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Review

Understanding the Potentiality of Artificial Intelligence in Psychological Disorders Detection and Diagnostics

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Abstract

Today, the advancement of assessment, forecasting, and therapy or medical attention for psychological healthcare is already using artificial intelligence (AI) technology, particularly machine learning, due to the introduction of digital tools to treat mental health conditions. In mental health treatment, the present and the future of artificial intelligence technologies hold both enormous promises and potential dangers. With the current global scenario, psychological disorders like clinical depression, general anxiety disorder, post-traumatic stress disorder, or bipolar disorder are being reported at an alarming rate. Nonetheless, from the perspective of artificial intelligence, we see a shifting trend in diagnosing and early detection of such disorders. The deep learning models and power of machine learning, including Support Vector Machine (SVM), Logistic Regression, Decision Trees, Random Forest, and deep learning models like Natural Language Processing, Neural Networks, etc., have been committed to helping experts build techniques and prediction models for the same. This article presents an eagle-eye view of the work being done in this field. It focuses on the four major psychological disorders mentioned above, artificial intelligence technology and its current applications in diseases, and a discourse on how artificial intelligence can complement patient care while considering its inherent challenges, limitations, and moral considerations. Artificial intelligence is a rapidly emerging and continuously expanding field of research, which offers many prospects to the healthcare sector along with the challenges.

Keywords
Artificial intelligence; machine learning; deep learning; depression; anxiety; PTSD; bipolar disorder

1. Introduction

Artificial intelligence (AI) and related technologies are increasing in business and society, and the healthcare industry is starting to see a significant increase in their use. These technologies can potentially revolutionize many aspects of patient care, pharmaceutical firms, and operational processes inside healthcare providers and insurers.

Over the previous few decades, various artificial intelligence (AI) definitions have emerged. The analysis of "intelligent agents," which are the devices that "recognize their surroundings and take decisions to increase their probability of success at a certain target," is defined as AI-based research and technology [1]. Artificial intelligence (AI) refers to systems or devices that carry out tasks by imitating human intelligence and may continuously ameliorate themselves based on the information they acquire. It describes the use of complex algorithms to organize the fulfillment of specific tasks in the healthcare industry. Researchers, scientists, and physicians input information into computers, and newly created algorithms can analyze, examine, and even provide solutions to complex medical issues. [2].

The present explosion in research in this area, where computers are taught to discover connections based on enormous amounts of raw information, such as the pixels of digital photographs, is due to the subfield of AI known as machine learning and one family of algorithms, in particular, deep learning [3]. Among the most often used kinds of AI is machine learning. Massive data sets are analyzed, and trends are found to assist decision-making. The essential elements of machine learning applications are algorithms, a collection of guidelines for carrying out several tasks, as described in Figure 1. Without human involvement, the algorithms are set up to learn from data. Without requiring programming, machine-learning systems improve predictive performance's accuracy over time. Using algorithmic processes, machine learning can improve the precision of treatment plans and clinical outcomes [4]. For instance, medical imaging and radiology are increasingly using deep learning. Deep learning is an advanced form of machine learning that imitates how the biological human brain functions. Employing neural networks that can use data to learn without supervision, deep learning programs may discover, identify, and assess malignant tumors from photos [5]. It is increasingly used in radionics, which refers to identifying clinically significant features in imaging data that are not apparent to the human eye. For example, Enlitic uses deep learning intelligence to detect health problems on Computed Tomography CT and X-ray images.

