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REVIEW ARTICLE

A machine learning approach for mortality prediction only using non-invasive parameters

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Abstract
At present, the traditional scoring methods generally utilize laboratory measurements to predict mortality. It results in difficulties of early mortality prediction in the rural areas lack of professional laboratorians and medical laboratory equipment. To improve the efficiency, accuracy, and applicability of mortality prediction in the remote areas, a novel mortality prediction method based on machine learning algorithms is proposed, which only uses non-invasive parameters readily available from ordinary monitors and manual measurement. A new feature selection method based on the Bayes error rate is developed to select valuable features. Based on non-invasive parameters, four machine learning models were trained for early mortality prediction. The subjects contained in this study suffered from general critical diseases including but not limited to cancer, bone fracture, and diarrhea. Comparison tests among five traditional scoring methods and these four machine learning models with and without laboratory measurement variables are performed. Only using the non-invasive parameters, the LightGBM algorithms have an excellent performance with the largest accuracy of 0.797 and AUC of 0.879. There is no apparent difference between the mortality prediction performance with and without laboratory measurement variables for the four machine learning methods. After reducing the number of feature variables to no more than 50, the machine learning models still outperform the traditional scoring systems, with AUC higher than 0.83. The machine learning approaches only using non-invasive parameters achieved an excellent mortality prediction performance and can equal those using extra laboratory measurements, which can be applied in rural areas and remote battlefield for mortality risk evaluation.

Keywords Early mortality prediction · Machine learning · Non-invasive parameters · Feature reduction

1 Introduction

Mining and analyzing multiple physiological parameters of patients and predicting their mortality can provide a timely and necessary medical intervention, to rationally dispose medical resources and decrease mortality. There are many traditional scoring systems in clinical to evaluate the intensive care patient's condition and mortality, such as the simplified acute physiology score (SAPSII) [1], sequential organ failure assessment (SOFA) [2], and acute physiological score (APS) [3]. The traditional scoring system performs weighted methods based on the demographic parameters; non-invasive physiological parameters; and laboratory measurements reflecting the patient's disease symptoms, vital signs, and laboratory indicators to quantify the criticality of the disease and predict life-threatening emergencies such as sepsis, cardiac arrest, and respiratory arrest. However, with the increasing complexity and diversity of patient data, the traditional scoring systems which are developed using the logistic regression model based on the linear relationship between multiple physiological parameters and the severity of illness cannot preferably reflect the nonlinearity and complexity in a real disease situation and are thus unable to fully satisfy the clinical requirements of timeliness and accurately detecting [4–6]. Furthermore, in recent years, more and more researchers are trying to improve the accuracy of mortality prediction by making effective use of hospital abundant data. The data-driven intelligence for mortality prediction has become one of the hot research fields in the world [7–9].

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Lee et al. [10] used six methods to estimate the missing physiological parameters and predicted mortality by using the logistic regression model. The minimum of sensitivity and positive predictive value are 0.516 and 0.482 for two test sets. Although the prediction results are more accurate than those of the SAPS I system, the incomplete data analysis was limited to the temporal parameter values, which led a considerable amount of statistical information lost in the time dimension. Weissman et al. [11] evaluated the performance of logistic regression, lifting tree models, random forest, and elastic network models in early mortality prediction. The results show that the lifting tree model has optimal discriminating ability with area under the curve (AUC) of 0.89. However, laboratory measurements, such as the maximum number of white blood cells and the maximum number of platelets, are included in Weissmann's model; professional laboratory equipment and personnel are thus necessary, which precludes a convenient application. Cooper et al. [12] used the super-learning model to predict 30-day neonatal postoperative mortality, which combined multiple models, and selected the optimal regression method by a weighted combination to obtain better results. It showed that the super-learning model outperforms the other models with an AUC of 0.91. However, the high computing ability is needed for the super-learning method. Increased demands of hardware greatly limit the practical application. Awad et al. [13] used an ensemble learning model involving four machine learning methods to construct an early mortality prediction framework for ICU patients and provided a more accurate prediction result than traditional scoring systems. With the AUC more than 0.82, random forest algorithm achieved the best prediction. However, because of a significant gap in quantity between classes, an over-fitting problem occurred [14]. In addition, only 6-h patient records after admission were analyzed by Awad, and patient information over 6 h after admission was ignored. Li et al. [15] proposed a method that uses the k-nearest neighbors (KNN) algorithm to "vote" to determine whether patients prefer "survival" or "death" and obtained a prediction accuracy of 76%. However, the undersampling method was used to address the problem of class imbalance, which inevitably resulted in data information reduction, which in turn degraded the performance of the prediction model. Rakjomar et al. [16] developed a deep learning model with electronic health record (EHR) data for mortality prediction and achieved high AUC of 0.95. Due to the great computation demanded by deep learning models, the clinical application of these models is limited by the relatively low computing power of the ordinary microprocessors.

On the whole, there are some pervasive problems that should not be ignored. The traditional scoring systems and the previous studies using laboratory measurements are unable to be used in the remote rural areas and battlefield, where medical laboratory equipment and professional laboratorians are unavailable. Early mortality prediction and medical intervention based on the traditional methods are thus impossible in the remote areas. In addition, the problems of the complexity of features, the high computational cost, and the over dependence on hardware performance prevent these methods in previous studies from being widely used in clinical practice, in spite of achieving good results. In order to conveniently and accurately get early mortality prediction in the areas where there is lack of medical laboratory equipment, four machine learning algorithms are trained by only using various non-invasive parameters which can be easily obtained from ordinary monitors and manual measurement. These machine learning algorithms include LightGBM, XGBoost, random forest, and logistic regression. The problem of class imbalance is solved by cost-sensitive classification [17], and the optimal and minimum feature subset is selected by a novel feature subset selection method proposed in this study to reduce the computational cost as much as possible. For evaluating the prediction performance, a comprehensive comparison between the five traditional scoring systems and the four machine learning models with and without laboratory measurements is performed.

2 Methods

2.1 Definitions

The non-invasive parameters included manual measurements such as age; gender; body mass index (BMI) (kg/m^2); Glasgow coma scale (GCS); mechanical ventilation status (vent); urine output (ml); and non-invasive physiological parameters from the ordinary monitors such as pulse oxygen saturation (SPO_2) (%), fraction inspiration O_2 (FIO_2) (%), body temperature (T) (°C), heart rate (HR) (bpm), non-invasive systolic blood pressure (NISBP) (mmHg), non-invasive diastolic blood pressure (NIDBP) (mmHg), non-invasive mean blood pressure (NIMBP) (mmHg), and respiration rate (RR) (rpm) (Figure 1).

The laboratory measurements included chloride (mEq/L), creatinine (mg/dL), glucose (mg/dL), potassium (mEq/L), sodium (mEq/L), platelet count (k/μL), and blood pH, which were employed by the traditional scoring systems and previous researches [1–3].

Study window is defined as the first 48 h after T_0. Forecast window is defined as 2 to 28 days after T_0. Mortality prediction of patients: the parameters during the study window were used to train for mortality prediction

2.2 Study population

The clinical data adopted in this work were obtained from the Medical Information Mart for Intensive Care III (MIMIC III) database [18]. The MIMIC III database contains subjects

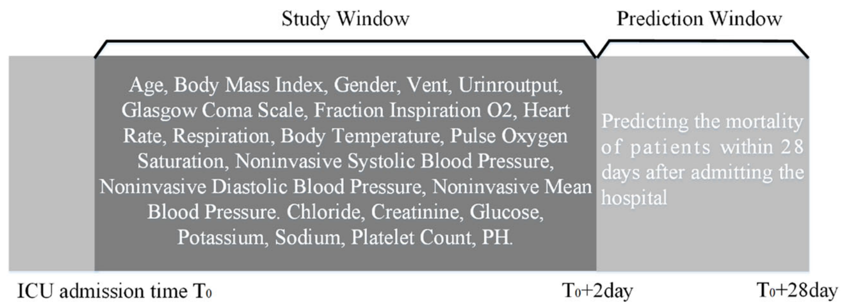


Fig. 1 Mortality prediction for patients within 28 days after admitting to hospital.

admitted to the critical care unit at the Beth Israel Deaconess Medical Center from 2001 to 2012 and includes demographic information, vital signals measured at bedside, laboratory measurements, pharmaceutical information, doctor's notes, and imaging reports.

The MIMIC III database contains in-hospital information of 46,520 patients who suffered from the general critical diseases including but not limited to cancer, bone fracture, and diarrhea. To simplify the data processing and eliminate the interference of confounding factors, 29,409 adult patients who were registered in the hospital and ICU only once were selected. Subsequently, 804 patients died outside the hospital within 28 days. A total of 20,179 patients who lacked more than 17% of feature variables defined in the section 2.4 were excluded. Finally, a total of 4503 patients were enrolled in the study, of which 1062 patients died in the hospital within 28 days and 3441 patients survived within 28 days.

The overall process for the selection of the available patient records was shown in Fig. 2.

2.3 Data preparation

The missing and abnormal values of clinical data, nonnumeric variables, and different units preclude the development of a machine learning model [19]. Data preparation is necessary for making the original data suitable for prediction model development. It consisted of five steps including abnormal value processing, one hot encoding, missing value imputation, data normalization, and derivative variable [20].

2.3.1 Abnormal value processing

According to the clinical experience, if the value of a physiological parameter was not within the normal range (HR 0–300 bpm, RR 0–70 bpm, BT 10–50 °C, SpO2 0–100%, FiO2 0–100%, NISBP 0–400 mmHg, NIDBP 0–300 mmHg, NIMBP 0–300 mmHg, GCS 0–15, chloride 5–250 mEq/L, creatinine 0–550 mg/dL, glucose 10–1100 mg/dL, potassium 1–150 mEq/L, sodium 5–250 mEq/L, platelet count 1–1500 k/μL, blood pH 6.5–7.9), it would be deemed as abnormal value and treated as a missing value.

2.3.2 One hot encoding [21]

One hot encoding was applied to encode type variables into a state value for further data analysis. In the present work, the type variables included gender and type of mechanical ventilation state.

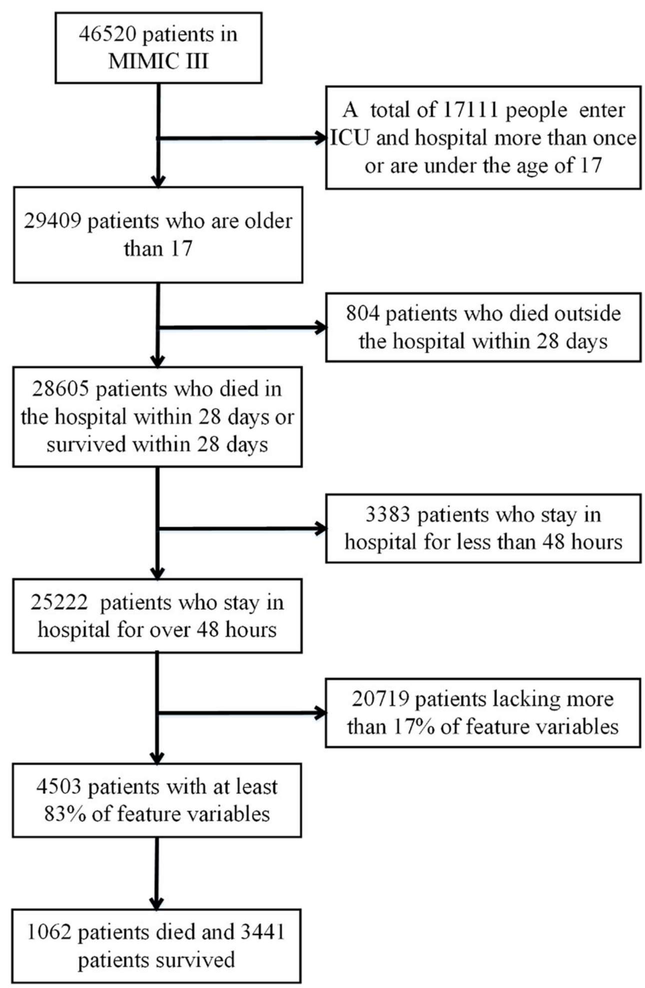


Fig. 2 Overall process for selection of available patient records

2.3.3 Missing value imputation

In this study, different imputation methods were adopted for different type of data missing. If FIO2 records existed before, the missing data could be substituted for the most previous FIO2 record. Otherwise, the FIO2 was assigned as 21% [22]. For the other physiological parameters, the feature variables were filled by using the LightGBM model.

2.3.4 Data normalization [23]

The Z-score method was employed for data normalization. After normalization, the value obeyed the standard normal distribution with a mean value of 0 and a variance of 1.

2.4 Feature variables

To obtain various feature variables from the time and statistical dimensions, 36 types of derivative variables were utilized as the feature variables for time-related parameters: maximum (max); minimum (min); mean; variance (var); standard deviation (stddev); range; and quartile (perc25, perc50, perc75) over for periods of 0–12 h, 12–24 h, 24–36 h, and 36–48 h after admission into the hospital. The feature variables for gender and mechanical ventilation state were obtained by using the one hot encoding method. Finally, a total of 584 feature variables including 332 non-invasive feature variables and 252 laboratory measurements feature variables were considered in this present study.

2.5 Feature selection

For wide application in ordinary microprocessors, it is significant to identify the feature subset for reducing the computation complexity. In the present study, the purpose of feature selection was to find the optimal feature subset (OPT_subset) and minimum feature subset (MIN_subset) for non-invasive parameters.

2.5.1 Feature evaluation

In the present study, three filter-type methods were used for feature evaluation: Relieff [24], Fisher [25], and Gini index [26]. The Relieff algorithm assigns different weights to the features according to the correlation between variables and label. The Fisher algorithm maximizes the distance among the data from different classes and minimizes the distance among the data from the same classes. In this way, Fisher measures the features with data distance. The Gini index calculates the probability that a random sample was misclassified and then sorts the features according to the degree of information confusion. The three algorithms evaluate the weight of features from different dimensions.

According to previous studies [27, 28], the combinational score summing the normalized results of these three filter methods was deemed as the final weight. The combinational score is calculated as follows:

$$\begin{aligned}\text{Comprehensive\_score} = {} & \text{Normalization\_Relieff\_score} \\ & + \text{Normalization\_fisher\_score} \\ & -\text{Normalization\_Gini\_score}\end{aligned}$$

Where Comprehensive_score was identified as the final combinational score, Normalization_Relieff_score, Normalization_fisher_score, and Normalization_Gini_score were defined as the normalized results obtained by the Relieff, Fisher, and Gini methods, respectively. The higher Comprehensive_score value means the higher importance of a feature variable.

2.5.2 Feature subsets selection method

Based on the feature evaluation result, a new feature selection method was proposed by using Bayes error rate, called FS-BER. The FS-BER method includes the following four steps:

Step 1: According to the ranking of feature importance, the features were successively added into the input set of the machine learning models for a 10-fold cross-validation. At each iteration of feature addition, the Bayes error rate (BER) values (mean and standard errors) were calculated for each machine learning model employed in this study. The mean of BER of 10-fold cross-validation and feature number were used as the independent and dependent variables respectively, so that a BER regression model was developed. The minimum BER mean determined the OPT_subset.

Step 2: The longest monotonically decreasing regression curve (LMDR-curve) was extracted from the BER mean regression model. In the LMDR-curve, the first key point P_1 was selected, which has the maximum first order right derivative below a threshold θ_1 among the points after P_1.

