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Development of a Machine Learning Model to Predict Cardiac Arrest during Transport of Trauma Patients

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Background: Trauma is a serious medical and economic burden worldwide, and patients with traumatic injuries have a poor survival rate after cardiac arrest. The authors developed a prediction model specific to prehospital trauma care and used machine learning techniques to increase its accuracy.
Methods: This retrospective observational study analyzed data from patients with blunt trauma injuries due to traffic accidents and falls from January 1, 2018, to December 31, 2019. The data were collected from the National Emergency Medical Services Information System, which stores emergency medical service activity records nationwide in the United States. A random forest algorithm was used to develop a machine learning model.
Results: The prediction model had an area under the curve of 0.95 and a negative predictive value of 0.99. The feature importance of the predictive model was highest for the AVPU (Alert, Verbal, Pain, Unresponsive) scale, followed by oxygen saturation (SpO_2). Among patients who were progressing to cardiac arrest, the cutoff value was 89% for SpO_2 in nonalert patients.
Conclusions: The machine learning model was highly accurate in identifying patients who did not develop cardiac arrest. (J Nippon Med Sch 2023; 90: 186–193)

Key words: machine learning model, trauma, cardiac arrest, emergency medical services

Introduction

Background

Trauma is a serious medical and health care burden and accounts for 10% of all deaths worldwide[1]. In the United States, trauma is the leading cause of death among persons aged 1 to 44 years[2]. Cardiac arrest after trauma injury is associated with a very poor survival rate (1-month survival rate <4%)[3].

The most common emergency prediction scores used in hospital general wards are the National Early Warning Score (NEWS)[4] and the Modified Early Warning Score (MEWS)[5]. The Emergency Medical System Modified Early Warning Score (EMEWS) was developed by applying MEWS in a prehospital setting[6]. In previous studies, MEWS++ was developed by applying machine learning to MEWS[7]. Machine learning techniques have the potential to improve prognostication[8]. Some studies have reported the use of machine learning in research on prehospital emergency medicine[9–12].

If cardiac arrest can be predicted before hospital admission, it might be possible to dispatch a physician to the scene. Such prediction would also enable transport to an appropriate medical facility and early start of treatment at the receiving hospital[13]. However, existing predic-

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tive scores have been created for specific medical conditions; therefore, a score specific to prehospital trauma care is needed.

The authors developed a predictive model specific to prehospital trauma care and used machine learning to increase its accuracy.

Methods

Study Design and Setting

This retrospective study analyzed data collected by the National Emergency Medical Services Information System (NEMSIS) from January 1, 2018, to December 31, 2019. NEMSIS is a public database maintained by the National Highway Traffic Safety Administration and records emergency medical service activity nationwide in the United States. The National Highway Traffic Safety Administration Office of Emergency Medical Services (EMS) and the University of Utah jointly manage data quality and administration. NEMSIS includes data on a wide range of injuries and illnesses, including endogenous, traumatic, out-of-hospital cardiac arrest (OHCA), and other exogenous conditions. Data available include demographics and vital signs, details of procedures performed, and drugs administered.

Using previously published cardiac arrest prediction scores, we developed a model to predict traumatic cardiac arrest. EMS-witnessed arrest was defined as an injured patient who experienced cardiac arrest after EMS arrival at the scene. Non-OHCA was defined as an injured patient who was not in cardiac arrest at the time of EMS contact and showed signs of life until arriving at the hospital[6]. One of the scores we referred to, EMEWS, is evaluated in terms of SBP, HR, RR, and AVPU (Alert, Verbal, Pain, Unresponsive) scale. An SBP lower than 90 or higher than 140 is scored as 1 point; an HR lower than 60 or higher than 100 as 1 point; an RR lower than 10 or higher than 20 as 1 point; and an AVPU classification of nonalert as 1 point. The total score is the sum of the scores for these components.

This study was approved by the Ethical Review Board of Nippon Sport Science University (approval no. 021-H 237).

