

Blood pressure prediction by exploiting informative features from ICU patients' ECG and PPG signals under a heterogeneous ensemble learning framework

Keke Qin (✉ masterqkk@outlook.com)

Chengdu Techman Software Co., Ltd. <https://orcid.org/0000-0002-6019-6397>

Guobiao Xu

Civil Aviation Flight University of China

Jun Huang

Chengdu Techman Software Co., Ltd.

Research article

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Abstract

Background

Although invasive methods are currently used to monitor blood pressure (BP) for intensive care patients, accurate and timely non-invasive BP monitoring in non-invasive way is still significant. Yet, physiological signal data of patients is irregular, with more noise and abnormal patterns included, making accurate and stable prediction challenging. The traditional BP measurement methods are cuff-based, and the prediction accuracy and stability of the machine learning based cuff-less prediction model needs to be further improved. Additionally, data must be cleaned and effective features must be grubbed from the irregular signals, which is a prerequisite for model training.

Results

In the present study, we proposed a novel heterogeneous ensemble learning BP prediction (ELBP) model, where: 1) Related features are systematically extracted and selected for systolic, diastolic and mean BP prediction tasks; 2) Then, multiple regression models are trained and then are weighted for final prediction, wherein the weights are learned from data; 3) Hyper-parameters of each model are optimised using Bayesian optimisation based on cross-validation. We experimentally verified the ELBP effectiveness, the mean absolute error of ELBP is 1.802 mmHg, 3.936 mmHg and 3.121 mmHg for diastolic, systolic and mean BP respectively on mimic-1, and 2.722 mmHg, 5.039 mmHg and 3.812 mmHg respectively on mimic-2. Further experiments demonstrated that ELBP performance is superior to state-of-the-art algorithms on seven evaluation metrics.

Conclusion

In conclusion, BP prediction precision can be further improved by integrating multiple learners appropriately, and this study is valuable in promoting BP prediction in practical application.

Full Text

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Figures

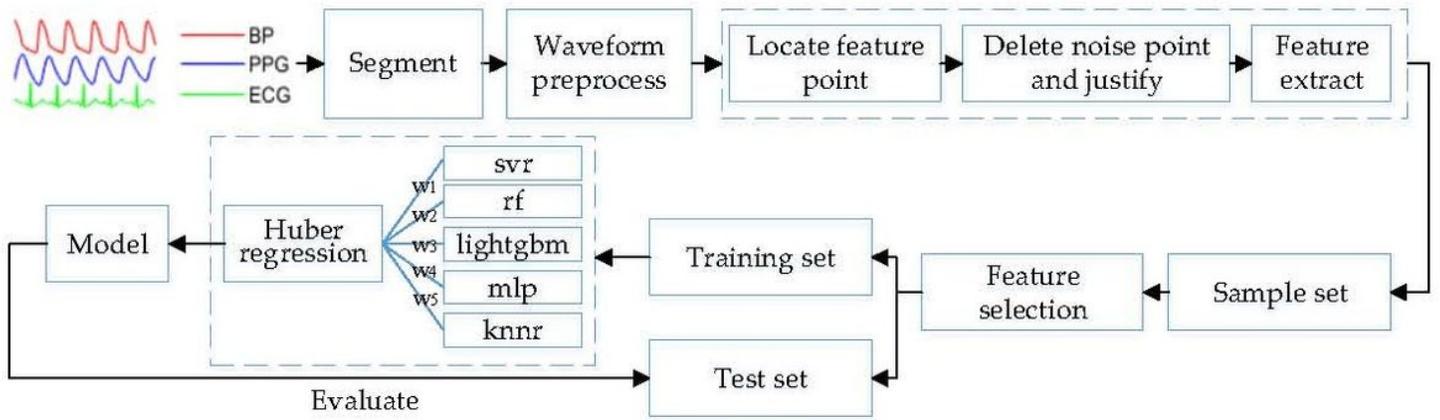
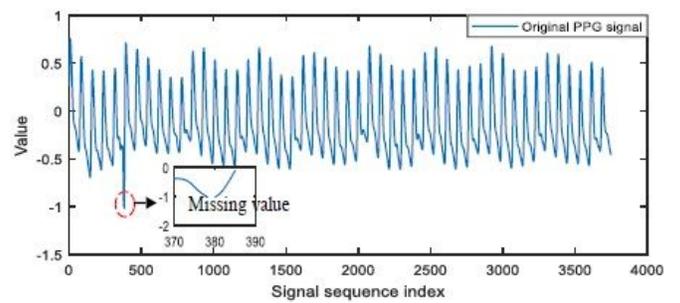
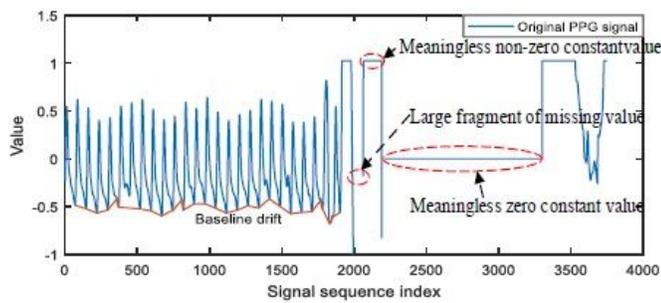
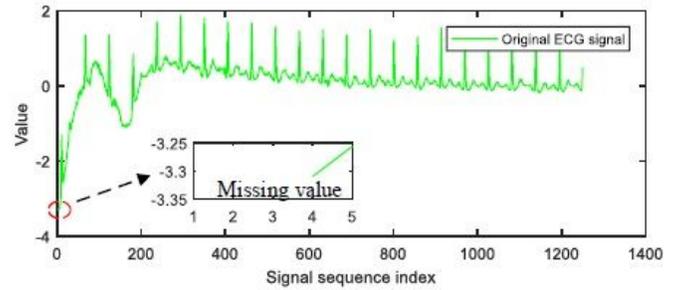
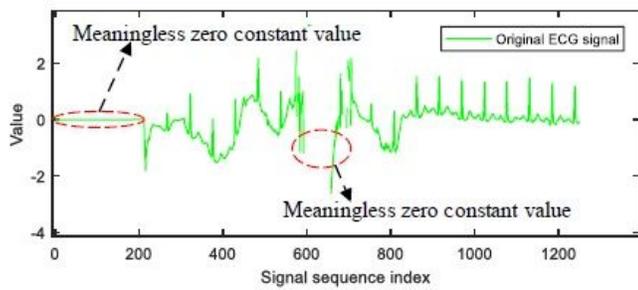


