

# Non-Invasive Blood Pressure Estimation Using Photoplethysmogram Morphological Features and Machine Learning

**Bingzhe Zhao \***

Department of Electrical &  
Electronic Engineering, University  
of Nottingham, Ningbo, China

\*Corresponding author: Bingzhe.  
Zhao@outlook.com

## Abstract:

Continuous and unobtrusive blood pressure monitoring is vital for the early diagnosis and effective management of cardiovascular diseases. Conventional pneumatic cuffs cause physical discomfort during repeated measurements, while invasive catheterization poses substantial clinical risks. To overcome these limitations, this work proposes a non-invasive cuffless blood pressure estimation framework based on single-channel photoplethysmogram signals. An automated signal processing pipeline segments individual pulse cycles and extracts 23 candidate morphological, area and derivative features. Then, screening by Pearson correlation identifies an optimal subset of twelve salient parameters. A strict subject-wise five-fold cross-validation scheme is used to systematically evaluate four representative machine learning regression models. The simulated data set contains 2,500 beat-to-beat samples, simulated according to benchmark hemodynamic distributions. XGBoost achieved the best performance in predicting systolic pressure, with MAE of 2.49 mmHg and correlation coefficient of 0.97. Random Forest performs slightly better for diastolic pressure (MAE = 4.21 mmHg) with a small difference with XGBoost (MAE = 4.28 mmHg,  $r=0.74$ ). The simulated conditions' numerical errors meet the benchmark thresholds of the ANSI/AAMI/ISO standard and the British Hypertension Society Grade A protocol. This does not mean clinical validation. These results validate the feasibility of lightweight, interpretable machine learning regression on wearable healthcare hardware for continuous cardiovascular monitoring.

**Keywords:** Photoplethysmography (PPG), Cuffless blood pressure estimation, Morphological features, Machine learning, Continuous cardiovascular monitoring.

## 1. Introduction

Cardiovascular diseases (CVD) remain one of the leading causes of death and long-term disability in the world, accounting for millions of deaths annually. Chronic hypertension remains a major preventable risk factor for CVD [1]. Sustained high pressure generally leads to stroke and myocardial infarction. Over time, it may also result in chronic heart failure. Continuous ambulatory monitoring of blood pressure is crucial to the detection of occult cardiovascular events regularly missed by spot-checks. This has become necessary because blood pressure fluctuates continuously during the day influenced by the circadian rhythms and activities.

Despite its diagnostic importance, the traditional measurement methods are severely restricted in the continuous situation. Invasive intra-arterial catheterization is the gold standard for the continuous beat-to-beat track of arterial blood pressure (ABP). Unfortunately, it also harbours serious infection risks, and its use is confined to intensive care units only. On the other hand, traditional non-invasive devices are based on pneumatic cuff-based oscillometric sphygmomanometers. Repetitive inflation by pneumatic cuffs leads to physical pain and disturbs sleep. Thus, cuff-based devices are not suitable for unobtrusive continuous monitoring of 24 hours.

Together with these constraints, optical sensing by photoplethysmography (PPG) has made rapid progress in the wearable sensing paradigm. Photoplethysmography detects microvascular blood volume changes in peripheral tissue beds non-invasively per heartbeat (during each cardiac cycle) [2]. Early types of cuffless continuous estimation relied mostly on the Pulse Transit Time (PTT) approach. PTT is inversely proportional to arterial blood pressure. But it requires simultaneous acquisition of ECG and PPG signals from different anatomical sites [3]. The co-acquisition leads to increased complexity of the hardware requirements. It also introduces a synchronization delay in the inter-channel acquisition. Thus, integration into a compact wearable wrist device is challenging.

Thus, single-channel PPG-based blood pressure estimation has emerged as an attractive, wearable-friendly alternative [2]. A single PPG waveform carries rich information of blood vessel characteristics, including arterial stiffness and peripheral resistance [4]. Some of such applications have preceded in this paradigm by two routes. One of these applies deep neural networks on the raw waveforms, the other relies on the regression models of extracted temporal landmarks. The deep learning-based approaches have strong prediction capabilities, but high computational demands and lack physiological understandings [5]. Meanwhile, medical evidences on PPG morphological features

have been made in the existing literature [4]. However, few works benchmark these features under a unified engineering framework. Derivative dynamics (VPG and APG) and waveform area metrics are seldom combined. Also, extensive evaluation against international clinical criteria on large-scale ICU datasets is still lacking.