Step 3: The second derivative of the first 1/t data after P_1 was taken where the t is an empirical value. The second key point P_2, the second derivative on the P_1 right closest to zero, was selected ($P_1 \neq P_2$).

Step 4: The original BER mean data segment which uses P_2 as the end points and has the length of $R(R = \max$ (the num of sub maps $\times$ 0.1 , $P_1 - P_2$)) was selected. The minimum BER mean and secondary minimum BER mean in this data segment were selected, and the slop value between them was also calculated. Two candidate MIN_subsets were defined according to the minimum BER mean and secondary minimum BER mean, respectively. The feature subset that has a smaller feature number is marked as set_1, while the other feature subset is marked as set_2. If the BER value of set_1 is less than that of set_2, then set_1 is regarded as the MIN_subset. If the BER value of set_1 is greater than that of set_2 and the slop value is less than θ_2 ($\theta_2 = \theta_1/5$), the MIN_subset is also set_1. Otherwise, set_2 is deemed as the MIN_subset.

2.6 Mortality prediction model

Four machine learning algorithms: LightGBM (LGBM) [29], XGBoost (XGB) [30], rand forest (RF) [31], and logistic regression model (LR) [32] were employed in this study. Five traditional scoring systems applied in the evaluation of intensive care patient's status which includes SAPSII [1], SOFA [2], APS [3], modified early warning score (MEWS) [33], OASIS [34] were used to compare with machine learning models. The four machine learning algorithms and five traditional scoring systems were briefly introduced in the Appendix.

Experimental environment: Intel (R) Xeon (TM) CPU Gold-5115 @ 2.40 GHz 2.39 GHz with 32.0 GB of RAM, pgAdmin III, Python 3.6.5, and MATLAB 2018a programming implementation.

2.7 Performance evaluation

2.7.1 Training and test sets

After missing value imputed, the original data set was divided into two parts: the training set and the test set. Both of the training set and validation set account for 80%, and the testing set accounts for 20% of the original data set. The test set was only used for testing purposes. The training set and validation set were used for calculating the feature weight, determining the OPT_subset and MIN_subset, adjusting the parameters of the machine learning model, and concluding the optimal threshold for classification.

In particular, a 10-fold cross-validation was employed to determine the optimal parameters of prediction models. In each fold, the ratio of training set to validation set is 9:1.

2.7.2 Performance measures

The true positive rate (TPR), true negative rate (TNR), BER, F1 score, accuracy (ACC), Matthews correlation coefficient (MCC), and AUC were used in this present work to evaluate the prediction performance [35]. Their definitions are described as follows:

The TPR is defined as the proportion of positive points that are correctly predicted by the algorithm model as positive points. The TNR is defined as the proportion of negative points that are correctly predicted by the algorithm model as negative points. The BER is defined as the lowest error rate that any classifier can achieve on a data set. F1score is defined as the harmonic mean of the accuracy and recall rate. ACC is defined as the ratio of points correctly predicted by the models to the total sample points (including positive and negative points). The MCC is defined as a correlation coefficient between the observed and predicted binary classifications. The AUC, the area under the receiver operating characteristic curve (ROC), is often used to indicate the pros and cons of the algorithm.

2.8 Overall process of mortality prediction

As shown in Fig. 3, the process of mortality prediction is generally introduced as follows: 1) data was extracted and preprocessed; 2) the significance and feature variables were calculated; 3) the features were evaluated and sorted according to the combinational score synthesizing the ReliefF, Fisher, and Gini scores; 4) the OPT_subset and MIN_subset were determined by the FS-BER method; 5) the model parameters and optimal classification thresholds were obtained by the cost-sensitive classification; 6) the models were trained using train set with different subsets; and 7) four machine learning algorithms and five traditional scoring systems were validated and compared using the test set. In this study, the OPT_subset and MIN_subset were only for non-invasive parameters.

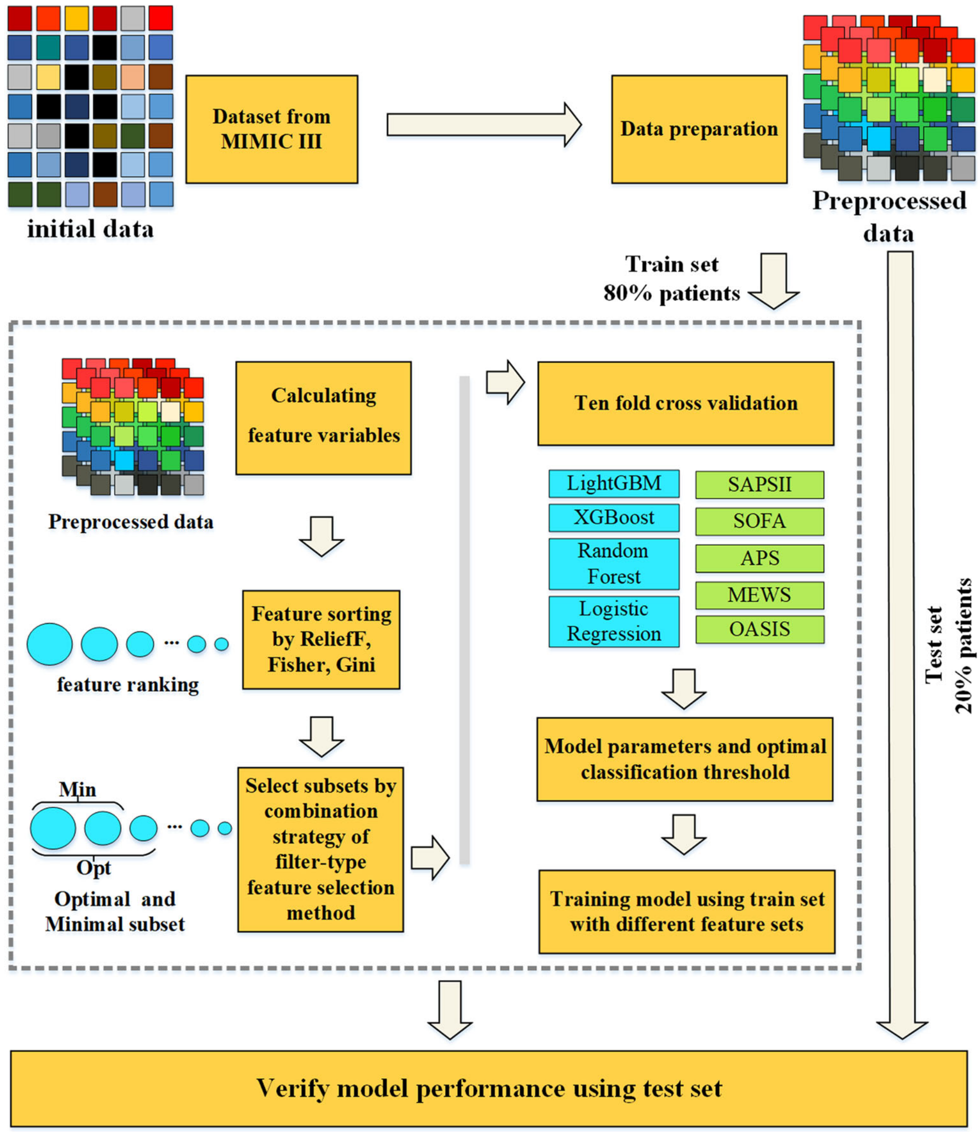
3 Results

Our development cohort included a total of 4503 patients, and 1062 (26.2%) patients died during hospitalization. The non-invasive parameters and laboratory measurements of survived and died patients are shown in Table 1.

3.1 Feature selection result

In the previous studies, the minimum feature subset, which was determined by one standard error of the lowest BER, was abbreviated as MIN_subset_SD and was compared with the OPT_subset [36, 37]. The BER values (mean and standard errors) and their corresponding feature numbers for each subset and algorithm are presented in Fig. 4 and Table 2. In the OPT_subsets, the numbers of feature variables were generally more than 150. In the MIN_subset_SDs, the numbers of feature variables, which range from 50 to 87, showed a huge

Fig. 3 The overall flow chart of mortality prediction



difference among the different prediction algorithms. Compared with the MIN_subset_SDs, the MIN_subsets had consistently similar feature numbers for all the prediction algorithms. In the MIN_subsets, the numbers of feature variables had been greatly reduced from 332 to no more than 50, with a dramatic decline of over 84.9%. The details on the feature extraction is shown in the Appendix Table 6. In order to explore the performance of non-invasive parameters in mortality prediction, the MIN_subset_SD, the MIN_subset, and the OPT_subset were all for the non-invasive feature variables with a total of 332 in the present study.

Figure 4 shows BER variation trend with feature number increasing and the result of feature selection for four machine learning algorithms. The marks and corresponding numbers for the MIN_subset and the OPT_subset are presented in this figure.

The COM_set is short for the complete feature set

Feature numbers and corresponding BER values for different subsets of non-invasive feature variables are shown in Table 2. The feature number of the MIN_subset of machine learning models reduced by at least 84.9%. For the MIN_subset of LGBM, it has the minimum quantity of feature variables with the number decreasing by 87%.

3.2 Validation results

Using both of the non-invasive parameters and laboratory measurements, the performance of four machine learning prediction algorithms are demonstrated in Table 3. Comparison between those machine learning algorithms with and without laboratory measurement variables is presented in Fig. 5.

Only using the non-invasive feature variables, four machine learning prediction algorithms were validated with

Table 1 Non-invasive physiologic parameters and laboratory measurements of the survived and died patients

Variable	All patients ($N = 4053$)	Survived ($N = 3441$)	Non-survived ($n = 1062$)	p value
Age (year), mean ± sd	62.7 ± 18.6	61.2 ± 18.5	67.6 ± 18.0	$p < 0.05$
Female sex, n (%)	2509	1915 (55.7%)	594 (55.9%)	$p = 1.00$
Vent, n (%)	1462.0	1170 (34.0%)	292 (27.5)	$p < 0.05$
BMI, mean ± sd	27.9 ± 4.6	28.0 ± 4.6	27.8 ± 4.7	$p = 0.28$
Urine output, mean ± sd	3973.4 ± 2956.8	4290.1 ± 2996.6	2937.7 ± 2563.8	$p < 0.05$
GCS, mean ± sd	12.5 ± 3.2	13.1 ± 2.8	10.8 ± 3.9	$p < 0.05$
FIO2, mean ± sd	50.2 ± 24.7	50.0 ± 24.6	50.9 ± 24.9	$p = 1.00$
HR, mean ± sd	90.3 ± 19.8	89.5 ± 19.1	92.9 ± 21.9	$p < 0.05$
RR, mean ± sd	19.8 ± 5.9	19.4 ± 5.8	21.2 ± 6.3	$p < 0.05$
T, mean ± sd	37.1 ± 1.0	37.1 ± 0.9	36.9 ± 1.1	$p < 0.05$
SPO2, mean ± sd	97.3 ± 3.6	97.4 ± 3.2	96.8 ± 4.6	$p < 0.05$
SBP, mean ± sd	113.9 ± 19.3	114.1 ± 18.8	113.1 ± 20.9	$p < 0.05$
DBP, mean ± sd	57.9 ± 13.2	58.2 ± 13.0	56.9 ± 14.0	$p < 0.05$
MBP, mean ± sd	73.8 ± 13.5	74.1 ± 13.1	73.0 ± 14.5	$p < 0.05$
Chloride, mean ± sd	105.5 ± 13.0	105.8 ± 12.7	14.5 ± 13.7	$p < 0.05$
Creatinine, mean ± sd	8.0 ± 29.7	7.7 ± 29.3	9.1 ± 30.8	$p < 0.05$
Glucose, mean ± sd	147.1 ± 75.7	145.2 ± 75.7	152.8 ± 75.4	$p < 0.05$
Potassium, mean ± sd	5.4 ± 7.8	5.3 ± 7.6	5.6 ± 8.4	$p < 0.05$
Sodium, mean ± sd	134.6 ± 22.6	134.9 ± 21.9	133.6 ± 24.8	$p < 0.05$
Platelet count, mean ± sd	173.8 ± 108.7	177.4 ± 105.2	163.2 ± 118.0	$p < 0.05$
pH, mean ± sd	7.36 ± 0.09	7.36 ± 0.08	7.34 ± 0.11	$p < 0.05$

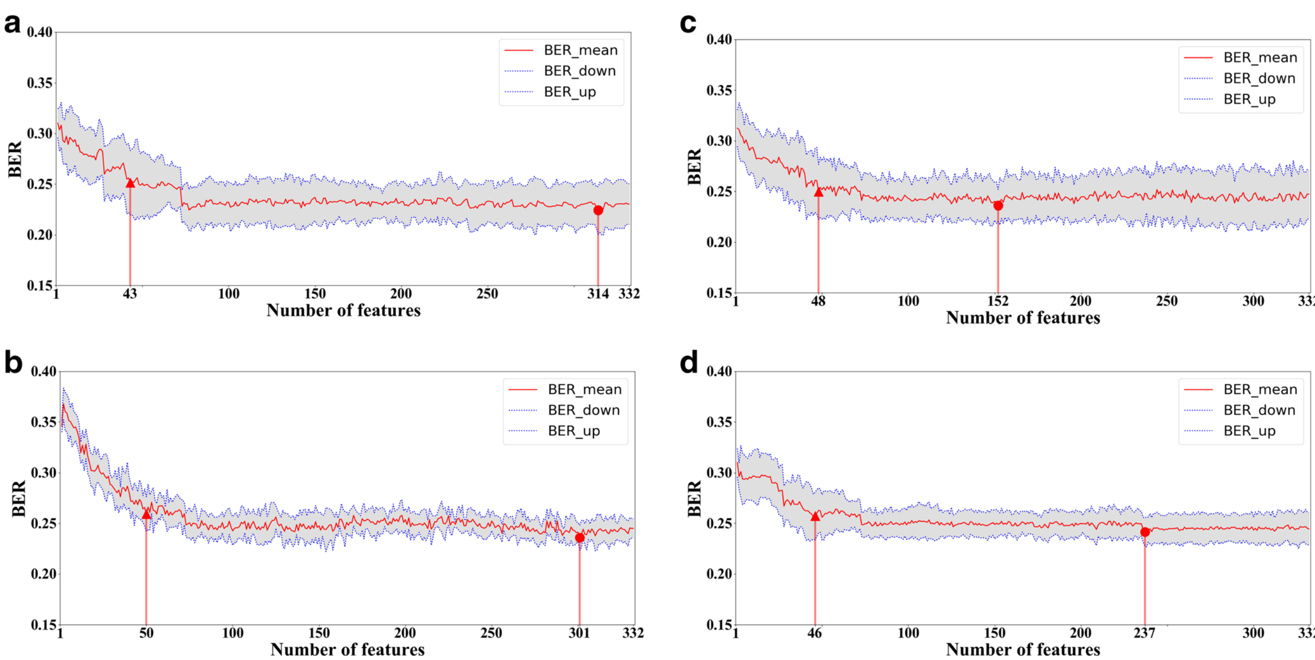


Fig. 4 Feature selection for four machine learning algorithms. Mean (central line) and standard errors (gray area). The triangle and dot marks and their corresponding numbers represent the MIN_subset and the OPT_subset, respectively. **a** The BER of LightGBM. The BER of XGBOOST. **c** The BER of random forest. **d** The BER of logistic regression

Table 2 Feature numbers and corresponding BER values for different subsets of non-invasive feature variables

Algorithm	Feature numbers/ BER values (mean ± sd) for COM_set	Feature numbers/ BER values (mean ± sd) for OPT_subset	Feature numbers/ BER values (mean ± sd) for MIN_subset	Feature numbers/BER values (mean ± sd) for MIN_subset_SD
XGB	332/0.245 ± 0.010	301/0.236 ± 0.012	50/0.259 ± 0.017	87/0.248 ± 0.012
LGBM	332/0.230 ± 0.020	314/0.224 ± 0.023	43/0.252 ± 0.032	54/0.248 ± 0.032
RF	332/0.247 ± 0.024	152/0.236 ± 0.016	48/0.250 ± 0.027	54/0.252 ± 0.028
LR	332/0.244 ± 0.016	237/0.242 ± 0.014	46/0.257 ± 0.023	50/0.256 ± 0.023

Table 3 Performance comparison between different methods with both of non-invasive parameters and laboratory measurements

Methods	ACC (95% CI)	AUC (95% CI)	BER (95% CI)	F1_score (95% CI)	MCC (95% CI)	TNR (95% CI)	TPR (95% CI)
XGB	0.788 (0.760~0.815)	0.881 (0.857~0.903)	0.205 (0.175~0.236)	0.651 (0.603~0.696)	0.527 (0.470~0.583)	0.809 (0.755~~0.861)	0.781 (0.749~0.812)
LGBM	0.801 (0.775~0.827)	0.888 (0.865~0.910)	0.188 (0.160~0.218)	0.672 (0.625~0.716)	0.558 (0.501~0.613)	0.832 (0.781~~0.880)	0.791 (0.760~0.821)
RF	0.779 (0.751~0.806)	0.879 (0.855~0.902)	0.214 (0.184~0.245)	0.639 (0.592~0.684)	0.510 (0.452~0.567)	0.800 (0.747~0.851)	0.772 (0.740~0.803)
LR	0.781 (0.754~0.808)	0.854 (0.829~0.881)	0.212 (0.183~0.243)	0.641 (0.593~0.687)	0.513 (0.455~0.570)	0.800 (0.747~0.852)	0.775 (0.743~0.806)

the COM_set, OPT_subset, and MIN_subset and compared with five traditional scoring systems. The performance of those prediction methods is presented in Table 4 and Fig. 6.

