Non-Invasive Blood Pressure Monitoring: The Future of Cuffless Technology

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Introduction

Convenience and Comfort

- Cuffless devices allow for more comfortability as they use non-invasive methods to get real time data
- Portable, as they are in a small form factor and do not require bulky equipment to use

Continuous Monitoring and Compliance

- Cuffless devices can continuously monitor without disrupting any of your daily activities
- The ease of use and comfortability aspect allow for more individuals to be more compliant with regularly monitoring themselves

Reduction in Measurement Anxiety

- Traditional measuring methods can often give users anxiety during the measuring phase which can significantly alter their results incorrectly
- Cuffless devices eliminate this anxiety by providing a much more relaxed and less intimidating environment for the user
- This elimination of anxiety would lead to more accurate results and reflect the true nature of the individual's health

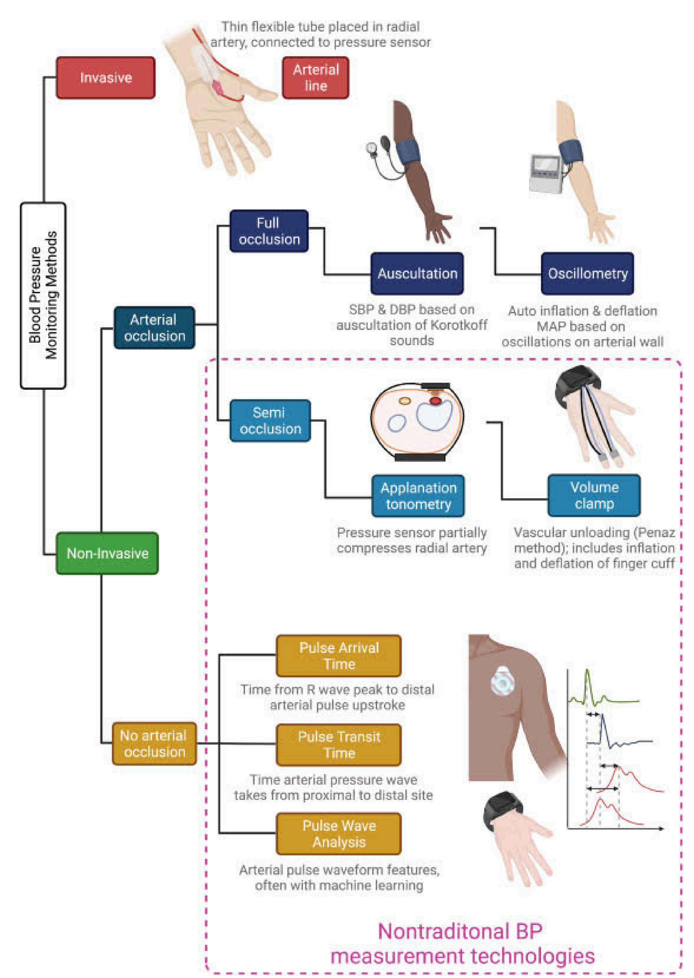

Figure 1. Infographic of blood pressure monitoring [1]

Materials & Method

Selection

- **Microcontroller**: Silicon Labs EFR32BG22C112F352GM32-CR
- **Sensors**: AD8232 ECG Sensor, MAX30102EFD+T
- **Battery**: 3.7V Lithium-Ion Polymer Rechargeable Battery
- **Software**: Altium Designer, Simplicity Studio, MATLAB, VS Code, Jupyter Notebook
- **Other components**: Resistors, Capacitors, Ferrite Beads, Inductors, Breadboard, Four Layer Copper PCB

Schematic Design

- Created and imported component symbols using Digikey CAD models
- Connected all the component symbols together
- Used Altium footprint manager to link footprints to all the components
- Implemented a net list to combine all schematic files together
- Validated schematics to check for errors or incomplete connections
- Created a Bill of Materials needed for manufacturing

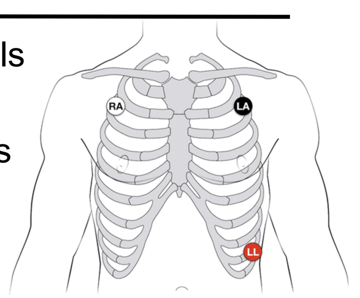
Figure 2. [2]

