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RESEARCH ARTICLE

Predicting Readmission of Cardiovascular Patients Admitted to the CCU using Data Mining Techniques

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Abstract:

Background:

Cardiovascular (CV) diseases account for a large number of readmissions.

Objective:

Using data mining techniques, we aimed to predict the readmission of CV patients to Coronary Care Units of 4 public hospitals in Shiraz, Iran, within 30 days after discharge.

Methods:

To identify the variables affecting the readmission of CV patients in the present cross-sectional study, a comprehensive review of previous studies and the consensus of specialists and sub-specialists were used. The obtained variables were based on 264 readmitted and non-readmitted patients. Readmission was modeled with predictive algorithms with an accuracy of >70% using the IBM SPSS Modeler 18.0 software. Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology provided a structured approach to planning the project.

Results:

Overall, 47 influential variables were included. The Support Vector Machine (SVM), Chi-square Automatic Interaction Detection (CHIAD), artificial neural network, C5.0, K-Nearest Neighbour, logistic regression, Classification and Regression (C&R) tree, and Quest algorithms with an accuracy of 98.60%, 89.60%, 89.90%, 88.00%, 85.90%, 79.90%, 78.60%, and 74.40%, respectively, were selected. The SVM algorithm was the best model for predicting readmission. According to this algorithm, the factors affecting readmission were age, arrhythmia, hypertension, chest pain, type of admission, cardiac or non-cardiac comorbidities, ejection fraction, undergoing coronary angiography, fluid and electrolyte disorders, and hospitalization 6-9 months before the current admission.

Conclusion:

According to the influential variables, it is suggested to educate patients, especially the older ones, about following physician advice and also to teach medical staff about up-to-date options to reduce readmissions.

Keywords: Forecasting, Patient readmission, Cardiovascular diseases, Coronary care units, Data mining, Physicians.

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1. INTRODUCTION

Increasing demand for health services, on the one hand, and limited resources, on the other hand, are major issues for health services. Therefore, it is suggested that health system policymakers and managers should aim for the optimal use oflimited resources available, including hospital beds, and increasing clinical effectiveness. One of the key indicators for assessing healthcare outcomes is the evaluation of readmission rates [1]. In general, readmission refers to rehospitalization within a specific time frame (usually within 30 days after discharge) in the same hospital or other ones on a planned or unplanned basis [2].

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Currently, cardiovascular (CV) diseases account for a significant proportion of readmission cases, and a sharp increase in readmission rates for these diseases is worrying [3]. CV diseases are the most common cause of death in most countries, including Iran, and the leading cause of disability [4]. About 17.9 million people lost their lives in 2019 due to CV diseases, accounting for 32% of deaths worldwide [5]. Over three-fourths of the deaths from CV diseases occur in low- and middle-income countries [5], where people suffering from these diseases do not have adequate access to appropriate and effective hospital services, including Coronary Care Units (CCUs) [6, 7]. Therefore, today, there is an urgent need for CCUs more than ever, and this is why hospitals are seeking to increase the number of their CCU beds [8]. Discharge from this unit at the earliest appropriate time will reduce the cost of healthcare facilities and increase access to intensive care for critically ill patients. However, the early discharge of CCU patients may increase the likelihood of readmission and worsen the disease process [9].

Determining the factors affecting the readmission of CV patients will provide an opportunity to meet the needs of the patients and the problems related to the services provided. The results of numerous studies demonstrated that readmission of CV patients was affected by several factors, including demographic and social ones, such as age [10 - 13], gender [14, 15], type of health insurance coverage [16, 17], length of stay [18 - 21], type of admission [22, 23], discharge destination [19, 24 - 26], ethnicity [13, 27], and discharge status [25, 28], as well as some clinical factors like cardiac or non-cardiac comorbidities [29, 30], body mass index (BMI) [13, 31, 32], infection [33 - 36], fluid and electrolyte disorders [37, 38], surgery [13, 39], chest pain [40, 41], and depression [13, 42].

On the other hand, due to the large volume of available data and their complexity, the ever-increasing need for using an efficient, effective, and reliable tool for discovering useful knowledge in this data is required in order to determine the factors affecting readmissions. This goal can be achieved through the use of data mining algorithms. Data mining has good potential to create a knowledge-rich environment that can significantly increase the quality of clinical decisions [43]. Hence, some studies have used different data mining algorithms, such as logistic regression [44 - 48], support vector machine (SVM) [48 - 50], artificial neural network [47, 48], random forest [48, 49], and decision tree [48] to identify the factors affecting readmission of CV patients. However, in these studies, different findings have been reported.

