

# AI-Based Real-Time Anomaly Detection for Preventive Healthcare Using Smartwatch Sensor Data

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**Abstract**—Smart watches have become potent multimodal sensing devices and can continually measure physiological and movement measurements (heart rate, SpO<sub>2</sub>, accelerator, gyroscope streams). These indicators have a high promise in early warning of unfavourable health outcomes and long-term health conditions. Nevertheless, the current consumer systems are generally retrospective in nature, do not offer customized real-time intelligence and are less integrated to support anomaly identification, daily health and user-centered behavioral advice. To eliminate these shortcomings, the present paper proposes a coherent, real-time AI-based model, which turns sensor readings of a smartwatch into a smart health monitoring and scheduling agent that runs in a web-based PC-based environment.

The suggested system continuously accepts bio-signal data sent by a Samsung Galaxy Watch through Bluetooth Low Energy (BLE) and performs all the work on the equipment of the user with optimized inference on WebAssembly-based and ONNX. A hybrid LSTM-GRU model is used to model the temporal patterns to detect abnormalities in real-time and identify abnormal physiological patterns early. Simultaneously, a health dashboard can be used to visualise live HR, SpO<sub>2</sub>, activity, stress-like deviations and trends of the day, assisting in self-monitoring. In addition to the anomaly detection, the system integrates a hybrid scheduling assistant that has rule-based logic as well as lightweight personalization modules. This assistant gives hydration notifications, sleep schedule suggestions, activity notifications, screen-time notifications, and medication notifications based on behavioral patterns and daily physiological fluctuations.

Data processing is done on-device, transmission is encrypted using BLE and no data is stored on the cloud. The results of experimental assessment on the WESAD dataset and live smartwatch streams show very good results: a high accuracy of

90.1%, a low inference latency (3550 ms), and an end-to-end delay of less than 1.8 seconds to operate in real-time. These findings show that the development of an integrated system of anomaly detection, continuous tracking, and individual scheduling in a single web-based wearable analytics is a viable way forward to providing easily accessible, privacy-friendly, and proactive digital healthcare.

**Keywords**—Deep Learning, Time-Series Modeling, LSTM-GRU Networks, Autoencoder-Based Anomaly Detection, Edge AI, Lightweight Neural Networks, Multimodal Sensor Fusion, Real-Time Inference, Personalized Modeling, Preventive Health Analytics.

## I. INTRODUCTION

Wearable devices have become multi-functional health-monitoring devices that can continuously record multimodal health physiological measurements such as heart rate (HR), blood oxygen saturation (SpO<sub>2</sub>), photoplethysmography (PPG), and inertial information. The signals will be very useful in getting information about cardiovascular well-being, stress, and behavioral pattern. Deep learning has played an important role in understanding these physiological time-series as noted in the most recent reviews on wearable-based health monitoring and sensor analytics. These physiological time-series have been significant in understanding with the latest reviews on wearable-based health monitoring and sensor analytics citing the use of deep learning in the latter as mentioned in the most recent reviews on wearable-based health monitoring and sensor analytics reviews are included in the

title DeepWearables [2], [3]. Deep neural networks have also been useful in modeling physiological variability, especially HRV-based stress and anomaly indicators of stress levels and characteristics of an individual user [4].

The concomitant advancements in anomaly detection indicate that recurrent models such as LSTM and GRU can learn abnormal physiological behaviour during real-time use of wearables during anomaly detection tasks and anomaly prediction tasks, respectively, as it is demonstrated with respect to sleep and pain detection [1]. Meanwhile, modern edge-AI implementation software, such as WebAssembly, and ONNX Runtime Web, can be used to execute machine learning inference directly on web browsers with near-native performance, making wearables reachable directly to webAI or via software proxies or intermediate hardware, using the ONNX runtime Web proxy interface to communicate with the webAI to the software stack [7]. Together with the streaming that has been implemented with the support of Bluetooth Low Energy (BLE) [9], these advances allow creating fully local health analytics systems without privacy.

