IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Ingénierie des Systèmes d'Information
Vol. 30, No. 11, November, 2025, pp. 3067-3075
Journal homepage: http://iieta.org/journals/isi

Cuffless Blood Pressure Estimation Using AI Models: A Comparative Study of SVR, LSTM, and LightGBM

Saadi Mohammed Saadi, Rasha Qasim Humadi, Batool Ali Majeed*, Batool Yasir Hardan, Zainab Ali Musa, Ammar Yasir Hardan

Ministry of Education, Iraqi Gifted School, Baghdad 10011, Iraq

Corresponding Author Email: ba5074963@gmail.com

https://doi.org/10.18280/isi.301124

Received: 30 September 2025
Revised: 15 November 2025
Accepted: 21 November 2025
Available online: 30 November 2025

Keywords:
blood pressure estimation, cuffless monitoring, PPG, ECG, machine learning, LSTM, SVR, LightGBM

ABSTRACT

One of the most significant biomarkers for stroke and cardiovascular disease, which are the world's leading causes of mortality, is blood pressure (BP). Researchers and healthcare professionals have focused on recognizing the early indicators of hypertension (high blood pressure) by routinely monitoring blood pressure and predicting future changes. Early detection enables prompt intervention and treatment, which lowers the risk of life-threatening health issues like heart disease, stroke, and kidney issues. In this paper, a smart BP forecasting system is proposed that utilizes machine learning (ML) and deep learning (DL) algorithms, aided by IoT technology represented by the MQTT protocol and an AWS server. Three ML models are tested and compared to select the best forecasting system, including Support Vector Regression (SVR), Long Short-Term Memory (LSTM), and Light Gradient-Boosting Machine (LightGBM). The performance evaluation reveals that the LSTM shows high performance compared to other approaches, with an RMSE of 12.36 using the Photoplethysmograph (PPG), Electrocardiogram (ECG), and arterial blood pressure (ABP) features.

1. INTRODUCTION

Blood pressure (BP) represents one of the key life-threatening illnesses, which necessitates an accurate and efficient diagnostic tool. A significant risk factor for cardiovascular disease, elevated blood pressure, or hypertension, is the cause of more than 9 million annual fatalities [1]. In fact, unusual changes in blood pressure can also put the kidney, liver, brain, heart, and other organs at significant risk for harm. Hypertension is characterized by systolic and diastolic blood pressures that are greater than 140 and 90 mmHg, respectively. If addressed, these unfavorable blood pressure levels might harm internal body organs. Hence, due to the large number of people affected by blood pressure issues, many researchers are attempting to make BP monitoring technologies more accurate and less inconvenient [2]. BP is often monitored using cuff-based devices, which are cumbersome and do not permit continuous measurement. Continuous blood pressure monitoring is extremely useful for learning about people's health issues [3]. On the other hand, for wearable technology and continuous monitoring, cuffless techniques are more practical. They are better suited for ambulatory and continuous monitoring because they do not need a cuff to be inflated and deflated. However, in specific medical situations or for clinical accuracy, cuffless approaches may face hurdles in terms of accuracy and may not be as dependable as cuff-based measures. It's crucial to remember that cuffless blood pressure monitoring is a field that is actively being researched and developed, and that these techniques' precision and dependability are continually being improved [4].

In this paper, ML and DL algorithms are used to improve the accuracy of the cuffless BP system. The following are the primary contributions of this paper:

- Comparing the effectiveness of the three ML algorithms, SVR, LSTM, and LightGBM, in terms of the accuracy of BP estimation.
- Application of the proposed system with the aid of IoT technology using an Amazon Web Server (AWS) to work anywhere, anytime.

The structure of the paper is as follows. Section 2 discusses prior research studies. Section 3 presents the key elements of the research. The suggested ML and DL methods are presented in Section 4. Section 5 presents the findings and the performance evaluation. In Section 6, the conclusion of the paper is illustrated.

2. RELATED WORK

A wide research contribution has been conducted to highlight this topic. A concise description is illustrated in this section.

Hsiao et al. [5] focused on the early heart disease prevention is hampered by the inconvenience and complexity of continuous monitoring associated with traditional blood pressure measurement techniques. To solve this issue, a wearable gadget was created that properly predicts blood pressure without the need for a cuff by utilizing PPG and BioZ sensors in conjunction with the Random Forest Regression algorithm. With a mean inaccuracy of less than 3.3 mmHg, the results showed great accuracy, indicating the model's efficacy; however, more varied human samples are required for testing. Song et al. [6] suggested a cuffless method for estimating blood pressure that uses smartwatch-derived PPG and ECG signals. Using a DNN, a two-stage deep model was created and tested against more conventional techniques like SVM and ANN, showing better accuracy and reduced error rates. Additionally, a customized adaptation method was suggested to maximize performance for every user.

The prevention of heart disease is limited by the inability of traditional blood pressure measurement techniques to offer convenient and ongoing monitoring. Qin et al. [7] proposed extracting many characteristics and increasing the accuracy of blood pressure prediction by using solely PPG signals with a deep network based on ResNet34. The model's efficacy and simplicity of integration into wearable technology, such as watches and smartphones, are demonstrated by the results on MIMIC data, which show that they satisfy international standards (AAMI and BHS).

Ganti et al. [8] developed a wearable gadget (smartwatch) for accurate, at-home blood pressure measurement. The device estimates blood pressure by calculating pulse transition time (PTT) from ECG, SCG, and PPG inputs. After calibration, the findings showed good accuracy (RMSE = 2.72 mmHg), and a semi-generalized adaptive model may be able to lessen the need for calibration. For the early detection and treatment of hypertension, our study is a significant step toward convenient and efficient remote blood pressure monitoring.

