International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

The Estimation of Pressure of Blood Using ECG Image based on Artificial Intelligent Strategy

Fariddah Fahmi, Emil, *

Universitas Andalas, Fakultas Keperawatan, Kampus Limau Manis, Padang
DOI : https://doi.org/10.55248/gengpi.6.0125.0318

A B S T R A C T

The monitoring of blood pressure is a main task in improving diagnosis and treatment of hypertension. Currently, the monitoring of blood pressure apply uncomfortable and unreliable cuff-based device. This cuff-based method cannot give an accurate measurement further the accurate intra-arterial pressure monitoring is not suitable for long-term monitoring, it left discomfort and not suitable for all patient. In order to handle these problems, the new non-invasive blood pressure measurement proposed. The proposed method used ECG images and deep learning model to predict the blood pressure of patients. The ECG images are generated from printing the ECG signal of the machine. This dataset is used to training the residual network (Resnet) model. The proposed method is able to predict the accurate blood pressure. The accuracy of the method is assessed using confusion matrix and ROC Curve. The accuracy of the proposed method is 98.5% and the ROC curve is relied above diagonal line. This new method can handle the non-accurate and discomfort problem of previous blood pressure measurement methods. Through this new method, the patient can obtain the improvement diagnosis and treatment for long-term medication.

Keywords: Blood pressure prediction, ECG image, deep learning, high accuracy

Introduction

The hypertension is a common risk of cardiovascular diseases of patient(CVD). The complicating of cardiovascular diseases because of hypertension infected to 9.4 million deaths every year[1]. Clinical intervention reduces blood pressure (BP) means reducing risk of CVD automatically. Nevertheless, the hypertension should be treated and diagnosed. Therefore, BP must be monitored to ensure that it remains controlled. High blood pressure is called the silent killer because it often has no warning signs or symptoms, and many people are not aware they have it. Further, it is important to check blood pressure regularly[2]. In general, the blood pressure method is divided into two main types. The first is non-invasive method, it worked based on Oscillometric principle[3]. This method used cuff devices to detect the blood pressure of the patient. This method left the pain and uncomfortable feeling of the patient. The second is invasive method. It used sensor attached over the artery tree. This method work was based on assessment of pulse wave velocity (PWV). The PWV is formulated as follow.

$$PWV = \frac{L}{PTT}$$

Where L is the distance between two arterial sites, Pulse Transit Time (PTT) is the time taken for pulse wave to travel from one arterial site to other. PWV is described as property of the propagating pressure value down the segment of the arterial tree. This method still left discomfort and woriness for the patient. This inconvenient became a concern of researcher to solve. There were many methods have performed so far. The ensemble machine learning can measure the blood pressure although the data mixed with noise. The original signal can be predict accurately using logistic regression model[4]. The use pulse transit time method to process electrocardiogram (ECG) and photoplethysmogram (PPG) signals. The forming of pulse transit time model based on residual network and long-short-term memory architecture. The spatio temporal information of ECG and PPG are the target of training process[5]. This method did not present uncomfortable feeling to patient. The use of pulse arrive time (PAT) method prevent the patient from the pain, stress and etc[6]. Besides, the inaccuracy and discomfort problem of previous blood pressure measurements, the need blood pressure estimation also used telemedicine services[7].

Background

The monitoring blood pressure is widely used estimation in clinical center with intelligent measurement system[8]. However, blood pressure is commonly assessed using cuff-based devices with tedious operation in practices which may not be effective to track blood pressure continuously. There were many methods available to predict blood pressure (BP) nowadays. The methods used various data type and procedures. The Electrocardiogram (ECG) and photoplethysmogram (PPG) are commonly data used to estimate blood pressure[2]. This method used two biomedical signals to process generating model through training. It was trained by hybrid neural network. This model would find the blood pressure[2]. The other method also using the two types of data to be trained. The method used pre-trained model. It was residual network and Long Short Term Memory (LSTM) architecture. The one-channel ECG signal used for estimating blood pressured using residual network and the long-short term memory architecture used for obtaining the spatial-temporal information of ECG signals[3]. The ANN–LSTM model used for handling various morphological contour of ECG and PPG signal due to various diseases of circulatory system[4]. This method contained two stages. The first is extracting the waveform features of ECG and PPG using ANN. The second is counting time domain variation of features extracted. Then the corresponding sequence vector of features consisted of SBP and DBP. This method also uses ECG and PPG waveform signals to predict the blood pressure[4]. Then, the monitoring and measurement of blood pressure used pulse wide velocity (PWV). Further, the other method measure blood pressure based on pulse arrive time (PAT). This method measured systolic blood pressure, diastolic blood pressure and mean arterial pressure (MAP)[5]. It estimated blood pressure through processing vital signals and extracting two types of features, which are based on psychological parameters of vital signals. At the end, the regression algorithm are employed for the BP estimation[9]. The block diagram of the PAT method is as shown in Figure 1.

