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Predictive Machine Learning Approaches for Mental Health Diagnoses in College Students

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Abstract

In recent years, the rise in mental health disorders among college students has spurred the adoption of machine learning for predictive diagnosis. This trend emphasizes the need for innovative strategies from educators, healthcare providers, and policymakers. The diagnostic process involves interviews, medical history assessments, and psychological tests, posing challenges and increasing the risk of misdiagnosis. Accurate diagnosis is crucial for college students, who face unique stressors such as academic pressures, social adjustments, financial constraints, and limited access to mental health resources, contributing to a disproportionately high prevalence of mental health issues in this demographic. Machine learning techniques, including Logistic Regression (LR), Random Forest (RF), Support Vector Machines (SVM), knearest Neighbors (KNN), and Convolutional Neural Networks (CNN), show promise in enhancing diagnostic accuracy and supporting mental health professionals in identifying conditions like Attention deficit /hyperactivity disorder (ADHD), Depression and anxiety, bipolar disorder, and Schizophrenia. This study focuses on preprocessing and analyzing a dataset to predict mental health issues using various machine learning approaches, highlighting Random Forest's notable performance. Specifically, the Random Forest classifier achieved an accuracy of 0.85, along with a leading F1Score of 0.86 and Area under curve (AUC) of 0.95, while CNN classifiers achieved a perfect recall score of 1.0.

Keywords: Mental Health; Machine Learning; Prediction; Classifier; College student; Deep Learning

Abbreviations: LR: Logistic Regression; RF: Random Forest; SVM: Support Vector Machines; KNN: k Nearest Neighbors; CNN: Convolutional Neural Networks; ADHD: Attention Deficit Hyperactivity Disorder; AUC: Area Under Curve; AI: Artificial Intelligence; SVM: Artificial Intelligence

Introduction

Machine learning techniques for predicting mental health diagnoses among students have recently gained traction due to the rising prevalence of mental health issues in this population. This trend highlights a significant concern for students and educators, as mental health affects emotions, reasoning, and social interactions, necessitating innovative prevention and intervention strategies, especially for college students. Mental illness is rising at epidemic rates globally, with WHO predicting that one in four people will be affected by mental and neurological disorders at some point in their lives. Depressive disorders are projected to become the second leading cause of the global disease burden by 2020 [1]. However, the growth in the number of professionals treating mental illness is significantly lower compared to the increase in the number of affected individuals. Diagnosing mental health problems involves various steps, including interviews, medical history assessments, physical examinations, and psychological tests. The complexity of diagnoses, compounded by similar symptoms leading to different mental health problems, poses challenges and the risk of misdiagnosis, especially in children. Hence, accurate diagnosis of mental health problems, particularly among students, is crucial.

Artificial Intelligence (AI) offers promising solutions, with researchers developing machine learning techniques to assist in diagnosing mental health problems. AI, the intelligence exhibited by machines, involves creating computer software capable of intelligent behavior, including imitating human reasoning and handling uncertain or incomplete information using probability concepts and other fields. Recent research has identified machine learning techniques capable of accurately diagnosing mental health problems over sample datasets. A comparison of these techniques has identified the top three, which can support mental health professionals in diagnosing various mental health issues faced by students. These problems include attention deficit hyperactivity disorder (ADHD), depression, anxiety, bipolar disorder, and schizophrenia, among others. Attention deficit hyperactivity disorder (ADHD) is one of the most common childhood disorders, persisting into adolescence and adulthood. Symptoms include difficulty staying focused, controlling behavior, and hyperactivity [2].

Depression disorders are characterized by sadness, loss of interest, guilt, disturbed sleep or appetite, fatigue, and poor concentration [3]. Depression can lead to severe symptoms affecting daily activities, and untreated depression can increase the risk of suicide [4]. Anxiety involves tension, worry, increased heart rate, and muscle tension, arising from perceived threats or stressors [5]. Bipolar disorders, involving extreme mood swings between emotional highs (mania or hypomania) and lows (depression), significantly impact daily functioning and lifespan [6,7]. Schizophrenia, a serious mental health condition characterized by delusions, hallucinations, disorganized speech/thinking, and negative symptoms, affects approximately 1 percent of the global population [8-11]. Its diagnostic criteria are outlined in the Diagnostic and Statistical Manual of Mental Disorders (DSM5) [11].

