Non-invasive Blood Pressure Estimation Using Photoplethysmography Signals

ALI SEIFI* and SAHAR MAVALI*, University of British Columbia, Canada

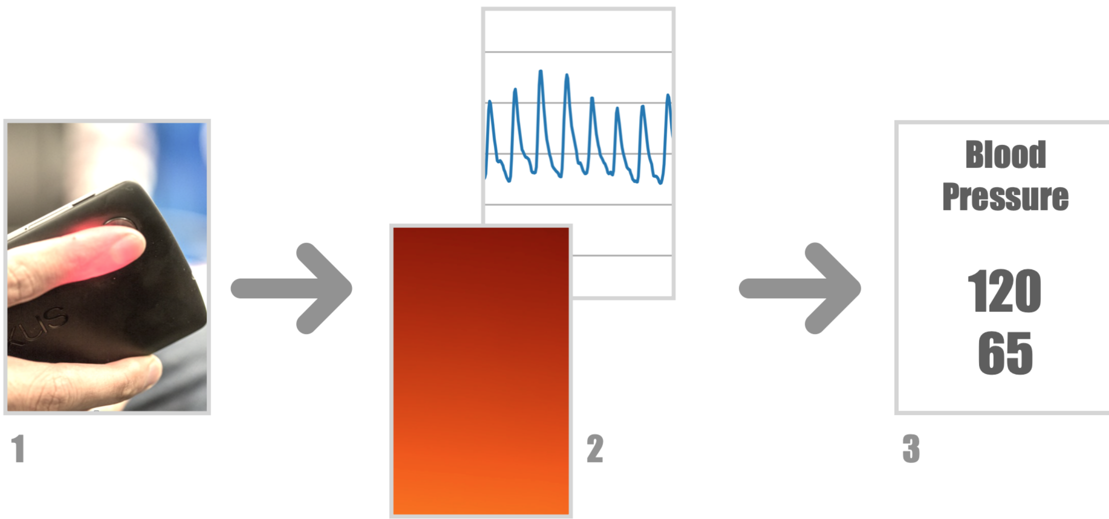

Fig. 1. The estimation process has 3 main steps, 1. the user has to record a video of his fingertip with the mobile phone, 2. the PPG signal is extracted based on light reflection, 3. the PPG is preprocessed and fed to a learning model and the blood pressure is reported to the user.

Regular measurement of blood pressure (BP) is extremely important for early detection and prevention of many diseases, especially cardiovascular conditions, hypertension and hypotension. Using common cuff-based methods for continuous BP measurement is not feasible. Therefore, an alternative method using Photoplethysmography (PPG) signals is proposed. In this project, we explore different machine learning techniques such as Random Forest Regression, Linear Regression, Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN) to estimate blood pressure from only PPG signals. We develop a smartphone application for recording videos and sending them to the server to be processed into PPG signals and report the estimated blood pressure to the user. Finally, we conduct a small study to evaluate our system in real-life cases.

Additional Key Words and Phrases: machine learning, blood pressure estimation, PPG, Photoplethysmography

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*Both authors contributed equally to this research.

Authors' address: Ali Seifi, aliseyfi@cs.ubc.ca; Sahar Mavali, smavali@student.ubc.ca, University of British Columbia, Vancouver, BC, Canada.

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1 INTRODUCTION

Blood pressure (BP) is one of the most important vital signs of the human body. Regular measurement of blood pressure can play a significant role in the early diagnosis and prevention of cardiovascular diseases. High BP which is also called hypertension, is one of the major recognized causes of stroke and heart attacks. In contrast low BP, or in other words hypotension, may lead to fainting or dizziness. Increased awareness of these conditions by measuring blood pressure can be effective in treating them on time[8].

Blood pressure is the pressure of blood on the walls of vessels. Normally BP is reported by two numbers, systolic pressure which is a highest pressure in a heartbeat and diastolic pressure which is the lowest pressure in a heartbeat. The systolic and diastolic blood pressures for a normal person in resting condition is about 120 mmHg and 80 mmHg respectively[8].

