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Dual Prediction of Blood Pressure and Blood Glucose Level using PPG Signals: Explore Deep Learning Models through Comparative Study

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Abstract

Monitoring blood pressure (BP) and blood glucose levels is vital for managing unremitting conditions such as hypertension and diabetes, which affect millions of individuals around the world. Conventional strategies for measuring BP, which depend exclusively on pulse amplitudes, often fail to provide exact readings, especially in patients with atherosclerosis or those who are obese, where pulse amplitudes may be frail or mutilated. Moreover, customary strategies for blood glucose estimation involve invasive strategies, causing discomfort. This research presents a novel approach to non-invasive dual prediction of BP and blood glucose levels utilizing photoplethysmogram (PPG) signals. Leveraging the power of LSTM network and XGBoostRegressor enables accurate and efficient forecast of both BP and blood glucose levels. LSTM is utilized to find time related patterns within PPG signal, while XGBoost enhances model performance by identifying the most relevant features for prediction. Then, the two pre-trained deep learning models (one for glucose prediction and another for blood pressure prediction) are loaded, and a test sample is reshaped to match the required input format for each model. These models are then used to make predictions on the reshaped sample. The results demonstrate promising performance, resulting in an RMS error of 8.014 mg/dL for blood glucose estimation and a Mean Absolute Error (MAE) of 25.336 mmHg for BP estimation. The model's performance reflects high potential for practical, non-invasive monitoring, offering a more comfortable and accessible alternative for patients requiring regular checking of both BP and glucose levels.

1. Introduction

Hypertension influences an evaluated global burden of 1.28 billion adults, largely concentrated in LMICs, and about half of those with the condition stay undiscovered or untreated. Which explores the worldwide burden of hypertension, its implications for premature death [1]. The global prevalence of diabetes also has risen dramatically, with over 830 million people affected in 2022, causing significant health complications and premature deaths [2] highlighting the urgent need for effective management strategies for both conditions. Traditional monitoring methods are often intrusive, requiring specialized equipment and frequent healthcare visits, limiting accessibility for patients, particularly those with chronic conditions like hypertension and diabetes. Blood pressure (BP), also alluded to as arterial blood pressure (ABP), is the pressure exerted by circulating blood on the walls of blood vessels. The foremost common approach to measure BP without clinical supervision is the automated BP cuff employing oscillometer. A cuff is wrapped around the upper arm, inflated above systolic pressure, and after that deflated underneath diastolic BP. A pressure sensor records the arterial throbs amid cuff deflation, and the amplitudes of these throbs are utilized to calculate systolic and diastolic BP. However, this approach has critical confinements. The essential restriction is its dependence on experimental coefficients to map pulse amplitudes to systolic and diastolic BP, which are device-specific and can vary over devices. Moreover, since it depends exclusively on pulse amplitudes, it falls flat to supply precise readings in patients with atherosclerosis or those who are obese, as their pulse amplitudes can be weak, leading to inaccurate results. In response to these growing health challenges, there's an expanded demand for ceaseless, non-invasive monitoring of critical health parameters such as blood pressure (BP) and blood glucose (BG). Conventional monitoring strategies are often intrusive, requiring specialized equipment and frequent healthcare visits, restricting accessibility for patients, especially those with chronic conditions like hypertension and diabetes. Photoplethysmogram (PPG) signals offer a promising alternative [3] by measuring blood volume changes in the microvascular bed, and can be effectively captured through wearable gadgets like smartwatches and wellness trackers. This strategy not only provides a convenient, real-time, and continuous way to monitor vital health measurements, but it is also a cost-effective arrangement, offering a non-invasive and cheaper alternative to conventional BP and BG monitoring. With its potential to revolutionize chronic health condition management, PPG technology empowers ceaseless health assessments, improving accessibility and patient outcomes in managing chronic diseases. The main aim of this paper is to create an innovative approach for the concurrent forecast of Blood Pressure (BP) and Blood Glucose (BG) levels using Photoplethysmogram (PPG) signal. This strategy addresses the existing gap where most frameworks predict only one parameter at a time. By leveraging non- invasive, continuous monitoring through wearable devices, this research aims to provide real-time, accessible health tracking without the need for obtrusive strategies or frequent healthcare visits. The paper too focuses on the improvement of a custom deep learning model incorporating Long Short-Term Memory (LSTM) networks for sequential pattern learning, enhanced by XGBoost to improve predictions. The objective is to revolutionize wearable health technology, enabling efficient, continuous monitoring of both BP and BG, thereby facilitating timely interventions for chronic conditions such as hypertension and diabetes.

