# Modern Technologies for Registration, Processing and Analysis of Physiological Signals (ECG, PPG), and Decision-making in Sensory Information Systems

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# Съвременни технологии за регистрация, обработка и анализ на физиологични сигнали (ЕКГ, ФПГ) и взимане на решения в сензорни информационни системи

***Abstract***

*This work presents an automatic notification mechanism within an intelligent cardiology information system based on electrocardiogram (ECG), photoplethysmography (PPG), and heart rate variability (HRV) analysis for the detection of deviations from the normal range of key HRV parameters. Particular attention is paid to signal preprocessing, noise suppression methods, and reliable detection of characteristic points. The proposed automatic notification system relies on developed algorithms for HRV parameter extraction and analysis, covering time-domain, frequency-domain, and nonlinear characteristics in order to identify physiological risk conditions. When deviations from normality are detected—for example, reduced SDNN values or an increased LF/HF ratio—the system triggers an automatic alert to the observing medical specialist. The system is designed for real-time operation and is suitable for deployment on edge or wearable devices. Experimental results demonstrate high performance of the proposed methodology when evaluated on recordings from a proprietary database created by the authors.*

***Keywords:*** *Sensor System; Electrocardiogram; Photoplethysmography; Heart Rate Variability; Cardio Database; Edge Devices.*

## 1. Introduction

Modern technologies for registration, processing and analysis of physiological signals open up new opportunities for early diagnosis, monitoring of health status and decision-making in real time. Signals such as electrocardiogram (ECG) and photoplethysmography (PPG) are among the most commonly used non-invasive methods for assessing cardiovascular function. These signals enable the derivation of Heart Rate Variability (HRV) parameters, which provide valuable information about autonomic nervous system regulation and the risk of adverse physiological conditions.

The integration of intelligent sensor information systems, combining reliable signal registration, pre-processing, feature extraction and automatic notification, is key to modern healthcare and to implement the concept of personalized medicine. In recent years, there has been growing interest in implementing algorithms for real-time ECG and PPG processing on edge devices, allowing rapid on-site analysis without reliance on centralized computing resources.

This article presents an intelligent sensor information system developed by the authors for monitoring and analysis of ECG, PPG and HRV. Particular attention is paid to automatic notification of deviations from the norm of the main HRV parameters. The system has been evaluated using recordings from a proprietary database created by the authors.

## 2. Literature Review

### *2.1. Physiological signal acquisition (ECG, PPG) and wearable sensors*

The last decade has witnessed rapid progress in compact biosensors and wearable devices for ECG and PPG measurements. ECG remains the "gold standard" for the electrical activity of the heart, while PPG offers an optical, low-power and convenient solution for long-term monitoring. Design trends include the integration of multi-sensor modules, embedded high-resolution ADCs, hardware mechanisms for suppressing interference and motion artifacts, as well as wireless interfaces (BLE/Wi-Fi) for low latency and energy efficiency. The data is often accompanied by accelerometric signals to capture motion-induced artifacts.

### *2.2. Preprocessing and noise suppression*

The quality of the recorded signals is critical for subsequent analysis. For ECG, artifacts from baseline drift, muscle noise and network interference are typical; for PPG – motion noise, sensor pressure variations and light changes. Well-established approaches are:

- Wavelet filters and multi-resolution analysis to separate high-frequency noise and baseline drift;
- Adaptive filters (LMS/RLS) with a reference accelerometer channel;
- Empirical Mode Decomposition (EMD), SSA, Savitzky–Golay smoothing and Kalman filters for dynamic cleaning;
- Hybrid methods for artifact suppression using a multi-channel (ECG+PPG+ACC (accelerometer signal)) approach.

### *2.3. Feature point detection*

Accurate localization of R-waves (ECG) and systolic peaks/zero crossings (PPG) is fundamental. Classical methods include Pan–Tompkins [1], differential operators, matched filtering and wavelet detectors. Differential PPG (dPPG), first/second derivative analysis and adaptive thresholding are often used in PPG. Learning models (CNN (Convolutional Neural Network)/UNet/LSTM(Long Short-Term Memory)/Transformers) are increasingly being applied for robust detection in noise and motion.

