Image-Based Analysis of Arterial Pulse Wave Signals Using Convolutional Neural Networks for Age Classification

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Abstract

The morphology of arterial pulse waveforms evolves with age, reflecting structural and functional changes in the cardiovascular system. Thus, vascular age is a valuable surrogate of cardiovascular health, and premature vascular ageing can indicate increased cardiovascular disease risk. Pulse wave analysis could support risk stratification in otherwise asymptomatic adults. We transformed pulse wave time-series data from photoplethysmography (PPG) and arterial tonometry signals into images, using Symmetric Projection Attractor Reconstruction (SPAR). We trained a convolutional neural network on SPAR images to distinguish between healthy subjects aged 35–40 and 50–55. The model demonstrated consistent classification performance on internal and external test sets, achieving F1 scores above 70% across different age ranges in both PPG and tonometry signals. These results suggest that SPAR-images from pulse waves contain discriminative features, even among healthy adults close in age. This proof-of-concept lays the groundwork for future research into the use of SPAR for early risk detection using smart wearables.

1. Introduction

Vascular Ageing (VA) is a complex process that involves the gradual deterioration of arterial structure and function over time, negatively impacting organ function [1]. The gold-standard measurement for VA is carotid-femoral pulse wave velocity, but this requires trained personnel and is not routinely clinically available [2]. In healthy ageing, chronological and vascular age typically correspond [3].

Early detection of premature VA is critical for the timely identification and treatment of cardiovascular disease (CVD), which remains a leading global health burden. Non-invasive signals from photoplethysmography (PPG) or tonometry can help assess vascular age, by analysing the shape of the pulse wave, which changes with age due to arterial stiffening. PPG is an optical method used in clinical and wearable devices to measure pulse waves at sites like the wrist and finger [4]. Arterial tonometry, mainly used clinically, measures pressure from superficial arteries such as the radial or carotid [5]. By comparing signal-based estimates of vascular age to a person's chronological age, we hypothesised we could identify early VA in community based settings.

This study focuses on image-based age classification leveraging PPG and tonometry-derived pulse waveforms, targeting two narrow yet clinically significant age cohorts (35–40 and 50–55 years), during which individuals may begin to manifest subclinical CVD risk. Pulse waves were converted into images using the Symmetric Projection Attractor Reconstruction (SPAR) method, which condenses time-series data into a single image [6]. These images were used to train a Convolutional Neural Network (CNN) to classify age, assigning each unseen image to the most likely of the two classes ($\leq$40 or $\geq$50).

2. Methods

2.1. Datasets

The datasets used in this study were Round 1 data from the Asklepios Study and the Vortal dataset (Table 1).
Both datasets comprised recordings from participants free from a CVD diagnosis at study initiation, collected in the supine position. The Asklepios Study [7] includes 2,524 individuals (30–59 years, 52% female) randomly sampled from two twinned Belgian communities. The exact age of each participant was labelled. Arterial tonometry waveforms (20 s, 200 Hz) were acquired at a single centre by

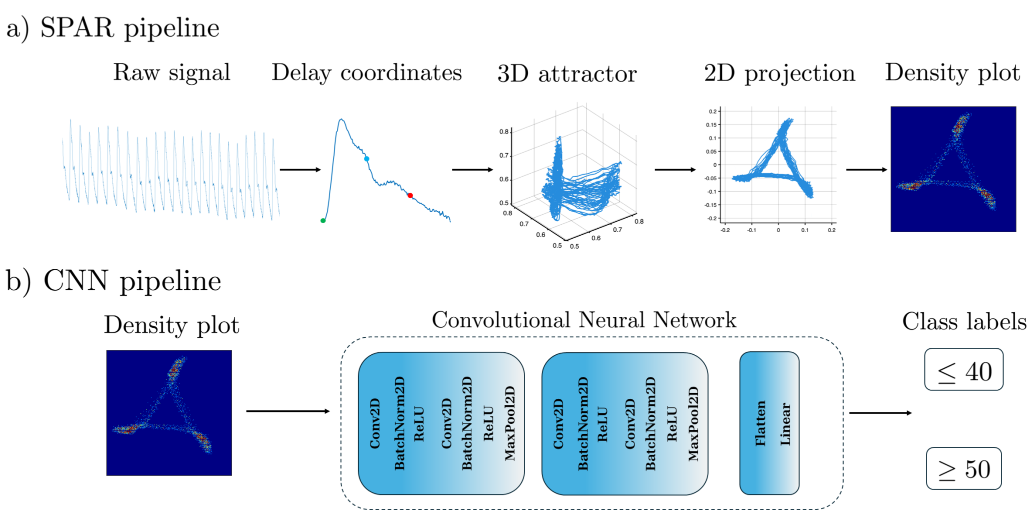

Figure 1. Full pipeline adopted in this study. Section a) illustrates the SPAR pipeline, which processes a raw signal into a SPAR attractor image (density plot). Section b) illustrates the CNN pipeline, where CNN takes as input the density plot and gives as output a class label.

