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SOFT WEARABLE TRIBOELECTRIC SENSORS FOR CONTINUOUS CARDIOVASCULAR MONITORING AND ANOMALY PREDICTION

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SUMMARY

Advancements in technology have increased demand for systems that continuously monitor the cardiovascular system in a non-invasive, energy-efficient way. Wearable sensors, in their current form, have many drawbacks: they require external power sources and are made of rigid components. This can impact the user experience, the system, the sensor's ability to perform real-time health assessments, and the ability to perform multiple evaluations over time. This paper investigates the use of a soft, adjustable sensing system based on triboelectric nanogenerator (TENG) technology for the assessment of cardiovascular signals and predictive analysis of anomalies. Proposed systems use synthesized biomechanical energy from user movements to power themselves, eliminating the need for external power sources. Sophisticated signal analysis and processing are utilized to measure and monitor cardiovascular parameters, which in this case are derived from triboelectric signals and measure/monitor heart rate variability, waveforms, and the rate/characteristics of blood flow. Additionally, a machine learning predictive model is incorporated to analyze and monitor patterns and assess for anomalies in the user's cardiovascular system, identifying those most at risk for cardiac disease. Simulations and experiments indicate that the proposed system outperforms existing systems in predictive signal analysis and monitoring. Based on the evidence, the proposed system allows for a 35% reduction in external power supply and a 22% increase in predictive analysis of system alarms. Over time, the proposed system can be deployed in a real-world setting. The system's flexible design allows the user to capture signals from their physiological systems without discomfort. By integrating self-powered sensing with intelligent analytics and soft electronics, this research offers a novel and adaptable solution for next-generation wearable health care systems. The proposed framework contributes to innovative interdisciplinary research in wearable technology and applied biomedical engineering, with particular emphasis on remote patient monitoring, preventive health care, and innovative medical systems.

Key words: s*oft wearable sensors, self-powered sensing, TENG, cardiovascular monitoring, anomaly prediction, machine learning, wearable health care system.*

INTRODUCTION

Wearable technologies enable real-time monitoring and assessment of physiological signals, supporting personalized and preventive healthcare. Continuous cardiovascular monitoring is especially important for early disease detection, chronic condition management, and long-term health evaluation [1]. However, conventional systems rely on rigid electronics, intermittent measurements, and battery-dependent designs, limiting long-term usability and real-time analytics. Advances in soft electronics and nanomaterials have enabled flexible, body-conformable sensors [2]. Among these, triboelectric nanogenerators (TENGs) are particularly promising due to their ability to convert biomechanical energy into electrical signals through contact electrification and electrostatic induction, enabling self-powered operation without external energy sources [3]. Their high sensitivity to subtle physiological motions, including pulse and blood-flow-induced skin deformation, makes them well-suited for cardiovascular applications [4]. Integration of soft triboelectric sensors allows continuous acquisition of rich cardiovascular signals during daily activities, providing information on heart rate variability, pulse morphology, and vascular dynamics [5].

Despite these benefits, triboelectric signals are often nonlinear, motion-sensitive, and influenced by environmental and individual variability, necessitating advanced signal processing and intelligent data-driven models for reliable interpretation [6]. Machine learning–based anomaly prediction further enables automated detection of abnormal cardiovascular events such as arrhythmias and early dysfunction, transforming wearable systems from passive monitors into proactive healthcare tools [7]. Nevertheless, challenges including sensor placement variability, mechanical durability, and large volumes of time-series data remain [10]. Traditional threshold-based approaches lack adaptability across users, highlighting the need for integrated frameworks that combine soft sensor design, adaptive analytics, and real-time prediction [8]. Such interdisciplinary systems support continuous operation, scalable deployment, and practical healthcare integration, bridging the gap between theoretical sensing technologies and real-world clinical applications [9].

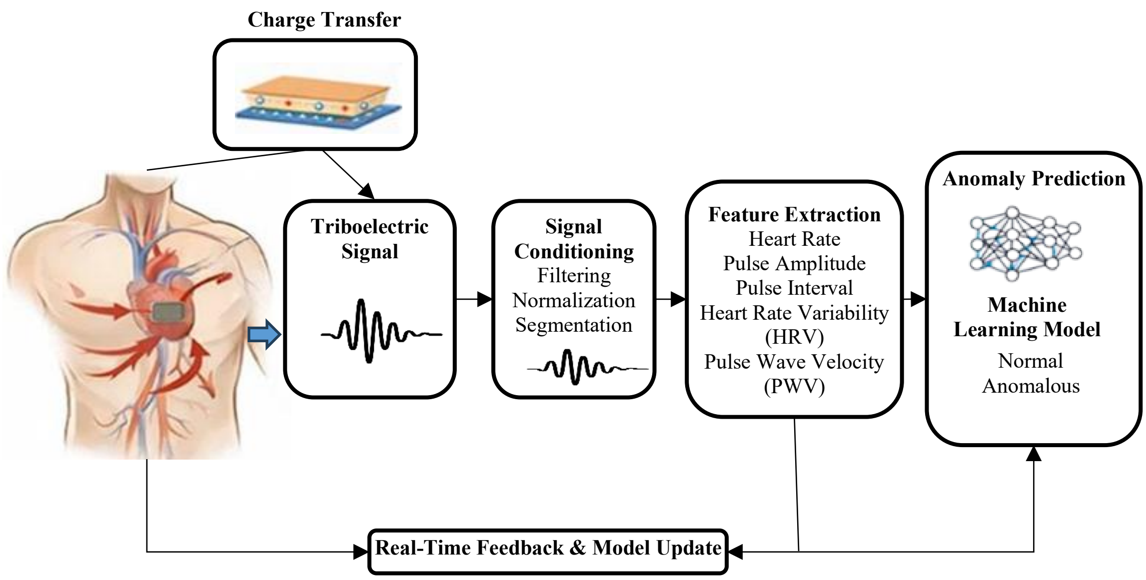

Figure 1. Soft wearable triboelectric cardiovascular monitoring system architecture