Figure 1

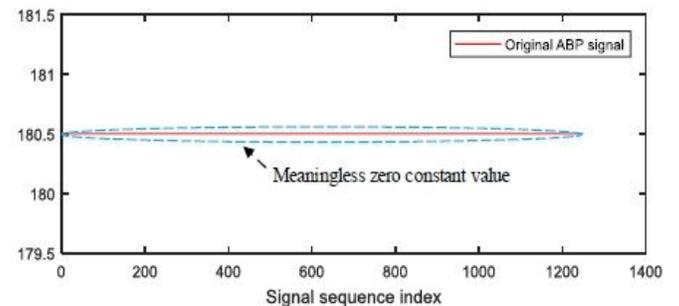
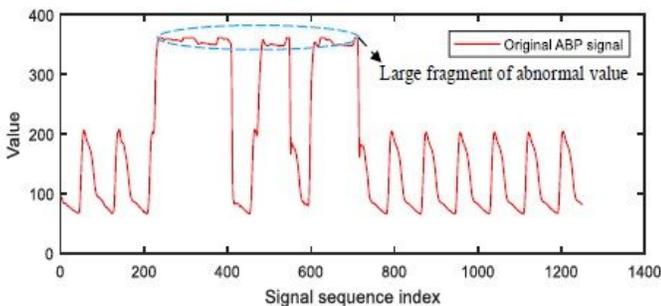
An overview flowchart for BP prediction.



(a)



(b)



(c)

Figure 2

Visualisation of original signal. (a)PPG signal fragment of record-437m; (b)ECG signal fragment of record-226m; (c)ABP signal fragment of record-212m.

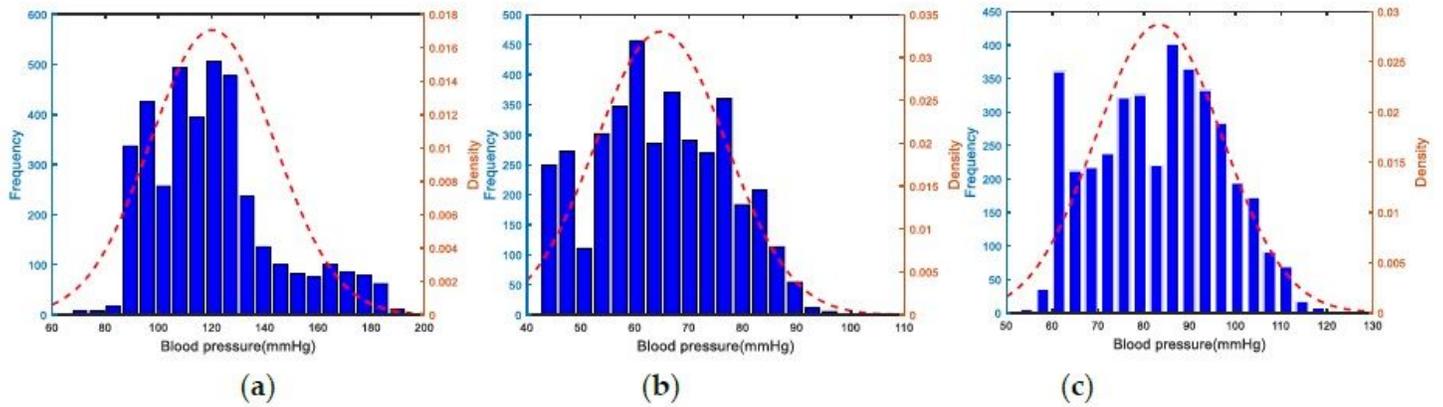


Figure 3

Histogram of BP distribution in mimic-1. (a)Systolic BP; (b)Diastolic BP; (c)Mean BP.