The key objective of this research is:

a. To perform preprocessing and analysis on the chosen dataset

b. To predict mental health problems using machine learning techniques namely Support Vector Machines (SVM), Logistic Regression (LR), Random Forest (RF), KNearest Neighborhood (KNN) and convolutional neural network(CNN).

Our performance analysis demonstrates that our method outperforms other algorithms and metrics used in the previous study. The subsequent sections of this work are organized as follows. The subject of related works is addressed in Section II. Section III presents the methodology and the data sets used in this research to predict mental health problems. Section IV evaluates various techniques using training and test data sets. Section V highlights findings by the other researchers to our scheme. Section VI, provides the conclusion and future work.

Related Work

The rise in mental health disorders, coupled with technological advancements, has spurred interest in employing machine learning for early detection and diagnosis. Recent studies highlight its potential in identifying disorders like bipolar disorder, ADHD, schizophrenia, depression, and anxiety, challenging traditional diagnostic methods due to their complexity. According to U. Madububambachu et al., (Tables 1-4) summarize related research on predicting mental health issues in college students employing various dataset data types, data sizes, and algorithms, and evaluate performance through metrics like accuracy, F-measure, and AUC, to improve early detection and support for students.

Methodology

To collect the dataset, we utilized survey data from individual college students. Specifically, we gathered 172 entries from the University of Southern Mississippi dataset, encompassing 20 features. We addressed missing data issues and performed feature scaling to enhance prediction accuracy. The dataset was split into two parts: training and testing. These subsets were used to train classification models such as LR, SVM, KNN, RF, and CNN. as shown in Figure 1.

Table 1: Summary of related Studies on Depression Anxiety [12].

Paper	Disease	Dataset	Data Type	Data Size	Algorithm	Accuracy	F-Measure	AUC	Motivation
[13]	DA	undergraduate students of Systems Engineering and Computer Science, university in peru	Categorical data	284	NB	87.72	79.17	-	To detect and intervene early using machine learning to improve anxiety prediction, offering timely support.
[14]	DA	Google Questionnaire	Categorical data	6,030	RF	99.03	-	98.82	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.
[15]	DA	R.G. Kar Medical College and Hospital, Kolkata Data	Categorical data	520	RF	89	89	94.3	To assist in predicting depression and anxiety in the life of the individual at an early stage.

[16]	DA	Reddit	Categorical data	2,809	CNN	0.6	0.4	-	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.
[17]	DA	College students during the Argentinean COVID-19 quarantine period	Categorical data	2,687	LR	0.78	0.73	0.9	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
[18]	DA	Social media posts from platforms (Twitter, facial expression databases such as YALE, and user interactions with chatbots.)	Image, Video, text	2,500,000	LR	0.98	0.98	0.91	It highlights the importance of removing stigma around mental health and the role of technology in providing support and interventions.

Table 2: Summary of related Studies om Bipolar Disorder [12].

Paper	Disease	Dataset	Data Type	Data Size	Algorithm	Accuracy	F-Measure	AUC	Motivation
[19]	BP	Clinical data, Hospital of Guangzhou Medical University	Images	80	SVM	87.5	-	0.939	The motivation stems from the challenges in accurately diagnosing BPD and the potential of neuroimaging techniques to provide valuable insights for improved diagnosis and treatment planning.
[20]	BP	sMRI	Images	212	CNN	99.72	99.75	99.75	To address the limitations of traditional machine learning techniques in effectively extracting deep information from neuroimaging data, which results in low classification accuracy of mental illnesses.

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[22]	BP	Time series data of self-reported mood ratings using a bespoke smartphone app.	Text	50	SVM	80	-	0.86	To improve psychiatric diagnosis accuracy using mobile technology for real time mood monitoring, employing a signature based learning method to analyze mood data from individuals with bipolar disorder, borderline personality disorder, and healthy volunteers.
[23]	BP	BIPFAT dataset	Categorical data	341	LR	0.77	0.75	0.84	To leverage machine learning techniques to enhance the diagnostic process of bipolar disorder. The authors aim to reduce misdiagnosis rates and improve the overall quality of life for individuals with bipolar disorder.