PCB Layout

- Designed a four-layer PCB stack-up specifically for RF signal integrity
- Added specific design rules to Altium to conform with our design
- Set a specific size for the PCB using an outline tool
- Placement of components and PCB antenna
- Routed tracks to appropriate component nets
- Added ground and signal vias
- Validated the PCB by running a design rule check

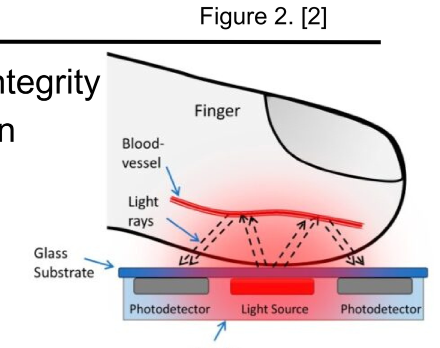

Figure 3. [3]

Production

- Generated the gerber and component placement list files
- Added assembly notes to specific to the files

Firmware and Software Creation

- Added C and header boiler plate files to the Simplicity Studio IDE
- Defined register addresses for the sensors in the header files
- Developed peripheral drivers using C to allow for communication between MCU and sensors using the SPI, and UART protocols along with the ADC
- Integrated Bluetooth capabilities into the device using the Silicon Labs Bluetooth GATT protocol allowing for the board to send data to a phone
- Used Pandas to extract ECG and PPG data from the device, and SciPy to further filter and clean the data using signal processing
- Utilized NumPy to extract heart rate and pulse arrival time from the ECG and PPG data
- Developed a machine learning algorithm using Python to get a blood pressure estimation from the dataset

Result

The result of this research project contains two parts: oxygen saturation (SpO2) algorithms and Blood pressure estimation algorithms. This allows us to calculate SpO2 from red light and infrared light PPG data, and estimate blood pressure from PPG and ECG data.

SpO2 Calculation Algorithm

The SpO2 algorithm derived oxygen saturation levels (SpO2) from photoplethysmography (PPG) data. PPG signals, which measure blood volume changes in the microvascular bed of tissue, are commonly used in non-invasive pulse oximetry. The algorithm focused on analyzing the red and infrared (IR) light absorption characteristics, which vary based on the oxygenation level of hemoglobin. The ratio of these absorptions (often referred to as the R/IR ratio) was used to calculate the SpO2 level.

Signal preprocessing included filtering the PPG signal to remove noise, normalizing the signals and applying peak detection algorithms to identify pulse waves. The R/IR ratio was then calculated to derive SpO2 levels. The algorithm resulted in a **mean absolute error** of **0.446** and a **mean percentage error** of **0.543%** on the sample dataset, with SpO2 levels ranging from 70 to 99%

Blood Pressure (BP) Estimation Algorithm

The BP estimation algorithm was designed to predict systolic and diastolic blood pressure values using physiological signals, primarily electrocardiogram (ECG) and PPG. The approach involved extracting pulse arrival time (PAT), heart rate (HR), and oxygen saturation level (SpO2) from the signals to estimate BP. PAT was derived from the difference between the R-Peak of ECG and the Systolic Peak of PPG. Machine learning models were employed to map these features to BP values, including linear (e.g., Linear Regression) and nonlinear (e.g., Adaptive Boosting).

