Certification

I am pleased to certify that **Marufa Yeasmin Misu** , examination Roll number: **1818047**, Reg. number: **1345**, has performed a Project entitled **"Comparative Analysis of Machine Learning Approaches for Non-invasive Blood Pressure Prediction."** under my supervision in the academic year 2018-2019 for the fulfillment of partial requirements of B.Sc. (Engg.) degree . So far as I concern this is an original Project work that he carried out for one year in the Department of Information and Communication Technology, Islamic University, Kushtia-7003, Bangladesh.

I strongly declare that this project has not been copied from any other project or submitted to elsewhere prior submission to this department.

Signature of the Supervisor

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Abstract

Accurate and non-invasive estimation of blood pressure (BP) is crucial for monitoring cardiovascular health and early detection of related disorders. This study investigates the use of photo plethysmography (PPG) and electrocardiogram (ECG) signals for estimating BP values through deep learning techniques. Two modeling approaches, linear regression and neural networks, are explored and evaluated for their ability to capture the complex relationships between the input physiological signals and the target BP values. The linear regression model is first employed as a baseline, utilizing five-fold cross-validation to assess its performance. While the model exhibits consistent results across different data subsets, with an average Root Mean Squared Error (RMSE) of 27.34, visualizations reveal deviations between the predicted and true BP values, suggesting the need for more sophisticated modeling techniques. To address these limitations, a neural network architecture is implemented, consisting of multiple dense layers, dropout layers, and non-linear activation functions. After training on a subset of the data, the neural network model (FNN) achieves an improved RMSE of 26.28 on the test set, outperforming the linear regression model. Comparative analysis of the two approaches highlights the superiority of the neural network model (FNN) in capturing non-linear relationships and providing more accurate BP predictions. However, both models exhibit non-negligible errors, indicating the need for further improvements and validation before practical deployment in healthcare applications. The findings of this study demonstrate the potential of machine learning techniques for vital parameter estimation from physiological signals. While the neural network model emerges as a promising approach, continued research and development are necessary to address remaining limitations and enhance the models' accuracy, interpretability, and practical applicability in healthcare settings.

Keywords: *Blood pressure estimation, photo plethysmography, electrocardiogram, machine learning, linear regression, neural networks, physiological signals, non-invasive monitoring*.

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1. Introduction

Vital parameter monitoring plays a crucial role in assessing an individual's health status and detecting potential abnormalities. Conventional methods for measuring vital signs, such as blood pressure, heart rate, and oxygen saturation, often involve obtrusive and cumbersome equipment, which can be uncomfortable for patients and challenging to use in remote or resource-constrained settings. Blood pressure (BP) is a recognized risk factor for cardiovascular diseases and an important indicator for diagnosing, preventing, and treating these conditions. Currently, BP is primarily measured using cuff-based methods (Sierra, 2017). They take about one to two minutes to produce one set of diastolic blood pressure (DBP) and systolic blood pressure (SBP) measurements before making another measurement. This type of measurement can be time-consuming and is often inaccurate.

Figure 1 Traditional blood pressure measurement device

In the past few years, various research groups have attempted numerous techniques in order to achieve cuff less BP measurement. The key measuring principle for cuff less BP estimation is based upon the time taken by a pulse from the heart to the finger (Buxi et al., 2015), they are known as pulse transit time (PTT) or pulse arrival time (PAT). The fundamental principle of the traditional approach to obtaining physiological data from PPGs and ECGs, which mainly depends on the pulse wave velocity (PWV) hypothesis. PWV, or pressure wave velocity, is the pulse of pressure that is started by the heartbeat and travels through arteries like an elastic-walled pipe. PWV and BP have been shown to be substantially correlated, and their correlation can be shown as :

$$PWV = \sqrt{\frac{E.h}{2.r.\rho}}$$

Where r, h, E and ρ denote the radius of the artery, the thickness of the artery, the elastic modulus of the arterial wall and the density of blood in of the artery, respectively. While there are a number of methods currently available for calculating PWV, pulse wave transit time, or pulse transit time (PTT), is the most frequently used methodology. The following is a representation of the relationship between PWV and PTT :

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

Where PTT is the time interval between a pulse wave being detected by two sensors and d is the distance between the sensors on the artery. From a theoretical standpoint, it could appear simple, but in practice, it would be quite difficult to implement because it is impossible to obtain all of the person-dependent data quickly. The alternative method involves taking the relative location of the ECG and PPG signals and extracting a set of representative time indices, such as PTT (p), PTT (d), and PTT (f), as seen in Figure 2. But given that the ECG waveform, in particular, has greater variability and its accuracy is still restricted for clinical applications, it remains a very difficult task.

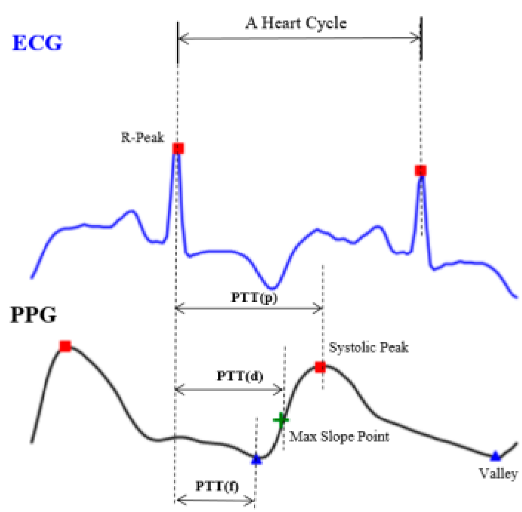

Figure 2 The expedient solution from engineers, including pulse transit time (PTT) (p), PTT (d) and PTT (f).