Table 3: Summary of related Studies on Schizophrenia [12].

Paper	Disease	Dataset	Data Type	Data Size	Algorithm	Accuracy	F-Measure	AUC	Motivation
[24]	SZ	rsfMRI data	Image	59	LR	63	-	75	To bridge the gap between neuroscience and clinical practice by leveraging advanced imaging techniques and machine learning methods to enhance the understanding and prediction of suicidal risk in individuals with schizophrenia, potentially leading to improved patient outcomes.
[25]	SZ Zurich Centre for Inpatient Forensic	Therapy Data	Text	370	Boosted Classification Trees	76.4	-	83	To investigate the factors that contribute to violent offending in individuals with schizophrenia spectrum disorders. Understanding these risk factors is crucial for developing effec- tive preventive and therapeutic strategies to reduce the occurrence of violent behavior among this population.
[26]	SZ	Survey data	Text	345	LR	67	-	71	To develop machine learning models to predict suicide attempts among individuals diagnosed with schizophrenia spectrum disorders.

[27]	SZ	Twitter Data	Text	671	SVM	90	90	95	To enhance the accuracy of identifying individuals with schizophrenia based on their social media activity.

Table 4: Summary of related Studies [12].

Paper	Disease	Dataset	Data Type	Data Size	Algorithm	Accuracy	F-Measure	AUC	Motivation
[28]	ADHD	fMRI ADHD 200 Global	Images	153	SVM-Linear	67.27	-	0.7792	To address the need for an effective, rapid, and objective diagnostic tool for attention deficit/hyperactivity disorder (ADHD) to improve understanding, prevention, and treatment of the condition.
[29]	ADHD	RsMRI, PKU, and NYU	Images	428	(XGBoost)	77	-	84.32	To address the significant impact of attention deficit hyper activity disorder (ADHD) on children, fill the gaps in understanding its pathophysiology, provide objective biological tools for diagnosis, develop an efficient ADHD diagnosis method, and investigate altered executive functioning in ADHD.
[30]	ADHD	UCLA Dataset containing rsfMRI	Images	138	SVM	66.9	67.7	-	To improve brain disorder diagnosis using fMRI data and deep learning.
[31]	ADHD	NHS (SWYP-FT)	Categorical data	69	RF	81.159	-	0.866	This develops a diagnostic tool for ADHD using clinical data from NICE compliant pathways to enhance clinician efficiency and accuracy, addressing the demand for reli- able diagnosis amidst increasing awareness of the disorder.

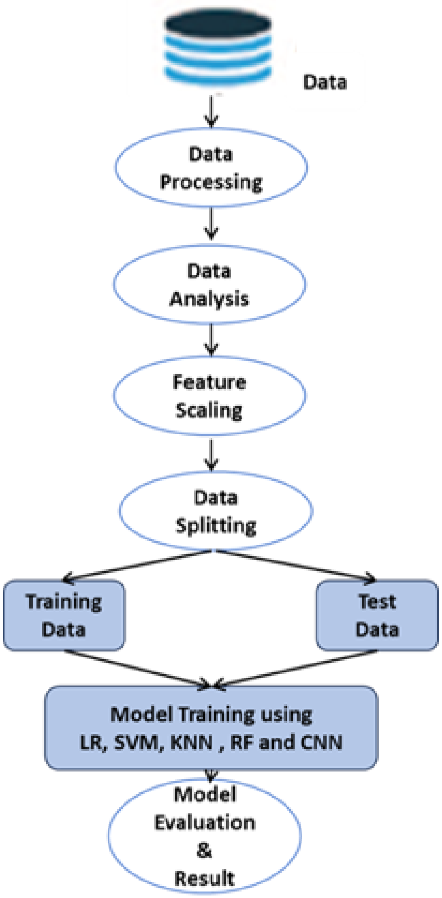

Figure 1: Proposed Methodology.