Where XGB, LGBM, RF, and LR are short for XGBoost, LightGBM, random forest, and logistic regression, respectively.

As shown in the tables and figures, the machine learning models obviously outperform the traditional scoring systems. In the case of using the MIN_subset, LGBM raised 13.3% and 15.2% in ACC and AUC than the values of ACC and AUC yielded by SAPSII, which is the best-performing traditional scoring system. For the machine learning models using the OPT_subset, TNR and TPR were more than 78.6% and 75.9%, respectively, which means that false positive rate and false negative rate were less than 21.4% and 24.1%, respectively. In contrast, the maximum TNR and TPR of traditional scoring system were only 69.8% and 63.3%, respectively. In addition, MEWS had an obvious problem of over-fitting with a great difference value of 18.5% between TNR and TPR, which did not arise in the machine learning algorithms. Using both non-invasive and laboratory measurements feature variables, LGBM outperformed the other three methods with the highest ACC and AUC values of 0.801 and 0.888, respectively. Without laboratory measurement feature variables, LGBM using the OPT_subset also had an excellent performance with the largest ACC of 79.7% and AUC of 87.9%. With similar ACC and AUC, there was no apparent difference between the mortality prediction performance with and without laboratory measurement feature variables for those four machine learning methods.

For the four machine learning algorithms, after reducing the number of feature variables to no more than 50, the relatively high prediction performance still could be maintained, with ACC higher than 75% and AUC higher than 83% in the MIN_subset. In particular, for LGBM, ACC and AUC only decreased by 3.0% and 1.8% with the number of feature variables decreasing by 87%.

4 Discussion

Mortality prediction can help doctors to evaluate patient condition accurately, revise the medical care plans objectively, and allocate the medical resources reasonably. With the provision of critical medical treatments in advance, the survival rate of critical patients is expected to improve.

In recent years, the mortality prediction of patients has become an important area of research, attracting considerable attention from researchers in the field of critical care medicine [4–6, 9–15, 38]. Currently, there are many scoring systems available for assessing clinical severity and predicting mortality. However, the traditional scoring systems often require a

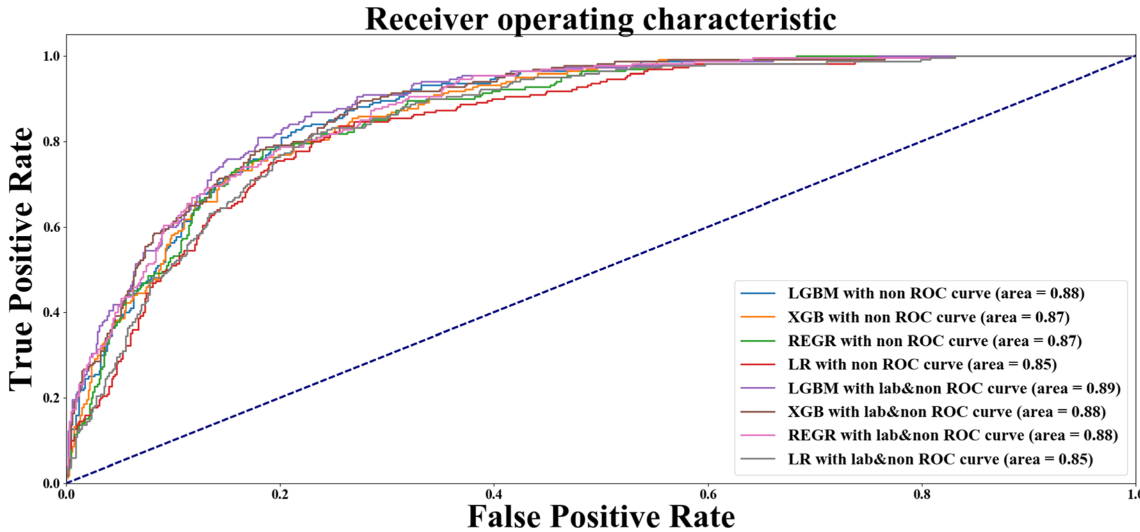


Fig. 5 Mortality prediction performance comparison between machine learning algorithms with and without laboratory measurements variables, where non is short for the non-invasive feature variables, lab&non is short for both non-invasive and laboratory measurements feature variables

large number of physiological indicators and the support of medical personnel, which will consume a large amount of manpower and financial resources [39]. Furthermore, conventional systems using the logistic regression model are unable to preferably reflect the nonlinearity and complexity in a real disease situation accurately. Awad and Li [15] provided an ensemble learning model and a KNN algorithm to predict mortality of ICU patients, respectively. Although the method achieved a relatively accurate prediction result, the problems of over-fitting, imbalanced data, and high computational dependency hinder the further improvement and extensive application of mortality prediction. More importantly, the traditional scoring systems and mortality prediction methods proposed in previous studies generally use laboratory measurements which are unavailable in the remote rural areas and battlefield. To improve the efficiency, accuracy, and applicability of mortality prediction in the remote areas, 4 machine learning algorithms were developed, which only used 14 types of non-invasive parameters readily available from ordinary monitors and manual measurement. In the terms of the feature evaluation, the FS-BER model was developed and used to determine the OPT_subset and MIN_subset. Finally, four machine learning algorithms using different subsets were compared with five traditional scoring systems.

The validation result shows that the machine learning algorithms generally outperform the traditional scoring systems. In addition, it shows that machine learning approaches only using non-invasive parameters still achieved 87.9% in AUC and can equal those methods using both non-invasive parameters and laboratory measurements. The non-invasive mortality prediction method provides a possible way for early mortality predication and timely medical intervention in rural areas and remote battlefield, where the professional laboratorians and medical laboratory equipment are unavailable.

For the reduction of computational cost and the facilitation of practical application, a new feature selection method called FS-BER was developed in this study. The FS-BER method can effectively eliminate redundant variable information while maintaining an excellent prediction performance. To more clearly show the ability of the FS-BER method in feature variable selection, the reduction in the number of feature variables and the concerning reduction in AUC for each machine learning algorithm based on the FS-BER method are presented in Table 5. Taking the LGBM algorithm as an example, the FS-BER method reduced the number of feature variables by 87.0% (289) while the AUC decreased by only 1.8%. In previous studies, the feature variables were usually selected by using one standard error of the lowest BER as selection threshold [36, 37]. Compared with previous methods, which decreased the number of feature variables by 74 to 85% in this study, the FS-BER method has a more stable feature selection performance, which reduced the number of feature variables by 85 to 87% for every algorithm. The MIN_subset is conducive to reduce the computational cost without degrading prediction performance. Because of the computing power limitation in the ordinary microprocessors, it is crucial to identify these smaller feature subsets for widespread application of mortality early warning in general monitors.

Number(OPT-MIN) and ΔAUC(OPT-MIN) are short for the reduction in feature variable number and the concerning reduction of AUC from using OPT_subset to using MIN_subset. Number(COM-MIN) and AUC(COM-MIN) are short for the reduction in feature variable number and the concerning reduction of AUC from using COM_set to using MIN_subset.

Table 4 Performance comparison between different methods only using non-invasive parameters

Subset	Methods	ACC (95% CI)	AUC (95% CI)	BER (95% CI)	F1_score (95% CI)	MCC (95% CI)	TNR (95% CI)	TPR (95% CI)
COM_set	XGB	0.768 (0.739–0.796)	0.870 (0.845–0.893)	0.217 (0.187–0.248)	0.631 (0.583–0.676)	0.500 (0.442–0.557)	0.814 (0.761–0.862)	0.753 (0.720–0.785)
	LGBM	0.794 (0.767–0.819)	0.877 (0.854–0.900)	0.195 (0.166–0.226)	0.662 (0.614–0.706)	0.544 (0.486–0.599)	0.827 (0.775–0.875)	0.783 (0.752–0.813)
	RF	0.775 (0.747–0.801)	0.865 (0.839–0.889)	0.217 (0.188–0.248)	0.634 (0.586–0.680)	0.504 (0.444–0.560)	0.800 (0.747–0.850)	0.767 (0.733–0.797)
	LR	0.775 (0.747–0.801)	0.847 (0.819–0.874)	0.220 (0.189–0.252)	0.632 (0.582–0.677)	0.499 (0.438–0.556)	0.791 (0.735–0.842)	0.769 (0.737–0.801)
OPT_subset	XGB	0.782 (0.755–0.809)	0.874 (0.849–0.897)	0.193 (0.165–0.223)	0.657 (0.611–0.701)	0.540 (0.484–0.594)	0.855 (0.805–0.9)	0.759 (0.726–0.791)
	LGBM	0.797 (0.770–0.822)	0.879 (0.855–0.901)	0.196 (0.167–0.226)	0.663 (0.616–0.708)	0.663 (0.616–0.708)	0.818 (0.767–0.868)	0.790 (0.759–0.82)
	RF	0.779 (0.751–0.806)	0.873 (0.848–0.896)	0.214 (0.183–0.245)	0.639 (0.590–0.684)	0.510 (0.451–0.567)	0.800 (0.745–0.851)	0.772 (0.740–0.803)
	LR	0.781 (0.754–0.808)	0.849 (0.821–0.875)	0.217 (0.186–0.249)	0.637 (0.589–0.683)	0.507 (0.447–0.565)	0.786 (0.731–0.839)	0.780 (0.748–0.811)
MIN_subset	XGB	0.754 (0.726–0.782)	0.852 (0.826–0.878)	0.226 (0.195–0.256)	0.617 (0.570–0.664)	0.481 (0.425–0.539)	0.814 (0.761–0.864)	0.734 (0.702–0.768)
	LGBM	0.764 (0.736–0.791)	0.859 (0.833–0.883)	0.219 (0.189–0.25)	0.627 (0.579–0.673)	0.494 (0.437–0.551)	0.814 (0.760–0.863)	0.747 (0.716–0.78)
	RF	0.772 (0.744–0.799)	0.856 (0.830–0.881)	0.223 (0.192–0.254)	0.628 (0.579–0.673)	0.494 (0.434–0.551)	0.786 (0.731–0.84)	0.768 (0.736–0.799)
	LR	0.762 (0.734–0.789)	0.836 (0.807–0.863)	0.229 (0.199–0.261)	0.480 (0.421–0.537)	0.786 (0.732–0.839)	0.786 (0.732–0.839)	0.755 (0.722–0.786)
Traditional scoring systems	SAPSII	0.631 (0.597~0.664)	0.707 (0.664~0.748)	0.368 (0.329~0.408)	0.455 (0.401~0.506)	0.229 (0.159~0.295)	0.635 (0.566~0.701)	0.629 (0.589~0.667)
	SOFA	0.554 (0.518~0.588)	0.638 (0.589~0.685)	0.410 (0.371~0.449	0.418 (0.369~0.468)	0.155 (0.087~0.222)	0.661 (0.594~0.728)	0.519 (0.478~0.559)
	APS	0.627 (0.593~0.661)	0.679 (0.635~0.722)	0.370 (0.331~0.410)	0.453 (0.398~0.504)	0.224 (0.155~0.292)	0.635 (0.567~0.703)	0.624 (0.585~0.663)
	MEWS	0.588 (0.554~0.622)	0.535 (0.491~0.580)	0.460 (0.420~0.500)	0.345 (0.291~0.398)	0.071 (0.001~0.141)	0.448 (0.378~0.518)	0.633 (0.593~0.670)
	OASIS	0.628 (0.594~0.661)	0.705 (0.661~0.746)	0.348 (0.310~0.387)	0.477 (0.424~0.527)	0.261 (0.193~0.327)	0.698 (0.631~0.763)	0.606 (0.566~0.645)