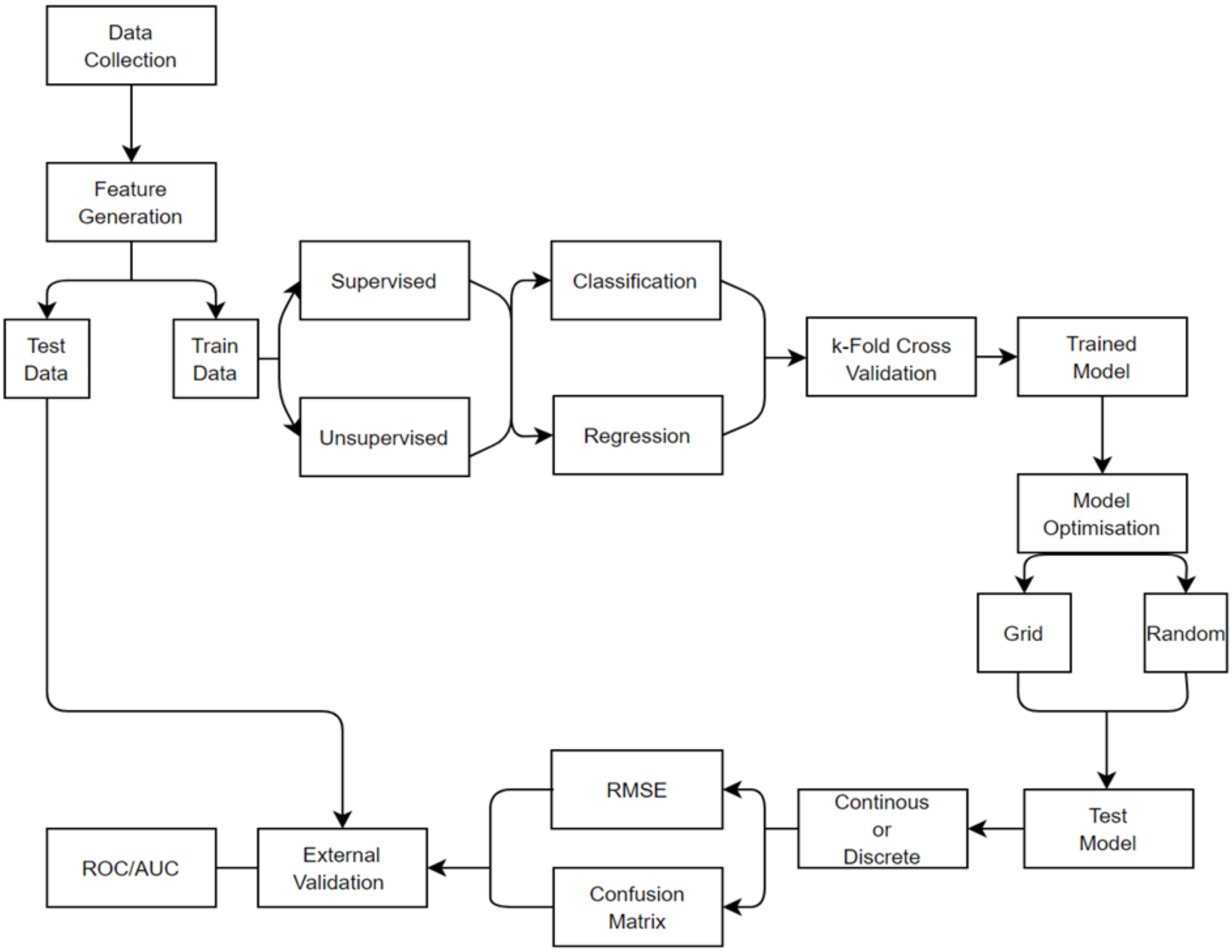

Figure 1 Workflow of generating an AI pipeline.

Concerning these advances and the broad horizon of their applicability, AI is now incorporated into the branch of the healthcare sector concerning psychiatric disorders and mental well-being. Mental health is an integral part of life that may drastically affect a person's life if neglected. We often come across instances where a person's diagnosis is usually too late to provide them with the appropriate medical attention. Deaths by suicides have increased at an alarming rate over the past few decades. According to a report by the World Health Organization, in 2019, 77% of worldwide suicide deaths were reported in low-to-middle-income countries, which in turn adds up to an estimate of more than 700,000 worldwide deaths [6]. This alone creates an immediate need to devise a method or a tool capable of early detection of a psychological disorder. Fortuitously, AI serves just the purpose. There have been vast loads of data being generated and stored in various formats associated with previously diagnosed psychological disorders. This 'big data' (a general term for the vast amounts of real-time data) can be of multiple forms, such as - doctors' assessment records, the population's social media usage patterns, audio recordings, behavioral patterns of diagnosed patients, etc. Researchers are using this data to build prediction and detection models with the aim of early diagnosis. This paper reviews the methodologies and results demonstrated by the researchers concerning some of the major psychiatric disorders, using different data types and comparing them to understand the research trend better.

2. AI in Healthcare

The recent advances in Artificial Intelligence have raised the possibility of using gathered healthcare data to create strong models that could automate diagnostics and offer a more precise approach to healthcare by personalizing treatments and directing resources with optimal efficiency in a fast and vigorous way [7]. The purpose of the application of AI in the medical field is to replicate human analytic functions [8]. Ideal change in healthcare can be noticed due to the availability of a vast amount of healthcare data and the fast growth in the availability and complexity of analytics tools [9].

Artificial intelligence (AI) can be calibrated on various healthcare-related datasets, which might be structured or unstructured [10]. Some prevalent techniques or methods of machine learning for structured data are the traditional support vector machine and neural networks, the current deep learning methods, and natural language processing for unstructured data [7]. Cardiology, neurology, and cancer are major illness areas where AI technologies are employed. With advancements in research, AI algorithms can also be applied to psychological disorders. Despite a large amount of Artificial intelligence in health and medicine, it is primarily focused on three disease types: cardiovascular diseases, nervous system diseases, and cancer. We will go over a few examples-

1. Cardiology: Siegel and Dilsizian showed how the Artificial Intelligence system could be used to detect myocardial-related problems using cardiac images [11]. United States Food and Drug Administration (FDA) has permitted Arterys to commercialize its Arterys Cardio DL program, which employs artificial intelligence that enables automatic, editable ventricular segmentation methods based on traditional myocardial MRI data [12].
2. Neurology: Farina and colleagues investigated the effectiveness of an offline interface that controls upper-limb prosthesis using the release timings of spinal motor neurons [13]. Bouton and colleagues created an Artificial Intelligence solution that enables quadriplegic people to regain command of their movements [14].
3. Cancer: IBM Watson for Oncology (the program) would be a trustworthy Artificial intelligence program for diagnosing cancer and identifying melanoma subgroups using medical photos [11].