Continuous monitoring is limited by the interference or inconvenience of traditional blood pressure measurement techniques. El-Hajj and Kyriacou [9] designed a bidirectional recurrent neural network with an attention mechanism based only on PPG signals as models for estimating systolic and diastolic blood pressure. To enhance performance, dimensionality was decreased, and twenty-two features were taken from the signal. The outcomes were in line with the AAMI global requirements for cuffless blood pressure measurement, showed excellent accuracy, and beat conventional ML techniques.

In order to provide more accurate and continuous monitoring, Yan et al. [10] introduced a new Deep-BP convolutional neural network-based model for cuffless blood pressure measurement. The model is distinguished by its capacity to extract deep features from data in a way that is not possible with conventional techniques, improving its estimation accuracy and noise resistance. The outcomes show that, both with and without calibration during training, the model performs better than current techniques.

By combining various datasets, such as PPG and ECG signals, with individual characteristics like age, height, weight, and gender, Yin et al. [11] suggested a method for continuous, instantaneous, and discrete blood pressure measurement. In comparison to conventional models based solely on PTT and PWPs, the results demonstrated that integrating this data greatly increased estimation accuracy, with lower RMSEs and higher correlations. This method emphasizes how crucial it is to consider every constraining factor in order to produce a more accurate and trustworthy model. In order to overcome the challenge of feature extraction in the presence of noise or signal distortion, Yang et al. [12] used a hybrid blood pressure prediction model that is based on directly inputting raw signals with an individual's physical characteristics (age, height, weight, and gender). This method exhibited promise as a continuous, non-invasive way to measure blood pressure. A concise summary of the most related works and their possible research limitations is shown in Table 1.

Table 1. Key types of approaches and limitations of prior literature

Ref.	Approach	Limitation
[13]	CNN-BiLSTM Hybrid Model with PPG only for non-interventional and continuous grade of blood pressure	The traditional gap in extracting features and dealing with noise exceeded the integration of spatial and temporal treatment, while eliminating the need for the cuff.
[14]	Bi-tree-net mild nerve tree	The need for low computer consumption models for portable devices, while maintaining accuracy.
[15]	A system based on an analog nerve network with low capacity	Treating the problem of energy consumption and efficiency of implementation in compact devices to estimate blood pressure.
[16]	AI and ML	A lack of validation across a range of populations, also it is constrained by practical implementation challenges, such as patient trust issues.
[17]	Enterable style (assembling AI models) to estimate continuous blood pressure in health applications	Dealing with individual data fluctuations and the need to integrate multiple results to improve stability and accuracy.
[18]	Hybrid deep learning-based PPG signals	Computationally heavy.
[19]	Watching blood pressure without an independent of the topic using a multi-variable analysis of PPG data from the finger/foot and ECG	Addressing the defiance of generalization across different people, the variation of indicative forms, and physiological characteristics.
[20]	Attention CNN-BiLSTM model depends on symmetrical PPG signals (bipolar) taken from a wearable wrist.	No external or extensive clinical validation was conducted, which restricts the results' applicability to all demographic groups.

In this work, to choose the optimal forecasting system, three ML models—SVR, LSTM, and LightGBM are evaluated and contrasted.

3. RESEARCH BACKGROUND

The fundamentals of the study, such as SVR, Long Short-Term Memory LSTM, and LightGBM, are briefly described in this section, as well as the used dataset.

3.1 Support Vector Regression algorithm

SVR is related to SVM in that it is an extension of SVMs, except that the latter deal with regression problems. An SVR attempts to find a regression function that is as flat as possible, if the deviations of the estimated values from the actual ones do not exceed some tolerance, ρ, a departure from SVMs, where the main goal is to find a hyperplane separating data points for classification, as shown in Figure 1. This uses an ϵ-insensitive loss function in which errors smaller than ϵ are ignored, but bigger ones are penalized through a cost parameter C.

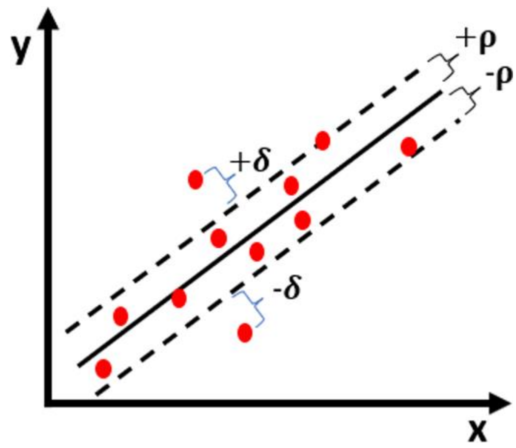

Figure 1. SVR-based regression approach

When the data show some nonlinear relationships, the SVR method uses appropriate kernel functions (linear, polynomial, RBF) to treat them accordingly.

The essential mathematical expression of the SVR is demonstrated as follows.

To keep the model as flat as possible, SVR attempts to fit a function f(x) with a maximum deviation ρ from the actual targets [21].

$$min_{w,b,\delta_i,\delta_i^*} \frac{1}{2}\|w\|^2 + C\sum_{l=1}^{n}(\delta_i + \delta_i^*) \tag{1}$$

where, the weight vector, w, determines the regression hyperplane's orientation and slope. The bias term (intercept) that causes the hyperplane to move up or down is denoted by b. $C\ is\ a$ parameter for regularization, $\delta_i,\ \delta_i^*$ represents the slack variables that manage errors by allowing specific points to fall outside the ϵ-insensitive tube. The SVR optimization problem is subject to:

$$\begin{aligned} & y_i - (w.\,x_i + b) \le \rho + \delta_i \\ & (w.\,x_i + b) - y_i \le \rho + \delta_i^* \\ & \delta_i, \delta_i^* \ge 0 \end{aligned} \tag{2}$$

Function of regression:

$$f(x) = \sum_{i=1}^{n}(\beta_i - \beta_i^*)K(x_i, x) + b \tag{3}$$

where, K(x_i, x) is the kernel function (such as RBF or linear), $\beta_i,\ \beta_i^*$ are used to quantify the degree to which the associated constraint is active.