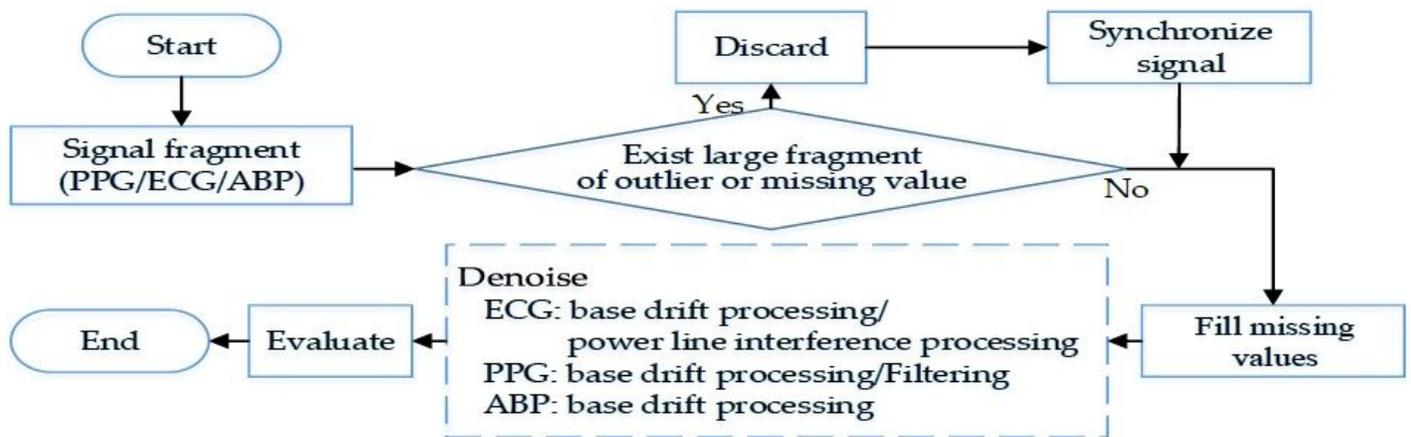


Figure 4

Waveform preprocessing process.

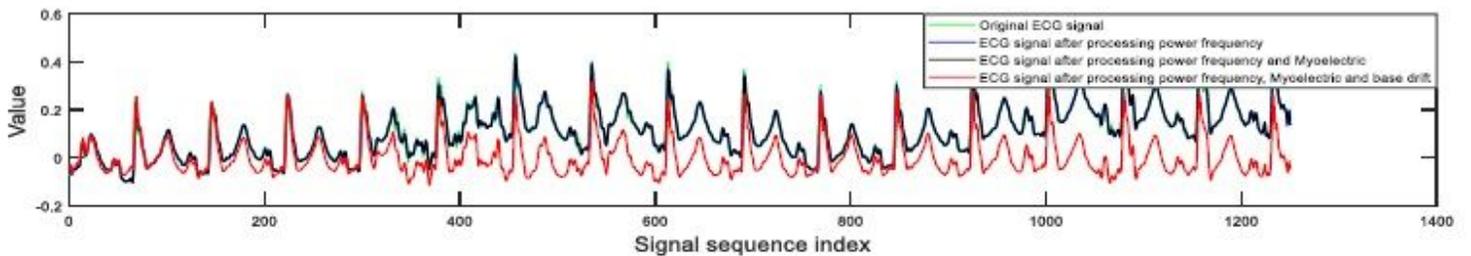


Figure 5

Denosing ECG signal for part of record-456m.

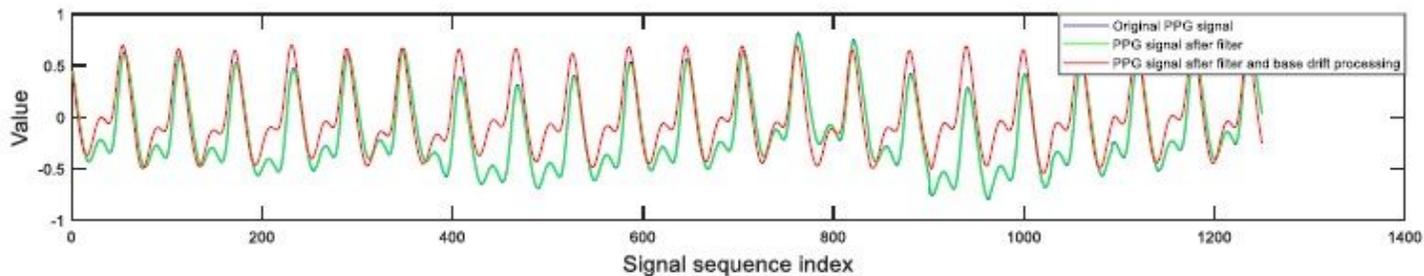


Figure 6

Denoising PPG signal for part of record-039m.

