Original Article

A Survival Prediction Model of Self-Immolation Based on Machine Learning Techniques

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Abstract

Background: Self-immolation is one of the violent methods of suicide in developing countries. Predicting the survival of self-immolation patients helps develop therapeutic strategies. Today, machine learning is widely used in diagnosing diseases and predicting the survival of patients. This study aims to provide a model to predict the survival of self-immolation patients using machine learning techniques.

Materials and Methods: A retrospective cross-sectional study was conducted on 445 hospitalized self-immolated patients admitted to a burn hospital between March 2008 and 2019. Python programming language version 3.7 was used for this goal. All possible machine-learning algorithms were used. Gradient Boosting, support vector machine (SVM), random forest, multilayer perceptron (MLP), and k-nearest neighbors algorithm (KNN) were selected as the high-performance machine learning technique for survival prediction, and then they were compared by evaluation metrics such as F1 score, accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve (AUC). Based on this comparison, the best model was reported.

Results: SVM was the best algorithm. F1 score, accuracy, and AUC for this machine-learning model were 91.8%, 91.9%, and 0.96, respectively. The machine learning model results revealed that surgical procedures, score, length of stay, anatomical region, and gender obtained the most important and had more impact than other factors on patients' survival prediction.

Conclusion: In this paper, machine learning algorithms were used to create a model for survival of self-immolation patients. The results of this study can be used as a model for predicting self-immolation patients' survival, better treatment management, and setting up policies and medical decision-making in burn centers.

Keywords: Data mining, machine learning, prediction, self-immolation, survival

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Introduction

Self-immolation, as one of the most severe and violent methods of suicide, is usually done by burning flammable substances such as gasoline or kerosene (paraffin), with more than 70% of deaths.[1] The history of self-immolation is ancient and culturally and politically more important than other methods of suicide because it is a method of protesting society's social and political structure, is very deadly, and has serious psychosocial consequences for survivors and their families.[2] In some countries, self-immolation, as a violent and dramatic way of suicide, is considered a common form of suicide.[3]

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Self-immolation is a rare method of suicide in the developed countries of the Western world, and it happens very rarely in these countries (0.06-1%).[4] Nevertheless, in developing countries such as India, Sri Lanka, and the Middle East countries, the rate of self-immolation is high.[5] Furthermore, in low-income countries such as Africa, the Middle East, and South Asia, it accounts for 40-70% of all suicides.[6] In Iran, the rate of self-immolation is estimated to be 4.5 cases per 100,000 population, and it is the cause of 16% of burns in hospitals.[7] Self-immolation in Iran includes 70% of successful suicides,[5] and 80% of self-immolation cases expire due to the severity of the burn.[8] Because burns are the most devastating type of trauma, they impose a high cost on the health care system, and their management represents a changing therapeutic challenge.[9] Patients who suffer burns need different and complex care depending on the severity of burn injuries, from local wound care for superficial burns to more severe burns that may require surgery.[10]

One of the crucial steps in managing burn patients is the classification of treatment priorities and care protocols, determining the prognosis of outcomes and mortality rates.[9] Efforts to develop prognostic scales have led to the development of predictive tools. Burn outcome prediction tools have been published under the headings of model and system scoring, such as the Baux system, which is calculated based on the age and level of the burn,[11] or the abbreviated burn severity index (ABS) scoring system, which is calculated based on gender, age, degree of burn, and level of burn.[12] However, predicting the model to determine outcomes with scoring systems is difficult because some mortality indicators are overemphasized or sometimes underestimated. Some do not apply to all age groups, and others are outdated.[13]

Machine learning is a subset of artificial intelligence that uses computer algorithms that automatically improve through experience. Today, machine learning techniques are used in health research, such as diagnosing types of cancer and diabetes, but their application is not limited to medical diagnosis. Predicting the survival of patients is also one of the important applications of these techniques.[14] Considering that it is challenging to translate the vast amount of research about suicide risk factors into clinically useful models for predicting suicides, there is hope that machine learning can solve the problem of predicting suicides.[15] However, machine learning helps to discover nonlinear patterns among factors influencing the survival of self-immolation patients. As mentioned, self-immolation is one of the most common methods of suicide in Iran, which is considered one of the East Asian countries, so it is necessary to predict survival in self-immolation to triage self-immolation patients and provide them with special care. The present study was conducted to provide a model to predict the survival of self-immolation patients based on machine learning techniques.

