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Computational Approaches for Anxiety and Depression: A Meta-Analytical Perspective

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Abstract

INTRODUCTION: Psychological disorders are a critical issue in today's modern society, yet it remains to be continuously neglected. Anxiety and depression are prevalent psychological disorders that persuade a generous number of populations across the world and are scrutinized as global problems.

METHODS: The three-step methodology is employed in this study to determine the diagnosis of anxiety and depressive disorders. In this survey, a systematic review of one hundred forty-one articles on depression and anxiety disorders using different traditional classifiers, metaheuristics, and deep learning techniques was done.

RESULTS: The best performance and publication trends of traditional classifiers, metaheuristics and deep learning techniques have also been presented. Eventually, a comparison of these three techniques in the diagnosis of anxiety and depression disorders will be appraised.

CONCLUSION: There is further scope in the diagnosis of anxiety disorders such as social anxiety disorder, phobia disorder, panic disorder, generalized anxiety, and obsessive-compulsive disorders. Already, a lot of work has been done on conventional approaches to the prognosis of these disorders. So, there is a need to scrutinize the prognosis of depression and anxiety disorders using the hybridization of metaheuristic and deep learning techniques. Also, the diagnosis of these two disorders among the academic fraternity using metaheuristic and deep learning techniques must be explored.

Keywords: Anxiety, Depression, Traditional classifiers, Metaheuristic techniques, Deep learning techniques.

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1. Introduction

Mental or psychological health covers a wide spectrum of cognitive, social, behavioral and emotional functioning. Like physical health, mental health is a continuum that ranges from excellent to bad and changes through time, under various circumstances. The social determinants of health, such as racial and ethnic minority status and any associated racial bias, social relationships, the presence or absence of crime, and factors that affect access to resources like education level, income level, and employment status, are all linked to mental health throughout life. The WHO, further characterize mental or psychological health as a "state of a healthy and prosperous life in which every person recognizes his or her inherent capacity, can easily cope with the stress of daily life, can do productive and fruitful work for community" [1].

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Mental health is peculiar and instrumental to the lives of human beings. It affects the way we feel, think, and behave. It supports our capacity for decision-making, relationship-building, and influencing the environment in which we live. Ultimately, there is no health or life without mental health. Additionally, people with mental health issues are more likely to be exposed to different neurological disorders (Alzheimer's, Parkinson's, epilepsy, schizophrenia, migraine), non-communicable disorders (cancer, diabetes, cardiovascular, chronic respiratory disease) and psychological disorders (mood disorder, stress, anxiety, depression, personality disorder, attention deficit, eating disorder). Furthermore, COVID-19 has also sparked major mental health issues in human life. Before the coronavirus pandemic in 2019, worldwide approximately 970 million people (52.4% females and 47.6% males) were living with a mental disorder [2]. Among its various effects, the COVID-19 pandemic has sparked a global mental health crisis that has harmed the mental health of millions of people by causing both short- and long-term stress.

All nations experience a high rate of mental illness. Figure 1 depicts the prevalence of mental disorders in WHO Regions.

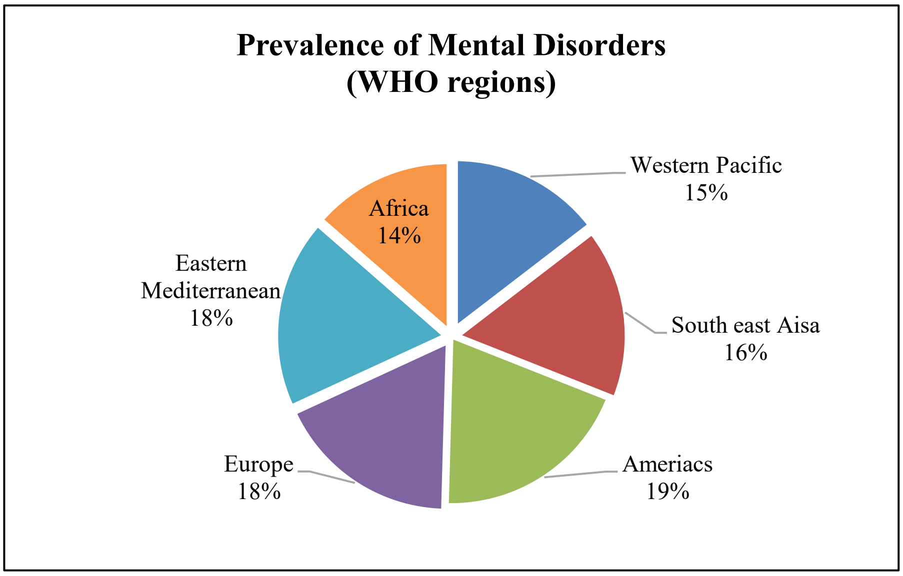

Figure 1: Prevalence of mental disorders (Across WHO Regions,2019)

Anxiety and depression are two extensive states in the giant spectrum of psychological health. Worldwide, disability is progressively increasing because of these two diseases. Psychologists play a very important role in the diagnosis of these prevalent disorders. However, diagnosis of these disorders is not an easy task as mental disorders are unpredictable, and symptoms vary from time to time and person to person. Machine learning techniques such as traditional classifiers (decision tree, support vector machine, naive Bayes, KNN), metaheuristic techniques (genetic algorithm, firefly, particle swarm optimization, artificial bee colony) and deep learning techniques (convolutional neural network, long short-term memory, autoencoder) deal with imprecision and uncertainty, whereas conventional computing techniques are based on analytical models. This study has mainly focused on traditional classifiers, metaheuristics, and deep learning techniques in the diagnosis of anxiety and depression disorders.

1.1. Related Studies and Contribution

Past studies witnessed that traditional classifiers or traditional machine learning techniques (TC), metaheuristic techniques (MT), and deep learning techniques (DLT) were effectively used for the early diagnosis of mental disorders**.** Table 1 presents a summary of related work on the diagnosis of different psychological disorders.

Table 1: Past related studies

Author/Year	Disease	Contribution
Matthew Squires et al.,2023[3]	Depression	An overview of the current applications of artificial intelligence in precision psychiatry is briefly explained in this survey. Every stage of the therapy cycle is explained using sophisticated algorithms.
S. Sharma et al.,2021[4]	Stress	A comprehensive review and evaluation of supervised learning and soft computing techniques for the diagnosis of stress.
Jiang Qiao et al.,2020[5]	Mental Disorder	Machine learning techniques have been used for the prediction of mental disorders on social media.
Muhammad Usman et al.,2020[6]	Depression	Machine learning techniques have been reviewed for the prediction of depression in older people.
Matthew Bracher-Smith et al.,2020[7]	Psychiatric disorders	A systematic review of machine learning techniques for predicting psychiatric disorders from genetics alone and performance is evaluated.
S. S.Panicker et al.,2019[8]	Mental Stress	A comprehensive survey of the detection of mental stress using machine learning techniques.
P.kaur and M. Sharma et al.,2019 [9]	Psychological Disorders	Diagnosis of mental disorders using different supervised and nature-inspired techniques.
S. Alonso et al.,2018 [10]	Mental Disorders	Data Mining techniques in the diagnosis of Dementia, Depression, etc. can perform better in clinical diagnosis for improving the patient's life.
E.G. Pintelas et al.,2018[11]	Anxiety Disorders	A comparative analysis was performed for the diagnosis of different types of anxiety disorders using machine learning techniques.
E.G Ceja et al.,2018[12]	Mental health	A Survey of the mental health monitoring system by using Machine learning and sensor data
A.Wongkoblap et al.,2017[13]	Mental Disorders	State-of art of different machine learning techniques in the diagnosis of mental diseases from social network data.

From existing related work, it has been analyzed that no review work has yet been published that compares and evaluates the effectiveness of the three above-mentioned machine learning algorithms in one study for the diagnosis of anxiety and depressive disorders. So, this comprehensive study will present a step towards addressing these gaps., The aim of this research work is outlined below:

- A comprehensive analysis of traditional classifiers comprehensive analysis of traditional classifier, MT, and DLT for the diagnosis of anxiety and depression disorder is presented.
- The publication details of these disorders have been explored.
- Comparison among these techniques has been also highlighted.
- Finally, research gaps and future aspects related to these techniques in the diagnosis of anxiety and depression disorders have also been identified.

