PulsECG - A Cuffless Non-Invasive Blood Pressure Monitoring Device through Neural Network Analysis of ECG and PPG signals

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***Abstract*—The monitoring of electrocardiogram (ECG), photoplethysmogram (PPG) and arterial blood pressure is crucial for preserving and enhancing individual health and well-being. These vital parameters offer profound insights into cardiac and pulmonary functions and are indispensable for the diagnosis and management of a plethora of health conditions. This paper presents the design and development of PulsECG, a portable medical device engineered to estimate arterial blood pressure using a cuffless approach. It acquires ECG signals according to the Einthoven's Triangle, monitors blood oxygen levels, and derives blood pressure non-invasively through the use of a neural network. The neural network at the heart of PulsECG leverages a combination of convolutional and bidirectional LSTM layers to process time-series input from dual-channel PPG and ECG signals. A custom database of 20 subjects is collected to train the network on real-life scenario. To this purpose, a custom data acquisition process has been designed, which alternates blood pressure measurements with ECG & PPG recordings, providing a dataset that underpins the network learning. The results show the neural network is able to correctly predict systolic and diastolic blood pressures, proving a high correlation with the ground truth (sphygmomanometer), despite a slight trend towards overestimation. This research advances the integration of neural network models into portable medical devices like PulsECG, fostering telemedicine and continuous health tracking. It opens novel ways for improved patient care, offering a solution for real-time health monitoring, and represents a step forward to combine artificial intelligence with medical technology.**

***Index Terms*—electrocardiogram, ECG, photoplethysmogram, PPG, non invasive cuffless arterial blood pressure monitoring, neural networks, telemedicine, portable devices**

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I. INTRODUCTION

In the context of health and disease prevention, medical devices have assumed an increasingly crucial role used across various healthcare settings. They enable healthcare professionals to track patient progress and adjust treatments when needed. This real-time monitoring enhances care quality and patient outcomes, starting from compensating for physical limitations, empowering them to lead more independent lives up to assisting in surgeries and helping manage chronic conditions. The global market boasts around two million distinct types of medical devices, categorized into over 7,000 generic device groups [1]. This diversity reflects significant technological advancements in healthcare. Within the vast selection of medical devices, a category of portable devices stands out for their primary features, including reliability, user-friendliness, long-lasting battery life, and reduced weight. The focus of this paper has been on designing and assembling PulsECG, a device capable of acquiring and processing electrocardiogram (ECG) [2] and photoplethysmogram (PPG) [3] [4] signals. Furthermore, preliminary efforts have been made to integrate a cuffless blood pressure measurement feature into the device through machine learning (ML) [5]. In the context of medical devices like PulsECG, ML algorithms can be trained to identify patterns and anomalies in medical data [6], [7], which might indicate potential health issues. This application is particularly crucial in early detection and prevention strategies for cardiovascular diseases [8], [9] which continue to be a leading cause of millions of deaths annually [10]. Furthermore, this innovation aligns with the broader concept of telemedicine [11], leveraging technology to remotely monitor and manage health, thereby contributing to the advancement of healthcare practices to engage the remaining portion of the population discouraged by the current system performance and encourage those who already use telemedicine to use it more extensively.

II. STATE OF THE ART

There are numerous medical devices on the market capable of performing electrocardiography and/or photoplethysmography; however, only a few manage to ensure performance that allows them to stay within a sufficiently low error range to be considered reliable. The main companies that come closest to our research focus are AliveCor, Withings, Apple and Samsung.

AliveCor [12] offers one of the most acclaimed devices for acquiring ECG, providing users with the option to subscribe and receive real-time diagnoses from a team of cardiologists. The product line is named Kardia and is paired with an intuitive application that guides users in performing single-lead or six-lead electrocardiograms, which are then filtered and converted into a PDF format. Withings [13] offers a wide range of products, primarily watches, capable of acquiring a diverse set of vital signals (e.g. ECG, SpO2, temperature). However, similar to Kardia, blood pressure calculation is not included among the measured signals unless using the BPM Core device with a cuff to be inflated. Likewise, Apple [14] also introduces watches capable of performing electrocardiograms, displaying them on-screen, and calculating SpO2, yet arterial blood pressure is not computed in this case either. Finally, Samsung [15], offers, among its various devices, the Galaxy Watch 5, which is capable of acquiring and displaying the ECG and the PPG signals, and deriving blood pressure from the latter one. The device asks the user to calibrate it by initially measuring the pressure using a highly accurate instrument.