2. Related Work

In recent years, predicting blood pressure (BP) and blood glucose levels using photoplethysmogram (PPG) signals has gained attention due to the potential of non-invasive monitoring for chronic diseases like hypertension and diabetes. Table I shows distinctive methodologies for PPG-based non-invasive assessment of blood glucose and blood pressure, highlighting input features and employed techniques. Researchers have employed various machine learning (ML) and deep learning (DL) techniques to develop models that predict this vital health parameters based on PPG and related bio signals. A number of significant contributions to this area are discussed below. Dias et al. (2022) [4] utilized PPG and BP signals from the MIMIC-II dataset and applied a Category Boosting algorithm (Cat-Boost) for BP prediction. They extracted 133 morphological and temporal features from the PPG signal, demonstrating the effectiveness of advanced machine learning models in the task. Their approach emphasizes the significance of selecting relevant features extraction to improve model accuracy. By leveraging PPG signals, their model shows promise in predicting BP, particularly in settings where invasive methods are not feasible. Liao and Fang (2023) [5] proposed a hybrid CNN-LSTM for glucose level estimation leveraging only PPG measurements. Their model, combining convolutional neural networks (CNN) for feature extraction and long short-term memory (LSTM) networks for temporal pattern recognition, aimed at improving the accuracy of glucose level predictions. This approach underlines the potential of hybrid models that can capture both spatial and temporal information from PPG signals, which is critical for predicting complex physiological parameters like blood glucose. Yan et al. (2025) [6] extended the multi-sensor approach by integrating Electrocardiogram (ECG), PPG, and pressure pulse waveform (PPW) data for BP prediction. They employed Random Forest Regression (RFR) alongside feature selection and fusion techniques to enhance the model's predictive power. Their study reinforces the value of multi-sensor record fusion to refine the robustness and accuracy of BP prediction models. By incorporating different physiological signals, their method benefits from the complementary information provided by each sensor, potentially increasing the reliability of the predictions. We design a hybrid system that fuses LSTM networks with XGBoost for predicting both BP and blood glucose levels from PPG signals. The LSTM component is employed for its ability to capture the temporal dynamics of PPG signals, while XGBoost is used for feature selection and boosting the predictive accuracy. This dual prediction model seeks to address the challenges of accurate BP and glucose prediction, leveraging the strengths of both deep learning and gradient boosting techniques. The World Health Organization (WHO) reports the increasing prevalence of hypertension and diabetes globally [1][2], making the development of effective non-invasive monitoring solutions a pressing need. In addition, studies like that of Jindal et al. (2008) [3], which explored non-invasive blood glucose monitoring using PPG, provide foundational insights into the feasibility of such approaches. The growing body of literature on the use of PPG for predicting vital signs highlights the promise of deep learning-based solutions for real time, non-invasive health monitoring. In summary, while various machine learning and deep learning approaches have been explored for BP and blood glucose level prediction, the integration of PPG with advanced modelling techniques like hybrid LSTM-XGBoost remains an innovative area of research. The use of multi-sensor data and fusion methods further enhances the potential for developing robust and reliable predictive models for chronic disease management. Table 1 shows Overview of Inputs and Methodological Approaches

