Iran J Public Health, Vol. 53, No.12, Dec 2024, pp.2802-2811

Original Article

From Data to Hope: Deep Neural Network-Based Prediction of Poisoning (DNNPPS) Suicide Cases

***Houriyeh Ehtemam* [1], **Mohammad Mehdi Ghaemi* [2], *Fahimeh Ghasemian* [3], *Kambiz Bahaadinbeigy* [4], **Shabnam Sadeghi-Esfahlani* [1], *Alireza Sanaei* [1], *Hassan Shirvani* [1]**

1. *Medical Technology Research Centre (MTRC), School of Engineering and the Built Environment, Anglia Ruskin University, Essex CM1 1SQ, UK*
2. *Health Services Management Research Center, Institute for Futures Studies in Health, Kerman University of Medical Sciences, Kerman, Iran*
3. *Department of Computer Engineering, Faculty of Engineering, Shahid Bahonar University of Kerman, Kerman, Iran*
4. *Medical Informatics Research Center, Institute for Futures Studies in Health, Kerman University of Medical Sciences, Kerman, Iran*

***Corresponding Authors:** Emails: shabnam.sadeghi-esfahlani@aru.ac.uk, academic.businessmail@gmail.com

(Received 10 Mar 2024; accepted 21 May 2024)

Abstract

Background: Suicide is a critical global issue with profound social and economic consequences. Implementing effective prevention strategies is essential to alleviate these impacts. Deep neural network (DNN) algorithms have gained significant traction in health sectors for their predictive capability. We looked at the potential of DNNs to predict suicide cases.

Methods: A descriptive-analytical, cross-sectional study was conducted to analyze suicide data using a deep neural network predictive prevention system (DNNPPS). The analysis utilized a suicide dataset comprising 1,500 data points, provided by a health research center in Kerman, Iran, spanning the years 2019-2022.

Results: Factors such as history of psychiatric hospitals, days of the week, and job were identified as the most important risk factors for predicting suicide attempts. Promising results were obtained by applying the DNNPPS model to a dataset of 1453 individuals with a history of suicide. The problem was approached as a binary classification task, with suicide history as the target variable. We performed preprocessing techniques, including class balancing, and constructed a DNN model using a sequential architecture with four dense layers.

Conclusion: The success of the DNN algorithm depends on the quality and quantity of data, as well as the model's architecture. High-quality data should be accurate, representative, and relevant, while a large dataset enables the DNN to learn more features. In our study, the DNNPPS model performed well, achieving an F1-score of 91%, which indicates high accuracy in predicting suicide cases and a good balance between precision and recall.

Keywords: Suicide; Neural network; Artificial intelligence; Deep neural network

Introduction

Suicide, a significant cause of death worldwide, refers to an intentional act of self-harm with fatal consequences (1). Global pandemics, such as COVID-19, can worsen mental health issues due to factors such as social isolation (2). Risk factors for suicide and repeat suicide attempts involve various aspects such as depression, family conflicts (particularly parental conflicts), parental education level, socioeconomic status, codependency, and behavioral patterns developed during schooling (3).

Machine learning (ML) models have become increasingly pivotal in the field of suicide prediction. Their impact is particularly pronounced in clinical research, where they offer valuable insights and aid in identifying individuals at risk. As technology advances, these models continue to evolve, providing hope for more accurate and timely interventions to prevent suicide. Researchers worldwide have dedicated substantial efforts to exploring the efficacy of ML in suicide prediction, leading to a growing body of evidence supporting their utility. For example, Ophir et al. employed a deep neural network to predict suicide using 83,292 social media texts. They explored two types of models: the Single Task Model (STM) and the Multi-Task Model (MTM). The MTM outperformed the STM in terms of accuracy and AUC. Overall, these findings demonstrate the utility of ML models for suicide prediction (4). Furthermore, Martinez et al. employed a convolutional neural network for predicting suicide using electronic health record data from 500,000 veterans. Based on the model's performance (positive predictive value = 0.54), they suggested that such models are valuable for suicide prediction (5).