Other researchers used vascular transit time (VTT) which was calculated from the time difference between photoplethysmography (PPG) measured at the fingertip and phonocardiograph measured at the chest (Ding et al., 2017). Using data from several pressure sensors on the radial artery tree, the tonometry approach was also used to monitor cuffless blood pressures (Gesche et al., 2016). Using modified normalized pulse volume and heart rate, another group of researchers devised the cuffless BP measuring technique (Kachuee et al., 2017). For the purpose of estimating cordless blood pressure, pulse wave velocity (PWV) has also been measured using a variety of magnetic sensors. The algorithms outlined above required at least two sensors (Wan-Hua et al., 2017), which made the cuffless BP devices unsuitable for actual wearable applications even though some of them attained overall acceptable accuracy. Therefore, creating a single PPG-based cuffless BP estimation algorithm that is accurate enough would be beneficial in both clinical and practical contexts.

Photoplethysmography (PPG) has emerged as a non-invasive and cost-effective technique for monitoring vital signs by analyzing the changes in light absorption in the blood vessels caused by the pulsatile nature of the cardiovascular system. PPG signals, obtained using simple optical sensors, contain valuable information about various physiological parameters, including heart rate, respiratory rate, and blood oxygen saturation (Shukla et al., 2015). However, the accurate extraction of these parameters from PPG signals can be challenging due to various factors, such as motion artifacts, sensor noise, and individual physiological variations. Traditional signal processing techniques may not be robust enough to handle these complexities, leading to inaccurate or unreliable vital parameter estimations. Deep learning, a branch of machine learning that employs artificial neural networks, has shown remarkable success in various domains, including signal processing and biomedical engineering (Marsumura et al., 2018). By leveraging the ability of deep learning models to learn complex patterns and representations from data, it is possible to develop more sophisticated and accurate methods for PPG signal analysis and vital parameter estimation.

2. Aim and Objective

This project aims to investigate the potential of machine learning techniques for accurate vital parameter estimation from PPG signals. By developing and evaluating machine learning models tailored to the characteristics of PPG signals, this study seeks to overcome the limitations of traditional signal processing methods and provide reliable and robust vital parameter monitoring solutions. The proposed approach has the potential to enhance patient care, enable remote health monitoring, and facilitate timely interventions in various healthcare settings.

In the following sections, an overview of the theoretical background, related work, and methodological approaches employed in this project is provided. Additionally, the experimental setup, data acquisition, and preprocessing techniques, followed by a detailed description of the machine learning models and their evaluation is also represented. Finally, the results, implications, and potential future directions for this research are discussed.

3. Literature review

Photoplethysmography (PPG) is a non-invasive technique used to measure changes in blood volume that occur due to the blood pulsatile nature of microvascular tissue under the skin (Sun and Thakor, 2015). Various studies have discussed the characteristics of the PPG waveform and its derivatives (Lin et al., 2020). These studies suggest that taking the first and second derivatives of the PPG waveform can help in detecting informative features. In terms of biomedical applications, PPG has been proven to be an effective technique for diagnosing various cardiovascular diseases (CVDs) and can be utilized in new medical tools, such as the Internet of Things and biosensors, as shown in (Moraes et al., 2018). The clinical applicability of PPG has also been verified in (Baldoumas et al., 2019), where the concept of natural time analysis (NTA) was applied to distinguish individuals with congestive heart failure from healthy individuals. The results obtained by PPG demonstrated a comparable level of accuracy to those obtained by electrocardiography (ECG).Two primary approaches can be employed for more precise blood pressure (BP) estimation: feature-based and whole-based methods. In a study published in (Khalid et al., 2018), five distinct features—pulse area, pulse rising time, pulse width at 25% of pulse height, pulse width at 50% of pulse height, and pulse width at 75% of pulse height—were extracted from a photoplethysmography (PPG) segment. Machine learning techniques, such as multiple linear regression (MLR), support vector machine (SVM), and regression tree, were applied using the regression tree. Another study of Wang et al. (2018) utilized several spectral and morphological features, including systolic upstroke time and diastolic time. This method employed an artificial neural network (ANN) architecture to simultaneously estimate diastolic blood pressure (DBP) and systolic blood pressure (SBP), resulting in reduced error compared to linear regression and regression support vector machine (RSVM). Conversely, deep learning models were used with the entire PPG waveform segment as input in (Ibtehaz and Rahman, 2020). Both models comprised a convolutional neural network (CNN) and its modification to capture the spatial features of the waveforms. Both models achieved high accuracy with a relatively low error distribution (Wang et al., 2020).

4. Methodology

In this study, the target variable is blood pressure, which is a continuous value. Both linear regression and FNNs are suitable for modeling continuous target variables, as opposed to classification models that are designed for discrete target variables. Besides, PPG signals are time-series data, capturing the variation of blood volume over time. Linear regression and FNNs can handle time-series input data by considering each time step as a feature or by incorporating appropriate feature engineering techniques. While the relationship between PPG signals and blood pressure may have some linear components, it is likely to exhibit non-linear characteristics due to the complex physiological processes involved. FNNs, with their ability to learn non-linear mappings, can potentially capture these non-linearities .

