Fast Cuffless Blood Pressure Classification with ECG and PPG signals using CNN-LSTM Models in Emergency Medicine

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***Abstract*—Cuffless blood pressure (BP) measurement is gaining a lot of attention as a promising new technology that can be embedded in a patch-like biosensor device. Electrocardiogram (ECG) and photoplethysmogram (PPG) waveforms are non-invasive by their nature - they can be recorded without sending any electrical impulses to the human body. These signals present different aspects of the cardiovascular system, thus using both of the signals for blood pressure classification seems like a viable strategy. Quick estimation of the blood pressure during the triage process in cases of natural disasters with many injured subjects, is an essential measure for following the hemostability of the injured. The main goal of this study is to develop a two-class classification model (Hypotension and Nothypotension) for fast prediction of the blood pressure category by utilizing ECG and PPG signals, in order to detect a BP sudden drop. The developed deep learning models are based on the LSTM architecture and its variants, CNN-LSTM. We also conducted three class classification model. The models were trained and tested using the data from the UCI Machine Learning Repository Cuff-Less Blood Pressure Estimation dataset with 12000 instances. The best result in the two-class model is AUROC = 0.74.**

Keywords*—*blood pressure (BP) estimation, triage, electrocardiogram (ECG), photoplethysmogram (PPG), long short term memory (LSTM), CNN-LSTM, artificial neural network, deep learning

I. Introduction

A multisensor patch-like device that can be attached to an injured's chest in mass casualties events could improve the START triage process. This device is capable of collecting and analysing information on vital parameters such as respiration rate (RR), heartbeat (heart rate – HR), blood oxygen saturation level (SpO2), blood pressure and body temperature [1]. Our interest in this research is to utilize the embedded electrocardiogram (ECG) and photoplethysmogram (PPG) sensors in the patch-like biosensor in order to follow the injured's hemostability (if there is an internal bleeding).

Blood pressure is the force that the blood exerts on the walls of the blood vessels, as the heart pumps blood. The heart on average beats 60 - 100 times a minute [2]. During each beat the heart performs a cardiac cycle that consists of two phases: the systole, when the heart contracts pumping the blood into the arteries and the diastole, when the heart relaxes after a contraction. With every beat of the heart, the blood pressure changes from the maximum, systolic (SBP), to the minimum, diastolic (DBP) [3]. This is a metric that is often measured by health care professionals during a medical checkup. ECG represents the electrical activity of the heart, while PPG shows the changes of blood volume in the microvascular tissue. The codependency among BP, ECG and PPG has been explored in many different studies [4] [5] [6] [7].

During the overview of the literature we have realized that the BP hypotension category (SBP<90, DBP<60) is not in the focus of most researches, while it is important for the project presented in [1]. Typical symptoms of hypotension are dizziness and fainting. Severely low blood pressure can deprive the brain and other vital organs of oxygen and nutrients, leading to a life-threatening condition - shock. Since our interest is to monitor the injured patient's hemostability in emergency situations, it's important to note that a sudden drop in the BP might be caused by an internal bleeding, leading to a change in the triage priority of giving a medical treatment (to triage label 'immediate'). As a main interest in this paper, we explore the BP categorisation as a two-class classification problem (classes Hypotension and Nothypotension).

As a proposed model for solving the categorization of the BP is a type of reccurent neural network - Long short term memory, LSTM. They are capable of processing sequential information, e.g. time series data (ECG, PPG signals), and are specifically built to be able to follow long term dependencies. This study focuses on CNN-LSTM models. The developed model architecture supports the idea of fast categorisation - the algorithm is simple and able to function in real time.

The proposed methodology is consisted of the following steps:

1) Cleaning the data, by excluding signals that have missing values or the difference between the SBP and DBP is less than 20 or greater than 100, or the value for DBP is greater than 130;

2) The data segments in the longer signals are transformed into smaller ones with uniform length - a format of the input vectors passed to the network models;
3) The ECG and PPG signals are transformed first by standardization and then by filtration;
4) BP categorization - two BP categories (First experiment) and three BP categories (Second Experiment);
5) Building the classification CNN-LSTM models;
6) Evaluation of the models.

The rest of the paper is organized as follows. Section 2 presents an overview on similar papers or related researches. The methodology is described in Section 3. The results of the experiments and the discussion are presented in Section 4, including the introduction of the dataset, the preprocessing part and the used methods. Section 5 presents the conclusion.

