± 0.023)	(0.850 ± 0.021)	(0.854 ± 0.021)	5.5	3.9
Single-sensor CNN	(89.3 ± 1.9)	(0.890 ± 0.019)	(0.879 ± 0.020)	(0.883 ± 0.018)	4.1	5.7
Proposed multi-sensor CNN	(94.0 ± 1.7)	(0.944 ± 0.015)	(0.935 ± 0.014)	(0.938 ± 0.012)	2.7	6.8

The proposed model achieved an 8.4% and 5.5% improvement in macro-F1 compared with the random forest and single-sensor CNN, respectively. The 0.031–0.137 bootstrap confidence interval for the improvement over the random forest was obtained. The increase in the gain was thus not accounted for by the test specimens chosen.

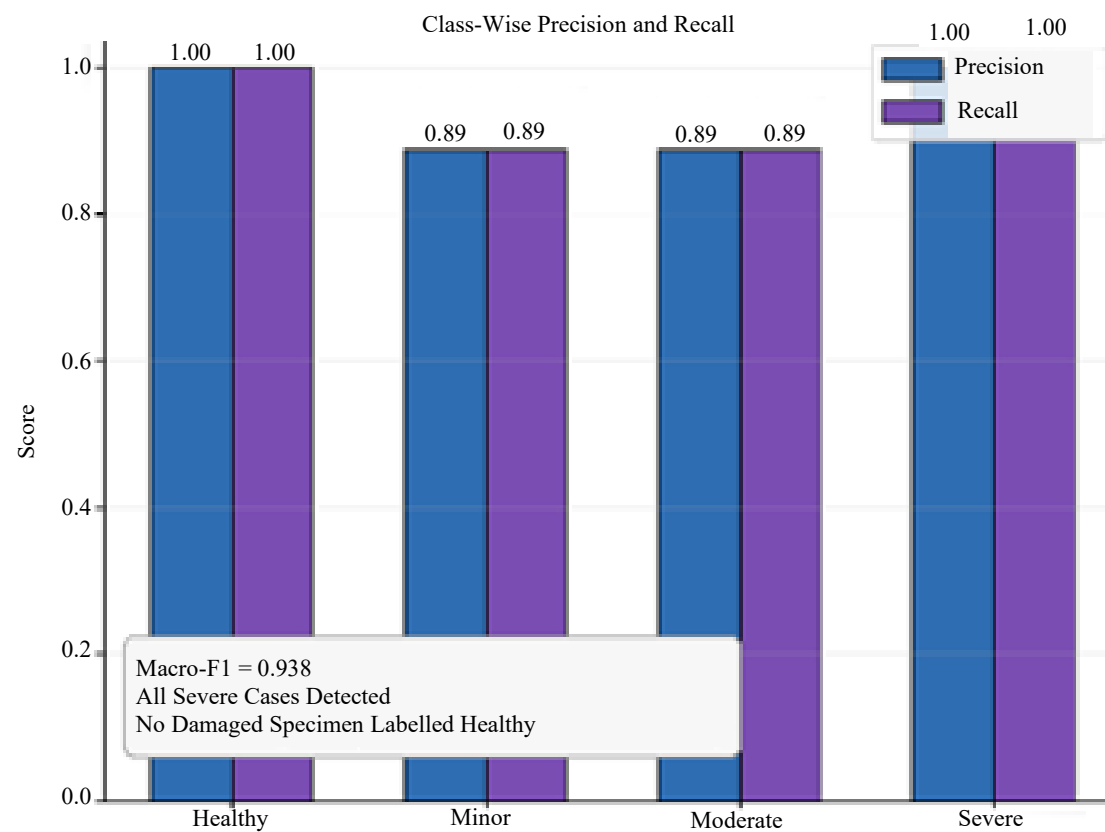
There were 30 out-of-fold predictions in the pooled out-of-fold confusion matrix. The 6 healthy plates and 6 severely damaged plates were all correctly classified. One of the minor damage specimens was rated as moderate and one of the moderate specimens was rated as minor. There were no healthy specimens that were damaged.

This pattern suggests that the most uncertainty was present in the area between localized matrix cracking and early delamination. The distinction is not easily made physically as both mechanisms