Materials and Methods

Patients

A retrospective cross-sectional study was conducted on hospitalized self-immolated patients admitted to a center affiliated between March 2008 to March 20, 2019.

Medical records of 445 patients in all age groups who committed self-immolation with the approval of clinicians and psychiatrists were included in the study. Available data of medical records of these patients were gathered. Variables were categorized into six dimensions: demographic information, admission information, self-immolation information, social history, inpatient data, and clinical history [Table 1]. Data were collected by a trained Medical Informatics student not involved in the patient's care and analysis.

Modeling

The schematic representation of the methodology of the study is shown in Figure 1. After data gathering, data preprocessing was performed to prepare the dataset for modeling. High dimensionality in the dataset led to complexity in data analysis.[16] Therefore, preprocessing was done to reduce dimensions. In this stage, using statistical analysis helps with feature selection. Feature selection was made statistically, assessing the correlation between each feature and patients' survival. However, each feature with a significant relationship to survival was selected for the next step.

Pearson correlation was the technique that we used for feature selection. Pearson correlation-based feature selection is used to find the best subset of features and is integrated with search strategies. The rank correlation coefficient measures the similarity between two features and can be used to evaluate the relationship's impact. The rank correlation statistics include the Spearman correlation, Kendall correlation, and Kruskal and Goodman coefficients. Spearman correlation measures the relationship between two features using a uniform function. The Kendall correlation coefficient measures part of the ranks between two datasets.[17]

Python programming language version 3.7 was used for the modeling phase. All possible machine-learning algorithms were applied to the dataset. In all the implemented models 5-Fold cross-validation technique was used.

Evaluation

Evaluation metrics of the model were performed by a clinical expert (who was not involved in the research) until the output was clinically significant. In this phase, included factors in the previous step were reviewed, and the clinical specialist decided on the inclusion and exclusion of factors [Figure 1].

Gradient Boosting, support vector machine (SVM), random forest, multilayer perceptron (MLP), and k-nearest neighbors algorithm (KNN) were selected as the high-performance machine learning technique for survival prediction. Predictor importance and misclassification costs were estimated in the model evaluation phase. A well-performed machine learning

Table 1: Characteristics of self-immolated patients

Variables	Total	Death	Alive	*P*
Demographic information				
Age	33	33	33	0.9382
Gender				0.184
Female	204 (45.843)	98 (42.795)	106 (49.074)	
Male	241 (54.157)	131 (57.205)	110 (50.926)	
Marriage status				0.2392
Single	189 (42.568)	106 (46.288)	83 (38.605)	
Married	244 (54.955)	117 (51.092)	127 (59.070)	
Divorce/widow	11 (2.477)	3 (2.620)	5 (2.326)	
Admission information				
Number of admission				>0.05#, *P*=0.02599
1	439 (98.874)	229 (100)	210 (97.674)	
2	5 (1.124)	0	5 (2.326)	
Length of stay	8	6	10	<0.001*
Insurance				0.4454
No	236 (53.273)	126 (55.022)	110 (51.402)	
Yes	207 (46.727)	103 (44.978)	104 (48.598)	
Self-immolation information				
Time interval from incident to hospitalization	0	0	0	0.07755
Self-burning place				0.877
Outdoor	100 (23.866)	51 (23.502)	49 (24.257)	
Indoor	318 (75.895)	165 (76.037)	153 (75.743)	
Self-burning time				0.5864
Morning	130 (31.175)	71 (33.649)	59 (28.641)	
Noon	87 (20.863)	40 (18.957)	47 (22.816)	
Evening	108 (25.899)	56 (26.540)	52 (25.243)	
Night	92 (22.062)	44 (20.853)	48 (23.301)	
Flammable substance				<0.001*
Petrol	261 (58.784)	153 (67.105)	108 (50)	
Electricity	6 (1.351)	2 (0.877)	4 (1.852)	
Alcohol	54 (12.162)	15 (6.579)	39 (18.056)	
Gas	28 (6.306)	8 (3.509)	20 (9.259)	
Oil	63 (14.189)	37 (16.228)	26 (12.037)	
Tinner and acetone	32 (7.207)	13 (5.702)	19 (8.796)	
Accompanying events				0.8286
No events	413 (92.809)	212 (92.576)	201 (93.056)	
Self-harm	15 (3.371)	8 (3.493)	7 (3.241)	
Self-poisoning	9 (2.022)	4 (1.747)	5 (2.315)	
Psychedelic drugs	2 (0.449)	2 (0.873)	0 (0)	
Others	6 (1.348)	4 (1.310)	3 (1.389)	
Social history				
Place of lives				0.2282
Rural	23 (5.204)	9 (3.965)	14 (6.512)	
Urban	419 (94.796)	218 (96.035)	201 (93.488)	
Income				0.1366
Low	229 (52.765)	111 (50.455)	118 (55.140)	
Lower-middle	156 (35.945)	77 (35.000)	79 (36.916)	
Upper-middle	43 (9.908)	29 (13.182)	14 (6.542)	
High income	6 (1.382)	3 (1.364)	3 (1.402)	
Level of education				0.0254 *
Illiterate	32 (7.512)	21 (9.589)	11 (5.314)	
High school	216 (50.704)	121 (55.251)	95 (45.894)	
Diploma	123 (28.873)	52 (23.744)	71 (34.300)	