Table 1 Overview of Inputs and Methodological Approaches

Authors (Year)	Input Features	Methodology
F. M. Dias (2022) [4]	PPG and BP signals from the MIMIC-II dataset	Category Boosting algorithm (Cat-Boost) that uses 133 morphological and temporal features from the PPG signal
C.-Y. Liao and W. C. Fang (2023) [5]	Only the PPG signal	Hybrid CNN-LSTM Deep Learning Network
J. Yan (2025) [6]	Electro cardiogram (ECG), Photoplethysmography (PPG), and pressure pulse waveform (PPW)	Random Forest Regression (RFR) through feature selection and feature fusion
Our Method	PPG and BP signals	Hybrid LSTM with XgBoost

3. Method

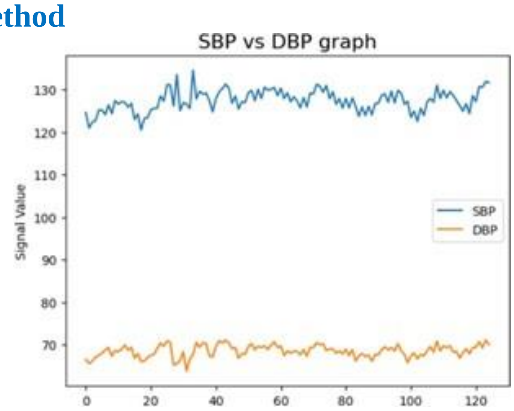

Figure 1 Comparison Between Systole and Diastole BP

3.1. Data Description

For this research, two separate datasets were utilized—one for predicting blood glucose levels and another for predicting blood pressure—both using photoplethysmogram (PPG) signals. Since there is no existing hybrid dataset that combines both PPG-based blood glucose and blood pressure data, the datasets were kept distinct, focusing on their individual applications. Figure 1 shows Comparison Between Systole and Diastole BP

Blood Glucose Dataset:

The blood glucose dataset consists of 67 PPG samples gathered from a group of 23 subjects. The collection procedure followed a well-defined protocol, beginning with the completion of a questionnaire by the volunteers to gather demographic information. Figure 2 shows Pre-processing of PPG Signals

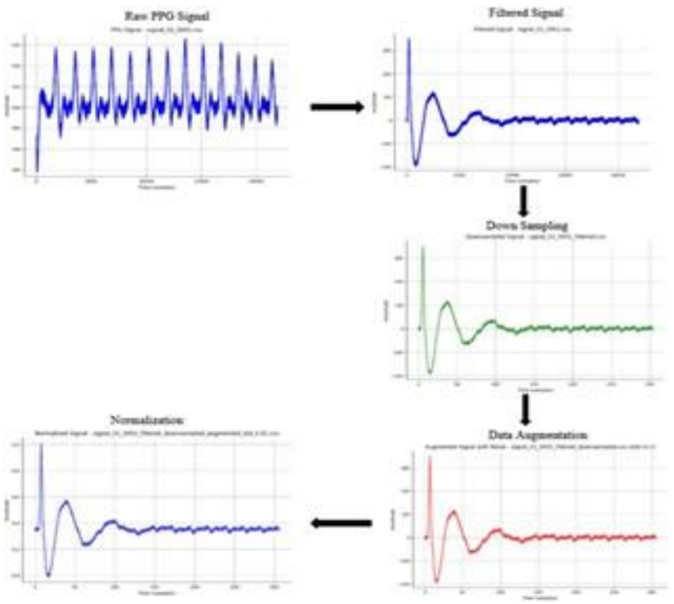

Figure 2 **Pre-processing of PPG Signals**

PPG signals were captured from the index finger using a green LED–based pulse sensor, and the outputs were amplified and filtered to reduce noise. Reference blood glucose values were simultaneously measured using an Accu-Check™ Active device (model 333). Figure 3 shows Model Architecture

