DEVICE AGNOSTIC MEASUREMENT OF BLOOD PRESSURE FROM RPPG SIGNALS

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ABSTRACT

Recent advances in sensing technologies enable the measurement of Blood Pressure (BP) on a smart phone by analyzing the patterns in a remote Photoplethysmograph (rPPG). In this paper, we propose a device agnostic method to non-invasively measure BP using rPPG signals. We achieve state-of-the-art results on 1276 rPPG samples collected from 18 different smartphone models by training a sequence model on the longitudinal features extracted from the signal. These features are invariant to changes in the sampling rate and are closely related to the underlying physiological processes. The results conform to the criteria established by the American and British measurement standards for BP measurement in certain ranges. Clinical validation of the algorithm on 111 rPPG signals using 4 different smartphones resulted in an average RMS error of 17.79 mmHg and 10.83 mmHg for systolic and diastolic BP measurements, respectively.

Index Terms— rPPG, LSTM, Smartphone, BP

1. INTRODUCTION

The heart's contraction and relaxation during each heartbeat correspond to higher and lower blood pressures, referred to as systolic and diastolic blood pressure respectively [1]. While cuff-based systolic and diastolic BP measurement is the clinical standard, the requirement of wearing a cuff for each BP measurement causes inconvenience and is obtrusive. Recent research on estimating BP without using a cuff has led to exploring Photoplethysmography (PPG) technology [2]. The PPG signal captures the sequence of events during the heartbeat and analyzing the PPG signal provides an indirect approach to measuring BP. There is sufficient evidence in literature that suggests PPG as a potential source for non-invasive BP measurement [3]. The typical workflow to measure BP from PPG signals involve a pre-processing step to remove power line interference, denoise, and detrend the signal. This is followed by feature extraction and regression for estimation for systolic and diastolic BP values [3].

Bandpass filters with cutoff at 0.1Hz (f_{cl}) and 8Hz (f_{ch}) are the usual choice to pre-process the signal for denoising [3]–[6]. Feature engineering methods involve feature extraction from the PPG signal, such as: (a) morphological features [6]–[9] and their second derivatives that are related to the pulse amplitude, pulse width, and peaks of systolic and diastolic values in the PPG signal; (b) frequency and time domain features and their first and second derivatives [10]; (c) anthropometric features, such as age, sex, height, and weight [11]. In recent years, there has been a growing interest in using deep networks as regressors to estimate the BP from PPG signal features. CNN-based architectures like LeNet and GoogleNet [12], [13], as well as sequence models like LSTMs [14]–[16], have been attempted for BP estimation. A common trend observed in existing approaches is the use publicly available datasets to train and validate the algorithms. One popular dataset is the MIMIC dataset [17] which comprises of PPG signals extracted from subjects under strictly controlled environments using medical graded devices with specialized sensors and fixed acquisition settings, such as constant sampling rate, for data collection.

There is increasing interest in the research communities and industry, particularly since the advent of COVID-19 pandemic, to develop algorithms for self-monitoring of health vitals such as BP using a smartphone device. BP measurement using a smartphone offers a non-invasive, unobtrusive, convenient, and user-friendly method. However, the luxuries of a controlled environment and fixed acquisition settings are not present when it comes to BP measurement on a smartphone. Furthermore, each smartphone manufacturer may have different hardware configurations that significantly impacts the sampling rate of the PPG signal, typically around 30fps, while medical grade devices like those used in [17] operate at over 125fps. As a results, existing approaches such as [10] restrict their analysis to the signals obtained from a single phone. Additionally, existing algorithms based on the MIMIC-III dataset implicitly rely on the sampling rate being 125fps to produce reliable results and are therefore not generalizable for use on smartphones. Furthermore, the features extracted by the existing algorithms do not capture the time dependent correlations that provides valuable information about the underlying physiology contributing to BP.

In this paper, a novel approach to estimate BP on any smartphone is proposed. The approach involves employing robust longitudinal features that are unaffected by changes in the sampling rate and are closely tied to the underlying physiological processes. The features are integrated into a deep learning framework using sequence model. The model can accurately estimate BP on various smartphone.

2. METHODOLOGY

This section provides detailed information about the dataset used and the proposed PPG-based BP measurement method utilizing the LSTM network.

