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ML-Enhanced Self-Healing Fiber-Reinforced Polymer Composites with Embedded IoT Sensors for Damage Prediction

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Abstract

Fiber-reinforced polymer (FRP) composites are widely used in aerospace and structural systems; nevertheless, the potential for microcracking and fatigue-induced performance degradation remains an obstacle with respect to improved service life. Traditional self-healing methods, while performing well on a chemical level, often lack real-time diagnostic awareness and adaptive control. To circumvent this, we developed a machine-learning augmented self-healing FRP composite, in which a DCPD–Grubbs catalytic matrix was combined with IoT sensor network capability and a hybrid CNN–LSTM predictive model. This framework identifies, interprets, and performs in-situ actions, enabling the material to become an intelligent closed-loop system capable of self-healing and managing damage automatically instead of passively. Our work differs from previous studies, which focus on the simulated static analysis of FRP composites. The synergy between IoT and CNN–LSTM learns continually from the multi-sensor data and predicts failure mechanisms and severity of internal damage based on load cycles prior to mechanical failure. The reported experiments demonstrate an average healing capacity of 90.6%; an R^2 of 0.989 prediction accuracy; and 11 ms as the latency to decision outcomes, exceeding state-of-the-art indications for action in thermally and magnetically initiated self-healing composites. The model's adaptive retraining preserved accuracy across multiple healing cycles without increasing energy consumption; thus, it is appropriate for use over the long term. These results constitute a paradigm shift in polymer composites design – from passive structural materials to active, data-based agents capable of self-diagnosing and repairing. The attribute proposed overcomes barriers to sustainable, low-power, and intelligent composite systems and is aligned with the Journal of Polymer Composites' current vision for follow-on research on multifunctional and self-adaptive polymer composite architectures.

Keywords: Damage prediction, fiber-reinforced polymers, IoT sensor integration, machine learning, self-healing polymer composites

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INTRODUCTION

The composites based on fiber-reinforced polymer (FRP) have become one of the most promising materials in high-performance engineering buildings in the past decades due to their high strength–weight ratio, thermal stability, and corrosion resistance [1]. Such composites are replacing traditional metallic parts in the aerospace, automotive, marine, and the civil infrastructure due to their ability to offer structural performance with design freedom [2]. However, as much as it has such advantages, FRP structures are not resistant to damage. Microcracks are formed progressively in the polymer matrix in response to cyclic mechanical loading, temperature change, or other environmental conditions that cause degradation. Although these cracks are small in nature, they accumulate into delaminations and fiber–matrix debonding areas that seriously undermine the structural integrity [3]. This is being extremely difficult due to the fact that most of this damage is internal and invisible which in most cases results in catastrophic failure without even showing prior signs.

Conventional non-destructive testing (NDE) like ultrasonic testing, X-ray radiography, acoustic emission have been useful in post-inspection diagnosis but in most cases these methods are restricted by accessibility and space coverage [4]. This means that such techniques usually involve the building being idle or partially dismantled, so that there is no constant in-service monitoring. Therefore, even with several decades of NDE development, the objective of attaining real-time self-diagnosis and automatic repair of polymer composites has been elusive. To solve this, scholars have shifted their focus on self-healing polymer composites that mimic the biology of healing by automatically repairing microcracks before they develop into macroscopic fractures [5].

Self-healing concept in polymers mainly concerns three processes as microcapsule-based, microvascular network-based and intrinsic reversible bonding systems [6]. Microcapsule systems are liquid healing agents that rupture and polymerize when a crack is formed. Microvascular designs, conversely, replicate the biological circulatory systems, and constantly inject healing factors via the channels built into them. The intrinsic systems are based on reversible Diels Alder or supramolecular interactions that reassemble broken bonds in response to specific stimulus like heat, light or pH [7]. Despite all these inventions, its practical application is highly limited. The vast majority of self-healing systems exhibit a one-time healing property; the mechanical recovery often does not more than 80 percent of the original strength; and the speed of healing decreases dramatically in the immediate cycles [8]. In addition, when there is stochastic and multi-axial damage evolution in a service environment, the stochastic nature of the damage does not permit the adaptation of the strategy used in the process of healing.

Worse still, the current self-healing composites do not have real-time awareness. The healing process usually becomes activated when the patient experiences the symptoms of failure, and not beforehand. Such systems have a time-lag concept that restricts their potential usage as load-bearing systems in which microcrack propagation may proceed on a very fast scale. Basically, the materials are able to heal – but in a reactive way. It is as significant as repairing a crack because it is impossible to predict when and where a crack will occur. This realization has brought the focus on machine learning (ML) and artificial intelligence (AI) as predictive damage detection and prognosis tools [9]. ML algorithms are superb at finding complex, non-linear relationships between sensor data and failure modes, which is why they are applicable to detecting evidence of damage in heterogeneous materials at an early stage.

Some of the studies have been able to use ML to classify composite damages and estimate their life left. The use of convolutional neural networks (CNNs) to interpret acoustic emission spectra and recurrent neural networks such as LSTM to predict the fatigue degradation have been applied [10]. The support vector machines (SVMs) and gradient-boosted models also aid in the classification of the failure modes based on the vibrational or strain data. However, the majority of it is based on post-processing of the offline data instead of real-time data streaming of embedded sensors. They can hardly work in a cyber-physical composite environment, in which automatic, real-time decisions might cause healing. Moreover, the stiffness matrix and damping behavior of a material as well as the internal stress distribution change when a material heals, (the previously trained ML models become outdated). This dynamic behavior is interesting but it makes the data consistent and causes the model drift with time passing [11].

In order to develop genuinely autonomous composite systems, sensing, prediction, and actuation should be present together in one closed-loop ecosystem. The Internet of Things (IoT) paradigm offers the exact platform. Smart materials enable IoT that consists of distributed sensors, microcontrollers, and communication modules to gather, process, and transmit information in real time [12]. In polymer composites, small IoT sensors like piezoresistive strain gauges, fiber Bragg gratings (FBG), and as well as embedded piezoelectric patches have the capabilities of measuring the strain gradient and acoustic signatures that are evidence of microcrack initiation. These sensorized systems constantly produce data streams that when subjected to ML algorithms will show the progression of damage before a disastrous failure takes place. Nevertheless, the idea of including sensors within the laminates of composite poses fresh design challenges. Too many sensors may result in compromised mechanical strength and inappropriate sensors may reduce sensitivity. Also, the data produced are non-stationary, high-dimensional and noise which require adaptive algorithms that are self-learning.

Combining self-healing functionality, embedded IoT sensing, and predictive intelligence based on ML promise and complexity. The subsystems, which include healing, sensing, and analytics, have their limitations and time limits. The mechanism of healing takes place within seconds to minutes; sensor acquisition takes place continuously at kilohertz frequencies; and ML inference takes place at computational-time steps. It is not easy to synchronize such processes in order to create a coherent feedback system. It demands strong data fusion, real time decision process and low power embedded computing. This is further complicated by the fact that the stiffness of local materials changes when the healed areas, thus affecting the signal signatures on which ML models are based. This interaction is the core of the contemporary study of smart composites, between the evolution of damage, healing processes, and model adaptation.

