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RESEARCH ARTICLE - ENGINEERING

Smart Patch for Non-Invasive Blood Pressure Monitoring in Epileptic Seizure Patients via the Sole

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Abstract

Epileptic seizures can cause sudden blood pressure changes, requiring continuous monitoring. However, traditional blood pressure monitoring methods are often invasive and uncomfortable for the patient. In addition, it is difficult to measure blood pressure during seizures. This research aims to design a non-invasive, comfortable device to monitor blood pressure during epileptic seizures continuously. Photoplethysmography (PPG) signals from the sole of the patient's foot were used to extract blood pressure data. A smart patch was designed to be worn comfortably on foot for continuous monitoring during seizures. The results show that the average systolic and diastolic blood pressure errors were 2.838 and 4.494 mmHg during epileptic seizures, respectively. These blood pressure changes could be related to the onset of seizures, suggesting that the device and methodology could be combined with other measures to analyze and predict seizure activity. This research offers a non-invasive and comfortable solution for continuous blood pressure monitoring during seizures, which may affect seizure prediction and management.

Publisher: Middle Technical University

Keywords: Blood Pressure; Diastolic; Epileptic Seizure; Non-Invasive Photoplethysmography; Plethysmography; Smart Patch; Systolic.

1. Introduction

Approximately 1% of people worldwide have epilepsy, a neurological disorder [1]. It is a condition characterized by the occurrence of recurrent seizures, which are episodes of abnormal electrical activity in the brain. Epileptic seizures can be life-threatening, so it is crucial to monitor individuals with epilepsy closely [2]. Measuring vital signs, including blood pressure, heart rate, and respiratory rate, is critical to monitoring individuals with epilepsy [3]. During a seizure, individuals may experience changes in their vital signs, such as increased blood pressure, heart rate, or respiratory rate. These changes can stress the body significantly and may lead to further complications [4]. One potential benefit of monitoring vital signs in individuals with epilepsy is predicting when a seizure may occur by identifying changes in blood pressure, heart rate, or respiratory rate before the event [5]. For example, some individuals may experience changes in their blood pressure or heart rate before a seizure, which can help predict when a seizure is imminent [6, 7]. It is crucial to monitor the vital signs of individuals with epilepsy before and after a seizure. This helps predict when a seizure is about to occur and ensures that individuals are stable and not experiencing any complications post-seizure [8]. For example, some individuals may experience a drop in blood pressure or heart rate after a seizure, putting them at risk of further complications [9]. Roughly a third of people with epilepsy may have seizures that do not respond to medication [1]. Certain medications used to treat epilepsy can potentially affect individuals' vital signs. This may involve alterations in their vital signs, such as blood pressure or heart rate. Monitoring vital signs can help identify these side effects and adjust medication doses accordingly [10, 11]. Thus, monitoring vital signs plays a critical role in the management of epilepsy, both in predicting and preventing seizures and in managing medication side effects [12, 13]. Over 3 million people in the US are impacted by epilepsy [14]. The seizures can take various forms and may involve motor, sensory, or autonomic symptoms. Epilepsy can affect individuals of all ages and can be caused by various factors, including genetic predisposition, brain injury, infection, or metabolic disorders [15, 16]. The impact of epilepsy on individuals' quality of life highlights the importance of effective management strategies [17], including monitoring vital signs [18]. Photoplethysmography (PPG) is a technique that can anticipate numerous vital health parameters including blood pressure, heart rate, haemoglobin, and blood glucose level [19, 20]. Research suggests that this method enables the non-invasive, cuff-less, and continuous measurement of blood pressure (BP) [21]. PPG utilizes an Infrared Light Emitting Diode (IR LED) along with a corresponding photodiode to measure minor changes in blood volume within the arteries. The PPG waveform comprises an AC component and a DC component [22].

Nomenclature & Symbols			
PPG	Photoplethysmography	VDT	Velocity Diastolic Time
VPG	Velocity Plethysmography	VST	Velocity Systolic Time
BP	Blood Pressure	*Ad*	Systolic Blood Pressure Coefficients 1
ST	Systolic Time	Bs	Diastolic Blood Pressure Coefficients 1
DT	Diastolic Time	*As*	Systolic Blood Pressure Coefficients 2
PPT	Peak-To-Peak Time	*Bd*	Diastolic Blood Pressure Coefficients 2

The AC component of the PPG waveform corresponds to the synchronized changes in blood volume that occur with each heartbeat, while the DC component reflects the overall tissue characteristics and average blood volume [23]. In the past few decades, extensive research has been dedicated to non-invasively estimating blood pressure (BP) through surrogate cardiovascular parameters, primarily pulse transit time (PTT) [24]. However, PTT-based BP predictions require the simultaneous measurement of an electrocardiogram (ECG) alongside PPG, necessitating the placement of electrodes on the body's surface [25, 26]. Recent advancements have shown promising developments in the continuous non-invasive measurement of BP. For instance, a study discovered an inverse correlation between BP and pulse transit time (PTT) [27]. PTT is shown in Fig. 1.

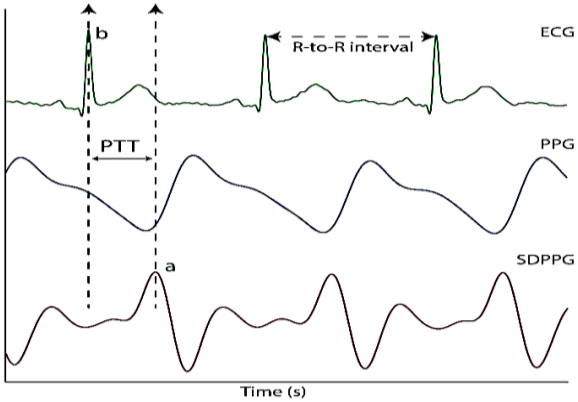

Fig. 1. ECG signal, and the PPT estimation from the difference (ms) between the systolic peaks of the ECG and PPG signals (second derivative photoplethysmography (SDPPG)) [28]

Recent research has shown a growing interest in developing novel approaches for monitoring blood pressure in epilepsy patients during seizures. However, these studies mainly relied on traditional blood pressure monitoring or ECG signals [29] to measure blood pressure [30, 31], which can be uncomfortable for the patient and cannot provide continuous monitoring. Several recent research studies have investigated non-invasive methods for continuous blood pressure monitoring, but few have focused specifically on monitoring blood pressure during seizures [32, 33]. The proposed approach in this study involves continuous blood pressure monitoring during seizures using PPG signals from ear loops. Compared to the cuffless systems proposed by Xie et al. [34] and Zhang et al. [35], which require sensors to be worn on the wrist or finger, the ear-loop sensors used in this study are less likely to be affected by motion artefacts and provide more stable measurements. The pulse wave analysis approach proposed by Kim et al. [36] does not provide continuous monitoring during seizures, and the machine learning algorithm proposed by Shahin et al. [37] may not be as effective during seizures due to sudden changes in blood pressure [38]. The proposed approach in this study aims to address these limitations by providing continuous blood pressure monitoring during seizures using non-invasive PPG signals from ear-loops. The potential advantages of this approach include improved accuracy, convenience, and safety for patients with epilepsy, as well as the ability to collect more comprehensive data for clinical diagnosis and treatment.

