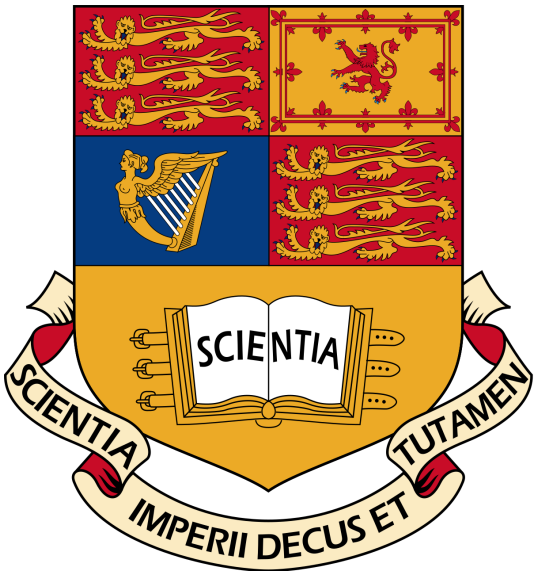
Imperial College London

Department of Electrical and Electronic Engineering

Final Year Project Final Report 2022



Project Title:	**Cuffless Blood Pressure Estimation from Photoplethysmography Signals using Recurrent Neural Networks**
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Second Marker:	**Dr Christos Bouganis**

Final Report Plagiarism Statement

I affirm that I have submitted, or will submit, an electronic copy of my final year project report to the provided EEE link.

I affirm that I have provided explicit references for all the material in my Final Report that is not authored by me, but is represented as my own work.

Abstract (CHANGE AT END)

Abstract should consist of motivation, methods, results, conclusion. All concise & capturing the reader within 200 words. Your abstract needs working and finalising once you have your results and concluding statement.

The prevention, evaluation, and treatment of hypertension have attracted increasing attention in recent years. The advancement of wearable technology has resulted in increasing importance into the monitoring of non-invasive ambulatory blood pressure, compared to the traditional invasive blood-pressure monitoring methods. As photoplethysmography (PPG) technology has been widely applied to wearable sensors, the noninvasive estimation of blood pressure (BP) using the PPG method has received considerable interest. For this project, systolic and diastolic BPs are estimated using PPG signals. A Recurrent Neural Network (RNN) is used for estimation. Due to their being several alternative existing methods for estimating blood pressure, it was necessary to perform a comparison between the best performing Deep Learning based methods. Overall, the proposed method obtains better accuracy. The model achieves a mean absolute error of mmHg for systolic BP and mmHg for diastolic BP.

Acknowledgements

Firstly, I would like to thank Dr Zaibaa Patel for her patience and guidance in the development of this project. I would also like to thank Professor Esther Rodriguez Villegas for her valuable feedback and for allowing me the opportunity to present my work.

Next, I want to thank all of my friends at Imperial for supporting me throughout my 4 years here and for helping me to grow as both an engineer and a person.

Finally, I want to thank my Mum and Dad for all of their support throughout my life. Without them, I would never have had the opportunity to study at such an amazing institution.

Contents

1 Introduction

1.1 Motivation

Cardiovascular disease is one of the main causes of death around the world. High blood pressure (BP), which is also known as hypertension, is a common condition which can be a cause of cardiovascular disease [44]. According to the World Health Organization (WHO), the mortality rate due to hypertension is 9.4 million per year and it causes 55.3% of total deaths in cardiovascular patients [22]. If hypertension is detected early and prevented, this will greatly lower the number of deaths associated with cardiovascular diseases [22].

Recent developments in technology have made wearable sensors, such as Electrocardiogram (ECG) and Photoplethysmography (PPG) sensors significantly more popular in today's world. These sensors provide real-time 24 hour monitoring of the human bodily function. Hence there is great potential in using these sensors to diagnose medical conditions, such as hypertension, in real-time, thus helping to save lives [46]. Ambulatory BP monitoring is seen as a promising method for detecting early symptoms of hypertension [25]. There is a lot of existing research to predict ambulatory BP using methods which are cuff-less, continuous and non-invasive [53]. Hence wearables are seen as a viable option for this. ECG and PPG sensors have been discovered to be a potential estimator of blood pressure that cause minimal harm to patients compared to existing cuff-based methods [15] [5].

The aim of this project is to implement and evaluate the different techniques that can be used to measure Ambulatory BP from ECG and PPG signals. The aims are to seek out implementations that have minimal computational complexity, whilst maintaining accuracy.

1.2 High-level problem statement

Needs rewriting. Aim: Your intention/what you hope to achieve.

Objectives: Statements of measurable outcomes/What will you be doing to achieve the aim/desire outcome. (this is the work you're going to do) The aim is not to implement and evaluate different techniques. The aim is to estimate cuffless BP using PPG for wearable technology purpose. I advise you to have a clear aim and clear objectives. Objectives can be listed as bullets or numerated. These objectives will reappear in your conclusion where you state if you completed them or not.

1.3 Overview of work

1.3.1 Autumn Term 2021

1.3.2 Spring Term 2022

1.3.3 Summer Term 2022

2 Background

Add an intro to the background, rather than jumping into the lit review. Set the scene for the reader.

2.1 Medical background

In this chapter, all of the medical knowledge required to understand the basis of this project will be discussed.

2.1.1 Hypertension

The heart can suffer from a variety of diseases and pathologies. Low blood pressure, or hypotension, has the potential to cause a lack of oxygen flowing to the brain and other organs, causing shock [48]. Whilst hypotension is a serious issue, hypertension has been identified by the World Health Organization (WHO) as the most significant risk factor for cardiovascular diseases [49]. According to the 2017 American Heart Association guidelines for hypertension, the risk of developing stage two hypertension, $\geq$ 140 mmHg systolic or $\geq$ 90mmHg diastolic is almost 90% [5] (see Table 1). Over 20% of adults have hypertension and its complications cause a major number of diseases, including heart attacks, strokes and heart failure. If hypertension is not diagnosed and properly treated it can even cause death [22].

Hypertension or high blood pressure (BP) is where blood continues to exert more and more pressure on the arterial walls. One particular disease linked to hypertension is hypertrophic cardiomyopathy, as indicated in Figure 1,

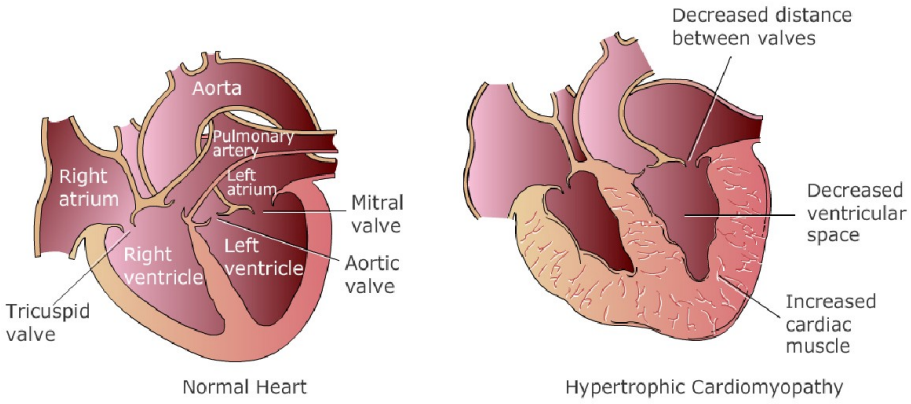


Figure 1: The effects of hypertension on the heart [13]

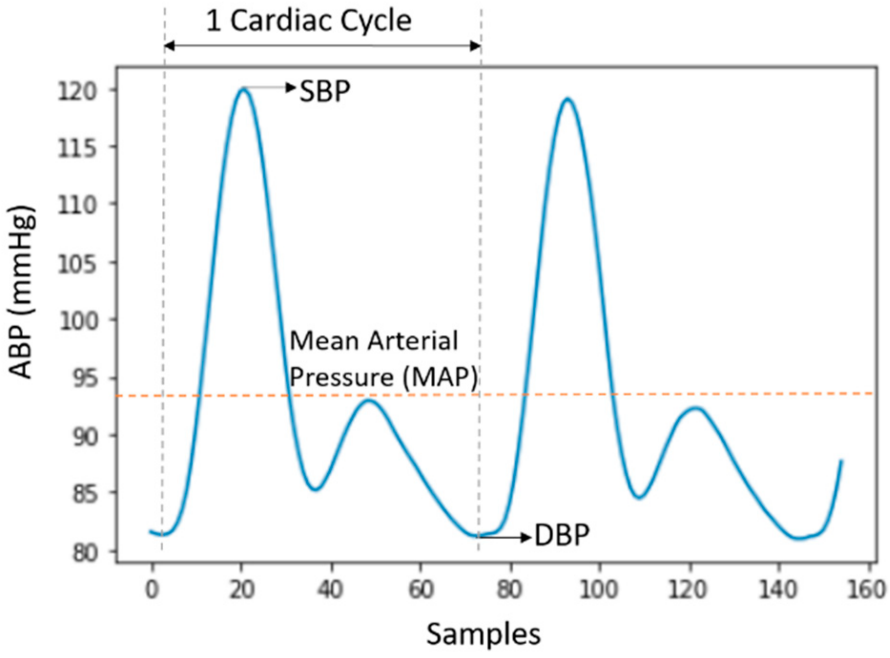
Hence it is clear that hypertension is one of the largest motivating factors for this project.