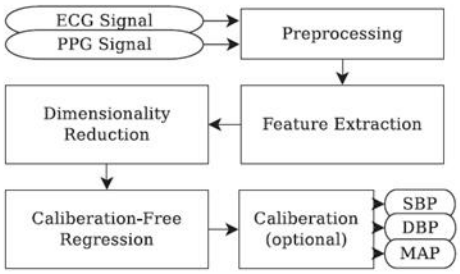

Fig 1. The block diagram of cuffless blood pressure estimation[9]

The previous problems while monitoring of blood pressure were accuracy and comfort. They become limitation of the previous methods. That, the new strategies to measure blood pressure is using electrocardiogram (ECG) signals only. The statistical signal features extracted from ECG which serve as input data to random forest regression[10]. The method used data from MIMIC III dataset for training and testing tasks. The data contains large range of blood pressure values. Moreover, the use of photo-plethysmography (PPG) sensors are often used to sense pulse-transit-time(PTT) that potential for measuring blood pressure[11]. The procedure of obtaining PPG signal is as shown in Figure 2.

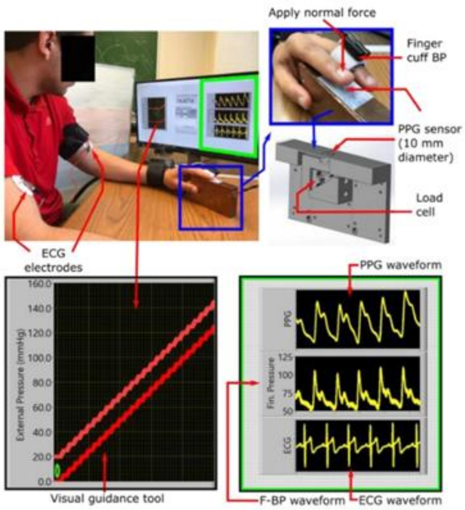

Figure 2. Measurement of PPG impact on blood pressure[11]

Figure 1 shows the an ECG and PPG waveforms from the fingertip, and contact pressure (CP) which measure simultaneously. The other task on ECG signal is classification ECG signals using machine learning. A classification of ECG and Korotkoff signal in order to detect the potential disease of the patient[4]. The advantage of early potential disease detection is the patient can prevent the disease better. Further, the use of ECG signal to predict the blood pressure use changes of morphological contours. The ECG signal is coupled with PPG signal to obtain features. The extracting information of signal waveform is perform using Artificial Neural Network architecture and Long-Short Term Memory algorithm[9]. The telemedicine process uses predicted blood pressure through gradient boosting decision tree (GBDT). The predicting blood pressure rate is taken from ECG and PPG data. This method used both signal waveforms. In order to prevent over fitting problem, the method optimized training parameters through cross-validation method to increase the predicting accuracy[7]. The estimation of blood pressure also applied using CNN and LSTM network. The ECG and PPG dataset used for training model. The model predicted systolic BP and diastolic BP[3]. The detail method is as shown in Figure 2.