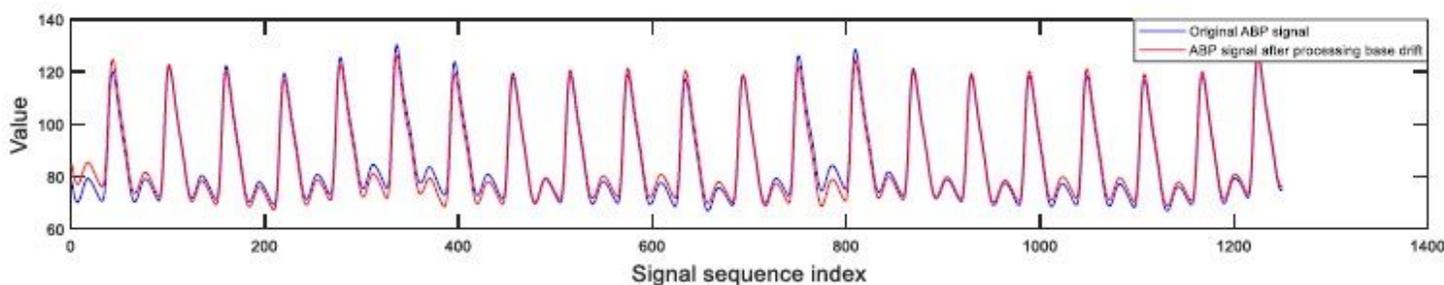
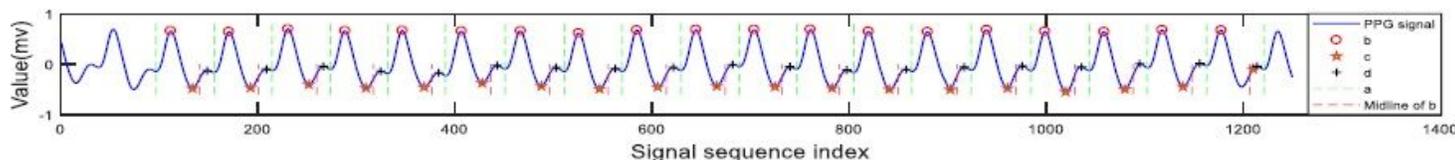
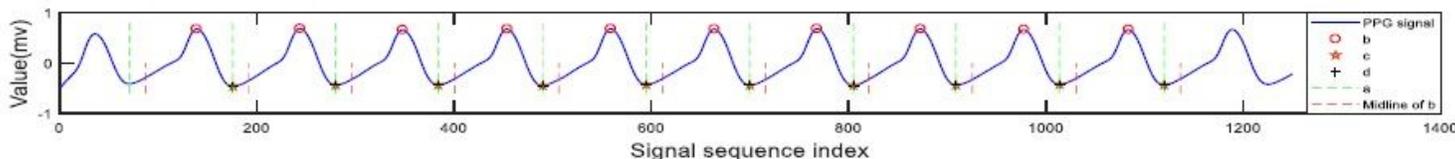


Figure 7

Denoising ABP signal for part of record-039m.



(a)



(b)

Figure 8

Positing feature points of PPG signal. (a) PPG signal fragment of record-039m with dicrotic notch; (b) PPG signal fragment of record-466m with-no clear dicrotic notch.

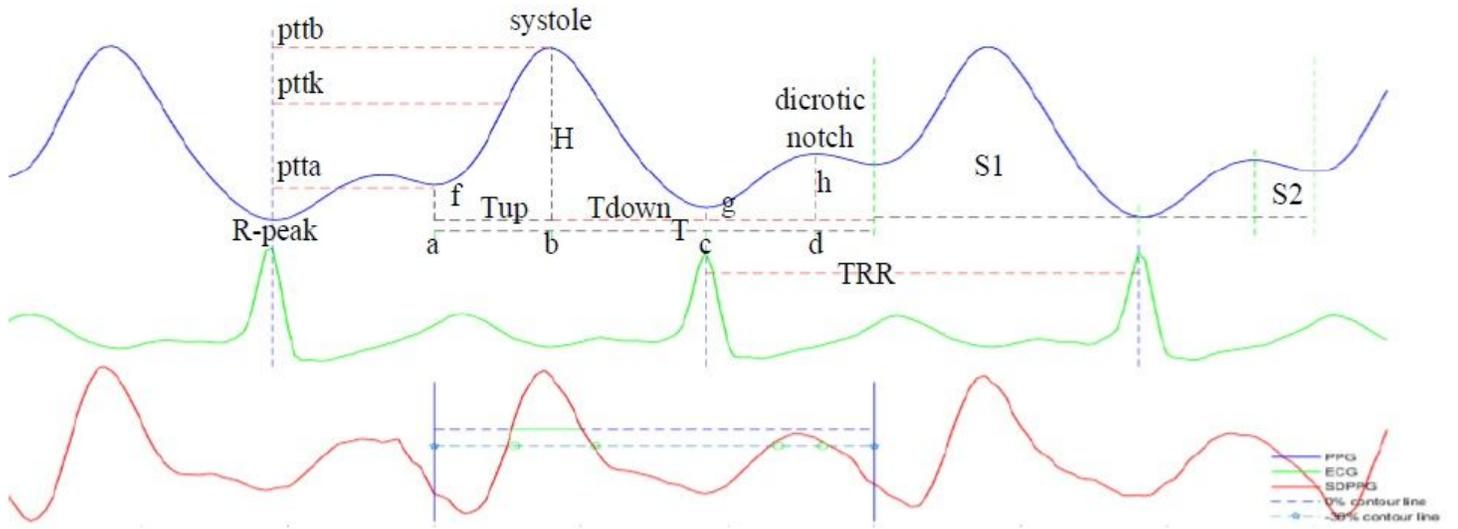


Figure 9

Schematic diagram of feature points and some features.