The overall algorithm steps can be illustrated as follows:

- Select the kernel function K, such as linear or RBF.
- Set ρ and C as hyperparameters.
- Determine β_i, β_i^* by solving the convex optimization problem.
- Determine bias b.
- Predict with f(x).

3.2 Long Short-Term Memory

LSTM is a type of RNN that is designed to handle long-range dependencies while preventing the vanishing gradient problem. A memory cell is utilized here, with gates to control flows of information: forget, input, and output. The difference between LSTM and a regular RNN is that LSTM can choose to keep or forget certain information over obviously large time sequences, so they are effectively used for time-series prediction, speech recognition, and natural language processing. The mathematical expression of LSTM is shown in the following expressions [22, 23].

$$l_t = \vartheta(S_f[H_{t-1}, F_t] + z_f) \tag{4}$$

$$k_t = \vartheta(S_i[H_{t-1}, F_t] + z_i) \tag{5}$$

$$\varphi = tanh(S_c[H_{t-1}, F_t] + z_c) \tag{6}$$

$$\varphi_t = l_t * \varphi_{t-1}, k_t * \varphi \tag{7}$$

$$O_t = \vartheta(S_o[H_{t-1}, F_t] + z_o) \tag{8}$$

$$H_t = O_t * \tanh(\varphi_t) \tag{9}$$

$$Out_{class} = \vartheta(H_t * S_{out}) \tag{10}$$

where, l_t is the forgetting layer's output; k_t is a function that the input gate uses; φ is the new candidate's values' vector; φ_t is the cell's most recent state; S_f, S_i, S_c, S_o, S_{out} are the weights; z_f, z_i, z_c, z_o are the biases; H_t is the output at time t; F_t is the input features; Out_{class} is the output of classification.

Layer (type)	Output Shape	Param #
InputLayer	(None, 100, 10)	0
LSTM	(None, 64)	19,200
Dense	(None, 32)	2,080
Dense	(None, 16)	528
Dense	(None, 2)	34
Total params:		21,842
Trainable params:		21,842
Non-trainable params:		0

Figure 2. The architecture of the proposed LSTM model

Steps of the LSTM Algorithm are as follows:

Step 1: Set cell state φ_0 and hidden state H_0 to zero.

Step 2: Every time step t.

a. Compute forget gate l_t from H_{t-1} and F_t.

b. Compute input gate k_t and candidate cell state φ.

c. Update cell state $\varphi_t = l_t.\varphi_{t-1} + k_t.\varphi$.

d. Compute output gate O_t.

e. Update hidden state $H_t = O_t \cdot \tanh(\varphi_t)$.

Step 3: For the last output layer, use the most recent hidden state (or series of hidden states).

The structure of the proposed LSTM model for blood pressure prediction is shown in Figure 2, and the hyperparameter values are listed in Table 2.

Table 2. Models hyperparameters

Hyperparameters	Value
Activation Function	RELU
No. Epochs	5
Loss	RMSE
Batch_Size	128
Optimizer	Adam
Learning Rate	0.001
SVR	RBF kernel, C = 100, γ = 0.1
LightGBM	100 trees, learning rate = 0.05, max depth = 6
Data Splitting	70% training, 15% validation, and 15% testing

3.3 Light Gradient Boosting Machine

LightGBM is a speedy implementation of Gradient Boosting Decision Trees (GBDT). A series of decision trees is constructed sequentially, where each tree fits negative gradients of the loss function and thereby corrects the errors committed by the preceding tree. LightGBM differs from traditional GBDT in that it grows trees leaf-wise instead of level-wise based on whichever split gives the maximum information gain. It employs Histogram-based binning to provide faster computation and can handle large datasets with a smaller memory footprint. The mathematical description of LightGBM is illustrated as follows. The model is updated as follows at iteration j. In other words, Eq. (11) outlines the gradual improvement of the ensemble [24].

$$f_j(x) = f_{j-1}(x) + \mu h_j(x) \tag{11}$$

where, $f_j(x)$ represents the improved model following j iterations, $f_{j-1}(x)$ is the model afterwards $j-1$ iterations, $h_j(x)$ At iteration j, a new decision tree (weak learner) is added, μ is the rate of learning ($0 < \eta \leqslant 1$), x is the input vector for features. Now, with regard to the split gain expression, which determines the optimal split, LightGBM employs a leaf-wise growth strategy based on histograms. When a node is divided into left and right child nodes, the gain (loss reduction). This means that Eq. (12) explains how LightGBM balances regularization and gradient information when choosing which feature and threshold to split at each node.

$$gain = \left(\frac{Q_L^2}{D_L + \lambda} + \frac{Q_R^2}{D_R + \lambda} - \frac{(Q_L + Q_R)^2}{D_L + D_R + \lambda} \right) - \phi \tag{12}$$

where, $gain$ is the objective function's improvement (better split equal to larger gain), Q_L, Q_R are the sum of the left and right child nodes' first-order gradients, or residuals, of the loss, D_L, D_R denote the sum of the loss's second-order gradients (Hessian) for the left and right child nodes, $Q_L + Q_R$ refer to the parent node's total gradient prior to splitting, $D_L + D_R$ are the parent node's total hessian prior to splitting, λ is the regularization on leaf weights, ϕ is the cost of complexity, or the penalty for taking a different leaf. Now, the steps that describe the LightGBM algorithm can be demonstrated as follows:

Step 1: Set the average target value (for regression) as the initial value for predictions.