Contd...

Table 1: Contd...

Variables	Total	Death	Alive	*P*
Social history				
University	55 (12.911)	25 (11.416)	30 (14.493)	
Conflict				0.8671
No	406 (91.236)	208 (90.830)	198 (91.667)	
Yes	39 (8.764)	21 (9.170)	18 (8.333)	
Suicide history				0.1554
No	395 (88.764)	208 (90.830)	187 (86.574)	
Yes	50 (11.236)	21 (9.170)	29 (13.426)	
Homicide idea				0.1595
No	421 (94.607)	220 (96.070)	201 (93.056)	
Yes	24 (5.393)	9 (3.930)	15 (6.944)	
Drug abuse				
Tobacco				0.1502
Yes	130 (29.213)	60 (26.201)	70 (32.407)	
No	315 (70.787)	169 (73.799)	146 (67.593)	
Cannabis				1
Yes	9 (2.022)	5 (2.183)	4 (1.852)	
No	436 (97.978)	224 (97.817)	212 (98.148)	
Opioids				0.251
Yes	83 (18.527)	38 (16.594)	45 (20.833)	
No	362 (81.348)	191 (83.406)	171 (79.167)	
Stimulants				0.361
Yes	73 (16.404)	34 (14.847)	39 (18.056)	
No	372 (83.596)	195 (85.153)	177 (81.944)	
Alcohol				0.315
Yes	22 (4.911)	9 (3.947)	13 (6.019)	
No	422 (95.045)	219 (96.053)	203 (93.981)	
Family problems				0.2076
Yes	257 (57.833)	126 (55.022)	84 (39.070)	
No	187 (42.117)	103 (44.978)	131 (60.930)	
Inpatient data				
Score				<0.001 *
II	96 (21.573)	12 (5.240)	84 (38.889)	
III	36 (8.090)	20 (8.734)	16 (7.407)	
II and III	313 (70.33)	197 (86.02)	116 (53.704)	
Anatomical Area				
Head				<0.001 *
No	88 (19.775)	27 (11.790)	61 (28.241)	
Yes	357 (80.225)	202 (88.210)	155 (71.759)	
Neck				0.001728 *
No	124 (27.679)	49 (21.397)	75 (34.722)	
Yes	321 (72.135)	180 (78.603)	141 (65.278)	
Trunk				<0.001 *
No	86 (19.326)	16 (6.987)	70 (32.407)	
Yes	359 (80.674)	213 (93.013)	146 (67.593)	
Hands				<0.001 *
No	92 (20.767)	30 (13.158)	62 (28.837)	
Yes	351 (79.233)	198 (86.842)	153 (71.163)	
Feet				<0.001 *
No	195 (43.820)	48 (20.961)	147 (68.056)	
Yes	250 (56.180)	181 (79.039)	69 (31.944)	
Genital region				<0.001 *
No	333 (74.831)	125 (54.585)	208 (96.296)	

Contd...

Table 1: Contd...