Selection of Patients

The current study included patients with blunt trauma injuries due to traffic accidents and falls. Patients were excluded if lights and sirens were off during transport, if the incident was not a 9-1-1 scene response, if the patient was not transported by ground, if the patient was younger than 18 years, if data on age were missing, if cardiac arrest occurred before EMS arrival, if data were missing for the time of arrest or for the vital signs systolic blood pressure (SBP), heart rate (HR), SpO_2, or respiratory rate (RR). Incidents that were not a 9-1-1 scene response and those for which lights and sirens were off during transport were excluded on the basis of previously published criteria[6]. The analysis also excluded injuries with a low risk of progression to cardiac arrest, which was defined with the EMS MEWS (EMEWS). Specifically, we defined a vital sign with an EMEWS score of 0 as low risk of progression to cardiac arrest (EMEWS values were 0 for an SBP 90-140 mm Hg, an HR of 60-100 bpm, an RR of 10-20 bpm, and an AVPU status of alert). The variables included in the analysis were age, sex, cause of injury, presence of head trauma, oxygen administration, SBP, HR, RR, SpO_2, AVPU, turnout time, time spent at the scene, and transport time. Dispatch time was defined as the time from the EMS call to arrival at the scene, scene time was defined as the time from arrival at the trauma scene to departure from the scene, and transport time was defined as the time from departure from the scene to arrival at the hospital. The NEMSIS variables used to generate this composite variable are described in Appendices 1 and 2 of the Supplementary Material (https://doi.org/10.1272/jnms.JNMS.2023_90-206). We included these vital signs and oxygen administration as features, which were selected concerning NEWS and EMEWS. The presence of head injury was included in the features because it could affect consciousness[14]. The final predictive model included age, sex, cause of injury, head injury, RR, SpO_2, HR, SBP, AVPU, and oxygen admission.

Statistical Analysis

The machine learning model was developed based on the flow chart shown in **Figure 1**. The training dataset (2018), under sampling[15], was performed to adjust the number of cases in the EMS-witnessed arrest and non-OHCA groups for balance. We performed cross-validation and a grid search for hyperparameter tuning and implemented model training. The test dataset (2019) was developed by using the results of a cross-validation and grid search performed on the training dataset (2018).

The predictive models used were random forest, logistic regression, and LightGBM. After machine learning was performed on all patient data, the data were categorized into three levels by using EMEWS, and the prediction accuracy was verified for each category. We defined risk of cardiac arrest for each EMEWS total point. Those with EMEWS values of 0-1 were considered at low risk,