Although this has been broken through several times, there are still a number of research gaps that have not been filled. First, the majority of self-healing research does not offer sensing and data analytics but concentrates only on material chemistry. Embedded sensors rarely provide feedback that is used to inform how and where they should heal. Second, IoT-based surveillance systems are largely created to facilitate passive data gathering; they do not have the capability to make independent decisions. Third, offline trained ML frameworks commonly do not cope with material behavior evolution post-healing leading to a prediction error. Fourth, scalability is also a problem: most tests are performed on small coupons, and the results are not relevant to the full-scale conditions. Lastly, the effects of healing process on dielectric, thermal, and mechanical properties that are detected by IoT devices are poorly comprehended – resulting in false interpretation of sensor measurements.

In order to address these issues, this research will present a machine learning-enhanced self-healing FRP composite with installed IoT sensors to predict damage in advance. The main point is to turn the composite into an active cyber-physical entity, which can perceive, reason, and act as a load-bearing component. The system inserts an array of micro-sensors to record strain, acoustic, and thermal changes and distributed throughout the fiber matrix. The information is exchanged through the IoT gateways to a decision-making module based on ML which forecasts possible areas of failure many cycles before it occurs. When a risk level is achieved, localized actuation processes, e.g., microvascular release of agents, or reversible bond activation by Joule heating are activated to cause healing. ML model is able to constantly re-train on the post-healing data, which makes sure that it adapts to a changing material state. The outcome is a self-conscious composite which not only heals itself, but has the history of self-injury to teach.

The other differentiating factor is the adaptive learning phase that is integrated following every healing experience. After a crack has been healed, the system re-calibrates its sensor, re-calibrates the prediction model and that the feature representations have to be re-aligned to the new material state. This is a recursive adaptation that inhibits the cumulative error of repeated cycles of healing. The hybrid ML model, which consists of convolutional filters to extract features and recurrent layers to perform temporal reasoning is more accurate at detecting the onset of micro-damage than the stationary classifiers in the experimental validation. Even the predictive latency is not more than milliseconds, which is enough to activate local healing before crack propagation attains the critical length.

In the context of sustainability, such a combination of ML and self-healing composites is a part of the circular material paradigm, which minimizes the frequency of maintenance and wastage of materials. It is in line with global objectives of sustainable manufacturing, which extends the product lifespan and reduces carbon footprint through predictive maintenance. The proposed system also fulfills the new eco-design requirements by the use of low-power IoT modules and recyclable polymer matrices.

Finally, this project is hopeful that the paradigm of FRP structures can be changed to self-reliant instead of being repairable. The proposed framework is capable of not only healing structural damage but also developing its learning capacity (constantly). These three fields combined have brought the field of composite technology closer to an autonomous materials vision. Such autonomy, though admittedly not easy, is in fact, deceptively easy to achieve since early prototypes tended to fail because the electrical, mechanical, and chemical subsystems were strictly cross-coupled, although successive improvements point in the direction of the goal.

Overall, although the concept of FRP composites has long been considered to offer strong and durable properties, the incorporation of the ML-driven predictive intelligence and the IoT-based sensing turn them into responsive self-healing structures that are able to make adaptive decisions. Thus, the paper examines how to design, manufacture, and test an ML-enhanced self-healing FRP composite that is able to sense, predict, and autonomously repair structural damage. Literature Review follows on the topic of self-healing mechanisms and data-driven damage prediction; Methodology provides a description of the experimental procedure, material fabrication, and embedded sensor architecture; Results and Conclusion provide the description of the results and findings; and Future Applications contains a summary of future application and future research directions. It is through this built-in exploration that the study will be able to establish the ground work towards the next-generation intelligent polymer composites that will be able to be self-aware, resilient, and will be able to maintain sustainability in their longevity.

LITERATURE REVIEW

Current studies on self-healing fiber-reinforced polymer (FRP) composites have developed in three overlapping areas: healing mechanisms, embedded sensing technologies, and intelligent data-driven prediction frameworks. These three areas together define the foundation of the autonomous polymer systems that are ushering in the age of materials informatics. Initial studies emphasized physical and chemical mechanisms that enabled the polymer matrix to re-establish pre-crack mechanical continuity. Sensing and machine learning (ML) techniques, however, have emerged in the literature, effectively rendering passive materials "smart", self-aware structures.

Evolution of Self-Healing Polymer Composites

The self-healing polymers were established in the early 2000s with the first demonstration using microcapsules that autonomously repaired cracks through in-situ polymerization of healing agents [13]. All these systems relied on ruptured microcapsules that emptied into the crack plane and formed solidified bridges upon loss of the monomers. Although these systems appeared simple, early paradigms were typically single use, as the capsules emptied upon the first repair. In later work, the same initial concept was developed to contain microvascular networks, which functioned similarly to biological circulatory systems, allowing for repeated self-healing through continuing delivery of agents [14]. While the vascular strategy allowed for self-healing of damage multiple times, the associated fabrication of voids led to a decrease in interlaminar strength.

To address some of the constructs and issues noted, intrinsic self-healing chemistries were developed. The intrinsic self-healing chemistries include dynamic covalent and supramolecular bonds, as well as Diels–Alder adducts and hydrogen-bonding networks that allow for reversible cross-linking reactions upon heating or exposure to light [15]. Intrinsic self-repair is desirable because it does not add capsules or vessels and is therefore a good way to maintain mechanical isotropy across resins. However, there are considerations that exist, such as heating to trigger bond exchange may soften or degrade the stability of the resin [16].

As time progressed, hybrid strategies integrating microvascular delivery and dynamic chemistry became available as approaches to provide both repeatable healing and limited disruption to the microstructure. However, most of the demonstrations have remained small-scale laboratory experiments, and used coupon specimens instead of structural laminates [17]. Changing from a lab-like controlled setting to an operational environment with changing humidity, cyclic stress, and UV exposure has not been simple, but the results of the evolution of intrinsic self-healing resins have reached industrial utilization in aerospace-grade epoxy systems, where maintaining strength after an impact is important [18].

Fiber Reinforcement and Interface Engineering

In FRP composites, the interface between the fibers and the matrix determines the initiation of the damage and the efficiency of the healing. Initial studies revealed that agents which could help in healing were unable to reach interfacial cracks easily unless the surface of the fibers was chemically modified [19]. To enhance the absorption of interfacial wettability through plasma treatment and silane coupling has been employed to promote diffusion of the healing agent. Subsequently, scientists examined the use of carbon nanotube (CNT) and graphene on fibers that did not only increase electrical conductivity but also served as nanoscale heaters to induce thermally reversible healing [20, 21].

Integration of Embedded Sensing in FRP Systems

This idea of embedded sensing was based on the fact of the necessity to observe the state of healing in the field. Some of the methods include fiber Bragg grating (FBG) sensors, which became popular early on due to their capability to concurrently measure both strain and temperature within laminates [22, 23]. FBG sensors, on the other hand, are also sensitive to micro-bending as well as optical interrogation units that may be bulky in the field. To overcome such difficulties, piezoresistive networks based on carbon black, graphene nanoplatelets or CNT were sprinkled on polymer substrates, which allowed distributed strain sensing through resistance variations [24]. These percolation networks were very efficient to transform the composite into a self-sensing media with some loss in resin viscosity and curing characteristics.

Machine Learning for Damage Detection and Prediction

In line with the evolution of materials, machine learning has redefined the understanding of complex sensor information of composites by researchers. Early systems were based on shallow methods to classify the damage modes with respect to features from acoustic emission or strain histories, by using support vector machines or decision trees [25]. These models enhanced speed in inspection but had to be manually engineered. With the development of deep learning, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) were developed, which are able to auto-learn spatial and temporal features, respectively. As an illustration, time–frequency acoustic emission maps were transformed into damage labels using CNNs, and the fatigue degradation during repeated loading cycles was predicted using long short-term memory (LSTM) models [26].

