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A Survey on Neuropsychiatric Tools and Machine Learning Approaches used in the Diagnosis of Depression

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Abstract— Depression is a psychiatric disorder that can become persistent and can result in significant obstacles in the person's ability to look after his/her daily activities. At worst it leads to self-harm. Depression is a prominent cause of disability and burden worldwide. Machine Learning (ML) is a promising area that can trace relationships between variables that humans cannot see or detect using conventional analytical approaches. The blend of ML and a large amount of data is an ideal match and has enormous potential in medical services. This study aims to review the different neuropsychiatric tools that are widely accepted for depression diagnosis and the contribution of machine learning in diagnosing depression.

Keywords- Neurological disorders, Depression, Neuropsychiatric Tools, Machine Learning, Algorithms.

I. INTRODUCTION

The central and peripheral nervous system diseases are neurological disorders. This would be the brain, backbone, cranial nerves, nerve roots, neurotransmission system and muscles, nerve roots, and autonomic nervous system. These conditions usually involve epilepsy, Alzheimer's disease and other types of Dementia, brain tumors, trauma disorders in the nerve system due to head trauma, multiple sclerosis, Parkinson's disease, neuro infection, and brain tumor [1]. Mental and neurological disorders affect feelings, emotions, actions, and relationships, with a wide range of problems and symptoms. In isolation or as an accompanying disease with other NCDs [non-communicable diseases], neurological or mental disorders, namely depression, dementia, autism, epilepsy, and schizophrenia can be experienced. The other non-communicable conditions overlap with risks and neurological and mental illnesses are often chronic as well [2].

Neurological diseases were the most common cause of Disability Adjusted Life Years [DALYs] and deaths worldwide. The total number of deaths from all neurological disorders increased by 39%, while DALYs increased by 15%. [3]. A portion of the investigations in 2017 gauge that, about 792 million individuals continued to live with a psychiatric illness. It is marginally more than one out of every ten individuals around the world (10.7%). Table-I exhibits estimates of the prevalence of mental health disorders and the disease burden associated with them [4].

TABLE I. THE PREVALENCE OF MENTAL HEALTH DISORDERS AND ASSOCIATED DISEASE BURDEN ESTIMATION IN 2017 [4].

Type of Mental Disorder	**The proportion of the global population affected by the disorder in Percentage**	**Total number of people affected by the disorder in million**
Any mental health related	10.7	792
Depression	3.4 [2-6]	264
Anxiety	3.8 [2.5-7]	284
Bipolar	0.6 [0.3-1.2]	46

Eating related (clinical anorexia & bulimia)	0.2 [0.1-1]	16
Schizophrenia	0.3 [0.2-0.4]	20
other mental or substance use disorder	13 [11-18]	970
Alcohol use related	1.4 [0.5-5]	107
Drug use related (excluding alcohol)	0.9 [0.4-3.5]	71

Over 80% of people with mental disorders live in Low and Middle-Income Countries (LMIC) [5]. India is witnessing a massive demographic transition, with an increase in non communicable diseases (NCDs), and mental disorders account for a sizable proportion of NCDs. In India, the mean crude prevalence rate of common neurological disorders is 2394, varying from 967 to 4070 for one lakh population, with a high incidence rate in rural areas compared to urban areas [6]. Mental disorders were the significant cause of YLDs in India in 2017, accounting for 14.5 % of all YLDs. As shown in Figure 1, depressive disorders contributed the most to DALYs due to mental disorders in India in 2017 [7].
Depression is the most frequently reported condition of the general population, which is identified by sadness, lack of interest or satisfaction, a feeling of sin, or low self-esteem. Depression, in the most extreme condition, can lead to self-harm and a higher risk of death [8].

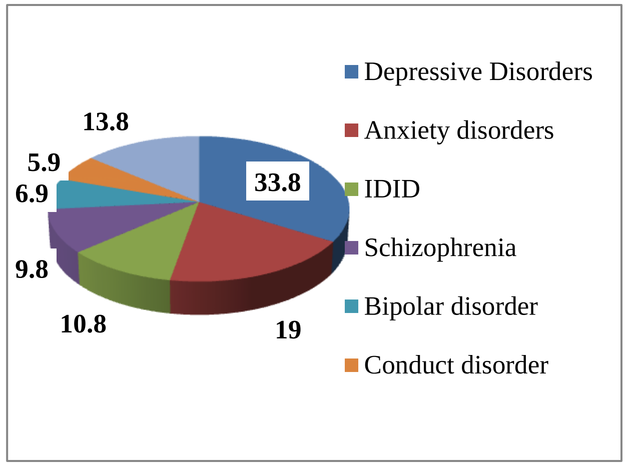

Figure 1: Mental Disorders Contribution to DALYs in % in India [7]

As stated by the World Health Organization (WHO), depression would rank second in the world in terms of disease burdens by 2020, also it was one of the conditions of priority addressed by the WHO's Mental Health Gap Action Programme [9]. As of 2017, approximately about 300 million people worldwide and 56 million people in India were affected by the depression [10][11].
Early screening and early interventions are essential to prevent the emergence of severe depression, instead of getting treatment for it. According to the Institute of Medicine (IoM) committee on the prevention of mental disorders, depression is an avoidable disorder [12].
Artificial intelligence (AI) and ML systems have reached (super) human levels of performance in a variety of processes that were initially thought to be complex in computation. Developments in these areas have occurred as a result of increased data availability and significant hardware advances coupled with modern optimization algorithms [13] [14]. Predictive data mining for medical diagnosis has been shown to greatly increase clinical decision efficiency and avoid unintended biases, errors, and unnecessary medical costs, thus impacting patient care quality [15].