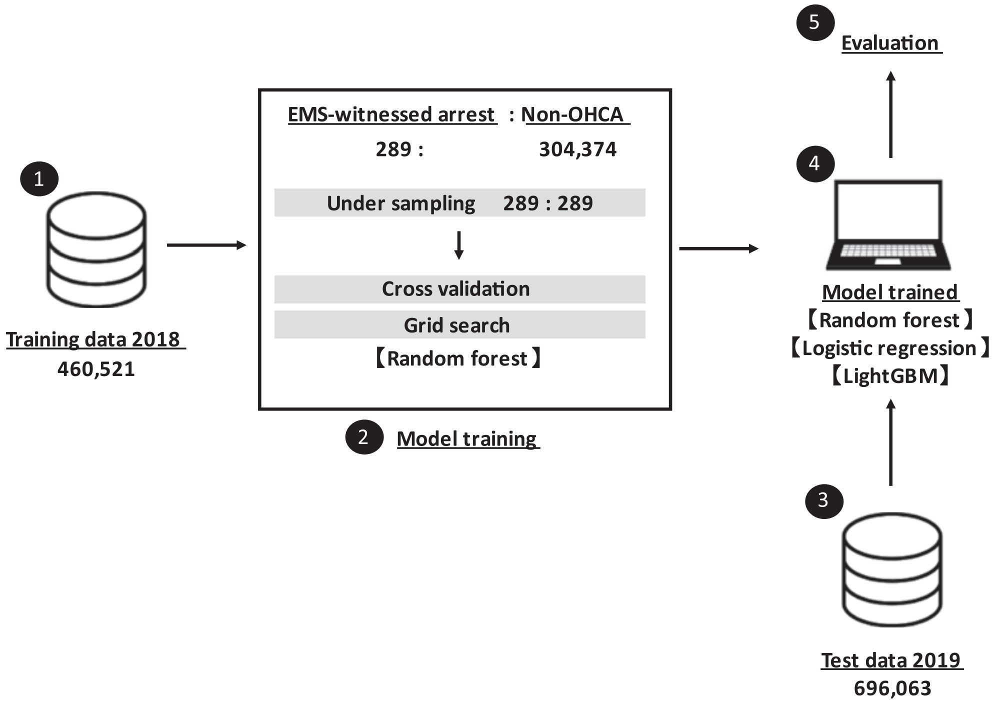

Fig. 1 Machine learning model flow
EMS = Emergency Medical System, LightGBM = Light Gradient Boosting Machine, OHCA = out-of-hospital cardiac arrest

those with values of 2-3 at moderate risk, and those with values of 4 at high risk[6].

We evaluated sensitivity, specificity, precision, accuracy, F1 score, area under the curve (AUC), and Brier score for all machine learning models. We used the chi-square test for categorical variables, and the Mann-Whitney U test for continuous variables. Statistical significance was set at $P<0.05$. Missing values were managed by multiple imputation. Python (version 3.9.7; Python Software Foundation, Beaverton, OR, USA) was used to develop the machine learning model. SPSS Statistics (version 28; IBM Corp., Armonk, NY, USA) was used for statistical analysis.

Results

Characteristics of Patients

The flowchart for including patients in this study is shown in **Figure 2**. Training data from 2018 recorded 22,532,890 individuals, 1,142,356 of whom suffered trauma in traffic accidents. Finally, after applying the study criteria, there were 289 patients in the EMS-witnessed arrest group and 304,374 in the non-OHCA group, respectively.

Test data from 2019 data yielded 34,203,087 individuals, 1,680,251 of whom were injured or ill because of a traffic accident. After applying the study criteria, 469 persons were in the EMS-witnessed arrest group and 695,594 were in the non-OHCA group. Patient characteristics are shown in **Table 1**. In 2018, the missing values were as follows: AVPU (27.9%), SpO_2 (25.6%), transport time (19.6%), scene time (13.8%), RR (6.1%), SBP (6.0%), and HR (5.2%). In 2019, the corresponding values were AVPU (25.1%), SpO_2 (21.2%), transport time (55.3%), scene time (50.1%), response time (43.1%), RR (6.9%), and SBP (5.5%).

Main Results

The AUC was 0.95 for random forest, 0.94 for logistic regression, and 0.95 for LightGBM. Other performance indicators are shown in **Table 2**. Random forest had the highest AUC, precision, and F1 score and was thus the main machine learning model used in this study. The feature importance of the random forest model was highest for AVPU, followed by SpO_2, RR, SBP, and HR. Other important features are shown in **Figure 3**. The AUC for the random forest model was 0.95. Other performance indicator scores were 0.92 for sensitivity, 0.92 for specificity, 0.02 for precision, 0.99 for negative predictive value, 0.05 for F1 score, 0.97 for accuracy, and 0.02 for Brier.

The AUC for risk of progression to cardiac arrest was 0.89 for low risk, 0.94 for moderate risk, and 0.68 for high risk. Other performance indicators are shown in **Table 3**.