Due to the diversity of techniques and their accuracy, authors used different data mining algorithms in the present study to identify the best algorithm for predicting the readmission of CV patients admitted to the CCUs of public hospitals in Shiraz, Iran, within 30 days after discharge in 2020.

2. MATERIALS AND METHODS

This was a cross-sectional study conducted on the patients admitted to the CCUs of public hospitals (4 hospitals) in Shiraz, Iran, in 2020 to predict the readmission of hospitalized CV patients through the use of data mining techniques. The Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology was used to provide a structured approach to planning the data mining project [51]. As it was an iteration loop model, some steps might be performed several times to achieve the desired result in modeling. The CRISP-DM method included the following steps:

2.1. Business Understanding

At this stage, a comprehensive review of the articles in English on determining the factors affecting readmission of CV patients indexed in Web of Science, PubMed, Scopus, and Embase databases and published between 2000.01.01 and 2020.12.30 was carried out. The articles were searched using the following keywords:

“Factor OR Determinant OR Element” AND” Readmission OR Rehospitalization OR Re_admission OR Readmit OR Re_hospitalization” AND” Heart disease OR Cardiac disease OR Cardiovascular disease OR Cardiovascular patient OR Coronary artery disease OR Cardio surgeries OR Coronary artery bypass.

Finally, 45 variables were obtained. Then, using the consensus of 8 specialists and subspecialists working in the CCUs of the studied hospitals, 5 more variables were added, and a total of 50 variables were ultimately obtained (Appendices A and B).

2.2. Data Understanding

The patients who experienced readmission within 30 days after discharge were identified. The data relating to their demographic and clinical variables, the variables related to the service providers, and the data related to the variables were respectively obtained from the patients’ records, the Statistics unit of Shiraz University of Medical Sciences, and through interviews with the patients. The number of readmitted patients studied was equal to that of non-readmitted ones, and a total of 264 patients were examined. In other words, there were 132 readmitted patients, all of whom were examined through the census method. There were also 7362 non-readmitted patients in the four hospitals studied, of whom 132 were selected through the stratified random sampling method proportional to the size and simple random sampling method. The number of patients not readmitted to the CCUs of studied hospitals was determined based on the stratified random sampling method proportional to size. Within each hospital, these samples were selected through the simple random sampling method using their medical record numbers.

2.3. Data Preparation

At this stage, two variables of hospital ownership and being a teaching hospital were excluded from the study because all of the hospitals under study were teaching hospitals. In addition, the variable of training the patient on how to take medications was excluded due to the provision of education to all patients by nurses and the existence of the training sheet in all medical records. As a result, among the variables obtained from the comprehensive review of the articles and the consensus of the specialists and subspecialists, 47 variables were examined.

Moreover, since the body mass index (BMI) had not been recorded in some medical records, it was calculated through height and weight values extracted from these records.

Furthermore, a medical records technician classified principal diagnoses into seven main categories of CV diseases based on the International Classification of Diseases, Tenth Revision (ICD-10) (Appendix A).

2.3. Modeling

The readmission of the CV patients admitted to the CCUs of the studied hospitals within 30 days after discharge was odellin using the following algorithms through the use of the IBM SPSS Modeler 18.0 software:

C5.0 [52], logistic regression [53], Decision list [54], Discriminant [55], Bayesian Network [53], K-Nearest Neighbors (KNN) [56], Random Forest [53], Support Vector Machine (SVM) [56], Chi-square Automatic Interaction Detection (CHAID) [57], Quantile Estimation after Supervised Training (Quest) [58], Classification and Regression (C&R) Tree [58], and Artificial Neural Network (ANN) [59].

The algorithms with an accuracy of >70%, namely SVM, CHIAD, artificial neural network, C5.0, KNN, logistic regression, C&R tree, and Quest algorithms, were selected.

The input variables of these models included 47 identified variables.

Before odelling, the data were classified into three categories: training, testing, and validation. The validation data were used to check the overfitting of each model. The data from one of the hospitals, which included 49 patients (18.6%) (23 readmitted and 26 non-readmitted), were considered validation data and were not used in the training and testing stages. The data from the remaining three hospitals were randomly divided between the training (70%) and testing (30%) classes.