Figure 3 presents the general flow diagram of the suggested research approach, which is broken down into the steps listed below:

(1) Take PPG signal segments and use the ABP and ECG signals as references. where each 125-size chunk is found. It determines the maximum and lowest blood pressure values for each segment, which stand for systolic and diastolic blood pressure, respectively.

(2) Utilize preprocessed PPG signal segments to extract waveform properties.

(3) Preprocess PPG signal segments, such as normalizing the PPG pulse waveform and removing the baseline.

(4) To assess the total estimation accuracy, train and test three distinct machine learning methods using 5-fold cross-validation.

(5) Using the RMSE (root mean square error) and MSE (mean square error) as assessment metrics which assess the estimation accuracy of the three machine learning algorithms particularly for each BP category.

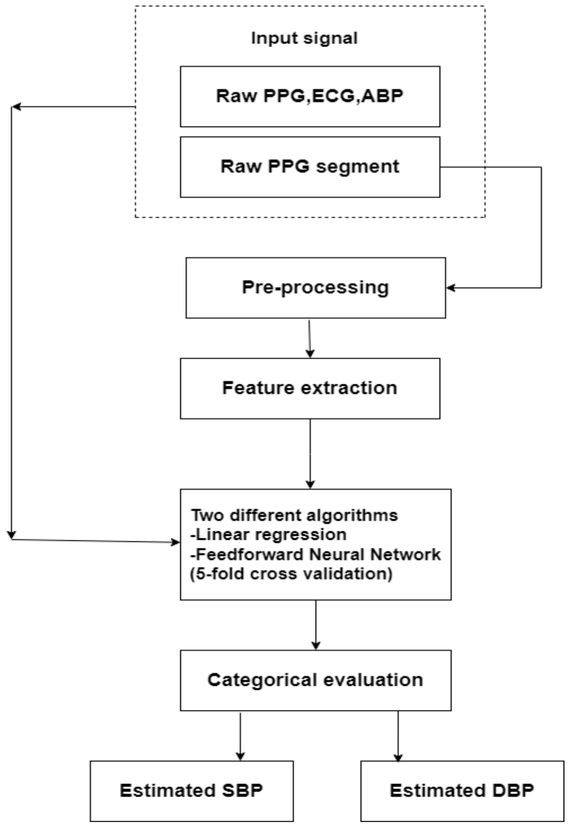

Figure 3 Flow diagram of research methodology

4.1 Online database:

The blood pressure dataset collected from a reliable online resource provides a valuable source for researchers endeavoring to develop cuff-less blood pressure estimation algorithms. Comprising meticulously curated and authentic signals, the dataset is conducive to the rigorous evaluation and refinement of such algorithms. Encapsulated within MATLAB files (. mat), the dataset encompasses raw electrocardiogram (ECG), photoplethysmography (PPG), and arterial blood pressure (ABP) signals organized as cell arrays of matrices. Each cell corresponds to a distinct record segment, with multiple record segments potentially originating from the same patient, albeit indistinguishable. Within each matrix, individual rows represent distinct signal channels, delineated as follows: PPG signal at a sampling frequency (FS) of 125Hz, sourced from fingertip photoplethysmographs; ABP signal, also sampled at 125Hz, derived from invasive arterial blood pressure measurements in millimeters of mercury (mmHg); and ECG signal, sampled at the same frequency, originating from channel II electrocardiograms. Notably, the dataset advocates for employing n-fold cross-validation during algorithm development and evaluation to mitigate the risk of contamination between training and test sets, particularly when faced with records from multiple patients.

4.2 PPG Signal Preprocessing

The preprocessing of the photoplethysmography (PPG) signal involves several key steps. First, it is iterating through 1000 samples within the dataset, each containing multiple readings. For each sample, the length of the signal is determined, providing insights into the temporal resolution of the data. Subsequently, the signal is partitioned into segments of fixed size (125 samples per segment) to facilitate further analysis. During this segmentation process, the PPG signal segments are extracted from each sample, ensuring consistency in segment size for subsequent processing. Significantly, the uniformity of data inputs is made possible by this segmentation technique, which is essential for the preprocessing processes that follow. Furthermore, it meticulously guarantees the synchronization of related arterial blood pressure (ABP) and electrocardiogram (ECG) readings, guaranteeing temporal coherence within the dataset. Ultimately, the retrieved PPG signal segments are reformed into a standard format so that they can be easily integrated into pipelines for further analysis. The harmonization and uniformity of PPG signals are guaranteed by this preprocessing technique, providing a strong basis for the following algorithmic development and assessment.

4.3 Features Extraction and Selection

Several crucial phases are involved in the extraction and selection of features from the photoplethysmograph (PPG) signal. The PPG signal is first formatted into a standard format, together with the related ECG and ABP signals, in order to make additional analysis easier. After that, the altered signals' dimensions are printed to ensure that they are compatible with further processing. The signals are then examined through the generation of visualizations, which help identify possible features. Plots of the ECG, BP, and PPG data provide information on possible linkages and their temporal dynamics. Moreover, the visualization of the diastolic blood pressure (DBP) and systolic blood pressure (SBP) signals independently enables the recognition of unique characteristics linked to every blood pressure category.

Additionally, cross-correlation analysis is performed between the PPG and BP signals to elucidate potential relationships and inform feature selection.This comprehensive approach to features extraction and selection ensures the robust characterization of the PPG signal and its relevance to blood pressure estimation algorithms. Finally, the root mean square error (RMSE) between the PPG signal and its cosine-transformed counterpart is computed to assess the fidelity of the signal representation, providing a quantitative measure of accuracy in signal analysis.