This study is divided into five sections. Section 1 discusses the principles of measuring blood pressure using PPG signals, and the techniques for estimating blood pressure from these signals are presented. Section 2 details the design of the smart patch and the signal processing algorithms employed. This section also describes the signal processing techniques used to isolate the PPG signals from the noisy signals recorded by the smart patch. Section 3 presents a MATLAB-based software developed for extracting blood pressure from the PPG signals. In Section 4, the results of the experiments are presented. Finally, Section 5 provides a conclusion that summarizes the significant contributions of the study and their potential impact on blood pressure monitoring.

2. Materials and Methods

In this study, we developed a smart patch to monitor the blood pressure of epileptic seizure patients. The device was designed to consist of two parts. The first part was a patch that was attached to the patient's ear-loop and contained an Arduino mini, a transmitter NRF2401 [39], and a PPG sensor (Ear-Loop PPG Sensor for Arduino from Wiki Company) [40] to detect the PPG signal of the patient. The PPG signal was then sent to the second part of the device, which analyzed it to continuously monitor the blood pressure and display the results on a 3.2-inch TFT screen [41]. The second part of the device used an Arduino Mega as a microcontroller and included an MP3 shield for Arduino (from Wiki Company) [42] to speak the value of the blood pressure and alert the patient or anyone around them.

2.1. Estimation of blood pressure

When the heart begins to pump blood into the blood vessels, the amount of blood pumped from the heart depends mainly on the elasticity of the blood vessels throughout the body; that is, when the blood vessels are naturally flexible, the heart does not need much effort to pump blood to all parts of the body (because Resist blood vessels to change size as a result of the passage of a quantity of blood as a result of contraction of the heart is minor because the elasticity of those blood vessels is in the appropriate range) If the elasticity of the blood vessels is less than what

it is in the first case, the heart will need a higher effort to pump blood into the blood vessels because of the higher resistance that the heart faces from the blood vessels, which leads to pumping more blood into the blood vessels.

In the first case, in which the elasticity of the blood vessels is less, the heart will not need a high effort to pump blood, meaning that the period for pumping blood by the heart will be longer compared to the second case, in which the blood vessels are less flexible in which the heart takes blood to the blood vessels Less time for greater blood vessel impedance. It is also known a close relationship between the elasticity of blood vessels and blood pressure, where the more significant the elasticity of the blood vessels, the lower the blood pressure due to the absence of any pressure from the blood vessels, and vice versa, that is, the lower the elasticity of the blood vessels, the higher the blood pressure.

From the above, we conclude that there is a close relationship between blood pressure and the time taken by one pulse. In this project, three parameters will be approved that are extracted from one pulse depending on time. These parameters are systolic time, diastolic time, and the time difference between them. It is known that the inverse relationship of age with the elasticity of the blood vessels (the more significant the age, the lower the elasticity of the blood vessels and vice versa), and accordingly, the equations were divided into two groups as follows:

The first group for patients aged lower than 25 years. Equations (1) and (2):

$$Systolic\ Blood\ Pressure = \frac{Diastolic\ time(ms) - As}{Bs} \quad (1)$$

$$Diastolic\ Blood\ Pressure = \left(Ad\ \times Diastolic\ time(ms)\right) + Bd \quad (2)$$

where As, Bs, Ad, and Bs are coefficients that calculate systolic and diastolic blood pressure.

The second group for patients above 25 years Equations (3) and (4):

$$Systolic\ Blood\ Pressure = (Diastolic\ time(ms) - As) + Bs \quad (3)$$

Diastolic Blood Pressure= (Ad ×Diastolic time (ms)-Systolic time (ms)) +Bd (4)

where As, Bs, Ad, and Bs are coefficients that calculate systolic and diastolic BP.

In Fig. 2, three characteristics of PPG signals were examined: systolic-upstroke time (ST), diastolic time (DT), and the time interval between the systolic and diastolic peaks (T1), also known as peak-to-peak time (PPT).

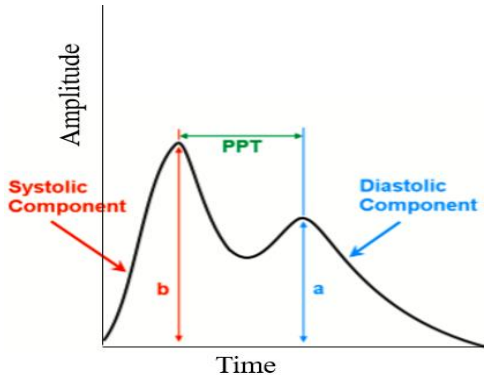

Fig. 2. Parameters obtained from PPG signal [43]

2.2. PPG Signal filtration

Three characteristics of PPG signals, namely Diastolic time, Systolic time, and the time delay between the systolic and diastolic peaks (PPT), were analyzed (Fig. 2). When determining the values of these parameters, it is crucial to accurately identify the positions of the peaks and troughs. In certain PPG recordings, the poor signal quality can make it challenging to precisely locate the peaks and troughs. To obtain these parameters, the raw data from MAX30100 may be passed through several processing steps, which are done by using MATLAB. These processing steps are described below:

- First processing step: The raw data comes with high noise (from tissue, bone, motion, etc.), so the first step is removing all frequencies lower than 0.7Hz and higher than 3.1 Hz. and removing the DC part of the PPG signal and done by using a bandpass filter. This processing step is shown in Fig. 3.
- Second processing step: To correctly interpret and analyze the PPG signal obtained from a reflective sensor, it is essential to consider the possibility of signal inversion and adjust the signal processing accordingly. This can be achieved through software-based techniques, such as scaling the signal or flipping the waveform, as shown in Fig. 4.
- Third processing step: Normalization of the PPG signal is a common preprocessing step to ensure that the signal values fall within a specific range or scale. In this step, the PPG signal is normalized between 0.5 and 1.5. This range is chosen to make the signal compatible with other physiological signals, such as ECG or EEG, typically normalized between -1 and 1, as shown in Fig. 5.
- Fourth processing step: To examine the PPG signal on a beat-to-beat basis, the signal is divided into separate pulses using peak detection algorithms. This segmentation process enables the analysis of individual pulses within the PPG signal. These algorithms identify the peaks or high points in the PPG waveform that correspond to each heartbeat and use them to define the boundaries of each pulse, as in Fig. 6.
- Fifth processing step: After the individual pulses have been extracted, the next step is calculating various parameters helpful in characterizing the waveform and estimating various parameters. The three parameters that are calculated in this step are sys ST, DT, and peak-to-peak time (PPT). ST refers to the pulse duration during the systolic phase, which corresponds to when the heart is contracting and pushing blood out of the arteries. Diastolic time, on the other hand, refers to the pulse duration during the diastolic phase, which corresponds

to the time when the heart is relaxed and filling up with blood. PPT, represents the duration between the peak of one pulse and the peak of the subsequent pulse, as shown in Fig. 7.