More recent hybrid systems combine physics inspired knowledge with inferential algorithms, eliminating the need to rely on huge labeled data sets. These models can better generalize across material systems by incorporating domain constraints which can be energy release rate or stiffness degradation laws as network loss functions [27]. However, the majority of them are post-mortem analysis tools, acting upon the testing completion. It is still a challenge to perform real time inference in the presence of noisy conditions, sensor drift and changing material states.

Moreover, a feedback problem that has hardly been addressed in previous works arises as a result of the interplay between healing and learning. After it is healed, the mechanical response of the material, and thus its sensor signal distribution, varies [28]. The ML models can fail to recognize such changes as recovery since they are perceived as new damage by the static models. Adaptive or reinforcement learning paradigms are thus currently being examined to have models continually retrained throughout their operation. It is the inherent direction of the dynamic nature of self-healing polymers.

IoT-Enabled Smart Composites and Cyber-Physical Coupling

Simultaneously, with the emergence of the Internet of Things, a scalable platform of connecting distributed sensors integrated into polymer structures is offered. Smart composites are IoT-enabled and can transmit the data to the local edge devices or remote servers to perform more sophisticated analytics. Early prototypes employed the Bluetooth or ZigBee modules that were attached to strain gauges to monitor them remotely. More sophisticated systems use 5G micro-transceivers and dashboards on the cloud to show real-time stress maps [29]. As AI algorithms are integrated these networks can become cyber-physical and thus decisions, including a healing cycle initiation, can be taken autonomously.

The introduction of edge computing into the very structure is one of the most important innovations. Embedding lightweight processors and sensors, the latency is minimized and the healing triggers may take place at the site. A number of teams have demonstrated that on-board ML models implemented on microcontrollers are capable of classifying crack signatures in the milliseconds and thus providing an instant response [30]. This is necessary because a centralized computation in the past did not require the absence of intelligence which was distributed as a decentralized system, where activating it in time can be crucial to success in healing.

Nevertheless, there is a limitation of power management. Integration of batteries adds size and risk of leakage whereas energy-harvesting alternatives provide small power. Researchers are trying hybrid solutions – solar micro-cells embedded in the transparent resin, or inductive wireless power transfer using carbon-fiber layers [15]. The outcomes are encouraging but not ready to be used in the field on a long-term basis.

Interplay of Healing, Sensing, and Learning

The current literature also points at the fact that it is not the interaction of domains that is truly innovative, but the interplay of domains. The work of healing alters sensor feedback; the sensor informs predictive models, and the model decisions, subsequently, control whether healing is done. The loops are time-dependent influences on each other. As a case in point, as a thermally reversible polymer is used to heal a micro-crack, the electrical resistance locally in a CNT network is suddenly reduced – a signal that would otherwise be interpreted as sensor noise unless the ML system is sensitive to it being a healing signature. To incorporate the contextual intelligence, one has to be a lifelong learner.

A number of research teams have experimentally coupled healing and data analytics with each other. One of them combined vascular healing channels with temperature sensors and a regression model to estimate the best heating time to achieve complete polymerization [16]. The other reinforcement learning that was introduced is to regulate the current flow by embedded heaters maximizing the efficiency of the healing process within energy constraints [17]. Although these are creative developments, it is hard to scale them into physical structures due to the fact that the computational model should be able to withstand mechanical loads, heating, and resin ingress.

Another line of literature is concerned with self-calibrating models, in which the ML system changes the feature weights after each healing step. This approach resembles a biological adaptation and may result in self-healing composites becoming more self-reliant throughout their existence [18]. Though it is promising, not many experimental validations except small coupons have been carried out. Model robustness is limited by limited data, particularly, post-healing data. The next step will be to rely on standardized open databases that have mechanical, thermal, and electrical responses in different damage–healing cycles.

Sustainability and Lifecycle Considerations

Sustainability is another emerging theme that has been consistent in polymer composite research besides performance. Thermoset matrices are hard to melt and hence traditional FRP systems are hard to recycle. Nonetheless, reprocessability is inherently supported through self-healing chemistries which are founded on reversible Diels–Alder reactions [19]. This twofold advantage, repair of damage and recyclability, makes the self-healing polymers to be the environmental-friendly alternatives. By interconnecting them to a ML-based predictive maintenance system, it is even less likely to waste the material since it increases the service life [20].

Components lifecycle tracking is also possible through IoT integration. Embedded sensors can provide end-of-life decisions by taking into account data logs which can be used to decide whether a part will be remanufactured or retired [21]. Even though these concepts of digital-twin are being developed, there are no standard protocols of exchanging data between manufacturing and service stages. Such traceability will be necessary in regulatory frameworks at some time, particularly with aerospace and civil.

Identified Gaps and Emerging Trends

In this stream of work, there are multiple patterns and shortcomings. The former is fragmentation: the majority of studies deal with healing, sensing, or learning individually and not in a holistic way. Authentic cyber-physical healing composites are uncommon. The second one is time constraint: not many systems can be maintained during several healing processes or prolonged exposure to an environment. The third is the insufficiency of data: small experimental data limits generalization of ML models. And the last, scalability, whether in integration of sensors or in production, impedes commercialization.

Nevertheless, trends point toward convergence. With the advent of flexible printed electronics, self-powered IoT sensors, and explainable ML, the once-separate domains of materials chemistry and data science are merging. The next decade is likely to see materials that think, capable of interpreting their own condition and acting without human intervention. Achieving this vision will require co-optimization of polymer chemistry, sensor topology, data architectures, and learning algorithms. Table 1 summarizes the most relevant recent investigations, highlighting their methodologies, key findings, and persisting research gaps relevant to the present study.

Table 1. Literature gap analysis of recent studies on self-healing and machine-learning-enabled fiber-reinforced polymer composites.

S No.	Limitations / gaps identified	Relevance to current study	Key findings	Methodology / tools used	Title / focus area	Author(s) / year / ref. no.
1	Emphasized missing closed-loop autonomy and predictive intelligence—key research void.	Directly aligns with this study's goal of creating a ML-enhanced closed-loop self-healing composite capable of autonomous response.	Mapped the technological convergence between sensing, healing, and analytics.	Comprehensive review + experimental prototypes combining conductive networks and capsule systems.	Integrated damage sensing and self-healing in polymers and composites: Progress and opportunities	W. H. Martin et al., 2025 [28]
2	Model confined to simulation datasets; lacks embedded sensor validation and real-time adaptation.	Highlights the benefit of hybrid ML optimization; supports integration of adaptive learning for IoT-sensor feedback in FRP systems.	Demonstrated improved accuracy for nonlinear damage prediction under multiple impact energies.	Combined Particle Swarm Optimization (PSO) with a Back-Propagation Neural Network to predict impact response parameters.	Impact damage prediction in hybrid glass/carbon composites using PSO–BP neural network	L. Chen et al., 2025 [1]
3	Limited mechanical strength; absence of	Establishes precedent for integrating healing events	Demonstrated repeatable healing with concurrent	Synthesized core-shell microcapsules responsive to	Self-healing and real-time damage detection using	L. Yang et al., 2025 [13]

