

Serum Sodium Fluctuation Prediction among ICU Patients Using Neural Network Algorithm: Analysis of the MIMIC-IV Database

Haotian Yu, Tongpeng Guan, Jiang Zhu, Xiao Lu, Xiaolu Fei,
Lan Wei, Yan Zhang, Yi Xin✉

Abstract: Sodium homeostasis disorder is one of the most common abnormal symptoms of elderly patients in intensive care unit (ICU), which may lead to physiological disorders of many organs. The current prediction of serum sodium in ICU is mainly based on the subjective judgment of doctors' experience. This study aims at this problem by studying the clinical retrospective electronic medical record data of ICU to establish a machine learning model to predict the short-term serum sodium value of ICU patients. The data set used in this study is the open-source intensive care medical information set Medical Information Mart for Intensive Care (MIMIC)-IV. The time point of serum sodium detection was selected from the ICU clinical records, and the ICU records of 25 risk factors related to serum sodium were extracted from the patients within the first 12 h for statistical analysis. A prediction model of serum sodium value within 48 h was established using a feedforward neural network, and compared with previous methods. Our research results show that the neural network learning model can predict the development of serum sodium in patients using physiological indicators recorded in clinical electronic medical records within 12 h, and has better prediction effect than the serum sodium formula and other machine learning models.

Keywords: serum sodium; structured electronic medical record; hypernatremia; hyponatremia; neural network; machine learning

1 Introduction

Sodium is the main extracellular cation and the most active solute in human body [1]. Sodium ion concentration is the main determinant of blood osmotic pressure. Under normal circumstances, although the daily intake of sodium and water varies, serum sodium remains stable within the physiological range. Sodium metabolism is

strictly regulated by the kidney through the interaction of many neurohormone mechanisms, including aldosterone-angiotensin-renin system, sympathetic nervous system, atrial natriuretic peptide and brain natriuretic peptide mechanisms [2]. The normal range of human serum sodium is 135–145 mmol/L.

Abnormal serum sodium is divided into hypernatremia and hyponatremia. Medically, hyponatremia is defined as serum sodium concentration < 135 mmol/L, and hypernatremia is defined as serum sodium concentration > 145 mmol/L [3]. Abnormality of serum sodium is the most common electrolyte disorder in clinic, and also one of the most common abnormal symptoms of intensive care unit (ICU) patients [4]. Due to pathophysiological disorder or iatro-

Manuscript received Feb. 22, 2023; revised Mar. 17, 2023; accepted Mar. 24, 2023. The associate editor coordinating the review of this manuscript was Dr. Hanshu Cai. This work was supported by the National Natural Science Foundation of China (No. 12345678).

Haotian Yu, Tongpeng Guan, Jiang Zhu and Xiao Lu are with School of Life Science, Beijing Institute of Technology, Beijing 100081, China.

Xiaolu Fei, Lan Wei, Yan Zhang and Yi Xin are with Xuanwu Hospital, Capital Medical University, Beijing 100053, China.

✉ Corresponding author. Email: ameko@bit.edu.cn
DOI: 10.15918/j.jbit1004-0579.2023.016

genic intervention, elderly people in ICU are particularly vulnerable to sodium metabolism disorder, with the prevalence rate between 25% and 45% [5]. Because of its impact on incidence rate and mortality, abnormal serum sodium has caused a considerable burden on medical resources [6].

Abnormality of serum sodium is often accompanied by central diseases, which is a common feature of acute diseases, such as acute cerebrovascular disease, acute stroke, medical diseases, etc. [7] Serum sodium concentration will affect the conformation of proteins and enzymes, the transmission of impulses and the excitation of nerves and muscles. Even a small range of changes in sodium concentration may cause physiological disorders in many organs, including the heart and brain. Some studies have shown that the occurrence of abnormal serum sodium is related to significantly higher mortality and longer hospital stay [8]. The mortality of mild and severe sodium disorders in patients with acquired sodium metabolism disorder (IAD) in ICU is close to 30% and 45% respectively, while the mortality of patients with normal serum sodium level is 16%.

At present, the serum sodium test in clinic depends on serum sampling test, and only the current and past serum sodium status of ICU patients can be obtained. If the development trend of serum sodium in ICU patients can be correctly predicted, intervention programs such as infusion therapy can be planned in advance to correct the abnormal serum sodium and maintain the patient's electrolyte balance.

2 Literature Review

Although some researchers have proposed some calculation formulas to evaluate serum sodium through the input of serum sodium, whole body water, sodium and potassium within 24 hours, such as the Adrogu é-Madias formula, hope to guide infusion therapy to correct serum sodium

[9–11]. However, most of these formulas are from strict clinical controlled trials and have not been evaluated in large-scale clinical studies, and some studies have pointed out that the results of these formulas in the clinical environment are not accurate [12].

