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A Prediction of in-Hospital Cardiac Arrest Risk Scoring Based on Machine Learning

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***Abstract*— According to the Korea Disease Control and Prevention Agency (KCDC), 591 out of 33,402 cardiac arrests in 2021 occurred in hospitals. A recent study shows that the golden time to detect a cardiac arrest is less than three minutes. It means early detection of cardiac arrest is important. However, early warning systems predict cardiac arrest with low precision and recall. We research data from ICU patients aged 19 and older who were hospitalized at the Korea University Anam Hospital from 2021 to 2022. We grouped patients with similar characteristics based on clustering the selection, such as in prospective studies. We clustered the training data by window sliding age, SBP, DBP, BT, RR, BP, and BT over 8 hours. We applied a long short-term memory (LSTM) model, a recurrent gated model (GRU) model, and a self-attention-based LSTM model. Instead of linear regression, we used multiple classifications to predict values from 0 to 100. We assign weight to each score. We proposed a cardiac arrest risk score and developed a prediction model for cardiac arrest risk score using ICU patients from the Korea University Anam Hospital. We used the cardiac arrest risk score to predict cardiac arrest within 8 hours, 24 hours, and 72 hours. We evaluated the predicted cardiac arrest risk score as 0 below the threshold and 1 above the threshold. Our proposed GRU model shows 0.11% precision and 94.34% recall.**

***Keywords*— Early prediction; cardiac arrest; cardiac arrest risk score; machine learning.**

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I. INTRODUCTION

In cardiac arrest, the heart stops beating, and the heart is pumping blood. The blood provides energy and oxygen to cells; when cells are deprived of energy and oxygen, body tissues can be damaged, and disability may become permanent. In the United States, 300,000 people die annually from out-of-hospital cardiac arrest [1], and 30,000 people in the Republic of Korea experience out-of-hospital cardiac arrest annually [2].

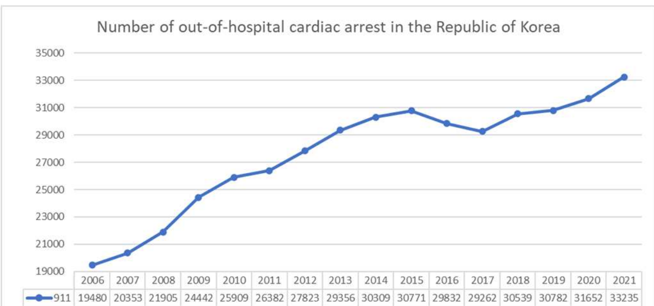

Fig. 1 Number of out-of-hospital cardiac arrests in the Republic of Korea

According to the Korea Disease Control and Prevention Agency (KCDC), 591 out of 33,402 cardiac arrests in 2021 occurred in hospitals [3]. The medical staff discovered the patient in cardiac arrest at 319 of 591 [3]. A recent study shows that the golden time to detect cardiac arrest is less than three minutes [4]. It means early detection of cardiac arrest is important. Hospitals have adopted early warning systems to identify high-risk patients, such as the national early warning score (NEWS) and modified early warning score (MEWS). However, early warning systems predict cardiac arrest with low precision and recall [5].

According to Vähätalo et al. [6], abnormal ECG signals are detected before a cardiac arrest. In addition, they reported a relationship between myocardial infarction and cardiac arrest [6]. In recent years, research on cardiac arrest has included early prediction studies in patients with acute coronary syndromes [7], early prediction of cardiac arrest in sepsis patients [8], early prediction of cardiac arrest in intensive care unit patients [9]-[11], early prediction of cardiac arrest in critically ill patients [12], [13], early prediction of cardiac arrest using ECG signals [14], [15], and early prediction of cardiac arrest or heart disease [15]-[26]. Early cardiac arrest prediction using ECG is highly performed, but ECG equipment must be worn. This study aims to early predict cardiac arrest using vital sign data collected to determine the health status of hospitalized patients.

II. Materials and Method

We collected data from ICU patients aged 19 and older who were hospitalized at the Korea University Anam Hospital from 2021 to 2022. We excluded patients hospitalized for less than 8 hours. This study was approved by the Institutional Review Board of the Korea University Anam Hospital (IRB No. 2022AN0571).

