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Methods of Blood Pressure Estimation Using Deep Learning : A Review

Praneeta Grace. M
PG Scholar, Department of Biomedical Instrumentation Engineering, School of Engineering, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore, Tamil Nadu, India.

ABSTRACT

This paper presents a review of different deep learning methods used in blood pressure estimation. The recent technique adopted the cuff-less method for blood pressure estimation. One of the common cuff-less methods uses the correlation between Pulse Wave Velocity (PWV) and ECG. But these methods do have some limitations, such as the necessity for periodic calibration as PWV and ECG varies from person to person. With the advent of Deep Learning, many new techniques are used for the estimation of BP. The VGGNet and CNN have automatics feature extraction and learning ability. Thus, these two techniques are found to be the best among all the techniques.

Keywords : Machine Learning, Deep Neural Network (DNN), Convolutional Neural Network (CNN), RNN, Blood pressure estimation

I. INTRODUCTION

Maintaining normal blood pressure is very important to lead a healthy life. Hypertension occurs when blood travels through the blood vessels with more force than considered normal. Prolonged hypertension can damage the arteries and blood vessel walls over time. This results in diseases such as coronary artery disease, enlarged left heart, and heart failure. It also causes chronic diseases to the brain, kidneys, and eyes. The brain depends on the blood supply to function properly. High Blood Pressure causes several problems including, Transient Ischemic Attack (TIA), stroke, dementia and in some cases mild cognitive impairment. The kidney filters excess fluids and wastes from the blood. Healthy blood vessels are essential for the proper functioning of the kidney. High blood pressure damages blood vessels that lead to kidney diseases like, kidney failure and glomerulosclerosis. High blood pressure also damages tiny delicate blood vessels that supply blood to the eye, causing, retinopathy, choroidopathy and optic neuropathy.

Blood pressure can be measured either invasively or non-invasively. Invasive method involves placing a catheter into the artery. Non-invasive methods include binding sphygmomanometer to the arm which is cuff-based, and cuff-less methods uses correlation between PWV and ECG. Also Pulse Transit Time (PTT) is one of the widely used attributes for BP estimation. To determine PTT, signals collected from two different locations of the body are required. So, it is combined with Electrocardiography (ECG) signals. Pulse Transit Time (PTT) can be obtained by using Photoplethysmography (PPG) sensor. PPG works on the principle of pulse oximetry, wherein a sensor emits light to the skin and measures the intensity of light which is reflected back or transmitted through the skin. PPG signal variations are caused by changes in arterial blood volume. The amplitude of the variations depends on the amount of blood rushing into the peripheral vascular bed, the optical absorption of blood, skin pigmentation, ambient light and the wavelength used to illuminate the blood [10].

In blood pressure measurements, physical, environmental and emotional states will lead to errors in measurements. The system must be calibrated periodically as PWV and ECG varies from person to person [3]. Thus, in order to overcome all these limitations a new revolution in technology, the Deep learning technique has arrived. Deep learning plays a vital role in diagnostic applications as it becomes more accessible, continuous analysis and more data storage. Deep learning is a type of Artificial Intelligence that trains a computer to perform human-made tasks, such as recognizing speech, identifying images or making predictions. Instead of organizing data to run through predefined equations, deep learning sets up basic parameters about the data and trains the computer to learn on its own by recognizing patterns using many layers of processing.

In this paper, various techniques of Deep Learning used in Blood Pressure estimation are discussed.

Table 1. Categories of Blood Pressure of American Heart Association [15]

Blood pressure Category	**Systolic (mmHg) High value**	**AND/OR**	**Diastolic (mmHg) Low value**
Normal	<120	AND	<80
High	129-120	AND	80-85
Hypertension Phase 1	139-130	OR	86-90
Hypertension Phase 2	≥140	OR	≥90
Hypertension crisis	≥180	AND/OR	>120

II. LITERATURE SURVEY

Zeng Ding Liu (2019) proposed a 16-layer VGGNet to construct cuff-less BP from Electrocardiogram (ECG) and Pressure Pulse Wave (PPW) signals, Here, feature extraction from raw signals is not needed. The deep network architecture can learn the features automatically. The CNN network based VGGNet (proposed by Visual Geometry Group) has the advantage of simple structure and outstanding feature learning ability.