Adopting a non-invasive cuffless blood pressure estimation framework, this paper proposes a combined PPG morphology feature engineering, machine learning regression algorithm solution to confront those problems. An end-to-end signal processing pipeline strategy obtains multi-domain pulse parameter feature from full pulse wave morphology. Main pulse geometry of pulse wave is extracted by temporal interval and amplitude ratio. In addition, waveform integration area and derivative landmark areas (Velocity and Acceleration Plethysmograms, VPG/APG) are extracted. Pearson correlation is used to discover the optimal most representative feature subset and reduce redundancy. Meanwhile, multiple good representative machine learning regression models (Linear Regression, Support Vector Regression (SVR), Random Forest (RF), Extreme Gradient Boosting (XGBoost)) are considered and benchmarked to figure out the best predictive model. To evaluate estimation reliability, the proposed framework is benchmarked in simulated pulse wave to adhere to benchmark hemodynamics distribution.

The estimation accuracy for it is evaluated against both the Association for the Advancement of Medical Instrumentation (AAMI) protocol and the British Hypertension Society (BHS) grading standard. The rest of the paper is organized as follows. Section II provides the data set and preprocessing. Section III gives the morphology feature extraction. Section IV describes the regression model. Section V reports the experimental results, and Section VI concludes the paper.

## 2. Data Preparation and Preprocessing

### 2.1 Simulated Benchmark Dataset and PPG Generation

Another step to understand regression performance on different types of arterial dynamics is to build a synthetic benchmark dataset consistent with the statistics of the MIMIC database [6]. The reference blood pressure targets are sampled from clinically representative distributions. Systolic pressure varies from 85 to 175 mm Hg, diastolic pressure from 52 to 115 mm Hg. Sampling frequency is sampled as 125 Hz to be consistent with that from bed measurement systems. For each PPG pulse, a two-component physiological model synthesis of a primary systolic

wave ( $p_1$ ) and reflected diastolic wave ( $p_2$ ) is used. Vascular stiffness is a nonlinear function of normalized systolic pressure to emulate arterial collagen stiffening of arteries. The reflected wave amplitude attenuation and phase shift with respect to time vary according to this index of vascular stiffness. Each waveform is subjected to a Gaussian optical sensor noise ( $\sigma = 0.02$ ) to emulate realistic acquisition artefacts.

A total of 2,500 paired beat-to-beat cycles were generated. These pulses were assigned across 53 simulated subject profiles (approximately 47 cycles per subject) to enable rigorous subject-wise cross-validation without data leakage. The synthesized continuous pressure trace served as the ground truth (benchmark). For each cycle, reference SBP was defined as the maximum pressure level, and reference DBP was defined as the beginning of valley level.

## 2.2 Signal Filtration and Quality Screening

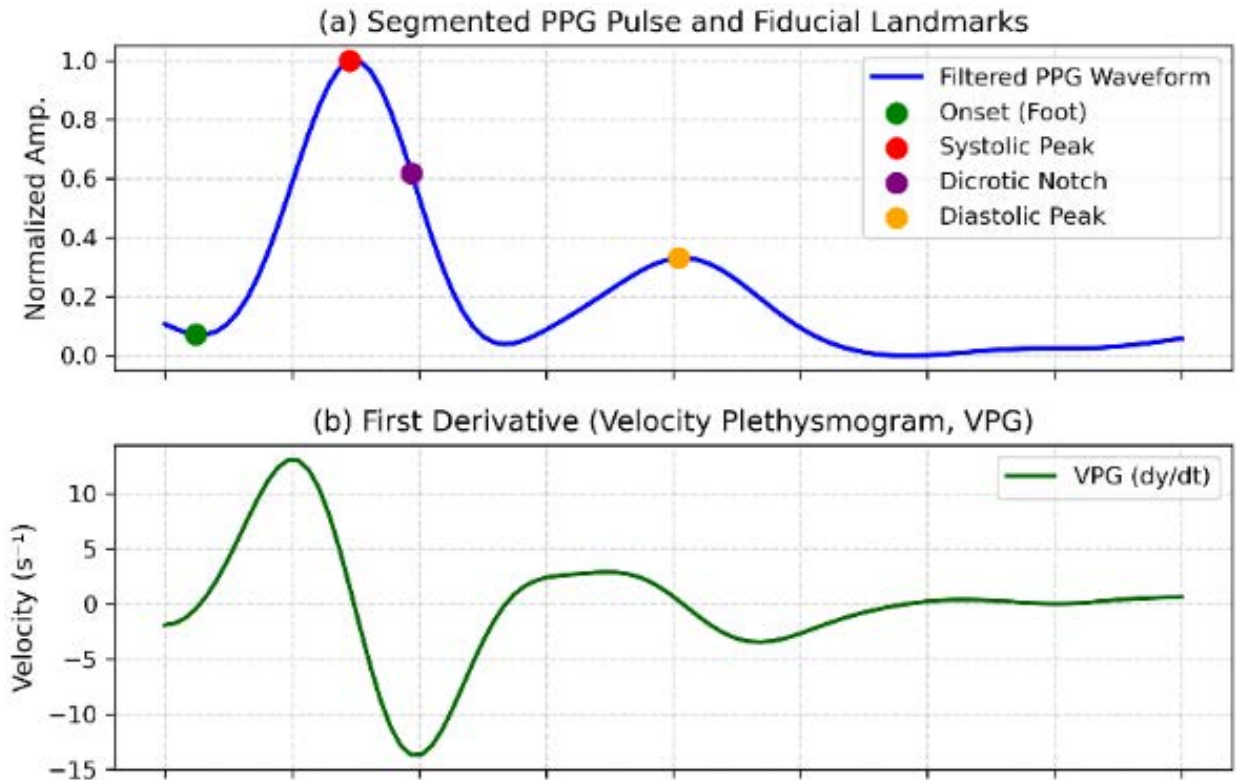
Raw optical PPG recordings are contaminated by noise. High-frequency artefacts result from electromagnetic interference and muscle tremors. Low-frequency artefacts originate from respiration and cause baseline wandering. To cancel out these artefacts without distorting the morphology of the hemodynamic waveform, a fourth order zero-phase Butterworth bandpass filter with cutoff frequencies of 0.5 Hz and 8.0 Hz was used. The forward-backward zero-phase implementation is required

