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Adaptive Baseline Modeling for Personalized Cardiovascular Anomaly Detection

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Abstract: ***Wearable devices such as smartwatches allow continuous monitoring of physiological signals, including heart rate and activity levels. Many current monitoring systems rely on fixed population-based thresholds that may not reflect individual physiological differences. This paper explores a personalised monitoring framework based on adaptive baseline modelling and anomaly detection. Physiological signals obtained from wearable sensors such as photoplethysmography (PPG), accelerometers, and gyroscopes are used to derive features including heart rate, heart rate variability, and motion activity. By learning an individual's normal physiological patterns over time, the system can identify deviations that may indicate unusual cardiovascular behaviour. The goal of this work is to outline a monitoring approach to support personalised health monitoring using wearable devices.***

Index Terms: ***Cardiovascular Monitoring, Wearable Sensors, Anomaly Detection, Adaptive Baseline Modelling, Autoencoder***

Nomenclature:
PPG: Photoplethysmography
CNNs: Convolutional Neural Networks
RNNs: Recurrent Neural Networks
HR: Heart Rate
HRV: Heart Rate Variability
IBI: Inter-Beat Interval

I. INTRODUCTION

Cardiovascular diseases remain a major global health concern [1]. Early identification of unusual physiological patterns can help support preventive healthcare and encourage timely medical evaluation. With the increasing availability of wearable devices, physiological signals such as heart rate and activity levels can now be monitored continuously outside clinical environments.

Many current monitoring systems rely on predefined population thresholds.

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However, physiological parameters vary significantly between individuals depending on lifestyle, fitness level, and daily activity patterns. As a result, fixed thresholds may produce false alarms or miss meaningful changes. Personalized monitoring approaches attempt to address this limitation by learning a user's normal physiological patterns over time. Deviations from this baseline can then be used to detect unusual physiological behaviour.

II. RELATED WORK

Machine learning has significantly influenced modern healthcare systems, enabling predictive modelling and analysis of physiological signals [2]. Deep learning approaches, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated strong performance in processing time-series biomedical data [3].

Unsupervised anomaly detection techniques have gained attention for their ability to model normal physiological behaviour without requiring labelled datasets. Among these, autoencoder-based methods are widely used to learn compact representations of normal patterns and identify deviations through reconstruction error [4].

Recent research highlights the importance of personalised physiological monitoring, in which individual baseline patterns are learned over time rather than relying on generalised population thresholds. Such approaches improve detection accuracy and reduce false alarms in wearable health monitoring systems.

III. METHODOLOGY

A. System Overview

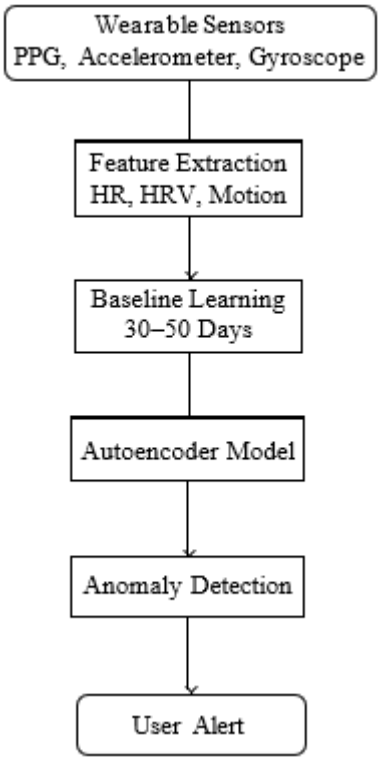
The monitoring framework uses sensors commonly available in wearable devices:

- Photoplethysmography (PPG)
- Accelerometer
- Gyroscope

From these sensors, physiological and contextual features are derived:

- Heart Rate (HR)
- Heart Rate Variability (HRV)
- Motion activity
- Device orientation

The overall workflow of the proposed system is illustrated in Fig. 1.



[Fig.1: Proposed Personalized Cardiovascular Monitoring Pipeline]

B. Heart Rate Estimation from PPG

If the time between two peaks is the inter-beat interval (IBI), heart rate is estimated as: 60

$$HR = \frac{}{|B|} \tag{1}$$

C. Heart Rate Variability

$$SDNN = \mathbf{u}^{\mathrm{u}} \frac{1}{N-1} \mathbf{i}^{N} \left(RR_i - \overline{RR)^2} \right. \tag{2}$$
$$i = 1$$

D. Motion Detection

$$A = \sqrt{\overline{x^2 + y^2 + z^2}} \tag{3}$$

E. Orientation Estimation

$$\vartheta(t) = \vartheta(t-1) + \omega \Delta t \tag{4}$$

F. Baseline Modelling

$$\mu = \frac{1}{N}^{N} x_i \tag{5}$$
$$\vec{\mathrm{u}}_{1=1} \sum_{N}$$

$$\sigma = N_{i=1}(x_i - \mu)^2 \tag{6}$$

G. Autoencoder-Based Anomaly Detection

$$\hat{x} = g(f(x)) \tag{7}$$

$$L = \|x - \hat{x}\|^2 \tag{8}$$

IV. DISCUSSION

Adaptive baseline modelling enables monitoring systems to detect deviations from a person's normal physiological behaviour rather than relying solely on fixed thresholds. Combining physiological and motion signals helps reduce false alarms caused by normal physical activity.

Autoencoder models can learn correlations between signals such as heart rate, HRV, and activity levels, enabling the detection of subtle anomalies that rule-based systems may miss.

V. CONCLUSION

This paper presented a framework for personalised cardiovascular anomaly detection using adaptive baseline modelling and autoencoder-based anomaly detection. Personalized base-lines improve sensitivity and reduce false positives compared to traditional threshold-based monitoring systems.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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REFERENCES

1. World Health Organization, "cardiovascular diseases (CVDs)," 2023. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)
2. S. Rajkomar, J. Dean, and I. Kohane, "Machine Learning in Medicine," New England Journal of Medicine, vol. 380, no. 14, pp. 1347-1358, 2019. DOI: http://doi.org/10.1056/NEJMra1814259
3. A. Esteva et al., "A Guide to Deep Learning in Healthcare," Nature Medicine, vol. 25, pp. 24-29, 2019. DOI: http://doi.org/10.1038/s41591-018-0316-z
4. G. Pang et al., "Deep Learning for Anomaly Detection: A Review," ACM Computing Surveys, vol. 54, no. 2, 2021. DOI: http://doi.org/10.1145/3439950