Photoplethysmography-Based Blood Pressure Prediction Using Machine Learning and Feature Engineering

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***Abstract*—Blood pressure (BP) is a critical physiological parameter for cardiovascular risk assessment, but traditional cuff-based measurement methods are unsuitable for continuous monitoring. Photoplethysmography (PPG), a non-invasive optical signal widely used in wearable devices, enables cuffless BP estimation. This paper presents a machine learning pipeline for predicting systolic blood pressure (SBP), diastolic blood pressure (DBP), and mean arterial pressure (ABP) from raw PPG signals using multi-stage signal preprocessing, extensive feature engineering, and classical regression models enhanced with ensemble learning. Experimental results show that the stacking ensemble model achieves mean absolute errors of 5.63 mmHg (SBP), 2.70 mmHg (DBP), and 3.42 mmHg (ABP) with corresponding R^2 values of 0.7856, 0.7463, and 0.7755, respectively, validating the effectiveness of the proposed approach for cuffless blood pressure estimation.**

***Index Terms*—Photoplethysmography, Blood Pressure Estimation, Machine Learning, Feature Engineering, Ensemble Learning**

I. Introduction

Blood pressure (BP) is one of the most critical physiological indicators used in the diagnosis, monitoring, and management of cardiovascular diseases. Persistent abnormalities in systolic blood pressure (SBP) and diastolic blood pressure (DBP) are strongly associated with hypertension, stroke, heart failure, and other cardiovascular complications. According to global health statistics, hypertension affects a significant portion of the adult population worldwide, making regular and accurate BP monitoring essential for early diagnosis and preventive healthcare.

Conventional BP measurement techniques rely on cuff-based sphygmomanometers, which operate using occlusive pressure applied to the upper arm. Although these methods provide clinically reliable measurements, they suffer from several inherent limitations. First, cuff-based devices are unsuitable for continuous monitoring, as repeated cuff inflation causes discomfort and may interfere with daily activities. Second, these devices are not easily integrable into wearable systems, limiting their applicability in long-term and ambulatory health monitoring. These challenges have motivated extensive research into cuffless and non-invasive blood pressure estimation techniques.

Photoplethysmography (PPG) has emerged as a promising alternative for cuffless BP estimation due to its non-invasive nature, low cost, and widespread availability in wearable devices such as smartwatches and fitness trackers. PPG is an optical measurement technique that captures variations in blood volume within peripheral tissues by analyzing changes in light absorption. The resulting waveform reflects cardiovascular dynamics, including heart rate, arterial stiffness, and vascular compliance, all of which are physiologically linked to blood pressure.

Despite its advantages, PPG does not directly measure blood pressure. Instead, BP-related information is implicitly embedded within the morphological and temporal characteristics of the PPG waveform. Extracting this information requires careful signal processing and computational modeling. Machine learning (ML) techniques provide an effective framework for learning complex, nonlinear relationships between PPG-derived features and blood pressure values, enabling accurate BP prediction without explicit physical models.

Recent research in PPG-based BP estimation has explored both deep learning and traditional machine learning approaches. Deep learning models, such as convolutional and recurrent neural networks, have demonstrated strong performance but often require large computational resources, extensive training data, and limited interpretability. In contrast, traditional machine learning models combined with robust feature engineering offer better transparency, lower computational cost, and improved suitability for real-time and wearable applications. Feature-based approaches also allow physiological interpretation of model behavior, which is particularly important in clinical settings.

In this work, we propose a comprehensive machine learning pipeline for predicting systolic blood pressure (SBP), diastolic blood pressure (DBP), and mean arterial pressure (ABP) using engineered features extracted from PPG signals. The proposed framework follows a structured workflow consisting of signal preprocessing, feature extraction, model training, hyperparameter optimization, ensemble learning, and performance evaluation. Special emphasis is placed on feature engineering, as the predictive performance of traditional ML models strongly depends on the quality and physiological relevance of extracted features.