to eliminate temporal phase shifts and retain the accurate timing of the landmarks of important waves.

After filtration, an automated physiological plausibility screening was performed to remove corrupted parts caused by sensor jittering, patient movement or an in-catheter flushing of the sensor. Waveforms that did not fulfil the physiological plausibility expectation were rejected: (1) SBP outside of the range of 80 mmHg to 180 mmHg; (2) DBP outside of the range of 50 mmHg to 120 mmHg; and (3) pulse pressure (the difference between SBP and DBP) smaller than 20 mmHg.

## 2.3 Pulse Cycle Segmentation and Landmark Identification

Each continuous PPG signal was segmented into separate, beat-to-beat cardiac cycles. To locate fiducial landmarks reliably, a hybrid adaptive threshold peak detection and derivative zero-crossings algorithm was developed. Systolic peaks ( $t_s, y_s$ ) were first located via a sliding window local maximum search. A dynamic amplitude threshold and minimum distance threshold (0.4 s, which was equivalent to a maximum heart rate of 150 bpm) were applied to purge false peaks. Starting at each peak, pulse onset ( $t_{\text{onset}}$ ) was located by backtracking to the local minimum, which coincided with the upward zero-crossing of the first derivative (VPG).



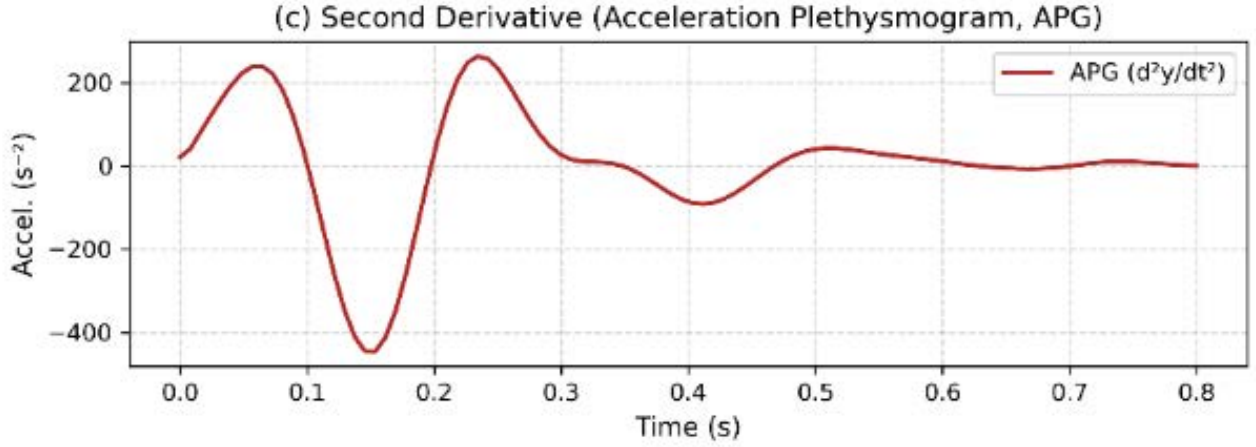


**Fig. 1 Typical segmented PPG pulse waveform and its first/second derivatives (VPG and APG), illustrating the identified fiducial landmarks (onset, systolic peak, diastolic notch, and diastolic peak).**