### *2.4. Feature extraction and HRV analysis*

- HRV quantifies the dynamics of the time intervals between heartbeats (RR for ECG and PPI for PPG). The literature distinguishes three groups of metrics [2], [3], [4];
- Time domain: mean RR/PP, SDNN, RMSSD, pNN50/pNN20, HRVTi, etc.;
- Frequency domain: VLF, LF, HF, LF/HF (estimated using FFT, AR models and Welch periodogram);
- Nonlinear measures: Poincaré (SD1/SD2), entropies (ApEn, SampEn, FuzzyEn), fractal/scale measures (DFA α1/α2, Hurst), recurrent quantifiers (RQA).

For PPG-derived HRV [5], [6], the comparability with ECG-derived HRV and the influence of artifacts are discussed, and procedures for artifact correction, interpolation, and quality indices are recommended before spectral and nonlinear analysis.

### *2.5. Application scenarios and decision-making*

HRV and related ECG/PPG features are used for:

- Assessment of autonomic regulation, stress and fatigue;
- Detection of arrhythmias (e.g. atrial fibrillation) and high-risk episodes;
- Monitoring of training recovery and exertion in athletes;
- Cardiorespiratory monitoring (incl. $SpO_2$ and respiratory modulation of PPG).

Solutions are increasingly implemented as rules/algorithms for alerting and classification models running in real-time on edge hardware.

### *2.6. Machine learning and deep learning*

Classical models (SVM, Random Forest, GMM, k-Means) remain strong for tabular features, while deep learning (1D-CNN, LSTM/GRU, CNN-LSTM, Attention/Transformers) [7], [8], [9], [10], dominates for raw signals and event detection. The following are observed:

- Self-supervised/contrastive methods for limited labeled data;
- Multi-task and multi-modal (ECG+PPG+ACC) architectures;
- Explainable AI (SHAP, Grad-CAM) for interpretation in clinical context;
- TinyML/edge machine learning (ML) optimizations (quantization, pruning, distillation) for performance on resource-constrained devices.

### *2.7. Databases, evaluations and standards*

Public datasets such as MIT-BIH Arrhythmia, MIT-BIH NSR, PhysioNet Fantasia, MIMIC (clinical ECG/PPG), BIDMC PPG and Respiration, CapnoBase (PPG/$SpO_2$/Respiration) [11], [12], [13] and others are widely used. Good practices are:

- Standardization of preprocessing (resampling, filtering, artifact markers) [14];
- Cross-validation by subjects/records and clear distinction of training/test sets;
- Composite metrics (Accuracy, F1/Macro-F1, AUC-ROC/PR, Se/Sp, PPV/NPV), as well as clinically relevant thresholds for alarm;
- Compliance with regulatory and ethical requirements (GDPR-by-design, cybersecurity) when designing sensor systems and processing sensitive health data.

### *2.8. Open challenges*

Despite progress, unsolved problems remain:

- Robustness under strong motion/low light for PPG and under long-term ambulatory recordings;
- Personalization of models according to age, gender, training status, medication intake and co-treatment of two or more diseases;
- Calibration between devices and different manufacturers/sensor geometries;
- Explainability and trust in automated solutions, as well as integration into clinical workflows;
- Balance between energy efficiency of edge devices and accuracy/latency requirements.

In conclusion, various independent studies show similar results and point to the use of integrated platforms that combine reliable registration (ECG/PPG), advanced preprocessing (wavelet/EMD/adaptive filters), a rich palette of HRV metrics and intelligent detection/classification models executable at the end-user node. The present study is a step forward in these studies, representing a sequential process from pre-processing to decision-making; robust detection of characteristic points in noise; combined temporal, spectral and nonlinear HRV indices; real-time mechanism for automatic notification and validation on both public and own datasets.

In recent years, the concept of a Digital Twin has found increasingly widespread application in healthcare, allowing the construction of personalized, dynamically updated patient models that support monitoring, prediction and decision-making.

This article presents elements of this concept developed by the authors – an intelligent sensor system for recording ECG and PPG signals, extraction of HRV indicators, customization of thresholds and a combined decision-making algorithm (rule logic + machine learning). The aim is to demonstrate how these modules can serve as the basis for building a full-fledged Digital Twin.