Variables	Total	Death	Alive	*P*
Anatomical Area				
Yes	112 (25.169)	104 (45.415)	8 (3.704)	
Performed Surgeries				
Graft				<0.001 *
No	252 (56.885)	200 (88.106)	52 (24.074)	
Yes	191 (43.115)	27 (11.894)	164 (75.926)	
Excision				<0.001 *
No	206 (46.396)	146 (64.035)	60 (27.778)	
Yes	238 (53.604)	82 (35.965)	156 (72.222)	
Escharotomy				0.0165 *
No	300 (68.027)	142 (62.832)	158 (73.488)	
Yes	141 (31.973)	84 (37.168)	57 (26.512)	
Debridement				<0.001 *
No	186 (41.798)	127 (55.459)	59 (27.315)	
Yes	259 (58.202)	102 (44.541)	157 (72.685)	
Bandage				0.003*
No	211 (47.630)	93 (40.789)	118 (54.884)	
Yes	232 (52.370)	135 (59.211)	97 (45.116)	
Amnion				<0.001 *
No	412 (92.584)	225 (98.253)	187 (86.574)	
Yes	33 (7.416)	4 (1.747)	29 (13.426)	
Fasciotomy				0.4508
No	438 (98.427)	224 (97.817)	214 (99.074)	
Yes	7 (1.573)	5 (2.183)	2 (0.926)	
Catheterization				0.2217
No	380 (85.393)	191 (83.406)	189 (87.500)	
Yes	65 (14.607)	38 (16.594)	27 (12.500)	
Drug therapy				0.8484
No	89 (20.090)	45 (19.737)	44 (20.465)	
Yes	354 (79.910)	183 (80.263)	171 (79.535)	
Clinical history				
Mental disorder				0.3356
No	210 (47.191)	103 (44.978)	107 (49.537)	
Yes	235 (52.809)	126 (55.022)	109 (50.463)	
Depression				0.5536
No	276 (62.022)	139 (60.699)	137 (63.426)	
Yes	169 (37.978)	90 (39.301)	79 (36.574)	
Dementia				0.124
No	441 (99.101)	225 (98.253)	216 (100)	
Yes	4 (0.899)	4 (1.747)	0 (0)	
BMD				0.1162
No	427 (95.955)	223 (97.380)	204 (94.444)	
Yes	18 (4.045)	6 (2.620)	12 (5.556)	
Schizophrenia				0.6976
No	432 (97.079)	223 (97.389)	209 (96.759)	
Yes	13 (2.921)	6 (2.620)	7 (3.241)	
Paranoid personality disorder				0.4508
No	438 (98.427)	224 (97.817)	214 (99.074)	
Yes	7 (1.573)	5 (2.183)	2 (0.926)	
PTSD				1
No	438 (98.427)	225 (98.253)	213 (98.611)	
Yes	7 (1.573)	4 (1.747)	3 (1.389)	
Sleep disorder				0.2866

Contd...

Table 1: Contd...

Variables	Total	Death	Alive	*P*
No	436 (97.977)	223 (96.956)	213 (99.070)	
Yes	9 (1.802)	7 (3.043)	2 (0.930)	
Physical disease				0.9213s
No	347 (77.978)	179 (78.166)	168 (77.778)	
Yes	98 (22.022)	50 (21.834)	48 (22.222)	
Medications usage				0.267
No	393 (88.315)	206 (89.956)	187 (86.574)	
Yes	52 (11.685)	23 (10.044)	29 (13.426)	
Mental medications usage				0.2454
No	375 (84.459)	197 (86.404)	178 (82.407)	
Yes	69 (15.541)	31 (13.596)	38 (17.593)	
Antianxiety medications				0.2784
No	387 (86.966)	203 (88.646)	184 (85.185)	
Yes	58 (13.034)	26 (11.354)	32 (14.815)	
Antipsychotic medications				0.8114
No	418 (94.144)	215 (93.886)	203 (94.419)	
Yes	26 (5.856)	14 (6.114)	12 (5.581)	
Mood stabilizer medications				0.1525
No	419 (94.582)	220 (96.070)	199 (92.991)	
Yes	24 (5.418)	9 (3.930)	15 (7.009)	
Antidepressant medications				0.1999
No	393 (88.514)	207 (90.393)	186 (86.512)	
Yes	51 (11.486)	22 (9.607)	29 (13.488)	

model was selected according to the evaluation metrics. F1-Score, sensitivity, specificity, precision, and accuracy and area under the receiver operating characteristic (ROC) curve (AUC)[18] were reported. Based on effective factors found in the model, the dataset was analyzed again through the finalized model.

Results

Evaluation metrics

The performance of five algorithms was evaluated in terms of F1 score, accuracy, specificity, sensitivity, precision, and AUC, using the 5-fold validation method [Table 2]. Based on comparing each evaluation metric for all the implemented models, SVM obtained an F1 score of 91.8, an accuracy of 91.9, and an AUC of 0.96 and performed better than other algorithms. Since SVM outperformed other algorithms, results showed that Gradient Boosting obtained the nearest evaluation metrics to SVM with 91.4 for the F1 score, 91.6 for accuracy, and 0.97 for AUC. The ROC diagrams of SVM and Gradian boosting are shown in Figure 2. Also, the confusion matrix of SVM as the best model is presented in Figure 3.

