Prediction of ABP and ECG signal from PPG signal using deep learning

MSc Research Project
Data Analytics

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Project Submission Sheet
School of Computing

Student Name:	Sarthak Sinha
Student ID:	x21178321
Programme:	Data Analytics
Year:	2022
Module:	MSc Research Project
Supervisor:	Teerath Kumar Menghwar
Submission Due Date:	18/09/2023
Project Title:	Prediction of ABP and ECG signal from PPG signal using deep learning
Word Count:	6700
Page Count:	20

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Prediction of ABP and ECG signal from PPG signal using deep learning

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Abstract

Heart disease risk factors have long and most commonly been associated with arterial blood pressure (ABP). Arterial blood pressure measurement is one of the most helpful metrics for the early diagnosis, prevention, and treatment of cardiovascular diseases. Inconvenient and painful for users, cuff-based systems for measuring blood pressure remain the norm today. The monitoring of the electrocardiogram (ECG) has a similar related problem. Electrodes are affixed to the body as part of the ECG measurement process, which irritates the skin and restricts the patient's movement while they are being continuously monitored. Due to these difficulties, it is required to provide a dependable and practical way to track these essential physiological markers.

This paper investigates the previous research carried out in this field; however, the studies have not yet developed a complete heart monitoring system using a Photoplethysmography signal as the only input. This study aims to develop an effective deep-learning model to predict both ABP and ECG signals from PPG signals using minimal patient data because previous research has only been done to predict one physiological parameter (ABP or ECG). Additionally, the estimation accuracy for three different models would be evaluated based on mean absolute error (MAE) and root mean square error (RMSE).

Keywords: Arterial Blood pressure (ABP), Photoplethysmography (PPG), Electrocardiography (ECG), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), multi-output regression, Transformers, signal processing

1 Introduction

1.1 Background and Motivation

Within our body, the heart acts like a generator, propelling blood throughout to supply organs with vital nutrients and oxygen. Monitoring heart health is vital to detect problems early and stop serious heart disorders from developing. In the usual approach, we rely on three measurements—Arterial Blood Pressure (ABP), Electrocardiogram (ECG), and Photoplethysmography signal (PPG)—to keep track of the heart's condition. By looking at these, we can understand how effectively the heart is working and spot any potential issues.

Fanelli and Heldt, 2014, ABP signifies the force that the heart generates to assist in pumping blood throughout the body. Monitoring of ABP is performed through cannulation wherein a thin intra-arterial catheter is inserted into the patient's vein. This might be painful and uncomfortable for a few patients particularly elderly people.

Madona, Basti and Zain, 2021, electrocardiography (ECG) record the electrical activity of the heart, providing insights into the rhythmic contraction and relaxation of its chambers. This data helps assess potential blockages in arteries. To monitor ECG signals, electrodes are positioned on the patient's chest. However, extended use of these electrodes can result in skin irritation for patients and restrict their ability to move comfortably.

Almarshad et al., 2022, PPG represents a simple optical technique utilized to detect variations in peripheral blood volume. This budget-friendly and non-intrusive method assesses parameters on the skin's surface.

While existing research predominantly focuses on predicting ABP using PPG and ECG signals separately, a notable gap exists in simultaneously predicting both ECG and ABP from PPG. The majority of research has been concentrated on using PPG signals alone to predict ABP, rather than simultaneously forecasting ECG, which would result in an all-inclusive, cost-effective, and practical cardiac monitoring system. This gap in research suggests an opportunity for additional investigation and advancement in this field.

Moreover, from the ethical point of view as mentioned in Mittelstadt, B. 2017, minimizing data collection is an essential aspect of responsible AI design. Collecting only the minimal data required for the intended purpose helps reduce privacy risks and potential misuse of information. It is important to carefully assess the necessity of each data point and prioritize data minimisation to achieve the desired outcomes without compromising user privacy. By adopting the principle of minimal data collection, AI systems can uphold ethical standards and prioritize user interests. In order to make a responsible AI model it is worth exploring different ways to utilize minimum patient data and develop a generalised AI model.

1.2 Research Question

- How effectively two physiological parameters (ABP and ECG) can be predicted using only one physiological parameter (PPG) using deep learning?

- Using minimum patients' data is it possible to achieve stable accuracy?

1.3 Research Objective

Multioutput deep learning architecture models are excellent for tasks that require predicting several outputs. Hence, they make it possible to model complicated real-world issues more effectively and efficiently. These models are used in the proposed approach to predict ABP and ECG signals. A recurrent neural network termed Long Short-Term Memory (LSTM) is especially good at managing long-term dependencies and is designed to handle sequential information, such as time series data from PPG signals. Convolutional neural networks

(CNNs) are frequently utilized in the analysis of signal data as they are proficient in identifying regional patterns and dependencies within signals. Trends in signal data are frequently visible within smaller data segments instead of across the full dataset. The machine-learning methods used for signal processing will progress as a result of this research. PPG needs the application of powerful machine-learning algorithms and optimization approaches to develop reliable and effective prediction models for ECG and ABP signals. These techniques might be improved by the findings of this study, making them more useful and efficient for a variety of signal-processing jobs.

1.4 Document Structure

The rest of the document is structured in the following six sections which are as follows: Related Work which will provide a summary of the work done in the field of BioSignal processing. Research Methodology will give insight into the workflow of this research. Design Specification which will provide the high-level design of the research implementation. Implementation which will provide information regarding tools and architecture of the implemented deep learning models. The evaluation section is where the models are evaluated, and the predicted values are compared with the actual values and at last the conclusion and future work are discussed briefly.

1.5 Acknowledgement

The research is conducted under the guidance and supervision of Mr Teerath Kumar Menghwar. I would like to acknowledge his valuable efforts in this research and specifically his contributions to data augmentation of the physiological signals data.

2 Related Work

2.1 Arterial Blood Pressure (ABP) Estimation Using Deep Learning

Maqsood et al., 2022 conducted a survey which calibrates different approaches for predicting blood pressure using machine learning algorithms which involve linear regression, support vector machine, K-Nearest Neighbour (KNN), boosting algorithms and deep learning model which involves Recurrent Neural Networks (RNN) with Long-Short Term Memory (LSTM) Models and Bidirectional LSTM model and Convolutional Neural Network (CNN) based model with Siamese Network Architecture and Hybrid CNN-LSTM model. While LSTM models work well with time-dependent data, CNN models can potentially extract spectro-temporal features of the PPG signals. The authors also confer about six different datasets that are involved in the research survey that hosts the vital sign information of patients who are admitted to the critical care unit of hospitals and require continuous monitoring of the heart However, in this study, most of the papers are trying to predict the two features of the ABP signal which are Systolic Blood Pressure (SBP) which represents the pressure in the arteries when the heart contracts and pumps blood out and Diastolic Blood Pressure (DBP) which is the pressure in the arteries when the heart is at rest between beats.

Harfiya, Chang and Li, 2021 discuss the importance of estimating continuous blood pressure due to the rate at which the blood pressure changes within seconds. The authors used only PPG signals to determine the ABP signal using the LSTM model and LSTM-based autoencoders. The author briefly discusses the flow of an LSTM model and how it retains the memory using memory cells which constitute of 3 gates input, output, forget gate and a cell state. The cell state in LSTM allows information to flow, while the gates regulate interactions between memory units to decide whether to add or remove information. The forget gate, based on the previous memory cell output at the time (t-1) and the current input at a time (t), determines what information to detach from the cell state using a sigmoid function. The input gate, using both sigmoid and hyperbolic tangent functions, decides which values to update and stores candidate values in the cell state. The updated cell state is determined by combining the results of the forget gate and input gate operations. Finally, the output gate filters the cell state information to produce the output, adjusting the values to fall within the range of $[-1, 1]$ using sigmoid and hyperbolic tangent functions. The authors used two layers of the LSTM network, each layer with 128 units of LSTM and to prevent overfitting a dropout layer with a rate of 0.2 was kept.

