(Table 1) contd.....

Paper	Disease	Dataset	Data Type	Sample size	Algorithm	Performance (%)			Motivation
				-		Accuracy	F-measure	AUC	
[71]	ADHD	NHS (SWYPFT)	Categorical data	69	SVM	72.46	-	0.784	This develops a diagnostic tool for ADHD using clinical data from NICE-compliant pathways to enhance clinician efficiency and accuracy, addressing the demand for reliable diagnosis amidst increasing awareness of the disorder.
					LR	72.46	-	0.795	
					DT	82.609	-	0.866	
					KNN	59.42	-	0.558	
					RF	81.159	-	0.866	
					NB	75.362	-	0.870	
Depression and Anxiety									
[42]	DA	Google Questionnaire	Categorical data	6,030	LR	9.897	-	98.89	Rising student mental health concerns necessitate early detection. This study utilizes Machine Learning to diagnose stress, anxiety, PTSD, ADHD, and depression, aiming to enhance prediction accuracy and mitigate adverse effects on academic performance and well-being. To develop an accurate diagnostic tool using resting-state fMRI (rs-fMRI) and a novel deep-learning approach to enhance the diagnosis of SZ and ADHD.
					RF	99.03	-	98.82	
					DT	92.58	-	92.87	
					KNN	98.57	-	98.98	
					NN	99.03	-	99.03	
[72]	DA	Reddit	Categorical data	2,809	BERT	0.924	0.924	-	
					CNN	0.6	0.4	-	
					LSTM	0.552	0.3562	-	
[43]	DA	R.G. Kar Medical College and Hospital, Kolkata Data	Categorical data	520	BN	79.8	79.7	88.9	To assist in predicting depression and anxiety in the life of the individual at an early stage.
					NB	79.6	79.4	85.3	
					LOG	72.4	72.2	81.1	
					MLP	77.8	77.8	85	
					SMO	75.3	74.6	75.9	
					KS	75.3	75.3	81.4	
					RS	87.5	87.5	91.7	
					J48	87.8	87.8	86	
					RF	89	89	94.3	
					RT	85.1	85.1	85	
[44]	DA	The American University of Beirut (AUB) and the Lebanese University (LU0 Survey)	Categorical data	329	MLP (D) (A)	-	68.42 68.29	73.90 72.60	University students face heightened mental health challenges exacerbated by COVID-19. We surveyed Lebanese students and developed ML models to predict depression, anxiety, and stress. Our aim is to enable early intervention and tailored support for students' mental well-being.
					LR (D) (A)	-	64.0 74.0	74.12 74.89	
					ADABOOST(D) (A)	-	68.0 69.0	76.25 74.89	
					RF(D) (A)	-	67.0 66.0	78.22 69.93	
					XGBOOST (D) (A)	-	68.0 68.0	75.55 6767	
					SVM(D) (A)	-	66.0 72.0	74.36 72.37	
					NB(D) (A)	-	65.0 76.0	74.12 76.37	
					KNN(D) (A)	-	46.0 62.0	66.63 61.05	
[45]	DA	College students during the Argentinean COVID-19 quarantine period.	Categorica l data	2,687	LR	0.78	0.73	0.90	To construct and evaluate machine learning (ML) algorithms aimed at forecasting depression levels among Argentinean students amidst the pandemic. To evaluate the effectiveness of classification and regression models by employing relevant performance metrics. To pinpoint the crucial features influencing the prediction of depression.
					RF	0.80	0.80	0.92	
					SVM	0.77	0.72	0.90	
[46]	DA	Social media posts from platforms (Twitter, facial expression databases,	Image Video text		LR	0.98	0.98	0.91	It highlights the importance of removing the stigma around mental health and the role of technology in providing support and interventions.
					RIDGE	0.98	0.98	0.8	
					DT	0.79	0.78	0.74	
					NB	0.67	0.75	0.64	
				2,500,000	LSTM	0.9	0.94	0.94	

(Table 1) contd.....

Paper	Disease	Dataset	Data Type	Sample size	Algorithm	Performance (%)			Motivation
				-		Accuracy	F-measure	AUC	
[47]	DA	3000 Tweets	Text-processing and Twitter Sentiment Analysis	3,000	DT	-	0.82	0.482	Various ML-based approaches are exploited to find whether a Twitter user is depressed or not based on his/her social network behavior and tweets.
					NB	-	0.461	0.461	
					SVM-L	-	0.558	0.558	
					SVM-K	-	0.650	0.650	
[48]	DA	Health Behaviors School Children questionnaire during the 2013-2014 academic year.	Categorica l data	3,984	DT(D) (A)	-	88.5 74.2	86.7 73.7	Early detection and intervention in the life of college students are crucial to mitigate the long-term consequences of these conditions. However, interventions are primarily focused on prevention or treatment rather than prediction and risk factors using machine learning.
					SVM(D) (A)	-	93.7 76.3	96.8 85.1	
					RF(D) (A)	-	93.3 78.5	97.2 86.8	
					ANN(D) (A)	-	92.3 75.7	96.8 84.0	
					NB(D) (A)	-	89.9 72.8	95.5 82.3	
[49]	DA	Two hundred eighty-four undergraduate students of Systems Engineering and Computer Science University in Peru (Using Generalized Anxiety Disorder Questionnaire (GAD-7))	Categorica l data	284	KNN	80.70	67.85	-	To detect and intervene early using machine learning to improve anxiety prediction, offering timely support.
					NB	87.72	79.17	-	
					DT	73.68	63.92	-	
					GB	89.49	63.68	-	
					SVM	96.49	91.68	-	
					SO-KNN	97.83	97.83	-	
					SO-SVM	97.83	97.88	-	
[50]	DA	5685 students in grades 5 to 9 (aged 10-15 years) from public schools administered by the Palestinian Authority and United Nations Relief and Works Agency (UNRWA) schools.	Categorica l data	294	DT (D) (A)	-	88.5 74.2	86.7 73.7	This study aims to predict depression and anxiety risk factors among Palestinian school children using machine learning, facilitating tailored prevention and intervention programs to enhance their mental health and cognitive development.
					SVM(D) (A)	-	93.7 76.8	96.8 82.1	
					RF(D) (A)	-	93.3 78.5	97.2 86.8	
					ANN(D)	-	92.3	96.8	
					(A)		75.7	84.0	
					RF(D) (A)	-	89.9 72.8	95.5 82.3	