The proposed method was tested on 89 subjects by the 5-fold cross validation (all subjects were randomly divided into 5 equal sets) [5].

Performance of accuracy and precision:

The Correlation Coefficient (CC) between estimated BP's and reference BP's, Mean Deviation (MD) and Standard Deviation (SD) of the estimation difference were used to evaluate the performance. The estimation errors for SBP and DBP were -2.06±6.89 mmHg and -4.66±4.91mmHg. These values met the AAMI standard for accuracy requirements of 5±8 mmHg. The correlation coefficients between the estimated BP and reference BP values were 0.91 and 0.89 respectively. This shows that there is a high correlation between the estimated BP and reference BP.

Ümit Şentürk (2018) proposed a new hybrid prediction model by combining Electrocardiogram (ECG) and PPG (Photoplethysmographic) signals with a Repetitive Neural Network (RNN) structure to estimate blood pressure continuously.

Data collection:

ECG, PPG, ABP database are collected from Physionet's MIMIC II (Multiparameter Intelligent Monitoring in Intensive Care).

The ECG and PPG signals obtained from the database have been cleared from noise and artifacts. And then ECG and PPG signals have been separated depending on the peak values of these signals.

Proposed method consists of two steps:

1) 22-time domain attributes (11 from ECG 11 from PPG) were obtained.

2) These time attributes are set as inputs to the RNN model and then BP is estimated.

The results have shown that RMSE (Root Mean Square Error) between the estimated SBP and the measured SBP with RNN model was 3.63 and the RMSE between the estimated DBP and the measured DBP values was 1.48 with RNN model. By changing the number of features of the system and the number of hidden layers of RNN, the system can get an optimum level. [3].

Yu-Fan Fang (2018) proposed the latest vision-based method for measuring SBP and DBP. Here, remote PPG (rPPG) has been used with Green Red Difference (GRD) and Euler Video Magnification (EVM) and Finite Impulse Response (FIR) band pass filter. Face cheek and radial artery (near palm) has been selected as the region of interest.

A total of 24 features are collected from the signalsA. after performing plane orthogonal to surface (POS) to the region of interest signal.Finite impulseresponse band pass filter is cascaded to make the rPPG signals smoother and with less noise [4].

Data collection

The database is created with data from a total of 15 students in NCTU, each with 10 times of 45 second camera recording with their willingness. A total of 24 features are recorded in each data point. 12 male and 3 female subjects are involved with the age ranging between 20 to 33.

Prediction models

The proposed method was performed using K Nearest Neighbour (KNN), Deep Belief Network – Deep Neural Network (DBN-DNN) and Artificial Neural Network (ANN) to test the efficiency of the SBP and DBP and the obtained results are compared.

Table 2. The RMSE for KNN, DBN-DNN, ANN

	KNN	DBN-DNN	ANN
SBP (mmHg)	13.54	11.83	11.22
PP (mmHg)	9.93	8.87	7.83

From the table it is clear that ANN gives the best result and lowest RMSE when compared to other models [4].

Fan Pan (2019) proposed a novel CNN based automatic BP determination. In addition, using this CNN based method, the effects of stethoscope contact pressure and position on BP measurement was evaluated.

Data collection:

A total of 30 healthy subjects (13 male and 17 female) aged between 23 to 63 years were selected. There were 36 SBP and 36 DBP values from each subject. They were measured with, 2 stethoscope positions, 3 contact pressures, 3 repeated recordings, 2 BP determination by manual auscultatory method and by CNN based method.

Bland-Altman and Linear Regression analysis were done to assess the relationship between the BP's obtained by manual auscultatory method and CNN based method.

