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SYSTEMS-LEVEL QUALITY IMPROVEMENT

Diagnosis of Human Psychological Disorders using Supervised Learning and Nature-Inspired Computing Techniques: A Meta-Analysis

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Abstract

A psychological disorder is a mutilation state of the body that intervenes the imperative functioning of the mind or brain. In the last few years, the number of psychological disorders patients has been significantly raised. This paper presents a comprehensive review of some of the major human psychological disorders (stress, depression, autism, anxiety, Attention-deficit hyperactivity disorder (ADHD), Alzheimer, Parkinson, insomnia, schizophrenia and mood disorder) mined using different supervised and nature-inspired computing techniques. A systematic review methodology based on three-dimensional search space i.e. disease diagnosis, psychological disorders and classification techniques has been employed. This study reviews the discipline, models, and methodologies used to diagnose different psychological disorders. Initially, different types of human psychological disorders along with their biological and behavioural symptoms have been presented. The racial effects on these human disorders have been briefly explored. The morbidity rate of psychological disordered Indian patients has also been depicted. The significance of using different supervised learning and nature-inspired computing techniques in the diagnosis of different psychological disorders has been extensively examined and the publication trend of the related articles has also been comprehensively accessed. The brief details of the datasets used in mining these human disorders have also been shown. In addition, the effect of using feature selection on the predictive rate of accuracy of these human disorders is also presented in this study. Finally, the research gaps have been identified that witnessed that there is a full scope for diagnosis of mania, insomnia, mood disorder using emerging nature-inspired computing techniques. Moreover, there is a need to explore the use of a binary or chaotic variant of different nature-inspired computing techniques in the diagnosis of different human psychological disorders. This study will serve as a roadmap to guide the researchers who want to pursue their research work in the mining of different psychological disorders.

Keywords Psychological disorders · Supervised learning techniques · Nature-inspired computing techniques · Classification · Accuracy

Introduction

Human disorders represent mutilation state that intervenes or modifies the imperative functioning of different organs or parts of the body. There is a huge list of human disorders. Bone diseases, genetic diseases, psychological disorders, neurological disorders, skin diseases, trauma, infectious disease, cardio diseases, tissue diseases and digestive diseases are some of the major categories of human diseases [1]. Nowadays, a large number of populations are suffering from psychological disorders all over the world. According to the World Health Organization (WHO) factsheet, around three hundred million people are suffering from depression globally. Whereas, 60 million, 47.5 million and 21 million population is affected by bipolar, dementia and Schizophrenia disorders respectively [2]. Moreover, the rate of disability in these disorders is very high. Therefore, in this study, the comprehensive analysis for the diagnosis of these human disorders has been carried out.

The psychological disorders are mental disorders that represent an ongoing dysfunctional pattern of thoughts, emotions, and behaviours that lead to a significant rate of distress.

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Table 1 Biological, psychological and social causes of the psychological disorder [9, 10]

Biological Causes	Psychological Causes	Social Causes
– Heredity – Pre-natal damage – Brain injury – Bacterial or virus infections – Poor nutrition – Physical health – Drug effects	– Psychological trauma – Negative thoughts – Excessive thinking Mood-related perceptions – High expectations – Temperament – Self-esteem	– Physical, sexual or emotional abuse – Environmental violence – Poor social relations – Family circumstances – Poverty

This kind of distress is not acceptable by the culture as well as the society (Butcher, Mineka, & Hooley, 2007) [3]. These disorders cover a range of brain-related problems viz. stress, anxiety, depression, schizophrenia, intellectual disabilities and may affect both mental and physical health status of the humans [4, 5]. Though, it is difficult to differentiate the states of normal or abnormal behaviour. Psychological dysfunction, cultural unexpectedness, and personal distress are three major representatives of these human disorders [6].

In general, these disorders can be diagnosed using distinct clinical assessment techniques in which several psychological, biological, social and emotional factors are extensively assessed for the classification of these disorders [7]. This information can be collected using structured and semi-structured interviews of patients. The psychiatrists, psychologists and healthcare professionals generally prepare a questionnaire so that they can collect physical, behavioural, social and emotional characteristics of the person [8]. Some of the major causes of these human disorders are presented in Table 1.

In this manuscript, ten major human psychological disorders such as stress, depression, autism, anxiety, Attention-deficit hyperactivity disorder (ADHD), Alzheimer, Parkinson, insomnia, schizophrenia and mood disorders have been studied. As far as human psychological disordered victims are concerned, there is no specific age and gender for these human disorders. Depression is one of the dominant human psychological disorder which is directly associated with sadness whereas, a patient suffering from mania feels in high energy states all the time [11, 12]. Insomnia is a sleep disorder state where a person may face difficulty in sleeping, waking up and in refreshing sleep [13]. However, a victim of hypersomnia feels sleepy throughout the day [14]. Schizophrenia is behaviour and thinking related disorder where a person is not able to recognize the differences between imaginations and reality [15]. ADHD is a

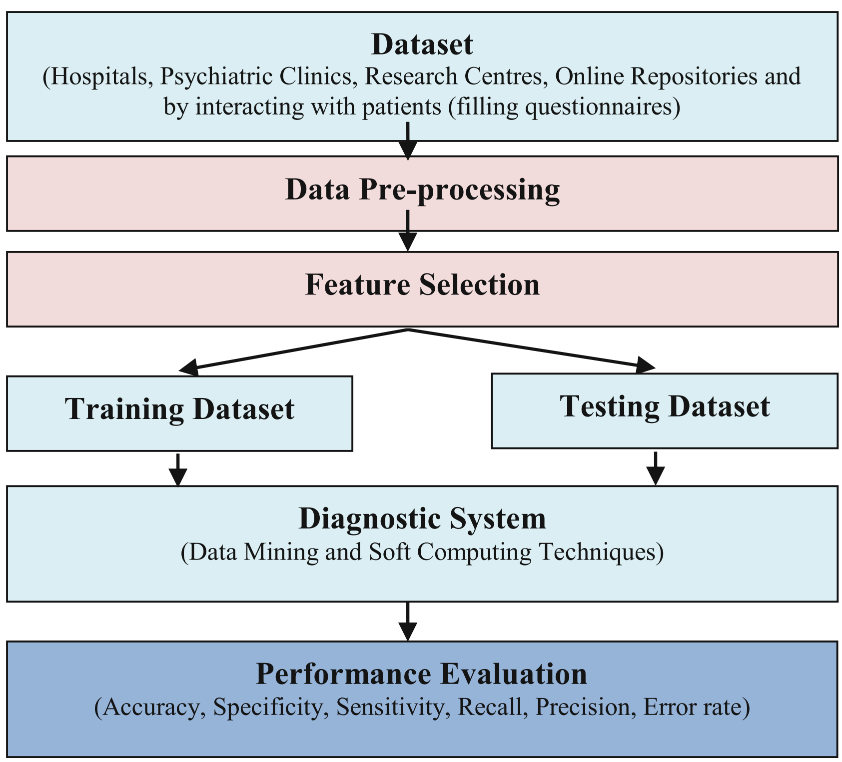

Fig. 1 A data mining based disease diagnostic framework

Table 2 Search keywords and dimensions used in the review

Search Dimension	Search Keywords
Disease Diagnosis	Psychological Disorder, Mental Disorder, Brain Disease
Psychological Disorders	Stress Analysis, Post-traumatic stress, Anxiety, Depression, ADHD, Autism, Insomnia, Schizophrenia, Parkinson, Alzheimer, Dementia.
Classification Techniques	Supervised learning, Nature Inspired Computing, Naive Bayes, C4.5, Random Forest, ID3, SVM, Regression, Decision Tree, Multilayer Perceptron, Genetic Algorithm, Particle Swarm Optimization, Artificial Bee Colony, Ant Colony Optimization, Ant Lion Optimizer, Firefly Algorithm, Moth flame Optimization, Grey Wolf Optimization, Cuckoo Search, Glow-worm Swarm Optimization, Flower Pollination Algorithm, Dragonfly Algorithm, Bat Algorithm, Multi-Variant Optimization, Crow Search Algorithm.

neurodevelopment disorder that generally affects the intellectual ability, communication, and mental growth of six months to twelve years children [16, 17]. In the last few years, several computing techniques including supervised learning (data mining) and nature-inspired computing techniques have been employed to mine the psychologically disordered patients.

Data mining is an eminent research area that combines traditional data analysis techniques with emerging computational algorithms to assist in collecting heterogeneous data from distinct sources, transform it into valuable information and use it in designing effective business strategies for an enterprise [18]. Supervised learning techniques are also known as classification techniques have been successfully employed to solve different real-life problems [19, 20]. Disease diagnosis is one of the critical and significant applications of data mining in the healthcare sector. The disease diagnosis framework is a multistage framework. Data collection, pre-processing, feature selection and data classification are an important stage of these frameworks [21]. Figure 1 represents the different stages of this model.

Nature-inspired computing techniques are the soft computing techniques which are inspired by the different nature creatures such as human, animal, birds, insects, flowers, water and universe etc. [22]. These techniques encourage the assimilation of methodologies that intends to design the solutions for real-life problems in several areas viz. medical science, agriculture, management, economics, query optimization, transportation and feature selection [23–25]. Some of the major nature-inspired computing techniques are Genetic Algorithm (GA) [26], Particle Swarm Optimization (PSO) [27], Ant Colony Optimization (ACO) [28], Harmony Search (HS) [29], Artificial Bee Colony (ABC) [30], Cuckoo Search (CS) [31],Ant Lion Optimizer (ALO) [32], Flower Pollination Algorithm (FPA) [33] and Grey Wolf Optimization (GWO) [34].

The objective of this study is to highlight the role of different supervised learning and nature-inspired computing techniques in the diagnosis of ten major human psychological disorders (stress, depression, autism, anxiety, ADHD, Alzheimer, Parkinson, insomnia, schizophrenia and mood disorder).

How this work is different from other related studies?

Several review papers have been published on the use of traditional data mining and soft computing techniques. However, no dedicated review has been found that describes the role and effectiveness of different supervised and nature-inspired computing techniques for the diagnosis of different human psychological disorders. Therefore, in this study, a comprehensive review of the same has

Table 3 The rate of articles from journals, conferences, books and links accessed

Year	Journals	Conferences	Book	Links
2019	1	–	–	2
2018	12	–	–	–
2017	15	1	–	–
2016	11	2	–	–
2015	10	3	1	–
2014	11	1	1	–
2013	7	–	1	–
2012	5	1	2	–
2011	7	–	3	–
2010	4	1	1	–
2009	4	–	1	–
2008	3	2	–	–
2007	1	–	2	–
2006	–	–	1	–
2005	–	–	1	–
2004	–	–	1	–
2002	–	–	1	–
2001	1	–	–	–
1997	1	–	–	–
1996	1	–	–	–
1995	–	1	–	–
1994	1	–	–	–
1992	–	–	1	–
1983	1	–	–	–
TOTAL	96	12	16	2