The calibration of the studied algorithms can be seen in Appendix C.

2.5. Evaluation

To evaluate the algorithms, the accuracy, sensitivity, specificity, positive predictive value, and negative predictive value measures were used, and to select the best algorithm for readmission prediction, the area under the Receiver Operating Characteristic (ROC) curve was also calculated.

3. RESULTS

The final 47 variables obtained from the comprehensive review of the published articles and the consensus of specialists and subspecialists are presented in appendices A and B. The values of accuracy, sensitivity, specificity, positive predictive value, and negative predictive value of each data mining algorithm used in the present study to predict readmission of CV patients are presented in Table **1** by training, testing, and validation data.

Table 1. Evaluation and validation of data mining algorithms in predicting readmission of cardiovascular patients.

Model	Classification	Accuracy (%)	Sensitivity (%)	Specificity (%)	Positive Predictive Value (%)	Negative Predictive Value (%)
SVM algorithm	Training	98.10	50.38	89.04	89.18	91.54
	Testing	97.80	52.38	90.90	91.66	88.33
	External validation	100.00	100.00	100.00	100.00	100.00
	Mean	98.60				
CHIAD algorithm	Training	96.00	49.20	87.67	87.32	86.48
	Testing	78.90	53.06	69.69	72.22	67.64
	External validation	93.90	50.00	85.84	85.84	83.48
	Mean	89.60				
Artificial neural network algorithm	Training	98.20	50.73	93.05	93.24	95.71
	Testing	82.10	61.53	60.60	71.11	83.33
	External validation	89.40	42.94	92.38	90.12	73.48
	Mean	89.90				
C5.0 algorithm	Training	97.10	47.40	97.26	96.96	89.87
	Testing	76.00	53.70	75.75	78.37	75.75
	External validation	91.00	52.10	85.84	86.84	90.09
	Mean	88.00				
KNN algorithm	Training	90.90	44.91	90.27	88.33	77.38
	Testing	74.90	46.93	78.78	76.66	65.00
	External validation	91.90	54.94	78.09	81.30	90.10
	Mean	85.90				
Logistic regression algorithm	Data set	79.90	77.30	82.60	82.50	77.27

(Table 1) contd.....

Model	Classification	Accuracy (%)	Sensitivity (%)	Specificity (%)	Positive Predictive Value (%)	Negative Predictive Value (%)
C&R tree algorithm	Training	76.00	43.24	86.30	82.75	72.41
	Testing	73.70	50.00	81.81	81.81	72.97
	External validation	86.10	55.74	72.64	76.98	86.51
	Mean	78.60				
Quest algorithm	Training	69.50	33.66	91.78	85.00	63.80
	Testing	75.50	34.46	96.96	95.23	65.30
	External validation	78.30	45.45	84.90	82.41	72.58
	Mean	74.40				

Abbreviations: SVM: Support Vector Machine, ANN: Artificial Neural Network, RBF: Radial Basis Function, CHAID: CHi-square Automatic Interaction Detection, KNN: K-Nearest Neighbour, QUEST: QUantile Estimation after Supervised Training, C&R: Classification and Regression.

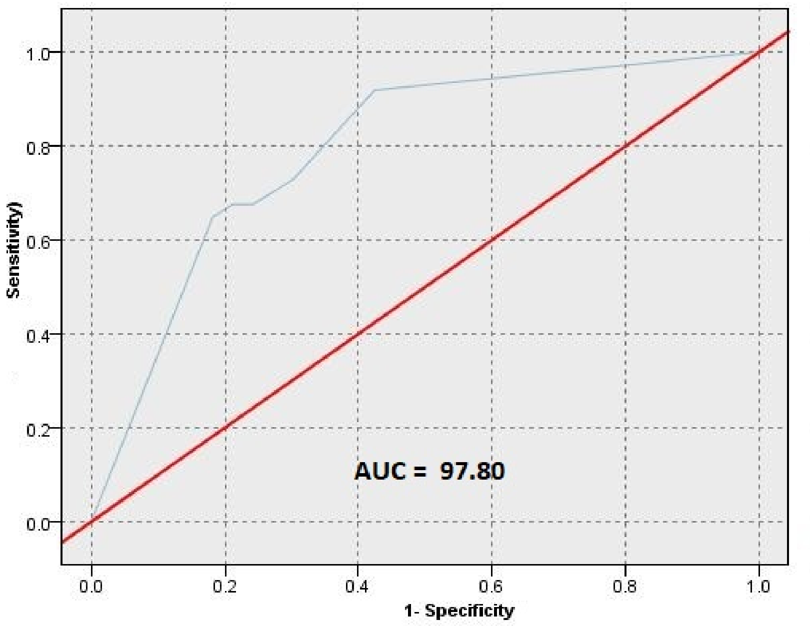

Fig. (1). The Receiver Operating Characteristic (ROC) curve of the Support Vector Machine (SVM) algorithm.