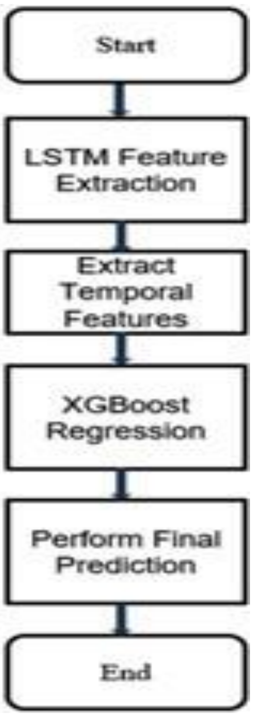

Figure 3 **Model Architecture**

The processed signal is then rectified through a diode and fed into the ADC pin of an Atmega328™ microcontroller. During the data collection process, precautions were taken to avoid movement, ensuring that the obtained PPG signals met standard signal conditions. The signals are recorded under controlled conditions from participants' fingertips. The dataset is provided in a zip archive named 'PPG_Dataset.zip', which contains three folders:

- Raw Data: Contains 67 .mat and 67 .csv files, where each file corresponds to a participant's PPG signal data (12-bit ADC output of the photodetector).
- Labels: Contains 68 .mat and 68 .csv files, with labels that include participant ID, gender, age, blood glucose level (mg/dL), height, and weight.
- Figures: Contains 67 JPG files, where each image represents a visual figure of the PPG signals.
- The total duration of the recording sessions is approximately 674,621 milliseconds. These labelled signals serve as the core data for blood glucose prediction. [7]

Blood Pressure Dataset:

The blood pressure dataset is designed for cuff-less blood pressure estimation using PPG signals, with a focus on clean and valid data for algorithm development. The data consists of ECG, photoplethysmogram and ABP signals, collected from physionet. Preprocessing and validation steps have been applied to ensure the dataset's quality and suitability for research purposes. This dataset includes the following signal channels, each sampled at 125 Hz:

- ✓ PPG Signal
- ✓ ABP Signal
- ✓ ECG Signal

The record is organized as a cell array of matrices, with each matrix corresponding to one record part. Each row in the matrix represents a signal channel, with individual records possibly spanning multiple parts. Records from the same participant are stored consecutively, but it is not always possible to distinguish between records from different patients. The dataset is split into multiple parts to facilitate easy loading on machines with limited memory capacity. To evaluate model performance robustly, the dataset recommends performing N-fold cross validation to ensure that test data is kept separate from training data, reducing the risk of the energy contamination from overlapping patient data. [8]

Data Availability:

Both datasets are publicly available for research purposes, with the blood glucose dataset being accessible via a download link containing the ‘PPG_Dataset.zip’ file. The blood pressure dataset, sourced from PhysioNet, is also available for download and is widely used in studies related to cuff-less BP estimation.

3.2. Signal Processing

The BP and ECG signals are extracted from the provided MAT file and stored in an array/list for further analysis. Additionally, systolic blood pressure (SBP) and diastolic blood pressure (DBP) are derived from the BP signal. Systole and diastole represent the two primary phases of a heartbeat. During systole, when the heart muscle contracts, the blood pressure increases as blood is pumped towards the peripheral arteries, while during diastole, when the heart relaxes and fills with blood, the blood pressure decreases. To capture these phases, the maximum value of the BP signal is used to determine SBP, and the minimum value is used to derive DBP. This approach allows for accurate extraction of the key BP parameters required for further analysis and prediction in this study. [9] Figure 1 shows the plot of SBP vs DBP that is obtained through the above process. Raw PPG dataset is passed through these preprocessing steps: [10] Figure 2 illustrates the preprocessing steps applied to the raw PPG dataset.