A. Dataset

We performed a retrospective study of 2,807 ICU patients at the Korea University Anam Hospital from 2021 to 2022. Table 1 shows the characteristics of our study population. There is an imbalance because 2.60% of ICU patients had cardiac arrest.

TABLE I
CHARACTERISTICS OF THE STUDY POPULATION

Characteristics	Description
Study period	January 2021 ~ November 2022
Total patients, n	2807
Patients with in-hospital cardiac arrest, n	73
Number of features	6
Age, years (mean ± SD)	66.7 ± 15.6
Hospital	Korea University Anam Hospital

Table 2 shows the EHR parameters. In this study, we performed early cardiac arrest prediction using ICU patients' vital sign data.

TABLE II
ELECTRONIC HEALTH RECORDS (EHR) DATA PARAMETERS

Variable	Description
Age	Age at hospitalization
SBP	Systolic blood pressure ($30 \leq SBP \leq 300$, mmHg)
DBP	Diastolic blood pressure ($30 \leq DBP \leq 300$, mmHg)
BT	Body temperature ($30 \leq BT \leq 45$)
RR	Respiratory rate (breaths per minute, $3 \leq RR \leq 60$)
BP	Blood pressure ($30 \leq BP \leq 300$, mmHg)

B. Cardiac arrest risk score

The MEWS was scored by considering the risk to vital signs. Other research uses predictive value threshold values, and the cardiac arrest risk score was calculated using Equations 1 and 2.

$$diff = (cardiac\ arrest\ time - measure\ time)/3600 \quad (1)$$

$$cardiac\ arrest\ score\ = \min(100 - diff, 0) \quad (2)$$

Our proposed cardiac arrest risk score assigns a higher score at the time of cardiac arrest. It gives an estimate of the probability and event time of cardiac arrest.

C. Workflow

The cardiac arrest prediction model was performed in the following sequence: First, we used the train test split function provided by sci-kit-learn to split the cardiac arrest patients into 50% training data, 30% early stopping data, 10% validation data, and 10% test data, while maintaining the ratio of cardiac arrest patients to non-arrest patients [27]. Second, we replaced the missing values with the recent measurement of the patient. Third, we performed clustering on the training data. Using clustering, we extracted 2,036 patients from 2,807 patients. Fourth, we constructed a dataset by performing window sliding on time series data in order to predict early cardiac arrest using data from the previous 23 hours and the current data. Fifth, our collected data set is unbalanced. In general, many researchers utilize oversampling or under sampling to solve imbalances in datasets. We applied the Synthetic Minority Oversampling Technique (SMOTE) to the training dataset [28]. Sixth, we applied a long short-term memory (LSTM) model [29], a recurrent gated model (GRU) model [30], and a self-attention-based LSTM model [31]. Instead of linear regression, we used multiple classifications to predict values from 0 to 100. Multiclassification support assigns weight. The default weight is the same. We assign weight to each value.

III. Result and Discussion

A. Extraction via Clustering Patients

Retrospective studies have limited patient data access, and prospective studies it has a target group and a comparison group. We grouped patients with similar characteristics based on clustering the selection of patients, such as in prospective studies. We clustered the training data by window sliding age, SBP, DBP, BT, RR, BP, and BT over 8 hours. Patients are contained in multiple clusters. We performed clustering to increase the number of clusters from 2 to 5. Table 3 shows the number of patients in the training data and the number of cardiac arrest patients in each cluster.

TABLE III
THE NUMBER OF PATIENTS WITH CARDIAC ARREST IN EACH CLUSTER

Number of Cluster	Cluster No	Number of patients in cluster	Number of patients in only specified cluster	Cardiac arrest patient
2	0	1394	1070	34
	1	326	2	2
3	0	1392	891	34
	1	241	1	1
	2	503	1	2
4	0	1392	613	34
	1	200	1	1
	2	779	1	2
	3	374	2	1
5	0	779	1	2
	1	200	1	1
	2	1059	194	13
	3	374	2	2
	4	1052	141	27

We set the number of clusters to four and extracted 2,036 ICU patients from a total of 2,807. Due to the small number of cardiac arrest patients, we extract all cardiac arrest patients independently of clusters.

