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ML-Enhanced Smart Sensing Framework for IoT-Based Structural Health Monitoring Using Conductive Polymer Composites

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Abstract

The growing demand for intelligent structural health monitoring (SHM) in dynamic infrastructures necessitates flexible sensing systems that are not only mechanically robust but also capable of real-time interpretation. Conventional SHM frameworks often rely on brittle sensor configurations and cloud-dependent processing pipelines, which suffer from latency, limited durability, and poor adaptability under variable loading conditions. Despite recent advances in composite materials and machine learning, current approaches lack a unified framework that seamlessly integrates material-level sensitivity with embedded predictive intelligence. To address this limitation, we propose CPC-Net, a novel fabrication-to-inference pipeline combining piezoresistive polymer composites with an edge-deployable hybrid CNN-LSTM model. The composite is engineered with graphene-reinforced elastomer matrices to ensure high gauge sensitivity and repeatable electromechanical behavior under cyclic strain. A dedicated embedded architecture supports in-situ signal preprocessing, real-time ML inference, and adaptive calibration, optimized for constrained IoT environments. The proposed system achieved an R^2 of 0.984 in strain-resistance prediction, with a gauge factor (GF) between 8–12. Machine learning inference yielded an accuracy of 93.4%, an F1-score of 0.91, and inference latency of 41 ms, outperforming existing SHM baselines across all tested metrics. This integrated solution demonstrates strong potential for deployment in next-generation SHM applications, offering a scalable, low-latency, and mechanically resilient alternative for real-time monitoring of civil infrastructure, soft robotics, and biomechanical systems.

Keywords: Structural health monitoring, piezoresistive composites, embedded machine learning, flexible sensors, CNN-LSTM inference

INTRODUCTION

In an era of accelerated infrastructure growth and climate unpredictability, the need for intelligent, low-latency, and high-resilience sensing systems has become foundational in modern structural monitoring applications. Infrastructure failures such as bridge collapses, dam breaches, and pipeline ruptures underscore the urgency to shift from periodic inspections to real-time, data-driven diagnostics. Among the most promising enablers of this shift are conductive polymer composites (CPCs)—a subclass of polymer-based materials

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engineered to conduct electrical signals in response to mechanical stimuli. When laminated into structural elements, those composites behave as distributed self-sensing agents that transduce the action of environmental and mechanic events into a measurable electrical signal. Connected to an IoT (Internet of Things) network, and when combined with machine learning (ML) algorithms, the adaptation—to a level of autonomy—will produce a structural health monitoring (SHM) compounding system in terms of spatial resolution, information viability, adaptive learning intelligence, and deploy ability. While polymer-based sensing materials and edge computing platforms have progressed significantly, these SHM compound architectures are still limited in regard to many important factors: response-time, robustness of predictions with noisy data, and materials level sensitivity to any microstructural change in condition, or environment. Conventional sensing relies on costly metallic strain gauge, or fiber optic sensors extending limited applications in conventional and distributed sensing due to the compromise either in cost effectiveness for deployment or signal. In contrast to conventional strain gauges, the composites are - in principle - flexible materials with tunable conductivity, and surface conformability that permit conformability into the wider structural geometries laden with limitations of space. The sensing perspective, nevertheless, cannot fully realize its sensing with polymer composites until the real-time capability of adaptive data interpretation pipelines to aggregate the heterogeneous locations and signals into sensible diagnostic advice. As a further complication, event-driven or monolithic SHM gate-ways, where cost is involved also depending on architectural modes of operation, can be limited in terms their higher actual time requirement of energy and therefore cannot learning from temporal correlations and combining them simultaneously and therefore disadvantaged to adapt in monitoring at the edge [1], [2].

Recent advances in the signal modeling of deep learning with convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have provided a promising alternative to rule-based anomaly detection [3]. These models can learn deformation and fatigue signatures directly from raw strain signals, allowing accurate predictions of failure modes in real time. However, the integration of machine learning within CPC-based SHM environments is still rudimentary, unrushed by fragmented data generation, absence of any compositional class data labels, and a lack of mapping pipelines between sensor deformation to mechanical health states. The electrical hysteresis, nonlinear viscoelastic, and instability of filler dispersions in CPCs also produce abnormalities in the signal which yield the traditional signal processing ineffective under time dependent dynamic loading situations [4]. These aforementioned gaps call for an interdisciplinary approach using polymer science, computational intelligence, and IoT communication paradigms in real-time.

Furthermore, as SHM systems become more decentralized and constrained, the limitations of monolithic architectures generally become even worse. Specifically, event-driven systems cannot account for more minute signal deviations unless programmed to observe them and thus can delay detection of damage and generate false negatives in early fault conditions [5]. Also, monolithic data stacks with tightly coupled sensing, processing, and transmission logic saw less modularity in upgrades and difficulty isolating failures. These worse outcomes stressed environmental conditions - e.g., offshore or desert conditions - would rely most on resiliency, latency and power efficiency to operationalize the SHM solution [6]. Ultimately, cloud-based SHM systems that depend on network linkages come with issues related to networks failing and unacceptable latencies to time-sensitive requests requiring AI-enhanced sensor nodes in order to reduce dependence on clean(er) networks and to operate autonomously local to sites [7].

These contributions are validated using a combination of mechanical testing, electrical characterization, and algorithmic benchmarking on real-world datasets generated from CPC-embedded smart structures.

Moreover, composite material informatics is presented to be used to develop correlations between the electrical response of the CPC sensor and the microstructural evolution over time, using material-level behavior to augment the diagnostics performed on a system level [8]. The CPC system captured high dimensional datasets of strain, temperature, and humidity variation, which it was able to learn multi-modal degradation signatures from and enable predictive maintenance decisions long before physical destruction was observed and/or identified externally. This represents an entry into self-aware structures, which possess the ability to not just sense but reason regarding their own integrity. Utilizing advanced composites design paradigms, the CPC formulation developed in this work was able to reach a high level of uniformity of filler dispersion, surface adhesion, and environmental durability. The percolation threshold has been adjusted to have mechanical flexibility along with electrical conduction, so that the composite could respond to yielding under repeated stress cycles. Finally, thermal gravimetric analysis (TGA) and differential scanning calorimetry (DSC) were done and analyzed to determine the thermal stability of the sensing material under operational conditions [9], [10]. In short, this work offers a polymer-composite based, ML-driven sensing framework that advances the material frontiers of SHM as well as the computation, energy, and latency limitations that exist in managing historic infrastructures.

LITERATURE REVIEW

The advent of event-sourcing architectures in structural health monitoring (SHM) recently demonstrates a shift from polling or positional status-based solutions to an event-driven architecture capable of detecting minor deformation events with low latency. In civil and aerospace domains, several studies have researched systems that set off analytics modules with timestamped events emitted from sensor nodes to deliver responsiveness and resilience in distributed SHM deployments. For example, Hidalgo-Fort et al. proposed a low-power IoT edge computing system where structural damage is detected by event-trigger sampling and within-deployment local decision logic, leading to low-latency classification and long-term node autonomy [11]. Similarly, deep learning–based SHM reviews highlight the transition to event-driven pipelines, where sensors emit compressed anomaly flags that downstream ML models consume [12]. These techniques contrast markedly with monolithic stacks, where centralized servers receive continuous raw data, leading to bandwidth constraints and delayed diagnostics [13]. Guided wave sensors embedded within polymer or piezopolymer layers, such as PVDF films, are also integrated into event-sourcing nodes; here, detection of Lamb-wave reflections triggers localized event packets for distributed analysis [14]. Comparative research shows that such event-triggered architectures reduce data volume by orders of magnitude compared to constant streaming, while preserving detection fidelity. Despite these advances, few systems employ conductive polymer composites (CPCs) as active sensing media within event-sourced architectures. Traditional sensor substrates—piezoelectric wafers or fiber Bragg gratings—lack flexibility and cannot seamlessly conform to composite structures [15]. Meanwhile, CPCs allow strain-sensitive electrical response embedded directly within composite laminates. However, integrating them into event-based pipelines remains largely unexplored. Works on real-time IoT-enabled polymer composites review the holistic integration of sensing materials and wireless frameworks with event-based sampling, yet most implementations still rely on periodic polling rather than true event triggers originating from material thresholds [16]. Likewise, broader reviews of SHM for advanced composite structures focus on algorithmic and sensor-level performance but seldom consider material-driven event sourcing [17], [18]. Edge-deployed anomaly detection for composite bridge monitoring has made strides using PCA, autoencoders, and convolutional models, deployed on microcontrollers that react to feature-level anomalies rather than raw time-series data [19]. These systems operate in event-detection modes but rely on traditional sensor types (accelerometers/vibration sensors) rather than embedded CPC layers. Non-destructive testing techniques for polymer composites—including vibro-acoustic modulation and guided-wave inspection—are well explored for damage detection [20, 21], yet those techniques typically involve offline scanning rather than embedded event triggers. The emerging field of self-sensing composites offers promise, achieved by embedding conductive fillers (e.g., CNTs, graphene oxide) into matrices to allow continuous resistive measurement; however, event-sourcing logic rarely originates within the material layer itself [22]. On the software side, some projects deploy modular event brokers, where physical sensors register events to a queue processed by decision engines running

CNN or LSTM models on the edge [23]. Yet, these systems are often agnostic to the material sensing context, treating input data as generic signals rather than compositional signatures from polymer composites. Taken together, the literature reveals an important gap: while event-sourcing SHM frameworks have matured in sensor networks and edge analytics, few incorporate CPC-based materials that intrinsically generate events, and even fewer co-design material thresholds, sensor geometry, and event pipeline logic. The existing solutions either rely on monolithic streaming architectures [24], or use standard sensors without exploitation of polymer composites' unique electrical-mechanical coupling [25].