At present, in clinical practice, the monitoring of serum sodium still needs regular and continuous blood sampling and test. The prediction of serum sodium mainly depends on doctors' judgment, which is subjective and very dependent on doctors' experience. Inappropriate liquid management will directly promote acquired sodium metabolism disorder in ICU, and attempts to correct sodium disorder based on empirical calculation will easily lead to high fluctuations in serum sodium concentration, thus increasing the incidence rate and mortality of patients [13]. If the development trend of serum sodium in ICU patients can be correctly predicted in advance, it will provide help for the design of medical intervention in advance, the clinical correction of sodium metabolism disorder, and the prevention of complications of infusion treatment.

The rapid development of electronic medical records makes it possible to apply machine learning data mining methods to the prediction of serum sodium. Recently, the application of machine learning methods in clinical electronic medical records has established many accurate prediction models for acute renal failure, sepsis, diabetes and other diseases [14–19]. Moreover, it is reported that some clinical indicators in the electronic medical record are related to abnormal serum sodium [20]. The purpose of this paper is to develop a prediction model of serum sodium fluctuation in ICU patients based on structured electronic medical records, to design a prediction software of serum sodium in order to correctly predict the development trend of serum sodium in ICU patients in clinical practice, and to provide reference for medical staff to arrange infusion volume.

3 Materials and Methods

3.1 Data Source

The database used for dynamic serum sodium fluctuation of ICU patients in this study is Medical Information Mart for Intensive Care (MIMIC)-IV database, which is a large relational database provided by the Computational Physiology Laboratory of Massachusetts Institute of Technology (MIT). Data was collected from MetaVision clinical information system, which included the actual inpatient clinical records of more than 40000 patients from Beth Israel Deaconess Medical Center from 2008 to 2019.

In our study, patients under 18 years of age were excluded. Among our researchers, the proportion of middle-aged and elderly people over 50 years old is more than 84%.

3.2 Pretreatment

In the same process, we searched the electronic medical record for the first time that the patient had hyponatremia in the ICU ward (the serum sodium value was less than 135 mmol/L), and extracted the normal serum sodium record of the same order of magnitude as the control.

Fig. 1 shows our strategy for building vectors. We first searched through the ICU records for the first time that the patient had hypernatremia in the ICU ward (the serum sodium value was greater than 145 mmol/L), and recorded the time point of the occurrence of hypernatremia at moment A . Extract the ICU test records of the patient within 12 h before time A , take the average of the physiological index test values measured many times within 12 h, and sum the urine volume recorded within 12 h of the patient. Retrieve the time of the patient's last serum sodium test within 48 h after time A , and record it as time B . Extract the infusion records between time A and time B , and take the serum sodium detection value at time B as the target of model prediction. Sum up the infusion volume during this period, which is the total infusion vol-

ume for infusion treatment after the occurrence of abnormal serum sodium. Extract basic information such as age and sex of patients with hypernatremia. Finally, we link tables to build one-dimensional vectors.

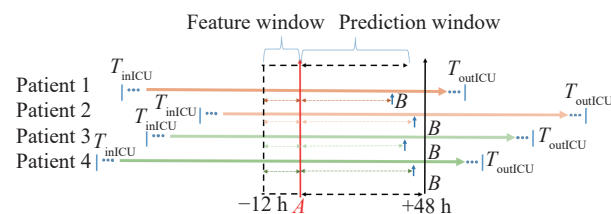


Fig. 1 Schematic diagram of vector construction scheme

Fig. 2 shows the construction and processing steps of vectors.

