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Prediction of Spontaneous Circulation Recovery in Out-of-Hospital Cardiac Arrest Cardiopulmonary Resuscitation Patients Using Machine Learning Algorithms

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ABSTRACT

Background: Machine learning algorithms have proven a highly efficient means of processing medical data, but there is little research on such prediction models for the cardiopulmonary 23 resuscitation (CPR) outcomes of in out-of-hospital cardiac arrest (OHCA) patients.

Objectives: In this study, we want to develop a machine learning algorithm for the prediction of spontaneous circulation recovery in OHCA patients, and which will provide data support for the 26 improvement of CPR success rates in OHCA patients.

Methods: We identified 463 patients who had undergone CPR following OHCA. The 75% data of the cases were used in training set to establish the model, and 25% were used as a test set for model verification. The performance of the models was evaluated by the area under a receiver 30 operating characteristic curve and the predictive accuracy.

Results: The area under the curve values for the logistic regression, random forest, parameter interpretation, and gradient boosting models were 0.73, 0.87,0.90, and 0.86, respectively. Using the random forest model to calculate the importance of each characteristic value, we concluded that the main predictors of spontaneous circulation recovery in OHCA patients are age, speed of CPR initiation, history of cardiopulmonary conditions, another person is present when cardiac 36 arrest occurs, chest compressions and defibrillation.

Conclusion: Machine learning has the potential to predict the recovery of spontaneous circulation in OHCA patients treated with CPR. A Random Forest model was found to provide 39 the most accurate predictions for this purpose. This can be used to provide data support and as a 40-reference source to improve the success rate of CPR.

INTRODUCTION

Machine learning is a branch of artificial intelligence that has proven increasingly useful in medicine Chen et al. (2022), Lu et al. (2022), Nanayakkara et al. (2018). The annual incidence of out-of-hospital cardiac arrests (OHCA) is 34.7–156.0/100000 people in the word Bujak et al. (2021). OHCA result in high mortality and poor prognoses. It is among the most serious and widespread public health problems in the world. While there has been a great deal of research on OHCA, relatively little of this has addressed the use of machine learning algorithms for prognosis prediction in OHCA patients Chen et al. (2018). In this study, four machine learning algorithms were used to analyze demographic and clinical variables and identify those most predictive of the return of spontaneous circulation (ROSC) in OHCA patients treated with cardiopulmonary resuscitation (CPR). The data were then used to 66 establish a predictive model.

METHODS

Data source and study population

The data were collected from the emergency digital intelligence platform (EDIP). From the medical records registered on the EPID of 1201 cardiac arrest patients who underwent CPR between September 2018 and April 30, 2022, the 463 patients who suffered OHCA were selected for retrospective participation in our study.

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The treatment of cardiac arrest patients is carried out according to the cardiopulmonary resuscitation guidelines and treatment procedures. For the treatment abandoned by the patient's family members, we will give informed notice and sign.

The cardiopulmonary resuscitation registration form used at the hospital is based on the Utstein resuscitation registry template Cummins et al. (1991), Langhelle et al. (2005), Peberdy et al. (2007), Peberdy et al. (2007).

This is the form used to record data on cardiac arrest patients treated with CPR. The form records data relating to six parameters: hospital data (grade and annual emergency volume), patient data (general condition and pre-hospital status), data from the early stage of cardiac arrest, resuscitation process data, post-resuscitation data, and outcome. Patient confidentiality is protected on the form by replacing identifying information with codes.

The form is based on published guidelines for the evaluation of CPR performed both in and out of hospital. It was developed after many demonstrations by the CPR Special Committee of the Chinese and the CPR Special Committee of the Hebei. A small program has been independently developed to allow the input of registration form data via mobile phones, tablets, and laptop and desktop computers.

The staff of the emergency departments of six hospitals in the Hebei Province who participated in this project had all been trained in filling out these registration forms. The inclusion criteria were as follows: registered patients who had suffered an OHCA, for which they underwent CPR, between September 2018 and April 30, 2022. The exclusion criteria were as follows: aged <18 years, incomplete data (including patients whose family members asked that CPR be discontinued), and in-hospital cardiac arrest patients. The study endpoint was ROSC, defined as the restoration of a palpable pulse and an autonomous cardiac rhythm lasting 99 for at least 20 minutes after the completion or cessation of CPR.

