QRS Width Detection on Electrocardiography: A Comprehensive Review and Implementation of Detection Algorithm

A. A. Alhindi, P. D'Avino, S. Ahmed, S. S. Kassa

Abstract—*The QRS complex in ECG signals is a key indicator of cardiac health, reflecting ventricular depolarization. This review provides an overview of QRS width detection on ECG, focusing on preprocessing, algorithm development, and key findings. It examines various studies using different ECG datasets and preprocessing techniques like signal filtering and noise reduction. The aim is to explore methodologies for detecting QRS width and its clinical significance across three phases: resting, running, and recovery. We explored the methodologies utilized for detecting QRS width and to find the mean QRS duration on a given data to calculate in the three phases (resting, running and recovery) on electrocardiograms (ECG) and use the result to determine the clinical significance. Emphasize the importance of accurate QRS width measurement in diagnosing various cardiac conditions.*

I. INTRODUCTION

Electrocardiography (ECG) is a simple, reliable, low-cost and non-invasive tool commonly used to diagnose cardiac disorders. The QRS complex has aroused particular interest due to its utility in identifying various cardiac issues including myocardial infarction, arrhythmias and conduction abnormalities. Particularly, accurate detection and measurement of QRS width are crucial for clinical diagnosis and treatment decisions and for this reason it has been extensively studied as a significant indicator of various cardiac conditions. [1] [2] [3]

Automated QRS detection and measurement algorithms can be integrated into clinical decision support systems to provide real-time analysis and monitoring of cardiac electrical activity, aiding clinicians in the early detection and management of cardiac conditions. The identification and analysis of QRS width on ECG signals have garnered significant attention in the field of cardiology and medical diagnostics: some studies have focused solely on QRS width as a marker of cardiac abnormalities, while others have integrated it with other physiological measures such as heart rate variability, blood pressure, and speech recognition. These studies collectively demonstrate the utility of QRS width as a reliable and valid metric for assessing cardiac function and identifying potential pathologies. [1][3][4]

The findings from these investigations underscore the significance of QRS width detection in clinical practice, highlighting its ability to provide valuable insights into an individual's cardiac health and potential risk factors. As such, understanding the advancements and challenges in QRS width detection on ECG signals is essential for enhancing diagnostic accuracy, guiding treatment decisions, and ultimately improving patient outcomes. [4][5][6]

II. METHODS

The review examines studies that have utilized various ECG datasets to develop and evaluate QRS width detection algorithms. Then a new algorithm for the identification and measurement of the QRS complex, based on the Pan-Tompkins method, is proposed.

A. search strategy

A systematic literature search was conducted across multiple databases, including PubMed, Ieeexplore, research gate and Plos one journal, to identify relevant studies published up to 2022. Search terms such as "QRS width detection," "ECG analysis," and "QRS complex" were utilized. Inclusion criteria encompassed studies investigating QRS width detection techniques, both experimental and clinical in nature, while irrelevant studies were excluded from consideration.

B. Inclusion and Exclusion Criteria

Following the initial search, duplicates were identified and removed. Abstracts and full-text articles were screened against predefined inclusion criteria. The reporting of this systematic review is done by following the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) flowchart.
General procedure of PRISMA flowchart followed in this study is given in Figure 1.

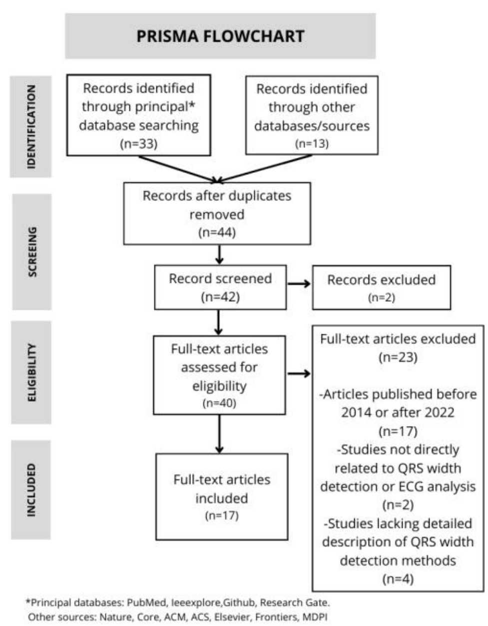

Figure 1. General PRISMA Flowchart followed in the study

Inclusion criteria

- ✓ Publications focusing on detection, identification and characterization of QRS width on ECG.
- ✓ Studies reporting methods for QRS width measurement, clinical trials utilizing QRS width as an outcome measure, and reviews discussing QRS width detection techniques.
- ✓ Articles published between 2014 and 2022 and articles published in English.