The BP measurement errors of the proposed method were 1.4 ± 2.4 mmHg for SBP and 3.3 ± 2.9 mmHg for DBP from all the measurements. Also, the method demonstrated that there were small SBP differences between the 2 stethoscope positions, respectively at the 3 stethoscope contact pressures, and that DBP from the stethoscope under the cuff was significantly lower than that from outside the cuff by 2.0 mmHg.

Limitation:

The manual auscultatory BP's are determined by electronic playback method (computer mouse). So, the values may not exactly correspond to clinical auscultation [6].

Nabeel P M (2019) proposed a novel image-free ultrasound system using by deep learning technique for cuffless and continuous monitoring of arterial BP parameters and the pressure waveform. The developed deep learning model takes the following as input:

1) The feature of the local diameter waveform
2) The feature correlating to the pulse propagation speed obtained from the dual diameter waveforms that are determined from proximally spaced locations.

Data collection:

Data was collected by conducting an in-vivo study on 20 young subjects aged between 27 to 35 years.

The results have gained acceptable beat-to-beat repeatability with an RMSE of 4 mmHg for DBP and 6 mmHg for SBP [7].

Md. Sayed Tanveer (2019) proposed a waveform-based hierarchical Artificial Neural Network – Long Short-Term Memory (ANN-LSTM) model for BP estimation. The model consists of two hierarchy levels, The lower hierarchy level uses ANNs to extract important morphological features from ECG and PPG waveforms.

1) The upper hierarchy level uses LSTM layers to account for the time domain variation of the features extracted by the lower hierarchy level.

A.

B. **Data collection:**

The ECG, PPG and ABP signals were collected from Physionet's MIMIC I database. Also, data from 39 patients in ICU have been collected and preprocessed.

C.

D. **Preprocessing:**

To remove baseline wandering and unnecessary noise, the windowed signals are bandpass filtered using Tunale-Q wavelet transform (TQWT)

The proposed model can extract the necessary features without requiring any feature extraction technique and is also able to learn the variations of the features with time.

The results show that, the mean absolute error (MAE) and the root mean square error (RMSE) for SBP estimation are1.10 and 1.56 mmHg, respectively, and for DBP estimation are 0.58 and 0.85 mmHg, respectively [8].

Ahmadreza Argha (2019) proposed a novel deep-learning based method for BP measurement trained with beat-by-beat (BBB) time-domain features extracted from OWs.

Initially, six time-domain features from each beat of the Oscillometric Wave (OW) was extracted, relative to the preceding beat. Then, using the extracted BBB features along with the equivalent cuff pressures, a feature vector for each OW beat was determined and mapped it in one of three different classes, namely pre-systolic (PS), between systolic and diastolic (BSD) and after diastolic (AD).

The proposed DBN-DNN classification can efficiently learn the complex nonlinear relationship between the artificial feature vectors and target classes adopting a 5-fold cross-validation scheme.

Data collection:

Totally 350 data records were collected from 155 individual subjects, (87 males, 68 female) aged between 23-97. Arm circumference ranged from 10-35 cm.

The results obtained from DBN-DNN model gave an average, mean absolute error of 1:1±2:9 mmHg for SBP and 3:0±5:6 mmHg for DBP relative to reference values [9].

Soojeong Lee (2016) developed a DBN-DNN to analyze the complex nonlinear relationship between the artificial feature vectors obtained from the oscillometric wave and the reference blood pressures using the DBN-DNN based-regression model.

Data collection:

Oscillometric BP measurements were obtained using an automated wrist BP monitors from 85 healthy subjects aged from 12 to 80 with 37 females and 48 males. 5 sets of measurements were taken from each volunteer, so totally 425were obtained. SBP and DBP was estimated using DBN-DNN model.

The results of the proposed method were 69.52 % (≤ 5 mmHg), 90.00 % (≤ 10 mmHg), and 95.48 % (≤ 15 mmHg) for the SBP and 76.19 % (≤ 5 mmHg), 95.71 % (≤ 10mmHg), and 98.82 % (≤ 15 mmHg) for the DBP [1].