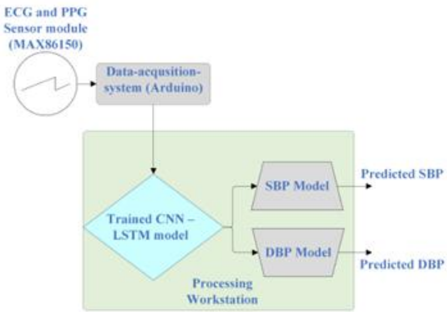

Figure 3. Schematic system design[3]

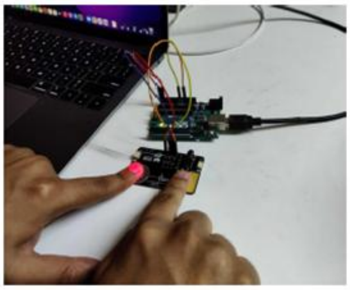

Figure 4. Snapshot of BP estimation system[3]

Figure 3 shows the acquisition of ECG and PPG signal from sensor module. This data is then trained through pre-trained model CNN-LSTM architectures. Two separated fully connected layers predicted DBP and SBP.

The other noninvasive method of blood pressure measurement is blood pressure classification. The trained model using ECG data. The method devided BP into three categories, namely, normotension (N), prehypertension(Pre) and hypertension (H)[12]. This method contained pre-processing, build a model based on 1D CNN and evaluation tasks. The method can classify the BP based on those categories. Moreover, the other cuff-less BP measurement can

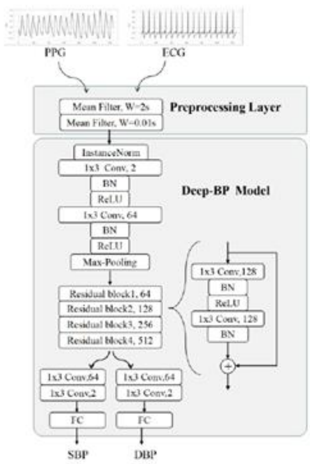

Figure 5. The architecture of deep –BP[13]

solve the sensitivity and non-ideal morphological signals[13]. The method used novel CNN architecture design. It is namely deep BP. The detailed architecture of network is as described in Figure 5. This new method can produce high accuracy and outperformed of the existing methods. The next cuffless blood pressure method is measuring BP using single ECG and single PPG signals[14]. Besides, this method also has ability to measure heart rate (HR). It used a modified long-term recurrent CNN and long-short term memory network (LSTM) to train a deep learning model. The designed architecture is as shown in Figure 6. This model produced accurately estimating BP and HR[14].

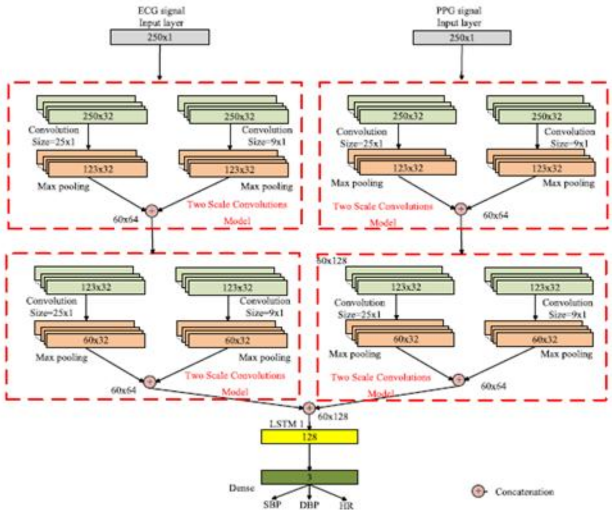

Figure 6. Architecture of two scales LRCN model[14]

Figure 6 shows the architecture of two scale LRCN network. The network contained filters with different sizes, they first is 25 x 1 and the second is 9 x 1. The classification layer classified BP into three classes. The HR, SBP and DBP classes obtained accurately. The other monitoring BP is used for early diagnosis and monitoring cardiovascular disease (CVD)[15]. The most important factor in determining CVD disease or not is hypertension subject. The hypertension phenomena detection is very important. This method used GoogleNet to classified PPG and ECG signals to find healthy and hypertension blood pressure. The detailed architecture is as shown in Figure 7.

