Smartphone Based BP Level Monitoring System Using DNN Model

Mahmuda
Department of Electrical and Electronic Engineering
Independent University, Bangladesh
Dhaka 1229, Bangladesh
2231669@iub.edu.bd

Barkatullah
Department of Electrical and Electronic Engineering
Independent University, Bangladesh
Dhaka 1229, Bangladesh
2231670@iub.edu.bd

Md Rezwanul Haque
Department of Electrical and Electronic Engineering
Independent University, Bangladesh
Dhaka 1229, Bangladesh
rezwanh001@gmail.com

Abdullah Al Noman
Phillip M. Drayer Department of Electrical and Electronic Engineering
Lamar University
Texas, United States
anoman1@lamar.edu

Emranul Haque
Department of Electrical and Electronic Engineering
Independent University, Bangladesh
Dhaka 1229, Bangladesh
emran1612@iub.edu.bd

Feroz Ahmed
Department of Electrical and Electronic Engineering
Independent University, Bangladesh
Dhaka 1229, Bangladesh
fahmed@iub.edu.bd

2023 International Conference on Advanced Technologies for Communications (ATC) | 979-8-3503-0132-8/23/$31.00 ©2023 IEEE | DOI: 10.1109/ATC58710.2023.10318933

***Abstract*—In this paper, a novel, non-invasive, cuff-less method is proposed for monitoring BP level from Photoplethysmography (PPG) signal based on Smartphone contact video instead of additional sensors or equipment. Since most people possess a smartphone, blood pressure (BP) can be measured using the smartphone's video through PPG signal rather than the conventional procedures, which still rely on BP measurement instruments that are not accessible to everyone. During data collection, participants placed their finger on the phone camera while the camera flashlight illuminated it. A total of 65 individuals provided fingertip videos for this study. From each subject's fingertip videos, PPG signal was generated at a frame rate of 60 fps (frame per second). After preprocessing to remove noise and baseline drift, 40 distinct features were extracted from the PPG signal using single period, first and second-order derivatives, and Fourier analysis. The extracted features are then used as input in a DNN model to train the model to evaluate the measurement. The PPG signal benefits from 60 fps frame rate as it enables precise tracking of subtle changes in blood flow and heart rate, whereas using the arPLS algorithm for baseline correction results in a clear PPG signal by eliminating baseline drift, allowing for a more dependable analysis of blood pressure levels. This approach provides an estimated R^2=0.963 and R^2=0.952 accuracy in the case of systolic and diastolic BP level measurements, respectfully.**

Keywords*—Pressure, PPG signal, Smartphone, Baseline correction.

I. Introduction

Heart disease and stroke are the two major causes of death worldwide. High blood pressure, commonly known as hypertension, is referred to as a “silent killer” ‘ because of its modest signs and occasionally fatal consequences [1]. High blood pressure (HBP) is a serious risk factor for cardiovascular disease and stroke that can be controlled, but precise and efficient techniques of diagnosis and treatment are required [2]. Therefore, it's crucial to often check blood pressure (BP) through regular BP monitoring. The conventional approach to BP level monitoring requires a BP monitoring device called a sphygmomanometer, and most people are unfamiliar with how to interpret blood pressure readings from these instruments due to their portability and complexity. Although there are portable gadgets for estimating blood pressure, these systems still need an arm cuff for blood pressure monitoring, which makes continuous monitoring challenging. Consequently, a non-invasive cuffless blood pressure monitoring system is necessitated to address the health needs of the expanding population and enhance people's quality of life. However, since everyone has a smartphone, it would be beneficial if BP monitoring could be done in some way utilizing a smartphone. The PPG approach has been used to quantify blood volume fluctuations in specific body regions [3]. A light source and a photodetector are used in the PPG system to illuminate the tissue's region while the detector picks up the reflected light. The blood flow from the heart to the finger's tip is reflected by it [4]. The amount of light that is consistently absorbed in response to variations in blood volume in the circulatory system can be utilized to obtain the PPG signal [5]. The smartphone's flash illuminates the finger's tissue, bones, and blood vessels, and the camera captures the light that is reflected from them. Most modern smartphones have high-resolution cameras processors, and light-emitting diode flashes (LEDs) which can be used to extract the PPG signal and can detect several important indications, including blood pressure, hemoglobin level, and glucose level [6]. As a result, people can easily monitor their blood pressure (BP) regularly and keep it under control. In this research, an innovative, non-invasive, cuff-less method to assess blood pressure levels has been proposed using PPG signals from fingertip videos that have been preprocessed and cleaned up using various filtering techniques. Additionally, DNN (deep neural network) based blood pressure estimation models have been created.