4.4 Machine Learning Algorithms to Estimate BPs.

The training dataset comprised 70% of the most significant PPG waveform features from each PPG segment, and the testing dataset included 30% of these features along with the matching reference BPs (SBP and DBP). Owing to the continuous nature of the data, two widely used methods were utilized in this investigation. They are as follows:

4.1.1 Linear Regression (LR)

Linear regression is a fundamental statistical technique used to model the relationship between a dependent variable (target) and one or more independent variables (features). The goal is to find the best-fitting linear line that minimizes the difference between the actual and predicted values. This paper considers the target variable as the blood pressure value, and the independent variables are likely the photoplethysmography (PPG) and electrocardiogram (ECG) signals.
The mathematical formula for simple linear regression with one independent variable is:

$$y = \beta_0 + \beta_1 x + \varepsilon$$

Where:
- y is the dependent variable (blood pressure)
- x is the independent variable (e.g., PPG or ECG signal)
- β_0 is the intercept (the value of y when x = 0)
- β_1 is the slope (the change in y for a one-unit change in x)
- ε is the error term, accounting for the deviation of the observed values from the predicted values

The goal of linear regression is to estimate the values of β_0 and β_1 that minimize the sum of squared errors between the observed and predicted values of y.
with multiple independent variables (PPG and ECG signals), the formula becomes:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon$$

Where $x_1, x_2, \ldots, x_n$ are the n independent variables (PPG and ECG signals), and $\beta_1, \beta_2, \ldots, \beta_n$ are the corresponding coefficients.

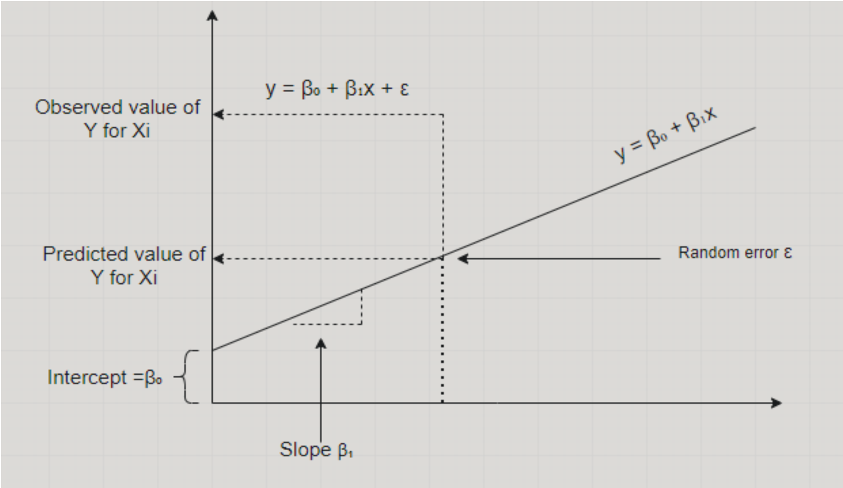

Figure 4 Visualization of Equation for Linear Regression

A fundamental tenet of linear regression is the linearity of the connection between the independent and dependent variables. In the event that this supposition is broken, the model might not effectively represent the underlying patterns; thus, non-linear methods such as FNNs might be more suitable.

4.1.2 Feedforward Neural Networks (FNNs)

FNNs are a type of artificial neural network inspired by the biological neural networks in the human brain. They are capable of modeling complex non-linear relationships between input features and output targets. The PPG and ECG signals would be the FNN's inputs, while the anticipated blood pressure reading would be its output.

Three layers make up a FNN: an input layer, an output layer, and one or more hidden layers. Every layer consists of nodes, or neurons, and there are weights attached to the connections between nodes in neighboring levels.

The mathematical formula for a single node in a hidden layer is:

$$h = \varphi(\Sigma(w_1x_1 + w_2x_2 + \cdots + w_nx_n + b))$$

Where:

- h is the output of the node

- $x_1, x_2, \ldots, x_n$ are the inputs to the node (from the previous layer)

- $w_1, w_2, \ldots, w_n$ are the weights associated with the connections

- b is the bias term

- φ is the activation function (e.g., ReLU, sigmoid, tanh). The activation function introduces non-linearity, allowing the FNN to model complex relationships.

This project claims that there are several layers, with each layer's output serving as the subsequent layer's input. The anticipated blood pressure reading is generated by the last output layer.

The weights and biases of the FNN are learned during the training process, where the model's predictions are compared to the actual blood pressure values, and the weights and biases are adjusted to minimize the error using optimization algorithms like gradient descent.