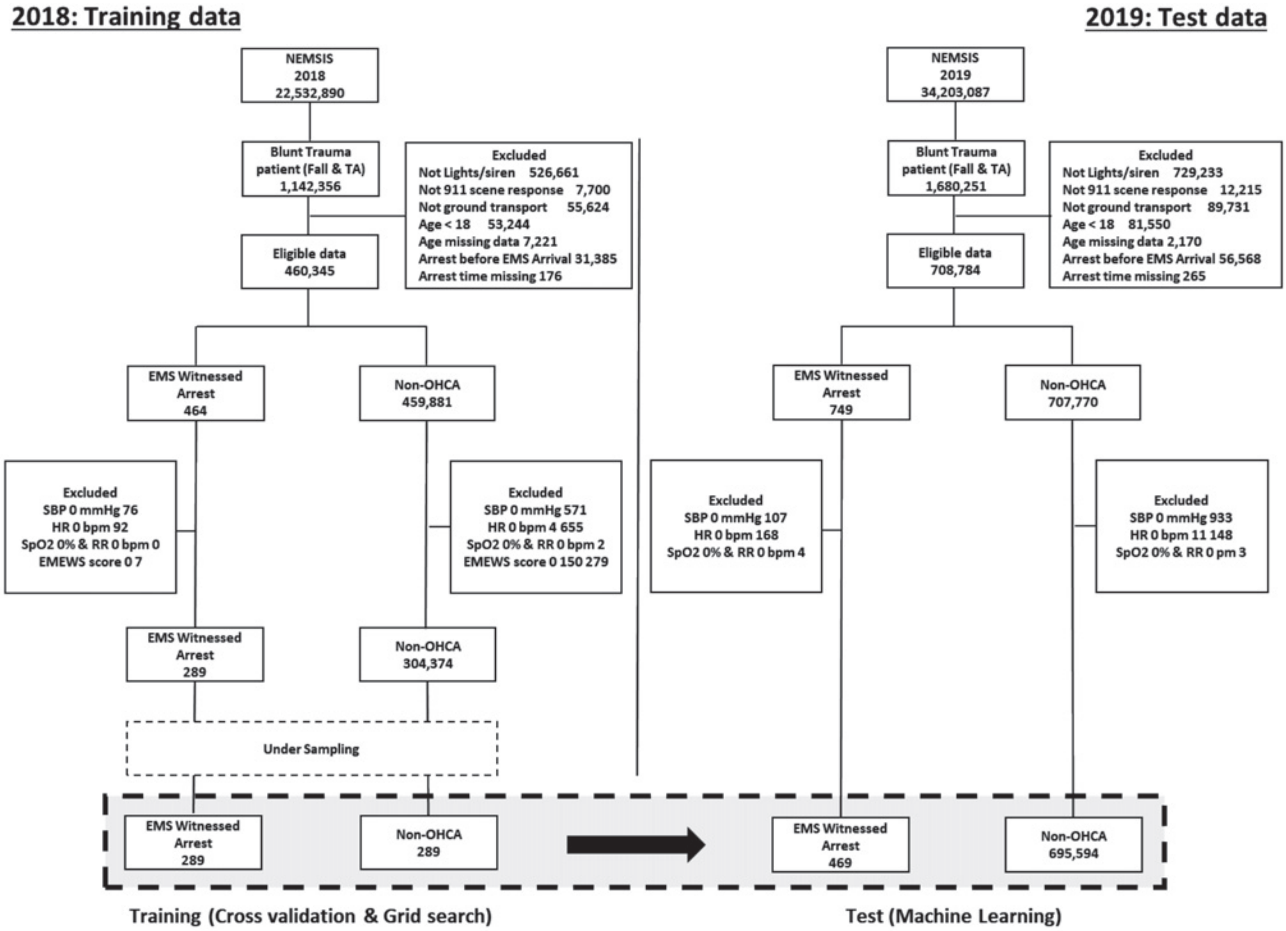

Fig. 2 Patient flow chart

AVPU = AVPU (Alert, Verbal, Pain, Unresponsive) scale, EMEWS = Emergency Medical System Modified Early Warning Score, EMS = Emergency Medical Services, HR = heart rate, NEMSIS = National Emergency Medical Services Information System, OHCA = out-of-hospital cardiac arrest, RR = respiratory rate, SBP = systolic blood pressure, SpO_2 = peripheral capillary oxygen saturation, TA = traffic accident