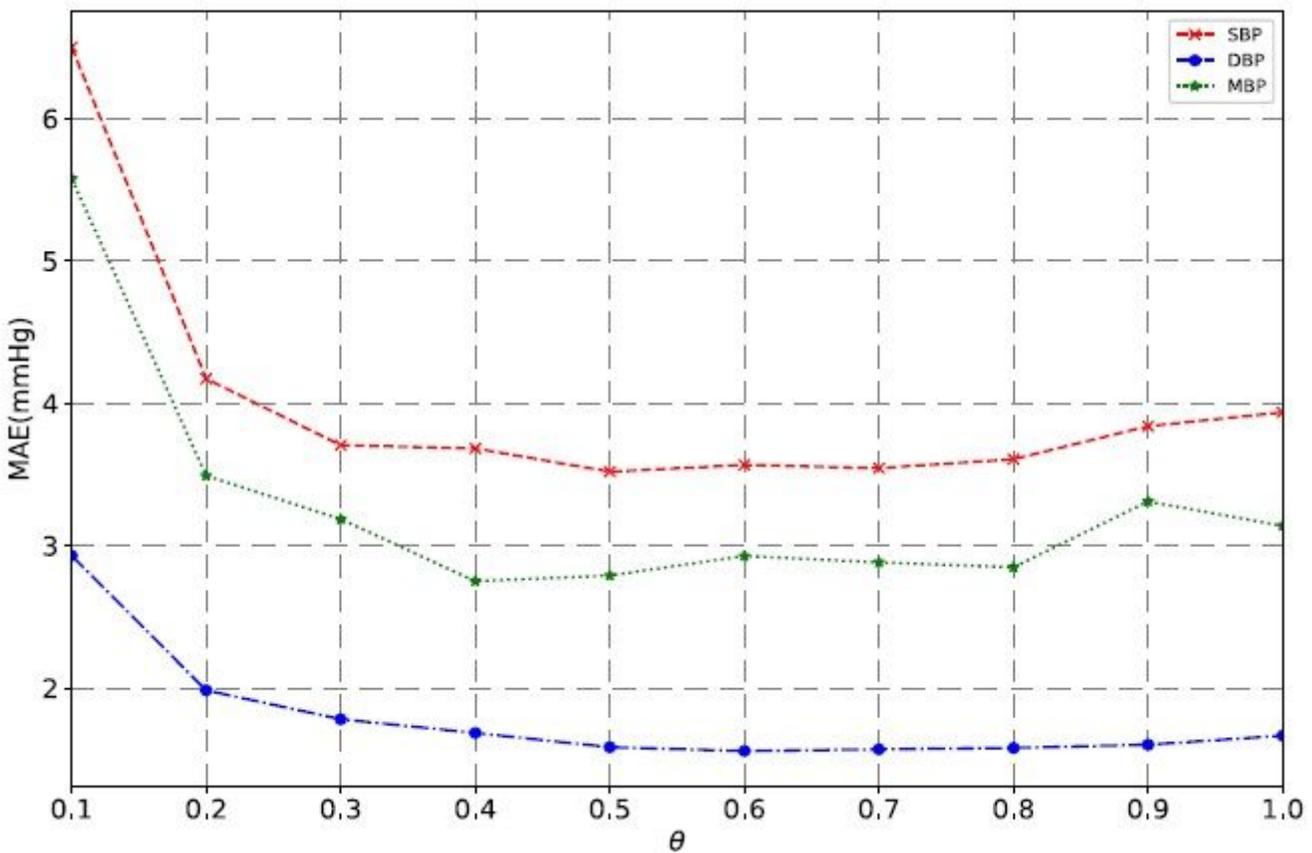


Figure 10

Mean absolute error of predicting SBP, DBP and MBP versus θ on mimic-1.

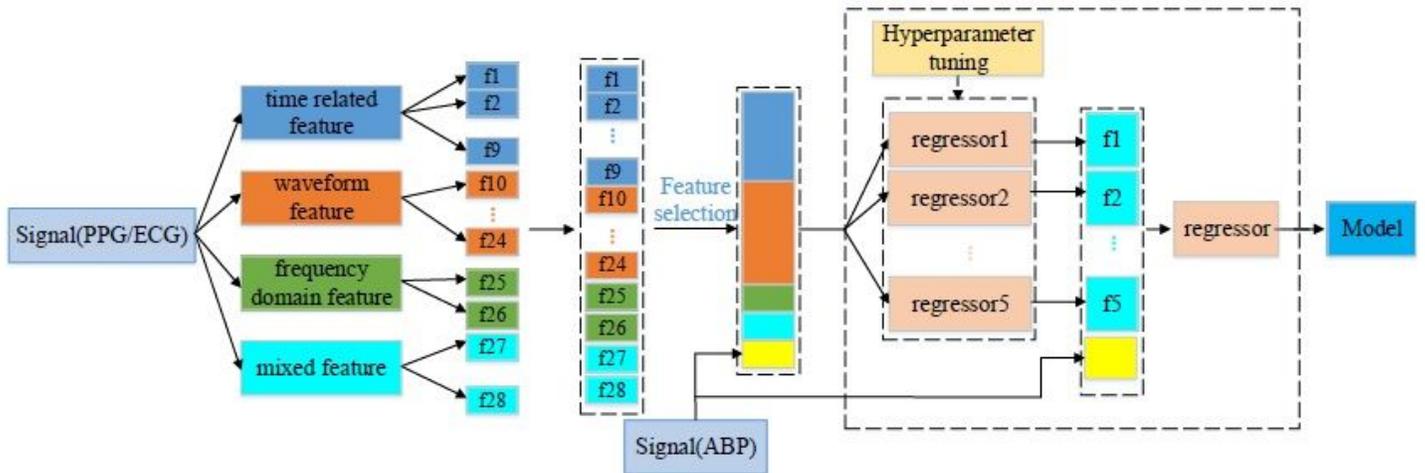


Figure 11

Model training framework.