II. Proposed System

Smartphone-based blood pressure monitoring can potentially help to increase patient compliance with blood pressure monitoring, since it is less cumbersome and can be integrated into daily routines more easily. This section presents the proposed system, encompassing various procedures including smartphone selection, data collection, raw PPG signal extraction and channel selection, raw PPG

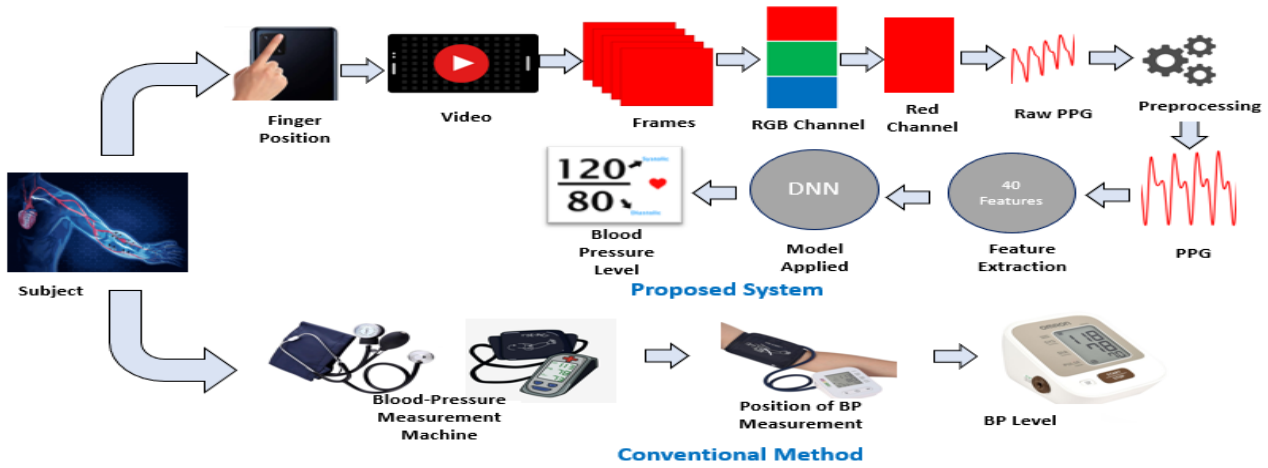


Fig. 1. System diagram of non-invasive BP monitoring with conventional method.

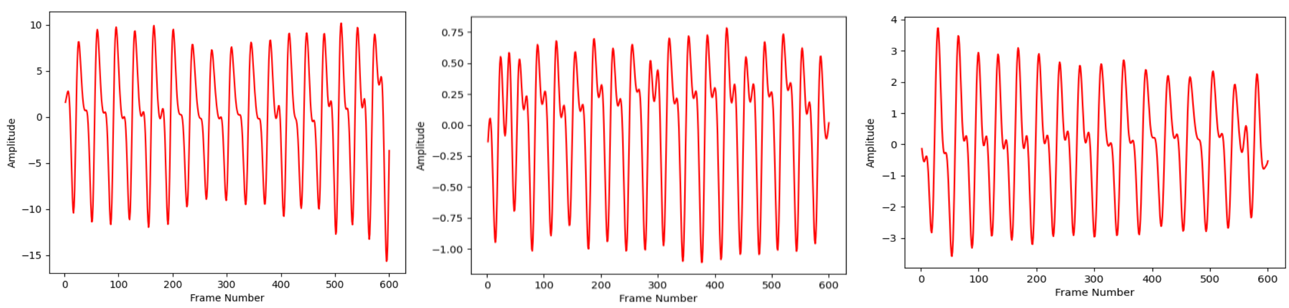
signal preprocessing, feature extraction, and model development, have all been briefly discussed. The experimental process of noninvasive sensing, along with the conventional method of measuring blood pressure levels, is depicted in Figure 1.

A. *SmartPhone Selection*

Over the last decade, there has been a significant enhancement in the quality of smartphone cameras, which has the potential to be valuable for gathering biomedical information. Almost all smartphones are capable of recording PPG signals. However, the quality of the captured signal can be significantly impacted by the resolution and number of images the camera records per second. After comparing the PPG signals from the three different smartphones, it is observed that the Samsung Galaxy Note 10 lite produced an appropriate ppg signal for the proposed system. Figure 2 shows the PPG signal extraction from different phones so that the best smartphone can be easily identified for the proposed system.