Note: D= Depression, A= Anxiety, ADHD = Attention Deficit Hyperactivity Disorder, fMRI = functional Magnetic Resonance Imaging, s-MRI = structural Magnetic Resonance Imaging, CNN = Convolutional Neural Network, SVM = Support Vector Machine, NN = Neural Network, LR= Logistic Regression, KNN = k-Nearest Neighbor, DT = Decision Tree, NB = Naïve Baye, RF = Random Forest, EEG = Electroencephalography, NHS (SWYPFT) = National Health Service Specialist Mental Health Provider (South West Yorkshire Partnership NHS Foundation Trust, XGBoost = extreme gradient boosting, CANTAB = Cambridge Neuropsychological Test Automated Battery, LASSO = Least Absolute Shrinkage and Selection Operator, BERT = Bidirectional Encoder Representations from Transformers (BERT), SVM-K = Support Vector Machine with kernel method, MLP = Multi-Layer Perceptron, SMO = Sequential Minimal Optimization (used for training support vector machines), BN = Bayesian Network, KS = K-Support, RS = Random Subspace, J48 = C4.5 Decision Tree algorithm, RT = Regression Tree.

4. RESULTS

The summary of datasets in Table **1** utilized in 30 studies included in this review spans a diverse array of sources, including data on male and female students covering grades 5 to 9, IBM® MarketScan® Commercial Subset, clinical data, resting-state functional magnetic resonance imaging (rsfMRI) data, Twitter data, and more. Dataset sizes ranged from 50 to 2,500,000 records, reflecting the variability and scale of the data sources utilized. The studies targeted a wide range of outcome variables, including near-term suicidal behaviors, diagnosis of Post-Traumatic Stress Disorder (PTSD), presence of Childbirth-related PTSD (CB-PTSD), suicide attempts, Bipolar Disorder (BD), Attention-Deficit/Hyperactivity Disorder (ADHD), depression, and anxiety. Prediction nature varied across studies, with aims such as predicting the likelihood of individuals engaging in suicidal behaviors, identifying PTSD patients from structured and unstructured medical records, and predicting PTSD diagnosis probability in firefighters exposed to trauma. Variable sources included surveys, experiments, observations, and existing databases, while variable types encompassed categorical, continuous, ordinal, and binary variables, highlighting the complexity and heterogeneity of mental health data.

The systematic review aimed to evaluate the performance of thirty classification algorithms in predicting five different diseases, particularly focusing on mental health. It encompassed advancements in machine learning algorithms from 2011 to 2024. Inclusion criteria involved scrutinizing research papers and employing a comprehensive search across databases. Measures, such as eliminating duplicates and adhering to the PRISMA flowchart, were implemented for reliability. The major evaluated classifiers included Random Forest, Logistic Regression, Support Vector Machine (SVM), Multi-layer Perceptron (MLP), Decision Tree, Naive Bayes, K-nearest neighbors, Gradient Boosting Machine (GBM), and Convolutional Neural Network (CNN).

4.1. Approaches for Bipolar Disorder Detection

Machine learning techniques have emerged as valuable tools for identifying and detecting bipolar disorder, a complex mental illness characterized by extreme mood swings. Timely diagnosis is crucial for effective management. Birner *et al*. examined how LR can aid in diagnosing bipolar disorder, aiming to decrease misdiagnosis rates and shorten diagnosis time [55]. Sonkurt *et al*. developed a prediction algorithm utilizing CANTAB neurocognitive battery and a novel machine-learning approach to differentiate bipolar disorder patients from healthy controls, achieving a 78% accuracy rate [56]. Passos *et al*. identified a suicidality signature among mood disorder patients, including bipolar disorder, using machine learning [57]. Chen *et al*. presented a support vector machine (SVM) for detecting brain structural changes as biomarkers from magnetic resonance images. The SVM demonstrates superior performance in bipolar disorder datasets, achieving an AUC of 80.6%. It offers the potential for automatic diagnosis and mechanism studies in neurological and psychiatric diseases [58]. These studies underscore the potential of machine learning to enhance early detection, diagnostic precision, and personalized treatment strategies for bipolar disorder.

4.2. Approaches for Schizophrenia Prediction

Several studies have showcased the effectiveness of machine learning (ML) techniques in predicting schizophrenia. While Bohaterewicz *et al*. concentrated on leveraging machine learning and advanced neuroimaging to improve prediction of suicide risk in schizophrenic patients [38], Kirchebner *et al*. employed Boosted Classification Trees to explore the factors influencing violent behavior in the same population [39]. This dual approach highlights the potential of machine learning for both improving risk prediction of suicide and identifying factors associated with violence in schizophrenia, paving the way for better patient outcomes and targeted interventions. Hahn *et al*. achieved an impressive 84% accuracy using Support Vector Machine (SVM) and diffusion tensor imaging data [59]. Building on prior research, Hettige *et al*. and Birnbaum *et al*. explored machine learning for mental health diagnosis using different algorithms, like SVM, LR, RF, *etc* [60, 61]. Notably, Birnbaum *et al*. performed better in identifying schizophrenia *via* social media analysis [61]. Similarly, Hettige *et al*. focused on developing models to predict suicide attempts among individuals already diagnosed with schizophrenia spectrum disorders [60].

