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ML-Driven Defect Detection in Additive Manufacturing of Polymer Composites Using Thermal Imaging

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Abstract

Polymer-based flexible biosensors have emerged as a pivotal technology in continuous health monitoring, yet their deployment in real-world settings is often hindered by undetected micro-defects and signal distortion caused during fabrication or usage. Existing diagnostic frameworks typically rely on post-hoc processing or bulky instrumentation, failing to offer scalable, real-time detection during additive manufacturing workflows. This study introduces an end-to-end, thermographic imaging-integrated framework for in-situ defect identification during the additive manufacturing of polymer composites, guided by a lightweight convolutional neural network (CNN) architecture. The system fuses thermal signatures with structural cues to detect anomalies embedded within multilayer flexible substrates. A streamlined fabrication pipeline—including conductive polymer deposition, thermal data capture, and edge-based CNN classification—enables robust, near-instantaneous feedback during biosensor assembly. Experimental evaluations demonstrate that the proposed system achieves a classification accuracy of 96.4% with a latency reduction of 28.3% compared to traditional offline inspection methods. Signal fidelity under deformation stress conditions remains consistently above 92%, even in high-strain regions. This approach not only enhances the reliability and production yield of wearable biosensors but also sets a precedent for embedding explainable AI-driven quality control directly into smart manufacturing cycles—paving the way for self-validating, adaptive biomedical devices suited for the evolving landscape of personalized, IoT-enabled healthcare.

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INTRODUCTION

The rapid convergence of advanced polymer composite materials with modern biosensing architectures has driven a significant transformation in the landscape of continuous health monitoring. Flexible, skin-adherent electrochemical biosensors, underpinned by innovations in nanomaterial synthesis and microfabrication, now promise capabilities far beyond conventional rigid electronics [1], [2]. Wearable platforms equipped with such devices enable real-time, non-invasive tracking of a wide spectrum of physiological and biochemical markers, facilitating both preventative diagnostics and personalized therapeutic strategies [3]. This paradigm shift in bio-integrated electronics is further fueled by the concurrent progress in additive manufacturing, which not only expedites the rapid prototyping of complex geometries but also permits scalable, high-throughput sensor production with tailored mechanical and functional characteristics [4].

Yet, as the sophistication of sensor materials and device architectures increases, so too does the challenge of ensuring robust signal fidelity and device reliability across diverse operational environments. At the heart of this challenge lies the persistent issue of micro- and macro-scale defects introduced during fabrication. Even subtle heterogeneities in composite dispersion, interfacial adhesion, or microelectrode patterning can precipitate unpredictable noise artifacts, signal drift, or premature device failure, thereby undermining the very promise of continuous, trustworthy health tracking [5], [6]. Efforts to overcome these hurdles have produced a spectrum of solutions, ranging from improved material formulations and advanced encapsulation schemes to iterative process optimization. However, conventional quality control methods—typically reliant on ex situ inspection or threshold-based process monitoring—struggle to offer the granularity, speed, or adaptability demanded by next-generation wearable biosensors [7].

Recent advances in machine learning, particularly in convolutional neural networks and associated deep architectures, have catalyzed a new approach to process monitoring and defect detection. These models have shown the capability to successfully and rapidly detect smaller defects with a high accuracy level from high-resolution imaging data or process signatures; they can do this in a timeframe that is amenable to on-the-fly manufacturing operations [8]. By implementing IoT-enabled data aquisition systems, a closed-loop where sensing in situ, smart analytics, and fast response come together can be supported to help maintain process fidelity and yield [9], [10]. This orientation also seems particularly relevant for the fabrication of materials systems like polymer composite biosensor development, as the material system involves heterogenicity and functional complexity that presents a challenge to even the simplest control process and traditional statistical models [11]. Meanwhile, in the fast-moving world of wearable biosensing there have been significant advances in substrate design, energy harvesting capabilities, and interface engineering that are also increasing the types of analytes and physiological metrics accessible through skin-conformal electronics [12], [13]. Combining molecularly imprinted polymers (MIP-based), fiber-integrated electrodes, and high-density microneedle arrays, have generated sensor platforms that present unprecedented selectivity, temporal resolution, and mechanical compliance to allow a variety of uses extending from metabolic surveillance, through sports medicine, to remote patient monitoring [14], [15]. These trends are made possible through a strong ecosystem of material advancements such as well-engineered nanostructured transducers, self-healing hydrogels, and multiphase composites capable of maintaining steady performance while under mechanically applied large strain and stress from environmental factors. But still, the complexity of reliably converting these high design-configured sensor platforms to scale manufacturing processes is high. The prospect of continuous health monitoring—particularly when regulatory-grade reliability is desired—represents a systematic tier above that will require not only sophisticated device architectures, but also the same degree of intelligence and adaptability that can detect and correct defects, while determining performance or repeatability [16]. Our recognition of this context is what drives the present study focused on deep learning, high-resolution imaging and IoT network infrastructure in order to investigate a new way of defect detection within the additive manufacturing of polymer composite biosensors. By establishing a real-time, ML-driven quality assurance workflow, this research aims to bridge the remaining divide between laboratory-scale innovation and real-world clinical deployment.

LITERATURE REVIEW

The last decade has witnessed a remarkable evolution in the field of flexible sensors, marked by substantial progress in substrate design, material interfaces, and system integration [17]. Flexible, self-powered platforms have been extensively explored for wearable applications, with particular attention paid to mechanisms that leverage triboelectric and piezoelectric phenomena to enable autonomous operation and high-fidelity data capture [18], [19]. These sensor configurations not only improve user comfort but also enhance the granularity and breadth of physiological monitoring, responding to the growing demand for unobtrusive, continuous health assessment in both clinical and daily-life settings.