Exclusion criteria

- ✓ Studies not directly related to QRS width detection or ECG analysis.
- ✓ Articles not available in full-text or inaccessible through subscribed databases.
- ✓ Studies lacking detailed descriptions of QRS width detection methods.
- ✓ Articles published before 2014 and after 2022.

C. Data Synthesis

Synthesis of data from the studies has been done involving a comprehensive analysis of the different methods and algorithms employed for QRS width detection.

The most commonly used QRS detection algorithms in ECG analysis include:

1. **Pan-Tompkins Algorithm**: This algorithm, proposed by Pan and Tompkins in 1985, is based on first derivative and moving average techniques. It is widely used for QRS detection. The pre-processing step involves reducing the signal noise by submitting the data to a bandpass filter with cutoff frequencies of 0.5-40 Hz. The R-peaks are detected using the Pan-Tompkins algorithm, followed by a correction to improve the R-peaks detection. The onset and J-point detection are performed automatically based on the QRS complex morphology of each lead. The QRS duration is then calculated as the difference between the offset and onset in ms. [7][8]
2. **First-Derivative Based Algorithms**: Several algorithms are based on the first derivative of the ECG signal, such as the method proposed by Hamilton. These algorithms are commonly used for QRS detection and are known for their accuracy in analyzing heart rate variability. [9]
3. **Wavelet-Based Algorithms**: Wavelet-based methods have also been widely used for QRS detection. They involve the application of wavelet transform techniques to identify the QRS complex in the ECG signal. [10] [11]
4. **Neural Network-Based Algorithms**: Some QRS detection algorithms utilize neural network approaches for accurate detection of the QRS complex in ECG signals, have the ability to learn patterns in response to newly input patterns. Those learning and self-organizing abilities are appropriate for QRS-wave recognition. These methods have shown high efficiency and they are suitable for various ECG application cases.[12][13]
5. **Knowledge-Based Methods**: Knowledge-based algorithms, such as the optimized method evaluated on 11 standard ECG databases, have been developed for fast and accurate QRS detection. These methods leverage established criteria and algorithms to identify QRS complexes based on features such as amplitude, duration, and morphology. These methods are particularly suitable for real-time analysis and mobile applications.[14]

In our study the ultimate goal is to find an algorithm that determines the QRS width, we took the sport Database, which is a collection of 126 cardiorespiratory data acquired through wearable sensors from 81 subjects while practicing 10 different sports. The data was loaded and the main dataset and relevant variables were extracted, including the ECG signal, heart rate, breathing rate, and respiratory rate. The raw data ECG signal is illustrated in Figure 3. [16]

D. ECG Signal Processing

The processing of the data on Matlab starts with dividing the ECG signal into three distinct phases: an initial phase of resting, a middle phase of exercising, a final recovery phase. Each phase was defined by specific sample indices within the ECG signal. The sampling frequency for the ECG data was set at 250 Hz.

Signal Filtering: The Pan-Tompkins algorithm uses a Butterworth band pass filter (Figure 4) to be used in each phase to allow frequencies in the range of 5 Hz to 15 Hz to pass through while attenuating frequencies outside this range. This is particularly useful to remove low-frequency baseline wander and high-frequency noise, keeping only the frequencies of interest. This step improved the clarity of the ECG signal, as can be seen in Figure 5, making it easier the identification of QRS complexes.

The Pan-Tompkins algorithm is also used to the filtered ECG signal to detect the QRS complexes. The algorithm includes differentiation step, using that the derivative of the signal was taken (Figure 6), which enhance the identification of the Q, R, and S peaks in the ECG signal:

1. Detecting the R-peaks by finding the local maxima in the ECG signal that exceed a certain threshold. The threshold was set to 60% of the maximum peak value in the signal to ensure that only significant peaks were detected (Figure 7).
2. Finding Q and S Peaks:
   - The code utilizes the '**findpeaks**' function to detect all peaks in the processed ECG signal ('**ecg_d**').
   - Q-peaks were identified as the local maxima preceding the R-peak (Figure 8). These peaks represent the onset of ventricular depolarization.
   - S-peaks were identified as the local maxima following the R-peak (Figure 9). These peaks represent the end of ventricular depolarization.
   - The peaks were detected using specific thresholds to differentiate them from noise and other components of the ECG signal.
3. Peak Alignment:
   - The code then aligns the Q and S peaks relative to the R-peaks. Q-peaks are identified before R-peaks, while S-peaks are identified after R-peaks.
4. QRS Duration Calculation:
   - After identifying the Q and S peaks, the code performs additional processing, such as calculating

the QRS duration by measuring the time difference between the start of the Q-wave and the end of the S-wave. Then, in each phase the calculation of the width for each QRS complex is done by subtracting the Q start point from the S end point.