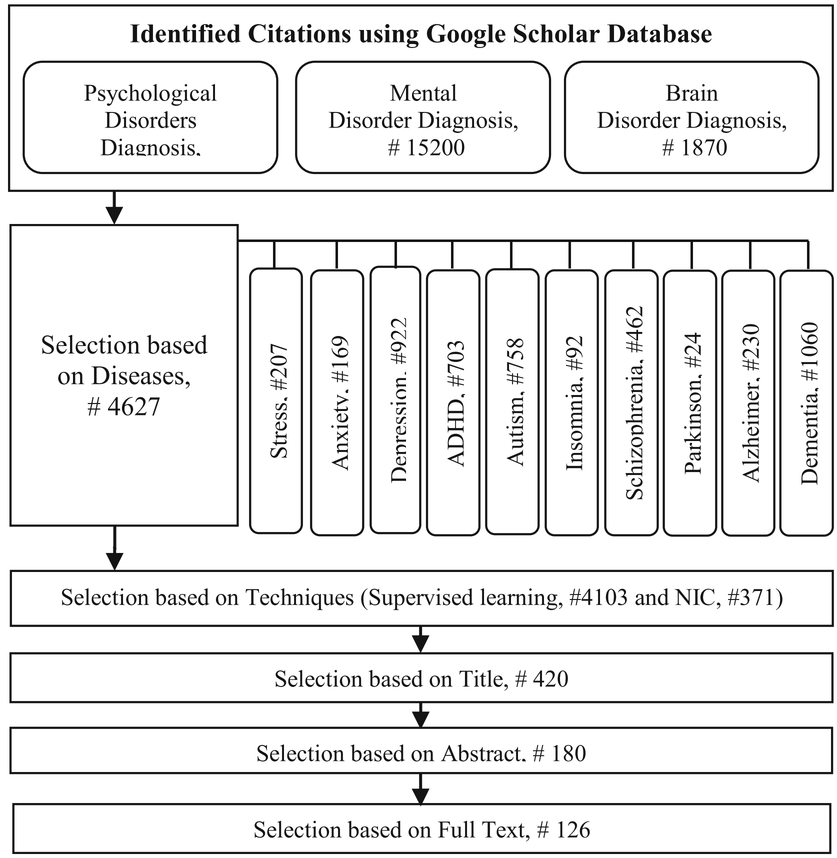

Fig. 2 Article selection procedure

been carried out. The different psychological disorders, their types and their associated symptoms have been described. The role and effectiveness of different supervised learning and nature-inspired techniques employed for diagnosis of different human psychological disorders (stress, depression, autism, anxiety, ADHD, Alzheimer, Parkinson, insomnia, schizophrenia, mood disorder etc.)have been accessed and presented. Additionally, the publication trends of related articles have been analysed from different perspectives. Finally, the future directions for the diagnosis of psychological disorders using these techniques have been identified. The key points of this study are:

– To briefly describe different types of psychological disorders.
– To highlight the classification of these disorders.
– To presents the symptoms associated with different psychological disorders.
– To comprehensively analyze the use and performance of different supervised learning and nature-inspired computing techniques in the diagnosis of different human psychological disorders.
– To examine the publication trends of articles related to the diagnosis of these human disorders.
– To highlight common datasets used in different studies.
– To depict the effect of feature selection on the performance of different classifiers used in diagnosing these disorders.

Section "Review methodology" explained the review methodology used in the study. The data synthesis and analysis has been presented in section "Data synthesis and analysis". The discussion of this manuscript is presented in section "Discussion". The concluding remarks along with future directions are represented in section "Conclusion".

Review methodology

Here, a comprehensive search strategy is devised to find unbiased and relevant research articles related to the diagnosis of ten major psychological disorders (Stress, anxiety, depression, ADHD, autism, insomnia, schizophrenia, Parkinson, Alzheimer, dementia) using different supervised learning and nature-inspired computing techniques. Initially, the articles were collected using three-dimensional search based on three distinct keywords as mentioned in Table 2. To ensure the relevant and sufficient scope, different keywords with similar meaning such as "Psychological Disorder", "Mental Disorder", "Brain Disease" are also explored.

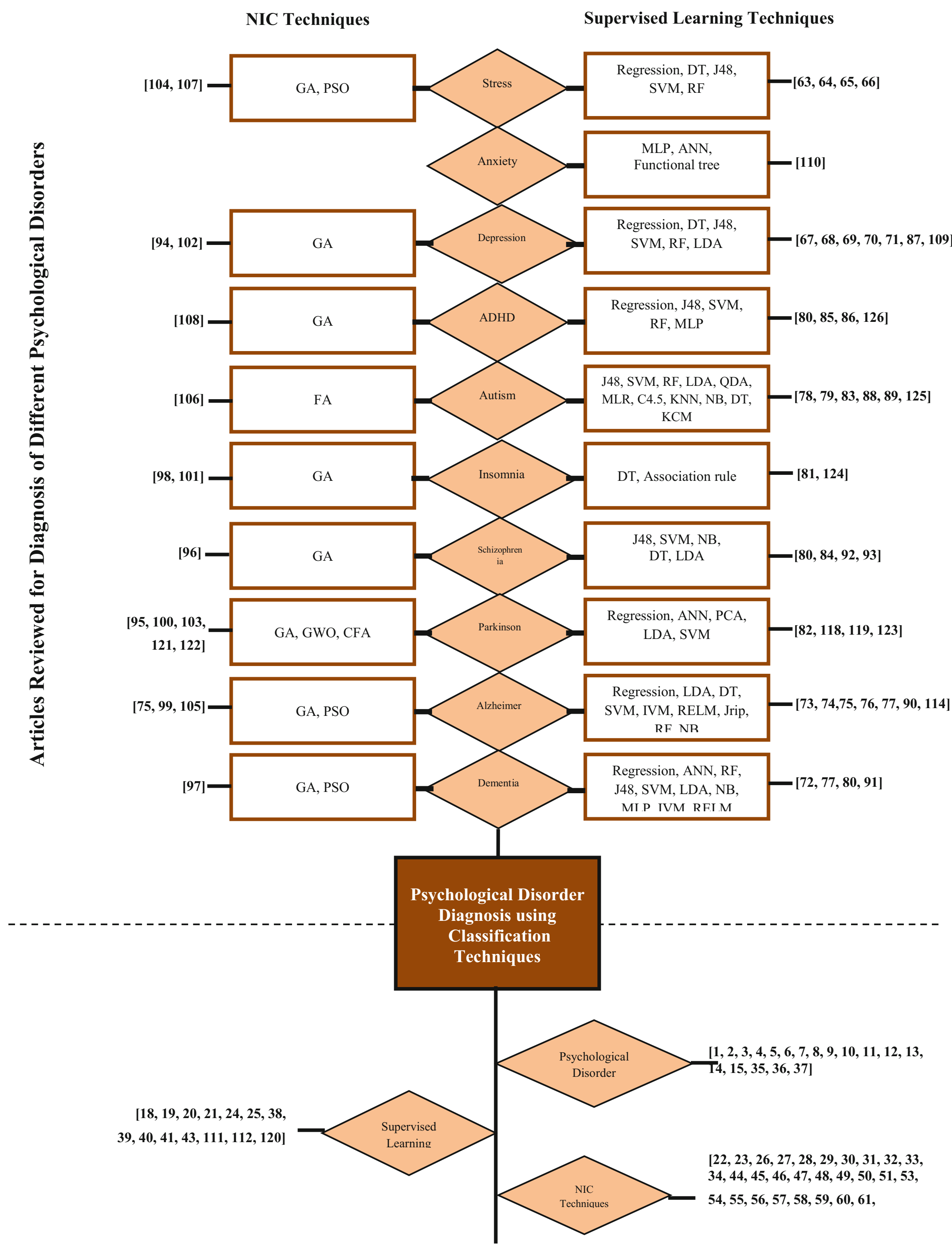

Fig. 3 Classification of research articles on the basis of classification techniques and psychological disorders

After planning the search strategy, the articles lie within the scope are selected by inclusion criteria as mentioned below.

- Articles related to psychological disorders mined using supervised learning and nature-inspired computing techniques have been included.
- Only human psychological disorders have been considered.
- Only peer-reviewed articles from reputed conferences/ journals are selected.
- The language was restricted to English only.

Fig. 4 Classification of psychological disorders [35]

Table 3 presents the rate of articles included in the study from journals and conferences in different years. Most of the articles are included from journals in the review. Whereas, only four articles are from conferences.

The research questions that need to be answered by this survey and the search strategy that should be followed while doing this study are mention below. The procedure of manuscript searching is entirely based on the design and content of the research questions. The remaining part of this section presents the research questions and the research methodology used to complete the study. In this manuscript, six research questions (as mentioned below) has been designed and answered.

- RQ1: What are the different human psychological disorders?
- RQ2: What are supervised learning and nature-inspired metaheuristic techniques?
- RQ3: What is the significance of using different supervised learning and nature-inspired metaheuristic techniques in the diagnosis of different psychological disorders?
- RQ4: What is the rate of publication of the articles where different supervised learning and nature-inspired metaheuristic techniques have been employed in the early diagnosis of different psychological disorders?
- RQ5: What are the common psychological disorders datasets?
- RQ6: What is the effect of using feature selection techniques in psychological disorder diagnosis?

Figure 2 depicts the article selection process by the Google Scholar database. This review includes the researches related to the diagnosis of different psychological disorders viz. stress analysis, bipolar disorders, schizophrenia, sleep disorders, dementia, mood disorder using data mining techniques.

Initially based upon the psychological, brain, and mental disorders total 19,500 articles were identified. Out of these, 4627 articles were related to the psychological disorders that have been taken in this analysis. These articles were then carefully reviewed based upon title, abstract and the complete content. Finally, 136 articles have been selected and studied in this comprehensive survey.

Figure 3 shows the categorization of research articles included in the study on the basis of different classification techniques.

Data synthesis and analysis

RQ1: What are the different human psychological disorders?

As per the Diagnostic and Statistical Manual, fifth edition (DSM-5) [35], psychological disorders can be classified as neurodevelopment disorders, psychotic disorders, bipolar &

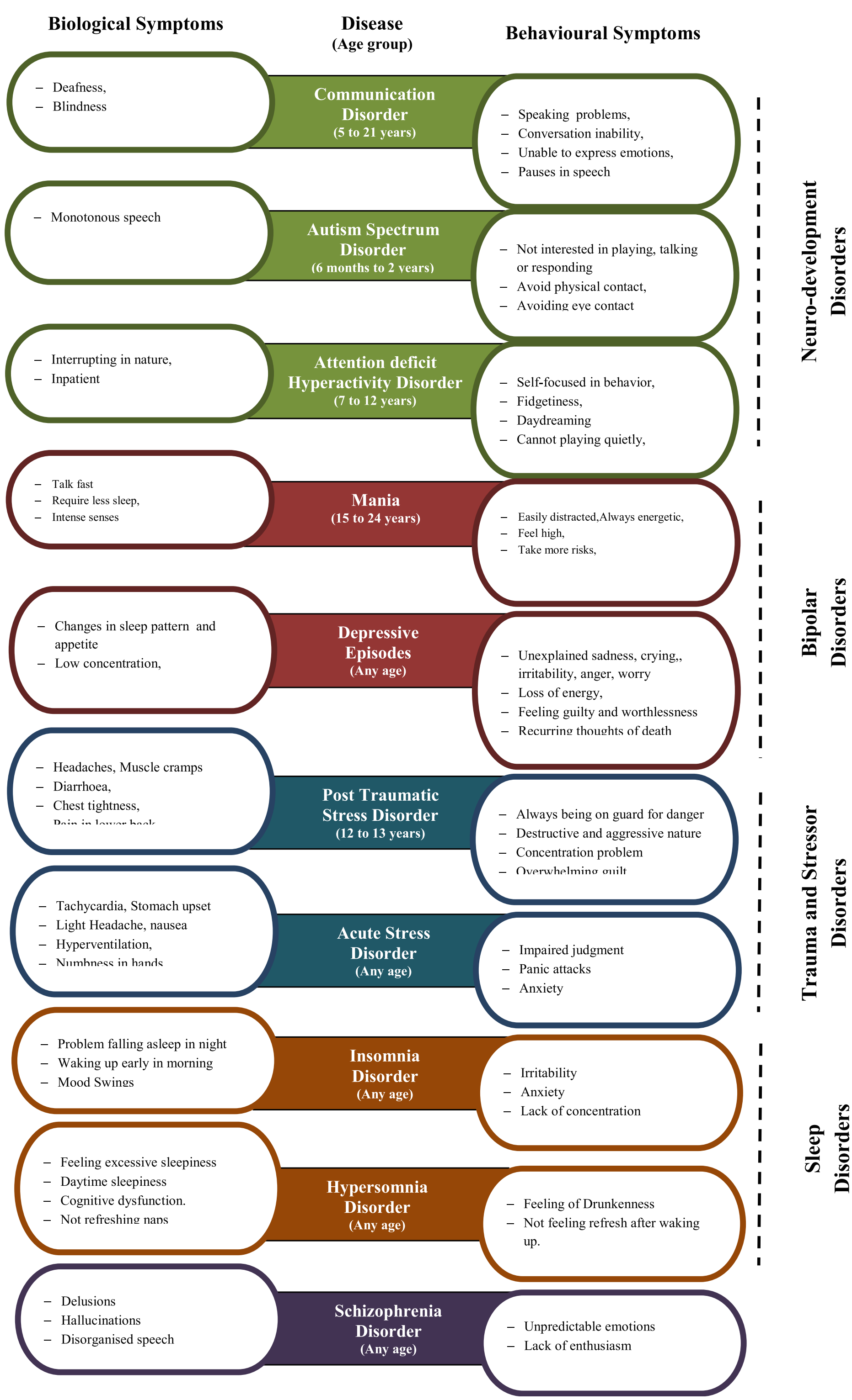

Fig. 5 Biological and behavioural symptoms of different psychological disorders

relative disorder, depressive disorder, anxiety disorder, obsessive/compulsive disorder, trauma & stressor-related disorder, dissociative disorder, feeding & eating disorder, elimination disorder, sleep-wake disorder, disruptive-impulsive disorder, addictive disorder, neurocognitive disorder, personality disorder and paraphilic disorders. Some of the major categories and subcategories of psychological disorders are presented in Fig. 4.