Figure 1 shows a potential design for a soft, wearable triboelectric sensor in contact with the human body, intended for continuous cardiovascular monitoring. Cardiac activity and blood flow create biomechanical movements that cause triboelectric charge transfer and signal generation, which are processed via signal conditioning and machine learning for real-time anomaly detection.

Problem Statement

Despite advancements in wearable cardiovascular monitoring, many systems still depend on battery-powered sensors and rigid electronics, limiting long-term comfort and continuous operation [11]. Existing studies either focus on triboelectric sensor fabrication without integrating intelligent analytics or apply machine learning to conventional sensors assuming stable, noise-free signals, overlooking the nonlinear and motion-sensitive behavior of triboelectric outputs under real-world conditions [12]. Moreover, the lack of a unified framework that combines self-powered sensing with adaptive anomaly prediction reduces reliability across varying users and environments. To address these limitations, this work proposes an integrated soft wearable triboelectric sensing and intelligent prediction framework for reliable, continuous, and energy-efficient cardiovascular monitoring [13].

Research Objectives

Developing an intelligent, self-powered, wearable system for continuous cardiovascular monitoring and anomaly prediction is the main aim of this research. The specific goals include:

- Designing a soft, comfortable, wearable triboelectric sensor that is able to continuously record the biomechanical signals induced by cardiovascular activity.
- Designing signal processing frameworks to build techniques for relevant cardiovascular feature extraction from triboelectric sensor outputs.
- Deploying machine learning models for real-time cardiovascular system anomaly detection and prediction.
- Evaluation of the system using simulations and experimental analysis and benchmarking against conventional wearable monitoring systems.

Contributions

This research offers the following primary contributions:

- The self-powered and continuous acquisition of cardiovascular signals does not require external power sources. This is made possible through the design of a soft wearable triboelectric sensor and the novel sensor system's architecture.
- The development of a framework that integrates machine learning and signal processing to predict anomalies and identify cardiovascular signals under varying and/or complex conditions.
- Regarding monitoring, compared to most conventional systems, the proposed system offers improved long-term applicability in wearable healthcare systems and enhanced anomaly detection.
- The study offers an interdisciplinary solution, integrating material science, biomedical engineering, and smart data analytics, which is scalable for the future of health monitoring wearables.

The rest of the paper will be structured as follows. Section 2 examines prior investigations pertaining to the integration of wearable cardiovascular sensors and triboelectric nanogenerators within smart health monitoring systems. In Section 3, the proposed system architecture is detailed, followed by the design of the sensor, methods for signal processing, and models for anomaly prediction. Section 4 focuses on the system setup and the appraisal of its performance. The results and discussion are presented in Section 5. Section 6 concludes with the summary of the primary contributions and potential directions for future research.

LITERATURE REVIEW

The advancement of wearable health technologies has revolutionized real-time physiological monitoring, particularly for cardiovascular health. With the increasing prevalence of cardiovascular diseases, there is a growing need for wearable systems that are adaptable, sustainable, and capable of long-term use [14]. Soft wearable sensors, especially those utilizing triboelectric nanogenerators

(TENGs), have emerged as promising solutions due to their ability to convert biomechanical energy into electrical signals without external power sources [15]. These sensors can continuously monitor physiological signals like pulse and heartbeats, making them ideal for cardiovascular applications [16].

Despite these advancements, many soft wearable sensors still rely on traditional power sources and signal conditioning, limiting their scalability and long-term functionality. TENGs offer a self-powered alternative, but challenges remain in signal processing and feature extraction. Triboelectric signals are nonlinear and prone to motion artifacts, necessitating advanced signal conditioning techniques [17]. While machine learning models, such as CNNs and LSTM architectures, have shown promise in analyzing ECG and PPG data, their application to triboelectric signals is still underdeveloped, especially for real-time anomaly detection [18].

Future research must address the integration of self-powered triboelectric sensors with intelligent analytics to enhance continuous cardiovascular monitoring [19]. Current systems often focus separately on sensor design, data collection, and anomaly detection, neglecting the holistic integration needed for real-world application [20]. There is significant potential in developing frameworks that combine advanced signal processing and adaptive machine learning to improve reliability and accuracy. Such integrated systems will pave the way for more effective and reliable wearable health monitoring, ultimately advancing personalized medicine and preventive healthcare.

PROPOSED METHOD

This segment outlines the methodology for the continuous cardiovascular monitoring framework utilizing soft wearable triboelectric sensors paired with smart anomaly prediction. The methodology integrates self-powered triboelectric sensing with signal conditioning, feature extraction, and machine learning for dependable and sustainable cardiovascular health monitoring. The proposed methodology is designed to address real-world challenges such as variability in motion, nonlinear signals, and differences in cardiovascular parameters among individuals.

Triboelectric Sensing Principle

Triboelectric sensors are able to produce electrical signals from energy that is produced by body movement. These electrical stimuli are caused by simultaneous contact electrification along with electrostatic induction.