Both first and second derivatives, VPG and APG, were used as auxiliary indices for detecting diastolic notch ( $t_n, y_n$ ) and diastolic peak ( $t_d, y_d$ ). The derivative assisted strategy was chosen because signal damping inhibited direct identifying from raw waveforms. Specifically, the diastolic notch was determined by finding the local minimum point of VPG value from systolic peak to the next cycle. The diastolic peak was then determined by tracking for the subsequent downward zero crossing of VPG. A typical cardiac cycle with identified fiducial landmarks and with first and second derivatives (VPG and APG) for it are illustrated in Fig. 1.

### 3. Morphological Feature Engineering

#### 3.1 Time-Domain Morphology and Waveform Area Features

It is also necessary to obtain a precise mapping between the optical pulse dynamics and arterial blood pressure. A set of morphological features was extracted from each PPG segment throughout a cycle. The variations of timing and amplitude during the cardiac cycle represent the flow of the ventricular stroke volume as well as peripheral vascular compliance. From the filtered PPG waveform, some key temporal intervals were extracted, including systolic rise time, diastolic decay time and total pulse duration. The peak-peak time interval ( $\Delta T_{s,d} = t_d - t_s$ ) was also extracted. In addition, pulse widths at 25%, 50% and 75% of pulse height ( $W_{25}, W_{50}, W_{75}$ ) were extracted to fully quantify the overall geometry sharpness of the systolic upstroke and diastolic descent, respectively.

Other features of interest include temporal parameters, but also amplitude ratios and integral area parameters have implications for vascular resistance. The systolic peak amplitude ( $A_s$ ), diastolic notch amplitude ( $A_n$ ), and diastolic peak amplitude ( $A_d$ ) were extracted alongside their difference ( $\Delta A = A_s - A_n$ ). These three parameters yielded Reflection Index ( $RI = A_d / A_s$ ) and the Diastolic Notch Ratio ( $NR = A_n / A_s$ ). The waveform was integrated to provide the systolic area ( $S_{\text{area}} = \int_{t_{\text{onset}}}^{t_n} y(t) dt$ ) and diastolic area ( $D_{\text{area}} = \int_{t_n}^{t_{\text{end}}} y(t) dt$ ). The area ratio, defined as  $R_{\text{area}} = D_{\text{area}} / S_{\text{area}}$ , is a good parameter of total peripheral resistance and stroke volume.

#### 3.2 Derivative Dynamics and Vascular Aging Indices

The raw PPG waveform is typically smooth, which can mask subtle hemodynamic inflection points [4]. To reveal these hidden features, numerical differentiation was applied to enhance high-frequency hemodynamic transients. The first derivative of the PPG (VPG) yielded the maximum upstroke velocity  $v_{\text{max}} = \max(dy/dt)$  and minimum deceleration velocity  $v_{\text{min}} = \min(dy/dt)$ . These parameters reflect ventricular ejection power and diastolic recoil. The second derivative of the PPG (APG) shows five distinct fiducial waves:  $a, b, c, d$ , and  $e$  [4]. Specifically, the  $a$  wave represents early systolic acceleration, while  $b$  denotes early systolic deceleration. The

$c$  and  $d$  waves reflect late systolic wave reflections, and  $e$  corresponds to aortic valve closure. Relative derivative ratios, including  $b/a, c/a, d/a$  and  $e/a$ , were calculated using the initial  $a$  wave as an internal reference. Furthermore, the composite Vascular Aging Index ( $AGI$ ) is defined as follows:

$$AGI = \frac{b - c - d - e}{a} \quad (1)$$

This index reflects arterial wall elasticity and increases with higher arterial stiffness and systolic blood pressure [4].