The device presented in this paper addresses the existing gap in the prominent device market by introducing an innovative and reliable method for cuffless blood pressure calculation through the use of a neural network, having as input not only the PPG but also the ECG to improve the accuracy of the estimation while maintaining competitive pricing. Furthermore, there is a well-known need to empower users to manage not only data in PDF format but also in numerical format. This feature allows physicians to filter ECG tracings at their discretion through the use of desktop applications, a functionality absent in all the products described above.

III. SYSTEM DESCRIPTION

PulsECG is an electronic device designed and assembled in the Neuronica laboratory at the Polytechnic of Turin. It is shaped like a bar and is conceived with the idea of monitoring heart conditions through the use of two electrodes [16] (according to Einthoven's triangle [17]). These electrodes, when in contact with specific areas of the human body, can capture a meaningful electrocardiographic signal. In addition to the ECG, the device is designed to acquire the photoplethysmographic signal (PPG) using an optical sensor. Once both ECG and PPG signals are acquired, the device can transmit them to an Android application using the bluetooth low energy (BLE) protocol to minimize power consumption.

PulsECG is composed by a first PCB, which contains the main components and the ECG acquisition part, connected using a 8-pin flat cable to a second PCB for the PPG recording, as shown in Figs. 1 and 2:

a) ECG PCB:

- Analog Front-end: This section is responsible of the ECG signal conditioning [18], which means to amplify and filter the ECG signals coming from the two electrodes. It is made of a TI INA333, followed by a high-pass filter ($f_c = 0.5$ Hz), a notch filter to remove powerline interference, and a low-pass filter with $f_c = 100$ Hz.
- Microcontroller (TI CC2640): this unit manages all other blocks and samples data from the ECG using its internal ADC Converter. It also monitors the battery, obtains PPG values via I2C communication and communicates to the user by means of LEDs, a switch, and the patch antenna.
- Power Management: the device is powered via a rechargeable Li-Po battery of 190 mAh, connected to a battery charger (MAXIM MAX1555) and a battery gauge (MAXIM MAX17048), which provide the information to the microcontroller about the charging mode and the battery status, respectively. In addition, the battery is connected to the voltage regulator (MAXIM MAX1759) to generate a steady power voltage for the digital section, while the TI REF2033 provides the reference voltage for the analog part.
- Patch Antenna: involved to communicate through BLE directly to an Android App.

b) PPG PCB: To allow a correct finger positioning on the PPG sensor and, thus, a noise-free PPG acquisition, it has been chosen to place the sensor near the top case of the device. At this purpose, a second PCB with only the MAXIM MAXM86161 PPG sensor was designed, connected to the ECG PCB via an 8-pin flat cable, carrying power lines and I2C lines.

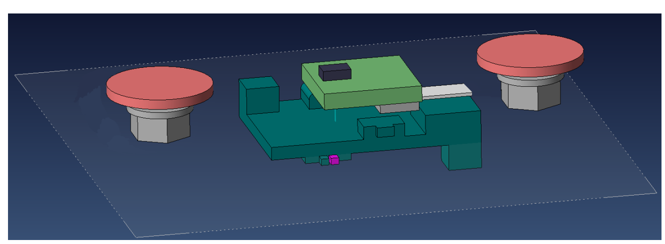

Fig. 1. 3D model of the PulsECG device. On the sides there are the electrodes (red plates); the two PCBs are superimposed to minimize space requirement, with the white flat cable to connect them: the ECG PCB is at the base (dark green), while the PPG PCB is on top of it (light green), with the PPG sensor above (black block).