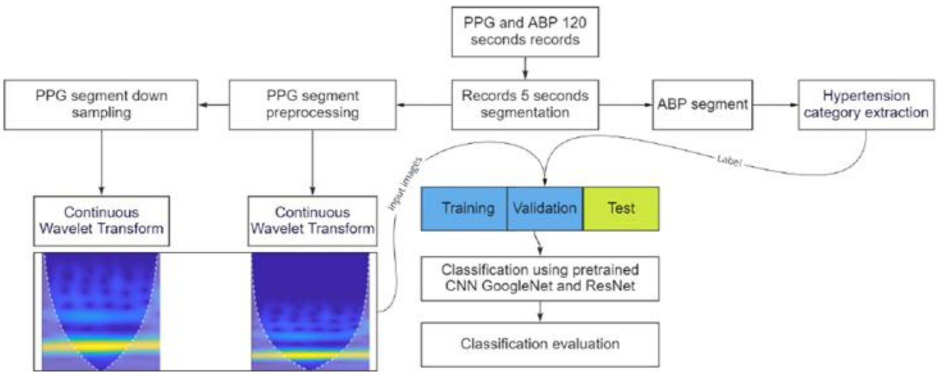

Figure 7. Block diagram of classification blood pressure[15]

Figure 7 shows the block diagram of classification BP method. The ECG and PPG signals are trained using pre-trained model such as GoogleNet to get new classification model. The results are two classes classification, hypertension and healthy categories. It can classify very accurate.

Based on those strategies, the previous method used both PPG and ECG signals, that more difficult to process.

The Proposed Method

The proposed method uses 3 channels ECG data. They are lead 1, lead 2 and lead 3. These leads are in image signals. The ECG images is as shown in Figure 8. The first task is filtering these ECGs images to remove the scale lines of the ECG image papers. The use of median filter and morphological filter sequentially is able to remove measurement lines clearly. The filtered ECG images is as shown in Figure 9. These filtered ECG images are then use for training pre-trained model. It Residual Network with 50 layers deep. The training process has hyperparameters such as iteration, mini batch size, learning rate, image size and optimization schemes. The setting of iteration is 100, mini batch size is 16, learning rate is 0.001, image size is 512 x 381 pixels and optimization scheme is ADAM. The block diagram of proposed method is as shown in Figure 10. Based on those hyperparameters, the training process spends about 3 hours to generate new model.

Figure 8. The ECG image with three leads

Figure 8 shows the ECG image of the printed ECG waveform signal of the ECG machine. The image has three leads and scalelines or measurement lines. These lines has darkness as high as ECG signals graphs. The suitable filter to handle this contrast is through applied median and morphological filters. The use the sequentially, can generate pure ECG signal image. It as shown in Figure 9.

Figure 9. Filtered EGC images

The filtered ECG images is divided into five classes. The classes of dataset become the input of the proposed model. The detail of works is as shown in Figure 10.

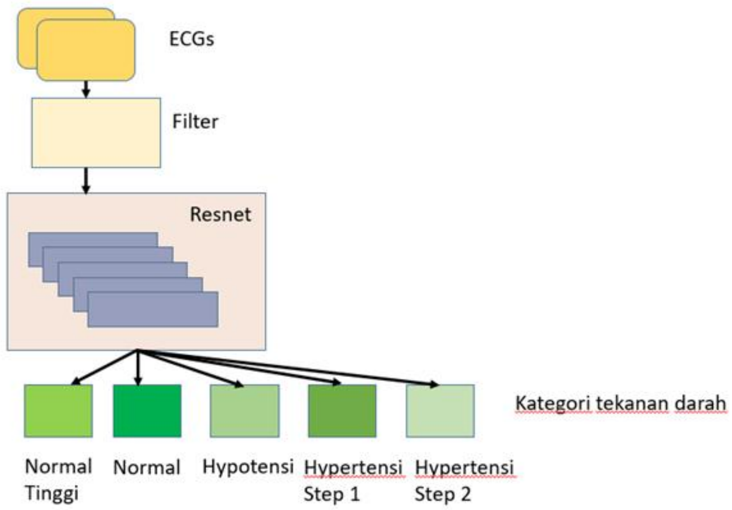

Figure 10 The Block diagram of proposed method

Figure 10 shows the flow of data processing of the proposed method. It started by the ECG images, filtering process, training process uses Resnet 50 pre-trained model. The new generated model is tested using testing dataset. The output of the proposed method is the ECG images can be classified into their suitable class. The suitable class is placed according to the range of blood pressure.

The Results

The proposed method has the training process accuracy very high. The iteration can generate accuracy almost 100% at the several iteration numbers. The total iteration is 100. The accuracy and lose progress as training process is ongoing is as shown in Figure 11.