The most practiced methods for measuring blood pressure include either an invasive or a non-invasive procedure. In the invasive method, the doctors perform arterial lines management to continuously monitor the patient's blood pressure in a high accuracy setting. This method has a high risk of infection and therefore not suitable for continuous BP measurement for most patients. In the non-invasive method, an inflatable arm cuff has to be worn by the patient. The cuff-based method is time-consuming and brings discomfort for many patients. It also presents mobility limitations and the patients should keep steady during the measurement process. Therefore, using the cuff-based method for continuous BP monitoring is not feasible[9].

Photoplethysmography (PPG) is a signal that is obtained by measuring the amount of light absorption or reflection by blood vessels[9]. The technique behind measuring this signal is very simple. A light source emits light that passes through the skin and the skin tissue and a photo detector measures the changes in the light intensity that occur because of the change of blood volume in the tissue. This signal can provide us with information regarding heart rate, blood oxygen saturation, and blood pressure. The technology behind PPG signals is versatile and low-cost. An important advantage of PPG signals is that they can be measured by smartphones and smartwatches without further need for other medical devices. In a clinical setting this signal can be measured by a pulse oximeter from the patient's fingertip. Alternatively the signal can be achieved by recording a video of the patient's fingertip using a smartphone. The non-invasive nature of this signal combined with its versatility makes it a great candidate for continuous blood pressure measurement. However, high levels of noise in measuring PPG signals are the main disadvantage of PPG-based measuring[8].

Machine learning and deep learning have proven to be specially effective for performing BP estimation using cuff-less methods. In this project we developed a smartphone application that provides a simple and understandable interface for extracting PPG signals without further need for medical devices. Several machine learning and deep learning techniques were explored and used for estimating blood pressure based on PPG signals and the best one using ANNs with predefined features was applied to the input signal. The blood pressure is then reported back to the user.

In section 2 we will discuss the related works in this area. In section 3 we will talk about our data acquisition and methodology. In section 4 we will talk about PPG extraction methods and the mobile app developed for this task, and in section 5 we will talk about the evaluation strategy and discuss the results.

2 BACKGROUND AND RELATED WORK

With recent advances in machine learning and deep learning many researchers have explored using these techniques to extract blood pressure from easy to obtain signals such as PPG. Kurylyak et al.[6] wrote one of the most cited papers in this area and his paper was one of the first papers to use deep learning for BP estimation. They extracted 21 features from each PPG heart beat and trained an artificial neural network with two hidden layers that gave systolic and diastolic BP as output per pulse. While their reported results are very satisfactory, their data was extremely limited and that could be a reason for the high accuracy of their method.

Schlesinger et al.[8] used a different approach and extracted frequency domain features from the PPG signal to use as training data. They used PPG and BP signals from MIMIC-II data base and performed extensive preprocessing to clean out data from possible outliers such as improbable BP values, noisy signals, unstable peaks in BP signal and unreliable patients. The trained a CNN of PPG signal spectrograms and reported their results once without calibration and once with calibration. They performed calibration using the first PPG frame of each patients record and implemented a Siamese network for predicting the error from the calibration window.

Wang et al.[10] used spectral features of the PPG signal with addition to two morphological features, the systolic upstroke time and the diastolic time. For spectral features they used MTM or Multi Tapering Method that uses multiple data windows called Slepian sequences to extract 20 spectral features from each PPG pulse. They feed the 22 extracted features to an artificial nerual network and compare their results with approaches using linear regression and RSVM based methods.

Khalid et al.[5] performed baseline removal and waveform normalization of PPG signals from University of Queensland vital signs dataset and extracted 5 time-domain features from each PPG signal and systolic and diastolic BP from reference BP signal. They tried and compared three machine learning algorithms, Multilple Linear Regression (MLR), Support Vector Machines (SVM), and Regression Tree among which Regression Tree had the best results in terms of mean absolute error.

3 METHODOLOGY

In this section, we discuss the our datasets, preprocessing techniques, feature extraction and machine learning methods that were used in our project.

3.1 Dataset

We used two datasets in this project. The first one from Kachuee et al.[4] consists of PPG signals from fingertip, ABP signals (invasive arterial blood pressure), and ECG signals from channel II. All three signals were collected with a frequency of 125 Hz. We only used the PPG and ABP signals in our project. The second dataset from Esmaili et al.[3] consists of vital signals such as PPG, BP, FSR, PCG, and ECG along with patients age, height, and weight for 26 patients.

We experimented with both datasets and chose the first one by Kachuee et al. for our final results because the data was cleaner and less noisy and the blood pressure could be extracted per pulse whereas in the second dataset the ABP was reported in certain time intervals.

