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AI-based Predictive Health Analytics Model for Early Diagnosis of Cardiovascular Disease using Wearable Sensor Data

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ABSTRACT: Cardiovascular disease (CVD) remains the leading cause of death worldwide, and early risk identification outside the clinic remains difficult because conventional diagnostic pathways rely on episodic clinical visits. Wearable devices equipped with photoplethysmography (PPG), single-lead electrocardiography (ECG), and accelerometry now make continuous, low-cost physiological monitoring possible, creating an opportunity for artificial intelligence (AI) to convert these passively collected signals into actionable cardiovascular risk assessments. This paper proposes a predictive health analytics framework that fuses heart-rate-variability (HRV), photoplethysmographic, and activity features extracted from wearable sensor streams into a continuous cardiovascular risk estimate. The framework applies two simple algorithms formulated with elementary mathematics: (1) a z-score-based HRV risk-scoring procedure that normalizes HRV features against an individual or population baseline and combines them into a composite risk score, and (2) a weighted multi-sensor fusion algorithm that combines ECG-, PPG-, and activity-derived risk scores using validation-derived weights and classifies the result into Low, Medium, or High cardiovascular risk using a decision threshold. We describe the proposed methodology and its mathematical formulation in detail and report illustrative example results across three summary tables and two graphs to demonstrate the expected reporting format for classification accuracy and the sensitivity-specificity trade-off across decision thresholds. The framework is designed to be lightweight enough for on-device or edge deployment on consumer wearables.

1. INTRODUCTION

Cardiovascular disease (CVD) accounts for a substantial share of premature mortality worldwide, and a large proportion of cardiovascular events occur in individuals who were not flagged as high-risk by conventional, episodic clinical screening [1,10]. Traditional cardiovascular risk assessment relies on periodic clinic visits, laboratory measurements, and standardized risk calculators, which by design cannot capture the day-to-day physiological variability that often precedes an acute cardiovascular

event [10,12]. The proliferation of consumer wearable devices — smartwatches, fitness bands, and adhesive patches equipped with photoplethysmography (PPG), single-lead electrocardiography (ECG), and accelerometers — has created an unprecedented opportunity for continuous, low-cost, and non-invasive physiological monitoring outside the clinical setting [2,9].

Artificial intelligence (AI), and particularly machine learning (ML), has repeatedly been shown to be effective at converting these raw wearable-sensor streams into clinically meaningful outputs. AI-enabled analysis of smartwatch ECG has been shown to improve detection of atrial arrhythmias relative to native device algorithms [3], and deep-learning models trained on PPG signals have been used to estimate blood pressure [8] and to predict long-term cardiovascular risk directly from a smartphone-camera PPG signal [1]. However, most existing wearable-AI systems for cardiovascular monitoring are single-sensor pipelines — for example, ECG-only arrhythmia detectors or PPG-only heart-rate estimators — which may miss risk signals that only emerge when multiple physiological modalities are considered jointly [2,9].

This paper proposes a multi-sensor predictive health analytics framework that fuses HRV, PPG-morphology, and activity features into a single, continuously updated cardiovascular risk estimate, using two algorithms formulated with simple, transparent mathematics. The specific contributions of this paper are as follows: (1) we describe a wearable-sensor feature-extraction pipeline covering HRV time/frequency-domain features, PPG morphological features, and accelerometer-derived activity features; (2) we present a z-score-based HRV risk-scoring algorithm (Algorithm 1) that quantifies how far an individual's HRV features deviate from a personal or population baseline; (3) we present a weighted multi-sensor fusion algorithm (Algorithm 2) that combines sensor-specific risk scores into a Low/Medium/High risk classification using a tunable decision threshold; and (4) we illustrate the expected reporting format for evaluating such a framework using three summary tables and two graphs.