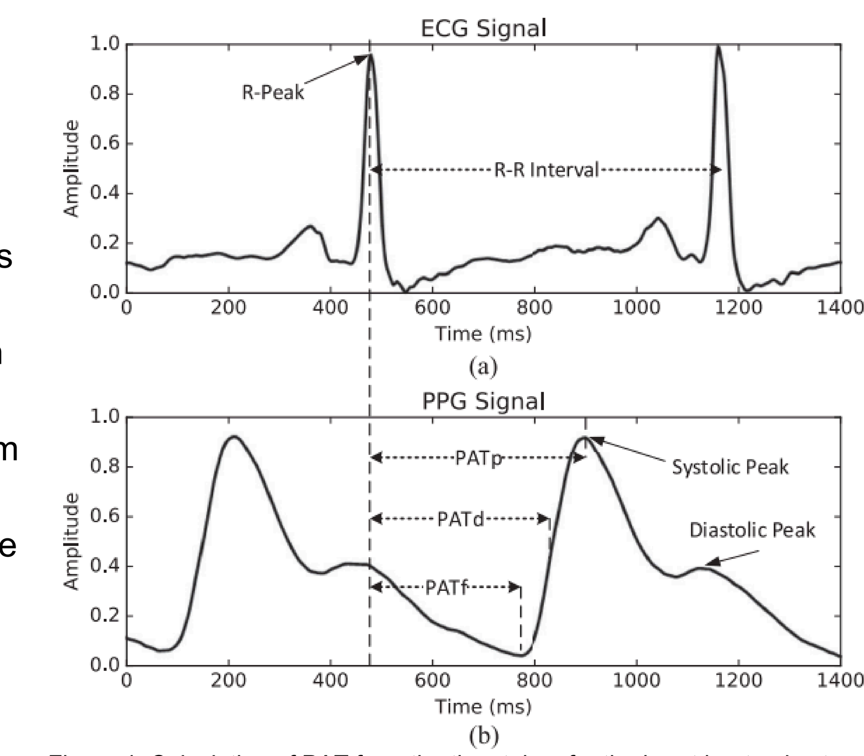

Figure 4. Calculation of PAT from the time taken for the heart beat pulse to arrive in the finger PPG signal [4]

Five different machine learning algorithms are employed to estimate the BP values in total, including Linear Regression, Decision Tree Regression, Support Vector Machine (SVM), Adaptive Boosting (AdaBoost), and Random Forest Regression (RFR). The best-performing algorithm is **Random Forest Regression**, which achieved an **R-squared value** of **0.44** for SBP and **0.56** for DBP and a **mean absolute error** of **8.45** mmHg for SBP and **5.08** mmHg for DBP.

	Systolic Blood Pressure (mmHg)		Diastolic Blood Pressure (mmHg)	
	MAE	STD	MAE	STD
Linear Regression	12.19	15.36	7.72	9.28
Decision Tree	10.15	14.10	5.37	7.34
Support Vector Machine	11.27	15.16	7.65	8.90
AdaBoost	9.53	**11.04**	5.21	6.62
Random Forest	**8.45**	11.34	**5.08**	**6.22**