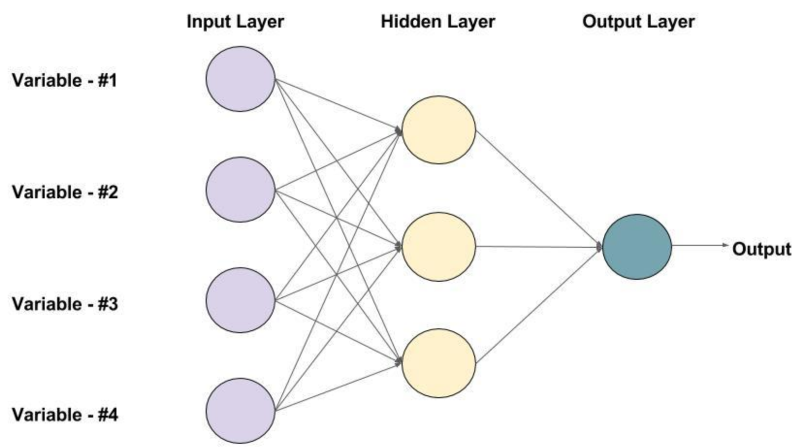

Figure 5 An example of a FNN with one hidden layer (3 neurons)

4.1.3 5-Fold Cross-Validation

A machine learning model's performance and its ability to generalize to new data are assessed using the cross-validation technique. The dataset is divided into k equal-sized subsets (folds) for k-fold cross-validation. Every fold is utilized as the validation set once during the model's k training and evaluation cycles. The remaining k-1 folds are used for training. Five-fold cross-validation, which divides the dataset into five equal folds, was used in this experiment. The following is a summary of the procedure:

1. There are five equal folds in the dataset (Fold 1, Fold 2,, Fold 5).

2. For every fold, such as Fold 1:

a. First Fold is the validation set.

b. The remaining 4 folds are used to train the model (linear regression or FNN).

c. An MSE or RMSE statistic is used to assess the model's performance on the validation set (Fold 1).

3. Using a different fold as the validation set each time, step 2 is performed for each of the remaining folds.

4. After accounting for all five folds, the average performance metric (RMSE or MSE) is determined.

This cross-validation approach helps to estimate how well the model will generalize to unseen data and reduces the risk of overfitting or under fitting caused by a single train-test split.

4.2 Evaluation of Metrics

Evaluation Metrics to Evaluate Overall Measurement Accuracy: To evaluate the overall measurement accuracy of the blood pressure prediction models, several evaluation metrics can be employed. These metrics provide quantitative measures of how well the models are performing and help in comparing their relative strengths and weaknesses.

4.2.1 Root Mean Squared Error (RMSE)

The RMSE is a commonly utilized assessment measure for regression issues, such as the blood pressure prediction task. The square root of the average squared discrepancies between the expected and actual values is what is measured.

The mathematical formula for RMSE is:

$$RMSE = \sqrt{(\Sigma(\mathrm{y}_{\mathrm{pred}} - y_{true})^2/n}$$

Where:

y_pred is the predicted blood pressure value

y_true is the actual (observed) blood pressure value

n is the number of data points

A lower RMSE value indicates better performance, as it means the predicted values are closer to the actual values.

4.2.2 Mean Squared Error (MSE)

Another commonly used metric is the Mean Absolute Error (MAE), which calculates the average absolute difference between the predicted blood pressure values and the actual values. It is less sensitive to outliers compared to metrics like RMSE, which square the errors, giving more weight to larger deviations.

The mathematical formula for MSE is:

$$MSE = (\Sigma(\mathrm{y}_{\mathrm{pred}} - y_{true})^2/n$$

Where the terms are the same as in the RMSE formula.

MSE and RMSE are related, as RMSE is simply the square root of MSE:

$$RMSE = \sqrt{MSE}$$

Both metrics evaluate the model's performance by quantifying the difference between predicted and actual values, but RMSE has the same units as the target variable (blood pressure), making it easier to interpret.

The performance of the linear regression is evaluated using RMSE, whereas the FNN models are evaluated using MSE on the test set and during cross-validation. For blood pressure readings, a smaller RMSE denotes higher forecast accuracy. Choosing the best model for a blood pressure prediction task requires comparing the prediction accuracies of these model on unseen data and estimating their generalization performance using 5-fold-cross-validation and RMSE as the evaluation metric.

5. Experimental Results

The objective of this study was to develop and evaluate models for predicting blood pressure values from photoplethysmography (PPG) and electrocardiogram (ECG) signals. Two different modeling approaches were explored: linear regression (LR) and feedforward neural networks (FNNs). The models were trained and evaluated on a dataset consisting of 1000 samples, with each sample containing PPG, ECG, and corresponding blood pressure measurements sampled at 125 Hz. The dataset was preprocessed by segmenting the continuous signals into windows of 125 samples each, resulting in a total of 32,061,000 segments. The performance of the LR and FNN models was assessed using the root mean squared error (RMSE) metric, computed between the predicted and true blood pressure values.

