Improving Multiclass Classification of Cardiac Arrhythmias with Photoplethysmography using an Ensemble Approach of Binary Classifiers

Katharina Post Marisa Mohr, Max Koeppel, Astrid Laubenheimer





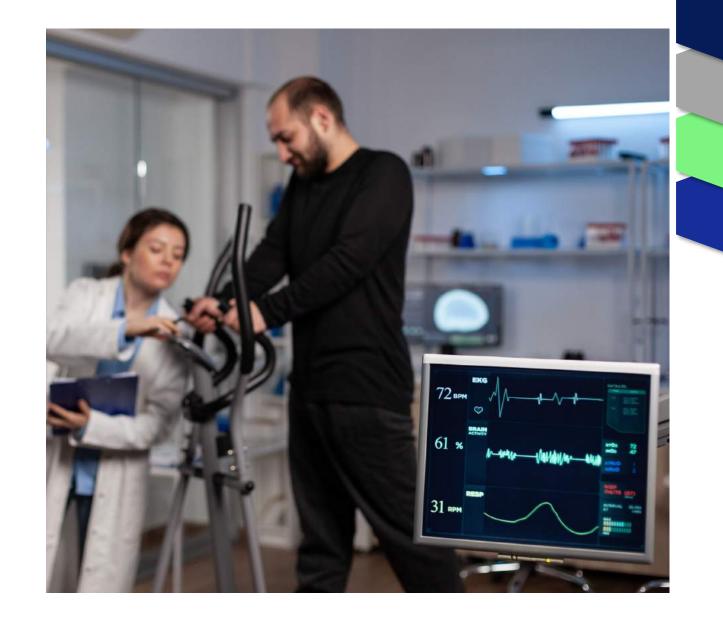
Agenda

Introduction

Related Work

System Design

Experimental Evaluation



Motivation



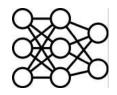
cardiac arrhythmias are one of the leading causes of death worldwide

17.8 million deaths



primary method for the detection of arrhythmias is the electrocardiogram

300 million² ECG-strips



classification of arrythmias with ML and DL based on ECGs

1 worldwide in 2017 2 worldwide per year

Motivation



ECGs are used in a medical context and do not allow long-term monitoring



application of photoplethysmography (PPG) in smart devices to detect arrhythmias



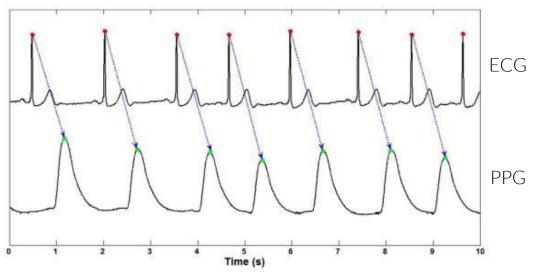
classification of multiple arrhythmias based on PPGs are limited

Improving the classification of various heart rhythm abnormalities by an ensemble of binary classifiers

ECG and PPG

ECG

- measures the electrical activity of all heart muscle fibres
- low portability
- maximum time of monitoring ≈ 3 days
- accurate



V. Kalidas and L. S. Tamil, "Cardiac arrhythmia classification using multi-modal signal analysis," Physiological Measurement, vol. 37, pp. 1253–1272, jul 2016.

PPG

- measures the volumetric changes of blood in the microvascular tissue bed
- build into smart divices
- constant monitoring
- can be inaccurate

PPGs and ECGs are related to each other

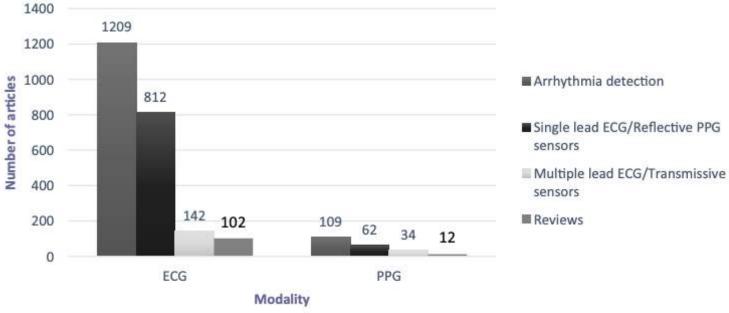
- peak of ECG = contraction of ventricles
- transport of blood through the veins
 - \rightarrow blood valume increases