B. *Data Acquisition with Smartphone*

PPG signals can be captured from a subject's earlobe or fingertips. Due to the ease and comfort of the process for the participant, the fingertip was used in our investigation to collect data. The subject was instructed to hold motionless and comfortably place their index finger on the smartphone camera and it's LED (Light Emitting Diode) flash during the recording [7]. The position of the fingertip on the camera, the pressure of the fingertip, and the lighting conditions all affects the quality of the video recording [8]. Here, the blood volumetric fluctuation has an influence on how much light can pass through a finger. A camera records this fluctuation in light absorption, that is then used to evaluate PPG. Continuous measurements are carried out and the change in color values is computed for each new obtained frame. Initially, 15-second video was captured using a smartphone (Samsung Galaxy Note 10 Lite) at a frame rate of 30 fps and resolution 1080 x 2400 pixels. To prevent shaky frames, the first three and the last two seconds of each fingertip video are removed. Motion artifacts, baseline drift, and excessive noise, which are also caused by the persistent interference of the contact between the finger and the smartphone camera, degrade the quality of signal [9]. The proposed method is produced twice as many frames and smoother frames by converting 30fps to 60 fps [10]. So, user can also easily maintain their index finger motionless within this short time. 600 frames are extracted from a fingertip video of 10 seconds.This study included 65



(a) iPhone 6 (b) Xiaomi Poco X3 Pro (c) Samsung Galaxy Note 10 Lite

Fig. 2. Smartphone Selection based on the PPG signal.

subjects, aged 20 to 70, with blood pressure readings between 60 to 156 mmHg and 60:40 male to female ratio. Each subject provided a minimum of three trials, for a total of 195 trials. Omron JPN500 BP machine is used to measure blood pressure so that the outcome of the proposed model can be compared.

C. Raw PPG Signal Extraction and Channel Selection

The proposed noninvasive technique is used to record a brief video (15s) of the subject's fingertip. After that, the video is transformed into frames, which contained data from three color channels with distinct wavelengths (red, green, and blue). Variations in blood perfusion are dependent on light wavelength because different light wavelengths penetrate and reach the vascular bed at different depths in the epidermal layers. Red light can penetrate tissue more deeply than green or blue light because it has a longer wavelength. The required PPG signal can then be extracted from the frames using the red channel data. To extract the ppg signal, the average intensity of the RGB channel is determined first, and then the highest intensity is identified among the mean intensities of the RGB channel. The intensity of the Red channel is greater compared to the Green and Blue channel. Lee *et al.* asserted that the green channel offered the best signal amplitude values for smartphones and that it was therefore preferable to the red and blue channels [11]. To obtain high-quality PPG, Po *et al.* performed several tests and compared the PPG signal strength in the three-color bands by using versus not using a flashlight [12]. According to Grimaldi *et al.* different smartphone models have varied distributions of the pixels in the green channel [13]. For various phones, Bolkhovsky *et al.* suggested alternative channels [14]. All these studies demonstrate that the choice of the channel can change depending on a number of factors, such as the phone model, the camera's attributes, the acquisition method (LED or not), and the region of interest (ROI). The smartphone's flash was used in the experiment to light up the finger's tissue, bones, and blood arteries, while the camera on the same side recorded the reflected light. As a result, the PPG signals extracted from the recorded video were found to be reversed and need to be inverted for proper operation, as demonstrated in figure 3. In this study, the raw PPG signal is extracted from all channels, and it is observed that the red channel is more conspicuous and less noisy than the green and blue channels as seen in figure 4.

D. Raw PPG Signal Preprocessing

Since the PPG signal represents the flow of blood from heart to the fingertip, its characteristics can provide the information of BP levels [15]. Blood pressure is expressed as two numbers: Systolic blood pressure (SBP), which reflects the pressure of the heartbeat on artery walls, and diastolic blood pressure (DBP), which represents the pressure of the heart relaxing on the vascular system. It is essential to perform the appropriate preprocessing in order to accurately estimate the BP level from the PPG signal. In order to prevent shaky frames, the first three and the last two seconds of each fingertip video are removed. 600 frames are extracted from a fingertip video of 10 seconds. Motion artifacts have a significant impact on the PPG signal's accuracy, which leads to inaccurate estimation of key characteristics. The user's respiration, finger pressure, finger movement, as well as lighting intensity have an impact on the PPG signal's quality. To enhance the constancy and reliability of PPG signal collection, it is essential to design a consistent sequence of preprocessing techniques. The raw PPG signal stream is passed through a Butterworth band pass filter to remove noise. As seen in Figure 5(a).

Normalization is used to scale the PPG signals in the 0–1 range. Figure 5(b) displays the normalized PPG signal, which preserves all values within the range [0, 1].

During the video capture, the smartphone camera is merely attached to the fingertip, which could easily result in motion aberrations in the retrieved PPG signals. The easiest way to record video with minimal motion has been found through experimental research, which involves holding the finger on the camera for a short duration of time like 10-15 seconds. Even a small amount of distortion can cause significant baseline fluctuations. Figure 5(c) shows a sample in this regard. The baseline correction procedure helps to eliminate motion interferences. Applying different weights based on how much the signal deviates from the baseline fitted is the basic idea behind it. Baseline correction in noisy signals is accomplished using the asymmetrically reweighted penalized least squares smoothing (arPLS) methodology, which employs the iterative procedure to adaptively acquire weights in line with the generalized logic function. Figure 5(d) depicts the PPG signal after baseline correction.