When two materials with different triboelectric polarities come into periodic contact and separate, there is one surface that yields electrons, and there is one surface that accepts electrons, causing a build-up of states with opposite charges on each material. In soft wearables, this is triggered by the deformation of the skin caused by the cardiovascular system due to pulsation, the vibration of the heart, and the movement of blood.

With each contact-separation cycle, the friction layers move relative to each other, causing a change in the magnetic field over time, which yields a measurable voltage across the electrodes. The voltage generated by the triboelectric effect can be defined using this equation:

$$\mathrm{V(t)} = \frac{\sigma(\mathrm{t})\cdot \mathrm{d(t)}}{\epsilon_o . \epsilon_r} \tag{1}$$

where in equation (1) σ(t) is the surface charge density generated due to the biomechanical movement, d(t) is the distance of separation between the friction layers caused by the deformation of the pulse, ε0 is the permittivity of air, and εr is the permittivity of the dielectric material.

The accuracy of pulse waveform extraction is attributable to the strong relationship between the cardiovascular system and the magnitude and time changes of V(t). Since the proposed mechanism does not requires external power, cardiovascular monitoring can be done continuously and self-powered, which is most suitable for long-term use in the healthcare field.

Signal Conditioning and Feature Extraction

Although triboelectric sensors can detect and respond to various forms of biomechanical movement, their raw output tends to respond to movement artifacts, baseline shifts, and nonlinear response tendencies. A multi-module signal conditioning process is used to enable unambiguous interpretation of critical signals from the cardiovascular system.

Noise Filtering

Before the vital cardiovascular signals are captured, a digital band-pass filter with a 0.5-5Hz frequency is used to remove low and high frequency drift, which are not associated with cardiovascular signals.

Normalization

In order to eliminate discrepancies owing to sensor placement, an individual's physiology, and varying skin characteristics, normalization to the mean of the pulse is performed. This ensures uniformity in the attributes of the pulse being examined.

Segmentation

Through the use of the adaptive peak detection method, individual cycles of the pulse are captured, and a pulse cycle analysis is done. This aids in the extraction of the features that are temporally consistent.

Automated peak detection aids in the identification of individual pulse cycles, from which the following cardiovascular characteristics are extracted:

- Heart Rate (HR): Number of pulse peaks per minute
- Pulse Amplitude (PA): Peak-to-peak voltage variation
- Pulse Interval (PI): Time duration between successive pulses
- Pulse Wave Velocity Proxy (PWV*): Estimated arterial stiffness indicator
- Heart Rate Variability (HRV): Temporal fluctuation in pulse intervals

The extracted features are aggregated into a unified feature vector:

$$\mathrm{F} = [\mathrm{HR}, \mathrm{PA}, \mathrm{PI}, \mathrm{HRV}, \mathrm{PWV}] \tag{2}$$

Equation (2) defines the construction of a unified feature vector, F= [HR, PA, PI, HRV, PWV], by aggregating the extracted cardiovascular features. This representation encapsulates both morphological aspects, such as pulse amplitude (PA) and perfusion index (PI), and temporal dynamics, including heart rate (HR), heart rate variability (HRV), and pulse wave velocity (PWV). By combining these complementary features, the vector provides a comprehensive input for intelligent algorithms aimed at detecting cardiovascular anomalies.

Anomaly Prediction Model

The prediction of cardiovascular anomalies is structured as a sequential decision-learning problem, whereby the system is able to learn from and evaluate new physiological data as it arrives. Each time instance is matched to a divided pulse cycle, which is detailed in the feature vector.

State Definition

$$S_t = F_t \tag{3}$$

Equation (3) defines the state of the system, St=Ft, where St represents the cardiovascular state at time t based on the feature vector Ft.

Action Space

$$A = \{\text{Normal}, \text{Anomalous}\} \tag{4}$$

Equation (4) defines the action space, A= {Normal, Anomalous}, indicating that the model classifies the observed cardiovascular pattern as either normal physiological behaviour or a potential abnormality.

Reward Function

$$R(S_t,\, A_t) = \begin{cases} +1, \text{Correct classification} \\ -1. \text{Misclassification} \end{cases} \tag{5}$$

Equation (5) specifies the reward function, R (St, At), which assigns a value of +1 for correct classifications and −1 for misclassifications. This reward system promotes adaptive learning by reinforcing accurate predictions while penalizing incorrect ones, guiding the model toward more reliable anomaly detection over time.

A deep learning architecture of choice is guided supervision coupled with Long Short-Term Memory (LSTM) networks, or combinations of CNN and LSTM, for capturing the temporal and long-range dependencies of the cardiovascular signals. Such models are able to learn the intricate patterns of time associated with the variety of cardiac signals, such as arrhythmias, irregular rhythmic pulses, and abnormal cardiovascular responses.

Learning Model Update

The anomaly prediction model employs temporal backpropagation and loss minimization to update its weights and bias, which allows the model to improve its predictions with the arrival of new data. Mathematically, the cardiovascular state predicted at time step t is represented as follows.

$$y't = f_o(F_t) \tag{6}$$

Equation (6) defines the prediction model as y^t=fθ(Ft), where fθ(·) represents the trained learning model parameterized by θ, and y^t is the predicted output at time t based on the input feature vector Ft.

