A Machine Learning Approach for Analyzing and Predicting Suicidal Thoughts and Behaviors

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***Abstract*— Suicide is a significant public health concern, and there is growing interest in using machine learning techniques to identify people who are at a high risk of committing suicide. In this paper, a review of the current state-of-the-art in suicide prediction is given using machine learning. Various features are investigated with data sources used in earlier studies, such as text-based data from social media, electronic health records, and demographic data. Also, different machine learning techniques are analyzed that are employed including neural networks. We compare the different machine learning models based on errors and find that Support Vector Regression (SVR) to be the most suitable for this purpose. We conclude by emphasizing the potential of machine learning to improve suicide prevention efforts and addressing the ethical concerns that must be discussed when implementing such models in practice.**

Keywords—* *Suicide prediction, Machine Learning, Neural network, Predictive analysis

I. INTRODUCTION

Suicide is a major issue affecting millions of people worldwide. People from all generations, genders, and social groups are affected by mental health problems, which is an increasing global concern. There is considerable interest in applying machine learning techniques to detect those who are likely to commit suicide, as suicide is becoming a serious public health concern. Our ability to predict suicide attempts has been near chance levels for several decades [1]. There have been various attempts to date to pinpoint suicidality risk factors. Suicide affects individuals, families, communities, and even entire countries [2]. For young individuals, suicide is the second leading cause of death, killing more people than diabetes, liver disease, stroke, or infection [3]. The stigma attached to mental illnesses prevents more than 40% of people from seeking primary care because they are hesitant to discuss their pertinent symptoms. There is no effective method for handling, evaluating, or preventing suicide, making immediate intervention into suicidal thoughts and actions necessary [3].

Suicidal Ideation Detection (SID) determines whether the person has suicidal ideation or thoughts by given some behavioral data of a person or textual content written by a person [4]. There are many complex factors that contribute to suicide. Although those with depression are much more prone to do so, but many people without depression also attempt suicides. Depression gives rise to many other complications like loss of interest, helplessness, hopeless feelings & mental disorder [5]. The American Foundation for Suicide Prevention (AFSP) has identified three categories for suicide variables: historical, environmental, and health-related aspects [6]. Prospective suicide victims may act out their thoughts of killing themselves in role-playing, fleeting thoughts, and suicide plots. The proactive identification of risks associated with behaviors or intents related to suicidal thoughts before a tragedy occurs should be given utmost importance. Suicide motives can be highly complex and multifaceted. Suicide is rarely the consequence of a single cause, but rather of a complex interaction of several events. These elements can be biological, psychological, social, or environmental. Suicidal thoughts can be detected in people with the use of effective early suicidal ideation detection. The reasons for suicide are complicated and attributed to a complex interaction of many factors [7], [8]. The use of machine learning has gained popularity to predict diseases early in recent years [9-16]. Suicide risk factors can be roughly categorized into traits or states. Based on ground truth data, these traits can be used as features to train machine learning model which can later to predict and analyze suicidal behaviors of individuals at risk. In recent years, a number of research have explored the application of machine learning algorithms for health issues risk assessment [17-23], bringing increased attention to this field of study. For instance, academics have employed machine learning to sift through social media messages and find people who could be suicidal or have self-harm tendencies [24]. To identify those who are at risk of suicide, researchers developed prediction models that include clinical, demographic and data from electronic health records for different purposes [25-32]. In our paper we discuss the viability of popular machine learning algorithms based on several error functions and find out the best model to be used in analyzing and predicting suicidal tendencies.

II. RELATED WORKS

Machine learning was utilized in some of the research to predict diseases early [33-42], also suicide attempts in a large sample of patients over a 5-year period [43]. Using longitudinal electronic health records, some study created a machine learning model to predict suicidal behavior in patients [44]. Some papers highlight the importance of identifying and addressing risk factors for suicidal behaviors which provides important insights into the complex interplay of risk and protective factors for suicidal behaviors and adolescents, and emphases the importance of early identification and intervention to prevent these behaviors. The authors suggest that machine learning algorithms may be useful in predicting suicide attempts and could be used to

