Screening Stage-2 Hypertension from Finger Photoplethysmography

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Abstract

Using UK Biobank data, we developed a machine learning model to screen for stage-2 hypertension from finger photoplethysmography waveforms and demographics data.

Keywords: hypertension, machine learning, PPG, screening

Introduction

Blood pressure (BP) is a strong predictor of cardiovascular (CV) disease and a key input for the calculation of established risk scores, such as Framingham's and atherosclerotic CV diseases risk scores [1]. Hypertension awareness remains very limited in the general population and especially in young adults [2]. In 2015, 8.5 million deaths were associated with hypertension worldwide [3], especially in low- and medium-income countries. We propose a system for screening stage-2 hypertension from finger photoplethysmography (PPG), a non-invasive and low-cost technology available on increasingly ubiquitous devices such as smartphones [4].

Methods

We used the UK Biobank dataset to retrieve finger PPG data from participants aged 40-74 years old and not receiving any hypertension medications (N=180,329 participants, 110,327 females), which were split into train (N=89,869), tune (N=40,063), and test (N=50,397) sets based on geographic information on the site of data collection. For the purposes of this work, we labeled participants with stage-2 hypertension as those with systolic BP ≥ 140 mmHg or diastolic BP ≥ 90 mmHg in the initial assessment visit (43% of the dataset).
We trained two one-dimensional residual neural networks (ResNet18) to learn two types of PPG representations from the raw PPG waveform: cardiovascular health representations (CVH-PPG) and systolic BP representations (SBP-PPG). For CVH-PPG, the ResNet18 was trained with multiple heads, including age, sex, systolic BP, HbA1c, total cholesterol, history of major adverse cardiac events, history of hypertension and presence of PPG notch [5]. For SBP-PPG, the ResNet18 was trained with a single head represented by the systolic BP of the participant, averaged if more than one measurement was available. Next, we concatenated the 512-dimension CVH-PPG embeddings and 512-dimension SBP-PPG embeddings with

demographics data, including age, sex, body mass index (BMI) and smoking status, and used L1-regularized logistic regression (C=0.001) to select features and classify people with stage-2 hypertension. The best model was selected as the one maximizing the area under the curve (AUC) on the tune set.

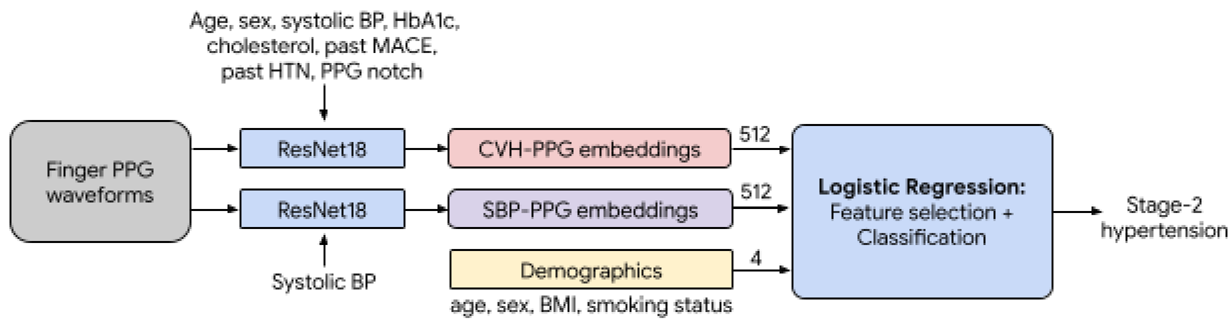

Fig. 1. Model architecture for predicting stage-2 hypertension.

Results

The model selected age, sex, BMI, 27 CVH-PPG embeddings and 23 SBP-PPG embeddings, for a total of 53 features. On the test set, the model achieved an AUC of 0.808, and sensitivity of 0.679 and specificity of 0.775. An alternative model based only on demographics achieved AUC of 0.688, sensitivity of 0.588 and specificity of 0.675. Previous models based on demographics and lifestyle metrics achieved AUC of 0.77 [6], while models based on clinical-grade ECG and PPG achieved sensitivity of 0.744 and specificity of 0.939 [7].

Conclusions

Information from finger PPG and demographics may have potential to help screen for stage-2 hypertension and increase people's awareness of their condition. Future work should explore if the near ubiquitous availability of PPG sensors in wearable and mobile devices can help reduce the underdiagnosis of hypertension globally.

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