Step 2: For every iteration of boosting:

a. Using the current predictions, calculate the gradients Q_j and hessians Dj.

b. Use Q_j and hessians Dj to determine the split with the highest gain for each leaf.

c. Expand the tree leaf by leaf until the maximum depth or minimum leaf data is attained.

d. Use Eq. (11) to update predictions.

Step 3: Provide the final model, which is the ensemble of trees.

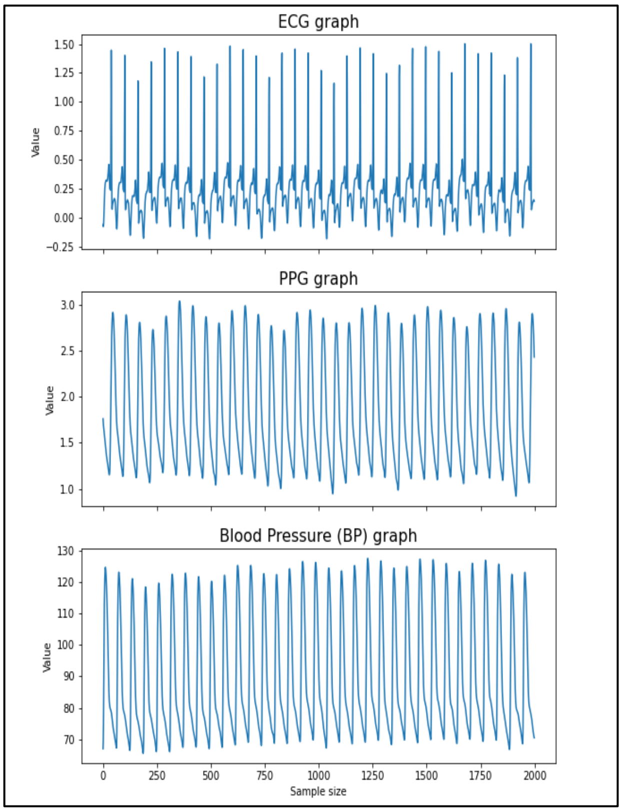

Figure 3. A sample from the applied dataset

3.4 Cuffless dataset description

The dataset illustrated in Table 3 is used in this study, namely the UCI ML Repository Cuffless Blood Pressure Estimation Dataset [25]. The applied dataset consists of a sample, which is depicted in Figure 3. It has 12000 samples in total. The signals ECG, PPG, and ABP are the only ones present in each sample, with a sampling rate of 125 Hz. First, the Electrocardiogram (ECG) represents a recording of the electrical activity of the heart muscle over time. The heart's electrical impulses are responsible for coordinating its contractions and making it possible for blood to flow through the body. Secondly, Photoplethysmography (PPG) is a non-invasive technique that uses light to measure blood flow in the capillaries of the skin. PPG provides important insights into the cardiovascular system; moreover, it is a non-invasive, portable, and cost-effective method. The third signal, arterial blood pressure (ABP), refers to the pressure that the blood exerts on the walls of the arteries. Blood pressure is interlinked to the heart cycle, which has two alternating phases: systole, when the heart contracts and propels the blood through the arteries, and diastole, when the heart relaxes after the contraction.

Table 3. UCI Cuffless Blood Pressure Dataset description

Properties	Descrpition
Number of subjects	12 people (multiple registrations)
Number of records	More than 2,000,000 signal samples
Available signals	Electrocardiogram (ECG) signal + Photoplethysmography (PPG) signal + Reference Blood Pressure (ABP) signal
Data type	Physiological time series
Sampling rate	125 Hz
Target variables	Systolic blood pressure (SBP) + Diastolic blood pressure (DBP)
Purpose	Developing artificial intelligence methods for non-invasive blood pressure estimation (Cuff-less)

3.5 Wearable cuffless for blood pressure hypertension

Cuffless, wearable blood pressure measurement devices offer a very convenient way to monitor hypertension and hypotension while increasing the opportunity for long-term management of blood pressure [26]. It makes use of biophysiological signals such as photoplethysmograms (PPG) and electrocardiograms (ECGs). However, some of its limitations are: first, calibration is necessary for accuracy when using cuff-based devices. Second, reliability may be lowered by signal noise, which includes skin tone, motion artifacts, and ambient light. Additionally, clinical-grade accuracy is still being validated. Several medical, technological, and practical requirements drive the decision to employ AI for Blood Pressure (BP) prediction or forecasting rather than more conventional techniques [27, 28], including

(1) motivation in healthcare

- Early and ongoing monitoring is necessary to identify abnormal blood pressure trends before complications like stroke, heart attack, or kidney failure arise because hypertension is a silent killer.

- Traditional cuff-based devices are unable to record the dynamic fluctuations in blood pressure caused by stress, activity, or sleep. These temporal variations can be modeled by AI.

- Personalized healthcare: Unlike one-size-fits-all cuff methods, AI models can adjust to the physiology of each patient.

(2) Technical inspiration

- Nonlinear physiological relationships: Heart rate variability, PPG, ECG, and other signals are intricate and interconnected. Traditional statistical techniques are unable to reveal hidden nonlinear patterns; AI can.

- Automation of feature extraction: AI (such as deep learning) eliminates the need for manually created features by automatically extracting significant features from unprocessed signals.

- Predicting future blood pressure trends: AI can predict future risks (such as the onset of hypertension) in addition to current blood pressure, something that traditional methods are unable to do.

(3) Realistic motivation

- Constant monitoring and comfort: Although wearable cuffless devices are comfortable, their unprocessed signals are noisy. By removing noise and identifying reliable patterns, AI increases accuracy.