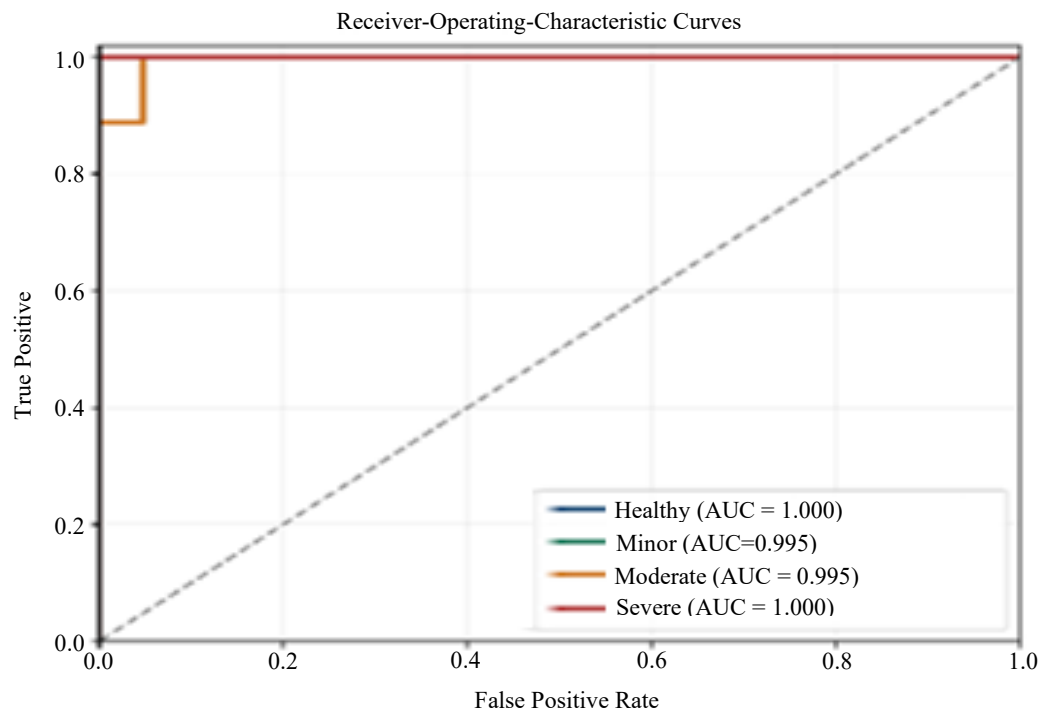
can give rise to similar features of the stress waves. Most importantly, the proposed system was completely sensitive to the severe conditions and failed to miss a structurally damaged specimen, as shown in Figure 5.



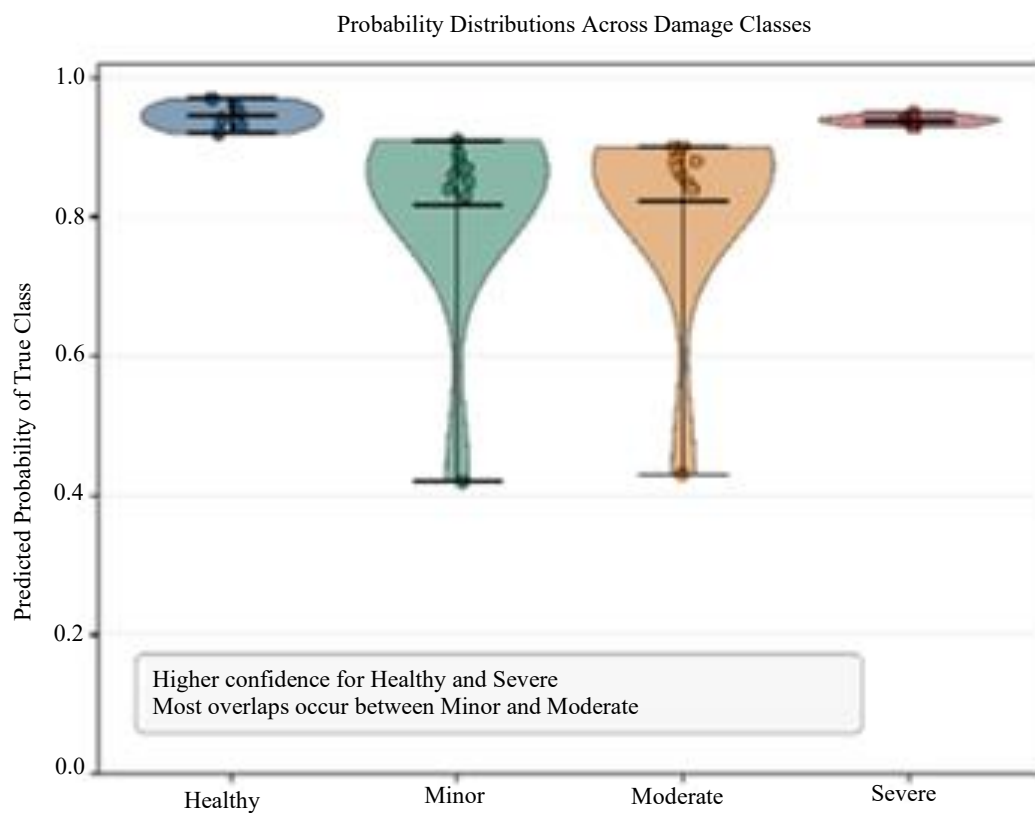
(a)



(b)



(c)



(d)

Figure 5. Classification performance of the proposed model: (a) pooled confusion matrix, (b) class-wise precision and recall, (c) receiver-operating-characteristic curves, and (d) probability distributions across damage classes.