The Pearson Correlation feature selection technique selected the subset of features. Among all the features in the original dataset, 30 features were selected for modeling [Table 3].

Variable importance

In total, 445 patients were included in the data mining procedure, 204 were female, and 241 were male. The patients' age range is 11-84, with a median of 33 years. More than half of the patients are married (244, 55%), and (189,42%) are single. Baseline characteristics are shown in Table 1.

A machine learning approach was carried out on the model building from 445 patients. The machine learning model results revealed that surgical procedures, score, length of stay, anatomical region, and gender could be more effective than other factors in patients' survival. The order of features in Table 4 could be clinically more consistent based on experience.

Discussion

This study was conducted to investigate the factors affecting the survival of self-immolation patients based on machine learning modeling. Suicide is reported as one of the three causes of death between the ages of 15 and 44.[19] In the present study, the highest rate of self-immolation was at the average age of 33 years. According to the results of this study, males commit self-immolation more than females, and 57.2% of men who commit self-immolation die. In previous studies, it has been shown that there is a significant difference in the suicide rate between men and women, and in general, men commit self-immolation more than women.[20]

According to the findings, most of the participants were married. Unlike other methods of suicide, which are more common among single people, self-immolation happens more often among married people. It is due to the pressures of married life, especially economic problems. In Ahmadi