Hamedani, Sadredini and Khodabakhshi, 2021 proposed a 1-D CNN model to capture the spatial representation in the PPG signal which helps in continuous ABP estimation through the PPG signal. CNNs are great at finding crucial patterns and features in data using convolutional layers. In signal processing, this helps them spot local patterns and features within signals.

In the proposed paper by Slapničar, Mlakar, and Luštrek (2019), they used a Spectro Temporal Deep Neural Network to estimate ABP signals using PPG signals. PPG signals are time series data reflecting blood volume changes due to the heart pumping. The network, like RNN or LSTM, models the temporal dependencies in PPG to learn patterns associated with ABP changes. The PPG signals were transformed into the frequency domain using the Fast Fourier Transform (FFT) to capture additional relevant information for ABP estimation. By combining both temporal and spectral information through a Spectro Temporal Deep Neural Network, it is possible that the model could learn complex patterns and relationships that aid in estimating ABP from PPG signals more accurately therefore, a hybrid CNN-LSTM was developed in the research.

Ibtehaz et al., 2022 to facilitate deep learning model training, the PPG and ABP signals were segmented out and bandpass filtering with global min–max normalization was performed. These segments were configured to have 1024 data points using Dirichlet rectangular windowing, catering to the requirements of deep learning frameworks. For filtering, a Butterworth filter with cutoff frequencies of 0.1 Hz and 30 Hz was employed. Notably, both PPG and ABP segments were separately normalized based on the global minimum and maximum values. This normalization is vital for deep learning models, as their sensitivity to high amplitude signals differs from classical machine learning models, especially when the input PPG exhibits lower amplitudes compared to the target ABP signals. Training the deep learning models with normalized ABP segments naturally yields normalized ABP segments during estimation.

In the study conducted by Baker, Xiang and Atkinson, 2022, distinct features were derived from both PPG and ECG signals. However, our research will primarily concentrate on the features extracted from PPG signals. These features encompass the determination of median peak height, trough depth, beat-to-beat (BTB) interval between consecutive peaks, wave height, and the duration of upward signal trajectory. Figure-1 shows the PPG Waveform and Features.

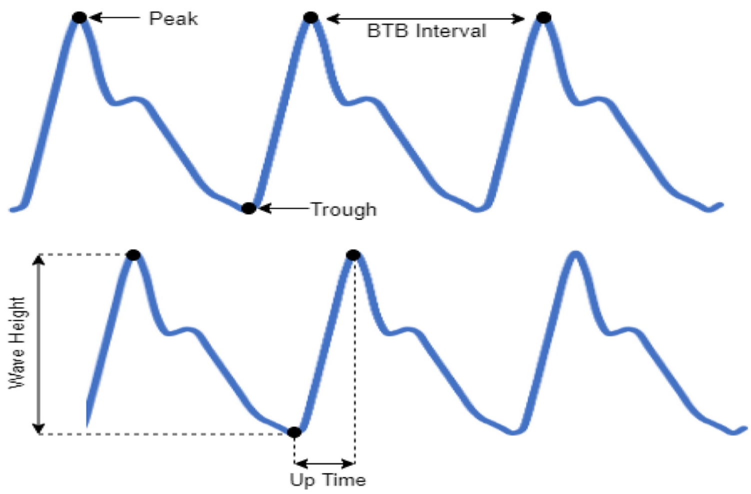

Figure-1 PPG Waveform and Features (Baker, Xiang and Atkinson, 2022)

Subsequently, the derived features from both the PPG and ECG signals are fed into a convolutional layer, followed by a forward-fed LSTM layer, culminating in the output layer. The model's efficacy was then assessed through two established benchmarks: the Advancement of Medical Instrumentation (AAMI) and the British Hypertension Society (BHS) protocol. This evaluation involved the computation of the mean absolute error and standard deviation of the model's predictions. In the forthcoming section, we will delve into the process of reconstructing ECG data using PPG signals.

2.2 Electrocardiogram (ECG) Estimation Using Deep Learning

Zhu et al., 2019 proposed a pilot study to recreate the ECG signal from the PPG signal, a transformation method is proposed using discrete cosine transform (DCT). This study helps in establishing a relationship between the ECG signal and the PPG signal. The signals are segmented and DCT values are obtained to match out the discrete components. Banerjee et al., 2014 proposed an approach where they predicted different components/ intervals of the ECG signal. An ECG signal is comprised of 3 intervals which are PR, QRS and QT intervals.

Cheng, Zou and Zhao, 2021 used a combination of CNN and the Bidirectional LSTM model to learn the representation of ECG signal using the filtering process with wavelet transform (WT) and median filter (MT).

2.3 Data Augmentation

Data augmentation is a technique of generating artificial data points from the original set of data. Aguirre et al., 2021 in their research performed data augmentation of ABP signals using two approaches which are the replacement of beats by artefacts and changes in the ABP baseline. Beats by artefacts involve simulating variations in ABP signals by introducing artificial artefacts that mimic real-world irregularities or noise. By replacing specific beats with these artefacts, the augmented dataset reflects scenarios where signal quality might be compromised due to measurement errors, sensor imperfections, or physiological anomalies. This augmentation technique can help the model learn to handle noise and outliers effectively, leading to improved performance when applied to actual ABP signals. The second approach focuses on perturbing the baseline of ABP signals. The baseline represents the average pressure level in the ABP waveform during periods of relative stability. The authors introduced controlled variations to the baseline, effectively simulating changes that could arise due to shifts in body position, posture, or other external factors. Augmenting the dataset with such variations enables the model to learn patterns that are relevant across different physiological contexts and conditions.

Tang et al., 2021 used a Generative adversarial network to perform data augmentation in signal modulation. It addresses the challenge of limited training data in deep learning-based radio signal classification by introducing the concept of using generative adversarial networks (GANs) for data augmentation. The GAN-based augmentation process involves generating additional realistic data samples that enhance the diversity and quantity of the training dataset. The positive impact of this augmentation is demonstrated through improved classification accuracy in signal-to-noise ratio scenarios, ultimately enhancing the effectiveness of deep learning models in radio applications.

Kumar et al., 2023 in their research proposed a novel data augmentation method which is Random Slices Mixing Data Augmentation which mixes two different data points through their segments. It comprises three different variations which are Random Slices Mixing Row-Wise (RSMDA-R) which refers to horizontal mixing, Random Slices Mixing Column-Wise (RSMDA-C) which refers to vertical mixing and Random Slices Mixing Row-Column-Wise (RSMDA-RC) which refers to horizontal and vertical both mixing.

3 Research Methodology

The research methodology followed to carry out this research KDD model was used due to the iterative nature of this process, which helped in continuous improvement in each iteration of the research. Figure-1 by Safhi, Frikh and Ouhbi, 2019 shows the steps that are followed to carry out the research.