The AI applications focus on the above critical areas for early detection and diagnosis, therapy, and outcome prediction/prognosis evaluation [15]. The clustering of these three disease types around artificial intelligence is not entirely surprising. Because these three disease types are primary causes of mortality, an early diagnosis is critical to preventing patients' health from deteriorating. Furthermore, it is possible to obtain an early diagnosis.

3. Psychological Disorders

Based on the 2017 Global Burden of Disease Study conducted by the Institute for Health Metrics and Evaluation, approximately 10.7% (79.2 crore individuals) of the global population is affected by various forms of mental disorders. This includes about 3.4% (26.4 crore individuals) dealing with depression, 3.8% (28.4 crore individuals) experiencing anxiety disorders, and 0.6% (46 million individuals) coping with bipolar disorder. The study also provides a breakdown of these percentages based on gender, highlighting the prevalence of each specific disease among males and females. [16].

As per the Diagnostic and Statistical Manual of Mental Disorders (DSM V, 2013), abnormality of behavior or psychological disorder is marked by significant impairments in cognition, behavior, and occupational and affective functioning, not defined by any other medical illness [17]. These kinds of disorders furthermore cause immense stress and disturbance for the person experiencing such symptoms. Over the years, psychologists, psychiatrists, and general practitioners have adopted diverse approaches to comprehend abnormal behavior. These approaches encompass the biomedical model, psychodynamic model, cognitive-behavioral model, existential-humanistic system, socio-cultural model, and bio-psycho-social model. [18]. The diverse approaches to defining and comprehending abnormal behavior or psychiatric illnesses have given rise to manuals such as the International Classification of Diseases (ICD) and the Diagnostic and Statistical Manual of Mental Disorders (DSM). These manuals play a valuable role in establishing a standardized and universally accepted method for identifying disorders in individuals.

3.1 AI for Psychological Disorders

In mental health, medical evidence traditionally consists of written materials and client feedback based on their perceptions. However, the mental health discipline holds significant potential for enhancement by integrating artificial intelligence. AI indeed offers substantial promise in reshaping how we diagnose and understand psychological disorders [19].

The integration of AI into the mental health field poses challenges, primarily because it demands extensive, large-scale datasets to uncover new correlations between psychological disorders and underlying factors. Obtaining such massive datasets with comprehensive phenotypic information presents a significant obstacle for researchers in the field of psychiatry [20].

3.1.1 Depression

Depression, assuredly among the increasingly pressing mental health disorders of the 21st century, is often described as a constant state of feeling sadness and a melancholy mood with a loss of interest in any or all activities. However, depression is sometimes divided into various subtypes, like Major Depressive Disorder (MDD), Persistent Depressive Disorder (Dysthymia), Premenstrual Dysphoric Disorder, and many others [17]. Diagnosis of depression relies on eliciting symptoms of the disorder and observations made of the patient in a clinical interview [21]. Despite extensive studies examining potential neurobiological determinants of illness, molecular genetic studies, and neuroimaging by multiple modalities (e.g., MRI, PET, SPECT), there are currently no laboratory-based tests that can unequivocally detect the presence of major depressive disorder in a patient [22]. Artificial intelligence-based detection tools are being studied closely as they offer potentially promising, accurate, and more dependable detection of depression in patients. Machine and deep learning models are widely employed to serve the purpose. The most popular algorithms in literature include Support Vector Machine (SVM), neural networks, Naïve Bayes, Natural Language Processing (NLP), decision tree algorithms, and various other classification algorithms. Lately, social media platforms have become a top-rated source of data. People tend to post all sorts of things online, and their daily mood is critical. This creates the opportunity for gathering data for the detection of mood disorders, such as depression. In 2017, a study by Deshpande and Rao demonstrated an AI-based tool using the social media platform - *Twitter* [23]. They performed text mining over a large set of tweets, which was then processed using NLP algorithms, followed by SVM and Naïve Bayes classifiers. Although they attained accuracies of 79% and above, gathering valuable data from social media platforms is not always necessarily constructive. A similar approach was followed in another study by Aldarwish and Ahmed in 2017 [24]. They monitored three social media platforms, *viz. LiveJournal, Twitter,* and *Facebook* used the SVM and Naïve Bayes classifiers. However, they could not achieve an accuracy higher than 63.3%. The reported cause of low accuracy was the difficulty of simultaneously finding individuals with the disorder across different platforms.