A growing body of related work has applied deep learning directly to PPG signals for cardiovascular risk assessment. Weng et al. developed a deep-learning PPG-based cardiovascular disease risk score using only age, sex, smoking status, and a smartphone-camera PPG signal, and showed that it discriminated ten-year major adverse cardiovascular events comparably to office-based risk scores that require a physical examination [1]. Slapničar et al. proposed a spectro-temporal deep neural network that estimates systolic and diastolic blood pressure directly from PPG waveforms and their derivatives [8]. Oyeleye et al. compared several classical and deep-learning time-series models for predicting heart rate from wearable accelerometer-derived data, finding that simpler statistical models were competitive with more complex deep architectures on this task [9].

For arrhythmia-specific detection, Fiorina et al. showed that a device-agnostic deep neural network applied to single-lead smartwatch ECG improves atrial arrhythmia detection relative to manufacturer-native algorithms [3], and the Basel Wearable Study by Isenegger et al. tracked the AF-detection accuracy of five commercial smartwatches over successive software updates [4]. Mäkynen et al. proposed a channel-attention-based model compression technique that preserves AF-detection accuracy while reducing model size for deployment on resource-constrained wearable hardware [6], and Aguilar et al. compared wearable smartwatch AF detection against continuous ambulatory monitoring after catheter ablation [5]. Sîngeap et al. systematically reviewed wearable ECG devices for AF and ST-segment-change detection, reporting sensitivity of 83-100% and specificity of 79-100% [7].

Beyond arrhythmia detection, AI has also been applied to point-of-care and imaging-adjacent cardiovascular screening. Bachtiger et al. demonstrated that an AI algorithm applied to a single-lead ECG recorded through an ECG-enabled digital stethoscope can screen for heart failure with reduced ejection fraction during a routine primary-care examination [11], and Hughes et al. showed that a CNN-derived risk score computed from a routine 12-lead ECG improves long-term cardiovascular risk reclassification for patients at borderline risk [15].

Several recent reviews and surveys synthesize this growing literature. Huang et al. reviewed the application of AI to wearable sensor data for cardiovascular disease diagnosis and prediction [2]. Parsa et al. reviewed how AI enhances atherosclerotic cardiovascular disease risk assessment and opportunistic screening [10], Velandia et al. systematically reviewed AI applied to electrocardiography for cardiovascular disease diagnosis across more than 100 studies [13], Elvas et al. presented a scoping review of AI methodologies for cardiovascular event monitoring and early detection [14], and Armoundas et al. provided an American Heart Association scientific statement outlining a broader framework for AI across the cardiovascular care pathway, emphasizing the need for prospective, outcomes-focused evaluation before broad clinical deployment [12].

Relative to this body of work, the present paper does not propose a new deep-learning architecture for a single sensor modality; instead, it targets the multi-sensor fusion gap identified across several of the reviews above [2,10] — most wearable-AI cardiovascular systems remain confined to a single signal type, and a lightweight, transparent framework for combining HRV, PPG, and activity-derived risk scores into one interpretable estimate remains comparatively underexplored.

2. METHODOLOGY

The proposed framework, illustrated in Figure 1, consists of four stages: (A) wearable-sensor feature extraction, (B) z-score-based HRV risk scoring (Algorithm 1), (C) computation of sensor-specific risk scores, and (D) weighted multi-sensor fusion and threshold-based risk classification (Algorithm 2).