In Figure.2 you can see the distribution of data we used in terms of systolic and diastolic BP based on values extracted per heart beat. A total of 1,075,840 pulses were used in training the models. The pulses with systolic BP higher than 140 or diastolic BP higher than 90 which corresponds with hypertension were 26.2% of heartbeats used as training data.

3.2 Data Preprocessing

Our data were raw PPG signals and ABP signals or reports depending on the dataset. Extracting windows and aligning blood pressure and PPG windows were required. For data from Esmaili et al. dataset data cleaning was also required to

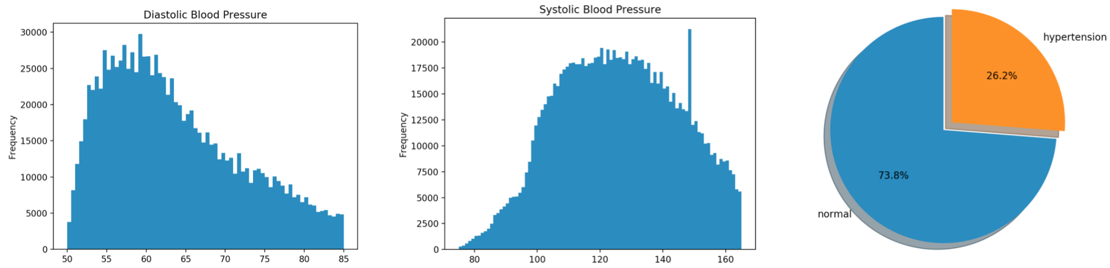

Fig. 2. You can see the distribution of systolic and diastolic blood pressures per pulse in the middle and left plots. On the right shows the percentage of normal and hypertensive pulses in the training data.

remove noise. Windows with systolic blood pressure outside the range of (75, 165) and diastolic blood pressure outside the range of (40, 85) were detected as outliers and removed because values outside these ranges are not possible.

3.3 Feature Extraction

Based on our readings and research on this topic we performed feature extraction both in time-domain and frequency domain. For frequency domain features, we normalized extracted windows from the preprocessing step and applied Short-Time Fourier Transform (STFT) on each window. In Figure.3 you can see the STFT of a single PPG window. As for time domain features, we experimented we two sets of features. The first one inspired from Kurylyak et al.[6] consisted of 21 features per PPG heart beat listed below:

- Systolic upstroke time (SUT), diastolic time (DT), and cardiac period
- Diastolic width at 10%, 25%, 33%, 50%, 66%, and 75% of pulse height
- Diastolic width + systolic width at 10%, 25%, 33%, 50%, 66%, and 75% of pulse height
- Diastolic width / systolic width at 10%, 25%, 33%, 50%, 66%, and 75% of pulse height

The second set of features were inspired by Khalid et al.[5] and consisted of pulse area, systolic upstroke time, diastolic time and pulse width at 25%, 50%, and 75% of the pulse height. The values for systolic and diastolic blood pressure was also extracted from each pulse in the ABP signal. The highest and lowest points in the pulse were reported as systolic and diastolic BP respectively.

3.4 Machine Learning Techniques

We experimented with different machine learning techniques and trained them on out datasets. In this section a brief explanation of each method is included.

3.4.1 Linear Regression. In linear regression with n input features, we define a linear model with n coefficients and seek to minimize the sum of square errors between the data points and the predictions made by the linear model.

3.4.2 Lasso Regression. Lasso regression is a form of linear regression in which the cost function is not just the sum of squared errors. The cost function is Lasso regression is altered by adding the squared sum of the coefficients[2]. With