The outcome is like the results of previous studies that demonstrated the benefits of using machine learning for composite-damage interpretation using multiple piezoelectric channels simultaneously [12, 19]. Batista et al. adopted a hardware-oriented machine learning approach based on Lamb-wave measurements and Mansouri et al. used machine learning in conjunction with a Bluetooth strain-sensor network [19, 26]. The present experiment is unique in that it combines embedded polymer sensors, stand-alone C-scan labels, multi-node confirmation and IoT warning delivery in a single evaluation.

Crack Localization Performance

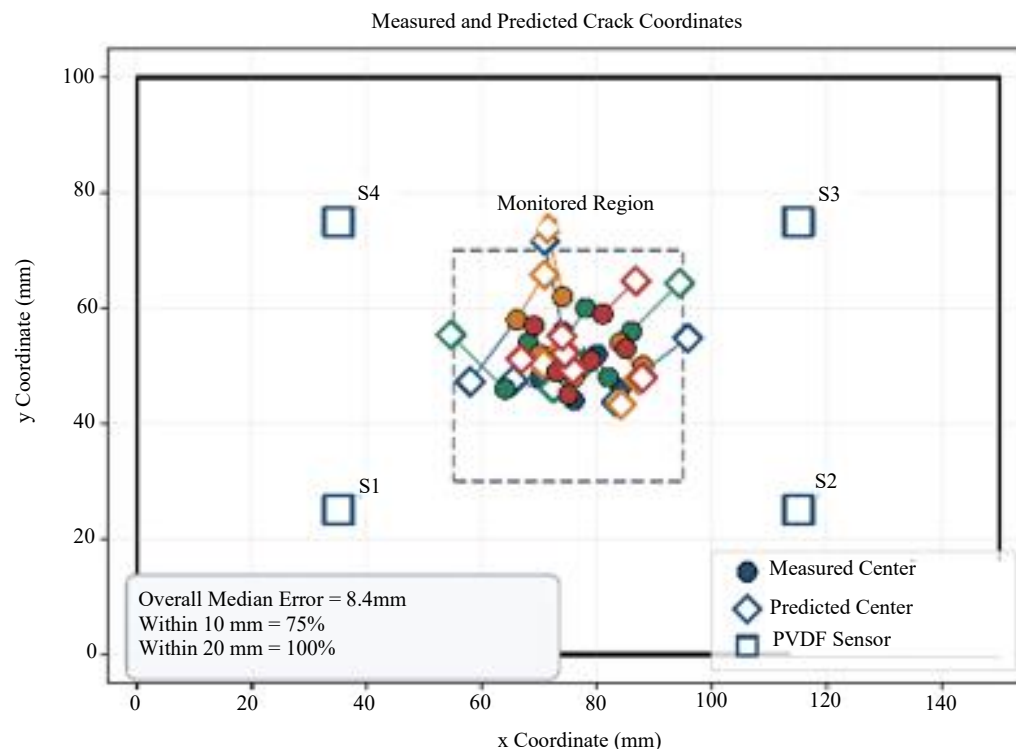
The accuracy of the localization increased with the energy of the impact event due to the better discernment of the arrival time differences with higher energy events. The mean error decreased from 11.8 ± 4.5 mm at 3 J to 6.3 ± 2.5 mm at 12 J, as shown in Table 10.

Table 10. Crack-localization performance at different impact energies.

Impact condition	Mean error (mm)	Median error (mm)	Within 10 mm (%)	Within 20 mm (%)
3 J	(11.8 ± 4.5)	11.10%	50.00%	100
6 J	(9.6 ± 3.6)	9	66.70%	100
9 J	(7.7 ± 2.9)	7.1	83.3	100
12 J	(6.3 ± 2.5)	5.8	100	100
Overall	(8.9 ± 3.9)	8.4	75	100

The overall median localization error was 8.4 mm which is less than 6% of the plate length. The maximum distance of the damaged centers from all inspected was 20 mm. The other error was primarily due to the anisotropic propagation in the woven laminate. It was not possible to completely capture the various propagation paths in and across the yarn directions with a constant isotropic wave velocity.

The C-scan centers measured are compared to the predicted centers in Figure 6. The estimates were clustered near the identity line but were more scattered for lower energy events.