We used the CPR registration form, our clinical practice experience, and relevant research to preliminarily screened and identify 74 variables related to OHCA and CPR with potential predictive value. First, pandas software for Python was used for data preprocessing Pandey et al. (2022). Those variables for which more than 50% of the data were missing were eliminated. Onehot code was used for the digitization of the tag data. The cumulative importance of the variables was analyzed, and 95% was taken as the threshold value. Those variables with cumulative importance exceeding the threshold value were selected and the remainder were eliminated. This left 14 variables with the highest accuracy of cumulative importance values were established, including patient basic 108 information, cardiac resuscitation steps, and important time nodes.

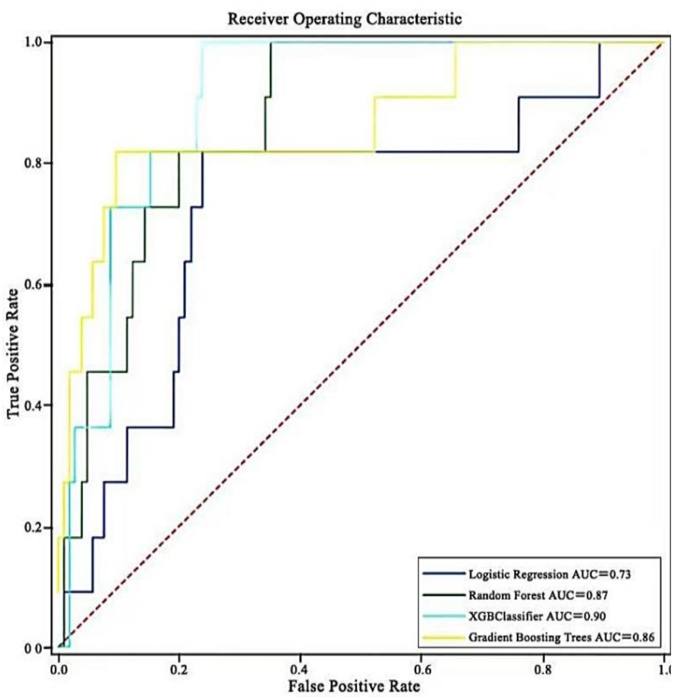
Statistical analysis

After data preprocessing, 75% of the samples were divided into training sets to build the model, 25% of the samples were divided into test sets for verification. We used four machine learning algorithms to train and test the data: Random Forest, XGBClassifier, Gradient Boosting Trees, and Logistic Regression. We used the RandomizedSearchCv module of the Scikit-Learn 114 package to enable the selection of the optimal parameters by automatic machine learning. In the Scikit-Learn classification of metrics package, the report function calculates the accuracy, recall, and F1 score for each model of the data set (Table 1) and compares the results of each model by creating a receiver operating characteristic curve and comparing the area under the curve (AUC) 118 of each model (Fig. 1). The appropriate model was selected for impact factor analysis.

Table-1: Prediction comparison of models

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	88.79	0.9	0.89	0.85
XGB Classifier	91.38	0.87	0.89	0.86
Gradient Boosting Trees	89.66	0.85	0.87	0.85
Logistic Regression	88.79	0.76	0.87	0.81

Figure 1: Comparison of model prediction ability



The stats module of the Scipy package was used for statistical analysis. Numerical measurement data were expressed as median (interquartile range). Mann–Whitney U tests were used for comparisons between groups. Label variables were described as n (%), and the Pearson correlation coefficient was used for intergroup comparison χ2 tests. A P-value <0.05 was 123 considered statistically significant.

RESULTS

A total of 463 OHCA patients were included in this study. Table 2 provides a comparison of the demographic and clinical data of the ROSC group and the resuscitation failure group. OHCA is more common in the middle-aged and elderly and in men (72.35%). ROSC occurred in 57 patients (12.3%), among whom the ROSC rate was very high (70.18%) due to the early CPR. The proportion of patients given CPR by bystanders was higher in the ROSC group (50.88%).

Variables that were found to be significantly correlated with whether or not the patient recovered spontaneous circulation were the patient's age, the speed with which CPR was initiated after the loss of spontaneous circulation, a previous or current electrolyte disorder, the use of a simple respirator, whether CPR was given, and whether the 134 patient was defibrillated ($P < 0.05$).