1.2. Aim of Study

This study aims to guide the researchers who are employing traditional classifiers, MT, and DLT in the diagnosis of depression and anxiety disorders. The effectiveness of deep learning, metaheuristic, and conventional classifiers in the diagnosis of these disorders is also a goal of this research.

This review is structured into many sections. Section 2 focuses on anxiety and depression disorders. Section 3 presents a methodological approach used in the diagnosis of these disorders. Data synthesis and analysis are presented in section 4. Section 5 outlines the publication work reviewed in this study. Sections 6 and 7 present a discussion and conclusion. A general framework of the manuscript is presented in Figure 2.

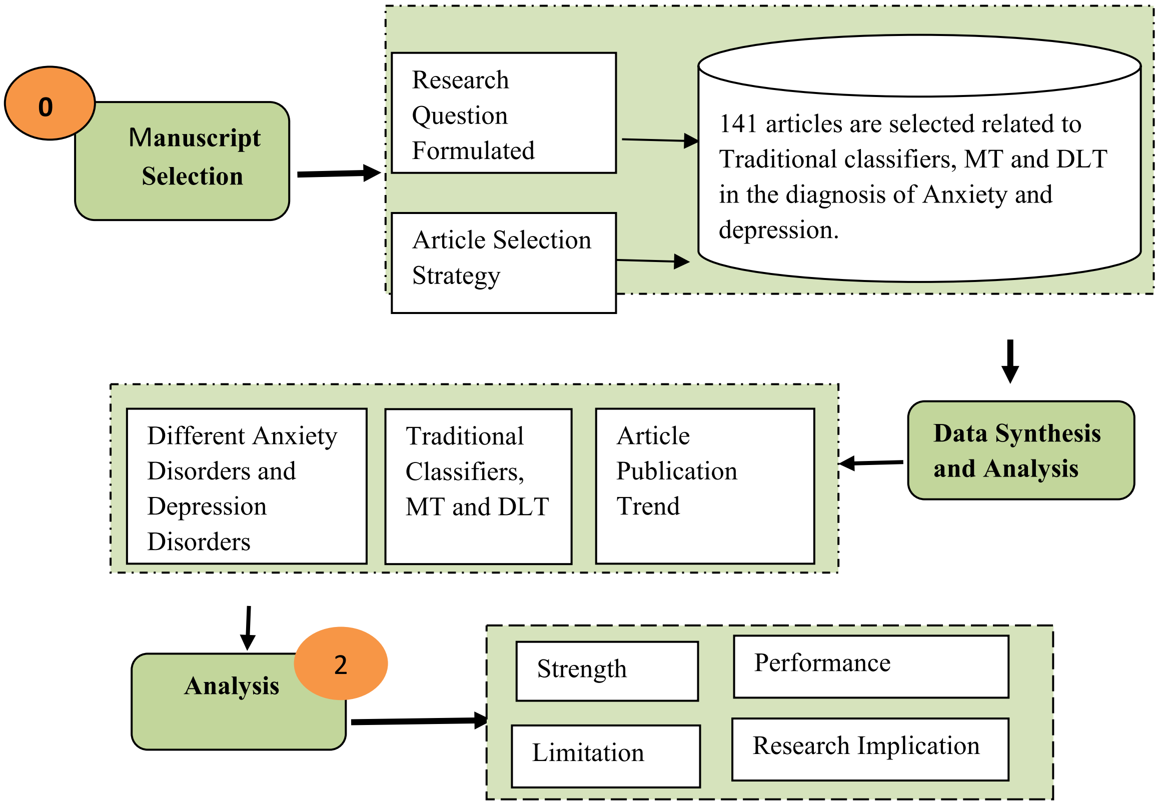

Figure 2: Framework of Manuscript

2. Background

Anxiety and depression (anxious depression) are the most predominant psychiatric disorders [14]. Extreme fear, high levels of anxiety, and irrational conduct are all the main characteristics of anxiety disorders (AD). When extreme and persistent symptoms cause significant distress or a decline in functioning, this disease may get worse. Compared to depressive disorders, anxiety disorders are more common at a younger age

According to the DSM-V, anxiety disorders can be stratified into the following: (1) fear circuitry-based AD, such as panic, phobia, Generalised anxiety disorder(GAD), and Social Anxiety Disorder(SAD); (2) anxiety related to compulsion and obsession, namely Obsessive-compulsive disorder(OCD); (3) trauma and stressor-related AD, e.g., post-traumatic stress disorder(PTSD) (4) AD related to dissociation, e.g., dissociative amnesia, depersonalization disorder and dissociative disorder[15]. Other childhood AD are separation anxiety disorder (SepAD) and selective mutism (SM).

Panic disorder is a frequent panic attack (extreme distress) that leads to extreme tension about a future attack. Trembling, sweating, fear of death, and chest pain are some symptoms of panic disorder [16]. Phobia Disorder is a type of anxiety disorder characterised by a fear of something non-dangerous. Acrophobia (height phobia) and agoraphobia (social phobia) are some common types of phobia disorders. Rapid heartbeat and desire to live alone are some common symptoms of phobia disorder [17]. PTSD is the most emerging and serious anxiety disorder that is triggered by horrible events. Some common symptoms of PTSD are severe anxiety, uncontrollable thoughts, negative thoughts, etc. [18]. GAD is characterised by persistent, intrusive, and excessive worry. A person suffering from GAD can expect an extreme level of severe tension, even when there is nothing wrong [19]. OCD is a long-lasting chronic disorder with uncontrollable thoughts. OCD is like an obsession (mental images, repeated thoughts) and compulsion (repeated behaviour) for something. Some common symptoms of OCD are fear of contamination, checking things, again and again, excessive handwashing, etc. [20]. SAD (Social Anxiety Disorder) is also called social phobia disorder with fear of being judged, rejection, having a negative image in public, and presenting oneself to society. A person with SAD can face blushing, boring, and awkward problems in society. Sweating, nausea, and a rapid heart rate are some common symptoms of social anxiety disorder [21].

Depression is another major heterogeneous and major psychiatric disorder with a consistent feeling of guilt, sadness, and worthlessness, as well as the loss of pleasure and interest. Weight appetite changes and irrationality are all signs of depression disorders. Together, all these symptoms negatively affect the quality of life of individuals as well as their work performance [22]. Genetic and environment-related factors (stress) are the biggest contributors to depression. Depression can be mild, moderate, or severe. Some major depressive disorders are major depression, persistent depressive disorder, perinatal depression, seasonal depression, situational depression, and atypical depression disorder.

Prevalence Rate

Anxiety and depression are the most prevalent and chronic psychiatric illnesses. Since 2000, both depressive and anxiety disorders have consistently been among the top ten leading causes of all YLDs worldwide. In 2019 worldwide, approximately 301 million and 280 million individuals were suffering from anxiety and depression disorders. As per the global burden of diseases, in 2020, there was a sudden rise in the percentage of people suffering from anxiety and depression disorders due to COVID-19. Additionally, in just one year, the prevalence of anxiety and depression disorders increased by 26% and 28%, respectively. As per the WHO, in 2019, 301 million people globally were living with anxiety disorders. Also, anxiety disorders accounted for 22% of the global burden of mental disorders. The prevalence of the various types of anxiety disorders (according to the NCS-A data) was determined to be 2.2% for GAD, 2.3% for panic disorder, 5% for PTSD, 9.1% for SAD, 2.4% for phobia disorder, and 7.6% for SepAD [23].

WHO estimates that in 2019, 280 million individuals worldwide suffered from depression disorders. YLDs caused by depressive disorders alone are the second most common worldwide, accounting for 5.6% of all YLDs. Figure 3 presents the prevalence rate of psychological disorders in India. /From Figure 3, it has been analyzed that depression and anxiety disorders have a high rate of prevalence in India as compared to other psychological disorders. Table 2 presents the prevalence rate of psychological disorders by gender by state.