II. Related Work

In this section, several researches on the subject of interest are explored - solutions for noninvasive continuous blood pressure estimation utilizing ECG and/or PPG signals. Some of these solutions attempt to manually extract relevant features from the signals, like pulse arrival (PAT) time that has been proven to have a correlation to blood pressure. Other authors rely on deep learning neural networks to automatically find and extract features.

Pulse transit time (PTT) measures the time taken for the arterial pulse pressure wave to travel from the aortic valve to a peripheral site. PAT is defined as the difference between the R-peak of an ECG and the systolic peak of a PPG. While the features are similar, they are not interchangeable [8]. They are both proven markers of BP with the latter gaining prominence in the recent publications [6] [9] [7]. Those features are not the only morphological characteristics extracted from the signals. Many papers suggest their own features as they believe contribute to more accurate estimations, i.e. Womersley number [10] that reflects the flow properties of blood. Other studies consider the main reason for the inaccuracy of the estimators in blood pressure is the assumption that artery diameter is a constant. The pulse intensity ratio (PIR) is suggested as an indicator for the evaluation of changes to the artery diameter and its correlation to blood pressure is experimentally proven [11]. In a seven-day experiment on 30 patients it has been shown that patients that suffer from hypertension have both higher average and higher variance PIR [12]. Another study relies on the hypothesis that a healthy biomedical system is highly complex, and that when abnormalities occur, the complexity of the system decreases. This paper utilizes a complexity analysis for feature extraction, achieves MAE of 8.64 mmHg for SBP, 18.20 mmHg for DBP, and 13.52 mmHg for MAP. These results improve further when models are calibrated: MAE of 7.72 mmHg for SBP, 9.45 mmHg for DBP and 8.13 mmHg for MAP [13]. Heart rate is another feature often taken into account since its easy to calculate from the ECG and an elevated heart rate usually indicates elevated blood pressure. Sometimes they are combined with other information about the patients like demographic characteristics. A study working with features extracted from a PPG signal and demographic characteristics achieves with RMSE of 6.74 and 3.59, for SBP and DBP respectively [14].

Other studies develop deep learning models. One proposed solution uses a waveform based hierarchical Artificial Neural Network–LSTM (ANN-LSTM). The lower hierarchy level ANN extracts necessary morphological features from ECG and PPG waveforms and the upper hierarchy level LSTM layers accounts for the time domain variation of the features extracted by lower hierarchy level. The proposed ANN-LSTM network achieves MAE of 1.10 for SBP and 0.58 DBP, and RMSE of 1.56 mmHg for SBP and 0.85 mmHg for DBP [15]. Another study attempt something similar by using a CNN-LSTM where the input into the neural network is the difference of the ECG and PPG signal [16]. The CNN layers extract morphological features, while the LSTM extract temporal features. A hybrid CNN-LSTM model developed to utilize both raw PPG and ECG data and physical features, achieves a MAE of 4.43 ± 6.09 mmHg for SBP and being 3.23 ± 4.75 mmHg for DBP [17].

Most of the referenced papers are using some subset of the MIMIC (Medical Information Mart for Intensive Care) databases. They have a varying degree of success and different approaches. It's important to note that some models are built with the assumption that the ECG and PPG signals are synchronized [18]. If this condition is not met, the features can't be extracted either manually or automatically from the combination of ECG and PPG signals.

III. Materials and Methods

In this section we describe the dataset, data preprocessing procedures, the developed CNN-LSTM model and the used evaluation metrics.

A. Dataset

The dataset used in this study is UCI Machine Learning Repository Cuff-Less Blood Pressure Estimation Dataset [19], [20]. It contains 12000 instances. Each instance contains only ABP, PPG and ECG signals sampled at 125 Hz.

1) PPG: Photoplethysmograph (PPG), is an optically gained plethysmograph that detects the changes in the volume of blood in the microvascular tissue. PPG gives valuable information for the cardiovascular system and it's a simple, portable, and a low-cost technology [5]. An example of a PPG signal, utilizing the Nurokit2 package is given in Figure 1.