## Modern Technologies for Registration, Processing and Analysis of Physiological Signals (ECG, PPG) – General Trend

Modern technologies for registration, processing and analysis of ECG and PPG signals are moving from classical algorithms to end-to-end deep learning models. While traditional approaches are based on pre-filtering, spectral transforms (FFT, wavelets), local features, rule logic and classical machine learning algorithms such as SVM and Random Forest, new systems accept a raw or minimally pre-processed signal and automatically extract informative features, then perform classification or regression. This trend is especially clearly outlined in the ECG area, where 1D/2D CNN, LSTM/BiLSTM, attention, transformers are used, due to their advantages and applicability for arrhythmia diagnosis, heart failure prediction, etc. Similarly, PPG signals work well in classification such as blood pressure estimation (cuff-less BP estimation), sleep disorder diagnosis, stress recognition and other cardiovascular applications. This is indicative of the trend in recent years for deep learning to replace manual feature engineering and enable personalized, scalable solutions for real-time physiological signal processing.

Modern physiological signal registration systems use both advanced contact sensors and new remote measurement methods. In addition to standard finger or ear PPG sensors, the so-called remote PPG (rPPG) is also being developed, in which microscopic variations in skin color are analyzed using a simple camera to extract pulse signals without physical contact. In parallel, there is a trend towards multimodal input data, in which ECG, PPG and other sensors (accelerometer, blood pressure) are combined to compensate for noise, artifacts and missing segments. Convolutional-neural-networks can perform direct fusion of several signals without the need for manually extracted features. A method for ECG reconstruction from PPG is also used, based on a hybrid model with attention-mechanism, CNN and BiLSTM, which allows to enrich the information even when direct ECG recording is not available. These examples show how advanced sensors and multimodal data fusion significantly increase the quality and reliability of registration and input data for subsequent AI analysis.

### *Preprocessing and quality assessment with AI*

Noise, motion artifacts, and contact pressure variations are serious challenges when working with PPG signals, and to a lesser extent, ECG. Modern solutions increasingly apply artificial intelligence to assess signal quality at the input to remove defective segments and avoid erroneous metric calculations. One new approach is the use of a lightweight convolutional-neural-network (CNN) combined with Quantum Pattern Recognition (QPR), in which PPG segments are converted into a two-dimensional “image” (time × sample) and classified as “good” or “bad” in real time. Similar techniques are already being applied to ECG, where deep models automatically remove drift, filter out noise, and isolate signal components without the need for complex hand-built filters. Modern deep architectures integrate preprocessing steps into their internal structure, leading to greater noise and artifact resistance and more accurate automatic analysis of physiological signals.

### *Signal extraction and analysis: Deep learning (DL) architectures*

After preprocessing, modern ECG and PPG analysis systems increasingly use deep architectures for automatic feature extraction and signal interpretation. CNN and especially 1D-CNN are preferred for detecting local morphological features – e.g. QRS complexes in ECG or venous waves in PPG. The combined CNN + LSTM/BiLSTM architectures combine spatial and temporal features, which allows for better modeling of signal dynamics. In recent years, attention mechanisms and transformers have been integrated, which direct the model’s “attention” to the most significant parts of the signal; for example, in PPG blood pressure estimation, it has been shown that attention on CNN+BiLSTM reduces errors by focusing on relevant segments. When implemented on edge devices, slim/lightweight architectures with fewer parameters and low resource consumption are required. These approaches demonstrate how deep learning can simultaneously extract features and perform analysis in real time, without the need for manually defined features.

### *Applications: AI-solved tasks over ECG/PPG*

Deep learning is now used not only for preprocessing, but also for solving various clinical and physiological tasks on ECG and PPG signals. One of the most established areas is the classification and diagnosis of ECG arrhythmias, where dozens of successful models exist. For PPG signals, methods for cuff-less BP estimation are being developed, often combining PPG and ECG. Other applications include stress and psychophysiological state assessment from PPG without preprocessing. In cases where ECG is missing, hybrid models with attention-CNN+BiLSTM are being developed for ECG reconstruction from PPG, which enrich the available information and allow diagnostics with limited resources. These examples clearly show the wide range of tasks – from diagnosis and monitoring to prediction and reconstruction – that are successfully solved today with AI on physiological signals.