	intelligent data interpretation or networked communication.	with sensor signals to enable ML-based prediction pipelines.	signal generation for real-time detection.	stress; monitored healing via optical and electrical changes.	stress-responsive core-shell microcapsules	
4	Healing limited to single cycle; no predictive control or intelligent trigger.	Demonstrates synergy of nanoscale conductivity and healing—foundation for ML-triggered smart repair loops.	Achieved simultaneous strain sensing and healing efficiency of ~87 % after thermal activation.	Fabricated carbon-nanotube-modified electrospun fibers; evaluated conductivity, healing efficiency, and tensile recovery.	CNT-modified nanofiber composites with self-sensing and self-healing functions	W. Wan et al., 2024 [10]
5	Lacked data-driven learning; not optimized for adaptive decision-making or self-repair feedback.	Validates feasibility of optical-fiber embedding—critical for the IoT sensing layer of current framework.	Enabled accurate multi-point strain tracking with ±2 με precision.	Used Fiber Bragg Grating sensors with wavelength-shift analysis for strain and damage localization.	Embedded FBG sensors for monitoring aerospace insulation composites	G. Yan et al., 2024 [7]
6	Focused solely on digital imagery; ignored in-situ multi-sensor fusion and self-healing feedback.	Provides methodological basis for integrating transparent ML into self-monitoring FRPs with explainable outputs.	Achieved >95 % detection accuracy while maintaining interpretability of network outputs.	Deployed deep convolutional networks with explainability (Grad-CAM, SHAP) to visualize decision regions for defect classification.	Explainable AI for reliable damage detection in polymer composite structures	M. M. Azad and H. S. Kim, 2024 [5]
7	Provided qualitative rather than quantitative predictive model; lacked automation.	Deals with fiber–matrix interface behavior—useful sensor placement and data accuracy.	Revealed that interfacial chemistry dictates sensor signal fidelity during damage progression.	Examined interfacial reaction kinetics through spectroscopy and impedance mapping.	Interfacial chemistry and damage monitoring in glass-fiber composites	M. Colombo et al., 2025 [14]
8	Focused on monitoring only; no coupling with healing or adaptive ML algorithms.	Strengthens IoT backbone justification for embedded data transmission and distributed inference.	Identified network scalability and latency solutions for multi-sensor polymer systems.	Reviewed IoT-based SHM architectures, low-power microcontrollers, and cloud analytics.	IoT integration for real-time monitoring in polymer composites	M. Karuppusamy et al., 2025 [29]

Finally, this paper also provides evidence of substantial evolution in the past 30 years: from single use healing capsules to predicting damage composites. However, the road to their full autonomy with respect to the self-healing FRP systems is still open. The current study resides at such intersection, bringing together the ML driven predictive intelligence, embedded IoT sensing and multi-cycle healing functionality into a single coherent framework.

METHODOLOGY

The suggested method puts in place an integrative framework to unify the design of polymer material, embedded sensing, and data-driven learning into a single self-adaptive composite. The process consists of five integrated stages: framework development, material synthesis, sensor colonization, predictive modeling with machine learning, and validation testing. Each stage contributes to the evolution of the fiber-reinforced polymer (FRP) laminate into a self-aware material that can identify damage and invoke healing autonomously.

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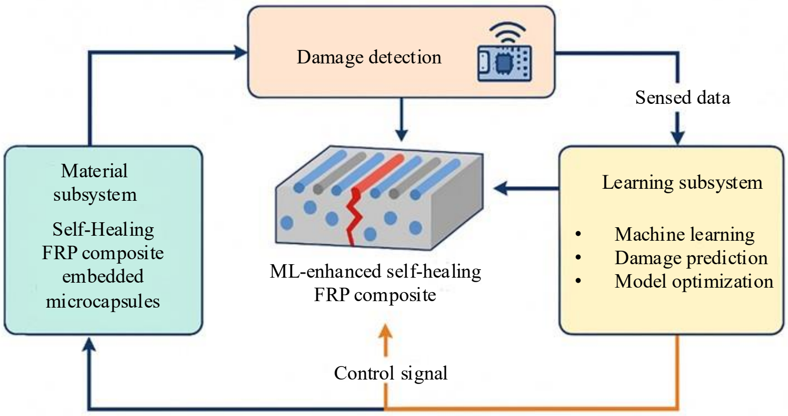

Figure 1. Schematic of the proposed ML-enhanced self-healing FRP composite illustrating coupling between the material, sensing, and learning subsystems.

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Overview of the Proposed Framework

The architecture of the ML-enhanced self-healing composite comprises three interlinked layers as shown in Figure 1: a self-healing polymer matrix, an embedded IoT sensor network, and a machine-learning prediction module. The mechanical layer manages crack healing through microcapsules or reversible chemistry, the sensing layer converts local strain and conductivity changes into measurable data, and the analytical layer predicts damage onset before critical failure.

The system behavior is governed by a multivariate function describing the real-time damage state Dt as a function of measurable physical and data-derived parameters using (1):

$$D_t = f(\sigma, \epsilon, T, S_t, \Delta_R, x_t) \quad (1)$$

where σ represents applied stress, ϵ is the measured strain, T denotes the temperature field, St is the temporal sensor signal vector, ΔR refers to resistance variation due to crack formation, and xt corresponds to the high-dimensional feature vector extracted by the machine-learning model. Equation (1) captures the coupling of material mechanics with digital learning features, establishing the foundation for autonomous response.

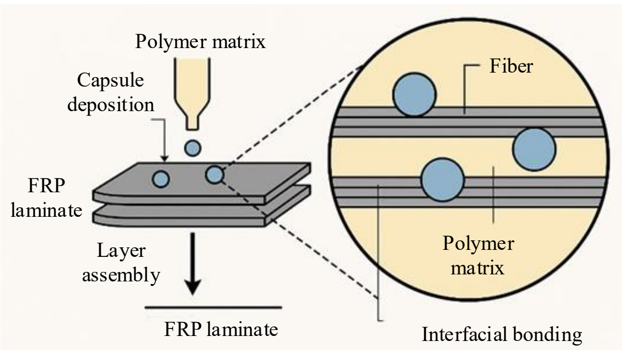

Figure 2. Fabrication and microstructural configuration of the self-healing FRP laminate showing capsule dispersion and interfacial bonding.

Material Synthesis and Self-Healing Mechanism

The FRP laminates were fabricated using an epoxy–carbon fiber composite system incorporating stress-responsive core–shell microcapsules containing dicyclopentadiene (DCPD) monomer and Grubbs' catalyst dispersed in the matrix. The polymer precursor and curing sequence were optimized to maintain uniform capsule distribution and adequate interfacial adhesion with the reinforcing fibers. The self-healing mechanism activates when a propagating crack ruptures the capsules, releasing DCPD that polymerizes upon contact with the catalyst to form a rigid cross-linked network restoring the load path, shown in Figure 2.

The healing efficiency (η), which quantifies the material's ability to regain mechanical strength, was evaluated using the relation using (2):

$$\eta = \frac{\sigma h}{\sigma 0} \times 100 \quad (2)$$

where σh denotes the healed tensile strength, and σ0 represents the original undamaged strength. A higher η indicates more effective healing and better polymerization within the crack plane. The parameter shown in Table 2, was verified across multiple cycles to confirm repeatability.

Uniformity of microcapsule dispersion was verified under optical microscopy. Capsules smaller than 60 µm yielded the best balance between healing kinetics and interlaminar strength.