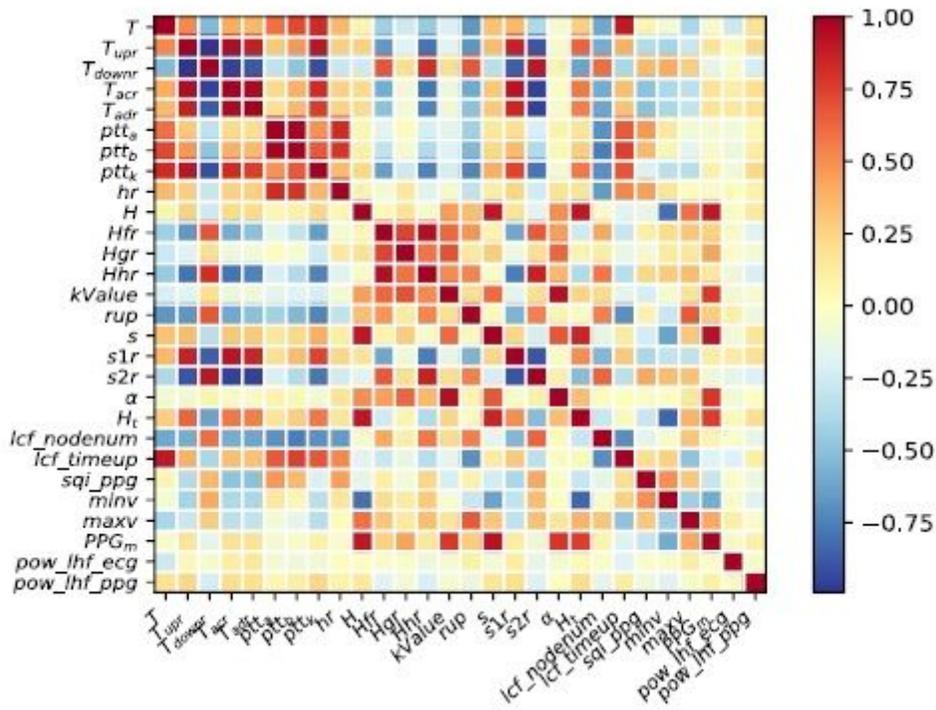


Figure 12

Pearson correlation coefficient matrix between features on mimic-1.

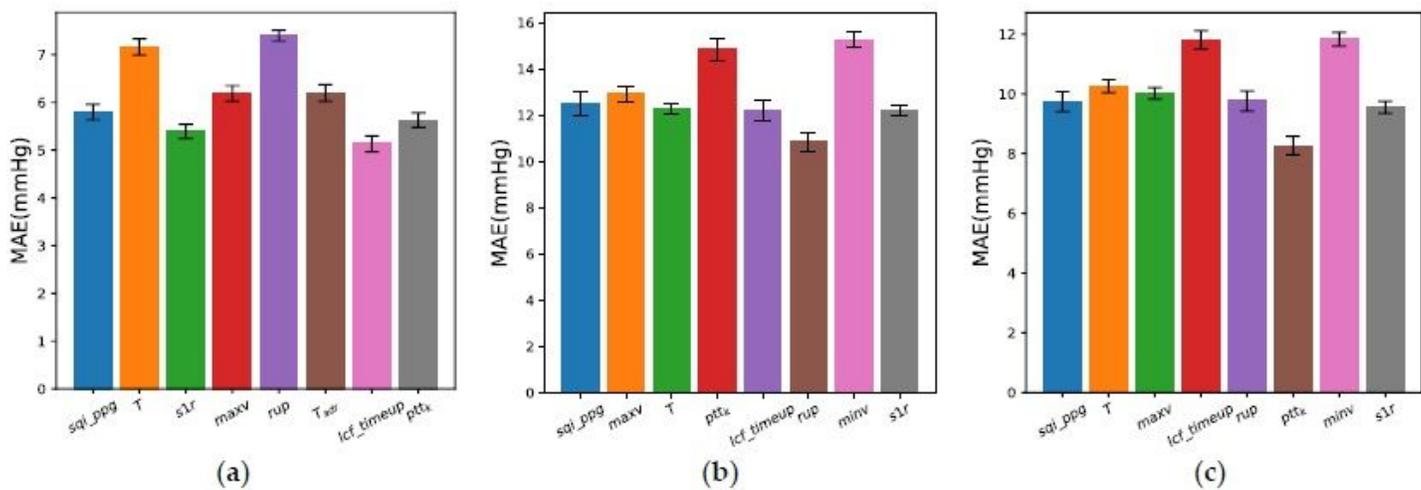


Figure 13

Comparison results of MAE of ELBP trained using each single feature for the three prediction tasks on mimic-1. (a) for DBP prediction; (b) for SBP prediction; (c) for MBP prediction.