2.1. Dataset Details

To facilitate the data collection process, we developed a dedicated mobile application specifically designed for Android devices. This application allows for easy recording of PPG data and the corresponding ground truth BP values. For accurate reference measurement, a standard clinical device manufactured by Omron (BP7100) is utilized. The BP measurement using BP7100 device is treated as ground truth and the readings are logged into the dedicated mobile application.

In the existing literature, it has been shown that the variation in the light intensity captured using a visible wavelength light source can capture pulsatile information related to heartbeat [18]. In this work the flashlight and camera sensor are utilized as light source and receiver, respectively for capturing the pulsatile information from the user's index finger. The video recording of the user's index finger placed on the camera sensor while the flashlight is turned on is used to extract PPG signal. Thus, the necessary data for designing PPG based BP measurement method is obtained. To ensure sufficient data for analysis and capture long-term dependencies in the PPG signal, the duration of video recording is set to 60sec. This duration allowed for the stabilization of the hand and facilitated the capture of vital information within the PPG signal.

The proposed experiment has obtained approval from an ethical committee (Ace Independent Ethics Committee: MFIN003) recognized by the regulatory authorities. Prior to data collection, trained nurses obtained verbal consent from the subjects for the collection of fingertip video data. The data collection process took place at two clinical sites, and a total of 18 different smartphone manufactured by OnePlus (112 samples), Xiaomi (496 samples), Samsung (73 samples), Oppo (170 samples), RealMe (139 samples), Vivo (226 samples), HMD Global (8 samples), Huawei (25 samples), and Google (14 samples) were used for data collection. For the training of BP measurement method, a total of 1,267 samples collected from the 18 smartphones were utilized. To validate the trained BP model, separate clinical test data was collected. This test data consists of 111 fingertip videos samples obtained using 4 different smartphone devices, namely Xiaomi (47 samples), Oppo (31 samples), Motorola (4 samples), and Samsung (30 samples) form the clinical test data.

To extract the pulsating information from the 60s fingertip video recording, the video is converted into a continuous 1-D signal. If the recorded video has a frame rate of 30fps, then

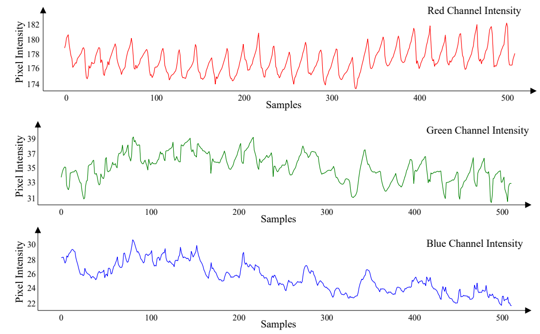

Fig. 1. Continuous 1-D extraction from R, G, and B channels

the total number of frames in a 60s video is 1800. To convert the video into a 1-D signal, the pixel intensities in each frame are averaged. In other words, the average of pixel intensities in i^{th} frame corresponds to i^{th} sample point in the 1-D signal. This process is performed separately for the red, green, and blue channels in the frames of the 60s video. The resulting continuous 1-D signal is shown in Fig. 1. It can be observed that the red channel contains prominent pulsating information compared to the green and blue channels. A sample PPG signal from the dataset shown in Fig. 1 demonstrates that, the amplitude range of the red channel is ~8 whereas, the amplitude range of the green and blue channels is ~4. The presence of prominent pulsating data over a larger amplitude range in the red channel benefits in detecting health vitals such as BP. Thus, the 1-D signal extracted from the red channel is considered as PPG signal for BP measurement.

2.2. Estimating BP from PPG signal

The proposed BP measurement method mainly includes three steps – signal preprocessing, derivative filter bank, and LSTM network as illustrated in Fig. 2.

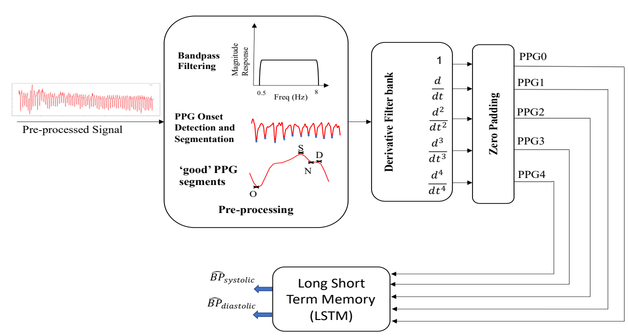

Fig. 2. Block diagram of the proposed BP measurement method.