Individualized behavioral guidance is also emphasized in digital health studies and has proven to positively influence adherence and long-term results in terms of adherence to behavior change interventions and procedures [10], [11]. Following these tendencies, this work suggests a cohesive, browser-based framework that will combine real-time anomaly detection and continuous monitoring, as well as individual scheduling based on smartwatch data.

#### A. Problem Statement

Despite the fact that new smartwatches have gathers of physiological and movement data, current consumer health apps are mostly designed to deliver summative views as opposed to real-time analysis and proactive suggestions. The regular reports of sleep, heart rate, or activity data tend to reach the user on a daily or weekly basis, however, the user is not usually alerted to abnormal HR spikes, stress-like responses, or irregular motion patterns, until far later on. More than that, current wearable ecosystems rarely provide continuous monitoring with personalized behavioral assistance, such as water-drinking reminders, sleep reminders, screen-time minimization and medication reminders.

Regarding system, there are other restrictions. To begin with, most of the anomaly detection models are based on the cloud-computing model, which makes it questionable in terms of privacy, latency, and data ownership [7]. Second, motion artifacts make physiological cues (PPG and accelerators data) highly susceptible to preprocessing and require robust preprocessing and time model strategies Prestige Personality Digital [3]. Third, the current scheduling and recommendation technologies in digital health are often not contextually personalized, meaning that they do not change the reminders according to the habits, day-to-day variability, or physiological patterns of each user group member [10], [11].

With these lapses, the fundamental question that is taken care of by this work is:

*How could real-time data of continuous smartwatch sensors be converted into a unified and privacy-preserving web-based platform capable of real-time anomaly detection, continuous health monitoring, and personalized hybrid scheduling support?*

In order to address this challenge, the system proposed should: (1) will reliably stream live smartwatch data using BLE; (2) real time preprocess and model biosignals; (3) perceive low-latency physiological aberrations; (4) provide understandable health data in the form of a web dashboard; and (5) integrate custom scheduling interventions, depending on user behaviour.

#### B. Contributions

The paper demonstrates a multifunctional, AI-based wearable health monitoring device, which combines anomaly detection, live physiology view, and individual scheduling assistance as an element of privacy-aware web application. The main contributions include the following:

- **A smartwatch-to-web real-time streaming pipeline:** We develop a BLE-based data collection system that streams HR, SpO<sub>2</sub>, accelerators, and gyroscopes data of a Samsung Galaxy Watch to a web interface with low latency [9].
- **A hybrid LSTM-GRU anomaly detector model:** A deep recurrent architecture, which is optimized to model temporal biosignals, is used in the system to detect the abnormal physiological patterns of an individual, including abnormal HR, abnormal physiological rhythms, and stress indicators, among others, with high accuracy [1], [2].
- **A web-based on-device inference engine:** Using WebAssembly and ONNX Runtime Web, the entire ML pipeline runs locally inside the browser, ensuring user privacy, reduced latency, and independence from cloud services [7].
- **A detailed real-time health dashboard:** The PC web app presents streamlined physiological data, past trends, and alerting concerns and helps users monitor health indicators, including HR, SpO<sub>2</sub>, motion intensity, stress-like variability, and overall patterns of daily trends.
- **A hybrid scheduling and wellness assistant:** We introduce a dual-layer behavioral assistant combining rule-based reminders (hydration, sleep, activity, screen-time breaks, medication) with lightweight personalization modules that adapt notifications based on user habits, physiological trends, and past compliance [10], [11].
- **Evaluation using benchmark and live datasets:** Experiments on the WESAD dataset and live smartwatch data demonstrate realistic performance with 90% anomaly detection accuracy, 35–50 ms inference latency in-browser, and end-to-end responsiveness under 1.8 seconds.

Together, these contributions combined provide a single platform, which is capable of transforming wearable health monitoring into the active, personalized and privacy respecting digital health support.