Soojeong Lee (2017) developed a DBN-DNN with mimic features based on the bootstrap inspired technique to understand the complex nonlinear relationship between the mimic feature vectors obtained from the oscillometric signals and the target blood pressures.

There are two problems in using DBM-DNN technique for BP measurement Input feature vectors are very small, which is a drawback for training DBN-DNN technique.

1) The special pre-training phase can trigger unstable estimation because there many random initialized assigns such as training datasets, weights and biases.

2)

In order to rectify these limitations, the bootstrap inspired technique is used as a fusion ensemble estimator based on the DBN-DNN based regression model, which is used to create the mimic features to estimate the SBP and DBP.

The results of the proposed DBN-DNN based fusion ensemble regression estimator were 71.06 % (≤5 mmHg), 90.82 % (≤10 mmHg), and 95.53 % (≤15 mmHg) for the SBP and 81.18 % (≤5 mmHg), 96.24 % (≤10 mmHg), and 99.29 % (≤15 mmHg) for the DBP [2].

Sanghyun baek (2019) proposed a calibration free, cuffless BP prediction method based on a deep convolutional neural network (CNN)

The proposed End to End CNN model,

1) can use raw signals for training without the feature extraction of PWV

2) automatically learns the characteristics of biomedical
   signals from other people.

Data collection:

ECG PPG, ABP signals are collected from Physionet's MIMIC II database. For preparing the training dataset, we sampled random segment from the raw signals to make all datasets the same length.

Preprocessing:

The preprocessing technique used are

1) random cropping
2) Fast Fourier Transform
3) Increasing input depth using its derivatives.

The accuracy of BP prediction was found to be SBP 9.60 ± 9.53 and DBP 5.14 ±5.10 for calibration-free, and SBP 5.98 ±6.17 and DBP 3.81 ±3.96 for calibration based respectively [11].

Gašper Slapniˇcar (2019) proposed a method for estimating BP with PPG using spectro-temporal deep neural network.

Data collection:

The PPG and ABP waveforms are obtained from Physionet's MIMIC III database of 510 subjects The PPG with its first and second derivative are used as inputs into a novel spectro-temporal deep neural network with persisting connections. The spectro-temporal DNN takes into account both temporal and frequency information contained in the PPG waveform and its derivatives.

Leave-one-subject-out experiment was conducted so that the network is able to model the dependency between PPG and BP, achieving mean absolute errors of 9.43 for systolic and 6.88 for diastolic BP [13].

Peng Su (2018) proposed a novel deep recurrent neural network (RNN) consisting of multilayered Long Short-Term Memory (LSTM), networks, which are incorporated with

1) A bidirectional structure to gain larger-scale factor information of input sequence,
2) Residual connections to allow gradients in deep RNN to propagate more efficiently.

A. Data collection:

a. *Static continuous BP dataset:* The dataset, including ECG, PPG and BP were obtained from 84 healthy subjects consisting of 51 males and 33 females. ECG and PPG signal were obtained from Biopac system and reference continuous BP was estimated by Finapres system simultaneously in each experiment.

b. *Multi-day continuous BP dataset:* Matching dataset was determined from 12 healthy subjects including 11 males and 1 female. The BP, ECG and PPG data of each subject were recorded for 8 minutes at the rest status in a multi-day period, namely 1st day, 2nd day, 4th day and 6 months after the first day.

The proposed deep RNN model was assessed on a static BP dataset, and it gained root mean square error (RMSE) of 3.90 and 2.66 mmHg for systolic BP (SBP) and diastolic BP (DBP) prediction respectively, exceed the accuracy of traditional BP prediction models. On a multi-day BP dataset, the deep RNN obtained RMSE of 3.84, 5.25, 5.80 and 5.81 mmHg for the 1st day, 2nd day, 4th day and 6th month after the 1st day SBP prediction, and 1.80, 4.78, 5.0, 5.21 mmHg for corresponding DBP prediction, respectively, which transcend all previous models with notable progress[12].