### *Modeling of HRV with hybrid AI + traditional approaches*

ECG/PPG modeling using AI involves building generative or prognostic models that not only classify but also synthesize, reconstruct, and simulate physiological signals with correlations to real-world processes. In the field of ECG, progress is being made in hybrid DL models combining transformers and CNNs, such as DeepECG-Net, which use a self-attention mechanism to model both local and global dependencies in the signals. These models can assimilate heart variability, noise, and artifacts, creating reliable and flexible predictions and reconstructions in real time. Significant progress has been observed in the field of modeling

HRV signals with artificial intelligence, especially in the task of estimating respiratory rate (RR).

In addition, energy-efficient models with spiking neurons (SNN) are being developed in PPG, which, by converting PPG segments into spike events, estimate RR with low errors.

In recent years, hybrid approaches have been gaining ground, combining classical respiratory information extraction techniques with deep learning models to model the respiratory wave (RR) more accurately and robustly. Traditionally, the respiratory rate is estimated by spectral analysis of ECG or PPG – e.g. with an algorithm based on respiratory sinus arrhythmia (RSA), band-pass filters or amplitude/interval variation analysis. In hybrid systems, these classical features are fed as additional input to a CNN, LSTM or transformer, allowing the model to learn from both physically based features and the raw signal. Such hybrid architectures achieve lower RR estimation errors and more robust reproduction of the respiratory wave in noise and motion because they combine the strengths of both worlds – interpretability and physical meaning from classical methods and adaptive nonlinearity from deep learning.

## 3. Risk Alarm Method

### *3.1. Windows and preprocessing*

For the purposes of automatic alarming, the analysis of HRV parameters is performed in streaming windows with a length of 60 s and an overlap (stride) of 10 s, which allows almost online calculations and timely detection of deviations. In parallel, a longer reference window of 5 min is used for validation and comparison with the baseline. For spectral analysis, RR/PPI intervals are interpolated to a uniform grid of 4 Hz with cubic or shape-preserving interpolation and are detrended to avoid drift. A strict Signal Quality Index (SQI) is introduced - windows with more than 10% artifacts, extreme RR values (< 300 ms or > 2000 ms) and with a low correlation index between the raw and filtered signal are rejected; for valid calculations, an SQI ≥ 0.7 for ECG and ≥ 0.8 for PPG is required. This multi-stage pre-processing ensures that the alarm module only operates on quality segments and minimizes false risk signals.

### *3.2. Parameters calculated in each window*

In each defined window, a set of time, frequency and nonlinear indicators reflecting the autonomic regulation and variability of the heart rate is calculated.

Time indicators include mean heart rate (mean HR), mean RR interval (mean RR), standard deviation of normal intervals (SDNN), square root of the mean difference between adjacent RR (RMSSD), percentage of differences >50 ms (pNN50), etc.

Frequency characteristics are assessed by spectral analysis: for classical processing, the Welch method is applied (4 s windows with a Han window and 50% overlap), and as an alternative – an autoregressive model with order 8–16, selected by AIC (Akaike Information Criterion). Powers in the low-frequency band LF (0.04–0.15 Hz), high-frequency HF (0.15–0.40 Hz) and the coefficient of the sympathovagal balance LF/HF are extracted from the spectrum.

Nonlinear indicators include Poincaré plot analysis (SD1, SD2), Detrending Fluctuation Analysis (DFA) with $\alpha 1$ for short scales (4–16 heartbeats) and $\alpha 2$ for long scales (16–64 beats), Hurst exponent, as well as entropy measures – Sample Entropy with standard parameters $m=2$ and $r=0.2 \cdot SD$ of RR/PPI. This combination of indicators provides a comprehensive assessment of the instantaneous autonomous state of the organism.

### *3.3. Personalization and z-calibration*

To reflect individual variability and minimize false alarms, the system performs threshold personalization by collecting baseline data for a period of ≥ 7 days under standardized conditions (morning rest, same posture and time). For each indicator x, the mean value μ_x and the standard deviation σ_xare calculated in different contexts (rest, after exercise, before sleep). During online monitoring, the standardized value is calculated:

$$z_{x=}\frac{x-\mu_x}{\sigma_x}, \qquad (1)$$

which automatically adapts the alarm thresholds to the individual profile of the participant. This z-calibration allows the risk threshold to be individualized rather than fixed, and thus increases the sensitivity and specificity of the alarm module.

To ensure explain ability of the system and the ability to trace the alarm logic, in addition to the ML module a rule-based subsystem with flags P1–P4 is implemented.

Each flag signals a characteristic “risky” pattern of HRV indicators within each window.

