ISSN: 2395-1680 (ONLINE)
DOI: 10.21917/ijme.2024.0317

DEEP LEARNING MODEL FOR CUFFLESS ESTIMATION OF BLOOD PRESSURE USING PPG

S.J. Alphonsa Salu and D. Jeraldin Auxillia
Department of Electronics and Communication Engineering, St. Xavier's Catholic College of Engineering, India

Abstract

Blood pressure is a vital sign used to measure the health of human heart. A persistent abnormal blood pressure can cause various cardiovascular diseases and if left untreated can lead to organ damage. Continuous and periodic blood pressure assessment is relevant for heart disease prevention. Regardless of the BP monitoring techniques in literature which are intermittent and cumbersome, several studies have considered using photoplethysmogram (PPG) signal as a cuffless and continuous measure of blood pressure. Here we propose a method to measure systolic BP using PPG and bidirectional GRU (Gated Recurrent Unit). The PPG signals of 219 subjects from the PPG-BP database are pre-processed using a zero-phase IIR Butterworth low pass filter. The pre-processed and normalized signal is then directly fed to the deep neural network architecture. The proposed work uses PPG signal with only 6 features along with Bi-GRU to estimate systolic BP. Certain PPG attributes such as cardiac period, systolic time, diastolic time, pulse area, systolic width and diastolic width are extracted from each cycle. The performance is measured based on metrics like mean absolute error (MAE) and standard deviation (SD). MAE of 4.56mmHg and SD of ±6.48mmHg are obtained for SBP meeting the requirement set by the AAMI standard.

Keywords:

Photoplethysmography, Systolic BP, Pulse Area, Cardiac Period, Bidirectional GRU

1. INTRODUCTION

The major reason for death throughout the world is hypertension or increased blood pressure. It can even be mentioned as a 'Silent Killer' contributing to the deaths of about 9.4 million people every year [1]. Nowadays, it has become a very common problem in adults. Hypertension paves way to serious illness such as heart failure, diabetes, stroke and even kidney diseases [2]. Regular monitoring of BP in a clinical or non-clinical environment is therefore much necessary. The ideal range is 90-120 mmHg for systolic BP (pressure when the heart beats) and 60-80 mmHg for diastolic BP (pressure when the heart rests) respectively. Above this signifies that the one being monitored is hypertensive and below is hypotensive [1] [3]. Rather than indicating harmful health issues, an individual's blood pressure assessment carries a lot of knowledge regarding the person's physical qualities. Hence, it is advised to have a regular check up on BP to avoid serious illness [3].

BP is measured either invasive or non-invasive. The different techniques involved in the measurement of BP are illustrated in Fig.1. The invasive method of BP assessment is the 'golden standard' for BP assessment internationally. It gives the most accurate BP value by placing a catheter with a blood pressure sensor invasively in order to calculate arterial BP. But the issue is that it carries risk of infection and pain. And used for patients in the critical care units during surgical procedures [4]. The non-invasive methods of BP measurement are broadly classified into two groups such as oscillometric method and auscultatory method. These are cuff-based non-invasive methods which do not cause any major side effects as invasive methods. But these devices assess BP with 2 minutes intervals between measurements which make the patient feel uncomfortable for a continuous and long-term monitoring. The frequent inflation and deflation cause pain and also interrupts the flow of blood [3] [5]. Moreover, the cuff-based instruments cannot be taken for assessing sleep patterns since the continuous inflation and deflation may lead to an awakening arousal.

In the auscultatory method, the brachial cuff located in the upper arm is inflated using sphygmomanometer until the brachial artery is blocked completely. After that it is deflated fully until the first Korotkoff sound indicating the beginning of blood flow is observed. The reading at this point represents the systolic BP. Afterwards the pressure gets released until there is no sound. The value at this point represents the diastolic BP [5] [6]. In oscillometric method, an electronic transducer is used to detect the pressure inside the cuff rather than using a stethoscope. Using this method mean diastolic and systolic BP are measured. Even though, the oscillometric method is prevalent with caregivers and professionals, accuracy matters. [7] [8]. Hence, the unavailability of continuous BP monitoring technique at present can be understood.

Over last few years calculation of BP using PPG (Photoplethysmography) signal has given lot of promise. PPG technique uses a pulse oximeter that measures the change in the volume of blood using infrared light [9]. PPG signal is also used to estimate the arterial stiffness and pulse rate variability (PRV). PRV refers to the change in pulse rate as a function of time correlated with BP [10].

