# Blood Pressure Prediction by a Smartphone Sensor using Fully Convolutional Networks

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***Abstract*— Heart disease and stroke are the leading causes of death worldwide. High blood pressure greatly increases the risk of heart disease and stroke. Therefore, it is important to control blood pressure (BP) through regular BP monitoring; as such, it is necessary to develop a method to accurately and conveniently predict BP in a variety of settings. In this paper, we propose a method for predicting BP without feature extraction using fully convolutional neural networks (CNNs). We measured single multi-wave photoplethysmography (PPG) signals using a smartphone. To find an effective wavelength of PPG signals for the generation of accurate BP measurements, we investigated the BP prediction performance by changing the combinations of the input PPG signals. Our CNN-based BP predictor yielded the best performance metrics when a green PPG time signal was used in combination with an instantaneous frequency signal. This combination had an overall mean absolute error (MAE) of 5.28 and 4.92 mmHg for systolic and diastolic BP, respectively. Thus, our CNN-based approach achieved comparable results to other approaches that use a single PPG signal.**

## I. INTRODUCTION

High blood pressure, clinically referred to as hypertension, is known as a "silent killer" due to its inconspicuous symptoms and potentially life-threatening complications. It is therefore important for individuals to control their blood pressure (BP) through regular BP measurements. However, BP may increase or decrease temporarily depending on an individual's situation, such as their location and the time of day when BP is measured. "Masked hypertension" occurs when the individual's BP is actually high but is measured as normal in a doctor's office. This phenomenon is present in approximately 10% of normal adults and may cause more damage to the heart or other organs than clinically detected normal, thus requiring more thorough BP control [1]. Conversely, "white coat hypertension" occurs when the patient is nervous when seeing a doctor and therefore their BP increases despite their actual BP being normal. This phenomenon is reported to occur in approximately 15% of the general population and in approximately one-third of patients diagnosed with hypertension [2]. Medication should be given to patients with white coat hypertension who also have damage to organs such as the heart, brain, and kidneys and those who are at high risk for cardiovascular disease. Therefore, in order to make an accurate diagnosis, it is important to self-measure BP periodically in a relaxed state in addition to regularly having BP measurements performed by a medical professional in a clinical setting. Periodic self-measurement of BP is highly reproducible and provides clinically important information in the diagnosis and treatment of hypertension, which is very useful for long-term BP management. Furthermore, self-measurement is beneficial for the evaluation of BP changes over time, and reduces the inconvenience and cost of regular visits to medical institutions for monitoring.

Despite the many advantages of self-measurement of BP, the conventional commercially available autonomous BP measuring devices are difficult to carry and use outside the home, and are challenging to use during walking. Therefore, it is necessary to develop a method for accurate, comfortable and convenient BP self-measurement that can be used in a variety of settings. Recently, various studies have been conducted regarding the prediction of BP through single photoplethysmography (PPG) signals measured by one PPG sensor [3]–[7]. In addition, multi-wavelength PPG detection technology has been shown to be superior to single-wavelength PPG, and it has been considered a powerful method for measuring PPG signals [8]. It has also been noted that PPG sensing light sources of different wavelengths are recommended for different skin tones [9]. Previous studies on BP prediction using PPG signals generally consist of feature extraction followed by machine learning or regression-based prediction. A variety of combinations of PPG signal features, including time-domain, frequency-domain, and entropy-based features, among others, have been used to date as key features for BP prediction. Recently, in BP prediction research using electrocardiography (ECG) in conjunction with PPG signals, an end-to-end approach with self-generated features using deep-learning technology has been used [10], [11]. In this paper, we propose a method for predicting BP without feature extraction using only PPG signals measured by smartphone using the convolutional neural networks (CNN) model proposed in the previous study [11]. Instead of using additional physiological cardiovascular signals, multiple wavelengths of PPG (infrared, red, green, blue) signals were measured using the smartphone's heart rate monitor sensor and analyzed to determine the optimal combination of PPG signals for