When we compared the effectiveness of the four machine learning models, we found that the AUC of Logistic Regression, Random Forest, XGBClassifier and Gradient Boosting Trees were 0.73, 0.87, 0.90, and 0.86, respectively. We choose the Random Forest model ordered the importance of the top five variables (Fig. 2), from most to least predictive value, as age, speed of CPR initiation, a history of electrolyte disorder, the use of airway management (simple respirator use) during CPR, and the presence of another person or people when cardiac arrest occurs.

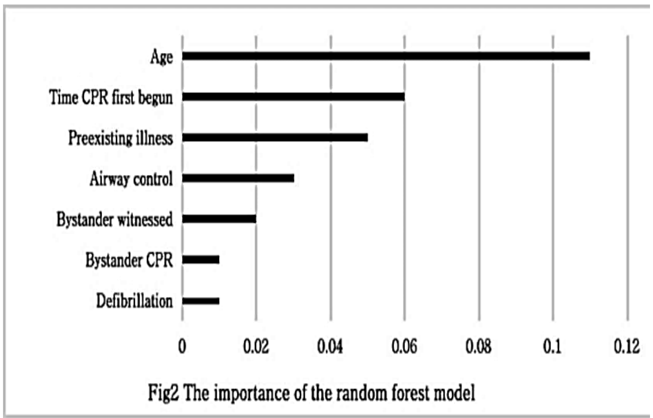
Table-2: Comparison of basic information between the ROSC group and the resuscitation failure group

Variable	All patients (n=463)	With ROSC (n=57)	Without ROSC (n=406)	Statistic (χ2/u)	P-value
Gender (n, %)					
Male	335 (72.35)	42 (73.68)	293 (72.17)	0.006	0.934
Female	128 (27.65)	15 (26.32)	113 (27.83)		
Age (year)	65 (54,76)	58 (50,76)	66 (56, 76)	10010	0.049
Pathogenesis (n, %)					
Cardiogenic	274 (59.18)	33 (57.89)	241 (59.36)	0.004	0.946
Non-cardiac	153 (33.05)	18 (31.58)	135 (33.25)	0.01	0.919
Agnogenic	36 (7.78)	6 (10.53)	30 (7.39)	0.318	0.572
Preexisting illness (n, %)					
Coronary heart disease	144 (31.10)	17 (29.82)	127 (31.28)	0.004	0.944
Hypertension	129 (27.86)	18 (31.58)	111 (27.34)	0.261	0.609
Cerebrovascular disease	45 (9.71)	9 (15.79)	36 (8.87)	1.998	0.158
Metastatic/ Hematological malignancy	16 (3.45)	2 (3.51)	14 (3.45)	0.132	0.716
COPD	11 (2.37)	2 (3.51)	9 (2.22)	0.018	0.892
Renal insufficiency/ Renal failure	12 (2.59)	2 (3.52)	10 (2.46)	0.001	0.983
Liver insufficiency/ Liver failure	10 (2.15)	3 (5.26)	7 (1.72)	1.524	0.216
Electrolyte disorder	8 (1.72)	4 (7.02)	4 (0.98)	7.453	0.006
Cardiomyopathies	6 (1.29)	2 (3.52)	4 (0.98)	0.907	0.341
Hypotension/Shock	4 (0.86)	0 (0.00)	4 (0.98)	0.001	0.99
Rheumatic heart disease	1 (0.21)	1 (0.18)	0 (0.00)	1.318	0.25
Bronchial asthma	1 (0.21)	0 (0.00)	1 (0.25)	1.318	0.25
Other	107 (23.11)	18 (31.58)	89 (21.92)	2.108	0.146