In summary, ML shows promise in schizophrenia prediction, especially when utilizing neuroimaging and genetic data in multimodal approaches. Overcoming challenges like sample sizes and embracing longitudinal research could advance the early detection and management of schizophrenia.

4.3. Approaches for Post-traumatic Stress Disorder Detection

Various machine learning techniques have been explored for detecting Post-Traumatic Stress Disorder (PTSD), leveraging diverse datasets and methodologies. Costa *et al*. proposed Support Vector Machines (SVM) using physiological signals [64], while Banerjee *et al*. focused on Long Short-Term Memory (LSTM) neural networks with textual features [65]. He *et al*. combined Random Forest, AdaBoost, and SVM with demographic and behavioral features [66]. Lekkas *et al*. explored the use of GPS data from smartphones to detect PTSD diagnostic status among previously traumatized women, achieving high predictive performance with an AUC of 0.816, balanced sensitivity of 0.743, balanced specificity of 0.8, and balanced accuracy of 0.771, suggesting the potential utility of GPS information as a digital biomarker for PTSD [67], Beymohammadi *et al*. used Convolutional Neural Networks (CNN) with EEG signals [68], and Miotto *et al*. utilized Deep Learning models with electronic health records [69]. Jeffrey *et al*. employed machine learning on social media data for PTSD signs [70]. These studies collectively illustrate diverse methodologies and data sources, contributing to a comprehensive understanding of PTSD detection. Despite limitations, this body of research highlights the potential of machine learning in aiding PTSD detection and advancing treatment strategies.

4.4. Approaches for Depression and Anxiety Detection

Recent studies have leveraged machine learning (ML) techniques to predict mental health conditions, such as depression and anxiety. Chen *et al*. [71] developed a diagnostic model for adult ADHD. They demonstrated promising statistical accuracy, suggesting the potential of machine learning models, such as (SVM) and KNN, to inform clinical practice in diagnosing ADHD. Ojo *et al*. [72] employed Natural Language Processing (NLP) and sentiment analysis on social media data for depression detection. Alghowinem *et al*. [73] differentiated depressed individuals from controls using Gaussian Mixture Models (GMM) and Mel Frequency Cepstral Coefficients (MFCC) from speech data.

Watts *et al*. [74] utilized algorithms like Random Forests and SVM on EEG data to predict major depressive disorder (MDD) diagnosis. Deep learning methods, including Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN), were applied by

Chiong *et al*. [75] for anxiety and depression detection from social media texts. Yoon *et al*. and Xezonaki *et al*. [76, 77] contributed to depression detection using Multimodal Vlog Dataset and Hierarchical Attention Networks. These studies underscore the potential of ML in mental health screening and intervention.

4.5. Approaches for Attention-deficit/hyperactivity Disorder Detection

ADHD, a neurodevelopmental disorder characterized by symptoms like inattentiveness, hyperactivity, and impulsivity, necessitates early and accurate detection for effective management. Sinan *et al*. [78] proposed a method employing Convolutional Neural Networks (CNN) with multimodal feature fusion using resting-state functional MRI (rs-fMRI) and EEG data for precise ADHD classification. Shoeibi *et al*. [79] introduced a 3D CNN-based framework for rs-fMRI analysis, showing promising results in automatic ADHD diagnosis. Gurcan *et al*. [80] utilized Deep CNNs on functional near-infrared spectroscopy (fNIRS) data, achieving high accuracy in distinguishing ADHD patients. Arbabshirani *et al*. [81] integrated machine learning algorithms with structural and functional brain scans for individualized ADHD prediction. As mentioned in Table **1**, results demonstrated that DT [71] outperformed other algorithms in predicting ADHD from images with an accuracy of 86.6%. This suggests that DT has slightly superior performance in ADHD prediction using provided images compared to other classification models.

5. DISCUSSION

The increasing prevalence of mental health disorders, coupled with the advancement of technology, has led to a growing interest in utilizing machine learning techniques for early detection and diagnosis. In recent years, the potential of machine learning in detecting a range of mental health disorders, including bipolar disorder, schizophrenia, PTSD, depression, and anxiety, has gained significant attention. These disorders pose a substantial challenge to mental healthcare due to their complex nature and the limitations of traditional diagnostic methods.

This review delves into a collection of studies that have explored the application of machine learning in detecting mental health disorders. These studies showcase the promise of machine learning approaches in improving the accuracy and efficiency of diagnosis. However, it is crucial to critically evaluate both the strengths and limitations of these studies to gain a comprehensive understanding of their implications.

Liu *et al*. and Johnson *et al*. [4, 5] employed natural language processing to anticipate bipolar disorder using textual data and demonstrated the potential of neuroimaging data in differentiating bipolar disorder patients from healthy controls. For instance, in the context of mental health disorders, studies conducted by López Steinmetz *et al*. and Joshi *et al*. [45, 46] highlight the extensive assessment of the COVID-19 mental health implications among Argentine college students, as well as the creative application of Artificial Intelligence and Machine Learning algorithms for diagnosing depression and emotional states. Birner *et al*. [55] proposed that because of the variety of symptoms associated with bipolar disorder, correctly diagnosing bipolar disorder can take over nine years. Individuals with bipolar illness may benefit from early detection and care, which might dramatically enhance their quality of life and lifespan. The hypothesis is that machine learning approaches can help with the diagnostic process, potentially lowering misdiagnosis rates.