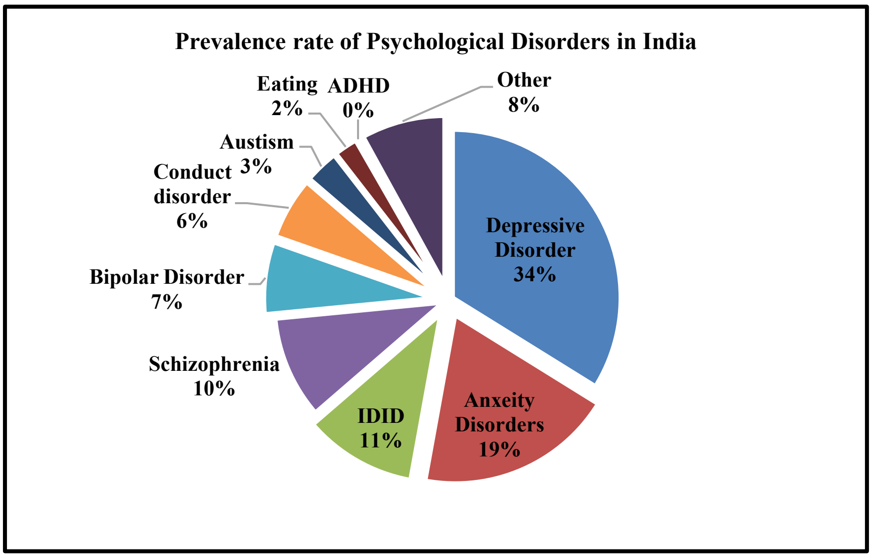

Figure 3: Prevalence rate of Psychological Disorders in India [4]

Table 2: Prevalence of Psychological disorders by gender [4]

Psychological Disorder	Males/ Females (Highest Prevalence)	States (Highest Prevalence)
Depressive Disorder	Females	Odisha, Telangana, Andhra Pradesh, Tamilnadu
Anxiety Disorders	Females	Kerala, Karnataka, Telangana, Tamil Nadu, Himachal Pradesh, and Maharashtra
Bipolar Disorder	Males	Goa, Kerala, Sikkim and Himachal Pradesh
Eating Disorder	Females	Delhi, Goa, and Sikkim
Conduct Disorder	Male	Uttar Pradesh, Bihar, Jharkhand, and Arunachal Pradesh
Autism Disorder	Males	Jammu and Kashmir and Arunachal Pradesh
ADHD	Males	Maharashtra, Meghalaya and Arunachal Pradesh
Schizophrenia	Males	Goa, Kerala, Tamil Nadu, and Delhi
Idiopathic developmental intellectual Disability (IDID)	Males	Uttar Pradesh, Bihar, Madhya Pradesh, and Assam
Attention-deficit hyperactivity disorder (ADHD)	Males	___

From Table 2, It has been analyzed that women are more likely than men to suffer from anxiety and depressive disorders. Moreover, the states of Kerala, Karnataka, Telangana, Tamil Nadu, Himachal Pradesh, and Maharashtra have the highest prevalence of anxiety disorders. Additionally, Odisha, Telangana, Andhra Pradesh, and Tamil Nadu have the highest rates of depression.

3. Review Methodology

To find significant articles related to traditional classifiers (TC), metaheuristic techniques (MT), and deep learning techniques (DLT) for the diagnosis of anxiety and depressive mental disorders, a thorough study has been performed. Identification, screening, eligibility, and inclusion of research articles are presented in Fig. 3. These steps are designed to identify the relevant articles for this in-depth analysis.

3.1. Research Questions

This comprehensive review is aimed to answer the following research questions.

RQ1. What are TC, MT, and DLT?

RQ2. What is the role of traditional classifiers, MT and DLT in the diagnosis of depression and anxiety disorders?

RQ3. What is the intensity of publication in the diagnosis of anxiety and depression using TC, MT, and DLT?

RQ4.Performance analysis of TC, MT, and DLT for the diagnosis of anxiety and depression Disorder.

3.2. Article Segregation Strategy

A literature expedition has been conducted to search relevant articles for answering the different research questions discussed in Section 3.1. The search was restricted to the English language only. Different search terms related to the study have been used to find relevant articles. Initially, a total of 5,532 articles related to the study (anxiety and depression) have been identified. Thereafter, publications related to traditional classifiers, MT and DLT for the diagnosis of anxiety and depression disorders were screened. Finally, a title-based (345), abstract-based (231), and full-text-based (141) selection has been performed to find out the relevant articles. Figure 4 outlines the article selection strategy. Figure 4 characterizes the selection process of articles using the Google Scholar, Web of Science and Springer database. Most relevant studies, including conference proceedings and journal papers (surveys, reviews, comparisons, related to applications books chapters) for the diagnosis of anxiety and depressive disorders have been included. Also, irrelevant studies have been excluded from the analysis.

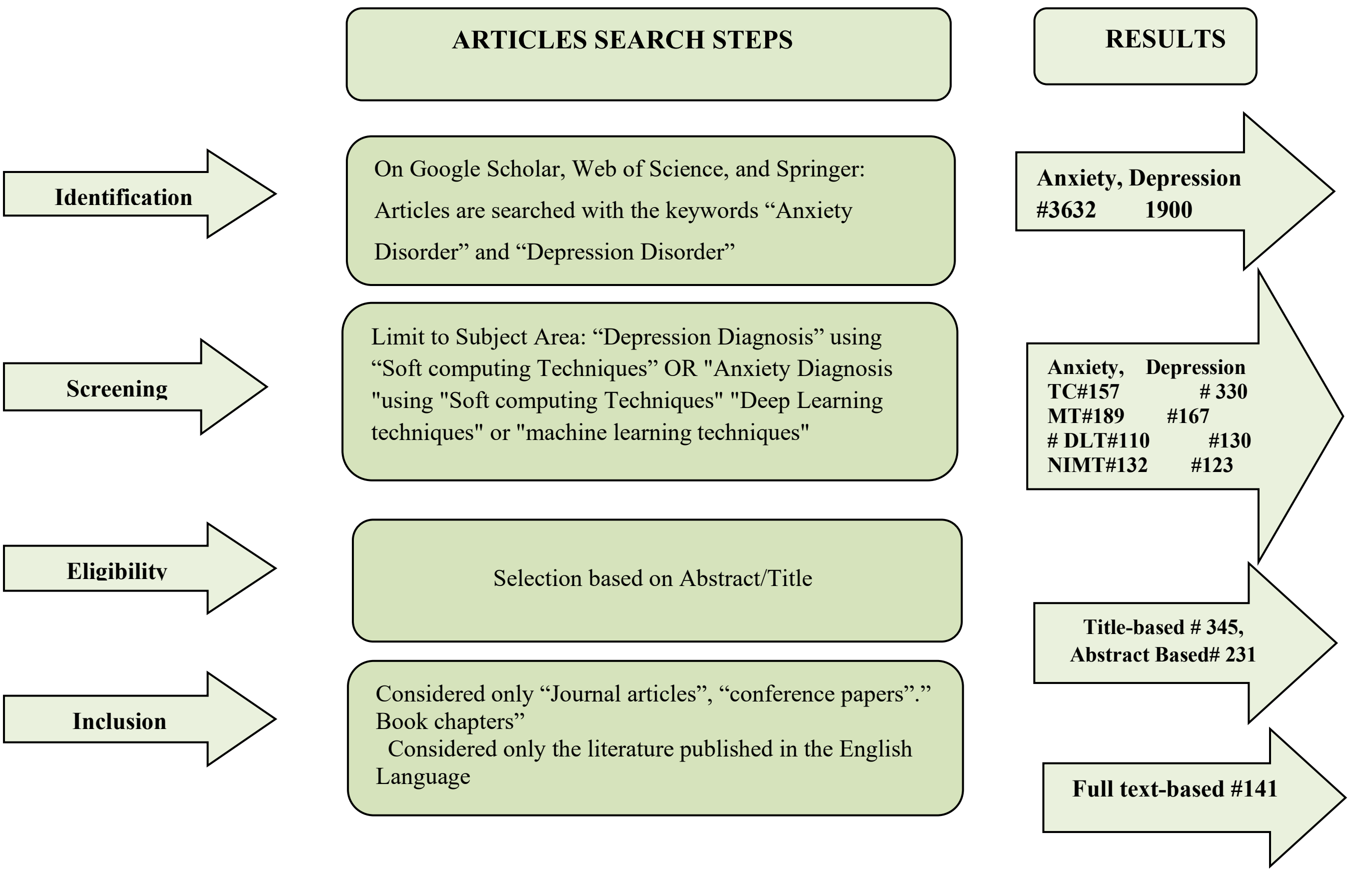

Figure 4: Search Strategy

4. Data Synthesis and Analysis

This section will answer the research questions fabricated in Section 3.1.