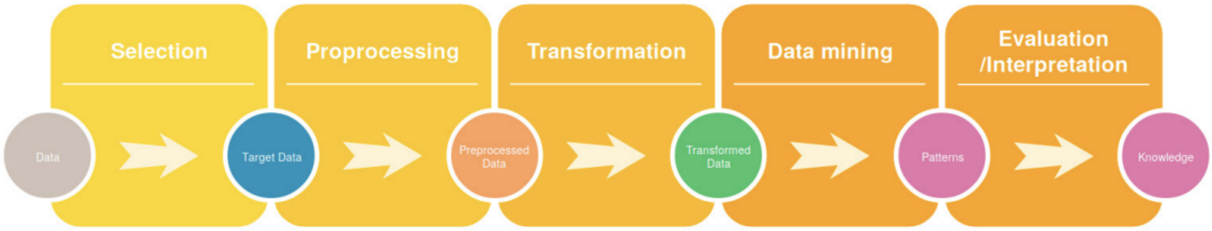

Figure-2 Knowledge Discovery Process (Safhi, Frikh and Ouhbi, 2019)

3.1 Data Selection

As surveyed by Maqsood et al., 2022 six different datasets have been used out of which MIMIC-III (Johnson et al., 2016) have been used in this research due to the volume of the data. The dataset includes the samples of 40000 adult patients with their physiological parameters of heart with PPG, ABP and ECG signals. As mentioned in Brophy et al., 2021 two open-source datasets were gathered from two sources which are Kaggle and the University of Queensland where the "Cuff-Less Blood Pressure Estimation dataset" from Kaggle[1] Kachuee et al., 2017 was used as a training dataset and "The University of Queensland Vital Signs Dataset" from University of Queensland[2] is used for evaluation to interpret the performance of the research. The training dataset was divided into 12 parts of 'mat' files where each signal was gathered at 125 Hz. The dataset contains an array of cell matrices where each row corresponds to different signals which are PPG, ABP and ECG.

3.2 Data Preprocessing

Data preprocessing is essential for extracting meaningful patterns and insights from PPG, ABP, and ECG signals and building accurate predictive models. It ensures data quality, enhances feature extraction, reduces noise, and aligns the data, leading to more reliable and interpretable results for predicting cardiovascular signals from PPG data.

- Few null values have been found in a few of the array cell matrices of the ECG signal which were replaced by the mode of the array using the 'SciPy stats' module in Python. By using the mode to replace null values, the resulting data points are more representative of the typical values observed in the ECG signal.
- The data is scaled using a min-max scaler as stated by Ibtehaz et al., 2022 to avoid biases and to limit the impact of outliers as it uses the range of the data to scale the features.

[1] https://www.kaggle.com/datasets/mkachuee/BloodPressureDataset
[2] https://outbox.eait.uq.edu.au/uqdliu3/uqvitalsignsdataset/index.html

3.3 Data Exploration and Visualization

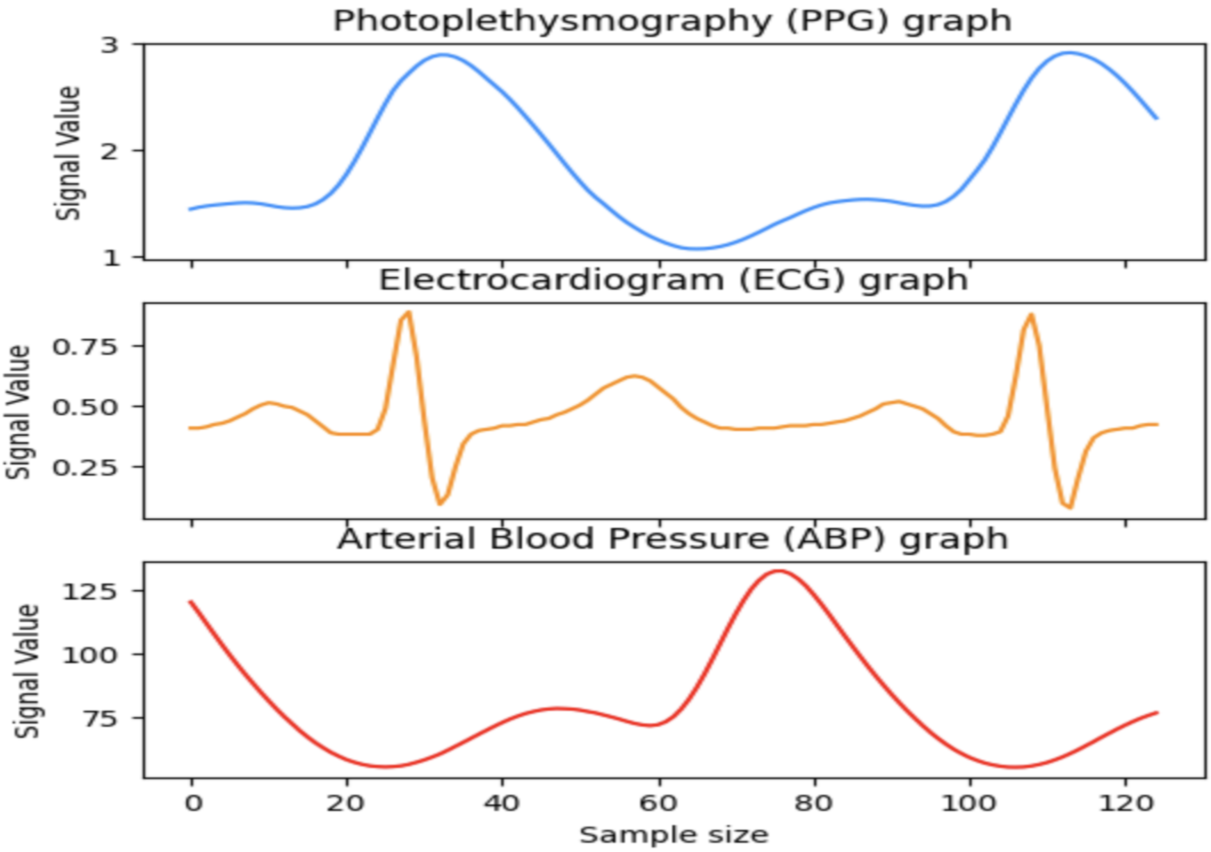

Figure-3 PPG, ECG and ABP signal sampled at 125 Hz

The above figure represents the Photoplethysmography (PPG) signals, Electrocardiogram (ECG) signals, and Arterial Blood Pressure (ABP) signals within a 1-second timeframe. Notably, an observable distinction arises in the signal ranges of PPG, ABP, and ECG. This variation in amplitude across these signals highlights the diversity in their respective signal magnitudes. A pertinent insight emerges from the research of Singh and Singh, 2022, underscoring the significance of feature normalization when dealing with deep learning models. This normalization process becomes imperative as it fosters several benefits, including accelerated convergence during model training, the establishment of stable gradients, and the enhancement of model generalization to previously unseen data instances. By acknowledging and implementing feature normalization, the research seeks to optimize the overall performance and robustness of deep learning models in the context of these diverse signals.