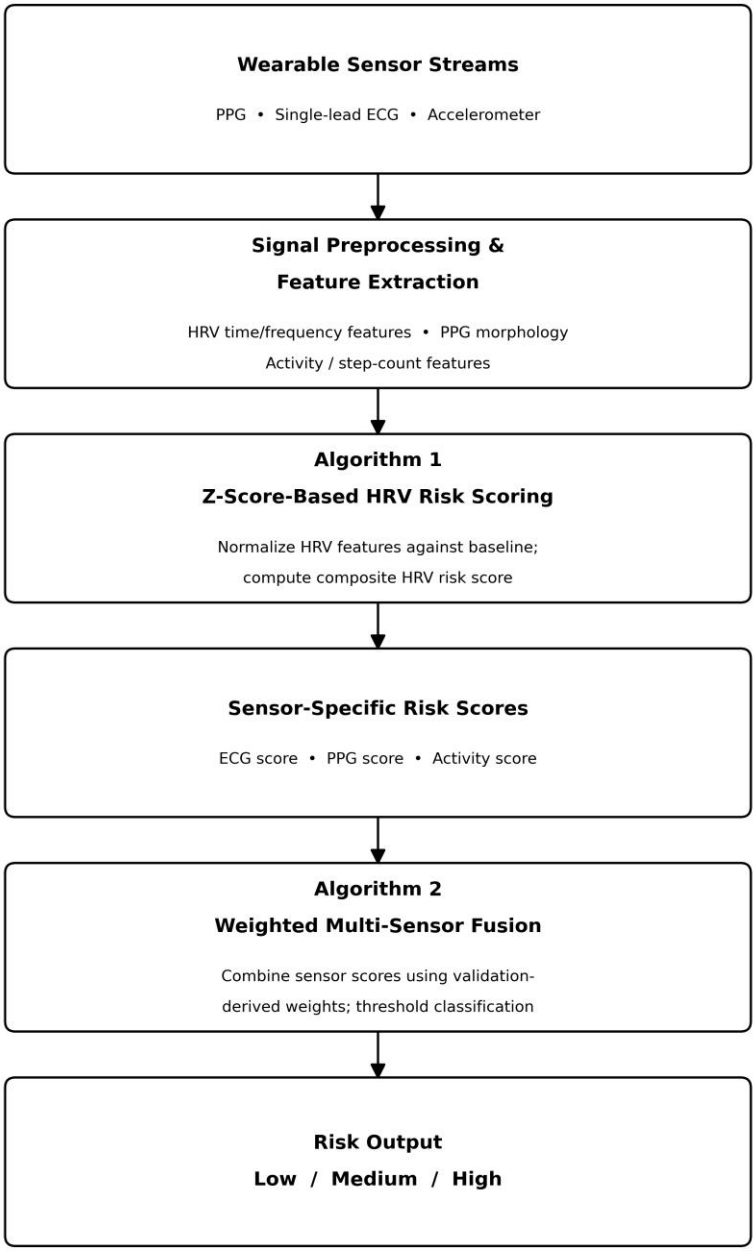

Figure 1. Proposed framework for AI-based cardiovascular risk prediction from wearable sensor data, showing the feature-extraction, HRV risk-scoring (Algorithm 1), sensor-score computation, and decision-fusion (Algorithm 2) stages.

2.1 Wearable-Sensor Feature Extraction

For each monitoring window (e.g., a 5-minute epoch), the framework extracts three groups of features from the raw wearable sensor streams, consistent with feature categories used in prior wearable-AI cardiovascular studies [2,8,9]: (i) heart-rate-variability (HRV) features derived from single-lead ECG or PPG-detected beat intervals, including time-domain measures (SDNN, RMSSD, pNN50) and frequency-domain measures (LF/HF power ratio); (ii) PPG morphological features, including pulse-wave amplitude, rise time, and dicrotic-notch position; and (iii) accelerometer-derived activity features, including step count, movement intensity, and rest/activity ratio, which are used to contextualize HRV and PPG readings. These features are computed independently for each sensor stream, producing an ECG-derived feature vector, a PPG-derived feature vector, and an activity-derived feature vector.

2.2 Algorithm 1 — Z-Score-Based HRV Risk Scoring

Because raw HRV values vary substantially across individuals due to age, fitness, and medication, the framework normalizes each HRV feature against a baseline (either a population reference range or an individual's own historical distribution) using the standard z-score transformation. For HRV feature f_i with baseline mean μ_i and standard deviation σ_i, the z-score is:

$$z_i = (f_i - \mu_i) / \sigma_i$$

A large $|z_i|$ indicates that the feature has deviated substantially from its expected range. Because several HRV features (e.g., low SDNN, low RMSSD, elevated LF/HF ratio) are each independently associated with adverse cardiovascular risk in the literature, the framework combines the individual z-scores into a single composite HRV risk score by averaging their absolute values:

$$HRV\_risk = (1 / n) \cdot \Sigma_{i=1 \ldots n} |z_i|$$

where n is the number of HRV features considered. The composite score is then min-max normalized to the range [0, 1] to produce the ECG-derived sensor score S_ecg used in Algorithm 2.