Transitioning to schizophrenia, Hahn *et al*. [59] showcased the power of neuroimaging data and support vector machines in achieving high accuracy in predicting schizophrenia. Hettige *et al*. [60] highlighted the serious problem of suicide among those suffering from schizophrenia, as well as the difficulty in recognizing those who are most likely to attempt suicide in the future. It emphasizes the ability of machine learning algorithms to include various risk variables and predict suicide attempts. However, it highlights the present ambiguity about how to effectively combine previously established risk variables into a useful prediction tool for evaluating the likelihood of suicide attempts in schizophrenia patients. Birnbaum *et al*. [61] reported that previous research demonstrated that language analysis of publicly available Twitter feeds may be used to discriminate persons who self-identify as having schizophrenia from healthy individuals. However, there have been few initiatives, including professional involvement, to examine the legitimacy of these diagnostic self-disclosures. The integration of multiple modalities, including clinical assessments, neuroimaging, and genetic information, demonstrated improved prediction accuracy and a better understanding of the heterogeneous nature of schizophrenia in studies by Bartal *et al*. [62] and Kim [63]. These articles explore innovative approaches to address mental health challenges; the first investigates using computational methods to screen for childbirth-related posttraumatic stress disorder, while the second focuses on developing an analysis model, leveraging AI algorithms and big data, to understand the prevalence of post-traumatic stress disorder among firefighters. However, sample size limitations and the dynamic nature of schizophrenia's progression pose challenges that need addressing.

In the case of PTSD, diverse approaches using physiological signals, textual features, EEG signals, and social media data have shown the potential of machine learning in detection. Costa *et al*. [30] utilized physiological signals, Banerjee *et al*. [65] focused on textual features, and Coppersmith *et al*., Beymohammadi *et al.,* and Miotto *et al*. [67-69] analyzed EEG signals by employing natural language processing and deep learning models, respectively, on various data sources, revealing the versatility of machine learning in assisting with PTSD detection.

In the realm of depression and anxiety, studies explored audio/visual features, social media data, speech data, and EEG data to detect these conditions [72-74]. The application of deep learning models trained on social media texts by Chiong *et al*. [75] further underlines the potential of machine learning in this domain. However, the limitations encompassing small sample sizes and the necessity for validation hinder the full realization of their potential.

In summary, this review sheds light on the potential of machine learning in detecting mental health disorders, such as bipolar disorder, schizophrenia, PTSD, depression, and anxiety. The use of machine learning models presents avenues for early detection and personalized interventions, promising to enhance patient outcomes. Nevertheless, researchers must acknowledge the limitations within these studies, including small sample sizes, diverse datasets, and ethical considerations. Addressing these challenges is crucial for further validation and the eventual implementation of machine-learning approaches in mental health diagnostics (Table **S1**).

CONCLUSION

This comprehensive study delves into the existing literature on the application of deep learning and machine learning techniques for predicting mental health outcomes, specifically among college students. The research demonstrates that these approaches exhibit promising potential in accurately diagnosing mental health conditions. Various algorithms and methods have been employed to analyze a range of data sources, including demographic data, clinical assessments, social media content, and neuroimaging data, effectively identifying individuals at risk of mental health disorders. Supervised learning methods, including Random Forest, Support Vector Machines (SVM), Extreme Learning Machine (ELM), as well as deep learning algorithms, such as Neural Network (NN) and Convolutional Neural Networks (CNN), have demonstrated effectiveness in forecasting mental health disorders.

Supervised learning methods, including Random Forest, Support Vector Machines (SVM), Extreme Learning Machine (ELM), as well as deep learning algorithms such as Neural Network (NN) and Convolutional Neural Networks (CNN), have demonstrated effectiveness in forecasting mental health disorders. Certain algorithms stood out using the author's dataset for each specific disease. Convolutional Neural Networks (CNNs) in bipolar disorder demonstrated outstanding performance, achieving an impressive accuracy rate and f-measure of 99.75%, surpassing other models. In the case of schizophrenia, SVM attained 90% for f-measure and 95% for AUC. For PTSD, both CNN and RF achieved a notable accuracy rate of 99%. In ADHD, ELM outperformed other algorithms with an AUC of 0.8757%. Lastly, neural networks showed the highest accuracy and AUC metrics of 99.03% for depression and anxiety.

However, challenges remain, including needing more extensive and diverse datasets, accounting for the diversity of mental health conditions, and integrating longitudinal data for temporal insight. Furthermore, improving the interpretability and transparency of machine learning models is crucial to fostering trust and acceptance in clinical settings. Despite these challenges, the application of machine learning in mental health prediction offers the potential for early detection, personalized interventions, and enhanced mental health outcomes among college students. Continuous research collaboration among researchers, clinicians, and policymakers is vital to fully harness the benefits of machine learning in mental health care.

AUTHORS' CONTRIBUTION

U.M conceptualized and designed the research study. U.M wrote the manuscript and coordinated the contributions of other authors. U.M, A.U, and U.I reviewed and edited the final manuscript. A.U provided critical feedback on the manuscript. U.M created and visualized the data. U.I itemized the author's guidelines. The 3 authors approved the final manuscript for submission.

LIST OF ABBREVIATIONS

RF	=	Random Forest
SVM	=	Support Vector Machine
ML	=	Machine Learning
WHO	=	World Health Organization

CONSENT FOR PUBLICATION

Not applicable.

STANDARDS OF REPORTING

PRISMA guidelines and methodology were followed.

AVAILABILITY OF DATA AND MATERIAL

All the data and supportive information are provided within the article.

FUNDING

None.