Related Work

- more research with ECG data
- approaches include statistical methods, machine learning, deep learning, etc.
- focus in publications with
 PPG data is primarly on the single-class classification

Number of articles on arrhythmia detection using ECG and PPG sensors

Neha, Sardana, H.K., Kanwade, R. et al. Arrhythmia detection and classification using ECG and PPG techniques: a review. Phys Eng Sci Med 44, 1027–1048 (2021). https://doi.org/10.1007/s13246-021-01072-5



Multiclass Arrhythmia Detection from PPG Signals



multiclass classification of five arrhythmias and sinus rhythm



 $\overset{\circ}{\gtrsim}$ deep convolutional neural network (DCNN) based on the VGGNet-16 architecture



own dataset with 228 patients and 118,217 10-second sequences

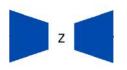


inter-patient approach

→ accuracy: 85% (imbalanced dataset)

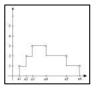
Multiclass Arrhythmia Detection from ECG Signals

combination of topological data analysis, handcrafted features, Fast Fourier Transformation, and deep learning



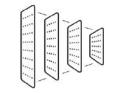
Autoencoder:

- compensation between normal and abnormal heart rhythm
- trained with sinus rhythm



Betti Curve:

- from ECG-sequences
- curve is processed in an CNN



Convolutional Neural Network:

• signal as input



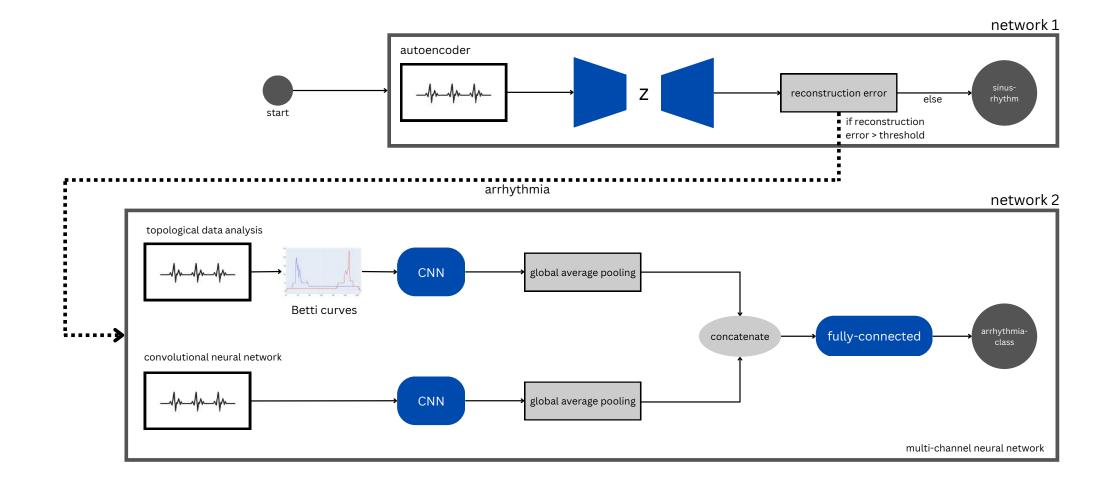
Others:

- Fast-Fourier-Transformation
- handcrafted features



model architecture as a baseline for the classification of arrhythmias with PPG data