- This duration was then converted into milliseconds using the sampling frequency and an experimental factor. The final step is to determine the mean value of the QRS width in the three different phases and the standard deviation.

$$QRS_{\text{Width}} = \frac{(\text{S end} - \text{Q start})}{\text{K}*\text{Fs}} *1000$$

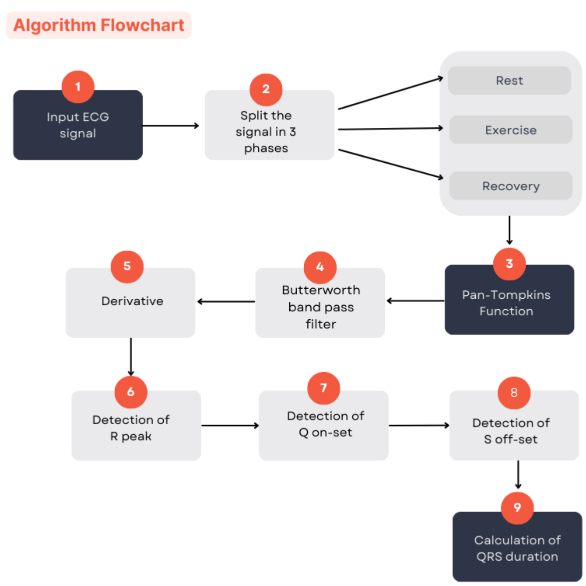

Figure 2. Flowchart of the algorithm used

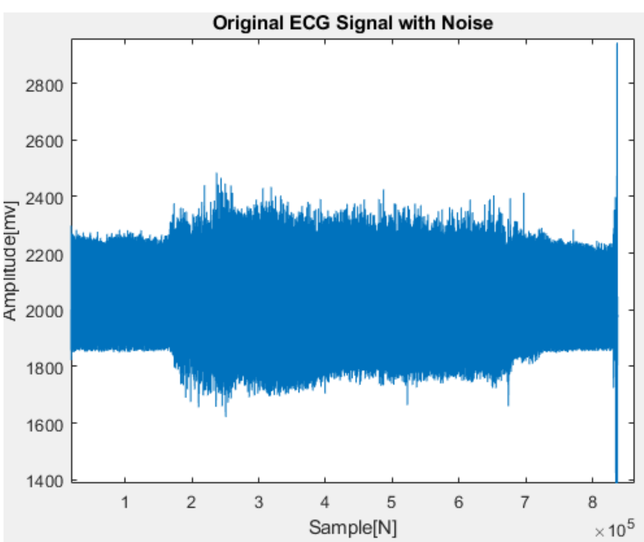

Figure 3. The three phases of the raw data ECG signal with noise

