Predicting Age From Real World Smartphone Acquired Photoplethysmography Using Deep Learning

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Abstract

Aging is linked to structural and mechanical changes in the vascular wall. In this study, we aim to predict age from real-world, multi-smartphone-acquired photoplethysmography (PPG) signals and identify how age is represented in the waveform of the PPG. Both a standalone deep learning (DL) regression model and a hybrid regression model augmented with heartrate features were trained. Saliency maps were calculated to highlight predictive regions for age within the PPG. We included 30370 PPGs from 6472 users with a mean age of 41.9 $\pm$ 14.7 years. The standalone model had the best performance and resulted in a mean absolute error of 8.1 $\pm$ 6.6 years and an r2-score of 0.49. Saliency maps highlighted the dicrotic notch as the most important region. This area has been linked to arterial stiffness and vascular age. This study demonstrated the feasibility and rationale to estimate of chronological from smartphone-acquired PPG signals.

1. Introduction

Photoplethysmography (PPG) is a low-cost, optical technique used to detect blood volume variations in the arteries resulting from the cardiac cycle. Analysis of the PPG and its derivatives yields valuable clinical information, such as blood pressure, arrhythmia presence and heart rate variability [1]. However, this analysis must consider that PPG is influenced by numerous, often correlated factors, including external influences like motion and ambient light, as well as patient characteristics such as skin thickness, arterial stiffness, and age [1, 2].

Age is one of the most critical factors for assessing cardiovascular health [3] and is linked to structural and mechanical changes in the vascular wall, leading to increased arterial stiffness and consequently influencing the PPG waveform [4]. Age has been found to manifest in the PPG waveform through differences in the timing of the waveform features as well as differences in their relative amplitudes (Figure 1) [1].

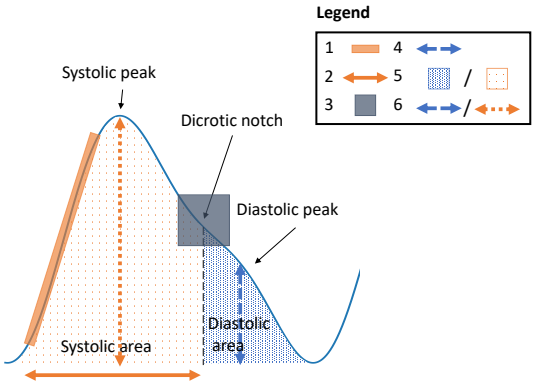

Figure 1. PPG waveform with age related fiducial points. 1: systolic rising edge, 2: systolic time, 3: dicrotic notch shape, 4: diastolic peak amplitude, 5: inflection point area = $\frac{diastolic\ area}{systolic\ area}$, 6: reflection index = $\frac{diastolic\ peak\ amplitude}{systolic\ peak\ amplitude}$.

Previous studies have focused on using the PPG waveform features to define models determining age from the PPG. Ferdinando et al. included 657 hospital recorded PPGs sampled at 1 kHz, classifying patients into decade age groups with an accuracy of 88% [5]. The studies of Abrisham et al. used a virtual PPG database sampled at 500 Hz containing 4374 subjects to classify decade age groups achieving an accuracy of up to 99% [6, 7]. Dall'Olio et al. was the first to report the use of real-world smartphone-acquired PPGs sampled at 30 Hz, and predicted age from 3612 users achieving a binary AUC

of 95.3% for classifying patient below 40 and above 60 and a root-mean-squared-error (RMSE) of 12.3 for their deep learning (DL) regression approach [8]. Lastly, Shin et al. used 752 controlled environment hospital PPGs that were acquired with a specially designed sensor, measuring at 125-250 Hz. Their DL approach focused on a single beat and obtained a RMSE of 10.3 years. They additionally highlighted the importance of the pulse onset for the prediction using Grad-CAM [9].

This paper proposes a regression model to predict chronological age using a large real-world, low-frequency, multi-smartphone-acquired PPG dataset, aiming to bridge the gap between controlled-environment performance and real-world applicability (RMSE 10.3 vs 12.3). Additionally, this study aims to identify the representation of age within the PPG waveform through the use of saliency maps.