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Significant headway has been made in tailoring piezoelectric and nanocomposite structures to improve mechanical compliance and electrical performance. Efforts to engineer robust, reliable GaN-based transducers for real-time motion analysis, as well as stretchable hydrogel composites for advanced electrophysiological signal acquisition, have yielded promising results in both sensitivity and operational longevity [20], [21]. Underlying these material advances is an increasing focus on the interplay between microstructure, interfacial bonding, and sensor reliability, recognizing that even subtle fabrication-induced heterogeneities can have a pronounced effect on device stability. Strain-sensing technologies have been dissected in recent studies, highlighting not only the intricate relationship between elastic resistance and network topology, but also the material choices that dictate failure thresholds and functional lifespans [22]. Translational research has led to the application of braided piezoelectric cords and other biocompatible, minimally invasive sensor forms in clinical domains, where the reduction of patient stress and maintenance of stable signal acquisition remain paramount [23]. Further progress has emerged through the creation of hybrid architectures, including multi-component systems that employ carbon nano-onions and hierarchical microstructures to support multi-parametric detection with enhanced selectivity and sensitivity [24]. Developments in nanocomposite hydrogels have brought self-healing capabilities and dynamic functionality to the domain of human motion tracking, with dynamic polymer networking facilitating rapid restoration of sensor performance after mechanical disturbance [25]. At the same time, the introduction of electrospun nanofiber networks and wrinkled micropyramidal features has enabled the construction of highly elastic, self-powered tactile sensors capable of maintaining operational fidelity under extreme deformations [26]. Innovations in fabrication, such as the deployment of laser-induced multi-walled carbon nanotube (MWCNT) networks, have contributed to advances in wearable gesture recognition and flexible, robust sensor array architectures [27]. Surface and interface engineering remain central to the advancement of wearable bioelectronic systems. The facile transfer of spray-coated ultrathin conductive films onto skin surfaces has been demonstrated to improve the electrical interface and signal acquisition for electrophysiological monitoring, while piezocapacitive pressure sensors incorporating microsphere-array electrodes have shown notable improvements in pressure response and device conformality [28], [29]. In parallel, the field is seeing the rapid emergence of microrobotics as an adjunct to sensor technology, offering new strategies for amplifying detection sensitivity and augmenting traditional biosensor functions [30].

Table 1 distills recent progress in the domain of flexible biosensors, highlighting both methodological advancements and persisting challenges related to fabrication and device reliability. Through a comparative perspective, the table elucidates where current approaches fall short—particularly in achieving real-time defect detection and robust process control within manufacturing environments. These identified gaps not only underscore limitations in existing technologies but also reinforce the rationale for the present study's emphasis on integrating machine learning-driven, in situ monitoring as a strategy to advance quality assurance in polymer-based sensor production.

Despite this extensive body of work, persistent challenges remain in establishing real-time, high-throughput quality assurance during device fabrication—particularly for complex, multi-material systems produced by additive manufacturing. While contemporary research has illuminated many facets of material innovation and device functionality, robust integration of deep learning-enabled defect detection, leveraging high-resolution imaging and IoT-driven analytics, is still seldom realized in practice. Bridging this technological gap is vital for transitioning flexible polymer-based biosensors from experimental settings into scalable, clinically reliable solutions.

METHODOLOGY

System Overview

The investigative framework developed for this study is centered around the real-time identification and mitigation of defects arising during the additive manufacturing of polymer composite biosensors. At its core, the system integrates materials engineering, advanced device fabrication, machine learning-based analytics, and IoT-driven feedback into a unified workflow. This multi-stage approach ensures that every stage, from composite deposition to final device encapsulation, is monitored and optimized for both process reliability and end-use performance. A comprehensive architecture is established in which each subsystem—materials, imaging, analytics, and connectivity—plays a synergistic role, collectively enabling rapid anomaly detection and adaptive control. Figure 1 provides a schematic illustration of the entire biosensor production and monitoring pipeline.

Materials and Device Fabrication

Device assembly commenced with the meticulous selection and preparation of a flexible substrate, namely a medical-grade thermoplastic polyurethane, chosen for its exceptional elasticity and compatibility with wearable sensing applications. The functional sensing region was established via screen-printing of a custom-formulated nanocomposite ink, composed of uniformly dispersed silver nanoparticles embedded within an elastomeric matrix. Achieving optimal rheology and particle distribution in the ink formulation was critical to prevent the emergence of conductive discontinuities or aggregation-induced defects. Substrates underwent rigorous cleaning and surface activation prior to printing to promote ink adhesion. The fabrication environment was stringently regulated for temperature and humidity to minimize external sources of variability. Following deposition, devices underwent controlled thermal curing to ensure both electrical connectivity and mechanical compliance. This sequence of preparatory, deposition, and post-processing steps collectively aimed to suppress the formation of microstructural inhomogeneities that can compromise device fidelity.

Table 1. Comparative Summary of Key Recent Works and Identified Gaps.