Data Collection and Processing

We read many research papers, some of which are mental health related to make our research work unique. The features used in this research include: Students living in the USA and few others who are outside the country, gender, ethnicity, occupation, knowledge about mental health conditions, the realization of mental health issues, frequency of mental health symptoms, support received when problems were identified, specific conditions like Anxiety and Depression, Bipolar Disorder Schizophrenia, ADHD, and others, types of treatment received, obstacles encountered when seeking help, the effectiveness of treatment, healing process speed, utilized resources or support systems, perceptions of seriousness from healthcare professionals, friends, or family, support from work or school.

Atmosphere, experience with suicidal thoughts or attempts, previous use of mental health related applications or services. However, our focus is on the following features: anxiety and depression, bipolar disorder, schizophrenia, ADHD, and other related conditions. The early prediction of mental health is unique and demands full work according to our concerns.

Data Analysis and Feature Scaling

Data Analysis and Feature Scaling: Before using the data, it is essential to preprocess it using learn to handle string features and normalize them. Standardizing the features, which involves transforming them to have a mean of 0 and a standard deviation of 1, ensures good performance. Alternatively, normalizing the data to a specific range (usually 0 to 1) is useful when the data is bounded, ensuring that all features contribute equally to distance calculations.

Data Splitting

In training our data, we used 80 percent of our overall 172 data points to train our system, and the remaining 20 percent was used for testing the model. To get the most accurate results, we used five classification models, as shown in the proposed methodology.

Model Training

We employ five different machine learning classifiers.

i Logistic Regression (LR): Logistic regression is one of the sections of the supervised machine learning process and it gives a special focus on classification issues using past information. By using the free factors arrangement, it has the capability to provide for two results and the discrete result is provided by the relevant variables. Another procedure that is obtained from the statistics field by machines gaining is logistic relapse which is worked with paired characterization issues using a goto strategy.

ii Support Vector Machine (SVM): The isolating hyperplane that has the capability to be characterized discriminative classifier known as a support vector machine. The hyperplane in two-dimensional space is partitioning a place into two sections using a line and each section is situated on either side of the line. Each section contains a numeric value the value is denoted by (x). Let's say, we have two types of information factors in an off-chance situation which will be framed in a two dimensional space [32]. So, a hyperplane divides information into different spaces using the line. As a result, in SVM, this process is applied to separate information spaces into different sections, each denoted by 0 or 1. The whole system is described by using an equation which is introduced below:

$$B_0+(B_1*X_1)+(B_2*X_2) = 0$$

In the above equation, B_0, B_1, and B_2 are defined as the co efficients X_1 and X_2 defined as two information factors [32].

iii K-Nearest Neighbor (KNN): In Knn, different groups of calcu lation are managed and adapted by using KNN and fall into managed adaptation groups of enumeration. The dataset that used different perceptions (x, y) implies different connections among x and y. Euclidean equation, which is introduced in below:

$$D(x,\ x')=sqrt(x_1,\ x'_1)^2+(x_2,\ x'_2)^2+\ldots(x_n,\ x'_n)^2.$$

iv Random Forest excels in handling high dimensional datasets with a large number of features. It's robust to overfitting and noise in the data, thanks to the averaging effect of multiple decision trees. Additionally, Random Forest provides insights into feature importance, which can be useful for understanding the underlying patterns in the data.

v CNNs: CNNs are a class of deep neural networks commonly applied to analyzing visual imagery. They are particularly effective in tasks such as image classification, object detection, and image segmentation. CNNs are inspired by the organization of the animal visual cortex and utilize convolutional layers to automatically and adaptively learn spatial hierarchies of features from input images. This hierarchical feature learning makes CNNs robust to variations in input images, such as changes in position, scale, and rotation. CNN also offers high performance on structured data, potentially optimizing recall with appropriate architecture tuning.

Model Evaluation and Results

In Table 5, we evaluated this classification model using five performance metrics for students with mental health issues, including those within and outside the United States of America as illustrated in Figure 2. Performance evaluation metrics are demonstrated as follows:

I. Accuracy = (TP + TN) / (TP + FN + FP+ TN)

II. Precision = TP / (TP + FP)

III. Recall = TP / (TP + FN)

IV. F1Score = (2 * (Precision * Recall)) / (Precision + Recall)

- AUC = $\int_0^1$ TPR(FPR) d

Where: TP, FP, FN, and TN represent True Positive, False Positive, False Negative, and True Negative, respectively. while TPR is a True Positive Rate and FPR is a False Positive Rate. The result shows that the Random Forest classifier demonstrated the highest accuracy of (0.85). Additionally, it performed exceptionally well in F1Score (0.86) and AUC (0.95). CNN classifiers achieved the highest recall score of (1.0). Logistic Regression and KNN stood out with a precision of (0.81). Importantly, all models achieved excellent recall (sensitivity), ensuring accurate identification of students with mental health issues as true positives.

