Prospects for heart failure diagnostics using photoplethysmography

M. Tiosavljević[1], P. Tadić[1], A, Lazović[2], V. Atanasoski[2], M. Ivanović[2], M. Stojanović[2], P. Beličev[2], A. Maluckov[2], Lj. Hadžievski[2], A. Ristić[3], V.Vukčević[4], J. Petrović[2]
[1]University of Belgrade – School of Electrical Engineering, [2]Vinca Institute of Nuclear Sciences, University of Belgrade, [3]Faculty of Medicine, University of Belgrade, [4]Clinical Center of Serbia

Abstract

Heart failure (HF) affects over 64 million people worldwide, making early diagnosis crucial. Diagnosis relies on costly medical examinations and tests, such as echocardiography. In this work, we explore the possibility of non-invasive HF detection from synchronized cardiac signals, achieving up to **82%** accuracy for binary and **76%** for multiclass classification.

Introduction

HF occurs when the heart muscle cannot pump blood efficiently, which results in inadequate oxygen-rich blood transportation to the rest of the body.
HF is a condition with mortality rates comparable to the most aggressive cancers.
Early diagnosis is essential, but current methods (e.g., **echocardiography, blood tests, X-ray**) are costly and often detect HF at late stages.
A key diagnostic parameter is the **ejection fraction (EF).** Based on its value, HF can be categorized into: **HF with preserved EF** (HFpEF, >50%), **HF with mid-range EF** (HFmrEF, 41- 49%), and **HF with reduced EF** (HFrEF, <40%).
Systolic time intervals (STI), derived from cardiac signals, are correlated with EF and may provide an accessible, non-invasive diagnostic alternative. These signals can be measured using simple wearable sensors, making them promising for low-cost, real-time HF detection.
Our study investigates HF detection using synchronized cardiac signals using **a deep learning approach.**

Database

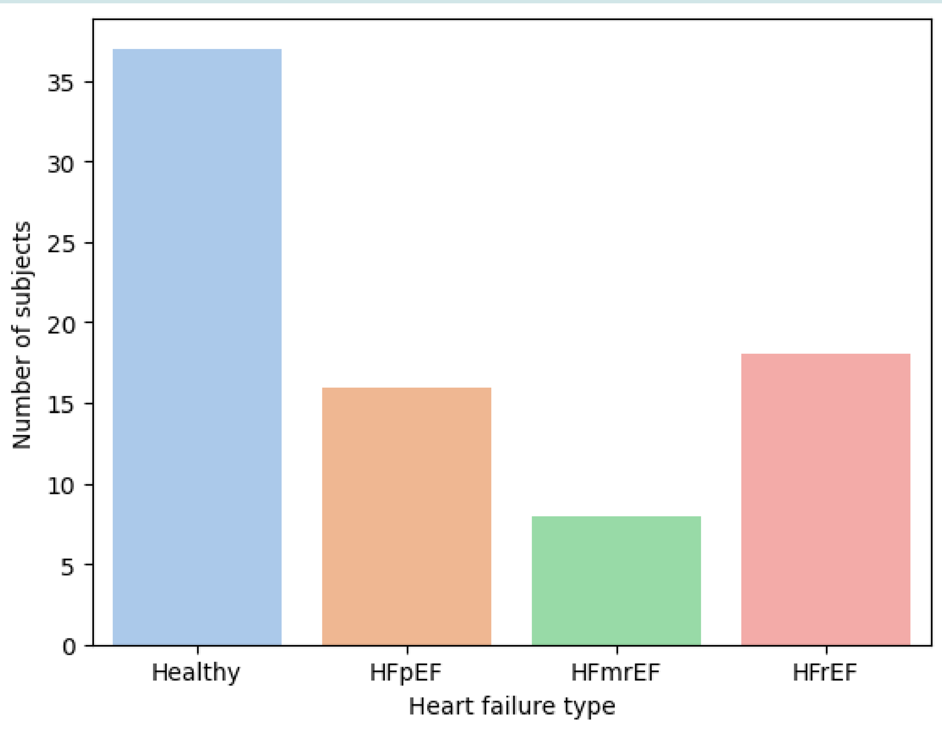

Figure 1. Distribution of HF subtypes

The *SensSmart* clinical database was used, which contains 407 recordings, each lasting 30 seconds, for 82 adult participants – 46 diagnosed heart patients and 36 healthy individuals.
All participants were categorized as either healthy or as HF patients with one of the following diagnoses – **HFpEF, HFmrEF** and **HFrEF.**