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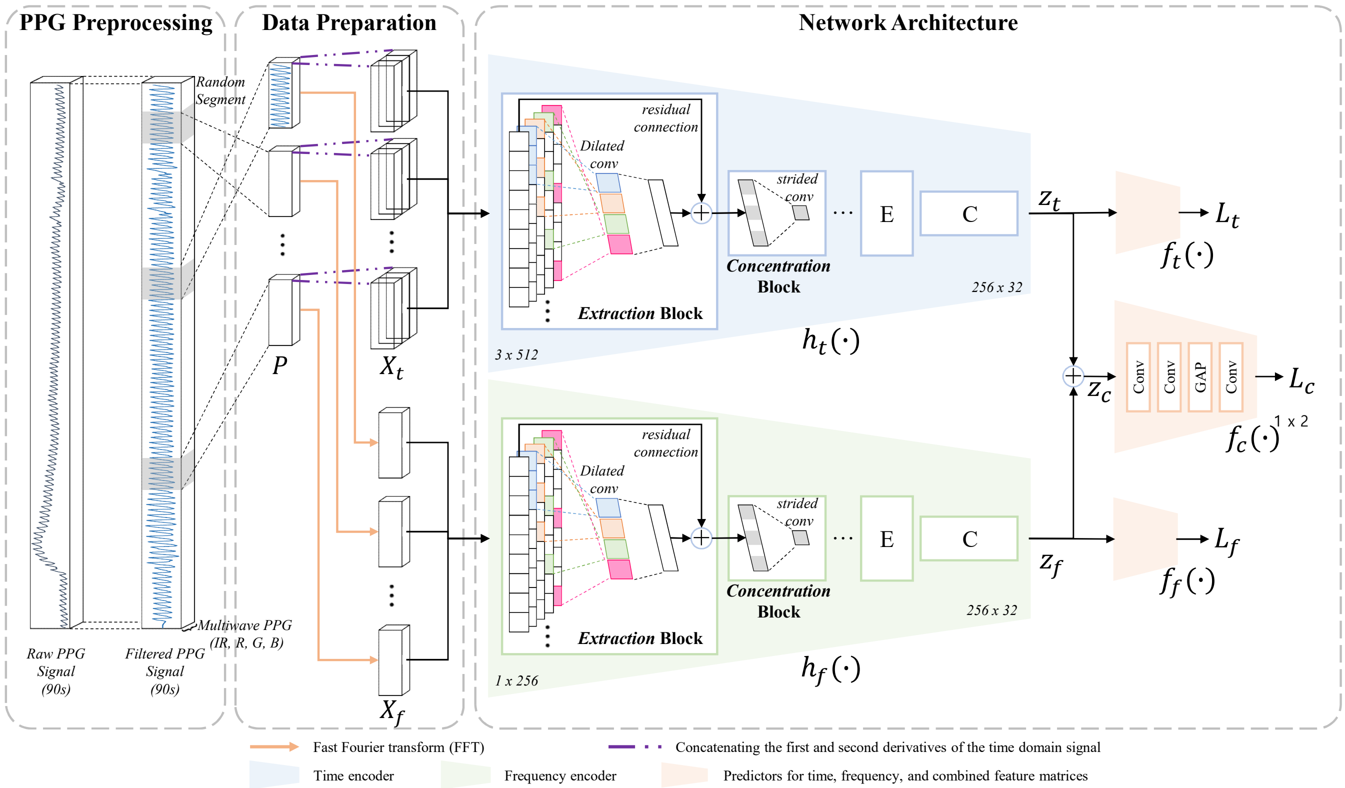


Fig. 1. Overview of the BP prediction methodology.

predicting systolic BP (SBP) and diastolic BP (DBP). The main contributions of our work are summarized as follows:

- We proposed a novel end-to-end method of predicting BP using only a single PPG signal without manual feature extraction
- We optimized BP prediction performance by testing various combinations of PPG signal wavelengths to maximize prediction accuracy
- Our CNN-based approach achieved comparable results to other approaches that require a single PPG signal

## II. Method

The BP prediction process involved acquiring multiple wavelengths of PPG signals from a smartphone, PPG signal preprocessing, data preparation, and BP predictions using a CNN-based prediction model. A schematic of the methodology is depicted in Fig. 1.