In the current study, we specifically examine the impact of using the DNN algorithm in predicting suicide. We discover that artificial intelligence (AI) offers distinct advantages over human capabilities in terms of categorizing, analyzing, and predicting data. These advanced capabilities can aid decision-making processes (6). In emergency and medical centers, resources are often prioritized for patients with greater urgency, considering limitations in infrastructure and high patient volumes. Our study proposes the development of decision-support software that can provide neuropsychiatric professionals with predictive data on the likelihood of recurrent suicide. Such a tool could greatly improve treatment planning and counseling efforts. Moreover, existing literature supports the potential benefits of mobile applications as supplementary tools to strengthen preventive measures against recurrent suicide (7, 8). Implementing our findings in practice can assist clinical experts in making well-informed decisions regarding patient hospitalization or discharge. Therefore, in this study, the DNNPPS algorithm is utilized to investigate its effectiveness in predicting suicides.

Materials and Methods

Ethical approval was received from Kerman University of Medical Sciences with the reference number IR.KMU.REC.1401.250. Data was collected based on a system designed by the Health Services Management Center at the Future Studies Research Institute in Iran. Various standard questionnaires were utilized, and a comprehensive health system approach towards suicide was followed. The data for our study was gathered from the years 2019 to 2022.

The information collected, stored in an Excel file format, consisted of approximately 1500 patients attempting suicide and were subsequently admitted to a psychiatric ward. The DNN model was applied to the data, and the quality and quantity of this data can significantly impact how well the model performs. The features of the dataset are provided in Table 1.

The study employed various preprocessing techniques to mitigate bias and enhance result accuracy. These techniques included balancing the dependent variable, addressing missing data, and scaling the data. To address imbalanced data, the Random Under-Sampling algorithm was utilized, reducing data from the majority class (which is particularly useful in the health field) (9, 10). The iterative imputation algorithm was employed to handle missing values and boost the ML model's performance. This involved predicting missing features based on the remaining features through multiple iterations, resulting in a more robust dataset (11). Scaling techniques were applied during preprocessing to normalize data and prevent significant differences in value ranges (12, 13).

Normalization ensured that larger data values did not exert undue influence on the DNN model, ensuring fair and accurate interpretation of all data values. After training a DNN model, it was crucial to assess its performance to determine its effectiveness. Evaluation involved measuring metrics such as the f1-score, which is particularly appropriate for imbalanced datasets (14). Prior to modeling, data validation was conducted by dividing the data into a 70% training set, 10% validation set, and 20% testing set. Table 1 shows the hyperparameter values used for training our deep neural network. During training, the dropout regularization technique was applied to prevent overfitting. It involves randomly "dropping out" a fraction of the input units or neurons in a layer during forward and backward passes. These units are temporarily ignored during the forward and backward passes of training. Given its purpose in predicting poisoning, this DNN model is named as 'DNNPPS'.

Table 1: Values of hyper-parameters for training DNNPPS model

Parameter Name	*Parameter Value*
Number of epochs	50
Activation function	Relu
Optimizer	Adam
Dropout rate	0.2
Number of layers	4
Number of neurons	[32, 32, 16, 1]
Learning rate	0.001
Batch size	32
Loss function	Binary cross entropy
Classification function	Sigmoid

Results

Sample Characteristics

Among 1500 individuals, we selected 1453. Most participants were male, accounting for 56% of the total sample, while females comprised 44%. Regarding their mental health history, 17% of participants sought assistance from a psychiatrist or psychologist, while the remaining 83% did not. The majority of suicide attempts occurred on Fridays, particularly on holidays, with approximately 233 cases. It was observed that around 51% of those who attempted suicide were unemployed. The median age of the participants was 27 years, with a standard deviation (S.D.) of 9.88 years.

Prediction Models

The results were obtained through the implementation of a DNNPPS using the Python programming language in Google Colab. The model was trained for 50 epochs. The f1-score and loss curve are depicted in Figs. 1,2. Based on the observations, there is no evidence of over fitting in the training process, and it occurs successfully.