2.2.1. Preprocessing and Derivative filter bank

To improve the quality of the noisy PPG signal, pre-processing steps are applied. The continuous PPG signal is subjected to band pass filtering between 0.5 Hz and 8 Hz using a 4th order Butterworth filter. This step removes the high-frequency noise caused by abrupt finger movement and eliminates any DC offset present in the signal. To ensure the reliability of the data for BP measurement, the first 5s and last

10s data of the PPG signal are excluded from consideration. It is assumed that the central 45s data contain fewer artifacts and provide a more representative portion of the signal.

The PPG signal is then segmented based on the detection of successive onsets (O) landmarks using peak detection method. For the peaks to be considered valid, its height must exceed the threshold of $0.5\,\sigma \pm \mu$, where σ is the standard deviation and μ is the mean of the PPG signal. Additionally, the distance between two peaks should be greater than 10 samples. The signal segment between two successive onset points corresponds to one heartbeat and it is referred to as a PPG segment. Within a PPG segment the systolic (S) and diastolic (D) peaks corresponds to the contraction and relaxation phases of the heart, respectively. The valley point between S and D peaks is known as notch (N)[19] To detect S, N, and D peaks, the peak detection method is employed again within each PPG segment. The amplitudes of the detected peaks are used to label the PPG segment as either 'good' or 'bad'.

The literature on PPG based BP measurement suggests that the features extracted PPG and its derivatives carry information related to BP. In order the capture the BP related information from PPG signal, this work proposes the use of filter bank that contains derivative filters. The filter bank is designed to perform numerical differentiation up to the 4^{th} order. The output signal length will be smaller compared to the input signal length due to numerical differentiation operation. In the training dataset, the average length of the 'good' PPG segments, which is the input to derivative filter bank is 21.05 ± 5.61 samples. The length of the resulting derived signal will be smaller compared to the original length. The length of the resulting derived signal varies depending on the order of the differentiation. To ensure the uniformity in the length of the derived signal, zero padding is applied. The uniform length of the signal is made equal to 50 samples and the zero-padded sequences are denoted as PPG0, PPG1, PPG2, PPG3, and PPG4 where the number in the suffix indicates the order of the derivative operation (as shown in Fig. 2).

2.2.2. LSTM Network

To extract the underlying blood pressure-related information from the PPG sequence and its derivatives, a LSTM-based neural network model is proposed. The architecture of the proposed model is depicted in Fig. 3.

The zero-padded uniform length signals, namely, PPG0, PPG1, PPG2, PPG3, and PPG4 serves as input to the LSTM network shown in Fig. 3 The proposed network has two layers of LSTM network, and both the layers are followed by batch normalization for improved performance. Subsequently, a dropout layer is incorporated for regularization purpose, which is then followed by a dense layer with two output nodes representing systolic and diastolic BP values. The PPG-based

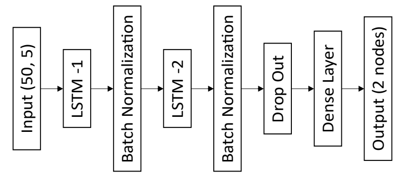

Fig. 3. LSTM architecture for PPG based BP measurement.

BP measurement method is formulated as a regression problem. The mean squared error given in (1) is utilized as a loss function to optimize the weights of the network.
In the equation (1), N represents the total number of training

$$loss = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{1}$$

samples, y_i and $\hat{y}_i$ represents the actual and predicted BP values of i^{th} sample, respectively. The proposed LSTM network is trained with a learning rate of 0.003 using Adam and the maximum number of training epochs was set to 50 with early stopping to prevent overfitting.