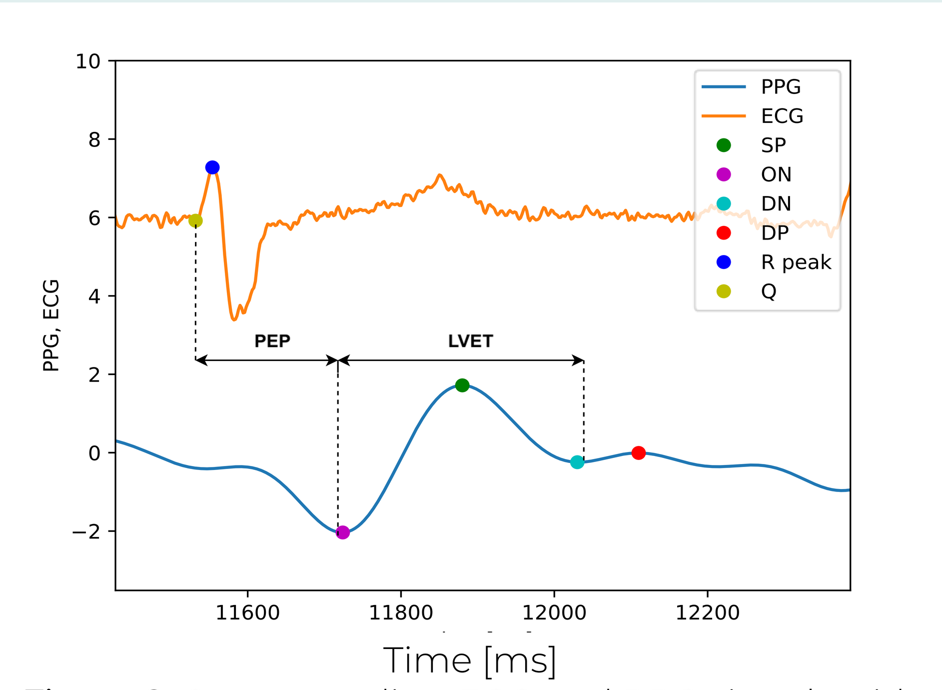

Figure 2. Corresponding ECG and PPG signals with STI

Each recording included three mechanical cardiac signals:

- **photoplethysmogram (PPG) from the left brachial artery,**
- phonocardiogram (PCG),
- seismocardiogram (SCG),

as well as electrocardiogram (ECG) signal, representing the heart's electrical activity.

Mechanical signals served as the inputs to our deep learning model, whereas ECG was used to identify the boundaries of each cardiac beat.