Several continuous and cuffless BP assessment techniques using PPG signals have been proposed. One of them is the calculation using Pulse Transit Time (PTT) which is very common. It is the time by which the pressure wave travels from proximal arterial site to distal arterial site within a single systole-diastole event in a cardiac cycle [11]. It is measured with sensors placed at two locations. A similar approach to measure BP is Pulse Arrival Time (PAT). It is time from the R-peak of ECG and PPG peak within a cycle [12]. Also, Pulse Wave Velocity (PWV) is a popular technique to estimate BP which is the velocity at which pressure wave propagates through the circulatory system. It is calculated as the ratio of the length of arteries between two different artery sites. In this method the temporal, spectral or the characteristics of the signal are extracted using a single sensor [13]. These methods require frequent calibration as the elasticity of the arteries vary from person to person.

Another popular approach of blood pressure measurement which has emerged recently is the Pulse Wave Analysis (PWA). In PWA the signal is subjected to temporal, spectral, spectro-temporal or chaotic analysis to extract the features of PPG signal

[15]. With developments in signal processing methods using artificial intelligence several algorithms are being put forth in order to achieve better accuracy. The aim of all these works is to reduce the error of BP estimation.

From literature, it is understood firstly that using PPG based models yields a relatively good and inexpensive way to estimate blood pressure. Also, PPG is measured directly on the microvascular bed of tissues. Secondly, the measurement of BP using PTT, PAT and PWV parameters requires more than one sensor as well as ECG recording which can be inconvenient for patients [16]. And both the signals need to be processed in order to clean the artefacts. Also, these methods require calibration as the elasticity of arteries varies from person to person. In all the above methods continuous monitoring of BP is extremely difficult.

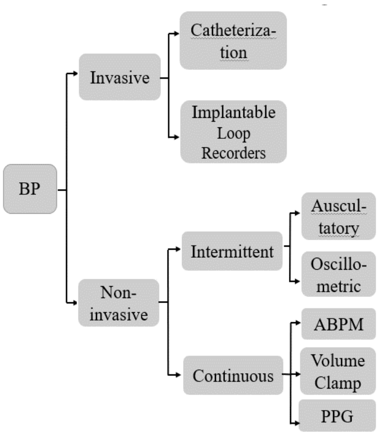

Fig.1. A hierarchical view of BP techniques

Certain linear and non-linear methods are used for the prediction of BP. Certain non-linear models like decision tree, SVR, Adaptive boosting and random forest regression showed good performance using features related to time between systolic peaks [17]. The problem with these models is that they are sensitive to outliers and missing peaks and produces biased predictions. In a work proposed by Elisa et al., XGBR and SVR uses PRV and morphological features for the prediction of BP using PPG. The combined features showed better performance but are found to be sensitive to noise. SVR with morphological features is able to estimate blood pressure accurately. But in SVR proper kernel selection is important to prevent overfitting [18]. The challenges while using PRV and morphological features are overcome by considering non-linear features extracted from the higher order derivatives. But higher order derivatives involve a lot of computation and also lacks generalization [19].

In spite of easy implementation classical ML models require handcrafted feature engineering and the performance depends on the quality of the features. Also, they struggle to capture the intricate relationship in high dimensional data. Considering these issues certain studies proposed algorithms based on neural networks that can handle high dimensional data efficiently. In a proposed work [20] ANN with Bayesian algorithm as learning function and Levenberg Marquardt algorithm used crossed Large Artery Stiffness Index (LASI) features and morphological elements to estimate BP. The results show that the network is unsuitable for long term predictions.

When continuous monitoring of BP is required, the ML and neural network models fail to capture time dependency in time series data. Considering the information regarding previous inputs together with the current input could yield much better learning of the model. Hence, some studies in the literature used recurrent NN that can learn from the previous input features with current input features to estimate BP. In a work proposed by Mohammad et al., chaotic features of PPG are used so that the model could learn the randomness of the signal as well as its deterministic behaviour to initial conditions. A deep bidirectional recurrent neural network implemented using LSTM and GRU cells along with attention layer is designed for learning significant features [21]. But the work involved a lot of computations which could affect the real time implementation. In another work a hybrid method using LSTM and ANN information about the previous signal features are preserved for the calculation and classification of BP [22]. This work also involves a lot of computations.

From the literature it is understood that the classical machine learning models require tedious feature engineering and identification of suitable features for generating a high-performance model for the calculation of BP using PPG. While considering deep learning models, retaining past information regarding the inputs could add to the ability of the model. Therefore, a deep recurrent NN that learns features automatically and considers the information gained from the previous inputs has to be implemented in order to eliminate the above said problems for a computationally efficient and accurate estimation of BP.