Model Architecture

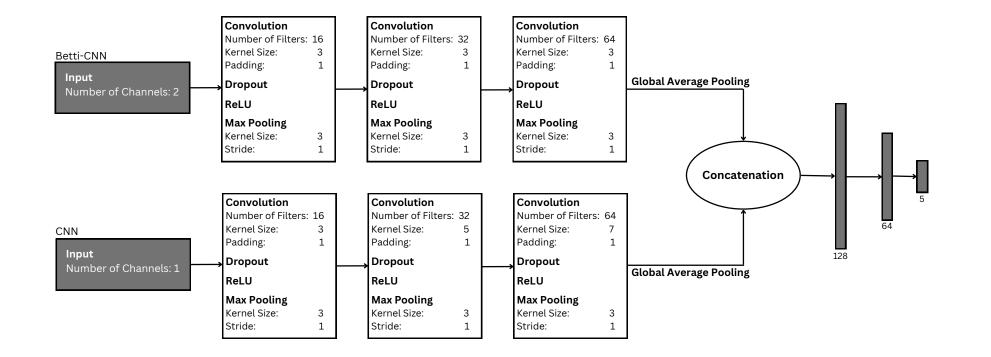


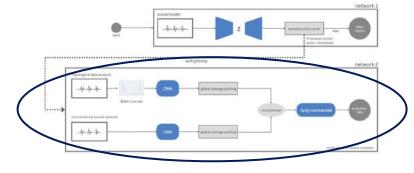
Katharina Post - Multiclass Classification of Arrhythmias using an Ensemble Model - CERC 2023



Multiclass Model Architecture Multiclass

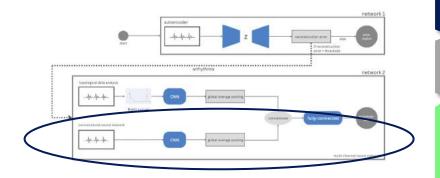
- application of small model architectures due to the small ٠ number of available samples
- model outputs one of five classes •

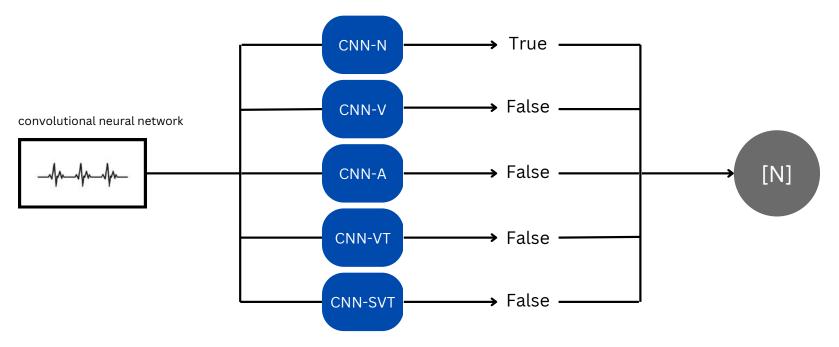




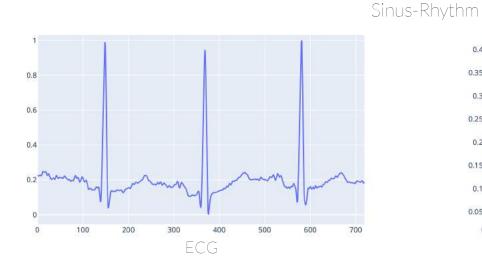
Ensemble of Multiple Binary Classifiers

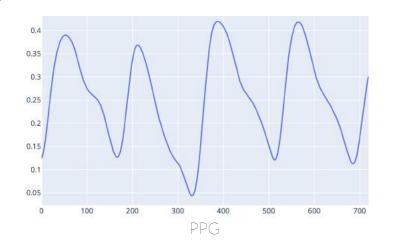
- division of the multiclass problem into subtasks
- each model performs a binary classification
- combined output carries out the classification
- one-vs-all combination