2. Materials and methods

2.1. Data

Data included was retrieved from real-world users between 18 and 75 years old with at least one sinus rhythm PPG measurement. Recording were acquired between January 1, 2023 and March 31, 2024, and collected with the user's personal smartphone using the Fibricheck app. To asses the effect of healthy aging, clinical parameters more prevalent in the elderly population such as diabetes, hypertension, stroke, heart failure, and artery disease, which are known to affect the PPG waveform, were excluded [10]. Additionally, users were excluded if they had no registered gender or age or had a pacemaker. On measurement level, PPG signals that contained ectopics or had a measured heart rate outside 50 to 100 beats per minute were excluded to ensure accurate waveform representation and minimize information loss due to the low sampling rate (30Hz) as compared to clinical PPGs (100-1k Hz)) reported in previous studies. Users were randomly split into training (70%), validation (10%) and test (20%) sets. For users with multiple PPGs over time, all PPGs were included in the training and validation sets to maximize the training data. In the test set, only the first available PPG was included, ensuring the performance reflects the demographics of the user group accurately.

2.2. Pre-processing

The reflected light, captured with the smartphone camera, is processed into r, g, b, and y channels. For this study, only the r and g channels were selected, in which the PPG is morphological more pronounced. All PPG signals were measured for 60 seconds and interpolated to a frequency of 30Hz. Next, the signals were filtered using a 6th order Butterworth bandpass filter with cutoff frequencies of 0.5Hz and 10Hz to remove baseline wander and high-frequency noise. Subsequently, the signals were normalized and truncated to 1800 samples. The pre-processed signals are segmented into windows of 16 consecutive heartbeats with a step size of 4 heartbeats and interpolated to a vector of 1024 samples to obtain equally sized inputs. Heartbeat detection was derived from a proprietary algorithm at Fibricheck [11]. During training, all windows were used as input for the model. In the evaluation phase, the average predicted age was calculated across all windows belonging to the same PPG signal.

2.3. Model

The InceptionTime architecture was implemented using TensorFlow (TensorFlow, Google, Mountain View, CA, USA) backend on Amazon Web Services (AWS, Seattle, WA, USA). InceptionTime is a DL architecture designed for time series classification, known for its robust performance, high versatility in capturing temporal patterns, efficient feature extraction and scalability [12]. To adapt the model for regression, modifications included removing the last SoftMax activation layer and replacing it with a dense linear layer.

Input to the model are windows of 16 consecutive heartbeats which are interpolated to the same length for all PPGs. The interpolation step causes the loss of information about the heart rate and heart rate variability (HRV) within each PPG. To asses the importance of these features, an additional hybrid DL model was trained that fuses both the signal features as well as the heartrate features (heartrate, HRV and scaling factor=original length/1024). The output layer was adapted by adding a fully connected layer of size 128 after the pooling operator. This layer was concatenated with the heartrate features to a layer of size (128+3) and an additional fully connected layer of size 64 was added before the output. Both the standalone DL and the hybrid DL model layout are shown in Figure 2.

The model was trained using the Adam optimizer, an initial learning rate of 0.001 and the mean absolute error loss. Training continued until no further improvements were observed in the validation loss for 7 consecutive epochs or when the model completed 30 epochs. Additionally, the learning rate was reduced by a factor of 10 if the validation loss did not improve over 5 consecutive epochs.

2.4. Evaluation metrics

The age estimation performance of the regression models was evaluated using the mean-absolute-error (MAE) and its standard deviation (std), the RMSE and the coefficient of determination (r^2). Saliency maps were used to

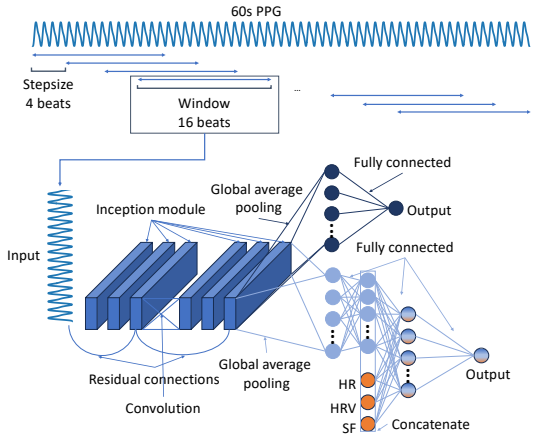

Figure 2. Model outline standalone versus hybrid. HR = heartrate, HRV = heart rate variability, SF = scaling factor.