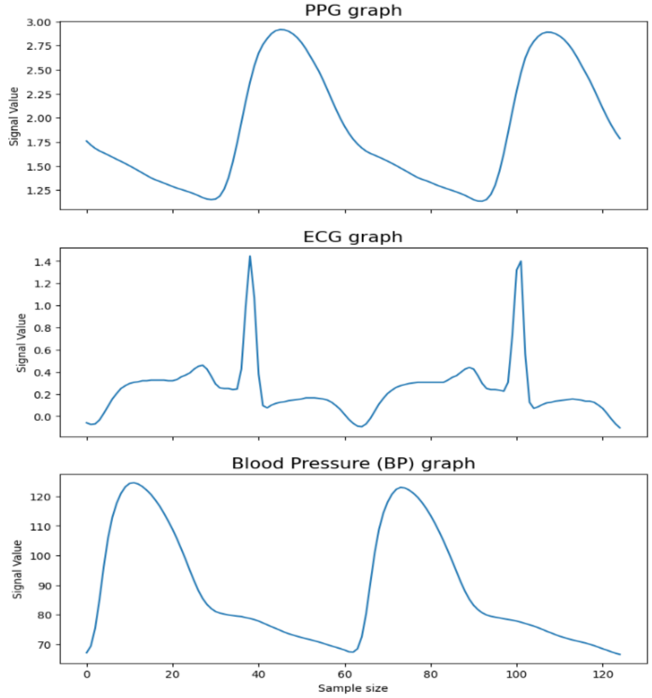

Figure 6 Plotting PPG, ECG, BP graph in accordance with the dataset

The PPG, ECG, and BP signals are reshaped and split into individual samples of a fixed size (125 samples per segment). For each sample segment, the maximum and minimum values of the BP signal are extracted and stored as the systolic BP (SBP) and diastolic BP (DBP), respectively. Figure 7 titled "SBP vs DBP graph" displays two sets of data over a time period, represented on the x-axis, which ranges from 0 to approximately 120. The y-axis represents signal values, which vary from about 70 to 130. The blue line represents the SBP (Systolic Blood Pressure) values. This line fluctuates within a range of approximately 110 to 130, showing some variability but generally maintaining a level above 110. The orange line represents the DBP (Diastolic Blood Pressure) values. This line is more stable and lower in value, ranging mostly from 70 to 90.

The graph is used to compare these two types of blood pressure readings over time, illustrating how each behaves relative to the other within the given timeframe. The SBP values are consistently higher than the DBP values, which is typical in blood pressure readings where systolic values (pressure during heartbeats) are higher than diastolic values (pressure between heartbeats).

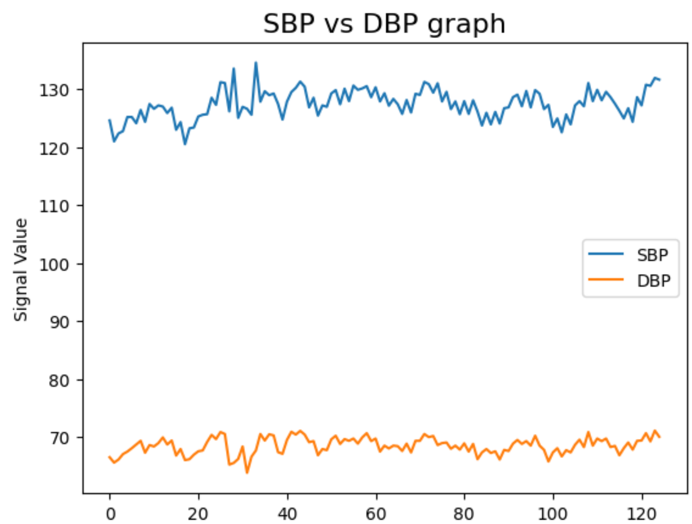

Figure 7 SBP vs DBP graph

The project performs a cross-correlation analysis between the PPG and BP signals to investigate the relationship between them. Figure 8 shows three plots related to analyzing data for predicting blood pressure (BP). The first two plots display the signal values over time for the photoplethysmography (PPG) and BP signals, respectively. Both signals exhibit a periodic, wave-like pattern, which is expected for physiological signals like these.

The third plot shows the cross-correlated resultant graph between the PPG and BP signals. Cross-correlation is a signal processing technique that measures the similarity between two signals as a function of the time lag applied to one relative to the other. The upward trending curve indicates a strong positive correlation between the PPG and BP signals when aligned properly.Analyzing the relationship and correlation between the PPG (which measures blood volume changes) and BP is crucial for developing models to predict BP values non-invasively from the more easily acquired PPG signal. The cross-correlation analysis demonstrates that there is indeed a strong link between these two signals, which provides the basis for using techniques like machine learning to map the PPG patterns to corresponding BP values.

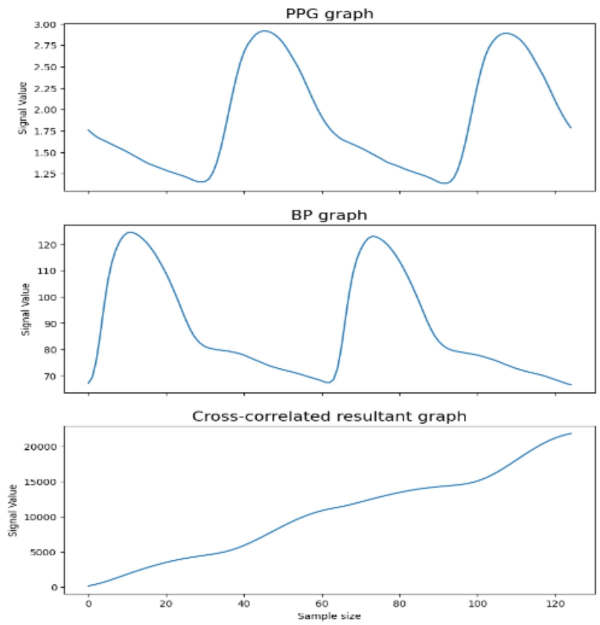

Figure 8 cross-correlation analysis between the PPG and BP signals

Applying the Discrete Cosine Transform (DCT) to the photoplethysmography (PPG) signal and then calculating the Root Mean Squared Error (RMSE) between the transformed PPG signal and the blood pressure (BP) signal the result we get is RMSE: 92.60. The purpose of utilizing the DCT on the PPG signal and contrasting it with the BP signal is to find out if the PPG signal's frequency components can be utilized to estimate or forecast the BP signal. By efficiently breaking down the PPG signal into its individual cosine components, the DCT is able to extract the frequency information.