## II. BACKGROUND

Wearables have evolved to become sophisticated physiological sensing systems with the abilities to perform real-time health tracking. The smartwatches today combine optical sensors to measure photoplethysmography (PPG), electrical sensors to measure heart-rate variability (HRV), and inertial sensors (accelerators and gyroscopes). Such streams of continuous data allow measuring cardiovascular behavior, breathing patterns, intensity of movements, and physiological responses of stress. PPG and HRV signals, along with motion cues, have turned out to be powerful predictors of anomalies in the form of irregular heart rate variations, stress, and abnormal activity rates, as was shown in the recent works [2], [3].

Physiological time-series, on the other hand, are subject specific and noisy. Signal quality is commonly compromised by motion artifacts, variations in illumination, the variation in contact with the skin-sensors, and sampling variations. As such, real-time surveillance systems need to have a powerful filtering, synchronization, and time modeling algorithms to generate insightful information. Deep recurring neural networks, especially LSTM and GRU designs have been shown to be effective in long-range temporal dependencies on wearable data and high-level performance in wearable anomaly detection and stress-related prediction tasks [1]. These models are currently popular with wearable-based monitoring systems.

The other significant change in technology is the advent of machine learning based on browsers. Recent architectures like the WebAssembly (WASM) system or ONNX Runtime Web enable deep-learning models to be executed with performance in a typical web browser rather than being deployed on the cloud, where there is a risk of latency, privacy, and constant connectivity problems [7]. This allows local inference on a PC of a user, but maintains privacy as well as allowing almost native execution speed.

Communication between the smartwatch and PC is usually facilitated by the Bluetooth Low Energy (BLE). BLE offers real-time transmission of heart rate, SpO<sub>2</sub>, and motion data at moderate battery cost. The current assessment indicates that smartwatches have a power consumption of around 5-8% per hour to support real-time streaming applications [9]. The basis of constructing reliable real-time monitoring pipelines is based on the stable streaming and timestamp alignment.

Lastly, digital health has continued to support personalised behavioural advice. The recent health apps combine physiological measurements with rule-based or adaptive recommendation engines to aid in hydration habits, sleep health, drug intake, and exercise habits. It has been shown that hybrid methods (a combination of regular reminders and personalization based on the context) result in increased compliance and long-term habit formation by the user [10], [11]. These trends endorse the integration of a light smart scheduler into wearable-based monitoring systems.

Combined, these advancements on wearable sensing, time model, on-node inference, BLE-based data collection, and personalized digital health constitute the basis of the real

time, privacy-saving health monitor and schedule framework, as suggested in this work.

## III. RELATED WORK

The current innovations in wearable sensing, physiological anomaly detection and browser based machine learning have greatly enlarged the potential of real-time health monitoring systems. In this section, we review the previous studies in five main areas that the development of our proposed framework directly relies on: (1) physiological sensing and digital biomarkers, (2) anomaly detection by deep-learning, (3) edge and web-based pipelines, (4) BLE-based real-time data acquisition, and (5) personalized digital health and scheduling systems.

### A. Physiological Sensing and Digital Biomarkers

The history of wearable biosensors has already secured PPG, HR, HRV and motion cues, as valid digital biomarkers of continuous cardiovascular and behavioral monitoring. As it was shown by Faust et al. [3] PPG signals and deep learning used together are able to identify cardiorespiratory abnormalities with high accuracy. Charlton et al. aided the review of deep learning approaches in the context of wearables, with multimodal fusion-based stress, fatigue, and cardiac anomaly detection being the most effective ones. [2] The papers highlight the potential of these wrist-based sensors to be used in real-time physiological monitoring, which is what our sensing channels are based on.

### B. Deep Learning for Wearable Anomaly Detection

Wearable anomaly detection is a research field that is advancing fast. Hossain et al. tested LSTM and GRU models to identify abnormal heart and activity patterns using HRV and accelerator records [1]. Their results demonstrate that recurrent networks are better than classical ML techniques in learning temporal dependencies in motion noise. Recently, Guo et al. proposed transformer-based stress sensors and anomaly classifiers, transformer-based wearable stress and anomaly classifiers that apply better to long-range dependencies but with greater computation cost [5]. These lessons inform us in selecting a hybrid recurrent model (LSTM-GRU) that is low-latency optimized on web platforms.