- Use of big data: AI can enhance population-level generalization by utilizing sizable medical datasets (from wearables, EHRs, and IoT systems).

- Integration with telemedicine: AI-powered cuffless blood pressure monitors can give physicians real-time decision support, early warnings, and remote monitoring.

Therefore, the goal of AI in blood pressure prediction is to overcome the drawbacks of conventional cuff-based systems and allow for continuous, personalized, and predictive hypertension management.

4. DESIGN OF THE AI BLOOD PRESSURE PREDICTION SYSTEM

The goal of the proposed approach is to use vital signs like ECG and PPG, which are available in the UCI Cuffless BP Dataset, to predict systolic and diastolic blood pressure (SBP/DBP) non-invasively (cuffless). In contrast to conventional approaches, the primary idea is to use ML and artificial intelligence techniques to increase accuracy and decrease error. The proposed cuffless blood pressure estimation pipeline can be described as follows: ECG and PPG signals are used as the input signals to the models. Arterial blood pressure (ABP) is not used as a predictive input. Instead, ABP serves as an invasive reference standard from which reference SBP and DBP values are extracted. Figure 4 illustrates the overall proposed system structure.

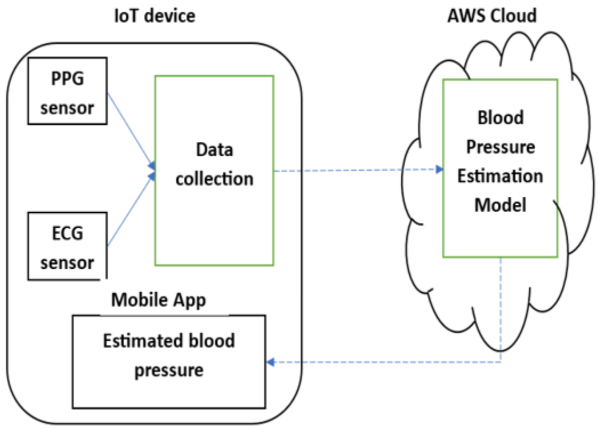

Figure 4. The proposed cloud-based cuffless blood pressure monitoring system

The system design has followed the following phases:

Phase 1: Data Acquisition

• Using data from the UCI Cuffless Blood Pressure Dataset.

• The data contains ECG, PPG, and ABP signals.

Phase 2: Preprocessing

• Noise Filtering.

• ECG Signal Processing:

A bandpass Butterworth filter (0.5–40 Hz, 4th order) is applied to remove baseline wander and high-frequency noise. R-peaks are detected using a modified Pan–Tompkins algorithm.

• PPG Signal Processing:

A bandpass Butterworth filter (0.5–8 Hz, 4th order) is applied to suppress motion artifacts and noise. PPG systolic peaks and foot points are identified using first-derivative and zero-crossing techniques.

• Feature Extraction: Extracting features such as PTT, PAT, and waveforms from the PPG/ECG.

- PTT and PAT Computation:

- Pulse Arrival Time (PAT): Computed as the time interval between the ECG R-peak and the corresponding PPG systolic peak.

- Pulse Transit Time (PTT): Computed as the time interval between the ECG R-peak and the PPG foot point.

Given the dataset sampling frequency of 125 Hz, the temporal resolution is approximately 8 ms.

Phase 3: Modeling

• SVR (Support Vector Regression): For predicting SBP/DBP as a linear and nonlinear method.

• LSTM (Long Short-Term Memory): For processing time sequences of vital signals, this model is the most robust for handling the long-term relationship between ECG/PPG and blood pressure.

• LightGBM: Used as a regression model for predicting of SBP/DBP.

It is worth stating that the input features to the proposed models consist of the following features (PTT, PAT, Heart rate, PPG features)

Phase 4: Evaluation

• RMSE and MAE metrics are used to measure model accuracy.

• Comparison between the three models.

Phase 5: Deployment & Visualization Stage

• The trained model (SVR or LSTM, or LightGBM) is deployed to the application.

• The application receives signals or processing results from the server/device.

• The readings are displayed directly to the user (real-time BP prediction).

• Graphs can be added to display the change in blood pressure over time.

The current study introduces a conceptual design in the form of an Amazon Web Services (AWS) based Internet of Things (IoT) architecture, illustrating the future installation of suggested models in a smart health monitoring setting. The present study revolves around the online assessment of blood pressure estimation models using standard databases, while hands-on implementation and real integration with AWS and mobile apps are considered.

The following reasons are the basis for the consideration of AWS as the cloud environment for the IoT-enabled smart blood pressure monitoring system in this work:

1. AWS IoT Core

• Functions as a communication mediator (MQTT Broker).

• Accepts the delivery of ECG and PPG data from the wearable devices.

• Guarantees safety in communication by the use of digital certificates (TLS).

2. AWS Lambda

• The platform for running algorithms for preprocessing and feature extraction (PTT, PAT).

• Provides the facility for the blood pressure prediction model to be implemented without needing a dedicated server.

3. AWS DynamoDB/S3

• Main storage for vital signs and their predictions.

• Facilitates access to the data for subsequent medical evaluation.

4. Mobile Application

• Primarily functions as a receiver of data.

• Shows estimated values (SBP/DBP) and also provides graphs for ECG and PPG signals.

It is worth stating that the last phase allows the user or doctor to interpret the results and monitor their health, as shown in Figure 5.