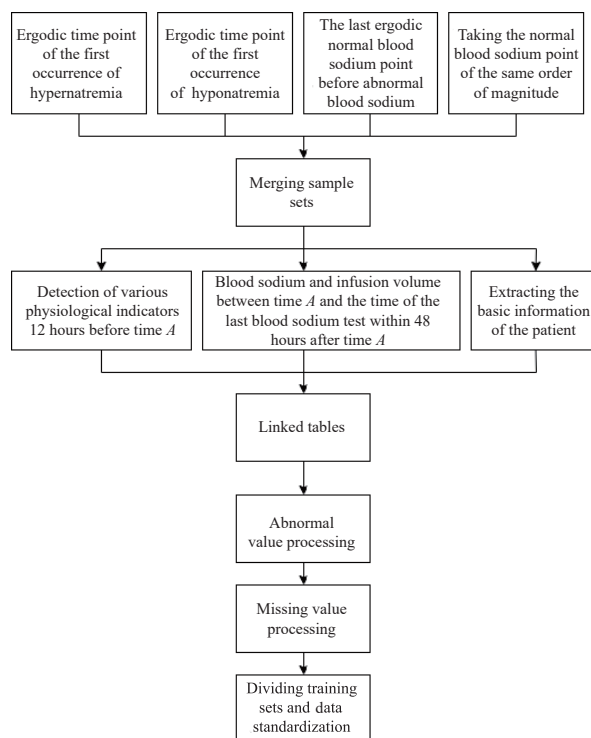


Fig. 2 Flow diagram of vector extraction

The gender of the patient is binary, 0 represents male and 1 represents female. The missing data may lead to deviation from the machine learning model, so variables with missing values greater than 40% are excluded. Use the box diagram method and combine with the physiological reality to delete the outliers. For other variables with less missing values, the average value is used to fill in the missing values.

3.3 Model

The structure of the fully connected feedforward neural network established in this study is shown in Fig. 3.

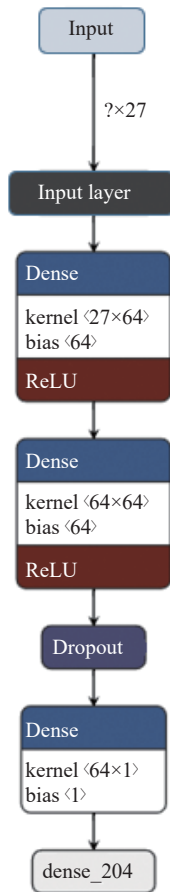


Fig. 3 Structure diagram of neural network

The network consists of two dense layers and a dropout layer. The number of hidden neurons in each layer is 64. The activation function is designated as Rectified linear unit (ReLU). The optimizer specified by the network is root mean square propagation (RMSProp), and the loss function is the mean square error. The validation method of the model is tenfold cross-validation.

4 Result and Discussion

In this paper, MIMIC-IV are utilized to evaluate the performance of the proposed method. The relevant information and the corresponding results are as follows.

4.1 Participants

According to the vector extraction scheme described above, 5581 samples were obtained in this study. A total of 3 cases were screened out through outlier processing, and a total of 5578 samples were collected in the final data set. See Tab. 1 for the basic information of cases.

This paper selected 25 physiological indexes. They are: gender, age, systolic blood pressure, diastolic blood pressure, Fahrenheit temperature, heart rate, mean arterial blood pressure, colloid infusion, crystal infusion, arterial carbon dioxide partial pressure, arterial oxygen partial pressure, urea nitrogen, bilirubin, phosphate ion, chloride ion, hematocrit, creatinine, glucose, platelet count, blood calcium, serum sodium, blood potassium, blood magnesium, and urine volume. Among them, the item of serum sodium includes the initial value of serum sodium, the average value of serum sodium and the current value of serum sodium, with a total of 27 characteristics. The colloidal infusion mentioned in this article includes: whole blood, plasma, albumin, levo-dextran, glycoside, etc., which are mainly used to expand blood volume, while the crystal infusion includes: hypotonic and isotonic physiological saline, 5%, 10% glucose solution, balance solution, etc. It is mainly to supplement water and electrolyte.

Tab. 2 shows the descriptive statistics and correlation coefficients of various physiological characteristics.

4.2 Implementation Details

Our model is implemented on a computer equipped with Intel Core i5-10200h central processing unit (CPU), 128 GB random access memory (RAM) and NVIDIA GeForce GTX 1650 graphics processing unit (GPU) using Python language based on the open source deep learning library Tensorflow. In the parameter adjustment stage, the training verification and parameter adjustment through K-fold cross-validation are carried out. Finally, the best hyperparameters of the model are obtained.

Tab. 1 Statistical results of selected samples

Variable	Category	Person-time	Proportion	
Gender	Male	3 354	60.13%	
	Female	2 224	39.87%	
Age	18—49	890	15.96%	
	50—59	1 006	18.04%	
	60—69	1 283	23.00%	
	70—79	1 248	22.37%	
	80—	1 151	20.63%	
	Hyponatremia at the current moment	Hypernatremia tendency	1 033	18.52%
		Normal serum sodium tendency	989	17.73%
Hyponatremia tendency		30	0.54%	
Total		2 052	36.79%	
Serum sodium	Normal serum sodium at the current moment	Hypernatremia tendency	433	7.76%
		Normal serum sodium tendency	946	16.96%
		Hyponatremia tendency	449	8.05%
		Total	1 827	32.75%
	Hyponatremia at the current moment	Hypernatremia tendency	46	0.82%
		Normal serum sodium tendency	1 104	19.79%
		Hyponatremia tendency	547	9.81%
		Total	1 697	30.42%
		Total	5 578	100%