one operator using the same device. The Vortal dataset [8] contains finger PPG recordings from 56 subjects: 40 labelled as 'Young' (18–35 years, 53% female) and 16 as 'Elderly' (70+ years, 56% female), collected in a London clinical trials unit (approx. 10 min per subject, 125 Hz).

2.2. Data selection

From the original Asklepios population, a subgroup was considered for this study. We included only participants aged 30-40 and 50-59. Obese subjects (BMI$\geq$30 kg/m^2) and those with high blood pressure (systolic$\geq$140 mmHg or diastolic$\geq$90 mmHg) were excluded, in keeping with the 2024 ESC guidelines for hypertension classification [9]. For the Vortal dataset, we used the whole cohort, as no metadata was available. The final population composition, all of which were assumed to be healthy, is shown in Table 2.

Table 1. Population composition for each dataset considered in this study.

	Asklepios	Vortal
No. of participants	2,524	56
Sex (M/F)	1,223/1,301	27/29
Age range	30-59	18-35,70+
Signal type	Tonometry	PPG
Raw signal length	20 s	10 min
Analysed signal length	20 s	20 s

Table 2. 'Total' and 'Selected' number of subjects in the Asklepios and Vortal datasets, along with the number of SPAR images used in each group.

Cohort	Total	Selected	Images
Asklepios 30-34	15	12	12
Asklepios 35-40	456	341	341
Asklepios 50-55	514	251	251
Asklepios 56-59	160	77	77
Vortal 18-35	40	40	1302
Vortal 70+	16	16	528

2.3. Symmetric Projection Attractor Reconstruction (SPAR) method

The SPAR method [6] is a non-fiducial points based method that combines mathematics and cardiovascular physiology to quantify morphological features and waveform variability. Given a raw pulse wave signal, the average cycle length is computed for the time length of the window selected. Next, a three-dimensional (3D) attractor is generated using three delay coordinates a distance of one third of the average cycle length apart. The 3D attractor is then projected onto a 2D plane normal to the unit vector and converted into a density plot (Figure 1a). This plot is the final attractor image used to train and validate CNNs in this work.

For the Asklepios Study dataset, we used one 20-second segment per subject, resulting in one attractor image per participant. For the Vortal dataset, we extracted multiple non-overlapping 20-second segments from the 10-minute

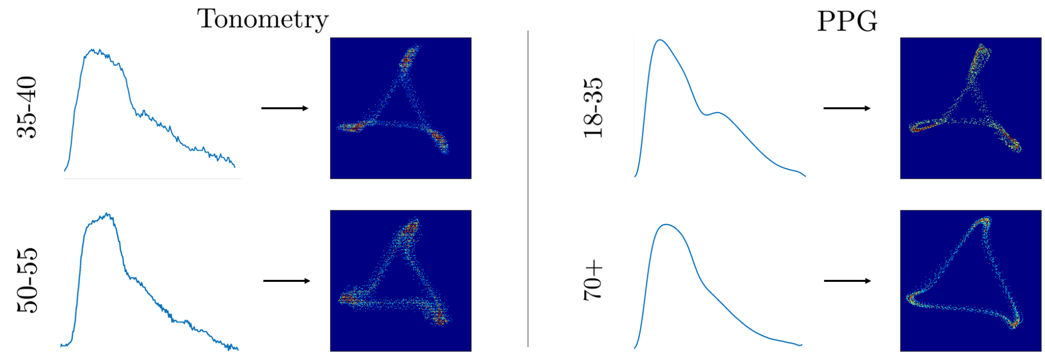

Figure 2. Examples of a single pulse wave and the correspondent SPAR attractor image, generated using 20s of data, for tonometry and PPG data.

recordings, generating around 30 images per subject.

