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Personalized Cardiovascular Monitoring Via Real-Time Smartwatch Data And Anomaly Detection

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Abstract: Real-time monitoring of physiological signals, specifically heart rate, is critical for the early identification of cardiovascular anomalies and general health monitoring. This article introduces a real-time heart rate monitoring system that employs consumer-level wearable technology, namely a Noise smartwatch, in order to obtain photoplethysmographic (PPG)-derived pulse information. The system proposed makes use of WebSocket-based communication for low-latency data transfer, incorporates a signal preprocessing pipeline for noise and artifact filtering, and employs rule-based anomaly detection algorithms to detect tachycardia and bradycardia conditions. A dynamic front-end interface provides responsive visualization of biometric trends and raises alerts on threshold violations. The backend infrastructure provides secure storage for longitudinal data analysis to enable trend identification and user-specific baselining. Experimental verification confirms system stability in regards to data integrity, latency of transmission, and accuracy of detection, placing this architecture as a viable solution for personalized, non-invasive cardiovascular monitoring and preventive medicine.

***Index Terms* -** Physiological Signal Processing**,** Wearable Data Analytics**,** Time-Series Anomaly Detection**,** Edge Computing in Healthcare**,** Health Informatics**.**

I. INTRODUCTION

The emergence of wearable technologies [1] has brought about a new age of personal health informatics, allowing for continuous, non-invasive tracking of physiological signals in everyday settings. Smartwatches, however, have emerged as omnipresent health-monitoring devices owing to their small size, modest price point, and the incorporation of sophisticated biosensors. Perhaps the most important parameter tracked by these devices is heart rate (HR), obtained from photoplethysmographic (PPG) signals [2] [3]. Heart rate is an important biomarker for cardiovascular well-being, stress, exercise intensity, and overall physiological status [4].

Live heart rate tracking is particularly critical in the early identification of cardiovascular abnormalities like tachycardia, bradycardia, and arrhythmias. Conventional heart monitoring devices—like Holter monitors—are clinically precise but are not portable and do not engage users [5]. Conversely, systems based on smartwatches are highly mobile and user-friendly but are usually limited by restricted computational capabilities, signal interference, and the lack of smart analytics. In addition, most commercial smartwatch platforms are more focused on fitness statistics than medically pertinent anomaly detection, with none of them providing real-time notifications or context-specific insights adjusted to specific users.

The other challenge is in the data flow architecture. Most current systems record heart rate data in a passive manner and sync it periodically with a cloud service [6] [7]. This asynchronous approach brings about latency, constraining its applicability to time-critical applications like early warning systems or biofeedback training. Also, the absence of customizable thresholding, user-specific baselining, and longitudinal data analysis functions disqualifies these systems from clinical usefulness and personalized application [8].

To overcome such limitations, this research suggests a real-time heart rate tracking framework that utilizes the sensing potential of a Noise smartwatch to record and stream beat-to-beat heartbeat information with minimal delay. The system design includes:

i. A real-time data acquisition module based on WebSocket communication,
ii. A noise-reduction and filtering pipeline for preprocessing PPG-derived HR signals,
iii. An anomaly detection engine based on rule-based thresholds,
iv. A web-based visualizing interface for real-time trend visualization and alert delivery,
v. A long-term storage backend for data to facilitate historical analysis and modeling of health trends [9].

By combining edge-level sensing with cloud-based computing and easy-to-use visualization, the system outlined here presents a scalable and extensible infrastructure for individualized cardiovascular monitoring. It is built to accommodate future additions like machine learning–based anomaly classification, decision systems based on context, and interoperability with electronic health records (EHRs) [10] [11].

Experimental testing of the system shows low transmission delay, high accuracy of heart rate estimation in comparison to clinical reference baselines, and fast detection of the abnormal events. These findings highlight the system's potential as an inexpensive, widely available tool for extended cardiac health monitoring and early anomaly detection for both personal health and telemedicine applications.

II. SYSTEM DESIGN AND ARCHITECTURE

The proposed system is architected to facilitate seamless, real-time acquisition, analysis, and visualization of heart rate data sourced from a commercial smartwatch [12]. The design emphasizes modularity, low-latency communication, and extensibility for future integration with additional biometric parameters or analytical models. The system comprises four core layers: Data Acquisition**,** Data Transmission**,** Processing & Analysis**,** and User Interface**,** underpinned by a persistent storage module for historical data retention.