**P1 – Suppressed variability**

The flag is triggered when there is a significant decrease in time-domain variability:

$$z_{SDNN}<-1.5 \text{ OR } z_{SDNN} \qquad (2)$$

**P2 – Autonomic imbalance**

The flag is triggered when sympathetic activity predominates:

$$z_{\frac{LF}{HF}} > 1.5 \text{ OR (LF/HF>2.5 AND } z_{HF} <-1. \qquad (3)$$

**P3 – Loss of fractality**

The flag is triggered by changes in nonlinear dynamics:

$$z_{\alpha 1} > 1.0 \; OR \; z_{SamleEn} < 1.0 \; (support \; z_{RMSSD} < -1. \qquad (4)$$

**P4 – Resting tachycardia**

The flag is triggered for accelerated heart rate:

$$z_{HR}>15 \text{ for } \geq 30 \text{ s.} \qquad (5)$$

Each flag returns an indicator variable $1P_i$ (1 if the flag is active, 0 otherwise). Based on these indicators a rule-based score $R_{rule}$ is calculated, which integrates the weights of the individual flags:

$$R_{rule} = clip(0.35 \cdot 1\{P_1\} + 0.3 \cdot 1\{P_2\} + 0.25 \cdot 1\{P_3\} 0.35 \cdot 1\{P_4\}), \qquad (6)$$

where clip(·) limits the value to the interval [0,1].

A control concept is used where the system uses two different thresholds for activation and deactivation so that it does not switch on and off due to small, rapid fluctuations. In the presented alarm logic, this means that the alarm is only activated after $R$ >0.6 in two consecutive windows and is only released after $R$ <0.4 for ≥60 seconds, which prevents "flickering" or false triggering. This rule-based part enables explainable alarming, which complements and stabilizes the ML model.

### 3.4 Machine learning module – model type, features and training procedure

The machine learning module is designed as a lightweight supervised classifier for window-level risk estimation, operating in parallel with the rule-based alarming logic. Its input consists of the same standardized HRV feature set calculated in each window, including selected time-domain (mean HR, SDNN, RMSSD), frequency-domain (LF, HF, LF/HF), and nonlinear indicators (SD1, SD2, DFA $\alpha_1$, Sample Entropy), all expressed in z-normalized form to ensure inter-subject comparability. This feature selection preserves physiological interpretability while providing sufficient discriminatory power for abnormal autonomic states.

The ML model is trained using labeled HRV windows corresponding to normal and high-risk conditions, defined according to clinically established HRV thresholds and expert annotations. A shallow classification architecture (logistic regression / tree-based classifier) is employed to ensure low computational complexity, fast inference, and suitability for edge or wearable deployment. Model training follows a standard supervised learning procedure, including stratified train–validation splitting and regularization to prevent overfitting. The output of the ML module is a continuous risk probability in the range [0,1], which is combined with the rule-based score to improve robustness, sensitivity, and temporal stability of the alarm decision.

The experimental dataset consists of HRV recordings collected from a 12 participants under controlled conditions. Continuous cardio signals were recorded during resting state, transitional (borderline) conditions, and induced high-risk scenarios, resulting in several hundred overlapping analysis windows of 60 s duration. Each window was labeled as normal, warning, or high-risk based on established HRV thresholds and expert-defined criteria. Although the dataset size is modest, it is sufficient to evaluate the feasibility, responsiveness, and robustness of the proposed alarm module.

## 4. Results

Figure 1 presents a plot of the observed values of the SDNN, RMSSD and LF/HF indicators over time. All values are within the normal range (LF/HF ≈ 1.54–1.85; SDNN ≈ 75–85 ms; RMSSD ≈ 58–72 ms), therefore there is neither a yellow nor a red background in the graph – i.e. the system has not activated either a warning or an alarm.