### 3.3 Pearson Correlation Analysis and Feature Screening

Furthermore, the multi-domain extraction yielded a total candidate feature vector of 23 physiological features of each cardiac cycle, which included 7 temporal features, 9 amplitude and area features and 7 derivative features. However, the highly dimensional feature space with high collinearity can be model overfitting and high-cost computational burden in regression. To optimize the feature space, Pearson's correlation was analyzed to measure the linear degree of association between each extracted feature  $X_i$  and continuous target of blood pressure  $Y$  (sepa-

rately analysed for SBP and DBP):

$$r(X_i, Y) = \frac{\sum_{k=1}^N (X_{i,k} - \bar{X}_i) (Y_k - \bar{Y})}{\sqrt{\sum_{k=1}^N (X_{i,k} - \bar{X}_i)^2} \sqrt{\sum_{k=1}^N (Y_k - \bar{Y})^2}} \quad (2)$$

Candidate features were screened to filter out highly collinear and redundant pairs and maintain multi-domain feature pairings that vary across temporal, amplitude, area and derivative domains. Redundant parameters were dropped. Auxiliary pulse width parameters ( $W_{25}, W_{75}$ ) and raw partial areas ( $S_{area}, D_{area}$ ) were dropped. Individual APG peak ratios ( $c/a, d/a, e/a$ ) were dropped. The screening procedure resulted in an optimal feature subset of 12 non-redundant parameters for downstream regression models. Table 1 reports the 12 selected morphological features and their Pearson correlation coefficients with reference SBP and DBP. Parameters of amplitude and area ratios, namely the Reflection Index ( $RI$ ,  $r = -0.95$ ) and Waveform Area Ratio ( $R_{area}$ ,  $r = -0.80$ ), showed strong negative linear correlations with arterial pressure. Parameters of temporal and derivatives added complementary multi-domain geometric baselines across the cardiac cycle.

**Table 1. Selected Morphological Features and Their Pearson Correlations**

| Feature Name                 | Symbol      | Category         | Pearson $r$ (SBP) | Pearson $r$ (DBP) |
|------------------------------|-------------|------------------|-------------------|-------------------|
| Systolic Rise Time           | $T_r$       | Temporal         | +0.05             | +0.03             |
| Diastolic Decay Time         | $T_d$       | Temporal         | -0.06             | -0.02             |
| Pulse Duration               | $T_{cycle}$ | Temporal         | +0.02             | +0.02             |
| Pulse Width at 50% Height    | $W_{50}$    | Temporal         | +0.03             | +0.03             |
| Systolic Peak Amplitude      | $A_s$       | Amplitude        | +0.01             | +0.01             |
| Reflection Index             | $RI$        | Amplitude        | -0.95             | -0.75             |
| Dicrotic Notch Ratio         | $NR$        | Amplitude        | +0.07             | +0.06             |
| Waveform Area Ratio          | $R_{area}$  | Area             | -0.80             | -0.63             |
| Peak Upstroke Velocity       | $v_{max}$   | Derivative (VPG) | +0.02             | +0.01             |
| Vascular Aging Index         | $AGI$       | Derivative (APG) | -0.01             | -0.01             |
| Early Systolic Ratio         | $b/a$       | Derivative (APG) | -0.05             | -0.03             |
| Peak-to-Notch Amplitude Drop | $\Delta A$  | Amplitude        | -0.07             | -0.06             |

## 4. Machine Learning Regression Framework

### 4.1 Mathematical Formulation of Blood Pressure Regression

From an academic point of view, the estimation of blood pressure was treated as a supervised multivariate regression problem. Let  $x_k \in \mathbb{R}^D$  be the  $D$ -dimensional feature vector extracted from the  $k$ -th PPG pulse cycle. The ground truth for reference arterial blood pressure was represented by a 2-dimensional vector  $y_k = [\text{SBP}_k, \text{DBP}_k]^T \in \mathbb{R}^2$ . The objective was to learn appropriate mapping functions, i.e. to minimize the difference between the predicted pressures and the reference ground-truth pressures. To cope with their different hemodynamic properties, two independent regression models,  $\hat{y}_{k,\text{SBP}} = f_{\text{SBP}}(x_k)$  and  $\hat{y}_{k,\text{DBP}} = f_{\text{DBP}}(x_k)$ , were trained separately.

### 4.2 Candidate Regression Models

Four representative regression algorithms from three categories, linear, kernel-based, and ensemble algorithms, were all selected for evaluation. LR was adopted as a baseline to examine the simplest linear correlation between the morphological parameters and blood pressure. SVR mapped input features into higher-dimensional space via an RBF kernel, minimizing an  $\epsilon$ -insensitive loss function while maximizing the geometric margin to enhance noise robustness. Unlike single-model algorithms, ensemble learning algorithms combine multiple decision trees to improve stability of model prediction. Random Forest created a randomized decision tree by bootstrap aggregation. Randomized decision trees gave independent predictions. Combining prediction of such different uncorrelated decision trees could reduce model variance and avoid the problems caused by overfitting for RF. XGBoost created an ensemble of decision trees iteratively based on gradient descent of the loss function. XGBoost exploited second-order Taylor expansions of the objective function and made explicit regularized terms. Such methods penalized the model complexity and enhanced the generalization ability during training of the model [7].