Table 1: Categories of blood pressure in adults [49] [45]

Blood pressure classification	Blood Pressure (mmHg)	
	Systolic	Diastolic
Hypotension	≤ 90	And ≤ 60
Normal	$<$ 90-119	And 60-79
Prehypertension	120-139	Or 80-89
Stage 1 hypertension	140-159	Or 90-99
Stage 2 hypertension	≥ 160	Or ≥ 100
Isolated Systolic hypertension	≥ 140	And < 90
Hypertensive crisis	≥ 180	Or ≥ 110

2.1.2 Blood Pressure measurements

Blood pressure (BP) is the force of the blood pushing against the arterial walls as the heart pumps blood. It is measured in millimeters of mercury (mmHg) [46]. BP is measured in terms of systolic blood pressure (SBP) and diastolic blood pressure (DBP). These values are the maximum and minimum pressure values of an Arterial Blood Pressure waveform during a cardiac cycle respectively [45] [33]. An example of this structure is provided in Figure 2.



(b)

Figure 2: Structure of an Arterial Blood Pressure signal [4]

As shown in Figure 2, the Systolic and Diastolic Blood Pressure values of the waveform are defined by the maximum and minimum ABP values within the provided sampling window.

BP has oscillations or pulses that mirror the oscillatory nature of the heart. The blood is

propelled during systole, also known as heart contraction, and the blood is rested during diastole, known as heart relaxation, as illustrated in Figure 3.

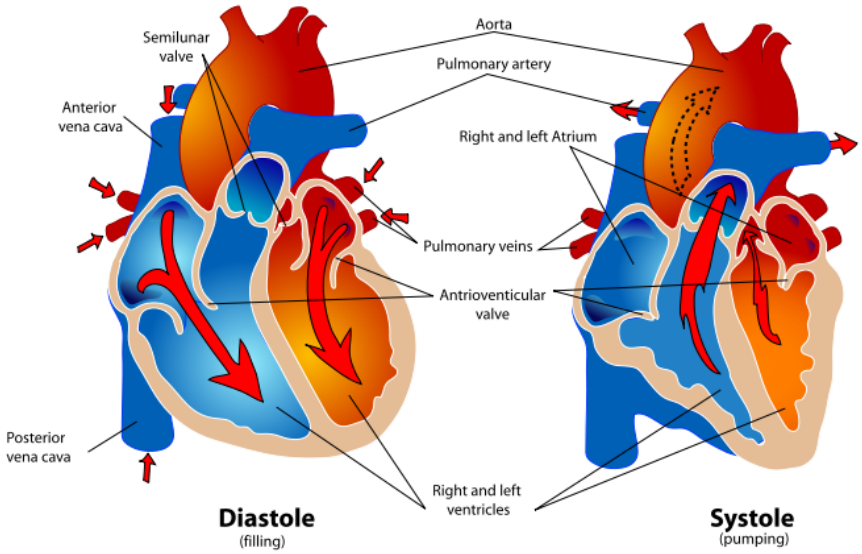


Figure 3: Visualisation for SBP and DBP [6]

There are two conventional methods for measuring blood pressure (BP). These are invasive and non-invasive methods.

If you're going to use firstly, there should be consistency. I.e where is secondly or finally? Check throughout report. Firstly, a description on invasive methods. The most popular form of invasive BP measurement is catheterization [53]. Invasive BP measurements are continuous and the most accurate from heartbeat to heartbeat. As a result these measurements are recognised as the gold standard internationally [44] [16]. However, this method is usually restricted to hospitals, as medical supervision is required [33]. In addition, this method poses several health risks, including bleeding and infection. As a result, invasive measurements are only utilised for critically ill patients in intensive care units and for use during surgery [53][16].

Check throughout the report: Type in 3rd person and not colloquial/chatty. Now a description on non-invasive methods. The gold standard for BP measurement is the use of a cuffed sphygmomanometer. Cuff-based methods provide BP measurements without any major side effects as opposed to BP measured invasively [16]. However, patients will feel uncomfortable with long term monitoring due to the painful cuff inflation which interrupts the regular blood flow [48]. In addition, these methods can only measure BP intermittently with intervals between measurements greater than at least two minutes. These devices are too cumbersome to wear during measurements. Also, it has been found that over three in ten home BP monitoring cuffs have produced inaccurate results [28].

As a result, the existing invasive and non-invasive BP measurement techniques are not feasible for an implementation involving continuous ambulatory BP monitoring [16]. Hence, after having assessed the viability of all aforementioned methods, it is clear that it is difficult for

these methods to be integrated with wearable technologies, which continue to gain popularity in commercial sectors and clinical practice [44].

2.1.3 Ambulatory Blood Pressure (ABP)

ABP monitoring (ABPM) is when BP is measured as the patient moves around, and it allows patients to still live their normal daily lives [20]. It has been classed as the gold standard for detecting and diagnosing hypertension and also assessing BP values over a 24 hour period [25]. ABPM provides data on several important and unique parameters [25]. This data can explain how changes in your BP may correlate with your daily activities and sleep patterns [20]. Conventionally, ABP is monitored by using a cuff attached to a portable device which is worn on the patient's waist [25]. In the data provided for this project, the blood pressure signals have been recorded from ICU patients. As a result, these waveforms are not ABP waveforms but are instead Arterial Blood Pressure waveforms.

2.1.4 Electrocardiogram (ECG) signals

ECG signals provide an overview of the electrical impulses occurring in the heart [45]. Electrical changes in the heart conduct through the body and are received at skin level. The record of these electrical fluctuations during the cardiac cycle is called the Electrocardiogram (ECG) [27]. The signals are recorded by measuring the electric potential difference by placing electrodes across the heart of an individual [48] [45]. These electrodes are connected to the ECG machine with recordings from 12 different places on the body, which is known as the 12-lead ECG. The standard ECG leads are I, II, III, aVF, aVR, aVL, V1, V2, V3, V4, V5, V6. Leads I, II, III, aVR, aVL, aVF are classed as the limb leads and the others are precordial leads [48].

The QRS complex of an ECG signal is detailed in Figure 4. This complex is first created through the generation of the electrical impulses from the heart. These signals then move along the electrical highway and as a result cause the ventricles to contract and pump oxygenated blood into the arteries. Physically, this whole describes the QRS complex [27].

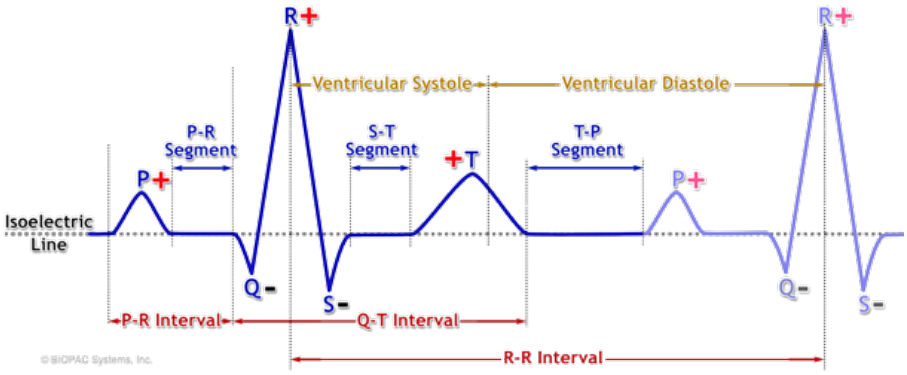


Figure 4: Structure of an ECG signal [50] [51]

2.1.5 Photoplethysmography (PPG) signals

Photoplethysmography (PPG) measures the blood volume changes per pulse. It is an optical and non-invasive technique that can determine a wide range of medical values, including an

estimate for BP [16]. Physically, the PPG signal is acquired by measuring the optical signal transmitted through or reflected from the subject's tissue [48]. The PPG sensor consists of two components. The first component is an Light Emitting Diode (LED) to light up the surface of the skin. The second component is a photodetector, which is utilised for measuring the changes in light absorption over a period of time [16] [27].