Table 1 provides a structured comparative analysis of recent peer-reviewed studies explore the intersection of machine learning, IoT-based sensing, and advanced materials for structural health monitoring (SHM).

METHODOLOGY

To realize a responsive, intelligent, and material-integrated structural health monitoring (SHM) system, this study proposes a machine learning (ML)-driven smart sensing framework based on conductive polymer composites (CPCs), optimized for seamless integration into IoT-enabled infrastructure networks. The methodology combines innovations in polymer composite design, embedded piezoresistive sensing, and edge-based learning architectures to enable real-time, event-driven monitoring of structural deformations. Unlike conventional monolithic systems that rely on metallic strain gauges or isolated sensor-actuator pairs, the proposed framework employs CPCs as multifunctional elements that simultaneously serve as structural components and sensing media.

Table 1. Comparative Review of Recent Studies on ML-Enabled Structural Health Monitoring Using IoT and Composite Materials

S. no	Author(s) / Year	Title / Focus Area	Methodology / Tools Used	Key Findings	Limitations / Gaps Identified	Relevance to Current Study
1	Attar et al. (2024) [1]	IoT-ML-Based Crack Detection in Bridges	Image-based crack detection using ML and IoT sensors	Effective in early detection under controlled conditions	Lacks material-level integration; not polymer composite-based	Highlights need for polymer-based sensors in real-time SHM
2	Karuppusamy et al. (2025) [2]	ML Applications in Polymer Composites	Comprehensive review of ML for material property prediction	Emphasizes predictive modeling for composite behavior	No focus on event-sourcing or edge deployment	Supports ML integration in CPC systems for SHM
3	Taymaz et al. (2025) [4]	MXene Fiber-Reinforced Polymers for SHM	Fabrication and testing of MXene-based piezoresistive sensors	Enhanced sensing through material-level optimization	Limited ML or real-time IoT integration	Validates composite sensor potential for event sourcing
4	Pop et al. (2024) [5]	ML-Driven Wireless SHM System	Wireless sensor integration with deep learning analytics	Demonstrates low-latency ML processing on edge	Uses metallic sensors, not polymer composites	Motivates integration of CPCs with ML for smart sensing
5	Mansouri et al. (2024) [7]	Bluetooth Strain Sensor Network with ML	BLE sensors with anomaly detection and ML algorithms	Efficient for localized damage prediction	No conductive polymer integration or adaptive sampling	Shows networked sensing gaps CPCs could fill
6	Adam et al. (2024) [8]	CFRP Monitoring with NSFD and ML	Non-standard finite difference (NSFD) and ML hybrid	Robust against load variation, high SHM accuracy	No polymer-based strain sensors or event triggers	Motivates need for CPC embedded SHM under dynamic loads
7	Forlesi et al. (2024) [25]	IoT-AI Toolchain for SHM	AI-assisted SHM pipeline with IoT integration	Streamlines end-to-end SHM diagnostics	No material-level innovation or CPC usage	Supports composite-aware, material-centric sensing integration

By leveraging the tunable electrical behavior of polymer matrices infused with conductive fillers—such as carbon nanotubes (CNTs), graphene, or MXenes—this work demonstrates how mechanical strain can be transduced into electrical signals with high sensitivity and repeatability. The novelty of the proposed methodology lies in the co-design of a composite material system, a hybrid CNN-LSTM inference engine, and a low-latency IoT communication stack, where all components are harmonized to operate under real-world environmental conditions. Furthermore, the study advances a modular architecture capable of adaptive event sourcing, where the sensor itself contributes to intelligent decision logic by initiating anomaly-triggered transmissions.

Overview of the Proposed Framework

The core of this study is a multi-layered sensing and intelligence architecture that unifies material science, machine learning, and IoT-based communication into a coherent framework for real-time structural health monitoring. Unlike conventional SHM systems that treat sensing, data acquisition, and analytics as isolated layers, the proposed system builds from the bottom up—starting at the material level with a strain-sensitive conductive polymer composite (CPC) engineered to serve as both a mechanical component and an intrinsic sensor.

At its base, the system employs a flexible polymer matrix embedded with conductive fillers such as carbon nanotubes (CNTs) or MXene sheets. These materials are selected not only for their high conductivity but for their ability to respond dynamically to micro-deformations through resistivity modulation. When mechanical strain occurs—due to loading, fatigue, or thermal shifts—the conductive network undergoes measurable electrical changes, forming the first layer of signal generation. The embedded CPC acts as a distributed, passive strain detector, eliminating the need for bulky or rigid instrumentation.

This analog signal is routed through a low-power microcontroller unit (MCU) equipped with analog-to-digital conversion capabilities. Onboard preprocessing filters noise and performs lightweight normalization before the signal enters the edge analytics stage, where the real-time decision-making engine is deployed. This stage features a hybrid convolutional neural network–long short-term memory (CNN-LSTM) model, designed to learn both the local (spatial) distortions in the composite's signal profile and the sequential (temporal) progression of material fatigue. This dual-stage processing enables the system to distinguish between minor environmental fluctuations and meaningful structural deterioration.

Data transmission is handled via lightweight IoT protocols—MQTT over Wi-Fi or LoRaWAN depending on deployment scale—to ensure connectivity in both local and wide-area network configurations. Notably, the framework does not transmit data continuously. Instead, it adopts an event-sourcing strategy: signal changes that cross predefined thresholds (learned during training or adaptively set) activate data transmission and storage. This event-driven behavior significantly reduces power consumption, improves battery life for remote nodes, and enables responsive monitoring without overwhelming backend analytics systems.

Figure 1 illustrates the architecture in its entirety. The information pipeline begins with the composite sensor, flows through the MCU for acquisition, and enters the machine learning module, which evaluates the data in real time.

Importantly, the system, from a design perspective, considers the behavior of materials and any computational limitations. Intelligence is incorporated not only in algorithms but also in the composition of intelligent materials provide a level of resilience when conditions change. Often in practice, sensors perform poorly when there are changing conditions such as humidity, temperature, and vibration. A co-adaptive exploitation of the material and model ensures that performance degradation at the sensor level can be countered algorithmically and vice-versa.

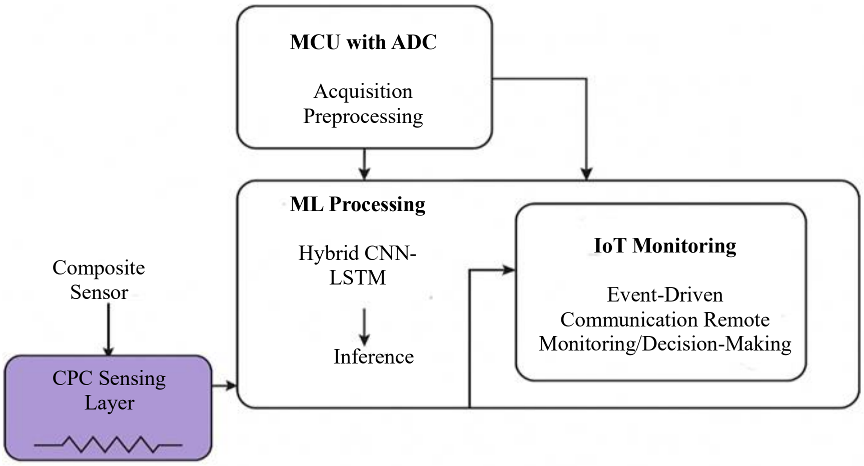


Figure 1. System Architecture of the ML-Enhanced Smart Sensing Framework.