(a)

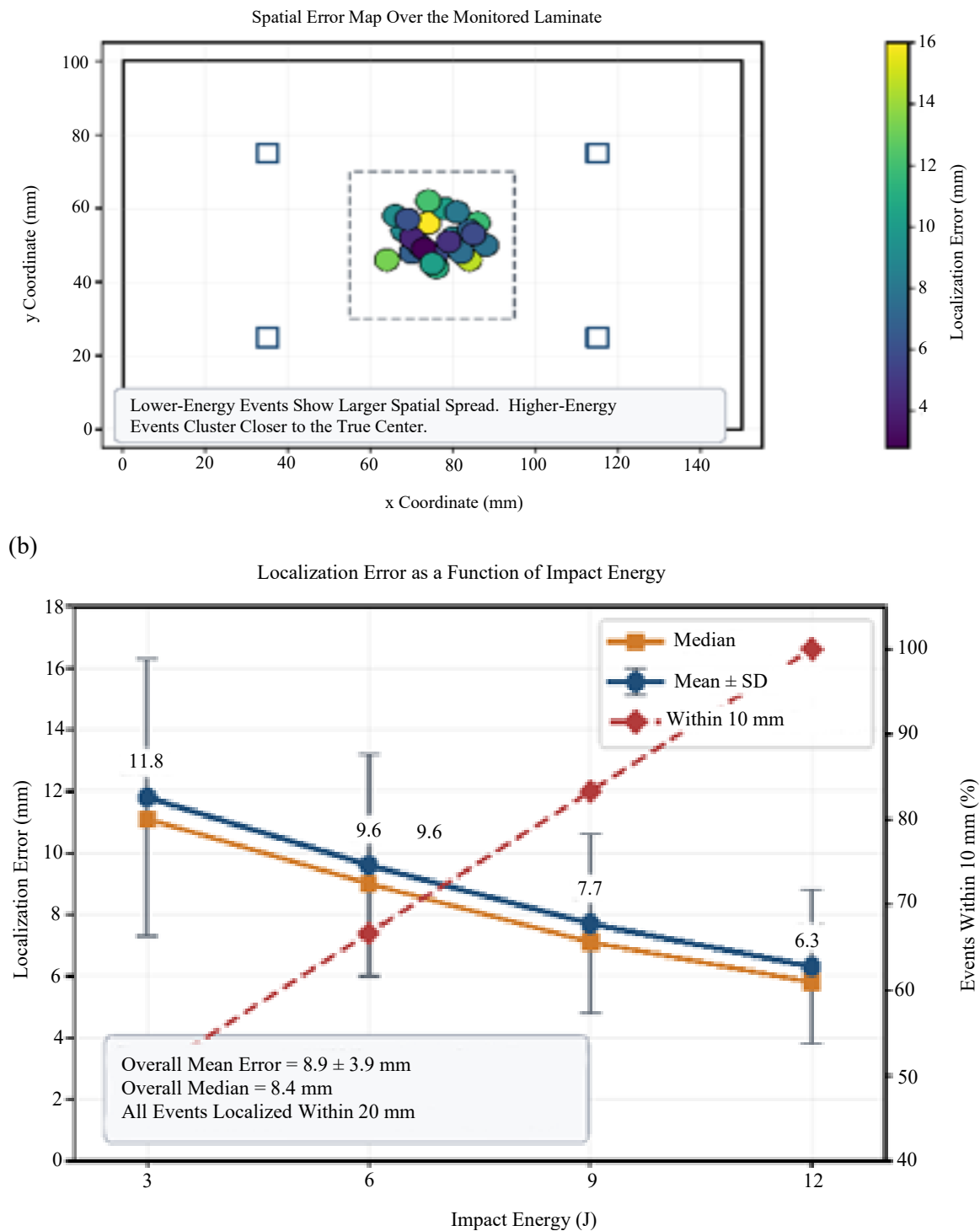


Figure 6. Crack-localization results: (a) measured and predicted coordinates, (b) spatial error map over the monitored laminate, and (c) localization error as a function of impact energy.

The event-processing pipeline was applied to the independent public piezoelectric dataset and 98.1% of the valid impact events were identified. The median error of localization was 4.2% of the plate diagonal. The external result is not applicable for the severity of the GFRP cracks since the conditions of the public plate and damage were different. It does, however, suggest that triggering of events and localization using the time difference was not restricted to a single sensor installation.