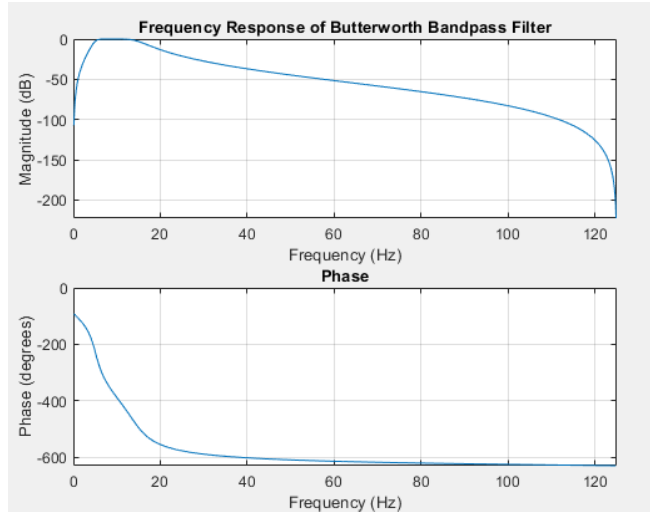

Figure 4. Butterworth bandpass filter

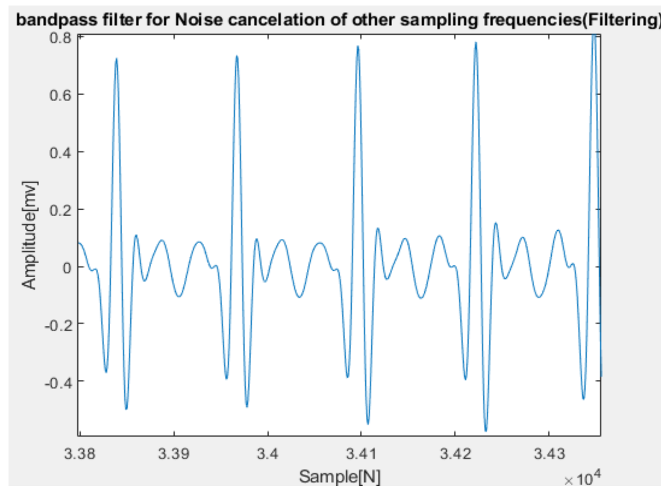

Figure 5. Filtered ECG signal using a Butterworth bandpass filter with a cutoff frequency of f1=5 Hz andf2=15Hz.

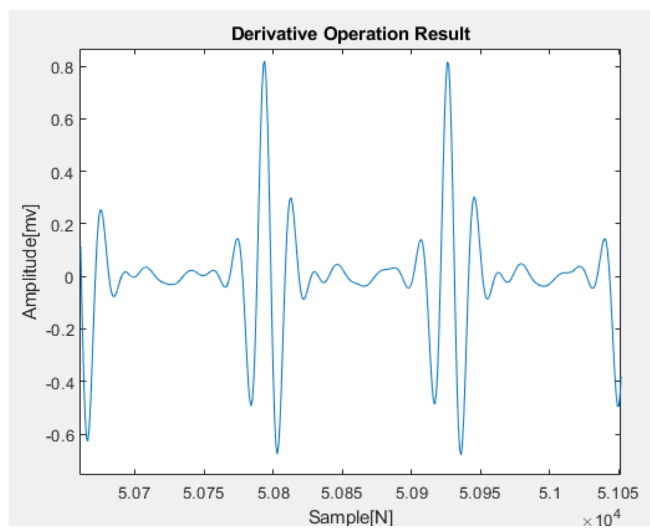

Figure 6. Result of the derivative operation after using pan Tompkins

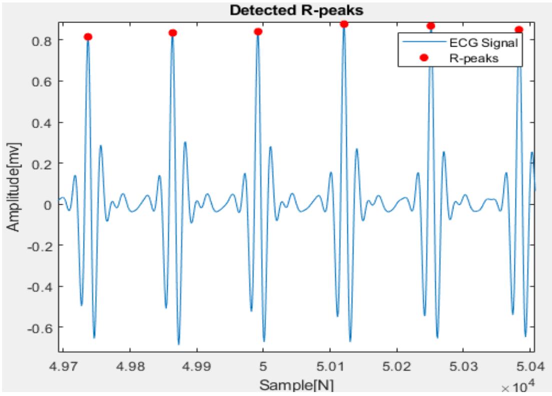

Figure 7. Detection of R-peaks in the ECG signal

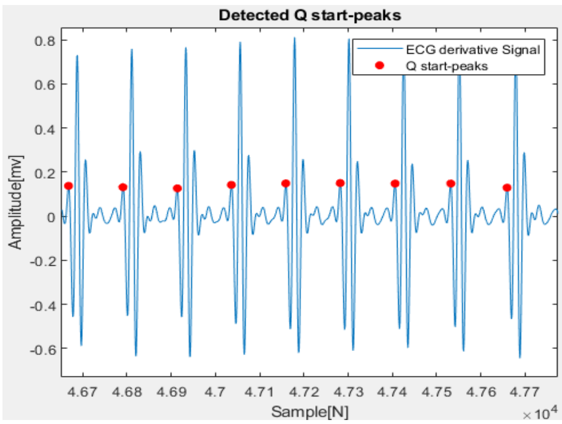

Figure 8. Identified Q peaks.