The contents in the following sections of the paper includes the materials and methods, results and discussions, conclusion and future scope of the study.

2. METHODS

2.1 PHOTOPLETHYSMOGRAPHY (PPG)

It is an optical method of calculating the change in the volume of blood within a cardiac beat using LED (Light Emitting Diode) and Photo Detector (PD). This technique shown in Fig.2 mainly includes two optical modes such as transmission and reflection. The blood volume changes are measured by placing the PPG device on the finger or on the wrist. An LED is used which emits light and the light gets into the body tissue. The changes in the volume of blood are measured from the change in absorption of light in a time period via a photodetector. The PPG is a wave-like and its frequency is almost similar to that of the working frequency of heart [23]. PPG signal contains two sections depicted in Fig.3. The top portion in the signal represents the heart contraction or the systolic portion. And the lower portion represents the heart expansion or diastolic portion.

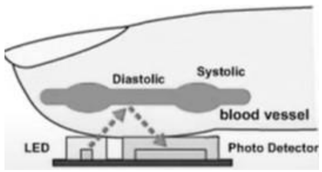

Fig.2. Technique of PPG acquisition

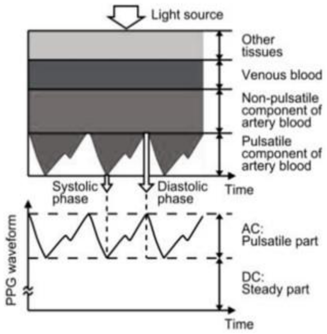

Fig.3. Basic principle of PPG

2.2 DATASET

The database used is taken from Guilin people's hospital, China. It is available online to be downloaded from the Fig share repository [24]. The data consists of signals collected from 219 subjects including 104 males and 115 females, aged 21-86 years, with average age of 57. The percentage of male subjects is 48. The data includes three segments of signals per subject with a duration of 2.1s making a total of 657 segments. It also includes clinical information like sex, age, BMI, weight, heart rate and disease record of subjects. The signal is sampled at a frequency of 1kHz with 12-bit A-D conversion precision. The dataset includes the signal quality index (SQI) value based on skewness which represents asymmetry of a distribution. The corresponding systolic BP and diastolic BP values are recorded simultaneously by a BP collection device. The data includes normotensive, prehypertensive and hypertensive (Stage-I and Stage-II) subjects with BP proportions 36.5%, 38.8% and 24.7% respectively. In the proposed work, among the three segments, the segments with high skewness value are preferred per subject. Hence, a total of 219 segments are used.

2.3 PREPROCESSING

The PPG signals are more complex signals and are prone to noise like baseline wander and motion artifacts. Baseline wander refers to the drift in the baseline caused by respiration or change in sensor pressure. This causes low frequency noise, primarily within 0.5 Hz. Motion artifacts can cause fluctuations in the frequency thereby masking the actual PPG waveform. This causes high frequency noise around 50Hz. Power-line noise cancontaminate the signal causing periodic fluctuations. Hence, for the proper analysis of PPG signal, preprocessing is essential. The block diagram representation shown in Fig.4 depicts the proposed work.

2.3.1 Signal Filtering and Normalization:

The filters have to perform well in order to retain the important aspects of PPG. Filtering includes a 10^{th} order zero-phase Butterworth IIR LPF. The significance of Butterworth filter is that it attenuates unwanted noise while maintaining signal fidelity [24]. In addition to filtering, normalization is also important in pre-processing. PPG signal amplitude is normalized in the range between 0 and 1 in order to get a simplified analysis of the signal. Min-max method is used here and it is given in Eq.(1). where Xn X_n represents the resulting normalized signal, min(X) and max(X) represents the minimum and maximum of the signal value.

$$X_n=(X-\min(X))/(\max(X)-\min(X)) \quad (1)$$

Removal of baseline wander in PPG signal facilitates the interpretation of signal and increases the enhancement of signal features. We removed the baseline wander by calculating the mean of normalized signal and subtracting it from the normalized signal. The raw PPG signal is shown in Fig.5 and filtered PPG signal is shown in Fig.6.