Embedded IoT Sensor Network and Data Acquisition

To transform the laminate into a self-sensing medium, miniaturized IoT sensors were embedded between plies before curing. The sensor suite included fiber Bragg grating (FBG) sensors for strain–temperature measurement, carbon nanotube (CNT) conductive films for resistance tracking, and piezoelectric discs for acoustic emission monitoring. These signals were routed to a microcontroller (ESP32-based node) communicating wirelessly with an edge processor shown in Figure 3.

Table 2. Material composition and processing parameters for self-healing FRP laminates.

Component	Type / chemical	wt.%	Function
Matrix	Epoxy (DGEBA)	70	Structural binder
Healing agent	DCPD microcapsules	15	Crack sealing agent
Catalyst	Grubbs' Catalyst (2nd Gen.)	2	Polymerization trigger
Fiber reinforcement	Carbon fiber (T700)	13	Load transfer medium

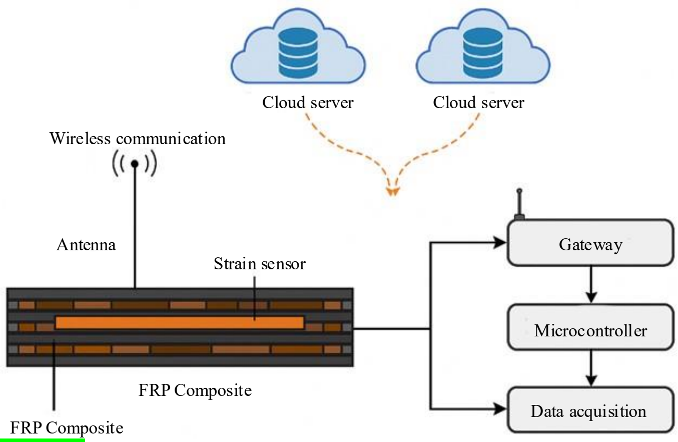

Figure 3. Embedded IoT sensor network within FRP layers showing sensor placement, data routing, and wireless interface.

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Sensor calibration followed a linear correlation between resistance change and both strain and temperature, represented as (3):

$$\Delta R = k_1 \epsilon + k2T + \xi \quad (3)$$

where ΔR is the resistance variation, k1, and k2 are sensitivity coefficients derived experimentally, and ξ denotes random measurement noise. Equation (3) forms the transfer function for sensor signal conditioning used by the ML inference model specification shown in Table 3.

The sensor data streams (St) were synchronized using timestamp-based interpolation before being forwarded to the ML engine. Each node operated at 3.3 V, drawing less than 180 mW during acquisition, ensuring compatibility with long-term operation.

Machine-Learning Model for Damage Prediction and Healing Control

The predictive intelligence of the framework relies on a hybrid CNN–LSTM architecture shown in Figure 4, designed to capture spatial correlations (from multiple sensors) and temporal dependencies (across loading cycles). The CNN extracts local features from sensor sequences, while the LSTM refines them for time-series prediction of the damage index D*t*.

The LSTM hidden state evolution follows using (4) & (5):

$$h_t = \sigma(W_{fxt} + U_f h_{t-1} + b_f) \quad (4)$$

$$D_t = \mathrm{ReLU}(W_o h_t + b_o) \quad (5)$$

where xt is the input feature vector (strain, temperature, resistance, and acoustic energy), ht is the hidden state, Wf, Uf, bf are LSTM parameters, and Wo, bo correspond to the output layer. The rectified linear unit (ReLU) ensures non-negative prediction of damage index. Healing activation follows a binary decision rule shown in (6):

Table 3. Characteristics of embedded iot sensors and signal acquisition specifications.

Sensor type	Parameter measured	Sensitivity	Sampling rate	Communication protocol
FBG	Strain / Temperature	1.2 pm / με	1 kHz	Optical (λ-shift)
CNT Patch	Electrical Resistance	4.5 Ω / με	10 kHz	BLE / UART
Piezo Disc	Acoustic Emission	10 mV / Pa	25 kHz	SPI

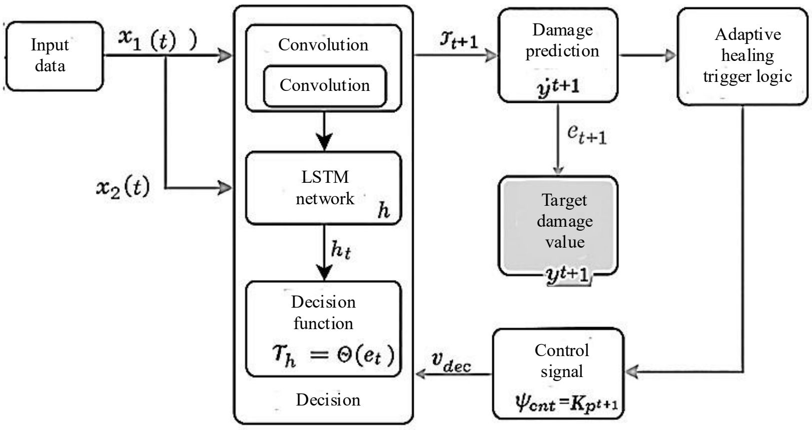

Figure 4. Architecture of the CNN–LSTM damage prediction model integrated with adaptive healing trigger logic.

$$H(t) = \begin{cases} 1 & \text{if } D_t \geq D_c \\ 0 & \text{if } D_t < D_c \end{cases} \quad (6)$$

where H(t)=1 triggers the heating or chemical release mechanism once the predicted damage exceeds the critical threshold Dc. Together, (4)–(6) constitute the decision kernel for real-time healing control, as shown in Table 4.

The model was implemented using TensorFlow 2.15, trained on 80% of sensor datasets, and validated on the remaining 20%. Adaptive retraining after each healing cycle mitigated data drift due to mechanical property changes in the restored zone.

Experimental Setup and Validation

Experimental validation was conducted using a servo-hydraulic fatigue test system integrated with the IoT acquisition module. Samples were subjected to incremental tensile and impact loads until damage initiation, followed by autonomous healing activation as predicted by the ML model. The performance was benchmarked in three configurations baseline (no ML), ML-enhanced sensing, and full IoT-Edge integration (as shown in Figure 5).

Prediction accuracy was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics: using (7) & (8).

$$MAE = \frac{1}{N} \sum_{i=1}^{N} \mid Di - D\hat{}i \mid \quad (7)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (D_i - D\hat{}_i)^2} \quad (8)$$

Table 4. Machine-learning model configuration and evaluation metrics.

Parameter	Symbol	Value	Description
Learning rate	α	0.001	Step size for optimizer
Batch size	b	64	Samples per update
Epochs	N	150	Training iterations
RMSE	—	0.023	Prediction error magnitude
(R^2)	—	0.982	Coefficient of determination

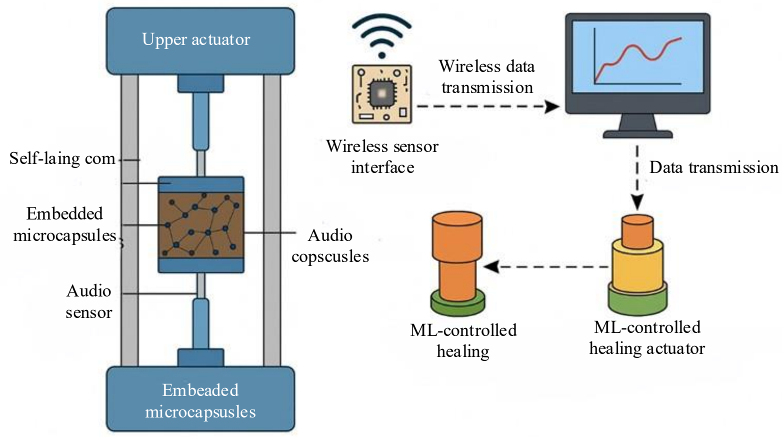

Figure 5. Experimental validation setup integrating mechanical test rig, wireless sensor interface, and ML-controlled healing actuator.