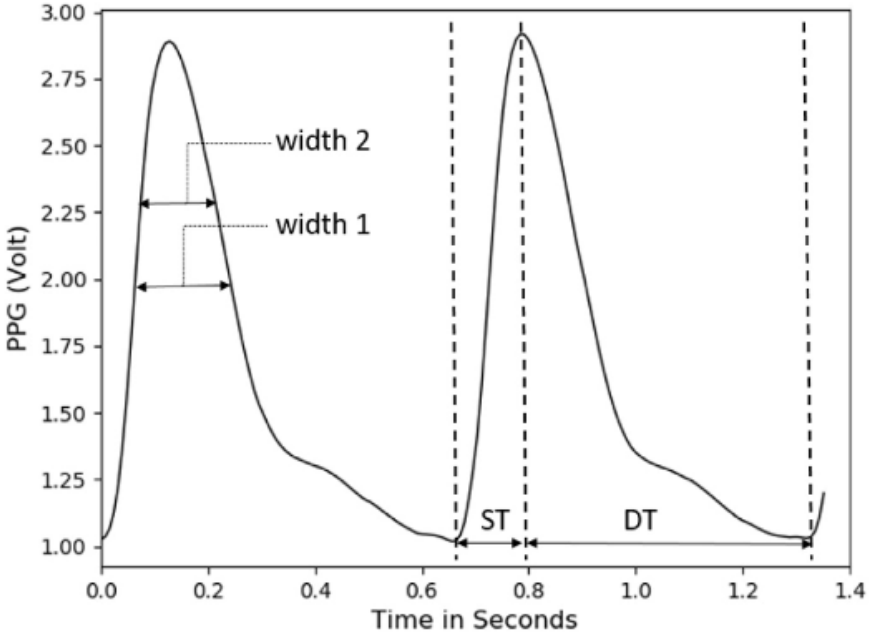


Figure 5: Structure of a PPG Signal [16]

In Figure 5, the four features are the Systolic upstroke Time (ST), Diastolic Time (DT), width at $\frac{1}{2}$ amplitude (width 1) and width at $\frac{2}{3}$ amplitude (width 2) [16]. PPG waveforms have a wide range of temporal features [16]. These features have been utilised in several experimentations, creating models to estimate blood pressure [33].

2.2 Cuff-less methods for deriving BP

Cuff-less methods have great potential in being used to estimate BP. This is because they provide continuous measurements, they cause minimal harm to the patients and they produce BP values over a long period of time [30]. There are three fundamental cuff-less methods which will now be discussed which can be used for deriving BP. These three methods rely on Pulse Transit Time (PTT), Pulse Arrival Time (PAT) and Pulse Wave Velocity (PWV) respectively [32]. These will each now be discussed in more detail.

2.2.1 Pulse Transit Time (PTT)

PTT is the time required for the arterial pressure wave to travel from the left ventricle to a distal arterial site. PTT holds an inverse relationship to blood pressure and as a result it is dependent on arterial compliance, arterial wall thickness, arterial radius, and blood density. PTT is conventionally found with the use of two PPG sensors [48] [49] [16], as indicated in Figure 6.

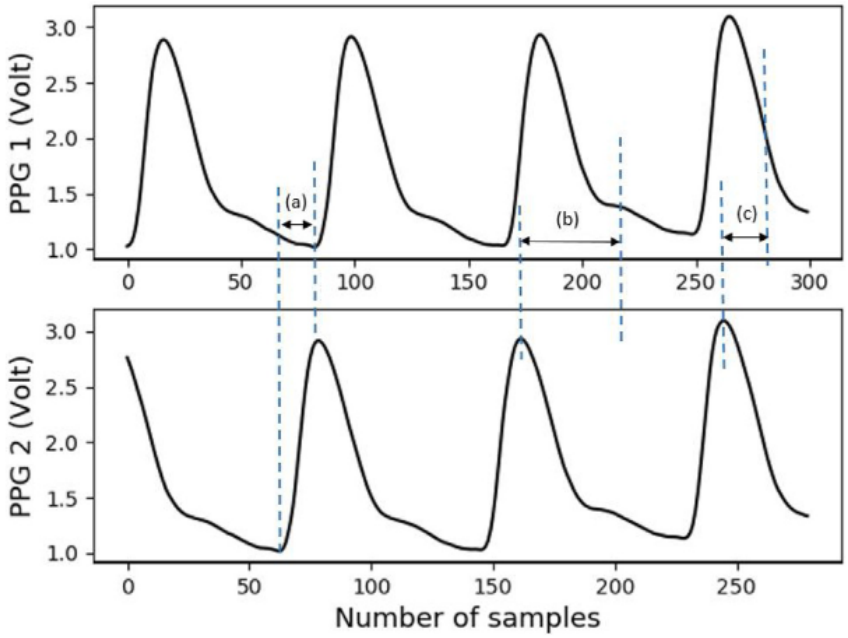


Figure 6: Pulse Transit Time (PTT) visualisation [16]

It is important to note for Figure 6 that the PTT can be measured at different points along the PPG waveforms. (a) represents a foot-to-foot time delay, (b) is a peak-to-dicrotic notch time delay and (c) is a peak to mid-point of the falling edge time delay [16]. As a proof of concept, increasing BP leads to an increase in the tension along the arterial wall tension, which therefore reduces the PTT. Hence, the opposite also applies [27].

2.2.2 Pulse Arrival Time (PAT)

The PAT is the difference in time between the R-peak of the ECG signal and the systolic peak of the PPG signal when measured during the same cardiac cycle, as indicated in Figure 7 [16] [15]. Physically, PAT is the interval in time between the activation of electrical impulses at the heart and the arrival of the pulse wave at a location on the body, such as the finger [23]. PAT is measured using two sensors, an ECG and a PPG sensor [16].

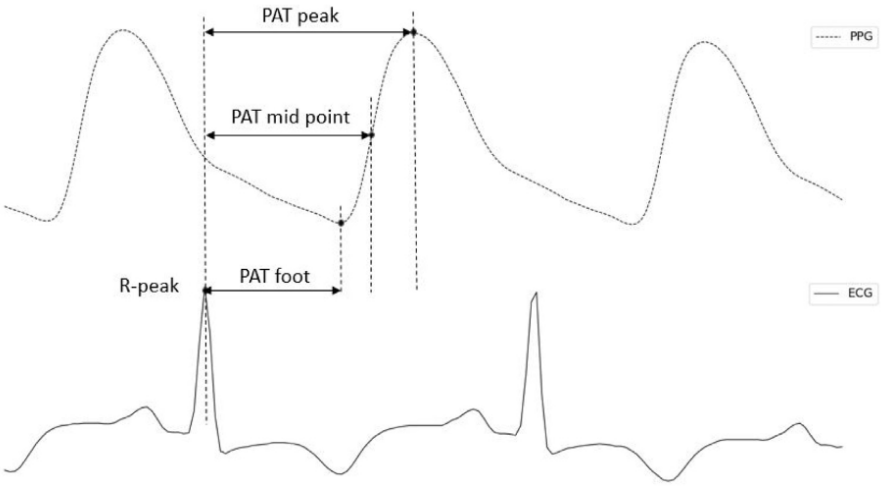


Figure 7: Pulse Arrival Time (PAT) visualisation [16]

The Pre-ejection Period (PEP) delay can also be briefly discussed. PEP is the time needed to convert the electrical signal into a mechanical pumping force and isovolumetric contraction to open the aortic valves,

$$PAT = PTT + PEP \tag{1}$$

2.2.3 Pulse Wave Velocity (PWV)

The PWV calculates the velocity of the pulse wave using two PPG sensors located on the same arterial branch at a known distance apart [33] [16]. The relation between PTT and PWV can be expressed as

$$PWV = \frac{d}{PTT} \tag{2}$$

where d is the arterial distance travelled by the pressure wave. PWV is related to the Young's modulus of the vessel wall by the Moens-Kortweg equation,

$$PWV = \sqrt{\frac{Eh}{\rho d}} \tag{3}$$

where

$$PWV = \text{ Velocity of the pulse wave (m/s)} \tag{4}$$
$$E = \text{ Young's modulus of vessel wall (Pa)} \tag{5}$$
$$h = \text{ vessel thickness (m)} \tag{6}$$
$$\rho = \text{ blood density (kg/}m^3\text{)} \tag{7}$$
$$d = \text{ arterial diameter (m)} \tag{8}$$

The Young's modulus of the vessel wall is then related to the arterial pressure by the Bramwell-Hills equation,

$$E = E_0 e^{\lambda P} \tag{9}$$

where E_0 and λ depend on the thoracic and abdominal aortas and P is the vessel blood pressure (mmHg) [22] [48] [52].

By equating and solving Equations 2 and 3, the final equation for estimated blood pressure is expressed as,

$$P = \frac{1}{\lambda} \ln \left(2r\rho \frac{\Delta X^2}{E_0 h}\right) - \frac{2}{\lambda} \ln \left(PTT\right) \tag{10}$$

where

$$r = \frac{d}{2} = \text{ arterial radius} \tag{11}$$

$$\Delta X = \text{ distance from heart to vessel} \tag{12}$$

2.2.4 Limitations

The blood pressure (BP) can be derived through mathematical models as soon as estimates have been calculated for PTT, PAT and PWV. Although these models are common approaches for BP monitoring in an environment that is non-invasive and cuff-less, there are many challenges to these implementations. As a result, none of these techniques by themselves have been established as a reliable indicator for the estimation of BP.

Firstly, all three of the aforementioned methods require two separate measurements from two synchronised sensor devices. This can be a very inconvenient process for patients who are uncomfortable with this method [23].