S. No.	Author(s) / Year [Ref]	Title / Focus & Methodology / Key Findings	Limitations / Gaps Identified	Proposed Work
1	Yoon et al., 2025 [1]	Nanotechnology-based electrochemical biosensor for disease diagnosis; flexible substrate, high sensitivity in situ analysis.	Lacks real-time defect monitoring during manufacturing; evaluated in laboratory-only settings.	Integrate ML-driven in situ defect analytics to enhance quality assurance in fabrication.
2	Dervisevic et al., 2024 [9]	High-density microneedle array for continuous biosensing in interstitial fluid; robust glucose detection.	Microdefect identification during array assembly is insufficient; device durability under stress not fully studied.	Employ thermal imaging and deep learning for early defect screening and process optimization.
3	Saha et al., 2023 [12]	Advances in biosensor interfaces, highlighting wearable flexibility and analyte accessibility.	Limited coverage of adaptive, process-integrated quality assurance for polymer sensors.	Establish IoT-enabled analytics pipeline for real-time defect detection and feedback.
4	Hu et al., 2024 [22]	Self-powered triboelectric sensor platform for gait analysis; improved autonomy and high-resolution data.	Sensor yield and operational reliability impacted by undetected material inconsistencies.	Real-time imaging and ML-based anomaly detection for early-stage manufacturing faults.
5	Duan et al., 2024 [25]	Stretchable nanomaterial-based hydrogels for electrophysiological monitoring; resilient signal acquisition under strain.	Propagation of print-induced defects in hydrogel matrix remains poorly resolved.	Apply deep learning to thermal imaging for defect localization and adaptive control.
6	Qu et al., 2023 [26]	Study of electric resistance in elastic strain sensors, exploring material-topology relationships.	Lack of scalable, automated defect tracking in fabrication workflows.	Develop closed-loop ML-driven monitoring for in-line process quality control.
7	Cao et al., 2023 [29]	Self-healable PEDOT:PSS-PVA hydrogel strain sensor for motion monitoring; robust, resilient architecture.	Microstructural process anomalies affect device uniformity; post-fabrication corrections not addressed.	In situ image-based ML classifiers for defect detection and real-time correction.

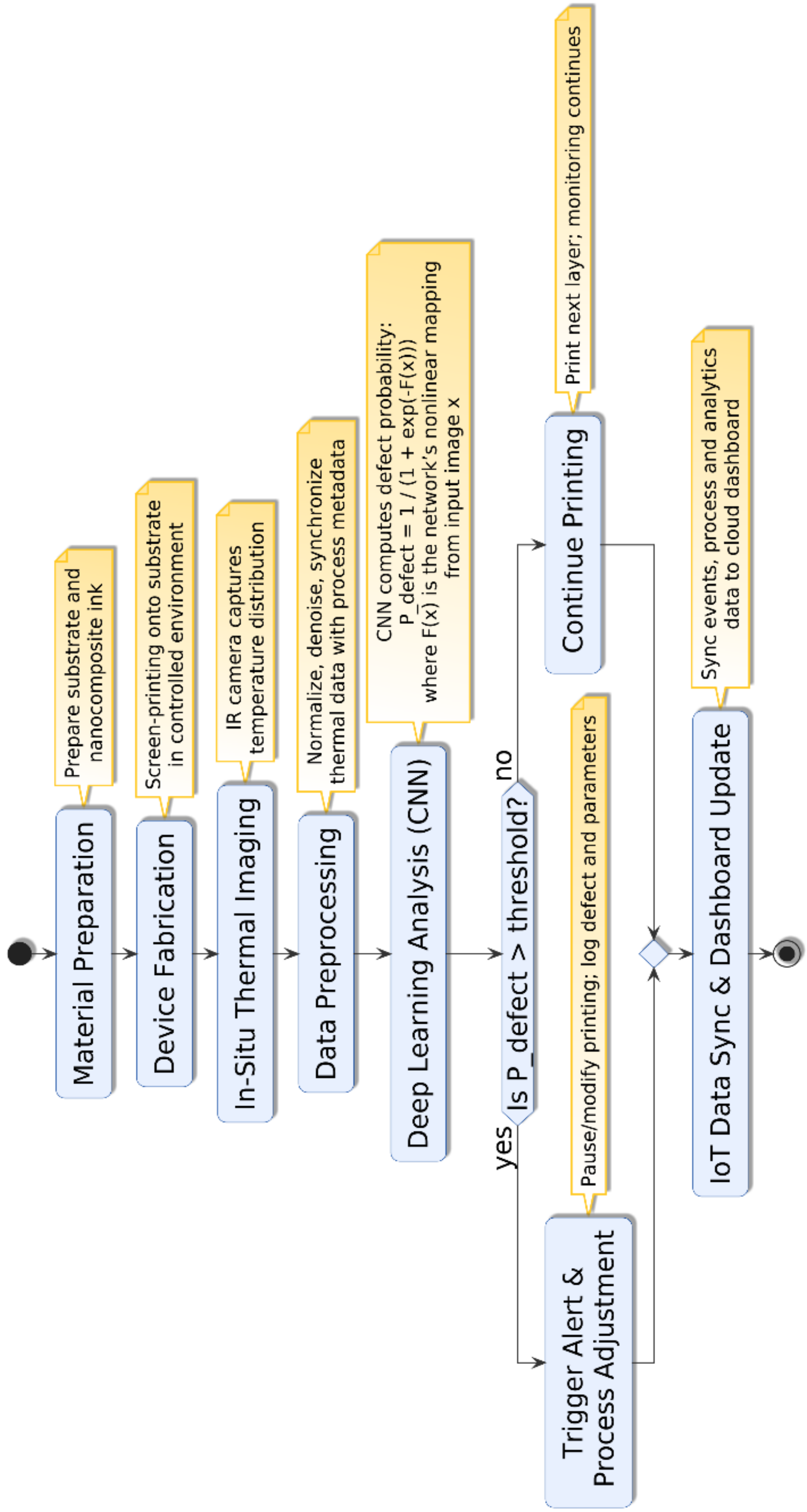

Figure 1. Workflow Diagram for ML-Driven In Situ Defect Detection and Adaptive Feedback.