The sound knowledge of different psychological disorders symptoms can assist in the precise diagnosis of these disorders.

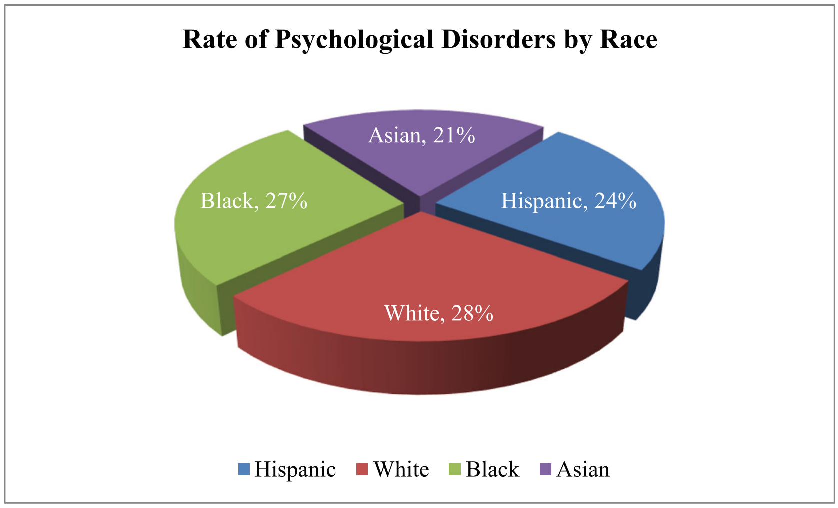

Fig. 6 Population suffering from different psychological disorders by race

Biological and behavioural symptoms of several psychological disorders have been presented in Fig. 5.

From Fig. 5, it is found that the psychological disorders can affect all types of age groups i.e. right from a child, adult to old age. Moreover, there is a wide range of biological and behaviours changes. Figure 6 represents the racial analysis of psychological disorders patients [36].

From Fig. 6, it is observed that each race has been equally affected by psychological disorders. As per the World Health Organization, a large of number population is suffering from psychological disorders all over the world, in which China and India are at first and second position respectively. Almost 7.5% of Indians are suffering from major or minor psychological disorders. The lifetime psychological morbidity rate in the different states of India is represented in Fig. 7 [37].

Here, Assam and Manipur have the lowest and highest morbidity rates. Mental illness can adversely affect the emotions and behaviour of human.

RQ2: What are supervised learning and nature-inspired metaheuristic techniques?

Data mining aims at discovering knowledge and hidden patterns from the momentous volume of data and represents it in the easily understandable form for humans [38]. Roots of data mining lie in statistics, artificial intelligence, and machine learning. Table 4 shows the evolution that how data collection transformed into data mining.

In general data mining techniques can be categorized by verification and discovery. Initially, the verification-driven

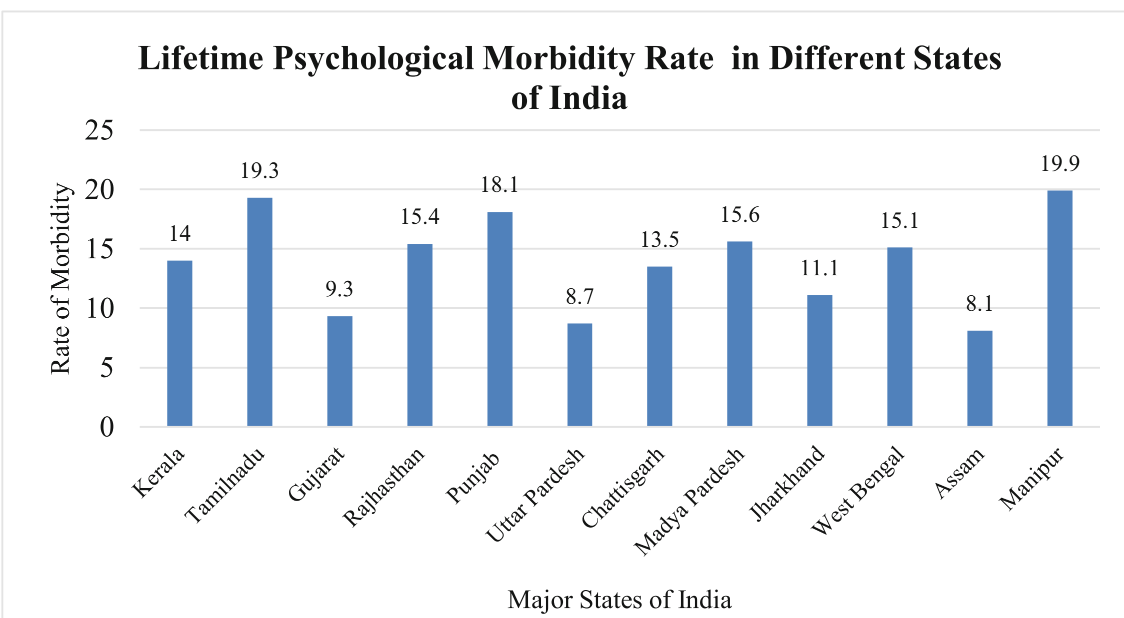

Fig. 7 Population suffering from different psychological disorders in different states of India

Table 4 Evolution of Data Mining [39]

Evolution	Year	Characteristic	Method	Example
Data collection	1960's	Retrospective, Static data delivery	Statistics	How many patients are suffering from depression in the last two years?
Data Access	1980's	Retrospective, Dynamic data delivery at the record level	Artificial Intelligence	How many patients are suffering from depression in India in 2017?
Decision Support and Data warehouse	1990's	Retrospective, Dynamic data delivery at multiple levels	Machine Learning	Analysing the symptoms of depressed patients in different states of the country.
Data Mining	Emerging today	Prospective, Proactive information delivery	Statistics, Artificial Intelligence and Machine Learning	Prediction of depression in patients at the early stage all over the world.

techniques are used to formulate the hypothesis by the user and then verify data to check its validity. These techniques perform some operations such as querying, validating hypothesis, reporting, statistical and multidimensional analysis etc. Verification-driven model emphasis on user whereas, the discovery-driven model emphasis on the system. These systems mined the databases automatically to discover information that is concealed in the data. Discovery-driven techniques are focused on supervised and unsupervised techniques [40, 41]. Figure 8 depicts the classification of data mining techniques.

The supervised learning techniques involve the process in which algorithm iteratively perform predictions using training dataset whereas unsupervised techniques used to devise underlying structures in the data. Clustering and association rule mining are examples of unsupervised techniques. Clustering is a process to group physical objects into the similar object classes called clusters from distance or similarity metric. Some methods used for clustering are partitioning method, hierarchical method, density-based method, grid-based method and model-based method. However, in association rule mining, the patterns discovered by data mining techniques can be represented in the form of association rules to find the relationship among the broad set of data items. Multilevel association rule, Multidimensional association rule, and Quantitative association rule are the types of association rules [40, 42].

Classification is a process of finding rules to assign new objects into a predefined category and can be performed in two steps. The first step involves the building of classifier using training dataset with the class attribute. In the second