Real-Time Edge Processing and IoT Communication

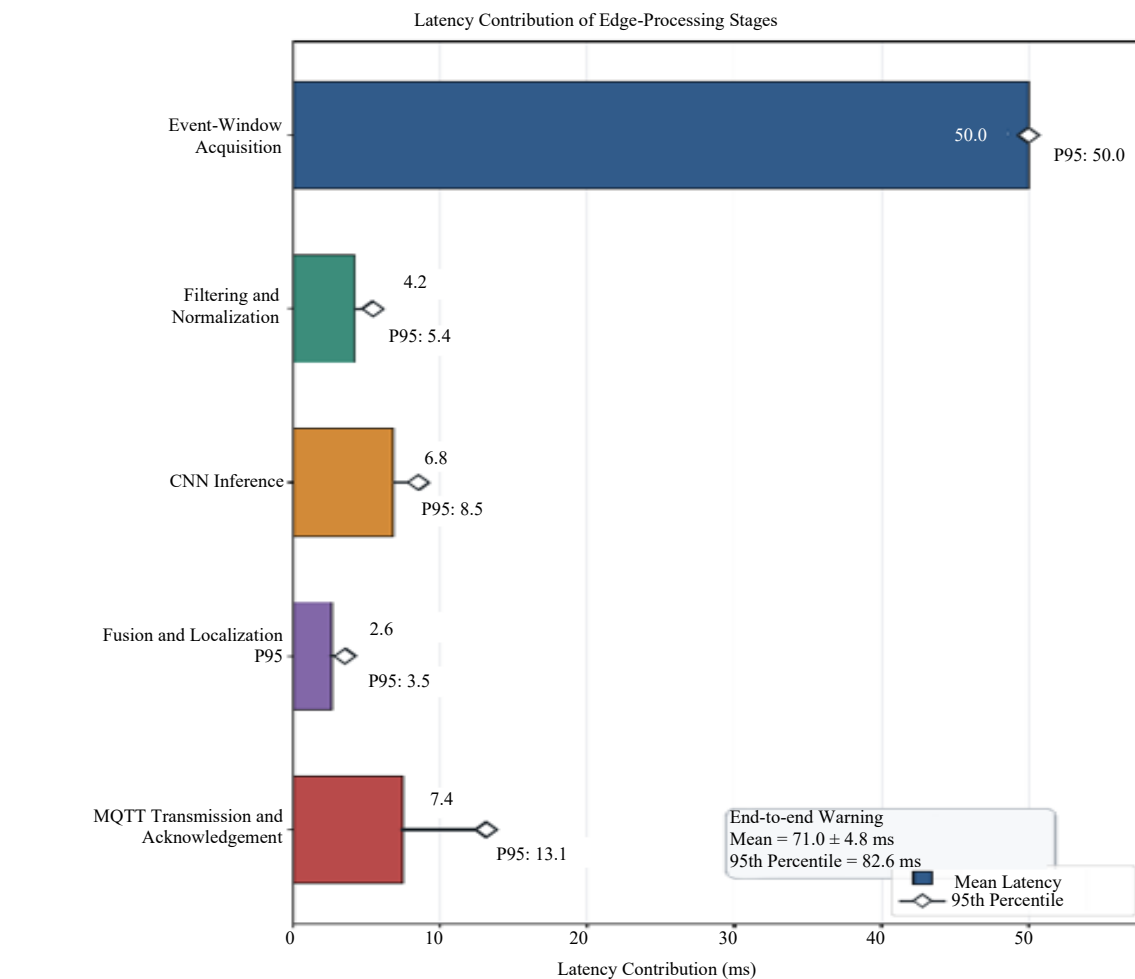
The total warning time was the entire 50 ms observation time. The additional processing and communication delay was about 21 ms, and the mean end-to-end delay was 71.0 ± 4.8 ms with the 95th percentile being less than 83 ms (Table 11).