B. Early Prediction of Cardiac Arrest Based on Each Model

We evaluated a LSTM model, a GRU model, and a self-attention-based LSTM model via validation data. We used the risk score to predict cardiac arrest within 8 hours, 24 hours, and 72 hours. We evaluated the predicted cardiac arrest risk score as 0 below the threshold and 1 above the threshold. Table 4 shows the results of predicting cardiac arrest within 8 hours as the threshold for the LSTM model. In the case of threshold 15, it has the best recall in the LSTM model, and there is no significant difference in precision.

TABLE IV
PREDICTION OF CARDIAC ARREST WITHIN 8 HOURS BASED ON LSTM MODEL

Threshold	Precision	Recall	F1 score
15	0.15%	92.45%	0.0031
27	0.16%	86.79%	0.0031
39	0.18%	81.13%	0.0033
48	0.21%	77.47%	0.0039
51	0.21%	73.58%	0.0041
55	0.20%	67.92%	0.0041
61	0.20%	60.38%	0.0041
68	0.23%	56.60%	0.0046
73	0.24%	50.94%	0.0048
74	0.23%	47.17%	0.0046
76	0.22%	41.51%	0.0043
77	0.17%	32.08%	0.0034
78	0.12%	22.64%	0.0024
79	0.09%	16.98%	0.0019
81	0.06%	9.43%	0.0011
92	0.04%	3.77%	0.0007
97	0.05%	3.77%	0.0010
100	0.08%	1.895	0.0014

Table 5 shows the results of predicting cardiac arrest within 8 hours as the threshold for the GRU model. In the case of threshold 3, it has the best recall in the GRU model, and there is no significant difference in precision.

TABLE V
PREDICTION OF CARDIAC ARREST WITHIN 8 HOURS BASED ON GRU MODEL

Threshold	Precision	Recall	F1 score
3	0.11%	94.34%	0.0023
10	0.12%	88.68%	0.0023
15	0.11%	83.02%	0.0022
17	0.10%	75.47%	0.0021
31	0.11%	71.70%	0.0021
45	0.11%	64.15%	0.0022
61	0.13%	58.49%	0.0026
63	0.12%	52.83%	0.0024
65	0.10%	45.28%	0.0021
67	0.09%	39.62%	0.0019
80	0.11%	35.85%	0.0022
82	0.09%	28.30%	0.0018
87	0.08%	18.87%	0.0016
92	0.08%	13.21%	0.0015
93	0.07%	11.32%	0.0014
99	0.06%	5.66%	0.0013
100	0.05%	1.89%	0.0010

Table 6 shows the results of predicting cardiac arrest within 8 hours as the threshold for the self-attention-based LSTM model. In the case of threshold 2, it has the best recall in the self-attention-based LSTM model, and there is no significant difference in precision. We found that the self-attention-based LSTM model performs best when we evaluate the models with a default threshold of 92 within 8 hours, but the GRU model performs best when we set the optimal threshold for each model and compare recall.

TABLE VI
PREDICTION OF CARDIAC ARREST WITHIN 8 HOURS BASED ON SELF-ATTENTION-BASED LSTM MODEL

Threshold	Precision	Recall	F1 score
2	0.11%	71.70%	0.0022
5	0.11%	66.04%	0.0021
26	0.12%	60.38%	0.0024
28	0.11%	56.60%	0.0023
59	0.16%	50.94%	0.0031
72	0.18%	45.28%	0.0035
76	0.17%	39.62%	0.0034
78	0.16%	35.85%	0.0032
86	0.21%	30.19%	0.0042
89	0.23%	28.30%	0.0046
90	0.23%	26.42%	0.0046
92	0.22%	22.64%	0.0044
95	0.21%	16.98%	0.0042
97	0.14%	9.43%	0.0027
100	0.14%	3.77%	0.0027

Table 7 shows the results of predicting cardiac arrest within 24 hours as the threshold for the LSTM model. In the case of threshold 5, it has the best recall in the LSTM model, and there is no significant difference in precision.