EMEWS score 0 = SBP of 90–140 mm Hg, HR of 60–100 bpm, RR of 10–20 bpm, and AVPU status of alert

Discussion

In this study, to predict prehospital cardiopulmonary arrest among trauma patients we constructed a model incorporating data from the United States EMS database on vital signs, patient background characteristics, and procedures performed. The results revealed an AUC of 0.95 for the predictive model and a negative predictive value of 0.99. The feature importance of the random forest model was highest for AVPU, followed by SpO_2. The AUC was 0.95 for the predictive model and 0.89 for patients at low risk of cardiac arrest.

Traumatic cardiac arrest witnessed by EMS accounted for 18.7% of OHCA. The 1-month survival rate for this group was previously reported to be 10.9%, and the rate of return of spontaneous circulation was 14.4%. Median time from injury to cardiac arrest was 18 min[16]. Because early intervention at the scene is critical for injured patients at high risk of cardiac arrest during transport, it is critical, on arrival at the scene, to promptly identify patients who are most likely to progress to cardiac arrest.

EMEWS is a scoring system that uses prehospital SBP, PR, RR, and AVPU to predict cardiac arrest during emergency transport of medically endogenous patients. The AUC of EMEWS was 0.74[6]. This scoring system is a modified version of MEWS, which predicts ward emergencies that are evaluable in a prehospital setting. The predictive model for the present trauma patients had an AUC as high as 0.89, for patients at low risk of cardiac arrest on EMEWS (low risk). Among the present patients with an EMEWS score of 1, 74.3% had an AVPU that was scored as not alert. In addition, many patients at low risk of cardiac arrest had a low SpO_2 value, which is not used in EMEWS (specificity: 0.779; AUC: 0.886; 95% confidence interval [CI]: 0.868-0.904]. The percentage of patients with an SpO_2 less than 89% was 25.0%, with an EMEWS score of 0, and 66.2% had an EMEWS score of 1.

Table 1 Patient characteristics

		2018 Training data		2019 Test data	
		EMS-witnessed arrest 289	Non-OHCA 289	EMS-witnessed arrest 469	Non-OHCA 695,594
Age		49 (32-66)	56 (37-73)	51 (30-67)	51 (31-69)
Gender					
	Male	200 (69.2%)	115 (39.8%)	349 (74.4%)	376,441 (54.1%)
Cause of injury					
	TA	229 (79.2%)	158 (54.7%)	362 (77.8%)	297 (63.9%)
	Fall	60 (20.8%)	131 (45.3%)	103 (22.2%)	168 (36.1%)
Head injury					
	Yes	29 (10.0%)	37 (12.8%)	39 (8.3%)	70,046 (10.1%)
Oxygen admission					
	Yes	93 (32.2%)	10 (3.5%)	180 (38.4%)	24,297 (3.5%)
SBP [mm Hg]		115 (92-142)	150 (137-168)	108 (88-130)	142 (128-158)
HR [bpm]		76 (55-112)	90 (78-105)	79 (55-113)	88 (78-100)
RR [bpm]		12 (6-18)	18 (16-20)	12 (7-16)	18 (16-18)
SpO2 [%]		84 (78-90)	97 (95-99)	82 (77-89)	98 (96-99)
AVPU					
	Awake	33 (11.4%)	274 (94.8%)	44 (9.4%)	673,715 (96.9%)
	Voice	7 (2.4%)	6 (2.1%)	19 (4.1%)	11,051 (1.6%)
	Pain	11 (3.8%)	5 (1.7%)	15 (3.2%)	4,784 (0.7%)
	Unresponsive	238 (82.4%)	4 (1.4%)	391 (83.4%)	6,044 (0.9%)
Time					
	Response	6:00 (4:00-10:00)	6:00 (4:00-9:00)	7:44 (4:31-11:18)	7:23 (4:51-10:59)
	Scene	19:00 (12:00-22:00)	17:00 (12:00-22:00)	15:45 (10:14-21:21)	16:00 (11:03-21:54)
	Transport	11:00 (7:00-22:00)	13:00 (8:00-21:00)	14:15 (8:53-21:08)	14:08 (8:49-20:46)