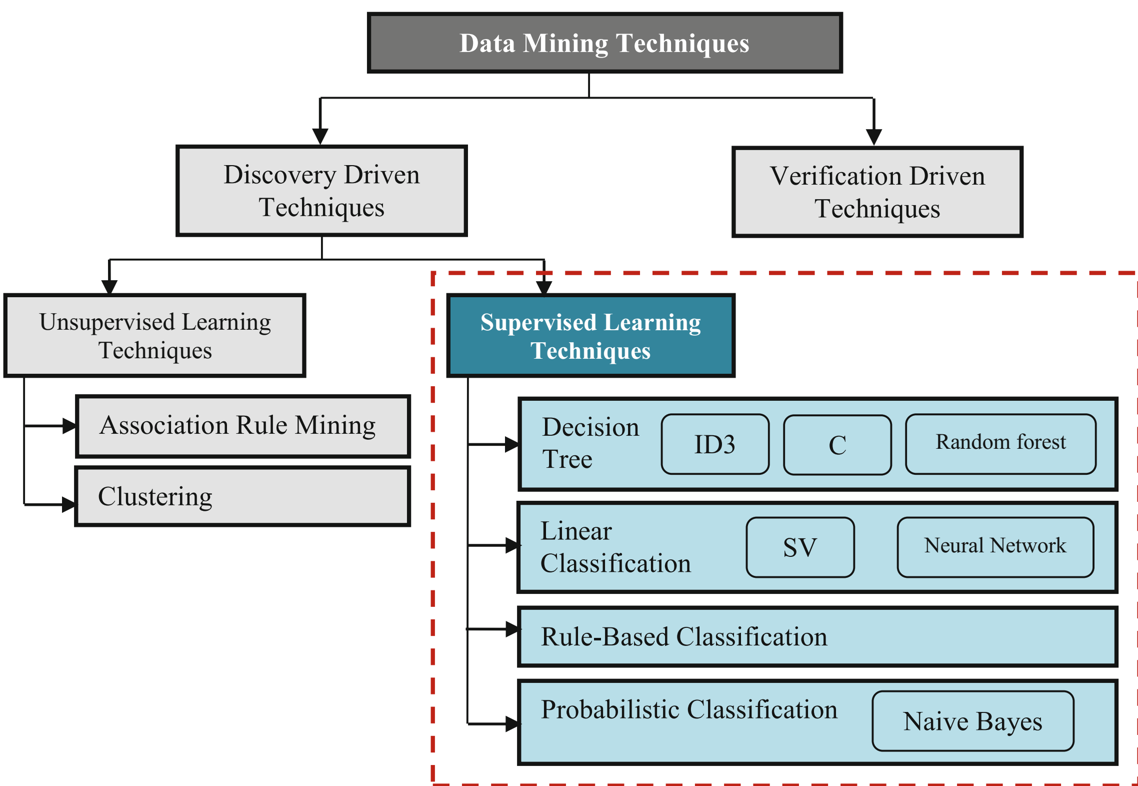

Fig. 8 Classification of data mining techniques

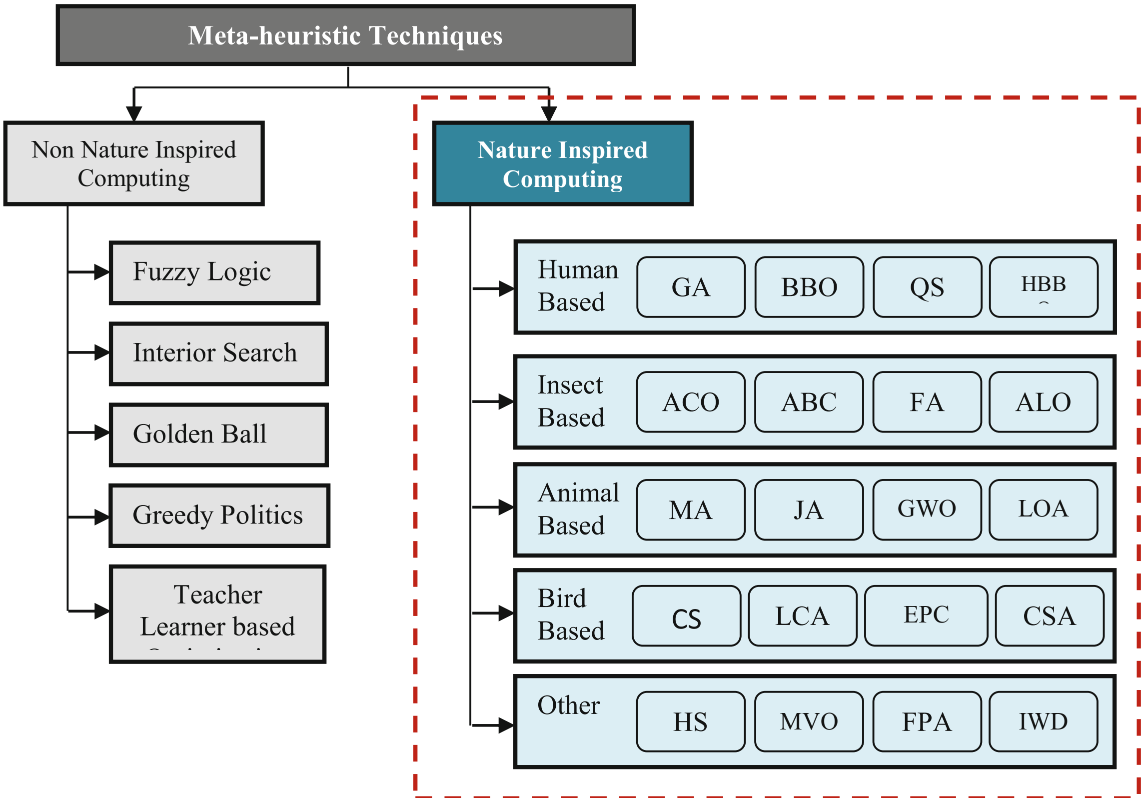

Fig. 9 Classification of soft computing techniques

step, the performance of the classifier is tested using test dataset. Some of the essential classification algorithms are ID3, C4.5, random forest, Support Vector Machine (SVM), Neural Networks (NN), and naïve Bayes etc. [43].

- A decision tree is like a flow chart that classifies instances depending upon on the features. Each internal node represents the test case, branches show results of tests and leaf nodes hold the labels of classes. This technique performs better when there are discrete features. Some algorithms used for inducing decision tree are ID3, C4.5, and random forest. To find the optimal solution for classification, ID3 is used with the minimized depth of the decision tree. In ID3, data is sorted to get the best split at every node whereas, in C4.5, one attribute is selected to split the samples into subsets [41, 42].
- Besides, SVM is used for classifying both linear and nonlinear data. It incorporates the structured risk minimization to decrease the error and to improve the effectiveness of classification. SVM classifier uses data points to create hyperplane and maximize the difference between data points by using SVM. Neural Network is a nonlinear statistical data modelling tool that helps to model relationships to find patterns in the dataset. By using pattern recognition and function estimation Artificial Neural Networks (ANN) can be created. Neural Networks are best for forecasting needs and identifying patterns [41, 42].
- Bayesian classification is based on Bayes theorem that is used to solve the diagnostic and predictive problems. Bayesian classifiers are statistical classifiers also called naive Bayesian classifier and are based on conditional probabilities. This algorithm finds the probability of occurring events by using the probability of already occurred events [41, 42].

Soft Computing encourages the integration of methodologies that aims to easily design the solutions of real-life problems that are difficult to model. Soft computing techniques are the blending of distinct methodologies that were designed to solve multifaceted real-world problems (medical science, management, agriculture, economics etc.) that were intractable to solve otherwise [44]. The major features of soft computing techniques are uncertainty, imprecision and approximation tolerance. It has been extensively premeditated and applied for engineering and healthcare computing. Generally, soft computing techniques are categorized as heuristic and meta-heuristic techniques. Heuristic methods can be practically implemented to get high-quality solutions with less computation time [45]. Meta-heuristics methods can be applied to large and complex real-world problems to find optimal solutions [46]. Furthermore, there are two sub-categories of meta-heuristic techniques called nature inspired and general (non nature-inspired) meta-heuristic techniques. There exist more than hundreds of nature-inspired meta-heuristic

Table 5 List of NIC techniques with year, category and mimic

NIC Technique	Abbreviation	Year	Category	Mimic
Genetic Algorithm [26]	GA	1992	Human-based	Biological evolution
Particle Swarm Optimization [27]	PSO	1995	Bird/ Fishes based	Bird flying/ fish schooling
Ant Colony Optimization [28]	ACO	1997	Insect based	Foraging behaviour
Harmony Search [29]	HS	2001	Music based	Analogy of music
Artificial Bee Colony [30]	ABC	2005	Insect based	Foraging behaviour of honey bees
Glow-worm Swarm Optimization [47]	GSO	2006	Insect based	Social behaviour of worms
Intelligent Water drops [48]	IWD	2007	Intrinsic	Dynamics of the river system
Monkey algorithm [49]	MA	2008	Animal-based	Food searching behaviour
Biogeography-Based Optimization [50]	BBO	2008	Human-based	Migration behaviour
Firefly Algorithm [51]	FA	2008	Insect based	Flashing behaviour of fireflies
Cuckoo Search [31]	CS	2009	Bird-based	Breeding behaviour
Bat Algorithm [52]	BA	2010	Insect based	Echolocation behaviour
Flower Pollination Algorithm [32]	FPA	2014	Plant-based	Pollination process of flowing plants
Ant Lion Optimizer [33]	ALO	2015	Insect based	Hunting behaviour
Moth Flame Optimization [53]	MFO	2015	Insect based	Navigation methods of moths
Grey Wolf Optimization [34]	GWO	2015	Animal-based	Hunting behaviour
Dragonfly Algorithm [54]	DA	2015	Insect based	Static and dynamic swarming behaviour
Multiverse Optimization [55]	MVO	2015	Intrinsic	Cosmology
Jaguar Algorithm [56]	JA	2015	Animal based	Hunting behaviour
Lion Optimization Algorithm [57]	LOA	2016	Animal-based	Lion pride behaviour
Laying Chicken Algorithm [58]	LCA	2017	Bird-based	Laying behaviour
Human Behaviour Based Optimization [59]	HBBO	2017	Human-based	Human behaviour in different fields
Crow Search Algorithm [60]	CSA	2017	Bird-based	Search strategy
Queuing Search [61]	QS	2018	Human-based	Human activities in queuing
Emperor Penguins Colony [62]	EPC	2019	Bird-based	Emperor behaviour of penguins

techniques. Based upon inspiration, these can be further categorised as insect-based, human-based, animal-based, plant-based, music-based and intrinsic (other natural phenomenon based) meta-heuristic techniques. Figure 9 represents some of the major NIC techniques. Table 5 summarized the brief details of some of the well-known nature-inspired techniques.

RQ3: What is the significance of using different supervised learning and nature-inspired meta-heuristic techniques in the diagnosis of different psychological disorders?

M. Deziel et al. [63] presented a survey on one of the Canadian university engineering students. In their study, the authors used five components (Ability to enjoy life, Resilience, Balance, Self-Actualization, and Flexibility) to analyze the mental health of students. Authors observed that the second year students have high mental health score than first and final year students. Secondly, students in an academic program with a flexible curriculum have high mental health score. At last, female students have lower mental health than male students. K. Kiruthika et al. [64] examined the association between the human stress level and usage of social media. The analysis was carried out using WEKA. The study reveals that people with age group 20–25 years have more stress in their life by using Facebook and Twitter. However, people with age group 25–30 years have more stress in their lives using emails. D. Umanandhini et al. [65] have employed different data mining techniques to diagnose academic stress level of students. The experimentation was carried out on the school going students of Tamil Nadu. Authors concluded that the rate of stress is more in science students as compared to the art students. Additionally, more level of academic stress has been obtained in male students as compared to females. Marinic et al. [66] proposed a study to analyze the post-traumatic stress in patients. The study used random forest classification techniques over 102 instances. Accuracy, specificity, and sensitivity were 74.5%, 53%, and 96% respectively.

Yoon et al. [67] stated that mentally sick, sexually molested and the person doesn't participate in any activity for more than three days are the general victim of the depression in the US population. Authors classified data of these types of patients

Table 6 Outcomes of different studies using data mining techniques

Author (Year)	Disease	Technique								Tool		Performance			
		J48	SVM	Decision Tree	Regression	Random Forest	LDA	Naive Bayes	NN and Other	WEKA	MATLAB	Worst		Best	
												Technique	Accuracy	Technique	Accuracy
Marinic et al. (2007) [66]	Post Traumatic Stress					√				√		Random forest on structured interview dataset	70.6%	Random forest on the interview and psychiatric scale dataset	74.5%
Khemphila et al. (2012) [82]	Parkinson								√	√		ANN with 22 features	80.77%	ANN with 16 features	83.3%
Doyle et al. (2014) [74]	Alzheimer				√						√	Regression with subset of dataset	54.2%	Regression on complete dataset	74%
Mohana et al. (2015) [83]	Autism		√			√	√		√			C4.5, KNN	93.2%	MLR	95.2%
McManus et al. (2015) [84]	Schizophrenia		√					√	√			Naive bayes	80.3%	SVM	89.3%
Mohammadi et al. (2015) [68]	Depression			√			√				√	LDA with 109 features	45%	LDA with 112 features	80%
Kim et al. (2015) [85]	ADHD	√	√		√	√						J48	69.2%	SVM	84.6%
Radhamani et al. (2016) [86]	ADHD		√						√	√		SVM	92%	MLP	95%
Kim et al. (2017) [87]	Depression				√							Regression (1-fold)	42.1%	Regression (10-fold)	96.9%
Benyoussef et al. (2017) [73]	Alzheimer			√	√		√					Regression	59%	LDA	66%
Lama et al. (2017) [77]	Alzheimer		√						√			SVM	60.2%	RELM	76.6%
Ramani et al. (2017) [88]	Autism		√			√		√	√			Naive Bayes	43.59%	Random forest	88.46%
Bekerom (2017) [89]	Autism	√	√			√		√				SVM	83.3%	J48	87.1%
Tejeswinee et al. (2017) [90]	Alzheimer		√	√		√		√	√	√		Random forest	88.3%	SVM	97.3%
Aram So et al. (2017) [91]	Dementia		√		√	√		√	√			Naive Bayes	81.3%	MLP	97.2%
Bae et al. (2017) [92]	Schizophrenia		√	√			√	√	√			Naive Bayes	81%	SVM	92.1%
Algunaid et al. (2018) [93]	Schizophrenia		√								√	SVM with l_o norm feature selection	53.57%	SVM with FSV feature selection	95%

Table 7 Outcomes of different studies using soft computing techniques

Author (Year)	Disease	Technique								Tool		Performance			
		GA	ACO	PSO	ABC	FA	ALO	GWO	CSA and Other	WEKA	MATLAB	Worst		Best	
												Technique	Accuracy	Technique	Accuracy
Hosseinifard et al. (2011) [94]	Depression	√												SVM	88.6%
Xiao et al. (2012) [95]	Parkinson	√										C4.5	85.1%	SVM	91.8%
Hiesh et al. (2013) [96]	Schizophrenia	√												SVM	88.24%
Sivapriya et al. (2013) [97]	Dementia			√								SVM	89%	PSO-LSSVM	96%
Hang et al. (2013) [98]	Sleep Apnea	√												SVM	91.63%
Yang et al. (2013) [99]	Alzheimer			√								SOM	88.24%	PSO-SVM	94.12%
Shahbakhi et al. (2014) [100]	Parkinson	√									√	GA (7 features)	93.58%	GA (4 features)	96.06%
Abedi et al. (2015) [101]	Sleep Apnea	√												SVM	90.09%
Mohammadi et al. (2015) [102]	Depression	√												LDA	80%
Naskar et al. (2016) [103]	Parkinson	√										NN	91.38%	GA-NN	96.55%
Ranjith et al. (2017) [104]	Stress detection			√								LDA	88.56%	FFNN	93.25%
Sayed et al. (2017) [105]	Alzheimer								√			GA	57.28%	MFO	78.33%
Vaishali et al. (2018) [106]	Autism					√				√		KNN	87.67%	SVM, MLP	96.66%
Shon et al. (2018) [107]	Stress detection	√										PCA	65.03%	GA	71.76%
Li et al. (2018) [108]	ADHD	√										Single feature	88.10%	Multiple features	96.6%

and found the rate of classification achieved using J48 lies between 80%–82%. M. Mohammdi et al. [68] tried to mine depressed patients' data using decision tree and genetic algorithm. The study analyzes the electroencephalogram (EEG) signals of 100 patients and classifies them into two categories such as major depressive disorder and healthy volunteer. A genetic algorithm was used to identify the significant features and a decision tree was used to develop the predictive model. The analysis of data was performed using Matlab. Mwangi et al. [69] introduced a hybrid method to predict depression in patients by using machine learning and feature selection methods. Authors used a dataset of 65 records with 72 attributes in the study. Relevance vector machine and SVM was used to predict depression in patients with the highest predictive rate of accuracy (~90%). Daimi et al. [70] proposed a study to predict depression in patients at an early stage. The study used a dataset of 1000 patients with 31 selected feature set. The J48 algorithm was implemented by using WEKA tool to classify the dataset. The predictive rate of accuracy has shown by the method was 83.3%. Dipnall et al. [71] used a hybrid method by using machine learning boosted regression algorithm and logistic regression to identify key biomarkers associated with depression. The author used the dataset of 5230 samples from the National Health and Nutrition Examination Study (2009–2010). The study selects 3 biomarkers (viz. Glucose, serum, Total bilirubin and Red cell distribution width) out of 20 associated with depression.