Tab. 2 Correlation coefficients of various physiological characteristics

Characteristic value number	Characteristic value name	Serum sodium that tends to be normal (mean $\pm$ standard deviation)	Hyponatremia tendency (mean $\pm$ standard deviation)	Hyponatremia tendency (mean $\pm$ standard deviation)	Correlation coefficient R^2
1	Na_first (mmol/L)	142.25 $\pm$ 3.52	139.53 $\pm$ 4.51	136.85 $\pm$ 3.3	0.47
2	Na_high (mmol/L)	145.35 $\pm$ 3.7	139.47 $\pm$ 6.38	135.04 $\pm$ 3.87	0.65
3	Gender	0.64 $\pm$ 0.48	0.59 $\pm$ 0.49	0.59 $\pm$ 0.49	0.05
4	Age	67.02 $\pm$ 14.98	64.5 $\pm$ 16.23	64.8 $\pm$ 15.79	0.04
5	Blood pressure h (mmHg)	153.65 $\pm$ 14.84	153.88 $\pm$ 15.1	154.02 $\pm$ 14.65	0.01
6	Blood pressure l (mmHg)	86.78 $\pm$ 9.9	86.84 $\pm$ 9.37	86.85 $\pm$ 10.1	0.01
7	Temperature ($^{\circ}$ F)	98.85 $\pm$ 1.94	98.75 $\pm$ 2.58	98.49 $\pm$ 2.87	0.06
8	Hr_high (bpm)	126.12 $\pm$ 18.36	125.74 $\pm$ 15.67	125.44 $\pm$ 17.42	0.01
9	Hr_low (bpm)	53.54 $\pm$ 8.27	53.16 $\pm$ 6.14	54.07 $\pm$ 8.02	-0.02
10	Mean arterial blood pressure (mmHg)	80.97 $\pm$ 8.98	81.17 $\pm$ 10.16	80.97 $\pm$ 15.15	0.02
11	Colloid_bolus (ml)	77.6 $\pm$ 393.45	61.79 $\pm$ 337.01	89.38 $\pm$ 371.52	-0.01
12	Crystalloid_bolus (ml)	658.65 $\pm$ 1430.88	536.63 $\pm$ 1430.97	704.13 $\pm$ 1547.75	0
13	PCO ₂ (mmHg)	35.22 $\pm$ 7.24	35.15 $\pm$ 6.95	34.62 $\pm$ 6.55	0.03
14	PO ₂ (mmHg)	98.49 $\pm$ 32.44	97.59 $\pm$ 29.31	96.71 $\pm$ 32	0.04
15	Urea nitrogen (mg/dL)	42.16 $\pm$ 26.6	32.34 $\pm$ 24.06	34.95 $\pm$ 29.22	0.12
16	Bilirubin (mg/dL)	3.38 $\pm$ 4.33	3.2 $\pm$ 3.99	3.5 $\pm$ 5.15	-0.01
17	Phosphate (mg/dL)	3.53 $\pm$ 1.12	3.49 $\pm$ 1.22	3.76 $\pm$ 1.41	-0.06
18	Chloride (mEq/L)	106.73 $\pm$ 5.25	103.55 $\pm$ 5.75	100.41 $\pm$ 4.92	0.43
19	Hematocrit (%)	29.42 $\pm$ 5.23	29.66 $\pm$ 5.05	29.56 $\pm$ 5.01	0
20	Creatinine (mg/dL)	1.47 $\pm$ 1.02	1.37 $\pm$ 1.19	1.72 $\pm$ 1.63	-0.07

Tab. 2 Correlation coefficients of various physiological characteristics

(Continued)

Characteristic value number	Characteristic value name	Serum sodium that tends to be normal (mean $\pm$ standard deviation)	Hypernatremia tendency (mean $\pm$ standard deviation)	Hyponatremia tendency (mean $\pm$ standard deviation)	Correlation coefficient R^2
21	Glucose (mg/dL)	151.56 $\pm$ 49.53	145.31 $\pm$ 62.2	142.67 $\pm$ 45.48	0.06
22	Platelet_count (K/ μ L)	198.07 $\pm$ 125.53	216.89 $\pm$ 125.23	218.63 $\pm$ 135.77	-0.05
23	Calcium (mg/dL)	7.01 $\pm$ 1.71	7.13 $\pm$ 1.73	6.86 $\pm$ 1.85	0.03
24	Sodium (mmol/L)	143.21 $\pm$ 2.69	139.57 $\pm$ 4.19	136.21 $\pm$ 2.55	0.65
25	Potassium (mmol/L)	4 $\pm$ 0.43	4.02 $\pm$ 0.45	4.12 $\pm$ 0.49	-0.1
26	Magnesium (mg/dL)	2.24 $\pm$ 0.41	2.14 $\pm$ 0.31	2.14 $\pm$ 0.31	0.12
27	Urine output (ml)	4199.44 $\pm$ 3095.02	3358.55 $\pm$ 2790.2	3216.6 $\pm$ 3110.99	0.16