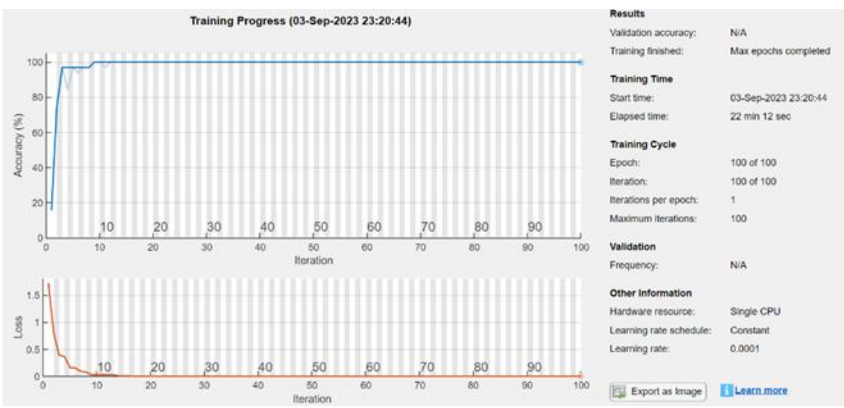

Figure 11 The progress of training process

The training process creates the model which has high accuracy. This accuracy is assessed by confusion matrix and ROC curve. The confusion matrix of the proposed method is as shown in Figure 12.

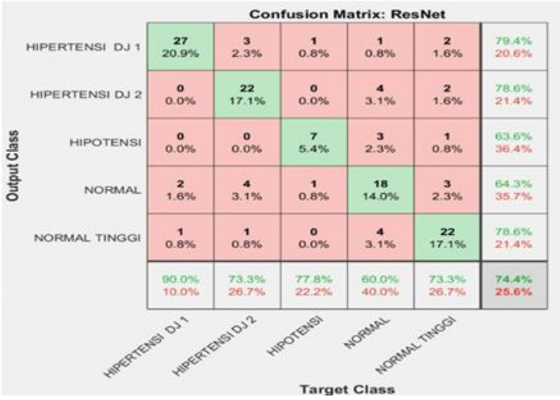

Figure 12. The confusion matrix of proposed method

In order to strengthen the accuracy, the other validation is performed to assess accuracy of proposed method. The use of ROC curve is applied. The ROC curve is as shown in Figure 13.

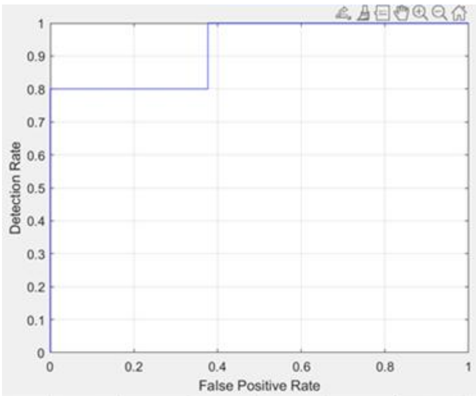

Figure 13. ROC curve of proposed method

Conclusion

The proposed method intends to solve the pain and stress of patients while monitoring and diagnose. Further, the proposed method also increase the accuracy of blood pressure The method uses three channel ECG images. The images are obtained from printing ECG signal of ECG machine. The process of obtaining important of the image is staring from the filtering tasks. The filtering task applies median and morphological filters. The pure ECG information in image is used as dataset. The portion of training and testing set 70 and 30 each. This percentage is determined by program automatically. The five classes of dataset contain high normal, normal, hypertension, hypertension stage 1 and hypertension stage 2. The result shows that the accuracy of the proposed method is 98.5 %. This value is very high and accurate to be applied to monitor and assess patient blood pressure. The use of three channels ECG signal and in image form become a novel and more efficient method of non invasive blood pressure measurement. That, this method can be applied more easly.

References

[1] S. Baker, W. Xiang, and I. Atkinson, “A computationally efficient CNN-LSTM neural network for estimation of blood pressure from features of electrocardiogram and photoplethysmogram waveforms,” *Knowledge-Based Syst.*, vol. 250, p. 109151, 2022, doi: 10.1016/j.knosys.2022.109151.