J. Maroco et al. [72] have employed data mining techniques such as neural networks, SVM, random forest, Discriminant analysis and logistic regression to classify dementia disorder patients. The performance of different classification techniques is compared on the basis of three major metrics i.e. sensitivity, specificity, and accuracy. The best predictive results were obtained using the random forest and linear Discriminant analysis. Benyoussef et al. [73] carried out a diagnostic study of Alzheimer patients authors employed three distinct data mining techniques such as decision tree, Discriminant analysis and logistic regression and found that the classification results obtained using Discriminant analysis are better than the outcomes of other two approaches. The highest rate of predictive accuracy achieved using Discriminant analysis was 66%. Doyle et al. [74] proposed a study to diagnose Alzheimer's disorder in patients using brain images. The study used a dataset with 1023 instances and 57 attributes. Accuracy, specificity, and sensitivity were 74%, 72%, 77% respectively. Johnson et al. [75] used GA and logistic regression to diagnose Alzheimer disease in patients. GA was used as feature selection and selects 8 features out of 11. Logistic regression was used as a classification technique applied with five folds. Koikkalainen et al. [76] proposed to diagnose Alzheimer disorder in patients using regression techniques. Authors have used 786 instances from the ADNI database. The predictive rate of accuracy given by the study was 87%. Lama et al. [77] diagnosed Alzheimer disease using three important data mining techniques i.e. SVM, IVM, RELM. Authors used MRI images dataset of 214 instances collected from the ADNI database. The author found a better diagnostic rate with RELM. The highest rate of prediction achieved using RELM was 76.61%.

Hasan et al. [78] have diagnosed autism using linear and quadratic Discriminant analysis. The experiments were performed over a data set of 48 children only. Out of 48, 24 were healthy and 24 were affected by this psychological disorder. Authors found that QDA performed better than LDA. The predictive rate of accuracy achieved using QDA found to be

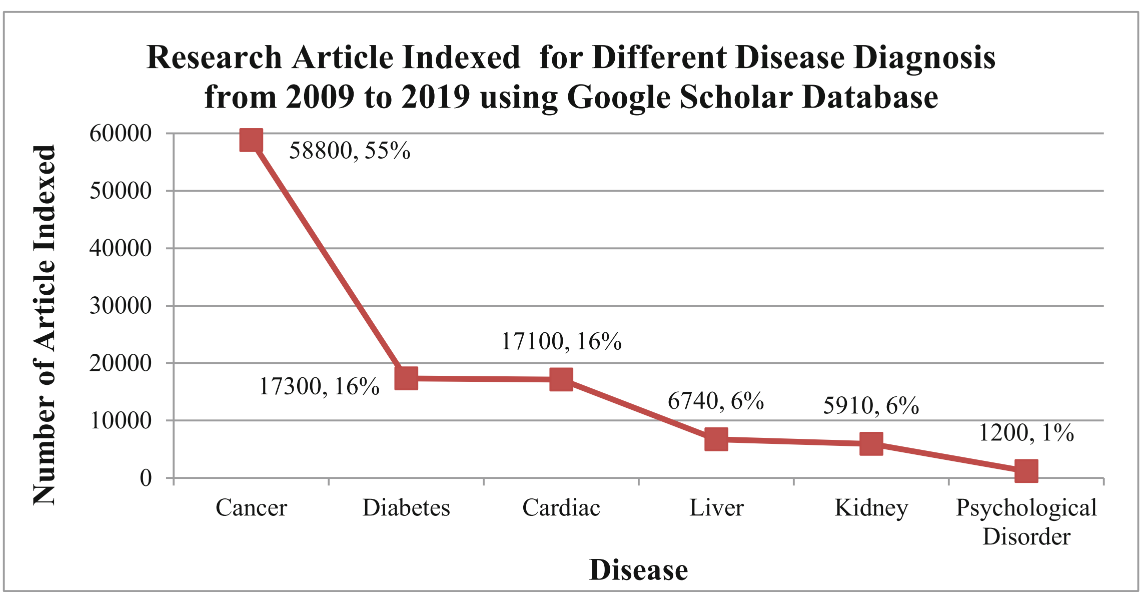

Fig. 10 Research done in the last ten years for different disease diagnosis using data mining techniques

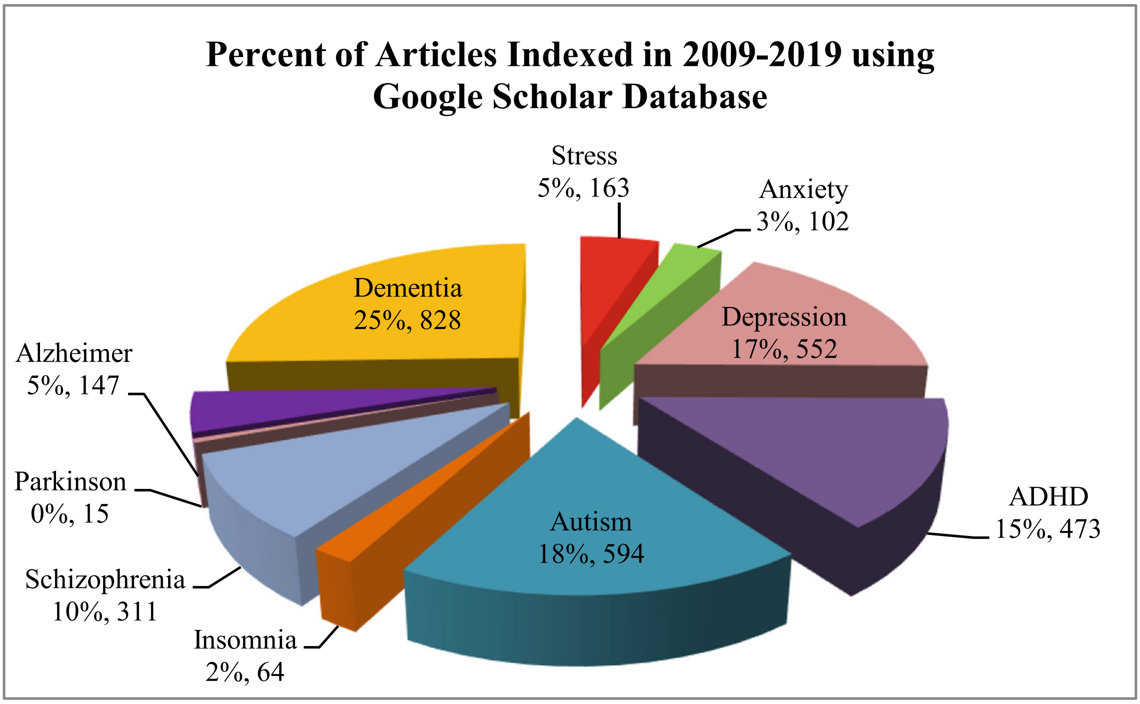

Fig. 11 The rate of articles indexed using Google Scholar Database(2009–2019) for diagnosing different psychological disorders

10.83% better than LDA. Grossi [79] conducted to diagnose autism in children by analyzing EEG signals using the random forest, KNN and KCM. Authors have used a dataset of 15 instances with 250 attributes. Among 250 features 24 features were selected using MS-ROM, TWIST techniques. The random forest has shown the best predictive accuracy i.e. 92.8%. Kundra et al. [80] have used the J48 algorithm to classify different psychological and related diseases. The specificity and sensitivity algorithm ranges from 94 to 100% and 70–100% respectively. Huang et al. [81] used data mining methods to confirm the prevalence of obstructive sleep disorder. The study has identifies that obesity is one of the key factor associated with this disease. Tables 6 and 7 summarized the role and performance of different supervised learning and nature-inspired meta-heuristic in the diagnosis of different psychological disorders.

Tables 6 and 7 highlights the research work of some of the key authors in diagnosing different psychological disorders with the details of techniques applied to diagnose the mentioned disease. Additionally, the tools used for implementation, worst and best data mining techniques along with their corresponding accuracies have also been mentioned. It is observed that most of the authors have used WEKA or MATLAB to implement their works. It is observed that the accuracies of different psychological disorders using supervised learning and NIC techniques lie between 66%–98% and 71%–97% respectively. However, dementia and stress diagnosis using different supervised learning techniques have shown the highest and lowest range of accuracies i.e. 94%–98% and 74%–84% respectively. Whereas, the highest accuracy achieved using SVM for diagnosing Alzheimer disease is 97.30%. The author found SVM, MLP, regression and

Table 8 Number of articles indexed from 2009 to 2018 with different publications for psychological disease diagnosis using data mining techniques

	Science Direct	Springer Link	IEEE Xplore	Wiley	Pub Med	Hindawi	Taylor & Francis
Stress Analysis	45	54	8	2	50	6	103
Anxiety	1	3	3	8	19	24	0
Depression	15	16	3	23	37	46	16
ADHD	7	8	1	14	2	2	8
Autism	6	12	2	2	11	6	6
Insomnia	0	1	25	2	5	15	0
Schizophrenia	7	8	1	8	6	10	10
Parkinson	6	3	6	5	7	14	1
Alzheimer	5	2	10	0	23	14	2