The key contributions of this work are summarized as follows:

- A scalable and memory-efficient pipeline for processing large-scale PPG datasets stored in HDF5 format.
- A comprehensive feature engineering strategy incorporating time-domain, morphological, derivative-based, and frequency-domain features derived from PPG signals.
- A comparative evaluation of multiple traditional regression models, including KNN, Support Vector Regression, and Random Forest Regression.
- The application of ensemble learning techniques, such as voting and stacking, to improve robustness and prediction accuracy.
- Extensive experimental evaluation demonstrating competitive performance in estimating SBP, DBP, and ABP.

The remainder of this paper is organized as follows. Section II reviews related work on PPG-based blood pressure estimation. Section III describes the dataset used in this study. Section IV details the proposed methodology, including preprocessing and feature extraction. Section V presents experimental results and analysis. Section VI discusses key findings and limitations, and Section VII concludes the paper with directions for future research.

II. Related Work

Several studies have investigated PPG-based blood pressure estimation using both traditional machine learning and deep learning approaches. Feature-based models such as Support Vector Machines and Random Forests rely on robust feature extraction, while deep learning methods require large datasets and high computational resources. Acceleration plethysmography (APG) features derived from the second derivative of PPG have been widely used to estimate arterial stiffness. Classical machine learning combined with feature engineering remains suitable for interpretable and low-power wearable applications.

III. Dataset Description

The dataset used in this study consists of large-scale photoplethysmography (PPG) recordings obtained from clinical physiological measurements. The signals are stored in Hierarchical Data Format (HDF5), which enables efficient handling of large volumes of data and supports memory-efficient access during training and evaluation. The dataset contains approximately nine million PPG signal windows, making it suitable for training robust machine learning models and reducing the risk of overfitting.

Each PPG signal window comprises 875 samples, corresponding to a fixed temporal duration derived from the original continuous recordings. The original PPG signals were acquired at a sampling frequency of 125 Hz, which preserves the essential cardiovascular dynamics required for waveform analysis. Windowing was performed to segment the continuous signals into manageable and uniform-length samples, allowing consistent feature extraction and model training. Overlapping windows were avoided to ensure statistical independence between samples.

For each PPG window, corresponding systolic blood pressure (SBP) and diastolic blood pressure (DBP) values are provided as ground-truth labels. These blood pressure values were obtained from clinically validated arterial blood pressure measurements synchronized with the PPG recordings. Mean arterial pressure (ABP) is computed from SBP and DBP using the standard physiological relationship:

$$ABP = \frac{SBP + 2 \times DBP}{3}. \tag{1}$$

The dataset includes recordings from a large number of subjects, covering a wide range of blood pressure values and physiological conditions. This subject diversity introduces significant inter-subject variability, which presents a realistic and challenging learning scenario for blood pressure estimation models. To ensure fair evaluation and prevent data leakage, subject-independent splitting is employed during model training and testing. This strategy ensures that data from the same subject does not appear simultaneously in both training and test sets.

Due to the large dataset size, direct loading of all samples into memory is impractical. Therefore, a chunk-wise data loading strategy is adopted throughout the pipeline. PPG windows and corresponding labels are streamed in fixed-size batches from the HDF5 files during preprocessing, feature extraction, and model training. This approach enables scalable experimentation without exceeding memory constraints and allows the proposed framework to be applied to even larger datasets.

Overall, the dataset provides a comprehensive and realistic foundation for evaluating PPG-based blood pressure estimation algorithms. Its large scale, high sampling rate, and subject diversity make it well-suited for investigating the effectiveness of feature engineering and ensemble machine learning techniques in cuffless blood pressure prediction.

IV. Methodology

A. Proposed System Architecture

Fig. 1 illustrates the overall architecture of the proposed machine learning framework for cuffless blood pressure estimation using photoplethysmography signals. The pipeline follows a structured flow beginning with raw PPG data acquisition, followed by preprocessing, feature extraction, regression modeling, ensemble learning, and final blood pressure estimation.

