Going Beyond Atrial Fibrillation in Arrhythmia Classification from Photoplethysmography Signals

Eniko Vargova[1], Andrea Nemcova[1], Radovan Smisek[1,2], Zuzana Novakova[3]

[1]Department of Biomedical Engineering, Faculty of Electrical Engineering and Communication, Brno University of Technology, Brno, Czechia
[2]Institute of Scientific Instruments of the Czech Academy of Sciences, Brno, Czechia
[3]Department of Physiology, Faculty of Medicine, Masaryk University, Brno, Czechia

Abstract

Photoplethysmography (PPG) offers a simple, affordable, and non-invasive method for continuous vascular system monitoring, seamlessly integrated into user-friendly smart devices. Considering the rapid expansion of smart devices, there exists a significant opportunity to extend health monitoring to a broader population.

This paper focuses on cardiac arrhythmia (CA) detection from PPG signals. CAs pose significant health risks, often leading to complications such as stroke and heart failure. While most studies focus solely on detecting atrial fibrillation (AF), our research aims to classify six different rhythm types into three classes: Sinus rhythm, AF, and Other.

To achieve this goal, we trained a machine learning model – Random Forest. The model was trained on 12 features, which include not only features derived from pulse intervals but also statistical and morphological features. Our results demonstrate an overall accuracy of 0.88 on the test set, indicating the efficacy of our method. Additionally, when tested on a completely independent dataset, the model achieved an accuracy of 0.87. This study highlights the potential of PPG technology to detect various types of CAs beyond AF, offering valuable insights for improved cardiovascular health monitoring.

1. Introduction

According to the World Health Organization (WHO), cardiovascular diseases (CVDs) are a major global health concern, claiming around 17.9 million lives each year [1]. Cardiac arrhythmia (CA) is a form of CVD characterized by cardiac rhythm disorder. This condition can significantly affect person's quality of life and is linked to serious complications such as stroke, heart failure, and sudden cardiac death [2]. Continuous monitoring is crucial for early detection of CAs, as they are often asymptomatic and intermittent in their early stages.

Arrhythmia diagnosis typically relies on conventional methods such as 12-lead electrocardiogram (ECG) and 24-hour Holter monitoring. ECG often requires sophisticated medical device fitted with multiple electrodes or demand active participation from patients during the recording period (smartwatch), leading to discomfort and inconvenience. In recent years, photoplethysmography (PPG) has emerged as a promising technology for monitoring the vascular system continuously. PPG signals can be recorded using smart devices, which have potential to extend preventive healthcare to a broader population.

Most of the publications are primarily focused on discriminating atrial fibrillation (AF) using PPG signals [3]. However, there are other frequent types of CAs, each carrying its own set of risks and implications. Only a few studies have investigated the detection of other types of CAs, such as premature ventricular contraction (PVC) [4], atrial flutter [5], bradycardia and ventricular tachycardia (VT) [6].

Jeanningros et al. [7] conducted binary classification into the following classes: normal and abnormal rhythm from PPG signals with eight different types of CAs using a simple recurrent neural network (RNN) and solely inter-beat intervals (IBIs) as an input. Liu et al. [8] addressed the issue by classifying PPG segments into six different types of cardiac rhythms using a deep convolutional neural network (DCNN).

In this study, we present a machine learning (ML) model capable of classifying PPG signals into three classes: Sinus rhythm (SR), AF, and Other, encompassing six different types of rhythm. It should be noted that our approach incorporates information beyond just pulse intervals. In the future, we plan to build on this work and focus on classifying individual beats, particularly within the "Other" class, which could significantly enhance and refine the classification of the different types of rhythm.

 ISSN: 2325-887X DOI: 10.22489/CinC.2024.110

2. Material and Methods

2.1. Dataset

Liu et al. [8] conducted a study involving patients diagnosed with CA who underwent radiofrequency catheter ablation (RFCA). A multiparameter monitoring system was utilized for data collection, employing a 5-lead ECG wiring configuration and a fingertip PPG sensor. The data were obtained from 228 patients who were positioned supine during data acquisition.

The dataset has been pre-processed by the authors [8], and this procedure will be described in this paragraph. Firstly, the original PPG signals, recorded at a sampling frequency of 250 Hz, were downsampled to 100 Hz. Additionally, a bandpass filter with a cut-off frequency of 0.5–10 Hz was applied to filter out the noise in the signal. The PPG signals were segmented into non-overlapping 10-seconds segments. Finally, to facilitate comparability and consistency, PPG signals were normalized using min-max normalization within each 10-second segment.