CONFLICT OF INTEREST

The authors declared no conflict of interest, financial or otherwise.

ACKNOWLEDGEMENTS

Declared none.

SUPPLEMENTARY MATERIAL

PRISMA checklist is available as supplementary material on the publisher's website along with the published article.

Supplementary material is available on the publisher's website along with the published article.

REFERENCES

[1] Cho G, Yim J, Choi Y, Ko J, Lee SH. Review of machine learning algorithms for diagnosing mental illness. Psychiatry Investig

2019; 16(4): 262-9.
http://dx.doi.org/10.30773/pi.2018.12.21.2.

[2] Pintelas EG, Kotsilieris T, Livieris IE, Pintelas P. A review of machine learning prediction methods for anxiety disorders. ACM 8th International Conference on Software Development and Technologies for Enhancing Accessibility and Fighting Infoexclusion.
http://dx.doi.org/10.1145/3218585.3218587

[3] Bengio Y, Lecun Y, Hinton G. Deep learning for AI. Commun ACM J 2021; 64(7): 58-65.
http://dx.doi.org/10.1145/3448250

[4] Liu XQ, Guo YX, Zhang WJ, Gao WJ. Influencing factors, prediction and prevention of depression in college students: A literature review. World J Psychiatry 2022; 12(7): 860-73.
http://dx.doi.org/10.5498/wjp.v12.i7.860 PMID: 36051603

[5] Johnson AE, Stone DJ, Celi LA, Pollard TJ, Mark RG. The MIMIC code repository: Enabling reproducibility in critical care research. J Am Med Inform Assoc 2016; 23(5): 952-60.
PMID: 29036464

[6] Kirlic N, Akeman E, DeVille DC, *et al.* A machine learning analysis of risk and protective factors of suicidal thoughts and behaviors in college students. J Am Coll Health 2023; 71(6): 1863-72.
http://dx.doi.org/10.1080/07448481.2021.1947841 PMID: 34292856

[7] Graduate research (Sophia). 2013. Available from: https://library.stkate.edu/archives/sophia

[8] Albreiki B, Zaki N, Alashwal H. A systematic literature review of student' performance prediction using machine learning techniques. Educ Sci 2021; 11(9): 552.
http://dx.doi.org/10.3390/educsci11090552.

[9] Mutalib Sofianita, Shafiee Nor Safika Mohd, Abdul-Rahman Shuzlina. Mental health prediction models using machine learning in higher education institution. TURCOMAT 2021; 12(5): 1782-92. Available from: https://turcomat.org/index.php/turkbilmat/article/view/2181

[10] Tate AE, McCabe RC, Larsson H, Lundström S, Lichtenstein P, Kuja-Halkola R. Predicting mental health problems in adolescence using machine learning techniques. PLoS One 2020; 15(4): e0230389.
http://dx.doi.org/10.1371/journal.pone.0230389 PMID: 32251439

[11] Iyortsuun NK, Kim SH, Jhon M, Yang HJ, Pant S. A review of machine learning and deep learning approaches on mental health diagnosis. Healthcare (Basel) 2023; 11(3): 285.
http://dx.doi.org/10.3390/healthcare11030285 PMID: 36766860

[12] Fried EI, van Borkulo CD, Cramer AOJ, Boschloo L, Schoevers RA, Borsboom D. Mental disorders as networks of problems: A review of recent insights. Soc Psychiatry Psychiatr Epidemiol 2017; 52(1): 1-10.
http://dx.doi.org/10.1007/s00127-016-1319-z PMID: 27921134

[13] WHO strategic communications framework for effective communications. 2017. Available from: https://www.who.int/docs/default-source/documents/communicating-for-health/communication-framework.pdf

[14] Okoli C. A guide to conducting a standalone systematic literature review. Comm Assoc Inform Syst 2015; 37: 43.
http://dx.doi.org/10.17705/1CAIS.03743

[15] Chung Jetli, Teo Jason. Mental health prediction using machine learning: Taxonomy, applications, and challenges. Appl comput intell soft comput 2022.
http://dx.doi.org/10.1155/2022/9970363.

[16] McIntyre RS, Berk M, Brietzke E, Goldstein BI, Kessing LV, Malhi GS. Bipolar disorders. Lancet 2020; 396(10265): 1841-56.
http://dx.doi.org/10.1016/S0140-6736(20)31544-0.

[17] Kerner B. Genetics of bipolar disorder. Appl Clin Genet 2014; 7: 33-42.
http://dx.doi.org/10.2147/TACG.S39297.

[18] Krishna R, Cherian J, Gohil K. Schizophrenia: Overview and treatment options. P T 2014; 39(9): 638-45.
PMID: 25210417

[19] Lavretsky H. History of schizophrenia as a psychiatric disorder. In: Mueser KT, Jeste DV, Eds. Clinical Handbook of Schizophrenia. New York, New York: Guilford Press 2008; pp. 3-12. Available from: https://guilford.com/excerpts/mueser3.pdf?t=1

[20] Crismon M, Rania S, Peter F. Schizophrenia. 2017. Available from: https://accesspharmacy.mhmedical.com/content.aspx?bookid=1861&sectionid=146064659

[21] Guze SB. Diagnostic and statistical manual of mental disorders. Washington: American Psychiatric Publishing 1995.
http://dx.doi.org/10.1176/ajp.152.8.1228.

[22] Ben-Zur H, Zeidner M. Threat to life and risk-taking behaviors: A review of empirical findings and explanatory models. Pers Soc Psychol Rev 2009; 13(2): 109-28.
http://dx.doi.org/10.1177/1088868308330104

[23] Schnurr P, Green BL. Trauma and health: Physical health consequences of exposure to extreme stress. 2004.
http://dx.doi.org/10.1037/10723-000.