Cardiac signal preprocessing

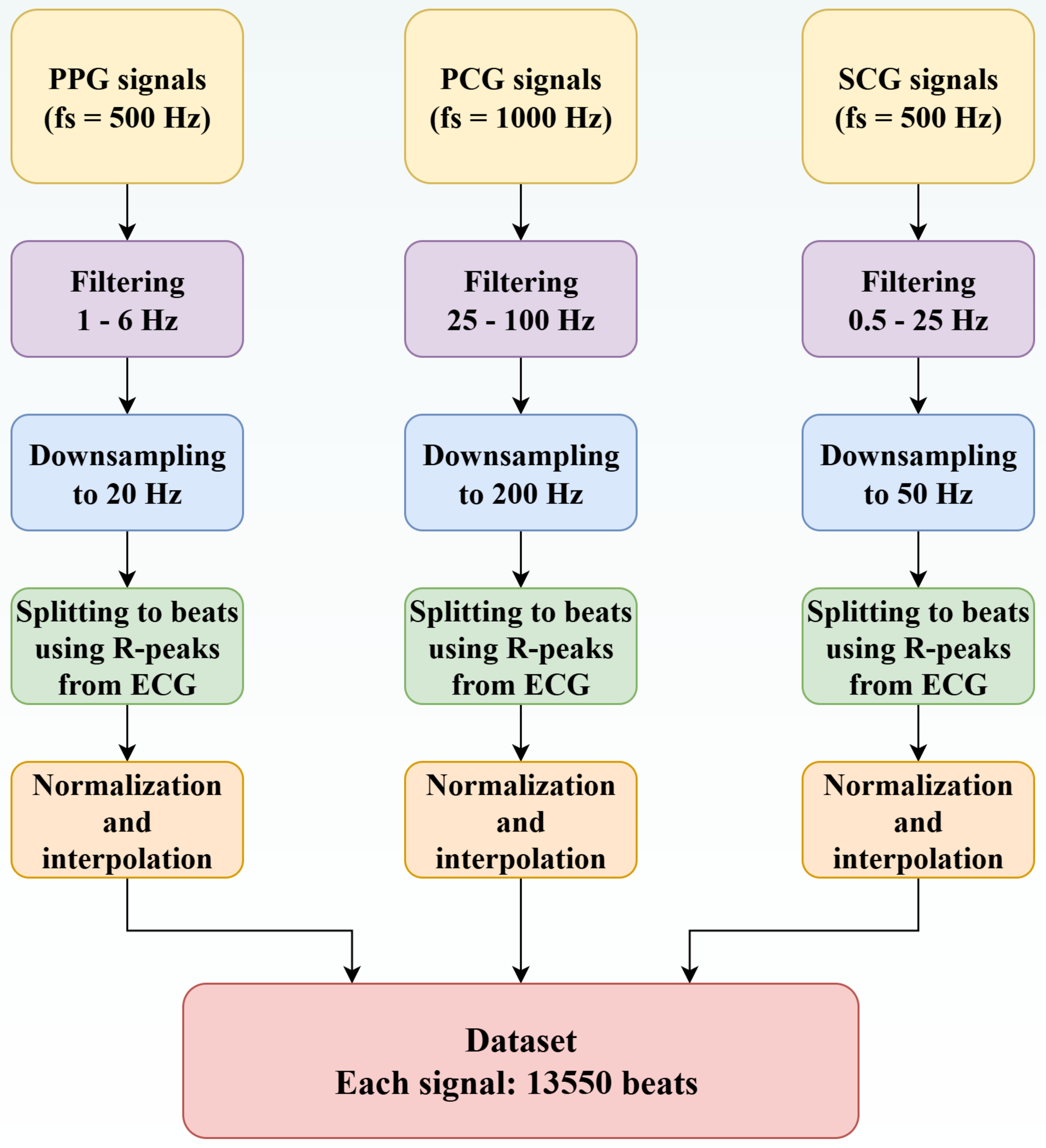

Figure 3. Preprocessing pipeline

Deep learning model

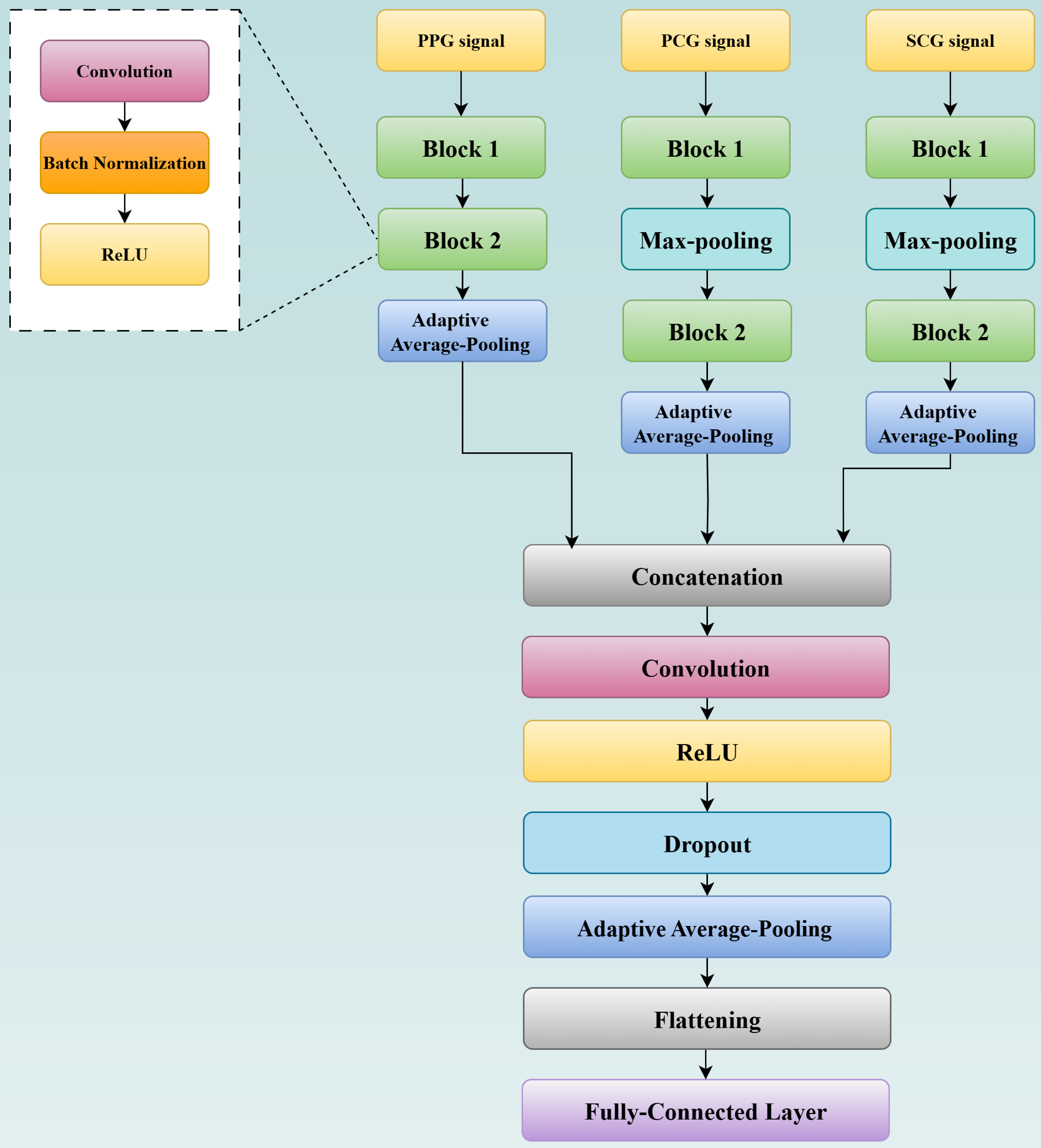

Figure 4. Deep learning model architecture

Model training

5-fold cross-validation was applied, ensuring that all classes were represented in each fold. Beats from a single subject were kept entirely within either the training, validation, or test set to prevent data leakage.
Model was trained for 50 epochs on 4 folds (20% for validation), with the fifth fold used to evaluate performance on unseen data.

Results and conclusion

Metrics	Mean	Standard deviation
Accuracy	0.7971	0.0631
Precision	0.7558	0.0781
Sensitivity	0.9356	0.0634
F1-score	0.8333	0.0551

Table 1. Performances on test data for single-beat binary classification

Metrics	Mean	Standard deviation
Accuracy	0.6449	0.0550
Precision	0.6741	0.0733
Sensitivity	0.6449	0.0550
F1-score	0.6426	0.0635

Table 2. Performances on test data for single-beat multiclass classification

When all beats from each subject were used for decision-making, accuracies were obtained using soft voting for binary classification and hard voting for multiclass classification.

Binary classification accuracy: 81.83%
Multiclass classification accuracy: 76.66%

Despite limited data and heterogeneity and imbalance among participants of the study, neural networks applied to **PPG** and other cardiac signals already show **strong diagnostic potential**, which is expected to improve further as these limitations are addressed.

Acknowledgements

This research was supported by the taxpayers of the Republic of Serbia, through the Science Fund of the Republic of Serbia, Grant. No. 7754338, Multi.SENSor SysteM and ARTificial intelligence in service of heart failure diagnosis – SensSmart and by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia under contract numbers 451-03-137/2025-03/200103 and 451-03-66/2024-03/200017.