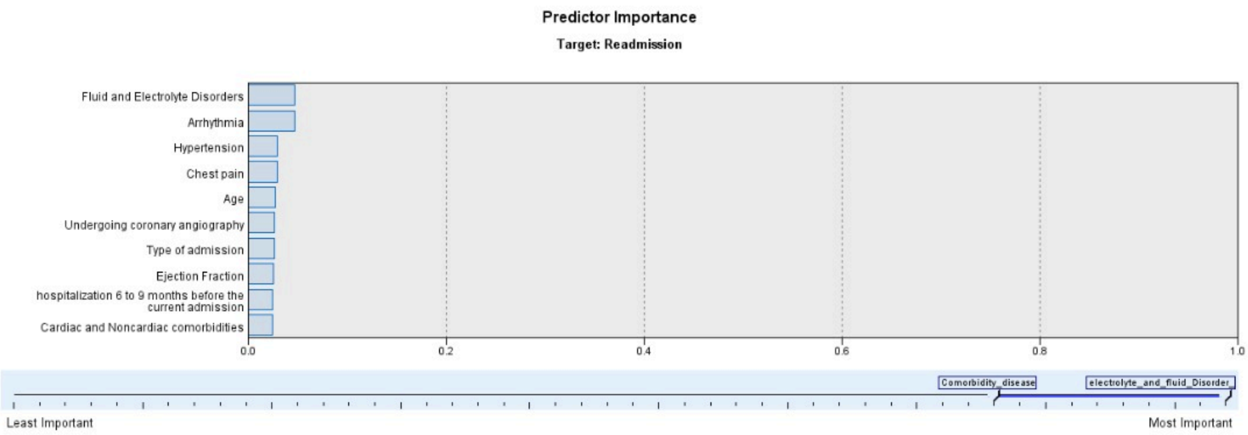

Fig. (2). Factors affecting the readmission of cardiovascular patients admitted to Coronary Care Units (CCUs) based on the Support Vector Machine (SVM) algorithm.

The results showed that the SVM algorithm was the best algorithm for predicting the readmission of CV patients (with 98.60% accuracy), while the Quest algorithm had the least accuracy (74.40%) (Table **1** and Fig. **1**).

Based on the results of the SVM algorithm, the factors affecting the readmission of CV patients admitted to the studied CCUs were age, arrhythmia, hypertension, chest pain, type of admission (elective or non-elective), cardiac or non-cardiac comorbidities, ejection fraction, undergoing coronary angiography, fluid and electrolyte disorders, and hospitalization 6-9 months before the current admission (Fig. **2**).

4. DISCUSSION

Readmission of CV patients is an important issue that can be investigated from various aspects, including the financial burden imposed on the patients and medical centers, the occupation of very valuable beds in the CCUs, and the lack of optimal use of facilities when providing services to CV patients [60]. This study aimed to predict the readmission for CV patients admitted to the CCUs of public hospitals in Shiraz, Iran, within 30 days after discharge in 2020 by using data mining techniques.

The results of the present study showed that the SVM algorithm, with an accuracy of 98.60%, was the best model for predicting readmission. The findings of the studies conducted by Yousefi *et al*. [61] and Zheng *et al*. [50] confirmed these results.

However, Golas *et al*. [62] reported that the accuracy of the deep unified networks (DUNs) model (76.4%) was higher than that of other models used to predict readmission of heart failure patients. In their cohort study, Wallmann *et al*. predicted the 30-day cardiovascular-disease-related readmissions from 2003 to 2009 at a Spanish academic tertiary care center using a predictive model developed by logistic regression and reported that the sensitivity, specificity, positive predictive value, and negative predictive value were 0.66, 0.7, 0.10 and 0.98, respectively [44]. Similarly, Desautels *et al*. conducted a study to identify patients who were likely to suffer unplanned ICU readmission at a single academic, tertiary care hospital in the UK from October 2014 to August 2016 on all patients who visited an ICU at some point during their stay using a logistic regression and showed that the accuracy of the logistic regression was 70.95% [45]. The results of these studies are inconsistent with those of the present study. Some reasons for the differences between the accuracy of the models in these studies and the present one can be differences in the population, hospital wards as well as the models used.