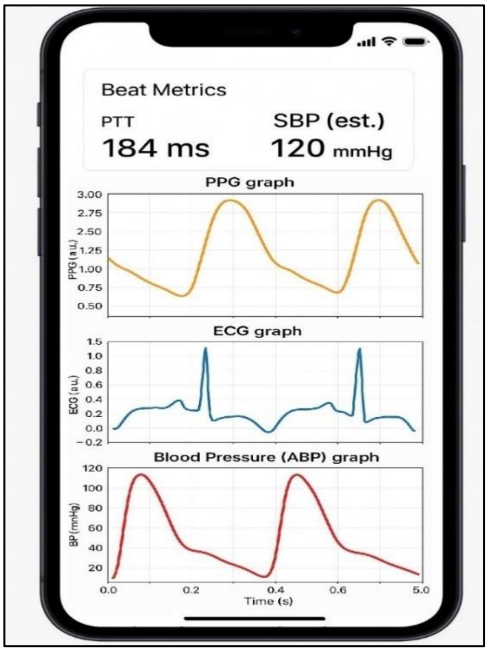

Figure 5. Mobile app for blood pressure monitoring

5. RESULTS AND DISCUSSION

The performance evaluation in this work is divided into three scenarios based on different combinations of selected datasets, which are the ABP, PPG, and ECG. Where the ABP is used as a ground truth for prediction. Regarding the evaluation metrics, the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), as illustrated in Eqs. (13) and (14), are used to testify the accuracy of the proposed three models (SVR, LSTM, and LightGBM). The RMSE can be determined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{13}$$

where, n is the number of samples, y_i is the i-th sample's actual (true) value, $\hat{y}_i$ The expected amount of the i-th sample.

Then the value of the Mean Absolute Error (MAE) can be calculated as follows:

$$MAE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|} \tag{14}$$

The reason behind using both the RMSE and the MAE is that the MAE directly measures the average amount of error (absolute error), while the RMSE gives greater weight to large errors (due to the squared).

Additionally, for statistical analysis measurement for the proposed models, the confidence interval (CI) metric is considered as follows.

$$\mathrm{CI} = \delta \pm \vartheta \sqrt{\frac{\rho(1-\rho)}{\epsilon}} \quad (15)$$

where, δ is the model's accuracy, ϑ is the z-score level, and ρ is the percentage of successes within the samples.

Now, in the first scenario, the PPG and ABP data are used to predict the blood pressure as depicted in Figure 6. It can be noted in Table 4 that the LSTM outperforms both the SVR and LightGBM in terms of prediction error.

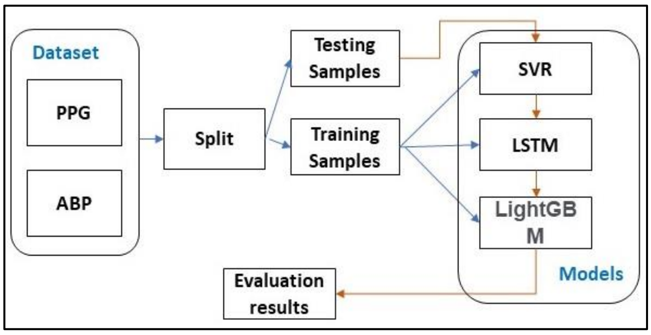

Figure 6. Evaluation process of the models for scenario A

Table 4. Results of scenario A (PPG+ABP)

Model	RMSE (95% CI)	MAE (95% CI)
SVR	23.78 (22.90 – 24.66)	17.54 (16.82 – 18.26)
LSTM	22.36 (21.55 – 23.17)	15.65 (14.98 – 16.32)
LightGBM	25.35 (24.40 – 26.30)	19.82 (18.95 – 20.69)

In the second scenario, the combination of the ECG and ABP is selected as input for predicting the BP, as shown in Figure 7. The evaluation results are shown in Table 5.

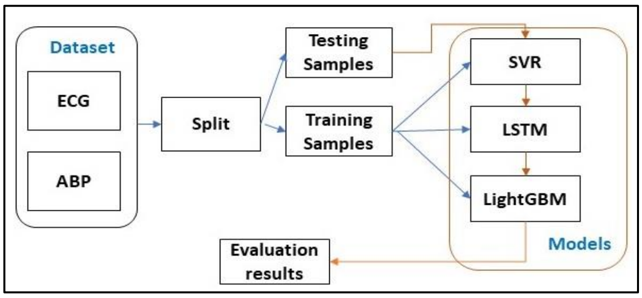

Figure 7. Evaluation process of the models for scenario B

Table 5. Results of scenario B (ECG+ABP)

Model	RMSE (95% CI)	MAE (95% CI)
SVR	22.58 (21.70 – 23.46)	20.03 (19.25 – 20.81)
LSTM	20.62 (19.85 – 21.39)	18.64 (17.92 – 19.36)
LightGBM	26.25 (25.30 – 27.20)	21.32 (20.45 – 22.19)

Likewise, the LSTM is the best model compared to other approaches in terms of the prediction error.

Finally, the third scenario combines PPG, ABP, and ECG, which are used for BP forecasting as illustrated in Figure 8.

Based on the results of scenario C, that shown in Table 6, it is worth stating that the LSTM also has the highest performance in terms of BP prediction.

Here, combining the (PPG, ECG, and ABP) achieved the best results compared to the first and the second scenarios due to BP correlates with Pulse Transit Time (PTT) / Pulse Arrival Time (PAT), measured between the ECG R-wave and PPG foot/peak; this timing is a strong surrogate for arterial stiffness/BP.