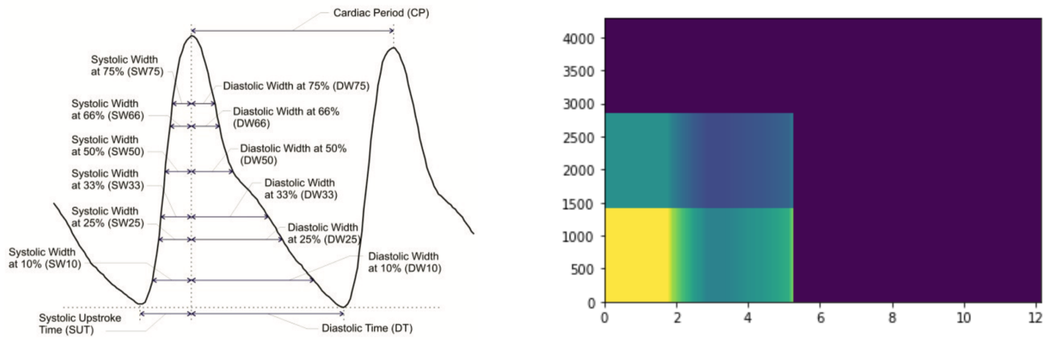

Fig. 3. On the right: the STFT for a single PPG pulse. On the left: 21 features extracted based on a paper from Kurylyak et al. [6] shown on a PPG pulse.

M data points and p input features the cost function is

$$\sum_{i=1}^{M}(y_i - \hat{y}_i)^2 = \sum_{i=1}^{M}(y_i - \sum_{j=0}^{p}(w_j \times x_{ij}))^2 + \lambda \sum_{j=0}^{p}|w_j|. \tag{1}$$

We used 1,075,840 pulses as training data and 226,241 pulses as test data for both Lasso and linear regression.

3.4.3 Random Forest Regression. Random Forest regression works by applying an ensemble method to perform regression using multiple decision trees. In Random Forest multiple trees are constructed and the output is the mean prediction of the decision trees. It uses Bootstrap Aggregation or bagging and trains each tree with a different sample of data. This prevents over-fitting and makes Random Forest method one of the most accurate existing learning methods[1]. We trained a Random Forest with 200 estimators (trees) and means squared error as criterion twice, each time on one of the two sets of data, first preprocessed with 5 input features and second preprocessed with 21 input features extracted from each PPG pulse. We used 1,075,840 pulses as training data and 226,241 pulses as test data.

3.4.4 Artificial Neural Networks. We trained a multi-layer feed forward ANN with two or three hidden layers. We tried different combinations of number of hidden layers and number of nodes in each layer. Our final output came from training with 2 hidden layers each with 128 nodes with Relu activation function. We used mean squared error as our loss function and Adam optimizer with batch size of 64 and 500 epochs of training. We trained the ANN with both 5 time domain features and 21 time domain features extracted per pulse. We had 1,075,840 pulses for training data, 226,241 pulses for test, and 174,720 pulses for validation.

3.4.5 Convolutional Neural Networks. A CNN with 5 convolutional layers with kernel size of 3 and tanh activation function with a Max pooling layer following the first, second and fifth convolutional layer and 2 fully connected layers with Relu activation function in the end was constructed and trained on Short-Time Fourier Series spectrograms extracted from the PPG signal. We used mean absolute error as loss function and Adam as optimizer. We had a train-test split of 70-15-15 for train, test, and validation data.

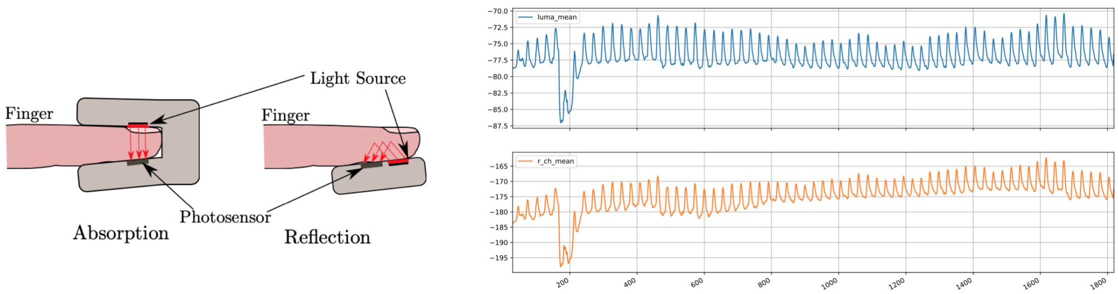

Fig. 4. On the left: the difference between reflection and absorption for PPG extraction[7]. On the right: PPG signal extracted from recorded video of user's fingertip.

4 PPG EXTRACTION

An important advantage of PPG signals is that they can be obtained easily using smartphones. We were very interested in this advantage and developed a smartphone application which extracted user's PPG signal using the phone's camera as a photo detector. We used a reflection based method for PPG signal extraction implemented by Lovisotto et al.[7] for detecting biometrics from PPG signals.