Xiaomao Fan (2019), proposed a novel attention-based multitask network with a weighting scheme for BP estimation by analyzing and modeling single lead electrocardiogram (ECG) signals. The proposed method consists of a sharing BiLSTM network, three identical two-layer fully connected task-specific networks with task-specific parameters for SBP, DBP, and MAP estimation task, and an attention layer appending to each task-specific network. To balance error losses among SBP, DBP, and MAP estimation sub-network, based on the AAMI standard requiring estimation error falling in ± 5 mmHg, we develop a conditioned error loss function as the optimized objective of the proposed method. PSO is evaluated to search the optimal task-specific weights of error losses of three BP estimation tasks.

Experiment results shows that this method could achieve mean error of SBP, DBP, and MAP estimation in levels of 0.18 ±10.83 mmHg, 1.24 ± 5.90 mmHg, and 0.84 ±6.47 mmHg, respectively.

Xiaoman xing (2016), a beat-to-beat optical blood pressure (BP) estimation paradigm using only photoplethysmogram (PPG) signal from finger tips. This method estimates subject-specific contribution to PPG signal and filters most of its influence by proper normalization. Key features such as amplitudes and phases of cardiac components were extracted by a fast Fourier transform and were used to train an artificial neural network, which was then used to estimate BP from PPG.

Data collection:

Totally 69 patient's data was collected from the MIMIC II database and 23 volunteers were involved for testing.

Result showed a difference of −1.67 ±
2.46mmHg for SBP and −1.29 ± 1.71mmHg for DBP.

Bing Zhang (2019), proposed a novel blood pressure prediction method based on the support vector machine regression (SVR) algorithm to work out the key gap between the requirement for continuous measurement for prophylaxis and the deficiency of an effective method for continuous measurement. The results of the algorithm were compared with those estimated from two classical machine learning algorithms, i.e., linear regression (LinearR), back propagation neural network (BP), with respect to six evaluation indexes (accuracy, pass rate, mean absolute percentage error (MAPE), mean absolute error (MAE), R-squared coefficient of determination $R2$ and Spearman's rank correlation coefficient).

The results shows that all four error ranges (±3 mmHg, ±5 mmHg, ±7 mmHg, ±10 mmHg). The accuracy of the SVR model predictions for Pd and Ps are 97.14% and 96.43% in the range (−3 mmHg,+3 mmHg), which is much higher than those of LinearR and BP.

Bing zhang (2017), proposed CART model for *BP* prediction based on biological attributes data ECG (AVR, AVL, AVF), PPG, PTT, SPO2 and HR collected from a health monitor. To verify the effect of the model, CART model were com- pared with other classical methods such as linear regression, ridge regression, SVM and neural networks in matrix of accuracy rate, *RMSE*, deviation rate and *TIC*. Pearson correlation coeffcient was also applied to selecting the most correlated variables.

Result

The experimental results show that the prediction result of CART model outperformed the other four models, with prediction accuracy rate of more than 90% within error range of [□5 mmHg, C5 mmHg]; Finally, by the feature correlation analysis, it is found that PTT and HR are the most related attributes to *BP* prediction.

Rui He (2016), proposed a random forest method to systematically explore the inherent connections betwwen PPG signal;s, ECG signals and ABP.

Data collection:

All the available data from physionet's MIMIC II database were collected and 18 features were extracted from PPG and ECG signals

Several models with most related features as inputs and beat-to-beat ABP as outputs were trained and tested on the collected data.

Result:

In the RF technique 4.44±3.72 mmHg for DBP and 8.29±5.84 mmHg for SBP, and in LR technique 4.98±4.31 mmHg for DBP and 9.32±7.65 mmHg for SBP were achieved.

Jialun Zhang (2019), proposed the feasibilty of convolutional autoencoder (CAE) to estimate continuous BP without calibration and hand-crafted feature extraction. 62 subjects were recruited in this experiment. First, the CAE on all the data were trained to extract the unsupervised features. Then, a regressor was trained to estimate BP values using the features learning from the CAE. 10-fold cross-validation tests were used to analyse the performance of our models.