II. REVIEW OF DEPRESSION ASSESSMENT TOOLS

Presently, major depressive disorder (MDD) is diagnosed primarily by subjective assessment and clinical observation of symptoms. At present, no biomarker has been accepted as part of the criteria for diagnosis of psychiatric condition. Biomarkers, on the other hand, can be useful in medication selection and assessing the trajectory of the disease in the initial stages [16]. Most clinical environments are designed to achieve multiple evaluation objectives in a short period; therefore tool selection is critical [17].
Assessment instruments are basic ways of collecting data that can be used to understand better a patient, their conditions, their life status, and other factors. These instruments, which usually consist of tests or assessments, are designed to target

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specific disorders. It is likely to employ several approaches and present findings to provide a systematic observation. The following factors should be considered when choosing a tool: Sensitivity: the ability of a test to correctly identify a subject with a disorder and Specificity: the ability of a test to correctly identify a subject without disorder [18].

The Mini-International Neuropsychiatric Interview (M.I.N.I.) is a brief standard clinical examination created collaboratively by clinicians and psychologists, with a processing period of roughly fifteen minutes; it was developed to satisfy the requirement of a short yet effective structured psychiatric interview for multicenter clinical studies and epidemiology studies. To gain a more in-depth comprehending, the questionnaires were combined with focus groups and semi-structured interviews [19][20]. The Beck Depression Inventory (BDI) consists of 21 multiple-choice questions. Participants are requested to score each based on 4 response options on the intensity of causes experienced in the previous week, varying from the lack of a symptom to a severe degree. The questionnaire was constructed based on clinical findings of behaviors and symptoms that were common in depressive psychiatric patients but uncommon in non-depressed psychiatric patients. While the questionnaire was originally designed to be performed by qualified interviewers, it is now generally self-administered. It takes 5–10 minutes to self-administer [21][22].

Clinicians make use of the Montgomery Asberg Depression Rating Scale (MADRS) to assess the level of depression in individuals with a diagnosis of depression. The MADRS consists of ten subtests. Interviews last between 20 and 60 minutes. Outpatients in primary care with mild to extreme depression are excluded from generalization [23] [24].

The PHQ-9 and PHQ-2, which are parts of the larger Patient Health Questionnaire, provide psychologists with descriptive, self-administered methods for evaluating depression. The PHQ-2, which consists of the first two elements of the PHQ-9, asks about a person's level of depression over the previous two weeks. Its aim is not to make a final diagnosis or to monitor the severity of depression, but instead to test for depression [25].

The PRIME-MD is a 2-stage system where the subject initially performs a Self-governed 26-item patient questionnaire (PQ) which tests for the most psychiatric disorders in clinical care. PRIME-MD is characterized by successive improvements of criteria and systematic interview procedures for diagnosing psychological conditions in primary care, but its administration time (up to 15 minutes) limits its clinical utility [26][27].

The Major Depression Inventory (MDI) was created covering the spectrum of depressive symptoms in the Diagnostic and Statistical Manual-IV (DSM-IV), and also MDD in the International Classification of Diseases-10 (ICD-10) Depression may be classified as mild, medium, or extreme [28].

The Composite International Diagnostic Interview (CIDI) is a thorough, completely organized interview that is used to evaluate mental illnesses. The CIDI, which uses computerized algorithms, offers both lifespan ("Ever") and present ("Past year" & "Past 30 days") diagnosis as specified by the DSM-IV and ICD-10 [29].

The Geriatric Depression Scale (GDS-15) is a commonly used diagnosing tool for symptoms of depression in the aged, although its ability to perceive changes in depressive symptoms over time has not been proven [30].

The Depression Anxiety Stress Scale-21 (DASS21) Test is a condensed (21-item) version of a 42-item self-report tool designed to assess three associated negative emotions: depression, anxiety, and tension/stress. The DASS-21 is a reliable and consistent tool for assessing signs of common mental disorders, particularly anxiety and depression, in Vietnamese adolescents. It may, however, be limited to be able to detect stress between these adolescents [31].