4.1 Method

In clinical pulse oximeters, absorption based detection of PPG signals is performed. In those devices the photo detector and light source are placed on two sides of the fingertip and therefore the photo detector is receiving the light that is not absorbed by the skin tissue. Lovisotto et al.[7] implemented the extraction system based on reflection. Using the smartphone's camera flash as a light source and the smartphone's camera as a photo detector, means that the camera is detecting the light reflected from the user's fingertip. In Figure.4 from their paper Seeing Red you can see this difference.

In this method, the user places his finger on the smartphone's camera while the camera flash is on. A video of the user's fingertip is recorded. To extract the PPG signal from this video, in each frame, the mean of pixel-wise luma component is calculated in RGB channels. If the input video is defined as a sequence of frames $f_1, f_2, ..., f_m$, then the PPG signal extracted from the video is constructed as $S = \{Y(f_1), ..., Y(f_m)\}$ and

$$Y(f) = \frac{1}{n} \sum_{i,j \in f} (0.299 f_{ij}^{(r)} + 0.587 f_{ij}^{(g)} + 0.114 f_{ij}^{(b)}). \tag{2}$$

The output signal can be seen in Figure.4. After extracting the signal S some preprocessing is applied. A rolling average with a window size of 1 with the signal is computed and subtracted. Then a low-pass filter with cut off frequency of 4 Hz is applied to remove further noise.

4.2 Smartphone Application

We developed a simple and easy to use android application for blood pressure estimation using smartphones. We implemented a simple client-server network with our computer containing the machine learning model and the signal extraction code based on the paper Seeing Red. The scenario of using this application consists of the following steps:

(1) The user chooses the SET IP option in the main menu.
(2) The user enters the computer's IP address to establish the client-server connection.