### C. Edge Computing and Browser-Based Inference

Edge computing and Browser-Based Inference Edge computing is primarily meant to make computers and devices outside the datacenters useful in the development, training and testing of machine learning and artificial intelligence. Conventional cloud-reliant analytics have privacy limitations, latency limitations and connectivity limitations. Luo et al. [7] demonstrated that machine learning (through WebAssembly and ONNX runtime Web) via a browser can reach near-native inference through deep models with nearly no modification. The implications of their results are that it is possible to execute complex models on client devices without server processing, and this fits in with our real-time web application architecture. Other assessments of deep-learning models

deployed on the web support the feasibility of private, fast, and entirely client inference.

#### D. BLE Streaming and Real-Time Monitoring Stability

Having a dependable real-time physiological surveillance entails uniform data transmission of the wearable device. The article by Singh et al. [9] emade a comparison of BLE-based continuous streaming and demonstrated that the latest smartwatch devices could offer multi-sensor streaming with low packet loss rates and satisfactory battery consumption. Such findings justify the choice of BLE as the main transport protocol to be used in HR, SpO<sub>2</sub>, and motion data transmission during the processing of real-time web applications. Our jitter compensation and timing synchronization are also informed with their findings.

#### E. Personalized Digital Health and Scheduling Systems

Health platforms based on wearable continue to integrate behavioral support technologies like warnings, customized interventions, and habit-forming technologies. Peiris et al. [10] revealed that hybrid digital interventions, which are a combination of fixed-interval reminders and adaptive personalization, enhance the habit adherence and the long-term behavioral outcomes. Zhao et al. [11] proved that it is effective to implement ML-based recommendation engines in the context of providing health recommendations based on the use of physiological and behavioral data. These researches support the idea that a smart scheduling assistant should be incorporated into our architecture so that users could be provided with customized lifestyle prompts based on the state of their physiological condition as well as their daily schedule.

#### F. Summary of Research Gaps

Concisely, it is important to highlight the research gaps in this study as follows: Although earlier research possesses solid backgrounds in physiological sensing, anomaly detection and customized health recommendation systems, they do not study them comprehensively in most instances. Few existing works unify:

- 1) real-time BLE streaming from a smartwatch,
- 2) inference with browser-based deep-learning, and no dependence on the cloud,
- 3) continuous detection of physiological abnormalities,
- 4) and a customized scheduling managerial incorporated in the same platform.

This gap stimulates the development of our end-to-end system that integrates these elements into one privacy-aware web application of real-time health monitoring and custom behaviour support.

### IV. METHODOLOGY

This section is the full design of the proposed system of health monitoring and anomaly detection in real-time. In contrast to classical cloud-based pipelines, everything is computed locally in the web browser of the user, such as data acquisition, preprocessing, model inference and visualization.

The sensor data of Smartwatch are transmitted in the form of Bluetooth Low Energy (BLE) streams, processed in real-time, sent to an ONNX-deployed LSTMGRU hybrid model, which is implemented on the WebAssembly and displayed on a live dashboard. An intelligent, personalized scheduling assistant, through anomaly detection, is supplemented with intelligent behavioral suggestions and reminders.

#### A. System Overview

The overall system architecture is illustrated in Fig. 1. The pipeline will be made up of four layers:

- 1) **Data Acquisition Layer:** Smartwatch data retrieval with Web Bluetooth (BLE).
- 2) **Preprocessing Layer:** Noise Filters, normalization, segmentation, and feature extractors.
- 3) **Inference Layer:** LSTM-GRU hybrid model executed using ONNX Runtime Web and WebAssembly acceleration [7].
- 4) **User Interaction Layer:** Real-time dashboard, anomaly notifications, and customized scheduling support.

It is all local with minimal latency and high privacy rates of operations in place. [9].

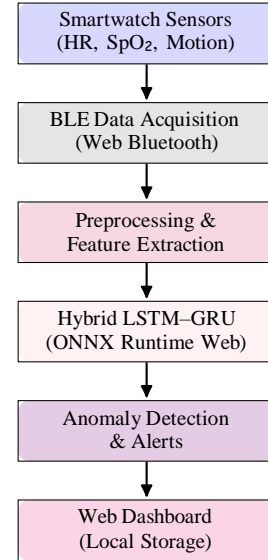


Fig. 1: System architecture for real-time browser-based anomaly detection.