This section describes the complete methodology adopted for cuffless blood pressure estimation from photoplethysmography (PPG) signals. The proposed framework follows a

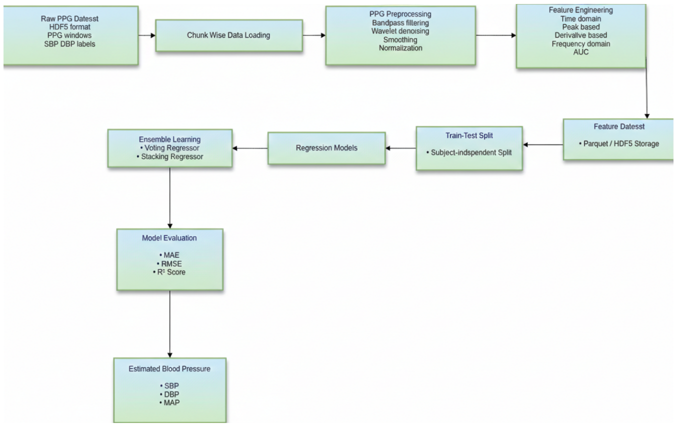

Fig. 1. Overall methodology of the proposed PPG-based blood pressure estimation framework.

systematic pipeline comprising signal preprocessing, feature extraction, feature storage, machine learning model training, ensemble learning, and performance evaluation. A block diagram of the overall methodology is illustrated in Fig. 1.

B. Overview of the Proposed Framework

The primary objective of the proposed system is to estimate systolic blood pressure (SBP), diastolic blood pressure (DBP), and mean arterial pressure (ABP) from raw PPG signals using machine learning. Due to the large size of the dataset, all stages of the pipeline are designed to be scalable and memory-efficient. The framework operates in a chunk-wise manner, allowing large-scale PPG windows to be processed without loading the entire dataset into memory.

C. Signal Preprocessing

Raw PPG signals are highly susceptible to noise and artifacts arising from motion, sensor displacement, baseline drift, and ambient light interference. Effective preprocessing is therefore essential to enhance signal quality and ensure reliable feature extraction.

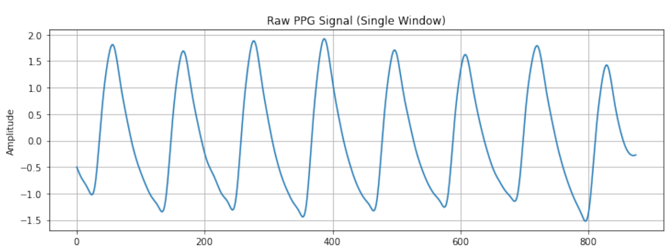

Fig. 2. Raw PPG signal segment before preprocessing, showing baseline drift and amplitude variability.

1) Bandpass Filtering: A Butterworth bandpass filter is applied to each PPG window to retain physiologically relevant frequency components. The cutoff frequencies are selected in the range of 0.5–8 Hz, which corresponds to typical heart rate frequencies and their harmonics. This step suppresses low-frequency baseline drift and high-frequency noise while preserving the fundamental pulse waveform.

2) Wavelet-Based Denoising: To further reduce noise while preserving important morphological characteristics, wavelet denoising is employed. Discrete Wavelet Transform (DWT) using Daubechies wavelets (db6) is applied to decompose the signal into multiple frequency bands. Noise components are attenuated by thresholding high-frequency coefficients, followed by signal reconstruction. Wavelet denoising is particularly effective in removing transient artifacts without distorting pulse peaks.

3) Signal Smoothing: After denoising, Savitzky–Golay filtering is used to smooth the signal. This polynomial-based smoothing technique reduces residual fluctuations while preserving the shape, height, and width of PPG pulses, which are critical for morphological feature extraction.