2.1. Data Acquisition Layer

The system interfaces with a Noise smartwatch equipped with a photoplethysmography (PPG) sensor capable of sampling heart rate data in real-time [13]. Custom firmware or companion mobile applications extract BPM (beats per minute) values from the smartwatch at a frequency of 0.1 Hz to 1 Hz, depending on hardware and battery constraints. The extracted data is formatted as JSON payloads and timestamped locally to preserve temporal consistency [14] [15].

2.2. Communication Layer

To enable low-latency streaming, the system employs WebSocket protocol for full-duplex communication between the smartwatch (via a mobile proxy or gateway) and the backend server. Unlike HTTP polling or REST APIs, WebSocket allows for persistent TCP connections that significantly reduce overhead, making it suitable for real-time biomedical data transmission. The mobile app acts as a relay node, parsing and forwarding the PPG-derived BPM data through a secured WebSocket tunnel to the backend server.

2.3. Processing and Analysis Layer

Upon reception, raw heart rate data undergoes preprocessing, which includes:

i. Outlier rejection based on statistical thresholds,
ii. Temporal smoothing using moving averages or low-pass filters, and
iii. Signal validation to exclude spurious or biologically implausible readings (e.g., < 30 BPM or > 200 BPM).

An anomaly detection module applies rule-based logic to flag potential cardiovascular irregularities. Configurable thresholding is used to detect:

i. Tachycardia: BPM > 120
ii. Bradycardia: BPM < 50

Each detected anomaly is logged and triggers a real-time alert event, which is sent to the front-end UI and optionally as a mobile push notification.

2.4. Visualization and Alerting Layer

The front-end is built using modern web technologies (e.g., React.js or Vue.js) and consumes a real-time data stream from the backend via WebSockets or Server-Sent Events (SSE). The interface displays:

i. A live line chart showing BPM fluctuation over time
ii. Alert timelines highlighting tachycardia or bradycardia occurrences
iii. A metrics dashboard summarizing average, min/max BPM, and percentage of time within normal heart rate ranges

The system supports responsive design for cross-device compatibility and provides dark/light modes for usability.

2.5. Data Storage and Logging

All received data is stored in a time-series database (e.g., InfluxDB or PostgreSQL with time extension), indexed by user ID and timestamp. This enables:

i. Retrospective analysis of biometric trends
ii. Visualization of historical performance
iii. Training future machine learning models on user-specific baselines
iv.

The data architecture adheres to data privacy norms such as **GDPR** and **HIPAA**, supporting anonymized storage and opt-in analytics.

2.6. System Flow Overview

A high-level flow of the system is as follows:

i. Sensor Reading: Smartwatch samples PPG signal and derives BPM
ii. Data Relay: Mobile app forwards data via WebSocket to server
iii. Preprocessing: Backend filters and validates heart rate data
iv. Anomaly Detection: BPM thresholds checked; alerts generated if violated
v. Data Logging: Events and metrics stored in time-series database
vi. User Feedback: Real-time dashboard and alerts update in browser or app.