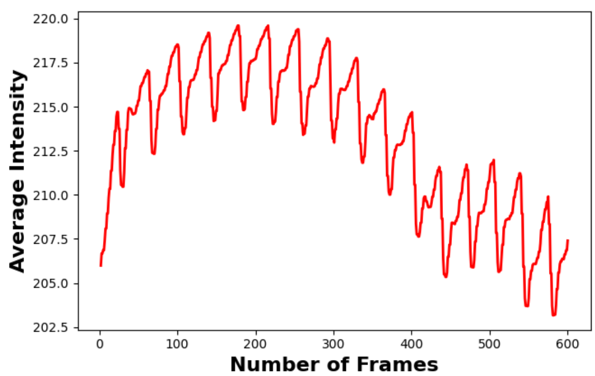


Fig. 3. Raw PPG signal of red channel in reflection mode.

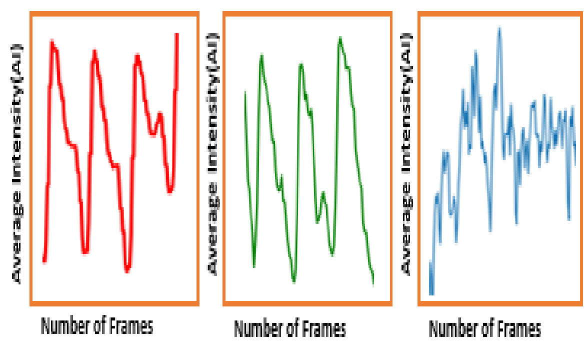


Fig. 4. Raw PPG signal of Red,Green and Blue Channel.