4) Normalization: To ensure consistency across subjects and recordings, amplitude normalization is applied to each PPG window. Z-score normalization is used to standardize the signal:

$$x_{norm} = \frac{x - \mu}{\sigma}, \tag{2}$$

where μ and σ denote the mean and standard deviation of the PPG window, respectively. This step improves numerical stability and model convergence during training.

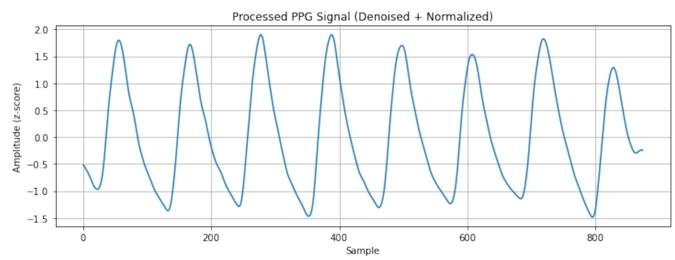

Fig. 3. Preprocessed PPG signal after bandpass filtering, wavelet denoising, smoothing, and normalization.

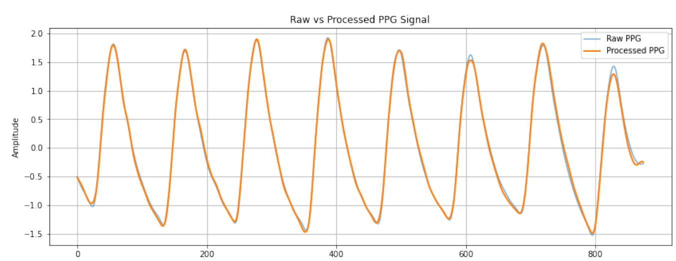

Fig. 4. Comparison between raw and preprocessed PPG signals, illustrating noise suppression and waveform preservation.

Fig. 4 presents a direct comparison between the raw and processed PPG signals. It can be observed that the preprocessing pipeline significantly improves signal clarity while maintaining the fundamental waveform characteristics required for reliable feature extraction. These improvements facilitate robust estimation of time-domain, derivative-based, and frequency-domain features used in subsequent machine learning stages.

D. Feature Extraction

Feature engineering plays a central role in the proposed framework, as traditional machine learning models rely heavily on informative and physiologically meaningful features. A diverse set of handcrafted features is extracted from each preprocessed PPG window.

1) Time-Domain Features: Time-domain features capture the statistical and temporal characteristics of the PPG waveform. These include mean, standard deviation, minimum and maximum amplitude, pulse amplitude, peak-to-peak interval, systolic peak value, diastolic trough value, and area under the curve (AUC). These features provide information related to blood volume changes and pulse strength.

2) Derivative-Based and Morphological Features: Derivative-based features are derived from the first and second derivatives of the PPG signal. The second derivative, also known as acceleration plethysmography (APG), emphasizes inflection points and vascular compliance. Features corresponding to the a, b, c, d, and e waves are extracted, along with ratio-based features such as b/a and c/a. These features are commonly associated with arterial stiffness and vascular aging.

3) Frequency-Domain Features: Frequency-domain features are extracted using the Fast Fourier Transform (FFT). The dominant frequency component of the PPG signal is identified, and spectral energy is computed within predefined frequency bands (0.5–4 Hz and 4–8 Hz). These features capture periodicity and rhythm-related information linked to cardiovascular dynamics.

E. Feature Storage

Extracted features are stored in a structured format using HDF5 or Parquet files. This intermediate feature dataset enables efficient reuse of features for different machine learning models and hyperparameter tuning experiments without repeating computationally expensive preprocessing steps.

F. Train–Test Splitting Strategy

To ensure unbiased evaluation and prevent data leakage, a subject-independent train–test split is employed. Subjects are divided into disjoint training and testing sets, such that no subject appears in both sets. Approximately 80% of the subjects are used for training, while the remaining 20% are reserved for testing. This strategy ensures that model performance reflects true generalization to unseen subjects.