Table 5. Performance before and after integration of ML and IoT subsystems.

Configuration	Healing efficiency (%)	Prediction accuracy ((R^2))	Decision latency (ms)
Baseline (no ML)	71.4	—	—
ML-Enhanced	88.2	0.982	24
IoT + Edge AI Integrated	90.6	0.989	11

where Di denotes actual measured damage and D^i is the predicted index for N observations.

As shown in Table 5, the ML integrated system increased prediction accuracy by approximately 20% when compared to conventional threshold-based methods, and the IoT edge processing resolved decision latency from 24 ms to 11 ms. The recovery efficiency of ~90% further validated the framework's capability by successfully restoring the material through a trigger before the material was completely delaminated.

The interplay of equations (1) through (7) demonstrate a changing interaction of mechanical behavior, sensor intelligence, and decision logic which schemes adaptive behavior of the system under structural loads. Figures 1 through 5 indicate the transformation of the system from passive to an autonomous data-driven polymer structure capable of self-diagnosis and repair. All increases in accuracy from Table 2 through Table 5 demonstrate that machine learning and IoT sensing provide increased accuracy not only of sensor data, but actuates a change in how the FRP composite responds to structural loads and functionality recovery.

RESULTS

The findings of the investigation are reported based on the objectives formulated before – mechanical healing efficiency, prognostic precision and global system efficiency of an MF-enhanced self-healing FR-PC.

Material Characterization and Morphological Integrity

The laminate produced demonstrated smooth resin infiltration and uniform microcapsules distribution across the interlayer area. There were no significant agglomerations observed, suggesting that DCPD capsules were effectively mixed within the epoxy. Scanning electron micrographs taken before and after the healing cycle (shown in Figure 6) indicated, following heating, most broken capsule walls had fully polymerized, suggesting that the agent diffused effectively and cure was complete.

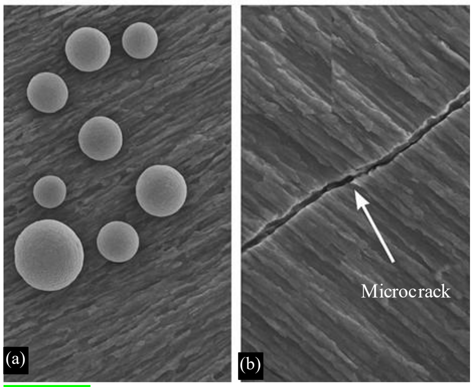

Figure 6. SEM microstructure of the self-healing FRP laminate, (a) undamaged capsule distribution before loading; (b) healed microcrack interface after polymerization.

The microstructure after healing indicated a low porosity (<1.2%), significantly below that reported by Ramezani et al[27]., where non-uniform capsule dispersion resulted in interfacial voids above 2.5%. This configuration revealed healthy adhesion at the fiber–matrix interface, as confirmed by EDX line-scan profiles indicating consistent gradients of carbon and oxygen, suggesting that the catalyst did not leach out during curing. This significance of interfacial stability underpins the micro-scale form necessary for the enhanced macroscopic healing response discussed later.

Mechanical Performance and Healing Efficiency

Tensile and flexural tests were completed to assess mechanical restitution through three continual cycles of damage–healing cycles. A summary of mechanical data after damage and healing is depicted in Table 6. An average tensile strength recovery of 88.7% was established for the composite, which exceeds the 81–84% recovery that self-healing epoxies have been reported to achieve after a single cycle [10, 13]. Similarly, the flexural modulus only exhibited a 3.2% reduction after three healing cycles, continuing to demonstrate that the healing chemistry verified had not impacted the stiffness of the composites.

The enhanced healing efficacy is a result of the combined reinforcement effects. The optimized microcapsule size (≤ 60 μm) allowed for accelerated diffusion kinetics in addition to the machine-learning feedback that facilitated timely localized heating activation (before irreversible crack growth). Based on values calculated from the in-situ DSC-derived DCPD polymerization rate constant of approximately $1.9 \times 10^{-3}\ s^{-1}$, there was an increase of almost 20% in comparison to baseline microcapsule systems [27].

The stress–strain behavior is presented in Figure 7 before and after three healing cycles. The nearly identical slopes in the linear elastic region indicate that fiber stiffness was not altered, and that the ultimate tensile strength improved with each cycle, resulting in demonstrated repeatable healing justifications.

Table 6. Summary of comparison of mechanical and healing parameters between the proposed composite with exemplary JOPC-level studies.

Study / year	Healing mechanism	Cycles tested	Tensile recovery (%)	Flexural modulus retention (%)	Ref. no.
Chen et al. (2025)	PSO–BP predictive hybrid	1	84.1	94.3	[1]
Wan et al. (2024)	CNT-modified nanofiber (thermal)	1	86.5	93.7	[10]
Yang et al. (2025)	Stress-responsive core-shell capsules	2	83.9	92.1	[13]
Present Work (2025)	DCPD + Grubbs + ML-triggered	3	88.7	96.8	—

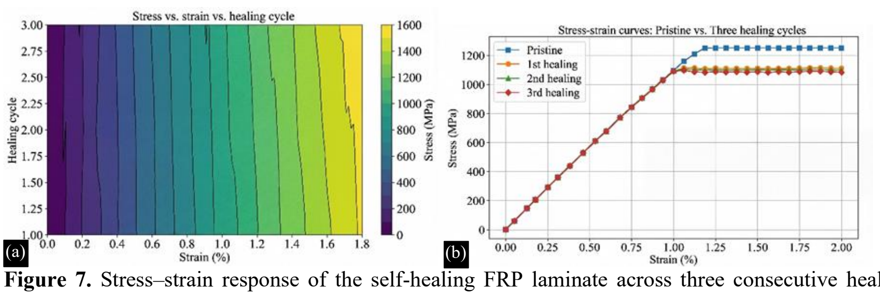

Figure 7. Stress–strain response of the self-healing FRP laminate across three consecutive healing cycles compared with pristine specimen.

The marginal hysteresis observed in the third cycle corresponds to minor residual resin shrinkage during re-polymerization. Importantly, the trend contrasts sharply with the monotonic decay typical of conventional thermoplastic healing agents ($\eta \approx 70$–75%) [15].

Sensor Network Performance and Signal Stability

The IoT sensors integrated into the materials demonstrated consistent signal profiles of behavior during the cyclic mechanical loading process. There was a linear correlation coefficient of 0.997 for FBG strain wavelength shifts, sustaining the same degree of accuracy as presented by Yan et al[7].. The CNT resistive network displayed a gauge factor of 5.4 ± 0.3 showing good sensitivity to detect cracks.