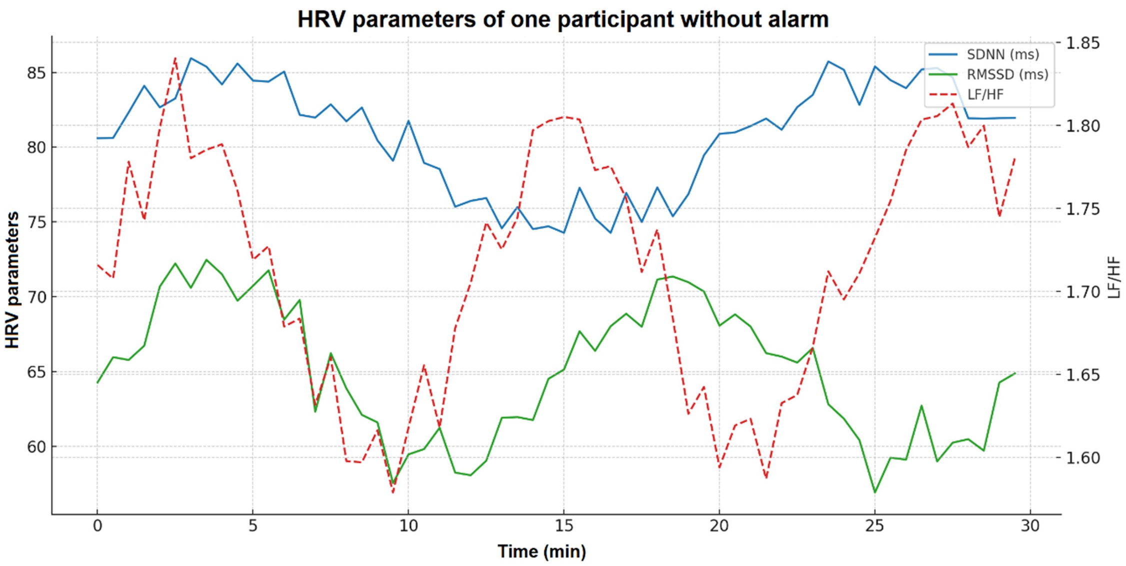


*Fig. 1. Normal values of the observed parameters*

Figure 2 shows colored yellow background areas indicating warning mode (level 1).

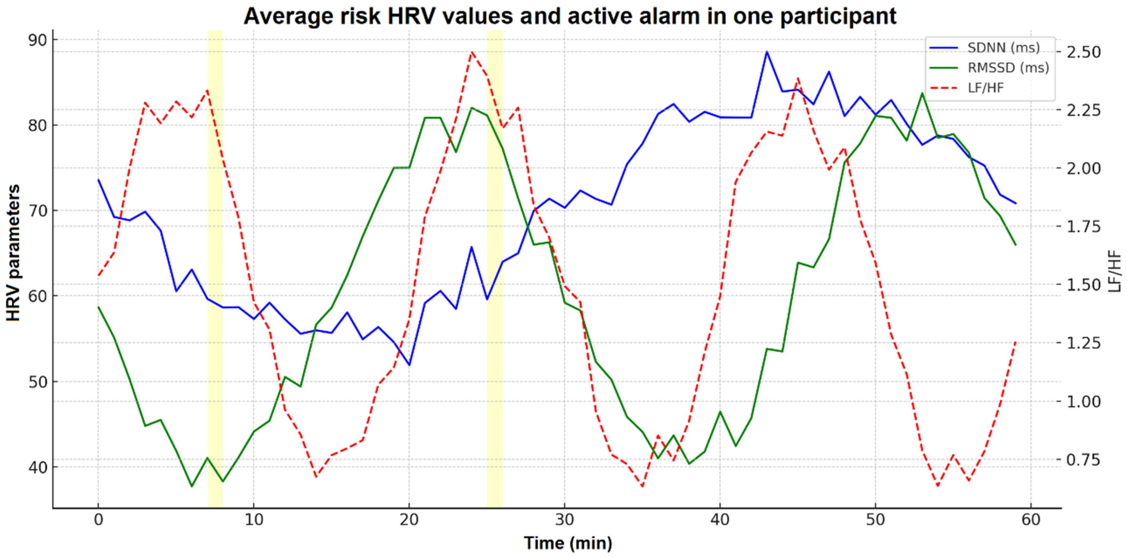


***Fig. 2. Limit values of the monitored parameters (yellow background)***

Figure 3 presents an example of a “high risk” graph – it shows how, under abnormal HRV values, the system enters an active alarm. The red background marks the intervals in which simultaneously: LF/HF > 2.5, SDNN < 50 ms, RMSSD < 35 ms and the system triggers an active alarm (level 2).