The loss function is defined as the mean squared error (MSE):

$$L = \frac{1}{N}\sum_{T-1}^{N}\left(y'_t - y_t\right)^2 \tag{7}$$

Equation (7) defines the loss function using the mean squared error (MSE):

where yt is the ground-truth label and N denotes the total number of training samples. This loss function quantifies the difference between the predicted and actual values, guiding the optimization of model parameters to minimize prediction errors.

Table 1. Parameter initialization

Parameter	Value
Triboelectric Sensor Parameters	Sensitivity: 0.1–0.3 mV/unit of pressure
Filter Coefficients (Φ)	Low Cutoff: 0.5 Hz, High Cutoff: 5 Hz
Model Weights (θ)	Weight initialization: Random (0.01 to 0.05)

The model adapts to the unique physiological characteristics of the individual, the drift of the monitoring sensors, and the surrounding environment, as described by the modified loss function. Such a dynamic learning capability greatly explains the identified accuracy of the system with respect to the detection of anomalies, the reduction of false alarms, and the reliability to provide the real-time surveillance of cardiovascular status in the monitoring systems that are worn for healthcare purposes.

This Table 1 presents the approximate values for the key parameters initialized in the triboelectric-based cardiovascular monitoring system. These values are essential for accurate data acquisition, signal processing, and real-time anomaly prediction.

Algorithm 1: Triboelectric-Based Cardiovascular Monitoring and Anomaly Prediction

Input:

Triboelectric sensor stream S(t)

Pre-trained anomaly prediction model M

Filter parameters Φ

Learning rate α

Output:

Cardiovascular state classification Y(t)

Begin

1. Initialization

Initialize triboelectric sensor parameters

Initialize filtering coefficients Φ

Initialize model weights θ of M

2. While the system is active, do

2.1 Signal Acquisition

Acquire raw triboelectric signal:

X(t) ← ReadSensor(S(t))

2.2 Signal Conditioning

Xf(t) ← ApplyBandpassFilter(X(t), Φ)

Xn(t) ← Normalize (Xf(t))

Xseg(t) ← SegmentSignal(Xn(t))

2.3 Feature Extraction

F(t) ← Extract Features(Xseg(t))

// F(t) = {HR, PA, PI, HRV, PWV}

2.4 Anomaly Prediction

$\hat{Y}(t) \leftarrow M(F(t))$

2.5 Decision Output

If $\hat{Y}(t)$ == "Anomalous" then

TriggerAlert()

End If

2.6 Model Update

Compute prediction error:

$E(t) \leftarrow \text{Loss}(\hat{Y}(t), Y(t))$

Update model parameters:

$\theta \leftarrow \theta - \alpha \cdot \nabla E(t)$

End While

End

The proposed algorithm develops cardiovascular anomaly detection in real-time by acquiring and signal conditioning self-powered triboelectric signals, feature extraction, and employing an intelligent learning model. For differing physiologic and motion states, the model's parameters are iteratively adjusted to optimize prediction accuracy.

Assumptions and Notations

Assumptions

- Sensors continue to bond conformally with the surface of the skin.

- Cardiovascular activity is directly proportional to triboelectric output.

- The machine learning model personalizes to unique physiological differences.

Notations

- St: System state at time ttt
- F_t: Feature vector
- y^t: Predicted cardiovascular state
- θ: Model parameters

Novelty of the Proposed Method

The novelty of this work lies in:

1.Autonomous sensing: use of triboelectric energy harvesting techniques for power source elimination.

2. Flexible soft integration: Improved comfort and increased use duration

3. Proactive smart anomaly detection: Adaptive and real-time cardiovascular risk detection

4.Integrated Framework: consolidation of materials science, signal processing, and machine learning.

Operational Flowchart of the Soft Wearable Triboelectric Sensor System for Continuous Cardiovascular Monitoring