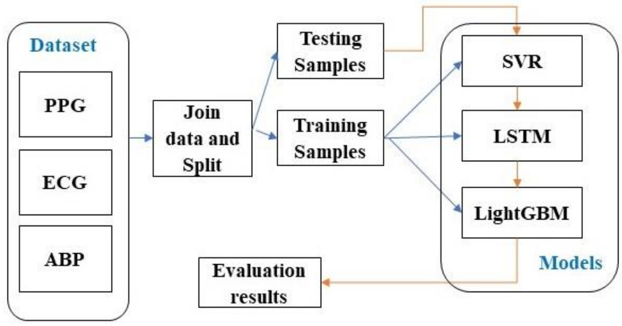

Figure 8. Evaluation process of the models for scenario C

Table 6. Results of scenario C (PPG+ECG+ABP)

Model	RMSE (95% CI)	MAE (95% CI)
SVR	16.15 (15.45 – 16.85)	14.64 (13.98 – 15.30)
LSTM	12.36 (11.82 – 12.90)	10.36 (9.88 – 10.84)
LightGBM	17.54 (16.80 – 18.28)	16.39 (15.70 – 17.08)

Furthermore, the experiments indicate that attempting to estimate BP with a PPG alone is an ambiguous and noise-sensitive task; combining the ECG+PPG signals increases the robustness and accuracy of the estimation.

Though it is difficult to make direct numerical comparisons among studies because of the various factors such as datasets, signal acquisition protocols, and evaluation strategies, the proposed LSTM model (RMSE = 12.36 mmHg, MAE = 10.36 mmHg for SBP) is still able to show performance that is on par with the latest PPG-based deep learning methods. Our approach, in contrast to attention-based or CNN-BiLSTM models such as the studies [9, 18], achieves similar accuracy with a less complex architecture and a different dataset. Meanwhile, multimodal systems, as in the study [5], report fewer errors, but they also require more sensing hardware. The proposed approach can work with just PPG signals, thus illustrating a favorable trade-off between accuracy and system complexity.

6. CONCLUSIONS

One of the most prevalent chronic illnesses in the world, high blood pressure (hypertension) is a significant risk factor for heart disease and stroke. The majority of traditional blood pressure monitors are cuff-based, which makes continuous monitoring challenging and uncomfortable for the patient. Consequently, cuffless measurement technologies that use biomarkers like ECG and PPG have surfaced, offering a more practical and comfortable way to monitor in real time. Accurately predicting systolic (SBP) and diastolic (DBP) blood pressure using physiological signals from the UCI Cuffless Blood Pressure Estimation Dataset is the primary issue this study attempts to solve. The objective is to create an AI-based model that, in contrast to conventional techniques, minimizes error. ECG and PPG signals were subjected to separate feature extraction and subsequent combination. SBP and DBP values were then predicted using ML and deep learning algorithms (including SVR, LightGBM, and LSTM). According to experiments, combining the ECG and PPG signals results in a higher accuracy (lower mean square error of 12.36 and MAE of 10.36) than using either signal alone. The results also demonstrated that the LSTM model performed the best when predicting both SBP and DBP using both signals together, and it significantly outperformed the other two models (SVR and LightGBM) in predicting blood pressure values.

REFERENCES

[1] Baker, S., Xiang, W., Atkinson, I. (2021). A hybrid neural network for continuous and non-invasive estimation of blood pressure from raw electrocardiogram and photoplethysmogram waveforms. Computer Methods and Programs in Biomedicine, 207: 106191. https://doi.org/10.1016/j.cmpb.2021.106191

[2] El-Hajj, C., Kyriacou, P.A. (2020). A review of machine learning techniques in photoplethysmography for the non-invasive cuff-less measurement of blood pressure. Biomedical Signal Processing and Control, 58: 101870. https://doi.org/10.1016/j.bspc.2020.101870

[3] Mohebbian, M.R., Dinh, A., Wahid, K., Alam, M.S. (2020). Blind, cuff-less, calibration-free and continuous blood pressure estimation using optimized inductive group method of data handling. Biomedical Signal Processing and Control, 57: 101682. https://doi.org/10.1016/j.bspc.2019.101682

[4] Pandit, J.A., Lores, E., Batlle, D. (2020). Cuffless blood pressure monitoring: Promises and challenges. Clinical Journal of the American Society of Nephrology, 15(10): 1531-1538. https://doi.org/10.2215/CJN.03680320

[5] Hsiao, C.T., Hong, S., Branan, K.L., McMurray, J., Coté, G.L. (2025). Predicting blood pressure without a cuff using a unique multi-modal wearable device and machine learning algorithm. Computers in Biology and Medicine, 192: 110357. https://doi.org/10.1016/j.compbiomed.2025.110357

[6] Song, K., Chung, K.Y., Chang, J.H. (2019). Cuffless deep learning-based blood pressure estimation for smart wristwatches. IEEE Transactions on Instrumentation and Measurement, 69(7): 4292-4302. https://doi.org/10.1109/TIM.2019.2947103

[7] Qin, C., Li, Y., Liu, C., Ma, X. (2023). Cuff-less blood pressure prediction based on photoplethysmography and modified ResNet. Bioengineering, 10(4): 400. https://doi.org/10.3390/bioengineering10040400

[8] Ganti, V.G., Carek, A.M., Nevius, B.N., Heller, J.A., Etemadi, M., Inan, O.T. (2020). Wearable cuff-less blood pressure estimation at home via pulse transit time. IEEE Journal of Biomedical and Health Informatics, 25(6): 1926-1937. https://doi.org/10.1109/JBHI.2020.3021532

[9] El-Hajj, C., Kyriacou, P.A. (2021). Deep learning models for cuffless blood pressure monitoring from PPG signals using attention mechanism. Biomedical Signal Processing and Control, 65: 102301. https://doi.org/10.1016/j.bspc.2020.102301

[10] Yan, C., Li, Z., Zhao, W., Hu, J., Jia, D., Wang, H., You, T. (2019). Novel deep convolutional neural network for cuff-less blood pressure measurement using ECG and PPG signals. In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, pp. 1917-1920. https://doi.org/10.1109/EMBC.2019.8857108