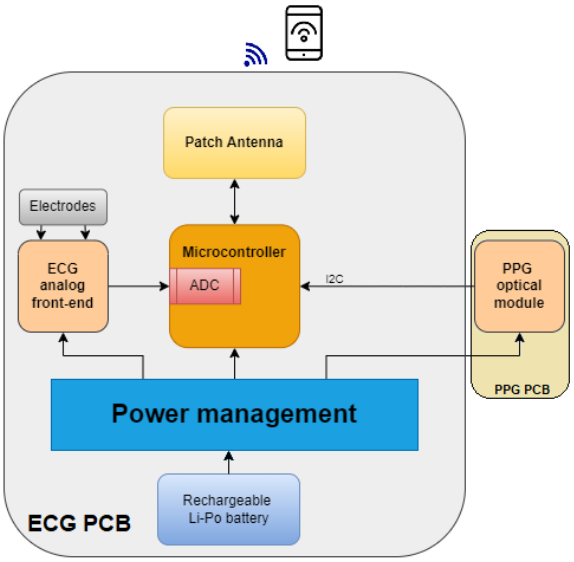

Fig. 2. PulsECG - Block diagram. Two PCBs connected via flat cable: ECG PCB (left) and PPG PCB (right)

The final prototype, with the two PCBs and the electrodes enclosed in a 3D-printed case, can be seen in Fig. 3.

Fig. 3. PulsECG - Final Prototype

IV. Neural Network for Blood Pressure Prediction

As previously mentioned, preliminary efforts have been made to measure blood pressure non-invasively [19]. Extensive research in this field is documented in the literature [20]–[22], with many studies focusing on large databases and complex neural networks. For instance, significant work in literature has been done using the MIMIC database [23]–[26]; however, this database presents certain challenges. It is primarily derived from ICU settings, employing specialized equipment for recording ECG, PPG, and invasive blood pressure measurements. Additionally, there is a lack of clarity regarding the database filtering processes and other specific details, making its application to real-world scenarios problematic. To address this issue, the proposed approach involved the collection of a database acquired using the PulsECG device, to capture a range of everyday scenarios and situations to enhance applicability and relevance. In addition, this approach ensures the control on the acquisition pipeline and the relative pre-propressing.

A. Dataset description

The dataset was meticulously compiled from 20 healthy subjects, including 5 females and 15 males, spanning a wide age range of 22 to 84 years. Each participant was carefully positioned in a seated, relaxed posture to ensure consistency in physiological responses and to mirror typical, everyday environmental conditions akin to a home setting. This choice of positioning and environment was pivotal in minimizing external variables that could influence the cardiovascular measurements.

Before the initiation of the dataset collection, a thorough health screening was conducted to confirm that all participants were free from acute cardiovascular or systemic diseases. However, it is notable that the cohort included individuals with varied cardiovascular profiles; one subject exhibited a consistently elevated heart rate of around 110 beats per minute, likely due to medication effects. Additionally, some participants showed signs of hypertension or hypotension, providing a valuable spectrum of blood pressure values within the dataset.

Each participant underwent a sequence of three blood pressure (BP) measurements interspersed with two recordings of ECG & PPG signals. Blood pressure was measured using a certified sphygmomanometer, the OMRON X7 Smart, and the ECG & PPG signals were acquired simultaneously. The initial BP measurement established the baseline blood pressure setting the reference point for the subsequent recording. It was immediately followed by the first ECG & PPG signal recording, to minimize BP change over time. Subsequently, a second blood pressure measurement was taken, leading to the second ECG & PPG recording, and the sequence was completed with a final blood pressure reading.

After the acquisition, the ECG & PPG data, with a total duration of 30 seconds, were divided into 228 windows of 8-seconds each. Blood pressure values for each window were determined through interpolation between the previous and subsequent blood pressure measurements, assuming that the BP variation in just 30 seconds was linear.

This pipeline was aimed at generating a comprehensive dataset for neural network training, ensuring a significant quantity of blood pressure samples and enhancing the numerical diversity of the dataset, which is crucial for the reliability of the model.