2) ABP: Arterial blood pressure (ABP) is defined as the force that is exerted by the blood on the arterial wall. Blood pressure is connected with the cardiovascular cycle that has two phases: systole, when the heart contracts and

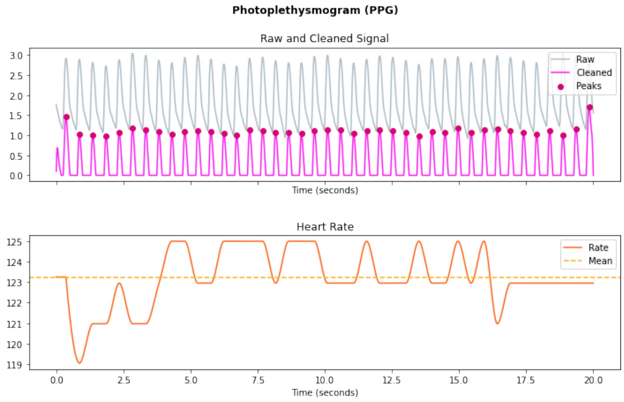

Fig. 1: Visualization of a PPG waveform using the Neurokit2 package

pumps the blood, and the diastole, when the heart relaxes after contraction [3].

3) ECG: Electrocardiogram (ECG) represents a graph of the electrical activity of the heart through time. The impulses coordinate the contractions of different parts of the heart allowing the blood to flow. An example of an ECG signal, utilizing the Nurokit2 package is given in Figure 2.

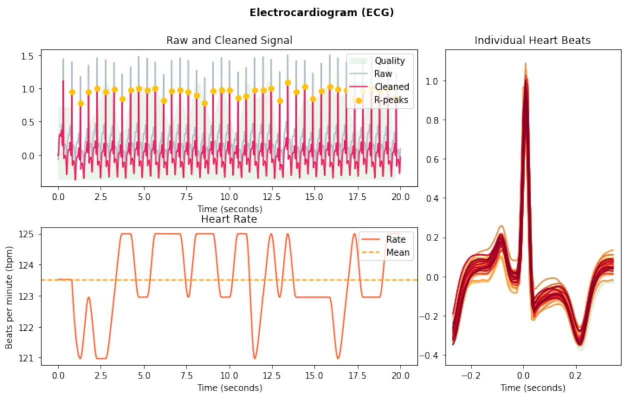

Fig. 2: Visualization of an ECG waveform using the Neurokit2 package

B. Preprocessing

1) Data Cleaning: The instances with missing data in any of the three signals are removed. The normal value of the ABP in a healthy person is between 40 and 60. An indication of a serious condition, but also a possible invalid signal if ABP value is less than 20, therefore these instances are excluded. ABP value above 100 is indication of many cardiovascular diseases and this big difference between the SBP and DBP is possible. Nevertheless, the instances where this abnormal condition occurs are not taken into consideration.

2) Segmentation: The average length of a signal in this dataset is 27807.5 data points, within the range [1000, 74000]. In this study, segments with 1000 data points at 125 Hz frequency are considered, or 8 seconds in time domain. This is done in order to avoid the exclusion of the instances with signal length of 8 sec. This approach increases the number of samples, but decreases their information gain. To further increase the number of training samples, multiple segments are taken from the longer signals, with no overlap. Each segment contains unique data. Different studies utilize signals with different length. More research needs to be done to find the optimal signal length.

3) Standardization: Standardization is the process of transforming different feature values to be on the same scale. Each signal is transformed to have a mean value 0 and variance value 1.

4) Filtering: Signals can be distorted while recording or transmitting, because of the presence of a noise. To eliminate both types of noise (low and high frequencies), the signals are filtered.

The ABP is not filtered in order to avoid a distortion in the SBP and DBP values. For filtering the ECG and PPG signals, both notch and bandwidth are typically used [21]. In this study the bandwidth filter of order 5 for ECG and the bandwidth filter of order 4 for PPG is used.

5) BP categorization: In order to prepare the labeling of the data, the values for SBP and DBP are calculated using the ABP values by finding the local maxima for SBP and local minima for DBP and averaging them [22]. An illustration of SBP and DBP extraction from ABP waveform is presented in Figure 3.