3. RESULTS

The proposed rPPG-based BP measurement method is trained using a dataset of 1,297 samples collected from 18 different smartphones. The trained method is then tested on the 111 PPG samples collected from 4 different smartphones. The contraction and relaxation cycle of the heartbeat is captured by 'good' PPG segments and the BP measured using a PPG segment is referred to as beat-to-beat BP. In this work, training and test dataset contains, 16,873 and 2059 'good' PPG segments, respectively. These segments are used to train and evaluate the performance of the rPPG-based BP measurement, respectively.

3.1. Performance Evaluation of the proposed method

The learning of the LSTM network is evaluated by monitoring the training and validation loss, measured in terms of Mean Absolute Error (MAE) and Mean Square Error (MSE). These losses are plotted using blue and orange colors, respectively, in Fig. 4. It can be observed that the losses decrease from their initial values and converge to a stable lower value. This indicates that the trained LSTM model is a good fit for the data and has learned the underlying pattern and relationships effectively.The trained LSTM model using

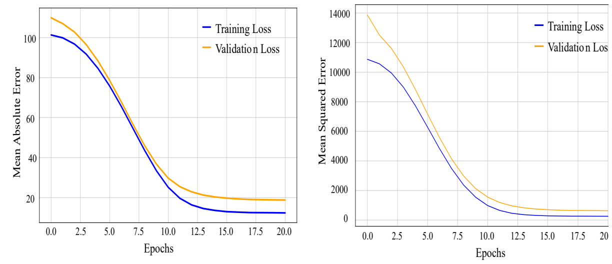

Fig. 4. Training loss of the proposed LSTM network.

derived signals up to order 2 (i.e., PPG0 to PPG2, model-3) achieved the best RMSE on the test data. For systolic blood pressure, the model achieved an RMSE of 17.79 $mmHg$, while for diastolic pressure, the RMSE is 10.83 $mmHg$. In comparison, the BP model trained using PPG0, PPG0 to PPG1, PPG0 to PPG3 and PPG0 to PPG4 achieved higher RMSE values, indicating lower accuracy in predicting blood pressure values. Therefore, model-3 trained with PPG0 to PPG2 demonstrates superior performance in estimating systolic and diastolic blood pressure values compared to other models.
The scatter plot in Fig. 5 represents the absolute error of the

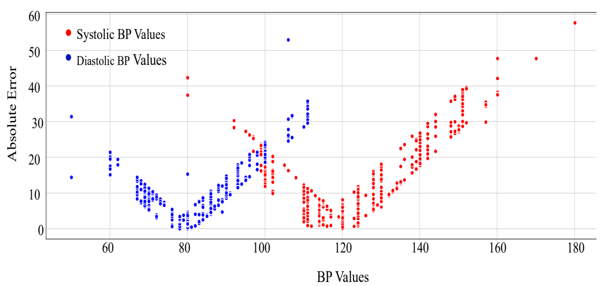

Fig. 5. Absolute error achieved between predicted and ground truth BP values on the test data.

BP model trained using PPG0, PPG1, and PPG2. The blue and red points in the scatter plot represents absolute error for diastolic and systolic BP, respectively. The scatter plot reveals that the absolute error is minimal for BP values within the normal range of diastolic (~80 mmHg) and systolic (~ 120 mmHg) blood pressure. This trend is similar to the absolute error observed in the BP measurement method using 125 Hz PPG dataset (MIMIC) [20]. The observed trend is attributed to the non-uniform distribution in the ground truths BP values. Approximately 80% of the PPG samples lie within the normal BP, resulting in higher absolute error when measuring abnormal BP values. This suggests that the limited performance of BP measurement method is influenced by the non-uniform data distribution of the ground truth BP values. Addressing this issue and improving the performance for abnormal BP values can explored as a potential area of future work.

3.2. Benchmarking the BP measurement method

The performance of the proposed rPPG-based BP measurement method is benchmarked against the US Association for Advancement of Medical Instrumentation (AAMI) and British Hypertension Society. The mean error of the proposed method for the systolic BP range of $115 - 125\ mmHg$ and $80 - 90\ mmHg$ is reported to be less than $5 \pm 8\ mmHg$ (Table I). This indicates that the average difference between the predicted and ground truth BP values fall within an acceptable range of AAMI. The percentage of cumulative mean error for the same systolic and diastolic BP range is reported in Table II. The proposed method achieves cumulative mean error greater than 60% for mean error $< 5\ mmHg$, greater thank 85% for mean error $< 10\ mmHg$, and greater than 95% for mean errors $< 15\ mmHg$. This indicates that the proposed method is graded as A as per BHI criteria within the said range of BP values.