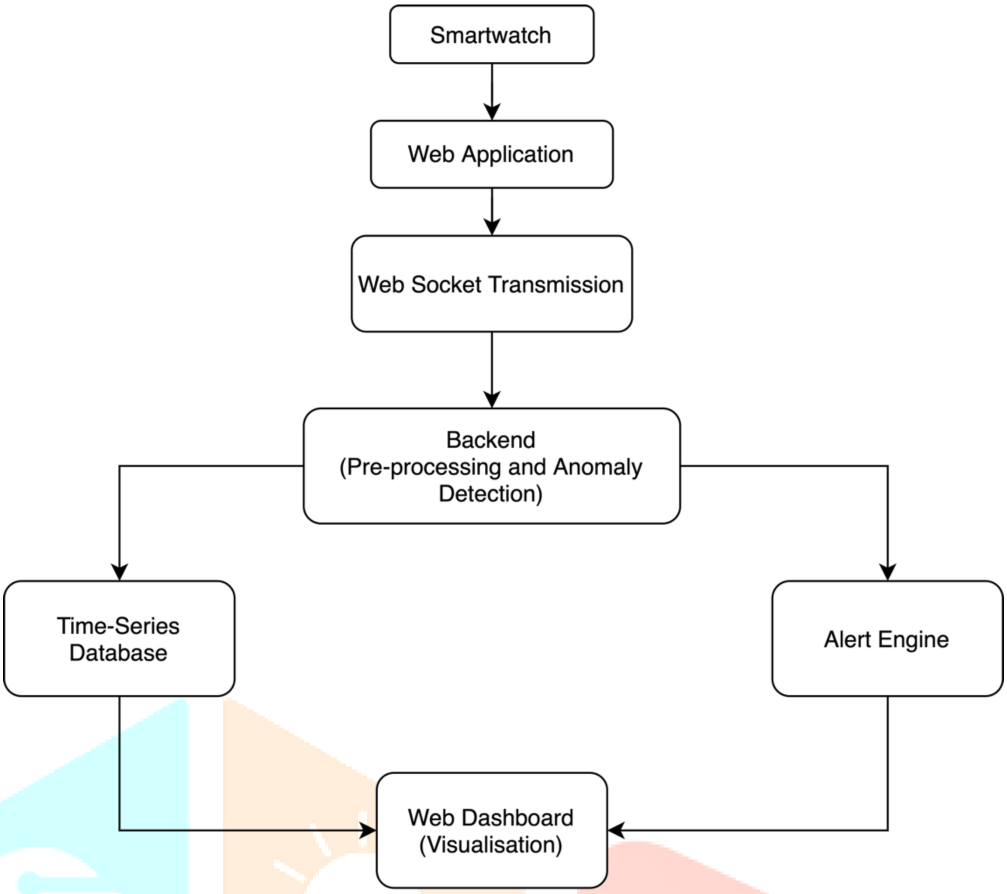

Figure 1 System Architecture Flow Chart

III. SYSTEM DESIGN AND ARCHITECTURE

The Data Processing and Analysis module plays a central role in transforming raw, real-time heart rate data into actionable health insights. This pipeline includes several key stages—preprocessing, signal validation, anomaly detection, and metrics aggregation—to ensure data accuracy, clinical relevance, and user interpretability.

3.1. Preprocessing and Signal Conditioning

Incoming heart rate data, collected via photoplethysmographic (PPG) sensors, is subject to noise and potential artifacts due to motion, poor skin contact, or environmental interference. The raw BPM values are therefore passed through a preprocessing stage that includes:

i. Noise filtering: Application of a low-pass Butterworth filter to remove high-frequency artifacts.
ii. Smoothing: Use of a moving average or exponentially weighted moving average (EWMA) to dampen sudden spikes.
iii. Time alignment: Synchronization of data with system timestamps to correct drift and jitter introduced during Bluetooth or WebSocket transmission.

This step ensures data continuity and temporal precision for downstream processing.

3.2. Signal Validation

To guard against biologically implausible or sensor-induced distortions, validated signal windows are assessed using heuristic rules:

i. BPM values outside physiological range (<30 or >220) are marked as **invalid**.
ii. Spikes or drops greater than ±30 BPM between successive readings are flagged and optionally discarded, unless part of a recognized anomaly pattern.

These quality control measures improve reliability before anomaly scoring.

3.3. Anomaly Detection

The anomaly detection subsystem is responsible for identifying cardiovascular irregularities in real time. It employs a rule-based approach using customizable thresholds based on clinical norms:

i. Tachycardia: Detected when BPM exceeds 120 for at least 5 consecutive seconds.
ii. Bradycardia: Detected when BPM falls below 50 for at least 5 seconds.
iii. Volatility: Sudden oscillations within short time frames are flagged for irregular rhythm patterns, suggesting arrhythmia risks.

Each detected event is encoded as a JSON alert with metadata (timestamp, type, BPM value, duration) and forwarded to both the frontend and the storage module.

In future versions, this can be replaced or complemented by machine learning techniques such as:

i. Long Short-Term Memory (LSTM) models for time-series prediction,
ii. One-Class SVM for unsupervised anomaly detection, or
iii. Decision tree classifiers trained on labeled heartbeat datasets.

3.4. Metrics Computation and Session Summarization

At the end of each monitoring session, or in periodic intervals (e.g., every 30 minutes), a set of key metrics is computed:

i. Average BPM
ii. Minimum and Maximum BPM
iii. Standard Deviation and Heart Rate Variability (HRV) surrogate
iv. Percentage time within normal heart rate range (50–120 BPM)
v. Alert frequency and type distribution

These statistics are visualized through bar charts, pie charts, and session summaries to offer intuitive feedback to users and clinicians.