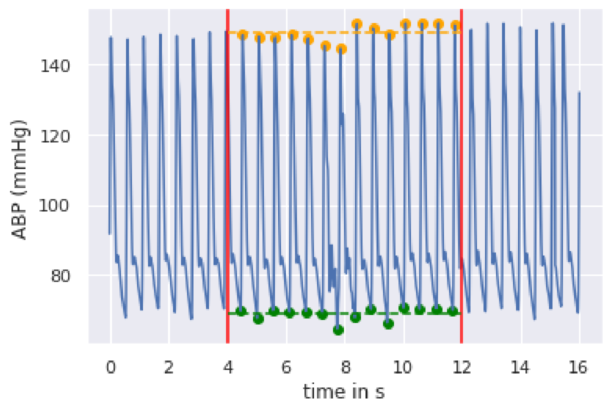

Fig. 3: Illustration of SBP and DBP extraction from ABP waveform

In this study, two different BP classification problems are explored - data is divided in two BP categories (First Experiment) and three BP categories (Second Experiment).

First experiment

The main goal of this research, as elaborated in the Introduction, is to develop a model to follow the hemostability of an injured patient by detecting the possible inner bleeding. This condition can be detected by a low BP - hypotension. Therefore, the data is divided in two BP categories: Hypotension and Nothypotension, presented in Table I.

TABLE I: Blood Pressure Categorization

Category	SBP	DBP	Number of Samples
Hypotension	< 90	< 60	9379
Nothypotension	≥ 90	≥ 60	34849

Second experiment

A Second experiment was developed in order to discern whether the same model can be used in the standard BP classification problem, slightly adapted to the dataset at hand. According to American College of Cardiology, BP is divided in the following categories/classes: Normal, Prehypertension, Stage 1 Hypertension, Stage 2 Hypertension [23].

Considering the used dataset (small number of samples in the Stage 1,2 Hypertension) the BP is divided in three categories, presented in Table II.

TABLE II: Blood Pressure Categorization

Category	SBP	DBP	Number of Samples
Normal	< 120	< 80	16597
Prehypertension	$120 - 139$	$80 - 89$	17689
Hypertension	≥ 140	≥ 90	9942

6) Balancing the classes: The used dataset suffers from class imbalance. An imbalanced dataset will skew the results favoring the most common class. The most popular balancing method SMOTE (Synthetic Minority Oversampling Technique) was not successful in this study, since the input vectors are presented as time distributed sequences.

The method of undersampling is utilized for the two-class classification (First experiment). The undersampling is done by randomly discarding majority class instances from the training dataset. As for the Second experiment with the three BP classes, another balancing method is used - the class weight method, simply by assigning more weight to the less represented class. The undersampling is abandoned, since a reduction of the training data in the three class-classification with this particular dataset negatively impacted the learning process.

C. Model Structure

Based on previous studies, it is concluded that LSTM neural networks are suitable for BP classification problem, following the fact that the input vectors are two chronological arrays of points, one of ECG and one of PPG signals.

A CNN-LSTM architecture combines CNN layers for extraction of features from input data with LSTM for sequence prediction [24]. CNN-LSTM contains both CNN and LSTM layers. The input into the ANN are two sequences each made up from 1000 data points representing PPG and ECG signals. These sequence are split into subsequences. Each subsequence represents the same signals in a different time step. A single input vector is a stream of real numbers, representing the filtered ECG and PPG signal, in the following format: (100, 10, 2), corresponding to (length of subsequences, timesteps, features).

The built model is an multivariate CNN-LSTM, an ensemble of two neural networks, one for each variable (PPG and ECG), with the same structure that link to the same output layer:

- First experiment: 2 neurons representing the blood pressure categories (0: Hypotension, 1: Nothypotension).

- Second experiment: 3 neurons representing the blood pressure categories (0: Normal, 1: Prehypertension, 2: Hypertension).

D. Evaluation Metrics

In this section, the used metrics in order to evaluate the models are elaborated. Since we developed classification models, the following evaluation metrics are used: accuracy, precision, recall, f1 score, AUROC values. Also, Support, as well as Macro and Weighted averaging schemas are presented. The schemas average the metrics into a single value to evaluate the performance of the model:

1) Support: The number of samples in the testing dataset labeled as a class.

2) Macro average: Macro average is a schema used in multiclass classification, i.e. calculating corresponding metrics independently and averages the results.

3) Weighted average: Weighted average is schema that averages metrics like precision and recall for all classes in a dataset by assigning weights to each class depending on their importance.

IV. Results and Discussion

In this section, the results obtained using the aforementioned methodology and the chosen LSTM-CNN model are presented.

A. Model Training and Evaluation

In the scope of this research, many different model structures have been explored. The model presented below was the most successful in the research so far. The network has a batch size of 128 and runs for 20 epochs.