- Band-pass filter: A band-pass filter is applied to expel any undesirable noise from the raw signal. The channel permits frequencies between 0.5 Hz (equivalent to 30 beats per minute) and 8 Hz (equivalent to 240 beats per minute) to pass through, eliminating irrelevant frequencies.
- Down sampling: The signal’s sampling rate is reduced from 2175 Hz to 30 Hz, which is sufficient since the highest relevant frequency is 8 Hz. This step helps minimize unnecessary data, aligning with the Nyquist principle that requires a sampling rate of at least twice the maximum frequency.
- Data Augmentation: To increase the dataset size from 67 to 269 samples, Gaussian noise with varying standard deviations is added to the training PPG signals. These noise types follow a normal distribution, which helps the model generalize better during training.
- Normalization: Normalization is an essential preprocessing technique in machine learning. It ensures that all features are treated equitably, facilitates smoother learning by preventing dominant features from overshadowing others, and provides a favorable environment for the activation functions. By properly scaling the features, normalization aids in more efficient training and improves convergence.
- Shuffling and Splitting Data: To reduce bias and enhance generalization, the dataset is shuffled prior to training, ensuring the model sees a diverse range of data points and is not influenced by the order of the data. The dataset is partitioned into training, validation, and testing subsets. Model training is performed on the training split, whereas the validation set supports hyperparameter tuning and controls overfitting. Finally, the test set, which is never seen during training, serves as a measure of how well the model performs on new, unseen data. Figure 4 shows Predicted Output

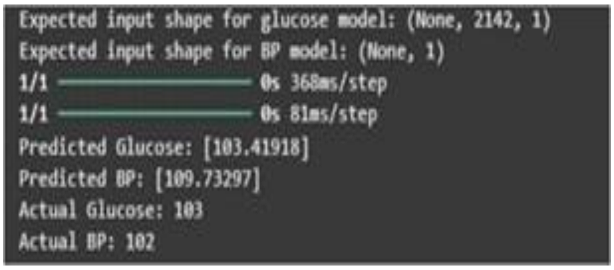

Figure 4 Predicted Output

3.3. Model Architecture

The proposed model for predicting blood pressure and blood glucose levels leverages the capabilities of LSTM to extract meaningful features, while XGBoost is applied for regression prediction. The architecture follows a two-step process: first, LSTM is utilized to extract meaningful temporal features from the photoplethysmogram (PPG) signals, followed by XGBoost to perform the final prediction. The architecture is designed to be robust, leveraging the strengths of both deep learning (LSTM) and machine learning (XGBoost) models. Figure 3 illustrates the overall architecture of the model.

Feature Extraction with LSTM

The model begins with an LSTM layer, which is well-suited to capture the sequential and temporal dependencies inherent in PPG signals. The LSTM model is designed to process the input data and extract meaningful features that can effectively represent the underlying dynamics of the blood pressure and blood glucose signals.