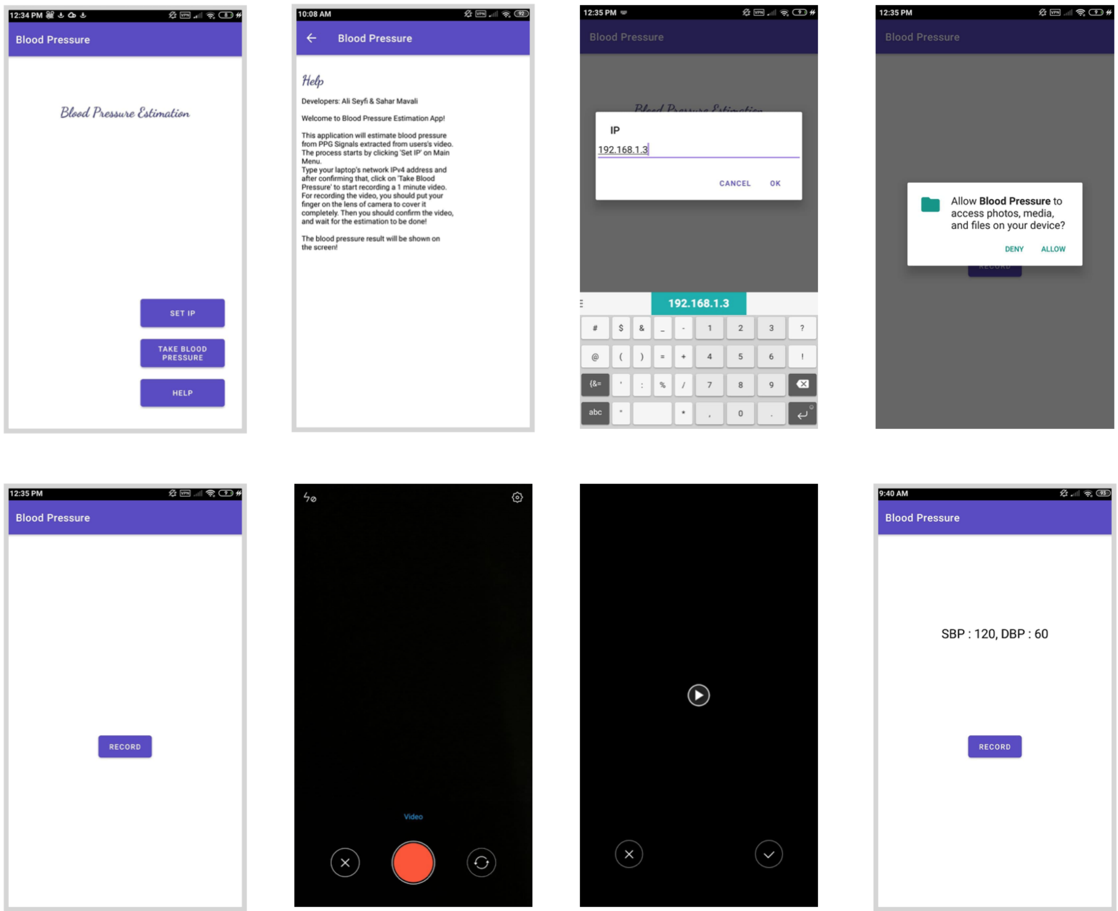

Fig. 5. Screenshots of different steps in the BP estimation smartphone application

(3) The user chooses the Take Blood Pressure option in the main menu.
(4) A prompt is shown asking for permission to access information on the device.
(5) The user grants permission to the application.
(6) The user presses Record button to activate the devices camera.
(7) The user puts his index fingertip on the smartphone's camera and presses the red button to start recording.
(8) A 60 second video of the fingertip is recorded and after 60 seconds the user is able to watch the video and accept it or try a new recording.
(9) The video is sent to the computer and the PPG signal is extracted.
(10) The signal is given to the machine learning model and the prediction is returned as output.
(11) The systolic and diastolic blood pressure values are sent back to the smartphone and displayed to the user.

Table 1. Mean squared error and standard deviation for learning methods in mmHg

Results	Random Forest	Lasso Regression	Linear Regression	CNN	ANN
Systolic Mean Absolute Error	18.63	15.24	15.24	19.11	13.82
Diastolic Mean Absolute Error	6.77	5.40	5.40	10.71	5.47
Systolic Standard Deviation	12.92	9.97	9.97	17.82	16.97
Diastolic Standard Deviation	5.04	3.81	3.81	12.05	6.69

Table 2. The results of study with 6 participants using ANN

results	Mean Absolute Error	Standard Deviation
Systolic	17.28	11.69
Diastolic	8.52	6.88

5 EVALUATION

5.1 Results

As mentioned in previous sections, we tried three different feature extraction methods and trained different machine learning models on these features. In Table.1 you can see the mean absolute error and standard deviations of our best experiments for systolic and diastolic blood pressure which were frequency features for CNN and 21 features for other methods.

We initially performed a train-test split on our data with 70% for training, 15% for testing, and 15% for validation. With these settings, we got very good results in terms of accuracy. When compared to the outputs of the model for custom extracted PPG signals, we found out that the models do not work well on custom PPG. We looked into the problem and found out that our test outputs were not reliable because some records in the test and train data belonged to the same people and the test data was contaminated by the training data. We acquired more data which were completely independent from the training data and trained our models with the new sets of test and validation data.

While the linear and Lasso regression show the best results numerically, after inspecting the outputs we found out that they reported outputs very near the mean values for systolic and diastolic in all cases and therefore were not reliable models. Disregarding these two models, the ANN had the best results in terms of MAE and the Random Forest had the best Standard Deviation.

5.2 Study

In order to better evaluate our system, we conducted a small user study with 6 participants (3 women and 3 men). We asked our participants to put their index finger on the mobile phone's camera while the flash was on and recorded a 60 second video. We repeated this process three times for each participant and measured their blood pressure with at home BP measurement devices. You can see the mean absolute error and standard deviation of these predictions using our ANN based method in Table.2. Because of COVID restrictions we only had access to a small number of participants (our family members).

6 CONCLUSION AND FUTURE WORK

In this project we explored different machine learning techniques and feature extraction schemes to predict and estimate systolic and diastolic blood pressure using PPG signals. We developed a smartphone application that used the camera to record videos of user's fingertip to extract PPG signals without need for clinical devices and report the predicted blood pressure values based on an artificial neural network model. There is room for improving the performance of our models. This can be done by looking into more learning methods or feature extractions and further fine-tuning of tried methods. A larger scale user study can be very effective for better evaluating the application and the prediction results for real situation. Experimenting with different datasets and preprocessing techniques can also lead to improvements in the model's outputs.

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