4.3 Model Results

In this study, the extracted data are put into multiple linear regression, Lasso regression, Ridge regression, decision tree regression, ensemble model and feedforward neural network model for training according to the ratio of training set: test set=8 : 2. The performance of the algorithm is evaluated by five indicators: average absolute error, root mean square error, average relative error, correlation coefficient, and sample proportion of error within 5 mmol/L. Tab. 3 shows the results of feedforward neural network and other machine learning methods on the test set, and compares them with the prediction results of traditional formula method. The results of the traditional formula method come from Gregor Lindner's study, and the data comes from 681 samples from 66 ICU patients who have been strictly screened and included in the clinical prospective experiment [12].

It can be seen from Tab. 3 that machine learning and deep learning methods are better than traditional formula methods in predicting serum sodium. The feedforward neural network has the best prediction performance. Its average absolute error and root mean square error are 3.29 and 4.41 respectively, the relative average error is 2.33%, and the correlation coefficient between the predicted value and the true value is 0.727. Among the traditional machine learning methods, bagging classifier has the best performance. Its average absolute error and root mean square error are 3.36 and 0.02 respectively. The results confirmed that the correlation features of serum sodium extracted in this paper can be used to predict the fluctuation of serum sodium in ICU patients, and also confirmed the superiority of neural network prediction model in prediction performance compared with traditional formula method and traditional machine learning method.

Tab. 3 Prediction effect of traditional formula method, machine learning method and deeplearning method in test set

Category	Method	Dataset	Mean absolute error $\pm$ root mean square error (mmol/L)	Average relative error	Correlation coefficient	Error<5 mmol/L sample proportion
Traditional formula	Adrog�-Madias formula	681 samples	4.56 $\pm$ 4.36	3.23%	0.52	—
	Barsoum-Levine formula	from 66 patients	3.37 $\pm$ 4.41	2.39%	0.57	—
	Kurtz-Nguyen formula	during ICU [12]	3.93 $\pm$ 4.76	2.79%	0.54	—
	Decision tree regression		4.22 $\pm$ 5.72	3.00%	0.61	62.70%
	Multiple linear regression		3.43 $\pm$ 4.45	2.43%	0.7	77.50%
Machine learning	Ridge return	5578 samples extracted from MIMIC-IV dataset	3.42 $\pm$ 4.45	2.43%	0.7	77.50%
	Least absolute shrinkage and selection operator (LASSO) regression		3.43 $\pm$ 4.46	2.44%	0.7	77.60%
	AdaBoost classifier		3.58 $\pm$ 4.76	2.55%	0.72	69.98%
	Bagging classifier		3.36 $\pm$ 0.02	2.39%	0.7	72.67%
	Feedforward neural network		3.29 $\pm$ 4.41	2.33%	0.73	78.20%

Fig. 4 shows the scatter diagram of the predicted value and the true value of the neural network model on the test set, and the points between the green dotted lines are the samples with the difference between the predicted value and the true value of the test set less than 3 mmol/L.

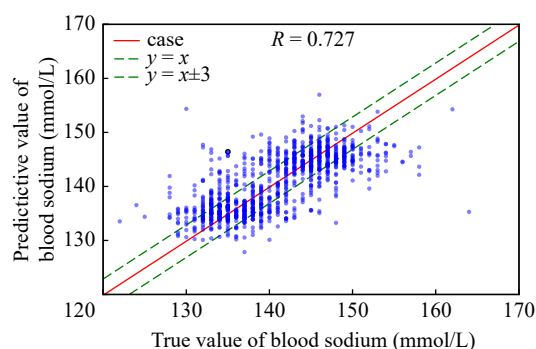


Fig. 4 The scatter diagram of the predicted value and the true value

4.4 Model Interpretation

We used Shapley Additive exPlanations (SHAP) for model interpretation, and Fig. 5 reflects the weights of various features in our neural network.