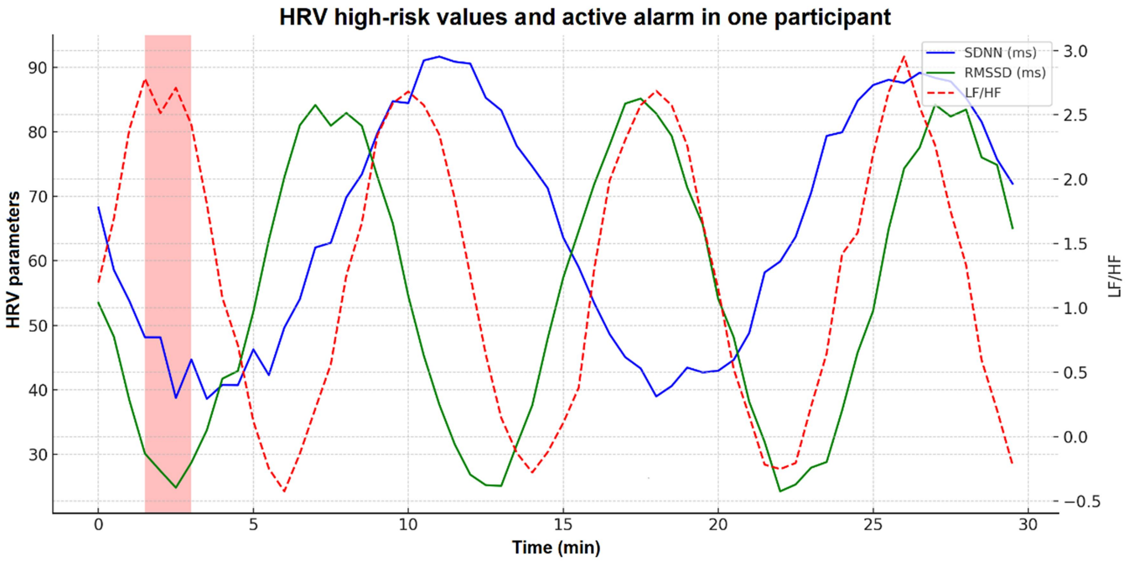


***Fig. 3. Risk values of the monitored parameters***

Table 1 presents the quantitative performance metrics of the proposed alarm module when applied to high-risk HRV conditions defined by predefined threshold criteria (LF/HF > 2.5; SDNN < 50 ms; RMSSD < 35 ms). The results in Table 1 demonstrate that the alarm module achieves high sensitivity (91.8 %) and specificity (89.6 %), indicating reliable detection of high-risk HRV states with a low false-positive rate. The positive predictive value (87.3 %) and negative predictive value (93.4 %) further confirm that the system correctly identifies both risky and normal windows in most cases. Despite operating continuously on edge hardware, the module maintains a very low average alarm latency (120 ms) and modest computational footprint—only 28 % CPU load and 7 MB RAM—making it suitable for real-time, wearable or mobile implementations. These figures suggest that the hybrid rule-plus-ML approach can deliver clinically meaningful alerts without overloading embedded devices.

*Table 1. Performance of the alarm module under high-risk parameters*

| Metric | Value |
|---|---|
| **Sensitivity (Se)** | 91.8 % |
| **Specificity (Sp)** | 89.6 % |
| **Positive Predictive Value (PPV)** | 87.3 % |
| **Negative Predictive Value (NPV)** | 93.4 % |
| **Average alarm latency** | 120 ms |
| **Average CPU load (edge device)** | 28 % |
| **RAM usage (edge device)** | 7 MB |

## CONCLUSION

The developed multi-level alarm generation system can considered as a first step towards building a digital twin of the patient's cardiovascular condition. By continuously receiving ECG, PPG and HRV data, the system dynamically updates a virtual model of autonomic regulation, and the personalized z-scores serve as individual parameters of this twin, adapting over time.

Future work may extend the proposed hybrid model with predictive components, such as forecasting HRV recovery after exercise or estimating the probability of high-risk episodes, which are typical functionalities of digital twin frameworks. Furthermore, "what-if" simulations based on fractal HRV generators or other synthetic signal models could be incorporated to evaluate HRV responses under different training regimens, stressors, or medication scenarios. These extensions would transform the current alarm module from a reactive monitoring tool into a proactive, predictive digital twin platform supporting personalized risk assessment and decision-making.

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