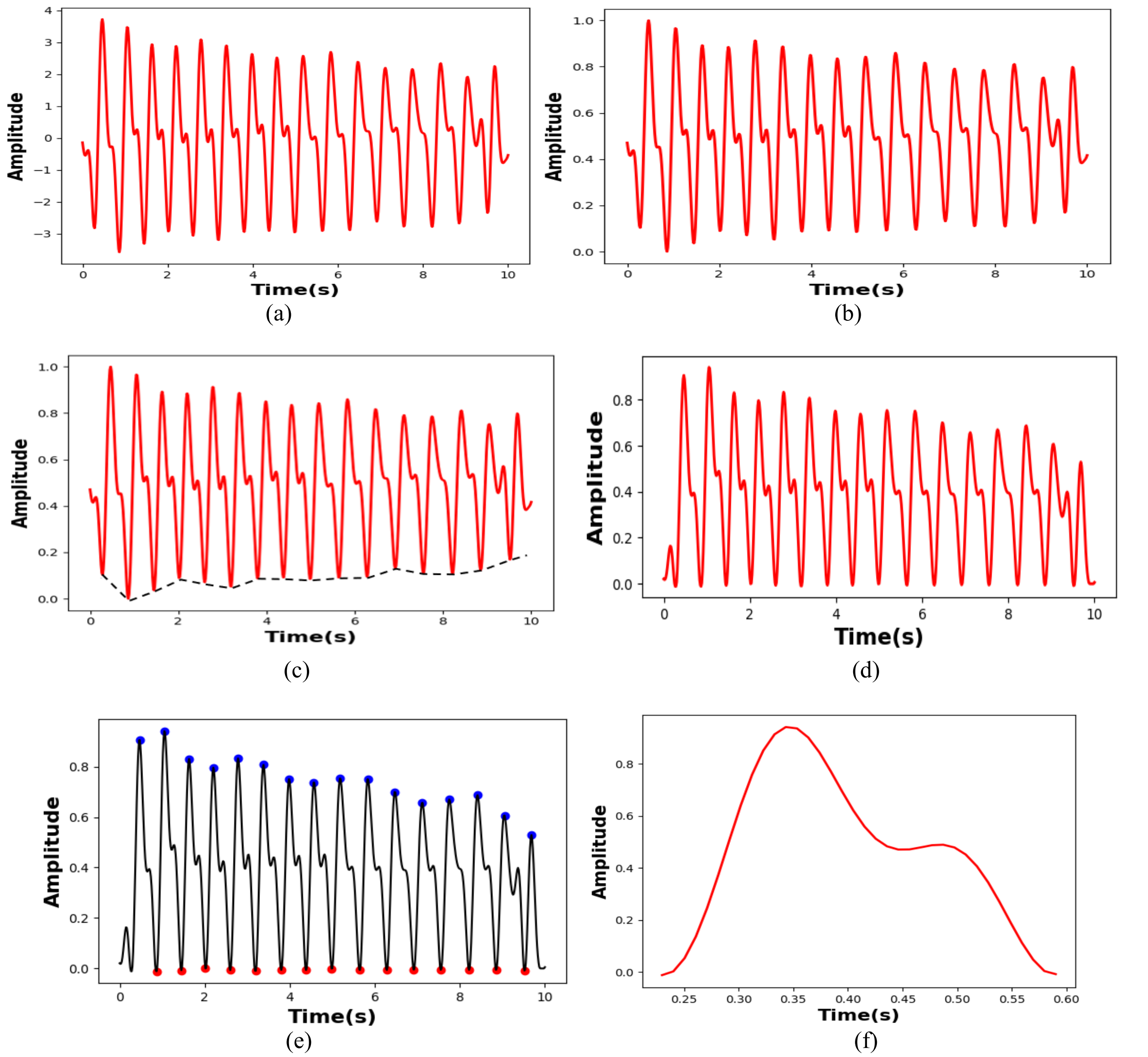


Fig. 5. (a) PPG signal after applying Butter-Worth BandPass Filter (b) PPG Signal after Normalization (c) Baseline Fluctuation (d) PPG Signal after Baseline Correction. (e) Peak Detection of the PPG Signal (f) Single period PPG signal

The signal peaks are identified using a peak detection technique. The peaks are recognized as a result systolic peak and the interval is calculated. Figure 5(e) depicts the min-max peak of the PPG signal. After that, the signal is split into single periods. Single-period PPG signals may have somewhat varied waveforms depending on the individual, but they all have the same properties. The feature extraction procedure is applied on this single PPG signal. Figure 5(f) depicts the single period from the continuous PPG signal.

After preprocessing, the first derivative, second derivative, FFT and the single period of the PPG signal are used to extract 40 characteristics. Figure 6 shows the characteristics which are listed in Table I. The age and gender of each subject are also included as features.

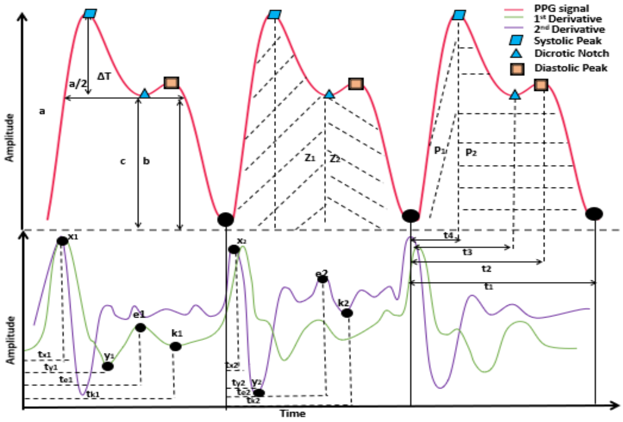


Fig. 6. PPG signal and it's 1st and 2nd derivative

TABLE I. EXTRACTED FEATURES FROM PPG SIGNAL

Feature	Definition	Feature	Definition
fe_1 : a	Systolic peak amplitude	fe_{21} : tx_2	Time from k_2 to x_2
fe_2 : b	Diastolic peak amplitude	fe_{22} : ty_2	Time from k_2 to y_2
fe_3 : c	Dicrotic notch	fe_{23} : tx_1/t_1	Time interval and pulse interval(tx_1) ratio
fe_4 : t_1	Single Period time	fe_{24} : ty_1/t_1	Time interval and pulse interval(ty_1) ratio