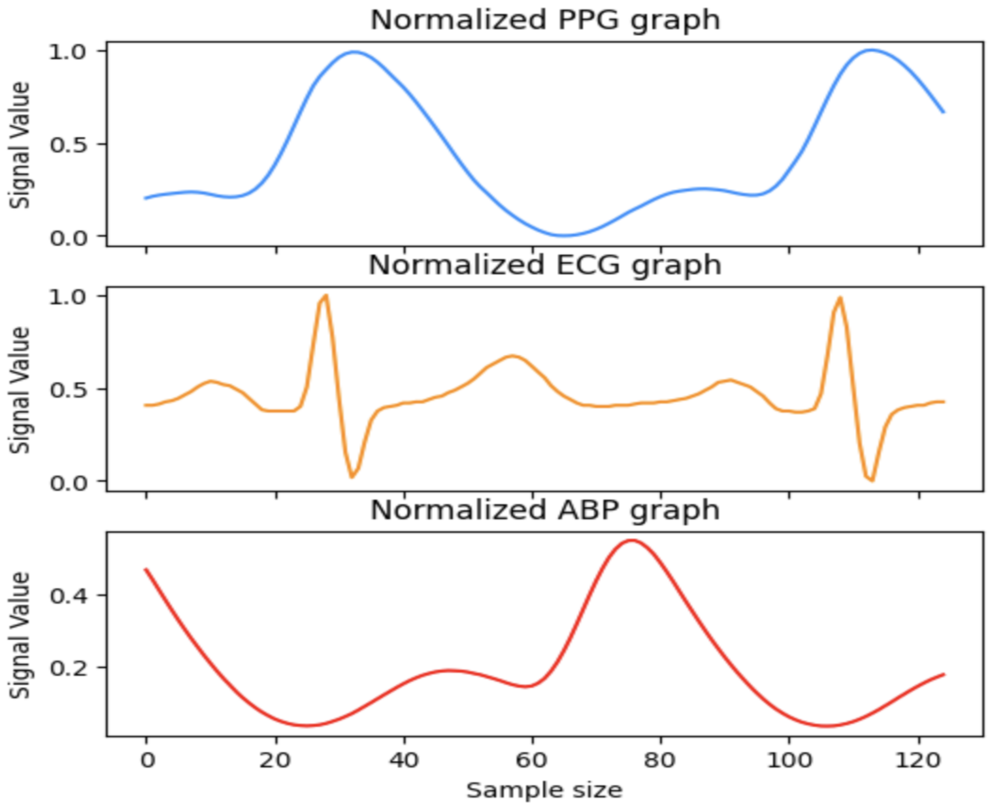

Figure-4 PPG, ECG and ABP Normalized using Min-Max Scaler

In the above figure it can be observed that the signal values PPG, ECG and ABP signal are normalized using min-max scaler, and the range of the signal values now range from 0 to 1.

To infer the relationship between the signals, the Pearson Correlation test has been performed where the correlation coefficient is as follows:

- Correlation between PPG and ECG signals: -0.125 This correlation is close to 0, suggesting a weak negative correlation between ECG and PPG signals. It means that the two signals have a slight tendency to move in opposite directions, but the relationship is not strong.
- Correlation between PPG and ABP signals: -0.241 The correlation between PPG and ABP signals is slightly stronger than the correlations with ECG. It is still negative, indicating a weak inverse relationship between PPG and BP signals.

3.4 Feature Extraction

The dataset is collected at a sampling frequency of 125 Hz, which means that every second there are 125 data points. A signal size of 1000 has been chosen to provide a reasonable number of training samples while not overwhelming the model's complexity. Having too few training samples might lead to overfitting, while too many samples might make the training process slower and more resource intensive. Therefore, each series of size 1000 values have been extracted which effectively captures data from a span of 8 seconds. This selection of 1000 values provides us with information over a specific time window, enabling analysis or processing of data within that 8-second interval.

3.5 Dataset Preparation

The dataset was split into training and testing data using the train-test split method used in the 'scikit-learn[3]' library in Python. For the training set 70% of the dataset was considered while to evaluate the deep learning models 30% of the dataset was considered.

3.6 Data Mining

The considerable dataset volume presents a promising opportunity to effectively deploy deep learning models. This advantage was harnessed in a survey conducted by Maqsood et al., 2022, specifically highlighted in Section – 2.1. In this study, we undertook an investigation utilizing three distinct deep learning models: Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Hybrid CNN-LSTM. To facilitate the implementation of these models, the 'TensorFlow' functional API was leveraged. This API allows for the creation of complex neural network architectures with multiple outputs, which aligns with the nature of the study's goals. The models were meticulously designed to incorporate this multi-output structure, enabling them to capture and predict various features simultaneously. In the experimentation phase, the models were subjected to training and evaluation processes. One crucial aspect of this research was the utilization of augmented data during the evaluation. Augmented data involves introducing artificially generated variations of the original dataset to fortify the model's ability to generalize across different scenarios. This augmentation technique helps to assess the robustness and stability of the models when faced with limited data availability. By validating the models' performance using augmented data, it was aimed to ascertain whether the models' predictive capabilities remain consistent even in cases where the dataset is relatively small.

4 Design Specification

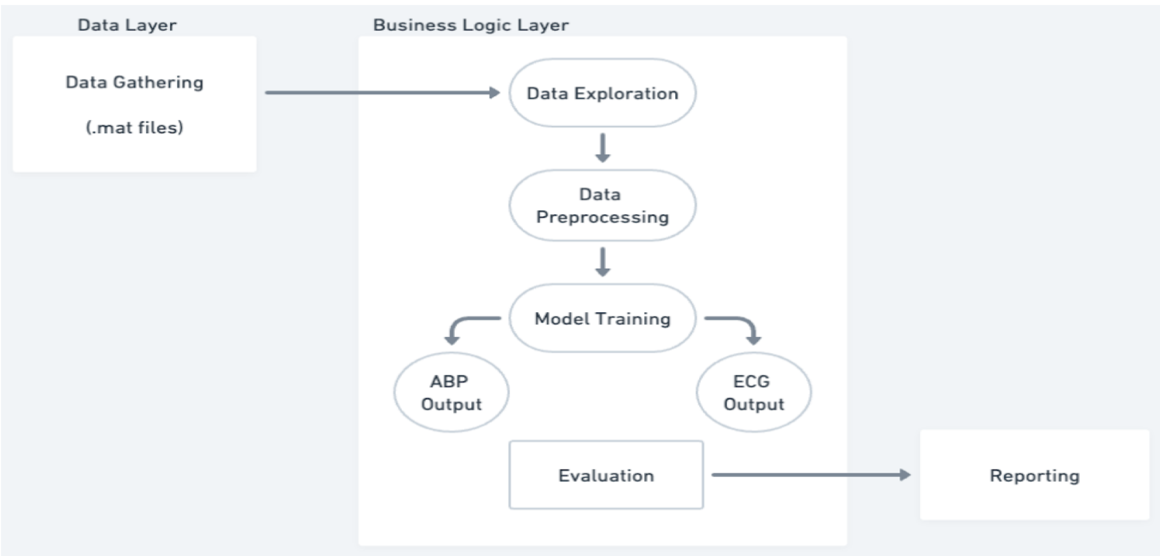

Figure-5 Design Specification[4]

[3] https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html
[4] https://whimsical.com/

Data Layer: In the data layer of the design specification, the initial dataset is available in the form of '.mat files', which contain various physiological signal data which includes PPG, ECG and ABP. The data within these files is the foundation for the subsequent analysis. To make this data usable for analysis, it needs to be processed and loaded into the system.

Business Logic Layer: This layer is where the real analysis and model development takes place. Once the data is loaded into the system, it's then explored and cleaned. Exploring the data involves understanding its structure, distribution, and potential issues. Cleaning the data is essential to remove any inconsistencies, missing values, or outliers that could adversely affect the subsequent analysis. In this layer, deep learning models are created. These models are designed with a specific architecture involving a single input, in this case, a PPG signal and multiple outputs (ABP and ECG). To build these models, the 'TensorFlow' [5] functional API is utilized. TensorFlow is a popular framework for building and training machine learning and deep learning models. The developed models are then trained using the preprocessed data. The training process involves exposing the models to the dataset and adjusting their parameters to learn patterns and relationships within the data. After training, the models are evaluated using a separate portion of the dataset that was set aside specifically for this purpose. This evaluation helps assess how well the models generalize to new, unseen data and how accurately they make predictions or classifications.

Reports and Visualization: After training and evaluating the models, it's important to gain insights into their performance and behaviour. This is where reports and visualization come into play. The 'Matplotlib' library is used to generate various types of visualizations that allow researchers and analysts to understand the model's performance visually. These visualizations include graphs showing the model's predictions compared to the actual values, histograms of errors, and other relevant plots. Reports might summarize the key findings from the analysis, including the performance metrics like Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) for different scenarios. These insights provide a deeper understanding of how well the models are performing and what areas might need improvement.

5 Implementation

5.1 Implementation Tools

To implement the project Python language with ‘Jupyter Notebooks’ has been used due to the flexibility of running the block of codes individually. AWS EC2 instance r5.4xlarge which is designed to provide high memory capacity suitable for memory-intensive workloads has been used to perform deep learning model training with Ubuntu OS, 16 vCPU and 128 GB RAM. This service is provided by the National College of Ireland[6].