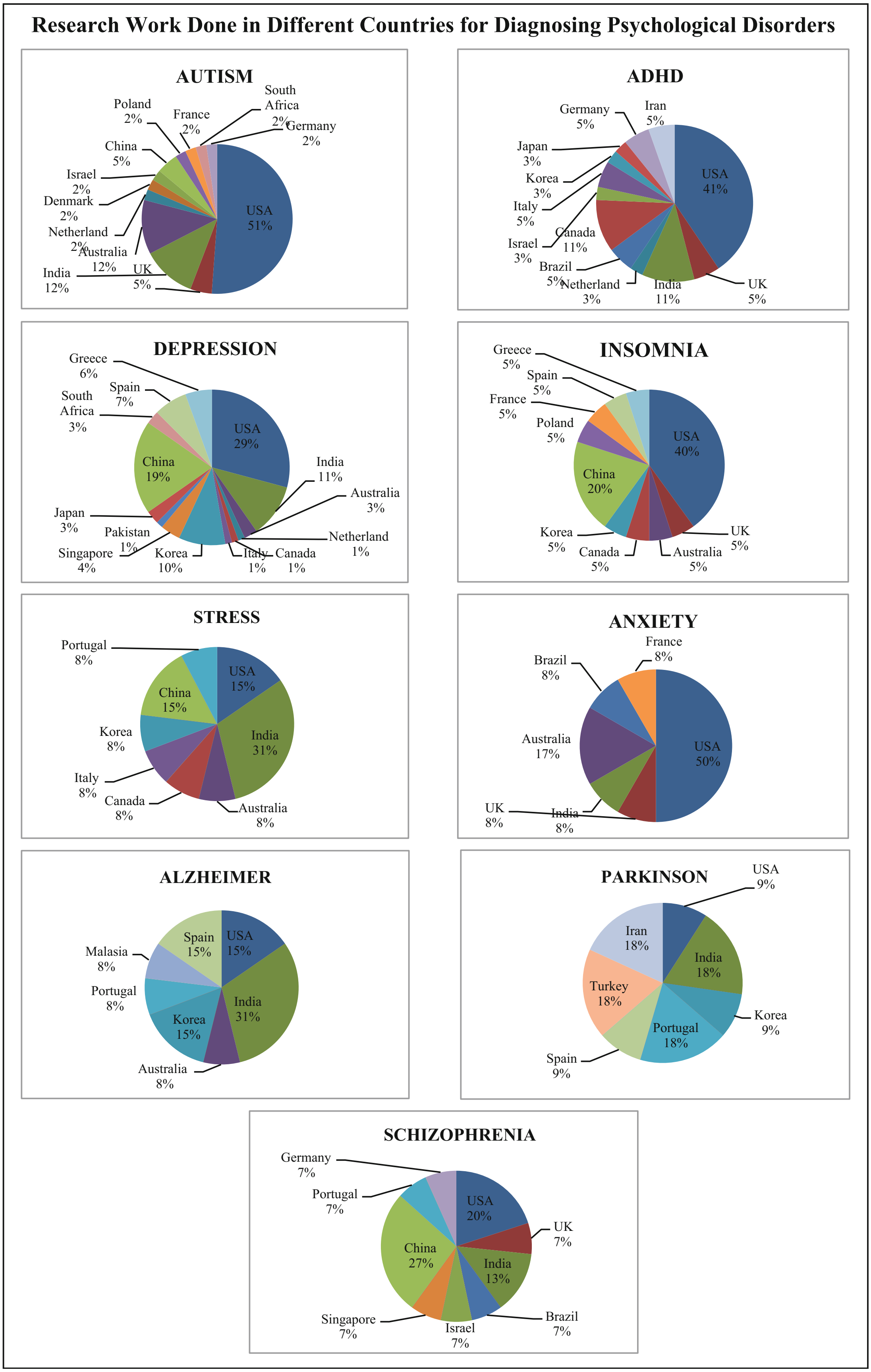

Fig. 12 Work done to diagnose different psychological disorders using data mining techniques in different countries

Table 9 The common dataset used for psychological disorder diagnosis

Data Source	Disease	Data type
Canadian University [63]	Stress analysis	Categorical, numeric
Social Media [64]	Stress analysis	Text
Department of Psychiatry, Dubrava University Hospital [66]	Posttraumatic Stress	Text, numeric
Hospitals (EEG Signals) [68]	Depression	Image
Grampian and Lothian NHS Research Ethics Committees [79]	Depression	Numeric, text and image
PTT Prozac zone in Taiwan [70]	Depression	Categorical
NHANES data set [71]	Depression	Text, Numeric and real
Santa Maria Hospital and memory clinic, Coimbra [72]	Dementia	Text, numeric
Open Access Series of Imaging Studies (OASIS) [73]	Alzheimer's disease	Image, text
US-based Alzheimer's Disease Neuroimaging Initiative (ADNI) and the European based AddNeuroMed program [76]	Alzheimer's disease	Image
National Autism Society of Malaysia (NASOM) [78]	Autism	Numeric, real
Vila Santa Maria Institute, Italy [79]	Autism	Image (EEG Signals)
New South Wales Inpatient Data Collection (1999–2004) [81]	Obstructive Sleep Apnea	Text, Numeric and categorical
Korea National Health Insurance Services (KNHIS) [87]	Depression	Text, Numeric and categorical
UCLA's Center for Autism Research and Treatment [88]	Autism	Numeric, text, real
Kyoto Encyclopaedia of Genes and Genomes(KEGG) database [90]	Alzheimer	Text, numeric
National Data Bank for Rheumatic Diseases, Wichita, Kansas [109]	Depression in patients with rheumatoid arthritis	Real, Numeric

random forest as the optimal predictor. The predictive rate of accuracies achieved is 97.3%, 97.2%, 96.9% and 96.3% respectively. Also, autism and ADHD diagnosis have shown the best accuracy using FA and GA respectively.

RQ4: What is the rate of publication of the articles where different supervised learning and nature-inspired meta-heuristic techniques have been employed in the early diagnosis of different psychological disorders?

To find the rate of publication of disease diagnosis based articles, several queries have been formulated and run on Google Scholar. Figure 10 presents the number of articles related to different human disorders indexed in Google Scholar. Most of the research work was done for cancer, diabetes and cardiac disorders. However, only 1% of articles have been found for psychological disorder mining.

To further explore the details of psychological disorders, several queries have been designed for major psychological disorders such as stress, anxiety, depression, ADHD, autism, insomnia, schizophrenia, Parkinson, Alzheimer and dementia.

As per Google scholar's data, the number of articles in last ten years related to stress, anxiety, depression, ADHD, autism, insomnia, schizophrenia, Parkinson, Alzheimer and dementia diagnosis using data mining are 163, 102, 552, 473, 594, 64, 311, 15, 147 and 828 respectively. However, only 0%, 2% and 3%ofwork have been found on Parkinson, insomnia and anxiety respectively. The publication summary of these disorders has been depicted in Fig. 11. However, dementia seems to be the more explored area.

The study leveraged different databases to conduct the searches of research articles such as Taylor & Francis, Hindawi, Pub Med, Wiley, IEEE-Xplore, Springer Link, Science Direct. Table 8 presents last ten years number of articles related to autism, ADHD, depression, mania, insomnia, hypersomnia, stress analysis, anxiety, Alzheimer, Parkinson, schizophrenia, mood disorder indexed in different reported indexing databases.

To get more detailed information, some of the queries have been fired. In addition to queries, some manual explanation is carried out to get the following results. Figure 12 represents the rate of research in mining different psychological disorders. It is found that the maximum mining of autism, ADHD, depression, insomnia and anxiety has been carried out by American researchers. Likewise maximum work of Alzheimer, stress, Parkinson has been explored by Indians. Maximum work on schizophrenia is carried out by Chinese researchers. The participation of countries like Singapore, Italy, Brazil, and Spain in the diagnosis of different psychological disorders is nearly low.

RQ5: What are common psychological disorders datasets?

The roots of data mining applications lie in their datasets. It is found that several datasets have been used in mining different types of different psychological disorders. Authors of different studies collected data from distinct sources like research

Table 10 Details of the feature set along with feature selection techniques used in the diagnosis of psychological disorders

Disease	Author (year)	Data Source	Data type	Feature Selection Technique	Instances	Feature set
Autism	Hasan et al. [78]	NASOM	Numeric, real	Independent t-tests, Mann-Whitney U- tests	48	25
	Grossi [79]	Vila Santa Maria Institute, Italy	Image (EEG Signals)	MS-ROM, TWIST	15	24
	Bekerom [89]	NSCH	Text, numeric	1-way filtering	95,577	256
	Vaishali et al. [106]	UCI machine learning repository	Textual categorical, numeric	Firefly algorithm	292	21
Anxiety	Sumathi et al. [110]	Hospitals	Categorical	Best first search	60	25
Stress analysis	Deziel et al. [63]	Canadian University	Categorical, numeric	–	312	13
	Marinic et al. [66]	Department of Psychiatry, Dubrava University Hospital	Text, numeric		102	–
	Ranjith et al. [104]		image	PSD	11	5
Depression	Mohammadi et al. [68]	–	Image (EEG Signals)	LDA + GA	96	58
	Mawangi et al. [69]	Grampian and Lothian NHS Research Ethics Committees	Numeric, text and image	Voxel-based morphometry (VBM) filtering	62	–
	Daimi et al. [70]	PTT Prozac zone in Taiwan	Categorical	Filtering	1000	31
	Dipnall et al. [71]	NHANES data set	Text, Numeric and real	Ensemble, boosted regression	5227	21
	Wolfe et al. [109]	National Data Bank for Rheumatic Diseases, Wichita, Kansas	Real, Integer	–	29,524	25
	Kim et al. [87]	KNHIS	Text, Numeric and categorical	Elastic net method	1,025,340	89
Obstructive Sleep Apnea	Huang et al. [81]	New South Wales Inpatient Data Collection (1999–2004)	Text, Numeric and categorical	–	60,197	31
Autism	Ramani et al. [88]	UCLA's Center for Autism Research and Treatment	Text, numeric, real	Fisher, Runs, ReliefF	60	19
Schizophrenia	Hiesh et al. [96]	National Taiwan University Hospital	Image	Genetic algorithm	5	800
Dementia	Sivapriya et al. [97]	OASIS	image	Particle swarm optimization		370
Alzheimer's	Johnson et al. [75]	–	Text, numeric, real	Genetic algorithm	–	8
	Koikkalainen et al. [76]	ADNI	Text, numeric, real		786	–
	Tejeswinee et al. [90]	KEGG	Text, numeric	Correlation Feature Subset Selection (CFS), Information Gain (IG) Gain Ratio (GR)	112	54, 42, 50
	Yang et al. [99]	Chang Gung Memorial Hospital, Lin-Kou, Taiwan	Image	PCA	22	40
	Sayed et al. [105]	National Alzheimer's Coordinating Centre (NACC)	Image	Moth flame optimization	20	60
Parkinson	Shahbakhi et al. [100]	Max Little of the University of Oxford with National Centre for Voice and Speech, Denver, Colorado	Voice signals	Genetic algorithm	31	22
	Xiao et al. [95]		Voice signals	Genetic algorithm	22	195

Table 11 Accuracy comparison of different studies with feature selection techniques for psychological disorder diagnosis

Author	Disease	Feature Selection Method	Before Feature Selection	After Feature Selection	Classification Technique	Accuracy
Hasan et al. [78]	Autism	Independent t-tests and Mann-Whitney U tests	78	25	LDA	82.50%
					QDA	71.67%
Grossi [79]	Autism	MS-ROM, TWIST	250	24	Random Forest	92.8%
					KCM	90%
					KNN	87.30%
Mohammadi et al. [68]	Depression	LDA and GA	112	58	Decision trees	80%
Bekerom [89]	Autism	1-way method	367	256	Naive bayes	86.5%
					SVM	83.3%
					J48	87.1%
					Random forest	85.1%
Ramani et al. [88]	Autism	Fisher filtering	264	19	Naive bayes	62.82%
					Random forest	88.46%
					SVM	64.10%
					C4.5	74.36%
					CS-CRT	69.23%
Ramani et al. [88]	Autism	Runs filtering	264	19	Naive bayes	58.97%
					Random forest	87.18%
					SVM	53.85%
					C4.5	70.51%
					CS-CRT	69.23%
Ramani et al. [88]	Autism	ReliefF filtering	264	19	Naive bayes	43.59%
					Random forest	53.85%
					SVM	47.44%
					C4.5	47.44%
					CS-CRT	44.87%
Tejeswinee et al. [90]	Alzheimer	CFS	1437	54	SVM	93.7%
					Random forest	89.2%
					Decision tree	82%
					Naive Bayes	91%
					KNN	83.8%
Tejeswinee et al. [90]	Alzheimer	IG	1437	42	SVM	97.3%
					Random forest	84.7%
					Decision tree	74.8%
					Naive Bayes	82.9%
					KNN	84.7%

Table 11 (continued)