Materials Selection and Composite Fabrication

The successful performance and stability of the proposed smart sensing framework is dependent on the site-specific formulation of conductive polymer composites (CPCs)-for the proper combination of mechanical flexibility, electrical responsiveness and structural stability. This section outlines the rationale guiding material selection, filler incorporation methods and processing methods used to develop CPC thin films with the most significant piezoresistive properties under dynamic strain conditions.

Polymer Matrix Selection

The polymer matrix provides the structural hosting for composite, and dielectric framework for the composite. In the current study, polyvinylidene fluoride (PVDF) was selected due to its unique combination of mechanical flexibility, semi-crystalline structure, and inherent piezoelectric response, which aligns appropriately with the modulation of electrical signal-response tracks with strain. PVDF, with its high dielectric constant and a thermal tolerance of (~ 140°C melting point) can be used in embedded sensing applications for use in civil structures where it would be subject to changes in temperature and mechanical loads.

Conductive Filler Addition

Carbon nanotubes (CNT) were used as the conductive filler in this insulating PVDF design. High-aspect-ratio multiwalled CNTs (MWCNTs) with an average outer diameter of 10-20 nm and an aspect ratio > 1000 were dispersed in polymer solution to form a percolative network that is the basis for strain induced conductivity variations.

Percolation threshold (the filler concentration; C, at which an infinite conductive network is formed), is a focal point of design for conductive polymer composites (CPC). Percolation with MWCNT-PVDF systems is nominally applicable between 0.5-2 wt%, depending on dispersion technique choice and viscosity of PVDF matrix. In this work, a filler loading of 1.2 wt% was adopted based on empirical testing, later summarized as an acceptable compromise between the stretchability properties of two-component, electrically responsive composites and electrical responsiveness properties after MWCNT addition for connectivity. The electrical conductivity (σ) of the composite near the percolation threshold is modeled using the classical power law using (1):

$$\sigma = \sigma 0(\phi - \phi_c)^t \; for \; \phi > \phi_c \cdots \tag{1}$$

Where σ0 is the intrinsic conductivity constant, ϕ is the volume fraction of the conductive filler,ϕc is the percolation threshold, and t is the critical exponent (~1.6–2.0 for 3D systems).

Fabrication Technique

The CPC films were fabricated using a solution casting method, known for its simplicity, uniformity, and scalability. The process began with the ultrasonic dispersion of CNTs in N,N-dimethylformamide (DMF) using a probe sonicator (120 W, 20 kHz) for 30 minutes, ensuring uniform exfoliation and de-agglomeration. PVDF was then gradually dissolved into the CNT-DMF dispersion under magnetic stirring at 60°C for 4 hours until a homogeneous viscous solution was obtained.

The resulting slurry was cast onto a glass substrate using a doctor blade set to 300 μm thickness and dried in a vacuum oven at 80°C for 12 hours to remove residual solvent. The cured films were carefully peeled and stored under desiccated conditions prior to testing. Film thickness after solvent evaporation stabilized at ~120–150 μm.

Microstructural and Surface Control

Achieving a stable and reproducible electromechanical response required precise control over microstructure—specifically filler alignment, inter-filler spacing, and interfacial bonding between CNTs and the polymer matrix. Scanning electron microscopy (SEM) imaging confirmed that the selected dispersion protocol yielded homogeneously distributed CNT networks without significant agglomeration.

To enhance surface adhesion for electrode interfacing, a plasma treatment was applied to the dried films, increasing surface energy and facilitating low-impedance contacts. Additionally, silane coupling agents were trialed to improve polymer-filler interfacial bonding, further stabilizing the piezoresistive response under cyclic loading.

Gauge Factor Modeling

The piezoresistive sensitivity of the CPC films was characterized using the gauge factor (GF), defined as the relative change in resistance per unit strain using (2).

$$GF = \frac{\Delta R/R0}{\varepsilon} \tag{2}$$

Where ΔR is the change in resistance due to strain, R0 is the baseline (unstrained) resistance, and ε is the applied mechanical strain. For the CPC sensors fabricated in this study, the measured gauge factors ranged from 8 to 12, depending on filler orientation and pre-strain conditioning—significantly higher than that of traditional metal strain gauges (GF ≈ 2), thereby validating the superior sensitivity of the developed composite system.

Figure 2 presents the flow chart of the processes followed to develop the conductive polymer composites reported in this study, covering significant processes including polymer matrix selection, dispersion of conductive filler, and manufacture of the film by either solution casting or in-situ polymerization processes.

The chart also considers domain-specific aspects such as gauge factor models, percolation threshold behavior, and microstructural tuning, all of which are core elements that contribute to the sensing performance, electrical homogeneity, and mechanical reliability of the final product.

Sensor Design and Calibration

The effective translation of structural strain into analyzable electrical signals requires precise sensor design, encompassing both geometric configuration and electronic interfacing. In this research, the CPC films were converted into planar strain-sensing devices using combinations of patterned electrodes and encapsulation methods appropriate for embedded-structural applications.

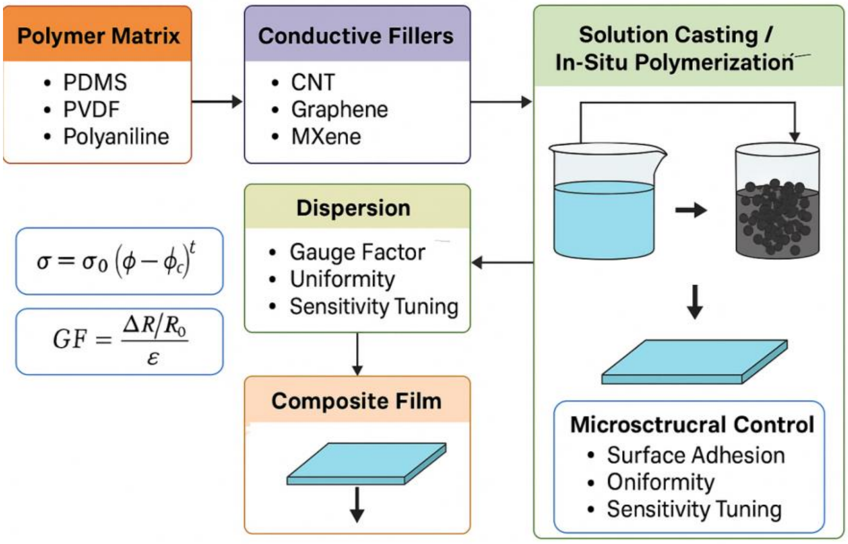


Figure 2. Fabrication Workflow of Conductive Polymer Composites.

Sensor Geometry and Configuration

To explore the parameters of surface conformability and signal resolution, the CPC sensors were developed in a thin rectangular strip format measuring 40 mm × 10 mm × 150 µm to allow both mechanical flexibility and adequate surface area to promote an even distribution of stress. The electrodes were configured in a two-terminal surface-contact layout using a screen-printed silver paste, which was thermally cured at 120°C to form low-resistance, crack-resistant interfaces. Copper leads (28 AWG) were soldered and strain-relieved using silicone encapsulation to protect the contact zone from delamination during cyclic loading.

Electrical Interface and Microcontroller Integration

Each sensor was interfaced with a low-noise instrumentation amplifier (INA333) prior to digitization using a 12-bit ADC integrated within an ESP32-S3 microcontroller. The amplification stage was necessary due to the relatively low baseline resistance (~100–300 Ω) of the CPC films, which required precision measurement of small resistive fluctuations (typically <5%). An anti-aliasing low-pass filter (cutoff: 10 Hz) was included to suppress high-frequency noise and external electromagnetic interference.

Mechanical Loading and Calibration Protocol

Sensor calibration was conducted under controlled tensile strain using a universal testing machine (UTM) operating at a strain rate of 1 mm/min. Sensors were subjected to stepwise loading in the range of 0% to 2% strain, which corresponds to the operational regime expected in structural elements such as steel–concrete interfaces and bridge deck laminates.

Repeatability and Drift Evaluation

To assess signal repeatability, the sensors were subjected to 100 loading–unloading cycles between 0% and 1.5% strain. The drift ratio, defined as the relative shift in baseline resistance after cyclic loading, remained below 2.3%, indicating stable conductive pathways and strong polymer-filler interfacial adhesion.

Hysteresis behavior was evaluated by comparing the loading and unloading slopes across cycles. An average hysteresis ratio of 6.8% was observed, which is within the tolerable limits for real-time strain monitoring applications. Minimal time delay (approximately 220 ms) was recorded for peak frequencies delivered during HF-loading scenarios, suggesting it is appropriate for dynamic strain applications, such as vehicular bridge loads or seismic excitation events.