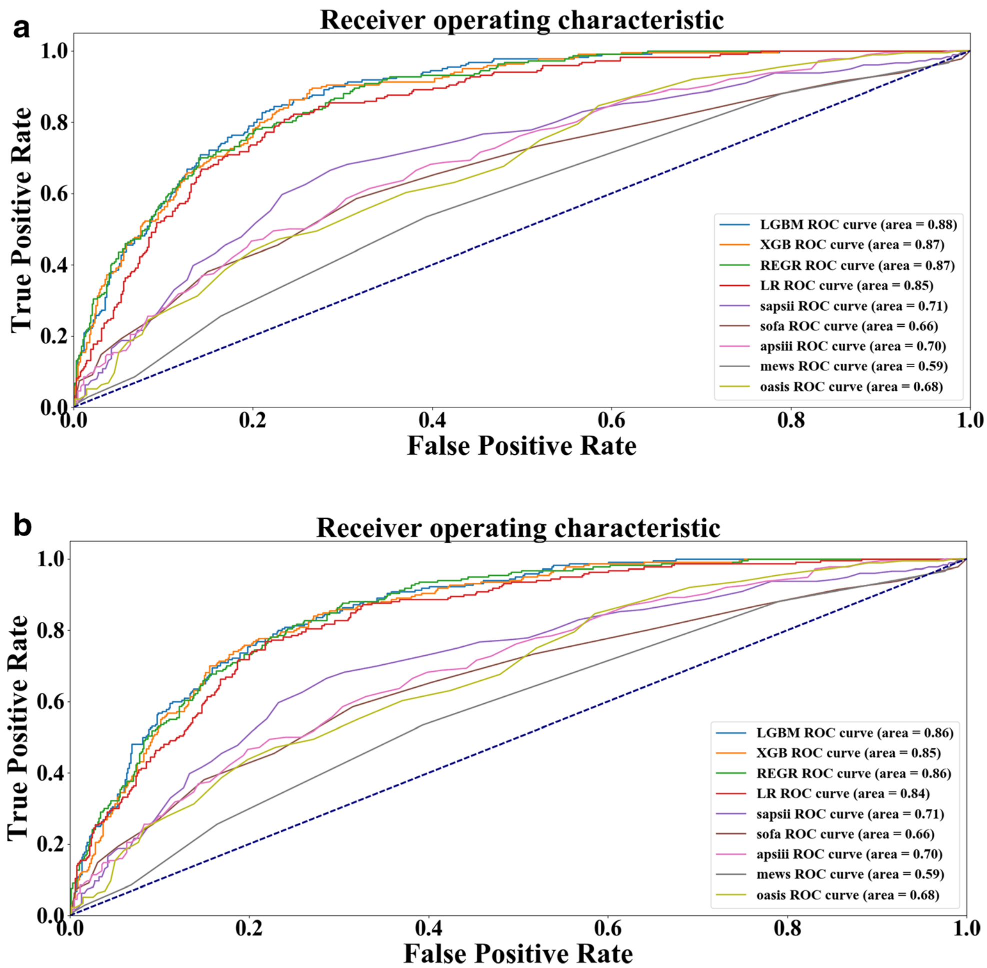


Fig. 6 Mortality prediction performance comparison between machine learning algorithms and traditional scoring systems for OPT_subset and MIN_subset. **a** ROC curve for OPT_subset. **b** ROC curve for MIN_subset

To avoid the problem of over-fitting, the threshold for classification was adjusted according to the optimal tradeoff between TNR and TPR. In the results, the values of TNR and TPR are very close for each algorithm, indicating that the cost-sensitive method can effectively solve the over-fitting problem [40, 41]. Although relatively accurate prediction results were achieved in this study, there are still some limitations. First, because there is correlation between the time-sensitive nature of physiological parameters and the progression of diseases, the time-related information of physiological parameters should be further extracted, which can further improve the performance of the predictor and will be considered in future studies. Second, for further improving the prediction performance, the mortality prediction models need to be calibrated according to the different medical environment and more algorithms will be verified to determine the optimal machine learning algorithm in the future. Third, because the dataset in this study has been handpicked to maintain a high quality, the performance in the presence of severe noise should be examined. For the application of the present methods in noisy clinical occasions, novel denoising algorithms should thus be developed in the future. Finally, the clinical data adopted in this work are from a single center. To prove the wide applicability of the present prediction algorithms in clinical practice, large-scale and multi-center trials are required in future study [16, 42].

5 Conclusion

In this study, with the optimal prediction results of 79.7% and 87.9% for ACC and AUC, the machine learning approaches

Table 5 Reduction in number of feature variables and concerning reduction in AUC using the FS-BER method

	LGBM	XGB	RF	LR
ΔAUC(OPT-MIN) /number(OPT-MIN)	0.020/271	0.022/251	0.017/104	0.013 /191
ΔAUC(COM-MIN) /number(COM-MIN)	0.018/289	0.018/282	0.009/284	0.011/286

only using non-invasive parameters can equal those using extra laboratory measurements. Based on the non-invasive parameters easily obtained from ordinary monitor and manual measurement, the non-invasive mortality prediction method can accurately and conveniently evaluate mortality risk and timely remind medical personnel to provide medical intervention in rural areas and remote battlefield, where the professional laboratorians and medical laboratory equipment are unavailable. It is hoped that this study can accelerate further developments in this field and provide valuable guidance for mortality prediction.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

Machine learning algorithms

As mentioned previously, four commonly used machine learning algorithms: LightGBM, XGBoost, Rand Forest and Logistic regression model, which have excellent classification performance were employed in this present study.

Random forest [1]

Random forest is an integrated classifier, which is composed of a set of decision tree classifiers. The optimal prediction result is determined by the decision tree classifier vote, as indicated by Equation (1).

$$\widehat{y} = \frac{1}{m}\sum_{j=1}^{m}\sum_{i=1}^{n} W_j(x_i, x')y_i = \sum_{i=1}^{n}\left(\frac{1}{m}\sum_{j=1}^{m} W_j(x_i, x')\right)y_i \tag{1}$$

The predictions $\widehat{y}$ for new points x' are achieved by seeking the neighboring point from a training set $\{(x_i, y_i)\}_{i=1}^{n}$. A forest averages the predictions of a set of m trees with individual weight functions W_j. $W_j(x_j, x')$ is the non-negative weight of the i-th training point relative to the new point x' in the same tree.

XGBOOST [2]

Boosting is a very effective integrated learning algorithm, which can transform a weak classifier into a strong classifier. Gradient boosting, which is an improved version of boosting, makes the loss function to fall along its gradient direction during the iteration process, thus improving algorithm robustness.

Based on the gradient boosting loss function, XGBoost performs a second-order expansion to achieve a faster search for the optimal solution.

The t-th loss function of XGBOOST is defined as Equation (2):

$$\mu^{(t)} \approx \sum_{i=1}^{n}\left[l\left(y_i, \widehat{y}^{(t-1)}\right) + g_i f_t(X_i) + \frac{1}{2}h_i f_t^2(X_i)\right] + \Omega(f_t) \tag{2}$$

where $g_i = \partial_{\widehat{y}} l\left(y_i, \widehat{y}^{(t-1)}\right)$, $h_i = \partial^2_{\widehat{y}^{(t-1)}} l\left(y_i, \widehat{y}^{(t-1)}\right)$ and $\Omega(f_t)$ are regular terms.

LightGBM [3]

The lightGBM algorithm is a gradient lifting framework that uses a histogram-based algorithm. Instead of finding the split points on the sorted feature values, the histogram-based algorithm buckets continuous feature values into discrete bins and uses these bins to construct feature histograms during training.

The white point indicates the leaf with the largest split gain, and the black point is other leaf.

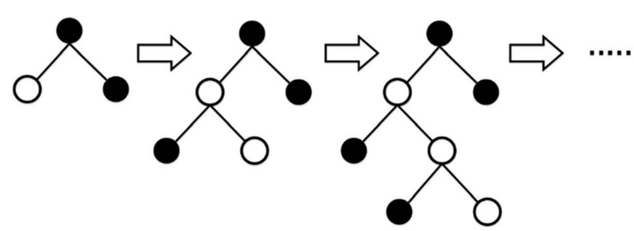

Fig. 7 Leaf-wise growth strategy

Logistic regression model (LR) [4]

The logistic regression model is a classical classification algorithm commonly used to resolve the binary classification problem. In LR, the sigmoid function presents a relationship between the predicted target variable $h_\theta(x)$ and input features x, as formulated by Equation (6).

$$h_\theta(x) = \left(1 + \exp\left(\theta_0 + \sum_{i=1}^{N} \theta_i x_i\right)\right)^{-1} \tag{6}$$

Where θ is a feature weight vector, which is optimized by the stochastic gradient decent algorithm.

Traditional scoring systems

Five traditional scoring systems were used to compare with machine learning models and these systems and models have been developed and tested on the same set of data. The traditional scoring systems are briefly introduced as follows:

SAPSII [5] assesses the severity of illness in patients who are older than 15 years in the ICU. The evaluation process is based on 17 parameters, e.g., age, HR, SBP, T, and GCS. The measurements should be finished within 24 h of admission to ICU, with integer measurement values between 0 and 163.

SOFA [6] is suitable for tracking the state of patients treated in the ICU. The SOFA score is based on six different scoring systems, which include the respiratory, cardiovascular, liver, coagulation, kidney, and nervous scoring system.

APS [7], which is based on the results of blood tests and vital signs, is widely used for assessment of the condition of patients in the emergency critical care unit (EICU). The higher the APS score is, the higher the mortality risk is.

Modified early warning score (MEWS) [8], which is suitable for ICU patients over 14 years of age is calculated based on five non-invasive parameters including heart rate, systolic blood pressure, breathing, body temperature, and consciousness. The scoring range of each parameter is from 0 to 3. The final score is the sum of each one of the parameter scores. The higher score value indicates the more deteriorated health condition.

The Oxford acute severity of illness score (OASIS)[9], which was developed for ICU patients using a hybrid genetic algorithm and particle swarm optimization approach, was designed to have an extremely low burden for data collection and quality control, using only 14 features without laboratory measurements, diagnosis, or comorbidity information.

Parameters weight

Table 6 The statistical result for non-invasive parameters

Rank	feature variables	Relief	Fisher	Gini	Comprehensive Score
1	nibp_diastolic_fe_mean	1	0.84	0.95	2.8
2	nibp_mean_ts_min	0.89	0.98	0.91	2.78
3	nibp_diastolic_twe_perc_75	0.9	0.94	0.88	2.71
4	nibp_systolic_fe_var	0.89	0.96	0.75	2.6
5	nibp_systolic_twe_stddev	0.8	0.8	0.96	2.56
6	spo2_ts_perc_75	0.75	0.93	0.86	2.54
7	gcs_twe_perc_75	0.88	0.94	0.69	2.51
8	nibp_mean_tf_perc_25	0.61	0.92	0.94	2.47
9	nibp_diastolic_ts_min	0.71	0.95	0.71	2.38
10	gcs_twe_range	0.79	0.63	0.95	2.37
11	gcs_ts_range	0.98	0.4	0.99	2.37
12	nibp_mean_fe_var	0.8	0.97	0.58	2.35
13	temperature_twe_stddev	0.71	0.82	0.79	2.32
14	nibp_systolic_ts_var	0.97	0.86	0.49	2.31
15	heartrate_twe_min	0.89	0.46	0.95	2.31
16	nibp_mean_ts_range	0.49	0.9	0.88	2.28
17	nibp_diastolic_ts_max	0.72	0.81	0.74	2.27
18	nibp_systolic_tf_mean	0.95	0.88	0.41	2.24
19	nibp_systolic_tf_range	0.67	0.95	0.61	2.23
20	spo2_twe_min	0.37	0.92	0.94	2.23

Table 6 (continued)

Rank	feature variables	Relief	Fisher	Gini	Comprehensive Score
21	fio2_ts_mean	0.72	0.99	0.52	2.23
22	spo2_twe_perc_50	0.85	0.64	0.73	2.22
23	fio2_fe_mean	0.41	0.81	1	2.21
24	fio2_twe_perc_25	0.98	0.22	0.99	2.2
25	fio2_twe_mean	0.78	0.61	0.82	2.2
26	nibp_mean_twe_mean	0.6	0.87	0.73	2.2
27	spo2_tf_mean	0.64	0.87	0.67	2.18
28	nibp_mean_tf_min	0.37	0.83	0.98	2.17
29	temperature_ts_range	0.51	0.72	0.93	2.16
30	spo2_tf_min	0.92	0.3	0.92	2.15
31	nibp_diastolic_tf_mean	0.64	0.56	0.94	2.14
32	heartrate_tf_var	0.7	0.64	0.81	2.14
33	heartrate_fe_min	0.72	0.79	0.63	2.14
34	gcs_tf_mean	0.67	0.78	0.68	2.13
35	nibp_diastolic_fe_stddev	0.97	0.69	0.47	2.13
36	nibp_mean_tf_range	0.82	0.65	0.66	2.13
37	fio2_fe_range	0.63	0.9	0.6	2.12
38	fio2_ts_max	0.52	0.86	0.69	2.08
39	temperature_tf_min	0.94	0.14	0.97	2.05
40	heartrate_fe_perc_50	0.23	0.89	0.92	2.05
41	nibp_mean_twe_stddev	0.36	0.89	0.78	2.04
42	gcs_fe_perc_75	1	1	0.04	2.03
43	respiratoryrate_tf_perc_75	0.98	0.7	0.36	2.03
44	fio2_tf_min	0.9	0.7	0.43	2.03
45	respiratoryrate_fe_perc_50	0.77	0.27	0.97	2.01
46	nibp_diastolic_fe_min	0.99	0.22	0.79	2
47	spo2_fe_stddev	0.79	0.21	0.99	2
48	nibp_mean_twe_range	0.65	0.5	0.84	1.99
49	respiratoryrate_tf_min	0.98	0.84	0.16	1.98
50	nibp_diastolic_fe_range	0.2	0.95	0.83	1.98
51	heartrate_tf_mean	0.58	0.76	0.64	1.98
52	respiratoryrate_twe_min	0.77	0.97	0.24	1.98
53	nibp_mean_fe_mean	0.86	0.48	0.62	1.97
54	fio2_tf_max	0.96	0.93	0.07	1.96
55	gcs_tf_perc_75	0.87	0.31	0.78	1.96
56	respiratoryrate_tf_max	0.48	0.58	0.9	1.96
57	nibp_systolic_fe_mean	0.83	0.62	0.5	1.96
58	gcs_twe_var	0.94	0.18	0.83	1.95
59	heartrate_tf_perc_50	0.69	0.49	0.77	1.95
60	gcs_fe_mean	0.93	0.35	0.65	1.93
61	spo2_fe_perc_50	0.9	0.91	0.12	1.93
62	respiratoryrate_ts_perc_25	0.21	0.77	0.95	1.93
63	temperature_ts_min	0.61	0.4	0.92	1.93
64	spo2_twe_stddev	0.91	0.91	0.09	1.91
65	gcs_tf_var	0.91	0.39	0.61	1.91
66	nibp_systolic_fe_stddev	0.55	0.48	0.87	1.9
67	heartrate_tf_range	0.66	0.3	0.93	1.89
68	spo2_twe_range	0.94	0.45	0.51	1.89
69	nibp_mean_fe_min	0.7	0.63	0.56	1.89

Table 6 (continued)