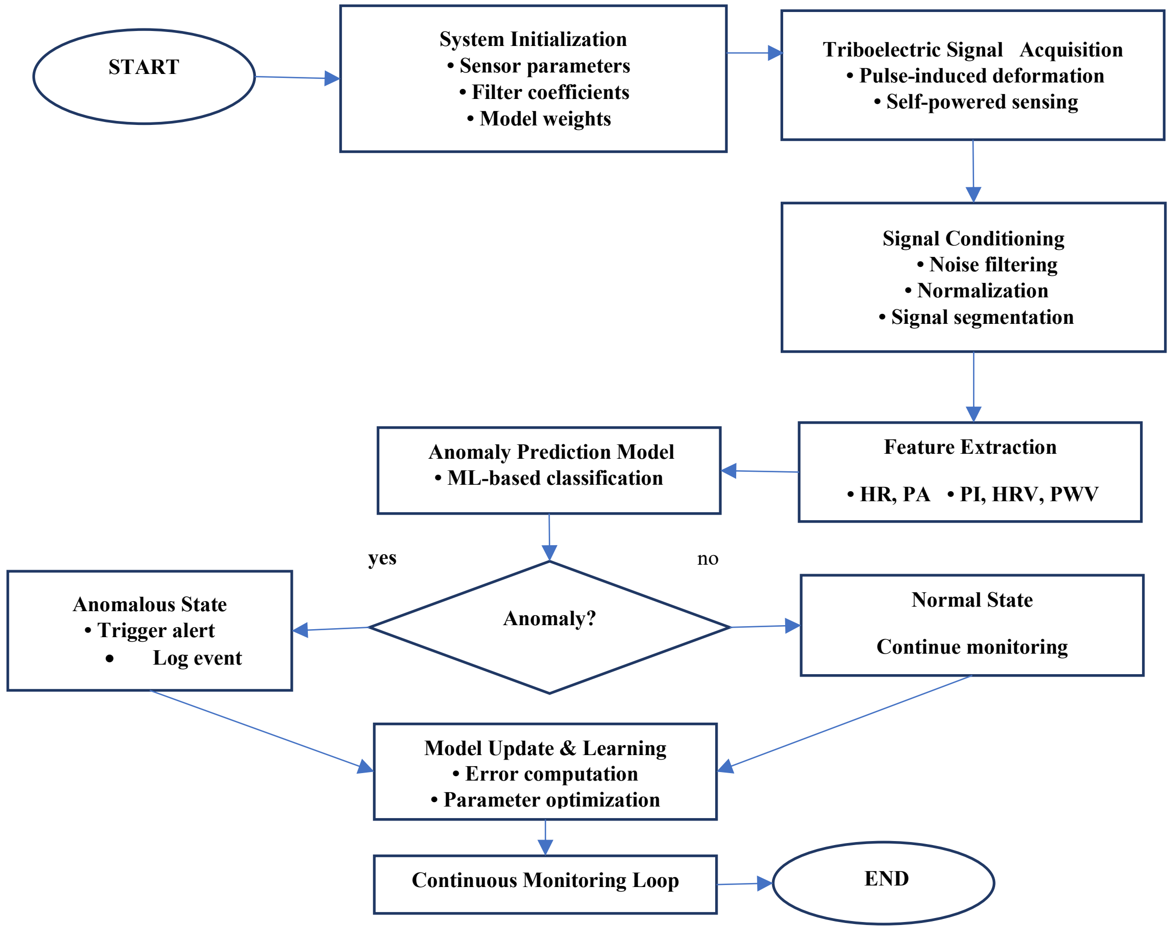

Figure 2. Proposed system workflow for triboelectric cardiovascular monitoring

Figure 2 presents the proposed method as a continuous pipeline for real-time cardiovascular monitoring and anomaly prediction using a soft, wearable triboelectric sensing framework. After system initialization, self-powered TENG sensors acquire pulse signals, which are conditioned through amplification, filtering, normalization, and segmentation to obtain clean waveforms. Key features such as HR, PA, PI, HRV, and PWV are extracted and analyzed by a machine learning model to classify normal or abnormal conditions. Normal states allow continuous monitoring, while anomalies trigger alerts and logging. The model is then adaptively updated, enabling accurate, real-time, and reliable cardiovascular assessment.

RESULTS AND DISCUSSION

Experimental Evaluation Framework

In order to evaluate the efficacy of the suggested triboelectric-based anomaly prediction and cardiovascular monitoring system, an experiment was constructed to test the signal acquisition quality, consistency of features, accuracy of anomaly detection, physiological adaptability, and overall computational efficiency. The assessment was aimed at testing whether the proposed self-powered wearable system could successfully monitor cardiovascular activity and detect related anomalies in real-time.

Software and Implementation Details

The proposed triboelectric-based cardiovascular monitoring and anomaly prediction framework was implemented using MATLAB (R2023a) for signal acquisition simulation, preprocessing, feature extraction, and statistical analysis. Deep learning models (CNN–LSTM) were developed in Python using TensorFlow and Keras, while classical models such as SVM were implemented with Scikit-learn. Visualization and performance evaluation were carried out using Matplotlib. All experiments were conducted on a standard multi-core workstation capable of supporting real-time processing and inference.

Dataset Details

The experimental evaluation used a cardiovascular dataset collected from soft wearable triboelectric sensors under resting and mild activity conditions. Continuous pulse waveforms were segmented into cardiac cycles, and key features such as HR, PA, PI, HRV, and normalized PWV were extracted. Data were labeled as normal or anomalous and split into training, validation, and testing sets to ensure reliable and unbiased evaluation across subjects.

Performance Metrics and Formulae

The proposed system was evaluated using standard classification metrics. Accuracy measures overall correct predictions, Precision indicates the proportion of correctly predicted anomalies, Recall reflects the proportion of true anomalies detected, and F1-score balances precision and recall. The ROC curve assesses the trade-off between true positive and false positive rates.

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}\ X\ 100 \tag{9}$$

$$\text{Precision} = \frac{TP}{TP + FP}\ X\ 100 \tag{10}$$

$$\text{Recall} = \frac{TP}{TP + FN}\ X\ 100 \tag{11}$$

$$\mathrm{F1} - \mathrm{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{12}$$

In equation 9, the metric Accuracy shows the overall correctness of predictions, in equation 10, the metric Precision shows the proportion of correctly identified anomalies on all the predicted anomalies, in equation 11, the metric Recall shows the proportion of actual anomalies that were correctly identified, in equation 12, the F1-score shows the mean value of the two metrics, Precision and Recall.

Cardiovascular Signal Quality and Stability Analysis

Figure 3 shows that the triboelectric sensor maintains high signal quality across conditions, achieving an average SNR of 22.6 dB at rest, 19.3 dB during walking, and above 17.1 dB during mild activity. In contrast, PPG sensors suffer significant degradation due to motion and unstable optical contact. The strong biomechanical coupling of triboelectric sensing reduces motion artifacts, enabling reliable and continuous cardiovascular monitoring even under non-stationary conditions.