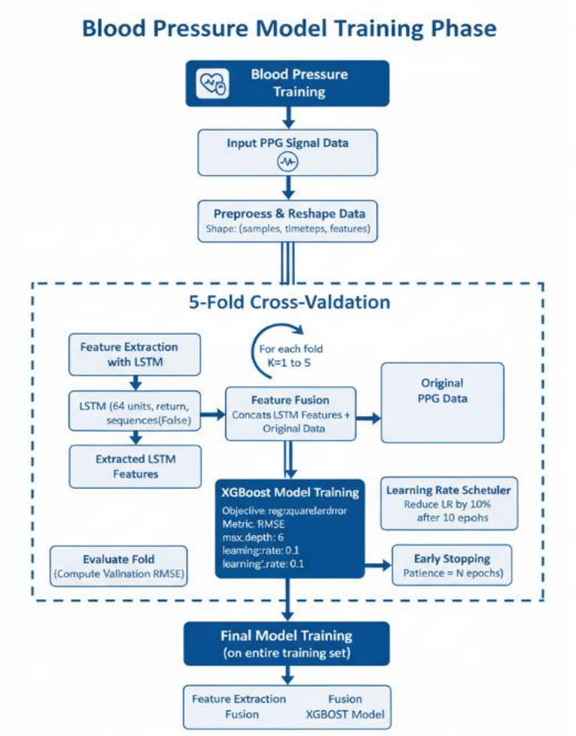

Figure 5 BP Model Training Phase

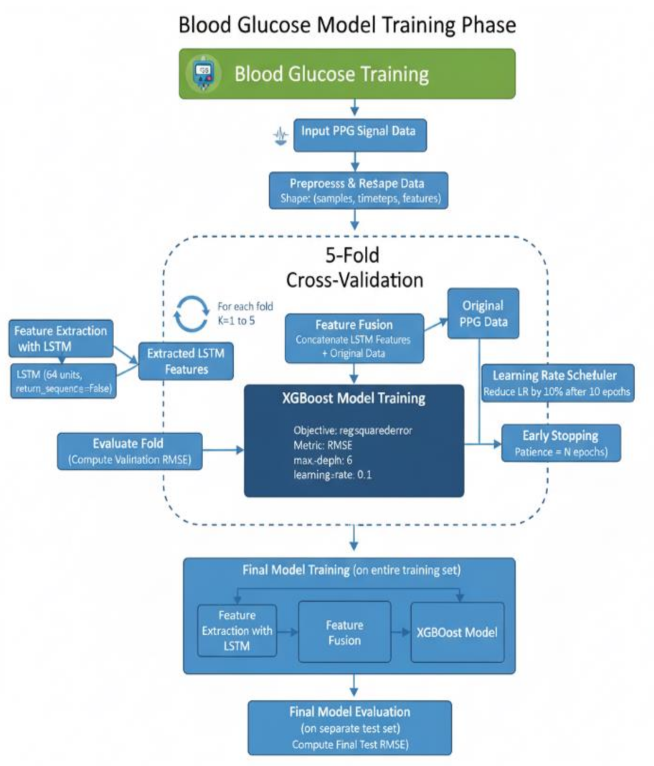

Figure 6 BG Training Phase

- Input Shape: The LSTM network receives the reshaped PPG data, where each input has a shape of (samples, timesteps, features), with timesteps representing the length of the PPG signal sequence and features being the number of PPG signal channels.
- LSTM Layer: A single LSTM layer with 64 units is used to process the temporal information from the PPG signal. The return_sequences=False argument ensures that the LSTM layer outputs only the final feature vector for each sequence, which is sufficient for regression tasks.
- Dense Layer: The output from the LSTM layer is passed through a dense layer with a single unit, which is used as the final output for regression. The output of this layer corresponds to the predicted value for either blood pressure or blood glucose levels.

Hyperparameter Tuning and Model Training:

Learning Rate Scheduler: A custom scheduler is applied to regulate the learning rate as training progresses. Initially, the learning rate remains constant, but after 10 epochs, it is reduced by 10% to prevent overshooting during optimization and to facilitate model convergence.

Early Stopping: To prevent overfitting, early stopping is implemented.

Feature Fusion with XGBoost

- Once the LSTM model is trained and the relevant features are extracted, the LSTM features are concatenated with the original PPG data.
- The enhanced feature set is subsequently fed into the XGBoost model for the final regression analysis.
- XGBoost: It is a gradient boosting machine, is employed to fine-tune the predictions made by the LSTM.
- XGBoost is trained on the combined features from LSTM and the original PPG data. The training objective is set to regression (reg:squarederror), and the evaluation metric is RMSE (Root Mean Squared Error).
- XGBoost Parameters: The model utilizes a max depth of 6 and a learning rate of 0.1. The model is trained with early stopping on the validation set to prevent overfitting.