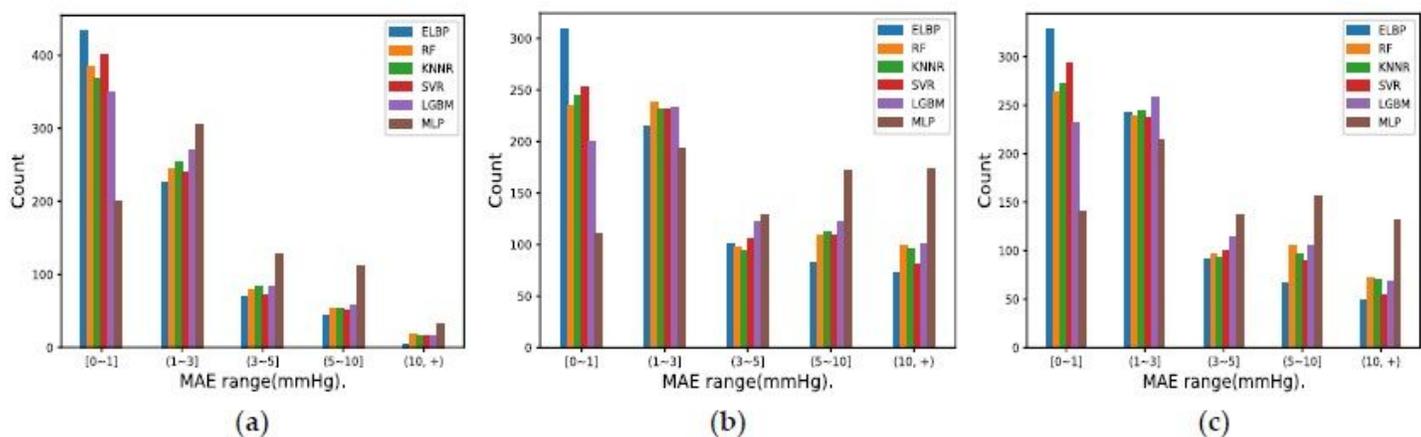
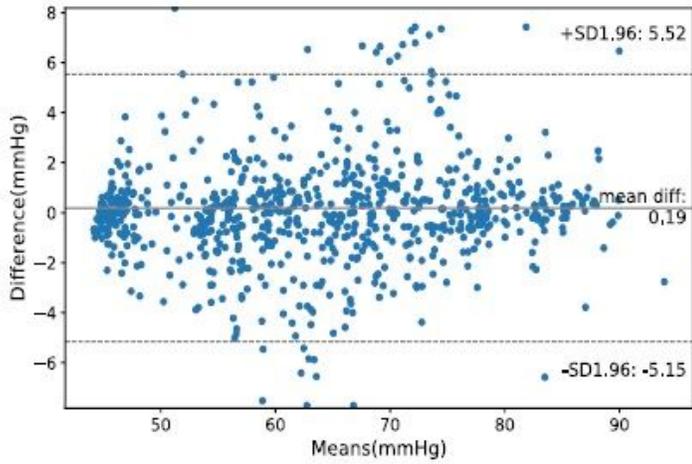
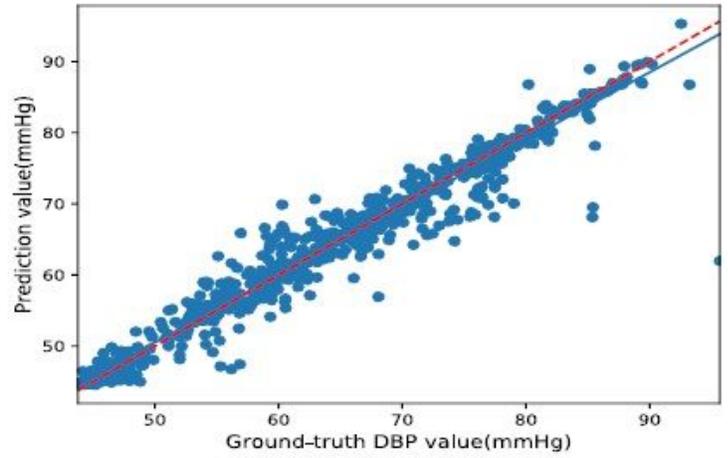


Figure 14

Histogram of mean absolute prediction error distribution on mimic-1. (a) for DBP prediction; (b) for SBP prediction; (c) for MBP prediction.



(a)

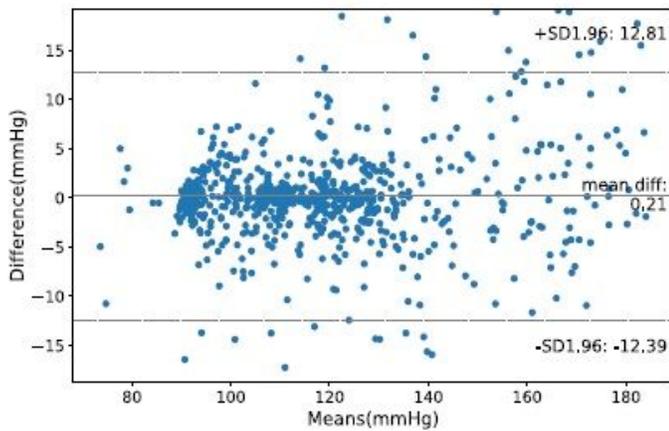


(b)

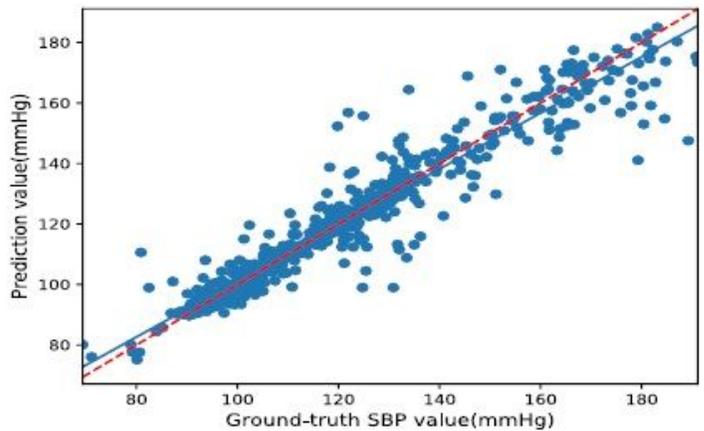
Figure 15

Scatter plot of prediction value of ELBP versus ground-truth value for DBP prediction on mimic- 1.