RQ1. What are traditional classifiers, metaheuristic and deep learning techniques?

Machine learning, a computer technique that automates learning from experience and enhances performance, is frequently used for this goal to produce more accurate predictions. Traditional classifiers, metaheuristic techniques, and deep learning techniques are the three main categories of machine learning [24]. A Traditional classifier performs two tasks: regression, and classification. In classification, categorical outputs are generated whereas in regression continuous outputs are generated. Also, classification techniques can be executed on both structured and unstructured datasets. Support vector machine (SVM), decision trees (DT) and naïve Bayes (NB) are different types of traditional classifiers. Table 3 presents category-wise traditional classifier techniques [25].

Table 3: Traditional Classifier Techniques

Type	Algorithm	Functionality	Advantages	Application	Example
Logic-Based	**Decision Tree**	Used in regression and classification	Deal with both categorical and numerical data needs less data processing	Financial analysis, And control systems	ID3, C4.5, CART, CHAID and QUEST
	Support Vector machine	Used in both regression and classification techniques	Handle high dimensional data, memory-efficient	Bioinformatics, face detection, and Handwriting recognition	-----
Static based	**Naïve Based**	A powerful technique for predictive modelling	Don't require large datasets.	Spam filtering, Text, and classification	------
Lazy Learning or Instance-based	**k-NN**	Used in both regression and classification techniques	Dynamic against noisy datasets.	E-discovery package	

NB is a probabilistic data mining technique used for classification purposes. The Bayes theorem and the theorem of total probability are the foundations of the naïve Bayes classifier. Probability is calculated by this classifier by measuring the frequency and different combinations of values from a given dataset. Random forest (RF) is a type of ensemble classifier that consists of different tree-structured classifiers. This method works with a random selection of features for the building of decision trees. SVM finds the optimal hyperplane for the separation of features from different datasets. Further, Instances (features) closest to the line are selected for processing, and these features are called support vectors. DT is a predictive model used as an analytical and visual decision support tool where the expected responses are calculated. In this model, roots and internal nodes are labelled with questions, and associated answers to questions are presented through arcs.

Metaheuristic techniques are techniques that mimic the collective behaviour of a group of creatures attempting to survive and are inspired by biological systems. MT can solve an immense range of problems without the help of specific knowledge [26]. Due to the stochastic nature of MT, no identical solution can be found even after starting from the same initial search point. Exploration and exploitation are two key features of meta-heuristic techniques. Population, randomness, selection, elitism, mutation, crossover, the guidance of the best solution, and algorithmic formulas are some major components of MT [27]. MT is broadly categorized into the following: 1) evolutionary algorithms (EA) 2) bio-inspired algorithms (swarm intelligence (SI) and no swarm intelligence-based 3); chemistry and physics-based algorithms; 4) other algorithms.

(a) EA is based on the Darwinian theory of evolution. Different classes of EA are genetic algorithm (GA), evolution strategy (ES), Genetic programming (GP), Differential evolution (DE), and evolutionary programming (EP). (b) Bio-inspired techniques are based on the biological system. SI with bio-inspired and bio-inspired but not SI are two categories of bio-inspired techniques. Particle swarm optimization (PSO), Firefly algorithm (FA), ant colony optimization (ACO), and cuckoo search (CS) are some categories of Bio-inspired with SI. Bio-inspired but not SI algorithms are flower pollination algorithm (FPA) and invasive weed optimization (IWO), etc. (c) Physics and chemistry-based algorithms are inspired by the resources of chemistry and physics, such as gravity and chemical laws. Harmony search (HS) and gravitational search algorithm (GSA) are examples of this category. (d) Recently, some optimization techniques inspired by social and emotional factors have been developed, such as social-emotional optimization techniques [28].

Deep learning has emerged as one of the most dynamic machine learning techniques where different layers of information processing stations are accomplished by learning by representation [29]. Originating from ANN, DL is characterized by multiple layers of neural networks that extract complex features from input images. Deep learning has become popular due to three factors: 1) good processing capabilities; 2) affordable hardware 3) recent developments in research on deep learning. Unsupervised, supervised and hybrid are three different classifications of deep learning. convolutional neural networks (CNN), autoencoder (AE), recurrent neural networks (RNN), and deep neural networks (DNN) are different types of deep learning techniques [30].

RQ2: What is the role of traditional classifiers, MT and DLT in the diagnosis of depression and anxiety disorders?

(a) Role of traditional classifiers in the diagnosis of anxiety and depression disorder:

Hsiu-Sen Chiang et al.,2013[31] diagnosed the level of mental stress using three data mining techniques namely decision tree, naïve Bayes and support vector machine. The authors experimented on the Physio net dataset of sixteen healthy persons with different parameters to assess mental stress such as blood pressure, heart rate, automatic nervous system, and heart rate variability. The decision tree outperforms other techniques in the diagnosis of mental stress with a detection rate of 90%. Hsiu-Sen Chiang et al., 2015[32] designed a rule-based reasoning model for the assessment of mental stress by the amalgamation of association Petri- -net (APN) and fuzzy techniques. The authors well compared the proposed method with other data mining techniques and achieved an excellent accuracy of 95.1% on sixteen SRAD datasets of the Physio net stress database. Sumathi M.R and B. Poorna et al., 2016 [33] worked with machine learning techniques for the diagnosis of mental illness among children using three parameters (accuracy, kappa statistics, and ROC area). The analysis was performed through an interview by selecting twenty-five attributes. The authors found that three machine learning classifiers such as the multiclass classifier, LAD tree, and multiclass perceptron outperformed other machine learning techniques.

(b) Role of MT in the diagnosis of anxiety and depression disorder:

W. Husain et al.,2017 [34] designed a classifier model using a feature selection technique, i.e. fuzzy rough set and PSO for the prediction of GAD. The analysis was carried out using four different classifiers, such as SVM, KNN, Naïve Bayes, and decision tree. The performance of all four classifiers was examined on an anxiety disorder set using features selected by the proposed method. The authors well compared the results using the hybridization of different techniques. Results achieved using SVM were found to be excellent as compared to other hybridization techniques. D.Shon et al.,2018[35] have proposed and employed two different techniques, i.e. GA and PCA as feature selection methods for the diagnosis of stress by using EEG signals. The authors used a KNN classifier for the features selected by the proposed method. The performance of GA (accuracy of 71.76%) is found to be superior as compared to the performance of PCA-KNN (65.03%) and KNN (67.08%).

(c) Role of DLT in the diagnosis of anxiety and depression order:

Lang He and Cui Cao.,2018[36] carried out a diagnostic study of depression using a deep convolutional neural network (DCNN). The authors found better performance with audio features using the AVEC2013 and AVEC2014 depression databases. Results were analyzed in terms of root mean square error (RMSE) and mean absolute error (MAE) of 9.9998 and 8.1919, respectively. U Rajendra Acharya et al.,2018[37] tried to mine depression among normal (fifteen) and depressive(fifteen) patients using a convolution neural network (CNN). The study analyzes the results using electroencephalogram (EEG) signals on the left and right hemispheres. The right hemisphere achieved the highest accuracy of 96.0% as compared to the left hemisphere (93.5%). The authors concluded that depressive signals were found to be more prevalent in the right hemisphere as compared to the left hemisphere.

Tables 4, 5 and 6 summarize the role and performance of different traditional classifiers, metaheuristics, and deep learning techniques in the diagnosis of anxiety and depression disorders.

Table 4 presents the results of different types of anxiety disorders diagnosed using traditional classifier techniques. It has been observed that the SVM classifier performs better than all other traditional classifiers for diagnosing the panic disorder, SAD, and GAD. Additionally, random forest yields the greatest outcomes when diagnosing PTSD.