In addition, there is a very likely possibility that these sensor devices will have different real-time sampling rates. Their operability depends on rather complicated arterial wave propagation models [16].

In order to be able to continuously measure BP, constant calibration of the methods is required. This is due to individual patients having different physiological parameters [23].

Finally, even with per-person calibration, these models can only provide BP estimation for a short period of time. As a result, this makes the models unreliable for the estimation of BP with every heartbeat [16].

To conclude this chapter, there is a lot of potential in the use of the three above parameters in the estimation of Ambulatory BP. However, there are still overarching limitations which currently hinder the progress of these parameters.

2.3 Neural Networks

You need an intro for neural networks. Again, you can't assume the reader knows what it is.
Include a summary to explain what neural network is, before diving into particular types.
Also summarise the type of networks you'll be discussing. You need to improve on organising and structuring here..

2.3.1 Artificial neural networks

Due to advancements in technology related to machine learning, there has been a lot of research into neural networks algorithms that can offer continuous BP measurements that are non-invasive and also cuff-less [33]. However, in this case BP estimation is motivated by how much data is available to the algorithm [16].

Artificial neural networks (ANNs) are a machine learning method that can be used to estimate blood pressure [33]. For this report, the aim is to experiment with Recurrent Neural Networks (TNNs). However, in order to properly understand RNNs, it is necessary to first introduce ANNs. ANNs are based on the neural networks found in the human body and aim to replicate their behaviour [52]. The structure of the ANN consists of multiple individual units called neurons, as shown in Figure 8.

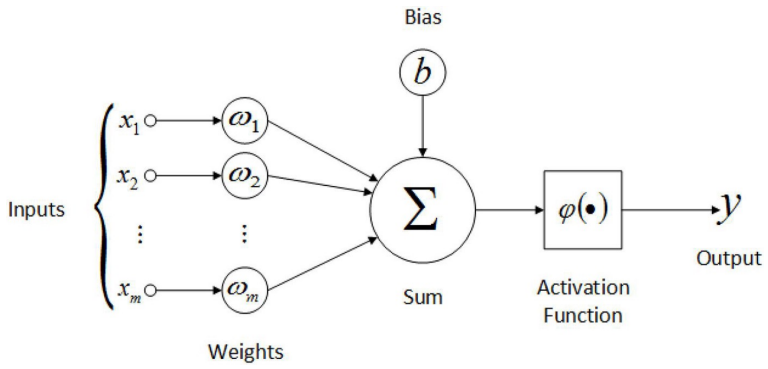


Figure 8: Structure of a neuron [3]

Each neuron has five critical components. These are inputs ($\boldsymbol{x}$), weights ($\boldsymbol{\omega}$), transfer function (Σ), activation function ($\phi(\cdot)$) and bias (b) [21]. In order to mathematically express the neuron unit, it is important to first understand its goal. The neuron applies a linear transformation to an m-dimensional input feature vector $\mathbf{x}$ by applying a dot product with the weights $\boldsymbol{\omega}$ and adding a scalar bias b to this dot product. After this, a non-linear activation function $\phi(\cdot)$ is applied to the linear mapping. This enables the neuron to model non-linear relationships. This is expressed mathematically as follows,

$$y = \phi(\sum_i \omega_i x_i + b) = \phi(\boldsymbol{\omega}^T \mathbf{x} + b) \tag{13}$$

where $\boldsymbol{\omega} \in \mathbb{R}^m$ and y, b are scalars. When each of these neurons are connected together with several other neurons across several layers, this forms a neural network, as shown in Figure 9. Each of the neurons in Figure 8 are represented by a grey unit in Figure 9. By having a network of multiple neurons, it is possible to model more complex relationships than just a

single neuron, provided that the activation functions $\phi(\cdot)$ are not linear for all neurons (since the combination of linear operations results in a linear operation). In addition, the output of the neural network can have as many units as needed depending on the task at hand (e.g. 5 neurons are needed for classification problems with 5 classes using one-hot encoding).

The network of a single fully-connected layer is mathematically expressed using Equation 14,

$$\mathbf{y} = \phi(\mathbf{\Omega}\mathbf{x} + \mathbf{b}) \tag{14}$$

where $\mathbf{\Omega} \in \mathbb{R}^{N \times M}$ is the weights matrix, $\mathbf{b} \in \mathbb{R}^{N}$ is the bias vector, $\mathbf{y} \in \mathbb{R}^{N}$ is the output vector and $\phi(\cdot)$ performs element-wise non-linear transformations.

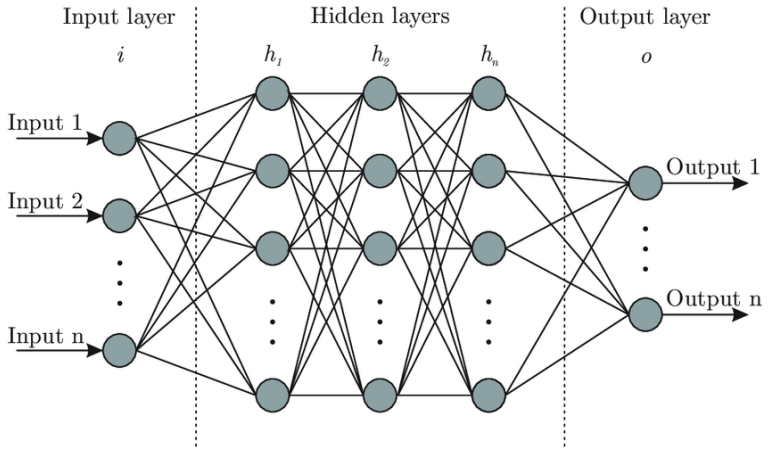


Figure 9: Structure of a multi-layer ANN

2.3.2 Recurrent Neural Networks (RNNs)

Traditional neural networks have found success in many fields, However it has been demonstrated that they cannot capture temporal dependencies in the data, making it unsuitable for signal processing applications. A Recurrent Neural Network (RNN) is a specific type of architecture that is widely used to deal with time-varying data [26]. RNNs contain additional memory states that retain and process information from previous time steps.

RNNs are called recurrent since they apply the same operation to each of the input sequences, with the output of an individual element being dependent on the previous one. Theoretically, RNNs establish a connection between the actual input and all the previous ones [26]. Although this is assumed, in the practice, RNNs have proven to only remember a limited number of inputs. In other words, RNNs have a memory that allows them to remember previous elements and use their information to deal with the current input [21]. Figure 10 shows the simplest version of an RNN, which can be easily derived from a simple feedforward architecture by adding a single loop:

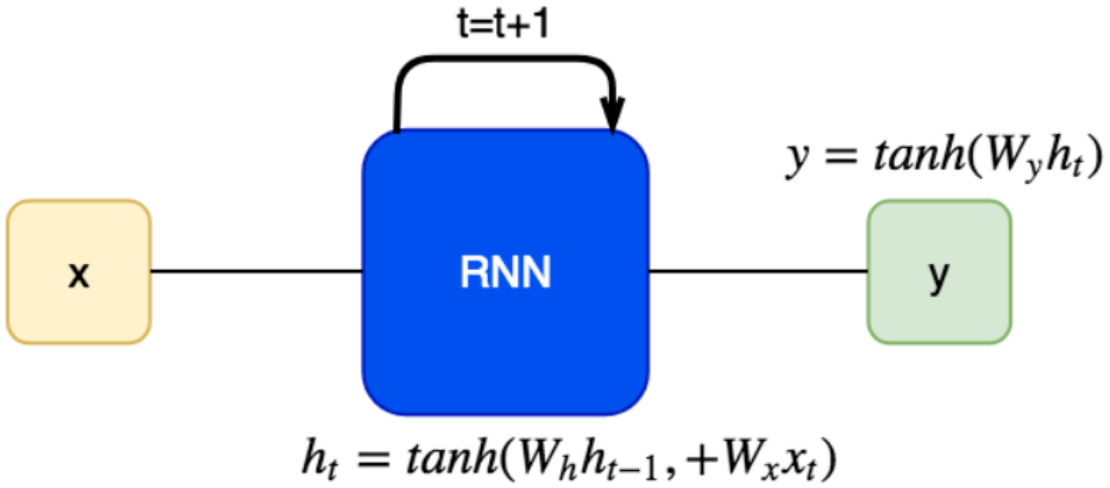


Figure 10: Simplification of a RNN

During training, the hidden state h is iteratively updated based on the input value x and the learned weights W_h and W_x. The final output y is estimated from the current state h_t and the matrix W_y. Although RNN can assure short-term dependencies within the network, simple RNNs become unable to learn to connect information as the gap between past and present information grows [11]. To overcome this limitation, in practical applications LSTM unit is adopted, that is a special RNNs architecture composed of multiple interacting layers.