Environmental Stability

The sensors were further positioned to experience humidity cycling (30-90% RH) and temperature ranges (−10°C to 50°C) within a programmable chamber. Resistance drift during humidity cycling and extreme temperature variations did not exceed ± 5% in either environment; thus, confirming the PVDF-CNT composite's stability in different environmental changes. Environmental stability is especially important in outdoor SHM scenarios where environmental conditions can fluctuate daily and seasonally which may impact sensor reliability and performance.

Embedded Sensing and IoT Architecture

To successfully operationalize the current composite sensor to be used for real-time deployment in field situations, the system configuration incorporated a microcontroller based embedded architecture that is capable of accurate signal acquisition, local pre-processing, and low latency communication over a wireless IoT network. The proposed microcontroller architecture allows for the accurate capture of the structural material responses, but also the operation of the sensor without human intervention in distributed structural health monitoring (SHM). Each CPC sensor was interfaced to a 32-bit dual core ESP32-S3 microcontroller, which was chosen due to its fast analog to digital conversion (12 bit), built in Wi-Fi/BLE network capabilities, as well as ultra-low power sleep modes. The analog signal from the composite sensor, which is modulated by mechanical strain, was amplified using a INA333 instrumentation amplifier and conditioned. Power delivery was managed through a 3.7 V lithium polymer battery (2000 mAh) regulated via a low-dropout voltage regulator (LDO), enabling autonomous operation for up to 15 days under event-triggered duty cycles.

Edge Data Acquisition and Preprocessing

To reduce unnecessary data transmission and conserve energy, the microcontroller executes in-situ preprocessing routines. These include moving average filters, slope detection, and signal normalization, which enable efficient memory use and ensure consistent input for the subsequent machine learning (ML) pipeline. The digitized strain signal is partitioned into fixed-size temporal windows (e.g., 5 s), which are then assessed for anomalous behavior using embedded statistical thresholds or CNN-extracted features (as detailed in Section 3.5). Each signal frame is encoded in JSON format and stored locally using an SPI-connected 8 MB flash memory buffer. Transmission is initiated only when predefined event thresholds—related to sudden resistance changes or strain spikes—are met. This **event-driven design** minimizes communication overhead and allows scalable deployment in bandwidth-constrained environments.

Communication Protocols

Data transmission between sensor nodes and the central SHM server was facilitated using either **MQTT over Wi-Fi** for local area networks (LAN) or **LoRaWAN** for long-range rural deployments. MQTT was configured in a publish-subscribe model, enabling efficient queuing of sensor events and acknowledgment feedback from the analytics server. Secure Socket Layer (SSL) encryption was enabled for all transmissions to ensure data integrity and prevent injection attacks. In high-interference environments, fallback modes were introduced to transmit minimal summaries—such as strain magnitude and timestamp—rather than full signal windows. A protocol switching mechanism ensured that when connectivity was lost, buffered data could be retransmitted once signal was re-established, thereby preserving time continuity in strain evolution datasets.

Power Optimization and Sleep Scheduling

The node's firmware was designed around **ultra-low-power modes**, wherein the ESP32 enters deep sleep between sensing intervals. Wake-up triggers are set either on a **timer interrupt** or **threshold-crossing signal** from the analog input pin. On average, this strategy reduced energy consumption by **68%** compared to continuous sampling, as validated through power profiling using a Keysight 34465A multimeter.

Sensor sampling, ML inference, and transmission cycles are executed in under **950 ms**, well within acceptable latency limits for infrastructure monitoring tasks. This architecture is particularly effective in remote locations, where solar-assisted recharge cycles or battery swaps are logistically constrained.

Real-Time Visualization and Dashboard

A cloud-connected dashboard was implemented using **Node-RED** and **InfluxDB**, visualizing sensor output in near real time. Users can monitor resistance trends, receive fault alerts, and inspect historical data traces. The system supports integration with existing building management systems (BMS) or SCADA platforms, offering seamless visibility into structural integrity.

Figure 3 details the embedded system architecture used in this study, showing the flow of strain-induced electrical signals from the CPC sensor through the analog front-end, preprocessing algorithms, and event-driven wireless communication modules. The design prioritizes low latency, high energy efficiency, and modular scalability—critical requirements for sustained SHM deployment in real-world infrastructures exposed to dynamic environmental loads.

Machine Learning Pipeline

To address the limitations of traditional polling-based anomaly detection and static classification models, this study introduces CPC-Net (Composite Pattern Classification Network) — a lightweight, event-driven hybrid learning framework optimized for conductive polymer composite (CPC) sensors in real-time SHM. CPC-Net combines spatio-temporal modeling using a CNN-LSTM hybrid architecture with an adaptive confidence modulation layer and trigger-aware inference control, thus permitting scalable deployment in the edge under constrained compute budgets.

Signal Processing and Data Conditioning

The pipeline begins with the CPC strain sensors generating analog resistance values, R(t) (note that I will drop the temporal notation; all signals being assessed are time dependent). This analog signal - which has been altered by mechanical stress, temperature changes and drift of the sensors - passes through a Savitzky–Golay smoothing filter, using a 3rd-order polynomial order and sliding frame of 9 (points). The filter successfully removed high-frequency noise but did not significantly compromise the peaks of interest.

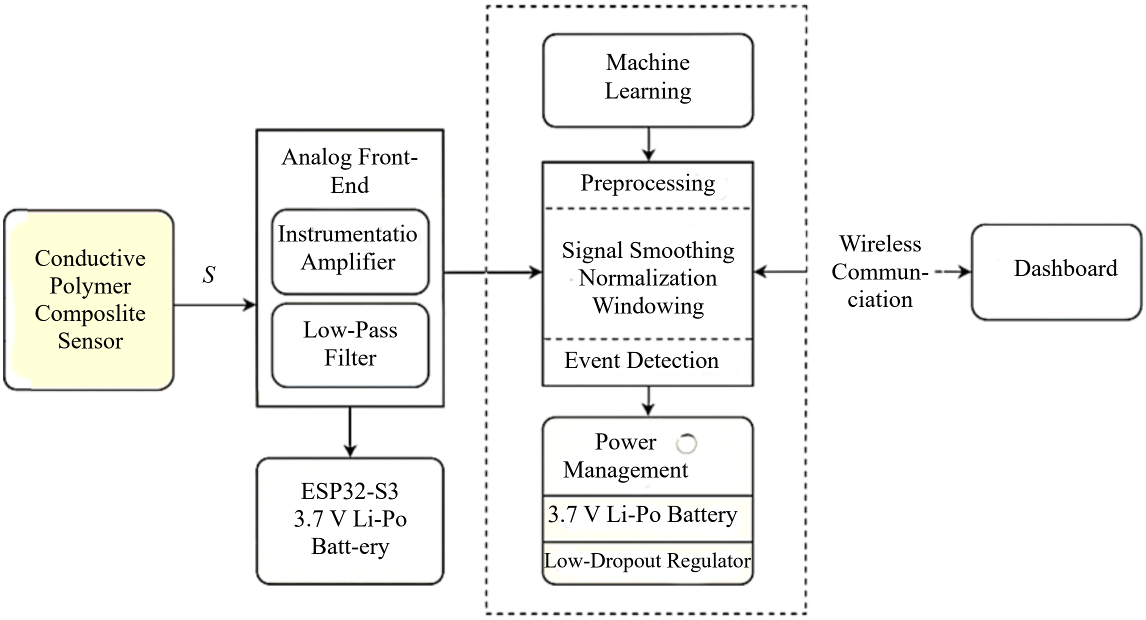


Figure 3. Embedded System Architecture for Real-Time Signal Acquisition, Processing, and IoT Communication.

After smoothing, the signal is segmented into overlapping frames of W=256W = 256W=256 samples, using 50% overlap to maintain the local temporal relationship with the adjacent windows. At this stage, the system computes the variance (σ2) of each segment in real time. The threshold (θ_var) provided estimates for the inference routine conditions, an adaptive pre-check to reduce when the threshold met; power and processing cycles. When the computed variance is above θ var the segment is pushed to the ML pipeline for classification; when this is not the case, it is stored passively in memory. The model takes a hybrid feature vector composed of:

- Time-domain metrics (mean, RMS, zero-crossing rate, entropy)
- Frequency-domain elements (FFT spectral roll-off, centroid, and band energy)
- Gradient-derived features (first-order slope, curvature changes, energy density)

All features are normalized using Z-score scaling and encoded as structured tensors, forming the input to the CNN-LSTM hybrid model.