Rank	feature variables	Relief	Fisher	Gini	Comprehensive Score
70	heartrate_ts_stddev	0.55	0.83	0.49	1.88
71	heartrate_fe_perc_25	0.87	0.87	0.13	1.87
72	spo2_tf_perc_25	0.86	0.76	0.26	1.87
73	spo2_tf_range	0.77	1	0.09	1.86
74	gcs_fe_perc_25	0.83	0.46	0.57	1.86
75	heartrate_ts_perc_75	0.93	0.11	0.82	1.86
76	gcs_fe_range	0.7	0.7	0.44	1.85
77	nibp_mean_twe_perc_25	0.84	0.98	0.02	1.84
78	nibp_systolic_twe_perc_25	0.95	0.84	0.05	1.84
79	nibp_diastolic_twe_range	0.5	0.75	0.58	1.83
80	heartrate_fe_range	0.8	0.68	0.34	1.83
81	fio2_twe_var	0.16	0.85	0.8	1.82
82	spo2_ts_stddev	0.81	0.31	0.69	1.81
83	nibp_systolic_ts_perc_50	0.62	0.26	0.93	1.81
84	temperature_twe_var	0.27	0.8	0.74	1.81
85	nibp_mean_tf_max	0.24	0.99	0.57	1.8
86	spo2_twe_max	0.62	0.32	0.86	1.8
87	gcs_fe_stddev	0.17	0.79	0.84	1.8
88	nibp_systolic_twe_perc_50	0.87	0.52	0.41	1.8
89	nibp_systolic_fe_max	0.47	0.97	0.36	1.8
90	nibp_diastolic_fe_perc_25	0.8	0.79	0.2	1.8
91	temperature_ts_mean	0.66	0.17	0.96	1.79
92	heartrate_twe_range	0.48	0.59	0.72	1.79
93	temperature_fe_max	0.45	0.77	0.58	1.79
94	nibp_mean_ts_perc_75	0.88	0.24	0.66	1.78
95	nibp_systolic_twe_range	0.46	0.48	0.84	1.78
96	respiratoryrate_fe_perc_75	0.22	0.66	0.89	1.77
97	spo2_tf_perc_75	0.21	0.69	0.87	1.77
98	nibp_mean_tf_perc_50	0.75	0.29	0.73	1.77
99	nibp_systolic_ts_perc_75	0.92	0.51	0.35	1.77
100	nibp_diastolic_tf_stddev	0.64	0.64	0.5	1.77
101	heartrate_twe_mean	0.27	0.71	0.8	1.77
102	gcs_ts_perc_75	0.76	0.98	0.02	1.76
103	temperature_fe_mean	0.11	0.78	0.88	1.76
104	temperature_twe_max	0.93	0.51	0.32	1.76
105	nibp_diastolic_tf_var	0.96	0.4	0.39	1.75
106	nibp_mean_fe_perc_25	0.76	0.96	0	1.73
107	urineoutput_tf	0.78	0.38	0.57	1.73
108	respiratoryrate_tf_perc_25	0.96	0.09	0.68	1.73
109	heartrate_tf_perc_75	0.32	0.99	0.42	1.73
110	heartrate_fe_stddev	0	0.82	0.91	1.73
111	respiratoryrate_twe_perc_75	0.68	0.5	0.55	1.73
112	respiratoryrate_fe_max	0.49	0.54	0.7	1.73
113	nibp_diastolic_ts_mean	0.73	0.18	0.8	1.72
114	fio2_ts_stddev	0.57	0.43	0.71	1.72
115	respiratoryrate_tf_stddev	0.73	0.48	0.5	1.71
116	vent	0.48	0.92	0.3	1.7
117	nibp_systolic_tf_perc_50	0.06	0.75	0.89	1.7

Table 6 (continued)

Rank	feature variables	Relief	Fisher	Gini	Comprehensive Score
118	spo2_tf_perc_50	0.54	0.88	0.28	1.7
119	nibp_systolic_ts_perc_25	0.76	0.26	0.66	1.68
120	nibp_systolic_tf_stddev	0.15	0.66	0.87	1.68
121	temperature_fe_stddev	0.64	0.73	0.3	1.67
122	fio2_tf_mean	0.73	0.8	0.14	1.67
123	fio2_ts_perc_25	0.23	0.96	0.47	1.67
124	spo2_tf_stddev	0.05	0.65	0.97	1.67
125	nibp_diastolic_twe_min	0.55	0.69	0.44	1.67
126	nibp_systolic_twe_perc_75	0.83	0.39	0.45	1.67
127	heartrate_twe_perc_75	0.77	0.66	0.24	1.67
128	temperature_twe_mean	0.49	0.78	0.39	1.66
129	heartrate_fe_perc_75	0.28	0.62	0.75	1.65
130	heartrate_tf_max	0.68	0.81	0.16	1.65
131	nibp_mean_fe_range	0.57	0.39	0.68	1.64
132	nibp_diastolic_fe_perc_50	0.38	0.92	0.35	1.64
133	nibp_diastolic_tf_min	0.03	0.74	0.86	1.64
134	gcs_twe_perc_25	0.61	0.12	0.9	1.63
135	nibp_mean_twe_max	0.23	0.86	0.54	1.63
136	nibp_systolic_ts_mean	0.89	0.15	0.56	1.6
137	respiratoryrate_ts_min	0.21	0.41	0.98	1.6
138	spo2_twe_perc_75	0.04	0.7	0.85	1.59
139	nibp_systolic_fe_perc_25	0.74	0.64	0.19	1.58
140	heartrate_ts_var	0.06	0.52	1	1.58
141	nibp_systolic_ts_stddev	0.38	0.93	0.27	1.58
142	temperature_ts_stddev	0.42	0.39	0.77	1.58
143	heartrate_fe_var	0.85	0.68	0.03	1.57
144	respiratoryrate_fe_min	0.95	0.21	0.42	1.57
145	nibp_systolic_twe_max	0.88	0.02	0.67	1.57
146	nibp_systolic_tf_perc_75	0.6	0.32	0.64	1.56
147	heartrate_ts_perc_25	0.59	0.2	0.76	1.55
148	fio2_tf_stddev	0.59	0.77	0.19	1.55
149	gcs_tf_perc_25	0.6	0.62	0.34	1.55
150	nibp_diastolic_ts_stddev	0.68	0.03	0.85	1.55
151	nibp_diastolic_fe_var	0.69	0.74	0.12	1.55
152	gcs_twe_stddev	0.66	0.61	0.27	1.54
153	spo2_fe_min	0.69	0.58	0.27	1.54
154	nibp_diastolic_twe_stddev	0.29	0.42	0.83	1.54
155	nibp_diastolic_twe_perc_25	0.08	0.53	0.91	1.52
156	respiratoryrate_ts_var	0.53	0.89	0.11	1.52
157	nibp_mean_twe_perc_50	0.75	0.01	0.76	1.52
158	nibp_mean_tf_perc_75	0.17	0.45	0.89	1.51
159	heartrate_ts_min	0.16	0.76	0.58	1.5
160	respiratoryrate_twe_perc_25	0.2	0.67	0.63	1.5
161	nibp_mean_ts_var	0.58	0.68	0.23	1.5
162	gcs_fe_max	0.39	0.9	0.2	1.49
163	spo2_fe_perc_75	0.73	0.21	0.54	1.48
164	gcs_ts_min	0.52	0.65	0.31	1.48
165	nibp_systolic_fe_perc_75	0.78	0.22	0.48	1.48

Table 6 (continued)

Rank	feature variables	Relief	Fisher	Gini	Comprehensive Score
166	spo2_twe_perc_25	0.95	0.13	0.4	1.48
167	nibp_systolic_fe_perc_50	0.71	0.37	0.39	1.48
168	fio2_tf_range	0.58	0.8	0.1	1.48
169	nibp_systolic_twe_mean	0.86	0.08	0.53	1.47
170	temperature_fe_perc_75	0.03	0.98	0.46	1.47
171	nibp_mean_ts_mean	0.09	0.6	0.77	1.46
172	temperature_twe_range	0.47	0.88	0.11	1.46
173	respiratoryrate_fe_range	0.33	0.61	0.52	1.46
174	gcs_tf_max	0.33	0.33	0.81	1.46
175	heartrate_ts_perc_50	0.99	0.38	0.08	1.45
176	heartrate_ts_mean	0.97	0.29	0.19	1.45
177	nibp_systolic_ts_max	0.41	0.61	0.42	1.45
178	fio2_fe_perc_25	0.81	0.44	0.21	1.45
179	respiratoryrate_fe_perc_25	0.2	0.85	0.38	1.43
180	fio2_tf_perc_50	0.84	0.31	0.27	1.42
181	gcs_fe_var	0.24	0.86	0.31	1.42
182	temperature_twe_perc_25	0.44	0.52	0.45	1.42
183	respiratoryrate_ts_perc_75	0.82	0.04	0.56	1.42
184	fio2_fe_perc_50	0.36	0.25	0.8	1.41
185	bmi	0.01	0.43	0.96	1.41
186	gcs_tf_range	0.5	0.32	0.59	1.41
187	temperature_fe_perc_50	0.67	0.57	0.17	1.41
188	temperature_ts_perc_50	0.74	0.41	0.25	1.4
189	spo2_fe_var	0.28	0.12	0.98	1.39
190	temperature_tf_mean	0.26	0.53	0.6	1.39
191	gcs_fe_perc_50	0.3	0.83	0.25	1.37
192	fio2_twe_max	0.57	0.59	0.22	1.37
193	spo2_tf_var	0.63	0.73	0.01	1.37
194	temperature_tf_max	0.58	0.17	0.63	1.37
195	heartrate_ts_range	0.45	0.19	0.72	1.37
196	spo2_twe_mean	0.04	0.85	0.49	1.37
197	spo2_twe_var	0.32	0.37	0.67	1.36
198	nibp_diastolic_twe_max	0.35	0.91	0.09	1.35
199	fio2_fe_var	0.31	0.67	0.37	1.35
200	spo2_ts_mean	0.44	0.01	0.9	1.35
201	temperature_tf_perc_25	0.19	0.57	0.59	1.35
202	respiratoryrate_tf_var	0.37	0.6	0.38	1.35
203	fio2_fe_min	0.22	0.34	0.78	1.34
204	nibp_mean_tf_mean	0.02	0.53	0.79	1.34
205	nibp_diastolic_twe_mean	0.99	0.17	0.18	1.34
206	nibp_systolic_twe_min	0.34	0.49	0.51	1.34
207	fio2_ts_perc_75	0.74	0.42	0.17	1.34
208	respiratoryrate_twe_mean	0.3	0.89	0.14	1.33
209	heartrate_twe_max	0.22	0.36	0.75	1.33
210	gender	0.33	0.75	0.24	1.33
211	temperature_twe_min	0.36	0.37	0.6	1.33
212	gcs_ts_mean	0.45	0.06	0.81	1.32
213	fio2_tf_var	0.31	0.74	0.26	1.31
214	nibp_diastolic_ts_range	0.36	0.33	0.61	1.31

Table 6 (continued)

Rank	feature variables	Relief	Fisher	Gini	Comprehensive Score
215	gcs_tf_perc_50	0.65	0	0.65	1.3
216	nibp_mean_ts_max	0.84	0.34	0.1	1.28
217	nibp_diastolic_twe_var	0.25	0.72	0.31	1.28
218	respiratoryrate_ts_stddev	0.31	0.67	0.3	1.28
219	nibp_diastolic_twe_perc_50	0.7	0.3	0.28	1.28
220	temperature_twe_perc_75	0.01	0.51	0.77	1.28
221	nibp_mean_tf_stddev	0.1	0.44	0.74	1.28
222	nibp_mean_tf_var	0.56	0.07	0.64	1.27
223	fio2_ts_var	0.26	0.03	0.98	1.27
224	heartrate_twe_perc_50	0.52	0.58	0.18	1.27
225	gcs_twe_perc_50	0.15	0.77	0.34	1.26
226	urineoutput_ts	0.56	0.05	0.65	1.26
227	nibp_diastolic_fe_max	0.03	0.41	0.82	1.26
228	temperature_tf_perc_75	0.53	0.14	0.59	1.26
229	urineoutput_fe	0.05	0.94	0.25	1.25
230	fio2_ts_range	0.3	0.57	0.37	1.25
231	temperature_tf_perc_50	0.12	0.83	0.3	1.25
232	temperature_fe_min	0.29	0.12	0.83	1.24
233	respiratoryrate_ts_mean	0.07	0.55	0.62	1.24
234	nibp_diastolic_tf_max	0.3	0.07	0.85	1.22
235	nibp_mean_twe_var	0.92	0.13	0.17	1.22
236	temperature_fe_range	0.19	0.42	0.61	1.22
237	temperature_tf_stddev	0.33	0.52	0.37	1.21
238	nibp_mean_ts_perc_25	0.82	0.16	0.23	1.21
239	nibp_systolic_fe_min	0.09	0.19	0.92	1.2
240	spo2_ts_perc_25	0.27	0.58	0.35	1.2
241	nibp_systolic_tf_min	0.4	0.36	0.45	1.2
242	spo2_fe_mean	0.45	0.73	0.01	1.19
243	spo2_fe_perc_25	0.79	0.38	0.02	1.19
244	spo2_ts_var	0.42	0.3	0.47	1.19
245	nibp_systolic_ts_range	0.35	0.71	0.12	1.18
246	gcs_twe_max	0.19	0.44	0.55	1.18
247	nibp_diastolic_fe_perc_75	0.43	0.2	0.55	1.18
248	respiratoryrate_twe_range	0.13	0.63	0.43	1.18
249	heartrate_fe_mean	0.52	0.11	0.55	1.18
250	fio2_fe_max	0.29	0.19	0.7	1.18
251	nibp_diastolic_tf_perc_50	0.02	0.26	0.89	1.18
252	fio2_tf_perc_25	0.05	0.72	0.4	1.17
253	gcs_ts_max	0.39	0.45	0.33	1.17
254	heartrate_tf_min	0.43	0.02	0.73	1.17
255	temperature_fe_var	0.13	0.33	0.7	1.16
256	urineoutput_twe	0.5	0.43	0.22	1.15
257	fio2_twe_perc_75	0.43	0	0.72	1.15
258	fio2_tf_perc_75	0.02	0.71	0.42	1.15
259	nibp_diastolic_tf_range	0.1	0.29	0.76	1.14
260	respiratoryrate_fe_mean	0	0.82	0.32	1.14
261	fio2_fe_perc_75	0.39	0.04	0.7	1.14
262	respiratoryrate_fe_stddev	0.85	0.08	0.21	1.14
263	nibp_diastolic_ts_perc_25	0.91	0.11	0.11	1.13

Table 6 (continued)

Rank	feature variables	Relief	Fisher	Gini	Comprehensive Score
264	respiratoryrate_twe_perc_50	0.14	0.47	0.52	1.13
265	respiratoryrate_twe_max	0.24	0.28	0.62	1.13
266	spo2_ts_min	0.44	0.18	0.51	1.13
267	gcs_tf_min	0.61	0.09	0.41	1.12
268	gcs_ts_var	0.12	0.13	0.86	1.11
269	nibp_diastolic_tf_perc_75	0.14	0.49	0.48	1.11
270	gcs_tf_stddev	0.41	0.67	0.03	1.11
271	gcs_twe_mean	0.56	0.47	0.06	1.1
272	spo2_ts_range	0.54	0.35	0.21	1.1
273	nibp_systolic_twe_var	0.08	0.55	0.46	1.1
274	temperature_fe_perc_25	0.08	0.54	0.48	1.1
275	temperature_ts_perc_25	0.51	0.56	0.03	1.1
276	nibp_systolic_tf_perc_25	0.62	0.11	0.36	1.09
277	gcs_ts_stddev	0.2	0.6	0.28	1.08
278	nibp_diastolic_ts_var	0.67	0.35	0.04	1.06
279	temperature_ts_var	0.09	0.95	0.02	1.06
280	fio2_twe_stddev	0.63	0.42	0	1.05
281	respiratoryrate_tf_mean	0.18	0.59	0.29	1.05
282	spo2_ts_perc_50	0.34	0.34	0.36	1.05
283	fio2_ts_min	0.07	0.55	0.44	1.05
284	gcs_fe_min	0.26	0.56	0.23	1.04
285	temperature_twe_perc_50	0.51	0.46	0.07	1.04
286	gcs_ts_perc_25	0.83	0.09	0.11	1.03
287	nibp_diastolic_ts_perc_50	0.28	0.36	0.39	1.03
288	spo2_ts_max	0.13	0.47	0.43	1.03
289	respiratoryrate_ts_max	0.47	0.04	0.52	1.02
290	nibp_mean_fe_max	0.4	0.16	0.45	1.01
291	fio2_twe_range	0.81	0.05	0.14	1
292	age	0.17	0.17	0.64	0.98
293	nibp_mean_ts_stddev	0.25	0.27	0.46	0.98
294	heartrate_twe_var	0.46	0.36	0.15	0.97
295	heartrate_tf_perc_25	0.34	0.45	0.17	0.96
296	nibp_mean_fe_perc_50	0.17	0.5	0.29	0.96
297	nibp_systolic_ts_min	0.18	0.05	0.71	0.95
298	temperature_ts_perc_75	0.08	0.54	0.33	0.95
299	respiratoryrate_ts_range	0.27	0.55	0.13	0.95
300	temperature_ts_max	0.55	0.24	0.15	0.94
301	temperature_tf_range	0.86	0.01	0.04	0.91
302	respiratoryrate_fe_var	0.65	0.25	0.01	0.9
303	respiratoryrate_twe_var	0.14	0.08	0.67	0.89
304	respiratoryrate_twe_stddev	0.11	0.24	0.53	0.88
305	nibp_mean_fe_perc_75	0.54	0.16	0.18	0.88
306	nibp_mean_twe_perc_75	0.06	0.33	0.48	0.86
307	gcs_twe_min	0.42	0.05	0.38	0.85
308	fio2_ts_perc_50	0.59	0.02	0.22	0.83
309	heartrate_ts_max	0.46	0.27	0.1	0.82
310	nibp_systolic_fe_range	0.18	0.28	0.33	0.8
311	spo2_fe_range	0.42	0.28	0.05	0.74