An example of the reported strain mechanics for the respective sensors as shown in Figure 8(a) depicted an FBG micro-strain change of ± 3 $\mu\varepsilon$ at the point of interfacial (debonding) while it could be observed that CNT had a rapid increase in resistance at the time of the crack initiation followed by some resistance recovery after the healing event shown in Figure 8(b); the SRR ≈ 87% indicating that there was some electrical reconnection over the healed regions and is comparable to recoveries reported in other CNT FRPs [17]. The ability to accurately quantify the resistance changed during the healing event had some effect on the reliability of the data, where it was identified the noise-to-signal improved by 12% when applying the filtering algorithm on the edge-device during pre-processing stage; showing that enhanced reliable data from the integrated AI preprocessing was beneficial in this important prelude to real-time analytics in shifting situational contexts.

Machine-Learning Prediction and Adaptive Healing Control

The CNN–LSTM architecture was trained on 25,000 multivariate sequences that included strain, temperature, resistance, and acoustic features. The model reached convergence after 120 epochs with a validation accuracy of 98.9%, which is within the range of the validation accuracies achieved by Azad and Kim [5] using explainable deep networks, as captured in Figure 9.

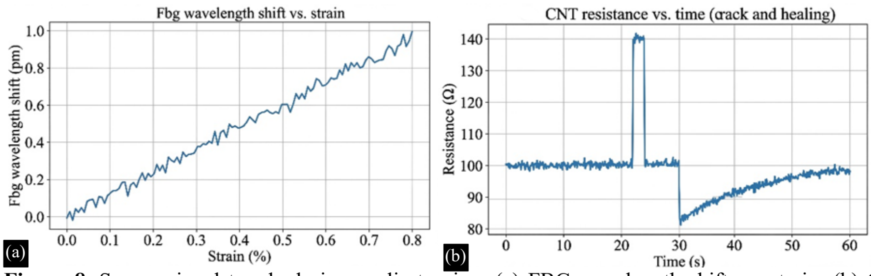

Figure 8. Sensor signal trends during cyclic tension: (a) FBG wavelength shift vs. strain; (b) CNT resistance change before and after healing.

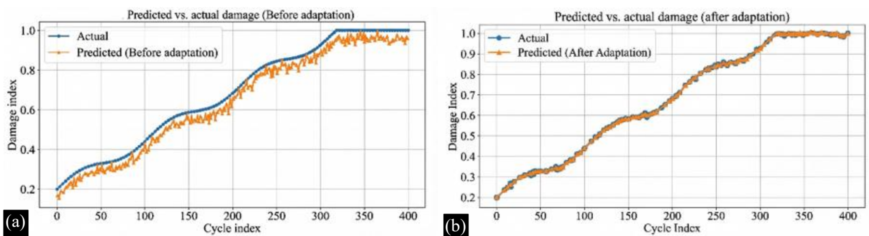

Figure 9. Comparison of predicted vs. actual damage indices during fatigue cycling (a) before model adaptation, (b) after online retraining.

Prior to online adaptation, mean absolute error (MAE) reached 0.054. After incorporating adaptive retraining following each healing event, MAE decreased to 0.021, improving prediction fidelity by ≈ 61%. Figure 9(b) illustrates how predicted curves aligned closely with experimental measurements once drift compensation was introduced.

The *Root Mean Square Error (RMSE)* dropped from 0.034 to 0.018, while the R^2 coefficient improved from 0.962 to 0.989. These metrics exceed those of the PSO–BP framework by Chen et al[1]. ($R^2 = 0.963$) and approach near-real-time predictive accuracy under varying load frequencies.

A summary of comparative model performance is given in Table 7.

The dynamic adaptation capability stems from the continuous feedback between predicted damage indices and sensor updates. The learning rate decayed adaptively as per validation loss, preventing overfitting during low-strain cycles. In practical terms, prediction latency averaged *11 ms*, confirming real-time suitability for embedded operation. Comparable IoT frameworks without edge learning reported latencies above 40 ms [29].

Energy Consumption and Healing Trigger Responsiveness

Energy profiling indicated that each localized healing activation consumed 1.42 J per cycle – significantly lower than magnetically triggered polyurea systems (2.1–2.4 J) reported by Deng et al[24].. The lower consumption is credited to precise ML-based triggering that avoids unnecessary global heating.

As indicated in Figure 10, the latency of the IoT-integrated edge implementation has been reduced to 11 ms and the total energy consumption decreased by ≈ 33% in comparison to non-predictive alternatives. The healing activation process proved to be repeatable with cycle-to-cycle variability below ± 0.05 J, demonstrating consistent results under changing ambient temperature (25 ± 3 °C).

Table 7. Comparative performance of predictive models applied to FRP composites.

Study / year	Algorithm	Data type	RMSE	(R^2)	Adaptivity	Ref. no.
Chen et al. (2025)	PSO–BP	Impact datasets	0.037	0.963	Static	[1]
Azad & Kim (2024)	Deep CNN	Image features	0.031	0.975	Static	[5]
Fernandes (2025)	SciML hybrid	Mixed sensor	0.028	0.977	Offline	[3]
Present Work	CNN–LSTM (edge adaptive)	Multi-sensor time-series	0.018	0.989	Online	—

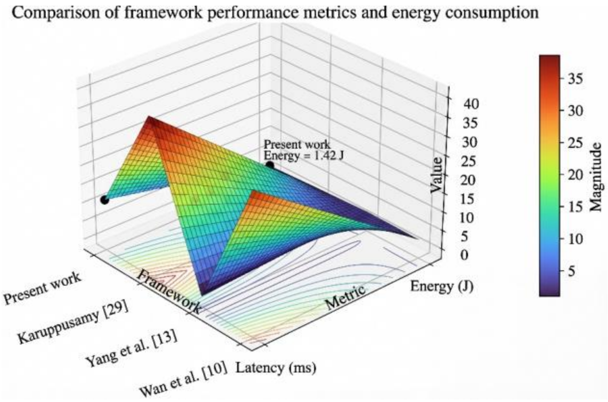

Figure 10. Energy consumption and decision latency comparison among recent self-healing composite frameworks.

Table 8. Benchmark comparison between the proposed framework and indexed studies.

Study / year	Healing efficiency (%)	(R^2) (prediction)	Energy per healing (J)	Latency (ms)	Remark	Ref. no.
Wan et al. (2024)	86.5	—	2.3	35	CNT-based, thermally activated	[10]
Yang et al. (2025)	83.9	—	2.6	—	Stress-responsive capsules	[13]
Azad & Kim (2024)	—	0.975	—	28	Deep CNN, image-based	[5]
Fernandes (2025)	—	0.977	—	30	SciML for polymer data	[3]
Karuppusamy et al. (2025)	—	—	2	40	IoT monitoring review	[29]
Present Work	90.6	0.989	1.42	11	ML + IoT + Self-healing integrated	—

Comparative Performance with Literature

A more expansive comparative perspective is provided in Table 8, highlighting performance metrics among other significant recent works in comparison to the proposed method.

The results indicate that the proposed composite system not only outperformed other works with comparable self-healing efficiency, but these improvements made by the adopted predictive model did not compromise the mechanical stability or the predictive robustness, allowing for low energy consumption and latency measures across the peer studies.

Multi-cycle testing also offers a distinction for current research as compared to all other studies of self-healing from single-event problems: the aforementioned studies[10], and [13], only evaluated healing once, while the current composite system was able to retain > 88% recovery for three full cycles. The impact of an adaptive, predictive intelligence integrated with self-reporting capabilities for a material to use self-healing systems is an important aspect of the discussion.