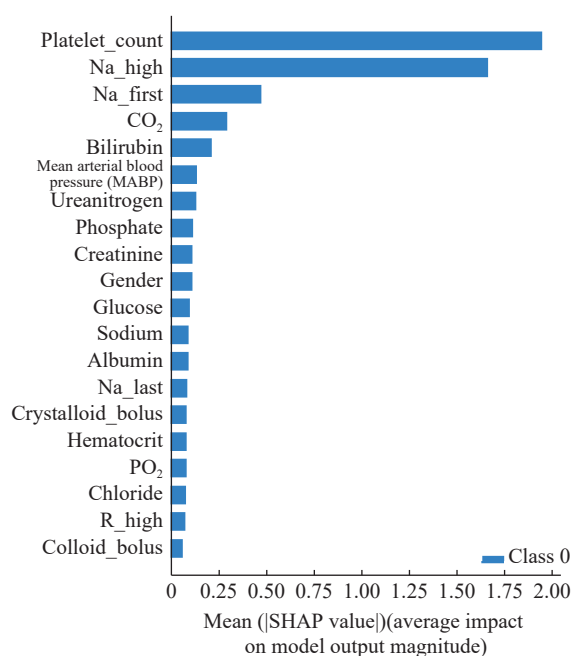


Fig. 5 Importance of independent variable

As can be seen from Fig. 5, platelets and current and past blood sodium values have the highest weight, indicating the impact of platelets

and current and past blood sodium values on future blood sodium fluctuations. At the same time, partial pressures of carbon dioxide, bilirubin, mean arterial blood pressure, and urea nitrogen also have important effects on blood sodium fluctuations.

4.5 Effect of Changing the Time Intercept Length on the Results

The interception of time length in this study is to take the physiological index information within 12 h before the patient's serum sodium concentration point to construct a vector. The length of the time window in the vector construction method described in section 3.1.1 is now changed from 12 h to 4 h, 8 h, 24 h and 48 h respectively to analyze the impact of the time intercept length on the prediction performance of the model, as shown in Fig. 6.

It can be seen from Tab. 4 that when the time intercept length increases to 24 h or 48 h, the prediction performance of the model on the test set decreases, which shows that the information reflecting the latest physiological condition of the patient is diluted with the time period. However, when the interception time is reduced to 8 h or 4 h, the prediction performance also decreases. This may be due to the short time window and the lack of effective detection records of patients, resulting in the increase of missing values, which reduces the prediction performance of the model. Based on the above reasons, this paper selects 12 h as the time intercept length.

Our research results show that models such as full connection network can solve the prediction problem of serum sodium in ICU. Moreover, we believe that these models can be applied to more clinical prediction problems. The limitation of this study is that we only analyzed patients with acquired serum sodium abnormalities in ICU, and our data are incomplete. In our study, due to the complexity of the type and inconsis-

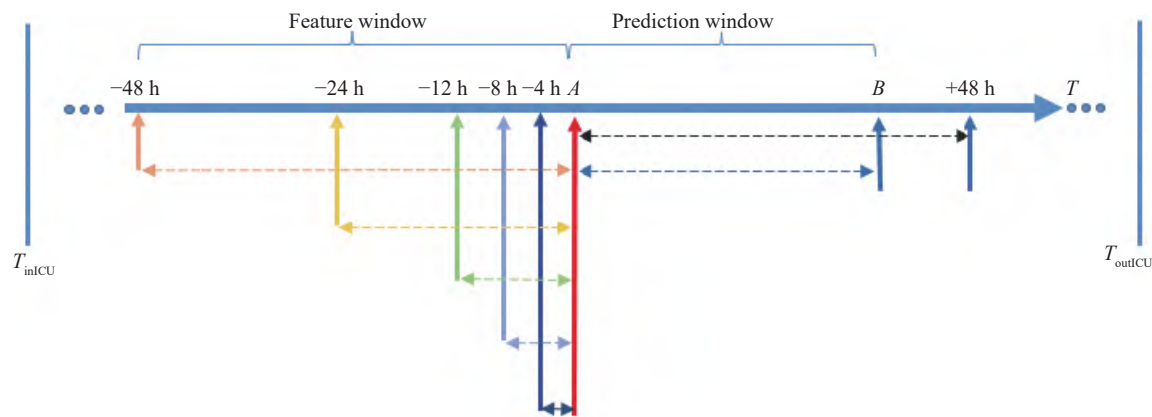


Fig. 6 Changing the time intercept length to construct a vector

Tab. 4 Effect of changing the time intercept length on prediction performance

Time interception length (h)	Average absolute error (mmol/L)	Root mean square error (mmol/L)	Root mean square error (mmol/L)
4	3.41	4.52	2.41%
8	3.43	4.49	2.43%
12	3.29	4.41	2.33%
24	3.38	4.51	2.39%
48	3.59	4.69	2.54%

tent size, we were unable to collect complete information about drug information and patient fluid input/output. This has a certain impact on our analysis and model performance. However, we have achieved satisfactory results.

