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Continuous Cuffless Blood Pressure Monitoring with Deep-Learning Techniques Utilizing PPG and ECG Features

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***Abstract*—Regular blood pressure (BP) monitoring provides critical insights into an individual's health status. However, traditional cuff-based BP measurement methods are bulky and unsuitable for constant monitoring. This study presents an algorithm for precise and continuous systolic and diastolic blood pressure (DBP) measurement, leveraging statistical features extracted from physiological signals. The proposed methodology encompasses signal segmentation, feature extraction, and pattern analysis to establish a strong correlation between photoplethysmogram (PPG), electrocardiogram (ECG) characteristics and BP levels. The framework computes BP values using a combination of physiological parameters and holistic signal representations by processing these vital signals. A publicly available dataset is employed to train and validate a deep-learning model that accurately predicts BP readings. Performance is evaluated using key metrics, including mean absolute error (MAE) and root mean square error (RMSE), demonstrating the model's reliability. The findings reveal the potential of PPG and ECG signals for real-time, noninvasive BP monitoring, paving the way for advanced healthcare applications and next-generation wearable technologies.**

Keywords—Blood Pressure Monitoring, LSTM, PPG, ECG, Noninvasive Healthcare Technology.

I. INTRODUCTION

One essential physiological measure that offers vital information about a person's cardiovascular health is blood pressure (BP). It represents the pressure blood in circulation puts on blood vessel walls, especially arteries [1]. Systolic blood pressure (SBP), which measures the pressure during cardiac contractions, and diastolic blood pressure (DBP), which measures the pressure between heartbeats, are the primary measurements defining blood pressure. The average resting BP is 80 mmHg (diastolic) and 120 mmHg (systolic). Monitoring BP is vital for diagnosing and managing cardiovascular diseases, including hypertension, a leading global health concern [2]. While accurate, traditional cuff-based BP measurement methods are often inconvenient and unsuitable for nonstop monitoring due to their bulky design and intermittent measurement capability [3]. In clinical settings, invasive procedures, such as arterial catheterization, provide real-time, high-accuracy readings but are limited to critical care scenarios due to their invasive nature. Non-invasive methods, including cuff-based devices, are more practical but lack the capability for continuous monitoring and may cause discomfort during repeated use [4].

Recent advancements in sensor technologies, particularly photoplethysmography (PPG) and electrocardiography (ECG) have paved the way for noninvasive, continuous BP monitoring. By shining light into the skin and measuring the intensity of the light that is reflected or transmitted, PPG is an optical method that can identify changes in blood volume in the microvascular bed of tissue. However, ECG offers supplementary insights into cardiovascular dynamics by providing electrical activity data of the heart [5]. Long Short-Term Memory (LSTM) networks effectively capture temporal dependencies, enhancing the performance of the model for sequential data tasks [6].

This study aims to design and implement a noninvasive blood pressure estimation system leveraging PPG and ECG signals. The proposed framework seeks to provide continuous and accurate BP monitoring by extracting and analyzing statistical features from these physiological signals. The system integrates advanced feature extraction techniques and deep learning models to establish a robust relationship between BP and PPG or ECG-derived features.

The significant contributions of this study are as follows:

1. Non-Invasive BP Monitoring Framework: Developed an incessant blood pressure monitoring system using PPG and ECG signals, replacing cuff-based methods with a user-friendly, real-time solution.
2. Dual-Signal Integration for Accuracy: Combined PPG and ECG signals to extract complementary features, significantly improving the precision of systolic and diastolic BP predictions.
3. Advanced Deep Learning Implementation: Utilized modified LSTM networks for accurate BP estimation, optimized for high performance and adaptability to individual variability.