AVPU = the AVPU scale (an acronym from "Alert, Verbal, Pain, Unresponsive"), HR = heart rate, OHCA = out of hospital cardiac arrest, RR = respiratory rate, SBP = systolic blood pressure, SpO2 = peripheral capillary oxygen saturation, TA = traffic accident

Response time = the time from unit notified by dispatch to unit arrived on scene; Scene time = the time from unit arrived on scene to unit left scene; Transport time = the time from unit left scene to patient arrived at destination.

Data given as number of positive observations/total number of observations (percentage) or as median (interquartile range).

Table 2 Performance indicators for each machine learning model

Measure	Random Forest	Logistic regression	LightGBM
AUC	0.95	0.94	0.95
Sensitivity	0.92	0.92	0.93
Specificity	0.92	0.92	0.93
Precision	0.02	0.02	0.01
NPV	0.99	0.99	0.99
F1 score	0.05	0.04	0.03
Accuracy	0.97	0.97	0.96
Brier	0.02	0.02	0.03

AUC = area under the curve, LightGBM = Light Gradient Boosting Machine, NPV = negative predictive value

Features	Importances
AVPU	0.414764
SpO2	0.265871
RR	0.134351
SBP	0.094028
Oxygen admission	0.040889
HR	0.040182
Gender	0.007454
Cause of injury	0.001422
Age	0.000996
Head injury	0.000044

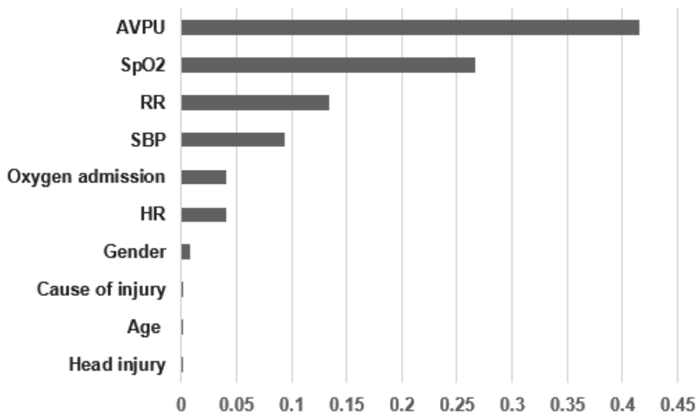

Fig. 3 Feature importance for all patients
AVPU = AVPU (Alert, Verbal, Pain, Unresponsive) scale, HR = heart rate, RR = respiratory rate, SpO_2 = peripheral capillary oxygen saturation, SBP = systolic blood pressure
Feature importance assigns the score of input features based on their importance to predict the output. The greater the extent to which features predict the output, the higher their score.

Table 3 Performance indicators for each risk in EMEWS

Measure	All patients	Low risk	Moderate risk	High risk
AUC	0.95	0.89	0.94	0.68
Sensitivity	0.92	0.98	0.95	0.98
Specificity	0.92	0.79	0.95	0.98
Precision	0.02	0.008	0.03	0.07
NPV	0.99	0.99	0.99	0.99
F1 score	0.05	0.01	0.07	0.13
Accuracy	0.97	0.98	0.94	0.41
Brier	0.02	0.01	0.05	0.4

AUC = area under the curve, NPV = negative predictive value
The EMS modified early warning score (EMEWS) is evaluated with SBP, HR, RR, and AVPU. SBP is scored 1 point if it is under 90 or over 140; HR is scored 1 point if it is under 60 or over 100; RR is scored 1 point if it is under 10 or over 20; AVPU is scored 1 point if it is Not alert. The total score is the sum of contributions from each score component.
Patients with EMEWS values of 0-1 were considered to be at low risk, those with EMEWS values of 2-3 at moderate risk, and those with EMEWS values of 4 at high risk.