TABLE II. SENSITIVITY AND SPECIFICITY OF VARIOUS DEPRESSION ASSESSMENT TOOLS

Reference	Number of subjects	Diagnostic instrument	Sensitivity	Specificity
Shabnam Nejati et.al [32]	192	International Neuropsychiatric Interview (M.I.N.I)	Used as the gold standard	Used as the gold standard
		Beck Depression Inventory (BDI-II)	86.9%	36%
		Montgomery–Asberg Depression Rating Scale–self-rating version (MADRS-S)	87.4%	18%
Fangyu LI, Hua HE [33]	377	PHQ-9	82%	87%
		PHQ-2	87%	78%
B Loerch 1, A Szegedi, R Kohnen, O Benkert [34]	704	PRIME-MD	73%	67%
Pim Cuijpers [35]	258	Major Depression Inventory (MDI)	66%	63%
H.U. Wittchen et.al [36]	1095	M-CIDI	87%	49.7%
Alexander W. Thompson et.al [37]	214	PHQ-9	54.3%	84.5%
		GDS-15	84.8	78.6%
Beaufort I.N et.al [38]	47	MINI	Used as the gold standard	Used as the gold standard
		DASS-21	84%	74%
Caneo, C et.al [39]	4767	PHQ-2	74.6%	93.9%
Rancans, E et.al [40]	1467	MINI	Used as the gold standard	Used as the gold standard
		PHQ-2	79%	79%
		PHQ-9	75%	79%

Some of the studies showing that MINI is more efficient in the classification of depression compare to CIDI [41] and SCID [42].

III. MACHINE LEARNING ALGORITHMS IN DEPRESSION DIAGNOSIS

ML algorithms such as Support Vector Machines (SVM), Gradient Boosting Machines (GBM), Random Forest, Nave Bayes (NB), and K-Nearest Neighbourhood (KNN) were commonly used in mental health, and each ML algorithm has its own set of advantages [43].

Zhang et al. extracted Mel-Frequency Cepstral Coefficients (MFCCs) by the participant's voice and used AdaBoost and collaborative representation (AdaBoost-CRC) algorithms in order to predict Severe Major Depression Disorders (SMDD). To handle the problem of unbalance data, an AdaBoost-CRC classifier structure has been developed in which AdaBoost was utilized to differentiate the results of each weak classifier based on its weight [44].

Seyed Habib Hosseini et al. established a classifier for detecting depression in social media networks that is on the basis of the multinomial Nave Bayes training algorithm. In this study, a bipolar characteristic vector containing characteristic from both the depressed and non-depressed categories was formed using a collection which systematically examined and recorded the behaviors and symptoms of depressed subject [45].

Hanshu Cai et al. evaluated the performance of various ML techniques such as SVM Classifier, K-Nearest Neighbor, Classification Trees, and Artificial Neural Network in diagnosing depression using psychiatric data collected by a three-electrode EEG acquisition system at the Fp1, Fp2, and Fpz electrode sites [46].

Hatoon A Sagri and Mourad Ykhlef, experimented on different combinations of feature values obtained from Twitter activity using ML algorithms such as SVM, NB, Decision Tree [47].

The intensity of depression was measured by Rouzbeh Razavi, Amin Gharipour, and Mojgan Gharipour by employing a random forest classifier for depression screening using mobile phone usage metadata and Beck Depression Inventory-2 (BDI-II) [48].

Joanna F, et al. identified key biomarkers linked to depression in the National Health and Nutrition Examination Study by making use of a 3-stage methodology that included several imputations, ML boosted regression algorithm, and logistic regression. The PHQ-9 depression scale was used to assess depression. [49].

Xiaohui Tao, Oliver Chi, and colleagues described a binary ensemble classifier that can differentiate the depressive subjects from the non-depressive subjects in a large health survey dataset from the National Health and Nutrition Examination Survey (NHANES), which included the PHQ-9 depression screen inventory [50].

Ryan S. McGinnis et al. proposed a ninety-second fear stimulating activity in which subject movement is tracked using commercially available sensor systems. KNN and Binary classification algorithms, as well as features extracted from a single twenty-second phase of the activity, are used to estimate and diagnosing anxiety and depression in a children's group [51].

SUMMARY AND CONCLUSION

From the literature review on ML application in diagnosing depression, it is observed that ML algorithms are capable of diagnosing the depression and it is noted that the research work investigates the classification and diagnosis of depression using data obtained from EEG, speech signal and features extracted from social media like Twitter and the application of ML algorithms on the data obtained from neuropsychiatric tool like MINI is a rare work.

This study involves a survey on the various types of neuropsychiatric tools which are used to diagnose depression and found that diagnosis of depression conditions are commonly used standardized diagnostic tools (i.e., structured interviews) like MINI, PHQ-9, PHQ-2 across clinical settings, and it is noted that in most of the research setting MINI depression assessment tool is used as the gold standard for reference and it is found that MINI is a more efficient diagnosing tool in the classification of depression.

The diagnosis of depression is commonly made using standardized structured interview-based diagnostic tools across research and clinical environments. Hence there is vast scope to focus study on building a predictive model for diagnosis of depression using machine learning algorithms on the data obtained from MINI.

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