fe_5 : t_4	Systolic peak time	fe_{25} : te_1/t_1	Time interval and pulse interval(te_1) ratio
fe_6 : t_3	Dicrotic notch time	fe_{26} : tk_1/t_1	Time interval and pulse interval(tk_1) ratio
fe_7 : t_2	Diastolic peak time	fe_{27} : y_2/x_2	Ratio of y_2 & x_2
fe_8 : b/a	Ratio of Diastolic peak and Systolic peak	fe_{28} : e_2/x_2	Ratio of e_2 & x_2
fe_9 : c/a	Ratio of Dicrotic notch and Systolic peak	fe_{29} : $(y_2+e_2)/x_2$	Ratio of (y_2+e_2) & x_2
fe_{10} : Δ t	Time from Systolic peak to Diastolic peak	fe_{30} : $(tx_1+tx_2)/t_1$	Ratio of (tx_1+tx_2) & pulse interval
fe_{11} : t_4/a	Rising slope of systolic peak	fe_{31} : $(ty_1+ty_2)/t_1$	Ratio of (ty_1+ty_2) & pulse interval
fe_{12} : b/t_1-t_2	Falling slope of diastolic peak	fe_{32} : $(e_1+t_2)/t_1$	Ratio of (e_1+t_2) & pulse interval
fe_{13} : t_1/t_4	Ratio of systolic peak time and single period time	fe_{33} : $(k_1+t_2)/t_1$	Ratio of (k_1+t_2) & pulse interval
fe_{14} : t_2/t_4	Ratio of Diastolic peak time and single period time	fe_{34} : |sbase|	Fundamental_component_magnitude
fe_{15} : t_3/t_4	Ratio of Dicrotic notch time and single period time	fe_{35} : f2nd	2nd_harmonic_frequency
fe_{16} : $\Delta t/t_4$	Ratio of del t and t_4	fe_{36} : |s2nd|	2nd_harmonic_magnitude
fe_{17} : tx_1	Time from k_1 to x_1 point (1st derivative)	fe_{37} : Z_1/Z_2	Inflection point area ratio
fe_{18} : ty_1	Time from k_1 to y_1 point	fe_{38} : P_1/P_2	Stress induced vascular response index
fe_{19} : te_1	Time from k_1 to e_1 point	fe_{39} : a- b/a	Alternative_augmentation_index
fe_{20} : tk_1	Time from k_1 to next k_1	fe_{40} : b-a/a	Nagative_augmentation_index