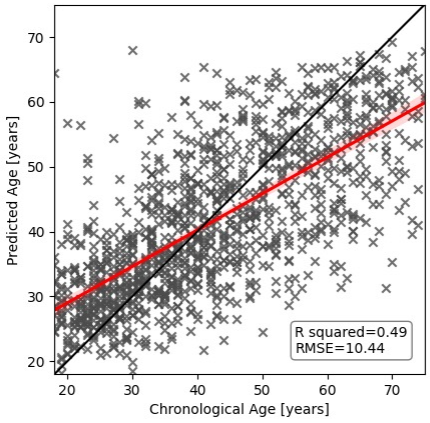

Figure 3. Scatter plot showing the chronological age versus predicted age. The red line represents the regression fit.

highlight areas in the PPG that were most influential for the age prediction. Saliency maps calculate the gradient over the output with respect to the input, with higher weight indicating higher relevance for the prediction [13]. For the estimation of the saliency maps, all windows of the first PPG for each user were used. For visualization, the waveform and the corresponding maps are averaged within and across patients .

3. Results

3.1. Data

After applying the exclusion criteria, 30370 PPGs from 6472 users were selected. The training, validation and test set consist of 4276, 623 and 1210 users with mean age at the index PPG of 41.9 $\pm$ 14.7 years, 41.8 $\pm$ 14.7 years and 41.8 $\pm$ 14.7 years respectively.

3.2. Performance

The results for the standalone and hybrid regression models are given in Table 1. Best performance was obtained for the standalone model. Figure 3 shows the comparison between the estimated and actual ages for this model.

Table 1. Model performances standalone model versus hybrid model. MAE = mean-absolute-error, RMSE = root-mean-squared-error, r^2 = coefficient of determination.

Model	MAE (years)	RMSE (years)	r^2
Standalone	**8.1 $\pm$ 6.6**	**10.4**	**0.49**
Hybrid	8.4 $\pm$ 6.6	10.6	0.48

Figure 4 shows the saliency map for the average waveform over 200 random PPGs in the testset. The results suggest that the area around the dicrotic notch, the diastolic peak and the systolic rising edge play an important role in the prediction of the age.

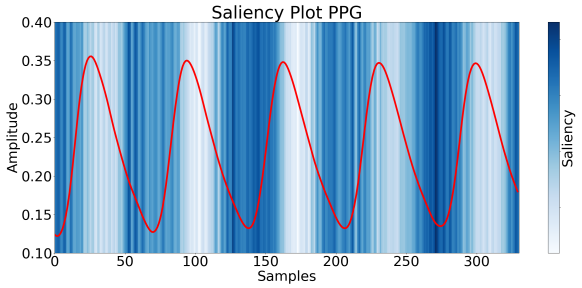

Figure 4. Saliency map of the average PPG zoomed in on the middle 5 heartbeat. The red line depicts the average PPG. The background indicates the gradient. Darker regions indicate higher weight in the prediction.

4. Discussion and conclusion

The best model (standalone model) achieved a MAE of 8.1 $\pm$ 6.6 years, a RMSE of 10.4 years, and an r^2 of 0.49, matching current state-of-the-art DL approaches. The saliency map emphasizes fiducial points often used for cardiac assessment and pulse wave velocity calculations [14], which serve to calculate vascular aging. However, the saliency results contrast with Shin et al.'s study [9], which focused more on the area around the systolic peak. This difference could be attributed to their focus on single heartbeats and the resulting loss of transitional information between beats but might also be attributed to the lack

of good evaluation metrics for saliency maps given current saliency metrics can be statistically unreliable and inconsistent [15].

Our approach distinguishes itself by using a large real-world, low-frequency, multi-smartphone-acquired PPG dataset, achieving performance previously obtained by models trained on PPGs from special dedicated clinical devices with high frequency rates, highlighting its high applicability and generalizability. Additionally, our DL approach avoids the need for an extensive list of PPG features, which highlights the expressiveness of PPG alone, especially its morphological features, in capturing age-related information.

Our model, while demonstrating strong overall performance, exhibits a MAE of over 8 years in chronological age prediction. This level of error is consistent with findings from age prediction models based on 12-lead ECG data, where reported MAEs range from 7-8 years. Notably, research has shown that this age-offset can serve as an independent predictor of both cardiovascular and all-cause mortality [16, 17]. Building on these insights, future work will focus on deepening our understanding of our model's predictions by exploring the relationship between the age-offset and various factors, including patient demographics and cardiovascular health outcome.

In conclusion, real-world smartphone-acquired PPG allows for the estimation of chronological age with similar performance obtained in controlled-environment PPG. Saliency maps highlight relevant areas for age prediction, providing rationale for the models prediction.

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