Table 6 (continued)

Rank	feature variables	Relief	Fisher	Gini	Comprehensive Score
312	respiratoryrate_tf_perc_50	0.11	0.1	0.53	0.74
313	respiratoryrate_ts_perc_50	0.39	0.15	0.2	0.74
314	temperature_tf_var	0.35	0.23	0.16	0.73
315	gcs_ts_perc_50	0.16	0.2	0.33	0.7
316	heartrate_tf_stddev	0.25	0.14	0.29	0.68
317	nibp_mean_ts_perc_50	0.02	0.27	0.4	0.68
318	fio2_twe_min	0.53	0.06	0.08	0.67
319	respiratoryrate_tf_range	0.48	0.14	0.05	0.67
320	fio2_twe_perc_50	0.04	0.06	0.54	0.64
321	nibp_diastolic_ts_perc_75	0.14	0.15	0.32	0.61
322	heartrate_twe_perc_25	0.23	0.23	0.14	0.6
323	nibp_diastolic_tf_perc_25	0.38	0.1	0.06	0.54
324	heartrate_twe_stddev	0.11	0.23	0.2	0.54
325	nibp_mean_fe_stddev	0.05	0.25	0.23	0.53
326	fio2_fe_stddev	0.4	0.07	0.05	0.53
327	spo2_tf_max	0.15	0.23	0.15	0.53
328	spo2_fe_max	0.32	0.03	0.13	0.47
329	nibp_systolic_tf_max	0.12	0.2	0.07	0.39
330	heartrate_fe_max	0.01	0.02	0.26	0.3
331	nibp_mean_twe_min	0.07	0.1	0.08	0.26
332	nibp_systolic_tf_var	0.1	0.08	0.06	0.23

Where (parameter)_XX_XX is the derivative variables of parameter, XX_twe_XX, XX_tf_XX, XX_ts_XX, XX_fe_XX is the derivative variables of the time series data of 0~12 h, 12~24 h, 24~36h, 36~48h after admitting to hospital, respectively and XX_XX_(eigenvalue) is the derivative variables about the eigenvalue.

Further details on feature extraction

Table 7 The OPT_subset and the MIN_subset of XGBoost

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
1	nibp_diastolic_fe_mean	nibp_diastolic_fe_mean
2	nibp_mean_ts_min	nibp_mean_ts_min
3	nibp_diastolic_twe_perc_75	nibp_diastolic_twe_perc_75
4	nibp_systolic_fe_var	nibp_systolic_fe_var
5	nibp_systolic_twe_stddev	nibp_systolic_twe_stddev
6	spo2_ts_perc_75	spo2_ts_perc_75
7	gcs_twe_perc_75	gcs_twe_perc_75
8	nibp_mean_tf_perc_25	nibp_mean_tf_perc_25
9	nibp_diastolic_ts_min	nibp_diastolic_ts_min
10	gcs_twe_range	gcs_twe_range
11	gcs_ts_range	gcs_ts_range
12	nibp_mean_fe_var	nibp_mean_fe_var
13	temperature_twe_stddev	temperature_twe_stddev
14	nibp_systolic_ts_var	nibp_systolic_ts_var
15	heartrate_twe_min	heartrate_twe_min
16	nibp_mean_ts_range	nibp_mean_ts_range
17	nibp_diastolic_ts_max	nibp_diastolic_ts_max
18	nibp_systolic_tf_mean	nibp_systolic_tf_mean
19	nibp_systolic_tf_range	nibp_systolic_tf_range
20	spo2_twe_min	spo2_twe_min
21	fio2_ts_mean	fio2_ts_mean
22	spo2_twe_perc_50	spo2_twe_perc_50
23	fio2_fe_mean	fio2_fe_mean
24	fio2_twe_perc_25	fio2_twe_perc_25
25	fio2_twe_mean	fio2_twe_mean
26	nibp_mean_twe_mean	nibp_mean_twe_mean
27	spo2_tf_mean	spo2_tf_mean
28	nibp_mean_tf_min	nibp_mean_tf_min
29	temperature_ts_range	temperature_ts_range
30	spo2_tf_min	spo2_tf_min
31	nibp_diastolic_tf_mean	nibp_diastolic_tf_mean
32	heartrate_tf_var	heartrate_tf_var
33	heartrate_fe_min	heartrate_fe_min
34	gcs_tf_mean	gcs_tf_mean
35	nibp_diastolic_fe_stddev	nibp_diastolic_fe_stddev
36	nibp_mean_tf_range	nibp_mean_tf_range
37	fio2_fe_range	fio2_fe_range
38	fio2_ts_max	fio2_ts_max
39	temperature_tf_min	temperature_tf_min
40	heartrate_fe_perc_50	heartrate_fe_perc_50
41	nibp_mean_twe_stddev	nibp_mean_twe_stddev
42	gcs_fe_perc_75	gcs_fe_perc_75
43	respiratoryrate_tf_perc_75	respiratoryrate_tf_perc_75
44	fio2_tf_min	fio2_tf_min
45	respiratoryrate_fe_perc_50	respiratoryrate_fe_perc_50
46	nibp_diastolic_fe_min	nibp_diastolic_fe_min

Table 7 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
47	spo2_fe_stddev	spo2_fe_stddev
48	nibp_mean_twe_range	nibp_mean_twe_range
49	respiratoryrate_tf_min	respiratoryrate_tf_min
50	nibp_diastolic_fe_range	nibp_diastolic_fe_range
51	heartrate_tf_mean	-
52	respiratoryrate_twe_min	
53	nibp_mean_fe_mean	
54	fio2_tf_max	
55	gcs_tf_perc_75	
56	respiratoryrate_tf_max	
57	nibp_systolic_fe_mean	
58	gcs_twe_var	
59	heartrate_tf_perc_50	
60	gcs_fe_mean	
61	spo2_fe_perc_50	
62	respiratoryrate_ts_perc_25	
63	temperature_ts_min	
64	spo2_twe_stddev	
65	gcs_tf_var	
66	nibp_systolic_fe_stddev	
67	heartrate_tf_range	
68	spo2_twe_range	
69	nibp_mean_fe_min	
70	heartrate_ts_stddev	
71	heartrate_fe_perc_25	
72	spo2_tf_perc_25	
73	spo2_tf_range	
74	gcs_fe_perc_25	
75	heartrate_ts_perc_75	
76	gcs_fe_range	
77	nibp_mean_twe_perc_25	
78	nibp_systolic_twe_perc_25	
79	nibp_diastolic_twe_range	
80	heartrate_fe_range	
81	fio2_twe_var	
82	spo2_ts_stddev	
83	nibp_systolic_ts_perc_50	
84	temperature_twe_var	
85	nibp_mean_tf_max	
86	spo2_twe_max	
87	gcs_fe_stddev	
88	nibp_systolic_twe_perc_50	
89	nibp_systolic_fe_max	
90	nibp_diastolic_fe_perc_25	
91	temperature_ts_mean	
92	heartrate_twe_range	
93	temperature_fe_max	
94	nibp_mean_ts_perc_75	
95	nibp_systolic_twe_range	

Table 7 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
96	respiratoryrate_fe_perc_75	
97	spo2_tf_perc_75	
98	nibp_mean_tf_perc_50	
99	nibp_systolic_ts_perc_75	
100	nibp_diastolic_tf_stddev	
101	heartrate_twe_mean	
102	gcs_ts_perc_75	
103	temperature_fe_mean	
104	temperature_twe_max	
105	nibp_diastolic_tf_var	
106	nibp_mean_fe_perc_25	
107	urineoutput_tf	
108	respiratoryrate_tf_perc_25	
109	heartrate_tf_perc_75	
110	heartrate_fe_stddev	
111	respiratoryrate_twe_perc_75	
112	respiratoryrate_fe_max	
113	nibp_diastolic_ts_mean	
114	fio2_ts_stddev	
115	respiratoryrate_tf_stddev	
116	vent	
117	nibp_systolic_tf_perc_50	
118	spo2_tf_perc_50	
119	nibp_systolic_ts_perc_25	
120	nibp_systolic_tf_stddev	
121	temperature_fe_stddev	
122	fio2_tf_mean	
123	fio2_ts_perc_25	
124	spo2_tf_stddev	
125	nibp_diastolic_twe_min	
126	nibp_systolic_twe_perc_75	
127	heartrate_twe_perc_75	
128	temperature_twe_mean	
129	heartrate_fe_perc_75	
130	heartrate_tf_max	
131	nibp_mean_fe_range	
132	nibp_diastolic_fe_perc_50	
133	nibp_diastolic_tf_min	
134	gcs_twe_perc_25	
135	nibp_mean_twe_max	
136	nibp_systolic_ts_mean	
137	respiratoryrate_ts_min	
138	spo2_twe_perc_75	
139	nibp_systolic_fe_perc_25	
140	heartrate_ts_var	
141	nibp_systolic_ts_stddev	
142	temperature_ts_stddev	
143	heartrate_fe_var	
144	respiratoryrate_fe_min	

Table 7 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
145	nibp_systolic_twe_max	
146	nibp_systolic_tf_perc_75	
147	heartrate_ts_perc_25	
148	fio2_tf_stddev	
149	gcs_tf_perc_25	
150	nibp_diastolic_ts_stddev	
151	nibp_diastolic_fe_var	
152	gcs_twe_stddev	
153	spo2_fe_min	
154	nibp_diastolic_twe_stddev	
155	nibp_diastolic_twe_perc_25	
156	respiratoryrate_ts_var	
157	nibp_mean_twe_perc_50	
158	nibp_mean_tf_perc_75	
159	heartrate_ts_min	
160	respiratoryrate_twe_perc_25	
161	nibp_mean_ts_var	
162	gcs_fe_max	
163	spo2_fe_perc_75	
164	gcs_ts_min	
165	nibp_systolic_fe_perc_75	
166	spo2_twe_perc_25	
167	nibp_systolic_fe_perc_50	
168	fio2_tf_range	
169	nibp_systolic_twe_mean	
170	temperature_fe_perc_75	
171	nibp_mean_ts_mean	
172	temperature_twe_range	
173	respiratoryrate_fe_range	
174	gcs_tf_max	
175	heartrate_ts_perc_50	
176	heartrate_ts_mean	
177	nibp_systolic_ts_max	
178	fio2_fe_perc_25	
179	respiratoryrate_fe_perc_25	
180	fio2_tf_perc_50	
181	gcs_fe_var	
182	temperature_twe_perc_25	
183	respiratoryrate_ts_perc_75	
184	fio2_fe_perc_50	
185	bmi	
186	gcs_tf_range	
187	temperature_fe_perc_50	
188	temperature_ts_perc_50	
189	spo2_fe_var	
190	temperature_tf_mean	
191	gcs_fe_perc_50	
192	fio2_twe_max	
193	spo2_tf_var	

Table 7 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
194	temperature_tf_max	
195	heartrate_ts_range	
196	spo2_twe_mean	
197	spo2_twe_var	
198	nibp_diastolic_twe_max	
199	fio2_fe_var	
200	spo2_ts_mean	
201	temperature_tf_perc_25	
202	respiratoryrate_tf_var	
203	fio2_fe_min	
204	nibp_mean_tf_mean	
205	nibp_diastolic_twe_mean	
206	nibp_systolic_twe_min	
207	fio2_ts_perc_75	
208	respiratoryrate_twe_mean	
209	heartrate_twe_max	
210	gender	
211	temperature_twe_min	
212	gcs_ts_mean	
213	fio2_tf_var	
214	nibp_diastolic_ts_range	
215	gcs_tf_perc_50	
216	nibp_mean_ts_max	
217	nibp_diastolic_twe_var	
218	respiratoryrate_ts_stddev	
219	nibp_diastolic_twe_perc_50	
220	temperature_twe_perc_75	
221	nibp_mean_tf_stddev	
222	nibp_mean_tf_var	
223	fio2_ts_var	
224	heartrate_twe_perc_50	
225	gcs_twe_perc_50	
226	urineoutput_ts	
227	nibp_diastolic_fe_max	
228	temperature_tf_perc_75	
229	urineoutput_fe	
230	fio2_ts_range	
231	temperature_tf_perc_50	
232	temperature_fe_min	
233	respiratoryrate_ts_mean	
234	nibp_diastolic_tf_max	
235	nibp_mean_twe_var	
236	temperature_fe_range	
237	temperature_tf_stddev	
238	nibp_mean_ts_perc_25	
239	nibp_systolic_fe_min	
240	spo2_ts_perc_25	
241	nibp_systolic_tf_min	
242	spo2_fe_mean	

Table 7 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
243	spo2_fe_perc_25	
244	spo2_ts_var	
245	nibp_systolic_ts_range	
246	gcs_twe_max	
247	nibp_diastolic_fe_perc_75	
248	respiratoryrate_twe_range	
249	heartrate_fe_mean	
250	fio2_fe_max	
251	nibp_diastolic_tf_perc_50	
252	fio2_tf_perc_25	
253	gcs_ts_max	
254	heartrate_tf_min	
255	temperature_fe_var	
256	urineoutput_twe	
257	fio2_twe_perc_75	
258	fio2_tf_perc_75	
259	nibp_diastolic_tf_range	
260	respiratoryrate_fe_mean	
261	fio2_fe_perc_75	
262	respiratoryrate_fe_stddev	
263	nibp_diastolic_ts_perc_25	
264	respiratoryrate_twe_perc_50	
265	respiratoryrate_twe_max	
266	spo2_ts_min	
267	gcs_tf_min	
268	gcs_ts_var	
269	nibp_diastolic_tf_perc_75	
270	gcs_tf_stddev	
271	gcs_twe_mean	
272	spo2_ts_range	
273	nibp_systolic_twe_var	
274	temperature_fe_perc_25	
275	temperature_ts_perc_25	
276	nibp_systolic_tf_perc_25	
277	gcs_ts_stddev	
278	nibp_diastolic_ts_var	
279	temperature_ts_var	
280	fio2_twe_stddev	
281	respiratoryrate_tf_mean	
282	spo2_ts_perc_50	
283	fio2_ts_min	
284	gcs_fe_min	
285	temperature_twe_perc_50	
286	gcs_ts_perc_25	
287	nibp_diastolic_ts_perc_50	
288	spo2_ts_max	
289	respiratoryrate_ts_max	
290	nibp_mean_fe_max	
291	fio2_twe_range	