III. DNN MODEL

The proposed model is trained by a feed-forward neural network with multiple layers. The output layer is composed of a single neuron, but the input layer has a number of neurons depending on the number of features in the dataset. With a batch size 32, the DNN model was trained by 50 epochs and two dropout layers, each with a dropout rate of 0.2, were inserted after the 2nd and 4th hidden layers of the neural network architecture. The table lists the number of neurons present in each hidden layer. The input and hidden layers both employ the Rectified Linear Units (ReLU) activation function, whereas the output layer utilizes a linear activation function. Adam was utilized as the optimizer function to expedite the processing of the training data and update the DNN's parameter. These modifications are intended to enhance the model's ability to recognize complex patterns in the dataset, making it a customized adaptation of a conventional DNN for the task of estimating blood pressure level from PPG signals. Table II depicts the hyperparameters utilized in the proposed DNN model.

TABLE II. HYPERPARAMETERS VALU

Parameters	Status
Batch size	32
Node of Input Layer	The number of extracted features
Number of hidden Layer	4
Node of each hidden layer	200,250,300,400
Dropout Layers at the 2nd and 4th hidden Layers	0.2
Node of Output Layer	1
Activation Function	ReLU , Linear
Optimizer	Adam

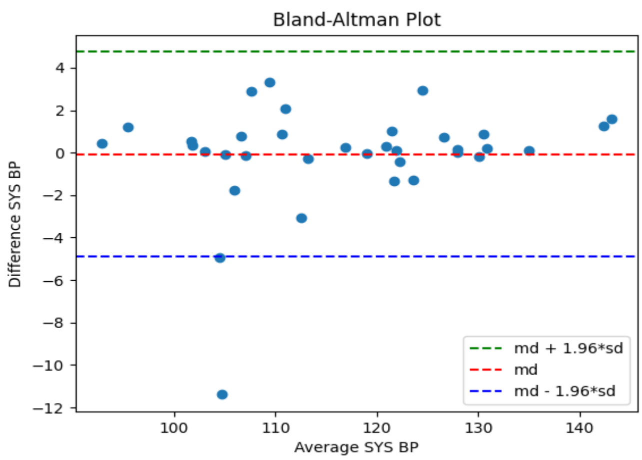


Fig. 7. Relatonship and Agreement SBP

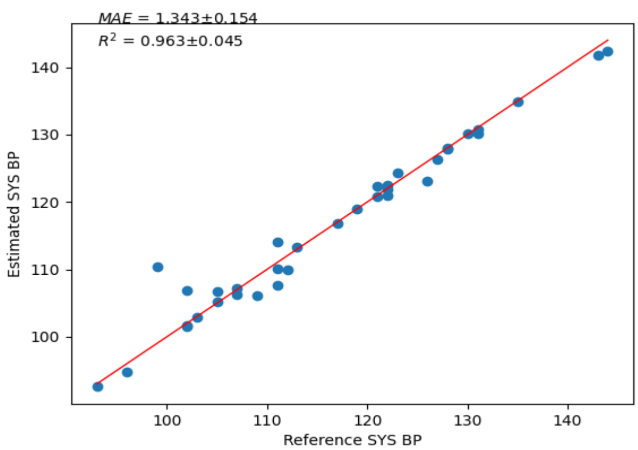


Fig. 8. Estimated and Reference SBP

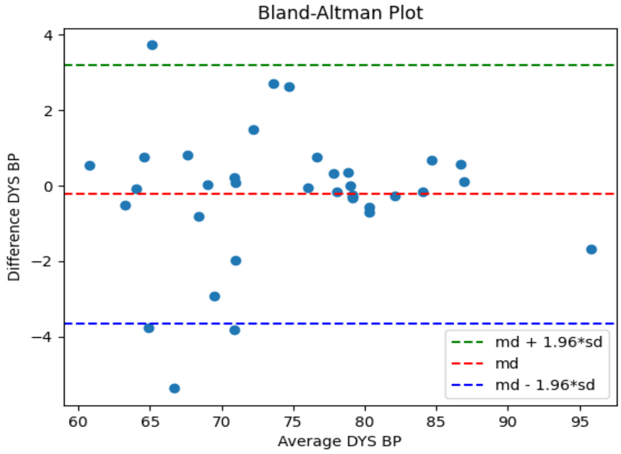


Fig. 9. Relatonship and Agreement DBP

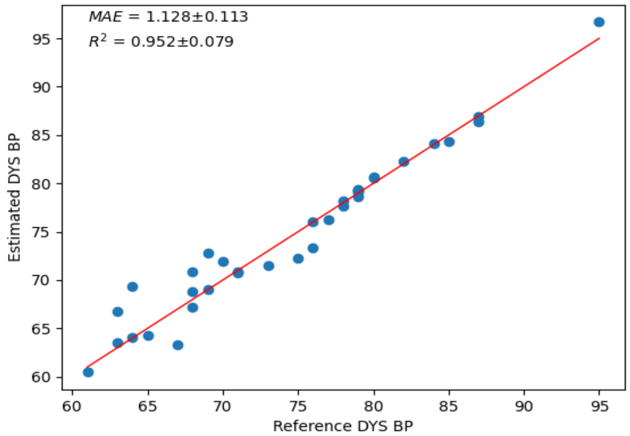


Fig. 10. Estimated and Reference DBP

Figures 7 and 9 show that most of the estimated systolic and diastolic blood pressure levels are within limits of agreement (bias 1.96 SD). Additionally, the figure highlights how much the predicted Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP) deviate from the reference value. The performance measurement indices coefficient of determination R^2 and mean absolute error MAE have been utilized to analyze the performance of the proposed method , as demonstrated in figure 8 and 10. The predicted accuracy of the proposed DNN models for systolic and diastolic blood pressure levels are R^2 =0.963 and 0.952, respectively while MAE for these measurements are 1.34 and 1.12.

IV. Comparison of Results

In this study, Table III is utilized to present a comparative analysis of blood pressure level estimate, effectively validating the contribution when compared to existing smartphone-based non-invasive procedures. The proposed system utilized the smartphone's built-in cameras to record fingertip video and extract the PPG signal, in contrast to other techniques that incorporate additional sensors or equipment. The finger position is exhibited in the proposed system because recent smartphone features include numerous cameras. Additionally, 60 fps is converted from 30 fps in order to eliminate motion artifacts as users often maintain finger contact for durations ranging from 10 to 15 seconds

TABLE III COMPARISON OF PROPOSED MODEL WITH SEVERAL EXISTING SMARTPHONE BASED NON-INVASIVE CUFFLESS BP MONITORING SYSTEM

Authors	**Smartphone & Additional Sensor**	**Video Length & fps**	**Algorithm**	**Performance**
F Tabei et al.[16]	iPhone X	1 min & 30 fps	Linear Regression	R=0.92 for SBP R=0.89 for DBP
A Gaurav et al.[17]	Samsung Galaxy Note 5 & PPG Sensor	30 sec &30 fps	Artificial Neural Network	Accuracy 93.2 for SBP & 95.3 for DBP
J Dey et al. [18]	Samsung Galaxy S6 & PPG Sensor	30 sec & 30 fps	Lasso Regression	Accuracy 93.1 for SBP & 95 for DBP
Proposed System	Samsung Galaxy Note 10 Lite	15 sec & 60 fps	DNN	R^2=0.963 for SBP & R^2=0.952 for DBP

and with this adjustment, 600 frames are recorded from 10-second video. A higher frame rate improves PPG signal analysis because it allows for more accurate and detailed tracking of subtle changes in the blood flow and heart rate. The baseline correction using the arPLS algorithm effectively removes baseline drift from PPG signals, resulting in a cleaner signal that enables more accurate and reliable analysis of BP level. Moreover, PPG signal extraction from several smartphones further demonstrates the validity of the proposed system. The proposed method maintains enhanced accuracy in blood pressure level estimation, as shown by R^2 values of 0.963 for SBP and 0.952 for DBP, while reducing hardware complexity, improving affordability and accessibility.