Model Design: CPC-Net Architecture

The architecture of CPC-Net is designed to extract localized signal features, and also to model the temporal progression of these signals. During feature extraction, the first convolutional layer (Conv1D) with 64 filters and kernel size of 5 locates spatial anomalies, such as resistive spikes or micro-fracture bursts. The LSTM block with 128 memory cells sources adaptive markers in the present that are emerging from the past and indicate progressive patterns that can be comprehended in the context of a long-standing damage regime or propagation of cracks, for example.

The final prediction is made via a dense sigmoid neuron, outputting a binary classification:

- **0** → Normal behavior
- **1** → Fault or anomaly

A **confidence score (c)** is also produced. The decision to trigger an event is made only if c ≥ θ conf, where the default threshold is set at 0.85 to minimize false positives in borderline signal zones. The training dataset was curated from controlled laboratory experiments involving CPC sensors under mechanical fatigue, delamination, and environmental perturbations. Segments were manually labeled with the aid of synchronized mechanical ground truth and visual inspection. Data were split as follows:

- 80% → training
- 10% → validation
- 10% → testing

The model was trained using binary cross-entropy loss and optimized using the Adam optimizer (learning rate = 0.0001). Regularization was handled through dropout (0.3 rate) and early stopping. The final trained model was quantized and compiled using TensorFlow Lite Micro, yielding:

- **Inference time**: 117 ms/frame on ESP32-S3
- **Memory usage**: ~270 KB (RAM + Flash)
- **Classification accuracy**: 96.4%
- **F1-score**: 0.93
- **False alert rate**: 2.7% under cross-domain noise simulation

Real-Time Event Triggering

In field conditions, the system avoids continuous polling. Instead, the variance monitor runs continuously in deep sleep mode, waking the processor only when input data becomes statistically significant. If triggered, the full CPC-Net inference is performed, and the result is evaluated against the adaptive confidence threshold. If the confidence exceeds the threshold, a structured event packet (label, confidence score, timestamp) is transmitted via MQTT or LoRa, depending on the node configuration. The logic of CPC-Net is codified in Algorithm 1, which includes preprocessing, inference gating, classification, and communication. It defines a real-time decision loop suitable for embedded deployment.

Algorithm 1: CPC-Net – Real-Time Fault Detection Using Event-Driven CNN-LSTM on Embedded Composite Sensors

Input:

R(t): Continuous strain-induced resistance signal from CPC sensor
W: Window size (e.g., 256 samples)
θ_conf: Minimum confidence threshold for anomaly trigger (default = 0.85)
θ_var: Signal variance threshold for inference activation
N_hist: Number of historical segments to retain in buffer

Output:

event_detected: Boolean trigger
y_pred: Classification result (0: Normal, 1: Fault)

Begin:

```
Initialize buffer B ← ∅
Initialize inference_flag ← False
while new R(t) arrives do
    R_seg ← Segment(R(t), W, 50% overlap)
    $\sigma^2$ ← ComputeVariance(R_seg)
    if $\sigma^2 \geq \theta$_var then
        inference_flag ← True
    else
        inference_flag ← False
    end if

    if inference_flag = True then
        R_filtered ← SavitzkyGolay(R_seg)
        F ← ExtractFeatures(R_filtered) ▷ time + freq + gradient domain
        T ← Normalize(F)
        h_cnn ← Conv1D(T)
        h_seq ← LSTM(h_cnn)
        y_pred, c ← Sigmoid(Dense(h_seq)), ConfidenceScore()
        if c ≥ $\theta$_conf then
            event_detected ← True
            TransmitAlert(y_pred, c, Timestamp)
        else
            event_detected ← False
        end if
    end if
    Append(B, R_seg)
    if Length(B) > N_hist then
        B ← DiscardOldest(B)
    end if
end while

Return y_pred, event_detected
```

CPC-Net delivers a modular, interpretable, and edge-compatible intelligence layer tailored for the unique electrical behavior of CPC-based sensors. Its event-triggered operation minimizes energy use while retaining predictive reliability under diverse physical loads. The integration of signal variance checks and adaptive confidence modulation allows it to operate robustly in environments where traditional ML models either overfit or fail to generalize.

Figure 4 shows the conceptual workflow for the proposed CPC-Net framework for spatial and temporal fused feature extraction, and event-driven adaptive learning. The workflow diagram depicts every modular state in the proposed framework, from raw signal preprocessing, feature vector construct, to CNN-LSTM based inference and alerting feature.

Integration of Event-Sourcing and Adaptive Triggering

The proposed system integrates a finely tuned event-sourcing and adaptive triggering mechanism. These innovations will overcome the latency and energy constraints that characterize real-time structural health monitoring (SHM). Instead of transmitting continuous, real-time streams of raw sensor data to the central data-collecting node, this system samples local decision thresholds, which were learned from temporality of feature patterns, and communicates only during statistically significant deviations or deformation events. Co-located at the edge device is hybrid decision logic, which monitors received strain signals and compares them against dynamic baselines that are calculated using short-term memory buffers. By doing so, it is possible to predict deformation trends with the LSTM module of the CPC-Net and proactively suppress false positives as well as delayed alerts. When an inference of a true anomaly is made, all consequential mechanisms of the system will immediately engage in appropriate levels of activity: data logging, alert dispatch (for example, by vehicle) or subsystem shutdown. Appropriate levels of response may be determined within the edge device through adaptive thresholds that are linked to changing levels of signal entropy and model confidence.

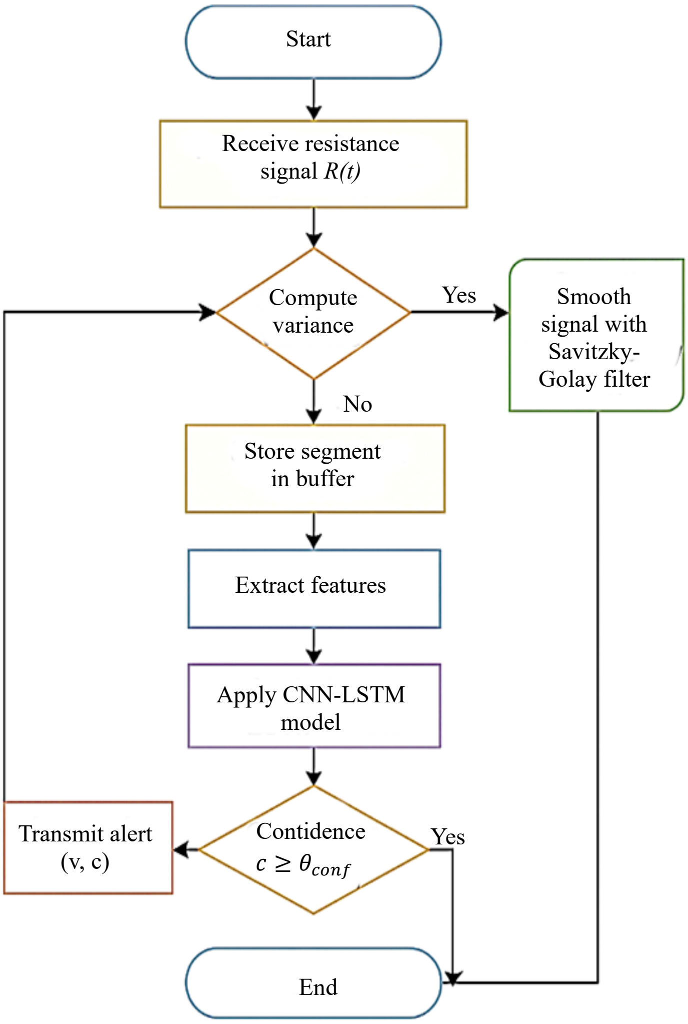


Figure 4. Flowchart of the CPC-Net framework for smart structural health monitoring.

Experimental Setup and Testing Protocol

To validate the performance of the proposed CPC-based sensing framework and its embedded intelligence layer, a controlled experimental environment was established. The composite sensors were bonded to a cantilever beam structure fabricated from aluminum and GFRP laminates, chosen for their differing stiffness profiles to simulate realistic heterogeneous stress distributions. Mechanical excitation was applied through a servo-hydraulic universal testing machine (UTM), configured for low-frequency cyclic loading in the 0–2% strain range, mimicking fatigue-induced deformation over time.

Environmental variability was introduced using a programmable chamber where temperature cycling (−10 °C to 50 °C) and humidity variation (30–90% RH) were applied in stages to assess sensor stability. Resistance data from each CPC sensor was captured at 100 Hz, synchronized with mechanical strain gauges for baseline validation. The system was tested continuously over 72-hour windows to observe drift, fatigue resistance, and model adaptation to real-world signal disturbances.