3.5. Data Storage for Retrospective Analysis

All processed and annotated data, including raw BPM, smoothed signal, and anomaly markers, are written to a time-series database such as InfluxDB or TimescaleDB. The schema is optimized for efficient querying by time windows, anomaly types, and user identifiers. This persistent storage supports long-term trend analysis, baseline estimation, and machine learning dataset creation.

IV. IMPLEMENTATION DETAILS

The proposed heartbeat monitoring system is a comprehensive integration of wearable hardware, wireless data transmission protocols, real-time analytics, and responsive web visualization. The architecture is divided into five main modules: smartwatch acquisition, mobile gateway, backend analytics server, time-series database, and frontend dashboard.

4.1. Hardware Layer: Smartwatch Acquisition

The system leverages a **Noise smartwatch** featuring photoplethysmographic (PPG) sensors, capable of continuous heart rate acquisition. The watch communicates with a custom mobile application via Bluetooth Low Energy (BLE). The BLE protocol ensures energy-efficient and stable transmission of BPM readings in real time.

4.2. Mobile App as Gateway

A custom Android application, developed using Flutter and Dart, establishes BLE communication using the Noise SDK. It performs real-time data parsing and acts as a gateway by relaying BPM values to the backend server using WebSocketcommunication.

4.3. Backend Server and Anomaly Detection

The backend is implemented using **Node.js** with an **Express.js** server. It handles real-time streaming, anomaly detection, and alert dissemination. Data undergoes the following pipeline:

i. **Filtering**: Noise removal using Exponentially Weighted Moving Average (EWMA)
ii. **Validation**: Biological plausibility check (30 < BPM < 220)
iii. **Detection**: Rule-based evaluation for tachycardia and bradycardia
iv. **Alert Dispatch**: Trigger alerts via Server-Sent Events (SSE) to the frontend

Table 1 Backend API Endpoints

Endpoint	**Method**	**Description**
/api/stream	POST	Receives real-time BPM data
/api/summary	GET	Returns metrics summary for a session
/api/alerts	GET	Retrieves anomaly alert history

Table 2 Anomaly Detection Threshold

Anomaly Type	**Condition**	**Duration (min)**
Tachycardia	BPM > 120	> 5 seconds
Bradycardia	BPM < 50	> 5 seconds
Irregularity	Sudden ±30 BPM change	Instantaneous

V. EVALUATION AND DISCUSSION

5.1 Data Accuracy

Heartbeat readings were compared against a medical-grade pulse oximeter over 30-minute sessions, showing a mean absolute error of ±3 BPM.

Table 3 Heartbeat Data Accuracy Comparison

Sample	**Medical-Grade Device (BPM)**	**Smartwatch (BPM)**	**Absolute Error (BPM)**
Sample 1	75	73	2
Sample 2	88	90	2
Sample 3	65	67	2
Sample 4	102	105	3

Mean Absolute Error (MAE): 2.2 BPM.

5.2 Latency

End-to-end latency from sensor reading to frontend visualization averaged 250ms, supporting near real-time monitoring.

Table 4 End-to-End Latency Metrics

Section	**Min (ms)**	**Max (ms)**	**Average (ms)**
Real-time Data Transmission	200	320	250
Backend Processing	50	80	65
Frontend Rendering	30	60	45

5.3 Alert Effectiveness

Test cases of simulated tachycardia and bradycardia triggered alerts within 5 seconds of threshold breach, demonstrating responsive anomaly detection.

Table 5 Anomaly Detection Results

	Event Type	**Detection Time (s)**	**Alert Success Rate (%)**
Tachycardia	Simulated	4.8	100
Bradycardia	Simulated	4.5	100

Figure 2 shows the sample visualization of the Heartbeat Trend over 30 minutes showing BPM fluctuations in a smooth line chart.