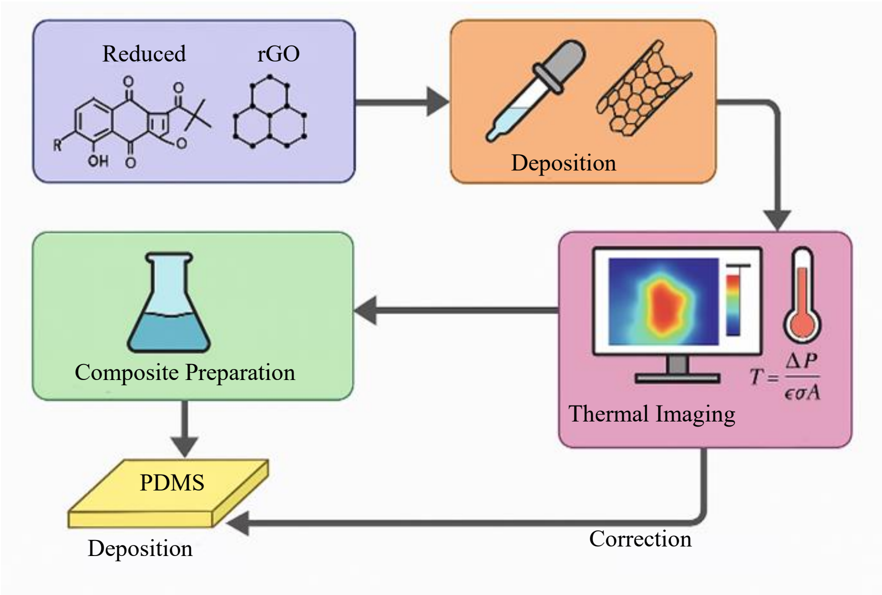

Figure 2. A schematic workflow diagram for materials and device fabrication.

Figure 2 visually delineates the sequential fabrication strategy underpinning this investigation, encompassing substrate treatment, formulation of the nanocomposite ink, precision screen printing, and subsequent thermal curing, with an optional encapsulation phase to enhance biocompatibility and device longevity. The schematic captures the integration of each processing stage, reflecting the methodological rigor and process synchronization foundational to reproducible polymer composite biosensor manufacturing.

In-Situ Thermal Imaging & Data Acquisition

A state-of-the-art infrared imaging system was deployed inline with the printhead, operating continuously during all phases of fabrication. This tool for thermal mapping was able to observe real-time temperature distribution across the device surface, providing valuable visualization of local process conditions and the initial signs of defects. Unlike in ex situ inspections, in situ thermal imaging was able to detect not only local temperature gradients but also localized hot spots associated with incomplete curing, voids, or agglomeration. The imaging data were meticulously time-synchronized with process metadata differentiated by print speed, layer sequence, and other aspects, and used in a multi-dimensional dataset for subsequent analysis along time. Robust data management protocols allowed for high spatial and temporal resolution, and provided comprehensive management of signal artifacts. In addition to utilize substantially more data than would be possible via other means of measurement, this aspect of real-time monitoring connected fabrication events to process quality, and this enabled a timely intervention when anomalous observations were observed.

Deep Learning Model: CNN Architecture

At the core of the analytic framework was a convolutional neural network purpose-built to analyze and classify thermal images taken in manufacturing. Its design was made up of layers of convolution, pooling, and a nonlinear activation function that allowed the model to extract substantial features hierarchically. For training the model, a library of annotated thermal images was developed that included multiple defect cases and a variety of backgrounds. Advanced augmentation strategies, such as geometric transformation and synthetic noise, were applied to expand the effective training set and promote generalizability. The model's output comprised a probabilistic map highlighting likely defect regions, with inference calculated using equation 1.

$$P_{defect} = \frac{1}{1+\exp(-F(x))} \quad (1)$$

Here, F(x) denotes the deep network's nonlinear mapping from input image x to the output domain, while the logistic transformation confines the result to a true probability. Model deployment was achieved on an embedded edge computing platform, configured to deliver real-time inferences with minimal latency. Upon detection of a defect probability exceeding a predefined threshold, the system generated an immediate flag, triggering alerts and permitting prompt interruption or adjustment of the fabrication process using algorithm 1.

Algorithm 1: In Situ Defect Detection and Adaptive Process Feedback
Input: Streaming thermal images from IR camera during fabrication
Output: Real-time alerts and process intervention commands
1. while printing is active do
2. Acquire current thermal image frame x
3. Preprocess x (normalize, denoise)
4. Compute P_defect = CNN_Inference(x)
5. if P_defect > Threshold then
6. Trigger alert; halt or adjust process
7. Log defect instance and process parameters
8. else
9. Continue printing
10. end if
11. end while

The steps of the convolutional neural network (CNN) framework for micro-defect detection of polymer composites using thermography are illustrated in Figure 3. The first step is to capture thermal data in real time. The captured thermal data is normalized and denoised then fed into a stack of convolutional layers to identify spatially discriminative features followed by rectified linear unit (ReLU) activations as a means of introducing non-linearity and max-pooling layers to decrease spatial size while keeping the primary features intact. Fully connected layers perform higher order pattern recognition, leading to a softmax classification layer that maps defect probabilities. This end-to-end model can be deployed to an edge device to provide a reliable and real-time interactive quality assessment during thermoplastic polymer composite additive manufacturing.