Table 5: Classification Result.

Model	Accuracy(%)	Precision(%)	Recall (%)	F1- Score(%)	AUC (%)
LR	0.82	0.81	0.85	0.83	0.88
RF	0.85	0.79	0.95	0.86	0.95
SVM	0.82	0.78	0.9	0.84	0.9
KNN	0.82	0.81	0.85	0.83	0.9
CNN	0.82	0.76	1	0.84	0.88

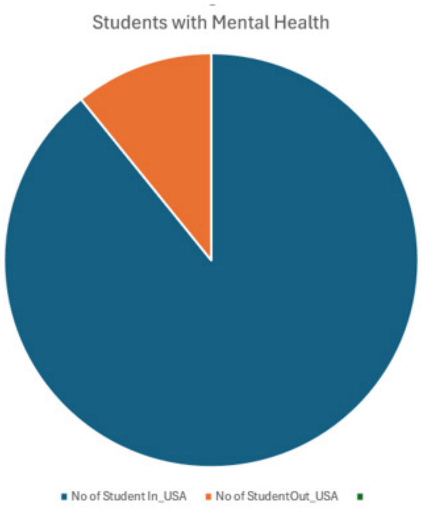

Figure 2: With Mental Health.

Discussion

Previous studies focused primarily on accuracy, F measure, and AUC, our approach in the field of mental health prediction stands out for its comprehensive evaluation across multiple metrics: Accuracy, Precision, Recall, F1score, and AUC. Despite working with a smaller dataset, our models have demonstrated strong performance across various mental health conditions (Figure 3,4). For instance, in depression and anxiety, [14] achieved a notable accuracy of 99.03 percent and an AUC of 98.82 percent using the Random Forest algorithm on a large Google Questionnaire dataset. Similarly, in bipolar disorder, [20] attained results with a CNN model on sMRI data, achieving 99.72 percent accuracy, 99.75 percent F measure, and AUC. In schizophrenia, [27] utilized Twitter data to achieve 90 percent accuracy and 95 percent AUC using SVM. For ADHD, [31] reached 81.159 percent accuracy and an AUC of 0.866 with Random Forest on NHS dataset. Comparatively, the Random Forest model in our scheme demonstrated an accuracy of 0.85 percent, precision of 0.79 percent, recall of 0.95 percent, F1score of 0.86 percent, and an AUC of 0.95 percent, while CNN recall performed at 1.0 percent. The LR, SVM, and KNN models also showed robust performance across all metrics, underscoring the reliability and effectiveness of our approach in predicting mental health issues.

Our results highlight the superiority of our scheme in providing a holistic evaluation of model performance, which is crucial for deploying effective early intervention strategies and support systems.

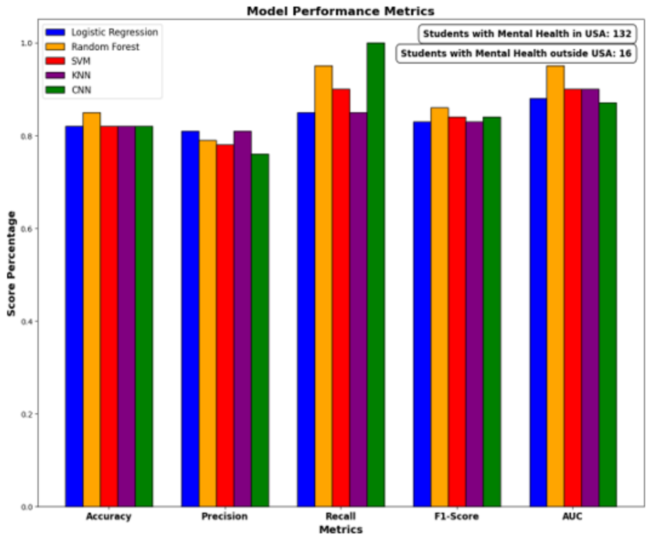

Figure 3: Model Performance.