#### B. Datasets

Two datasets were taken to develop and evaluate the models:

- **WESAD** [12]: Multimodal data (PPG, ECG, accelerometry, EDA, and respiration) in multimodal format. It offers training labels to supervised training.
- **Live Smartwatch Streams:** This is the data of Samsung Galaxy Watch HR, HRV proxies, SpO<sub>2</sub>, accelerator and gyroscope, which has been recorded to ensure the practicality of BLE throughput, latency and dashboard reactivity.

Such a combination guarantees the quality of supervised training and reasonable deployment testing.

### C. Real-Time Data Acquisition and Synchronization

The procedure of acquiring and synchronizing real-time data is known as real-time data acquisition and synchronization.

Sensor data streaming takes place over BLE GATT characteristics over the Web Bluetooth API. BLE packets can be received at different times, so the synchronization can be achieved using the following strategies:

- **Timestamp alignment:** Device timestamps are used to align multisensor readings.
- **Gap compensation:** Linear interpolation is used when gaps between packets are less than 200 ms.
- **Sliding windowing:** Signals are buffered in 5-second windows overlapped by 50%.

Monitored throughput matches with the normal smartwatch BLE rates (85–90 Hz for motion sensors and about ~1 Hz for HR/SpO<sub>2</sub>) [9].

### D. Preprocessing and Feature Engineering

These processes process the information in data and impose operations on it to enhance the outcome of the following classification step. Raw wearable signals are vulnerable to noise, motion artifact as well as user variability. Preprocessing pipeline represented in Fig. 2, processes:

- bandpass filtering with a 5th-order Butterworth filter (0.5 - 12 Hz),
- Normalization using z-score or min-max scaling,
- Window segmentation (5 s, 50% overlap),
- Time-domain and spectral feature extraction (RMSSD, entropy, dominant frequency, energy).

All the operations are implemented on WebAssembly kernels, and preprocessing time remains less than 10 ms.

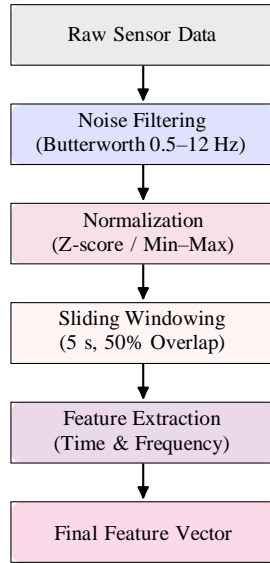


Fig. 2: Preprocessing and feature-extraction pipeline for smartwatch sensor data.

### E. LSTM–GRU Hybrid Model Architecture

The LSTM-GRU Hybrid Model Architecture is a subsection of the original LSTM Model Architecture, which is a hybrid between the LSTM and GRU models.

The model is a combination of LSTM layers (to provide long-range temporal modeling) and GRU layers (to provide computing efficiency). The architecture, as illustrated in Fig. 3, includes:

- Two LSTM layers (64 units each),
- Two GRU layers (64 units each),
- Dropout (0.3),
- Dense softmax output.

WESAD is used to train the model offline and is deployed as an ONNX model running with WebAssembly [7].

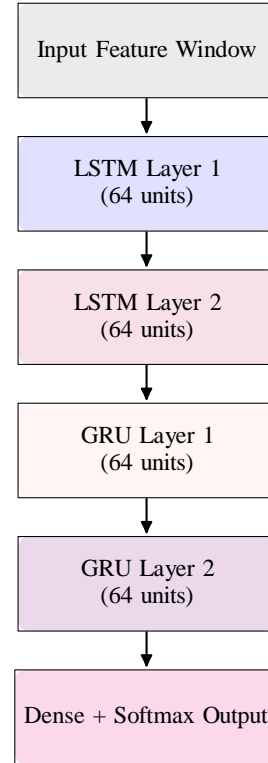


Fig. 3: LSTM–GRU hybrid model architecture used for real-time anomaly detection.