[2] S. Baek, J. Jang, and S. Yoon, “End-to-end blood pressure prediction via fully convolutional networks,” *IEEE Access*, vol. 7, pp. 185458–185468, 2019, doi: 10.1109/ACCESS.2019.2960844.

[3] G. Thambiraj, U. Gandhi, and U. Mangalanathan, *Data-driven models for cuffless blood pressure estimation using ECG and PPG signals*. INC, 2022.

[4] M. Seera, C. P. Lim, W. S. Liew, E. Lim, and C. K. Loo, “Classification of electrocardiogram and auscultatory blood pressure signals using machine learning models,” *Expert Syst. Appl.*, vol. 42, no. 7, pp. 3643–3652, 2015, doi: 10.1016/j.eswa.2014.12.023.

[5] F. Miao *et al.*, “Continuous blood pressure measurement from one-channel electrocardiogram signal using deep-learning techniques,” *Artif. Intell. Med.*, vol. 108, no. September 2019, 2020, doi: 10.1016/j.artmed.2020.101919.

[6] M. Kachuee, M. M. Kiani, H. Mohammadzade, and M. Shabany, “Cuffless Blood Pressure Estimation Algorithms for Continuous Health-Care Monitoring,” *IEEE Trans. Biomed. Eng.*, vol. 64, no. 4, pp. 859–869, 2017, doi: 10.1109/TBME.2016.2580904.

[7] B. Zhang, J. Ren, Y. Cheng, B. Wang, and Z. Wei, “Health data driven on continuous blood pressure prediction based on gradient boosting decision tree algorithm,” *IEEE Access*, vol. 7, pp. 32423–32433, 2019, doi: 10.1109/ACCESS.2019.2902217.

[8] X. Fan, H. Wang, F. Xu, Y. Zhao, and K. L. Tsui, “Homecare-Oriented Intelligent Long-Term Monitoring of Blood Pressure Using Electrocardiogram Signals,” *IEEE Trans. Ind. Informatics*, vol. 16, no. 11, pp. 7150–7158, 2020, doi: 10.1109/TII.2019.2962546.

[9] M. S. Tanveer and M. K. Hasan, “Cuffless blood pressure estimation from electrocardiogram and photoplethysmogram using waveform based ANN-LSTM network,” *Biomed. Signal Process. Control*, vol. 51, pp. 382–392, 2019, doi: 10.1016/j.bspc.2019.02.028.

[10] C. Wuerich, F. Wichum, O. El-kadri, K. Ghantawi, and N. Grewal, “Blood Pressure Estimation based on Electrocardiograms,” vol. 8, no. 2, pp. 53–56, 2022.

[11] A. O. P. Ppg, “PPG Sensor Contact Pressure Should Be Taken Into Account for Cuff-Less Blood,” *IEEE Trans. Biomed. Eng.*, vol. 67, no. 11, pp. 3134–3140, 2020, doi: 10.1109/TBME.2020.2976989.

[12] W. Liu, X. K. Wang, and L. H. Wang, “Noninvasive Blood Pressure Classification based on ECG with ResNet Algorithm,” *2021 IEEE Int. Conf. Consum. Electron. ICCE-TW 2021*, pp. 1–2, 2021, doi: 10.1109/ICCE-TW52618.2021.9603088.

[13] C. Yan *et al.*, “Novel Deep Convolutional Neural Network for Cuff-less Blood Pressure Measurement Using ECG and PPG Signals,” *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, pp. 1917–1920, 2019, doi: 10.1109/EMBC.2019.8857108.

[14] C. T. Yen, S. N. Chang, and C. H. Liao, “Estimation of Beat-by-Beat Blood Pressure and Heart Rate From ECG and PPG Using a Fine-Tuned Deep CNN Model,” *IEEE Access*, vol. 10, no. August, pp. 85459–85469, 2022, doi: 10.1109/ACCESS.2022.3195857.

[15] J. Cano, L. Facila, P. Langley, R. Zangroniz, R. Alcaraz, and J. J. Rieta, “Application of Deep Neural Network Models for Blood Pressure Classification based on Photoplethysmograpic Recordings,” *2021 9th E-Health Bioeng. Conf. EHB 2021*, no. Cvd, pp. 2021–2024, 2021, doi: 10.1109/EHB52898.2021.9657658.