SpO_2 values were included as a feature in the predictive model. In MEWS―a common hospital-based score that predicts rapid change―SpO_2 values are not used for scoring. SpO_2 values are used in NEWS, and if SpO_2 is 91% or less than 3 points, the maximum score for each item is added. The presence or absence of oxygen administration, which affects SpO_2, was also used for scoring, and 2 points were added to the score if oxygen was administered[4]. In this study, SpO_2 values and need for oxygen administration were added to the characteristics, with reference to NEWS. Few studies have examined the association of SpO_2 with the outcomes of trauma patients, and the results have been inconsistent[17]: studies of trauma patients reported that SpO_2 was[18] and was not[19,20] a predictor of mortality upon arrival at hospital.

It is unclear if low SpO_2 values are due to hypoxemia or peripheral circulatory failure, thus preventing accurate assessment. Physiologically, SpO_2 reflects oxygenation and circulation. However, oxygen saturation values differ when SpO_2 is measured transcutaneously or by arterial blood gas analysis. A study that measured SpO_2 and SaO_2 simultaneously in patients admitted to an ICU found a discrepancy in mean oxygen saturation values: SpO_2 was 94.6% and SaO_2 was 95.9%, a difference of 1.3%[21]. Divergence in SpO_2 and SaO_2 values is a concern when SpO_2 or SaO_2 is low. When there is no abnormality, the correlation is strong, so whether hypoxia or shock is the indicator of cardiac arrest progression.

Machine learning was used to obtain accurate results. MEWS++ is a version of MEWS that uses machine learning[7]. It predicts in-hospital cardiac arrest, similar to MEWS. A previous study reported that a random forest algorithm yielded higher prediction accuracy than logistic regression (receiver operating characteristic curve: 87.9 vs. 79/187.9)[7]. In the present study, the random forest model had a higher predictive accuracy than traditional logistic regression analysis.

The shock process consists of pre-shock, shock, and non-compensatory phases[22]. Because of the compensatory functions of the organism, SBP and HR may be normal in the pre-shock and shock phases[23]. Severe shock is easily determined, but such compensatory periods are difficult to identify[24]. The American College of Surgeons classifies hemorrhagic shock as a mental status of confusion when blood loss exceeds 30% (Shock class IV)[25]. As shock progresses, hypoxemia and acidosis develop[26]. Therefore, in this study, AVPU and SpO_2 values may have been important in predicting cardiac arrest.

Limitations

This study has some limitations. First, it was a retrospective observational study, and the data were not collected for the purpose of this study. Many data points were missing. Data on AVPU and SpO_2, which were important predictors of cardiac arrest, were missing in approximately 25% of patients in the study. In this study, multiple imputation was used for missing values. Second, we were unable to precisely identify the site of trauma in this study; however, previous studies have shown that the most common site of injury that causes death in trauma patients is the head, followed by the chest[27]. We performed a sensitivity analysis by excluding cause of injury and head injury related to AIS from the features used in this study. The prediction model yielded an AUC of 0.95. The results of this sensitivity analysis are reported in Appendix 3, Supplementary Material (https://doi.org/10.1272/jnms.JNMS.2023_90-206). The present sensitivity analysis indicates that use of data on cause of injury and head injury did not significantly affect the accuracy of the prediction model. Third, it was unknown whether emergency medical technicians (EMTs) administered IV fluids or performed tracheal intubation, thoracentesis, or other procedures. Thus, it was unclear whether patients avoided cardiac arrest because of procedures performed by EMTs.

In the results for the prediction model, the AUC of the predictive model was 0.95 and the negative predictive value was 0.99. Patients who did not progress to cardiac arrest could be identified with high accuracy.

Data Availability

The data analyzed in this study are openly available in NEMSIS (https://nemsis.org/).

Conflict of Interest: This work was supported by the [ZENKYOREN (National Mutual Insurance Federation of Agricultural Cooperatives)] under Grant.

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