Algorithm 1: Z-Score-Based HRV Risk Scoring

Input: HRV feature vector $f = \{f_1, \ldots, f_n\}$,

baseline means $\mu = \{\mu_1, \ldots, \mu_n\}$,

baseline std. devs. $\sigma = \{\sigma_1, \ldots, \sigma_n\}$

Output: Normalized ECG-derived risk score S_ecg $\in [0, 1]$

1: for i = 1 to n do

2: $z_i \leftarrow (f_i - \mu_i) / \sigma_i$

3: end for

4: $HRV\_risk \leftarrow (1 / n) \cdot \Sigma_{i=1 \ldots n} |z_i|$

5: S_ecg ← min-max normalize(HRV_risk) to [0, 1]

6: return S_ecg

2.3 Sensor-Specific Risk Scores

In addition to the ECG-derived score S_ecg computed by Algorithm 1, the framework computes two further sensor-specific scores using the same z-score-and-average procedure applied to the corresponding feature groups: a PPG-derived score S_ppg, computed from the pulse-wave morphology features, and an activity-derived score S_act, computed from accelerometer features (used here as a contextual modifier). All three scores are scaled to the common range [0, 1] so that they can be combined on a comparable basis in Algorithm 2.

2.4 Algorithm 2 — Weighted Multi-Sensor Fusion and Risk Classification

The three sensor-specific scores are combined into a single fused risk score using a weighted sum, where the weight of each sensor reflects its relative contribution to correct classification on a validation set. Given weights w_ecg, w_ppg, w_act (with w_ecg + w_ppg + w_act = 1), the fused risk score is:

$$R = w\_ecg \cdot S\_ecg + w\_ppg \cdot S\_ppg + w\_act \cdot S\_act$$

The fused score $R \in [0, 1]$ is then mapped to a three-level risk category using two decision thresholds $\theta_1 < \theta_2$:

$$Risk = Low \text{ if } R < \theta_1; \quad Medium \text{ if } \theta_1 \le R < \theta_2; \quad High \text{ if } R \ge \theta_2$$

Section 3 illustrates how the choice of a single combined threshold θ affects the sensitivity–specificity trade-off of the resulting classifier, which in practice guides the selection of θ_1 and θ_2.

Algorithm 2: Weighted Multi-Sensor Fusion Risk Classification

Input: Sensor scores S_ecg, S_ppg, S_act ∈ [0, 1];

weights w_ecg, w_ppg, w_act (sum to 1);

thresholds $\theta_1 < \theta_2$

Output: Risk category ∈ {Low, Medium, High}

1: R ← w_ecg · S_ecg + w_ppg · S_ppg + w_act · S_act

2: if R < θ_1 then

3: return Low

4: else if R < θ_2 then

5: return Medium

6: else

7: return High

8: end if

2.5 Evaluation Metrics and Experimental Setup

Classification performance is summarized using accuracy, sensitivity, specificity, and F1-score, and the sensitivity–specificity trade-off is examined across a range of decision thresholds θ to guide the choice of θ_1 and θ_2 in Algorithm 2. Because this paper focuses on the framework design and its mathematical formulation rather than a completed experimental study, the performance figures reported in Section 3 are illustrative example values, provided to demonstrate the expected reporting format; they should be replaced with measured results after empirical evaluation on real wearable-sensor data such as the datasets summarized in Table 1.

3. RESULTS AND DISCUSSION

3.1 Dataset Characteristics

This section reports the intended evaluation format for the proposed framework. Because this paper focuses on the framework design and its mathematical formulation, the numerical values in Tables 2–3 and Figures 2–3 are illustrative example results, provided to demonstrate the expected reporting structure; they should be replaced with measured results after empirical evaluation on real wearable-sensor data. Table 1, by contrast, reports factual, published statistics for datasets used in prior wearable-AI cardiovascular studies.