V. Neural Network Structure

The neural network uses a multilayered architecture to process time-series input from dual-channel PPG and ECG signals, each comprising 1000 time points (8 seconds). It starts with an input layer, followed by two consecutive convolutional blocks. Each block contains a convolutional layers with 128 filters (kernel size 3, 'same' padding), batch normalization, and ReLU activation, facilitating feature extraction while ensuring normalization and non-linearity.

After the initial convolutional layers, a residual connection captures the network's state before the sequence undergoes downsampling through a max pooling layer. This is followed by three bidirectional LSTM layers, each with 128 units, designed to capture temporal dependencies in both directions of the input sequence.

Subsequently, the network applies two more convolutional layers (128 filters, kernel size 3, 'same' padding) with batch normalization and ReLU activation. Data upsampling is achieved via a transposed convolutional layer (256 filters, kernel size 2, stride 2, 'same' padding), which doubles the sequence length. A concatenation layer merges this upsampled output with the earlier residual connection, aiming to restore spatial resolution lost during pooling.

The architecture concludes with three final convolutional layers (128 filters, kernel size 3, 'same' padding) with batch normalization and ReLU activation, leading to a single feature map. This map is then flattened and passed through a dense layer to produce the final predictions for systolic and diastolic blood pressure (SBP and DBP).

The network is compiled with the Adam optimizer, using a mean squared error loss function and tracking mean absolute error as a metric for prediction accuracy.

VI. RESULTS

To assess the performance of the PulsECG, it was first measured the quality of the ECG and PPG signals acquired by the device. Once confirmed the reliability of these two signals with regard to a medical golden standard, it was performed a second quality test on the neural network BP prediction.

A. Device

All the electronic features for which the device was designed were tested, with particular focus on the ECG and PPG signals. Hundreds of acquisitions were performed on various members of the Neuronica laboratory, ensuring the deterministic behavior of the device and consistency of the acquired signals. Once confidence in the signal waveforms was established, tests were conducted using a General Electric (GE B105) medical device as the golden reference.

The test was performed as follows:

- 5 subjects.
- 5 acquisitions per each subject using the golden reference GE B105 (ECG, PPG).
- 5 acquisitions per each subject using the prototype (ECG, PPG).

All the acquisitions were performed in parallel to have the closest actual scenario. The signals were compared both in the time and frequency domains. For the latter, starting from the Fast Fourier Transform (FFT), the power spectral density (PSD) [27] was calculated to verify that the signal energy distribution over the spectrum was similar to the GE B105:

$$PSD(f) = \frac{(\Delta t)^2}{T} \left| \sum_{n=1}^{N} x_n e^{-i\omega n \Delta t} \right|^2 \qquad (1)$$

Fig. 4 and 5 show the comparison between the PSD of the ECG and PPG acquired by the PulsECG and the corresponding GE B105, respectively. In order to perform a quantitative

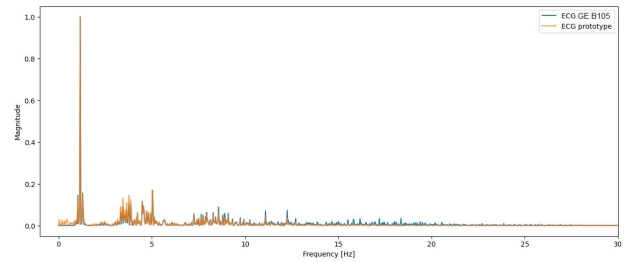

Fig. 4. Frequency Domain (PSD) comparison of the ECG acquired by the PulsECG (blue) and the corresponding GE B105 one (red).