Nonetheless, direct examinations or health assessments are a prominent method of generating data. In 2020, Baek and Chung constructed neural networks and used data from a health examination survey [25]. The survey was built with a combination of questions to be answered with a numerical value. These symptoms typically involve rating scales or scores to assess the severity or frequency of each symptom, such as anhedonia, loss of energy/fatigue, changes in activity, and depressed mood. The responses to these questions would be numerical values reflecting the degree or intensity of each symptom. They attained accuracy above 84%, as detailed in Table 1 [26].

Table 1 Recent studies for AI-based detection of depression.

Year	Data source	Algorithms	Performance	Ref
2021	Psychiatric assessment of 4,184 college students	XGBoost, Random Forest, SVM, KNN, ANN	AUC = 0.67; Sensitivity = 0.55; Specificity = 0.70	[26]
2020	-	ANN	Accuracy = 90.0; Sensitivity >0.85; Specificity = 0.85	[27]
2017	Text mining from 10,000 Twitter feeds	NLP, Naïve Bayes, SVM	**Naive Bayes**: Accuracy = 83.0; Sensitivity = 0.83; Precision = 0.836 **SVM**: Accuracy = 79.0; Sensitivity = 0.79; Precision = 0.804	[23]
2017	Set of 6,773 social media posts (including 2,073 depression and 4,700 normal posts)	SVM, Naïve Bayes	Accuracy = 63.3; Precision = 1.0; Sensitivity = 0.57	[24]
2020	Korea National Health and Nutrition Examination Survey containing data for 39,225 individuals	ANN, Context-DNN	**ANN**: Accuracy = 85.46; Validation Accuracy = 84.57 **C-DNN**: Accuracy = 95.46; Validation Accuracy = 94.57	[25]
2019	Publically available audio recordings datasets - AVEC 2013 and AVEC 2017	Random Forest, SVM, Gradient Boosting, ANN	**AVEC 2013**: Accuracy = 72.85; Precision = 0.70; Sensitivity = 0.72 **AVEC 2017**: Accuracy = 80.11; Precision = 0.59; Sensitivity = 0.64	[28]
2016	-	BayesNet, Logistic Regression, MLP, SMO	**BN**: Accuracy = 91.67; Precision = 0.92; ROC = 0.98	[29]

		(Sequential minimal optimization), DT (decision tree)	**LR**: Accuracy = 76.78; Precision = 0.78; ROC = 0.89 **MLP**: Accuracy = 87.0; Precision = 0.88; ROC = 0.96 **SMO**: Accuracy = 93.33; Precision = 0.94; ROC = 0.94 **DT**: Accuracy = 90.0; Precision = 0.90; ROC = 0.29	
2013	EEG data of 90 individuals from Psychiatry Centre Atieh, Iran	KNN, Linear Discriminant Analysis, Logistic regression	**KNN:** Accuracy = 80.0 **LDR:** Accuracy = 87.0 **LR:** Accuracy = 90.0	[30]

3.1.2 Generalized Anxiety Disorder

Anxiety disorders are one of the most prevalent mental health problems that affect a significant proportion of people around the globe every year. The prevalence of anxiety disorders has been reported by several epidemiological studies and public surveys [31-35].

Anxiety disorder shares features of excessive fear and anxiety (anticipated future threat) and behavioral issues. Anxiety disorders can be understood as having cognitive, physiological, and behavioral components [36]. While the negative mood, worrying about possible future threats, preoccupation, and sense of loss of prediction and control over the future are classified as markers of cognitive components, chronic arousal, prime to fight-flight response, and strong tendencies to avoid dangerous situations are a few components of physiological and behavioral characteristics of anxiety disorders [37].

There are various types of anxiety disorders, such as social anxiety disorder, substance or medication-induced anxiety disorder, panic disorder, separation anxiety disorder, selective mutism, agoraphobia, and other specific phobias and unspecified anxiety disorders [38]. These differ in terms of particular stimuli or situations that invoke fear and anxiety responses. The occurrence ratio of females to males is 2:1. The lifetime prevalence rate for anxiety disorder across the globe is 4%, whereas it stands at 3% for males and 4.7% for females (WHO, World Data 2016). Though the DSM V diagnostic criterion for each anxiety disorder differs, some key features, similar across them, include excessive anxiety and feeling of apprehension that occurs frequently for at least 6 months. Individuals face difficulty in exercising control over worry behavior. Individuals have also observed and reported significant distress or feeling impairment in social, occupational, or other functioning areas [39, 40].

Additionally, Generalized anxiety disorder (GAD) is often characterized by symptoms like irritability, mental agitation, susceptibility to fatigue, muscle tension, and difficulty in sleeping [41]. Often, patients with GAD tend to worry about minor, everyday life events. This tendency is a critical marker of the disorder [42]. Such individuals may also show vigilance for possible signs of threat in the environment and subtle procrastination behaviors. Epidemiological and meta-analytic studies of GAD have established a prevalence rate of 5.8% in Indians (Chandrashekhar and Reddy, 1998). According to Hoffman and colleagues (2010), females are twice as susceptible as males. Moreover, clinical data has found that GAD is often comorbid with other disorders like social phobia, major depressive disorder, and post-traumatic stress disorder (PTSD).