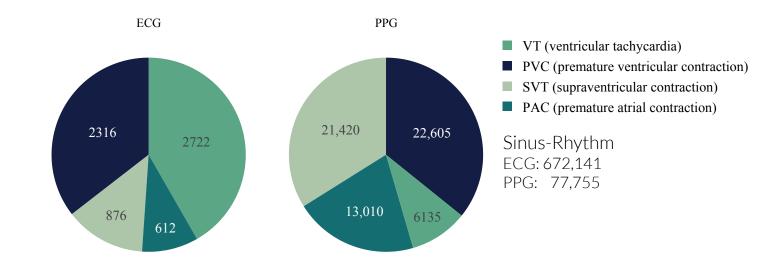


Data





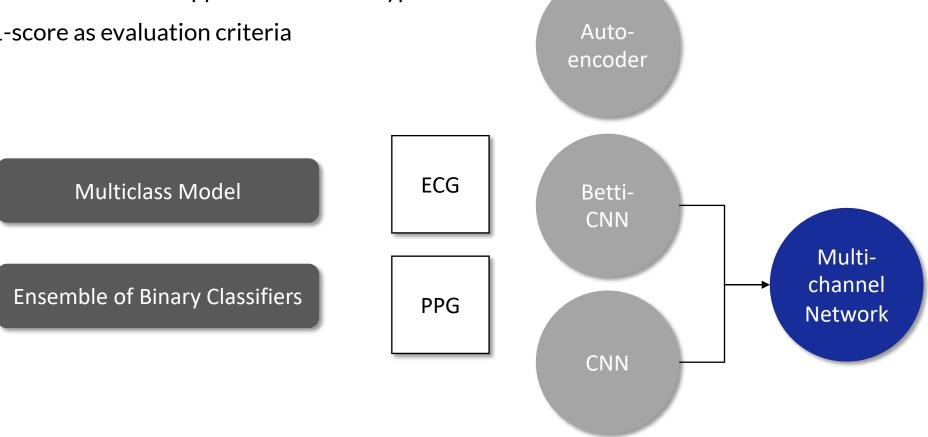
- data from different patients and different databases
- extraction of twosecond long sequences
- inter-patient approach



Experimental Evaluation

Results

- models are tested independently •
- one model for each approach and data type •
- F1-score as evaluation criteria



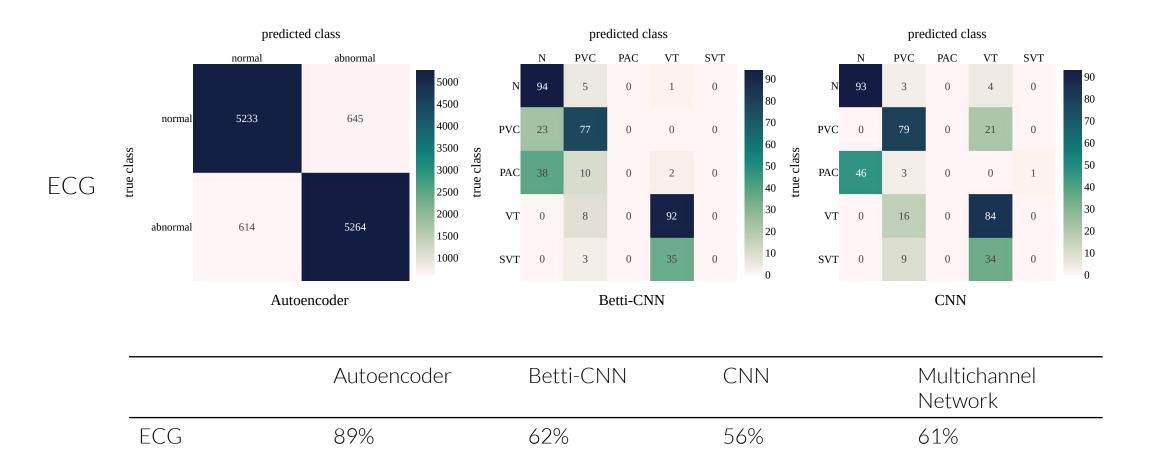
Results

PPG

65%

Multiclass Model

18%



F1-scores of each model in the multiclass model for each data type

35%

Katharina Post - Multiclass Classification of Arrhythmias using an Ensemble Model - CERC 2023

7%

Results

_	Class	Betti-CNN	CNN	Number of Samples
ECG	sinus rhythm	91%	96%	>5,000,000
	premature ventricular contraction	93%	92%	2,316
	ventricular tachycardia	92%	89%	2,731
	premature atrial contraction	66%	50%	612
	supraventricular tachycardia	91%	88%	867

F1-scores of each model in the binary ensemble trained on ECG data for each class and the number of samples.