TABLE VII
PREDICTION OF CARDIAC ARREST WITHIN 24 HOURS BASED ON LSTM MODEL

Threshold	Precision	Recall	F1 score
5	0.32%	82.58%	0.0063
32	0.36%	76.52%	0.0072
45	0.41%	70.45%	0.0081
48	0.43%	66.67%	0.0085
53	0.41%	56.06%	0.0081
57	0.39%	49.24%	0.0076
60	0.37%	44.70%	0.0073
67	0.39%	40.15%	0.0078
70	0.36%	34.09%	0.0073
74	0.33%	27.27%	0.0065
76	0.30%	23.48%	0.0060
78	0.21%	15.91%	0.0042
81	0.16%	10.61%	0.0031
94	0.17%	6.06%	0.0032
100	0.08%	0.76%	0.0014

Table 8 shows the results of predicting cardiac arrest within 24 hours as the threshold for the GRU model. In the case of threshold 3, it has the best recall in the GRU model, and there is no significant difference in precision.

TABLE VIII
PREDICTION OF CARDIAC ARREST WITHIN 24 HOURS BASED ON GRU MODEL

Threshold	Precision	Recall	F1 score
3	0.29%	96.97%	0.0058
6	0.28%	89.39%	0.0056
9	0.27%	84.85%	0.0055
16	0.27%	79.55%	0.0054
25	0.26%	74.24%	0.0052
31	0.26%	69.70%	0.0052
36	0.26%	65.91%	0.0051
45	0.25%	59.09%	0.0050
51	0.27%	55.30%	0.0053
55	0.27%	51.52%	0.0053
61	0.26%	46.21%	0.0051
65	0.24%	40.91%	0.0047
74	0.22%	34.09%	0.0044
76	0.22%	32.58%	0.0044

Threshold	Precision	Recall	F1 score
82	0.21	25.76%	0.0042
88	0.23	20.45%	0.0045
96	0.30	15.15%	0.0058
99	0.28	9.85%	0.0054
100	0.34	5.30%	0.0064

Table 9 shows the results of predicting cardiac arrest within 24 hours as the threshold for the self-attention-based LSTM model. In the case of threshold 2, it has the best recall in the self-attention-based LSTM model, and there is no significant difference in precision. We discovered that the GRU model performs best when the models are evaluated with a default threshold of 76 for predicting cardiac arrest within 24 hours, and it performs best when the optimal threshold value is set for each model.

TABLE IX
PREDICTION OF CARDIAC ARREST WITHIN 24 HOURS BASED ON SELF-ATTENTION-BASED LSTM MODEL

Threshold	Precision	Recall	F1 score
1	0.27%	69.70%	0.0053
6	0.27%	65.15%	0.0053
21	0.26%	55.30%	0.0051
29	0.25%	50%	0.0050
51	0.31%	45.45%	0.0061
57	0.30%	40.15%	0.0059
68	0.28%	35.61%	0.0063
76	0.31%	28.79%	0.0060
81	0.30%	23.48%	0.0060
90	0.38%	17.42%	0.0075
96	0.40%	12.12%	0.0077
100	0.35%	3.79%	0.0064

Table 10 shows the results of predicting cardiac arrest within 72 hours as the threshold for the LSTM model. In the case of threshold 1, it has the best recall in the LSTM model, and there is no significant difference in precision.

TABLE X
PREDICTION OF CARDIAC ARREST WITHIN 72 HOURS BASED ON LSTM MODEL

Threshold	Precision	Recall	F1 score
1	0.73%	82.41%	0.0145
6	0.73%	77.47%	0.0146
16	0.73%	70.37%	0.0144
28	0.74%	66.67%	0.0147
39	0.76%	61.42%	0.0152
46	0.81%	55.25%	0.0159
50	0.85%	50.31%	0.0167
54	0.82%	45.06%	0.0160
59	0.81%	40.74%	0.0159
66	0.82%	35.19%	0.0160
70	0.79%	29.63%	0.0153
74	0.74%	24.69%	0.0143
78	0.63%	19.14%	0.0123
83	0.62%	15.12%	0.0118
95	0.79%	11.11%	0.0148
98	0.60%	6.79%	0.0110
100	0.60%	2.47%	0.0097

Table 11 shows the results of predicting cardiac arrest within 72 hours as the threshold for the GRU model. In the case of threshold 1, it has the best recall in the GRU model, and there is no significant difference in precision.