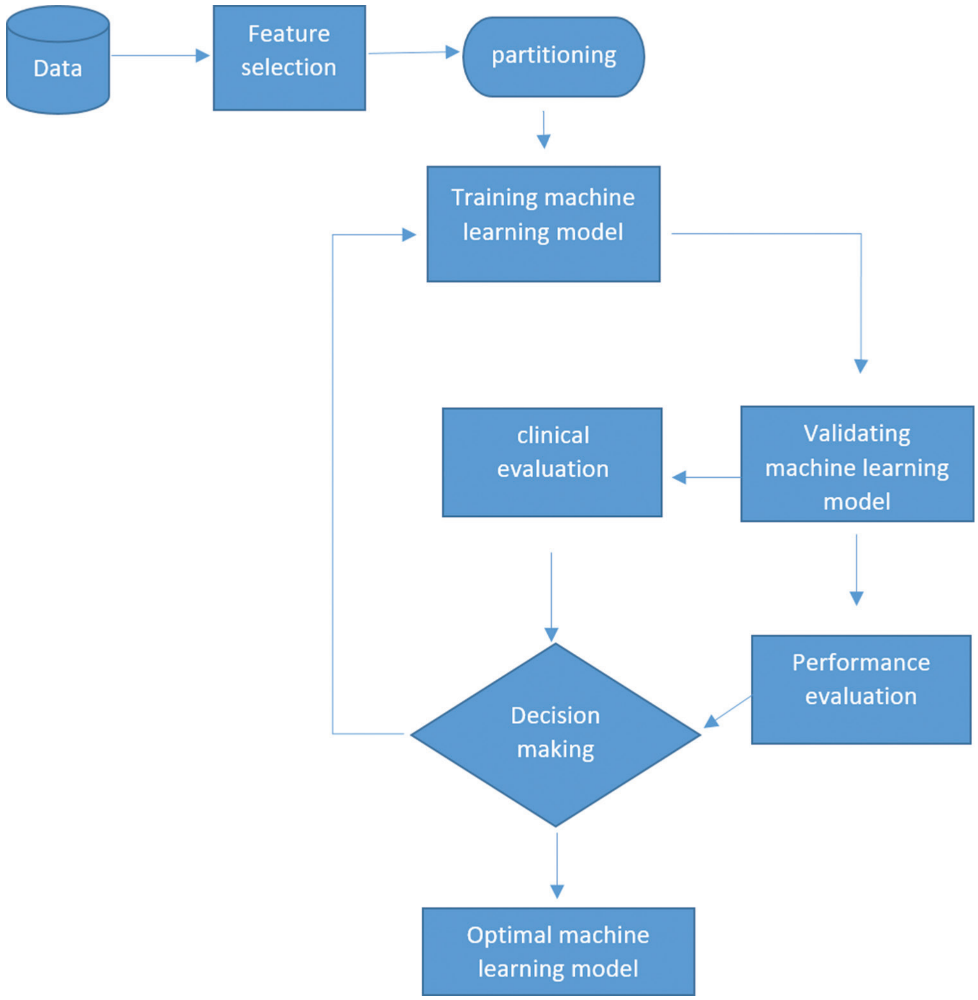

Figure 1: Methodology of modeling

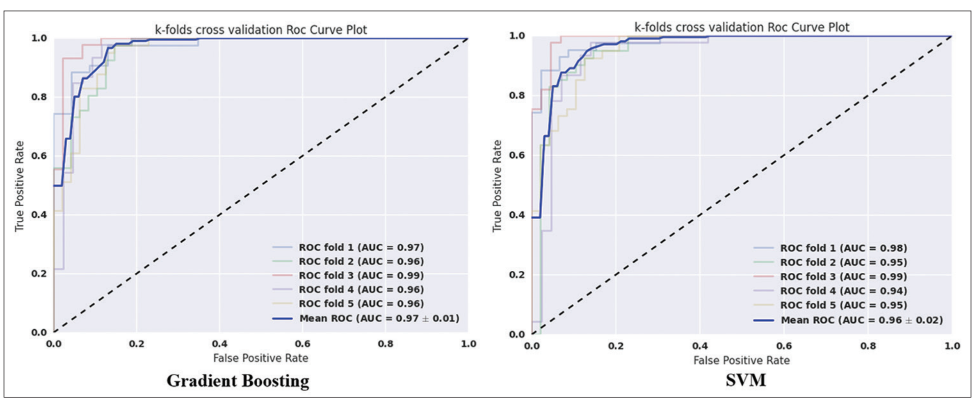

Figure 2: ROC curve diagram of the best two models

et al.[19] and Kikhavani *et al.*[21] studies, it has been stated that the problems of married life and forced marriage can be one of the causes of self-immolation among married people. Also, over half of the self-immolated people had less than a diploma. In this regard, the results of Mojahedi *et al.*'s study[20] also showed that the suicide rate has a significant relationship with the low level of education, and having a high level of education can play a protective role in this field.

Income level and family problems were among the social factors investigated in this study. 52.8% of patients were unemployed and had no income in some way, and 57.8% of them had family problems. Studies have shown that unemployed young men are more affected by self-immolation.[22] Also, family and marital problems are the most important reasons influencing self-immolation.[23] In general, the social and economic status of people has a significant impact on self-immolation.[19,24] In

Table 2: Features importance

Variables	Accuracy	Specificity	Sensitivity	Precision	AUC	F1 Score
SVM	91.9	89.5	94.3	89.4	0.96±0.02	91.8
Gradient Boosting	91.6	90.4	93.0	90.2	0.97±0.01	91.4
Random Forest	91.2	87.5	95.2	87.6	0.96±0.02	91.2
KNN	90.7	90.0	91.6	89.7	0.95±0.02	90.5
MLP	89.2	87.8	90.7	87.8	0.95±0.02	88.8

Table 3: Features selection

Number	Features
1	PlaceType
2	Gender
3	Length of stay
4	Marriage
5	Age
6	Acttime
7	Opioids
8	Tobacco
9	Events
10	HTN
11	Renal disease
12	Heart disease
13	Lung disease
14	Digestive disease
15	Cancer
16	Oil
17	Petrol
18	Neck
19	Feet
20	Trunk
21	Head
22	Genital region
23	Scarotomy
24	Graft
25	Score
26	Excision
27	Catheterization
28	Drug Therapy
29	Anti-anxiety medication
30	Medicine Use

Table 4: Survival predictors based on the machine learning model

Rank	Predictor	Importance
1	Graft	0.6
2	Score	0.12
3	Length of stay	0.1
4	Feet	0.07
5	Trunk	0.05
6	Gender	0.03

a study conducted in Iran, Ramim *et al.*[11] reported that the economic status of most people who committed self-immolation in Tehran in 2013 was poor and unfavorable. Also, Macedo *et al*. stated in their study that unemployment is one of the leading causes of self-immolation.[25]

The present study investigated mental disorders as an essential clinical factor in self-immolation patients. The results indicated that among those who committed self-immolation, 52.8% of them had mental disorders, of which 38% were depressed. The most common mental disorder in people who committed self-immolation was depression and anxiety. Other studies[25] also confirm the results of this study. In their study, Khelil *et al.*[22] reported that mental illness was the most common reason for self-immolation. 32.8% of patients had a psychiatric history, of which 17.9% and 12.3% had schizophrenia and depression, respectively. The World Health Organization (WHO) considers the existence of a psychiatric disorder to be the most significant risk factor for suicide, and for this reason, the prevention and treatment of mental disorders undoubtedly have a substantial effect on preventing suicide.[26]

Based on this, screening programs for mental disorders, improving access to psychological services, training communication skills in the family, training young people, and empowering them to solve marital problems and such initiatives seem necessary to have a safe and healthy society.