### A. Data Acquisition

PPG data were acquired using the heart rate sensor of the Samsung Galaxy Note8 smartphone. The sampling frequency was 100 Hz and four multi-wavelength PPG signals were used: infrared (IR), red (R), green (G), and blue (B). The data was collected from 26 volunteers. In all experiments, informed consent was obtained from all subjects and the data were used anonymously only for the intended research purpose. Also, the principles outlined in the Helsinki Declaration were followed. The PPG data was collected 23 times in 90 s length under various conditions including resting, exercising and sleeping. In the resting condition, the subject was seated and the reference BP measurement and PPG signal gathering was performed simultaneously in 2 minute intervals. During the exercise condition—which was intended to induce an increase in BP—the subject performed the leg press exercise with a weight in the range of 5 to 40 kg depending on their exercise abilities. After the exercise session, the subject was asked to sleep for 2 hours to decrease their BP. For the reference BP reading, two trained nurses measured BP simultaneously using the auscultatory method. The nurses' values for each reference reading were averaged unless the values had a difference of greater than 4 mmHg.

### B. Preprocessing of the PPG signals

The PPG signal was first resampled at a sampling rate of 250 Hz and detrended to remove direct current components. Next, a bandpass filter with a passband of 0.4-8 Hz was applied to separate out the noise components.

### C. PPG signal selection

To investigate the influence of the four multi-wavelength PPG signals on the performance of the BP prediction method, we investigated 15 PPG signal combinations as follows: IR, R, G, B, IR+R, IR+G, IR+B, R+G, R+B, G+B, IR+R+G, IR+R+B, IR+G+B, R+G+B, IR+R+G+B.

### D. Data preparation for CNN model training

The dataset contained a set of 90 s of raw IR, red, green, blue PPG signal data in the form $P_i =$

$(p_i^{\mathrm{IR}}, p_i^{\mathrm{Red}}, p_i^{\mathrm{Green}}, p_i^{\mathrm{Blue}})$, with SBP and DBP values denoted by $Y_i = (y_i^{\mathrm{SBP}}, y_i^{\mathrm{DBP}})$, where $i$ is the subject index. The PPG signal data was separated into training (60 s), validation (10 s), and test (20 s) datasets. The data was prepared as input and output data pairs (x,y) suitable for CNN model training. Three data preparation techniques were used: random cropping, increasing input depth using its derivatives, and fast Fourier transform (FFT). Random cropping allows the model to learn signals from multiple points of input. Since our model required both time and frequency components as input signals, we concatenated the first and second derivatives of the time-domain signal to the original time-domain signal to increase the depth of the input signal as follows [12]:

$$X_t = X_t \oplus \Delta X_t \oplus \Delta^2 X_t \tag{1}$$

Finally, we converted the original time-domain signal to a frequency-domain signal using FFT. Thus, the dataset $(X_t, X_f, Y)$ was prepared for CNN model training.