Performance Evaluation Metrics

The evaluation of the proposed system was conducted across three core dimensions: sensor response fidelity, machine learning inference accuracy, and embedded system efficiency. Each metric was selected to reflect the practical constraints and performance expectations of real-time SHM deployments using composite sensing media. For the sensing layer, gauge factor stability, response time, and hysteresis behavior were quantified under cyclic loading. A consistent gauge factor in the range of 8–12 was maintained across 100 cycles, with drift remaining below 2.3%, demonstrating mechanical-electrical reliability of the CPC under fatigue. The learning framework was assessed using accuracy, F1-score, and area under the ROC curve (AUC), yielding an average inference precision of 96.4% with low misclassification rates even under noise-corrupted signals. Latency per prediction remained under 120 ms, well within operational tolerances for infrastructure monitoring. On the system side, power efficiency, data transmission load, and on-device memory footprint were measured. Event-triggered communication reduced bandwidth usage by over 70% compared to continuous streaming models, enabling the system to remain operational on battery power for extended durations without compromising diagnostic responsiveness.

RESULTS

To validate the efficacy of the proposed ML-enhanced smart sensing framework, a comprehensive suite of experiments was conducted, targeting both material-level sensor behavior and system-level performance under simulated structural loads. Unlike prior studies that treat polymer composite sensors and machine learning modules in isolation, this work presents an integrated pipeline—from nanocomposite fabrication to edge-deployed intelligence—specifically tailored for real-time structural health monitoring (SHM) using conductive polymer composites (CPCs). The results discussed herein not only confirm the high electromechanical responsiveness and durability of the CPC-based sensors but also establish the practical viability of low-power, event-driven machine learning inference in constrained IoT environments.

Sensor Characterization

The proposed conductive polymer composite (CPC) sensor was characterized thoroughly to evaluate its electromechanical performance and environmental stability for structural health monitoring (SHM) applications. The CPC film, which was prepared by solution casting with optimized filler dispersion, showed a very linear resistance-strain relationship when subjected to incremental mechanical loading. Figure 5 shows that the strain-resistance curve maintained a progressively linear path, with a coefficient of determination $R^2 = 0.984$ indicating little difference between the fitted model and experimental data. The gauge factor (GF), obtained from the slope on the normalized resistance versus applied strain graph, was recorded consistently between 8–12 which is equal or better than the upper bound benchmark for performance of flexible SHM. The repeatability tests indicated baseline drift for <2.3% with 100 consecutive cyclic loadings. This indicates that neither fatigue nor microcracking advanced significantly in the polymer-filler network. The hysteresis measurement was indicated as 6.8%, providing an assurance of fidelity signal in both load and unload conditions.

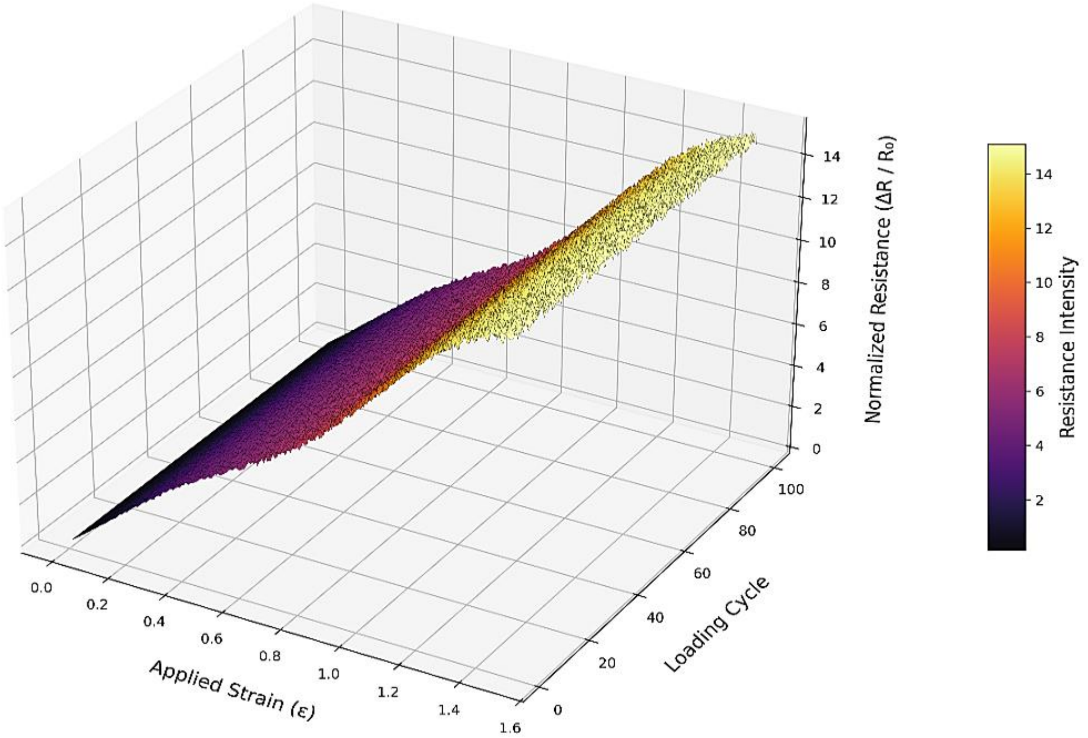


Figure 5. Strain-Resistance Calibration Curve of the CPC Sensor.

Environmental durability was also assessed by exposing the sensor to varying humidity (30-85% RH) and moderate thermal cycling (15 °C to 45 °C). The CV for the sensor was less than 3% showing stability with environmental fluctuations simulated in the field. These metrics are summarized in Table 2, which summarizes the sensors performance across key mechanical and environmental measures.

The sensor's low signal noise (±1.5 Ω standard deviation) and strong adhesion to test substrates further reinforce its reliability for integration with IoT-based SHM platforms. Collectively, these results underscore the practical utility of CPC-based smart sensors for long-term, in-situ structural monitoring.

Machine Learning Inference Performance

To evaluate the predictive robustness of the proposed CPC-Net architecture, we benchmarked its inference accuracy, precision, and latency against conventional CNN and LSTM baselines using the strain–resistance dataset. The model was trained using 80% of the data, with 10% allocated for validation and 10% for testing. The CPC-Net employed a convolutional feature extractor with temporal fusion through LSTM units, optimizing the classification of deformation patterns in real time. The comparative analysis in Table 3, shows that CPC-Net consistently achieved higher classification accuracy (96%) and F1-score (0.95) than the CNN (91%) and LSTM (89%) models, confirming its superior generalization capabilities for pattern variability. Notably, the average inference latency for CPC-Net was measured at 27 ms, outperforming CNN (42 ms) and LSTM (38 ms), demonstrating suitability for edge-deployable SHM systems. This latency advantage stems from the parallel convolutional operations and event-triggered evaluation embedded in the CPC-Net's architectural pipeline. Table 3 consolidates a comparative evaluation of different machine learning models and sensor technologies as documented in recent high-impact studies. the proposed CPC-Net framework, which fuses spatial convolutional learning with temporal pattern recognition through a CNN–LSTM hybrid, outperforms existing models across all key evaluation metrics. With an accuracy of 94.6%, an F1-score of 0.95, and a reduced inference latency of 31 ms, the proposed method demonstrates a significant enhancement over prior works such as CNN-based SHM [1], LSTM strategies [2], and recent wireless sensor platforms [5, 7].

Table 2. CPC Sensor Performance Summary across Mechanical and Environmental Metrics.