In the presented experiments 85% of the dataset is used to train the model, while the remaining 15% is used for testing, i.e. evaluating the model's results. A validation dataset containing 10% from the training dataset is used to prevent overfitting. An ADAM optimizer with a learning rate of 0.03 was used to train the models. The learning rate is selected utilizing a naive approach, by experimenting with different values - it is concluded that this value gives the best loss.

The First Experiment

The overall accuracy of the best model is 0.76. The model evaluation is given in Table III with the class labels: '0' as Hypotension and '1' as Nothypotension. The AUROC value is 0.74. The precision for the Hypotension class is small-scale, partly due to the fact that this is the minority class. However, reasonably good recall and f1 scores rates are achieved. The model takes 147.14s to train and uses 148 MB of RAM.

TABLE III: Results - First experiment

	precision	recall	f1-score	support
0:Hypotension	0.46	0.71	0.56	1395
1:Nothypotension	0.91	0.78	0.84	5240
accuracy			0.76	6635
macro avg	0.69	0.75	0.70	6635
weighted avg	0.82	0.76	0.78	6635

In Table IV the confusion matrix from the First experiment is presented.

TABLE IV: Confusion matrix - First experiment

		Predicted labels	
		Hypotension	Nothypotension
True	Hypotension	996	399
	Nothypotension	1165	4075

The Second Experiment

The overall accuracy of the best model is 0.66. The model evaluation is given in Table V with the class labels: '0' as Normal, '1' as Prehypertension and '2' as Hypertension. The precision and recall rates for the Normal class are fairly high. Evaluation of the model shows that it has trouble distinguishing between the Prehypertension and Hypertension classes. Prehypretension is a less advanced form of hypertension. The AUROC values for each of the classes are 0.791, 0.688 and 0.729, respectively. The model takes 358.33s to train and and uses 148 MB of RAM.

TABLE V: Results - Second experiment

	precision	recall	f1-score	support
0:Normal	0.78	0.70	0.74	2461
1:Prehypertension	0.60	0.68	0.64	2653
2:Hypertension	0.61	0.57	0.59	1521
accuracy			0.66	6635
macro avg	0.66	0.65	0.65	6635
weighted avg	0.67	0.66	0.66	6635

In Table VI the multiclass confusion matrix from this experiment is presented.

TABLE VI: Confusion matrix - Second experiment

		Predicted labels		
		Normal	Prehyper-tension	Hyper-tension
True	Normal	1717	674	97
	Prehypertension	393	1806	454
	Hypertension	90	569	862

B. Discussion

The obtained results give an excellent starting point to develop a classification model for BP estimation that can be embedded on a compact patch-like biosensor that contains ECG and PPG sensors. Once the model is built, the classification process is delivered in real time, as the real-life situations require.

The First experiment with the two classes is an idea that presents itself as a simplified version of the classic BP classification problem. The achieved reasonably good recall rates (0,71 and 0,78 for the two classes) and the f1 score rates, lead us to believe that further research in this direction would be productive. We also tried a four-class classification (Hypotension, Normal, Prehypertension and Hypertension), but the obtained results were not satisfactory.

There are several reasons that impacted the results in the First and Second experiment - the value of the segment size (8 sec.) might be too short of an interval to accurately deduce the blood pressure. Further study focusing on this aspect is required. Still, the model can distinguish between the different categories and training the same model on a larger dataset can improve the results.

The model is limited by the fact that it works with fixed segments instead of dynamic ones. Blood pressure varies during the span of the day. The changes to BP can happen gradually. Other works have proven that calibrating a model to a patient produces far better results because it allows the model to learn the patient specific morphological characteristics. This study attempts to build a generalized model, a model that's expected to perform reasonably well on any patient.

Using an extensive dataset from different sources will help to overcome the pointed obstacles.

V. Conclusion

The goal of this research is to create a model that can be used on a patch-like device, capable of fast BP category classification. The proposed solution is developed to be used during assessment of subjects in emergency situations with high number of casualties. The patch-like multisensor needs to function with no regard of the person's age and gender. The only information that can be used are the momentarily values of the detected ECG and PPG signals. The developed model is to perform in real-time and to allow continuous monitoring of blood pressure on a device with limited memory capacity and limited battery life [1].