### 4.3 Hyperparameter Optimization and Validation Protocol

Model performance was evaluated using a strict subject-wise 5-fold cross-validation. 53 simulated sub-

ject profiles were randomly split into five groups with non-overlapping subjects. In each fold, all pulse cycles from around 42 subject profiles (about 80%) were used to train the model. The pulse cycle segments from the remaining 11 subject profiles (about 20%) were used as unseen test data. Such subject-wise split strictly avoids data leakage across different profiles. There is no pulse cycle from the same subject existing both in the training set and unseen set. Hyper-parameters are optimized using a grid search only in the training set of each fold. For XGBoost, the learning rate was set to 0.05, the maximum tree depth was fixed as 6 and the subsample ratio was set to 0.8.

### 4.4 Quantitative Evaluation Metrics

Four standard statistical metrics were used to quantify estimation accuracy and error. These metrics were assessed independently for SBP and DBP values where  $y_k$  and  $\hat{y}_k$  are the reference and predicted scalar pressure values:

$$\text{MAE} = \frac{1}{N} \sum_{k=1}^N y_k - \hat{y}_k \quad (3)$$

The Root Mean Squared Error (RMSE) penalizes larger prediction deviations more heavily:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{k=1}^N (y_k - \hat{y}_k)^2} \quad (4)$$

Furthermore, the Standard Deviation of Error (SD) and the Pearson correlation coefficient ( $r$ ) were computed to evaluate error dispersion and linear tracking consistency.

## 5. Experimental Results and Analysis

### 5.1 Comparative Performance Across Regression Algorithms

The 4 machine learning models were tested on a total of 2500 paired pulse segments across the different subjects under subject-wise cross-validation. Table 2 lists the estimation performance of both the systolic blood pressure and the diastolic blood pressure for all the algorithms. Among the candidate models, the SVR algorithm with RBF kernel had a worse estimation error for non-normalized physiological features (SBP MAE = 9.85 mmHg, DBP MAE = 5.78 mmHg), and the baseline linear regression estimated an SBP MAE of 2.94 mmHg and a DBP MAE of 4.21 mmHg.

Tree-based ensemble learning algorithms obtained competitive predictive abilities. Random Forest had an SBP MAE of 2.51 mmHg and DBP MAE of 4.21 mmHg. The proposed XGBoost model produced the best results overall for systolic pressure, obtaining an SBP MAE of 2.49

mmHg, an RMSE of 3.49 mmHg and a correlation coefficient of 0.97. For DBP, XGBoost had the MAE of 4.28 mmHg, an RMSE of 5.39 mmHg and a correlation coef-

ficient of 0.74. Table 2 listed performance comparison of machine learning algorithms under subject-wise cross-validation.

**Table 2. Performance Comparison of Machine Learning Models under Subject-Wise Cross-Validation**

| Target | Model              | MAE (mmHg) | RMSE (mmHg) | Mean $\pm$ SD (mmHg) | Pearson $r$ |
|--------|--------------------|------------|-------------|----------------------|-------------|
| SBP    | Linear Regression  | 2.94       | 4.02        | -0.00 $\pm$ 4.02     | 0.96        |
|        | SVR (RBF Kernel)   | 9.85       | 12.39       | 0.22 $\pm$ 12.39     | 0.89        |
|        | Random Forest      | 2.51       | 3.50        | -0.01 $\pm$ 3.50     | 0.97        |
|        | XGBoost (Proposed) | 2.49       | 3.49        | 0.06 $\pm$ 3.49      | 0.97        |
| DBP    | Linear Regression  | 4.21       | 5.30        | -0.01 $\pm$ 5.30     | 0.75        |
|        | SVR (RBF Kernel)   | 5.78       | 7.22        | 0.02 $\pm$ 7.22      | 0.72        |
|        | Random Forest      | 4.21       | 5.29        | -0.00 $\pm$ 5.29     | 0.75        |
|        | XGBoost (Proposed) | 4.28       | 5.39        | 0.04 $\pm$ 5.39      | 0.74        |

## 5.2 Statistical Correlation and Bland-Altman Consistency Analysis

To evaluate estimation consistency, scatter plot and Bland-Altman analyses were performed on predictions.

As shown in Fig. 2, scatter plots of the predictions had a strong linear correlation to the reference for SBP ( $r = 0.97$ ). Estimates of DBP, however, showed moderate linear consistency ( $r = 0.74$ ).