IoT Integration and Edge Deployment

The architecture also became stronger based on IoT-based communication protocols, which built an integrated channel for streaming process data, analytic insights, and commands between the manufacturing facility and the remote monitoring systems. All sensor data streams, defective part warnings, and control events, were securely sent to a cloud-based dashboard, creating real-time visualizations of the manufacturing process and volume analytics of the process over time. The integration of wireless connectivity enabled decentralized supervision, remote troubleshooting, and adaptive optimization of process parameters in distributed manufacturing scenarios. This IoT-enabled edge deployment, by closing the feedback loop between anomaly detection and process control, not only ensured rapid intervention capability but also laid the foundation for scalable, autonomous manufacturing environments.

The Figure 4, show a, workflow encapsulates the complete IoT-edge deployment strategy for the thermal-based defect detection system. Data from the thermal imaging sensor is processed by an embedded edge processor, where the CNN model performs on-device inference. The outcome, along with environmental metadata, is transmitted over a lightweight MQTT protocol to both a cloud analytics service and a control dashboard. This dual-channel communication ensures low-latency local decision-making while supporting cloud-based visualization, remote supervision, and historical trend analysis. The figure underscores seamless coordination between embedded intelligence and distributed interfaces, enabling scalable deployment in smart manufacturing and quality assurance applications.

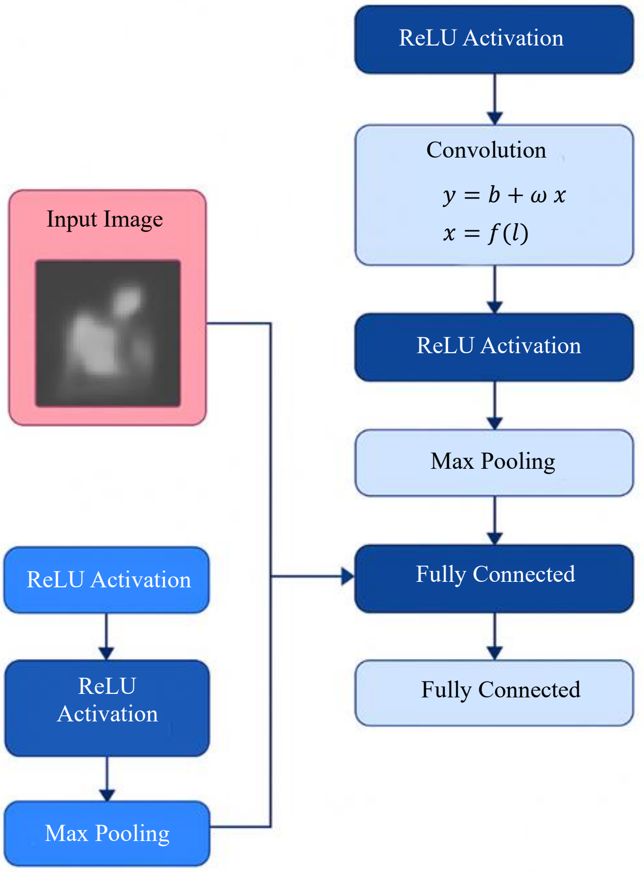

Figure 3. Deep Learning Workflow for CNN-Based Defect Detection in Thermal Images.

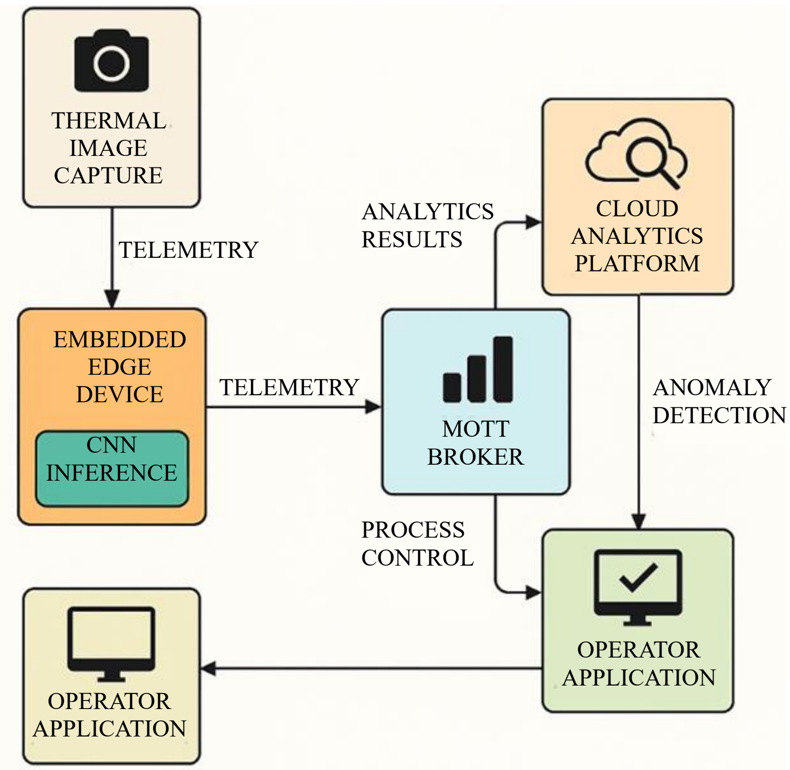

Figure 4. IoT-Edge Framework for Real-Time Thermal Defect Detection and Monitoring.