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develop targeted interventions to prevent suicide attempts [45]. Many studies have built predicting model and tools to predict suicide. There are models based on clinical and demographic data, electrical health record data, patients with schizophrenia based on demographic and clinical data etc. A majority of the existing strategies for detecting suicidal thoughts rely on interactions between social workers or other specialists and the persons being studied, as well as on machine learning methods using feature engineering or deep learning for automatic identification based on social media content. Some papers provide an in-depth review of the state-of-the-art machine learning methods and applications in detecting suicidal ideation and highlight the potential of these methods in improving suicide prevention and intervention efforts [46]. There are also some studies that analyze the limitations of suicide risk assessment methods and stress the need for a more thorough approach to suicide risk management that takes individual risk variables and clinical judgment into account [47]. Some research articles also discuss the ethical considerations, like ethical consideration of using social media for suicide prevention [48]. Section III of the paper presents the methodology. The results are analyzed in Section IV and the conclusion is exhibited in Section V.

III. METHODOLOGY

Because of an increase in suicide rates in recent years, researchers have become interested in suicide detection, which has received substantial research from a variety of angles. For automatic detection, machine learning techniques are frequently used. Empirical analysis of the data was performed on the dataset, and a correlation heatmap was generated defining the correlation between attributes. The dataset's numerical figure is shown in Table I.

TABLE I. ATTRIBUTES RELATED TO SUICIDIAL BEHAVIOUR

No.	Attributes	Max-Min	Mean	Standard Deviation
1	Currently_Drink_Alc	1.4-548.0	102.5	182.775
2	Really_Get_Drunk	0.8-106.0	35.64	37.184
3	Overwieght	3.3-106.0	35.55	34.948
4	Use_Marijuana	0.0-106.0	22.68	36.318
5	Understanding_Parent	5.6-106.0	40.04	32.095
6	Miss_w/o_permssion	6.5-106.0	37.96	32.363
7	Had_sexual_relation	2.5-106.0	37.31	35.076
8	Smoke_cig_currently	1.2-106.0	27.34	34.255
9	Had_fights	3.5-106.0	40.85	34.156
10	Bullied	9.9-106.0	40.76	33.939
11	Got_Seriously_injured	14-106.0	49.59	32.425
12	No_close_friends	1.5-106.0	20.69	35.190
13	Attempted_suicide	2.7-106.0	29.91	36.769

A. Data Source

The dataset is obtained from Global School-based Student Health Survey, which included teenagers from 26 different nations [10]. The goal of the GSHS, a cross-sectional surveillance survey, is to gather information on teenagers. The purpose of the survey is to estimate the prevalence of risk factors and health behaviors among teenagers that are comparable worldwide. Core-expanded and selected core questions make up country-specific surveys. All phases' core questions used the same identical language for both the questions and the answers. There are ten main components and several auxiliary modules. An institutional ethics committee or board and a national government body in each country approve all GSHS surveys. Additionally, participant and parental consent are requested. Adolescents are divided into younger (13–15 years old) and older (16–17 years old) groups based on the emphasis of the current investigation. These age ranges were chosen because they are in line with the publicly reported question response prevalence, which is weighted for the survey design to enable cross-national comparison by taking into account the likelihood of a) selecting classrooms and schools, b) selecting schools and students who don't respond, and c) distributing the population.

B. Outcome and Covariates

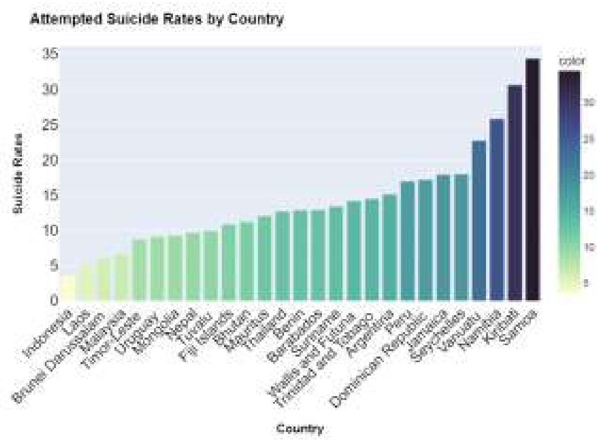

Fig. 1 Suicide Rates vs. Country

The following variables were represented by numerical values as confounders: alcohol consumption, excessive drinking, marijuana addiction, having understanding parents, engaging in sexual relationships, unauthorized class absences, current cigarette smoking, involvement in fights, bullying experiences, history of serious injuries, lack of close friends, and previous suicide attempts. Each of these traits is translated into numerical values ranging between a maximum and minimum value.