GAD has also been studied closely with a view of AI-based diagnostic techniques. Recent studies suggest that clinical assessment data is a robust data source used to develop AI-based detection systems. Earlier in 2015, Månsson et al. demonstrated a prediction model using an SVM algorithm, with an accuracy of 91.7%, based on primary diagnosis data of anxiety disorders [43]. More details are mentioned in Table 2. In studies conducted by Carpenter *et al.* [44] and Hilbert *et al.* [45], they used the DSM-V dataset to construct their assessment and questionnaire. The DSM-V data primarily includes factors such as risk and predictive analysis, clinical diagnosis, identification of suicidal tendencies, demographic data, comorbidity, and other associated features.

Table 2 Recent studies for AI-based detection of GAD.

Year	Data source	Algorithms	Performance	Reference
2021	Psychiatric assessment of 4,184 college students	XGBoost, RF, SVM, KNN, ANN	AUC = 0.73; Sensitivity = 0.66; Specificity = 0.7	[26]
2015	Primary diagnosis data of 26 patients with anxiety disorder	fMRI and SVM	Accuracy = 91.7	[43]
2016	Preschool Age Psychiatric Assessment of 1,073 Children	Decision Trees	Accuracy = 97.4; Sensitivity = 1.0; Specificity = 0.972	[44]
2017	Clinical questionnaire of 57 individuals (accounting for case and disorder classification data)	SVM	**Case classification**: Accuracy = 90.1 **Disorder classification** = 67.46	[45]
2021	Demographic/medical data of 11,081 Dutch citizens collected by 'Lifelines' (Netherlands)	Logistic regression, Random Forest, Gradient Boosting, SVM, ANN	**LR:** AUC = 0.608 **GB:** AUC = 0.7714 **SVM:** AUC = 0.9228 **ANN:** AUC = 0.5892	[46]
2020	Outpatient data of 200 patients with clinical diagnoses of multiple psychiatric conditions	SVM, RF, ANN	AUC = 0.83; Sensitivity = 0.75; Specificity = 0.71	[47]
2020	887 anxiety disorder patients' data addressing 5 domains (clinical, psychological, sociodemographic, biological, lifestyle)	Random Forest	AUC = 0.67; Accuracy = 62.4; Sensitivity = 0.62; Specificity = 0.628	[48]
2019	3 datasets - NTU RGB + D, UTD-MHAD and HMDB51	3D-CNN, GRU (Gated Recurrent Unit)	**NTU RGB+D:** Accuracy = 91.88 **UTD-MHAD:** Accuracy = 94.28	[49]

			HMDB51: Accuracy = 70.33	

3.1.3 Post-Traumatic Stress Disorder

Patients with PTSD suffer a 54% higher risk of Time-Varying PTSD and early mortality, so it becomes very crucial to address the problem [50]. PTSD is the result of a traumatizing incident that may occur in a person's life. It often causes the person's mind to re-experience the incident, developing feelings of distress, anxiousness, emotional numbness, or trouble feeling/expressing emotions, and may also lead to depression, based on the severity [51]. Usually, the symptoms of PTSD do not surface in the initial periods after a traumatic incident, i.e., in more than 85% of cases, the person may start showing the symptoms as late as three years after the incident [52]. This obstructs the early detection and treatment of PTSD, as the traditional interview-based diagnostic methods may fail to report the symptoms accurately. Consequently, it becomes essential to develop the means of early detection or prediction of PTSD.

Researchers have been focusing on developing AI-based detection tools that can allow the timely detection of PTSD and help patients avoid the mental burden as machines, particularly those utilizing advanced algorithms and AI technology, excel at examining extensive datasets and recognizing patterns or subtle cues indicative of PTSD symptoms that may not be readily apparent during a conventional clinical interview. Deep learning and machine learning-based models have been reported in various studies that focus on the same. The generated models may vary based on the datasets, targets, and types of features (see Table 3). A recent study by Marmar et al. reports an AI model that works on the speech recordings of a person and predicts the prevalence of PTSD [53]. Data from the emergency room (ER), like patient admissions, medical conditions, and treatments, is also used to build prediction models. Earlier in 2015, Karsoft and others used ER records and developed an ML-based model for early detection of PTSD using the SVM algorithm. They were able to achieve an AUC (area under the curve) score of 0.75 [54]. In another similar study, Levy et al. achieved an AUC score of 0.82 by applying the SVM algorithm to ER data [55]. The ER data included factors such as the severity of the incident, distress perceived during the incident, loss of a relative, etc. In another study by Worthington and colleagues, the National Epidemiological Survey on Alcohol and Related Conditions (NESARC), based on the DSM-IV, was used to construct three classification models - classification trees, logistic regression, and Bayesian additive regression trees [56]. The data included factors associated with crime and violence.