Table 1. Comparison of the performance using various machine learning algorithms

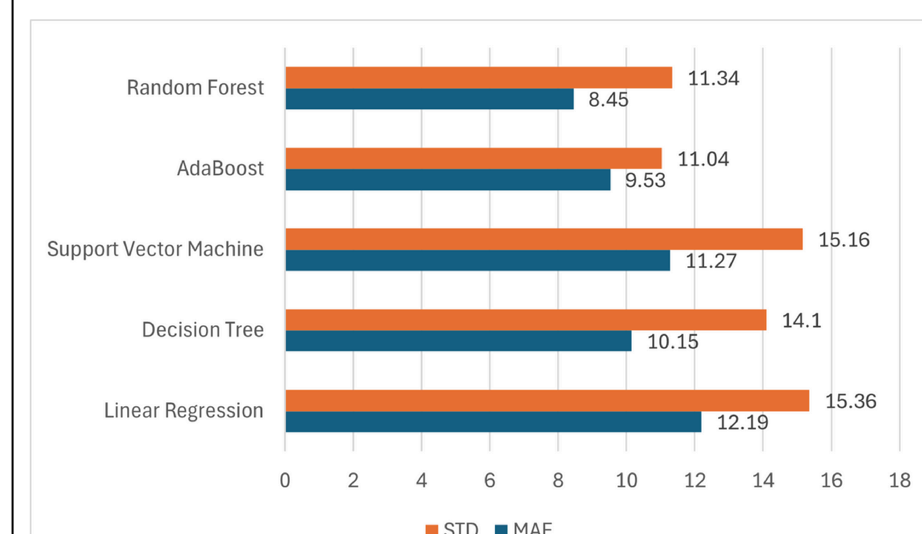

Figure 5. Performance of various machine learning algorithms for SBP

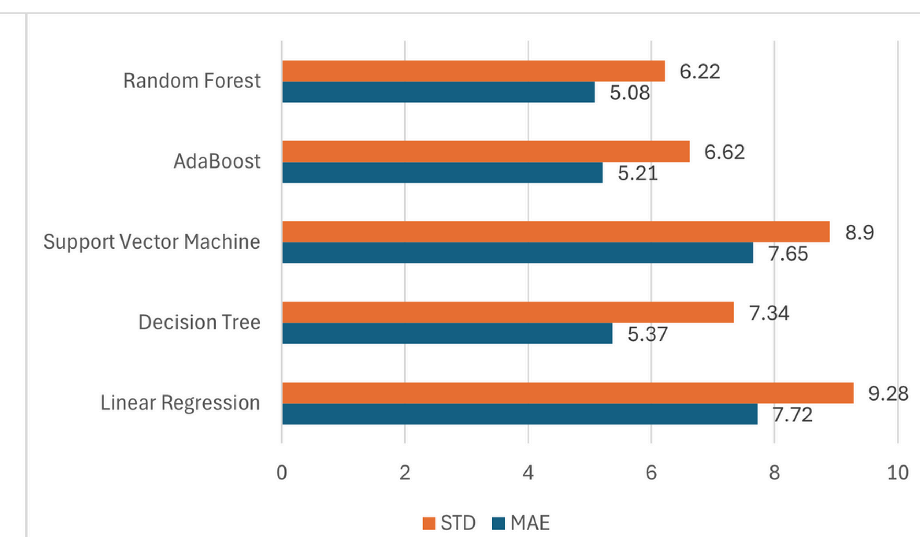

Figure 6. Performance of various machine learning algorithms for DBP

Additionally, we compared the performance of AdaBoost and Random Forest in estimating BP with different sets of features, including PAT only, PAT and heart rate, and PAT, heart, and SpO2. We can see that the performance improves with more features added to the estimation.

AdaBoost	Systolic Blood Pressure (mmHg)			Diastolic Blood Pressure (mmHg)		
	MAE	STD	r	MAE	STD	r
PAT	13.18	14.46	0.03	7.94	8.64	0.17
PAT-HR	9.40	10.71	0.34	6.35	7.52	0.35
PAT-HR-SpO2	9.53	11.04	0.40	5.21	6.62	0.51

Table 2. Performance of Adaptive Boosting algorithm using PAT, PAT-HR, and PAT-HR-SpO2 as features, respectively

Random Forest	Systolic Blood Pressure (mmHg)			Diastolic Blood Pressure (mmHg)		
	MAE	STD	r	MAE	STD	r
PAT	14.43	18.20	-	9.95	10.88	-
PAT-HR	9.15	11.94	0.39	6.96	8.13	0.25
PAT-HR-SpO2	8.45	11.34	0.44	5.08	6.22	0.56

Table 3. Performance of Random Forest Regression algorithm using PAT, PAT-HR, and PAT-HR-SpO2 as features, respectively

Weakness and Limitation

While the SpO2 algorithm based on PPG data showed promising results, there are limitations that need to be addressed. The algorithm's weaknesses are signal quality variability and environmental sensitivity. PPG signals are highly susceptible to noise, especially due to motion artifacts and ambient lighting. This can lead to inaccurate SpO2 readings, particularly in real-world settings where patients are not stationary. The algorithm's performance can degrade under different environmental conditions like light and temperature changes.

The BP estimation algorithm can also present certain challenges. BP results can vary based on inter-subject variability. The relationship between PAT and blood pressure can vary between individuals due to factors such as age and underlying health conditions. The current model may struggle with real-time prediction due to the need for extensive signal preprocessing and feature extraction. The algorithm may also require frequent calibration to maintain accuracy, especially in changing physiological states or long-term monitoring, which could be inconvenient for users.