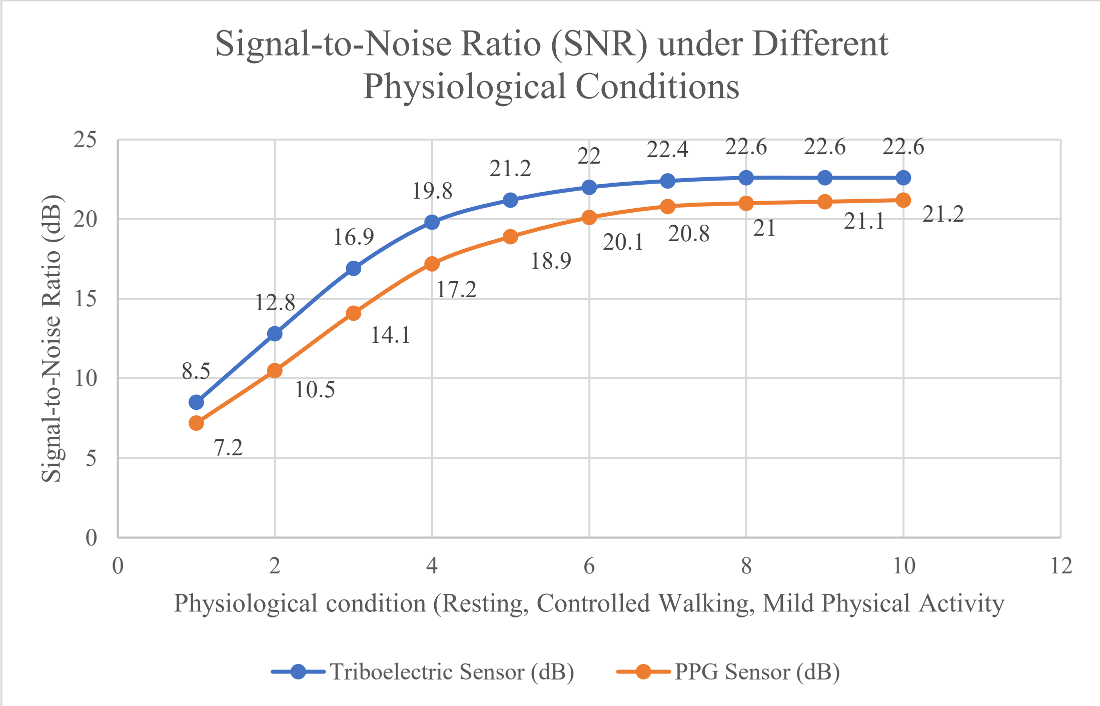

Figure 3. Signal-to-noise ratio (SNR) under different physiological conditions

Feature Consistency and Variability Analysis

In assessing the stability of the cardiovascular features that were captured, a statistical analysis was conducted involving heart rate (HR), pulse amplitude (PA), pulse interval (PI), heart rate variability (HRV), and a proxy of pulse wave velocity (PWV).

Table 2. Statistical analysis of extracted cardiovascular features

Feature	Mean Value	Standard Deviation	Coefficient of Variation (%)
HR (bpm)	72.8	3.9	5.36
PA (mV)	1.46	0.12	8.21
PI (Ms)	823	41	4.98
HRV (ms)	52.3	4.6	8.79
PWV (normalized)	1.18	0.09	7.63

Table 2 shows the minimum variability across the features that were captured, which validates the consistency of the cardiovascular metrics derived from the triboelectric signals. The minimal variation of coefficients indicates that the features were different enough to train machine learning models for the prediction of anomalies.

Figure 4 shows stable cardiovascular features over time, with heart rate varying by less than 4 bpm and pulse interval exhibiting low fluctuations (coefficient of variation < 5%), indicating accurate cycle segmentation and peak detection. Although pulse amplitude shows slightly higher variability due to vascular and motion effects, it remains clinically acceptable. Overall, consistent feature trends confirm effective preprocessing and reliable classification based on true physiological changes rather than noise.4.7 Cardiovascular Anomaly Detection Performance