Table 3 Recent studies for AI-based detection of PTSD.

Year	Data source	Algorithms	Performance	Reference
2019	Audio recordings of 129 clinical interviews	Random Forest	AUC = 0.954; Sensitivity = 0.904, Specificity = 0.883	[53]
2015	Emergency room (ER) records of 957 patients	SVM	AUC = 0.75	[54]
2017	ER records of 270 patients	SVM	AUC = 0.82	[55]
2020	National Epidemiological	Classification	**CT:** Accuracy =	[56]

	Survey on Alcohol and Related Conditions (year 2001-2002 and 2004-2005)	Trees, Logistic Regression, Bayesian Additive Regression Trees	92.03; Sensitivity = 0.92, Specificity = 0 **LR:** Accuracy = 92.3; Sensitivity = 0.933; Specificity = 0.558 **BART:** Accuracy = 95.09; Sensitivity = 0.977; Specificity = 0.677	
2020	Field activity report data of 17 fire departments	SVM, ANN	Accuracy = 89.0; Precision = 0.89; Sensitivity = 0.89	[57]
2021	Global Positioning System (GPS) data of 185 individuals	XGBoost	Accuracy = 77.1; AUC = 0.816; Sensitivity = 0.743; Specificity = 0.8	[58]
2020	PTSD symptom trajectories (phase-1, N = 430) and PTSD checklist (PCL-5) assessment (phase-2, N = 437)	Random Forest, SVM	**Phase-1 -** **RF:** AUC = 0.78; Sensitivity = 0.78; Specificity = 0.71 **SVM:** AUC = 0.88; Sensitivity = 0.89; Specificity = 0.79 **Phase-2 -** **RF:** AUC = 0.85; Sensitivity = 0.88; Specificity = 0.69 **SVM:** AUC = 0.87; Senstivity = 0.80; Specificity = 0.85	[59]
2020	170 statutory sexual abuse victims	ANN	Accuracy = 99.2	[60]
2019	Clinical studies of 90 patients	Logistic Regression, Naïve Bayes, SVM, Random Forest	**LR:** Accuracy = 87.0; AUC = 0.83 **Naïve Bayes:** Accuracy = 87.0; AUC = 0.84 **SVM:** Accuracy = 86.0; AUC = 0.84 **RF:** Accuracy 0.82; AUC = 0.78	[61]

3.1.4 Bipolar Disorder

Affecting approximately 45 million people globally, Bipolar disorder (BD) is a chronic mood disorder [62, 63]. According to the World Health Organisation (WHO), BD costs more disability-adjusted life-years than various other neurological diseases and cancer [64]. Typically beginning in early adulthood or adolescence, BD impacts several aspects of the patient's life, like occupation, education, and relationships [65]. BD affects a patient's quality of life [63]. A person suffering from this mental disorder experiences sudden and unusual shifts in their mood [66]. BD is characterized by three episodes: manic, depressive, and hypomanic. Manic episodes are highly thrilled, exasperated, or energetic periods. Depressive episodes, the opposite of manic episodes, are periods of hopelessness, sadness, or indifference. Hypomanic episodes are similar to manic episodes but have less severe symptoms [67]. BDs are mainly of three types- Bipolar Disorder I (BD-I), Bipolar Disorder II (BD-II), and Cyclothymic Disorder (CD). In Bipolar I disorder, individuals experience at least one manic episode, whereas BD-II involves a pattern of manic and hypomanic episodes [68]. CD is defined by the duration of symptoms of hypomanic and depressive episodes, but these symptoms cannot be diagnosed as hypomanic or depressive episodes [66]. A person who is experiencing symptoms of BD but does not fall into any of the main types of BD, then they might be suffering from "other specified bipolar and related disorder" and "unspecified bipolar and related disorder" [67, 68].

Diagnosing BD at an initial phase is crucial for formulating and optimizing treatment outcomes. Anxiety, ADHD (attention deficit and hyperactivity disorder), and various psychiatric disorders interfere with the diagnosis of BD, making its accurate diagnosis very challenging. Misdiagnosis of BD increases the inappropriate use of medicines, comorbidities, and suicide risks [68, 69]. Hence, there is an urgent need to develop methods for early diagnosis and prediction of BD. There are several existing techniques to diagnose BD. The mood disorder questionnaire followed by a clinical interview is one such technique [70]. The Bipolar Spectrum Diagnostic Scale, the Bipolar Disorder Screening Scale, and the affective disorder evaluation are also used for diagnosing BD [71, 72]. These screening methods are not very sensitive, having greater than 25% false negatives [73]. These methods are time-consuming as well, which is another disadvantage.