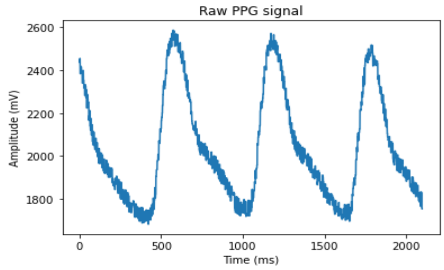

Fig.5. Raw PPG signal

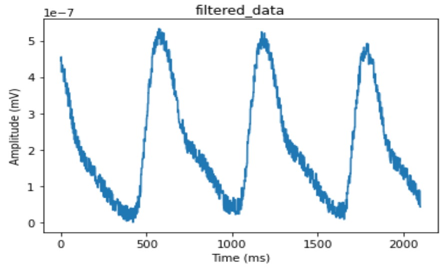

Fig.6. Filtered PPG signal -10^{th} order Butterworth LPF

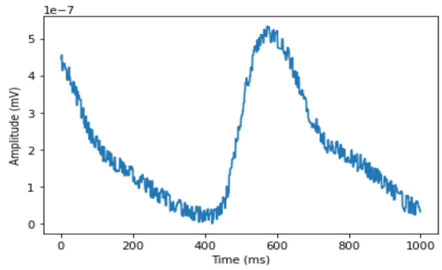

Fig.7. Single cycle PPG signal extracted from filtered output

2.4 BP ESTIMATION USING DEEP RECURRENT NEURAL NETWORK

2.4.1 Feature Extraction:

Feature extraction is done on a 2.1s PPG segment where 6 important attributes such as cardiac period, systolic time, diastolic time, pulse area, systolic width and diastolic width extracted from each cycle. Single cycle of PPG is shown in Fig.7. Each cycle has a peak and two valleys. The time interval between two successive heartbeats is known as the cardiac period. The calculation is done by detecting the peaks which corresponds to individual heartbeats and computing the time between them. The systolic time is calculated from the duration between ventricular contraction onset and the aortic valve closure. It is calculated from PPG by measuring the time from the systolic peak to the dicrotic notch. Dicrotic notch is a point in the PPG waveform which marks the end of a systole and beginning of a diastole.

The time from the closure of the aortic valve and the onset of the next ventricular contraction is the diastolic time. From PPG it is calculated by measuring the time between the dicrotic notch and systolic peak. Another feature extracted from PPG is the pulse area. It is the volume of blood which is pumped during a single cycle and the calculation of pulse area from PPG is done by integrating the area under the systolic region of the waveform. The duration of diastolic phase is represented as diastolic width. The time from the systolic peak to the systolic foot is the systolic width. The arterial stiffness and the vascular health are assessed by the systolic width of a PPG signal. The extracted features are as shown in Fig.8.

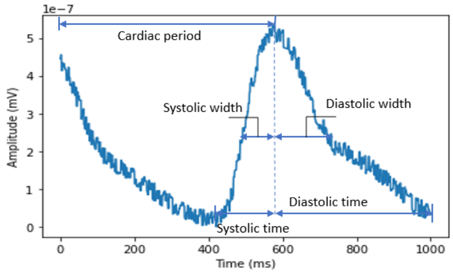

Fig.8. Features extracted from a single cycle PPG

2.4.2 Feature Selection Process:

The explicit knowledge about the morphological features that has direct correlation with BP is unpredictable because the contours in the PPG waveform varies among different subjects. For example, in younger subjects the dicrotic notch is more visible than in older subjects. The morphological features such as, systolic and diastolic time, and width are found to be correlated with BP in a work carried out by Teng and Zhang [26]. Linder et al. [27] suggested that the cardiac period is an important feature to consider because low cardiac period consequently means high systolic blood pressure. In a related work done by Kurylyak et al. [28] to estimate blood pressure, pulse area is considered to be one of the important features as it indicates the changes in vascular tone (vasoconstriction/vasodilation). Considering all these the features are selected.

2.4.3 Bi-GRU (Bidirectional Gated Recurrent Unit) Model:

In this study the estimation of BP is performed using Bidirectional GRU. The traditional GRU model is modified as the bidirectional GRU in order to enhance its capability to obtain time dependencies in data. This is acquired when the input is processed both in forward direction and backward. The inputs are features extracted and then fed to the Bi-GRU unit and then to the fully connected output layer. The input time sequence is processed both in the forward and backward direction within hidden layers and finally, the output in hidden layer is fed to fully connected output layer to obtain the output parameter (systolic BP). The major advantage of Bi-GRU that makes it perfect for sequence modelling tasks is that it gets knowledge from past and future time steps. This aspect of Bi-GRU model is especially important for BP estimation from PPG signals, that is a mixture of complex and non-linear relationships between the input and target to be predicted.