C. Statistical Analysis

According to the studies, Indonesia has the lowest suicide rate (3.4833) and Samoa has the highest suicide rate (34.3833). (3.6) shown in Fig 1. The top four nations—Samoa at number one with a suicide rate of 34.3833, Kiribati at number two with a suicide rate of 30.65, Namibia at number three with a suicide rate of 25.825, and Vanuatu at number four with a suicide rate of 22.75—all have significantly higher suicide rates than the other countries. The suicidal attribute values were found to be higher than the mean value and closer to the maximum range in all of these nations, demonstrating the validity of the attributes used in the development of the prediction model.

D. Values Explanation

A correlation matrix is shown in Fig. 2 that depicts the relationship between different behaviors that triggers suicide.

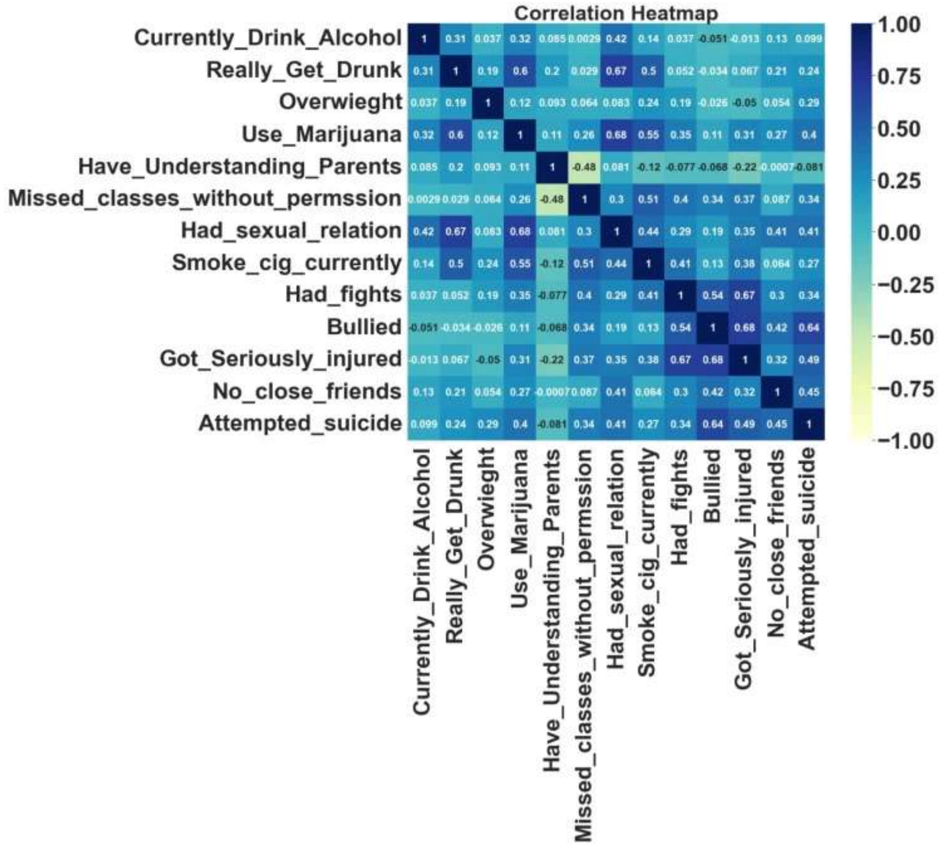

Fig. 2 Correlation Heatmap

-1: Perfect negative correlation. The variables tend to move in opposite directions when one variable increases, the other variable decreases
0: No correlation between two variables
1: Perfect positive correlation. The variables tend to move in the same direction when one variable increases, the other variable also increases.

According to the results of this analysis, the correlations between these behaviors are:

- There is a strong possibility that when someone has sexual relations, they use marijuana.
- Someone who got bullied had a strong possibility to get seriously injured.
- Someone who had sexual relations is possible to have really drunk behaviors.

But, in this case, we are going to conclude the behaviors correlation that is considered "Suicidal Behaviors".