2.4. Model and metrics

The CNN considered in this study is a relatively simple architecture, designed after the TinyVGG originally presented by Wang et al. [10]. It comprises two main blocks and a final classification layer, as shown in Figure 1b. Model performance was evaluated using sensitivity (TP / (TP + FN)), specificity (TN / (TN+FP)) and the F1 score, which is the harmonic mean of precision (TP / (TP + FP)) and sensitivity; with TP being the true positives, TN the true negatives, FP the false positives and FN the false negatives. In the context of this study, the positives were the 50-55 years class, the negatives the 35-40 years. Therefore, sensitivity measures the model's ability to assign a test subject who is 50 or older to the correct class, while specificity measures the model's ability to correctly classify those that are 40 or younger.

2.5. Training and testing

The model was trained on 80% of the Asklepios data from age groups 35-40 and 50-55. Of the remaining data from these groups, 10% was used as validation set and 10% as test set. Given the relatively small size, 10-fold cross-validation was performed to improve robustness, thus obtaining 10 different sets of model weights which were evaluated separately when testing. The model was then tested on different test sets, reported in Table 2. The division in 10 different test sets was maintained when testing on the larger Asklepios population, to avoid bias. The Vortal test remained constant across evaluations.

3. Results

The model reached F1 scores of least 70%, with sensitivity >67% and specificity >79% across all test sets (Table 3). Performances generally improved with larger test sets and broader age ranges (Table 2), suggesting good generalisation. Higher sensitivity in these sets indicates a more accurate classification of older subjects. Additionally, standard deviations decreased with broader test sets, reflecting more consistent performance across cross-validation folds.

Table 3. Model performance on different test sets.

	F1 score (%)	Sens (%)	Spec (%)
Test Asklepios 35-40 and 50-55	70.9 ± 8.6	67.0 ± 12.3	85.0 ± 6.3
Test Asklepios 30-40 and 50-59	79.3 ± 2.0	70.5 ± 3.1	84.3 ± 4.8
Test Vortal	72.8 ± 2.5	86.9 ± 5.9	79.0 ± 2.0

Evaluation on PPG signals showed improved F1 scores compared to the baseline test on the Asklepios dataset, together with an increase in sensitivity and a slight decrease in specificity. This highlights the ability of the model, combined with the SPAR method, to detect age-related morphological changes across both signals. Figure 2 illustrates these morphological differences. In younger individuals (35-40 for tonometry, 18-35 for PPG), distinct second peaks in both signals, result in SPAR attractors with "looped" edges and closed centres. In older age groups (50-55 for tonometry, 70+ for PPG), the second peak is attenuated or absent, producing more open attractors with reduced looping, highlighting age-related waveform changes.

4. Discussion and conclusion

We have presented a simple model that can classify chronological age in a healthy population with no CVD diagnosis, using two non-invasive pulse wave signals. We purposefully selected healthy individuals in this analysis, such that chronological age was expected to closely match vascular age. Good classification performances in the larger tonometry and PPG test sets showed that both pulse wave types contained enough information in their shape to distinguish between the two age groups. Our analysis therefore detected changes in the cardiovascular system that underline those morphological differences between subjects of different ages.

It is relevant to note that the presence of noise in tonometry recordings (Figure 2) did not impact the final attractor quality, when compared to the PPG-attractors, suggesting the SPAR method to be invariant to this noise.

The main limitation of this work lies in the small size of the training set, which was addressed by doing 10-fold cross validation to increase the robustness of the results. Furthermore, the sub-selection criteria applied to the Asklepios dataset could not be applied to the Vortal dataset due to the absence of detailed age-related metadata on the population. As a result, it is possible that individuals with high blood pressure or a BMI of over 30 were present in the Vortal dataset. However, given the large age difference between the younger and older groups, Vortal was deemed a suitable proof-of-concept PPG test set for age classification.

Model performance could be increased by implementing a more complex CNN model and using a larger population as a training set. This would allow for evaluation of the interplay between model complexity and performance. Whilst CNNs could be applied to raw pulse waves signals themselves, SPAR's robustness on noisy signals and at-a-glance summary of multiple pulse waves as a single 2D image may be more intuitive for end users for visual interpretation.

In summary, while age-related differences in pulse wave morphology are well established, we present a simple SPAR-based CNN model that classifies individuals into two closely spaced age groups within a CVD-free population. We further show tonometry and PPG signals are sufficiently related for this task. Given the infrastructure demands of gold-standard pulse wave velocity measurements for VA classification, our findings support further research into the use of SPAR with community-worn PPG devices for the detection and stratification of cardiovascular risk.

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