### E. Network architectures

To learn the frequency characteristics as well as time features from the original PPG, we proposed a CNN-based BP prediction model. It consists of three parts: a time encoder, a frequency encoder, and three predictors for time, frequency, and combined feature matrices. The time encoder $h_t(\cdot)$ learns representative features from time-series inputs $x_t$, and outputs the corresponding feature matrix $z_t$. In parallel with the time encoder, the frequency encoder $h_f(\cdot)$ outputs the feature matrix $z_f$ for the frequency domain inputs, $x_f$. Each encoder is composed of two stacked core modules named the *extraction* and *concentration blocks*, which are designed to effectively learn latent features from the periodic data. The *extraction block* can learn the various relationships between different neighboring pixels through multiple dilated convolutions, whereas the *concentration block* can consider a wide range of multiple pixels together in the down-sampling step through strided convolution. Both the time encoder and the frequency encoder consist of four *extraction*+*concentration* combinations. After feature extraction through both the time and frequency encoders, the combined feature matrix $z_c = z_t \oplus z_f$ can be defined. The combined predictor $f_c(\cdot)$ consists of a double stacked convolution layer, global average pooling, and a dimension reduction convolution layer. The output $\hat{y}_c$ of $f_c(\cdot)$ is two real numbers which indicate SBP and DBP. The prediction minimizes the distance between the target $y$ and the prediction $y_c$. The minimization objective is defined as

$$L_c = d(y_c, \hat{y_c}), \tag{2}$$

where $d$ can be any distance metric between real numbers; in this case, L1. In addition to this, two auxiliary flows from the predictors $f_t(\cdot)$ and $f_f(\cdot)$ were added which take the pre-concatenated features $z_t$ and $z_f$ as inputs, respectively. Both auxiliary predictors have a simpler structure which consists of one convolution layer, global average pooling, and a dimension reduction convolution layer. Auxiliary loss is a well-known technique to help the model's gradient flow in the back-propagation phase and improve performance. We introduce the importance factor $\alpha$ to both losses $L_t$ and $L_f$ . Our final loss is then defined as follows:

$$L_{\mathrm{total}} = L_c + \alpha(L_t + L_f), \tag{3}$$

where the weight of auxiliary loss $\alpha$ = 0.2, in this case.

TABLE I

BP PREDICTION PERFORMANCE BY THE INPUT PPG COMBINATIONS

| | SBP | | DBP | |
|---|---|---|---|---|
| | MAE† | STD‡ | MAE | STD |
| Infrared | 5.69 | 1.64 | 5.02 | 1.79 |
| Red | 6.24 | 2.40 | 5.74 | 2.98 |
| Green | **5.28** | 1.80 | **4.92** | 2.42 |
| Blue | 5.53 | 1.77 | 4.92 | 2.05 |
| Infrared+Red | 6.02 | 1.91 | 5.42 | 2.25 |
| Infrared+Green | 5.92 | 2.49 | 5.32 | 2.04 |
| Infrared+Blue | 5.67 | 2.20 | 5.36 | 2.51 |
| Red+Green | 5.38 | 1.73 | 5.10 | 2.16 |
| Red+Blue | 5.56 | 1.86 | 5.29 | 2.93 |
| Green+Blue | 5.56 | 2.06 | 5.44 | 2.46 |
| Infrared+Red+Green | 6.03 | 4.17 | 5.58 | 2.66 |
| Infrared+Red+Blue | 5.78 | 2.27 | 5.63 | 2.49 |
| Infrared+Green+Blue | 5.81 | 2.13 | 5.34 | 2.54 |
| Red+Green+Blue | 5.68 | 1.80 | 5.21 | 2.38 |
| Infrared+Red+Green+Blue | 5.32 | 1.49 | 5.32 | 2.49 |

† MAE = mean absolute error, ‡ STD = standard deviation

## III. Experimental Results

### A. Implementation details

The CNN-based model was implemented in Python with Pytorch [13] based on a deep learning framework, which was trained with a maximum of 50 epochs. The Adam optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and no weight decay was used. The initial learning rate was 0.0001 and the dropout rate was set to 0.2 for the entire network. In this study, the model was run on a machine with six central processing units (CPUs; Intel i7-6850K CPU @ 3.6GHz) on an Ubuntu 16.04 platform. Four graphic processing units (GPUs; NVIDIA RTX 2080 Ti) were also used to accelerate the processing of the experiments.