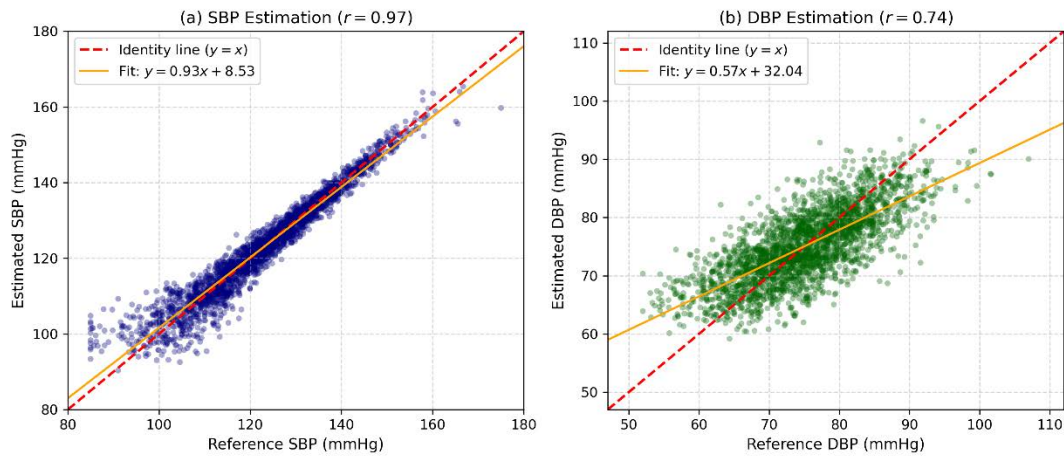


**Fig. 2 Scatter plots of reference versus estimated blood pressure using the proposed XGBoost model: (a) Systolic Blood Pressure (SBP); (b) Diastolic Blood Pressure (DBP). The red dashed line denotes the ideal identity line ( $y = x$ ).**

As illustrated in Fig. 3, the Bland-Altman plots show the distribution of prediction errors for every measured value against average of measured value and predicted value. The mean difference (bias) of SBP was 0.06 mmHg and the 95% limits of agreement was between -6.78 and 6.90 mmHg. For the estimation of diastolic blood pressure,

the random error dispersion was larger than that for the estimation of the systolic blood pressure (its wider limits of agreement). For DBP, the mean difference was 0.04 mmHg and its 95% boundaries were from -10.52 mmHg to 10.59 mmHg. Nevertheless, more than 95% of tests lay within 95% agreement boundary limits.

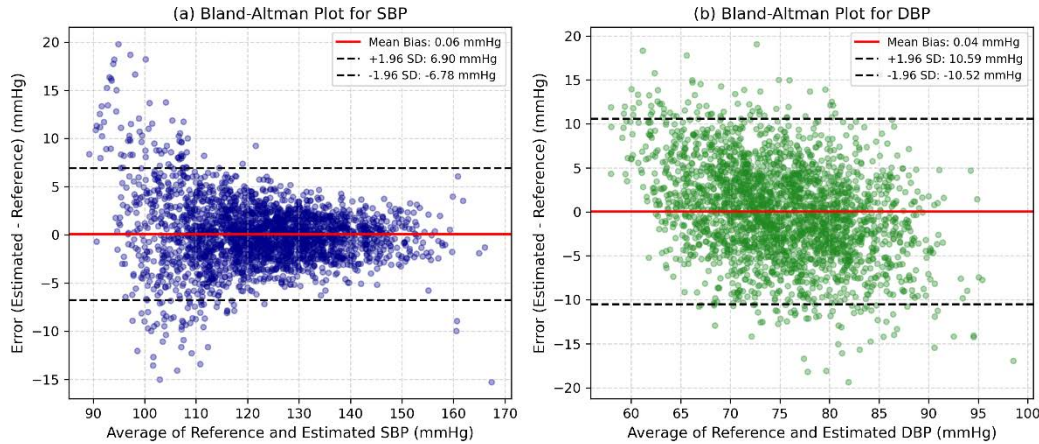


**Fig. 3 Bland-Altman consistency plots of estimation errors for (a) SBP and (b) DBP. The solid center line represents the mean difference (bias), and the dashed lines denote the 95% limits of agreement (mean  $\pm 1.96SD$ ).**

### 5.3 Compliance with International Standards

Additionally, the estimation performance of the proposed framework was compared with two widely adopted international validation benchmarks [8]. Under the ANSI/AAMI/ISO standard, criterion 1 specifies the mean difference of test versus reference BP measurement  $\leq 5$  mmHg with an  $SD \leq 8$  mmHg [8]. This criterion is applied separately to SBP and DBP [8]. The proposed XGBoost model achieved an error of  $0.06 \pm 3.49$  mmHg for SBP and  $0.04 \pm 5.39$  mmHg for DBP. For simulated results, both metrics satisfied the numerical error requirements of the ANSI/AAMI/ISO standard, though this does not represent clinical validation.