Table 5 depicts that the decision tree and neural network outperform the diagnosis of depressive disorder. Also, SVM and probabilistic neural networks (PNN) achieved the best predictive accuracy in the diagnosis of the same.

The effectiveness of DLT and MT in the diagnosis of anxiety and depressive disorders is shown in Table 6. Additionally, it has been determined that for the diagnosis of depressive disorder, GA and differential evolution produced the best classification accuracy, at 71.76% and 98.40%, respectively. Review findings indicate that DLT performs better than MT in the diagnosis of anxiety and depression disorders.

RQ3: What is the intensity of publications in the diagnosis of anxiety and depressive disorder using traditional classifiers, MT, and DLT?

To scrutinize the publication trend of diagnosis of these diseases using traditional classifiers, MT and DLT different queries have been fired. The scanning was performed using different keywords such as anxiety, depression, stress, soft computing, data mining, and deep learning. Figure 5 represents the last ten-year publication trend of TC, MT, and DLT in the diagnosis of the same.

From Figure 5, it has been evaluated that meta-heuristic and deep learning techniques are less explored in the diagnosis of anxiety and depression disorders. Also, less work has been found on depression disorder using these techniques as compared to anxiety disorder.

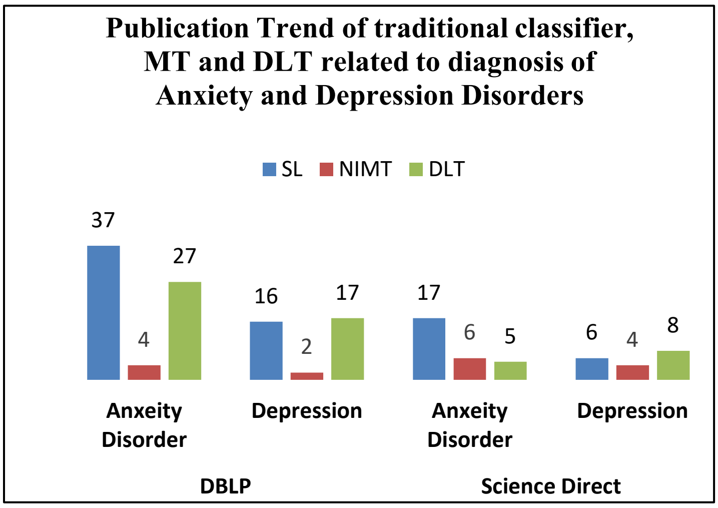

Figure 5: Publication detail of anxiety and depression disorder using traditional classifiers, MT, and DL techniques (last 10 years)

Table 4: Past studies related to anxiety disorders using traditional classifiers

Author (Year)	**Disease**	**Instance/Features**	**Traditional Machine Learning Technique (* means no value)**															
			Naïve Bayes	**Decision Tree**	**SVM**	**Fuzzy**	**Bayesian Network**	**Random Forest**	**KNN**	**Logistic Regression**	**ANN**	**Leave one out Validation**	**Multilayer Perceptron**	**Cat boost**	**Ad boost**	**Sequential minimal23optimization**	**Best Technique**	**Results**
Abdulhakim Al-Ezzi et al.,2023[38]	SAD	66	*	*	√	*	*	*	*	*	*	*	*	*	*	*	SVM and partial directed coherence, Graph Theory	Accuracy (92.78%), Sensitivity (95.25%), Specificity (94.12%)
Jiangling Jiang et al.,2023[39]	GAD	60	*	*	*	*	*	*	*	*	*	*	*	*	*	*	Machine Learning	Not Given
Shaurya Bhatnagar et al.,2023[40]	Anxiety Disorder	127	√	√	√	*	*	√	*	*	*	*	*	*	*	*	Random Forest	Accuracy (78.9%)
Faisal Mashel Albagmi et al.,2022[41]	GAD	3017	*	*	√	*	*	*	*	*	*	*	*	*	*	*	SVM	Accuracy (100%), Precision (100%), Recall (100%)
A. Tushar Umrani and P. Harshavardhanan.,2022[42]	Anxiety Disorders	112	*	*	*	*	*	*	*	*	√	*	*	*	*	*	ANN	Accuracy (96.67 %)
Abdulhakim Al-Ezzi et al.,2022[43]	SAD	88	√	*	*	√	*	*	*	*	*	*	*	*	*	*	Naive Bayes and Fuzzy	Accuracy (86.93%), Sensitivity (92.46%),

																	Entropy measure	Specificity (95.32%)
Zhongxia Shen et al.,2022[44]	GAD	81	×	×	√	×	×	×	×	×	×	×	×	×	×	×	SVM	Accuracy (97.83%), Sensitivity (97.78%), Specificity (97.95%)
Hao Xiong et al.,2021[45]	Separation AD, Social AD, GAD	297	×	×	×	×	√	×	×	×	×	×	×	×	×	×	Bayesian	AUC (0.9091)
Abhilash Saj George et al.,2021[46]	Anxiety Disorder	23	×	×	√	×	×	√	×	×	×	×	×	×	√	×	SVM	Accuracy (82.2%)
Kyoung-Sae Na et al.,2021[47]	Panic Disorder	121	×	×	×	×	×	×	×	√	×	×	×	×	×	×	Regularized logistic regression	Accuracy (78.4%), Sensitivity (83.3%), Specificity (73.7%)
Mirza Naveed Shahzad et al.,2021[48]	PTSD	28	×	×	×	×	×	×	×		√	×	×	×	×	×	ANN	Accuracy (94.5%)
Z. Li et al.,2019[49]	Anxiety Disorders	12	×	×	√	×	×	×	√	×	×	×	×	×	×	×	SVM	Accuracy (62.56%)
A.Sau and I. Bhakta et al.,2019[1]	Anxiety Disorder	470	√	×	√	×	×	√	×	√	×	×	×	√	×	×	Cat boost	Accuracy (82.6%), precision (84.1%)
Aris Supriyanto et al.,2018 [50]	Postpartum Depression	50	×	√	×	×	×	×	×	×	×	×	×	×	×	×	Decision Tree	Accuracy (62%), Sensitivity (65.62%), specificity (77.77%)
D. Leightley et al.,2018 [51]	PTSD	13,690	×	√	√	×	×	√	×	×	√	×	×	×	×	×	Random Forest	Accuracy (97%), Sensitivity (60%), specificity (98%)
G.N.Saxe et al., 2017 [52]	PTSD	163	×	×	√	×	×	√	×	√	×	×	×	×	×	×	SVM	Mean AUC 0.79

K. Hilbert et al.,2016 [53]	GAD	57	×	×	√	×	×	×	×	×	×	×	×	×	×	×	SVM	Accuracy (90.10%)
W. Husain et al.,2016 [54]	GAD	182	×	×	×	×	×	√	×	×	×	×	×	×	×	×	Random Forest	Accuracy (92.85%)
H. Chen et al.,2015 [55]	Anxiety Disorder	517	×	×	×	×	√	×	×	×	×	×	×	×	×	×	Bayesian Network	Accuracy (75%)
U. Lueken et al.,2015 [56]	Panic Disorder	369	×	×	×	×	×	×	×	×	×	√	×	×	×	×	Leave one out of cross-validation	Accuracy (73%), Sensitivity (77%), Specificity (70%)
S. Omurca et al., 2015 [57]	PTSD	391	√	×	×	×	×	×	×	×	×	×	√	×	×	√	Naïve bayes	Accuracy (78.9%)
F. Dabek et al.,2015 [58]	GAD	89,840	×	×	×	×	×	×	×	×	√	×	×	×	×	×	ANN	Accuracy (82.35%)
F.Liu et al.,2015 [59]	PTSD	40	×	×	√	×	×	×	×	×	×	×	×	×	×	×	SVM	Accuracy (92.5%), sensitivity (90%), Specificity (95%)
M. Chatterjee et al.,2014 [60]	Anxiety Disorder	48	√	×	×	×	√	×	×	√	×	×	×	×	×	×	Bayesian Network	Accuracy (73.33%)
S.P. Pantazatos et al.,2014 [61]	Panic Disorder	32	×	×	√	×	×	×	×	×	×	×	×	×	×	×	SVM	Accuracy (82%)
S.P. Pantazatos et al.,2014 [61]	SAD	35	×	×	√	×	×	×	×	×	×	×	×	×	×	×	SVM	Accuracy (89%)
W. Zhang et al.,2014 [62]	SAD	40	×	×	√	×	×	×	×	×	×	×	×	×	×	×	SVM	Accuracy (76.25%), sensitivity (70%), Specificity (82.5%)
Frick et al.,2014 [63]	SAD	26	×	×	√	×	×	×	×	×	×	×	×	×	×	×	SVM	Accuracy (72.6%)
I. Galatzer-Levy et al., 2014 [64]	PTSD	957	×	×	√	×	×	√	×	×	×	×	×	×	√	×	Hybrid	AUC (0.78)
Z. S. Estabragh et al.,2013 [65]	SAD	438	×	×	×	×	√	×	×	×	×	×	×	×	×	×	Bayesian Network	AUC of .898, Sensitivity (100%),