The PPG recordings from these patients were labelled by two cardiologists into the following classes: SR and five types of CAs (PVC, Premature Atrial Contraction - PAC, VT, Supraventricular Tachycardia - SVT, and AF). All types of CAs and their manifestations in the PPG signal can be observed in the Figure 1. The authors [8] provided data from 91 patients freely.

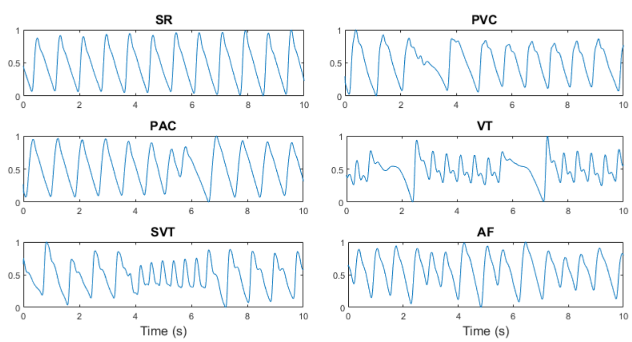

Figure 1. Various cardiac rhythms in PPG signals

For the purposes of this paper, the freely available data were used, including 46,827 10-second PPG segments from 91 individuals with CAs. The overall occurrences for each rhythm type are in Table 1.

Table 1. Number of segments for each rhythm type

Type of rhythm	Label	Segments
Sinus rhythm	0	14,604
Premature ventricular contraction	1	4,425
Premature atrial contraction	2	3,773
Ventricular tachycardia	3	2,179
Supraventricular tachycardia	4	5,677
Atrial fibrillation	5	16,169
Total	-	46,827

The objective of this paper is to classify each PPG segment into one of three classes: SR, AF, and Other. The distribution within these three classes can be seen in the Table 2.

Table 2. Number of segments for SR, AF and Other

Type of rhythm	Segments
Sinus rhythm	14,604
Atrial fibrillation	16,169
Other	16,054
Total	46,827

2.2. ML-based classification algorithm

Feature extraction was performed to obtain relevant information from the PPG signals. This process involved computing features derived from heart rate variability (HRV) analysis to capture temporal variations in heart rhythm. Additionally, morphological and statistical features from each PPG segment were computed. Altogether, 49 features were extracted. To compute HRV features, it was necessary to detect peaks in the PPG signals. Peak detection was performed using the *QPPG* detector from PPG-beats framework provided by Charlton et al. [9], which was identified as the most successful method for peak detection in CA data [10].

The next step involved handling outliers in the dataset. Outliers were identified using the interquartile range (IQR) method for each specific feature. Any data points that fell outside a certain range defined by the IQR were considered outliers and replaced with the mean value of the respective feature. To assess the statistical significance of parameters across the classes of SR, AF, and Other, a non-parametric Kruskal-Wallis test was employed. The results of this test indicated that all features appear to be significant.

Subsequently, the dataset was partitioned into training, validation, and test sets, ensuring that samples from the same patient were present only in one set.

Data underwent standardization to ensure that all features had a mean of zero and a standard deviation of one. Table 3 summarizes the distribution of data across the training, validation, and test sets after train-validation-test split.

Feature selection was performed using the forward selection method, aiming to find the best combination and number of features. The description of 12 features that were selected is in Table 4 (listed in order of importance from the highest to the lowest using permutation feature importance).

Table 3. Distribution of data across the training, validation, and test sets

Dataset	Rhythm	Segments	∑ Segments	Subjects
Train	SR	9,550	29,726	63
	AF	10,010		
	Other	10,166		
Validation	SR	3,515	9,365	14
	AF	3,150		
	Other	2,700		
Test	SR	1,539	7,736	14
	AF	3,009		
	Other	3,188		

On these features, a RF model was trained. Optimal hyperparameters for model were calculated using the grid search method with 3-fold cross-validation on the validation data (max_depth = 8, min_samples_leaf = 3, min_samples_split = 3, n_estimators = 100).