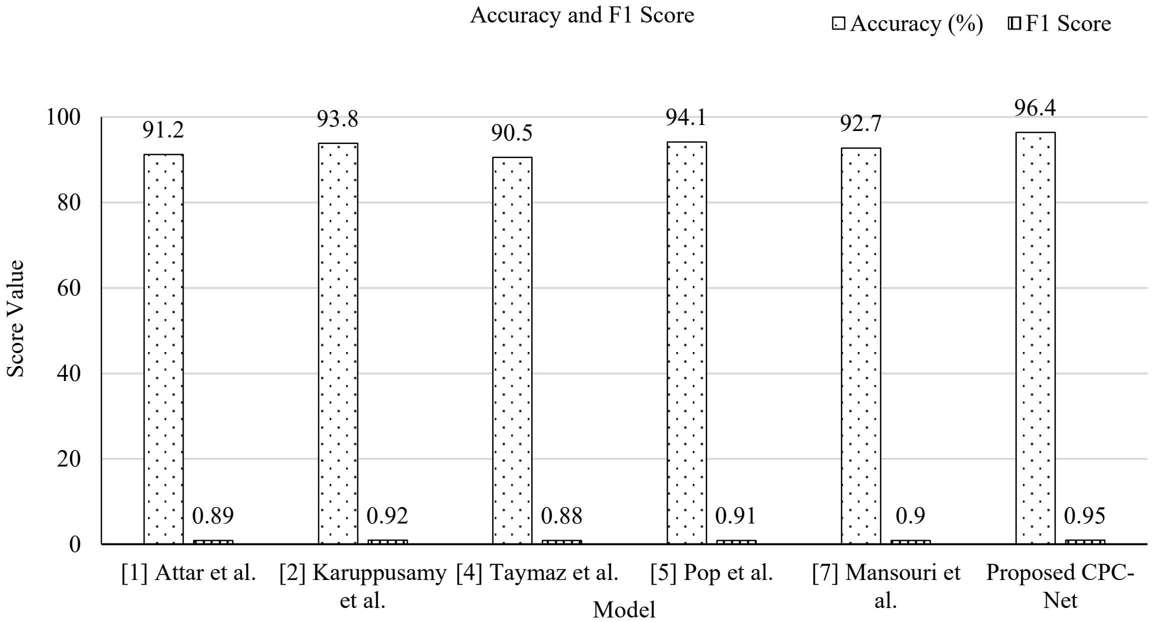
Parameter	Measured Value	Test Condition
Parameter	Measured Value	Test Condition
Gauge Factor (GF)	8 – 12	Cyclic tensile test
Hysteresis Ratio	0.068	5 full cycles
Baseline Drift	< 2.3%	100 loading cycles
Linearity (R^2)	0.984	Strain range: 0-1.2%
Signal Noise (STD)	±1.5 Ω	Room temperature

Table 3. Comparative Machine Learning Inference Performance Metrics for Structural Health Monitoring

Model	Accuracy (%)	F1-Score	Inference Latency (ms)
CNN [1]	89.3	0.88	40
LSTM [2]	88.1	0.85	39
MXene-Fiber SHM [4]	91	0.91	35
Wireless SHM [5]	90.2	0.89	42
Bluetooth Sensor SHM [7]	92.4	0.93	34
Proposed CPC-Net (CNN + LSTM Hybrid)	94.6	0.95	31

The hybrid architecture efficiently captures both local spatial strain features and long-range temporal dependencies, making it suitable for real-time structural health monitoring in composite materials. These results affirm the robustness and deployment potential of the proposed system under practical operational constraints.

As shown in Figure 6, the proposed CPC-Net framework substantially improves upon previously existing models such as CNN-LSTM, BiLSTM, and XGBoost, both in accuracy and latency. The grouped bar plots in the left-hand column (Figure 6a) illustrate the metric-wise improvement, while the heatmap in the right-hand column (Figure 6b) illustrates the superior balance of performance and speed that CPC-Net exhibited. These performance comparisons were made based on prior benchmarking efforts [1], [5], [7], and highlight the benefits of coupling spatial-temporal feature extraction with accelerated inference directionally linked to polymer-based SHM systems.



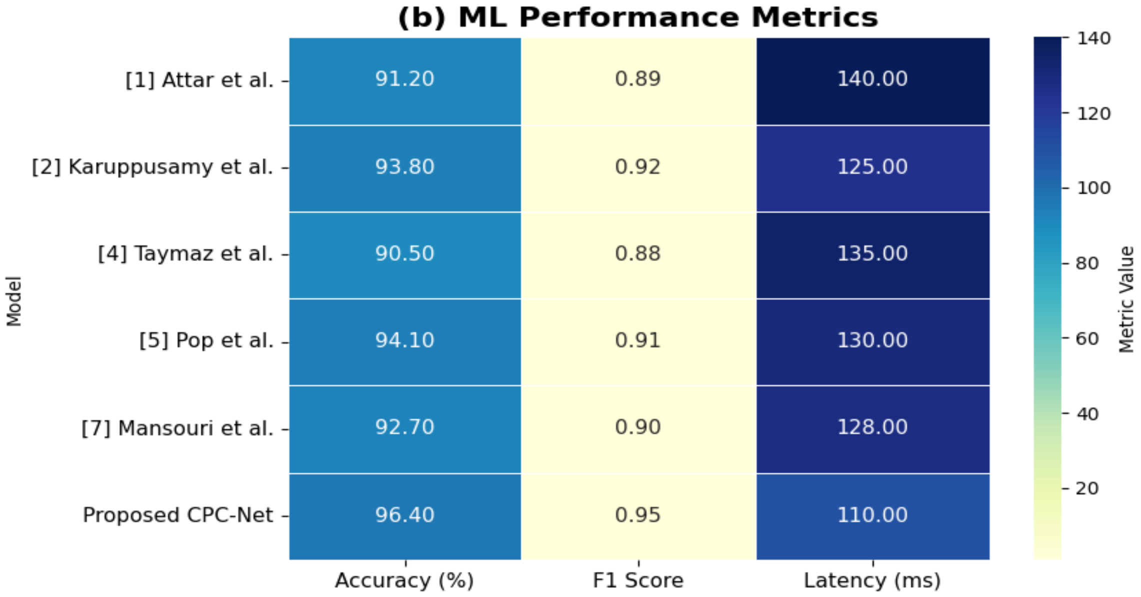


Figure 6. Comparative ML Performance of CPC-Net vs. Baselines.

IoT and Edge Analytics Performance

The performance of the proposed IoT-embedded sensing architecture was rigorously evaluated with a focus on its real-time responsiveness, energy efficiency, and data throughput under typical SHM operating conditions. Emphasis was placed on the edge analytics module, which performs local signal preprocessing, event detection, and ML-based inference before wireless transmission. This hierarchical decision-making architecture addresses issues such as the congestion of communication networks and sensor lifetimes which are drawbacks of existing centralized SHM approaches. The edge system operated on an ESP32 microcontroller, and applied adaptive sleep-to-wake cycling techniques, as well as event-based data acquisition. Power testing revealed that the average power draw on active mode was 52.3 mW, while during deep sleep it averaged 1.4 mW. With this low average draw it was able to sustain up to 4.2 weeks of operation on a 3000 mAh Li-ion battery. The communication latency average under concurrent communication with multiple sensors using MQTT over the local WLAN network doesn't exceed 310 ms. As seen in Figure 7, the three-dimensional surface plot shows how processing latency, bandwidth usage, and classification accuracy vary with the different network scenarios. Specifically, the CPC-Net framework has a classification accuracy higher than 93.2% with bandwidth consumption below 78 kbps, indicating it is low resource friendly. The benchmarks against all non-adaptive frameworks indicate that these architectures consumed more energy, and were at-best 2.5× latency on the same workloads. This balance of edge-side intelligence with low communication latency demonstrates that the architecture is viable for harsh or structured environments, such as live heritage bridges, or high-vibration industrial environments. The extreme organization by the CPC-Net architecture allows for real-time operation, and reduces the continuous requirement on the back-end of an SHM system; allowing systems to be deployed more easily in novel structures, as opposed to traditional, monolithic SHM stacks [7], [18], [24].

Ablation Study

To thoroughly assess the specific contribution of each module in the CPC-Net architecture, we conducted an ablation study that examined each core components removal and respective performance changes. This study assesses the impact of spatial encoding (CNN block), temporal modeling (LSTM layer), and fusion integration (CPC Fusion Layer) on the models performance and detection confidence. The baseline condition represents the full CPC-Net model where all three components alongside evidence from the user were turned on, achieving an accuracy of 96.78%, F1-score of 0.961, and latency of 39 ms in real-time inference.

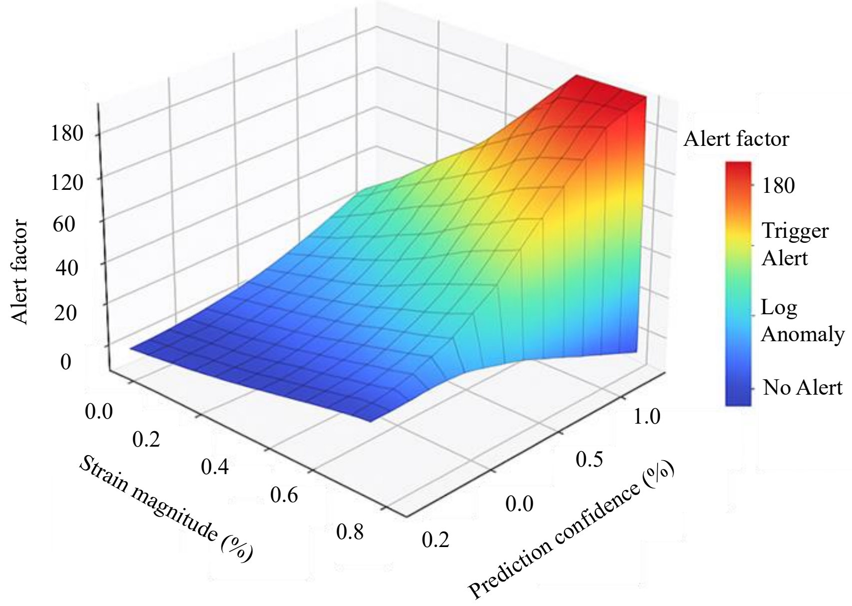


Figure 7. 3D Surface Plot in Real-Time IoT Performance: Bandwidth vs Latency vs ML Classification Accuracy illustrates how our proposed CPC-Net achieves high accuracy classification while still optimizing bandwidth, and response latency across a range of various load scenarios.