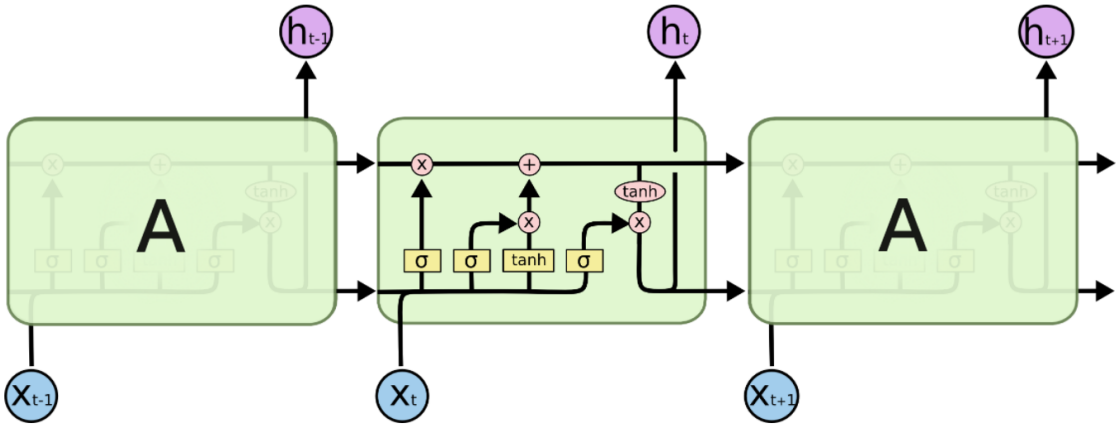


Figure 11: LSTM network

2.3.3 Activation Functions

Activation functions transform the output of a neural network unit element-wise, allowing it to model non-linear functions. For this project, the estimation of BP is treated as a regression problem. Hence,

2.3.4 Loss Functions

Loss functions are objective functions that the neural network aims to minimize when being trained. For this project, the loss function of concern is the Mean Squared Error (MSE) loss

function, which is defined in Equation 15.

$$l_{\text{MSE}}\left(\mathbf{y}, \hat{\mathbf{y}}\right) = \frac{1}{N}\sum_{i=1}^{N}(\mathbf{y}_i - \hat{\mathbf{y}}_\mathbf{i})^2 \tag{15}$$

where N is the number of training examples, $\mathbf{y}_i$ is the target output vector, and $\mathbf{y}_{\hat{y}_i}$ is the predicted output vector. The MSE is effective for ensuring that the trained model has no outlier predictions with huge errors, since the MSE puts larger weight on theses errors due to the squaring operation of the function.

2.3.5 Neural Network Training

In the same manner for any other machine learning algorithm, neural networks aim to learn an underlying pattern present in the data by minimizing an error measure defined by a loss function given some sample data (a process known as training). Formally, this problem is done by finding the optimal weights of the model per layer as defined in Equation 16, where $\hat{\mathbf{y}}$ is the estimate of the true label $\mathbf{y}$ and l is the loss function.

$$\mathbf{\Omega}_{opt} = \arg\min_{\mathbf{\Omega}}\{\mathbb{E}(l(\mathbf{y}, \hat{\mathbf{y}}))\} \tag{16}$$

At the end of this chapter, I advise you to summarise what the reader should take from this chapter. What is the takeaway message and how are you moving forward from this knowledge. Here you restate your aim and objective and how you are going to move forward. (The summary should flow into the next chapter)

2.4 SECTION CLARIFYING WHAT COMPLEXITY MEANS FOR THIS PROJECT?

2.5 Literature Review

Initial remarks:Where is the use of the PRISMA criteria? Query equation? Where is the inclusion, exclusion diagram? Your literature review does not highlight the work you have done for your lit review.

A lot is missing here... After reading remarks: This is not a literature review. By only placing papers into a table as a summary is not sufficient. - what comments do you have on the results you've tabulated? - You mention factors were considered.. why? and when you considered them, what about them? Why is it important? - What should the reader be left with?

What are the advantages and disadvantages?

Currently, the literature review is below average. You need to work on this.

2.5.1 Survey Equation

2.5.2 PRISMA checklist

2.5.3 Literature survey table

2.5.4 Critical analysis of literature survey table

2.5.5 Conclusions of literature survey

Before providing the background information on this project, it is important to highlight the literature review process taken in order to decide on which BP estimation method to use.

Firstly, it was important to formulate a literature survey equation in order to search for the suitable resources. The phrase chosen was: (Extraction OR Estimation OR Review) AND (Blood OR Arterial OR Ambulatory OR Cuffless) AND (Pressure) AND (ECG OR PPG) AND (Machine Learning OR Signal Processing).

The database chosen to research for papers was IEEE Xplore. The papers returned were then filtered to only those published between 2012 and 2022, i.e. the last 10 years. As a result the following tables summarise the most relevant papers for this project.

As a reference, the original literature survey matrix can be found on the Github repository [7]. Firstly, in Table 2, a simplified literature survey has been detailed out for the best performing methods which do not employ machine learning methods.

Table 2: Overview of performance of the best non-invasive non-ML cuff-less methods for measuring BP

Study	Source	No. Subjects	Age	Implementation	MAE SBP
[2]	ECG, PTT-CP	10	24-63	Numerical solution	± 5.93
[10]	ECG	5	N/A	Analytical solution	9 ± 5.6
[12]	PPG	16	18-48	Frequency analysis	0.8 ± 7
[8]	ECG, PPG, PTT	N/A	N/A	Analytical solution	7.49 ± 8.8
[29]	PTT	127	N/A	Wavelet transforms	± 7.63
[14]	PTT, PPG	27	21-29	Analytical solution	-0.37 ± 5.21

Table doesn't fit on the page. Consider either turning it landscape or redesigning the table to fit.

Redesigning could be making a key for different sources and/or the method. E.g ECG = filled square, PPG = filled circle.

If you are abbreviating or using symbols, state clearly in your table captions.

Table 3: Overview of performance of the best non-invasive ML cuff-less methods for measuring BP

Study	Source	No. Subjects	Age	Method	MAE SI
[52]	ECG, PPG	14 males	17-43	ANN	7.99 ± 10
[17]	PPG	65	22-65	Wavelet, SVM	$5.1 \pm 4.$
[24]	PPG	MIMIC II	Adults	Linear Reg., ANN, SVM	13.84 ± 1
[46]	ECG	51	16-83	Complexity analysis + ML	7.72 ± 10
[49]	PPG	72	N/A	ANN (MLP)	$4.02 \pm 2.$
[33]	ECG, PPG	MIMIC II	Adults, neonatal	ANN (150 neurons)	$5.76 \pm 6.$
[48]	ECG, PPG	39	20-100	ANN-LSTM	1.10
[9]	PTT, ECG, PPG	MIMIC I	N/A	SVM, Lin Reg.	$3.27 \pm 5.$
[43]	PTT	250	MIMIC I	ANN-RBM	3.70

The Mean Absolute Error (MAE) of the Systolic BP (SBP) was used as the uniting accuracy measure in this paper, as it was the most readily available parameter in all of the aforementioned papers.

It is important to note that other factors were considered in this literature survey. These factors were,

- Range of SBP and DBP values
- Sampling frequency
- Denoising and detection techniques used
- Computational complexity
- Feasibility in a wearable context

However, due to a lack of regular occurrences of these factors over all the papers, they were not included in the above two tables.

The results show that the established non-ML methods do produce MAE values noticeably lower than the majority of the ML methods. However, a main factor to consider about these results is that machine learning based methods and neural networks are data driven. As shown in Table 3, there is a very limited number of subjects available for each study. If these studies had been extended to include more test patients, it is possible that these MAE SBP values were lower. An additional point is that another study [47] did a study into using a 4-layer LSTM architecture to estimate BP from ECG and PPG signals with 84 patients. This study resulted in an RMSE SBP of 3.9 mmHg but no available MAE. Hence there is a lot of potential in ML methods when there is sufficient data available.

3 Analysis and Design

3.1 Choice of programming language

Python is used as the sole programming language for this project. Python has a wide variety of easy to use and powerful libraries [35]. The scientific libraries from Python that are used for this project are `numpy` [38] and `pandas` [39]. In addition, the machine learning libraries used are `tensorflow` [41], `keras` [36] and `scikit-learn` [40]. In addition the `heartpy` [34] and `wfdb-python` [42] packages were installed, which are libraries of tools for reading, writing, and processing Waveform-Database (WFDB) signals and annotations.

MATLAB was also considered as a potential programming language to use, due to it having a wide range of signal processing and machine learning add-on toolboxes. However Python has been shown to offer a wider set of choices in graphics packages and toolsets, such as through `matplotlib` [37], and it also produces more compact and readable code.

3.2 Choice of dataset

Give a better explanation of the dataset you're using. Age range, gender split, any medical conditions.. This can all be found in the dataset website or the relevant papers linked to the dataset. As previously discussed in the literature review in Chapter 2, the chosen dataset is the Medical Information Mart for Intensive Care (MIMIC) dataset. Did you? I must have overlooked it. The MIMIC Database includes data recorded from over 90 ICU patients. The data in each case include signals and periodic measurements obtained from a bedside monitor as well as clinical data obtained from the patient's medical record. The recordings vary in length; almost all of them are at least 20 hours, and many are 40 hours or more If you know how many, state it. Don't be chatty.. In all, the database contains nearly 200 patient-days of real-time signals and accompanying data [31]. I don't understand.. You say there are over 90 ICU patients (again state the exact number because it is known). So where do the 200 come from? (again can't be nearly 200.. Be exact.) - Did you use all 90 or 200 patients data. Everything you write in your methods needs to be clear for someone to repeat exactly what you have done. This will also help us review your code and run it to produce the exact same results you will be showing in the report.