Implication and Future Research

The development of the algorithms is situated within the broader field of digital health and wearable technology. This area of research aims to leverage advanced technologies, including wearable sensors, machine learning, and data analytics, to monitor, diagnose, and predict health conditions in real-time. The ultimate goal is to enhance patient outcomes through early detection and personalized interventions while also reducing the burden on the healthcare system.

Future research could focus on developing advanced signal processing techniques, such as adaptive filtering and machine learning-based noise reduction, to improve the robustness of calculation and estimation in noisy environments. Integrating multiple physiological signals, such as SpO2, BP, and other vital signs, into a unified monitoring system could provide a more comprehensive view of a patient's health. Adapting advanced machine learning techniques such as deep learning, transfer learning, and federated learning could further improve the accuracy and help address data privacy issues and adaptability to new conditions.

Conclusions

- Using Python and its libraries, we can take ECG and PPG signals, derive their respective pulse arrival time, and use a machine learning algorithm to get an accurate cuffless blood pressure measurement
- The findings give a clear perspective of the potential a cuffless blood pressure device has to continuously monitor blood pressure non-invasively while being comfortable, accurate, and compliant
- Although this research alludes to these devices being accurate and reliable, more testing will be needed for diverse populations to ensure this accuracy and reliability holds true in different settings

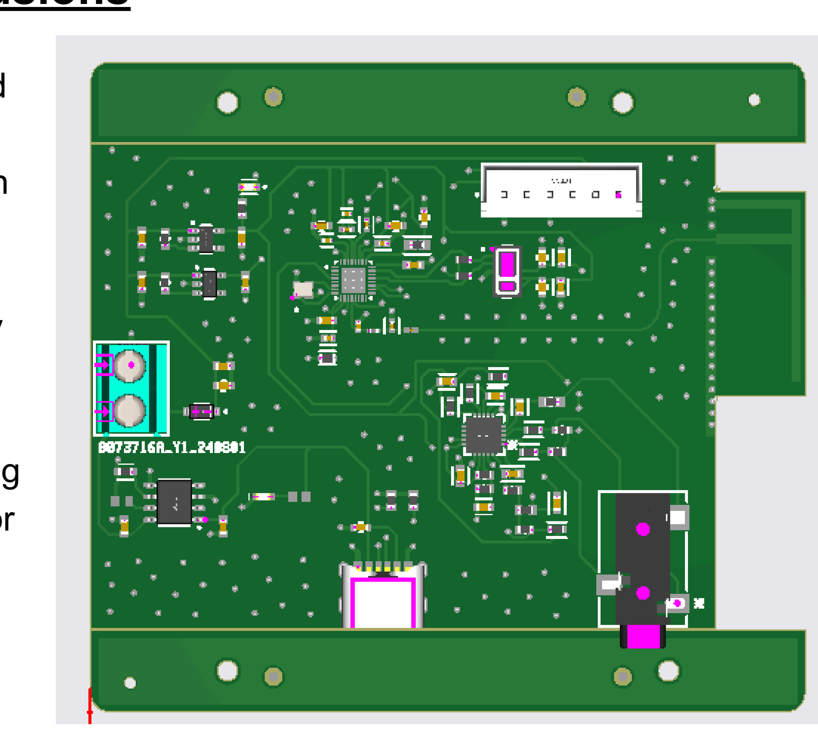
Figure 7. Printed circuit board of the monitoring device

[1] J.-R. Hu et al., "Validating cuffless continuous blood pressure monitoring devices," Cardiovascular Digital Health Journal, vol. 4, no. 1, pp. 9–20, Feb. 2023, doi: https://doi.org/10.1016/j.cvdhj.2023.01.001.
[2] M. Cadogan, "ECG Lead Positioning LITFL Medical Blog ECG Library Basics," LITFL Medical Blog, Jan. 31, 2019. https://litfl.com/ecg-lead-positioning/
[3] F. Elsamnah, A. Bilgaiyan, M. Affiq, C.-H. Shim, H. Ishidai, and R. Hattori, "Reflectance-Based Organic Pulse Meter Sensor for Wireless Monitoring of Photoplethysmogram Signal," Biosensors, vol. 9, no. 3, p. 87, Jul. 2019, doi: https://doi.org/10.3390/bios9030087.
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