[24] Tull MT, Weiss NH, McDermott MJ. Post-traumatic stress disorder and impulsive and risky behavior: Overview and discussion of potential mechanisms. Comprehensive Guide to Post-Traumatic Stress Disorders. 2016; pp. 803-16.
http://dx.doi.org/10.1007/978-3-319-08359-9_16.

[25] Adams ZW, Moreland A, Cohen JR, Lee RC, Hanson RF, Danielson CK. Polyvictimization: Latent profiles and mental health outcomes in a clinical sample of adolescents. Psychol Violence 2016; 6(1): 145-55.
http://dx.doi.org/10.1037/a0039713.

[26] Wilson HW, Pettineo L, Edmonds A, Goodman EA, Emerson E, Donenberg GR. From violence exposure to development of sexual risk in low-income urban girls: The role of psychopathology. Child Psychiatry Hum Dev 2015; 46(2): 270-80.
http://dx.doi.org/10.1007/s10578-014-0466-2.

[27] Cavanaugh CE, Hansen NB, Sullivan TP. HIV sexual risk behavior among low-income women experiencing intimate partner violence: The role of posttraumatic stress disorder. AIDS Behav 2010; 14(2): 318-27.
http://dx.doi.org/10.1007/s10461-009-9623-1

[28] Lamoureux BE, Palmieri PA, Jackson AP, Hobfoll SE. Child sexual abuse and adulthood-interpersonal outcomes: Examining pathways for intervention. Psychol Trauma 2012; 4(6): 605-13.
http://dx.doi.org/10.1037/a0026079.

[29] Moore AA, Overstreet C, Kendler KS, Dick DM, Adkins A, Amstadter AB. Potentially traumatic events, personality, and risky sexual behavior in undergraduate college students. Psychol Trauma 2016.
PMID: 27348066

[30] Costantini L, Pasquarella C, Odone A, *et al.* Screening for depression in primary care with Patient Health Questionnaire-9 (PHQ-9): A systematic review. J Affect Disord 2021; 279: 473-83.
http://dx.doi.org/10.1016/j.jad.2020.09.131 PMID: 33126078

[31] Shorey S, Ng ED, Wong CHJ. Global prevalence of depression and elevated depressive symptoms among adolescents: A systematic review and meta-analysis. Br J Clin Psychol 2022; 61(2): 287-305.
http://dx.doi.org/10.1111/bjc.12333 PMID: 34569066

[32] Harmer B, Lee S, Duong TVH, Saadabadi A. Suicidal ideation. StatPearls. Treasure Island, FL, USA: StatPearls Publishing 2022. Available from: https://www.ncbi.nlm.nih.gov/books/NBK565877/

[33] American Psychological Association. Anxiety. Available from: https://www.apa.org/topics/anxiety

[34] American Psychiatric Association. Diagnostic and statistical manual of mental disorders. American Psychiatric Publishing 2013.
http://dx.doi.org/10.1176/appi.books.9780890425596.

[35] Perez Arribas I, Goodwin GM, Geddes JR, Lyons T, Saunders KEA. A signature-based machine learning model for distinguishing bipolar disorder and borderline personality disorder. Transl Psychiatry 2018; 8(1): 274.
http://dx.doi.org/10.1038/s41398-018-0334-0 PMID: 30546013

[36] Li H, Cui L, Cao L, *et al.* Identification of bipolar disorder using a

combination of multimodality magnetic resonance imaging and machine learning techniques. BMC Psychiatry 2020; 20(1): 488. http://dx.doi.org/10.1186/s12888-020-02886-5 PMID: 33023515

[37] Li Z, Li W, Wei Y, *et al.* Deep learning based automatic diagnosis of first-episode psychosis, bipolar disorder and healthy controls. Comput Med Imaging Graph 2021; 89: 101882. http://dx.doi.org/10.1016/j.compmedimag.2021.101882 PMID: 33684730

[38] Bohaterewicz B, Sobczak AM, Podolak I, *et al.* Machine learning-based identification of suicidal risk in patients with schizophrenia using multi-level resting-state fMRI features. Front Neurosci 2021; 14: 605697. http://dx.doi.org/10.3389/fnins.2020.605697 PMID: 33505239

[39] Kirchebner J, Sonnweber M, Nater UM, Günther M, Lau S. Stress, schizophrenia, and violence: A machine learning approach. J Interpers Violence 2022; 37(1-2): 602-22. http://dx.doi.org/10.1177/0886260520913641 PMID: 32306866

[40] Zafari H, Kosowan L, Zulkernine F, Signer A. Diagnosing post-traumatic stress disorder using electronic medical record data. Health Informatics J 2021; 27(4) http://dx.doi.org/10.1177/14604582211053259 PMID: 34818936

[41] Gagnon-Sanschagrin P, Schein J, Urganus A, *et al.* Identifying individuals with undiagnosed post-traumatic stress disorder in a large United States civilian population – A machine learning approach. BMC Psychiatry 2022; 22(1): 630. http://dx.doi.org/10.1186/s12888-022-04267-6 PMID: 36171558

[42] Sahu S, Debbarma T. Mental health prediction among students using machine learning techniques. Evol Comp Intell Smart Innov Sys Technol 2023; 529-41. http://dx.doi.org/10.1007/978-981-19-7513-4_46.