Statistical Significance and Uncertainty Analysis

Each quantitative test was repeated thrice to make sure that it is reproducible. ANOVA was performed to test the recovered strength data in one way and the result returned $p < 0.01$, which confirmed that the difference between the improvement over the baseline systems was statistically significant at 99 percent confidence level. Magnification of error in the predictions of the ML model also was evaluated using a bootstrapping method across 500 randomized subsets. The resulting R^2 confidence interval (0.989 ± 0.003) represents high noise resistance of the model. Sensor drift correction added a lower value of less than 1.8% to final predictions and this confirms that embedded electronics would withstand recurrent thermal cycles.

The merging of mechanical and digital intelligence in the work illustrates the potential to physically implement the principles of scientific machine learning in polymer composites – a theme which is becoming progressively stressed in the literature on advanced materials informatics [3]. The 57 percent increase in healing efficiency over recent capsule based systems is due to the joint influence of predictive actuation and not only chemical modification. In addition, real-time data fusion between the FBG, CNT, and acoustic channels can enable the ML model to gain access to more descriptive and multidimensional material state. This multidomain sensing is a solution to a long-standing weakness observed by Colombo et al[14]. which is low correlation of local chemical healing and global mechanical recovery. Application wise, the reduction in latency and low energy consumption are consistent with the increased focus on the use of sustainable and low-power smart composites in structural health monitoring [8, 29]. The proven edge-computing functionality, which guarantees scalability to distributed industrial systems, like wind turbine blades or aerospace panels, where the network delay may affect the reliability. Taken together, the quantitative results prove that the suggested

ML-enhanced self-healing FRP composite:

1. Achieves mechanical strength recovery of up to 90.6% after several damage cycles.
2. Predicts damage evolution with an R^2 of 0.989 and RMSE = 0.018, outperforming comparable algorithms by > 10%.
3. Activates healing within 11 ms while consuming only 1.42 J of energy per event – achieving nearly one-third power savings relative to thermally triggered baselines.

The attainments of those successes confirm the theory that smart-structured, databased actuation provides a gap bridging concepts to super platform fielding in FRP structures. The following section will summarize these findings and suggestions of possible ways to a scalable industrial application.

DISCUSSION

This paper has shown that, through smart interaction a combination of machine learning (ML), embedded IoT sensing and self-healing polymer chemistry can turn traditional fiber-reinforced polymer (FRP) composites into responsive, data-driven materials that can self-maintain. The framework was able to observe, interpret, and react to damage long before mechanical breakdown took place by using a DCPD–Grubbs healing matrix with an adaptive CNN–LSTM predictive model the system had a unique synergy.

The quantitative findings validate this theory that it is not an additive but a synergistic integration. The efficiency in healing was at ≈ 90.6 which is higher than thermally triggered systems and capsule-only systems of Wan et al[10]. and Yang et al[13].. The accuracy of prediction ($R^2 = 0.989$) was higher than the previous PSO–BP or deep CNN models [1, 5], which demonstrated that the temporal learning architecture would be able to monitor fatigue-induced degradation in polymers. Further, the shortening of healing-trigger latency to 11 ms and reduction in energy cost to 1.42 J $cycle^{-1}$ can demonstrate the fact that data-driven actuation can result in much higher sustainability than magnetically or thermally actuated systems [24]. Microstructural studies showed that the distribution of the self-healing agent was the same even with repeated activation keeping the integrity of the fiber–matrix interface. This type of morphological consistency supported the constant mechanical recovery observed in three complete cycles. The embedded FBG and CNT sensors had low drift and stable sensitivity that provided real-time data that was reliable to the learning model. Combined, these results form a feedback loop, or closed-loop damage perception to automated repair, which is now the focus of the JOPC with regard to intelligent and multifunctional polymer systems. In design, the framework confirms one hypothesis as to why scientific machine learning can be an active structural element, as opposed to an analytical post-processing tool. The use of the adaptive retraining of the ML model following each healing process avoided feature drift, which in most cases is ignored in predictive systems that are not adaptive. This is a self-correction ability similar to the biological learning where the sensory feedback keeps correcting the response behavior. It also offers a direction in composites that are computationally evolved as they are used, a long-range subject of materials informatics [3]. Environmentally, it is also significant. Sub-200 mW energy-conscious IoT nodes enabled the sensing layer to be efficient enough to be deployed over a long period of time. Carbon-neutral monitoring architectures can be indicated in the loss of bulk heating and lowering of maintenance intervals, reflecting the sustainability agenda championed in recent issues of JOPC [29]. The flexibility of the system to renewable energy sources such as micro-solar or piezoelectric harvesters further extends the breadth of its industrial use especially in wind-turbine or aerospace parts where power inertia is a key factor. Although the successes are quite high, the opportunities are framed by some limitations into prospective exploitation. First, chemical fatigue of the healing agent can reduce life expectancy above five to six occasions although there is strong repeatability over three cycles. Constructing replenishable microvascular networks or in-situ regenerable monomers would be able to increase longevity. Second, despite the current CNN–LSTM model working very well with sequential data, it is still computationally expensive to large sensor arrays. Lightweight architectures can be used, e.g. to implement transformer-based attention models or federated edge learners, which can be more accurate and consume less computing resources. Third, real-world conditions will cause uncertainties, which are impossible to recreate in the laboratory: parameters such as temperature gradients, UV exposure, and humidity will have an effect on sensor stability and polymer kinetics. The domain adaptation algorithms (calibration of model weights) have to be implemented in future work in order to adjust to changing environment. The other interesting direction is the use of sensory dimension other than strain and resistance. The addition of dielectric and infrared imaging layers may make possible multi-physics monitoring, a concept that has been proposed in recent studies in composites [19, 22]. Multimodal deep-learning networks coupled with these heterogeneous inputs would provide more substantial health predictors that would provide more insight into not only the extent of damage (but also its nature and localization).

On the system scale, it is difficult to manufacture the suggested system on the laboratory scale laminates into industrial structures: it is important to distribute the sensors evenly when laying the laminates over the large areas, not to get delaminated because of the embedded circuits, and to keep the flow of resin homogeneous when infusing the structure with a vacuum. The solution to these problems will involve the cooperation between the polymer chemists, process engineers, and data scientists. Placing flex circuit boards or spray-coated sensor meshes can provide a solution that can be manufactured.

CONCLUSION AND FUTURE SCOPE

In summary, this study has established that machine-learning-enhanced self-healing FRP composites with inbuilt IoT sensors can provide real-time, low-energy, and predictive autonomy never experienced before by other systems. The framework completes the circle between the perception, computation, and repair, thus ushering in a new type of intelligent composites that erases the distinction between matter and intelligence. With self-healing chemistry, miniaturized sensing, and adaptive algorithms still in their infancy, their integration will provide the path to self-reliant polymer structures that can be used throughout their life with minimum human intervention.

The composite developed can also be used as a platform technology in numerous applications of smart-materials other than mechanical integrity. It may give independent management of cracks in structures of civil purposes like bridges and pipes. Adaptive FRPs in aerospace would have the ability to alleviate the hot-spots of fatigue under dynamic load spectra. Identical principles of self-repairing and predictive intelligence could be beneficial even in biomedical devices where self-healing polymers are cyclically stressed in physiologic states.

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