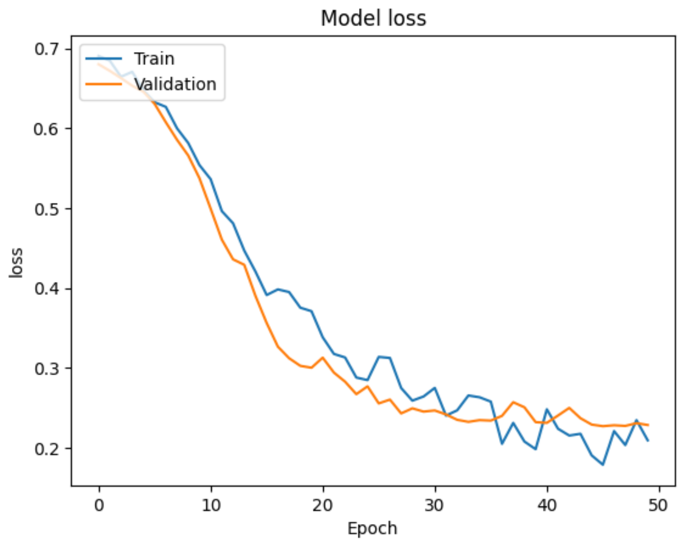

Fig. 1: Train and validation loss during the training process

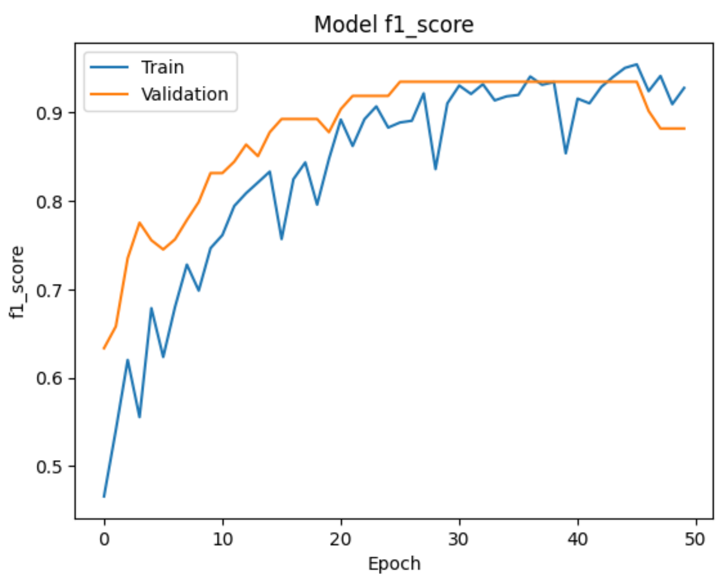

Fig. 2: Train and validation f1-score during the training process

The confusion matrices for the training and test data are illustrated in Fig 3. Fig. 4 respectively. DNNPPS model exhibits excellent predictive capabilities for identifying suicide, and its ability to generalize is deemed satisfactory based on the evaluation conducted using the test data.