### B. Effect of PPG combination on BP prediction

Evaluations on the different input combinations of PPG signals for the CNN were conducted. The model was trained using only the selected PPG signals according to the specified input combination. Table 1 shows the BP prediction accuracy of the CNN-based BP prediction for different input PPG signal combinations. As shown in Table 1, using only the green signal as an input yielded the best performance on average compared to other input signal combinations. This indicates that the green PPG signal has the most required information for accurate BP prediction. In most subjects, the highest accuracy was achieved with the green PPG signal only as an input, but higher accuracy was observed for some subjects with a blue signal as input. Reflecting the most

TABLE II

COMPARISON OF BP PREDICTION ACCURACY TO OTHER WORKS

| | SBP | | DBP | |
|---|---|---|---|---|
| | MAE | STD | MAE | STD |
| Y. Zhang [3] | 11.64 | 8.20 | 7.62 | 6.78 |
| S. Khalid [5] | 4.82 | 4.31 | 3.25 | 4.17 |
| M. Radha† [7] | 7.86 | 1.57 | 6.49 | 1.59 |
| S. Baek‡ [11] | 5.32 | 5.54 | 3.38 | 3.82 |
| Ours (Green) | 5.28 | 1.80 | 4.92 | 2.42 |
| Ours (Best) | 4.47 | 1.53 | 4.03 | 1.48 |

† Root-mean-square-error (RMSE)

‡ End-to-end BP prediction using ECG, PPG

accurate results for each subject, the BP prediction errors are SBP 4.47 and DBP 4.03, which are 15.3 and 18.1% better than the green signal alone as an input, respectively.

### C. Performance comparison with other related works

Table 2 shows the comparison of BP prediction accuracy between the proposed method and previous studies. From Table 2, it can be seen that the CNN-based BP prediction method in this study showed comparable performance to other studies using a single PPG signal. In addition, it can be seen that the performance are equivalent when compared with the end-to-end BP prediction study using both ECG and PPG. From an application perspective, we can expect that the proposed method will be robust for a wearable device, which limits the use of multiple sensors.

## IV. DISCUSSION

Our CNN-based BP prediction method achieved the best performance in most cases using a green PPG time signal in combination with an instantaneous frequency signal. It used the raw PPG signal as an input without unique feature extraction. Notably, an on-device application is advantageous as there is no need for additional equipment or special conditions for feature extraction. Interestingly, some subjects had greater BP prediction accuracy with the blue PPG signal as the input. In BP estimation, a red or IR PPG light is often used because the long wavelength is able to penetrate deeper into the skin and is more capable of detecting signals from the deep arteries [14]. However, since the light also travels through the epidermis and dermis, the variation in the detected light is a complex result of the concurrent changes in the volume of the arteries, arterioles, capillaries, and veins. In other words, signals such as green and blue, which have low skin penetration depth, have information that is most relevant to predicting BP. Since the amount of data used in the experiment was small and no additional information such as skin color was identified, the explanation of the improved accuracy of the blue PPG signal for some subjects cannot be confirmed, but it is possible that this effect was due to variations in skin tone. Future research will focus on improving personalized BP prediction performance by using PPG light combinations tailored for each individual.

## V. CONCLUSION

In this paper, we proposed a method for predicting BP without feature extraction using a single PPG signal measured by smartphone using fully convolutional networks. The concept of estimating BP using a single biomedical signal such as PPG that can be easily measured from a mobile device without the inconvenience of wearing a cuff is promising for self-monitoring of BP. Unlike many previous studies, we have shown that BP can be estimated directly from raw signals without preprocessing to extract features from the PPG signal. Our study was limited given that data acquisition was from only 26 volunteers and no other additional information such as skin color was recorded. We plan to expand our research, including by acquiring data that can be verified by IEEE Standard 1708-2014, a universal standard for the validation of BP measuring devices.

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