(a)Bland-Altman plot; (b)Regression plot.



(a)



(b)

Figure 16

Scatter plot of prediction value of ELBP versus ground-truth value for SBP prediction on mimic- 1.

(a)Bland-Altman plot; (b)Regression plot.

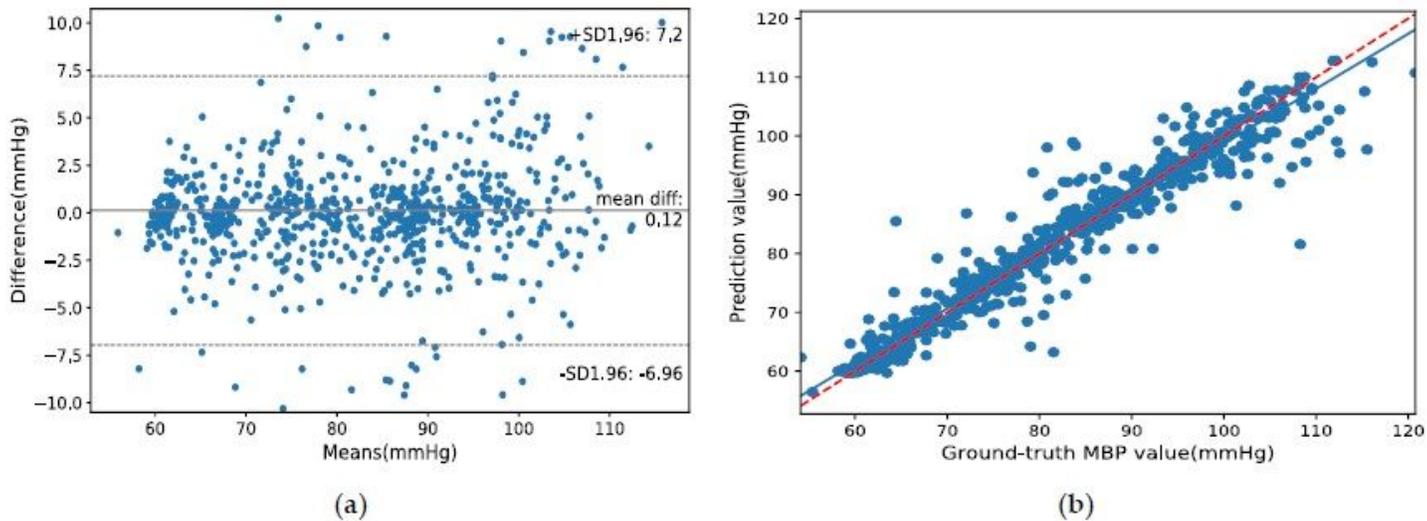


Figure 17

Scatter plot of prediction value of ELBP versus ground-truth value for MBP prediction on mimic-1. (a)Bland-Altman plot; (b)Regression plot.

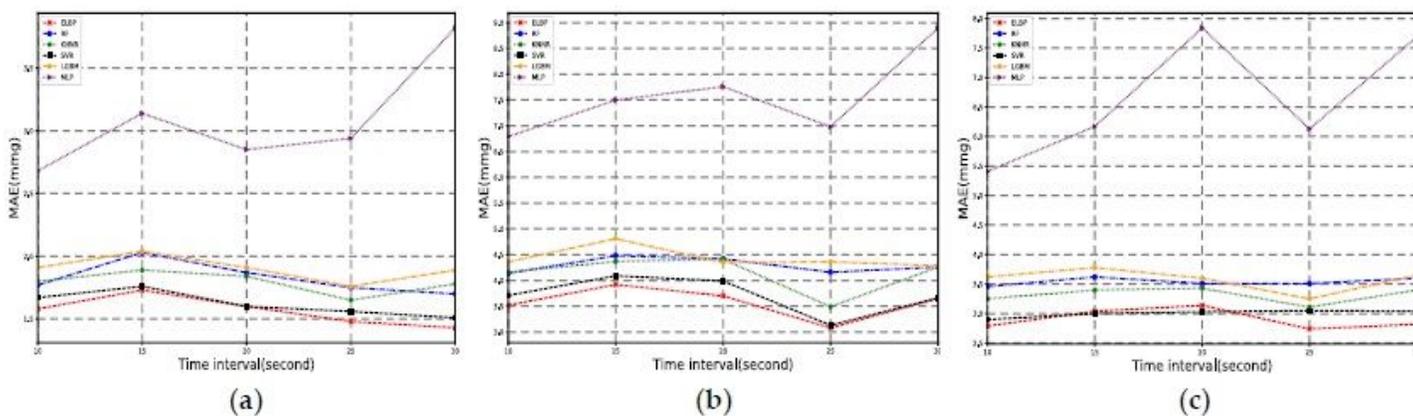


Figure 18

The effect of the time interval corresponding to each sample on the mean absolute error on mimic-1. (a) for DBP prediction;(b) for SBP prediction;(c) for MBP prediction.