Machine learning algorithms have been employed to analyze large datasets efficiently to detect, predict, or differentiate BD from other diseases [74, 75]. They can be used on several BD diagnosis questionnaire data to compute BD [76]. Another type of data where ML algorithms can be applied is neuroimaging data. A study used machine learning to neuroimaging data to identify BD scans. They constructed a support vector machine (SVM) classifier with an accuracy of 87.5% [77]. Another study, published in 2020, used neuroimages and neuropsychological data to distinguish BD from healthy individuals, and for this, they built an SVM model [78]. Nunes et al. also constructed an SVM classification model using the MRI scan data of 3020 individuals and achieved a 58.67% accuracy [79]. For the diagnosis of BD, gene expression data can also be used. A research study achieved 97.01% diagnostic accuracy on a gene expression dataset, and the ML algorithm they used was the deep neural network (DNN) [80]. Sun et al. applied a convolutional neural network (CNN) over a genotypic dataset and obtained an accuracy of 79%. They used genome-wide association analysis as a feature selection method [81].

A group of researchers have designed a risk calculator for identifying early BD. They have incorporated clinical and demographic variables derived from a 22-year birth group and used a regular linear regression algorithm called elastic net [82]. Another fascinating study used mRNA expression levels of various genes and concluded that mRNA expression levels of PIK3R1 and FYN can be used to diagnose BD effectively. To find the best ML algorithm suited for their data, they evaluated the performance of various algorithms such as artificial neural networks (ANN), gradient boosting, SVM, and many more. Finally, the SVM model worked best for their data [83]. Overall, ML algorithms can aid in the practical and accurate diagnosis of BD (summarized in Table 4).

Table 4 Recent studies for AI-based detection of Bipolar Disorder.

Year	Data source	Algorithms	Performance	Ref
2020	The Affiliated Brain Hospital of Guangzhou Medical University (Guangzhou Huiai Hospital, Guangdong, China): MRI scans of 44 patients with BD and 36 healthy controls	SVM	Accuracy = 87.50 Sensitivity = 0.864 Specificity = 0.889	[77]
2020	Psychiatry clinic at the Government Medical College, Aurangabad, India: MRI scans and neuropsychological test data of 30 patients with BD-I and 30 healthy individuals	SVM	Accuracy = 87.60, Sensitivity = 0.823 Specificity = 0.927	[78]
2020	13 cohorts in the Enhancing Neuro Imaging Genetics through Meta-Analysis (ENIGMA) consortium| MRI scans of 853 BD and 2167 healthy individuals	SVM	**Before cross-validation-** Accuracy = 65.23 AUC-ROC = 0.7149 **After cross-validation-** Accuracy = 58.67	[79]
2020	Clinical and demographic data of 3,778 individuals belonging to a birth	Elastic net algorithm	AUC = 82.0 Accuracy = 75.0 Sensitivity = 0.72 Specificity = 0.77	[82]

	cohort in Pelotas, Brazil			
2021	-	CNN- mdrp (multimodal disease risk prediction), Linear Regression, SVM, Decision Tree, Random Forest	**CNN:** Accuracy = 94.30 **LR:** Accuracy = 63.30 **SVM:** Accuracy = 88.90 **DT:** Accuracy = 91.30 **RT:** Accuracy = 94.30	[84]
2021	Gene Expression Omnibus (GEO) database: Gene expression data of 33 BD patients and 34 healthy people	DNN	Accuracy = 97.01	[80]
2019	WTC (The Wellcome Trust Case Control Consortium) | Genotypes of 22416 samples	CNN	Accuracy = 79.0	[81]
2019	MDD Questionnaire data of 983 people | 864 MDD positive and 119 MDD negative	Decision tree classifier	Accuracy = 88.07	[76]
2021	mRNA expression levels of genes (PIK3R1, FYN, TP53, PRKCZ, PRKCB, and YWHAB) in 43 BD patients and 47 healthy people	SVM	AUC = 0.951 Sensitivity = 0.928 Specificity = 0.937	[83]

4. Discussion

The patient instances in the datasets used by the researchers are often primarily classified as positive or negative regarding having a particular disorder based on the assessments and structured interviews verified under the medically accepted standards. The specific characteristics/features/data for diagnosis are incited and calculated following the pertinent research findings regarding their correlations with specific negative or positive outcomes or predictors of psychological disorders, which include stress distress, anxiety as well as other personal characteristics, resilience/vulnerability, depression, or PTSD. As a result, these traits are evaluated and defined using a conceptual approach. Good examples of these kinds of features include different aspects of speech sounds, psychophysiological allostasis based on heart rate variability (HRV), heartbeat frequency (heart rate) and HRV, prefrontal cortex activity throughout different cognitive tasks, electrodermal activity and electromyography, respiratory sinus arrhythmia and parietal electroencephalographic asymmetry associated with the alpha band. Other data sets may include features like numerous mood assessment measures or psychometric scales, data on language and speech, information based on innovative detection systems like smart wearables or smartphones, data from brain imaging, facial data, and physiologic signals in the periphery to generate features, blood biomarkers, evaluation of attention using eye-gaze information, information culled from social media channels and the oculometric system's dynamics. Since a single trait could prove to be a poor differentiator in the evaluation and forecasting of mental health decline, this integrative multifaceted physiological forecasting of mental health disorders highlights the significance of fusing several comprehensive variables to increase the predictive potency as a suggested strategy [85].