This paper proposes a solution to the given request - models an input as a sequence of ECG and PPG signals and outputs a BP category. Since we are dealing with raw signals, the focus is on the preprocessing part. The instances of the used dataset [19] have 3 features: ABP, PPG and ECG waveforms. The SBP and DBP are extracted from the ABP signals, while the PPG and ECG signals are standardized and filtered to serve as the input vectors, processed by a trained CNN-LSTM model.

Two different experiment were undertaken. The First one is the main goal of this study, the two-class BP classification (Table I). The AUROC value is 0.74. The precision for the Hypotension class is small-scale, partly due to the fact that this is the minority class. However, sufficiently good recall (0,71 and 0,78) and f1 scores rates are achieved. In the Second experiment, the dataset is divided in three BP categories (Table II). The AUROC values for each of the classes are 0.791, 0.688 and 0.729, respectively. The Normal BP is classified distinctively well (f1=0,74; precision=0,78; recall 0,70), but the recognition of the other two classes was not successful.

The summarised results from the First experiment indicate that the two-class classification including the hypotension category should be considered as a solution for the fast BP categorization during the triage process. We believe that this simplified BP classification is more suitable for the patch-like device, since it can help in the detection of the sudden BP drop as the first sign of possible internal bleeding.

Future work includes adjusting the segment size making sure that segments from the same signal are all either in the train or in the test set. Also, we intend refining the results by developing regression models for BP estimation with deep learning approach, using Big Data.

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REFERENCES

[1] F. Lehocki, A. M. Bogdanova, M. Tysler, B. Ondrusova, M. Simjanoska, B. Koteska, M. Kostoska, M. Majak, and M. Macura, "Smartpatch for victims management in emergency telemedicine," in *2021 13th International Conference on Measurement*, 2021, pp. 146–149.

[2] American Heart Association, "All about heart rate (pulse)," [retrieved: Feb, 2022]. [Online]. Available: https://www.heart.org/en/health-topics/high-blood-pressure/the-facts-about-high-blood-pressure/all-about-heart-rate-pulse

[3] G. D. James and L. M. Gerber, "Measuring arterial blood pressure in humans: Auscultatory and automatic measurement techniques for human biological field studies," *American Journal of Human Biology*, vol. 30, no. 1, p. e23063, 2018. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/ajhb.23063

[4] Y.-H. Li, L. N. Harfiya, K. Purwandari, and Y.-D. Lin, "Real-time cuffless continuous blood pressure estimation using deep learning model," *Sensors*, vol. 20, no. 19, 2020. [Online]. Available: https://www.mdpi.com/1424-8220/20/19/5606

[5] Y.-C. Hsu, Y.-H. Li, C.-C. Chang, and L. N. Harfiya, "Generalized deep neural network model for cuffless blood pressure estimation with photoplethysmogram signal only," *Sensors*, vol. 20, no. 19, 2020. [Online]. Available: https://www.mdpi.com/1424-8220/20/19/5668

[6] Y. Choi, Q. Zhang, and S. Ko, "Noninvasive cuffless blood pressure estimation using pulse transit time and hilbert–huang transform," *Computers & Electrical Engineering*, vol. 39, no. 1, pp. 103–111, 2013, special issue on Recent Advanced Technologies and Theories for Grid and Cloud Computing and Bio-engineering. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0045790612001711

[7] C. Poon and Y. Zhang, "Cuff-less and noninvasive measurements of arterial blood pressure by pulse transit time," in *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*, 2005, pp. 5877–5880.

[8] G. Zhang, M. Gao, D. Xu, N. B. Olivier, and R. Mukkamala, "Pulse arrival time is not an adequate surrogate for pulse transit time as a marker of blood pressure," *Journal of Applied Physiology*, vol. 111, no. 6, pp. 1681–1686, 2011, pMID: 21960657. [Online]. Available: https://doi.org/10.1152/japplphysiol.00980.2011

[9] S. Goli and Jayanthi, "Cuff less continuous non-invasive blood pressure measurement using pulse transit time measurement," *International Journal of Recent Development in Engineering and Technology*, vol. 2, no. 1, pp. 86–91, 2014.

[10] G. Thambiraj, U. Gandhi, U. Mangalanathan, V. J. M. Jose, and M. Anand, "Investigation on the effect of womersley number, ecg and ppg features for cuff less blood pressure estimation using machine learning," *Biomedical Signal Processing and Control*, vol. 60, p. 101942, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1746809420300987

[11] X.-R. Ding and Y.-T. Zhang, "Photoplethysmogram intensity ratio: A potential indicator for improving the accuracy of ptt-based cuffless blood pressure estimation," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2015, pp. 398–401.