Result:

Mean absolute error (MAE) and standard deviation (SD) of absolute error are used as evaluation criteria. The error for SBP is 9.61±7.75 mmHg and for DBP is 6.73±5.13 mmHg.

Jun Xu (2017), proposed a novel BP estimation method combining a classical PWTT model and a Back Propagation Neural Network (BPNN) model.

The novel method is consists of five steps: signal pre-processing, feature extraction, initial PTT model selection, model correction by neural network model, and final PTT model identification.

Data collection:

Data for validation was collected from Physionet's MIMIC database. Also 10 subjects ranging from 21 to 73 years were also involved in this experiment.

Result:

Mean value of error of DBP estimation is within 3.4±82.44 mmHg and mean value of error of SBP estimation is within 4.5±161.44mmHg.

Yue Zhang (2017), proposed a Support Vector Machine (SVM) method for continuous blood pressure estimation from a PPG Signal

Data collection:

The Dataset we selected was The University of Queensland Vital Signs Dataset, which covers a wide range of BP values, recorded from 32 surgical cases

Result:

Thel results shows that the correctness of the proposed method. The mean error is 11.6415±8.2022 mmHg for SBP and 7.617±6.7837 mmHg for DBP

III. CONCLUSION

The standard requirement of SBP and DBP according to Association of Advancement of Medical Instrumentation (AAMI) is 5±8 mmHg. According to the AAMI standards most of the above mention techniques satisfies the requirement. Many methods are based on manual feature extraction which cannot identify the complex relationship between the physiological signals and BP. Thus, automatic feature extraction and feature learning technique would be more feasible and accurate. Thus, the VGGNet and CNN have automatic feature extraction and learning ability and would give the best prediction of BP.

IV. REFERENCES

[1]. S. Lee and J. Chang, "Oscillometric Blood Pressure Estimation Based on Deep Learning", IEEE Transactions on Industrial Informatics, Vol. 13, no. 2, pp. 461-472, 2017.

[2]. S. Lee and J. Chang, "Deep Belief Networks Ensemble for Blood Pressure Estimation", IEEE Access, Vol. 5, pp. 9962-9972, 2017.

[3]. U. Senturk, I. Yucedag and K. Polat, "Repetitive neural network (RNN) based blood pressure estimation using PPG and ECG signals", 2018 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), 2018.

[4]. Y. Fang, P. Huang, M. Chung and B. Wu, "A Feature Selection Method for Vision-Based Blood Pressure Measurement", 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 2018.

[5]. Z. Liu, F. Miao, R. Wang, J. Liu, B. Wen and Y. Li, "Cuff-less Blood Pressure Measurement Based on Deep Convolutional Neural Network", 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), (2019).

[6]. F. Pan, P. He, F. Chen, J. Zhang, H. Wang and D. Zheng, "A Novel Deep Learning based Automatic Auscultatory Method to Measure Blood Pressure", International Journal of Medical Informatics, Vol. 128, pp. 71-78, 2019.

[7]. N. P.M., V. Chilaka, R. V., J. Joseph and M. Sivaprakasam, "Deep Learning for Blood Pressure Estimation: an Approach using Local Measure of Arterial Dual Diameter Waveforms", IEEE International Symposium on Medical Measurements and Applications (MeMeA), 2019.

[8]. M. Tanveer and M. Hasan, "Cuffless Blood pressure estimation from Electrocardiogram and photoplethysmogram using waveform-based ANN-LSTM network", Biomedical Signal Processing and Control, vol. 51, pp. 382-392, 2019.

[9]. Argha, J. Wu, S. Su and B. Celler, "Blood Pressure Estimation from Beat-by-Beat Time-Domain Features of Oscillometric Waveforms Using Deep-Neural-Network Classification Models", IEEE Access, Vol. 7, pp. 113427-113439, 2019.

[10]. Biswas, D., Simoes-Capela, N., Van Hoof, C. and Van Helleputte, N. (2019). Heart Rate Estimation from Wrist-Worn Photoplethysmography: A Review. IEEE Sensors Journal, 19(16), pp.6560-6570.