Table 4. Description of selected features

Feature	Description
CVSD	The root mean square of successive differences divided by the mean of the PP (pulse-to-pulse) intervals.
minNN	The minimum of the PP intervals.
pNN50	The percentage of successive PP intervals differing by more than 50 ms.
meanNN	The mean of the PP intervals.
pNN20	The percentage of successive PP intervals differing by more than 20 ms.
MCVNN	The median absolute deviation of the PP intervals divided by the median of the PP intervals.
maxArea	Maximal area under the curve of each PPG beat.
meanArea	Mean area under the curve of each PPG beat.
IQRNN	The interquartile range (IQR) of the PP intervals.
variance	Variance of the PPG segment.
HTI	HRV triangular index.
kurtosis	Statistical metric that characterizes how data is distributed around its mean.

3. Results

The performance of the RF classifier was evaluated using two metrics: accuracy (ACC) and F1 score (F1). Table 5 summarizes the achieved results of the RF classifier with optimal hyperparameters for the training, validation and testing data. Notably, the model achieved an overall accuracy and F1 score of 0.88 on the test set.

Table 5. Results of classification

	Train	Validation	Test
ACC	0.90	0.88	0.88
F1	0.90	0.88	0.88

Figure 2 shows the percentage of each rhythm type correctly classified into one of the three classes – SR, AF and Other.

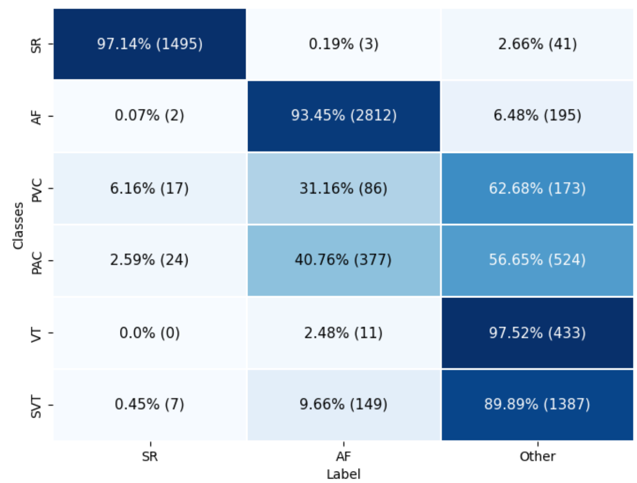

Figure 2. Classifier outputs per CAs

The classifier underwent additional testing on distinct data freely available from Han et al. [11][12][13]. This dataset contains PPG signals from MIMIC III database representing SR, AF, PAC and PVC. Each PPG signal had a duration of 30 seconds and was sampled at a frequency of 50 Hz. From this dataset, 15 PPG signals were randomly selected, comprising 5 SR, 5 AF, and 5 PAC/PVC signals. These signals were segmented into 10-second segments containing the respective pathology and were preprocessed using the same methods as for the training data. Subsequently, the same 12 features were extracted, and standardization was performed.

The ACC and F1 scores on this subset dataset are 0.87, indicating the model's capability to perform consistently across different datasets.

4. Discussion

The overall accuracy of the classifier stands at 88%. Upon closer examination of the individual rhythm classifications on the test data, SR is correctly identified in 97% of cases, while AF is accurately classified in 93% of instances. Similarly, segments corresponding to VT and SVT are correctly identified as Other rhythm in 98% and 90%, respectively. However, the classification performance is slightly lower for PAC and PVC, often misclassified as AF. The reason could be inaccurate detection of certain PPG peaks, particularly in the presence of isolated PAC and PVC instances. Conversely, the model demonstrates improved performance when detecting consecutive runs of 3 or more ectopic beats (VT, SVT).

Liu et al. [8] classified 6 rhythm types into 6 classes with an overall accuracy of 0.85 using DCNN. Jeanningros et al. [7] presented binary classification (normal and abnormal rhythm) of PPG signals containing eight different types of CAs using RNN with IBIs as input, achieving an overall accuracy of 0.84. The authors correctly classified SR into the normal rhythm class with an accuracy of 93.5%, while our approach achieved 97.2%. They classified AF as abnormal rhythm with an accuracy of 99.6% and VT as abnormal rhythm with an accuracy of 80.2%. If we merged the AF and Other classes into an “Abnormal class”, we would achieve a 99.9% success rate in AF classification and 100% success rate in VT classification.