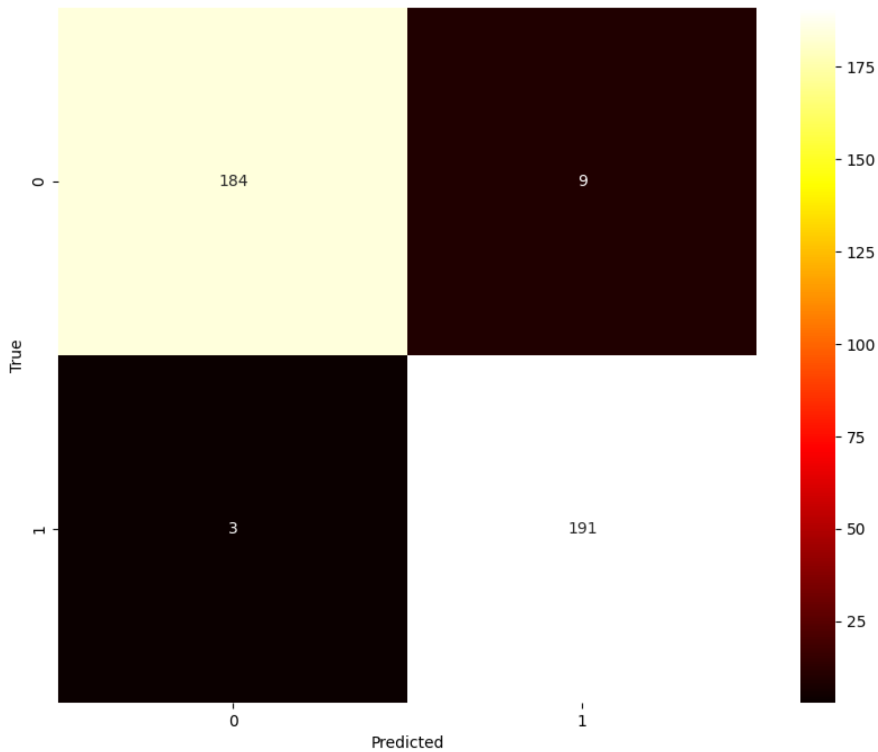

Fig. 3: The confusion matrix of DNNPPS model for the training data

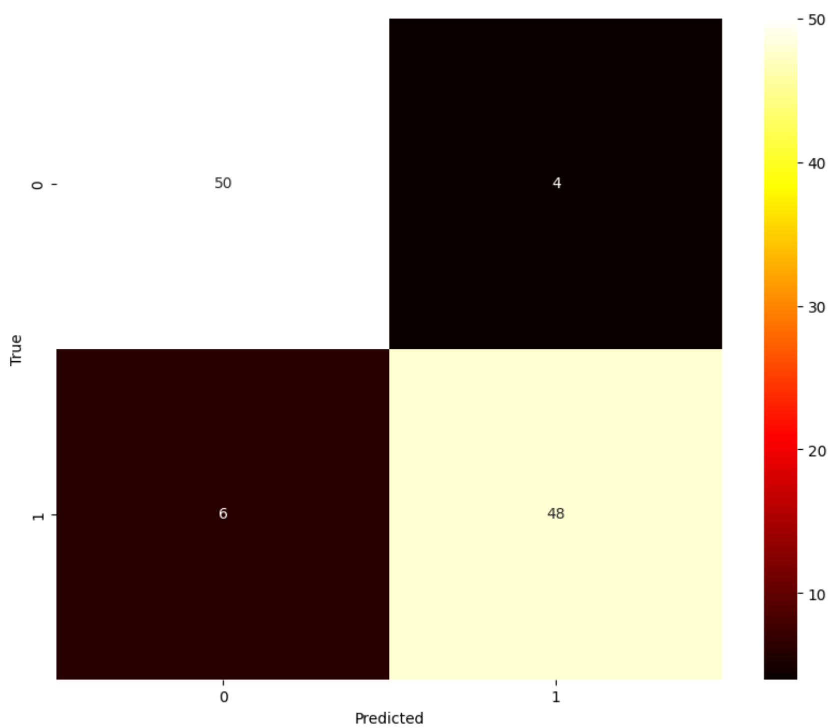

Fig. 4: The confusion matrix of DNNPPS model for the test data

We evaluated the performance of the model using accuracy, defined as the percentage of correctly classified samples in Fig. 5. The model achieved an accuracy of over 95% on the training set and over 85% on the validation set.

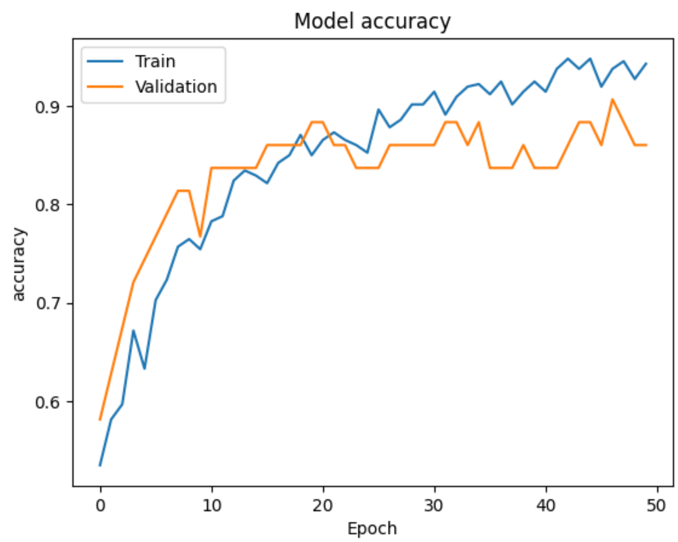

Fig. 5: Accuracy of train and validation sets of DNNPPS model

The performance of the model was evaluated using a receiver operating characteristic (ROC) curve, which plots the true positive rate against the false positive rate at various classification thresholds. The area under the ROC curve (AUC) for the training set was calculated to be 0.99, indicating excellent discrimination between positive and negative samples (Fig. 6).