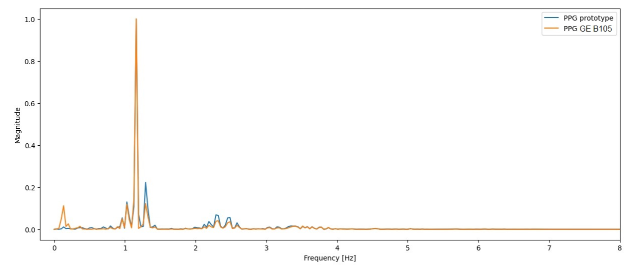

Fig. 5. Frequency Domain (PSD) comparison of the PPG acquired by the PulsECG (blue) and the corresponding GE B105 one (red).

comparison, the Cumulative Spectral Power (CSP) was also calculated, which derives from the PSD using a cumulative sum normalized with the total power [28]. The resulting curve, CSP(f), is a monotonically increasing function that represents the percentage of energy contained in the frequencies below a certain frequency of interest:

$$CSP(f) = \sum_{n=1}^{f} PSD(n) \qquad (2)$$

Fig. 6 and 7 show the comparison between the CSP of the ECG and PPG acquired by the PulsECG and the corresponding GE B105, respectively.

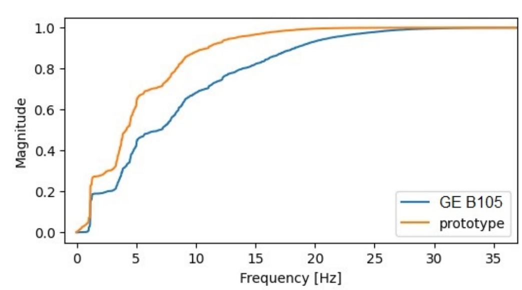

Fig. 6. Frequency Domain (CSP) comparison of the ECG acquired by the PulsECG (blue) and the corresponding GE B105 one (red).

Based on this function, in TableI and TableII it is possible to see the frequency at which ECG and PPG signals, respectively, reach a specific fraction of the total power, and thus, the information content.

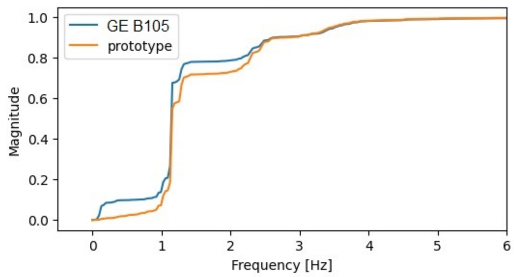

Fig. 7. Frequency Domain (CSP) comparison of the PPG acquired by the PulsECG (blue) and the corresponding GE B105 one (red).

TABLE I
CSP COMPARISON FOR THE ECG SIGNAL

Device	f 20% [Hz]	f 50% [Hz]	f 80% [Hz]
GE B105	2.58	6.96	13.90
PulsECG	1.16	4.16	8.38

TABLE II
CSP COMPARISON FOR THE PPG SIGNAL

Device	f 20% [Hz]	f 50% [Hz]	f 80% [Hz]
GE B105	1.06	1.16	2.15
PulsECG	1.12	1.16	2.28

Finally, Figs. 8 and 9 show the comparison in the time-domain between the ECG and PPG acquired by the PulsECG and the corresponding GE B105, respectively.

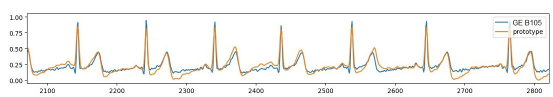

Fig. 8. Time Domain Comparison of the ECG acquired by the PulsECG (blue) and the corresponding GE B105 one (red).

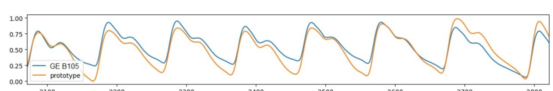

Fig. 9. Time Domain Comparison of the PPG acquired by the PulsECG (blue) and the corresponding GE B105 one (red)

All the above comparisons show a good result with the ECG acquisition and an optimal performance for the PPG. Indeed, the ECG CSP shows an higher difference in the distribution of power over the spectrum with regard to the golden reference. On the contrary, Table II shows a almost perfect match among the CSP of PulsECG PPG and the GE B105 one. It is important to highlight that the PulsECG ECG will be subsequently processed through the use of digital filters to eliminate certain components arising from noise, thus improving the quality of the signal.