K-Fold Cross-Validation

To ensure the robustness of the model, K-Fold Cross-Validation (with 5 folds) is used. This method splits the dataset into 5 subsets, training the model 5 times and ensuring that every fold serves as both training and validation data. This helps mitigate issues related to overfitting and ensures the model generalizes well to unseen data. Figure 5 shows BP Model Training Phase Figure 6 shows BG Training Phase

Final Model Training and Evaluation

Once the model has undergone K-Fold Cross-Validation and the best hyperparameters are selected, the final model is trained on the entire training set and evaluated on a separate test set. The final test RMSE is computed as a performance evaluation metric. The two pre-trained deep learning models (one for glucose prediction and another for blood pressure prediction) are loaded, and a test sample is reshaped to match the required input format for each model. These models are then used to make predictions on the reshaped sample. The model has shown good accuracy in predicting blood glucose levels, with minimal error between the estimated outputs and the ground-truth values. The prediction for blood pressure is reasonably close to the actual value, though slightly higher. The error may be attributed to the complexity of predicting BP from PPG signals, which can be influenced by many factors, including body type, physical activity, and the quality of the input signals as illustrated in Figure 4.

4. Results and Discussions

4.1. Blood Glucose Framework Comparison

The evaluation outcome of the proposed blood glucose evaluation framework, which leverages the temporal modeling capability of LSTM networks and XGBoost, is compared against several previous models. The CNN+GRU model achieved an RMSE of 26.2, which was improved by the addition of Fully Connected (FC) layers and Regression, resulting in an RMSE of 19.66. Figure 7 shows Predicted Output

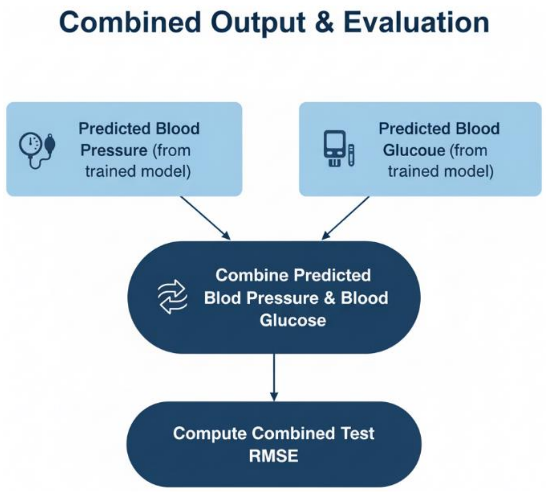

Figure 7 Predicted Output

Further refinement with K-fold Cross-Validation and Retraining led to an RMSE of 17.8. In contrast, our LSTM+XGBoost (Proposed Model) demonstrated a significant improvement, achieving an RMSE of 8.014. Figure 8 shows True BP vs Predicted BP

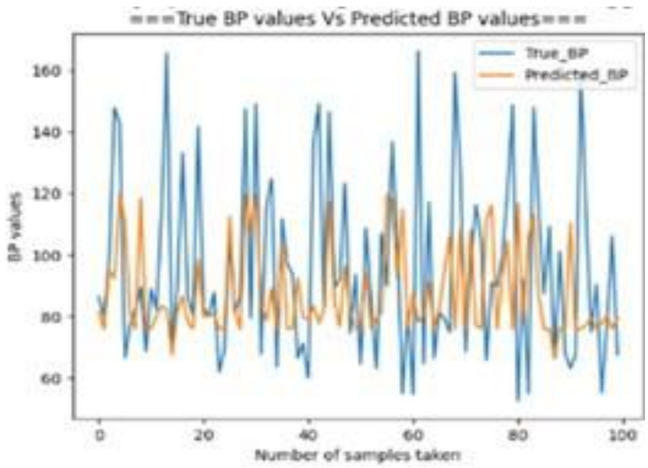

Figure 8 True BP vs Predicted BP

This reduction in RMSE indicates the effectiveness of our hybrid approach, which captures both temporal dependencies from the PPG signals using LSTM and enhances prediction accuracy through feature selection via XGBoost. Our model outperforms all previous iterations, proving that combining deep learning techniques and boosting methods leads to more accurate blood glucose prediction. Table 2 shows Blood Glucose Method Comparison