2.4.4 Gated Recurrent Unit (GRU):

In this section basic GRU which is a RNN (Recurrent Neural Network) is discussed. The architecture of a single GRU cell is as shown in Fig.8. The traditional RNNs are incapable of capturing long-term and short-term dependencies in sequential data. The important aspect of GRU lies in its gating mechanism which enables the model to selectively update and pass information through time. GRU consists of two main gates such as the update gate and reset gate. The amount of information retained by the hidden state is calculated by the reset gate and the amount of new information which is to be added to the current hidden state is determined by the update gate. It controls the amount of information that flows from the previous state to the current time step. Reset gate decides the amount of information that is forgotten by the hidden state and the amount of new input used for computing candidate hidden state. It helps to decide the information which is relevant to the current time step. By applying the tanh activation to the previous state and current input candidate hidden state $\tilde{h}_t$ is computed. It gives the new information that should be added to hidden state. Finally, update gate computes the new hidden state h_t by blending the previous hidden state with the candidate hidden state.

This gating mechanism allows GRU to capture long-range dependencies and helps to retain important information over long-range sequences. The activation functions allow the gates to learn which information to remember or forget current information in the cell. The architecture of a Bi-GRU network is typically composed of multiple GRU cells, each of which are interconnected in a chain-like fashion.

2.4.5 Dense layer

A dense layer in GRU is a form of fully connected layer which processes the output in the last GRU unit in the sequence and generates final output. A group of learnable weights and biases are applied to generate an output. Basically, in neural networks, activation is used in order to transform the input values of neurons. Actually, non-linearity is introduced into the network so that it learns the relationship among input and output values. Output of GRU unit is passed through one or more dense layers before the final output is generated. The dense layer(s) maps the higher-dimensional hidden state to a lower-dimensional space to perform non-linear transformations, thereby adding more capacity to the network so that complex patterns can be learned.

Reset gate (r_t) is given by:

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{2}$$

where

x_t - input at time step t

r_t - reset gate at time step t

h_{t-1} - previous time step;

σ is the sigmoid function

U_r, W_r - weight matrices of reset gate

Update gate (z_t) is given by the equation:

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{3}$$

where

x_t - input at time step t

z_t - update gate at time step t

U_z, W_z - weight matrices of update gate

Candidate hidden state $\left(\tilde{h}_t\right)$:

$$\left(\tilde{h}_t\right) = \tanh\left(W_h x_t + U_h \left(r_t \odot h_{t-1}\right) + b_h\right) \tag{4}$$

where

x_t - input at time step t

r_t - reset gate at time step t

h_{t-1} - previous time step

σ - sigmoid function,

U_h, W_h - weight matrices of candidate hidden state

Hidden state (h_t):

$$h_t = (1-z_t) \odot h_{t-1} + z_t \odot \left(\tilde{h}_t\right) \tag{5}$$

$$\text{Output layer } (y_t) = \text{softmax}\,(Wh_t+b) \tag{6}$$

Dense layer output is computed as follows:

$$y = \text{activation function}\,(Wy_t+b) \tag{7}$$

where

x - input to the layer

W - metrics of learnable weights

b - vector of biases

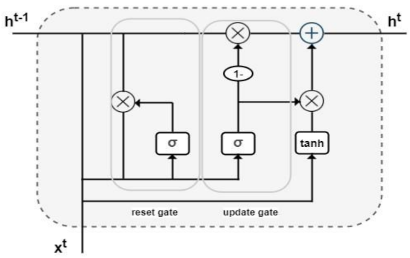

Fig.9. A single GRU cell

3. RESULTS AND DISCUSSION

The method of calculation of BP using bidirectional GRU model is discussed. The proposed method overcome the limitations in the existing methods which are either invasive or cuff-based and intermittent. A zero-phase Butterworth IIR LPF is used for low frequency baseline wandering, noise and artifacts removal. In this chapter, pre-processed PPG signal, features extracted and bidirectional GRU model for parameter estimation are being discussed. The features of a 2.1 s PPG segment are shown in Table.1.

Table.1. Extracted features from segments

Seg	Cardiac period (s)	Systolic time (s)	Diastolic time (s)	Pulse area (mVs)	Diastolic width (s)	Systolic width (s)
0	0.796	0.0805	0.7638	1.475	0.531	1.281
1	0.9237	0.0823	0.7224	1.654	0.455	0.726

3.1 HYPERPARAMETER CHOICE AND OPTIMIZATION

In hardware implementation there is always a trade-off between accuracy and complexity. To facilitate hardware implementation only 1 hidden layer is used. To avoid underfitting and overfitting, the number of neurons is chosen to be 128. Adam optimizer is chosen as it converges faster than gradient descent optimizer. Experiments are done with three learning rates 0.0001, 0.001 and 0.01. As the learning rate is varied from 0.0001 to 0.001, the performance improved. But above 0.001 the model faced an issue of overfitting and hence as an optimum value 0.001 is chosen and used constantly throughout the entire process. The list of hyperparameters is given in Table.2. Initially, the batch size is set to 40 and varied up to 80. The mean absolute error was minimum for a batch size of 60. Table.3. shows the performance of the model for different batch sizes.