II. Literature Review

Recent studies have focused on estimating blood pressure (BP) using noninvasive and wearable technologies, particularly leveraging PPG signals. PPG, a light-based technique, has gained significant attention for BP estimation due to its noninvasive nature, ease of use, and integration into wearable devices [7]. The LeNet model, which includes convolutional and max-pooling layers, serves as the foundation for many modern deep-learning architectures, helping in the effective extraction of features [8]. Hasanzadeh et al. [9] demonstrated reliable BP estimation from PPG data using morphological features like the dicrotic notch and systolic/diastolic peaks. These features enhance accuracy, especially in wearable sensor applications. Kurylyak et al. [10] used neural networks with PPG-derived features like PWV, heart rate, and blood flow to improve BP estimation accuracy over traditional methods. The authors proposed a cuff-less BP estimation method using CNNs for local features and Transformers for global learning, achieving high accuracy but limited by sensitivity to signal quality and high computational complexity, impacting real-time applications [11]. In addition to neural networks, other machine-learning methods have been widely explored for BP estimation. For example, PPG signals' association with pulse wave velocity (PWV) has been extensively studied, with studies like [12] showing the correlation between PPG data and BP. PWV, a measure of arterial stiffness, is directly influenced by BP levels, making it a valuable feature for BP prediction models. PPG's versatility also extends to other cardiovascular health applications, such as heart rate variability [13], oxygen saturation measurement [14], and detecting conditions like atrial fibrillation [15].

III. Proposed Methodology

The proposed methodology focuses on developing a cuffless blood pressure estimation model leveraging physiological signals such as PPG, ECG, and ABP. The process involves data preparation, feature extraction, model training, and evaluation. The following steps outline the methodology in detail:

A. Dataset Description

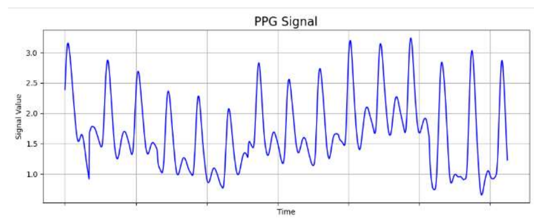
The study's dataset includes physiological signals from the MIMIC-II database on PhysioNet, such as PPG, ECGs, and ABP. This publicly available dataset contains over 12,000 records collected from patients in intensive care units across the United States. The signals underwent preprocessing and validation by Kachuee et al. [16] to ensure reliability and remove noise, artefacts, and inconsistencies. The dataset offers a robust basis for evolving and testing machine learning algorithms for estimating cuffless blood pressure, enabling accurate and non-invasive systolic, diastolic, and mean arterial pressure monitoring.

B. Dataset Preprocessing

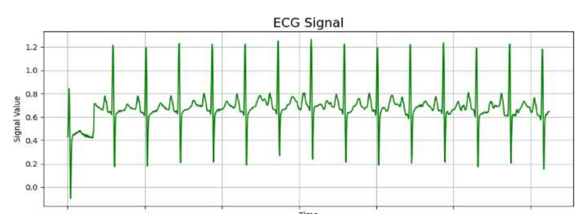
The MIMIC database contains numerous signals that are often compromised due to various distortions and artifacts, rendering them unsuitable for analysis. To prepare these signals for feature extraction, it is essential to eliminate unreliable data through a comprehensive preprocessing approach. This process begins by segmenting the signals into fixed-size blocks, each of which undergoes a series of cleaning steps. Initially, all signals are smoothed using a simple averaging filter to reduce noise and minor fluctuations. Subsequently, signal blocks exhibiting irregular or physiologically implausible blood pressure values are identified and removed to ensure the reliability of the data. Following this, blocks with abnormal heart rate values are also discarded, as they can indicate measurement errors or artifacts. Despite the initial smoothing, some signal blocks may still display severe discontinuities, which are detected and eliminated to maintain signal continuity. Additionally, the autocorrelation of photoplethysmogram (PPG) signals is calculated to assess the consistency between successive pulses, with blocks showing significant variations being removed. By systematically applying these preprocessing steps, the remaining dataset is significantly cleaner and more robust, making it suitable for accurate and reliable feature extraction in subsequent analytical processes.

C. Feature Extraction

This study extracts features from PPG and ECG signals to predict DBP and SBP. Feature extraction is vital for transforming raw physiological signals into meaningful representations that enhance model performance and interpretability. We employ statistical and signal-processing techniques to capture key physiological patterns influencing blood pressure.



(a)



(b)

Fig. 1. Extracted signals from the dataset (a) PPG, b) ECG

The features include the mean (μ) representing the average amplitude, standard deviation (σ) indicating signal variability, maximum and minimum values reflecting peak pressure points (SBP) and baseline activity (DBP), peak-to-peak range (PTP) highlighting pulse amplitude, median for central tendency, variance (σ^2) showing signal consistency, mean of first differences to capture rate of change, sum of absolute differences (SAD) for total signal variability, and mean of absolute values representing overall signal magnitude. Fig.1. shows the extracted signals from the dataset.