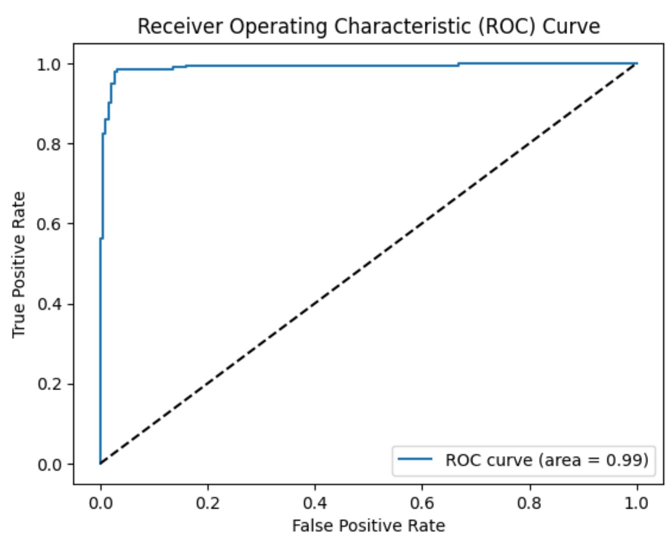

Fig. 6: ROC carve train of DNNPPS model

According to Fig. 7 the ROC curve for the training set had an AUC of 0.93, indicating excellent discrimination between positive and negative samples.

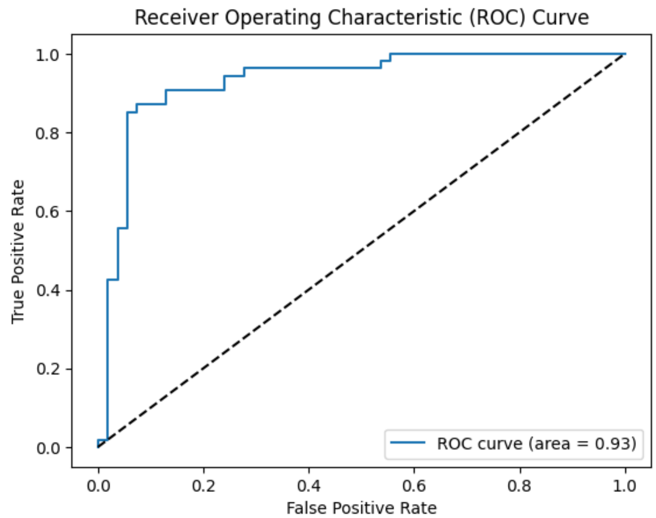

Fig. 7: ROC curve test of DNNPPS model

The evaluation results using the test data showed 0.92 for the precision, 0.81 for recall, and 0.91 for f1-score of the model. The results demonstrate satisfactory performance in predicting suicide cases. In the context of predicting suicide cases, an f1-score of 91 percent suggests that the model is effective in identifying individuals at risk of suicide.

Discussion

This study employed DNNPPS model to assess the predictive accuracy of the model in identifying potential suicidal tendencies. The objective was to provide essential support to clinical experts in their decision-making processes concerning patient hospitalization or discharge. The implementation of the DNNPPS model allowed for a comprehensive analysis of various factors and variables linked to suicide prediction, ultimately equipping healthcare professionals with valuable insights to make informed judgments regarding patient care.

In various studies, gender has been proposed as an important risk factor for suicide. The findings of this study are consistent with previous research, which suggested that an admission history increases suicide risk relatively more in men than women (15). Studies conducted in Iran, however, more men die by suicide than women, but women commit suicide more than men, and this may be because men are more likely to use more serious methods of suicide, such as guns (16). Although the importance of suicide prevention is not different for both sexes, according to the results obtained, when doctors and public health workers seek to prevent and manage suicidal thoughts, gender differences should be considered. In addition, the differences in cultural causes in different societies related to the difference in the prevalence of suicide by gender in Iran should be further investigated.