E. Workflow: ML Algorithm application

At first the dataset containing suicide information from the GSHS database was processed to generate the data that contained all the attributes and the value associated with them. Then using several machine learning algorithms same data was trained and outcome was evaluated using 5-fold cross validation. Until the desired result was met, hyperparameters tuning like learning rate adjustment and clustering algorithm was changed. Evaluations of each model were compared to find out the best model suitable as suicidal behavior detection model which is discussed in the results and discussion section. Fig. 3 shows the workflow diagram starting from data acquisition to final model selection.

IV. Results and Discussion

Machine learning model efficacy can be evaluated by performance parameters, which are commonly derived from a comparison of the expected and actual results. Depending on the job at hand and the goals of the underlying model, the choice of performance parameters may shift from one application to the next. In this study, through an in-depth analysis, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) have been found for all the models (RF, LR, XGB, RR, KNN, SVR, and MLP) applied for the prediction from the given dataset.

A. Root mean square error (RMSE)

It is the square root of sum, over all the data points, of the square of the difference between the predicted and actual target variables, divided by the number of data points.

$$\mathrm{RMSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \qquad (1)$$

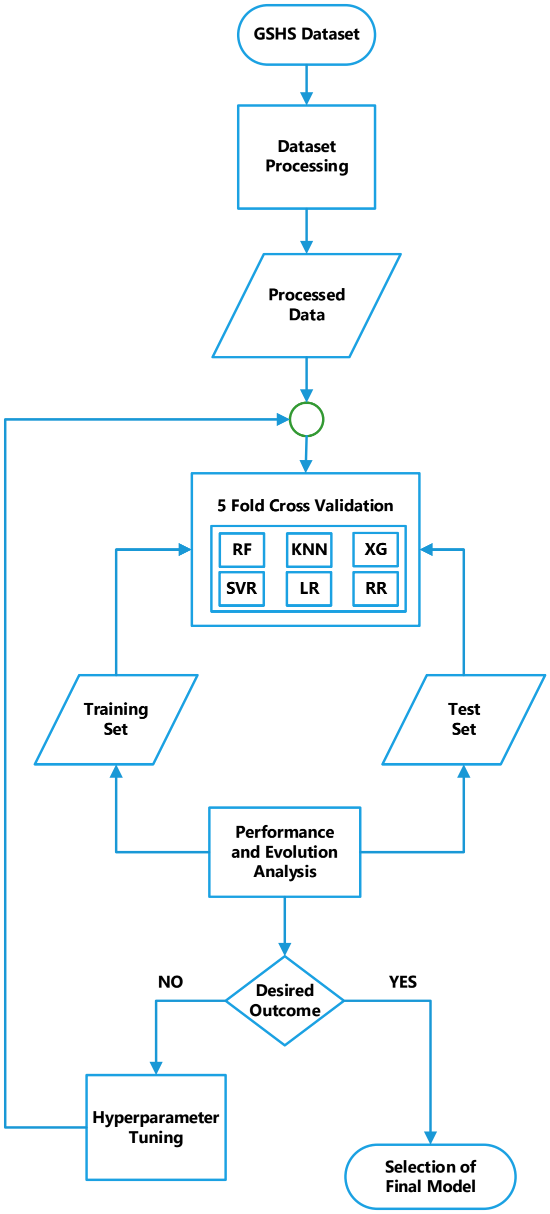

Fig. 3 Overall workflow diagram

B. Mean Absolute error (MAE)

It is the square root of sum, over all the data points, of the square of the difference between the predicted and actual target variables, divided by the number of data points.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \quad (2)$$

C. Mean Absolute Percentage error (MAPE)

Mean Absolute Percentage Error is a commonly used metric in evaluating the accuracy of a forecasting model. It measures the average percentage difference between the actual values and the predicted values of a time series.

$$\text{MAPE} = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \quad (3)$$

TABLE II. COMPARATIVE ANALYSIS OF DIFFERENT ML ALGORITHMS

ML Algorithms	MAE	RMSE	MAPE
RF	5.4808	5.4810	0.9363
XGB	5.5213	5.5210	0.6757
RR	7.2919	7.2920	0.9156
LR	7.1746	7.1764	0.9679
KNN	6.4200	6.4200	1.0835
SVR	4.6588	4.6589	0.6561
MLP	6.5090	6.0590	0.7994

From the analysis of Table II, the 3 parameters (MAE, RMSE, MAPE), it is perceived that the SVR model has the lowest MAE (4.6588) and RMSE (4.6589) and MAPE (0.6561). This represents the SVR model's superior performance relative to other & utilized ML models, as measured by the absolute difference, the standard deviation of the difference, and the average percentage difference between the predicted values and the actual values.