The modeling results showed that surgical procedures (Graft), degree of burn, length of stay, anatomical region (legs and trunk), and gender had influenced survival due to self-immolation. Patients with burn injuries can undergo skin grafting to achieve timely healing.[27] An autograft is always associated with specific problems in deep and extensive burns due to a lack of skin donors. These patients face high mortality due to the loss of water and solutes, metabolic problems, and infectious complications of open wounds.[28]

The degree of the burn was the second most important factor in predicting the survival of patients. In deep burns, severe disturbances occur in the general systems of the body, especially in the blood circulation, cardiovascular and respiratory systems; these disturbances put a person's life at risk and threaten his health.[29] Therefore, patients with a higher degree of burn should be hospitalized without wasting time and receive the necessary treatment. The length of hospitalization was another factor in predicting the survival of patients. The study's results showed that the mortality rate is higher in the first days of admission. In general, the severity of injuries and greater depth of burns can cause the patients to die faster, and as a result, the duration of their stay will be shorter.[30] Therefore, it can be concluded that one of the critical reasons for this death is the loss of water and electrolytes, so the first step to saving self-immolation patients should be to supply water and electrolytes lost to their bodies. Total body area surface is one of the most critical factors in self-immolator survival. In this study, the anatomical region of the trunk and legs was the fourth most important factor in predicting the survival of patients. According to The Wallace rule of nines, the front and back of the trunk and legs make up 72% of the body surface. Moradinazar *et al.*'s study showed that for each unit increase in burn percentage, the death risk ratio (HR) increases 1.2 times.[31] A study conducted on 952 unintentional burns in the United States showed that burns' survival rate and mortality rate were most related to the total body surface area.[32]

Another factor in predicting the survival of self-immolation patients was the male gender. Similar studies have shown that the percentage of burns among men who committed