																	Specificity (100%)
Hsiu-Sen Chiang et al.,2013 [31]	PTSD	16	√	√	√	×	×	×	×	×	×	×	×	×	×	×	Decision tree	Accuracy (90%)
C. D. Katsis et al.,2011 [66]	GAD	#	×	×	√	√	×	√	×	×	√	×	×	×	×	×	Fuzzy	Accuracy (84.3%)
Hsiang-Yang Chen et al., 2010 [67]	Parenting Stress	206	×	√	×	×	×	×	×	×	×	×	×	×	×	×	Decision Tree	Not Mentioned
I. Marinić et al.,2007 [68]	PTSD	102	×	×	×	×	×	×	×	×	×	×	×	×	×	×	Random forest	Accuracy (74.5%)

Table 5: Outcomes of Depression disorder using traditional classifier techniques

Author (Year)	Traditional Machine Learning Technique for Depression Diagnosis (* means No value)															
	Leave n Out	Naïve Bayes	Decision Tree	SVM	RBF	Bayesian Network	Random Forest	KNN	Logistic Regression	ANN	Fuzzy	PNN	XG Boost	Instances/features	Best Performance	
															Technique	Results
Devesh Kumar Upadhyay et al.,2024[69]	×	×	×	√	×	×	×	×	×	×	×	×	×	137	SVM	Accuracy (89.4%)
Muzafar Mehraj Misgar et al.,2024[70]	×	×	×	×	×	×	√	×	×	×	×	×	×	55	RF with Augmentation	Accuracy (98.65%), Sensitivity (99.89%), Specificity (97.36%)

															RF without Augmentation	Accuracy (74.29%), Sensitivity (73.56%), Specificity (74.80%)
Ayan Seal et al.,2023[71]	×	×	×	×	×	×	×	×	×	×	×	×	√	#	XGBoost	Accuracy (87%)
Duyan Geng et al.,2023[72]	×	×	×	×	√	×	×	×	×	×	×	×	×	80	Bayesian optimised extremely randomized trees classifier	Accuracy (86.32%), Sensitivity (85.85%), Specificity (86.49%)
Li Yi et al.,2023[73]	×	×	×	√	×	×	×	×	×	×	×	×	×	55	SVM	Accuracy (92.7%)
Lady L. González et al.,2023[74]	×	×	×	×	×	×	√	√	×	√	×	×	×	55	ANN	Accuracy (57%)
Kennedy Opoku Asare et al.,2021[75]	×	×	×	×	×	×	√	√	×	×	×	×	√	629	KNN	Accuracy (98.14%)
Jung-Gu Choi et al.,2021[76]	×	×	×	×	×	×	×	×	×	×	×	×		14	XGBoost	Accuracy (97.88%)
Cacheda et al.,2019 [77]	×	×	×	×	×	×	√	×	×	×	×	×		887	Random forest	Not Mentioned
Ellen W. McGinnis et al.,2019 [78]	×	×	×	×	×	×	×	×	√	×	×	×		71	Logistic Regression	Accuracy (80%), Sensitivity (54%), Specificity (93%)
Norhatta Mohd and Yasmin Yahya ,2018 [79]	×	×	×	×	×	×	×	×	√	√	×	×		216	ANN	Accuracy (71.8%)
Virginia Mato-Abad et al.,2018 [80]	×	×	×	×	×	×	×	×	×	√	×	×		96	ANN	Accuracy (86%), Sensitivity (82%), Specificity (89%)
Ryan S. McGinnis et al.,2018 [81]	×	×	×	×	×	×	×	×	√	×	×	×		63	Logistic Regression	Accuracy (80%)
Anna Maridaki et al.,2018 [82]	×	×	×	√	×	×	×	×	×	×	×	×		200	SVM	F1 Score (81.93%)
Md. Rafiqul et al.,2018 [83]	×	×	√	×	×	×	×	×	×	×	×	×		#	Decision Tree	Accuracy (71%)
Wajid Mumtazet al.,2017 [84]	×	√	√	√	×	×	×	×	√	×	×	×		#	SVM	Accuracy (98%), Sensitivity (99.9%), Specificity (95%)

Bo Sun et al.,2017 [85]	×	×	×	×	×	×	√	×	×	×	×	×		79	Random Forest	RMSE 4.98 MAE 3.87
David M Schnyer et al.,2017 [86]	×	×	×	√	×	×	×	×	×	×	×	×		97	SVM	Accuracy (76%), Sensitivity (68%), Specificity (84%)
Subhagata Chattopadhyay,2017 [87]	×	×	×	×	×	×	×	×	×	×	√	×		352	Neuro-Fuzzy	Accuracy (95.50%)
Hong Zheng et al.,2016 [88]	×	×	×	√	√	×	×	×	×	×	×	×		126	SVM and RBF	Accuracy (88%)
Babak Mohammadzadeh et al.,2016 [89]	×	×	×	×	×	×	×	×	×	×	√	×		65	Fuzzy	Accuracy (87.2%)
Blessing Ojeme and Audrey Mbogho et al.,2016 [90]	×	×	×	×	×	√	×	×	×	×	×	×		580	Bayesian network	ROC 0.975
U. Rajendra Acharya et al.,2015[91]	×	×	×	√	×	×	×	×	×	×	×	×		30	SVM	Accuracy (98%), Sensitivity (97%), Specificity (98.5%)
Dimitrios Galiatsatos et al.,2015 [92]	×	×	×	×	×	√	×	×	×	×	√	×		7145	Bayesian network Fuzzy logic	Accuracy (83.51%)
Ekong, Victor E et al.,2015 [93]	×	×	×	×	×	×	×	×	×	√	√	×		80	ANN and Fuzzy	Accuracy (92.4%)
M. Mohammad et al.,2015 [94]	×	×	√	×	×	×	×	×	×	×	×	×		96	Decision Tree	Accuracy (90%), Sensitivity (70%), Specificity (76%)
Meenal J. Patel et al.,2015[95]	×	×	√	×	×	×	×	×	×	×	×	×		68	Decision Tree	Accuracy (87.27%)
OLIVER FAUST et al.,2014 [96]	×	×	×	×	×	×	×	×	×	×	×	√		30	PNN	Accuracy (99.5%), Sensitivity (99.2%), Specificity (99.7%)
A. K. Rostamabad et al.,2013 [97]	√	×	×	×	×	×	×	×	×	×	×	×		22	Leave n Out	Accuracy (87.9%), Sensitivity (94.9%), Specificity (80.9%)
B.Hosseinifard et al.,2013 [98]	×	×	×	×	×	×	√	√	×	×	×	×		90	KNN, LR	Accuracy (90%)
B.Mwangi et al.,2012 et al., [99]	×	×	×	√	×	×	×	×	×	×	×	×		62	SVM	Accuracy (90%), Sensitivity (93%), Specificity (87%)
Alexandru Floares et al.,2006 [100]	×	×	√		×	×	×	×	×	√	×	×		48	Neural Network and Decision Tree	Accuracy (100%)