Table.2. List of hyperparameters

Number of layers	1
Number of neurons	128
Optimizer	Adam
Learning rate	0.001
Batch size	60
Number of epochs	160

Dataset is partitioned such that 60% data is taken for training, 20 % each for validation and testing. The best optimised model is obtained using the validation set for which the accuracy of test samples is given in the results. The model was trained using a batch size of 60 which stops before 160 epochs. Mean Absolute error (MAE) is the loss function.

Table.3. Performance for different batch sizes

Batch size	MAE (mmHg)
40	10.28
50	8.12
60	4.56

3.2 TRAINING AND VALIDATION

Training and validation loss graph in Fig.10 represents the value at the 1st epoch is 8189.224, and at the 150th epoch, it is 5.621. And the validation loss graph represents the value at the 1st epoch is 8311.812, and at the 150th epoch it is 5.398. Monitoring the loss graph is necessary during training for assessing the model's learning progress. Lower loss represents the model predictions are accurate while a higher loss represents that the predictions are less accurate. The efficiency is evaluated using a performance metric to achieve its intended goals and objectives. The performance measures to evaluate the model includes MAE and Standard deviation (SD). In this study it is inferred that MAE obtained is 4.56mmHg and SD is obtained as ±6.48mmHg for the calculation of systolic BP.

3.3 GENERALIZABILITY OF THE MODEL

The generalizability of the model is verified with another dataset specified as PPG-based-BP-assessment dataset. This data is collected in a laboratory, and it includes PPG records from 56 subjects (22 men and 34 women) with an average age of 52.48 ± 7.16 years. Each record includes a 2-min PPG segment sampled at 100 Hz. The model produced a MAE of 5.27mmHg and a SD of ±4.86. The comparative results are given in Table.4.

Table.4. Performance comparison of model with PPG-based-BP-assessment dataset

Dataset	No. of subjects	MAE (mmHg)	SD (mmHg)
PPG-BP Dataset	219	4.56	±6.48
PPG-based-BP-assessment dataset	56	5.27	±4.86

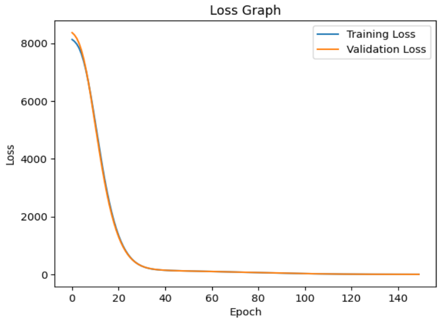

Fig.10. Training loss and validation loss graph

To compare the ability of the proposed work with the global standards for cuffless BP estimation, we use AAMI standard. The Table.5 represents a comparison of the work with certain other similar works. According to AAMI, the mean error (ME) should be 5mmHg and standard deviation (SD) should be 8 mmHg. This study shows that the model satisfies the requirements of AAMI and hence suitable for BP estimation. The performance of the proposed model is more than the conventional methods. The MAE for the proposed model was around 4.56mmHg and SD between ±6.48mmHg for BP estimation. From this study it is inferred that the estimation error is lower.

Table.5. Comparison with other models

Model	MAE (mmHg)	SD (mmHg)
Linear Regression model (Choudhury et al. 2014)	7.8	±13.1
Support vector Machine model (Liu et al. 2017)	8.54	±10.9
Proposed model	4.56	±6.48

In this work, Gated Recurrent Unit model with bidirectional connection is used for estimating BP with a single PPG sensor in a cuffless and continuous manner. The model is evaluated on using the PPG-BP database collected online from the Fig share repository. The 6 features extracted from the PPG segments form inputs to the Bi-GRU model. To prevent overfitting and optimizing the model parameters, the data was divided as train set, validation set and test set. The work is compared with multilinear regression and SVM. The results in Table.5 demonstrates that the model shows a better performance with reduced error.

3.4 LIMITATIONS AND POSSIBLE CHALLENGES

The proposed model uses only temporal features (time domain), adding derivative features (features obtained from higher order derivatives of the signal) would enhance the model's performance. Though the dataset includes blood pressure data from both normal and diseased subjects, the number of subjects is only 219. Increasing the number of subjects above 500 could improve the performance of the model. Also, this work involves a small set of features and hence less computation is required. But, in real time implementation, the model could face a problem of underfitting due to reduced number of features and data. In conclusion if the number of data and number of features are increased the model's performance could improve. Moreover, in this work only systolic BP is estimated.