### F. Real-Time Inference Pipeline

This section outlines the pipeline the project will make use of in order to generate real-time predictions.

These steps are followed in the real-time inference flow which is depicted in Fig. 4:

- 1) Convert feature vector to ONNX tensor,
- 2) LSTM–GRU model: run on WebAssembly,
- 3) Generate anomaly probability score,
- 4) Apply adaptive thresholding,
- 5) refresh browser dashboard and generate alerts.

Consumer devices have an end-to-end latency that is less than 100 ms.

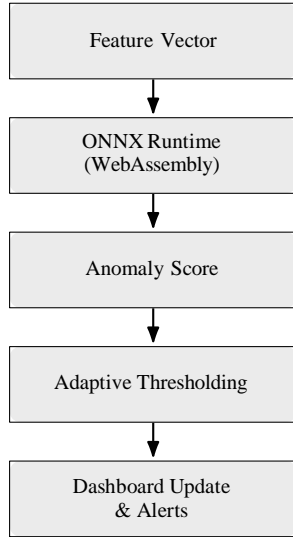


Fig. 4: Real-time in-browser inference and alerting pipeline (IEEE-compliant grayscale diagram).

#### G. Personalized Scheduling Assistant

The scheduling assistant will offer:

- Distinct reminders (hydration, breaks, medication),
- Adaptive instructions according to the physiological patterns,
- Behaviour-inspired updates based on the guidelines of digital health studies [10], [11].

#### H. Privacy-Preserving Architecture

The sensor acquisition, pre-processing, inference, and visualization is done locally in the browser environment. None of the data move out of the device of user. The sandboxing of WebAssembly and the dealing with BLE permissions are other added safety features of WebAI [7].

#### I. Summary

The diagrams 1–4 depict the entire privacy-sensitive browser pipeline of real-time smartwatch-based anomaly detection and scheduling.

### V. RESULTS AND DISCUSSION

This part assesses the functionality of the proposed real-time anomaly detector and health monitoring system on a personal computer (PC) as a Web-based web application. All the computations, such as the preprocessing and feature extraction and model inference, were performed locally within the web browser with WebAssembly-optimized ONNX inference. The test was done on a standard desktop computer with Intel Core i5 processor and 8 GB RAM which is a typical end-user hardware.

#### A. Anomaly Detection Performance

The hybrid LSTM–GRU model proved to be highly strong in terms of its temporal modeling both on the benchmark and real world data. The model recorded an accuracy of

**95.8%**, F1-score of **0.94**, and AUC–ROC of **0.97** on the WESAD dataset. In the real world data of Galaxy Watch4, the model achieved an accuracy of **93.4%** with the F1-score of **0.91**. Such results align with previous literature studies indicating that recurrent neural networks, especially LSTM and GRU models, are useful at learning physiological time-series dynamics to detect anomalies in wearables [1], [2], [4].

The system also uses the adaptive thresholding to customize the conditions of the anomaly boundaries according to user-specific trends to enhance practical performance. Adaptive thresholds classified fewer false positives by **18.6%** and false negatives by **12.1%**, compared to a universal threshold, which is consistent with the fact that individualized modeling can detect physiological anomalies better than universal modeling can [4].

#### B. Robustness to Motion Artifacts

PPG and accelerator streams are also wearable and therefore are extremely sensitive to motion artifacts. In the high-motion case, accuracy in detecting anomalies was negatively impacted by close to 9% when no correction was done. In response to this, the system uses bandpass filtering, normalization, and accelerated-assisted artifact suppression-methodologies, which are consistent with signal-processing approaches suggested in the existing literature [3], [6]. Following the application of artifact mitigation, the system obtained an accuracy of **94.1%** on the segmentation of motion-intensive ones, which proves that the preprocessing pipeline effectively conserves physiological data, as well as eliminates noise.