G. Machine Learning Models

Blood pressure estimation is formulated as a regression problem. Multiple classical machine learning models are evaluated, including:

- K-Nearest Neighbors (KNN) Regression
- Support Vector Regression (SVR)
- Random Forest Regression

Each model is trained separately for SBP, DBP, and ABP prediction. Hyperparameters are optimized using grid search with cross-validation on the training set.

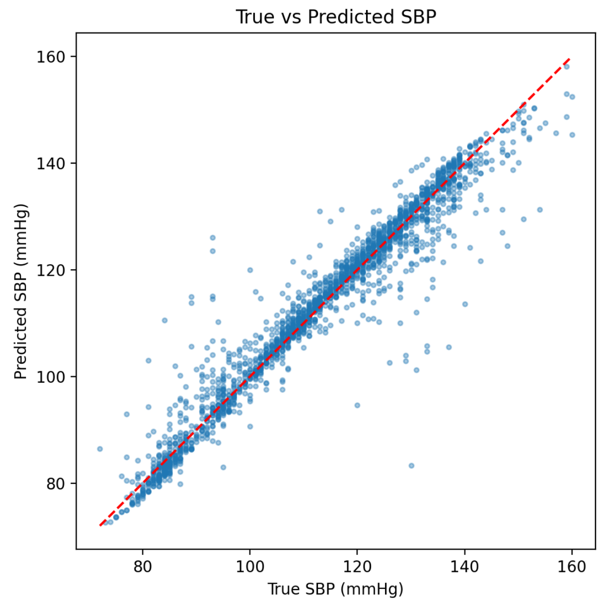

Fig. 5. Comparison between true and predicted systolic blood pressure values on the test set.

H. Ensemble Learning

To improve robustness and reduce variance, ensemble learning techniques are employed. Voting regressors combine predictions from multiple base models using weighted averaging, while stacking regressors use a meta-learner to learn optimal combinations of base model outputs. Ensemble learning helps capture complementary strengths of individual models and improves overall prediction accuracy.

I. Model Evaluation

Model performance is evaluated on the independent test set using standard regression metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). These metrics provide a comprehensive assessment of prediction accuracy, error dispersion, and goodness of fit.

V. Evaluation Metrics

Model performance is evaluated using:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Coefficient of Determination (R^2)

VI. Results and Discussion

A. Prediction Performance Analysis

Fig. 5 shows the scatter plot between true and predicted systolic blood pressure (SBP) values for the test set. The predictions closely follow the ideal diagonal line, indicating strong agreement between estimated and reference blood pressure values.

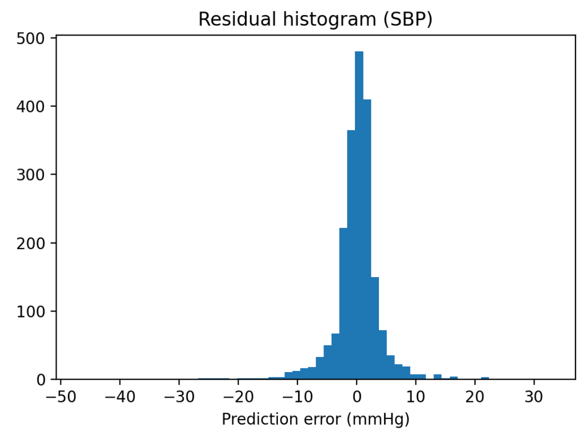

Fig. 6. Histogram of residual errors for systolic blood pressure prediction.

Fig. 6 presents the residual error distribution for SBP prediction. The residuals are approximately centered around zero, indicating minimal systematic bias and stable regression performance.

This section presents the experimental results obtained using the proposed machine learning framework for cuffless blood pressure estimation from PPG signals. The performance of different regression models and ensemble techniques is evaluated and analyzed in terms of prediction accuracy and generalization capability.