	Model	Multiclass Approach	Binary Ensemble
	Betti-CNN	35%	59%
PPG	CNN	7%	71%
	Multichannel Model	18%	89%

Comparison of F1-score performance between the multiclass approach and the ensemble of binary classifiers.

Conclusion



improvement of the multiclass classification of cardiac arrhythmias in PPG signals



ensemble of multiple one-vs-all binary classifiers



F1-score of 89% for five classes on PPG data, outperforming other methods



advantages of ensemble approach:

- benchmark results with small model structures and less training data
- multiple labels per sequence
- practical for smart device applications



verification of CNN performance with larger training data and more complex structure

inovex is an IT project center driven by innovation and quality, focusing its services on 'Digital Transformation'.

- founded in 1999
- 500+ employees
- 8 offices across Germany



www.inovex.de

Sources

WHO: World health organization cardiovascular disease risk charts: revised models to estimate risk in 21 global regions. Lancet Global Health 7 (2019). https://doi.org/10.1016/S2214-109X(19)30318-3

Dindin, M., Umeda, Y., Chazal, F.: Topological data analysis for arrhythmia detection through modular neural networks. In: Goutte, C., Zhu, X. (eds.) Advances in Artificial Intelligence. pp. 177–188. Springer International Publishing, Cham (2020)

Irfan, S., Anjum, N., Althobaiti, T., Alotaibi, A.A., Siddiqui, A.B., Ramzan, N.: Heartbeat classification and arrhythmia detection using a multi-model deep-learning technique. Sensors 22(15) (2022). https://doi.org/10.3390/s22155606, https://www.mdpi.com/1424-8220/22/15/5606

Wu, M., Yang, W., Wong, S.: A study on arrhythmia via ecg signal classification using the convolutional neural network. Frontiers in computational neuroscience 14 (2021). https://doi.org/10.3389/fncom.2020.564015

Biswas, D., Everson, L., Liu, M., Panwar, M., Verhoef, B.E., Patki, S., Kim, C.H., Acharyya, A., Van Hoof, C., Konijnenburg, M., Van Helleputte, N.: Cornet: Deep learning framework for ppg-based heart rate estimation and biometric identification in ambulant environment. IEEE Transactions on Biomedical Circuits and Systems 13(2), 282–291 (2019). https://doi.org/10.1109/TBCAS.2019.2892297

Liu, Z., Zhou, B., Chen, X., Li, Y., Tang, M., Miao, F.: Multiclass arrhythmia detection and classification from photoplethysmography signals using a deep convolutional neural network. Journal of the American Heart Association 11 (2022). https://doi.org/10.1161/JAHA.121.023555

Polania, L., Mestha, L., Huang, D., Couderc, J.P.: Method for classifying cardiac arrhythmias using photoplethysmography. In: Annual International Conference of the IEEE Engineering in Medicine and Biology Society. vol. 2015, pp. 6574–6577 (08 2015). https://doi.org/10.1109/EMBC.2015.7319899

Aschbacher, K., Yilmaz, D., Kerem, Y., Crawford, S., Benaron, D., Liu, J., Eaton, M., Tison, G.H., Olgin, J.E., Li, Y., Marcus, G.M.: Atrial fibrillation detection from raw photoplethysmography waveforms: A deep learning application. Heart Rhythm O2 1(1), 3–9 (2020). https://doi.org/10.1016/j.hroo.2020.02.002, https://www.sciencedirect.com/science/article/pii/S2666501820300040

Lorena, A., Carvalho, A., Gama, J.: A reviewon the combination of binary classifiers in multiclass problems. Artificial Intelligence Review 30, 19–37 (12 2008). https://doi.org/10.1007/s10462-0099114-9

Galar, M., Fernández, A., Barrenechea, E., Bustince, H., Herrera, F.: An overview of ensemble methods for binary classifiers in multi-class problems: Experimental study on one-vs-one and one-vs-all schemes. Pattern Recognition 44(8), 1761–1776 (2011). https://doi.org/10.1016/j.patcog.2011.01.017, https://www.sciencedirect.com/science/article/pii/S0031320311000458