In our proposed method, features based on pulse intervals were not the sole input; we incorporated other features (2 statistical and 2 morphological features) outlined in Table 4. However, the effectiveness of this classifier is constrained by the limited number of patients, making it unsuitable for deep learning approaches. Although this limitation might appear restrictive, it offers a significant advantage: the method remains medically interpretable, allowing clear insight into the algorithm's decision-making process. In future research, we intend to improve our methodology by focusing on classifying each individual PPG pulse/beat rather than entire PPG segments. We anticipate that this approach is good basis which will enhance the accuracy of rhythm classification.

5. Conclusion

This study demonstrates the classification of six rhythm types from PPG into three classes: SR, AF and Other, using a RF classifier. RF model achieves an overall ACC and F1 score both of 0.88 on the test data. SR and AF are identified with high accuracy, as well VT and SVT are correctly classified as Other. However, the ability to classify PAC and PVC into the Other class was less accurate. The future improvement will go deeper and will focus on the classification of individual beats.

Acknowledgments

Brno Ph.D. Talent Scholarship Holder – Funded by the Brno City Municipality.

This work has been funded by the United States Office of Naval Research (ONR) Global, award number N62909-23-1-2050. The authors wish to thank LCDR Geirid Morgan from ONR Code 342 and Dr. Martina Siwek from ONR Global Prague Office for their support.

References

[1] Cardiovascular diseases. World Health Organization [online]. https://www.who.int/health-topics/cardiovascular-diseases#tab=tab_1.

[2] A. Sijerčić and E. Tahirović, “Photoplethysmography-Based Smart Devices for Detection of Atrial Fibrillation”, *Texas Heart Institute Journal*, vol. 49, no. 5, Sep. 2022.

[3] T. Pereira et al., “Photoplethysmography based atrial fibrillation detection: a review,” *Digital Medicine*, vol. 3, no. 1, Art. no. 1, Jan. 2020.

[4] M. R. Yousefi et al., “Automatic Detection of Premature Ventricular Contraction Based on Photoplethysmography Using Chaotic Features and High Order Statistics”, in 2018 *IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, pp. 1-5, 2018.

[5] L. M. Eerikainen et al., “Detecting Atrial Fibrillation and Atrial Flutter in Daily Life Using Photoplethysmography Data”, *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 6, pp. 1610-1618, 2020.

[6] A. Sološenko, B. Paliakaitė, V. Marozas, and L. Sörnmo, “Training Convolutional Neural Networks on Simulated Photoplethysmography Data: Application to Bradycardia and Tachycardia Detection”, *Frontiers in Physiology*, vol. 13, Jul. 2022.

[7] L. Jeanningros, J. Van Zaen, C. Aguet, M. Le Bloa, A. Porretta, C. Teres et al. “Abnormal cardiac rhythm detection based on photoplethysmography signals and a recurrent neural network,” *Computing in Cardiology Conference (CinC)*, 2023.

[8] Z. Liu et al., “Multiclass Arrhythmia Detection and Classification From Photoplethysmography Signals Using a Deep Convolutional Neural Network,” *Journal of the American Heart Association*, vol. 11, no. 7, p. e023555, Apr. 2022.

[9] P. H. Charlton et al., “Detecting Beats in the Photoplethysmogram: Benchmarking Open-Source Algorithms,” *Physiological Measurement*, vol. 43, no. 8, p. 085007, Aug. 2022.

[10] L. Jeanningros et al., “A comparative study on detecting heart beats in photoplethysmography signals in presence of various cardiac arrhythmias,” *Computing in Cardiology Conference (CinC)*, 2023.

[11] D. Han et. al., “Premature Atrial and Ventricular Contraction Detection Using Photoplethysmographic Data from a Smartwatch”, *Sensors*, vol. 20, no. 19, 2020.

[12] S. K. Bashar et al., “Atrial Fibrillation Detection During Sepsis: Study on MIMIC III ICU Data”, *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 11, pp. 3124-3135, 2020.

[13] S. K. Bashar et al., “Noise Detection in Electrocardiogram Signals for Intensive Care Unit Patients”, *IEEE Access*, vol. 7, pp. 88357-88368, 2019.

Address for correspondence:

Enikö Vargová
Department of Biomedical Engineering, Faculty of Electrical Engineering and Communication, Brno University of Technology, Technická 3058/12, 61600 Brno, Czech Republic.
xvargo02@vutbr.cz