Table 2 Blood Glucose Method Comparison

Model	RMSE
CNN+GRU	26.2
CNN+GRU+FC+ REGRESSION	19.66
CNN+GRU+FC+ REGRESSION+ K-Fold+ RETRAIN	17.8
LSTM+XGBOOST (Proposed Methodology)	8.014

4.2. Blood Glucose Model Comparison

For blood pressure prediction, the proposed LSTM+XGBoost model again outperforms several traditional and deep learning-based models. The Linear Regression model achieved an RMSE of 27.3, while Deep Learning models with Dense and Activation Layers resulted in an RMSE of 25.9, and Deep Learning with Batch Normalization and Bagging achieved a slightly better RMSE of 25.37. The LSTM+XGBoost (Proposed Model) provided a marginal improvement over the batch normalization approach, yielding an RMSE of 25.336. While the improvement in RMSE is not as dramatic as in the blood glucose model, this result still showcases the robustness of our hybrid model in handling complex, multivariate data and producing reliable blood pressure predictions. Figure 8 illustrates the comparison of True BP vs Predicted BP. Table 2 shows Blood Glucose Method Comparison Table 3 shows Blood Pressure Method Comparison

Table 3 Blood Pressure Method Comparison

Model	RMSE
Linear Regression	27.3
Deep Learning (Dense and Activation Layer)	25.9
Deep Learning (Batch Normalization +Bagging)	25.37
LSTM+XGBOOST (Proposed Methodology)	25.336

4.3. Discussion

Improvement and Comparison with Previous Models: Through experimentation, it is evident that our hybrid approach (LSTM+XGBoost) results in significant improvements in both blood glucose and blood pressure prediction over previous models. The improvement in the blood glucose model, where the RMSE dropped from 26.2 to 8.014, highlights the power of combining LSTM for temporal feature extraction with XGBoost for feature selection and enhancement. This demonstrates a clear advancement over earlier models that employed single techniques such as CNN or GRU. Previous research typically focused on individual models, often relying on a single deep learning model or a regression-based approach. [6] In contrast, our proposed hybrid approach utilizes the advantages offered by both LSTM for extracting long-term dependencies and XGBoost for efficient feature selection, yielding better results. The dual prediction of both blood glucose and blood pressure using pre-trained models further contributes to the model's robustness and generalizability. The successful prediction of both BP and BG levels using PPG signals, achieved through the hybrid model, offers promising potential for non-invasive monitoring of these health parameters. The combination of pre-trained models ensures that both prediction tasks are handled efficiently, making this method highly suitable for practical, real-world applications.

Conclusion

In this paper, a novel and cost-effective non-invasive monitoring system for blood glucose and blood pressure levels is proposed, addressing the limitations of conventional invasive methods. The proposed hybrid model combines Long Short-Term Memory (LSTM) networks for capturing temporal dependencies in the PPG signal and XGBoost for efficient feature selection and boosting prediction accuracy. This approach enables accurate and real-time estimation of both blood glucose and blood pressure levels, offering a promising alternative to traditional methods that are often painful and inconvenient. The proposed model significantly outperforms existing state-of the-art methods, as evidenced by the RMSE of 8.014 for blood glucose prediction and 25.336 for blood pressure prediction. These results highlight the potential of combining deep learning techniques to achieve high-accuracy predictions. Furthermore, applying pre-trained frameworks for dual-task processing ensures a robust and efficient approach, paving the way for practical, non-invasive monitoring solutions. However, due to the scope of the dataset used in this study, which is limited in size and range, further work is needed to enhance the model's generalizability. Future extensions will focus on collecting a more diverse and extensive dataset, encompassing a wider range of blood glucose and blood pressure values, and incorporating additional samples to better represent various physiological conditions. These improvements will further solidify the potential for this system to be deployed in healthcare settings, offering an accessible and non-invasive solution for continuous monitoring of blood glucose and blood pressure.

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