3.3 Choice of signal channel

3.4 Feature extraction

3.5 Decision between signal-processing based or ML based method

3.6 Choice of ML model to use

3.7 Performance metrics

The two considered error calculations used in this experimentation are the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). They are defined by the following equations,

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|a_{i_M} - b_{i_M}| \tag{17}$$

$$RMSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}|a_{i_M} - b_{i_M}|^2} \tag{18}$$

In the context of BP estimation, b_{i_M} and a_{i_M} represent the true value and BP estimate respectively for the Mth element of the time sequence.

4 Implementation

4.1 Description of dataset

As discussed in Section 3, the MIMIC Database includes data recorded from over 90 ICU patients. For the purposes of this project, a subset of this data is used for experimentation. Further details of the data used are shown in Table 4.

Why a subset? Why not all? If you're doing a split, explain this. Are you only using 8 patients out of the 90?

Patient Number	Gender	Age	Health issue faced by the patient
224	Male	21	Sepsis
225	Male	73	Pulmonary edema
230	Female	75	Cardiac Heart Failure/Pulmonary edema
232	Male	68	Myocardial infarction/Cardiogenic shock
235	Female	67	Myocardial infarction/Cardiogenic shock
240	Male	68	Angina
252	Male	52	Respiratory Failure
255	Male	67	Cardiac Heart Failure/Pulmonary edema

Table 4: Characteristics of the patients from the MIMIC-I database

4.2 Extracting the ground truth blood pressure values

The ground truth Systolic and Diastolic blood pressure values are calculated by taking the respective maxima and minima of the arterial blood pressure signal within each window of the signal.

4.3 Signal preprocessing steps

4.4 Windowing of PPG and ABP data

4.5 Convolutional Neural Network (CNN) model

What type of information should the reader gather from this figure? It needs explaining and annotations/labelling.

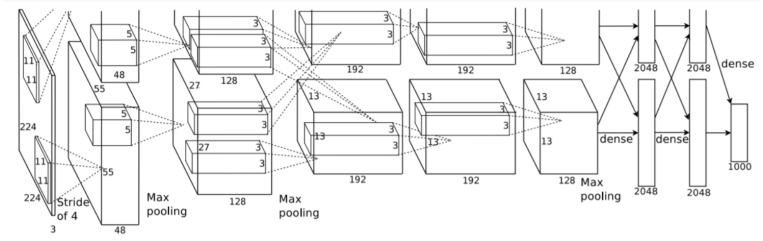


Figure 12: Overview of the AlexNet architecture

4.6 ResNet model

5 Overview of Results

For all results:

1. Ensure all results have units (if it doesn't have units, it's A.U for arbitrary units)
2. If you have sub figures or diagram, label them a, b, c and include a short description in the caption.

5.1 Overview of testing parameters

5.2 Performance of AlexNet architecture

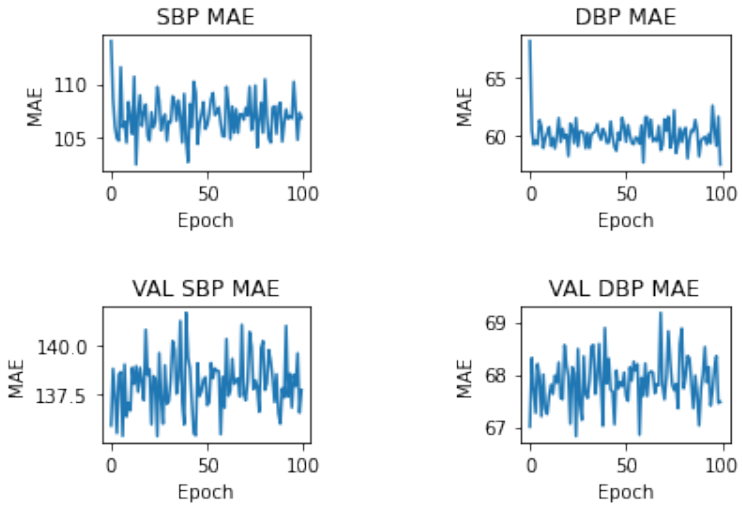


Figure 13: MAE of SBP and DBP for AlexNet architecture

5.3 Performance of ResNet architecture

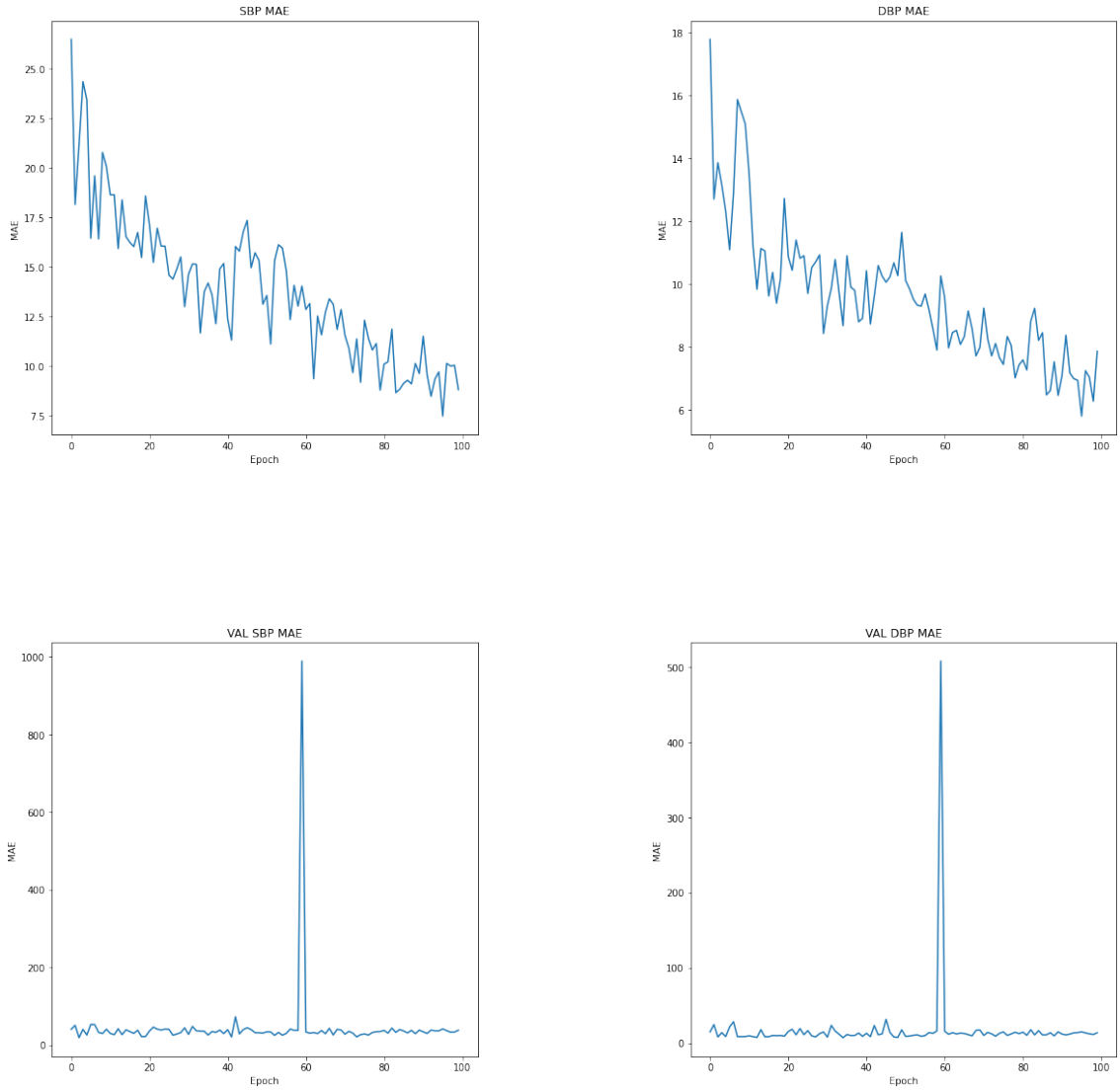


Figure 14: MAE of SBP and DBP for ResNet architecture

6 Evaluation of results

This Chapter (or possibly section of the conclusions) is distinct from your results. It must contain your critical evaluation of your work as compared to previous analysis, algorithms, products, and when related to your original objectives. To what extent have your original objectives been fulfilled? If they have changed, what is your rationale for this? What are the advantages, disadvantages of your approach compared with related work? How does the scope of your work differ from related work? Examiners expect your project report to show evidence of your ability to think as an engineer, and that includes the ability to critically reflect on your own work and evaluate its significance.