On the other hand, the study by Najafi-Vosough *et al*. indicated that the random forests algorithm was more accurate in predicting the readmission of heart failure patients than the SVM model [49]. The reason for the difference between their finding and that of the present study could be the difference in the type of variables and data studied. In their study, Futoma *et al*. compared data mining models to predict early hospital readmissions and suggested that the random forests and deep neural networks were better predictors of the readmission risk compared to the SVM algorithm [47], which is not in line with the results of the present study. The difference between the results could be due to the use of deep learning and some other techniques by Futoma *et al*. and the lack of using them in the present study. Another reason could be the difference in the studied populations (*i.e*., not only the patients with CV disease but also with obstructive pulmonary disease, pneumonia, and knee arthroplasty).

Awan *et al*. used machine learning methods to predict the readmission of heart failure patients and performed their modeling with the multilayer perceptron, logistic regression, random forest, decision tree, and support vector machine models. In their study, the multilayer perceptron model was selected as the best with the highest accuracy [48]. The reasons for the difference between the results of their study and the present research could be the imbalance of the data in their study as well as the difference in the studied populations (*i.e*., patients with a mean age of 81 years).

According to the results of the present study, the factors affecting readmission in the SVM algorithm included fluid and electrolyte disorders, arrhythmia, hypertension, chest pain, age, undergoing coronary angiography, type of admission (elective and non-elective), cardiac ejection fraction percentage, hospitalization 6-9 months before the current admission, and cardiac or non-cardiac comorbidities.

The present study indicated that fluid and electrolyte disorders were an effective factor in the readmission of CV patients. This is in line with the results of the studies conducted by Ranna *et al*. [38], Vogel *et al*. [27], and Lima *et al*. [11]. Due to the reduced cardiac ejection fraction percentage in patients with systolic heart failure, blood flow to the kidneys is also reduced, and kidney function is usually impaired. Kidney dysfunction in patients with heart failure is associated with the worsening of the symptoms of the disease and an increase in the length of hospital stay [63].

Also, usually, a large number of patients with CV diseases experience atrial fibrillation after heart surgery and are prone to persistent arrhythmias after discharge [64]. Therefore, it could be concluded that postoperative atrial fibrillation is common, and this is in line with the results of the studies conducted by Maniar *et al*., Iribarne *et al*., Arora *et al*., and Cedars *et al*. [34, 36, 65, 66].

In the present study, hypertension was identified as a factor affecting readmission, which is consistent with the results of the studies conducted by Kim *et al*. [67] and Bavishi *et al*. [68]. Hypertension is known as a gradual and quiet killer that can cause diseases, such as stroke. Due to the critical condition of patients studied in the present study, readmission is very common among people who also have hypertension. However, it is not in line with the results of the studies by Aranda Jr *et al*. [69] and Ferraris *et al*. [70], who stated that hypertension during hospitalization had an inverse relationship with readmission. The difference in the results could be due to differences in the studied populations and samples. Aranda *et al*. studied a population consisting of Medicare patients from the Centers for Medicare and Medicaid Services, and Ferraris *et al*. studied patients who underwent heart surgery.

Chest pain is one of the main symptoms of CV diseases [71] and is an effective factor in the readmission of CV patients in the present study. Given that chest pain can be a warning sign of cardiac ischemia, lack of adequate care for such patients might cause recurrent pain and readmission. The studies by Pellitier *et al*. [40] and Jarvinen *et al*. [41] confirmed the results of the present study.

The present study suggested that age was one of the factors affecting the readmission of CV patients. The results of the studies by Benuzilla *et al*. [72] and Bavishi *et al*. [68] confirmed this finding. Older people might not have all of their medical needs met before discharge. In addition, they may suffer from comorbidities and need more support and care in the community, and if this is not taken into account, they will be more likely to be readmitted.