[5] https://www.tensorflow.org/guide/keras/functional_api
[6] https://cloud.ncirl.ie/

5.2 Model Building

Convolutional Neural Network (CNN): CNNs can automatically learn meaningful features from raw input data without the need for manual feature engineering. In the case of PPG signals, which contain complex temporal patterns and variations, CNNs can automatically extract relevant features that are useful for predicting ECG and ABP. The below figure shows the architecture for CNN model layers and the number of training parameters.

```
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_1 (InputLayer)           [(None, 1000, 1)]    0           []

 conv1d (Conv1D)                (None, 998, 256)     1024        ['input_1[0][0]']

 max_pooling1d (MaxPooling1D)   (None, 499, 256)     0           ['conv1d[0][0]']

 conv1d_1 (Conv1D)              (None, 497, 128)     98432       ['max_pooling1d[0][0]']

 max_pooling1d_1 (MaxPooling1D)  (None, 248, 128)    0           ['conv1d_1[0][0]']

 conv1d_2 (Conv1D)              (None, 246, 64)      24640       ['max_pooling1d_1[0][0]']

 max_pooling1d_2 (MaxPooling1D)  (None, 123, 64)     0           ['conv1d_2[0][0]']

 flatten (Flatten)              (None, 7872)         0           ['max_pooling1d_2[0][0]']

 bp_out (Dense)                 (None, 1000)         7873000     ['flatten[0][0]']

 ecg_out (Dense)                (None, 1000)         7873000     ['flatten[0][0]']

==================================================================================================
Total params: 15,870,096
Trainable params: 15,870,096
Non-trainable params: 0
```

Figure-6 CNN Architecture

It begins with input sequences of length 1000, each containing one piece of information. These sequences are then processed through a series of convolutional layers (conv1d), where each layer transforms the data to capture relevant features. After each convolutional layer, a max pooling layer (max_pooling1d) reduces the dimensions of the data to focus on the most important information. This process is repeated with multiple convolutional and max pooling layers to progressively extract finer details. The last step involves flattening the data, which means reshaping it into a one-dimensional form. This flattened data is then fed into two separate dense layers named "bp_out" and "ecg_out". The "bp_out" layer predicts blood pressure, while the "ecg_out" layer predicts electrocardiogram values. Each dense layer generates a sequence of 1000 values based on the flattened data.

Long Short-Term Memory Model (LSTM): LSTM networks are a type of recurrent neural network (RNN) that have become popular for sequence prediction tasks, especially when dealing with time series data. PPG signals are inherently sequential data, representing changes in blood volume over time. LSTMs are well-suited for handling time series data and can effectively model the temporal dependencies and patterns present in PPG signals. The below figure shows the LSTM Model architecture.

```
___________________________________________________________________________________________________
 Layer (type)                   Output Shape          Param #     Connected to
===================================================================================================
 input_1 (InputLayer)           [(None, 1000, 1)]     0           []

 lstm (LSTM)                    (None, 1000, 64)      16896       ['input_1[0][0]']

 dropout (Dropout)              (None, 1000, 64)      0           ['lstm[0][0]']

 lstm_1 (LSTM)                  (None, 32)            12416       ['dropout[0][0]']

 bp_out (Dense)                 (None, 1000)          33000       ['lstm_1[0][0]']

 ecg_out (Dense)                (None, 1000)          33000       ['lstm_1[0][0]']

===================================================================================================
Total params: 95,312
Trainable params: 95,312
Non-trainable params: 0
___________________________________________________________________________________________________
```

Figure-7 LSTM Architecture

This model is designed to work with physiological signals, like predicting blood pressure and electrocardiogram signals. It starts with input sequences of 1000 time steps, each containing one piece of information. These sequences go through a main layer called LSTM, which creates a sequence of 64 hidden units for each time step. To prevent overfitting, a dropout layer is used to deactivate some of these units during training. After that, a second LSTM layer comes after the dropout layer, refining the output to a sequence of 32 hidden units. This refined sequence is then sent to two different layers called "bp_out" and "ecg_out". The "bp_out" layer predicts blood pressure, while "ecg_out" predicts electrocardiogram values. Each of these layers generates a sequence of 1000 values per batch sample, based on the data processed by the second LSTM layer. In simple terms, this model aims to predict physiological readings using a step-by-step process involving special LSTM layers and dense layers.

Hybrid CNN-LSTM Model: As discussed in section-2.1 by Baker, Xiang and Atkinson, 2022, CNNs are excellent at capturing spatial features within data, making them well-suited for tasks involving images, and time-series data and LSTM on the other hand excel at capturing temporal dependencies and long-range patterns in sequential data. The below figure shows the implementation of the Hybrid CNN-LSTM model.

```
Layer (type)                      Output Shape          Param #     Connected to
==================================================================================================
input_1 (InputLayer)              [(None, 1000, 1)]     0           []

conv1d (Conv1D)                   (None, 998, 256)      1024        ['input_1[0][0]']

max_pooling1d (MaxPooling1D)      (None, 499, 256)      0           ['conv1d[0][0]']

conv1d_1 (Conv1D)                 (None, 497, 128)      98432       ['max_pooling1d[0][0]']

max_pooling1d_1 (MaxPooling1D)    (None, 248, 128)      0           ['conv1d_1[0][0]']

conv1d_2 (Conv1D)                 (None, 246, 64)       24640       ['max_pooling1d_1[0][0]']

max_pooling1d_2 (MaxPooling1D)    (None, 123, 64)       0           ['conv1d_2[0][0]']

reshape (Reshape)                 (None, 123, 64)       0           ['max_pooling1d_2[0][0]']

lstm (LSTM)                       (None, 100)           66000       ['reshape[0][0]']

bp_out (Dense)                    (None, 1000)          101000      ['lstm[0][0]']

ecg_out (Dense)                   (None, 1000)          101000      ['lstm[0][0]']

==================================================================================================
Total params: 392,096
Trainable params: 392,096
Non-trainable params: 0
__________________________________________________________________________________________________
```

Figure-8 Hybrid CNN-LSTM Architecture

The input consists of sequences with a length of 1000, each containing a single feature. These sequences go through a series of convolutional layers (conv1d), which capture relevant patterns within the data. Subsequent max pooling layers (max_pooling1d) then reduce the dimensions, focusing on key information. Multiple convolutional and max pooling layers are utilized to progressively uncover more detailed patterns. Afterwards, the data is reshaped to prepare it for an LSTM layer, a type of recurrent neural network that captures temporal dependencies. The LSTM layer processes the reshaped data and produces an output sequence of 100 units, capturing complex temporal relationships. This output is used for predicting both blood pressure (bp_out) and electrocardiogram (ecg_out) values using separate dense layers.

5.3 Data Augmentation

TensorFlow provides a function called "Sequence" which is used to implement data augmentation. It is also designed to handle the process of data loading and batching and perform data augmentation for machine learning models, particularly when dealing with large datasets that may not fit entirely in memory. It's particularly useful when you need to train deep learning models on large datasets while efficiently managing memory usage. This function helps in generating the augmented data on the fly without necessarily loading the whole dataset into the memory.