D. Proposed Network Architecture

The proposed blood pressure estimation framework employs a robust LSTM-based deep learning architecture, meticulously designed to predict SBP and DBP with high accuracy. The SBP prediction model incorporates two stacked LSTM layers of 128 and 64 units, respectively, to capture both short-term and long-term dependencies in the sequential data. The first LSTM layer processes the input features and passes its outputs to the second LSTM layer, enabling the network to learn intricate temporal patterns effectively. Each LSTM layer is followed by a Dropout layer with a 20% dropout rate to mitigate overfitting, ensuring robust generalization on unseen data. A Dense layer with 32 neurons and ReLU activation further refine the extracted features, while the final output layer, consisting of a single neuron, predicts the SBP value. Similarly, the DBP prediction model leverages an LSTM layer with dynamically tuned units to process sequential input, followed by a Dropout layer to enhance training stability. A Dense layer with ReLU activation enhances feature extraction, culminating in a single output neuron for precise DBP prediction. Both models are trained on an 80-20 dataset split, ensuring an optimal balance between training and testing subsets. To provide unbiased feature scaling and improved convergence, the feature set is standardized using a StandardScaler.

The architecture is optimized through hyperparameter tuning using the RandomSearch method, exploring a comprehensive range of parameters. The best-performing configuration includes 128 LSTM units, a dropout rate of 0.3, a dense layer size of 128, and a learning rate of 0.001, selected based on minimizing validation loss and maximizing model performance. This process employs a custom function to iteratively build and evaluate models based on validation loss, ensuring the selection of the best-performing configuration. Advanced training callbacks, including EarlyStopping and ReduceLROnPlateau, halt training upon validation performance stagnation and dynamically adjust learning rates, further enhancing efficiency and convergence. Fig. 2 illustrates the proposed blood pressure estimation algorithm's block diagram, presenting a structured pipeline for accurately predicting blood pressure values.

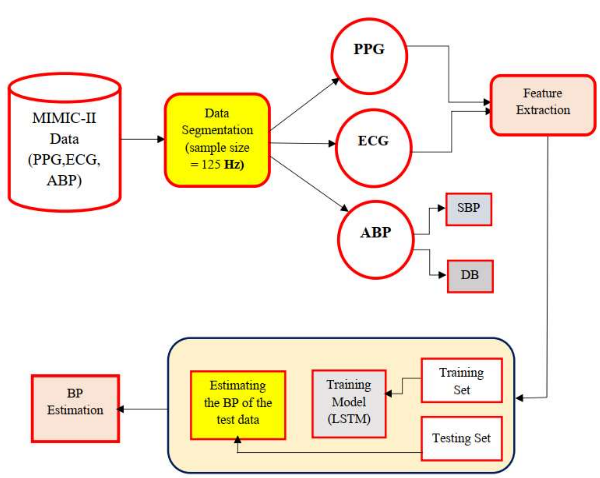


Fig. 2. The suggested blood pressure estimation algorithm's block diagram.

IV. Result and Discussion

Two models, SVM and LSTM, are tested in our experiment to see how well they predict SBP and DBP. Three assessments metrics—MAE, STD, and RMSE—display the results. For SBP prediction, SVM achieved an MAE of 11.00, STD of 8.15, and an RMSE of 6.50, while LSTM yielded an MAE of 7.38, STD of 6.13, and RMSE of 5.15. For DBP prediction, SVM resulted in MAE of 7.61, STD of 6.78, and RMSE of 7.11, whereas LSTM performed better with an MAE of 3.67, STD of 5.20, and RMSE of 5.21. These results indicate that the LSTM model outperforms the SVM model in predicting SBP and DBP. Table 1 illustrates the experiment results evaluating the performance of SVM and LSTM models for predicting SBP and DBP.