V. Conclusion

This research describes a novel BP level measuring system based on the PPG signal. PPG signal was obtained by capturing a video of the fingertip using a smartphone camera and illuminating it with the device's flash. The frame rate was consistently maintained at 60fps. Further, filtering techniques and a baseline correction algorithm were implemented to eliminate any noise or baseline drift from the signal. Then, features retrieves from the PPG signal, its first and second order derivatives, and Fourier analysis, which are then used to train DNN model. The results of this model demonstrate that the proposed BP monitoring system provides measurements with the optimum degree of accuracy. The technology uses a data collection method that is much more natural and pleasant than traditional methods, and it can forecast blood pressure levels precisely just using a smartphone, which is now accessible to many of individuals. The PPG signal that extracts utilizing a variety of smartphones increased the method's viability. As a result, in the future the technique may also be applied to low-cost feature phones and the dataset will expand from a diverse group of individuals to improve the dataset's more balance.

References

[1] M. Lubin, D. Vray2, S. Bonnet, "Blood pressure measurement by coupling an external pressure and photo-plethysmographic signals",

42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) , pp.49996-4999, IEEE 2020.

[2] E. J. Benjamin, et al. Heart disease and stroke statistics—2017 update: A report from the american heart association, ISSN 0009-7322, Circulation 2017.

[3] M. B. Mashhadi, E. Asadi, M. Eskandari, S. Kiani, and F. Marvasti, “Heart rate tracking using wrist-type photoplethysmographic (ppg) signals during physical exercise with simultaneous accelerometry,” IEEE Signal Processing Letters, vol. 23, no. 2, pp. 227–231, Feb 2016.

[4] M. Panwar, A. Gautam, D Biswas, A Acharyya, “A deep learning framework for PPG-Based blood pressure and heart rate estimation," IEEE Sensors Journal, vol. 20, no.17 pp. 10000 – 10011, April,2020.

[5] P.M. Nabeel, S Karthik, J. Joseph, M Sivaprakasam “Arterial blood pressure estimation from local pulse wave velocity using dual-element photoplethysmograph probe," IEEE Transactions on Instrumentation and Measurement, vol. 67, no. 6, pp. 1399 - 1408, June 2018.

[6] G. Zhang, J. Mei, Y. Zhang, X. Ma, B. Lo, “A non-invasive blood glucose monitoring system based on smartphone PPG signal processing and machine learning, " pp. 1-10, IEEE,May, 2020.

[7] H. Tjahjadi, K. Ramli, H. Murfi, ” Noninvasive classification of blood pressure based on photoplethysmography signals using bidirectional long short-term memory and time-frequency analysis” ,IEEE journal, vol. 8, pp. 20735 – 20748,January, 2020.

[8] F. Lamonaca, Y. Kurylyak, D. Grimaldi, V. Spagnuolo, “Reliable pulse rate evaluation by smartphone,” 2012 IEEE International Symposium on Medical Measurements and Applications Proceedings, pp. 1–4, June 2012.

[9] T. T. Islam, M. S. Ahmed, M. Hassanuzzaman, S. A. B Amir, T. Rahman, “blood glucose level regression for smartphone PPG signals using machine learning”, Applied Science, pp. 1-20, 2021

[10] https://academy.wedio.com/30fpsvs60fps/#:~:text=Because%2060%20fps%20capture%20more,the%20end%20for%20doing%20it, visited.

[11] J. Lee, K.Matsumura , K. Yamakoshi, P. Rolfe, S. Tanaka,T. Yamakoshi “Comparison between red, green and blue light reflection photoplethysmography for heart rate monitoring during motion”, 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 1724-1727, 2013

[12] L. M Po,X. Xu, L. Feng, Y. Li, K. Cheung, C. H. Cheung, “Frame adaptive ROI for photoplethysmography signal extraction from fingertip video captured by smartphone,” IEEE International Symposium on Circuits and Systems (ISCAS), pp. 1634-1637, 2015

[13] D. Grimaldi, Y. Kurylyak, F. Lamonaca, A Nastro “Photoplethysmography detection by smartphone's videocamera,” Proceedings of the 6th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems, pp. 488-491, 2011

[14] J. B. Bolkhovsky , C. G. Scully, K. H. Chon “Statistical analysis of heart rate and heart rate variability monitoring through the use of smart phone cameras,” Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp1610-1613. ,2012

[15] H. Yuan, S. F. Memon, T. Newe, E. Lewis, G. Leen, ``Motion artefact minimization from photoplethysmography based non-invasive hemoglobin sensor based on an envelope _ltering algorithm," Measurement, vol. 115, pp. 288_298, Feb. 2018.

[16] F.tabei,J M Gresham, B Askarian , K Jung, J W Chong ,“Cuff-Less blood pressure monitoring system using smartphones”, vol.8, January 2020,IEEE

[17] A Gaurav, M Maheedhar, V. N. Tiwari and R. Narayanan “Cuff-less PPG based continuous blood pressure monitoring – a smartphone based approach”, “38th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)”,pp. 607-610, July 2016.

[18] J. Dey, A. Gaurav & V. N.Tiwari “InstaBP: Cuff-less blood pressure monitoring on smartphone using single PPG sensor”,” 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society”, pp. 5002-5005 ,2018.