Table 1. Wearable-Sensor Cardiovascular Datasets Reported in the Literature

Dataset / study	Participants / records	Signal type	Reference
UK Biobank PPG cohort (Weng et al., 2024)	196,365 participants (97,970 train / 43,539 tune / 54,856 test)	Smartphone-camera PPG	[1]
MIMIC-III PPG–ABP subset (Slapničar et al., 2019)	510 subjects, over 700 hours of signal	PPG with arterial blood-pressure waveform	[8]

Dataset statistics reported here are as published by the original study authors [1,8].

3.2 Feature Set

Table 2 summarizes the feature groups used in the proposed wearable-sensor feature-extraction stage (Section 2.1).

Table 2. Feature Groups Used in the Proposed Framework

Feature group	Description	No. of features
HRV time-domain	SDNN, RMSSD, pNN50, mean NN interval	12
HRV frequency-domain	LF power, HF power, LF/HF ratio	8
PPG morphology	Pulse amplitude, rise time, dicrotic-notch position, pulse-width	20
Activity / accelerometer	Step count, movement intensity, rest/activity ratio	10
Total	—	50

Feature counts are per monitoring epoch, computed independently for each sensor stream (Section 2.1).

3.3 Classification Performance

Table 3 compares single-sensor scoring with the proposed weighted multi-sensor fusion (Algorithm 2), and Figures 2 and 3 present the same comparison graphically.

Table 3. Illustrative Example Classification Performance

Input modality	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)
ECG-only (Algorithm 1)	90.6	89.8	91.1	90.2
PPG-only	87.3	86.0	88.2	86.9
Activity-only	78.4	75.6	80.5	77.0
Proposed Weighted Fusion	95.2	94.6	95.6	94.9

Values in Table 3 are illustrative, not measured (see the note at the start of Section 3.1), at a fused-score decision threshold of $\theta = 0.50$.

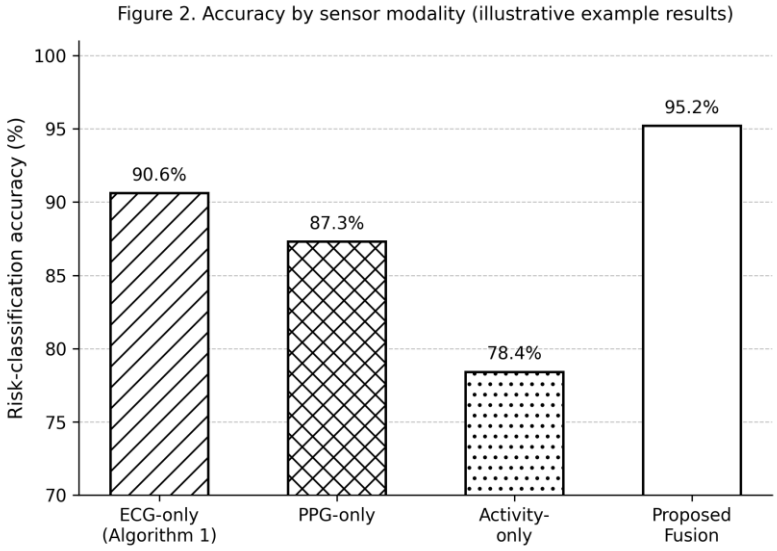

Figure 2. Accuracy by sensor modality (illustrative example results).