On the other hand, the findings of this study contradict the results of Qin and et.al (17), which indicated suicide risk is significantly higher in patients who received less than the median duration of hospital treatment. Many suicides occur on Fridays; the holidays can be a difficult time for people struggling with mental health issues. Based on our findings, there is a higher incidence of suicide attempts during holidays compared to other days. This could be attributed to the fact that individuals often undergo intensified emotions of loneliness, isolation, and sadness during holiday periods, which can potentially amplify suicidal thoughts. These findings challenge the conclusions drawn by Nishi and et al, suicide rates were lowest during holidays but significantly increased on the day immediately following (18).

The findings of this study contribute to the growing body of evidence supporting a significant association between unemployment and the risk of suicide attempts. The findings of this study are aligned with previous research that reported unemployment as a significant factor in committing suicide (19). Our results indicate that a substantial proportion of individuals who attempted suicide were unemployed, highlighting the detrimental impact of unemployment on mental well-being and suicide risk.

The studies included in the analysis that used DNN model to predict suicidal attempts demonstrated overall good performance. The findings of this study are consistent with previous research which confirmed acceptable performance of DNN in Predicting death by suicide (20). Developing a deep graph neural network model can be functional for the remote evaluation of suicide risk in the general population (21). However, in a study evaluated three ML algorithms, such as support vector machine (SVM), logistic regression (LR), decision tree (DT), and DNN in order to identify high risk groups for suicide, they concluded that SVM had far better performance than DNN model (22).

This study had two main limitations. Firstly, the hospital that data collection was carried out there was poisoning suicide which may not adequately reflect the patients' features in predicting suicide. Furthermore, it is essential to recognize the limitations of relying solely on a DNN model. While it can provide valuable insights and aid in decision-making, human judgment and expertise should always remain a crucial component of the clinical process. Collaborative efforts between ML models and healthcare professionals are encouraged, ensuring the responsible and effective utilization of these predictive technologies in real-world clinical settings. The strength of this study is that the DNN model offers a level of objectivity and consistency that can complement the subjective nature of clinical assessments. It eliminates potential biases and personal judgments that may influence decision-making, providing a standardized framework for evaluating patients' risk levels. This contributes to the overall reliability and fairness of the predictions, ultimately benefiting both patients and healthcare providers. Another strength of this study is the emphasis placed on the practical application of the research findings. By considering the needs of clinical experts, the study recognizes the importance of translating research into actionable insights that can be readily implemented in real-world settings. The integration of the DNN model into clinical decision-making processes has the potential to significantly impact patient care outcomes, leading to more efficient hospitalization or discharge decisions and potentially saving lives.

Conclusion

The findings of this study contribute to the growing body of research focused on suicide prevention and mental health support. By leveraging advanced technological tools such as the DNN model, healthcare professionals can rely on evidence-based predictions to supplement their clinical expertise. This integration of ML methodologies into clinical practice has the potential to enhance patient outcomes and minimize the risks associated with inadequate suicide risk assessments. Although the models developed in this study demonstrated significant promise, further research and evaluation are encouraged to refine and enhance the model's performance. This ongoing development will ultimately empower clinicians with the knowledge and confidence to make informed decisions regarding patient hospitalization or discharge in mental health contexts.

Journalism Ethics considerations

Ethical issues (Including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc.) have been completely observed by the authors.

Acknowledgements

The authors would like to thank Health Services Management Research Center (Kerman, Iran) for providing data.

Data Availability

The data of this study are available on request from the corresponding author [Sh.S, MM.G]. The data are not publicly available due to their containing information that could compromise the privacy of research participants.

Conflict of interest

The authors declare that there is no conflict of interests.