- Sixth processing step: The velocity plethysmography (VPG) signal is a derivative of the PPG waveform that captures the rate of change of the signal over time. This signal is calculated by taking the first derivative of the PPG waveform concerning time. The resulting signal provides information about the slope or gradient of the PPG waveform, which can help detect subtle changes or variations in the waveform that may not be apparent in the raw signal. One of the key advantages of the VPG signal is its ability to capture diastolic peaks that may be difficult to detect in the PPG waveform. This is because the diastolic peaks are often less prominent and occur over a shorter period than the systolic peaks. By using the VPG signal, it is possible to amplify these peaks and make them more visible, improving the accuracy and reliability of pulse parameter measurements. This step is shown in Fig. 8. The features extracted from the PPG and VPG signals are described in Table 1.

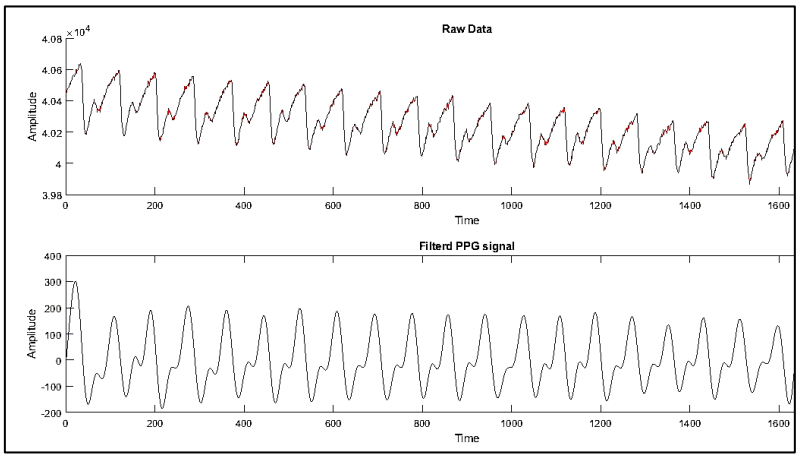

Fig. 3. Raw data and filtered PPG signal

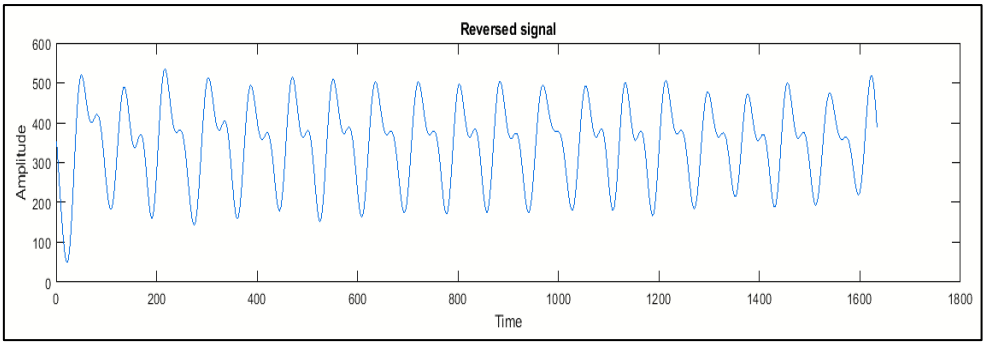

Fig. 4. Reversed signal

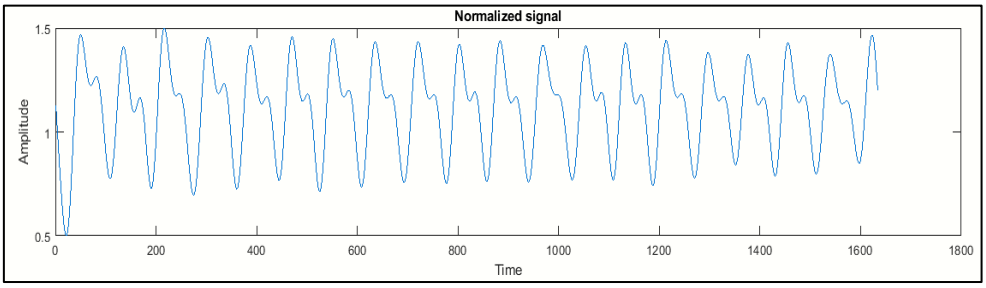

Fig. 5. Normalized signal

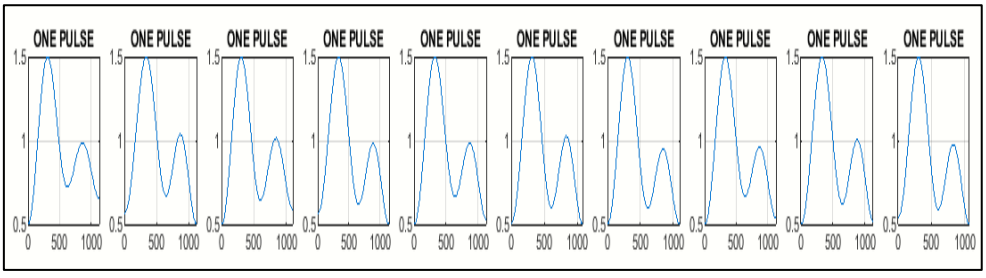

Fig. 6. Sampling the PPG signal

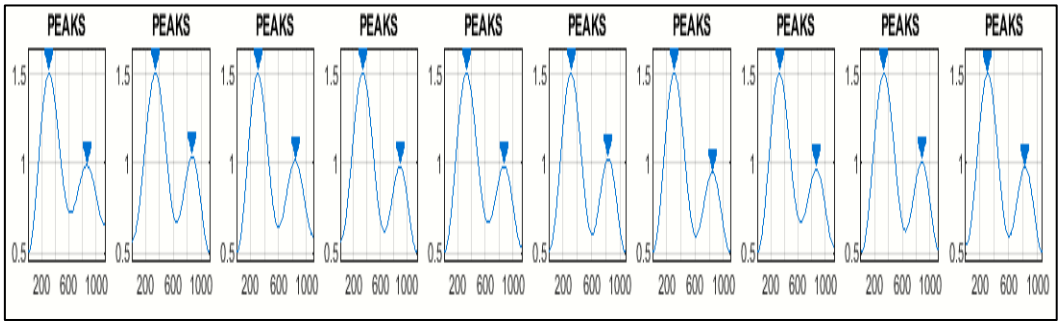

Fig. 7. Peaks of PPG signals

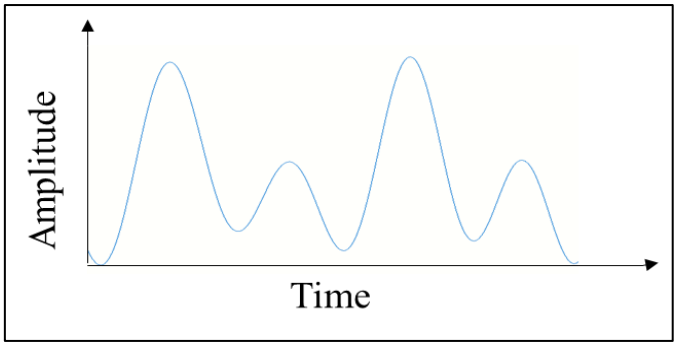

Fig. 8. VPG signal