Table 6: Past Study on Depression and Anxiety Disorders using Metaheuristic and Deep Learning Techniques (* Mean Absolute Error (MAE) and Root Mean Square Error (RMSE))

Author	Disease	Instances/feature	Modality	Classification Technique	Results
Bazen Gashaw Teferra et al.,2023[101]	GAD	2000	Speech Transcripts	Transformer-based Neural Networks	AUCROC (0.64)
Nagisa Masuda and Ikuko Eguchi Yairi et al.,2023[102]	Anxiety Disorder	32	EEG and peripheral physiological signals	CNN-LSTM	accuracy (98.79%) F1 score (99.01%)
Momoko Ishimaru et al., 2023[103]	Depression	189	Audio	Graphical Convolutional Neural Network	Accuracy (92%–98 %.)
Adil O. Khadidos et al.,2023[104]	Depression	64	EEG Signals	CNN	Accuracy (98.13%), Sensitivity (97%), Specificity (99%)
Amel Ksibi et al.,2023[105]	Depression	128	EEG signal	CNN	Accuracy (97%)
Wei Liu et al.,2023[106]	GAD	81	EEG	multi-scale spatial-temporal local sequential and global parallel convolutional model	Accuracy (99.47%), Precision (99.48%) Recall (99.59%) F1 Score (99.54%)
Gosala Bethany et al.,2023[107]	Depression	64	Brain Signals	Logistic Regression	Accuracy (88.4%)
				SVM	Accuracy (89.3%)
				Deep Learning	Accuracy (90.2%)
Jeewoo Yoon et al.,2022[108]	Depression	961	Video	Cross Attention	Precision (65.40%) Recall (65.57%) F1 Score (63.50%)
Harnain Kour and Manoj K. Gupta .,2022[109]	Depression	2558	online social media data	CNN-biLSTM	Accuracy (94.28%)

Vivek Sharma et al.,2022[110]	Depression	38	Electrodermal data	Stacked Autoencoders, DNN	Accuracy (92 %–94 %), Sensitivity (100%), Specificity (100%)
Qianqian Wang et al.,2022[111]	Depression	533	Neuroimaging Data	Graph convolutional network with feature fusion	Accuracy (66%)
Katharina Schultebraucks et al.,2022[112]	PTSD and Depression	81	Speech	DL	AUC (0.86)
Wanqing Xie et al.,2022[113]	Depression	303	Binary	CNN-LSTM	Accuracy (83.78%)
Shikha et al.,2021[114]	Anxiety Disorder	23	EEG	Stacked Sparse Autoencoder	Accuracy (83.93%)
				Decision Tree	Accuracy (70.25%)
Caglar Uyulan et al.,2021[115]	Depression	48	EEG signals	ResNet-50 and long-short-term memory	Accuracy (90.22%)
Ayan Seal et al.,2021[116]	Depression		EEG	CNN	Accuracy (99.37%)
Danish M. Khan et al.,2021[117]	Depression	60	EEG Signals	3D-CNN	Accuracy (100%)
Jing Yang et al.,2021[118]	PTSD	86	MR imaging	Deep Learning	Accuracy (71.2%)
Abdulhakim Al-Ezzi et al.,2021[119]	SAD	89	EEG	CNN+LSTM	Accuracy (96.43%), Sensitivity (87.50%), Specificity (100%)
Nicholas C. Jacobson et al.,2021[120]	Anxiety Disorder	265	Binary	Deep auto-encoder paired with a multi-layered ensemble deep learning model	Accuracy (68.7%), Sensitivity (84.6%), Specificity (52.7%)

Ziyu Zhu et al.,2021[121]	PTSD	126	rs-fMRI	Deep Learning	Accuracy (80%)
				SVM	Accuracy (50%)
D.Banerjee et al., 2019 [122]	PTSD	26	Audio	Deep Learning	Accuracy (68%)
				SVM	Accuracy (57%)
W. Mumtaz and A. Qayyum,2019[123]	Depression	63	EEG	CNN	Accuracy (98.32%), Precision (99.78%), Recall (98.34%)
M.H. Fazel Zarand et al.,2019[124]	Depression	484	Numerical	Fuzzy Expert System	Accuracy (95%)
S.D. Kumar and S.D.P.,2019 [125]	Depression	30	EEG signals	LSTM	RMSE (0.000064)
A. McDonald et al.,2019 [126]	PTSD	107	Integer, real	CNN	AUC (0.63)
				SVM	AUC (0.67)
				Random forest	AUC (0.66)
Maria Zelenina et al.,2019 [127]	Depression	900	EEG	Deep Learning	Accuracy (99.5%)
Jihoon Oh et al.,2019 [128]	Depression	19,725	Integer	Deep Learning	AUC (0.92)
Betul Ay et al.,2019 [129]	Depression	30	EEG signals	LSTM-CNN	Accuracy (99.12%), Sensitivity (97.67%)
Sandheep Pet al.,2019 [130]	Depression	30	EEG Signals	CNN	Accuracy (99.31%)
D. Shon et al.,2018 [35]	Emotional Stress	32	EEG	GA	Accuracy (71.76%)
				PCA	Accuracy (65.3%)
Xiaowei Li et al.,2019 [131]	Depression	28	EEG	SVM	Accuracy (86.05%)
				Deep Learning	Accuracy (84.75%)
Jinming Li et al.,2018 [132]	Depression	84	Audio	Deep Learning (Audionet)	MAE (7.07), RMSE (9.15)
Wandeng Mao et al.,2018 [133]	Depression	34	EEG	CNN	Accuracy (77.20%)
U . R Acharya et al.,2018 [37]	Depression	4838	EEG Signals	CNN	Accuracy (96%), Sensitivity (84.99%), Specificity (95.99%)

Qing Cong et al.,2018 [134]	Depression	9000	Integer, Text	X-A-BiLSTM (Deep Learning)	Precision (0.69), Recall (0.53), F1 Score (0.60)
Megat. A. H.M S et al.,2018 [135]	Depression	200	Audio, Video	Transfer learning	Accuracy (83%)
Lang He and Cui Cao et,2018 [136]	Depression	292	Audio	DCNN	RMSE (9.9998), MAE (8.1919)
Yalin Li et al.,2018 [137]	Depression	20	Facial Expression	Differential Evolution, KNN	Accuracy (98.40%)
Yu Zhu et al.,2017 [138]	Depression	340	Video	DNN	RMSE (9.55), MAE (7.47)
Le Yang et al.,2017 [139]	Depression	189	Audio, Video and Text	DCNN	Not Mentioned
				DNN	Not Mentioned
Yajun Kang et al.,2017 [140]	Depression	292	Visual	DNN	RMSE (9.43), MSE (7.74)
				Back Propagation Algorithm	
W. Husain et al.,2016 [141]	GAD	183	Integer	PSO	Not Mentioned
				SVM	Accuracy (96.7%)

RQ4 Performance analysis of traditional classifier, MT, and DLT for diagnosis of Anxiety and Depression Disorders.

Different traditional classifiers (SVM, decision tree, Naïve Bayes, Bayesian network, KNN, ANN, fuzzy approach, cat boost, AdaBoost, leave n out, random forest, and logistic regression), Metaheuristic algorithms (GA, differential evolution, and PSO), and DL techniques (DCNN, CNN, LSTM, transformers, and attention) have been observed to be used in the diagnosis of anxiety and depression disorders on some benchmark and collected datasets. Leading benchmark datasets for the diagnosis of anxiety and depression disorders have been examined by researchers. These include the DEEP dataset (40 videos, EEG signal), SEED dataset (70 videos, EEG signal), DAIC-WOZ dataset (189, text, binary, speech, audio), NHANES dataset (28,280, binary), AVEC2013 depression dataset (342, video), and AVEC2014 depression dataset (50, audio). To aid in the diagnosis of these two disorders, researchers have also collected datasets from many institutions and hospitals, such anxiety dataset (533, MRI Image), depression dataset (4788, EEG), and psychiatry dataset (4348, EEG signals) for diagnosis of these two disorders.