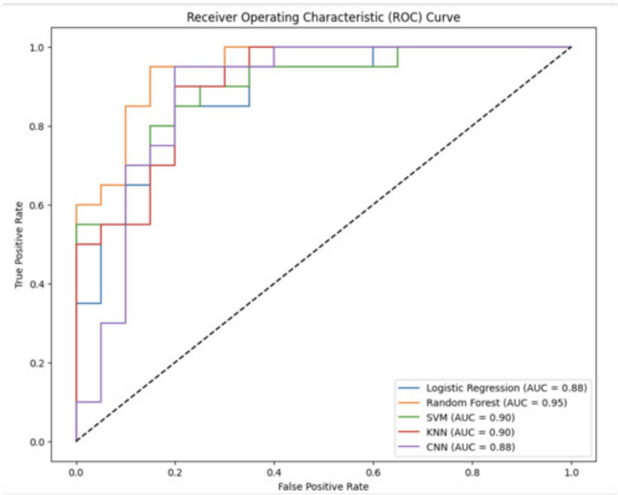

Figure 4: ROC Area Values for all Models.

Conclusion

In conclusion, addressing student mental health issues requires accurate predictive models. AI, particularly machine learning, offers promising solutions. Our research goal is to predict mental health problems using various algorithms which was achieved. The future direction is to refine our models by expanding datasets and exploring advanced machine learning algorithms. The aim is to improve predictive accuracy and support mental health interventions for college students.

Authors' Contribution

U.M. conceptualized and designed the research study, wrote the manuscript, and coordinated the contributions of other authors. U.M., A.U., and S.A. analyzed the data and edited the final manuscript, while A.U. and S.A. provided critical feedback. U.M. and A.U. also created and visualized the data, while U.I. assisted in documenting references. All four authors approved the final manuscript for submission.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Dr Samir Parikh (2024) Mental health in india: A wake-up call.

2. A Shah, N Banner, C Heginbotham, B Fulford (2014) 7 american psychiatric association (2013) diagnostic and statistical manual of mental disorders, 5th (Edn). american psychiatric publishing, arlington va, 8. bechara a, dolan s and hindes, a (2002) decision-making and addiction (part ii): myopia for the future or hypersensitivity to reward? neuropsy- chologia, 40, 1690-1705. 9. office of public sector information (2005) the mental capacity act 2005. 21(5): 9.

3. H Ben Zur, M Zeidner (2009) Threat to life and risk-taking behaviors: A review of empirical findings and explanatory models. Personality and Social Psychology Review 13(2): 109-128.

4. NSM Shafiee, S Mutalib (2020) Prediction of mental health problems among higher education student using machine learning. International Journal of Education and Management Engineering 10(6): 1.

5. J Maloney (2023) Anxiety disorders in elementary students: Interventions for classroom use.

6. RS McIntyre, M Berk, E Brietzke, BI Goldstein, C Lo´pez Jaramillo, et al. (2020) Bipolar disorders. The Lancet 396(10265): 1841-1856.

7. B Kerner (2014) Genetics of bipolar disorder. The application of clinical genetics 7: 33-42.

8. KR Patel, J Cherian, K Gohil, D Atkinson (2014) Schizophrenia: overview and treatment options. Pharmacy and Therapeutics 39(9): 638.

9. H Lavretsky (2008) History of schizophrenia as a psychiatric disorder. Clinical handbook of schizophrenia 1.

10. T Joseph (1999) Pharmacotherapy: A pathophysiologic approach. Appleton & Lange.

11. P Barrett, A Duffy (1994) American psychiatric association. diagnostic and statistical manual of mental disorders, Washington dc, barrett pm, dadds mr and rapee rm (1996) family treatment of childhood anxiety: A con Marriage and Family 66: 893-905.

12. U Madububambachu, A Ukpebor, U Ihezue (2024) Machine learning techniques to predict mental health diagnoses: A systematic literature review.