6 Evaluation

The models are evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) which can be observed in the Results in Table-1. MAE measures the average absolute difference between predicted values and actual values. It provides a straightforward understanding of the average magnitude of errors in the predictions. MAE is robust to outliers and treats all errors equally, making it suitable to understand the average accuracy of the model. RMSE also quantifies the errors between predicted and actual values, but it considers the squared differences between these errors. By squaring the errors, RMSE penalizes larger errors more heavily than MAE. This makes RMSE more sensitive to outliers and helps emphasize the impact of larger errors on the overall performance of the model. The combined consideration of both MAE and RMSE provides a more comprehensive evaluation. Moreover, the models are evaluated based on Normalized, Non-Normalized and Data Augmented signal values to infer the model's performance with different experiments.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Predicted_i - Actual_i)^2}{N}}$$ where, N is the total number of data points

$$MAE = \frac{\sum_{i=1}^{n} \left|Predicted_i - Actual_i\right|}{N}$$ where, N is the total number of data points

Predicted Signal	**Experiment**	**Root Mean Square Error (RMSE)**	**Mean Absolute Error (MAE)**
LSTM Model results			
Arterial Blood Pressure (ABP)	Non-Normalized	80.44	75.31
	Normalized	0.2173	0.1816
	Data Augmentation	0.2207	0.1691
Electrocardiogram (ECG)	Non-Normalized	0.6169	0.4689
	Normalized	0.1933	0.1460
	Data Augmentation	0.2076	0.1391
CNN Model results			
Arterial Blood Pressure (ABP)	Non-Normalized	18.339	14.0131
	Normalized	0.1138	0.0844
	Data Augmentation	**0.1087**	**0.0808**
Electrocardiogram (ECG)	Non-Normalized	1.2179	0.9459
	Normalized	0.1781	0.1332
	Data Augmentation	**0.1721**	**0.1293**
Hybrid CNN-LSTM Model results			
Arterial Blood Pressure (ABP)	Non-Normalized	56.7733	49.1812
	Normalized	0.2853	0.2452
	Data Augmentation	0.4469	0.3705
Electrocardiogram (ECG)	Non-Normalized	0.5903	0.4720
	Normalized	0.3105	0.2793
	Data Augmentation	0.2194	0.1762