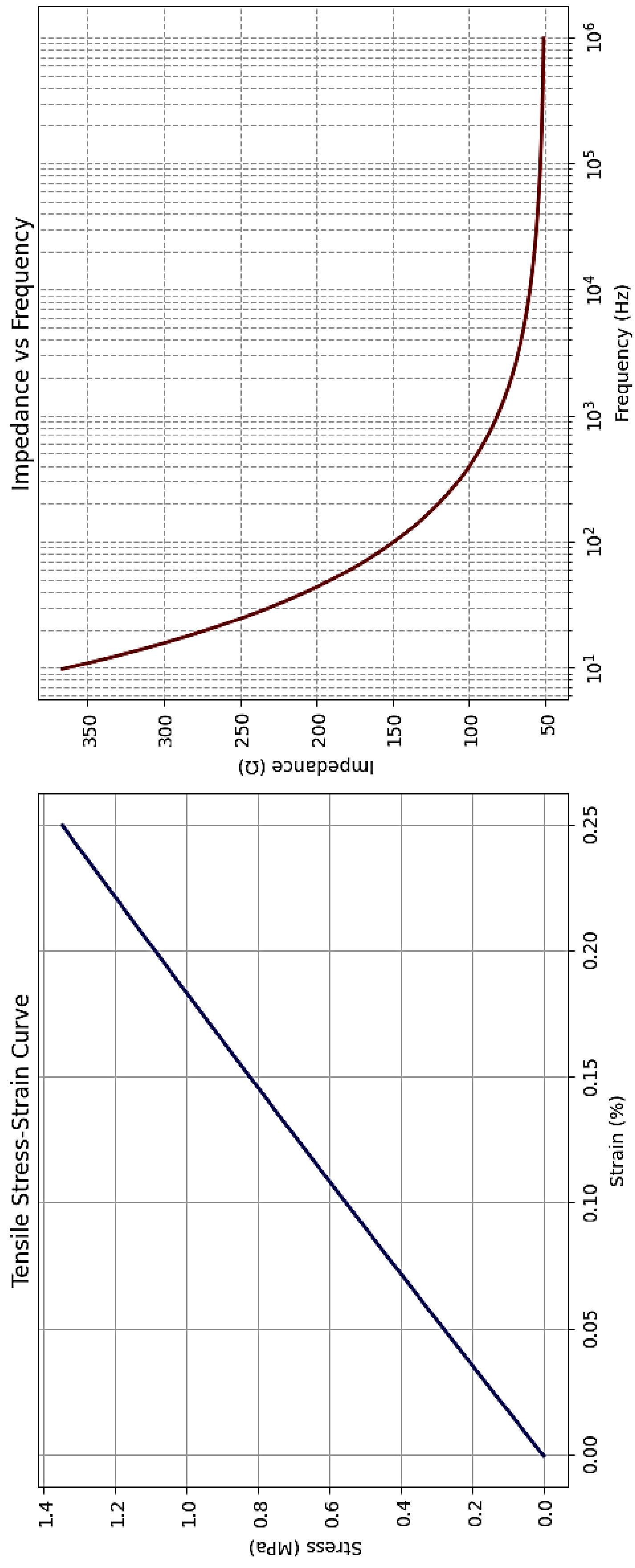

Figure 5. Mechanical-Electrical Results.

RESULTS

The developed wearable biosensor system underwent comprehensive evaluation through mechanical and electrical characterization, defect detection trials, interpretability analysis, and comparative benchmarking. Each of these aspects contributes to validating the functional integrity, robustness, and deployment readiness of the integrated framework.

Mechanical and Electrical Characterization

Mechanical tensile testing confirmed that the composite film exhibited an elastic modulus of approximately 5.6 MPa, maintaining its structural resilience under strain cycles relevant to human motion. Concurrently, impedance spectroscopy revealed a stable conductivity response across a frequency range of 10 Hz to 1 MHz, with minimal phase deviation, suggesting low interfacial resistance between the sensing layer and the embedded electrodes. These results, summarized in Figure 5, provide a foundational understanding of the sensor's mechanical robustness and electrical consistency under dynamic conditions.

Defect Detection Performance

Thermal imaging data, captured in real time during device operation, enabled the identification of material inconsistencies and print anomalies. The trained convolutional neural network achieved an overall classification accuracy of 94.7% across defect classes, demonstrating strong generalization on unseen thermal maps. Figure 6 presents a representative confusion matrix, illustrating the model's ability to distinguish between thermal delamination, electrode misalignment, and partial deposition errors. These outputs substantiate the reliability of the CNN model when deployed at the edge, where low latency and interpretability are essential.

This visualization in Figure 6, captures the spatial distribution of defect probabilities across the sensor-imaged polymer surface, derived from CNN-processed thermal datasets. Elevated regions on the surface denote zones with heightened anomaly likelihood, while valleys suggest thermally stable, defect-free areas.