Material here will compare project outcomes with initial objectives and requirements captured. Usually your Interim Report will contain these. Where these have changed significantly over the course of the project this should be explained and reasons given. This section should not require examiners to read your Interim Report, and will not reference it. Changes between final and initial objectives should be explained in a self-contained manner.

Note that here you will reference and summarise, rather than repeat, your description of Requirements Capture earlier in the Final Report.

7 Ethical, Legal and Safety Plan

7.1 Ethical considerations

This section discusses the ethical implications of this project through the perspective of the Four Pillars of Medical Ethics: beneficence, non-maleficence, autonomy, and justice [19].

7.1.1 Beneficence

Beneficence is the duty to do good. During the process of this project, it must be ensured that actions must be taken with the intent of helping patients. The purpose of future wearable technologies is to help people to detect early risk factors of heart-related pathologies.

The issues that may arise would be due to the occurrence of false positives and negatives in the data, such as a normotensive result for a person who is actually hypertensive. Ideally, a blood pressure monitor which is cuffless should operate accurately over a range of blood pressure values after having been calibrated. However this has not been tested according to the established medical standards, such as AAMI and ESH. Measurements that are inaccurate will naturally cause a false sense of reassurance with the patients, unnecessary health care utilization, or improper administration of hypertension medications. An incorrect diagnosis also causes unnecessary psychological stress and the unnecessary reactions to the negative side effects of prescribed medication. For example, if there is a range of ± 5 mmHg in error, this could lead to approximately twenty-seven million hypertensive and twenty-one million normotensive patients being classified incorrectly [5]. This can only be minimised through robust tuning of the parameters in the neural networks used.

7.1.2 Non-maleficence

Non-maleficence is the duty to not harm. Through the recording of ECG and PPG data, it must be ensured that any actions must not be harmful to the patients. An instance where the product could harm patients would be if the models falsely classify a patient to be normotensive, whereas the patient indeed is hypertensive in real life. If test accuracy could be proven, it would be possible to see if a model is provably 100% accurate, or otherwise justify to an Ethics Board that the risks would be worth the reward. However, with neural networks of this complexity, it is practically impossible to prove any estimate of test accuracy.

7.1.3 Autonomy

Autonomy is the respect of patients' freedom of choice and consent. During the data acquisition process, it must be ensured that there are no actions taken that are non-consensual to the patients. Those concerned should also be informed about the benefits and risks of using a particular wearable technology product for BP measurement, such as the validation accuracy and inference time, allowing them to make an informed decision.

Another general issue of using deep neural networks is that it is very difficult to explain how models obtain their results. It is impossible to explain what features an individual or end-to-end model detects and what any of their weights correspond to. This can be an issue if

the user wants an explanation as to why they have been classified wrongly as hypertensive or hypotensive, as they should have the right to know.

7.1.4 Justice

Justice is the principle of fairness towards all patients and the idea of treating all people equally and equitably. The product must ensure it does not discriminate between patients and medical staff on any basis. An obvious concern is whether the dataset used to train the models are balanced in representing both gender and ethnicity. Although the dataset was created taking such biases into account, it is difficult to overcome subconscious biases and availability of a balanced dataset. This is important as it ensures that future products in wearable technologies have both a sustainable customer base but is also sustainable in today's social ecosystem, as it is actively standing against racism.

7.2 Legal considerations

Legally this project poses no risk. The Python programming language and its required libraries are Open Source, including the version which I intend to use (3.10). Python has a license agreement under the Python Software Foundation (PSF). Hence it is a tool that can be legally used freely for the purposes of this project. [35]. In addition, the ECG and PPG data is provided by a website called Physionet. PhysioNet is a data repository of medical signals which are free to use. The repository is managed by the MIT Laboratory for Computational Physiology [18] [1]. As this code will be published online, the produced code could be plagiarised in the future. However, I myself will bear no responsibility in the distribution of my code to others.

7.3 Safety considerations

With regards to this project, there are no safety issues to consider, as all experimentation will be conducted online at home. It is critical that necessary measures are taken such that strains or injuries from desk work are prevented. This can easily be done by following NHS guidelines.

As highlighted in Chapter 3, there are a few points to consider if this work becomes implemented in a future wearable technology product. Firstly, it is important to remember these are only simulations. Training a machine learning model on Python will not accurately reflect the behavior in real life. Secondly, any results discussed in this report will not be officially recognised by the AAMI or ESH protocols. This is something that future active projects will need to consider, in order to have substantial results.

8 Conclusions and Further Work

8.1 Summary of project achievements

- Design choices: Aim was to minimize complexity of the neural network model in order to effectively monitor BP
- What was most difficult: 2 parts to this: Firstly the choice of how to preprocess the signal for effective analysis. This was solved by surveying the relevant literature and assessing the most feasible set of steps. Secondly, designing the ideal neural network architectures
- What I learned: Despite what was expected from the theory, the CNN Resnet performs better on the PPG signal data than the LSTM networks
-

8.2 Future work

- Discuss the transformer papers and the attention mechanism. The main reason the transformer model was not explored for this paper is due to its high model complexity. However, this could be tested on in the future and see if the results are any/much better than the Resnet/LSTM models
-

9 Bibliography

[1] Physionet documentation. https://physionet.org/about/.

[2] S. Ahmad, S. Chen, K. Soueidan, I. Batkin, M. Bolic, H. Dajani, and V. Groza. Electrocardiogram-assisted blood pressure estimation. *IEEE Transactions on Biomedical Engineering*, 59:608–618, 3 2012.

[3] H. Almusawi and A. Burhan. Evaluation of the productivity of ready mixed concrete batch plant using artificial intelligence techniques. *IOP Conference Series: Materials Science and Engineering*, 901:012020, 09 2020.

[4] 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*, 21(5), 2021.

[5] D. M. Bard, J. I. Joseph, and N. van Helmond. Cuff-less methods for blood pressure telemonitoring. *Frontiers in Cardiovascular Medicine*, 6, 4 2019.

[6] D. Between. Difference between systolic and diastolic. http://www.differencebetween.net/science/health/difference-between-systolic-and-diastolic/, 1 2021.

[7] A. Bhattacharyya. Final year project literature survey matrix. https://github.com/ab10918/FinalYearProject---BP-from-ECG-PPG/blob/main/Literature%20Survey.xlsx, 1 2022.

[8] K. W. Chan, K. Hung, and Y. T. Zhang. Noninvasive and cuffless measurements of blood pressure for telemedicine. *Annual Reports of the Research Reactor Institute, Kyoto University*, 4:3592–3593, 2001.

[9] S. Chen, Z. Ji, H. Wu, and Y. Xu. A non-invasive continuous blood pressure estimation approach based on machine learning. *Sensors (Switzerland)*, 19, 6 2019.

[10] Z. Chen, X. Yang, J. T. Teo, and S. H. Ng. Noninvasive monitoring of blood pressure using optical ballistocardiography and photoplethysmograph approaches. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, pages 2425–2428, 2013.

[11] Colah. Understanding lstm networks. https://colah.github.io/posts/2015-08-Understanding-LSTMs/, 8 2015.

[12] N. Daimiwal, M. Sundhararajan, and R. Shriram. Respiratory rate, heart rate and continuous measurement of bp using ppg. *International Conference on Communication and Signal Processing, ICCSP 2014 - Proceedings*, pages 999–1002, 11 2014.

[13] W. N. Dillon. High blood pressure and hypertensive heart disease. https://medium.com/@WayneDillon/high-blood-pressure-and-hypertensive-heart-disease-1f5cab7c6bbc, 2015.

[14] X. R. Ding, Y. T. Zhang, J. Liu, W. X. Dai, and H. K. Tsang. Continuous cuffless blood pressure estimation using pulse transit time and photoplethysmogram intensity ratio. *IEEE Transactions on Biomedical Engineering*, 63:964–972, 5 2016.

[15] M. P. Ebrahim, F. Heydari, T. Wu, K. Walker, K. Joe, J. M. Redoute, and M. R. Yuce. Blood pressure estimation using on-body continuous wave radar and photoplethysmogram in various posture and exercise conditions. *Scientific Reports*, 9, 12 2019.

[16] C. El-Hajj and P. A. Kyriacou. A review of machine learning techniques in photoplethysmography for the non-invasive cuff-less measurement of blood pressure. *Biomedical Signal Processing and Control*, 58, 4 2020.

[17] S. C. Gao, P. Wittek, L. Zhao, and W. J. Jiang. Data-driven estimation of blood pressure using photoplethysmographic signals. *Proceedings of the Annual International Conference*

of the IEEE Engineering in Medicine and Biology Society, EMBS, 2016-October:766–769, 10 2016.

[18] A. L. Goldberger, L. A. N. Amaral, . L. Glass, J. M. Hausdorff, . Plamen, C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and . H. E. Stanley. Physiobank, physiotoolkit, and physionet components of a new research resource for complex physiologic signals. `http://www.physionet.org`, 2000.