Furthermore, the estimation performance was evaluated using the BHS grading scheme. The BHS standard grades using the percentages of total errors less than 5, 10, and 15 mmHg. For DBP, percentages of total errors were 65.8% ( $\leq 5$  mmHg), 93.6% ( $\leq 10$  mmHg) and 99.4% ( $\leq 15$  mmHg) and attained Grade A. For SBP, the corresponding percentages were 89.1%, 98.1% and 99.5%, which also passed Grade A criteria. These results confirm the algorithmic validity of the framework on synthetic benchmarks. Still, formal in-vivo clinical trials are required for clinical translation.

## 6. Conclusion

In this paper, a non-invasive cuffless blood pressure estimation framework based on single-channel PPG morphological feature engineering and machine learning was proposed. 23 candidates morphological, area and derivative features were extracted from an individual cardiac cycle to reflect peripheral resistance and arterial compliance. After

Pearson correlation screening, 12 significant features were selected for model training. Under a strict subject-wise 5-fold cross validation regime, multiple regression models were evaluated for prediction on unseen subjects. Among the tested models, XGBoost yields the best predictive accuracy for SBP, with an MAE of 2.49 mmHg ( $r = 0.97$ ). For DBP, Random Forest is slightly better (MAE = 4.21 mmHg), with almost no difference to XGBoost (MAE = 4.28 mmHg,  $r = 0.74$ ) prediction result under simulated benchmark scenarios. The numeric errors satisfied the benchmark thresholds of ANSI/AAMI/ISO and BHS Grade A. But this is not clinical validation.

But this study does have limitations that should be addressed in the future. At present, the evaluation relies on simulated pulse waveforms and thus lacks physiological complexity and motion artefact effects of daily life. In the future, research will focus on validating the framework on in-vivo clinical cohorts and developing adaptive motion artefact cancellation algorithms.

## References

- [1] G. A. Roth et al., 'Global Burden of Cardiovascular Diseases and Risk Factors, 1990-2019: Update From the GBD 2019 Study', *Journal of the American College of Cardiology*, vol. 76, no. 25, pp. 2982–3021, Dec. 2020, Accessed: Aug. 30, 2026. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0735109720377755>
- [2] J. Allen, 'Photoplethysmography and Its Application in Clinical Physiological Measurement', *Physiological Measurement*, vol. 28, no. 3, pp. R1-R39, Feb. 2007, doi: 10.1088/0967-3334/28/3/r01.
- [3] H. Gesche, D. Grosskurth, G. Küchler, and A. Patzak,

‘Continuous Blood Pressure Measurement by Using the Pulse Transit Time: Comparison to a Cuff-Based Method’, *European Journal of Applied Physiology*, vol. 112, no. 1, pp. 309–315, May 2011, doi: 10.1007/s00421-011-1983-3.

[4] M. Elgendi, ‘On the Analysis of Fingertip Photoplethysmogram Signals’, *Current Cardiology Reviews*, vol. 8, no. 1, pp. 14–25, Jun. 2012, doi: 10.2174/157340312801215782.

[5] G. Slapničar, N. Mlakar, and M. Luštrek, ‘Blood Pressure Estimation From Photoplethysmogram Using a Spectro-Temporal Deep Neural Network’, *Sensors*, vol. 19, no. 15, p.

3420, Aug. 2019, doi: 10.3390/s19153420.

[6] A. L. Goldberger et al., ‘PhysioBank, PhysioToolkit, and PhysioNet’, *Circulation*, vol. 101, no. 23, Jun. 2000, doi: 10.1161/01.cir.101.23.e215.

[7] T. Chen and C. Guestrin, ‘XGBoost: A Scalable Tree Boosting System’, Jun. 2016. Accessed: Sep. 03, 2026. [Online]. Available: <https://arxiv.org/pdf/1603.02754>

[8] G. S. Stergiou et al., ‘A Universal Standard for the Validation of Blood Pressure Measuring Devices’, *Hypertension*, vol. 71, no. 3, pp. 368–374, Mar. 2018, doi: 10.1161/hypertensionaha.117.10237.