5 Conclusion

To sum up, the research generated by this hypothesis shows that the physiological indicators recorded in the clinical electronic medical record within 12 h can be used to predict the development of the patient’s serum sodium, and the neural network learning model can accurately predict the patient’s serum sodium status and serum sodium value within the next 48 hours. And it has better prediction effect than other machine learning models. Further epidemiological studies will help us verify our results and determine the risk of serum sodium imbalance in ICU patients.

References:

[1] A Mente, M O’donnell, and S Yusuf, “Sodium intake and health: What should we recommend based on the current evidence? ” *Nutrients*, vol. 13, no. 9, pp. 3232, 2021.

[2] S. P. Juraschek, L. C. Kovell, L. J. Appel, E. R. Miller Iii, F. M. Sacks, A. R. Chang, R. H. Christenson, H. Rebuck, and K. J. Mukamal, “Effects of diet and sodium reduction on cardiac injury, strain, and inflammation: The DASH-sodium trial,” *Journal of the American College of Cardiology*, vol. 77, no. 21, pp. 2625-2634, 2021.

[3] L. M. Castello, F. Gavelli, M. Baldrighi, L. Salmi, F. Mearelli, N. Fiotti, F. Patrucco, M. Bellan, P. P. Sainaghi, and G. Ronzoni, “Hypernatremia and moderate-to-severe hyponatremia are independent predictors of mortality in septic patients at emergency department presentation: A sub-group analysis of the need-speed trial,” *European Journal of Internal Medicine*, vol. 83, pp. 21-27, 2021.

[4] R. M. Reynolds, P. M. Stewart, J. R. Seckl, and P. L. Padfield, “Assessing the HPA axis in patients with pituitary disease: A UK survey,” *Clinical Endocrinology*, vol. 64, no. 1, pp. 82-85, 2010.

[5] G. C. Funk, G. Lindner, W. Druml, B. Metnitz, C. Schwarz, P. Bauer, and P. Metnitz, “Incidence and prognosis of dysnatremias present on ICU admission,” *Intensive Care Medicine*, vol. 36, no. 2, pp. 304-311, 2010.

[6] E. Schwartz, K. Willcutts, M. Chung, R. Brody, S. T. Jewell, and L. Byham-Gray, “Oral urea supplementation in the treatment of acute hyponatremia among hospitalized adults: A systematic review,” *Journal of the American Nutrition Association*, pp. 1-13, 2022.