Uncertain	116（25.05)	11（19.30)	105（25.86)	0.888	0.346
By stander CPR (n,　%)	208（44.92)	29（50.88)	179（44.09)	0.676	0.41
By stander witnessed CPR (n, %)	255（55.08)	40（70.18)	215（52.96)	5.314	0.021
CPR (n,　%)	396（84.45)	57（100.00)	339（83.50)	9.074	0.001
Time CPR first begun (min)	10（1,　20)	5（0,　10)	10（1,　20)	10016	0.048
Duration of CPR (min)	60（30,　90)	22（12,　45)	60（35,　92)	5743	3.562
First monitored rhythm (n, %)					
Asystole	186（40.17)	22（38.60)	164（40.39)	0.013	0.908
PEA	55（11.88)	5（8.77)	50（12.32)	0.38	0.578
Bradycardia	13（2.81)	4（7.02)	9（2.22)	2.645	0.103
Ventricular fibrillation	13（2.81)	0（0.00)	13（3.20)	0.887	0.346
Ventricular tachycardia	4（0.86)	2（3.51)	2（0.49)	2.371	0.123
Defibrillation (n,　%)	39（8.42)	10（17.54)	29（7.14)	5.726	0.016
First use time of adrenaline (min)	5（0.5,　19.61)	3.32（0.48, 10)	5.49(0.50,19.76)	10624.5	0.158
Adrenaline (mg)	10（4,　20)	4（2,　9)	10（5,20)	6990	5.861
Airway control (n,　%)					
Endotracheal tube	329（71.06)	40（70.18)	289（71.18)	1.021	0.999
Simple respirator	44（9.50)	10（17.54)	34（8.37)	3.878	0.048
Tracheotomy	3（0.65)	0（0.00)	3（0.74)	0.053	0.817

ROSC = return of spontaneous circulation. CPR =cardiopulmonary resuscitation. COPD = chronic obstructive pulmonary disease. PEA =pulseless electrical activity. a. Time CPR first begun=The time from cardiac arrest to the start of cardiopulmonary resuscitation. b. First use time of adrenaline=The time from the discovery of cardiac arrest to the first administration of adrenaline.

Figure 2: The importance of the random forest model



DISCUSSION

Machine learning algorithms have proven a highly efficient means of processing medical data. They have been widely studied and used as prediction models relating to genes, proteins, drugs, and diseases De Velasco Oriol et al. (2019), Nguyen et al. (2022), Suzuki et al. (2019). At present, there is little research on such prediction models for the CPR outcomes of OHCA patients.

In this study, four machine learning models were developed to predict ROSC in OHCA patients: Random Forest, parameter interpretation, gradient boosting, and Logistic Regression. We found that these models have better predictive ability than the logistic regressions used in previous studies.

Taking the Random Forest model as an example, with the 14 variables selected, the predictive accuracy of the test set results was found to be 0.85, and the AUC of the model's prediction ability was 0.87. The main factors affecting ROSC were analyzed.

Cardiac arrest is one of the most severe and urgent medical emergencies and can be caused by many factors. Rapid, accurate judgment and the early implementation of CPR when it is required are key to successful resuscitation Neumar et al. (2015). Modern CPR technology uses external chest compressions, artificial respiration, and defibrillation Kleinman et al. (2018), Kotini-Shah et al. (2021), Soar et al. (2018), and these significantly reduce the mortality rates of cardiac arrest patients. In this study, we found a greater frequency of OHCA in males (72.35%), but gender was not correlated with ROSC.

This was consistent with the findings of a study of OHCA published in the United States in 2021 Soar et al. (2018).

The success rate of resuscitation in this study was 12.31%, which was lower than the 26.3% reported in previous research McNally et al. (2010). This disparity may be attributable to the enthusiasm of those present when OHCA occurs to implement CPR despite poor mastery of the skills required Zhang et al. (2021), Zhang et al. (2021), Beibei et al. (2021), Caili et al. (2022). This suggests a need to strengthen public training in CPR. In addition, our data included cardiac arrest patients in whom external chest compressions were not administered during CPR (67, 15.55%), and this may also have affected the resuscitation success rate in our sample.

In this study, we drew on the basic clinical and demographic data of the patients, the resuscitation steps implemented, and the outcomes (ROSC) of OHCA patients following CPR to establish machine learning prediction models. We found that patient age, speed of CPR initiation after cessation of breathing and heartbeat, medical history (mainly electrolyte disorders), the use of airway management (with a simple respirator), the presence of other people when cardiac arrest occurs, the administration of extrathoracic cardiac compression, and the application of defibrillation were independent predictors of the likelihood of ROSC in OHCA patients. The age of cardiac arrest patients was found to be the strongest predictor of ROSC following CPR in cardiac arrest patients. The younger the patient, the fewer the comorbidities, the better the organ function, and the greater the possibility of ROSC. CPR should be administered to cardiac arrest patients as soon as possible. The earlier CPR is initiated, the greater the probability of ROSC, particularly with defibrillation.