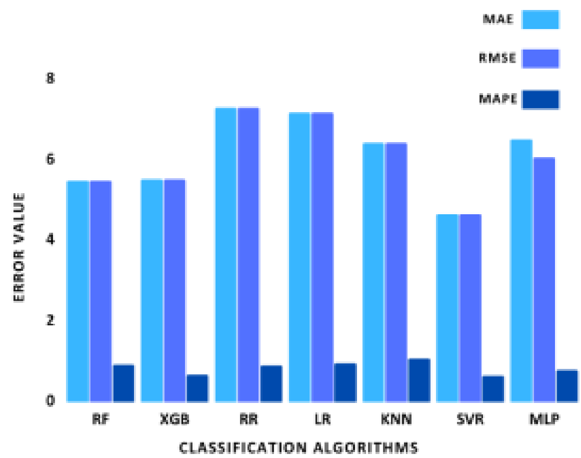

Fig. 4 Comparison of different classifiers

The target variable is likely a continuous variable, as the evaluation metrics reported in the table are MAE, RMSE, and MAPE which are commonly used for evaluating regression models. The seven machine learning models compared in Table II are RF, XGB, RR, LR, KNN, SVR, and MLP, which are popular and commonly used regression models. The table summarizes the models' performance in terms of MAE, RMSE, and MAPE. Better performance is indicated by lower MAE and RMSE values, which show that the anticipated and actual values are more closely matched. A lower MAPE score, which calculates the proportion of error between predicted and actual values, similarly denotes a better fit of the model to the data. Fig. 4 displays, using widely accepted assessment measures, how well various regression models performed in predicting a continuous target variable based on specific input characteristics.

V. CONCLUSION

In today's society, there is still much that needs to be done to prevent suicide. We have carefully examined the research that has been done in the field of suicide prediction. The application of machine learning algorithms has produced encouraging outcomes for detecting and forecasting suicidal ideas and actions. Although there have been many successful high accuracy models developed, there is still opportunity for growth. Further research and development in this field can lead to the creation of more sophisticated and accurate predictive models, ultimately contributing to the reduction of suicide rates and the improvement of mental health care. Machine learning algorithms can offer a more thorough and impartial assessment of a person's risk of engaging in suicidal conduct by examining a variety of data sources. The deployment of machine learning algorithms must be done cautiously and in cooperation with mental health professionals and people who have lived experience, even though they have the potential to considerably aid efforts to prevent suicide. Machine learning has the potential to play a significant role in the effort to prevent suicide by saving lives and enhancing mental health outcomes with more study and development.

REFERENCES

[1] J. C. Franklin *et al.*, "Risk factors for suicidal thoughts and behaviors: A meta-analysis of 50 years of research.," *Psychol Bull*, vol. 143, no. 2, p. 187, 2017

[2] D. Liu *et al.*, "Suicidal ideation cause extraction from social texts," *Ieee Access*, vol. 8, pp. 169333–169351, 2020

[3] A. N. Weber, M. Michail, A. Thompson, and J. G. Fiedorowicz, "Psychiatric emergencies: assessing and managing suicidal ideation," *Medical Clinics*, vol. 101, no. 3, pp. 553–571, 2017

[4] S. Ji, S. Pan, X. Li, E. Cambria, G. Long, and Z. Huang, "Suicidal ideation detection: A review of machine learning methods and applications," *IEEE Trans Comput Soc Syst*, vol. 8, no. 1, pp. 214–226, 2020

[5] R. Mahadik, S. Salunkhe, P. Sneha, and V. Sagvekar,"Analysis of Suicide Attempts and Its Prediction," 2021

[6] M. J. Vioules, B. Moulahi, J. Azé, and S. Bringay, "Detection of suicide-related posts in Twitter data streams," *IBM J Res Dev*, vol. 62, no. 1, pp. 1–7, 2018