Author	Disease	Feature Selection Method	Before Feature Selection	After Feature Selection	Classification Technique	Accuracy
Tejeswinee et al. [90]	Alzheimer	GR	1437	50	SVM	83.8%
					Random forest	85.6%
					Decision tree	83.8%
					Naive Bayes	82%
					KNN	82.9%
Yang et al. [99]	Alzheimer	PCA	Not mentioned	Not mentioned	PSO + SVM	94.12%
					SVM	82.35%
					SOM	88.24%
Shahbakhi et al. [100]	Parkinson	GA	22	4	SVM	96.06%
				7	SVM	93.58%
				9	SVM	93.61%
Vaishali et al. [106]	Autism	FA	21	10	Naive bayes	93.15%
					J48	91.10%
					SVM	96.66%
					KNN	87.67%
					MLP	96.66%
Sayed et al. [105]	Alzheimer	GA	Not mentioned	Not mentioned	SVM	57.28%
		GWO			SVM	67.05%
		MFO			SVM	78.33%
Xiao et al. [95]	Parkinson	GA	22	10	C4.5	85.1%
					KNN	87.7%
					PNN	89.7%
					SVM	91.8%
Hiesh et al. [96]	Schizophrenia	GA	Not mentioned	Not mentioned	SVM	88.24%
Sivapriya et al. [97]	Dementia	PSO	Not mentioned	Not mentioned	SVM	89%
					LSSVM	90%
					PSO-LSSVM	96%
Hosseinifard et al. [94]	Depression	GA	Not mentioned	Not mentioned	SVM	88.6%
Ranjith et al. [104]	Stress detection	PSO	Not mentioned	Not mentioned	FFNN	93.25%

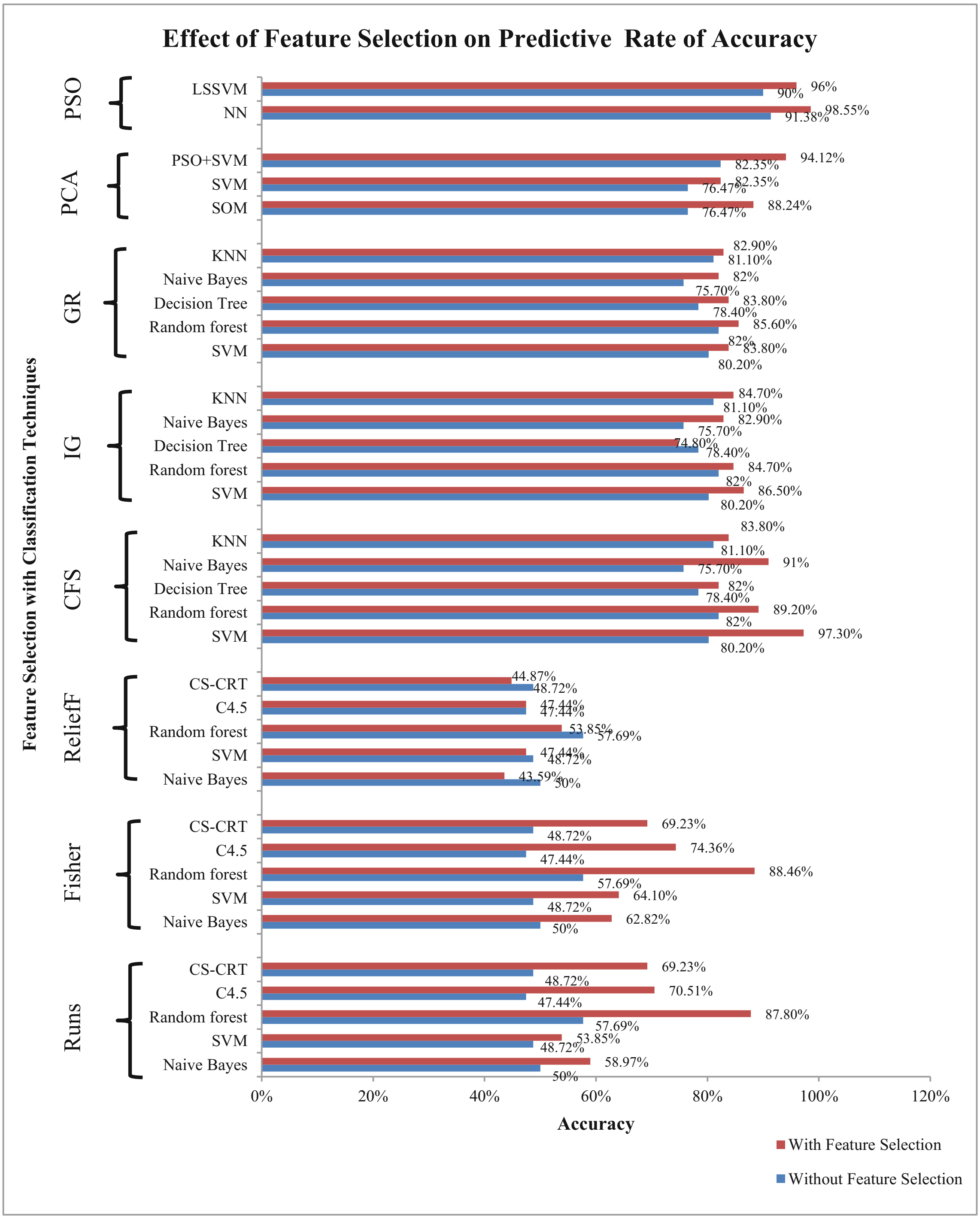

Fig. 13 The accuracy achieved with and without feature selection techniques for psychological disorder diagnosis

centres, hospitals, psychiatric clinics, online repositories and from patients directly.

From Table 9, it is observed that maximum work of autism and depression has been mined using textual, numeric and image datasets. However, dementia, stress, and sleep disorder related to patient's data have been mined using textual and numeric datasets. In spite of dataset, the number and selection of features are very important in mining any dataset. Authors have employed different feature selection techniques in mining the data of psychological disorder patients. Table 10 shows the feature set, instances, data type and data sources used by several authors in the diagnosis of the different psychological disorders.

From Table 10, it is found that there is a significant variation in the number of instances and features used by different researchers who tried to diagnose distinct psychological

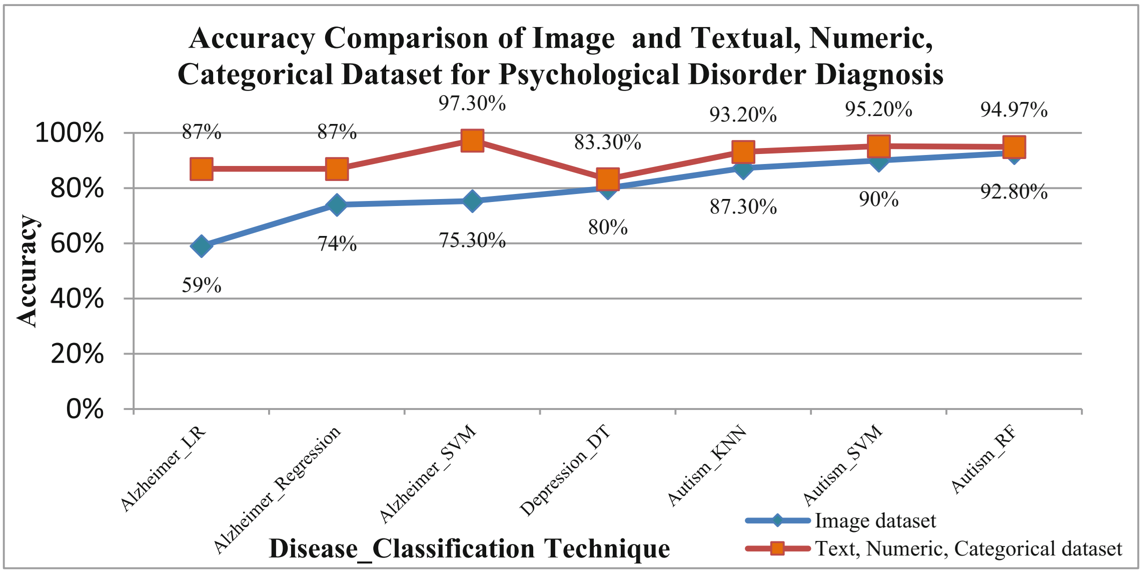

Fig. 14 The accuracy achieved image and text, numeric, categorical dataset

disorders. The maximum number of instances has been used for depression. Moreover, there are certain cases where researchers have explored merely 50 instances.

RQ6: What is the effect of using feature selection techniques in psychological disorder diagnosis?

The feature selection process involves the efficient selection of a subset of variables and avoids the effect of noise and irrelevant variables on predictive results. It can be performed by using filtering, wrapper and embedded techniques over the whole dataset to produce the subset of efficient features [111, 112]. Selection of the right feature set improves the performance of the diagnostic system. Table 11 presents the different feature selection methods used by several authors in their studies along with the total features in the dataset, number of selected features, data mining technique and predictive rate of accuracy.

It is observed from Table 11 that the predictive rate of accuracy to diagnose Alzheimer has been reached to 98%. Table 11 presents the number of features before and after the implementation of feature selection techniques. It is analyzed that the combination of feature selection technique with classification techniques improves the predictive rate of accuracy. Figure 13 shows the comparison of accuracies achieved by different studies before and after implementing feature selection techniques.

Figure 13 presents the rate of accuracy in diagnosing several human psychological disorders with and without using the effect of feature selection techniques. It is observed that the predictive rate of accuracy is improved using feature selection methods in different studies. Additionally, some feature selection method such as Runs, Fisher, Relief Filtering, Correlation Feature Subset Selection (CFS), Information Gain (IG) and Gain Ratio (GR) are used with different classification techniques viz. SVM, Naive Bayes, Random Forest, C4.5, Decision Tree, and KNN etc. in various studies. It is observed that the use of runs, fishers and relief has significantly improved the predictive rate of accuracy of random forest. The use of CFS seems to be best suited for SVM. The effective use of information gain in feature selection has significantly improved the performance of naive Bayes.

A variety of datasets (text, numeric, categorical, images) have been used in the diagnosis of different psychological disorders. Most of the researchers have focused on text, numeric and categorical datasets. However, some of the researchers tried to diagnose psychological disorders using images, particularly electroencephalogram (EEG) images. The performance of using different datasets in diagnosing distinct psychological disorders is presented in Fig. 14.

EEG image dataset seems to be useful for diagnosing psychological disorders. However, the predictive rate of accuracy achieved using EEG images is not as high as accomplished with textual, numeric and categorical datasets. From Fig. 14, it is observed that the predictive rate of accuracy achieved using text, categorical and numeric dataset ranges between 83%–98%. Whereas, the accuracy achieved using image dataset ranges between 59%–93%.

Discussion

This study presented a comprehensive review often major human psychological disorders (stress, anxiety, depression, ADHD, autism, insomnia, schizophrenia, Parkinson, Alzheimer, dementia) mined using different supervised learning and nature-inspired techniques. The remaining part of this section will discuss metrics used in the inclusion/ exclusion