The studies discussed in this review follow a basic protocol for developing and testing prediction models based on machine learning or deep learning. Out of the data used as the foundation for constructing the models, a certain proportion of the data is preserved (i.e., not used for training) and used as independent case testing. This testing then gives the performance measurements, such as accuracy, sensitivity, specificity, AUC, etc., as reported in Tables- 1, 2, 3, and 4. The patient instances in the datasets used by the researchers are often primarily classified as positive or negative regarding having a particular disorder based on the assessments and structured interviews verified under the medically accepted standards.

Given the current trends, it is observable that the healthcare sector, which was once an utterly biology-oriented field, has come a long way. It has come to a point where automation has become an integral part of it. AI is employed in almost all healthcare disciplines, whether concerned with designing a medicine, diagnosing a disorder, or coming up with treatment [86-89].

Having said this, Artificial Intelligence tools and techniques are simplified and upgraded. Psychiatric practitioners would be able to further rationally specify psychological disorders than what is presently there inside the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-V), which recognizes these disorders in such an early phase when intervention strategies are far more efficient, and personalized treatments build on a patient's distinctive traits. However, caution is required to avoid misinterpretations of early findings, and much more work is needed to close the gap between Artificial Intelligence research and clinical psychology practice [19].

Although Artificial Intelligence applications provide new chances to improve people's lives, they introduce new issues that must be carefully addressed. Since human safety is at risk, the problems are particularly formidable in the mental healthcare sector [90]. A lack of available reviewed evidence-based investigations has been one of the downsides, along with challenges in locating a market for digital psychological disorders management services, particularly amid dominating reductionism in psychological disorders management research.

5. Conclusions

AI is a field that still holds tremendous potential that has yet to be discovered. So naturally, concerning diagnosing psychological disorders, there is a lot of scope for further research that would positively impact and fill the underlying gaps in the current technology.

After the systematic review of the use of AI, specifically machine learning and deep learning, we can observe an aggressive change in the trends for the detection and diagnostics of psychological disorders. However, it is very challenging to decide on pathological states of psychological disorders due to uniquely human interaction-based diagnosis. The most common choice of methodology is supervised learning, in which the classification algorithms are trained over well-structured data. These classification algorithms widely include SVM, regression, neural networks, and tree-based classifiers that can achieve a high accuracy rate combined with the appropriate data types. Nevertheless, many important factors, such as data preprocessing, model selection, hyperparameter tuning, and cross-validation techniques, also create a huge difference in prediction accuracy and real-time applicability of a trained model.

The ongoing trends suggest a vast dependence on clinical data as the source of the preliminary data as the foundation of the AI models. However, as mentioned above, there have been studies where researchers have tried to utilize data sources other than clinical assessments, such as social media feeds, voice recordings, genetic expression data, etc. [23, 28, 53]. This can indicate the onset of a change in the trends. Combining different data types in the training dataset can lead to developing detection models with even higher accuracy. Combining the clinical data along with the gene expression data and training the classification models over the properly structured data can significantly reduce the limitations such as the high rate of false positives and false negatives, low accuracies, and other variable constraints that might restrict the reliance and applicability of the model.

Unfortunately, minimal research on trustworthiness, usability, and repeatability hamper such techniques. Generally, researchers believe in using artificial intelligence to differentiate between computer algorithms and humans and to change a person's judgment with an Artificial Intelligence-based judgment call. Given continuous advancements in the area, the debates for and against the issue will probably continue in the coming years [91].

6. Future Prospects

Although the research work in this field has not been most advanced and up-to-date recently, it has now been moving at an acceptable pace. Understandably, we are still far from perfection. Many different methods are yet to be explored for building the model and selecting data. For example, we could explore the possibilities of developing peculiar detection models that incorporate a specific combination of varying data formats, which might drive us to achieve far more accurate and dependable results.

As we reach perfection, there should be an initiative to design more effective mobile applications that would make the whole process of early detection and diagnosis accessible to the concerned family members, where they could note and feed in a person's behavioral patterns and get a probable risk analysis. In the long and successful run, this could significantly impact the statistics for the better.

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Author Contributions

Background (KA, SK, AC, CJ), Artificial Intelligence (KA, SK), Psychological disorders background (SK, KT), Depression (KA), General anxiety disorder (KA, SK), PTSD (KA, SK), Bipolar disorder (IV), Discussion/Conclusion (KA, KT, CJ), Future prospects (KA).

Competing Interests

The authors have declared that no competing interests exist.

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