[11]. Baek, S., Jang, J. and Yoon, S. (2019). End-to-End Blood Pressure Prediction via Fully Convolutional Networks. IEEE Access, 7, pp.185458-185468.

[12]. Su, P., Ding, X., Zhang, Y., Liu, J., Miao, F. and Zhao, N. “Long-term blood pressure prediction with deep recurrent neural networks. 2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI).

[13]. Slapničar, G., Mlakar, N. and Luštrek, M. (2019). Blood Pressure Estimation from Photoplethysmogram Using a Spectro-Temporal Deep Neural Network. Sensors, 19(15), p.3420.

[14]. Kachuee, M.; Kiani, M.M.; Mohammadzade, H.; Shabany, M. Cuffless blood pressure estimation algorithms for continuous health-care monitoring. IEEE Trans. Biomed. Eng. 2017, 64, 859–869.

[15]. American Heart Association, Healthy and unhealthy blood pressure ranges, http://www.heart.org/HEARTORG/Conditions/HighBloodPressure/KnowYourNumbers/Understanding-Blood-Pressure Readings_UCM_301764_Article.jsp#.WmYc8rxl9dg, 2018-01-22

[16]. World Health Organization (WHO), A global brief on HYPERTENSION, world health day 2013.

[17]. A. Stojanova et al., “Continuous blood pressure monitoring as a basis for ambient assisted living (AAL) – review of methodologies and devices,” J. Med. Syst., Vol. 43, no. 24, pp. 1–12, 2019.

[18]. E. Chung et al., “Non-invasive continuous blood pressure monitoring: a review of current applications,” Front. Med., Vol. 7, no. 1, pp. 91–101, 2013.

[19]. S. G. Khalid et al., “Blood pressure estimation using photoplethysmography only: comparison between different machine learning approaches,” J. Health. Eng., Vol. 2018, no. 1548647, pp. 1–13,2018.

[20]. P. M. Nabeel et al., “Bi-modal arterial compliance probe for calibration free cuffless blood pressure estimation,” IEEE Trans. Biomed. Eng., Vol.65, no. 11, pp. 2392–2404, 2018.

[21]. X. Fan, H. Wang, F. Xu, Y. Zhao and K. Tsui, "Homecare-oriented Intelligent Long-term Monitoring of Blood Pressure Using Electrocardiogram Signals", IEEE Transactions on Industrial Informatics, pp. 1-1, 2020.

[22]. X. Xing and M. Sun, "Optical blood pressure estimation with photoplethysmography and FFT-based neural networks", Biomedical Optics Express, vol. 7, no. 8, p. 3007, 2016.

[23]. B. Zhang, H. Ren, G. Huang, Y. Cheng and C. Hu, "Predicting blood pressure from physiological index data using the SVR algorithm", BMC Bioinformatics, vol. 20, no. 1, 2019.

[24]. B. Zhang, Z. Wei, J. Ren, Y. Cheng and Z. Zheng, "An Empirical Study on Predicting Blood Pressure Using Classification and Regression Trees", IEEE Access, vol. 6, pp. 21758-21768, 2018.

[25]. R. He, Z. Huang, L. Ji, J. Wu, H. Li and Z. Zhang, "Beat-to-beat ambulatory blood pressure estimation based on random forest", 2016 IEEE 13th International Conference on Wearable and Implantable Body Sensor Networks (BSN), 2016.

[26]. J. Zhang, D. Wu and Y. Li, "Cuff-less and Calibration-free Blood Pressure Estimation Using Convolutional Autoencoder with Unsupervised Feature Extraction", 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2019.

[27]. J. Xu, J. Jiang, H. Zhou and Z. Yan, "A novel Blood Pressure estimation method combing Pulse Wave Transit Time model and neural network model", 2017 39th Annual International Conference of the IEEE

Engineering in Medicine and Biology Society (EMBC), 2017.

[28]. M. Moghadam and M. Moradi, "Model based Blood Pressure estimation during exercise test using modified fuzzy function", 2014 21th Iranian Conference on Biomedical Engineering (ICBME), 2014.

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