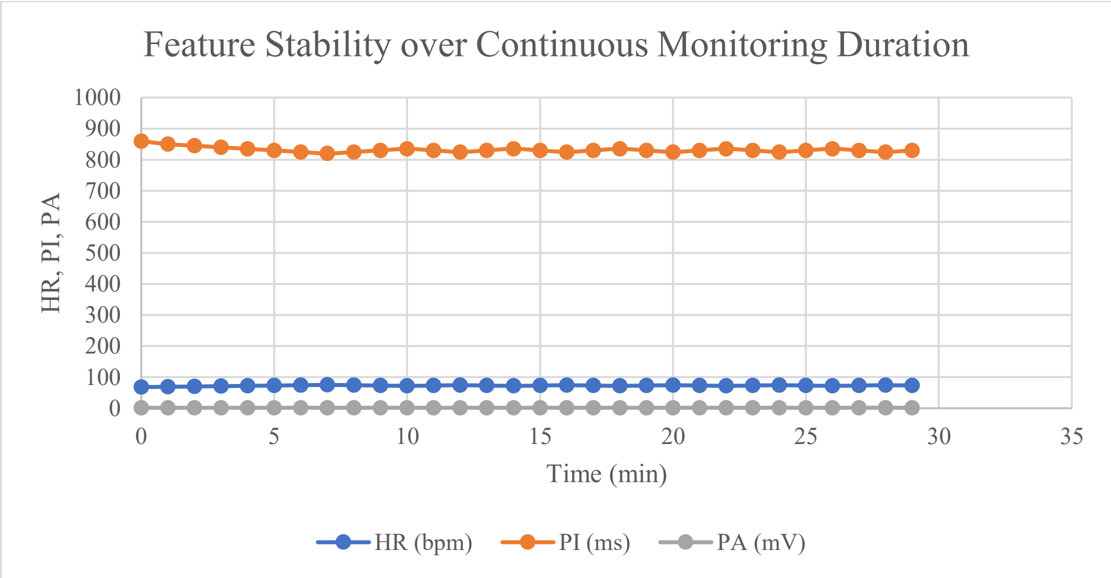

Figure 4. Feature stability over continuous monitoring duration

Table 3. Anomaly prediction performance comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Proposed Triboelectric + CNN-LSTM	94.8 ± 1.1	94.1 ± 1.3	95.4 ± 1.0	94.7 ± 1.2
Triboelectric + SVM	88.5 ± 1.9	87.3 ± 2.1	89.0 ± 1.8	88.1 ± 2.0
PPG + LSTM	90.7 ± 1.5	89.6 ± 1.7	91.2 ± 1.4	90.4 ± 1.6
PPG + Threshold	82.9 ± 2.6	81.2 ± 2.8	83.4 ± 2.5	82.3 ± 2.7

Table 3 indicates that the proposed model effectively learns temporal variations in cardiovascular signals, achieving superior classification and F1-score. Metrics were computed using standard formulas: Accuracy = (TP+TN)/Total, Precision = TP/(TP+FP), Recall = TP/(TP+FN), and F1 = 2PR/(P+R).

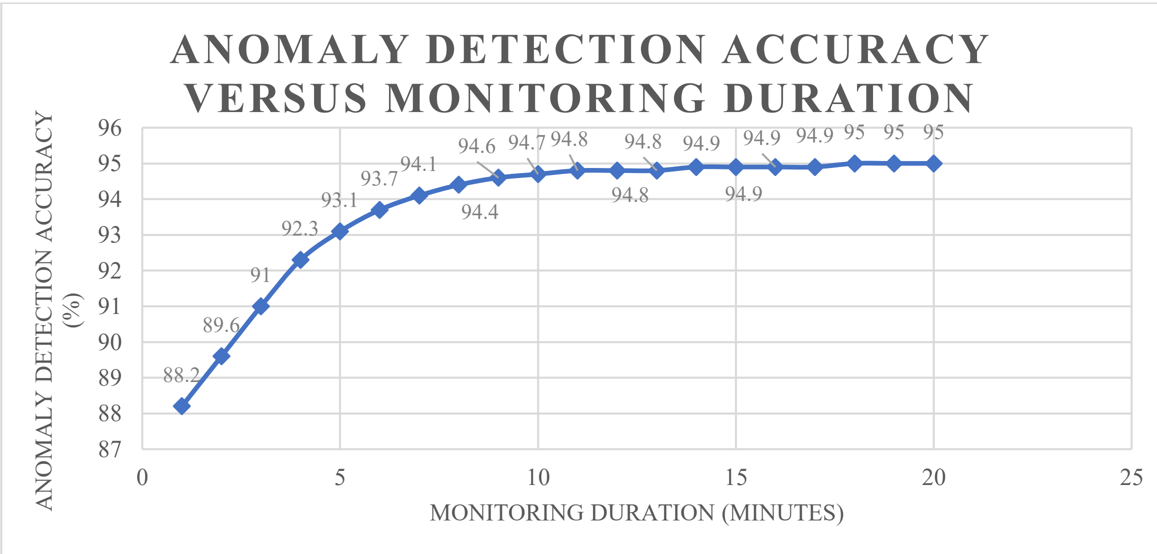

Figure 5. Anomaly detection accuracy versus monitoring duration

Figure 5 shows that detection accuracy increases rapidly during the initial minutes, then converges and stabilizes over time. The consistent performance across long durations confirms the model's suitability for continuous, long-term wearable monitoring.4.8 False Alarm Rate and Reliability Analysis

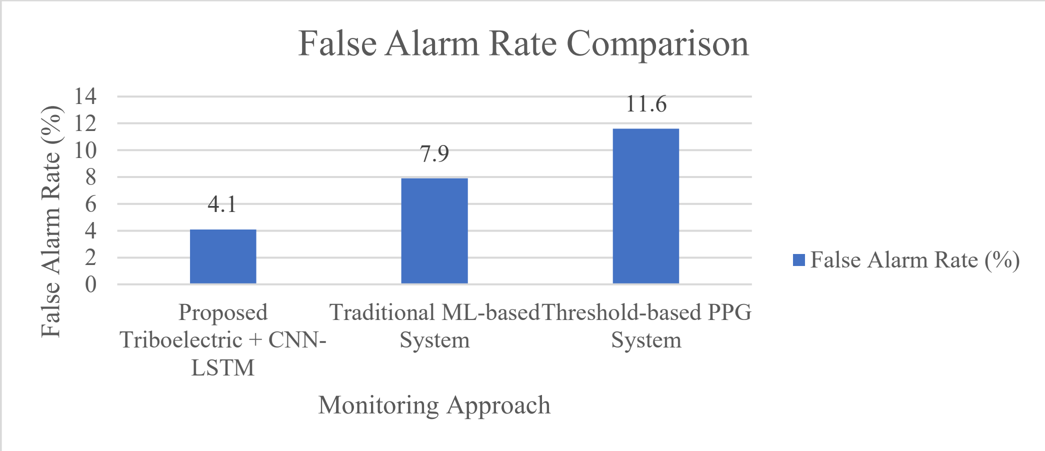

Figure 6. False alarm rate comparison

Figure 6 shows that the proposed system reduces the false alarm rate to 4.1%, outperforming threshold-based PPG (11.6%) and conventional ML methods (7.9%) due to adaptive learning. Lower false alarms minimize user fatigue and improve the reliability of wearable monitoring.