Table 1. Features extracted from the PPG and VPG signals

Signal	Features	Suggested name
PPG	Time of Systolic	ST
	Time of Diastolic	DT
	peak-to-peak time	PPT
VPG	Time of Systolic	VST
	Time of Diastolic	VDT
	peak-to-peak time	VPPT

3. Smart Patch Program

The smart patch program is written by MATLAB and used to monitor the patients that use the patch. (as shown in Fig. 9). This program gives the orders to the dongle, receives the data from the dongle, processes the data received from the dongle, displays them on the program interface, and sends the processed data to the dongle. These steps are shown in Fig. 10. When the smart patch program starts, it shows two options to the user:

- New patient: option allows to user to add new patient and enter their information (patient information include name, age, gender, etc.); then, after clicking on create; the program goes to the next page.
- Open patient: option allows the user to open the patient already saved in previous time and monitor them.

These two options are shown in Fig. 11.

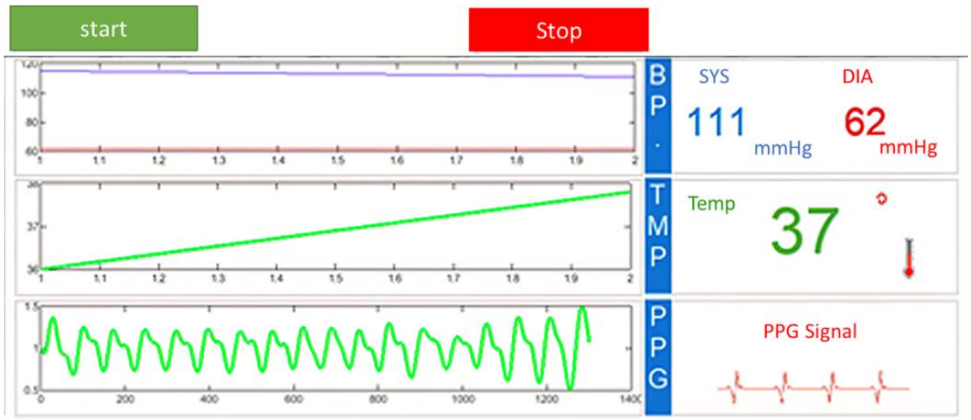

Fig. 9. Smart patch program

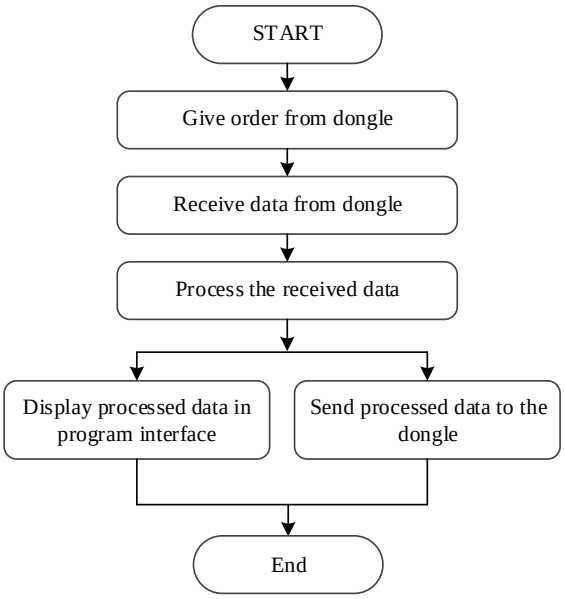

Fig. 10. Processing steps of smart patch program

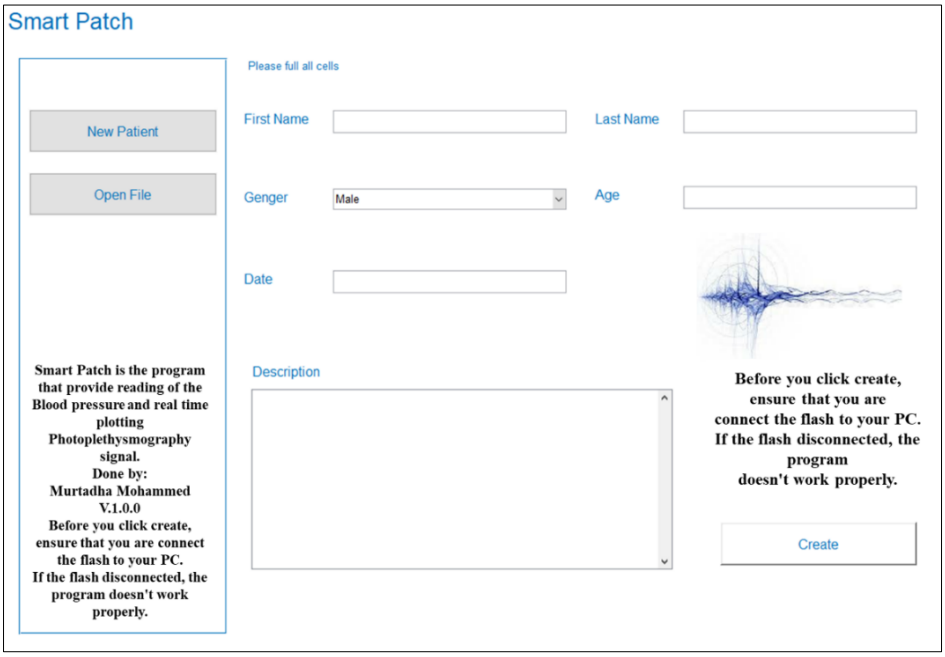

Fig. 11. GUI of smart patch program

4. Results

The findings from this study can be presented for systolic and diastolic BP in the subsequent sections.