Then, to obtain a trustworthy estimate of the model's performance, a 5-fold cross-validation was applied to the Linear Regression Model. Given the range of BP values, the average root mean squared error (RMSE) over the 5 folds was 27.34, which appears to be a reasonable figure. The RMSE was 27.38 when evaluated on a broader subset of the data, which was in close agreement with the cross-validation error.

Figure 9 contains two graphs related to evaluating the performance of a model for predicting blood pressure (BP) values from some input data. The graph on the left shows the training error (root mean squared error) plotted against the number of folds used in cross-validation. The U-shaped curve suggests that with too few or too many folds, the error increases, while an optimal number of folds (around 2-3 in this case) minimizes the error.

The graph on the right compares the true BP values (blue) against the BP values predicted by the model (orange) over a number of samples. It is seen that while the predicted values follow the general trends of the true BP, there are deviations where the model over or under-predicts certain peaks and valleys in the BP curve.

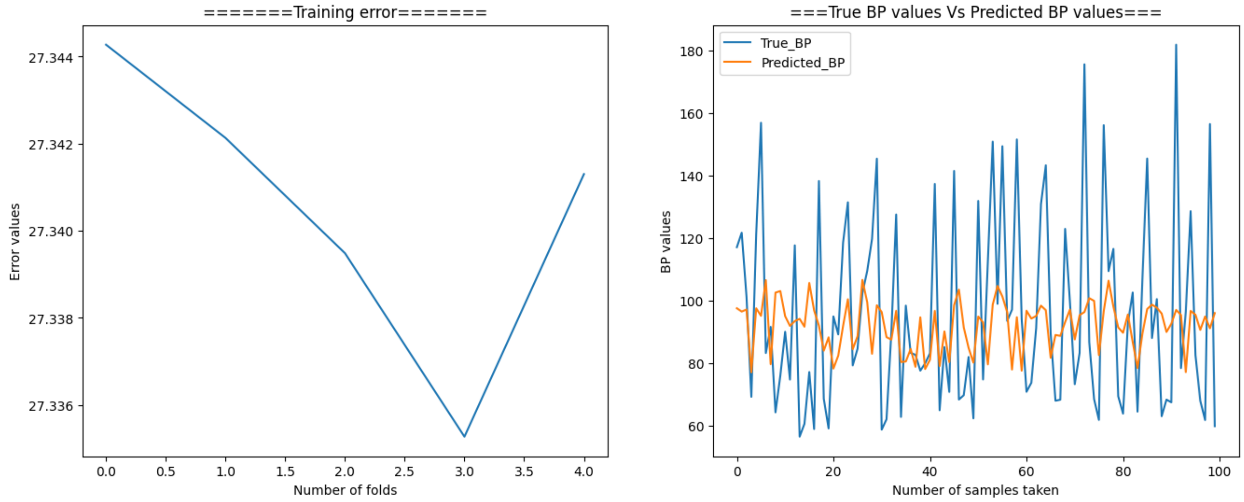

Figure 9 : plotting error values and predictions of BP curve

Then the same goal of predicting blood pressure from the input PPG and ECG signals is implemented using a neural network model (FNN). A deep neural network with 3 hidden layers was constructed. The model was trained on a subset of 1 million samples with the Huber loss function. Evaluation on a test set of 1 million samples gave an RMSE of 26.28.

This RMSE is slightly better than the linear regression model, though the improvement is modest. Figure 10 displays the training loss and mean absolute error (MAE) of the FNN model over 100 epochs.

The model's loss during training is indicated by the blue line labeled "Loss." The degree to which the model's predictions agree with the actual data is indicated by the loss. A poor fit to the data is shown by the substantial loss at first. The loss falls off quickly as the number of epochs rises and finally stabilizes, indicating that the model is gradually learning and refining its predictions.

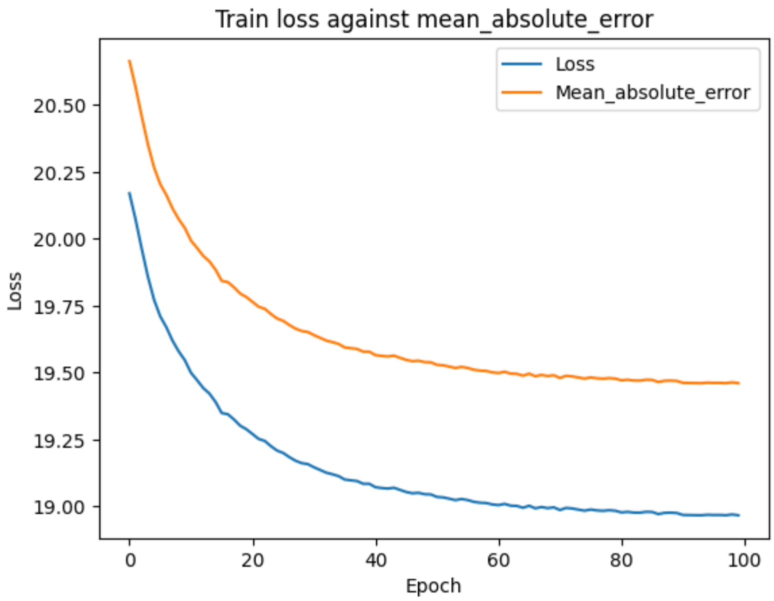

Figure 10 Train loss against MAE

Another parameter to assess the success of the model is the mean absolute error, which is represented by the orange line (Mean Absolute Error). Without taking into account the direction of the errors, MAE calculates the average size of the errors in a set of predictions (i.e., overestimations and underestimations are considered equally). The MAE shows that the accuracy of the model is increasing as the number of epochs grows, similar to the loss.