TABLE XI
PREDICTION OF CARDIAC ARREST WITHIN 72 HOURS BASED ON GRU MODEL

Threshold	Precision	Recall	F1 score
1	0.69%	94.44%	0.0136
4	0.68%	90.74%	0.0136
6	0.66%	85.80%	0.0131
10	0.64%	80.56%	0.0128
18	0.64%	75.62%	0.0126
28	0.65%	72.84%	0.0130
38	0.65%	66.67%	0.0128
44	0.62%	59.88%	0.0122
49	0.62%	55.25%	0.0122
53	0.61%	50.31%	0.0122
59	0.60%	44.75%	0.0118
66	0.57%	39.81%	0.0112
72	0.55%	35.19%	0.0108
80	0.58%	31.17%	0.0113
84	0.56%	25%	0.0110
89	0.60%	20.68%	0.0117
93	0.61%	15.74%	0.0117
98	0.62%	10.80%	0.0118
100	0.83%	5.25%	0.0144

Table 12 shows the results of predicting cardiac arrest within 72 hours as the threshold for the self-attention-based LSTM model. In the case of threshold 1, it has the best recall in the self-attention-based LSTM model, and there is no significant difference in precision. We discovered that the GRU model performs best when the models are evaluated with a default threshold of 28 for predicting cardiac arrest within 72 hours, and it performs best when the optimal threshold value is set for each model.

TABLE XII
PREDICTION OF CARDIAC ARREST WITHIN 72 HOURS BASED ON SELF-ATTENTION-BASED LSTM MODEL

Threshold	Precision	Recall	F1 score
1	0.66%	70.99%	0.0131
11	0.69%	66.05%	0.0137
28	0.66%	54.01%	0.0131
45	0.76%	50.31%	0.0150
50	0.73%	44.75%	0.0144
55	0.70%	39.81%	0.0138
68	0.77%	35.19%	0.0150
74	0.76%	30.56%	0.0148
80	0.78%	25.93%	0.0151
83	0.77%	21.30%	0.148
90	0.85%	15.74%	0.0161
95	0.77%	10.19%	0.0144
99	0.77%	6.48%	0.0138
100	0.84%	3.70%	0.0137

C. *Cardiac Arrest Risk Scoring Based on GRU Model*

We performed early prediction of cardiac arrest within 8 hours, within 24 hours, and within 72 hours. We found that the GRU model was better than other models. We evaluated the GRU model via test data. Figure 2 shows that the cardiac arrest risk score increases with the event time of cardiac arrest in cardiac arrest patients, and however, it shows low precision.

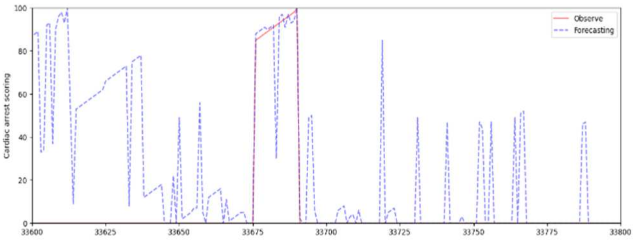

Fig. 2 Graph of cardiac arrest risk scoring

The MAE and RMSE of the GRU model are 52 and 62.69, respectively. Table 13 shows the results of early cardiac arrest prediction based on the GRU model via the cardiac arrest risk score.

TABLE XIII
EARLY PREDICTION OF CARDIAC ARREST BASED ON GRU MODEL

Time	Threshold	Precision	Recall	F1 score
Within 8 hours	92	0.07%	13.21%	0.0015
	3	0.11%	94.34%	0.0023
Within 24 hours	76	0.22%	32.58%	0.0044
	3	0.29%	96.97%	0.0058
Within 72 hours	28	0.65%	72.84%	0.0130
	1	0.69%	94.44%	0.0136

D. *Discussion*

Previous studies have focused on early cardiac arrest prediction. Despite the significance of the results in predicting cardiac arrest, it is difficult to determine the patient's risk level for cardiac arrest. We proposed a cardiac arrest risk score to provide significant information. To determine the patient's risk level, we assigned a score of 100 at the time of cardiac arrest. We performed multiple classifications rather than a linear regression, setting a higher weight to the time of the cardiac arrest. Table 14 shows the results of the LSTM model, the GRU model, and the self-attention-based LSTM model in predicting early cardiac arrest within 72 hours based on the weight of multiple classifications. We found that default weights have a little higher precision but poorer recall than optimized weights. If contiguous numbers have different priorities, researchers may consider multiple classifications.