- [7] A. Eckart, P. Hausfater, D. Amin, A. Amin, S. Haubitz, M. Bernard, A. Baumgartner, T. Struja, A. Kutz, and M. Christ-Crain, "Hyponatremia and activation of vasopressin secretion are both independently associated with 30-day mortality: Results of a multicenter, observational study," *Journal of Internal Medicine*, 2018.
- [8] D. C. Marshall, J. D. Saliccioli, R. J. Goodson, M. A. Pimentel, and J. Shalhoub, "The association between sodium fluctuations and mortality in surgical patients requiring intensive care," *Journal of critical care*, vol. 40, pp. 63-68, 2017.
- [9] H. J. Adrogué and N. E. Madias, "Aiding fluid prescription for the dysnatremias," *Intensive Care Medicine*, vol. 23, no. 3, pp. 309-316, 1997.
- [10] N. R. Barsoum and B. S. Levine, "Current prescriptions for the correction of hyponatraemia and hypernatraemia: Are they too simple?" *Nephrology, Dialysis, Transplantation: Official Publication of the European Dialysis and Transplant Association - European Renal Association*, vol. 7, pp. 1176-1180, 2002.
- [11] M. K. Nguyen and I. Kurtz, "A new quantitative approach to the treatment of the dysnatremias," *Journal of Clinical & Experimental Nephrology*, vol. 7, no. 2, pp. 125-137, 2003.
- [12] L. Gregor, S. Christoph, K. Nikolaus, K. Ludwig, O. Rainer, and D. Wilfred, "Can we really predict the change in serum sodium levels? An analysis of currently proposed formulae in hypernatraemic patients," *Nephrology, Dialysis, Transplantation: Official Publication of the European Dialysis and Transplant Association - European Renal Association*, vol. 11, pp. 3501-3508, 2008.
- [13] A. Katsiampoura, D. Toumpanakis, K. Konsta, A. Varkaris, T. Vassilakopoulos, and C. Lazzeri, "Prediction of dysnatremias in critically ill patients based on the law of conservation of mass. Comparison of existing formulae," *The Public Library of Science*, vol. 13, no. 11, 2018.
- [14] S. Nemati, A. Holder, F. Razmi, M. D. Stanley, G. D. Clifford, and T. G. Buchman, "An interpretable machine learning model for accurate prediction of sepsis in the ICU," *Critical Care Medicine*, vol. 46, no. 4, pp. 547, 2018.
- [15] B. Shickel, P. J. Tighe, A. Bihorac, and P. Rashidi, "Deep EHR: A survey of recent advances in deep learning techniques for electronic health record (EHR) analysis," *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 5, pp. 1589-1604, 2017.
- [16] A. Baniyadi, S. Rezaeirad, H. Zare, and M. M. Ghassemi, "Two-step imputation and AdaBoost-based classification for early prediction of sepsis on imbalanced clinical data," *Critical Care Medicine*, vol. 49, no. 1, pp. 91-97, 2021.
- [17] L. M. Fleuren, T. L. Klausch, C. L. Zwager, L. J. Schoonmade, T. Guo, L. F. Roggeveen, and E. L. Swart, A. R. Girbes, P. Thorald, and A. Ercole, "Machine learning for the prediction of sepsis: A systematic review and meta-analysis of diagnostic test accuracy," *Intensive Care Medicine*, vol. 46, no. 3, pp. 383-400, 2020.
- [18] P. Y. Tseng, Y. T. Chen, C. H. Wang, K. M. Chiu, Y. S. Peng, S. P. Hsu, K. L. Chen, C. Y. Yang, and O. K. S. Lee, "Prediction of the development of acute kidney injury following cardiac surgery by machine learning," *Critical Care*, vol. 24, no. 1, pp. 1-13, 2020.
- [19] X. Li, X. Xu, F. Xie, X. Xu, Y. Sun, X. Liu, X. Jia, Y. Kang, L. Xie, and F. Wang, "A time-phased machine learning model for real-time prediction of sepsis in critical care," *Critical Care Medicine*, vol. 48, no. 10, pp. 884-888, 2020.
- [20] H. T. Stelfox, S. B. Ahmed, F. Khandwala, D. Zygun, R. Shahpori, and K. Laupland, "The epidemiology of intensive care unit-acquired hyponatraemia and hypernatraemia in medical-surgical intensive care units," *Critical Care*, vol. 12, no. 6, pp. 162, 2008.



Haotian Yu was born in Anhui Province, China in 2000. He received the B.E. degree in biomedical engineering in 2022. His mentor is Yi Xin, an Associate Professor with School of Life Science, Beijing Institute of Technology. His major research direction is physiological signal processing.



Tongpeng Guan was born in Henan Province, China in 1997. He received a master's degree in biomedical engineering from Beijing Institute of Technology, China. His mentor is Yi Xin, an associate professor with School of Life Science, Beijing Institute of Technology. His major research direction is physiological signal processing.



Jiang Zhu was born in Jiangsu Province, China in 1996. He received a master's degree in biomedical engineering from Beijing Institute of Technology, 2022. His major research direction is physical signal processing.



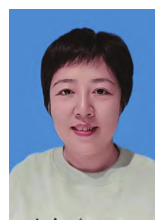
cal records.

Xiao Lu was born in Jinan, Shandong Province, China in 1990. She is currently pursuing a doctoral degree in biomedical engineering at Beijing Institute of Technology. Her main research direction is big data modeling and analysis of medical structured electronic medi-



and the Ph.D. degree in medical imaging and nuclear medicine from Capital Medical University. Her main research field is information and data governance in the construction of medical informatization, as well as value based evaluation and analysis of various technologies in the digital medical environment.

Xiaolu Fei is the chief engineer of the Information Center of Xuanwu Hospital, a professor-level senior engineer, and a professor and doctoral supervisor of Capital Medical University. She received the B.E. and master's degree in biomedical engineering from Tsinghua University,



Her research interests include medical data analysis and medical information systems.

Lan Wei is the software team leader and senior engineer of the Information Center of Xuanwu Hospital, Capital Medical University. She received a double B.E. degree in computer software engineering from Tsinghua University and biomedical engineering from Capital Medical University and received a master's degree in biomedical engineering from Capital Medical University.



and treatment of neurocritical diseases.

Yan Zhang is the ICU director and chief physician of the Department of Neurology, Xuanwu Hospital, and an Associate Professor and postgraduate supervisor of Capital Medical University. Her main research interests include neurocritical medicine, diagnosis, monitoring,



Her major research direction is physiological signal processing.