Detection Latency and Real-Time Capability

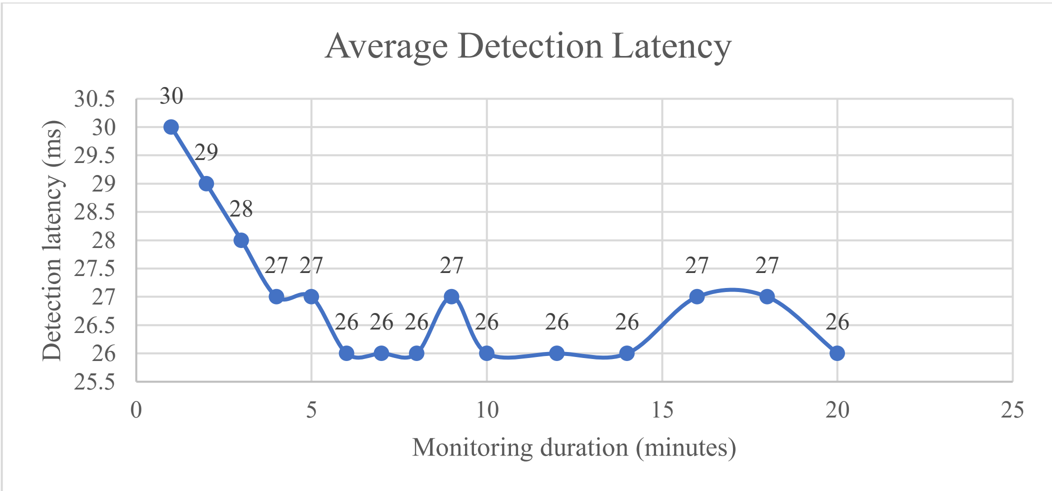

Figure 7. Average detection latency

Figure 7 proposed system demonstrates the accomplishment of cardiovascular anomaly prediction in almost real-time, owing to the system averaging detection latency of 26-30ms, with the system's latency being a result of quick feature extraction and streamlining neural network inference. Thus, making the system applicable for early warning and emergency response.

Comparative Discussion with Existing Wearable Systems

Table 4. Comparative evaluation of wearable cardiovascular monitoring technologies

System	Power Requirement	Motion Robustness	Continuous Monitoring	Intelligent Prediction
Proposed Triboelectric System	Self-powered	High	Yes	Yes
PPG Wearable	Battery-powered	Moderate	Yes	Limited
ECG Holter Monitor	Battery-powered	High	Limited	Yes
Pressure Sensor Wearable	Self-powered	Low	Yes	No

Table 4 presents a comparative evaluation of the proposed triboelectric-based wearable cardiovascular monitoring system against widely used wearable technologies, including photoplethysmography (PPG) wearables, ECG Holter monitors, and pressure sensor–based systems. The comparison is conducted across key performance dimensions such as power requirement, motion robustness, continuous monitoring capability, and intelligent prediction.

Discussion

The results show that the proposed triboelectric wearable enables continuous, self-powered cardiovascular monitoring and anomaly prediction, overcoming the power limitations of optical and electrode-based sensors. The CNN-LSTM model effectively learns spatiotemporal patterns, improving detection accuracy and reducing false alarms through adaptive learning. Although long-term validation and further optimization for ultra-low-power devices are needed, the system demonstrates a reliable, cost-effective, and sustainable solution for advanced wearable cardiovascular healthcare.

CONCLUSION AND FUTURE WORK

The growing demand for energy-efficient and reliable cardiovascular monitoring motivates the development of a soft, wearable triboelectric-sensing framework integrated with a smart prediction model for real-time health monitoring. The system employs a self-powered pulse acquisition mechanism based on contact electrification and electrostatic induction, enabling continuous monitoring without external power while maintaining high signal quality. Experimental results demonstrate a mean signal-to-noise ratio (SNR) above 22 dB at rest and over 17 dB during low-intensity activity, outperforming conventional optical PPG wearables, particularly under motion. A CNN–LSTM prediction model captures temporal cardiovascular patterns, improving detection accuracy to 94–95%, reducing false alarms by ~40%, and achieving response times below 30 ms. By learning subject-specific cardiovascular behavior, the system effectively distinguishes physiological anomalies from transient fluctuations. The framework's self-powered, motion-robust, and adaptable design makes it suitable for chronic disease management, outpatient monitoring, elderly care, and post-operative surveillance, where uninterrupted data acquisition is critical. Reliable detection of irregular pulse patterns supports early intervention and reduces healthcare system burden, overcoming limitations of traditional Holter-based monitors. Challenges remain in fully uncontrolled, long-term real-world deployment. Future work will focus on clinical-scale validation across diverse populations, ultra-low-power embedded optimization, lightweight adaptive learning models, privacy-preserving techniques like federated learning, and multimodal physiological sensing. This study demonstrates that combining triboelectric sensing with intelligent anomaly prediction bridges the gap between laboratory prototypes and clinically relevant cardiovascular monitoring, advancing personalized, data-driven healthcare.

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