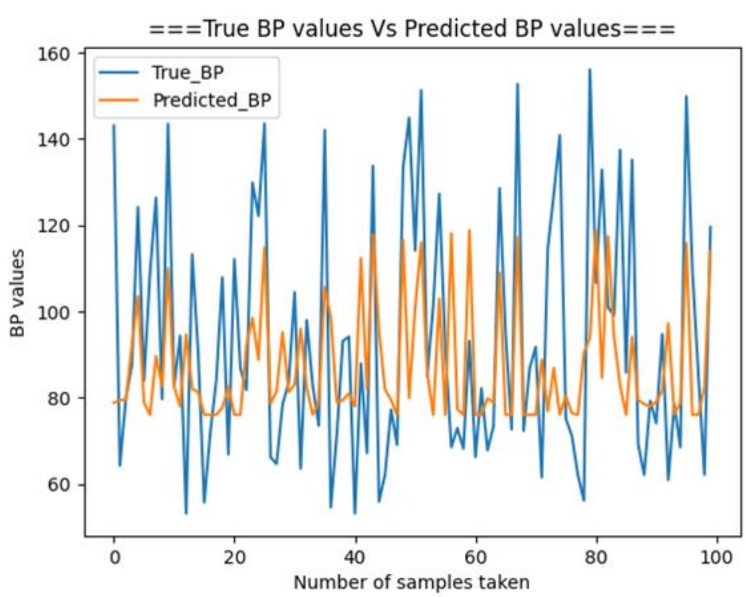

Figure 11 True BP values VS predicted BP values by FNN model

Lastly, Figure 11 presents a comparison between the actual blood pressure (BP) values over a range of samples (represented by the blue line) and the BP values predicted by the FNN model (shown by the orange line).

This graph assess how well the predictive model can monitor and forecast the real blood pressure patterns over time. Among the most important findings are that the model can accurately represent the overall trends and oscillations in BP because the genuine and predicted BP lines show comparable periodic, oscillating patterns. There are, however, certain deviations where the genuine BP peaks and valleys are not accurately represented by the predicted BP, indicating potential for additional model improvement.

6. Discussion

This study explored the use of machine learning techniques for estimating blood pressure (BP) values from photoplethysmography (PPG) and electrocardiogram (ECG) signals. Two different modeling approaches were investigated: linear regression and neural networks.

Linear Regression Model: The linear regression model was initially employed to establish a baseline for BP prediction. Five-fold cross-validation was performed to evaluate the model's performance and generalization capabilities. The average Root Mean Squared Error (RMSE) across the five folds was 27.340492591740976, indicating a relatively consistent performance across different subsets of the data. However, when visualizing the true BP values against the predicted values, it became evident that the linear regression model struggled to capture the complex, non-linear relationships between the input signals (PPG and ECG) and the target BP values. The predicted BP values showed deviations from the true values, suggesting that a more sophisticated modeling approach might be required.

Neural Network Model: To address the limitations of the linear regression model, a neural network architecture was implemented. The neural network model consisted of multiple dense layers, dropout layers, and non-linear activation functions, enabling it to capture intricate patterns and non-linear relationships within the data. After training the neural network model on a subset of the data, its performance was evaluated on the test set. The neural network achieved an RMSE of 26.28078969044924, which is a noticeable improvement over the linear regression model's performance on the test set (RMSE of 27.378014818270035). When visualizing the true BP values against the predicted values from the neural network, a closer match was observed, indicating that the neural network model could better capture the underlying complexities in the data and provide more accurate BP predictions.

The results demonstrate the superiority of the neural network model over the linear regression model for the task of BP estimation from PPG and ECG signals. The neural network's ability to learn non-linear mappings and extract relevant features from the input data allowed it to achieve better prediction accuracy.

7. Conclusions and Future Work

This study explored the application of machine learning techniques, specifically linear regression and neural networks (FNN), for the non-invasive estimation of blood pressure (BP) values from photoplethysmography (PPG) and electrocardiogram (ECG) signals. The findings revealed the superiority of the neural network approach over the linear regression model in capturing the complex, non-linear relationships between the input physiological signals and the target BP values. While the neural network model emerged as the more promising approach in this study, it is crucial to validate its performance on diverse datasets and real-world scenarios before considering practical deployment in healthcare applications. Collaboration with healthcare professionals and conducting clinical studies would also be essential to assess the model's accuracy and reliability against existing clinical standards and practices. To sum up, the study showed how machine learning methods—especially neural networks—can be used to accurately and non-invasively estimate blood pressure using PPG and ECG inputs. Ongoing research and development endeavors are imperative to tackle the residual constraints, augment the interpretive capacity of the models, and guarantee their pragmatic implementation in healthcare environments. The outcomes of this investigation add to the expanding collection of studies concerning non-invasive vital parameter estimation and open the door to more developments in this area.

More sophisticated neural network topologies, like convolutional neural networks (CNNs) or recurrent neural networks (RNNs), may be better able to capture temporal and spatial relationships in the input signals. These could be the subject of future research. The models' capacity for generalization and resilience to noise and variability may also be enhanced by adding bigger and more varied datasets developments in this field.

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