TABLE I. MEAN ERROR OF BP MEASUREMENT – AAMI.

Systolic BP		*Diastolic BP*	
Range (mmHg)	*MAE*	*Range (mmHg)*	*MAE*
< 115	16.99 ± 7.50	< 80	12.09 ± 5.77
$115 - 125$	$\mathbf{2.03 \pm 1.80}$	$80 - 90$	$\mathbf{3.43 \pm 2.32}$
> 125	19.12 ± 10.06	> 90	15.83 ± 6.92
Full Range	14.78 ± 19.87	Full Range	8.39 ± 6.84

TABLE II. PERCENTAGE CUMULATIVE MEAN ERROR – BHI.

MEAN ERROR →		≤ 5	≤ 10	≤ 15
Systolic (mmHg)	< 115	11.57 %	29.35 %	77.76 %
	$115 - 125$	**97.87** %	**100** %	**100**%
	> 125	17.62 %	25.29 %	49.43 %
	Full range	13.84 %	39.1 %	58.23 %
Diastolic (mmHg)	< 80	0.71 %	23.31 %	45.01 %
	$80 - 90$	**95.74** %	**100.0**%	**100.0**%
	> 90	17.62 %	29.12 %	31.80 %
	Full range	40.40%	62.07 %	85.19 %

3.3. Comparison of Results

To the best of our knowledge, the existing PPG-based BP measurement methods are reported only on the PPG data with fixed 125 Hz sampling rate. The proposed work is first of its kind to test the PPG based BP measurement on a real-world dataset. To ensure a fair comparison, existing methods that utilize PPG and its derivates ([12, 17, 18]) are implemented on the same dataset used in this work. The average RMSE achieved on the test dataset using different methods is reported in Table III.

TABLE III. COMPARISON OF RMSE.

BP Measurement Method	Average RMSE	
	Systolic BP (mmHg)	Diastolic BP (mmHg)
InstaBP [10]	18.43	12.77
LSTM + LASSO [15]	19.30	10.85
GRU [16]	19.30	10.85
Proposed Method	**17.79**	**10.83**

According to the reported RMSE in Table III, the proposed method achieves an RMSE of 14.78 $mmHg$ and 8.39 $mmHg$ for systolic and diastolic BP, respectively. The proposed method achieves lowest RMSE compared to the existing methods. These results highlight the effectiveness of the proposed method and its potential to provide more accurate and reliable BP measurement in real-world scenarios.

4. CONCLUSION

In this paper, we present a groundbreaking approach to estimate BP using any smartphone. The proposed method incorporates robust features that are not affected by the variations in the hardware dependent sampling rate and are closely related to underlying physiological processes. This work utilizes diverse real-world dataset collected from multiple smartphones using dedicated mobile application, ensuring generalizability of the method across various mobile platforms. The proposed rPPG-based BP measurement method demonstrates promising results, achieving an average RMSE of 17.79 mmHg and 10.83 mmHg for systolic and diastolic BP, respectively. Notably, proposed method meets AAMI and BHI performance criteria for measuring BP in normal ranges. In future, work needs to be done to address the imbalance nature of the dataset and conduct large scale clinical trials to further validate the method. These future effors will enhances the robustness and reliability of the proposed method, ultimately advancing the field of rPPG based BP measurements on smartphone.

5. REFERENCES

[1] A. J. Weinhaus and K. P. Roberts, "Anatomy of the human heart," *Handbook of Cardiac Anatomy, Physiology, and Devices*, pp. 51–79, 2005.

[2] E. Chung, G. Chen, B. Alexander, and M. Cannesson, "Non-invasive continuous blood pressure monitoring: a review of current applications," *Frontiers of Medicine*, vol. 7, no. 1, pp. 91–101, Jan. 2013.

[3] C. El-Hajj and P. A. Kyriacou, "A review of machine learning techniques in photoplethysmography for the non-invasive cuff-less measurement of blood pressure," *Biomed Signal Process Control*, vol. 58, p. 101870, Apr. 2020.