B. Neural network

To assess the accuracy of the trained neural network model, Figs.10 and 11 show the scatter plots of the neural network predictive performance for SBP and DBP, respectively. Each plot correlates the neural network prediction (x-axis) with the actual true measured values of the sphygmomanometer (y-axis).

Fig.10 shows a pronounced linear relationship between the predicted and actual values, with the data points densely populating a diagonal trend. This indicates that the neural network predictions for SBP are generally accurate, with a positive correlation between predicted and measured values. While there is some degree of scatter, which suggests variability and prediction error, the overall trend suggests a well-performing model. The same observations can be made for the DBP (see Fig.11), which also shows a slight tendency to overestimate the blood pressure values, as the points generally lie above the line of perfect prediction.

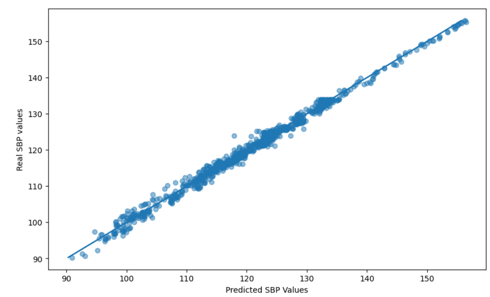

Fig. 10. Scatterplot for SBP showing predicted (x-axis) vs ground truth from the sphygmomanometer (y-axis)

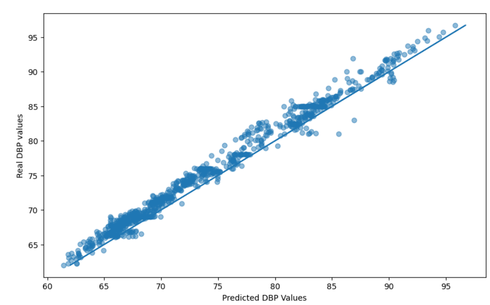

Fig. 11. Scatterplot for DBP showing predicted (x-axis) vs ground truth from the sphygmomanometer (y-axis)

VII. CONCLUSIONS

Telemedicine is everyday gaining more ground in the overall population. The benefits of having smart devices that can ensure high standards of reliability and streamline, consequently improving the healthcare system, are huge. All of this is made more accessible with the integration of artificial intelligence at every engineering level.

This paper presented a novel device for acquiring ECG and PPG signals and, from these, estimating the arterial blood pressure using a neural network model; thus, the proposed approach does not require an inflation of a cuff over the arm, which is actually uncomfortable and can cause some degree of pain. The comparison of the device performance with a certified vital sign monitor, the GE B105, showed the PulsECG reliability and robustness in acquiring human biological signals, giving the close similarity with the golden standard corresponding recordings. At the same time, the neural network performance in predicting systolic and diastolic blood pressure values, as evidenced by the scatter plots, demonstrates a good predictive capability with a high correlation between the predicted and actual values.

Given the above, the overall results can be considered very satisfactory and provide a foundation for future optimization to enhance prediction accuracy and reduce overestimation biases. The findings from this analysis indicate that with further refinement, the PulsECG has the potential to be a reliable tool for a cuffless non-invasive blood pressure monitoring, which could have significant implications for clinical practice and remote patient monitoring. However, there are areas for improvement in the prototype, the dataset and neural network model.

One notable limitation is the challenge of implementing PulsECG in real-world clinical settings. Addressing this involves expanding the study to include a larger and more diverse subject pool. Increasing the number of subjects will not only enhance the robustness and generalizability of the findings but also augment statistical power and diminish bias risk. This expansion is crucial for validating the cuffless blood pressure monitoring method's effectiveness across various demographic groups and medical conditions.

Future research will deal with improving the ECG analog front-end and the subsequent digital filtering phase to reach the golden standard quality, especially in low-frequency part of ECG spectrum. Additional sensors will be embedded to provide users to monitor more vital parameters, such as human body temperature, and the amount of acquired ECG leads will be increased to all the peripheral ones, i.e. six.

Through these enhancements and expansions, future research aims to address current limitations and elevate the PulsECG device's capability, further solidifying its role in advancing cuffless blood pressure monitoring technologies.

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