4. CONCLUSION

The proposed work is a model for cuffless BP calculation from PPG signals using Bi-GRU Using bidirectional recurrent structures helps in estimating BP continuously, while GRU structure models the temporal variations of the extracted features. Here the model used a set of 6 features acquired from PPG and thus the complexity is reduced. The network is trained with back propagation algorithm. The system is evaluated using performance metrics like mean absolute error and standard deviation. The MAE of 4.56 mmHg and a SD of ±6.48mmHg falls below 8 specified by the AAMI standard thus meets the acceptable criteria set by the AAMI standard. Also, it is inferred from the literature that the proposed work shows a better performance. The proposed study can be extended to adding more features of PPG signal to increase the performance. Additionally, a more complex dataset could be examined to enhance the capabilities of the prediction model. Also, the future work aims to contribute to the classification of various blood pressure states, including normal, hypertensive, and hypotensive.

REFERENCES

[1] World Health Organization, A Global Brief on Hypertension: Silent Killer, Global Public Health Crisis: World Health Day 2013 Available at https://www.who.int/publications/i/item/a-global-brief-on-hypertension-silent-killer-global-public-health-crisis-world-health-day-2013, Accessed in 2013.

[2] I. Hajjar, J.M. Kotchen and T.A. Kotchen, "Hypertension: Trends in Prevalence, Incidence and Control", *Annual Review of Public Health*, Vol. 27, pp. 465-490, 2006.

[3] G. Ogedegbe and T. Pickering, "Principles and Techniques of Blood Pressure Measurement", *Clinical Cardiology*, Vol. 28, pp. 571-586, 2010.

[4] M.C. Irigoyen, K. De Angelis, F. Dos Santos, D.R. Dartora, B. Rodrigues and F.M. Consolim-Colombo, "Hypertension, Blood Pressure Variability and Target Organ Lesion", *Current Hypertension Reports*, Vol. 18, No. 4, pp. 31-36, 2016.

[5] H. Smulyan and M.E. Safar, "Blood Pressure Measurement: Retrospective and Prospective Views", *American Journal of Hypertension*, Vol. 24, No. 6, pp. 628-634, 2011.

[6] P.A. Iaizzo, "Handbook of Cardiac Anatomy, Physiology and Devices", *Journal of Cardiac Surgery*, Vol. 21, No. 3, pp.327-327, 2006.

[7] H. Gesche, D. Grosskurth, G. Küchler and A. Patzak, "Continuous Blood Pressure Measurement by using the Pulse Transit Time: Comparison to a Cuff-based Method",

European Journal of Applied Physiology, Vol. 112, No. 1, pp. 309-315, 2012.

[8] B.S. Alpert, D. Quinn and D. Gallick, "Oscillometric Blood Pressure: A Review for Clinicians", *Journal of the American Society of Hypertension*, Vol. 8, pp. 930-938, 2014.

[9] E. Mejia-Mejia, J.M. May, M. Elgendi and P.A. Kyriacou, "Differential Effects of the Blood Pressure State on Pulse Rate Variability and Heart Rate Variability in Critically Ill Patients", *NPJ Digital Medicine*, Vol. 4, No. 82, 2021.

[10] Y. Choi, Q. Zhang and S. Ko, "Non-Invasive Cuffless Blood Pressure Estimation using Pulse Transit Time and Hilbert-Huang Transform", *Computers and Electrical Engineering*, Vol. 39, No. 1, pp. 103-111, 2013.

[11] M. Sharma, K. Barbosa, V. Ho, D. Griggs, T. Ghirmai, S. Krishnan, T. Hsiai, J.C. Chiao and H. Cao, "Cuff-Less and Continuous Blood Pressure Monitoring: A Methodological Review", *Technologies*, Vol. 5, No. 2, pp. 21-27, 2017.

[12] Y. Chen, C. Wen, G. Tao, M. Bi and G. Li, "Continuous and Non-Invasive Blood Pressure Measurement: A Novel Modelling Methodology of the Relationship Between Blood Pressure and Pulse Wave Velocity", *Annals of Biomedical Engineering*, Vol. 37, No. 11, pp. 2222-2233, 2009.

[13] P. Nabeel, V.R. Kiran, J. Joseph, V. Abhidev and M. Sivaprakasam, "Local Pulse Wave Velocity: Theory, Methods, Advancements and Clinical Applications", *Annual Review of Biomedical Engineering*, Vol. 13, pp. 74-112, 2019.