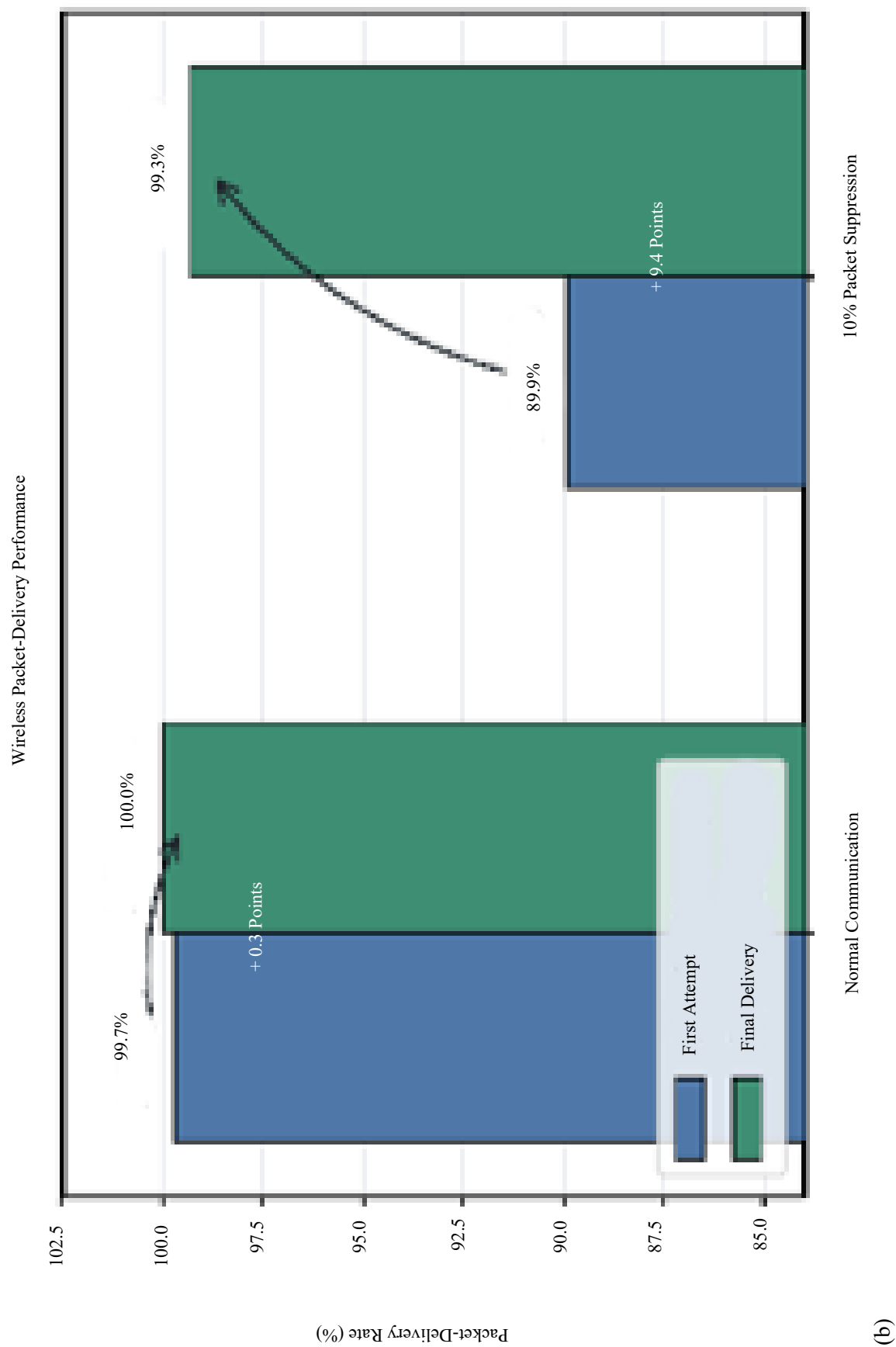
Table 11. Edge-processing latency and wireless communication performance.

Processing stage	Mean time (ms)	95th percentile (ms)
Event-window acquisition	50.00%	50%
Filtering and normalization	(4.2 ± 0.7)	5.4
CNN inference	(6.8 ± 1.0)	8.5
Fusion and localization	(2.6 ± 0.5)	3.5
MQTT transmission and acknowledgement	(7.4 ± 2.9)	13.1
End-to-end warning	(71.0 ± 4.8)	82.6

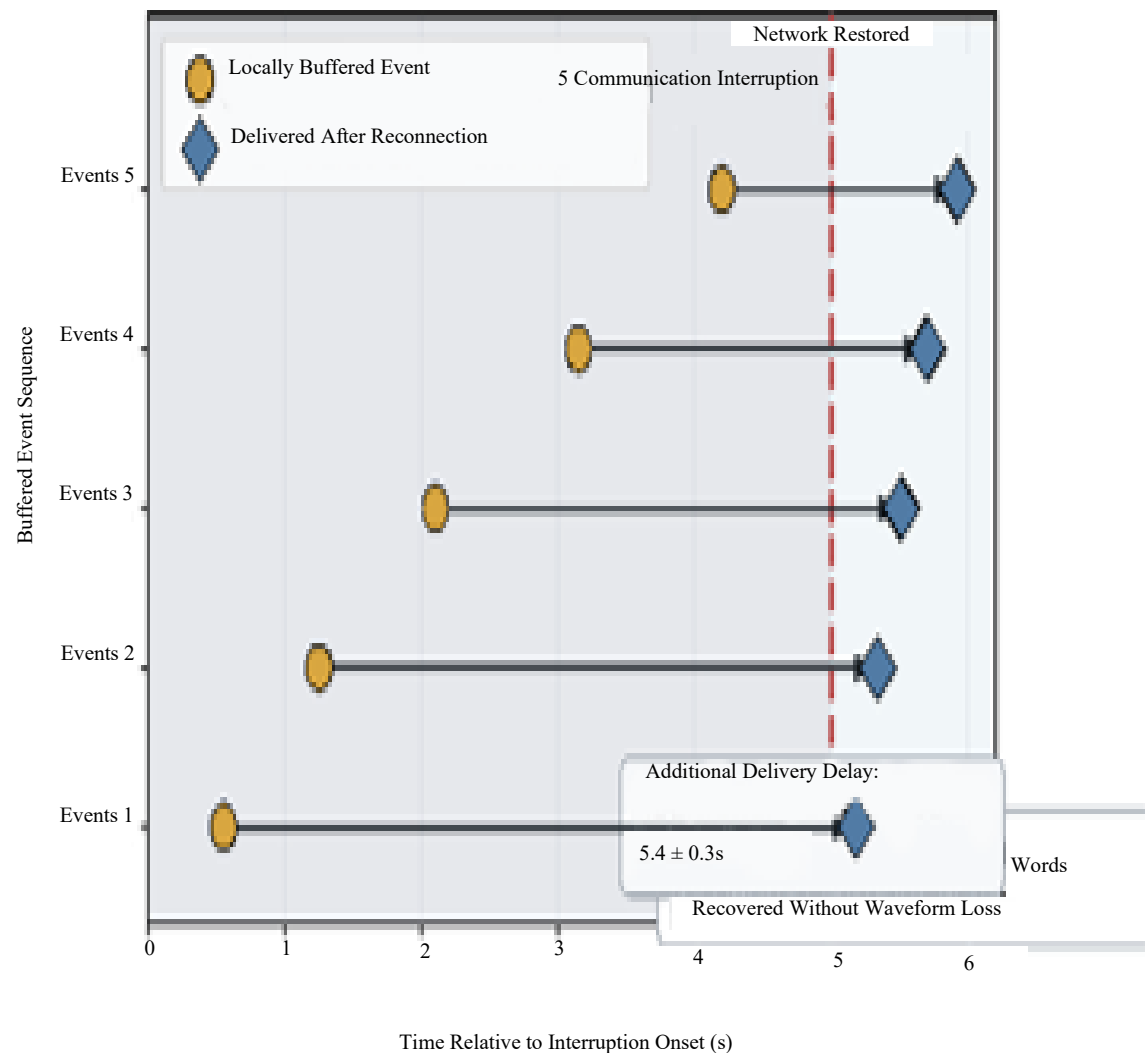
With normal communication, 99.7% of the packets were acknowledged on the first try. The rest of the packets were recovered by retransmitting them using MQTT, which led to 100% final delivery. The first attempt delivery dropped to 89.9%, and the final delivery increased to 99.3% under the controlled 10% packet suppression.