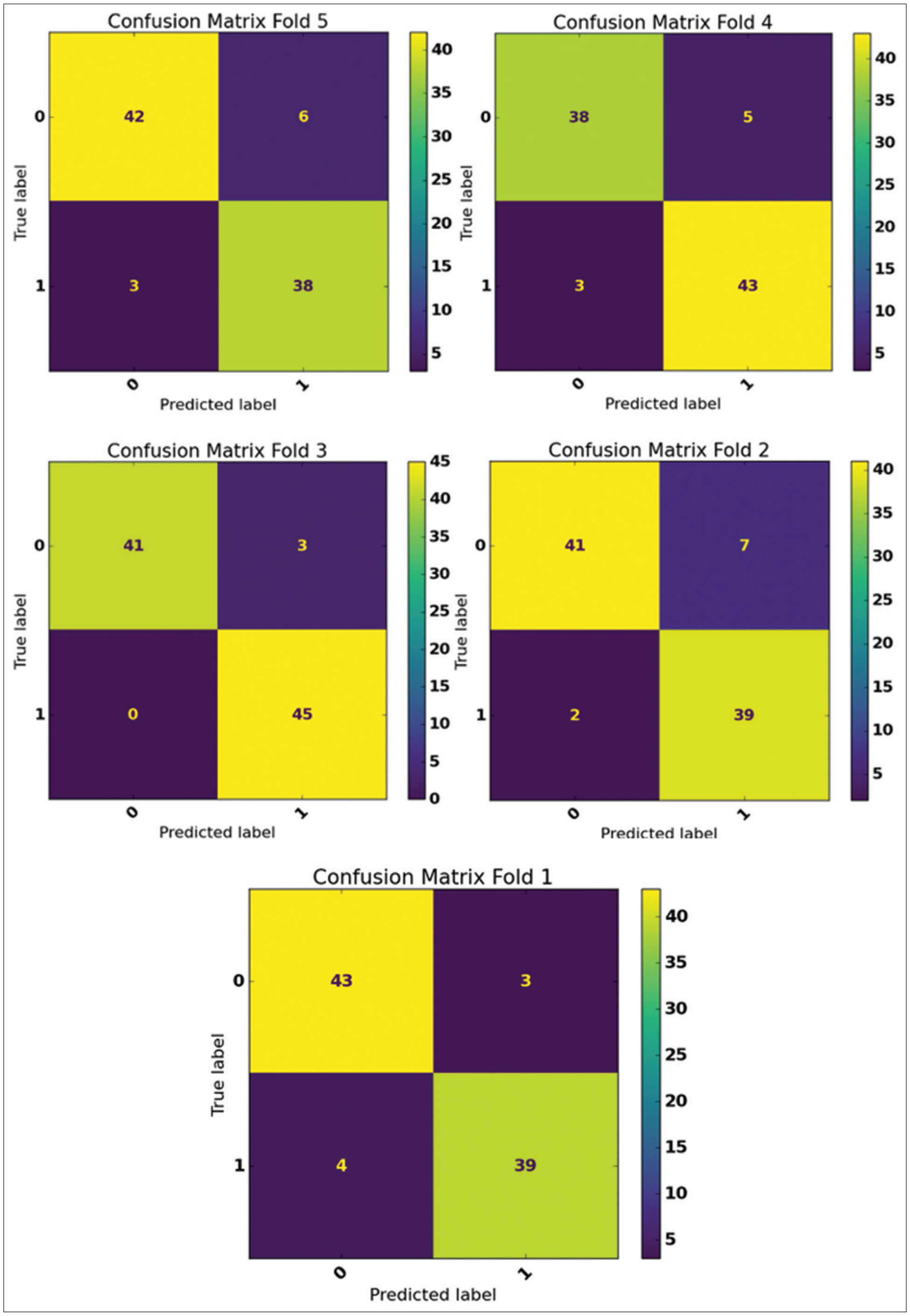

Figure 3: Confusion Matrix of SVM

self-immolation is more than among women. Therefore, it can be concluded that self-immolation in women is a kind of cry for help. Also, the interview results with these people have shown that most women intend to commit self-immolation unsuccessfully, which causes the number of female survivors of self-immolation to be higher than that of men.[19]

Prediction of survival will lead to optimal use of available resources in treating patients. For this purpose, it is essential to use suitable algorithm models. The research results showed that the SVM algorithm has high accuracy in predicting the survival of self-immolation patients. According to our knowledge, no studies in predicting the survival of self-immolation used machine learning techniques; therefore, it is impossible to compare the algorithm with other studies. Nevertheless, in other fields, for example, in Ding *et al.*'s study,[33] the K-means clustering algorithm was used to predict survival prognosis in cervical cancer. Also, Montazeri *et al.*, in their study,[34] used many algorithms for the prediction of breast cancer survival prediction, such as Naive Bayes (NB), trees random forest (TRF), 1-nearest neighbor (1NN), support vector machine (SVM), AdaBoost (AD), RBF network (RBFN), and MLP. The authors announced that the trees random forest (TRF) technique was better than other techniques (NB, 1NN, AD, SVM, RBFN, and MLP). Furthermore, they reported that accuracy, sensitivity, and the AUC of TRF were 96%, 96%, and 93%, respectively. Finally, TRF was recommended as a helpful breast cancer survival prediction tool.

Conclusion

This study conducted retrospective cross-sectional research on hospitalized self-immolated patients for their survival prediction using machine learning algorithms. Modeling results revealed that two variable categories are more important than the others. From clinical point of view, surgical procedures, score, length of stay and anatomical region are more important and among demographic features, age is the most important feature in this model. The results of this study can be helpful as a prediction model for policy-makers and clinical professionals involved in treating self-immolation patients for health planning, medical decision-making, optimal use of resources, and prevention of actions that lead to self-immolation.

Limitations

Machine learning enables the modeling on a dataset to predict self-immolation survival. However, more information is needed, including socioeconomic factors that are not traditionally examined in a clinical setting. Therefore, this study's limitations were the low quality of the data and the lack of completion of information related to some fields in medical records. These can reduce the accuracy of the prediction model. Considering that these limitations were related to the medical records data, researchers were not involved in them, and these limitations were unavoidable in this study. However, the researchers solved some of them by using Health Information System (HIS) reports or referring to the nursing registers.

Ethics approval

Ethical approval for the study was obtained from the Ethical Committee of Iran University of Medical Sciences with number IR.IUMS.REC.1397.910.

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Author contributions

Conceptualization, M.S and B.B; Data curation, R.TA; Formal analysis, M.S and B.B; Investigation, M.S and M.JS; Methodology, A.K, M.S and MJ.S; Project administration, M.S; Software, A.K and MJ.S; Validation, M.S and MJ.S; Writing – original draft, M.S, All authors reviewed the manuscript.

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Conflicts of interest

There are no conflicts of interest.

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