The results of the SVM algorithm in the present study showed that undergoing coronary angiography was an influential factor in readmission because coronary angiography could cause complications. The femoral approach was the standard access site for coronary angiography, the use of which for angiography might cause complications, such as bleeding, hematoma, and embolism of the lower parts of the catheter entrance, due to the trauma to the artery wall [73, 74]. These complications could lead to readmission. The results of a study by Dunlay *et al*. confirmed these findings [75].

Based on the results of the present study, comorbidities (either cardiac or non-cardiac) are a factor determining the readmission of CV patients. It might be concluded that due to the lack of complete management and control of comorbidities and insufficient attention to them by patients and the severity of these diseases, CV patients with comorbidities usually need hospital care and readmission. According to the findings of previous studies, non-cardiac comorbidities [26, 76 - 83] and cardiac comorbidities [17, 20, 26, 68, 85 - 88] have been factors influencing the readmission of CV patients.

The present study had some limitations, including its cross-sectional design, small sample size as well as the non-use of complete pharmacological and laboratory data of the studied patients.

CONCLUSION

According to the results of the present study, SVM was the best algorithm in terms of accuracy. Based on the results of this algorithm, the factors affecting the readmission were age, arrhythmia, hypertension, chest pain, type of admission (elective and non-elective), cardiac or non-cardiac comorbidities, ejection fraction, undergoing coronary angiography, fluid and electrolyte disorders, and hospitalization 6-9 months before the current admission. Therefore, it is recommended to teach the patients, especially the older ones, about the regular use of the drugs and following physician advice after discharge. It is also suggested to train medical staff about the relevant and up-to-date options in order to reduce the likelihood of patient readmissions.

AUTHOR CONTRIBUTIONS

RR, PB, and MN designed the study. MS collected the required data. MK and MS analyzed the data. All authors interpreted the data. RR and MS wrote the first draft of the manuscript. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Shiraz University of Medical Sciences Ethics Committee (Code: IR.SUMS.REC.1398.272).

HUMAN AND ANIMAL RIGHTS

No animals were used in this research. All procedures performed in studies involving human participants were in accordance with the ethical standards of institutional and/or research committee and with the 1975 Declaration of Helsinki, as revised in 2013.

CONSENT FOR PUBLICATION

To participate in this study, all the patients gave their written informed consent, and all were assured of the confidentiality of their responses.

STANDARDS OF REPORTING

STROBE guidelines were followed.

AVAILABILITY OF DATA AND MATERIALS

The datasets used and/or analyzed during the current study are available from the corresponding author [R.R] upon reasonable request.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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APPENDIX

Appendix A: Qualitative variables identified in the business understanding step.

	Variables	Data variable categories	Variable definition	Type	References		Variable	Data variable categories	Variable definition	Type	References
1	Gender	Female = 0 Male = 1	Male & female	Input	[14, 15]	22	Having cardiac or non-cardiac comorbidities	No = 0 Yes = 1	Having cardiac or non-cardiac comorbidities at the time of admission	Input	[29, 30, 89]
2	Marital status	Married = 0 Single = 1	Patient's marital status at the time of admission to the CCU	Input	[29, 90]	23	Having peripheral artery diseases	No = 0 Yes = 1	Diseases that affect blood vessels outside the heart and brain, such as the arms, legs, etc.	Input	[83]
3	Education level	Illiterate = 0 Elementary = 1 Middle school = 2 Diploma = 3 Academic education = 4	Patient education level at the time of admission to the CCU	Input	[91]	24	Having chest pain	No = 0 Yes = 1	Having chest pain, according to the patient's report and the contents of the patient's medical records	Input	[40, 41, 68, 92]
						25	Having depression	No = 0 Yes = 1	Having patient depression, according to the physician's diagnosis and the patient's medical records	Input	[42]
						26	Pregnancy	No = 0 Yes = 1	Being pregnant, according to the patient's report and the contents of the patient's medical records	Input	[89]
4	Occupation	Self-employed = 0 Housewife = 1 Employee = 2 Retired = 3	Being self-employed, housewife, employee, or retired	Input	[92]	27	Having infection	No = 0 Yes = 1	Having patient infection at the time of admission to and during hospitalization in the CCU	Input	[33 - 36]
						28	Undergoing dialysis	No = 0 Yes = 1	Having undergone dialysis at the time of admission to the CCU	Input	[32]
5	Housing status	Owner = 0 Tenant = 1	Being an owner or tenant at the time of admission to the CCU	Input	[93]	29	Poor right ventricular function	No = 0 Yes = 1	Poor right ventricular function according to the echocardiographic results	Input	[94]