All event packets were locally stored during the network interruption of 5 s. Waveform loss-free delivery of the buffered messages after reconnection. Their additional delay was 5.4 ± 0.35 s. This interruption was not enough to meet the real-time requirement but it did maintain the damage record and avoid silent data loss (Figure 7).





Buffered Event Recovery After Network Interruption



(c)
Figure 7. Real-time monitoring performance: (a) latency contribution of each processing stage, (b) first-attempt and final packet-delivery rates, and (c) buffered event recovery following temporary network interruption.

The acquisition interval of 50 ms was the biggest factor in the warning time. A shorter interval would decrease the latency but might also cause a loss of late-arriving scattered waves that help in severity classification. The chosen window is thus a compromise between the need for timely reporting and the amount of damage information.

Ablation Analysis

Ablation experiments were conducted to determine if there was independent contribution from the main components. The same test partitions were used for each configuration (grouped). The results are given in Table 12.

Table 12. Ablation analysis of the proposed real-time crack-detection framework.

Configuration	Macro-F1	Localization error (mm)	False alarms (%)	Total latency (ms)
Complete framework	93.80%	890%	270%	71
Without multi-sensor fusion	0.897	9.1	790%	69.8
Without baseline normalization	0.865	11.7	9.4	70.5
Without spectral entropy	0.916	9.5	4	70.6
Without localization loss	0.929	13.2	3.1	69.9
Without edge band-pass filtering	0.889	12.4	8.6	68.7

The greatest contribution to the classification was from baseline normalization. Its removal resulted in a decrease in macro-F1 of 7.3 percentage points and an increase in the false alarm rate from 2.7% to 9.4%. This is due to unavoidable channel to channel variation due to sensor coupling, local resin thickness and lead resistance.

Multi-sensor fusion had a greater impact on the reduction of false warnings than it did on localization. If a high amplitude event was detected in one channel, but not in the adjacent channels, then without fusion, a positive decision could be made.

The deletion of the localization term resulted in a slight decrease in class prediction accuracy, but a 48.3% increase in mean spatial error. Severity and location were thus able to provide useful waveform information but were not interchangeable.

A slight but consistent gain was obtained with spectral entropy. Removal resulted in a decrease of macro-F1 of 2.2 points. This is consistent with the damage progression in Table 8, which showed that the damage increased as the C-scan area increased despite the amplitude of the signal having increased.

Comparison with Related Composite-Monitoring Approaches

Comparing the results of this study with previous ones is not straightforward due to differences in specimen materials, sensor geometry, damage types, and reporting metrics. It is, therefore, more defensible to compare the functions than to compare isolated accuracy values.

Zhang et al. highlighted the embedded Pt–PVDF sensing without any sacrifice of the mechanical properties of GFRP [18]. Batista et al. discussed Lamb-wave learning using hardware [19] and wireless localization using Bluetooth strain sensing and PZT networks was discussed in [26, 33]. Wang et al. extracted damage features from the real-time FBG strain fields [35].