Table 12 Brief details of publications used in the study

Author	Author's Country	University	Journal (Impact factor)	Publisher	Rate
Marinic et al. [66]	Croatian	Dubrava University	Croatian Medical Journal (1.619)	PubMed Central	24
Mohammadi et al. [68]	Canada	University of Ottawa	BMC Medical Informatics and Decision Making (1.021)	BioMed Central	5
Mawangi et al. [69]	United Kingdom	University of Dundee	Brain A Journal of Neurology (10.848)	PubMed	109
Dipnall et al. [71]	Australia	Deakin University	Plos One Journal (2.766)	Public Library of Science	14
Maroco et al. [72]	Portugal	ISPA Instituto University	BMC Research Notes (0.801)	BioMed Central	148
Doyle et al. [74]	United Kingdom	King's College London	Plos One Journal (2.766)	Public Library of Science	23
Johnson et al. [75]	Australia	Commonwealth Scientific and Industrial Research Organisation	BMC Bioinformatics (2.213)	BioMed Central	24
Koikkalainen et al. [76]	Finland	Kuopio University	PloS One Journal (2.766)	Public Library of Science	25
Lama et al. [77]	Republic of Korea	National Research Center for Dementia	Journal of Healthcare Engineering (1.261)	Hindawi	5
Grossi [79]	Italy	Villa Santa Maria Institute	Computer Methods and Programs in Biomedicine (2.674)	Science Direct	4
E. Radhamani et al. [86]	India	Madurai Kamaraj University	Diagnosis of Alzheimer's Disease using Rule-based Approach (0.707)	Informatics Publishing Limited	3
Tejeswinee et al. [90]	USA	Columbia University	Studies in Health Technology and Informatics	STM Publishing House	8
Aram So et al. [91]	Korea	Korea University	Applied Sciences (1.689)	MDPI	4
Yang et al. [99]	Taiwan	Chang Gung University	Computational and Mathematical Methods in Medicine (1.545)	Hindawi	22
Shahbakhi et al. [100]	Iran	Islamic Azad University	Journal of Biomedical Science and Engineering (0.61)	Scientific Research	59
Mohammadi et al. [102]	Canada	University of Ottawa	BMC Medical Informatics and Decision Making (1.021)	BMC	16
Li et al. [108]	China	Changzhou University	Current Bioinformatics (0.54)	Bentham Science	1
Chaovalitwongse et al. [113]	USA	Rutgers University	IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans	IEEE	18
S. R. Bhagya Shree et al. [114]	India	PES College of Engineering	International Journal of Science and Technology (0.707)	Informatics Publishing Limited	4
Usman et al. [115]	Pakistan	Shaheed Zulfikar Ali Bhutto Institute of Science and Technology	Computational and Mathematical Methods in Medicine (1.545)	Hindawi	0
Shmiel et al. [116]	Australia	University of Technology Sydney	Special Section on Intelligent Systems for The Internet of Things	IEEE Access	0
Mora et al. [117]	Spain	University of Alicante	Sensors (2.475)	MDPI	2
Lalo et al. [118]	France	University of Paris	IRBM (0.897)	Elsevier Mansson	0
Hariharan et al. [119]	Malaysia	Universiti Malaysia Perlis	Computer Methods and Programs in Biomedicine (2.674)	Elsevier	80
Gupta et al. [120]	India	Maharaja Agrasen Institute of Technology	Computers and Electrical Engineering (1.747)	Elsevier	24
Sharma et al. [121]	India	Maharaja Agrasen Institute of Technology	Cognitive Systems Research (1.425)	Elsevier	81
Gupta et al. [122]	India	Maharaja Agrasen Institute of Technology	Cognitive Systems Research (1.425)	Elsevier	44

Table 13 Highest accuracy achieved by different researchers for psychological disorders diagnosis using supervised learning and NIC techniques

Disease	Author	Technique	Accuracy
Stress	Deziel et al. [63]	Regression	84%
	Ranjith et al. [104]	PSO	93.25%
Parkinson	Fatlawi et al. [123]	Neural Networks	94%
	Naskar et al. [103]	GA	96.55%
Schizophrenia	Algunaid et al. [93]	SVM	95%
	Hiesh et al. [96]	GA	88.24%
Insomnia	Lin et al. [124]	Decision Tree	95.1%
	Hang et al. [98]	GA	91.63%
Autism	Sunsirikul et al. [125]	Decision Tree	95.65%
	Vaishali et al. [106]	FA	96.66%
Depression	Kim et al. [87]	Regression	96.9%
	Hosseinifard et al. [97]	GA	88.6%
ADHD	Abibullaev et al. [126]	SVM	97%
	Li et al. [108]	GA	96.6%
Dementia	Aram So et al. [91]	MLP	97.2%
	Sivapriya et al. [97]	PSO	96%
Alzheimer	Tejeswinee et al. [90]	SVM	97.3%
	Yang et al. [99]	PSO	94.12%

criterion, performance of different mining techniques and analysis of publication trend.

Metrics

Several publication metrics such as language, title, abstract, publisher along with a number of citation have been considered while selecting the relevant articles. Here, the language has been restricted to English only. Some good quality publisher like Elsevier, IEEE and Springer have been considered along with the rate of citation of the articles. Table 12 shows the publication details along with the rate of a citation for some of the related articles.

It is observed from Table 12 that the number of authors from different countries viz. India, USA, UK, Australia, Pakistan, Italy, Canada etc. are working on psychological disorders diagnosis. The rate of citations of these articles lies in between 0 to 148. The maximum number of citations has been found for BMC research notes. The articles have been published over a wide range of publishers like IEEE, BMC, PLoS, Hindawi, Springer, MDPI, Elsevier and some other reputed publishers.

Performance in mining different psychological disorder

From existing literature, it is found that supervised learning (SVM, random forest, decision tree, naive Bayes, KNN, C4.5 etc.) and nature-inspired computing (GA, ALO, ABC, PAO, ACO, FA, BA, GWO, GSO etc.) have been used for diagnosis of different psychological disorders. SVM and GA found to be widely used techniques. Whereas, LDA, GSO, SVM and CSA have been least used for diagnosis of these human disorders. As far as performance is concerned, Table 13 presented the psychological disorder along with with the best classifiers as well the predictive rate of accuracy in the diagnosis of the particular human psychological disorder.

It is observed from Table 13 that the range of highest accuracies for diagnosing different psychological disorder lies between 84% - 98%. The highest rate of classification has been accomplished for Alzheimer whereas, stress diagnosis is on the lowest side.

Publication trend analysis

The publication trends reveal that the percentage of articles indexed related to cancer, diabetes, cardiac, liver, kidney and psychological disorders are 55%, 16%, 16%, 6%, 6%, and 1% respectively in last ten years. This analysis shows that a massive amount of data has been mined for diabetes and cancer diagnosis. However, only a little research work has been done for psychological disorder diagnosis.

Table 14 shows the research done using different classification algorithms in the last ten years to diagnose different psychological disorders. This analysis is performed by using the Google Scholar database.

It is observed from Table 14 that SVM has been dominantly used for diagnosis of depression, ADHD, schizophrenia, and dementia. Likewise, most of the researchers have employed decision tree for diagnosis of anxiety, autism, and insomnia. For stress, Parkinson and Alzheimer, regression was found to be the most explored technique.

Similarly, in nature-inspired computing techniques, GA and PSO have been used for diagnosis of different psychological disorders. A potation scope has been found to use and explore the performance of different nature-inspired computing techniques such as ACO, ALO, FA, MFO, GWO, CS, GSO, FPA, DA, MA as well as for CSA for diagnosis of different human psychological disorders.

Research implication and practice

This study presents a meta-analysis of 126 different manuscripts related to the diagnosis of human psychological disorders using different supervised learning and nature-inspired computing techniques. This comprehensive review has implication for the students and the researchers who want to carry out their research on supervised learning, nature-inspired computing techniques or wish to explore/mine the data related to the different human psychological disorders. Furthermore, this study will also be interesting for researchers who want to

Table 14 Articles indexed for psychological disorder diagnosis using different supervised learning and NIC techniques

		Stress	Anxiety	Depression	ADHD	Autism	Insomnia	Schizophrenia	Parkinson	Alzheimer	Dementia
Supervised Learning	Naive bayes	15	2	61	23	52	2	25	3	19	98
	SVM	54	7	220	155	152	9	128	6	116	402
	Decision tree	49	31	162	78	176	25	117	8	77	255
	C4.5	9	1	28	12	18	0	11	2	4	45
	Random forest	8	6	91	50	73	2	51	3	36	193
	ID3	9	0	12	5	10	0	6	2	0	15
	Regression	212	12	54	39	29	11	17	23	250	77
	MLP	7	2	44	10	17	0	17	0	5	48
NIC Techniques	GA	30	1	57	13	28	0	19	2	16	58
	PSO	9	1	13	4	20	0	5	0	6	30
	ABC	0	1	2	0	0	0	2	0	0	9
	ACO	1	0	9	1	2	0	1	1	0	5
	ALO	0	0	0	0	0	0	0	0	0	0
	FA	2	0	0	0	2	0	0	0	0	2
	MFO	0	0	0	0	0	0	0	0	1	0
	GWO	0	0	0	0	0	0	0	0	0	1
	CS	0	0	0	1	2	0	0	0	0	3
	GSO	0	0	0	0	0	0	0	0	0	0
	FPA	0	0	0	1	1	0	0	0	0	0
	DA	0	0	0	0	0	0	0	0	0	0
	BA	0	0	2	1	1	0	1	0	0	2
	MVO	0	0	0	0	0	0	0	0	1	0
	MA	0	0	0	0	0	0	0	0	0	0
	CSA	0	0	0	0	0	0	0	1	0	0

design a smart and dynamic diagnostic framework for different human psychological disorders. In spite of using supervised learning and nature-inspired computing techniques in the diagnosis of different human psychological disorders, these techniques can also be effectively used to solve different problems related to the areas like clinical query optimization, feature selection for disease diagnosis, finance, agriculture, astronomy, social networks, bioinformatics etc. Finally, the future directions laid down in this manuscript will give new directions to the researchers.

Limitations

The maximum effort has been put to incorporate the details of relevant manuscripts. However, it's not possible to cover all the manuscripts in one single study. All related manuscripts published in a non-English language like Thai, Chinese, Japanese, Indian, etc. were ignored in this study. Additionally, the manuscripts related to the psychological disorders other than stress, depression, autism, anxiety, Attention-deficit hyperactivity disorder (ADHD), Alzheimer, Parkinson, insomnia, schizophrenia and mood disorder also been not considered during the synthesis of this work.

Conclusion

Psychological disorders cover various brain-related problems and have biological and environmental repercussion. Here, a comprehensive of psychological disorders have been carried out which mainly focuses on the types of psychological disorders, the associated biological and behavioural symptoms, their mining using different supervised and nature-inspired computing techniques. A systematic review methodology has been followed for selection and synthesis of data and results. A three-dimensional search space based upon disease diagnosis, psychological disorders and supervised learning and nature-inspired computing techniques have been explored. Six different research questions have been framed and answered.

First of all, a categorical list of human psychological disorders based upon the fifth edition (DSM-5) has been presented. The biological and behavioural symptoms for the same have been also highlighted. It has been observed that there is no bias in race i.e. each racial community have been equally affected by psychological disorders. Globally, China and India are at the first and second position respectively. The statistics of morbidity rate of psychological disorders for Indian people have been examined. It is exposed that Assam and Manipur have the lowest and highest morbidity rates. The second research question intended to briefly describe supervised and nature-inspired computing techniques. The significance of using different supervised learning and nature-inspired meta-heuristic techniques in the diagnosis of different psychological disorders have been elucidated in the third question. The summary of different supervised learning techniques such as J48, SVM, decision tree, regression, random forest, LDA, naïve Bayes along with the tools used and their performance in the diagnosis of different human psychological disorders have been also presented. Likewise, the details for different nature-inspired computing techniques like GA, ACO, PSO, ABC, FA, GWO and CSA have also provided. For supervised learning techniques, the performance of SVM, MLP and regression in the diagnosis of different human psychological disorders found to be more effective as compared to other classifiers. In nature-inspired computing, FA and GA found to be more effective. The complete publication trend of the related articles has been explored in the fourth question. It is found that most of the research work was done for cancer, diabetes and cardiac disorders. However, only 1% (1200) articles have been found for human psychological disorders. Different Google queries have been formulated to access the trend for some of the major psychological disorders such as stress, anxiety, depression, ADHD, autism, insomnia, schizophrenia, Parkinson, Alzheimer, dementia. However, dementia seems to be the more explored area. Moreover, the research work was done by different countries in the diagnosis of autism, ADHD, depression, insomnia, stress, anxiety, Alzheimer, Parkinson and schizophrenia have been also presented. Common datasets used in the diagnosis of these disorders have been presented in the fifth question. It is observed that authors of different studies collected data from distinct sources like research centres, hospitals, psychiatric clinics, online repositories and from patients directly. The maximum work of autism and depression has been mined using textual, numeric and image datasets. However, dementia, stress, and sleep disorder related to patient's data have been mined using textual and numeric datasets. The effect of using feature selection on the predictive rate of accuracy has been examined in the sixth question.

There is full scope for diagnosis of mania, insomnia, mood disorder using emerging nature-inspired computing techniques. Moreover, there is a need to explore the use of a binary or chaotic variant of different nature-inspired computing techniques in the diagnosis of different human psychological disorders. Likewise, the effect of a random walk, levy flight and feature selection is still needed to examine as far as different human psychological disorders are concerned. Finally, the implementation of the proposed model is still pending.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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