Variables		Data variable categories	Variable definition	Type	References
6	Governmental health insurance coverage	No = 0	Having governmental health insurance coverage		[17, 16]
		Yes = 1		Input	
7	Place of residence	Urban area = 0	Being a resident of a city or a village	Input	[95]
		Rural area = 1			
8	Nationality	Iranian = 0	Being Iranian or a foreigner	Input	[13, 27]
		Foreigner = 1			
9	Taking herbal medicines	No = 0	Taking herbal medicines after discharge	Input	Specialists' and sub-specialists' consensus
		Yes = 1			
10	Following a special diet suitable for cardiovascular patients	No = 0	Following a special diet suitable for cardiovascular patients after discharge	Input	Specialists' and sub-specialists' consensus
		Yes = 1			
11	Discharge on weekend	No = 0	Discharge on the weekend (Thursday and Friday)	Input	[98, 99]
		Yes = 1			
12	Destination after discharge	Home = 0	Destination of patients after discharge from hospital (home or other medical centers or non-medical centers, such as nursing homes)	Input	[19, 24 - 26]
		Other medical centers = 1			
		Non-medical centers = 2			
13	Type of admission	Elective = 0	Patient status at the time of admission	Input	[22, 23]
		Non-elective (emergency) = 1			
14	Discharge season	Spring = 0	The season when the patient was discharged	Input	[103]
		Summer = 1			
		Fall = 2			
		Winter = 3			

Variable		Data variable categories	Variable definition	Type	References
30	Undergoing coronary angiography	No = 0	Having or not having undergone coronary angiography at the time of hospitalization	Input	Specialists and sub-specialists consensus
		Yes = 1			
31	Having arrhythmia	No = 0	Having abnormal heart rhythm	Input	[30]
		Yes = 1			
32	Training the patient on how to take medications	No = 0	Existence of the drug use instruction sheet in the patient's medical records	Input	[92]
		Yes = 1			
33	Prescribing special medicines	No = 0	Type of special medicines prescribed by physicians for after discharge, such as beta-blockers and anticoagulants	Input	[29, 79, 96]
		Yes = 1			
34	Fluids and electrolyte disorders	No = 0	Disorders of factors, such as creatinine, potassium, etc.	Input	[37, 38]
		Yes = 1			
35	Hematocrit level	Normal = 0	Normal: 40% to 52% Abnormal: <40	Input	[39, 97]
		Abnormal = 1			
36	Hemoglobin levels	Normal = 0	Normal: 12 to 16.5 g/dl	Input	[36, 100, 101]
		Abnormal = 1			
37	Red blood cell levels	Normal = 0	Normal: 4.50 to 5.90 ml / m3	Input	[102]
		Abnormal = 1			
38	Blood cholesterol levels	Normal = 0	200 mg / dL is normal, and above this value is abnormal.	Input	[103]
		Abnormal = 1			

	Variables	Data variable categories	Variable definition	Type	References
15	Hospitalization 6 to 9 months before the current admission	No = 0	Hospitalization 6-9 months before the current admission	Input	[79, 92, 98]
		Yes = 1			
16	Physician's Certificate	Specialist = 0	Under-treatment by a specialist or a sub-specialist	Input	[104]
		Sub-specialist = 1			
17	Hospital ownership	Public = 0	Being public or private	Input	[105]
18	Type of hospital	Teaching = 0	Being teaching or non-teaching	Input	[106]
19	Having hypertension	No = 0	Blood pressure> 14 mm Hg	Input	[27, 68]
		Yes = 1			
20	Having hyperlipidemia	No = 0	Increased levels of lipids in the blood	Input	[109]
		Yes = 1			
21	Readmission	No = 0	The patient returns to the hospital within 30 days after discharge	**Target**	[1, 2]
		Yes = 1			

	Variable	Data variable categories	Variable definition	Type	References
39	Principal diagnoses	Cardiac ischemia = 0	Principal diagnoses by physicians at the time of admission to the hospital	Input	Specialists' and sub-specialists' consensus
		Other heart diseases = 1			
		Cerebrovascular diseases = 2			
		Blood pressure diseases = 3			
		Chronic rheumatic disease = 4			
		Complications of prostheses, implants, and grafts = 5			
		Abnormal clinical signs not classified elsewhere = 6			
40	Heartbeat	Normal = 0	Normal: 60 to 100 beats/ min	Input	[107]
		Abnormal = 1			
41	Smoking	No = 0	Consumption of hookah, cigarette, etc.	Input	[87, 108]
		Yes = 1			
42	Discharge status	With the physician's permission = 0	Discharge with physician's permission or voluntarily with personal consent	Input	(23, 24
		Voluntarily with personal consent =1			
43	Surgery	No = 0	Having undergone heart surgery during hospitalization	Input	[13, 39]
		Yes = 1			

Appendix B: Quantitative variables identified in the business understanding step.