4.1. Results-based systolic BP

The results of the PPG-based systolic blood pressure measurements are presented in Figs. 12 to 15. Fig. 12 shows all patients' systolic blood pressure values and the benchmark systolic value. The y-axis displays the systolic BP values in mmHg, while the x-axis indicates the patient number. The minimum and maximum values measured were 87 mmHg and 152 mmHg, respectively. Fig. 13 displays the error values between the benchmark and PPG sensor results for systolic blood pressure measurements. The y-axis displays the error value in mmHg, and the x-axis shows the patient number. The average error value was 2.787 mmHg, and the minimum and maximum errors were 0.315 mmHg and 6.992 mmHg, respectively.

Fig. 14 depicts the correlation between the benchmark and predicted systolic BP. The y-axis represents the predicted systolic BP values in mmHg, while the x-axis represents the benchmark systolic BP values. The two's correlation coefficient (R2) was 0.9768, indicating a strong positive relationship between the variables. This suggests that the PPG signal measurement is a highly reliable method for predicting systolic BP and can explain a significant proportion of the variability in systolic BP. Fig. 15 shows the cumulative distribution function (CDF) for the error between the benchmark value and predicted systolic blood pressure. The Y-axis represents the CDF, and the X-axis represents the error value in mmHg. The CDF analysis revealed that 90% of the error between the benchmark and predicted systolic blood pressure (BP) values

obtained from measuring photoplethysmography (PPG) signal was lower than 6 mmHg, suggesting that the PPG-based system performed well in predicting systolic blood pressure values with high accuracy.

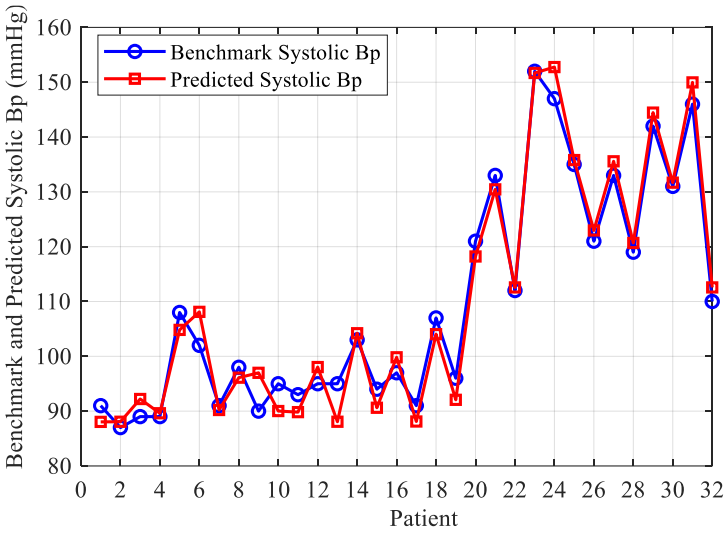

Fig. 12. Systolic BP (benchmark) and predicated systolic BP

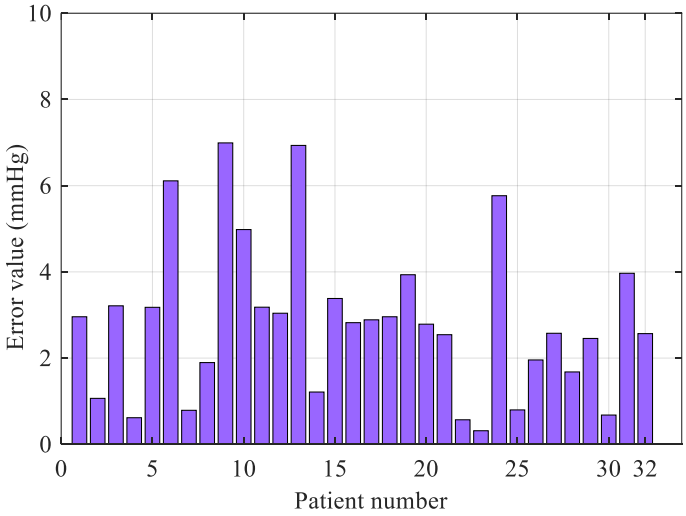

Fig. 13. Error values of systolic BP

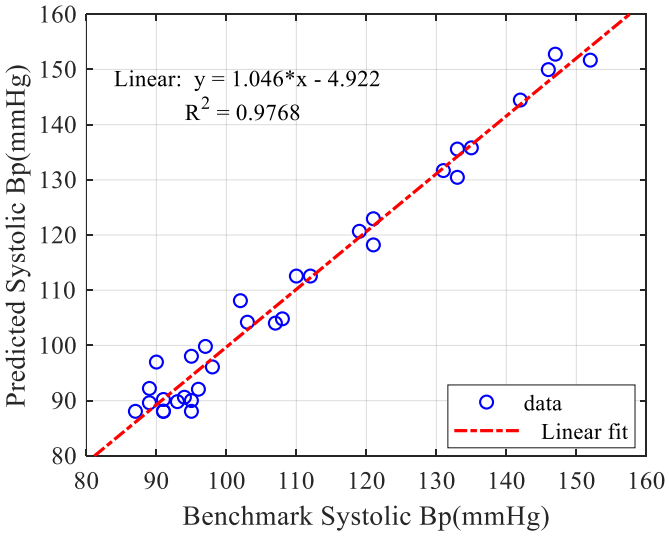

Fig. 14. Correlation between the benchmark and predicted systolic BP

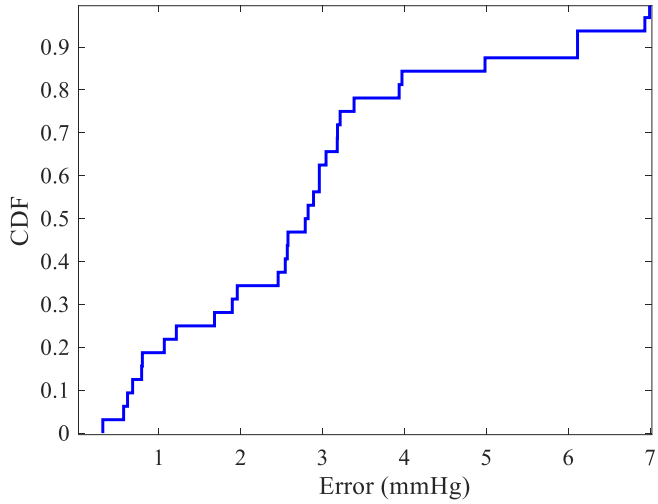

Fig. 15. CDF for error between the benchmark and predicted systolic BP

4.2. Results-based diastolic BP

The PPG-based diastolic blood pressure measurement is reported in Figs. 16 to 19. Fig. 16 presents all patients' diastolic blood pressure values and the benchmark diastolic value. The y-axis represents the diastolic BP values in mmHg, and the x-axis indicates the patient number. The minimum and maximum values measured were 54 mmHg and 94 mmHg, respectively. Fig. 17 demonstrates the error values of the diastolic blood pressure measurements between the benchmark and PPG sensor results. The y-axis shows the error value in mmHg, and the x-axis shows the patient number. The average error value was 4.181 mmHg, while the minimum and maximum errors were 0.425 mmHg and 9.913 mmHg, respectively.