[43] Sau A, Bhakta I. Predicting anxiety and depression in elderly patients using machine learning technology. Healthc Technol Lett 2017; 4(6): 238-43. http://dx.doi.org/10.1049/htl.2016.0096

[44] El Morr C, Jammal M, Bou-Hamad I, *et al.* Predictive machine learning models for assessing lebanese university students' depression, anxiety, and stress during COVID-19. J Prim Care Community Health 2024; 15: 21501319241235588. http://dx.doi.org/10.1177/21501319241235588 PMID: 38546161

[45] López Steinmetz LC, Leyes CA, Dutto Florio MA, Fong SB, López Steinmetz RL, Godoy JC. Mental health impacts in Argentinean college students during COVID-19 quarantine. Front Psychiatry 2021; 12: 557880. http://dx.doi.org/10.3389/fpsyt.2021.557880 PMID: 33746788

[46] Joshi ML, Kanoongo N. Depression detection using emotional artificial intelligence and machine learning: A closer review. Mater Today Proc 2022; 58: 217-26. http://dx.doi.org/10.1016/j.matpr.2022.01.467

[47] Alsagri HS, Ykhlef M. Machine learning-based approach for depression detection in twitter using content and activity features. IEICE Trans Inf Syst 2020; E103(D): 1825-32. http://dx.doi.org/10.1587/transinf.2020EDP7023

[48] Qasrawi R, Vicuna Polo SP, Abu Al-Halawa D, Hallaq S, Abdeen Z. Assessment and prediction of depression and anxiety risk factors in schoolchildren: Machine learning techniques performance analysis. JMIR Form Res 2022; 6(8): e32736. http://dx.doi.org/10.2196/32736 PMID: 35665695

[49] Daza A, Arroyo-Paz , Bobadilla J, Apaza O, Pinto J. Stacking ensemble learning model for predict anxiety level in university students using balancing methods. Informatics in Medicine Unlocked 2023; 42: 101340. http://dx.doi.org/10.1016/j.imu.2023.101340

[50] Shen Y, Yang H, Lin L. Automatic depression detection: An emotional audio-textual corpus and A Gru/Bilstm-based model. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). http://dx.doi.org/10.1109/ICASSP43922.2022.9746569.

[51] Wu MJ, Passos IC, Bauer IE, *et al.* Individualized identification of euthymic bipolar disorder using the Cambridge Neuropsychological Test Automated Battery (CANTAB) and machine learning. J Affect Disord 2016; 192: 219-25. http://dx.doi.org/10.1016/j.jad.2015.12.053 PMID: 26748737

[52] Vaishnavi K, Kamath UN, Rao BA, Reddy NS. Predicting mental health illness using machine learning algorithms. J Phys Conf Ser 2022; 2161(1): 012021. http://dx.doi.org/10.1088/1742-6596/2161/1/012021

[53] Peng X, Lin P, Zhang T, Wang J. Extreme learning machine-based classification of ADHD using brain structural MRI data. PLoS One 2013; 8(11): e79476. http://dx.doi.org/10.1371/journal.pone.0079476 PMID: 24260229

[54] Yin W, Li T, Mucha PJ, *et al.* Altered neural flexibility in children with attention-deficit/hyperactivity disorder. Mol Psychiatry 2022; 27(11): 4673-9. http://dx.doi.org/10.1038/s41380-022-01706-4 PMID: 35869272

[55] Birner A, Mairinger M, Elst C, *et al.* Machine-based learning of multidimensional data in bipolar disorder – Pilot results. Bipolar Disord 2024; 26(4): 364-75. http://dx.doi.org/10.1111/bdi.13426 PMID: 38531635

[56] Sonkurt HO, Altınöz AE, Çimen E, Köşger F, Öztürk G. The role of cognitive functions in the diagnosis of bipolar disorder: A machine learning model. Int J Med Inform 2021; 145: 104311. http://dx.doi.org/10.1016/j.ijmedinf.2020.104311 PMID: 33202371

[57] Passos IC, *et al.* Identifying a clinical signature of suicidality among patients with mood disorders: A pilot study using a machine learning approach. J Affect Disord 2018; 233: 1-9. PMID: 26773901

[58] Chen Y, Storrs J, Tan L, Mazlack LJ, Lee JH, Lu LJ. Detecting brain structural changes as biomarker from magnetic resonance images using a local feature based SVM approach. J Neurosci Methods 2014; 221: 22-31. http://dx.doi.org/10.1016/j.jneumeth.2013.09.001 PMID: 24041480

[59] Hahn T, *et al.* Prediction of psychosis across protocols and risk cohorts using automated language analysis. World Psychiatry 2019; 18(1): 67-75. PMID: 30600629

[60] Hettige NC, Nguyen TB, Yuan C, *et al.* Classification of suicide attempters in schizophrenia using sociocultural and clinical features: A machine learning approach. Gen Hosp Psychiatry 2017; 47: 20-8. http://dx.doi.org/10.1016/j.genhosppsych.2017.03.001 PMID: 28807134

[61] Birnbaum ML, Ernala SK, Rizvi AF, De Choudhury M, Kane JM. A collaborative approach to identifying social media markers of schizophrenia by employing machine learning and clinical appraisals. J Med Internet Res 2017; 19(8): e289. http://dx.doi.org/10.2196/jmir.7956 PMID: 28807891

[62] Bartal A, Jagodnik KM, Chan SJ, Babu MS, Dekel S. Identifying women with postdelivery posttraumatic stress disorder using natural language processing of personal childbirth narratives. Am J Obstet Gynecol MFM 2023; 5(3): 100834. http://dx.doi.org/10.1016/j.ajogmf.2022.100834 PMID: 36509356

[63] Kim JB. A study on the development of analysis model using artificial intelligence algorithms for PTSD (Post-Traumatic Stress Disorder) data. Int J Curr Res Rev 2020; 12(16): 60-5. http://dx.doi.org/10.31782/IJCRR.2020.12163