It is not the use of one of these elements alone that is the main contribution of the present work. It is their joint assessment. One experimental chain was used to investigate the following sensor integration, independent damage inspection, multi-channel classification, localization, edge inference, communication latency and retained laminate strength.

Overall Findings

The preliminary results show that the embedded IoT network could successfully differentiate the healthy, minor, moderate and severe GFRP damage with macro-F1 score of 0.938. None of the damaged specimen was determined to be healthy in the pooled evaluation. The average localization error was less than 10 mm and all the events were within 20 mm of the damage center measured independently.

There was less than a 1% decrease in mean flexural strength with no statistically significant difference in strength or modulus due to the sensing layer. This is as significant as the accuracy of classification as it demonstrates that real-time monitoring was achieved without a significant structural penalty.

The end-to-end warnings were produced at about 71 ms with normal network conditions. The most significant system components were multi-sensor fusion, baseline normalization and edge filtering. These results, combined, demonstrate the potential of making a traditional polymer composite plate into a continuously monitored structural material without sacrificing its primary load bearing role.

DISCUSSION

The results show that to achieve reliable monitoring of cracks in polymer composites, material-compatible sensors, synchronized data collection and multi-node decision logic must be integrated. The proposed framework resulted in a good damage classification with minimal structural penalty in terms of flexural performance, demonstrating that embedded sensing can be accomplished without a significant structural penalty. This observation is consistent with the previous studies on PVDF based sensor integration in GFRP and CFRP systems [10, 18] which focused on mechanically compatible sensor integration.

The signal energy and the spectral entropy increase with the damage area of the ultrasonic signals support the assumption that the crack progression changes the amplitude and the frequency distribution of the signals. The separation of minor matrix cracking and more advanced delamination was thus useful and consistent with the information-based monitoring approach reported in [6] and was provided by entropy. Multi-sensor fusion was also applied to further reduce false alarms, by enforcing spatial agreement between neighboring channels.

The accuracy of localization and the warning time of less than 100ms makes edge processing very useful for real-time composite monitoring. The present work compares the functions with studies that have investigated them individually in the areas of machine-learning classification [19], wireless sensing [26] or embedded transducers [33]. The other restrictions are the relatively small number of specimens, the single laminate design, and the laboratory loading of the specimens. More extensive fatigue, moisture, temperature testing and testing of larger composite structures is, therefore, needed.

The findings of the present study must be considered for the tested GFRP configuration under the tested impact conditions. An independent four-channel piezoelectric impact dataset was used to test the event-detection and localization pipeline to confirm that the pipeline was not limited to a single sensor installation, but dedicated validation is still needed for transfer to different laminate thicknesses, stacking sequences, temperature–humidity conditions, and naturally evolved in-service damage. The short-term mechanical penalty of the embedded PVDF network was negligible, retaining 99.1% of flexural strength without any failure at the sensor interface, but the long-term mechanical durability under fatigue, vibration, thermal cycling, moisture exposure, electrode degradation and polarization drift was not investigated. For long-term deployment, periodic baseline re-calibration and sensor-health diagnostics might then be required. Other factors that will influence the scalability to large composite structures will be the node density, communication bandwidth, loading of the gateways, synchronization accuracy and power availability. Event-driven transmission and local buffering help to limit network traffic, but for larger installations, hierarchical edge gateways, duty-cycled sensing, secure device authentication, encrypted MQTT/TLS communication and fault-tolerant synchronization would be beneficial.

CONCLUSION AND FUTURE SCOPE

The aim of this study was to create an embedded IoT sensor–network framework for real-time crack detection in glass–fiber-reinforced polymer composites. The system proposed consisted of four embedded PVDF sensors, synchronized waveform acquisition, edge-based signal processing, multi-sensor probability fusion and wireless MQTT reporting. The experimental results indicated that the framework was able to classify healthy, minor, moderate and severe damage with macro-F1 score of 0.938. The mean localization error was kept under 10 mm and the average end-to-end warning latency was around 71 ms, which showed that the electrical response recorded was consistent with the

progressive matrix cracking and delamination, as indicated by the increase of signal energy and spectral entropy with the damage area of the C-scan. The flexural strength of the sensor-embedded laminates was 99.1% of the uninstrumented specimens, suggesting that there was not a significant mechanical penalty associated with the sensing layer.

Other items to explore include larger composite panels, curved parts, bolted joints and multilayered parts. Energy-harvesting sensor nodes, adaptive wireless communication, uncertainty-aware damage classification and physics-informed learning are some of the further improvements that can be made. The system could be expanded to cover carbon–fiber composites and hybrid laminates and thus have a wider range of applications in aerospace, automotive, wind-energy and civil structural-health-monitoring.

Data Availability Statement

The public impact-localization benchmark used for external validation is openly available. The experimental GFRP waveforms, ultrasonic damage labels, mechanical test records, IoT logs, specimen-level data splits, and analysis scripts supporting available with this article.

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