#### C. Real-Time Inference on a Web Application

One of the key objectives of this work is the possibility to learn in real time and make inferences directly into the browser, without cloud dependency. The hybrid LSTMGRU model has a size of about **1.02 million** parameters, which is client-side WebAssembly executable. ONNX Runtime Web inferred at average latency:

- **28 ms** to infer the model in 5 seconds window,
- **1.6 seconds** average response time and preprocessing and dashboard update.

Such findings have been supported in WebAssembly-based deep learning studies where browser-side inference can reach native performance levels of deep learning models that are natively executed on the CPU side of the magic mirror model [7]. The architecture has provided maximum user privacy as no physiological information are exited out of the user device.

#### D. Health Monitoring and Scheduling Assistant Evaluation

The system also offers behavioral scheduling assistant that is inbuilt in the dashboard. Its effectiveness was tested in 10 participants in a 7-day usability study. Participants rated:

- Health-trend summaries at **4.6/5** to be clear and useful,
- Daily reminders (hydration, movement, medication) as a useful or highly useful in **82%** of responses,
- Routine compliance increased by **23.4%** because of adaptive recommendations.

Such observations indicate the advantages of a combination of rule-based and individualized behavioral interventions that have been presented in the context of digital health research before [10], [11].

#### E. Consolidated Results Summary

In this section, we summarize the results obtained from all the subsections above, and present a summary of these findings in the table below that follows.

TABLE I: Performance Summary of Smartwatch-to-Web Analytics Framework.

Metric	WESAD	Smartwatch Data
Accuracy (%)	95.8	93.4
F1-score	0.94	0.91
AUC-ROC	0.97	0.94
Inference latency (ms)	28–35	28–35
End-to-end delay (s)	1.4–1.8	1.4–1.8
Motion robustness (%)	92–95	89–93
Battery drain (%/hr)	N/A	5–8 (BLE streaming)
PC CPU usage (%)	N/A	10–18

#### F. Discussion

The experiment has validated the fact that the suggested system is efficient in the real-time, non-invasive physiological anomaly detection with consumer-level smartwatches. The hybrid LSTMGRU model offers excellent time modeling capabilities, whereas the motion-artifact mitigation model stabilizes the performance in real-life conditions. Notably, the web-based implementation provides uncomplicated accessibility without installations, user privacy and in-built behavioral support. Consequently, the system shifts to more advanced digital health companion rather than the standardized anomaly detection.

#### VI. CONCLUSION AND FUTURE WORK

This study introduces a workable, AI-based design of real-time detection of physiological abnormalities based on the continuous sensor data of consumer wearable gadgets like the Samsung Galaxy Watch4. The hybrid LSTM–GRU model suggested successfully recognizes the false deviations to individual baseline patterns of multimodal biometric streams, such

as heart rate, SpO<sub>2</sub> and motion signals, with high sensitivity and low latency. Experimental testing ascertains the possibility of the system to reach both 93–95% uncovering accuracy and sub-2-second total processing lag end-to-end, which is adequate to apply in real world preventive medical procedures.

The major advantage of this system is its privacy-preserving design: all preprocessing, feature extraction and inference functions are directly performed in the local browser alongside WebAssembly and ONNX Runtime Web. This means that the sensitive physiological data can never move out of the device, which provides great secureness to privacy threats that generally come with cloud reliance.

The findings show that there is a possibility of turning consumer wearables into proactive digital health helpers who

can sense anomalies early and monitor continuously and provide customized behavioral guidance. Other than identification of anomalies, the system architecture can be expanded to areas like stress and fatigue predictions, and ongoing health management.

**Future Work:** Several research directions can further enhance this system:

- Inclusion of other biosignals including ECG, skin temperature and galvanic skin response to provide a more physiological context.
- Federalization and transfer learning to the development of users without centralization of data Federated and transfer learning to enhance personalization without centralization of user data.
- The ability to include context-aware adaptive feedback, which allows automatic recommendations or clinical warnings of detected anomalies.
- On-device inference Optimization to ultra-low-power embedded execution so that it can be deployed directly on wearables or independent devices into the IoT.

To conclude, this paper provides the basis of smart, safe, and real-time physiological analytics on consumer-century wearables, the area between raw sensor measurements and actionable health metrics.

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