[64] Reinertsen E, Nemati S, Vest AN, *et al.* Heart rate-based window segmentation improves accuracy of classifying posttraumatic stress disorder using heart rate variability measures. Physiol Meas 2017; 38(6): 1061-76. http://dx.doi.org/10.1088/1361-6579/aa6e9c PMID: 28489609

[65] Banerjee D, Islam K, Mei G, Xiao L, Zhang G, Xu R, *et al.* A Deep Transfer Learning Approach for Improved Post-Traumatic Stress Disorder Diagnosis In: 2017 IEEE International Conference on Data Mining. ICDM 2017; pp. 11-20.https://ieeexplore.ieee.org/document/8215473 http://dx.doi.org/10.1109/ICDM.2017.10

[66] He Q, Veldkamp BP, Glas CAW, de Vries T. Automated assessment of patients' self-narratives for posttraumatic stress disorder screening using natural language processing and text mining.

Assessment 2017; 24(2): 157-72.
http://dx.doi.org/10.1177/1073191115602551 PMID: 26358713

[67] Lekkas D, Jacobson NC. Using artificial intelligence and longitudinal location data to differentiate persons who develop posttraumatic stress disorder following childhood trauma. Sci Rep 2021; 11(1): 10303.
http://dx.doi.org/10.1038/s41598-021-89768-2 PMID: 33986445

[68] Beykmohammadi A, Ghanbari Z, Moradi MH. PTSD diagnosis using deep transfer learning: An EEG study. 29th National and 7th International Iranian Conference on Biomedical Engineering (ICBME).
http://dx.doi.org/10.1109/ICBME57741.2022.10052954

[69] Miotto R, Wang F, Wang S. Deep learning for healthcare: Review, opportunities and challenges. Brief Bioinform 2018; 19(6): 1236-46.
http://dx.doi.org/10.1093/bib/bbx044.

[70] Sawalha J, Yousefnezhad M, Shah Z, Brown MRG, Greenshaw AJ, Greiner R. Detecting presence of PTSD using sentiment analysis from text data. Front Psychiatry 2022; 12: 811392.
http://dx.doi.org/10.3389/fpsyt.2021.811392 PMID: 35178000

[71] Chen T, Antoniou G, Adamou M, Tachmazidis I, Su P. Automatic diagnosis of attention deficit hyperactivity disorder using machine learning. Appl Artif Intell 2021; 35(9): 657-69.
http://dx.doi.org/10.1080/08839514.2021.1933761

[72] Ojo O, Adewuyi I, Oni O, Oyinloye O, Gbolade I, Ojo A. An intelligent-based system for detecting depression on social media platform. 2023.
http://dx.doi.org/10.21203/rs.3.rs-2931653/v1

[73] Alghowinem S, Goecke R, Wagner M. Automatic detection of depression symptoms in speech using Gaussian mixture models. IEEE Trans Affect Comput 2016; 7(3): 218-29.

[74] Watts D, Pulice RF, Reilly J, Brunoni AR, Kapczinski F, Passos IC. Predicting treatment response using EEG in major depressive disorder: A machine-learning meta-analysis. Transl Psychiatry 2022; 12(1): 332.
http://dx.doi.org/10.1038/s41398-022-02064-z PMID: 35961967

[75] Chiong R, Budhi GS, Dhakal S, Chiong F. A textual-based featuring approach for depression detection using machine learning classifiers and social media texts. Comput Biol Med 2021; 135: 104499.
http://dx.doi.org/10.1016/j.compbiomed.2021.104499 PMID: 34174760

[76] Yoon J, Kang C, Kim S, Han J. D-vlog: Multimodal vlog dataset for depression detection. Proc Conf AAAI Artif Intell 2022; 36(11): 12226-34.
http://dx.doi.org/10.1609/aaai.v36i11.21483

[77] Xezonaki D, Paraskevopoulos G, Potamianos A, Narayanan S. Affective conditioning on hierarchical attention networks applied to depression detection from transcribed clinical interviews. arXiv 2020.
http://dx.doi.org/10.48550/arXiv.2006.08336

[78] Altun S, Alkan A, Altun H. Automatic diagnosis of attention deficit hyperactivity disorder with continuous wavelet transform and convolutional neural network. Clin Psychopharmacol Neurosci 2022; 20(4): 715-24.
http://dx.doi.org/10.9758/cpn.2022.20.4.715 PMID: 36263646

[79] Shoeibi A, Ghassemi N, Khodatars M, *et al*. Automatic diagnosis of schizophrenia and attention deficit hyperactivity disorder in rs-fMRI modality using convolutional autoencoder model and interval type-2 fuzzy regression. Cogn Neurodynamics 2023; 17(6): 1501-23.
http://dx.doi.org/10.1007/s11571-022-09897-w PMID: 37974583

[80] Taşpinar G, Özkurt N. 3D CNN based automatic diagnosis of ADHD using fMRI volumes. Deu Muhendislik Fakultesi Fen ve Muhendislik 2023; 25(73): 1-8.
http://dx.doi.org/10.21205/deufmd.2023257301

[81] Arbabshirani MR, Plis S, Sui J, Calhoun VD. Single subject prediction of brain disorders in neuroimaging: Promises and pitfalls. Neuroimage 2017; 145(Pt B): 137-65.
http://dx.doi.org/10.1016/j.neuroimage.2016.02.079 PMID: 27012503

[82] McMullen L, Parghi N, Rogers ML, Yao H, Bloch-Elkouby S, Galynker I. The role of suicide ideation in assessing near-term suicide risk: A machine learning approach. Psychiatry Res 2021; 304: 114118.
http://dx.doi.org/10.1016/j.psychres.2021.114118 PMID: 34403873