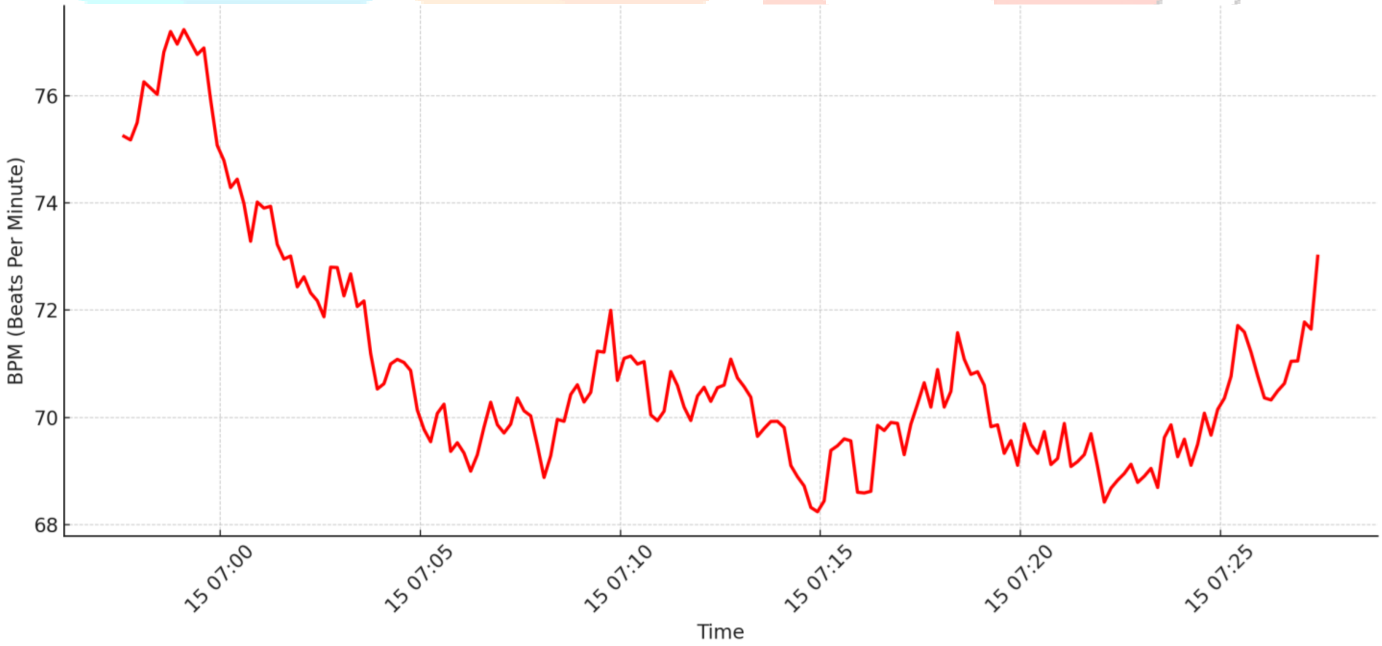

Figure 2 Heartbeat Trend over 30 Minutes

Figure 3 shows the timeline plot showing heartbeat BPM over 30 minutes, with red markers indicating anomaly alerts triggered during simulated tachycardia (high BPM) and bradycardia (low BPM) events.