13. A Daza, J Bobadilla, O Apaza, J Pinto, Arroyo Pazet (2023) Stacking ensemble learning model for predict anxiety level in university students using balancing methods. Informatics in Medicine Unlocked 42: 101340.

14. S Sahu, T Debbarma (2022) Mental health prediction among students using machine learning techniques. in International Conference on Frontiers of Intelligent Computing: Theory and Applications, pp 529-541.

15. A Sau, I Bhakta (2017) Predicting anxiety and depression in elderly patients using machine learning technology. Healthcare Technology Letters 4(6): 238-243.

16. O Ojo, I Adewuyi, O Oni, O Oyinloye, I Gbolade, et al. (2023) An intelligent-based system for detecting depression on social media platform.

17. LC Lopez Steinmetz, CA Leyes, MA Dutto Florio, SB Fong, RL Lo´pez Steinmetz, et al. (2021) Mental health impacts in argentinean college students during covid-19 quarantine. Frontiers in psychiatry 12: 557880.

18. ML Joshi, N Kanoongo (2022) Depression detection using emotional artificial intelligence and machine learning: A closer review. Materials Today: Proceedings 58: 217-226.

19. H Li, L Cui, L Cao, Y Zhang, Y Liu, et al. (2020) Identification of bipolar disorder using a combination of multimodality magnetic resonance imaging and machine learning techniques. BMC psychiatry 20(1): 488.

20. Z Li, W Li, Y Wei, G Gui, R Zhang, et al. (2021) Deep learning based automatic diagnosis of first-episode psychosis, bipolar disorder and healthy controls. Computerized Medical Imaging and Graphics 89: 101882.

21. Bala Sakthi Ganesh M, Jagatheeshwaran S, Apurva SV (2023) Bipolar disorder detection using machine learning.

22. I Perez Arribas, GM Goodwin, JR Geddes, T Lyons, KE Saunders (2018) A signature-based machine learning model for distinguish-ing bipolar disorder and borderline personality disorder. Translational psychiatry 8(1): 274.

23. LV Kessing, K Munkholm, M Faurholt Jepsen, KW Miskowiak, LB Nielsen, et al. (2017) The bipolar illness onset study: research protocol for the bio cohort study. BMJ open 7(6): e015462.

24. B Bohaterewicz, AM Sobczak, I Podolak, B Wo´jcik, D Mtel, et al. (2021) Machine learning-based identification of suicidal risk in patients with schizophrenia using multi-level resting-state fmri features. Frontiers in neuroscience 14: 605697.

25. J Kirchebner, M Sonnweber, UM Nater, M Gunther, S Lau (2022) Stress, schizophrenia, and violence: a machine learning approach. Journal of interpersonal violence 37(1-2): 602-622.

26. B Masoudi, S Daneshvar, SN Razavi (2021) A multi-modal fusion of features method based on deep belief networks to diagnosis schizophre-nia disease. International Journal of Wavelets, Multiresolution and Information Processing 19(3): 2050088.

27. AC Lahti (2023) Discovery of early schizophrenia through neuroimaging. Psychiatry Research 322: 114993.

28. X Peng, P Lin, T Zhang, J Wang (2013) Extreme learning machine-based classification of adhd using brain structural mri data. PloS one 8(11): e79476.

29. W Yin, T Li, PJ Mucha, JR Cohen, H Zhu, et al. (2022) Altered neural flexibility in children with attention-deficit/hyperactivity disorder. Molecular Psychiatry 27(11): 4673-4679.

30. A Shoeibi, N Ghassemi, M Khodatars, P Moridian, A Khosravi, et al. (2023) Automatic diagnosis of schizophrenia and attention deficit hyperactivity disorder in rs-fmri modality using convolutional autoencoder model and interval type-2 fuzzy regression. Cognitive neurodynamics 17(6): 1501-1523.

31. T Chen, G Antoniou, M Adamou, I Tachmazidis, P Su (2021) Auto-matic diagnosis of attention deficit hyperactivity disorder using machine learning. Applied Artificial Intelligence 35(9): 657-669.

32. AN Tusher, MS Sadik, MT Islam (2022) Early brain stroke predic-tion using machine learning. in 2022 11th International Conference on System Modeling & Advancement in Research Trends (SMART) 1280-1284.