Table 7 identifies the most effective techniques and their classification accuracy for diagnosing various anxiety and depression conditions. From Table 7, it has been noticed that random forest, SVM, and fuzzy traditional classifier or traditional machine learning techniques achieved an excellent rate of accuracy of 97%, 92.5%, and 95.1% respectively in the diagnosis of PTSD. Also, SVM outperforms in the diagnosis of SAD, GAD, and panic disorder by achieving an accuracy of 92.78%,100% and 82% respectively.

Additionally, a remarkable accuracy of 100% has been attained by the hybridization of a decision tree and neural network in the diagnosis of depression. Moreover, a 98% accuracy rate in the diagnosis of depression disorder was also attained using random forest(traditional classifier).

For depression diagnosis, a remarkable accuracy of 100% has been achieved by the fusion of a neural network and a decision tree. Furthermore, random forest with augmentation i.e., traditional classifier also achieved an accuracy of 98% in the diagnosis of depression disorder.

It has been found that GA (71.76%) and differential evolution (98.40%) yield better results when analyzing the outcomes of metaheuristic techniques in the diagnosis of anxiety and depression disorders. It is noted that GA and DE are the only metaheuristic techniques utilised for the diagnosis of anxiety and depression disorders.

Furthermore, the performance of DLT has also achieved excellent results in the diagnosis of anxiety and depression disorders. The best performance of DLT in the diagnosis of anxiety disorders i.e. PTSD, GAD, and SAD have been recorded at 68%, 99.47%, and 96.4% respectively. Also, deep learning techniques achieved an accuracy of 100% in the diagnosis of depression disorder.

The study also examined the sensitivity and specificity parameters in addition to the accuracy parameter. Nevertheless, a thorough examination has revealed that very few researchers have looked at measures for sensitivity and specificity in their studies. Thus, the accuracy parameter is considered as the sole basis for analysis in this study.

From the literature review, it has been observed that metaheuristic techniques (advanced machine learning techniques) have also not received any attention from researchers for the diagnosis of anxiety and depression disorders. Although the results of deep learning techniques are excellent in the diagnosis of these two disorders. However, deep learning techniques need special attention to anxiety and depression disorders.

Table 7: Performance Analysis of Traditional Classifier, Metaheuristic, and DLT

Disease	**Type**	**TRADITIONAL CLASSIFIER/MT/DLT**	**Author**	**Technique**	**Accuracy**	**Sensitivity**	**Specificity**
Anxiety Disorder	**PTSD**	**Traditional classifier**	D. Leightley et al.,2018[51]	Random Forest	97%	60%	80%
			Hsiu-Sen Chiang et al., 2015[32]	Fuzzy	95.1%	×	×
			F. Liu et al.,2015[59]	SVM	92.5%	90%	95%
		MT	D. Shon et al.,2018[35]	GA	71.76%	×	×
		DLT	D.Banerjee et al., 2019 [122]	Deep Learning	68%	×	×
	GAD	**Traditional classifier**	Faisal Mashel Albagmi et al.,2022[41]	SVM	100%	×	×
			W. Husain et al.,2016[54]	Random Forest	92.5%	×	×
			Zhongxia Shen et al.,2022[44]	SVM	97.83%	97.78%	97.95%
		DLT	Wei Liu et al.,2023[106]	multi-scale spatial-temporal local sequential and global parallel convolutional model	99.47%	×	×
	SAD	**Traditional classifier**	Abdulhakim Al-Ezzi et al.,2023[38]	SVM	92.78%	95.25%	94.12%
		DLT	Abdulhakim Al-Ezzi et al.,2021[119]	CNN+LSTM	96.43%	87.50%	100%
	Panic Disorder	**Traditional classifier**	S.P. Pantazatos et al.,2014 [61]	SVM	82%	×	×
Depression		**Traditional classifier**	Alexandru Floares et al.,2006[100]	Neural Network and Decision Tree	100%	×	×
			Olivr Faust et al.,2014[96]	PNN	99.5%	99.2%	99.7%
			Muzafar Mehraj Misgar et al.,2024[70]	Random Forest with Augmentation	98.65%	99.89%	97.36%
		MT	Yalin Li et al.,2018 [137]	Differential Evolution	98.40%	×	×
		DLT	Maria Zelenina et al.,2019[127]	Deep Learning	99.5%	×	×
			Sandheep P et al.,2019[130]	CNN	99.31%	×	×

		Betul Ay et al.,2019[129]	LSTM and CNN	99.12%	97.67%	×
		Danish M. Khan et al.,2021[117]	3D-CNN	100%	×	×

5. Discussion

5.1 Strength of this Study

This study has conferred a comprehensive survey of one hundred forty-one articles related to TC, MT and DLT for the diagnosis of anxiety and depression diseases. A brief detail of all three techniques along with their different categories has been presented. The complete study has been carried out using four different research questions. This is the only meta-analysis that has covered a review of the two chronic psychological disorders (Anxiety and depression) using TC, MT and DLT.

5.2 Limitations

Diagnosis of anxiety and depression disorder using TC, MT, and DLT is the key part of this survey. So, all the relevant articles related to the study have been incorporated into this comprehensive review. However, it is not possible to incorporate all the articles into one study. This study is restricted to the English language only. Additionally, studies related to only two psychological disorders have been considered. Also, articles related to other psychological disorders except anxiety and depression were not considered during the synthesis of this study. However, the mathematical details of TC, MT, and DLT and their consequences have not been studied in this study.

5.3 Research Implications

This study epitomizes one hundred forty-one reviewed studies related to TC, MT, and DLT for the early diagnosis of anxiety and depression disorders. This is the only study that incorporates an amalgamation of three emerging techniques for the diagnosis of two major and chronic disorders. No significant review analogous to the title and objectives of this survey paper is available. Thus, researchers can avail of great advantages for their research work from this summarized work. Therefore, in the future, more concentration should be given to MT and DLT in the diagnosis of both mental disorders. Also, the hybridization of TC, MT, and DLT should be employed for the diagnosis of other psychological and neurological disorders.

6. Conclusion and Future Directions

Anxiety and depression are chronic psychiatric disorders that are related to psychosocial outcomes and negative health. Both have emerged as a significant burden on public health with a high rate of disability. TC, MT, and DLT are powered by the advancement in disease diagnosis and have shown exceptional performance in the diagnosis of anxiety and depression disorders. Here, a comprehensive literature review of different TC, MT, and DLT in the diagnosis of these disorders has been presented. For an exhaustive analysis of these techniques and their role in the diagnosis of these diseases, four different research questions have been drafted. First of all, a brief introduction of TC, DLT and MT techniques along with their categories are explored. In response to the second question, the publication trend of anxiety and depression disorders using the same techniques has been explored. It has been found that traditional classifiers in the diagnosis of anxiety and depression disorders are explored more as compared to metaheuristic and deep learning techniques. So, there is an intense need to explore metaheuristic and deep learning techniques for the diagnosis of the same.

The third research question exploits the role of divergent TC, MT, and DLT in the diagnosis of depression and anxiety disorders. The performance of all three techniques is well compared in the diagnosis of these disorders. The performance of random forest (traditional classifier) is more efficacious in the diagnosis of anxiety disorder i.e. PTSD. In addition, the SVM classifier also achieved impressive results in the diagnosis of SAD, GAD and panic disorders. As far as depression is concerned, the performance of the deep learning technique and decision tress is noticed to be exceptional as compared to other techniques. Here, it can be concluded that traditional classifiers achieved remarkable results in the diagnosis of anxiety and depression disorders. It has been also analyzed that very few articles have been published on anxiety and depression disorders using metaheuristic techniques. Despite that, the performance of GA and differential evolution (MT) is shown to be admirable. Moreover, the results of deep learning techniques are also remarkable in the diagnosis of depression and anxiety disorders.

Furthermore, it can be concluded that MT such as swarm intelligence techniques and DLT are much less explored in the diagnosis of these disorders as compared to traditional classifiers. So, MT and DLT need more insights into the diagnosis of depression and anxiety disorders. However, there is a prospective scope to use MT and DLT in the diagnosis of different psychological disorders. Also, the diagnosis of anxiety and depression among the academic fraternity using these techniques needs to be explored. In the future, research needs to delve into the hybridization of traditional classifiers, metaheuristic, and deep learning techniques for the diagnosis of psychological disorders.

Declarations

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