Fig. 18 shows the correlation between the benchmark and predicted diastolic BP. The vertical axis denotes the predicted diastolic BP in mmHg, while the horizontal axis represents the benchmark diastolic BP. The correlation coefficient (R^2) between them was 0.8641, and the strong correlation coefficient of 0.8641 between the benchmark and predicted diastolic BP values indicates a dependable relationship between the two variables. This suggests that the PPG-based method of measuring diastolic BP is a precise means of prediction and can account for a significant portion of the variation in diastolic BP. The cumulative distribution function (CDF) in Fig. 19 displays the error distribution between the benchmark and predicted diastolic BP values obtained from PPG signal measurement. The y-axis represents the CDF, while the x-axis represents the error value in mmHg. The analysis of the CDF showed that the PPG-based system had a high accuracy in predicting diastolic blood pressure values, as 90% of the error between the benchmark and predicted values were lower than 8 mmHg.

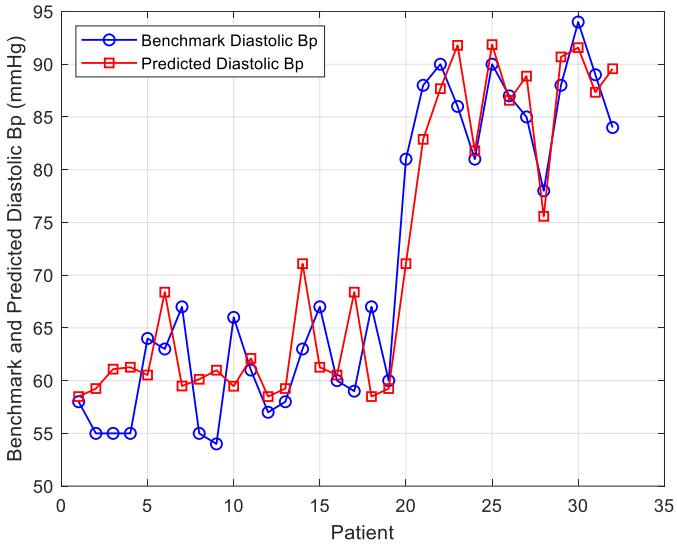

Fig. 16. Systolic BP (benchmark) and predicated diastolic BP

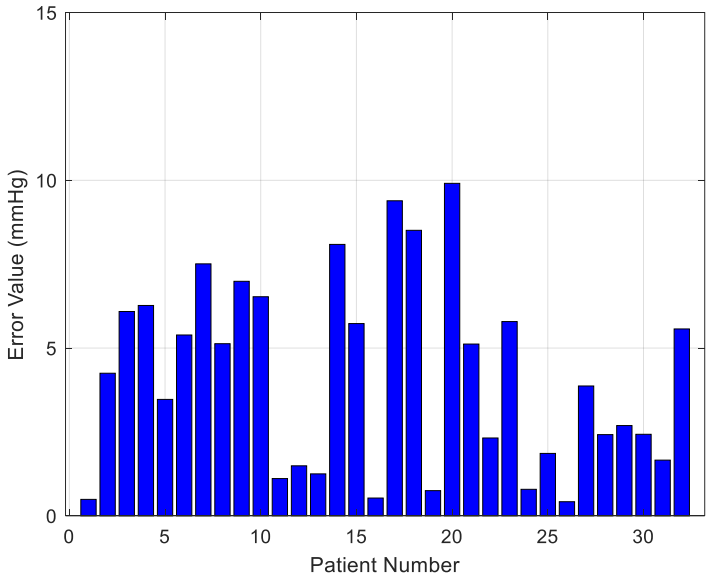

Fig. 17. Error values of diastolic BP

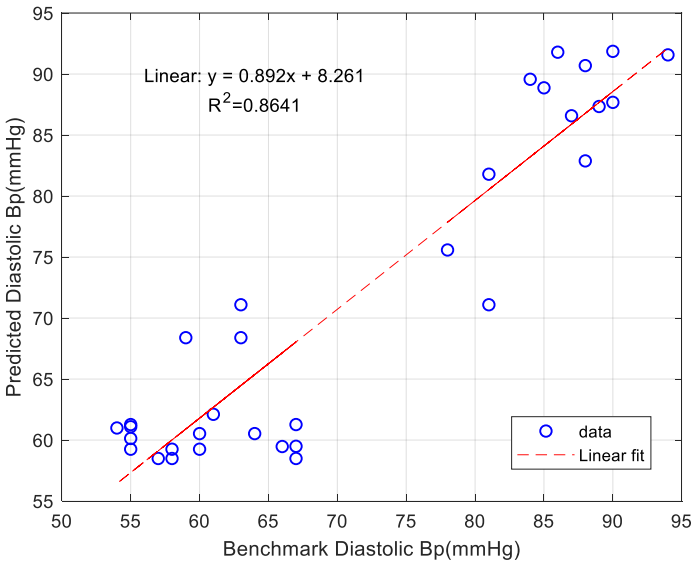

Fig. 18. Correlation between the benchmark and predicted diastolic BP

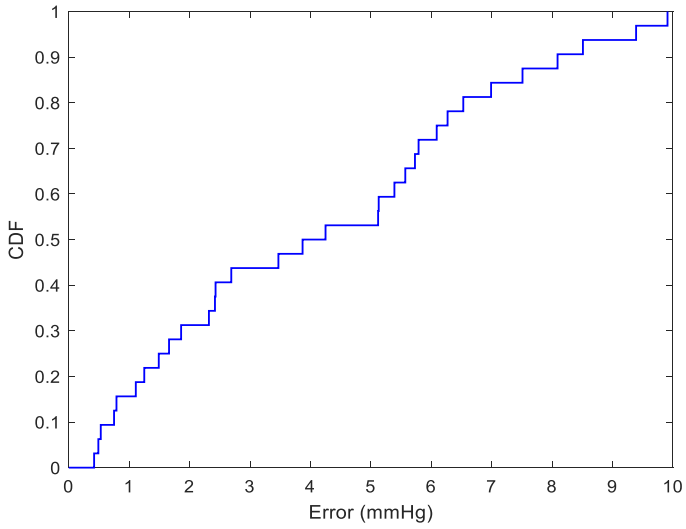

Fig. 19. CDF for error between the benchmark and predicted diastolic BP

5. Conclusions

This research paper presents a novel solution for continuously monitoring blood pressure in epileptic seizure patients using a photoplethysmography (PPG) sensor. Epileptic seizures are characterized by sudden and unpredictable changes in the brain's electrical activity, which can lead to a range of symptoms, including changes in blood pressure. The proposed approach aims to improve the management of epilepsy by providing real-time monitoring of blood pressure during seizures, which can help healthcare professionals quickly respond to any changes in the patient's condition. The proposed approach has several potential benefits for the management of epilepsy. First, it provides real-time blood pressure monitoring during seizures, which can help healthcare professionals quickly respond to changes in the patient's condition. Second, it is non-invasive and easy to use, which can improve patient compliance with the monitoring process. Finally, it can help identify patterns in blood pressure changes during seizures, providing valuable insights into the underlying mechanisms of epileptic seizures.