TABLE XIV
PERFORMANCE RESULT OF CARDIAC ARREST WITHIN 72 HOURS BASED ON WEIGHT

Algorithm	Weight	Precision	Recall	F1 score
LSTM model	Default	4.90%	3.40%	0.0086
	Optimized	0.74%	66.67%	0.0147
GRU model	Default	5.07%	6.17%	0.0094
	Optimized	0.65%	72.84%	0.0130
Self-attention-based LSTM model	Default	2.85%	3.70%	0.0070
	Optimized	0.66%	54.01%	0.0131

In this study, clustering was used to extract similar patient populations. We hope that the information obtained from the retrospective study will assist us in identifying a group of patients who are similar to those who have experienced cardiac arrest. However, it has not been clinically validated.

TABLE XV
RESULT OF EWS AND OUR METHOD

Author	Algorithms	Precision	Recall	F1 score
Traditional EWS [5]	SPTTS	0.4%	60.7%	0.008
	MEWS ≥ 3	0.5%	63.0%	0.010
	MEWS ≥ 4	0.6%	49.3%	0.012
	MEWS ≥ 5	0.6%	37.3%	0.013
J. Kwon et al. [5]	Random forest	0.4%	75.3%	0.008
	Linear regression	0.2%	76.3%	0.004
	DEWS ≥ 2.9	0.5%	75.7%	0.010
	DEWS ≥ 3.0	0.5%	75.3%	0.010
	DEWS ≥ 7.1	0.8%	63.0%	0.0165
	DEWS ≥ 8.0	0.8%	60.7%	0.016
	DEWS ≥18.2	1.4%	49.3%	0.028
	DEWS ≥ 52.8	3.7%	37.3%	0.071
S. L. Javan et al. [8]	Stacking Early prediction within 6 hours	15%	74%	0.31
T. T Wu et al. [7]	XGboost	88.5%	73%	0.800
	Logistic regression	84.1%	58.7%	0.692
	Random forest	93.5%	46.0%	0.617
	Support vector machine	93.5%	46.0%	0.617
L. Yijing et al. [13]	XGBoost	-	86%	-
S. Hong et al. [9]	Logistic regression	-	75%	0.093
	Random forest	-	88%	0.198
	Recurrent neural network	-	84%	0.143
J. Kim et al. [12]	Char gated recurrent unit	0.8%	90.2%	-
Our method		0.11%	94.34%	0.0023

Our proposed research demonstrates a higher recall rate than other studies utilizing only vital sign data. Other studies demonstrate greater precision with clinical data. However, applying a model that predicts cardiac arrest based on clinical data to patients without measured clinical data is challenging. Our paper has three limitations. First, our dataset has a missing value. The vital signs of ICU patients are measured every 1 to 2 hours. However, the number of patients with no missing values is small. We use measured values to solve the missing values problem in this paper. However, a patient's health differs significantly from the last measured health condition. The missing values degrade machine learning training performance. Methods for interpolating missing values include substituting them with previous values, substituting them with subsequently measured values, or inferring additional items using the MICE algorithm. The MICE algorithm is a method for compensating for missing values based on another measuremenit, but vital signs data are measured at the same time. If one item is missing, other items are frequently missing. Second, our study was conducted as a single cohort at the Korea University Anam Hospital.

Accordingly, we have been unable to validate them through external sources. Third, our model is low precision.

IV. Conclusion

We proposed a cardiac arrest risk score and developed a prediction model for cardiac arrest risk score using ICU patients from the Korea University Anam Hospital. We extracted patient populations similar to cardiac arrest using clustering. Multiple classifications were used to predict cardiac arrest risk scores in a patient population with cardiac arrest-like characteristics. We evaluated the performance of each model, and our proposed GRU model had a high recall. We will improve the proposed model's precision and recall in the future. And we will conduct validation and multi-cohort studies using medical data from the Konyang University Hospital.

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