[12] Y. Chen, Y. Zhu, H. T. Ma, and H. Huang, "A study of photoplethysmography intensity ratio in hypertension," in *2016 IEEE International Conference on Real-time Computing and Robotics (RCAR)*, 2016, pp. 317–320.

[13] M. Simjanoska, M. Gjoreski, M. Gams, and A. Madevska Bogdanova, "Non-invasive blood pressure estimation from ecg using machine learning techniques," *Sensors (Basel, Switzerland)*, vol. 18, no. 4, p. 1160, Apr 2018, 29641430[pmid]. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/29641430

[14] M. H. Chowdhury, M. N. I. Shuzan, M. E. Chowdhury, Z. B. Mahbub, M. M. Uddin, A. Khandakar, and M. B. I. Reaz, "Estimating blood pressure from the photoplethysmogram signal and demographic features using machine learning techniques," *Sensors*, vol. 20, no. 11, 2020. [Online]. Available: https://www.mdpi.com/1424-8220/20/11/3127

[15] M. S. Tanveer and M. K. Hasan, "Cuffless blood pressure estimation from electrocardiogram and photoplethysmogram using waveform based ann-lstm network," *Biomedical Signal Processing and Control*, vol. 51, pp. 382–392, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1746809419300722

[16] D. U. Jeong and K. M. Lim, "Combined deep cnn–lstm network-based multitasking learning architecture for noninvasive continuous blood pressure estimation using difference in ecg-ppg features," *Scientific Reports*, vol. 11, no. 1, p. 13539, Jun 2021. [Online]. Available: https://doi.org/10.1038/s41598-021-92997-0

[17] S. Yang, Y. Zhang, S.-Y. Cho, R. Correia, and S. P. Morgan, "Non-invasive cuff-less blood pressure estimation using a hybrid deep learning model," *Optical and Quantum Electronics*, vol. 53, no. 2, p. 93, Jan 2021. [Online]. Available: https://doi.org/10.1007/s11082-020-02667-0

[18] Y. Liang, D. Abbott, N. Howard, K. Lim, R. Ward, and M. Elgendi, "How effective is pulse arrival time for evaluating blood pressure? challenges and recommendations from a study using the mimic database," *Journal of Clinical Medicine*, vol. 8, no. 3, 2019. [Online]. Available: https://www.mdpi.com/2077-0383/8/3/337

[19] M. Kachuee, M. M. Kiani, H. Mohammadzade, and M. Shabany, "Cuff-less high-accuracy calibration-free blood pressure estimation using pulse transit time," in *2015 IEEE International Symposium on Circuits and Systems (ISCAS)*, 2015, pp. 1006–1009.

[20] H. M. Mohamad Kachuee, Mohammad Mahdi Kiani and M. Shabany, "Cuff-less blood pressure estimation data set," [retrieved: Feb, 2022]. [Online]. Available: https://archive.ics.uci.edu/ml/datasets/Cuff-Less+Blood+Pressure+Estimation

[21] Pareeknikhil, "Getting the beat right!!" [retrieved: Feb, 2022]. [Online]. Available: https://towardsdatascience.com/getting-the-right-beat-e18acd48b8c1

[22] T. Athaya and S. Choi, "An estimation method of continuous non-invasive arterial blood pressure waveform using photoplethysmography: A u-net architecture-based approach," *Sensors*, vol. 21, no. 5, 2021. [Online]. Available: https://www.mdpi.com/1424-8220/21/5/1867

[23] A. V. Chobanian, G. L. Bakris, H. R. Black, W. C. Cushman, L. A. Green, J. L. Izzo, D. W. Jones, B. J. Materson, S. Oparil, J. T. Wright, E. J. Roccella, and null null, "Seventh report of the joint national committee on prevention, detection, evaluation, and treatment of high blood pressure," *Hypertension*, vol. 42, no. 6, pp. 1206–1252, 2003. [Online]. Available: https://www.ahajournals.org/doi/abs/10.1161/01.HYP.0000107251.49515.c2

[24] Jason Brownlee, "Gentle introduction to cnn lstm recurrent neural networks with example python code," [retrieved: Feb, 2022]. [Online]. Available: https://machinelearningmastery.com/cnn-long-short-term-memory-networks/