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References

[1] World Health Organization, ‘Epilepsy Fact Sheet,’ Mar. 2021. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/epilepsy.
[2] Epilepsy Foundation, ‘Epilepsy Overview,’ Oct. 2020. [Online]. Available: https://www.epilepsy.com/learn/about-epilepsy-basics/what-epilepsy.
[3] A. Middleton, S. L. Fritz, and M. Lusardi, "Walking speed: the functional vital sign," J. Aging Phys. Act., vol. 23, no. 2, pp. 314-322, Apr. 2015, https://doi.org/10.1123/japa.2013-0236.
[4] J. van Andel, C. Ungureanu, R. Aarts, F. Leijten, and J. Arends, "Using photoplethysmography in heart rate monitoring of patients with epilepsy," Epilepsy Behav., vol. 45, pp. 247-251, Mar. 2015, https://doi.org/10.1016/j.yebeh.2015.02.018.
[5] M. Glasstetter, S. Böttcher, N. Zabler, N. Epitashvili, M. Dümpelmann, M. P. Richardson, and A. Schulze-Bonhage, "Identification of ictal tachycardia in focal motor- and non-motor seizures by means of a wearable PPG sensor," Sensors, vol. 21, no. 18, article no. 6017, Sep. 2021, https://doi.org/10.3390/s21186017.
[6] R. El Atrache, E. Tamilia, F. Mohammadpour Touserkani, S. Hammond, C. Papadelis, K. Kapur, M. Jackson, B. Bucciarelli, M. Tsuboyama, R. A. Sarkis, and T. Loddenkemper, "Photoplethysmography: a measure for the function of the autonomic nervous system in focal impaired awareness seizures," Epilepsia, vol. 61, no. 8, pp. 1617-1626, Aug. 2020, https://doi.org/10.1111/epi.16621.
[7] A. Chittala, T. Bhupathi, D. P. Alakunta and N. K. Punna, "Machine Learning and IoT Based EEG Signal Classification for Epileptic Seizures Detection," 2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), Bangalore, India, 2021, pp. 531-537, https://doi.org/10.1109/RTEICT52294.2021.9573727.
[8] S. P. Shashikumar, A. J. Shah, Q. Li, G. D. Clifford and S. Nemati, "A deep learning approach to monitoring and detecting atrial fibrillation using wearable technology," 2017 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), Orlando, FL, USA, 2017, pp. 141-144, https://doi.org/10.1109/BHI.2017.7897225.
[9] Epilepsy Society, ‘Recovery after a seizure,’ [Online]. Available: https://www.epilepsysociety.org.uk/recovery-after-seizure#.YjvNKi1Q3n0.
[10] J. -L. Song, Q. Li, B. Zhang, M. B. Westover and R. Zhang, "A New Neural Mass Model Driven Method and Its Application in Early Epileptic Seizure Detection," in IEEE Transactions on Biomedical Engineering, vol. 67, no. 8, pp. 2194-2205, Aug. 2020, https://doi.org/10.1109/TBME.2019.2957392.
[11] I. A. Ibrahim, J. Santhosh and M. Moghavvemi, "A new approach for an effective eye movement artifact elimination from EEG signal," 2015 IEEE International Conference on Signal and Image Processing Applications (ICSIPA), Kuala Lumpur, Malaysia, 2015, pp. 557-562, https://doi.org/10.1109/ICSIPA.2015.7412253.
[12] H. N. Lemus and R. A. Sarkis, "Epilepsy care in nursing facilities: Knowledge gaps and opportunities," Epilepsy Behav., vol. 138, article no. 108997, 2023, https://doi.org/10.1080/14740338.2022.2023128.
[13] B. N. Blond, K. Detyniecki, and L. J. Hirsch, "Assessment of treatment side effects and quality of life in people with epilepsy," Neurologic Clinics, vol. 34, no. 2, pp. 395-410, May 2016, https://doi.org/10.1016/j.ncl.2015.11.002.
[14] Epilepsy Foundation, ‘Epilepsy in the United States,’ Oct. 2020. [Online]. Available: https://www.epilepsy.com/learn/about-epilepsy-basics/epilepsy-united-states.
[15] S. M. Krishna, J. V. Moxon, and J. Golledge, "A Review of the Pathophysiology and Potential Biomarkers for Peripheral Artery Disease," Int. J. Mol. Sci., vol. 16, no. 5, pp. 11294-11322, 2015. doi: 10.3390/ijms160511294.
[16] M. J. Brodie and P. Kwan, "Epilepsy in elderly people," BMJ, vol. 331, no. 7528, pp. 1317-1322, Dec. 2005. doi: 10.1136/bmj.331.7528.1317.
[17] A. Goshvarpour and A. Goshvarpour, "The potential of photoplethysmogram and galvanic skin response in emotion recognition using nonlinear features," Phys. Eng. Sci. Med., vol. 43, pp. 119-134, 2020. doi: 10.1007/s13246-019-00825-7.
[18] A. A. Asadi-Pooya, M. Emami, N. Ashjazadeh, A. Nikseresht, A. Shariat, P. Petramfar, G. Yousefipour, A. Borhani-Haghighi, S. Izadi, and A. Rahimi-Jaberi, "Reasons for uncontrolled seizures in adults; the impact of pseudointractability," Seizure, vol. 22, no. 4, pp. 271-274, 2013. doi: 10.1016/j.seizure.2013.01.010.
[19] Patel S, Hu S, Sahu S, Patel M. A review on photoplethysmography and its emerging applications. Int J Biosens Bioelectron. 2019;5:197-202. doi:10.11648/j.ijbb.20190506.17.
[20] Q. Wang, W. Zeng, and X. Dai, "Gait classification for early detection and severity rating of Parkinson's disease based on hybrid signal processing and machine learning methods," Cogn. Neurodyn., 2022. doi: 10.1007/s11571-022-09925-9.