Table 7 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
292	age	
293	nibp_mean_ts_stddev	
294	heartrate_twe_var	
295	heartrate_tf_perc_25	
296	nibp_mean_fe_perc_50	
297	nibp_systolic_ts_min	
298	temperature_ts_perc_75	
299	respiratoryrate_ts_range	
300	temperature_ts_max	
301	temperature_tf_range	

Table 8 The OPT_subset and the MIN_subset of LightGBM

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
1	nibp_diastolic_fe_mean	nibp_diastolic_fe_mean
2	nibp_mean_ts_min	nibp_mean_ts_min
3	nibp_diastolic_twe_perc_75	nibp_diastolic_twe_perc_75
4	nibp_systolic_fe_var	nibp_systolic_fe_var
5	nibp_systolic_twe_stddev	nibp_systolic_twe_stddev
6	spo2_ts_perc_75	spo2_ts_perc_75
7	gcs_twe_perc_75	gcs_twe_perc_75
8	nibp_mean_tf_perc_25	nibp_mean_tf_perc_25
9	nibp_diastolic_ts_min	nibp_diastolic_ts_min
10	gcs_twe_range	gcs_twe_range
11	gcs_ts_range	gcs_ts_range
12	nibp_mean_fe_var	nibp_mean_fe_var
13	temperature_twe_stddev	temperature_twe_stddev
14	nibp_systolic_ts_var	nibp_systolic_ts_var
15	heartrate_twe_min	heartrate_twe_min
16	nibp_mean_ts_range	nibp_mean_ts_range
17	nibp_diastolic_ts_max	nibp_diastolic_ts_max
18	nibp_systolic_tf_mean	nibp_systolic_tf_mean
19	nibp_systolic_tf_range	nibp_systolic_tf_range
20	spo2_twe_min	spo2_twe_min
21	fio2_ts_mean	fio2_ts_mean
22	spo2_twe_perc_50	spo2_twe_perc_50
23	fio2_fe_mean	fio2_fe_mean
24	fio2_twe_perc_25	fio2_twe_perc_25
25	fio2_twe_mean	fio2_twe_mean
26	nibp_mean_twe_mean	nibp_mean_twe_mean
27	spo2_tf_mean	spo2_tf_mean
28	nibp_mean_tf_min	nibp_mean_tf_min
29	temperature_ts_range	temperature_ts_range
30	spo2_tf_min	spo2_tf_min
31	nibp_diastolic_tf_mean	nibp_diastolic_tf_mean
32	heartrate_tf_var	heartrate_tf_var
33	heartrate_fe_min	heartrate_fe_min

Table 8 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
34	gcs_tf_mean	gcs_tf_mean
35	nibp_diastolic_fe_stddev	nibp_diastolic_fe_stddev
36	nibp_mean_tf_range	nibp_mean_tf_range
37	fio2_fe_range	fio2_fe_range
38	fio2_ts_max	fio2_ts_max
39	temperature_tf_min	temperature_tf_min
40	heartrate_fe_perc_50	heartrate_fe_perc_50
41	nibp_mean_twe_stddev	nibp_mean_twe_stddev
42	gcs_fe_perc_75	gcs_fe_perc_75
43	respiratoryrate_tf_perc_75	respiratoryrate_tf_perc_75
44	fio2_tf_min	-
45	respiratoryrate_fe_perc_50	
46	nibp_diastolic_fe_min	
47	spo2_fe_stddev	
48	nibp_mean_twe_range	
49	respiratoryrate_tf_min	
50	nibp_diastolic_fe_range	
51	heartrate_tf_mean	
52	respiratoryrate_twe_min	
53	nibp_mean_fe_mean	
54	fio2_tf_max	
55	gcs_tf_perc_75	
56	respiratoryrate_tf_max	
57	nibp_systolic_fe_mean	
58	gcs_twe_var	
59	heartrate_tf_perc_50	
60	gcs_fe_mean	
61	spo2_fe_perc_50	
62	respiratoryrate_ts_perc_25	
63	temperature_ts_min	
64	spo2_twe_stddev	
65	gcs_tf_var	
66	nibp_systolic_fe_stddev	
67	heartrate_tf_range	
68	spo2_twe_range	
69	nibp_mean_fe_min	
70	heartrate_ts_stddev	
71	heartrate_fe_perc_25	
72	spo2_tf_perc_25	
73	spo2_tf_range	
74	gcs_fe_perc_25	
75	heartrate_ts_perc_75	
76	gcs_fe_range	
77	nibp_mean_twe_perc_25	
78	nibp_systolic_twe_perc_25	
79	nibp_diastolic_twe_range	
80	heartrate_fe_range	
81	fio2_twe_var	
82	spo2_ts_stddev	

Table 8 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
83	nibp_systolic_ts_perc_50	
84	temperature_twe_var	
85	nibp_mean_tf_max	
86	spo2_twe_max	
87	gcs_fe_stddev	
88	nibp_systolic_twe_perc_50	
89	nibp_systolic_fe_max	
90	nibp_diastolic_fe_perc_25	
91	temperature_ts_mean	
92	heartrate_twe_range	
93	temperature_fe_max	
94	nibp_mean_ts_perc_75	
95	nibp_systolic_twe_range	
96	respiratoryrate_fe_perc_75	
97	spo2_tf_perc_75	
98	nibp_mean_tf_perc_50	
99	nibp_systolic_ts_perc_75	
100	nibp_diastolic_tf_stddev	
101	heartrate_twe_mean	
102	gcs_ts_perc_75	
103	temperature_fe_mean	
104	temperature_twe_max	
105	nibp_diastolic_tf_var	
106	nibp_mean_fe_perc_25	
107	urineoutput_tf	
108	respiratoryrate_tf_perc_25	
109	heartrate_tf_perc_75	
110	heartrate_fe_stddev	
111	respiratoryrate_twe_perc_75	
112	respiratoryrate_fe_max	
113	nibp_diastolic_ts_mean	
114	fio2_ts_stddev	
115	respiratoryrate_tf_stddev	
116	vent	
117	nibp_systolic_tf_perc_50	
118	spo2_tf_perc_50	
119	nibp_systolic_ts_perc_25	
120	nibp_systolic_tf_stddev	
121	temperature_fe_stddev	
122	fio2_tf_mean	
123	fio2_ts_perc_25	
124	spo2_tf_stddev	
125	nibp_diastolic_twe_min	
126	nibp_systolic_twe_perc_75	
127	heartrate_twe_perc_75	
128	temperature_twe_mean	
129	heartrate_fe_perc_75	
130	heartrate_tf_max	
131	nibp_mean_fe_range	

Table 8 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
132	nibp_diastolic_fe_perc_50	
133	nibp_diastolic_tf_min	
134	gcs_twe_perc_25	
135	nibp_mean_twe_max	
136	nibp_systolic_ts_mean	
137	respiratoryrate_ts_min	
138	spo2_twe_perc_75	
139	nibp_systolic_fe_perc_25	
140	heartrate_ts_var	
141	nibp_systolic_ts_stddev	
142	temperature_ts_stddev	
143	heartrate_fe_var	
144	respiratoryrate_fe_min	
145	nibp_systolic_twe_max	
146	nibp_systolic_tf_perc_75	
147	heartrate_ts_perc_25	
148	fio2_tf_stddev	
149	gcs_tf_perc_25	
150	nibp_diastolic_ts_stddev	
151	nibp_diastolic_fe_var	
152	gcs_twe_stddev	
153	spo2_fe_min	
154	nibp_diastolic_twe_stddev	
155	nibp_diastolic_twe_perc_25	
156	respiratoryrate_ts_var	
157	nibp_mean_twe_perc_50	
158	nibp_mean_tf_perc_75	
159	heartrate_ts_min	
160	respiratoryrate_twe_perc_25	
161	nibp_mean_ts_var	
162	gcs_fe_max	
163	spo2_fe_perc_75	
164	gcs_ts_min	
165	nibp_systolic_fe_perc_75	
166	spo2_twe_perc_25	
167	nibp_systolic_fe_perc_50	
168	fio2_tf_range	
169	nibp_systolic_twe_mean	
170	temperature_fe_perc_75	
171	nibp_mean_ts_mean	
172	temperature_twe_range	
173	respiratoryrate_fe_range	
174	gcs_tf_max	
175	heartrate_ts_perc_50	
176	heartrate_ts_mean	
177	nibp_systolic_ts_max	
178	fio2_fe_perc_25	
179	respiratoryrate_fe_perc_25	
180	fio2_tf_perc_50	

Table 8 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
181	gcs_fe_var	
182	temperature_twe_perc_25	
183	respiratoryrate_ts_perc_75	
184	fio2_fe_perc_50	
185	bmi	
186	gcs_tf_range	
187	temperature_fe_perc_50	
188	temperature_ts_perc_50	
189	spo2_fe_var	
190	temperature_tf_mean	
191	gcs_fe_perc_50	
192	fio2_twe_max	
193	spo2_tf_var	
194	temperature_tf_max	
195	heartrate_ts_range	
196	spo2_twe_mean	
197	spo2_twe_var	
198	nibp_diastolic_twe_max	
199	fio2_fe_var	
200	spo2_ts_mean	
201	temperature_tf_perc_25	
202	respiratoryrate_tf_var	
203	fio2_fe_min	
204	nibp_mean_tf_mean	
205	nibp_diastolic_twe_mean	
206	nibp_systolic_twe_min	
207	fio2_ts_perc_75	
208	respiratoryrate_twe_mean	
209	heartrate_twe_max	
210	gender	
211	temperature_twe_min	
212	gcs_ts_mean	
213	fio2_tf_var	
214	nibp_diastolic_ts_range	
215	gcs_tf_perc_50	
216	nibp_mean_ts_max	
217	nibp_diastolic_twe_var	
218	respiratoryrate_ts_stddev	
219	nibp_diastolic_twe_perc_50	
220	temperature_twe_perc_75	
221	nibp_mean_tf_stddev	
222	nibp_mean_tf_var	
223	fio2_ts_var	
224	heartrate_twe_perc_50	
225	gcs_twe_perc_50	
226	urineoutput_ts	
227	nibp_diastolic_fe_max	
228	temperature_tf_perc_75	
229	urineoutput_fe	

Table 8 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
230	fio2_ts_range	
231	temperature_tf_perc_50	
232	temperature_fe_min	
233	respiratoryrate_ts_mean	
234	nibp_diastolic_tf_max	
235	nibp_mean_twe_var	
236	temperature_fe_range	
237	temperature_tf_stddev	
238	nibp_mean_ts_perc_25	
239	nibp_systolic_fe_min	
240	spo2_ts_perc_25	
241	nibp_systolic_tf_min	
242	spo2_fe_mean	
243	spo2_fe_perc_25	
244	spo2_ts_var	
245	nibp_systolic_ts_range	
246	gcs_twe_max	
247	nibp_diastolic_fe_perc_75	
248	respiratoryrate_twe_range	
249	heartrate_fe_mean	
250	fio2_fe_max	
251	nibp_diastolic_tf_perc_50	
252	fio2_tf_perc_25	
253	gcs_ts_max	
254	heartrate_tf_min	
255	temperature_fe_var	
256	urineoutput_twe	
257	fio2_twe_perc_75	
258	fio2_tf_perc_75	
259	nibp_diastolic_tf_range	
260	respiratoryrate_fe_mean	
261	fio2_fe_perc_75	
262	respiratoryrate_fe_stddev	
263	nibp_diastolic_ts_perc_25	
264	respiratoryrate_twe_perc_50	
265	respiratoryrate_twe_max	
266	spo2_ts_min	
267	gcs_tf_min	
268	gcs_ts_var	
269	nibp_diastolic_tf_perc_75	
270	gcs_tf_stddev	
271	gcs_twe_mean	
272	spo2_ts_range	
273	nibp_systolic_twe_var	
274	temperature_fe_perc_25	
275	temperature_ts_perc_25	
276	nibp_systolic_tf_perc_25	
277	gcs_ts_stddev	
278	nibp_diastolic_ts_var	

Table 8 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
279	temperature_ts_var	
280	fio2_twe_stddev	
281	respiratoryrate_tf_mean	
282	spo2_ts_perc_50	
283	fio2_ts_min	
284	gcs_fe_min	
285	temperature_twe_perc_50	
286	gcs_ts_perc_25	
287	nibp_diastolic_ts_perc_50	
288	spo2_ts_max	
289	respiratoryrate_ts_max	
290	nibp_mean_fe_max	
291	fio2_twe_range	
292	age	
293	nibp_mean_ts_stddev	
294	heartrate_twe_var	
295	heartrate_tf_perc_25	
296	nibp_mean_fe_perc_50	
297	nibp_systolic_ts_min	
298	temperature_ts_perc_75	
299	respiratoryrate_ts_range	
300	temperature_ts_max	
301	temperature_tf_range	
302	respiratoryrate_fe_var	
303	respiratoryrate_twe_var	
304	respiratoryrate_twe_stddev	
305	nibp_mean_fe_perc_75	
306	nibp_mean_twe_perc_75	
307	gcs_twe_min	
308	fio2_ts_perc_50	
309	heartrate_ts_max	
310	nibp_systolic_fe_range	
311	spo2_fe_range	
312	respiratoryrate_tf_perc_50	
313	respiratoryrate_ts_perc_50	
314	temperature_tf_var	

Table 9 The OPT_subset and the MIN_subset of Random Forest

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
1	nibp_diastolic_fe_mean	nibp_diastolic_fe_mean
2	nibp_mean_ts_min	nibp_mean_ts_min
3	nibp_diastolic_twe_perc_75	nibp_diastolic_twe_perc_75
4	nibp_systolic_fe_var	nibp_systolic_fe_var
5	nibp_systolic_twe_stddev	nibp_systolic_twe_stddev
6	spo2_ts_perc_75	spo2_ts_perc_75
7	gcs_twe_perc_75	gcs_twe_perc_75
8	nibp_mean_tf_perc_25	nibp_mean_tf_perc_25
9	nibp_diastolic_ts_min	nibp_diastolic_ts_min
10	gcs_twe_range	gcs_twe_range
11	gcs_ts_range	gcs_ts_range
12	nibp_mean_fe_var	nibp_mean_fe_var
13	temperature_twe_stddev	temperature_twe_stddev
14	nibp_systolic_ts_var	nibp_systolic_ts_var
15	heartrate_twe_min	heartrate_twe_min
16	nibp_mean_ts_range	nibp_mean_ts_range
17	nibp_diastolic_ts_max	nibp_diastolic_ts_max
18	nibp_systolic_tf_mean	nibp_systolic_tf_mean
19	nibp_systolic_tf_range	nibp_systolic_tf_range
20	spo2_twe_min	spo2_twe_min
21	fio2_ts_mean	fio2_ts_mean
22	spo2_twe_perc_50	spo2_twe_perc_50
23	fio2_fe_mean	fio2_fe_mean
24	fio2_twe_perc_25	fio2_twe_perc_25
25	fio2_twe_mean	fio2_twe_mean
26	nibp_mean_twe_mean	nibp_mean_twe_mean
27	spo2_tf_mean	spo2_tf_mean
28	nibp_mean_tf_min	nibp_mean_tf_min
29	temperature_ts_range	temperature_ts_range
30	spo2_tf_min	spo2_tf_min
31	nibp_diastolic_tf_mean	nibp_diastolic_tf_mean
32	heartrate_tf_var	heartrate_tf_var
33	heartrate_fe_min	heartrate_fe_min
34	gcs_tf_mean	gcs_tf_mean
35	nibp_diastolic_fe_stddev	nibp_diastolic_fe_stddev
36	nibp_mean_tf_range	nibp_mean_tf_range
37	fio2_fe_range	fio2_fe_range
38	fio2_ts_max	fio2_ts_max
39	temperature_tf_min	temperature_tf_min
40	heartrate_fe_perc_50	heartrate_fe_perc_50
41	nibp_mean_twe_stddev	nibp_mean_twe_stddev
42	gcs_fe_perc_75	gcs_fe_perc_75
43	respiratoryrate_tf_perc_75	respiratoryrate_tf_perc_75
44	fio2_tf_min	fio2_tf_min
45	respiratoryrate_fe_perc_50	respiratoryrate_fe_perc_50
46	nibp_diastolic_fe_min	nibp_diastolic_fe_min
47	spo2_fe_stddev	spo2_fe_stddev
48	nibp_mean_twe_range	nibp_mean_twe_range
49	respiratoryrate_tf_min	-