[14] A. Avolio, J. Cox, K. Louka, F. Shirbani, I. Tan, A. Qasem and M. Butlin, "Challenges Presented by Cuffless Measurement of Blood Pressure if Adopted for Diagnosis and Treatment of Hypertension", *Pulse (Basel)*, Vol. 10, No. 1, pp. 34-45, 2022.

[15] M. Elgendi, R. Fletcher, Y. Liang, N. Howard, N.H. Lovell, D. Abbott, K. Lim and R. Ward, "The use of Photoplethysmography for Assessing Hypertension", *NPJ Digital Medicine*, Vol. 2, No. 1, pp. 1-11, 2019.

[16] Y.B. Liang, Z.C. Chen, G.Y. Liu and M. Elgendi, "Data Descriptor: A New Short-Recorded Photoplethysmogram Dataset for Blood Pressure Monitoring in China", *Scientific Data*, Vol. 5, pp. 1-5, 2018.

[17] Seyedeh Somayyeh Mousavi, Mohammad Firouzmand, Mostafa Charmi, Mohammad Hemmati, Maryam Moghadam and Yadollah Ghorbani, "Blood Pressure Estimation from Appropriate and Inappropriate PPG Signals using A Whole-based Method", *Biomedical Signal Processing and Control*, Vol. 47, pp. 196-206, 2019.

[18] Elisa Mejía-Mejía, Karthik Budidha, Panayiotis A. Kyriacou, Mohammad Mamouei, "Comparison of Pulse Rate Variability and Morphological Features of Photoplethysmogram in Estimation of Blood Pressure", *Biomedical Signal Processing and Control*, Vol. 78, pp. 1-6, 2022.

[19] S. Gupta, A. Singh, A. Sharma and R.K. Tripathy, "Higher Order Derivative-Based Integrated Model for Cuff-Less Blood Pressure Estimation and Stratification using PPG Signals", *IEEE Sensors Journal*, Vol. 22, No. 22, pp. 22030-22039, 2022.

[20] Maher Nashat, G.A. Elsheikh, W.R. Anis and Emara Tamer, "Enhancement of Blood Pressure Estimation Method Via Machine Learning", *Alexandria Engineering Journal*, Vol. 60, pp. 5779-5796, 2021.

[21] C El-Hajj and PA Kyriacou, "Deep Learning Models for Cuffless Blood Pressure Monitoring from PPG Signals using Attention Mechanism", *Biomedical Signal Processing and Control*, Vol. 65, pp. 1-7, 2021.

[22] Noor Faris Ali and Mohamed Atef, "An Efficient Hybrid LSTM-ANN Joint Classification-Regression Model for PPG based Blood Pressure Monitoring", *Biomedical Signal Processing and Control*, Vol. 84, pp. 1-6, 2023.

[23] H. Tjahjadi, K. Ramli and H. Murfi, "Noninvasive Classification of Blood Pressure based on Photoplethysmography Signals using Bidirectional Long Short-Term Memory and Time-Frequency Analysis", *IEEE Access*, Vol. 8, pp. 20735-20748, 2020.

[24] Gengjia Zhang, Daegil Choi and Jaehyo Jung, "Development of Continuous Cuffless Blood Pressure Prediction Platform using Enhanced 1-D SENet–LSTM", *Expert Systems with Applications*, Vol. 242, pp. 1-7, 2024.

[25] M. Elgendi, "On the Analysis of Fingertip Photoplethysmogram Signals", *Current Cardiology Reviews*, Vol.8, No.1, pp.14-25, 2012.

[26] X. Teng and Y. Zhang, "Continuous and Noninvasive Estimation of Arterial Blood Pressure using a Photoplethysmographic Approach", *Proceedings of International Conference on Engineering in Medicine and Biology Society*, pp. 3153-3156, 2023.

[27] S.P. Linder, S.M. Wendelken, E. Wei and S.P. McGrath, "Using the Morphology of Photoplethysmogram Peaks to Detect Changes in Posture", *Journal of Clinical Monitoring and Computing*, Vol. 20, pp. 151-158, 2006.

[28] Y. Kurylyak, F. Lamonaca and D. Grimaldi, "A Neural Network-based Method for Continuous Blood Pressure Estimation from a PPG Signal", *Proceedings of International Conference* on *Instrumentation and Measurement Technology*, pp. 280-283, 2013.

[29] C El-Hajj, P.A Kyriacou, "Cuffless Blood Pressure Estimation from PPG signals and its Derivatives using Deep Learning Models", *Biomedical Signal Processing and Control*, Vol. 70, pp. 1-12, 2021.