References

1. Wang X, Lu Z, Dong C (2022). Suicide resilience: A concept analysis. *Front Psychiatry,* 13:984922.
2. Mathieu S, Treloar A, Hawgood J, Ross V, Kõlves K (2022). The Role of Unemployment, Financial Hardship, and Economic Recession on Suicidal Behaviors and Interventions to Mitigate Their Impact: A Review. *Front Public Health,* 10: 907052.
3. Bae SM, Lee SA, Lee SH (2015). Prediction by data mining, of suicide attempts in Korean adolescents: a national study. *Neuropsychiatr Dis Treat,* 11:2367-75.
4. Ophir Y, Tikochinski R, Asterhan CSC, Sisso I, Reichart R (2020). Deep neural networks detect suicide risk from textual facebook posts. *Sci Rep,* 10 (1):16685.
5. Martinez C, Levin D, Jones J, et al (2023). Deep sequential neural network models improve stratification of suicide attempt risk among US veterans. *J Am Med Inform Assoc,* 31 (1):220-230.
6. Duan Y, Edwards JS, Dwivedi YK (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *Int J Inf Manage,* 48:63-71.
7. Malakouti SK, Rasouli N, Rezaeian M, et al (2020). Effectiveness of self-help mobile telephone applications (apps) for suicide prevention: A systematic review. *Med J Islam Repub Iran,* 34:85.
8. World Health Organization (2021) Suicide. WHO, Geneva
9. Adams RS, Jiang T, Rosellini AJ, et al (2021). Sex-Specific Risk Profiles for Suicide Among Persons with Substance Use Disorders in Denmark. *Addiction,* 116 (10):2882-2892.
10. Barak-Corren Y, Castro VM, Nock MK, et al (2020). Validation of an Electronic Health Record–Based Suicide Risk Prediction Modeling Approach Across Multiple Health Care Systems. *JAMA Netw Open,* 3 (3):e201262.
11. Delgado-Gomez D, Baca-Garcia E, Aguado D, et al (2016). Computerized Adaptive Test vs. decision trees: Development of a support decision system to identify suicidal behavior. *J Affect Disord,* 206:204-209.
12. Delgado-Gomez D, Blasco-Fontecilla H, Alegria AA, et al (2011). Improving the accuracy of suicide attempter classification. *Artif Intell Med,* 52 (3):165-168.
13. Delgado-Gomez D, Blasco-Fontecilla H, Sukno F, et al (2012). Suicide attempters classification: Toward predictive models of suicidal behavior. *Neurocomputing,* 92:3-8.
14. Jeni LA, Cohn JF, Torre FDL (2013). Facing Imbalanced Data--Recommendations for the Use of Performance Metrics. *Int Conf Affect Comput Intell Interact Workshops, 2013:245-251.*
15. Griffin E, Corcoran P, Arensman E, et al (2023). Suicide risk following hospital attendance with self-harm: a national cohort study in Ireland. *Nat Ment Health,* 1 (12):982-989.
16. Zarani F, Ahmadi Z (2021). Suicide in Iranian culture: A systematic review study. *Rooyesh-e-Ravanshenasi Journal(RRJ),* 10 (9):205-216.
17. Qin P, Nordentoft M (2005). Suicide Risk in Relation to Psychiatric Hospitalization: Evidence Based on Longitudinal Registers. *Arch Gen Psychiatry,* 62 (4):427-432.
18. Nishi M, Miyake H, Okamoto H, Goto Y, Sakai T (2000). Relationship between suicide and holidays. *J Epidemiol,* 10 (5):317-20.
19. İlgün G, Yetim B, Demirci Ş, Konca M (2020). Individual and socio-demographic determinants of suicide: An examination on

WHO countries. *Int J Social Psychiatry,* 66 (2):124-128.
20. Sanderson M, Bulloch AG, Wang J, et al (2020). Predicting death by suicide using administrative health care system data: Can recurrent neural network, one-dimensional convolutional neural network, and gradient boosted trees models improve prediction performance? *J Affect Disord,* 264:107-114.
21. Choi KS, Kim S, Kim B-H, et al (2021). Deep graph neural network-based prediction of acute suicidal ideation in young adults. *Sci Rep,* 11 (1):15828.
22. Amini P, Ahmadinia H, Poorolajal J, Moqaddasi Amiri M (2016). Evaluating the High Risk Groups for Suicide: A Comparison of Logistic Regression, Support Vector Machine, Decision Tree and Artificial Neural Network. *Iran J Public Health,* 45 (9):1179-1187.