[21] K. S. -K. Ma, H. Hao, H. -C. Huang and Y. -H. Tang, "Entropy-Facilitated Machine Learning for Blood Pressure Estimation Using Electrocardiogram and Photoplethysmogram in a Wearable Device," 2021 14th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), Shanghai, China, 2021, pp. 1-6, doi: 10.1109/CISP-BMEI53629.2021.9624370.
[22] A. Jubran, "Pulse oximetry," Intensive Care Med., vol. 30, no. 11, pp. 2017–2020, 2004, doi: 10.1007/s00134-004-2399-x.
[23] L. Hussain, "Detecting epileptic seizure with different feature extracting strategies using robust machine learning classification techniques by applying advance parameter optimization approach," Cogn. Neurodyn., vol. 12, no. 3, pp. 271-294, Jun. 2018. doi: 10.1007/s11571-018-9477-1.
[24] A. Souri, M. Y. Ghafour, A. M. Ahmed, F. Safara, A. Yamini, and M. Hoseyninezhad, "A new machine learning-based healthcare monitoring model for student's condition diagnosis in Internet of Things environment," Soft Computing, vol. 24, pp. 17111-17121, 2020. doi: 10.1007/s00500-020-05003-6.
[25] Huang CM, Chan GSH, Ting CK. A comprehensive review of non-invasive blood pressure monitoring techniques. J Clin Monit Comput. 2019 Dec;33(6):901-913. doi: 10.1007/s10877-019-00348-w.
[26] A. Jahanbekam, J. Baumann, R. D. Nass, C. Bauckhage, H. Hill, C. E. Elger, and R. Surges, "Performance of ECG-based seizure detection algorithms strongly depends on training and test conditions," Epilepsia Open, vol. 6, no. 4, pp. 656-663, 2021. doi: 10.1002/epi4.12520.
[27] T. Wibmer, C. Denner, C. Fischer, B. Schildge, S. Rüdiger, C. Kropf-Sanchen, W. Rottbauer, and C. Schumann, "Blood pressure monitoring during exercise: comparison of pulse transit time and volume clamp methods," Blood Pressure, vol. 24, no. 6, pp. 353-360, Nov. 2015. doi: 10.3109/08037051.2015.1053253.
[28] K. Budidha and P. A. Kyriacou, "Photoplethysmography for quantitative assessment of sympathetic nerve activity (SNA) during cold stress," Front. Physiol., vol. 9, article no. 1863, Jan. 2019. doi: 10.3389/fphys.2018.01863.
[29] F. Attivissimo, L. De Palma, A. Di Nisio, M. Scarpetta, and A. M. L. Lanzolla, "Photoplethysmography Signal Wavelet Enhancement and Novel Features Selection for Non-Invasive Cuff-Less Blood Pressure Monitoring," Sensors, vol. 23, no. 4, article no. 2321, 2023. doi: 10.3390/s23042321.
[30] R. Mukkamala, D. H. Mathews, Y. Gao, M. P. Purnell and J. R. Hahn, 'Noninvasive blood pressure monitoring using pulse transit time,' in Proceedings of the IEEE, vol. 97, no. 3, pp. 390-403, March 2009. DOI: 10.1109/TBME.2018.2865751
[31] S. Z. Hassanpour and M. R. Ayatollahi, 'Blood pressure estimation using photoplethysmography and pulse transit time,' in IEEE Transactions on Instrumentation and Measurement, vol. 63, no. 2, pp. 275-282, Feb. 2014. DOI 10.1088/1361-6579/ab1f17
[32] M. Simjanoska, M. Gjoreski, M. Gams, and A. M. Bogdanova, "Non-Invasive Blood Pressure Estimation from ECG Using Machine Learning Techniques," Sensors, vol. 18, no. 4, article no. 1160, 2018. doi: 10.3390/s18041160.
[33] G. Wang, M. Atef and Y. Lian, "Towards a Continuous Non-Invasive Cuffless Blood Pressure Monitoring System Using PPG: Systems and Circuits Review," in IEEE Circuits and Systems Magazine, vol. 18, no. 3, pp. 6-26, thirdquarter 2018, doi: 10.1109/MCAS.2018.2849261.
[34] Xie, J., Chen, Y., Gong, E., Liu, J., Li, L., Sun, H., & Wang, H., A wearable cuffless blood pressure monitoring system using photoplethysmography and electrocardiogram signals. Journal of medical systems, 42(4), 68, 2018, doi: 10.1007/s10916-018-0916-y.
[35] Zhang, Y., Feng, X., Zhu, X., Liu, Y., & Wang, X., A wearable cuffless blood pressure monitoring system using a single photoplethysmography sensor and convolutional neural network. Journal of healthcare engineering, 2021, 1-11. doi: 10.1155/2021/66.
[36] Kim, D. H., Lee, D. Y., Kim, D. H., Lee, J. W., & Kim, J. H., Continuous blood pressure monitoring using pulse wave analysis and photoplethysmography. Scientific reports, 9(1), 1-8, 2019, doi: 10.1038/s41598-019-43147-8.
[37] Shahin, S., Haghi, M., & Ward, R., Continuous non-invasive blood pressure monitoring using photoplethysmography and machine learning. Scientific reports, 10(1), 1-10, 2020, doi: 10.1038/s41598-020-64292-2.
[38] G. Thambiraj, U. Gandhi, V. Devanand, and U. Mangalanathan, "Noninvasive cuffless blood pressure estimation using pulse transit time, Womersley number, and photoplethysmogram intensity ratio," Physiol. Meas., vol. 40, no. 7, article no. 075001, Jul. 2019. doi: 10.1088/1361-6579/ab1f17.
[39] Nordic Semiconductor, "NRF2401 datasheet," 2021. [Online]. Available: https://www.nordicsemi.com/Products/Low-power-short-range-wireless/nRF24-series/nRF2401.
[40] Wiki Company, "Ear-Loop PPG Sensor for Arduino," 2021. [Online]. Available: https://www.wiki-company.com/index.php?title=Ear-Loop_PPG_Sensor_for_Arduino.
[41] Adafruit Industries. (2021). 3.2" TFT LCD Display. https://www.adafruit.com/product/1480.
[42] SparkFun Electronics, "MP3 Player Shield Hookup Guide," 2021. [Online]. Available: https://learn.sparkfun.com/tutorials/mp3-player-shield-hookup-guide/all#introduction.
[43] Y. Xu, M. Luo, T. Li, and G. Song, "ECG Signal De-noising and Baseline Wander Correction Based on CEEMDAN and Wavelet Threshold," Sensors, vol. 17, no. 12, article no. 2754, 2017. doi: 10.3390/s17122754.