This is consistent with the recommendations of various domestic and foreign CPR guidelines for early identification, early CPR, and early defibrillation Bougouin et al. (2020). In addition, this study found that when cardiac arrests were caused by an electrolyte disorder rather than other chronic diseases, there was a significantly higher rate of ROSC. In airway management, The ROSC rate was also found to be higher in patients whose CPR airway management comprised simple respirator-assisted ventilation than in those given tracheotomies and endotracheal intubation. This is consistent with the existing literature McMullan et al. (2014). The greater incidence of ROSC in those who receive more basic airway management can probably be explained in part by the fact that endotracheal intubation and tracheotomy during out-of-hospital CPR require the interruption of chest compressions, while respirator-assisted ventilation does not. This lack of interruption ensures that the compression score reaches the level required for optimum efficacy (>60%).

It may also be that the patients given respirator-assisted ventilation has suffered a less severe cardiac arrest that did not reach the degree necessary to establish an advanced airway. The duration of CPR and the dose of epinephrine given have little impact on ROSC, indicating that the longer the resuscitation time and the greater the dose of epinephrine, the greater the impact on ROSC, which is consistent with the actual clinical situation. We found that the main reason for CPR in OHCA patients is cardiogenic disease, and the first detected rhythm type is usually cardiac arrest with no electrical pulse activity.

Again, this is consistent with previous research results Gräsner et al. (2016). The predictive model developed in this study can be used in clinical practice to more effectively evaluate OHCA patients and inform the interventions used in their treatment.

Limitations

This study had some limitations. Although the medical records included were completed by multiple people in collaboration and there was doubled quality control before and after form-filling, we were still obliged to exclude some cases and variables due to a large number of missing values during data preprocessing. Increasing the sample size and improving data collection would improve the utility of the data. In addition, abdominal pressure CPR is an effective means of establishing artificial circulation in cardiac arrest patient Caili et al. (2022), Li et al. (2019), Wang et al. (2017), Zhan et al. (2019), but the number of cases in which this was used was too small to analyze its relationship with ROSC. In our future research, we hope to provide a structured case history of CPR, carry out prospective registration, and improve the accessibility of EPID.

CONCLUSION

Machine learning algorithms were successfully used to establish a prediction model of ROSC in OHCR patients following CPR. This can be used to provide data support and as a reference source to improve the success rate of CPR.

ABBREVATIONS

OHCA = out-of-hospital cardiac arrests

ROSC = return of spontaneous circulation.

CPR = cardiopulmonary resuscitation.

EDIP = the emergency digital intelligence platform.

AUC = the area under the curve.

ROC curve = relative operating characteristic curve

COPD = chronic obstructive pulmonary disease.

PEA = pulseless electrical activity

DECLARATIONS

Ethics approval and consent to participate

This study was approved by the Institutional Review Board of The First Hospital of Hebei Medical University (Approval No. 20200622) and performed according to the ethical standards of the Declaration of Helsinki (1964) and its later amendments. All patients enrolled in the study provided written informed consent. The original forms were collected and stored at The First Hospital of Hebei Medical University in accordance with national regulation on the protection of personal data, and anonymized data were then centralized in the emergency digital intelligence platform（EDIP).

Availability of data and materials

The data sets generated and analysed during this study are not publicly available due to the data is improving, but are available who get the permit of the corresponding author's hospital on reasonable request.

Correspondence and requests for materials should be addressed to Ying Chen.

Consent for publication

All patients enrolled in the study provided written informed consent. The original forms were collected and stored at The First Hospital of Hebei Medical University in accordance with national regulation on the protection of personal data, and anonymized data were then centralized in the emergency digital intelligence platform（EDIP).

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Authors' contributions

Wentao Li, Jiaqi Zhang, Lu Zhang, Yingjie Nie, had full access to all of the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis.

Concept and design: Ying Chen, Wentao Li, Jiaqi Zhang.

Acquisition, analysis, or interpretation of data: Ying Chen, Wentao Li, Jiaqi Zhang.

Drafting of the manuscript: Ying Chen, Wentao Li, Jiaqi Zhang.

Critical revision of the manuscript for important intellectual content: Ying Chen.

Statistical Analysis: Jiaqi Zhang, Lu Zhang.

Conflict of Interest Disclosures:

None of the authors have any conflict of interests that were reported.

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