Table 9 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
50	nibp_diastolic_fe_range	
51	heartrate_tf_mean	
52	respiratoryrate_twe_min	
53	nibp_mean_fe_mean	
54	fio2_tf_max	
55	gcs_tf_perc_75	
56	respiratoryrate_tf_max	
57	nibp_systolic_fe_mean	
58	gcs_twe_var	
59	heartrate_tf_perc_50	
60	gcs_fe_mean	
61	spo2_fe_perc_50	
62	respiratoryrate_ts_perc_25	
63	temperature_ts_min	
64	spo2_twe_stddev	
65	gcs_tf_var	
66	nibp_systolic_fe_stddev	
67	heartrate_tf_range	
68	spo2_twe_range	
69	nibp_mean_fe_min	
70	heartrate_ts_stddev	
71	heartrate_fe_perc_25	
72	spo2_tf_perc_25	
73	spo2_tf_range	
74	gcs_fe_perc_25	
75	heartrate_ts_perc_75	
76	gcs_fe_range	
77	nibp_mean_twe_perc_25	
78	nibp_systolic_twe_perc_25	
79	nibp_diastolic_twe_range	
80	heartrate_fe_range	
81	fio2_twe_var	
82	spo2_ts_stddev	
83	nibp_systolic_ts_perc_50	
84	temperature_twe_var	
85	nibp_mean_tf_max	
86	spo2_twe_max	
87	gcs_fe_stddev	
88	nibp_systolic_twe_perc_50	
89	nibp_systolic_fe_max	
90	nibp_diastolic_fe_perc_25	
91	temperature_ts_mean	
92	heartrate_twe_range	
93	temperature_fe_max	
94	nibp_mean_ts_perc_75	
95	nibp_systolic_twe_range	
96	respiratoryrate_fe_perc_75	
97	spo2_tf_perc_75	
98	nibp_mean_tf_perc_50	

Table 9 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
99	nibp_systolic_ts_perc_75	
100	nibp_diastolic_tf_stddev	
101	heartrate_twe_mean	
102	gcs_ts_perc_75	
103	temperature_fe_mean	
104	temperature_twe_max	
105	nibp_diastolic_tf_var	
106	nibp_mean_fe_perc_25	
107	urineoutput_tf	
108	respiratoryrate_tf_perc_25	
109	heartrate_tf_perc_75	
110	heartrate_fe_stddev	
111	respiratoryrate_twe_perc_75	
112	respiratoryrate_fe_max	
113	nibp_diastolic_ts_mean	
114	fio2_ts_stddev	
115	respiratoryrate_tf_stddev	
116	vent	
117	nibp_systolic_tf_perc_50	
118	spo2_tf_perc_50	
119	nibp_systolic_ts_perc_25	
120	nibp_systolic_tf_stddev	
121	temperature_fe_stddev	
122	fio2_tf_mean	
123	fio2_ts_perc_25	
124	spo2_tf_stddev	
125	nibp_diastolic_twe_min	
126	nibp_systolic_twe_perc_75	
127	heartrate_twe_perc_75	
128	temperature_twe_mean	
129	heartrate_fe_perc_75	
130	heartrate_tf_max	
131	nibp_mean_fe_range	
132	nibp_diastolic_fe_perc_50	
133	nibp_diastolic_tf_min	
134	gcs_twe_perc_25	
135	nibp_mean_twe_max	
136	nibp_systolic_ts_mean	
137	respiratoryrate_ts_min	
138	spo2_twe_perc_75	
139	nibp_systolic_fe_perc_25	
140	heartrate_ts_var	
141	nibp_systolic_ts_stddev	
142	temperature_ts_stddev	
143	heartrate_fe_var	
144	respiratoryrate_fe_min	
145	nibp_systolic_twe_max	
146	nibp_systolic_tf_perc_75	
147	heartrate_ts_perc_25	

Table 9 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
148	fio2_tf_stddev	
149	gcs_tf_perc_25	
150	nibp_diastolic_ts_stddev	
151	nibp_diastolic_fe_var	
152	gcs_twe_stddev	

Table 10 The OPT_subset and the MIN_subset of Logistic Regression

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
1	nibp_diastolic_fe_mean	nibp_diastolic_fe_mean
2	nibp_mean_ts_min	nibp_mean_ts_min
3	nibp_diastolic_twe_perc_75	nibp_diastolic_twe_perc_75
4	nibp_systolic_fe_var	nibp_systolic_fe_var
5	nibp_systolic_twe_stddev	nibp_systolic_twe_stddev
6	spo2_ts_perc_75	spo2_ts_perc_75
7	gcs_twe_perc_75	gcs_twe_perc_75
8	nibp_mean_tf_perc_25	nibp_mean_tf_perc_25
9	nibp_diastolic_ts_min	nibp_diastolic_ts_min
10	gcs_twe_range	gcs_twe_range
11	gcs_ts_range	gcs_ts_range
12	nibp_mean_fe_var	nibp_mean_fe_var
13	temperature_twe_stddev	temperature_twe_stddev
14	nibp_systolic_ts_var	nibp_systolic_ts_var
15	heartrate_twe_min	heartrate_twe_min
16	nibp_mean_ts_range	nibp_mean_ts_range
17	nibp_diastolic_ts_max	nibp_diastolic_ts_max
18	nibp_systolic_tf_mean	nibp_systolic_tf_mean
19	nibp_systolic_tf_range	nibp_systolic_tf_range
20	spo2_twe_min	spo2_twe_min
21	fio2_ts_mean	fio2_ts_mean
22	spo2_twe_perc_50	spo2_twe_perc_50
23	fio2_fe_mean	fio2_fe_mean
24	fio2_twe_perc_25	fio2_twe_perc_25
25	fio2_twe_mean	fio2_twe_mean
26	nibp_mean_twe_mean	nibp_mean_twe_mean
27	spo2_tf_mean	spo2_tf_mean
28	nibp_mean_tf_min	nibp_mean_tf_min
29	temperature_ts_range	temperature_ts_range
30	spo2_tf_min	spo2_tf_min
31	nibp_diastolic_tf_mean	nibp_diastolic_tf_mean
32	heartrate_tf_var	heartrate_tf_var
33	heartrate_fe_min	heartrate_fe_min
34	gcs_tf_mean	gcs_tf_mean

Table 10 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
35	nibp_diastolic_fe_stddev	nibp_diastolic_fe_stddev
36	nibp_mean_tf_range	nibp_mean_tf_range
37	fio2_fe_range	fio2_fe_range
38	fio2_ts_max	fio2_ts_max
39	temperature_tf_min	temperature_tf_min
40	heartrate_fe_perc_50	heartrate_fe_perc_50
41	nibp_mean_twe_stddev	nibp_mean_twe_stddev
42	gcs_fe_perc_75	gcs_fe_perc_75
43	respiratoryrate_tf_perc_75	respiratoryrate_tf_perc_75
44	fio2_tf_min	fio2_tf_min
45	respiratoryrate_fe_perc_50	respiratoryrate_fe_perc_50
46	nibp_diastolic_fe_min	nibp_diastolic_fe_min
47	spo2_fe_stddev	-
48	nibp_mean_twe_range	
49	respiratoryrate_tf_min	
50	nibp_diastolic_fe_range	
51	heartrate_tf_mean	
52	respiratoryrate_twe_min	
53	nibp_mean_fe_mean	
54	fio2_tf_max	
55	gcs_tf_perc_75	
56	respiratoryrate_tf_max	
57	nibp_systolic_fe_mean	
58	gcs_twe_var	
59	heartrate_tf_perc_50	
60	gcs_fe_mean	
61	spo2_fe_perc_50	
62	respiratoryrate_ts_perc_25	
63	temperature_ts_min	
64	spo2_twe_stddev	
65	gcs_tf_var	
66	nibp_systolic_fe_stddev	
67	heartrate_tf_range	
68	spo2_twe_range	
69	nibp_mean_fe_min	
70	heartrate_ts_stddev	
71	heartrate_fe_perc_25	
72	spo2_tf_perc_25	
73	spo2_tf_range	
74	gcs_fe_perc_25	
75	heartrate_ts_perc_75	
76	gcs_fe_range	
77	nibp_mean_twe_perc_25	
78	nibp_systolic_twe_perc_25	
79	nibp_diastolic_twe_range	
80	heartrate_fe_range	
81	fio2_twe_var	
82	spo2_ts_stddev	
83	nibp_systolic_ts_perc_50	

Table 10 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
84	temperature_twe_var	
85	nibp_mean_tf_max	
86	spo2_twe_max	
87	gcs_fe_stddev	
88	nibp_systolic_twe_perc_50	
89	nibp_systolic_fe_max	
90	nibp_diastolic_fe_perc_25	
91	temperature_ts_mean	
92	heartrate_twe_range	
93	temperature_fe_max	
94	nibp_mean_ts_perc_75	
95	nibp_systolic_twe_range	
96	respiratoryrate_fe_perc_75	
97	spo2_tf_perc_75	
98	nibp_mean_tf_perc_50	
99	nibp_systolic_ts_perc_75	
100	nibp_diastolic_tf_stddev	
101	heartrate_twe_mean	
102	gcs_ts_perc_75	
103	temperature_fe_mean	
104	temperature_twe_max	
105	nibp_diastolic_tf_var	
106	nibp_mean_fe_perc_25	
107	urineoutput_tf	
108	respiratoryrate_tf_perc_25	
109	heartrate_tf_perc_75	
110	heartrate_fe_stddev	
111	respiratoryrate_twe_perc_75	
112	respiratoryrate_fe_max	
113	nibp_diastolic_ts_mean	
114	fio2_ts_stddev	
115	respiratoryrate_tf_stddev	
116	vent	
117	nibp_systolic_tf_perc_50	
118	spo2_tf_perc_50	
119	nibp_systolic_ts_perc_25	
120	nibp_systolic_tf_stddev	
121	temperature_fe_stddev	
122	fio2_tf_mean	
123	fio2_ts_perc_25	
124	spo2_tf_stddev	
125	nibp_diastolic_twe_min	
126	nibp_systolic_twe_perc_75	
127	heartrate_twe_perc_75	
128	temperature_twe_mean	
129	heartrate_fe_perc_75	
130	heartrate_tf_max	
131	nibp_mean_fe_range	
132	nibp_diastolic_fe_perc_50	

Table 10 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
133	nibp_diastolic_tf_min	
134	gcs_twe_perc_25	
135	nibp_mean_twe_max	
136	nibp_systolic_ts_mean	
137	respiratoryrate_ts_min	
138	spo2_twe_perc_75	
139	nibp_systolic_fe_perc_25	
140	heartrate_ts_var	
141	nibp_systolic_ts_stddev	
142	temperature_ts_stddev	
143	heartrate_fe_var	
144	respiratoryrate_fe_min	
145	nibp_systolic_twe_max	
146	nibp_systolic_tf_perc_75	
147	heartrate_ts_perc_25	
148	fio2_tf_stddev	
149	gcs_tf_perc_25	
150	nibp_diastolic_ts_stddev	
151	nibp_diastolic_fe_var	
152	gcs_twe_stddev	
153	spo2_fe_min	
154	nibp_diastolic_twe_stddev	
155	nibp_diastolic_twe_perc_25	
156	respiratoryrate_ts_var	
157	nibp_mean_twe_perc_50	
158	nibp_mean_tf_perc_75	
159	heartrate_ts_min	
160	respiratoryrate_twe_perc_25	
161	nibp_mean_ts_var	
162	gcs_fe_max	
163	spo2_fe_perc_75	
164	gcs_ts_min	
165	nibp_systolic_fe_perc_75	
166	spo2_twe_perc_25	
167	nibp_systolic_fe_perc_50	
168	fio2_tf_range	
169	nibp_systolic_twe_mean	
170	temperature_fe_perc_75	
171	nibp_mean_ts_mean	
172	temperature_twe_range	
173	respiratoryrate_fe_range	
174	gcs_tf_max	
175	heartrate_ts_perc_50	
176	heartrate_ts_mean	
177	nibp_systolic_ts_max	
178	fio2_fe_perc_25	
179	respiratoryrate_fe_perc_25	
180	fio2_tf_perc_50	
181	gcs_fe_var	

Table 10 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
182	temperature_twe_perc_25	
183	respiratoryrate_ts_perc_75	
184	fio2_fe_perc_50	
185	bmi	
186	gcs_tf_range	
187	temperature_fe_perc_50	
188	temperature_ts_perc_50	
189	spo2_fe_var	
190	temperature_tf_mean	
191	gcs_fe_perc_50	
192	fio2_twe_max	
193	spo2_tf_var	
194	temperature_tf_max	
195	heartrate_ts_range	
196	spo2_twe_mean	
197	spo2_twe_var	
198	nibp_diastolic_twe_max	
199	fio2_fe_var	
200	spo2_ts_mean	
201	temperature_tf_perc_25	
202	respiratoryrate_tf_var	
203	fio2_fe_min	
204	nibp_mean_tf_mean	
205	nibp_diastolic_twe_mean	
206	nibp_systolic_twe_min	
207	fio2_ts_perc_75	
208	respiratoryrate_twe_mean	
209	heartrate_twe_max	
210	gender	
211	temperature_twe_min	
212	gcs_ts_mean	
213	fio2_tf_var	
214	nibp_diastolic_ts_range	
215	gcs_tf_perc_50	
216	nibp_mean_ts_max	
217	nibp_diastolic_twe_var	
218	respiratoryrate_ts_stddev	
219	nibp_diastolic_twe_perc_50	
220	temperature_twe_perc_75	
221	nibp_mean_tf_stddev	
222	nibp_mean_tf_var	
223	fio2_ts_var	
224	heartrate_twe_perc_50	
225	gcs_twe_perc_50	
226	urineoutput_ts	
227	nibp_diastolic_fe_max	
228	temperature_tf_perc_75	
229	urineoutput_fe	
230	fio2_ts_range	

Table 10 (continued)

Rank	feature variables of the OPT_subset	feature variables of the MIN_subset
231	temperature_tf_perc_50	
232	temperature_fe_min	
233	respiratoryrate_ts_mean	
234	nibp_diastolic_tf_max	
235	nibp_mean_twe_var	
236	temperature_fe_range	
237	temperature_tf_stddev	

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