Table-1 RMSE and MAE scores for different deep learning models

6.1 Prediction Graphs of LSTM Model

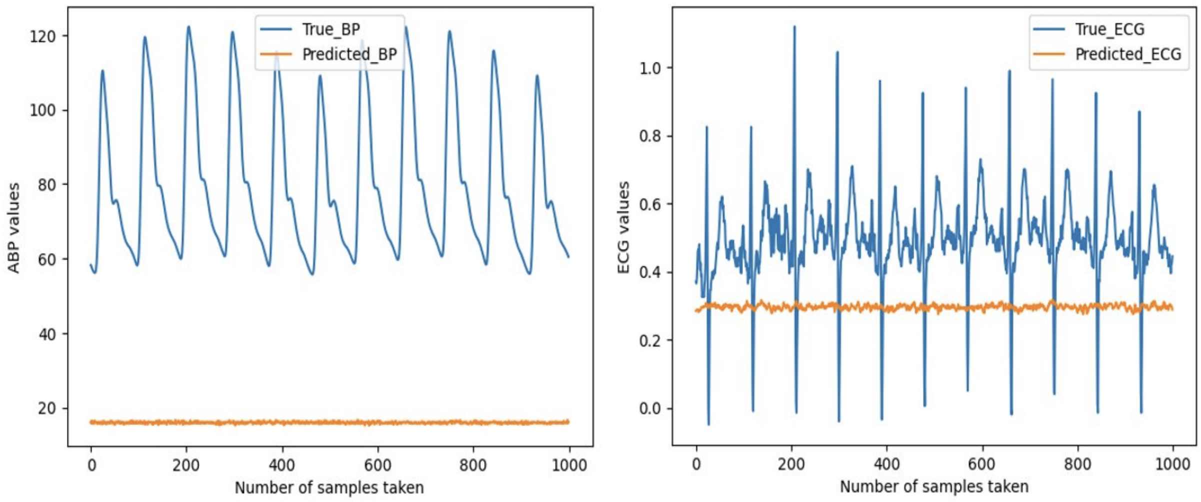

Figure-9 Non-Normalized Predicted & Actual ABP and ECG Values for LSTM

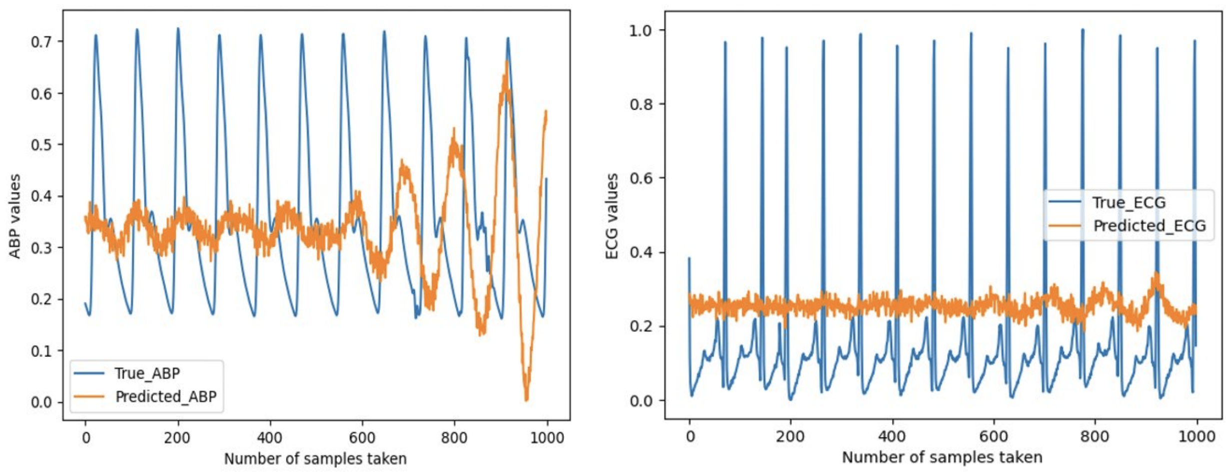

Figure-10 Normalized Predicted & Actual ABP and ECG Values for LSTM

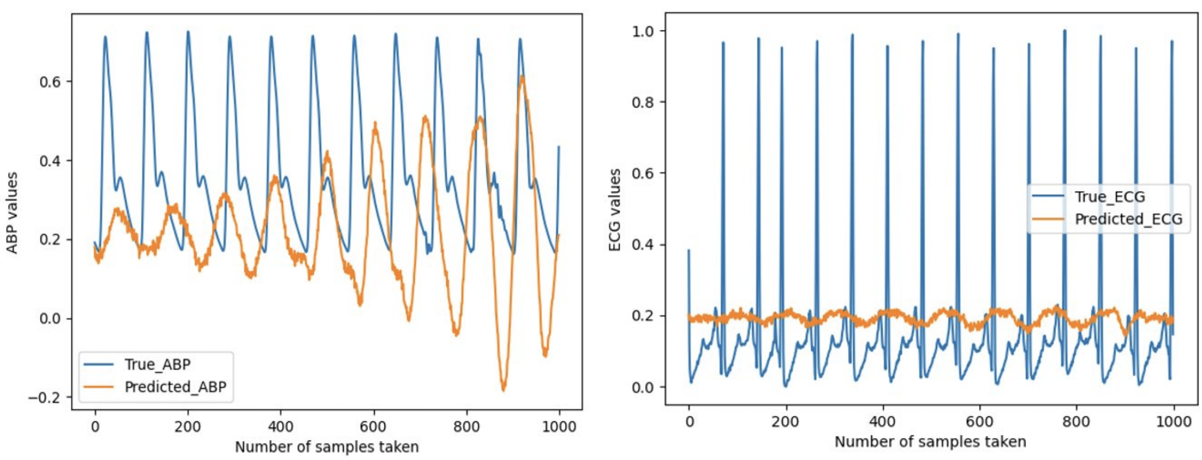

Figure-11 Augmented Predicted & Actual ABP and ECG Values for LSTM

6.2 Prediction Graphs of CNN Model

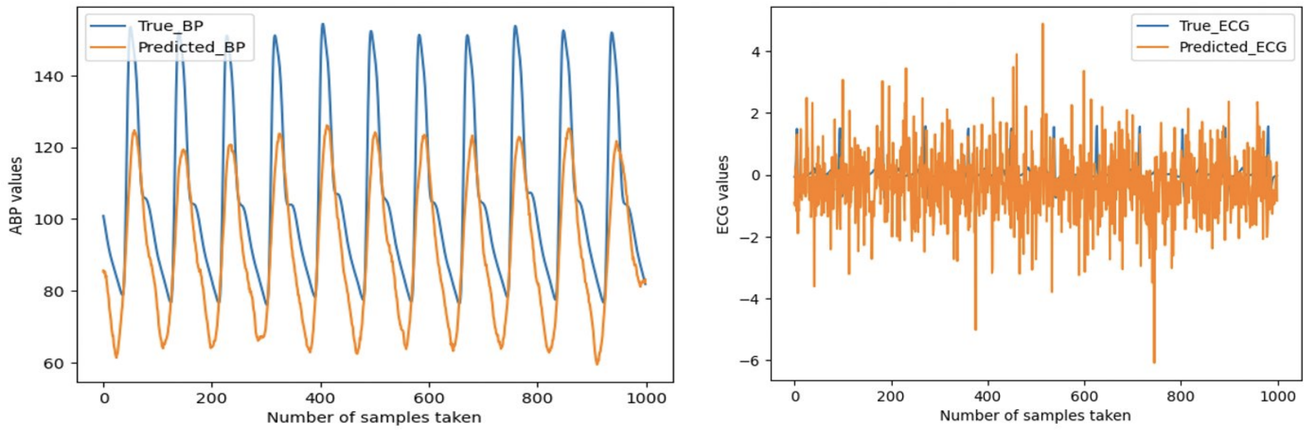

Figure-12 Non-Normalized Predicted & Actual ABP and ECG Values for CNN

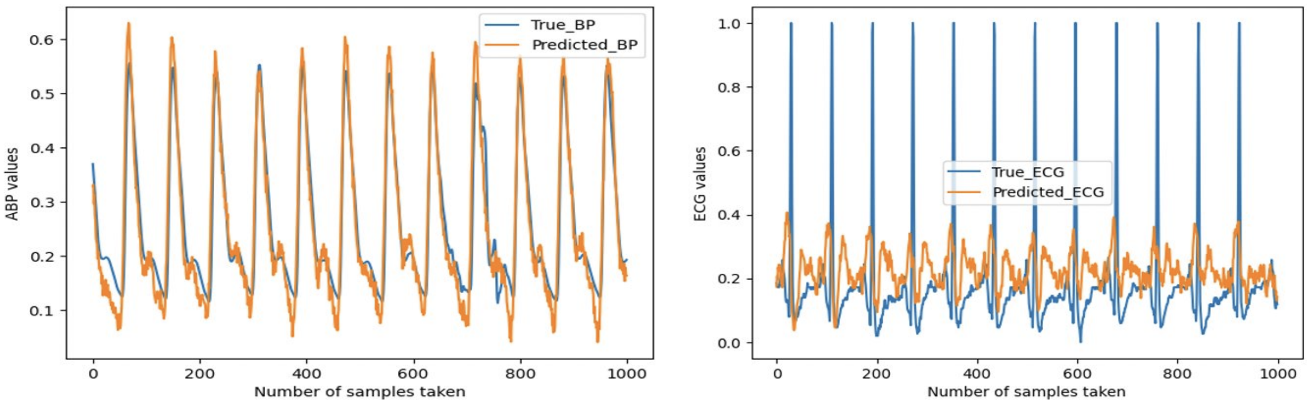

Figure-13 Normalized Predicted & Actual ABP and ECG Values for CNN

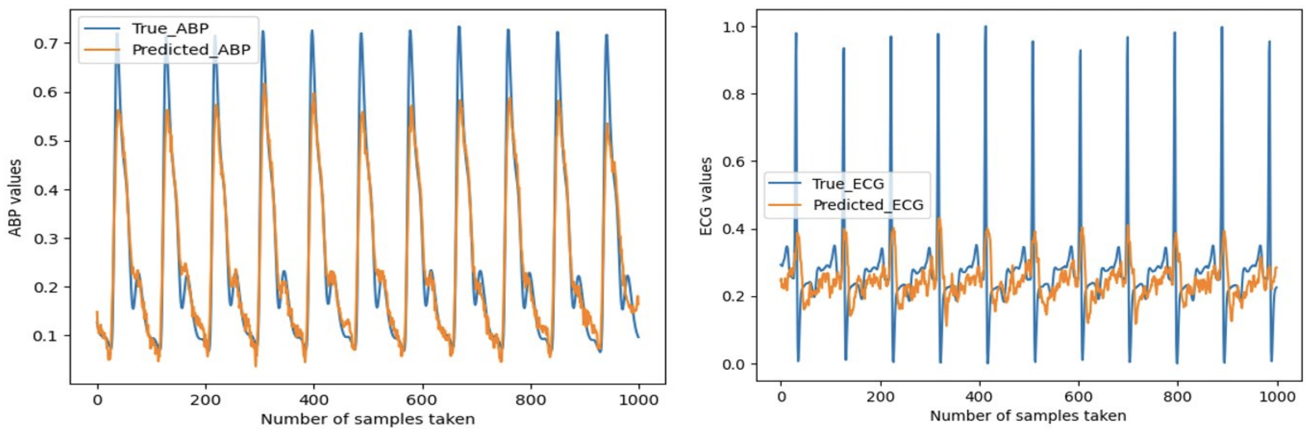

Figure-14 Augmented Predicted & Actual ABP and ECG Values for CNN

6.3 Prediction Graphs of Hybrid CNN-LSTM Model

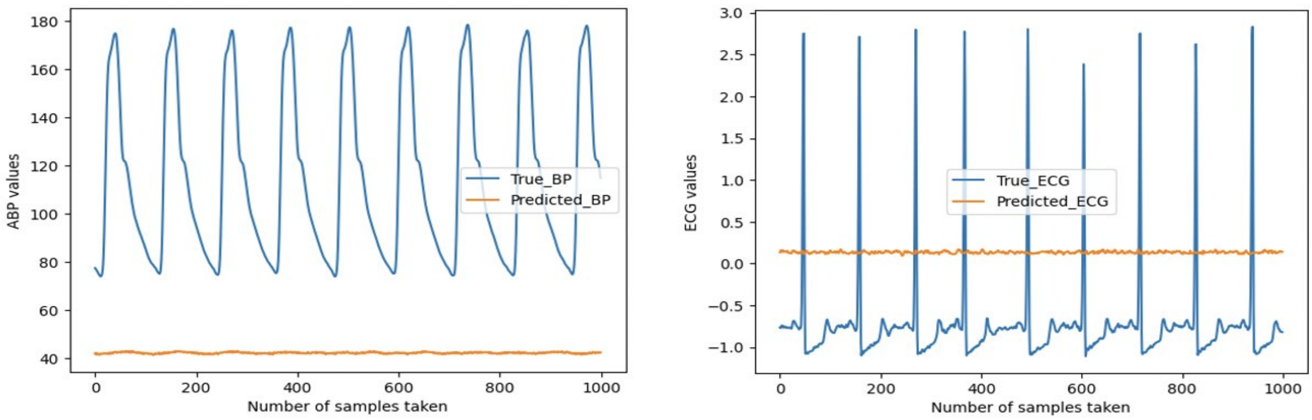

Figure-15 Non-Normalized ABP and ECG Values for Hybrid CNN-LSTM

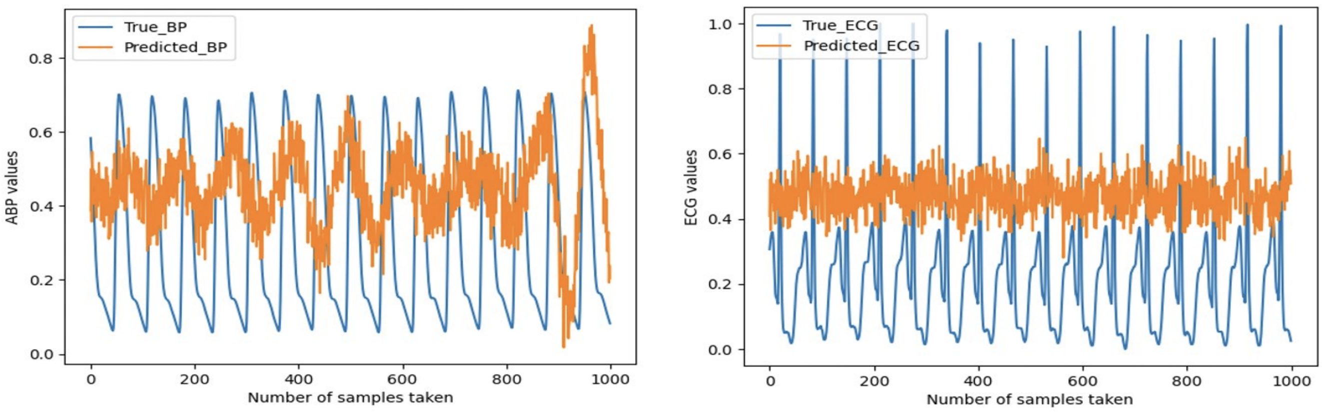

Figure-16 Normalized ABP and ECG Values for Hybrid CNN-LSTM

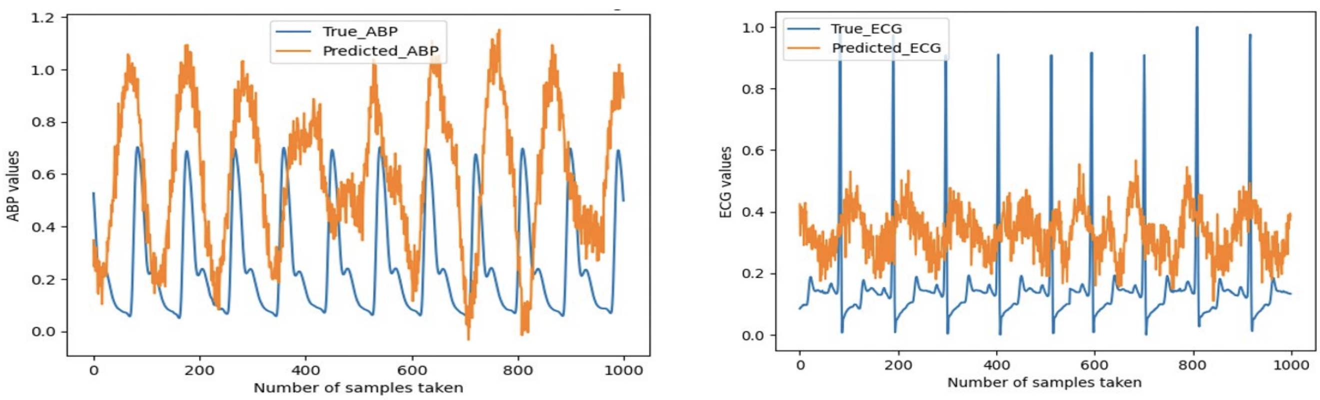

Figure-17 Augmented ABP and ECG Values for Hybrid CNN-LSTM

6.4 Discussion

The above table (Table-1) presents the results of an experiment that evaluates the performance of different models in predicting physiological signals, specifically Arterial Blood Pressure (ABP) and Electrocardiogram (ECG) signals. The evaluation metrics used are Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), which are standard measures of how well a model's predictions match the actual data. In the conducted research, an LSTM model, a CNN model, and a Hybrid CNN-LSTM model are being compared and each model is tested under different conditions (Non-Normalized, Normalized, and with Data Augmentation).

In section 6.1 the graphs demonstrate the result of the long short-term memory (LSTM) model, Figure-9 it can be observed that the LSTM model with non-normalized signal values has very little fluctuation in predicting both ABP and ECG signals. This shows that the LSTM model with non-normalized signal values is under-fitted and is unable to capture any pattern. Figure-10, shows a graph of normalized signal values where it can be observed that the LSTM model is trying to capture a few patterns both for ABP and ECG signals because of the finite range of the signal values. In Figure-11, the model is able to capture more complex patterns because of the diversity added by the data augmentation. From these three graphs, it can be concluded that LSTM does not perform well using the smaller number of data points.

In section 6.2, the graphs demonstrate the capability of the convolutional neural network (CNN) model to predict the ABP and ECG signal, Figure-12 shows the predicted and the actual value for the CNN model it can be observed that even though the signals were not normalized, the CNN is able to capture the patterns as in the wave height and width of the ABP signal and for ECG we can observe a lot of fluctuations due to the varying range of the signals. In Figure-13 by normalizing the signals we can observe that the predictions have been improved and CNN is able to capture the complex patterns of ABP signals, however, for ECG signals some variations can be observed but the patterns are not aligned with the actual values. In Figure-14 with augmented data, we can observe that the variations and patterns are mostly aligned with the actual values of both ABP and ECG signals which shows the ability of the CNN to learn and generalize the predictions using the data augmentation.