Reference	Variable definition	Variable	
[10 - 13]	Patient's age at the admission time	Age	1
[105]	Patient's weight at the admission time	Weight	2
[18 - 21]	Length of stay in hospital	Length of stay	3
[53]	Number of active and available hospital beds	Hospital bed	4
[110]	The ratio of nurses to the CCU beds	The ratio of nurses to the CCU beds	5
Specialists' and sub-specialists' consensus	The ratio of physicians to the CCU beds	The ratio of physicians to the CCU beds	6
[13, 31, 32]	kg/m^2, where kg is a patient's weight in kilograms, and m^2 is his/her height in meter square	Body Mass Index	7
[15, 86]	It is a measure used by physicians to calculate the percentage of blood coming out of the ventricles in each contraction.	Ejection fraction (EF) percentage	8

Appendix C: Calibration of the studied algorithms.

Model	Specification	Value	Model	Specification	Value
SVM	Use partitioned data	True	KNN	Use partitioned data	True
	Partition	Partition		Partition	Partition
	Stopping criteria	1.0E-03		What type of analysis do you want to perform?	Predict a target field
	Kernel type	RBF		What is your objective?	Balance speed and accuracy
	Regularization parameter	10		Focal face value	0
	Regression precision (ε)	0.1		Normalize range input	True
	RBF gamma	0.1		Distance computation	Euclidean metric
	Gamma	1		Prediction for range target	The mean of the nearest neighbor value
	Bias	0		Automatically select K	True
	Degree	3		K	3
	Algorithm	SVM		Minimum	3
	Model type	Classification		Maximum	5
NN	N Neural network model	Multilayer perceptron (MLP)		Number to select	10
	Hidden layer	Automatically compute the number of units		Minimum change	0.01
	Hidden layer 1	1		Number of folds	10
	Hidden layer 2	0	C&R Tree	Use partitioned data	True
	Random seed	229176228		Partition	partition
	Replicate results	True		Calculate predictor importance	True
	Minute	15		Level below root	5
	Use maximum training time (per component model)	True		Model	Expert
	Overfit prevention set (%)	30		Maximum surrogate	5
	Missing value in predictors	Delete list wise		The minimum change in the impurity	0.0
	Method	Neural network		Impurity measure for categorical target	Gini
CHAID	Use partitioned data	True		Stopping criteria	Use percentage
	Partition	Partition		Minimum records parents branch (%)	2
	Calculate predictor importance	True		Minimum records child branch (%)	1
	Method	CHAID		Prune tree	True
	Level below root	5		Prior probabilities	Based on training data
	Alpha for splitting	0.05	QUEST	Use partitioned data	True
	Alpha for merging	0.05		Partition	Partition
	Epsilon for convergence	0.001		Calculate predictor importance	True
	Use Bonferroni adjustment	true		Level below root	5
	Maximum iterations for convergence	100		Mode	Expert
	Chi-square method	Pearson		Maximum surrogates	5
	Stopping criteria	Use percentage		Alpha for splitting	0.05
	Minimum records parents branch (%)	2		Stopping criteria	Use percentage
	Minimum record child branch (%)	1		Minimum records parents branch (%)	2
C5.0	Use partitioned data	True		Minimum record child branch (%)	1
	Partition	Partition		Prune tree	True
	Calculate predictor importance	True		Prior probabilities	Based on training data
	Output type	Decision tree		Algorithm	QUEST
	Mode	Simple		Model type	Classification
	Favor	Accuracy			
	Tree depth	10			
	Expected noise (%)	0			
	Model type	Classification			

Abbreviations: SVM: Support Vector Machine, ANN: Artificial Neural Network, RBF: Radial Basis Function, CHAID: CHi-square Automatic Interaction Detection, KNN: K-Nearest Neighbour, QUEST: QUantile Estimation after Supervised Training, C&R: Classification and Regression

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