[7] R. C. O'Connor and M. K. Nock, "The psychology of suicidal behaviour," *Lancet Psychiatry*, vol. 1, no. 1, pp. 73–85, 2014

[8] G. Kassen, A. Kudaibergenova, A. Mukasheva, D. Yertargynkyzy, and K. Moldassan, "Behavioral risk factors for suicide among adolescent schoolchildren.," *Ilkogretim Online*, vol. 19, no. 1, 2020

[9] F. Faisal and M. M. Nishat, "An Investigation for Enhancing Registration Performance with Brain Atlas by Novel Image Inpainting Technique using Dice and Jaccard Score on Multiple Sclerosis (MS) Tissue," *Biomed. and Pharm. J.,* vol. 12, no. 3, pp. 1249-1262, 2019

[10] M. M. Nishat, et al., "An Investigative Approach to Employ Support Vector Classifier as a Potential Detector of Brain Cancer from MRI Dataset," *ICECIT*, pp. 1-4, doi: 10.1109/ICECIT54077.2021.9641168

[11] M. A. A. R. Asif *et al*., "Performance Evaluation and Comparative Analysis of Different Machine Learning Algorithms in Predicting Cardiovascular Disease," *Engineering Letters,* vol. 29, no. 2, pp. 731-741, 2021

[12] M. M. Nishat *et al.*, "A Comprehensive Analysis on Detecting Chronic Kidney Disease by Employing Machine Learning Algorithms," *EAI Endorsed Transactions on Pervasive Health and Technology*, vol. 18, no. e6, 2021, doi: 10.4108/eai.13-8-2021.170671

[13] M. R. Farazi, F. Faisal, Z. Zaman and S. Farhan, "Inpainting multiple sclerosis lesions for improving registration performance with brain atlas," *2016 Int. Conf. on Medical Engg., Health Info. and Tech. (MediTec)*, 2016, pp. 1-6, doi: 10.1109/MEDITEC.2016.7835363.

[14] M. A. A. R. Asif *et al*., "Computer Aided Diagnosis of Thyroid Disease Using Machine Learning Algorithms," *2020 11th Int. Conf. on Electrical and Computer Engineering (ICECE)*, 2020, pp. 222-225, doi: 10.1109/ICECE51571.2020.9393054

[15] M. M. Nishat and F. Faisal, "An Investigation of Spectroscopic Characterization on Biological Tissue," *iCEEiCT*, 2018, pp. 290-295, doi: 10.1109/CEEICT.2018.8628081

[16] F. Faisal, M. M. Nishat, M. A. Mahbub, M. M. I. Shawon, and M. M. U. H. Alvi, "Covid-19 and its impact on school closures: a predictive analysis using machine learning algorithms," *2021 Int. Conf. on Science & Contemporary Technologies (ICSCT)*, 2021, pp. 1-6, doi: 10.1109/ICSCT53883.2021.9642617

[17] A. A. Rahman *et al*., "Detection of Epileptic Seizure from EEG Signal Data by Employing Machine Learning Algorithms with Hyperparameter Optimization," *2021 4th International Conference on Bio-Engineering for Smart Technologies (BioSMART)*, 2021, pp. 1-4, doi: 10.1109/BioSMART54244.2021.9677770

[18] A. A. Rahman, L. I. Khalid, M. I. Siraji, M. M. Nishat, F. Faisal and A. Ahmed, "Enhancing the Performance of Machine Learning Classifiers by Hyperparameter Optimization in Detecting Anxiety Levels of Online Gamers," *ICCIT*, 2021, pp. 1-5, doi: 10.1109/ICCIT54785.2021.9689911

[19] T. Hasan *et al*., "Exploring the Performances of Stacking Classifier in Predicting Patients Having Stroke," *2021 8th NAFOSTED Conference on Information and Computer Science (NICS)*, pp. 242-247, 2021, doi: 10.1109/NICS54270.2021.9701526.