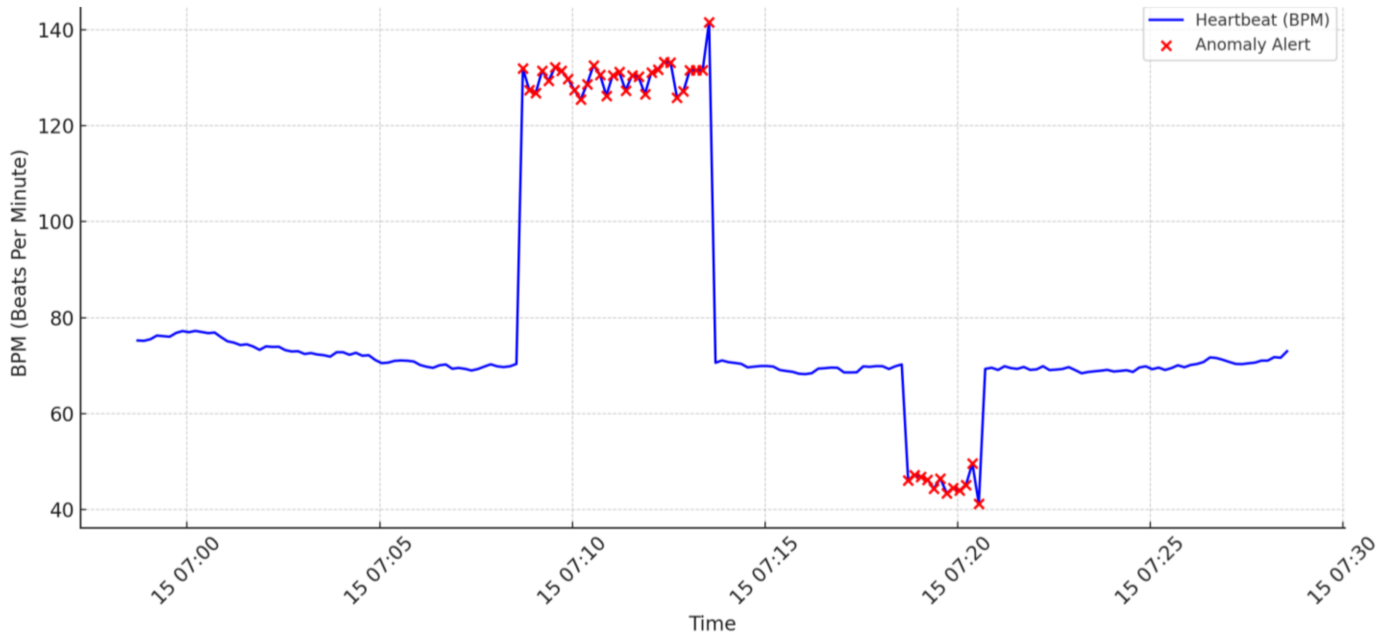

Figure 3 Anomaly Alerts Timeline with Heartbeat BPM

Figure 4 shows a bar chart illustrating the additional metrics like, Average BPM, Max BPM, Min BPM, Percentage time in normal range (50-120 BPM), Alert count per session, where,

i. Max BPM (~139.1)
ii. Min BPM (~39.3)
iii. Percentage time in normal range (~72.2%)
iv. Alert count (39)