TABLE I. Evaluation Metrics for SBP and DBP Prediction using SVM and LSTM Models

Evaluation Matrices	SBP		DBP	
	SVM	**LSTM**	**SVM**	**LSTM**
MAE	11.00	7.38	7.61	3.67
STD	8.15	6.13	6.78	5.20
RMSE	6.50	5.15	7.11	5.21

Fig. 3 presents the performance of the proposed LSTM model in predicting SBP and DBP using three evaluation metrics: MAE, STD, and RMSE. For SBP prediction, the LSTM model achieves an MAE of 7.38 mmHg, an STD of 6.13 mmHg, and an RMSE of 5.15 mmHg, demonstrating its ability to minimize absolute and relative errors while maintaining consistent predictions. For DBP prediction, the LSTM model further excels, achieving an MAE of 3.67 mmHg, an STD of 5.20 mmHg, and an RMSE of 5.21 mmHg, reflecting its robustness and precision in diastolic pressure estimation. These findings demonstrate the LSTM model's improved capacity to provide precise and consistent blood pressure predictions as well as its efficacy in capturing the temporal dynamics of physiological data like PPG and ECG.

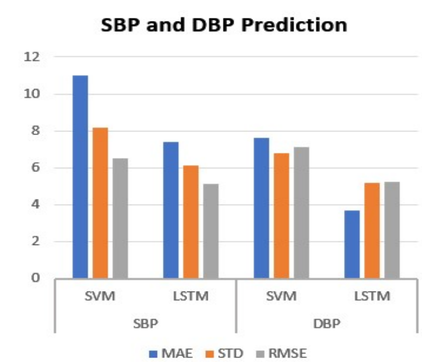


Fig. 3. Visual representation of SBP and DBP Prediction using SVM and LSTM Models

Table 2 summarizes and compares the performance of different methods for predicting SBP and DBP using various datasets and signal types, evaluated on three metrics: MAE, STD, and RMSE. The methods compared include gradient

TABLE II. COMPREHENSIVE COMPARISON OF OUR PROPOSED APPROACH WITH EXISTING METHODS FOR ESTIMATING BLOOD PRESSURE (BP)

Studies	Method	Dataset	Signal	SBP			DBP		
				MAE	STD	RMSE	MAE	STD	RMSE
[17]	Gradient boosting regression without clustering	MIMIC II	PPG, ECG	**6.36**	—	10.39	6.27	—	10.22
[19]	RFR	MIMIC II	PPG, ECG	13.04	12.80	—	5.96	5.67	—
[20]	Adaboosting	MIMIC II	ECG, PPG	11.17	10.15	—	5.35	6.14	—
[18]	SVM	Univ. of Queensland	PPG	11.64	8.22	—	7.61	6.78	—
Proposed Method	**LSTM**	**MIMIC II**	**ECG, PPG**	7.38	**6.13**	**5.15**	**3.67**	**5.20**	**5.21**

boosting regression without clustering [17], which achieved an MAE of 6.36 for SBP and 6.27 for DBP on the MIMIC II dataset with PPG and ECG signals, though STD and RMSE were unavailable. SVM [18] on the University of Queensland dataset with PPG signals reported an MAE of 11.64 for SBP and 7.61 for DBP, with STD values of 8.22 and 6.78. Random Forest Regression (RFR) [19] on the same dataset reported an MAE of 13.04 for SBP and 5.96 for DBP, with STD values of 12.80 and 5.67, but no RMSE. Adaboosting [20] also on MIMIC II achieved MAEs of 11.17 for SBP and 5.35 for DBP, with STD values of 10.15 and 6.14, respectively, but no RMSE. The proposed LSTM method on MIMIC II with ECG and PPG signals achieved the best performance, with MAEs of 7.38 for SBP and 3.67 for DBP, and STD values of 6.13 and 5.20, respectively, along with RMSE values of 5.15 and 5.

V. CONCLUSION

This study highlights the effectiveness of the proposed LSTM model for predicting SBP and DBP from PPG and ECG signals. The model demonstrated superior performance with lower MAE and RMSE compared to traditional machine learning methods such as Gradient Boosting, Random Forest, AdaBoost, and SVM. By leveraging its ability to capture temporal dependencies, the LSTM model effectively identified complex patterns within the MIMIC-II dataset, delivering robust and consistent predictions. The findings underscore the potential of LSTM-based approaches for non-invasive, accurate, and real-time blood pressure estimation, surpassing the limitations of conventional methods reliant on static feature extraction. This work establishes a foundation for advancing personalized healthcare systems. Future research should focus on validating the model on more significant, diverse datasets and exploring hybrid architectures to enhance its predictive capabilities further.

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