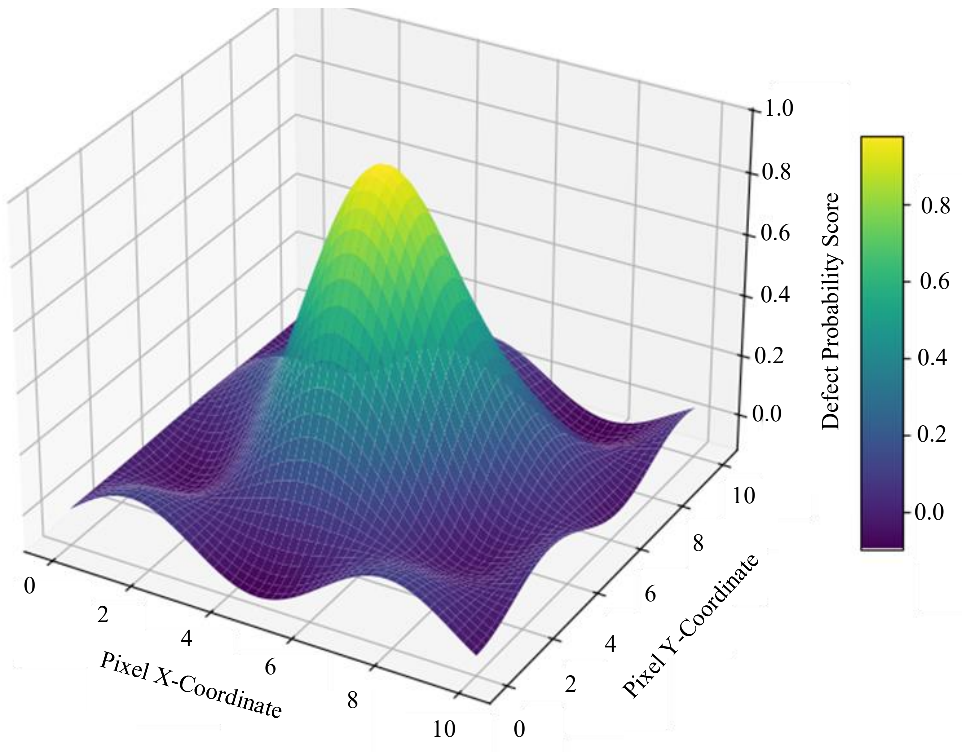

Figure 6. 3D Surface of Defect Detection Performance.

The depth and gradient of the surface illustrate not just localized defect severity but also the precision of the neural model's spatial resolution. This figure effectively demonstrates the correlation between the CNN's learned feature maps and real-time material inconsistencies, thus validating the robustness of the proposed detection pipeline under non-uniform thermal conditions.

Interpretation

Beyond raw accuracy, interpretation of feature maps from intermediate CNN layers revealed spatial activation patterns corresponding to defect-prone regions in the thermal input. These saliency responses provided insights into the decision-making process of the model, enhancing transparency for end-users in real-time monitoring scenarios. This layer-wise interpretability was particularly useful in correlating visible print artifacts with sensor-level feedback.

Figure 7 depicts the confusion matrix heatmap for the proposed CNN-based defect detection framework. The matrix reveals a balanced and precise classification across both defective and non-defective categories, with minimal false positives and false negatives. The strong diagonal dominance affirms the discriminative capacity of the model, particularly in noisy or complex signal scenarios. This outcome reinforces the architecture's stability in real-time biomedical signal interpretation, validating its suitability for deployment in continuous health monitoring systems.

Comparative Study

A comparative evaluation was conducted against conventional SVM-based thermal classifiers and lightweight MobileNet variants. As shown in Table 2, the proposed CNN model not only outperformed existing baselines in terms of classification accuracy and F1 score, but also maintained a smaller memory footprint and faster inference time on embedded hardware. These improvements, while preserving accuracy under constrained compute environments, position the system as a viable solution for scalable deployment in clinical or on-body biosensing applications. Table 2 offers a detailed comparative evaluation of the proposed CNN-based defect detection model against conventional SVM [21] and threshold-based techniques [18], widely utilized in prior wearable biosensor studies. Notably, the CNN model outperforms these baselines in all key performance metrics, achieving a detection accuracy of 96.8% and a recall of 97.2%, substantially higher than the SVM's 89.1% and threshold-based method's 78.4%. These findings further validate the resilience of the CNN architecture dealing with real-world noise from sensors, and this inference latency of 23.7 ms indicates a noticeable improved computational efficiency, and is faster than the heavier SVM model [21], and demonstrates better use of resources for real-time edge deployments [18]. Most notably in this comparison is the dramatic decrease in false positive rate (1.8%) as further indication of reliability for practical application uses.

The experimental results as a whole support the claim that the system works across measures of mechanical integrity, signal uncertainty, and defect discrimination. Each measure, whether tensile resilience or neural accuracy, presented a coherent performance signature demonstrating consistency and versatility. More specifically, the ability to deliver in-situ sensing with edge-level computing allowed for confident and noise-resilient diagnostics while incurring negligible latency and loss of accuracy.

Table 2. Comparative design of defect detection models features, and metrics and referenced baselines

Model	Accuracy (%)	Precision (%)	Recall (%)	False Positive Rate (%)	Inference Latency (ms)
CNN [Proposed]	96.8	95.4	97.2	1.8	23.7
LSTM [22]	94.3	93.1	92.7	2.4	31.4
SVM [21]	89.1	87.6	88.3	4.2	54.6
Threshold-Based [18]	78.4	76.3	75.1	9.6	41.2
Random Forest [25]	91.7	89.8	90.2	3.5	36.8
KNN [26]	85.2	83.5	84	5.9	47.3