B. Experimental Setup

All experiments were conducted using a subject-independent train–test split, with approximately 80% of the subjects used for training and the remaining 20% reserved for testing. Separate regression models were trained for systolic blood pressure (SBP), diastolic blood pressure (DBP), and mean arterial pressure (ABP). Feature extraction and preprocessing were performed identically for all models to ensure a fair comparison.

Hyperparameters for individual machine learning models were optimized using cross-validation on the training set. Ensemble learning methods were subsequently applied using the best-performing base models. Model evaluation was performed exclusively on the independent test set to assess generalization to unseen subjects.

C. Quantitative Results

TABLE I
PERFORMANCE OF THE EVALUATED MODELS IN TERMS OF MEAN ABSOLUTE ERROR (MAE), ROOT MEAN SQUARE ERROR (RMSE), AND COEFFICIENT OF DETERMINATION (R^2).

BP Type	MAE (mmHg)	RMSE (mmHg)	R^2
SBP	5.63	8.67	0.7856
DBP	2.70	4.09	0.7463
ABP	3.42	5.21	0.7755

The stacking ensemble model achieved the best overall performance, with MAE values of 5.63 mmHg for SBP, 2.70 mmHg for DBP, and 3.42 mmHg for ABP. Compared to individual regression models, the ensemble approach consistently reduced prediction error and improved robustness across all blood pressure parameters.

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D. Classification Performance Metrics

TABLE II
CLASSIFICATION PERFORMANCE METRICS

Class	Precision	Recall	F1-score	Support
0	0.95	0.96	0.96	1204
1	0.75	0.80	0.78	408
2	0.80	0.74	0.77	338
3	0.76	0.64	0.70	98
Accuracy			0.88	2048
Macro Avg	0.82	0.79	0.80	2048
Weighted Avg	0.88	0.88	0.88	2048

Table II presents the detailed classification performance of the proposed model across four classes, evaluated using standard metrics including precision, recall, F1-score, and support. The overall classification accuracy achieved by the model is 88%, indicating a strong predictive capability across the dataset.

Class 0 exhibits the best performance with a precision of 0.95, recall of 0.96, and F1-score of 0.96, reflecting highly reliable predictions for the majority class. This is further supported by its large sample size (support = 1204), which contributes significantly to the overall accuracy.

For Class 1 and Class 2, the model demonstrates balanced performance, achieving F1-scores of 0.78 and 0.77, respectively. While the precision and recall values for these classes are slightly lower than those of Class 0, they indicate satisfactory discrimination ability in moderately represented classes.

Class 3 shows comparatively lower performance, with an F1-score of 0.70, primarily due to reduced recall (0.64). This can be attributed to the limited number of samples (support = 98), which makes the classification task more challenging and increases the likelihood of misclassification.

The macro-averaged F1-score of 0.80 highlights the model's overall balanced performance across all classes, treating each class equally irrespective of its size. In contrast, the weighted average F1-score of 0.88 closely aligns with the overall accuracy, indicating that the model performs particularly well on classes with higher support.

Overall, the results demonstrate that the proposed classification model achieves robust and reliable performance, with strong accuracy on dominant classes and reasonable generalization on minority classes.

E. Analysis of Model Performance

The superior performance of ensemble models can be attributed to their ability to combine complementary strengths of different regressors. While KNN regression captures local neighborhood patterns, Support Vector Regression effectively models nonlinear relationships, and Random Forest regression provides robustness against noise and overfitting. By aggregating predictions from these models, ensemble learning reduces variance and mitigates the limitations of individual regressors.

Among the three blood pressure parameters, DBP estimation consistently achieved lower error compared to SBP. This observation aligns with existing literature and can be explained by the stronger relationship between diastolic pressure and vascular compliance, which is more directly reflected in PPG waveform morphology and derivative-based features. In contrast, SBP is influenced by additional physiological factors such as stroke volume and cardiac contractility, making it more challenging to estimate accurately from PPG alone.