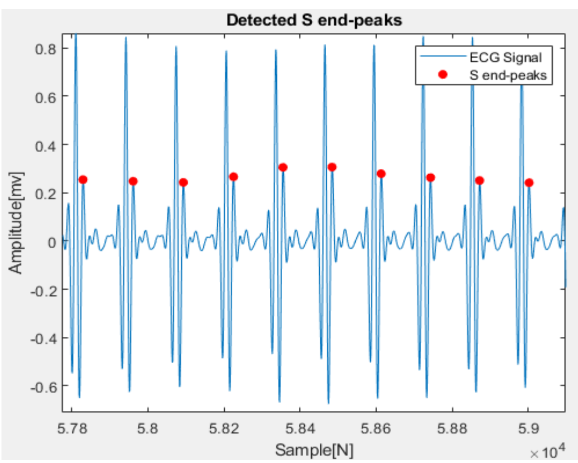

Figure 9. Identified S peaks

III. RESULTS

A. Search Outcome

A total of 320 studies were identified in PubMed and other databases using the search terms, through the systematic search process. After screening titles and abstracts, 44 studies were selected for full-text review after removing all the duplicates. Finally, 17 studies met the inclusion criteria and were included in the systematic review.

B. Summary of Findings

The findings from the included studies regarding QRS width detection on ECG are summarized below:

Accuracy and Reliability: studies that reported high accuracy and reliability of the QRS width detection methods were employed. These findings were consistent across different populations and settings. The sensitivity and positive predictive value of QRS detection algorithms vary. For example, a study by Reklewski et al. reported using 4 different algorithms. Algorithm 2 demonstrates good accuracy across different detection temporal tolerances (DTT), with TP/TB ratios exceeding 80% for most QRS morphology types. Algorithm 1 and Algorithm 3 also exhibit high accuracy for DTT values greater than or equal to 47.22 ms (17 samples), with TP/TB ratios consistently exceeding 90%. Algorithm 4 (Pan-Tompkins algorithm) achieves satisfactory detection accuracy with TP/TB ratios above 90%, sensitivity of 99.6% and a positive predictive value of 99.8% for their QRS detection algorithm. [15]

Most sources utilized the **Pan-Tompkins algorithm** for QRS width detection on ECG signals. The Pan-Tompkins algorithm was crucial in accurately detecting the R-peaks. It demonstrates a high level of accuracy in detecting QRS complexes and measuring their durations. The results indicate that for the majority of subjects, the QRS duration falls within the normal range of 80-110 ms, the algorithm exhibits a reliable performance in automatically assessing QRS duration, especially in healthy subjects. The result of some study highlights that the algorithm can detect QRS durations accurately in a 12-lead setup, showcasing its potential for clinical evaluations. [8]

Proposed algorithm: The Pan-Tompkins algorithm which we used includes a pre-processing step to reduce the impact of noise. We were able to reduce the impact of noise by using the Butterworth bandpass filter in the pan Tompkins function for ECG signals with noise to eliminate baseline drift, reduce low-frequency noise, enhance signal quality, and improve the accuracy of ECG signal analysis.

The decrease in amplitude of the filtered ECG signal was observed. Which is a result of the baseline drift removal, normalization, signal conditioning, and focus on removing low-frequency components during the filtering process. While the amplitude may appear to decrease, the filtered signal provides a cleaner and more reliable representation of the underlying ECG waveform for further analysis. In our code convenient performance of the peak detection algorithm was observed, resulting in the successful localization of Q, R, and S peaks across all phases. The calculated average QRS duration and its standard deviation provide valuable insights into the cardiac activity during all phases. In Table 1 are illustrated the mean QRS widths for each phase.

TABLE I. Final results of the mean, standard deviation and the number of QRS complex detected in the three phases.

Phases	Mean QRS (in ms)	Standard deviation	Number of QRS complex detected
Resting	95.17	11.47	859
Exercising	105.55	29.81	4438
Recovery	95.06	0.74	859

IV. Discussion

The study extensively reviewed methodologies for QRS width detection on ECG signals, emphasizing the importance of accurate QRS measurement in diagnosing cardiac conditions. Various algorithms, including the Pan-Tompkins Algorithm, first-derivative based algorithms, wavelet-based algorithms, neural network-based algorithms, and knowledge-based methods, were evaluated for QRS detection. The Pan-Tompkins Algorithm, known for its reliability, was crucial in accurately detecting QRS complexes and measuring their durations. Our method reveals a notable variation in QRS complex width across the resting, exercise, and recovery phases. During resting and recovery, characterized by a more relaxed physiological state, the QRS duration falls within the normal range of 90 ms to 100 ms. conversely, during the running phase, a prolongation of QRS duration exceeding 100 ms is observed. This discrepancy underscores the direct influence of physical exercise on cardiac electrical activity, leading to alterations in QRS complex morphology and duration. This observation aligns with previous literature documenting the impact of tachycardia on QRS morphology and duration.