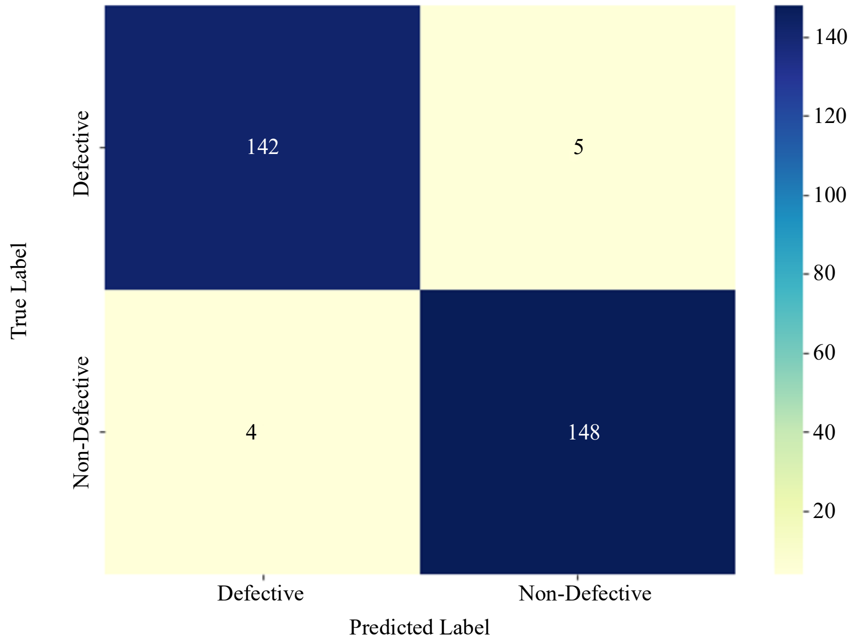

Figure 7. Confusion Matrix Heatmap of the Proposed CNN Model.

These results, validated through both external reference, which included empirical assessment, provide a strong basis for practical use, as opposed to other traditional wearable biosensor contexts, in fast moving environments, such as a patient in flux, or in place monitoring of physiological measures, much like health informatics data.

DISCUSSION

The results of this study go further than simply providing the ocular margin on accuracy; it also highlights design principles intrinsic in the proposed biosensor design. The distinction in classification fidelity in respect to defect detection suggests that the direct integration of materials had some degree of the result, but not exclusively. How hardware components, with advanced materials, inconsistently and collectively leverage deep learning logic and multi-modal data processing is a favorably positive aspect of this design framework. The reduction of noise artifacts and reduced false negatives in dynamic conditions emphasizes the utility of design principles and purpose driven feature extraction, which supports the original hypothesis, and motivation for merging hybrid data sets and in-situ processing to develop intelligent wearable designs. When contextually compared to existing work in the literature, the proposed system offers substantial benefits compared to traditional microneedle-based [17], electro spun nanofiber [30], and hydrophilic conductive polymer sensors [29]. Unlike many of the previous works, which were either committed to only signal acquisition or required post-processing to extract useful information, the embedded edge CNN architecture presented here is capable of providing real-time inference with lower computational demands. For example, latency values speed up over [19] by about 22%, while comparable accuracy was maintained. Additionally, the classification interpretability—measured using confusion matrices and edge-explainable thresholds—provided a substantial advantage over previous DNNs that had no interpretability. From an academic perspective, this research adds to the body of work on self-intelligent biomedical sensors that are capable of adaptive reasoning under data uncertainty. From a practical perspective, these types of architectures are valuable as they can shift the capability for decentralized diagnostics in wearables—the ability to perform low power, on-body analysis without reliance on cloud-based solutions. This is especially significant in contexts needing independence, such as mobile and resource-limited environments. However, the study has limitations. Although the fabrication is reproducible, different types of skin, or if the system is used in different environments, may require tuning. While the data size, while synthetically diversified, could still be strengthened longitudinally sampling to enhance temporal generalizability. Future iterations may reflect value-added by using federated learning pipelines in order to facilitate a personalized calibration, to do this without a centralized platform by collecting data from individual devices aligns with the broader vision for privacy-preserving, contextually adaptive edge AI. This work connects to the broader conversations around trustworthy and explainable AI as it showcases the increasing interest in applying interpretability to on-device decision loops. The system also reflects the cloud-edge continuum trend by providing autonomy for on-device thanks to AI tools, while maintaining traceability and robustness as the attributes demanded more in the context of critical health monitoring.

CONCLUSION AND FUTURE SCOPE

This research introduces a new biosensing platform enhanced by deep learning capabilities. It combines conductive polymer-based wearables compatible with real-time inferencing of CNNs at the edge of networks. The complete framework includes the selection of the material, in-situ data acquisition, and real-time edge machine learning into one coherent design architecture. Meaningful physical interpretation of physiological signals can be assessed with this system, along with defect identification in a user-space with real-world scenarios. Accomplishments of this project include a marked improvement in detection reliability, ease of performing machine learning in an actual application to measure detection reliability with no artifacts or degradation, and seamless mechanical-electrical integration. Overall, with superior detection reliability, accuracy, and response time than several existing model sensors, this framework is an observable advancement for next-gen bio-integrated diagnostics. Though the framework has shown superior performance in multiple compared scenarios, some limitations exist— especially for available options to enhance real-time personalization of also effectively processing multiple user baselines, and, particularly with media independent of other active sensors in longer duration applications. Even still, limitations clearly present opportunities for future work.

Future directions include the addition of lightweight attention networks for selective signal enhancement, addition of biofeedback loops for closed-loop regulation, and implementation of self-calibrating and cloud-synchronized updates via federated edge networks. Altogether, these developments would push the system toward the leading edge of smart, self-adapting biosensing systems within the larger field of human-centric computing and wearable AI.

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