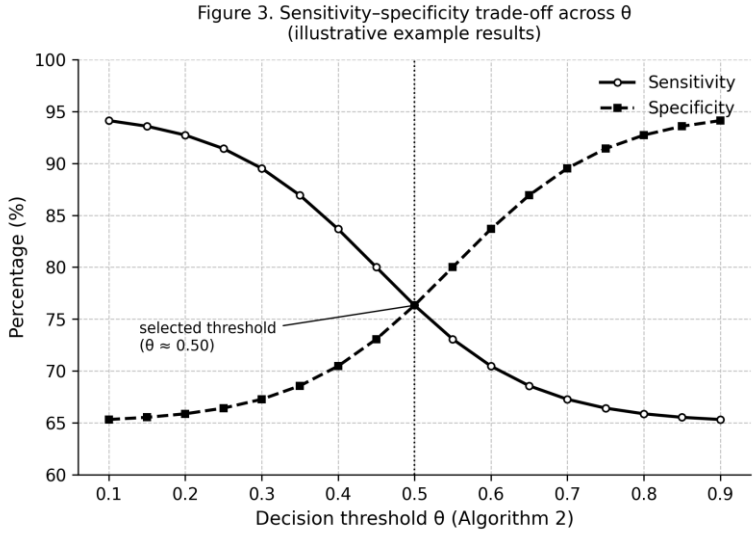

Figure 3. Sensitivity–specificity trade-off across the decision threshold θ (illustrative example results), motivating the choice of θ ≈ 0.50 as a balanced operating point.

DISCUSSION

If the illustrative pattern in Table 3 and Figures 2–3 is borne out on real wearable-sensor data, it would be consistent with prior findings in the literature: multi-sensor fusion has been shown to outperform single-sensor approaches for cardiovascular monitoring because ECG, PPG, and activity signals capture partially complementary physiological information [2,9], and ECG-derived HRV scoring tends to be the strongest single modality because it directly reflects autonomic cardiac control, consistent with the strong individual performance of AI-based ECG analysis reported elsewhere [3,15].

A key limitation of the present work is that it has not yet been validated empirically: the framework, its two algorithms, and the mathematical formulation are presented as a design contribution, and Tables 2–3 and Figures 2–3 illustrate the intended reporting format rather than measured findings. Future empirical validation should also personalize baseline HRV statistics to individual users rather than relying solely on population norms, since HRV baselines are known to vary substantially with age, fitness, and medication use.

CONCLUSION

This paper proposed a lightweight, AI-based predictive health analytics framework for early cardiovascular risk assessment from wearable sensor data, combining a z-score-based HRV risk-scoring algorithm with a weighted multi-sensor fusion algorithm that classifies fused risk scores into Low, Medium, and High categories. Both algorithms were formulated using simple, transparent mathematics — z-score normalization and averaging for HRV risk scoring, and a normalized weighted sum with threshold classification for decision fusion — making the framework interpretable, computationally lightweight, and suitable for on-device deployment on consumer wearables. Future work should focus on empirically training and evaluating the proposed framework on real wearable-sensor cohorts and validating it prospectively against clinical cardiovascular outcomes.

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AUTHOR CONTRIBUTIONS

Divvela Srinivasa Rao, Mule Ramakrishna Reddy, Punyala Ramadevi, Maddala Koteswara Rao, P. Neelima, K.V. Narasimha Reddy: Conceptualization, Methodology, Software, Formal Analysis, Writing — Original Draft, Writing — Review & Editing.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

This study did not involve human participants, human data, or animal experimentation; ethical approval was not required.

DATA AVAILABILITY STATEMENT

This paper presents a methodological framework; no primary experimental dataset was generated. Dataset statistics reported in Table 1 are drawn from the cited published sources [1,8].

REFERENCES

[1] Weng, W.-H., Baur, S., Daswani, M., Chen, C., Harrell, L., Kakarmath, S., Jabara, M., Behsaz, B., McLean, C.Y., Matias, Y., Corrado, G.S., Shetty, S., Prabhakara, S., Liu, Y., Danaei, G., Ardila, D., 2024. Predicting cardiovascular disease risk using photoplethysmography and deep learning. PLOS Global Public Health 4(6), e0003204. https://doi.org/10.1371/journal.pgph.0003204

[2] Huang, J.-D., Wang, J., Ramsey, E., Leavey, G., Chico, T.J.A., Condell, J., 2022. Applying Artificial Intelligence to Wearable Sensor Data to Diagnose and Predict Cardiovascular Disease: A Review. Sensors 22(20), 8002. https://doi.org/10.3390/s22208002