[19] S. Holm. Principles of biomedical ethics, 5th edn. *Journal of Medical Ethics*, 28(5):332–332, 2002.

[20] Q. F. Huang, W. Y. Yang, K. Asayama, Z. Y. Zhang, L. Thijs, Y. Li, E. O'Brien, and J. A. Staessen. Ambulatory blood pressure monitoring to diagnose and manage hypertension. *Hypertension*, pages 254–264, 2021.

[21] Y. B. Ian Goodfellow and A. Courville. *Deep Learning*. 2017.

[22] G. Janjua, D. Guldenring, D. Finlay, and J. McLaughlin. Wireless chest wearable vital sign monitoring platform for hypertension. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, pages 821–824, 9 2017.

[23] 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*, 11, 12 2021.

[24] M. Kachuee, M. M. Kiani, H. Mohammadzade, and M. Shabany. Cuff-less high-accuracy calibration-free blood pressure estimation using pulse transit time. *Proceedings - IEEE International Symposium on Circuits and Systems*, 2015-July:1006–1009, 7 2015.

[25] K. Kario, S. Hoshide, Y. C. Chia, P. Buranakitjaroen, S. Siddique, J. Shin, Y. Turana, S. Park, K. Tsoi, C. H. Chen, H. M. Cheng, T. Fujiwara, Y. Li, V. M. Huynh, M. Nagai, J. Nailes, J. Sison, A. A. Soenarta, G. P. Sogunuru, A. Sukonthasarn, J. C. Tay, B. W. Teo, N. Verma, T. D. Wang, Y. Zhang, and J. G. Wang. Guidance on ambulatory blood pressure monitoring: A statement from the hope asia network. *Journal of Clinical Hypertension*, 23:411–421, 3 2021.

[26] A. Karpathy. The unreasonable effectiveness of recurrent neural networks. `http://karpathy.github.io/2015/05/21/rnn-effectiveness/`, 5 2015.

[27] S. Kumar and S. Ayub. Estimation of blood pressure by using electrocardiogram (ecg) and photo-plethysmogram (ppg). *Proceedings - 2015 5th International Conference on Communication Systems and Network Technologies, CSNT 2015*, pages 521–524, 9 2015.

[28] A. A. Leung, K. Nerenberg, S. S. Daskalopoulou, K. McBrien, K. B. Zarnke, K. Dasgupta, L. Cloutier, M. Gelfer, M. Lamarre-Cliche, A. Milot, P. Bolli, G. Tremblay, D. McLean, S. W. Tobe, M. Ruzicka, K. D. Burns, M. Vallée, G. V. Prasad, M. Lebel, R. D. Feldman, P. Selby, A. Pipe, E. L. Schiffrin, P. A. McFarlane, P. Oh, R. A. Hegele, M. Khara, T. W. Wilson, S. B. Penner, E. Burgess, R. J. Herman, S. L. Bacon, S. W. Rabkin, R. E. Gilbert, T. S. Campbell, S. Grover, G. Honos, P. Lindsay, M. D. Hill, S. B. Coutts, G. Gubitz, N. R. Campbell, G. W. Moe, J. G. Howlett, J. M. Boulanger, A. Prebtani, P. Larochelle, L. A. Leiter, C. Jones, R. I. Ogilvie, V. Woo, J. Kaczorowski, L. Trudeau, R. J. Petrella, S. Hiremath, D. Drouin, K. L. Lavoie, P. Hamet, G. Fodor, J. C. Grégoire, R. Lewanczuk, G. K. Dresser, M. Sharma, D. Reid, S. A. Lear, G. Moullec, M. Gupta, L. A. Magee, A. G. Logan, K. C. Harris, J. Dionne, A. Fournier, G. Benoit, J. Feber, L. Poirier, R. S. Padwal, and D. M. Rabi. Hypertension canada's 2016 canadian hypertension education program guidelines for blood pressure measurement, diagnosis, assessment of risk, prevention, and treatment of hypertension. *Canadian Journal of Cardiology*, 32:569–588, 5 2016.

[29] Z. D. Liu, B. Zhou, Y. Li, M. Tang, and F. Miao. The wavelet transform of pulse wave

and electrocardiogram improves accuracy of blood pressure estimation in cuffless blood pressure measurement. 11, 3 2018.
[30] Z. D. Liu, B. Zhou, Y. Li, M. Tang, and F. Miao. Continuous blood pressure estimation from electrocardiogram and photoplethysmogram during arrhythmias. *Frontiers in Physiology*, 11, 9 2020.
[31] G. B. Moody and R. G. Mark. A database to support development and evaluation of intelligent intensive care monitoring. *Computers in Cardiology*, 0:657–660, 1996.
[32] R. Nye, Z. Zhang, and Q. Fang. Continuous non-invasive blood pressure monitoring using photoplethysmography: A review. *4th International Symposium on Bioelectronics and Bioinformatics, ISBB 2015*, pages 176–179, 12 2015.
[33] L. Pradenas. A novel non-invasive estimation of arterial blood pressure from electrocardiography and photoplethysmography signals using machine learning. *Biomedical Journal of Scientific & Technical Research*, 30, 9 2020.
[34] Python. Heartpy documentation. `https://python-heart-rate-analysis-toolkit.readthedocs.io/en/latest/`, 6 2022.
[35] Python. History and license for python. `https://docs.python.org/3/license.html`, 6 2022.
[36] Python. Keras documentation. `https://keras.io/`, 6 2022.
[37] Python. Matplotlib documentation. `https://matplotlib.org/stable/index.html`, 6 2022.
[38] Python. Numpy documentation. `https://numpy.org/doc/stable/`, 6 2022.
[39] Python. Pandas documentation. `https://pandas.pydata.org/docs/`, 6 2022.
[40] Python. Scikit-learn documentation. `https://scikit-learn.org/stable/`, 6 2022.
[41] Python. Tensorflow documentation. `https://www.tensorflow.org/api_docs`, 6 2022.
[42] Python. Wfdb-python documentation. `https://wfdb.readthedocs.io/en/latest/`, 6 2022.
[43] V. Ripoll and A. Vellido. Blood pressure assessment with differential pulse transit time and deep learning: A proof of concept. *Kidney Diseases*, 5:23–27, 2019.
[44] M. Sharma, K. Barbosa, V. Ho, D. Griggs, T. Ghirmai, S. Krishnan, T. Hsiai, J.-C. Chiao, and H. Cao. Cuff-less and continuous blood pressure monitoring: A methodological review. *Technologies*, 5:21, 5 2017.
[45] M. Simjanoska, M. Gjoreski, A. M. Bogdanova, B. Koteska, M. Gams, and J. Tasič. Ecg-derived blood pressure classification using complexity analysis-based machine learning. *HEALTHINF 2018 - 11th International Conference on Health Informatics, Proceedings; Part of 11th International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2018*, 5:282–292, 2018.
[46] M. Simjanoska, M. Gjoreski, M. Gams, and A. M. Bogdanova. Non-invasive blood pressure estimation from ecg using machine learning techniques. *Sensors (Switzerland)*, 18, 4 2018.
[47] P. Su, X.-R. Ding, Y.-T. Zhang, J. Liu, F. Miao, and N. Zhao. Long-term blood pressure prediction with deep recurrent neural networks. 5 2017.
[48] M. S. Tanveer and M. K. Hasan. Cuffless blood pressure estimation from electrocardiogram and photoplethysmogram using waveform based ann-lstm network. *Bangladesh University of Engineering and Technology*, 11 2018.
[49] L. Wang, W. Zhou, Y. Xing, and X. Zhou. A novel neural network model for blood pressure estimation using photoplethesmography without electrocardiogram. *Journal of Healthcare Engineering*, 2018, 2018.
[50] Wikipedia. Electrocardiography. `https://en.wikipedia.org/wiki/Electrocardiography`, 6 2022.

[51] Wikipedia. Qrs complex. https://en.wikipedia.org/wiki/QRS_complex, 6 2022.
[52] S. Yang, W. S. W. Zaki, S. P. Morgan, S.-Y. Cho, R. Correia, and Y. Zhang. Blood pressure estimation with complexity features from electrocardiogram and photoplethysmogram signals.
[53] W. S. Zaki, S. P. Morgan, S.-Y. Cho, R. Correia, L. Wen, and Y. Zhang. Blood pressure estimation from photoplethysmogram and electrocardiogram signals using machine learning. *University of Nottingham*, 2018.

10 Appendix

10.1 Health standards requirements for blood pressure estimation

- The Advancement of Medical Instrumentation (AAMI) standard requires a mean BP difference of $\leq$ 5 mmHg with a standard deviation of $\leq$ 8 mmHg against auscultatory reference measurement
- Significant variation in BP measurements($>$ 12 mmHg systolic or $>$ 8 mmHg diastolic) from the validated reference device is an exclusion criterion in the AAMI protocol [5]
- The European Society of Hypertension (ESH) protocol requires that the majority of subjects have investigational BP readings within $\leq$ 5 mmHg of the reference measurement.

10.2 Complete FYP Gantt chart