[11] Yin, S., Li, G., Luo, Y., Lin, L. (2021). Cuff-less continuous blood pressure measurement based on multiple types of information fusion. Biomedical Signal Processing and Control, 68: 102549. https://doi.org/10.1016/j.bspc.2021.102549

[12] Yang, S., Zhang, Y., Cho, S.Y., Correia, R., Morgan, S.P. (2021). Non-invasive cuff-less blood pressure estimation using a hybrid deep learning model. Optical and Quantum Electronics, 53(2): 93. https://doi.org/10.1007/s11082-020-02667-0

[13] Li, Y., Chen, M., Wang, C., Li, Y., Wang, Y., Wei, S. (2025). Continuous Cuff-less blood pressure estimation using lightweight binary tree neural network. IEEE Transactions on Instrumentation and Measurement, 74: 1-12. https://doi.org/10.1109/TIM.2025.3545993

[14] Alimisis, V., Mylona, A., Cheliotis, K., Moustakas, V., Foufas, Z., Sotiriadis, P.P. (2025). A cuff-less blood pressure estimation system based on low-power analog integrated neural network. In 2025 14th International Conference on Modern Circuits and Systems Technologies (MOCAST), Dresden, Germany, pp. 1-6. https://doi.org/10.1109/MOCAST65744.2025.11083960

[15] Shimbo, D., Shah, R.U., Abdalla, M., Agarwal, R., et al. (2025). Transforming hypertension diagnosis and management in the era of artificial intelligence: A 2023 national heart, lung, and blood institute (NHLBI) workshop report. Hypertension, 82(1): 36-45. https://doi.org/10.1161/HYPERTENSIONAHA.124.22095

[16] Haque, R., Wang, C., Pala, N. (2025). An ensemble-based AI approach for continuous blood pressure estimation in health monitoring applications. Sensors, 25(15): 4574. https://doi.org/10.3390/s25154574

[17] Mohammadi, H., Tarvirdizadeh, B., Alipour, K., Ghamari, M. (2025). Cuff-less blood pressure monitoring via PPG signals using a hybrid CNN-BiLSTM deep learning model with attention mechanism. Scientific Reports, 15(1): 22229. https://doi.org/10.1038/s41598-025-07087-2

[18] Dehghanojamahalleh, S., Gamage, P.T., Ahmed, M., Petersen, C., et al. (2025). Subject-independent cuff-less blood pressure monitoring via multivariate analysis of finger/toe photoplethysmography and electrocardiogram data. BioMedInformatics, 5(2): 24. https://doi.org/10.3390/biomedinformatics5020024

[19] Lopez-Jimenez, F., Deshmukh, A., Bisognano, J., Boehmer, J., et al. (2025). Development and internal validation of an AI-enabled cuff-less, non-invasive continuous blood pressure monitor across all classes of hypertension. Journal of Cardiovascular Translational Research, 18(2): 280-290. https://doi.org/10.1007/s12265-024-10589-5

[20] Comito, C., Pizzuti, C. (2022). Artificial intelligence for forecasting and diagnosing COVID-19 pandemic: A focused review. Artificial Intelligence in Medicine, 128: 102286. https://doi.org/10.1016/j.artmed.2022.102286

[21] Nasser, A.R., Mahmood, A.M. (2021). Cloud-based parkinson's disease diagnosis using machine learning. Mathematical Modelling of Engineering Problems, 8(6): 915-922. https://doi.org/10.18280/mmep.080610

[22] Zhou, Y., Wang, W., Wang, K., Song, J. (2022).

Application of LightGBM algorithm in the initial design of a library in the cold area of China based on comprehensive performance. Buildings, 12(9): 1309. https://doi.org/10.3390/buildings12091309
[23] Kachuee, M., Kiani, M.M., Mohammadzade, H., Shabany, M. (2015). Cuff-less high-accuracy calibration-free blood pressure estimation using pulse transit time. In 2015 IEEE International Symposium on Circuits and Systems (ISCAS), Lisbon, Portugal, pp. 1006-1009. https://doi.org/10.1109/ISCAS.2015.7168806
[24] Kuzmanov, I., Bogdanova, A.M., Kostoska, M., Ackovska, N. (2022). Fast cuffless blood pressure classification with ECG and PPG signals using CNN-LSTM models in emergency medicine. In 2022 45th Jubilee International Convention on Information, Communication and Electronic Technology (MIPRO), Opatija, Croatia, pp. 362-367. https://doi.org/10.23919/MIPRO55190.2022.9803582
[25] Vijetha, K.J., Priya, S.S.S. (2024). A comparative analysis of CNN architectures and regularization techniques for breast cancer classification in mammograms. Ingénierie des Systèmes d'Information, 29(6): 2433-2441. https://doi.org/10.18280/isi.290630
[26] Min, S., An, J., Lee, J.H., Kim, J.H., et al. (2025). Wearable blood pressure sensors for cardiovascular monitoring and machine learning algorithms for blood pressure estimation. Nature Reviews Cardiology, 22: 629-648. https://doi.org/10.1038/s41569-025-01127-0
[27] Nasser, A.R., Alani, O.Y. (2025). Investigation of multiple hybrid deep learning models for accurate and optimized network slicing. Computers, 14(5): 174. https://doi.org/10.3390/computers14050174
[28] Mahsup, Febriani, P.A., Syaharuddin, Mandailina, V., Abdillah, Ibrahim. (2024). Accuracy rate of least square support vector machine method and its various modifications: A forecasting evaluation on multi-type data. Ingénierie des Systèmes d'Information, 29(3): 1209-1208. https://doi.org/10.18280/isi.290337