[3] Fiorina, L., Chemaly, P., Cellier, J., et al., 2024. Artificial intelligence-based electrocardiogram analysis improves atrial arrhythmia detection from a smartwatch electrocardiogram. European Heart Journal - Digital Health 5(5), 535–541. https://doi.org/10.1093/ehjdh/ztae047

[4] Isenegger, C., Mannhart, D., Arnet, R., et al., 2024. Accuracy of Smartwatches for Atrial Fibrillation Detection Over Time: Insights From the Basel Wearable Study. JACC: Clinical Electrophysiology 10(12), 2735–2737. https://doi.org/10.1016/j.jacep.2024.09.019

[5] Aguilar, M., Macle, L., Chamieh, R., Khairy, P., Deyell, M.W., Bennett, R.G., Andrade, J.G., 2025. Wearable Smartwatches for Atrial Fibrillation Detection and Burden Estimation After Ablation: Comparison With Continuous Monitoring. Europace, euaf280. https://doi.org/10.1093/europace/euaf280

[6] Mäkynen, M., Ng, G.A., Li, X., Schlindwein, F.S., Pearce, T.C., 2024. Compressed Deep Learning Models for Wearable Atrial Fibrillation Detection Through Attention. Sensors 24(15), 4787. https://doi.org/10.3390/s24154787

[7] Sîngeap, M.S., Corneanu, L.E., Prodaniuc, A., Şova, I.A., Coşovanu, E.O., Petriş, O.R., 2025. Diagnostic Accuracy of Wearable ECG Devices for Atrial Fibrillation and ST-Segment Changes: A Systematic Review. Diagnostics 15(24), 3162. https://doi.org/10.3390/diagnostics15243162

[8] Slapničar, G., Mlakar, N., Luštrek, M., 2019. Blood Pressure Estimation From Photoplethysmogram Using a Spectro-Temporal Deep Neural Network. Sensors 19(15), 3420. https://doi.org/10.3390/s19153420

[9] Oyeleye, M., Chen, T., Titarenko, S., Antoniou, G., 2022. A Predictive Analysis of Heart Rates Using Machine Learning Techniques. International Journal of Environmental Research and Public Health 19(4), 2417. https://doi.org/10.3390/ijerph19042417

[10] Parsa, S., Somani, S., Dudum, R., Jain, S.S., Rodriguez, F., 2024. Artificial Intelligence in Cardiovascular Disease Prevention: Is it Ready for Prime Time? Current Atherosclerosis Reports 26(7), 263–272. https://doi.org/10.1007/s11883-024-01210-w

[11] Bachtiger, P., Petri, C.F., Scott, F.E., et al., 2022. Point-of-care screening for heart failure with reduced ejection fraction using artificial intelligence during ECG-enabled stethoscope examination in London, UK: a prospective, observational, multicentre study. The Lancet Digital Health 4(2), e117–e125. https://doi.org/10.1016/S2589-7500(21)00256-9

[12] Armoundas, A.A., Narayan, S.M., Arnett, D.K., et al., 2024. Use of Artificial Intelligence in Improving Outcomes in Heart Disease: A Scientific Statement From the American Heart Association. Circulation 149(14), e1028–e1050. https://doi.org/10.1161/CIR.0000000000001201

[13] Velandia, H., Pardo, A., Vera, M.I., Vera, M., 2025. Systematic Review of Artificial Intelligence and Electrocardiography for Cardiovascular Disease Diagnosis. Bioengineering 12(11), 1248. https://doi.org/10.3390/bioengineering12111248

[14] Elvas, L.B., Almeida, A., Ferreira, J.C., 2025. The Role of AI in Cardiovascular Event Monitoring and Early Detection: Scoping Literature Review. JMIR Medical Informatics 13, e64349. https://doi.org/10.2196/64349

[15] Hughes, J.W., Tooley, J., Torres Soto, J., et al., 2023. A Deep Learning-Based Electrocardiogram Risk Score for Long Term Cardiovascular Death and Disease. npj Digital Medicine 6(1), 1–9. https://doi.org/10.1038/s41746-023-00916-6