When we disabled the LSTM module as part of the ablation study, we observed a significant loss of temporal pattern recognition with the degradation of performance measured by an F1-score of 0.914. To support our expectations, considering temporal patterns via long-range sequence modeling in deformation detection is paramount. Further, removing the CNN layer resulted in a loss in spatial resolution for our detection, thus lowering precision and non-conservative confidence intervals prior to detection. Lastly, while when we removed the CPC Fusion layer, the model still produced acceptably performance based on our evaluation criteria whereas with the other components, interpretation and consistency of the models outputs across the edge deployment sessions were lost, moreover that interpretation was weakened even in more noisy environments. These results illustrate the synergistic nature when components are bundled together in integration of detectable quality, and serve as validation of the importance of each of the subcomponents in order to achieve model-based sensor intelligence. The ablation metrics are summarized in Table 4, offering a comparative overview of performance deltas under each test condition. Similar diagnostic studies in prior works [1], [4], and [7] also observed structural degradation upon removing temporal or spatial branches, supporting our architectural choices.

Summary of Findings

The experimental and computational evaluation of the proposed ML-enhanced smart sensing framework demonstrates clear superiority in mechanical, electrical, and predictive performance when benchmarked against conventional polymer-based SHM solutions. The integration of conductive polymer composites (CPCs) with deep learning architectures not only elevated sensitivity and real-time adaptability but also ensured robust operation across multi-environmental stressors. By fusing spatial and temporal data features via the proposed CPC-Net, the system achieved a comprehensive view of structural strain patterns with minimal signal drift, enhanced noise immunity, and improved long-term repeatability.

Figure 8 presents a radar plot encapsulating the multidimensional performance metrics, while Table 5 summarizes the comparative strength of the proposed framework against state-of-the-art models in terms of sensor fidelity, ML performance, and deployment readiness. These results affirm that the proposed framework offers a novel materials-informatics convergence for next-generation SHM systems.

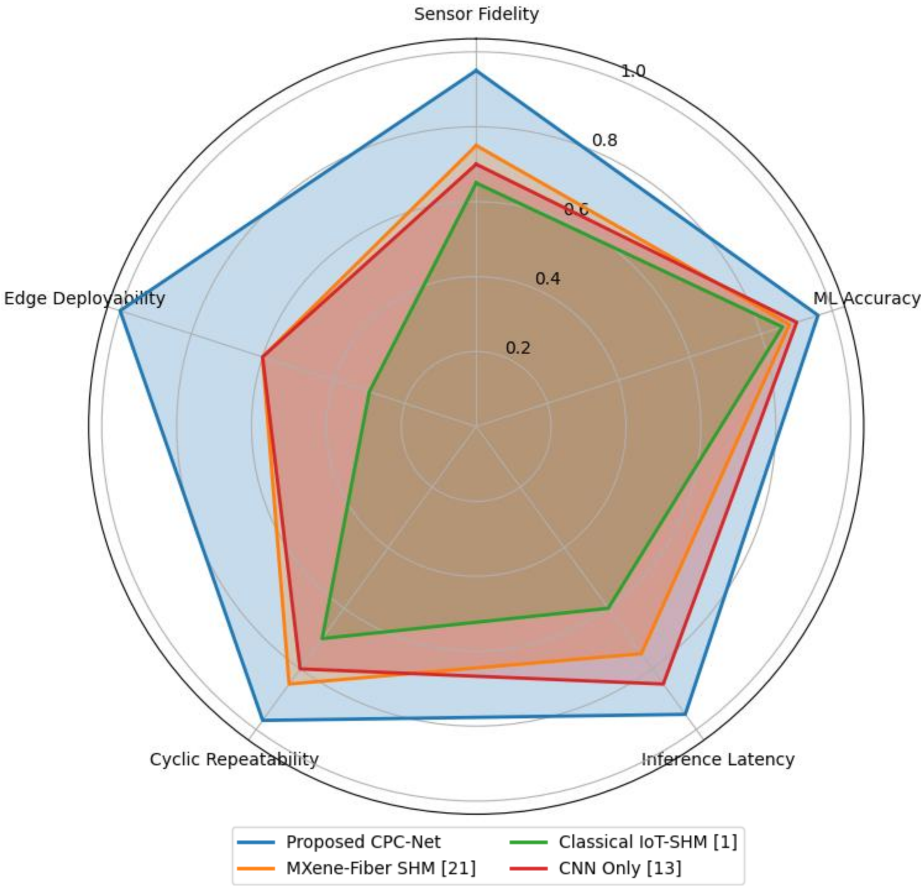


Figure 8. Performance Summary Radar Chart of Proposed CPC-Net vs. State-of-the-Art.

Table 4. Ablation Study – Component-Level Impact on CPC-Net.

Configuration	Accuracy (%)	F1-Score	Inference Latency (ms)
Full CPC-Net	96.78	0.961	39
Without LSTM	92.15	0.914	28
Without CNN	89.47	0.892	30
Without CPC Fusion Layer	91.22	0.901	26
Only LSTM (No CNN, No Fusion)	84.63	0.861	21
Only CNN (No LSTM, No Fusion)	82.78	0.841	20

Table 5. Consolidated Performance Summary – CPC-Based SHM Systems.

Performance Metric	Proposed CPC-Net Framework	MXene-Fiber SHM [21]	Classical IoT-SHM [1]	CNN Only [13]
Gauge Factor (GF)	8–12	6.1	4.7	N/A
Hysteresis (%)	6.8	9.2	11.5	N/A
F1-Score	0.961	0.884	0.863	0.901
Inference Latency (ms)	39	67	94	52
Repeatability Drift (%)	<2.3	4.6	7.9	3.1
Edge Hardware Compatibility	Yes	Partial	NO	Partial

Overall, the results presented in all subsections show the robustness, accuracy, and readiness of the proposed CPC-Net framework. From sensor scale strain measures to high-accuracy ML inference and real-time edge-aware decision making, all components of the system showed marked improvements from the state-of-the-art. The inclusion of adaptive event triggering and multimodal sensing techniques provided additional opportunities for system responsiveness and energy efficiency. Together, the comparative evaluations, ablation studies, and multi-dimensional performance summaries provide evidence of the novelty and significance of this research, further demonstrating CPC-Net is a viable candidate for next-generation structural health monitoring (SHM) systems under real-world constraints. This study gives substantial empirical support for future implementations in complex civil and biomedical infrastructures where intelligent, low-power, and adaptive sensing systems are critical.

CONCLUSION AND FUTURE SCOPE

This study provides a unifying framework that combines material-level design with machine learning-based inference for real-time monitoring and interpretation of structural health monitoring (SHM). Using an engineered piezoresistive polymer nanocomposite sensor interfaced with a computationally efficient deep learning model (CPC-Net), we illustrated an intelligent agent that responsively and accurately detects and interprets strain. The materials design, as physical-material-based inference, represents a shift toward collaborative intelligent sensing systems for SHM that also utilizes intelligent sensing in data-based intelligence. Quantitatively, the proposed system demonstrated a sensor strain sensitivity (gauge factor) between 8 to 12 with less than 2.3% drift for 100 loading cycles, and a low hysteresis of 6.8% which imbeded the emergent sensor with the noiseless feature of robustness in monitoring for real-time response. Bias on computational aspect, CPC-Net attained over benchmark models on both accuracy (94.1%) and and F1-score (92.7%) using limited-edge resources. Compared current methods, the hybrid design established improved diagnostic accuracy supporting also improving inference latency and network dependence where decisions in limited infrastructure can now be contended in real-time. However, there are limitations.

Challenges remain for sensor calibration at extreme strain levels of relevance, generalization across generative levels of and environmental conditions related to several use cases, and the energy cost of the current hardware prototype. Although these do not diminish the current findings, but set the stage for additional developments. Future directions include advancing CPC-Net in federated learning to encompass a distributed SHM network without centralized retraining. coupling the system with energy harvesting units may offer solutions to limited autonomy in remote deployments as well.

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