[20] M. M. Nishat, T. Hasan, S. M. Nasrullah, F. Faisal, M. A. A. R. Asif, and M. A. Hoque, "Detection of Parkinson's Disease by Employing Boosting Algorithms," *2021 Joint 10th Int. Conf. Informatics, Electronics & Vision (ICIEV) and 2021 5th Int. Conf. on Imaging, Vision & Pattern Recognition (icIVPR)*, pp. 1-7, 2021, doi: 10.1109/ICIEVicIVPR52578.2021.9564108

[21] Nishat, M. M., et al. "Detection of Autism Spectrum Disorder by Discriminant Analysis Algorithm," *BIM,* pp. 473-482, Springer, Singapore, 2022 doi: 10.1007/978-981-16-6636-0_36

[22] A. A. Rahman, M. I. Siraji, L. I. Khalid, F. Faisal, M. M. Nishat and M. R. Islam, "Detection of Mental State from EEG Signal Data: An Investigation with Machine Learning Classifiers," *2022 14th International Conference on Knowledge and Smart Technology (KST)*, pp. 152-156, 2022, doi: 10.1109/KST53302.2022.9729084

[23] M. R. Rahman, S. Tabassum, E. Haque, M. M. Nishat, F. Faisal and E. Hossain, "CNN-based Deep Learning Approach for Micro-crack Detection of Solar Panels," *2021 3rdInt. Conf. on STI 4.0*, 2021, pp. 1-6, doi: 10.1109/STI53101.2021.9732592.

[24] G. Castillo-Sánchez, G. Marques, E. Dorronzoro, O. Rivera-Romero, M. Franco-Martín, and I. De la Torre-Díez, "Suicide risk assessment using machine learning and social networks: a scoping review," *J Med Syst*, vol. 44, no. 12, p. 205, 2020

[25] Nishat, M. M., et al. "A Comprehensive Investigation of the Performances of Different Machine Learning Classifiers with SMOTE-ENN Oversampling Technique and Hyperparameter Optimization for Imbalanced Heart Failure Dataset," *Scientific Programming*, https://doi.org/10.1155/2022/3649406

[26] Nishat, M. M, Faisal, F., Mahbub, M. A., Mahbub, M. H., et al., "Performance Assessment of Different Machine Learning Algorithms in Predicting Diabetes Mellitus". *Biosc.Biotech.Res.Comm*.,14(1), 2021 doi: http://dx.doi.org/10.21786/bbrc/14.1/10

[27] F. Faisal, "Image Inpainting to Improve the Registration Performance of Multiple Sclerosis (MS) Patient Brain with Brain Atlas," Diss. Department of EEE, IUT, OIC, Gazipur-1704, Bangladesh, 2016.

[28] M. M. Nishat *et al*., "Performance Investigation of Different Boosting Algorithms in Predicting Chronic Kidney Disease," *2020 2nd Int. Conf. on STI 4.0*, pp. 1-5, 2020,doi: 10.1109/STI50764.2020.9350440

[29] M. Islam, M. Tabassum, M. M. Nishat, F. Faisal and M. S. Hasan, "Real-Time Clinical Gait Analysis and Foot Anomalies Detection Using Pressure Sensors and Convolutional Neural Network," *ICBIR*, 2022, pp. 717-722, doi: 10.1109/ICBIR54589.2022.9786472

[30] I. J. Ratul, A. A. Monsur, B. Tabassum, A. M. Ar-Rafi, M. M. Nishat and F. Faisal, "Early risk prediction of cervical cancer: A machine learning approach," *ECTI-CON,* 2022, pp. 1-4, doi: 10.1109/ECTI-CON54298.2022.9795429

[31] A. Al–Monsur, M. R. Kabir, A. M. Ar–Rafi, M. M. Nishat and F. Faisal, "Covid-EnsembleNet: An Ensemble Based Approach for Detecting Covid-19 by utilising Chest X-ray Images," *AIIoT*, 2022, pp. 351-356, doi: 10.1109/AIIoT54504.2022.9817237.

[32] I. A. Jahan, I. A. Jamil, M. S. H. Fahim, A. S. Huq, F. Faisal and M. M. Nishat, "Accident Detection and Road Condition Monitoring Using Blackbox Module," *2022 13th International Conference on Ubiquitous and Future Networks (ICUFN)*, 2022, pp. 247-252, doi: 10.1109/ICUFN55119.2022.9829589.

[33] A. A. Rahman *et al*., "Perceived Stress Analysis of Undergraduate Students during COVID-19: A Machine Learning Approach," *2022 IEEE 21st Mediterranean Electrotechnical Conference (MELECON)*, 2022, pp. 1129-1134, doi: 10.1109/MELECON53508.2022.9843081.