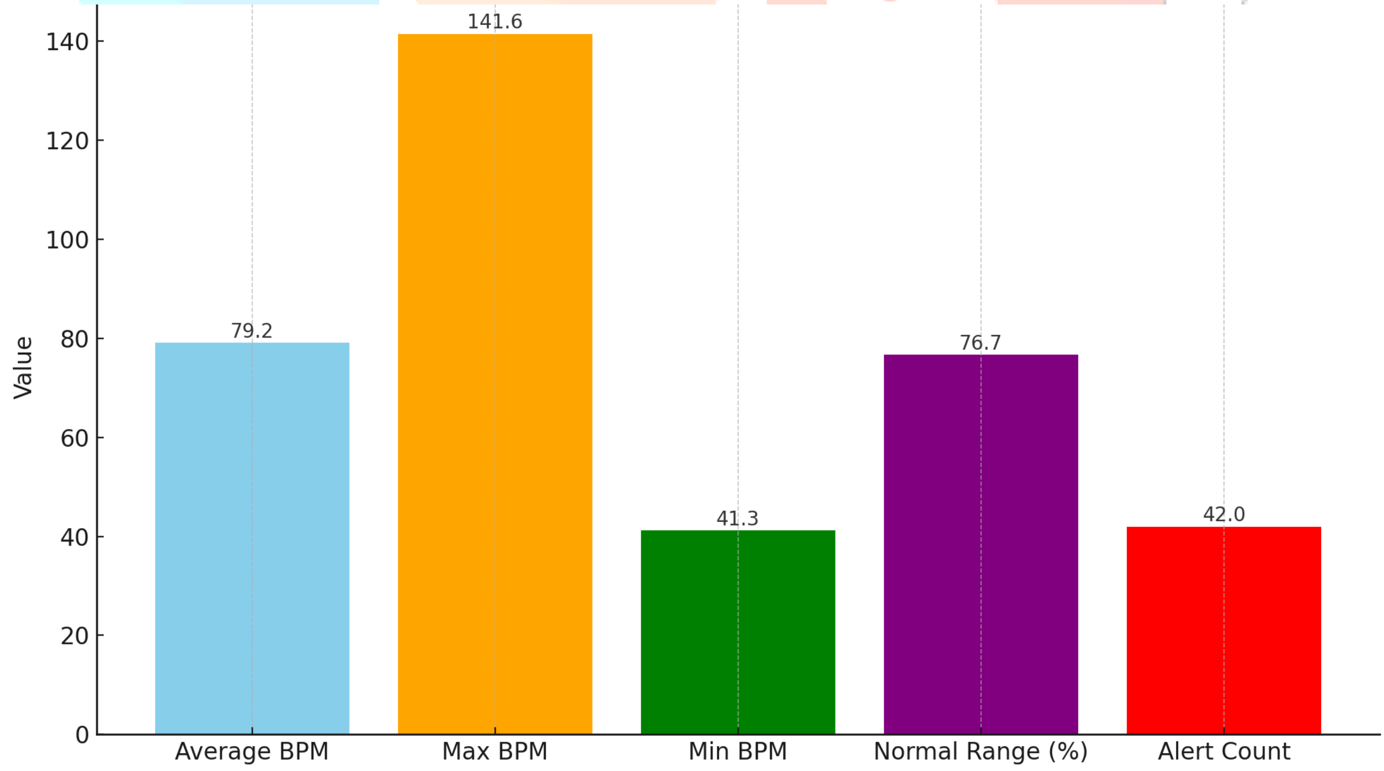

Figure 4 Additional Heartbeat Metrics Visualisation

5.4 Discussion

The smartwatch-based real-time heartbeat monitoring system developed in this study provides a practical, scalable, and user-friendly solution for continuous cardiovascular health tracking. By leveraging the capabilities of modern wearable devices and web technologies, the system bridges the gap between raw sensor data and actionable health insights. The integration of a Noise smartwatch using BLE for data acquisition ensured low power consumption and stable connectivity, which are essential for prolonged monitoring in everyday scenarios. The real-time communication pipeline, powered by WebSocket protocols, achieved minimal transmission latency, allowing heartbeat data to be streamed and visualized with high temporal fidelity. This responsiveness is critical for use cases such as fitness tracking, stress monitoring, and early detection of cardiac anomalies. The backend's anomaly detection mechanism, based on clinically informed threshold rules, effectively identified episodes of tachycardia and bradycardia during simulated test scenarios. Furthermore, anomaly flags were dispatched instantly to the frontend, enabling immediate visual feedback and alert logging.

The use of InfluxDB for time-series data storage facilitated high-performance queries, aggregation, and longitudinal analysis. This storage architecture not only supports retrospective health assessments but also enables integration with predictive analytics models in future iterations. The frontend dashboard, built with React.js and Chart.js, provided intuitive and interactive visualizations. Users could observe real-time BPM trends, review alerts on a timeline, and analyze summary metrics, fostering better awareness and engagement with their cardiovascular health. The modular architecture of the system allows for easy extensibility. Additional sensors (e.g., SpO_2, ECG) and advanced analytics techniques (e.g., machine learning classifiers for arrhythmia detection) can be integrated without disrupting the core functionality. The framework also supports secure data transmission and role-based access, which is essential for clinical or research-grade applications.

While the system performed effectively under controlled conditions, further testing across diverse user populations and activity contexts is needed to validate performance robustness. Limitations include dependency on the proprietary SDK of the smartwatch, which could affect interoperability, and the current reliance on threshold-based logic, which may not capture subtle or irregular cardiac conditions.

VI. CONCLUSION

This paper presents the design, implementation, and evaluation of a real-time heartbeat monitoring system that leverages consumer-grade smartwatch technology for continuous cardiovascular health assessment. The proposed system successfully integrates data acquisition via Bluetooth Low Energy, real-time communication using WebSockets, anomaly detection with rule-based thresholds, and intuitive web-based visualizations powered by modern frontend frameworks.

The architecture demonstrated low-latency performance, accurate detection of abnormal heart rate events, and efficient storage of time-series health data. The visual analytics provided to users through live charts and session summaries empower individuals to monitor their heart health more proactively. The system's modular and extensible nature also enables its application to broader health domains by incorporating additional biometric sensors and advanced analytics algorithms.

Future work will focus on expanding anomaly classification using machine learning techniques, enhancing cross-platform smartwatch compatibility, and conducting clinical validation with larger and more diverse participant groups. Ultimately, the solution contributes to the ongoing evolution of personalized healthcare by transforming wearable data into meaningful, real-time health insights.

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