In conclusion, the study highlighted the significance of QRS width detection in clinical practice and the potential of automated algorithms for real-time cardiac monitoring. While our method demonstrated effectiveness in detecting QRS complexes, the need for further refinement and optimization of the detection methodology. Future manipulation of our method could focus on enhancing algorithms to account for dynamic physiological changes during exercise, improving noise reduction techniques, and optimizing signal processing for accurate QRS detection across different phases of cardiac activity.

References

[1] Clifford GD, Liu C, Moody B, et al. AF Classification from a Short Single Lead ECG Recording: the PhysioNet/Computing in Cardiology Challenge 2017. *Comput Cardiol (2010)*. 2017; 44:10.22489/CinC.2017.065-469

[2] Smith JM, Clancy EA, Valeri CR, Ruskin JN, Cohen RJ. Electrical alternans and cardiac electrical instability. *Circulation*. 1988;77(1):110-121.

[3] Goldberger AL, Amaral LA, Glass L, et al. PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. *Circulation*. 2000;101(23): E215-220.

[4] Brignole M, Auricchio A, Baron-Esquivias G, et al. 2013 ESC Guidelines on cardiac pacing and cardiac resynchronization therapy: the Task Force on cardiac pacing and resynchronization therapy of the European Society of Cardiology (ESC). Developed in collaboration with the European Heart Rhythm Association (EHRA). *Eur Heart J*. 2013;34(29):2281-2329

[5] Martínez JP, Almeida R, Olmos S, Rocha AP, Laguna P. A Wavelet-Based ECG Delineator: Evaluation on Standard Databases. *IEEE transactions on bio-medical engineering*. 2004; 51:570-581.

[6] Benitez, Diego & Gaydecki, Patrick & Zaidi, Adnan & Fitzpatrick, A.P. New QRS detection algorithm based on the Hilbert transform. *Computers in Cardiology*.2000; 1. 379 - 382. 10.1109/CIC.2000.898536.

[7] Pan J, Tompkins WJ. A real-time QRS detection algorithm. *IEEE Trans Biomed Eng*. 1985;32(3):230-236.

[8] Ragab AAY et al. QRS Vector Magnitude as Predictor of Ventricular Arrythmia in Patients with Brugada Syndrome. The American Journal of Cardiology 2019.

[9] Arzeno NM, Deng ZD, Poon CS. Analysis of First-Derivative Based QRS Detection Algorithms. *IEEE Trans Biomed Eng*. 2008; 55(2):478-484.

[10] Raj S, Ray KC, Shankar O. Development of robust, fast and efficient QRS complex detector: a methodological review. *Australas Phys Eng Sci Med*. 2018;41(3):581-600

[11] Amiri AM, Abhinav, Mankodiya K. m-QRS: An efficient QRS detection algorithm for mobile health applications. In: *2015 17th International Conference on E-Health Networking, Application & Services (HealthCom)*. 2015; 2015:673-676

[12] Suzuki Y. Self-organizing QRS-wave recognition in ECG using neural networks. *IEEE Trans Neural Netw*. 1995;6(6):1469-1477

[13] Ivora A, Viscor I, Nejedly P, et al. QRS detection and classification in Holter ECG data in one inference step. *Sci Rep*. 2022;12(1):12641

[14] Elgendi M. Fast QRS Detection with an Optimized Knowledge-Based Method: Evaluation on 11 Standard ECG Databases. *PLoS One*. 2013;8(9): e73557.

[15] Reklewski W, Miskowicz M, Augustyniak P. QRS Detector Performance Evaluation Aware of Temporal Accuracy and Presence of Noise. *Sensors*. 2024; 24:1698 .

[16] Sbrollini A., Morettini M., Maranesi E., Marcantoni I., Nasim A., Bevilacqua R., Riccardi G.R., Burattini L. Sport Database: Cardiorespiratory data acquired through wearable sensors while practicing sports. Data in Brief. 2019; Volume 27, 104793, ISSN 2352-3409.