In section 6.3, the graphs show the performance of the hybrid CNN-LSTM model. Figure-15 shows the result of the hybrid CNN-LSTM model when the signals are not normalized and it can be observed that the model is unable to learn the patterns present in the signal. However, when the signals are normalized we can observe the variations in the prediction of the hybrid CNN-LSTM model but still, there are a lot of errors. Similar errors and trends can be observed in Figure-17 with augmented data.

7 Conclusion and Future Work

Owing to the first research question mentioned in Section-1.2 “How effectively two physiological parameters (ABP and ECG) can be predicted using only one physiological parameter (PPG) using deep learning?”, it is evident that CNN with augmented data points can capture ABP and most segments of ECG signals from PPG signal. When comparing CNN with the other two models (LSTM and Hybrid CNN-LSTM) the former model outperformed the latter models showing RMSE of 0.1087 and MAE of 0.0808 for predicting ABP and RMSE of 0.1721 and MAE of 0.1293 for predicting ECG with data augmentation.

For the second research question mentioned in Section-1.2 “Using minimum patients' data, is it possible to achieve stable accuracy?”, Data Augmentation is a fair approach to add diversity to the small segment of the training data as seen in the evaluation tables in section-6.1, 6.2 and 6.3.

The publicly available Kaggle dataset was split into train and test datasets. Additionally, only feature extraction, scaling, and data augmentation were performed on the recovered data. The test dataset's relevance to real-world scenarios contributes to the acceptable performance of the research’s approach. We might achieve better outcomes, with more effort put into cleaning and preparing the datasets. As real-world data is often messy and noisy, making it hard to work with, the dataset was used without much cleaning for this project. In the upcoming effort, the aim would be to make these models better.

The future task at hand will be to determine whether it is feasible to extract and predict the electrocardiogram and arterial blood pressure signals from the photoplethysmography signal using the transformer. Finding out and analysing how the Photoplethysmography (PPG) signal can be represented contextually and combined with a sequence-to-sequence model (transformer) to obtain Arterial Blood Pressure and Electrocardiogram data will be interesting.

The upcoming effort will be a small portion of broader research that will assess how much Sequence-to-Sequence modelling, which is utilized in Natural Language Processing, may be applied to Non-Language Sequence data.

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