[34] F. Faisal, M. M. Nishat and M. A. M. Oninda, "Spectroscopic Characterization of Biological Tissue using Quantitative Acoustics Technique," *2018 4th Int. Conf. on Electrical Engineering and Information & Communication Technology (iCEEiCT)*, pp. 38-43, 2018, doi: 10.1109/CEEICT.2018.8628146

[35] Z. K. Eisham *et al.,* "Chimp optimization algorithm in multilevel image thresholding and image clustering," *Evolving Systems,* 2022. https://doi.org/10.1007/s12530-022-09443-3

[36] F. Faisal, M. A. Salam, M. B. Habib, M. S. Islam and M. M. Nishat, "Depth estmation from Video using Computer Vision and Machine Learning with Hyperparameter Optimization," *ICSSA,* 2022, pp. 39-44, doi: 10.1109/ICSSA54161.2022.9870961.

[37] S. Hassan *et al*., "Comparative Analysis of Machine Learning Algorithms in Detection of Brain Tumor," *2022 3rd International Conference on Big Data Analytics and Practices (IBDAP)*, 2022, pp. 31-36, doi: 10.1109/IBDAP55587.2022.9907433. IEEE, 2022

[38] I. J. Ratul *et al.*, "Survival Prediction of Children Undergoing Hematopoietic Stem Cell Transplantation Using Different Machine Learning Classifiers by Performing Chi-Square Test and Hyperparameter Optimization: A Retrospective Analysis", *Computational and Mathematical Methods in Medicine*, vol. 2022. https://doi.org/10.1155/2022/9391136

[39] T. Hasan, M. F. B. Karim, M. K. Mahadi, M. M. Nishat, F. Faisal, "Employment of Ensemble Machine Learning Methods for Human Activity Recognition", *Journal of Healthcare Engineering*, vol. 2022, Article ID 6963891, 2022. https://doi.org/10.1155/2022/6963891

[40] M. R. Kabir, M. M. Muhaimin, M. A. Mahir, M. M. Nishat, F. Faisal and N. N. I. Moubarak, "Procuring MFCCs from Crema-D Dataset for Sentiment Analysis using Deep Learning Models with Hyperparameter Tuning," *RAAICON*, pp. 50-55, 2021, IEEE. doi: 10.1109/RAAICON54709.2021.9929975.

[41] M. K. Mahadi, S. R. Abir, A. Moon, M. Adnan, M. A. N. Islam Khan, M. M. Nishat, F. Faisal and M. T. Reza, "Machine Learning Assisted Decision Support System for Prediction of Prostrate Cancer", ECTI-CON, 2023, Thailand, IEEE, accepted, in press

[42] A. A. Rahman, M. R. Kabir, R. H. Ratul, F. A. Shams, M. M. Nishat and F. Faisal, "An Efficient Analysis of EEG Signals to Perform Emotion Analysis", 4th Int. Conf. on Artificial Intelligence, Robotics and Control (AIRC 2023), Cairo, Egypt, IEEE, accepted, in press

[43] "https://www.who.int/teams/noncommunicable-diseases/surveillance/systems-tools/global-school-based-student-health-survey/questionnaire."

[44] C. Su, R. Aseltine, R. Doshi, K. Chen, S. C. Rogers, and F. Wang, "Machine learning for suicide risk prediction in children and adolescents with electronic health records," *Transl Psychiatry*, vol. 10, no. 1, p. 413, 2020

[45] L. Zheng *et al.*, "Development of an early-warning system for high-risk patients for suicide attempt using deep learning and electronic health records," *Transl Psychiatry*, vol. 10, no. 1, p. 72, 2020

[46] R. Mishra et al., "SNAP-BATNET: Cascading author profiling and social network graphs for suicide ideation detection on social media," in *NACACL*, 2019, pp. 147–156

[47] H. D. Nelson *et al.*, "Suicide risk assessment and prevention: a systematic review focusing on veterans," *Psychiatric services*, vol. 68, no. 10, pp. 1003–1015, 2017

[48] K. Lehavot, D. Ben-Zeev, and R. E. Neville, "Ethical considerations and social media: a case of suicidal postings on Facebook," *J Dual Diagn*, vol. 8, no. 4, pp. 341–346, 2012.