[4] S. G. Khalid, J. Zhang, F. Chen, and D. Zheng, "Blood Pressure Estimation Using Photoplethysmography Only: Comparison between Different Machine Learning Approaches," *J Healthc Eng*, vol. 1, 2018.

[5] S. S. Mousavi, M. Firouzmand, M. Charmi, M. Hemmati, M. Moghadam, and Y. Ghorbani, "Blood pressure estimation from appropriate and inappropriate PPG signals using A whole-based method," *Biomed Signal Process Control*, vol. 47, pp. 196–206, Jan. 2019.

[6] X. F. Teng and Y. T. Zhang, "Continuous and Noninvasive Estimation of Arterial Blood Pressure Using a Photoplethysmographic Approach," *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, vol. 4, pp. 3153–3156, 2003.

[7] Y. Kurylyak, F. Lamonaca, and D. Grimaldi, "A Neural Network-based method for continuous blood pressure estimation from a PPG signal," *IEEE Instrumentation and Measurement Technology Conference*, pp. 280–283, 2013.

[8] K. Duan, Z. Qian, M. Atef, and G. Wang, "A feature exploration methodology for learning based cuffless blood pressure measurement using photoplethysmography," *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, vol.1, pp. 6385–6388, Oct. 2016.

[9] A. Gaurav, M. Maheedhar, V. N. Tiwari, and R. Narayanan, "Cuff-less PPG based continuous blood pressure monitoring - A smartphone based approach," *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, vol. 2016-October, pp. 607–610, Oct. 2016.

[10] J. Dey, A. Gaurav, and V. N. Tiwari, "InstaBP: Cuff-less Blood Pressure Monitoring on Smartphone using Single PPG Sensor," *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, vol. 2018-July, pp. 5002–5005, Oct. 2018.

[11] S. Shimazaki, S. Bhuiyan, H. Kawanaka, and K. Oguri, "Features Extraction for Cuffless Blood Pressure Estimation by Autoencoder from Photoplethysmography," *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, vol. 2018-July, pp. 2857–2860, Oct. 2018.

[12] W. Wang, P. Mohseni, K. Kilgore, and L. Najafizadeh, "Cuff-Less Blood Pressure Estimation via Small Convolutional Neural Networks," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, pp. 1031–1034

[13] Y. Liang, Z. Chen, R. Ward, and M. Elgendi, "Photoplethysmography and Deep Learning: Enhancing Hypertension Risk Stratification," *Biosensors (Basel)*, vol. 8, no. 4, Oct. 2018.

[14] C. El-Hajj and P. A. Kyriacou, "Cuffless blood pressure estimation from PPG signals and its derivatives using deep learning models," *Biomed Signal Process Control*, vol. 70, p. 102984, Sep. 2021.

[15] Di. Wang, X. Yang, X. Liu, L. Ma, L. Li, and W. Wang, "Photoplethysmography-Based Blood Pressure Estimation Combining Filter-Wrapper Collaborated Feature Selection with LASSO-LSTM Model," *IEEE Trans Instrum Meas*, vol. 70, 2021.

[16] C. El Hajj and P. A. Kyriacou, "Cuffless and Continuous Blood Pressure Estimation From PPG Signals Using Recurrent Neural Networks", *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 4269-4272, 2020.

[17] A. E. W. Johnson *et al.*, "MIMIC-III, a freely accessible critical care database," *Scientific Data 2016 3:1*, vol. 3, no. 1, pp. 1–9, May 2016.

[18] Y. Sun and N. Thakor, "Photoplethysmography Revisited: From Contact to Noncontact, from Point to Imaging," *IEEE Trans Biomed Eng*, vol. 63, no. 3, pp. 463–477, Mar. 2016.

[19] M. Elgendi, "On the Analysis of Fingertip Photoplethysmogram Signals," *Curr Cardiol Rev*, vol. 8, no. 1, p. 14, Jun. 2012.

[20] F. Schrumpf, P. Frenzel, C. Aust, G. Osterhoff, and M. Fuchs, "Assessment of deep learning based blood pressure prediction from PPG and RPPG signals," in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, IEEE Computer Society, Jun. 2021, pp. 3815–3825.