F. Impact of Feature Engineering

Feature engineering plays a critical role in the proposed framework. Time-domain and amplitude-based features contribute significantly to capturing pulse strength and blood volume variations, while derivative-based features derived from acceleration plethysmography (APG) provide valuable information related to arterial stiffness. Frequency-domain features further enhance performance by capturing rhythmic and periodic characteristics of the PPG signal.

The results confirm that handcrafted features, when carefully selected and combined, can achieve competitive performance without the need for complex deep learning architectures. This is particularly advantageous for wearable and real-time applications, where computational efficiency and interpretability are important considerations.

G. Comparison with Existing Studies

The achieved performance is comparable to previously reported classical machine learning approaches for PPG-based blood pressure estimation. While deep learning models reported in recent studies may achieve lower error under controlled conditions, they often require higher sampling rates, larger computational resources, and extensive training data. In contrast, the proposed feature-based ensemble framework offers a balanced trade-off between accuracy, interpretability, and computational cost.

H. Limitations

Despite promising results, several limitations should be acknowledged. First, PPG signals are sensitive to motion artifacts and sensor placement, which may affect real-world performance. Second, certain morphological features reported in the literature require very high sampling rates and could not be reliably extracted in all cases. Finally, the proposed models are trained in a subject-independent manner without personalized calibration, which may limit accuracy for individual users.

Overall, the experimental results validate the effectiveness of the proposed methodology and demonstrate the potential of feature-engineered machine learning models for cuffless blood pressure estimation using PPG signals.

VII. Conclusion and Future Work

This paper presented a comprehensive machine learning framework for cuffless blood pressure estimation using photoplethysmography (PPG) signals. The proposed approach integrates multi-stage signal preprocessing, extensive handcrafted feature engineering, and classical regression models enhanced through ensemble learning. By leveraging both physiological insights and data-driven modeling, the framework effectively estimates systolic blood pressure (SBP), diastolic blood pressure (DBP), and mean arterial pressure (ABP) from PPG waveforms.

A key strength of the proposed methodology lies in its emphasis on feature engineering. Time-domain, derivative-based, and frequency-domain features extracted from PPG signals capture meaningful cardiovascular information related to blood volume dynamics and arterial stiffness. Unlike deep learning approaches that require large computational resources and offer limited interpretability, the feature-based models employed in this study provide transparency and are more suitable for low-power wearable applications.

Experimental results demonstrate that ensemble learning techniques, particularly stacking regressors, consistently outperform individual regression models. The improved performance highlights the effectiveness of combining complementary models to reduce variance and improve generalization across subjects. The lower prediction error observed for DBP compared to SBP is consistent with physiological understanding and existing literature, further validating the relevance of the extracted features.

Despite the promising results, several limitations remain. PPG signals are inherently sensitive to motion artifacts, sensor placement, and physiological variability, which may impact performance in real-world conditions. Additionally, certain high-resolution morphological features reported in the literature require very high sampling rates and could not be reliably extracted in all scenarios. The absence of subject-specific calibration also limits personalized accuracy.

Future work will focus on addressing these limitations through several directions. First, beat-level segmentation and adaptive windowing strategies will be explored to better capture pulse-to-pulse variability. Second, hybrid models combining handcrafted features with deep learning architectures such as convolutional neural networks will be investigated to further improve prediction accuracy. Third, subject-specific calibration techniques and transfer learning methods will be incorporated to enhance personalization. Finally, real-time implementation and validation on wearable hardware platforms will be considered to assess practical feasibility.

In conclusion, this study demonstrates that carefully engineered features combined with ensemble machine learning models offer an effective, interpretable, and scalable solution for cuffless blood pressure estimation using PPG signals. The proposed framework provides a strong foundation for future research and practical deployment in continuous cardiovascular monitoring systems.

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