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CLASSICAL AND INTELLIGENT COMPUTING METHODS IN PSYCHIATRY AND NEUROPSYCHITRY: AN OVERVIEW

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Abstract: *This review paper presents an overview of the related work in the area of classical and intelligent computing methods in the diagnosis of psychiatric and neuropsychiatric diseases. Overview and related work is concerned with the presentation of various computing methods, reflecting the perspectives of computation and medical diagnosis. The overview and related work is divided in two parts: One for classical (parametric and heuristic methods) and other for intelligent computing methods comprised of rule-based systems/knowledge-based systems, case-based reasoning, neural network, data mining and their combination among themselves & with other parametric & heuristic methods. Total 34 papers review presented in this paper. Out of 34 papers, 4 papers described about the classical methods and rest of the papers described about intelligent computing methods.*

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1. INTRODUCTION

Neuropsychiatry is an integrative and collaborative field that brings together brain and behavior, but its diagnosis is complex and controversial due to the conflicting, overlapping and confusing nature of the multitude of symptoms, hence neuropsychiatry attempts to bridge the artificial boundaries between neurology and psychiatry in order to treat the multitude of clinical manifestations of the singular brain. Neuropsychiatry is primarily focused on the assessment and treatment of the cognitive, behavioral, and mood symptoms of patients with neurological disorders. However, an equally important focus for neuropsychiatrists is the understanding of the role of brain dysfunction in the pathogenesis of primary psychiatric disorders. Therefore, not only does neuropsychiatry bring the psychiatric assessment and treatment of psychotic or mood symptoms to the neurology arena, it also does neuropsychiatry bring the psychiatric assessment and treatment of psychotic or mood symptoms to the neurology arena, it also returns clinicians to the objective rigors of physical diagnosis and testing, which are often not practiced in psychiatry today.

Neuropsychiatric diagnosis process is based on elicitation of clinical symptoms, identification of neuropsychiatric syndromes, construction of a differential diagnosis, use of laboratory tests and neuroimaging techniques to support or exclude specific diagnoses, and identification of the primary etiology of the behavioral disturbance. In some cases, longitudinal assessment and careful monitoring of treatment responses may be necessary to clarify obscure diagnosis. Treatment depends on accurate diagnosis.

Sign and symptoms plays very important role in the detection and diagnosis of neuropsychiatric diseases. Due to the subjectivity and uncertainty involved in the signs and symptoms and lack of clear diagnostic understanding of electroencephalogram (EEG) and functional magnetic resonance imaging (FMRI) test alone. So, there is a need to perform comprehensive assessment for neuropsychiatric diagnosis which involves physiological, psychological and cognitive parameters along with EEG & FMRI parameters & features [35-39]. So, the combination of EEG parameters, FMRI parameters, physiological, psychological and cognitive parameters are required for the detection of neuropsychiatric diseases such as: Attention deficit hyperactivity disorder (ADHD) [40-43], Dementia [44-49], Mood Disorder (MD) [50] [51], Obsessive-compulsive disorder (OCD) [52-54] and Schizophrenia

(SZ) [50] [55-58].

This paper presents the review of work presented by different authors. The paper is organized as follows: Section 1 described about neuropsychiatric diseases and its diagnosis process. In Section 2, a brief introduction on classical methods and reported work presented. Intelligent computing methods comprised of rule-based system/knowledge, case-based reasoning is discussed in Section 3. Application of data mining methods discussed in Section 4. Section 5 forwarded on work reported in the area of neural network and combined methods comprised of classical and intelligent computing methods. Finally Section 6 presents the conclusion to the paper.

2. CLASSICAL METHODS

The work [1] deployed discriminant analysis and Bayes's theorem to distinguish patients with multiple personality disorder from patients with other psychiatric disorders. Two subgroups used for this study. Discriminant analysis is used for classification purpose and Bayes's theorem, which allows for the calculation of the positive predictive value and the negative predictive value of a screening test. According to discriminant analysis of the total study group, the scale's sensitivity was 76% and its specificity was also 76%; according to discriminant analysis of the more representative subgroup, the scale's sensitivity was 76% and its specificity was 85%. These results indicate that the dissociative experiences scale performs quite well as a screening instrument to identify subjects with multiple personality disorder. In addition, the consistency of responses to scale items across centers indicates that the symptoms reported by patients with multiple personality disorder are highly similar across diverse geographic centers. This consistency supports the reliability and validity of the diagnosis of multiple personality disorder across centers.

The reported work [2] deployed statistical machine learning methodology using electroencephalograph (EEG) data for diagnosis of schizophrenia. Large collections of candidate features, consisting of various statistical quantities, are calculated from the subject's EEG. This large set of candidate features is then reduced into a much smaller set of most relevant features using a feature selection procedure. The selected features are then used to evaluate the class likelihoods, through the use of a mixture of factor analysis statistical model. The average correct diagnosis rate attained using the proposed method is over 85%. The proposed methodology could serve as a valuable adjunctive tool for the medical practitioner.

This work [3] identified distinctive electrophysiological profiles associated with different psychiatric disorders. Quantitative features are extracted from two minutes of artifact- free eyes closed resting EEG data, log transformed to obtain Gaussianity, age-regressed, and Z-transformed relative to population norms. Small subsets of neurometric features, multiple stepwise discriminant analyses were used to construct mathematical classifier function. Using this approach, the system demonstrated high discriminant accuracy in independent replications separating many populations of psychiatric patients from normal patient; the work includes major affective disorder, schizophrenia, dementia, alcoholism, and learning disabilities. The result shows classification accuracy curves which allow one to assess the sensitivity and specificity achieved by the discriminant function. Preliminary results suggest that baseline membership in some neurometric subtypes may be highly correlated with response to treatment.

This work comprised [4] of the uses of electroencephalogram (EEG) signals of 13 schizophrenic patients and 18 age-matched control participants are analyzed with the objective of classifying the two groups. For each case, multi-channels (22 electrodes) scalp EEG is recorded. Several features including autoregressive (AR) model parameters, band power and fractal dimension are extracted from the recorded signals. Leave-one (participant)-out cross validation is used to have an accurate estimation for the separability of the two groups. Boosted version of direct linear discriminant analysis is selected as an efficient classifier which applied on the extracted features. To have comparison, classifiers such as standard linear discriminant analysis, Adaboost, support vector machine, and fuzzy support vector machine are applied on the features. Results show that the boosted version of direct linear discriminant analysis is more discriminative than others such that their classification rates are reported 87.51%, 85.36% and 85.41% for the boosted version of direct linear discriminant analysis, linear discriminant analysis, Adaboost, respectively. Results of support vector machine and fuzzy support vector machine classifiers were lower than 50% accuracy because they are more sensitive to outlier instances. In order to determine robustness of the suggested classifier, noises with different amplitudes are added to the test feature vectors and robustness of the boosted version of direct linear discriminant analysis was higher than the other compared classifiers.

The above reported work presented in tabular form as shown in Table 1. The table shows various classical diagnosis systems with their method, parameters, purpose for which is used and result.

Table 1: Classical methods

Researcher	Method	Parameters / Diagnostic criteria	Diseases	Result: Classification accuracy	Remark
[1]	Discriminant analysis and Bayes's theorem	Clinical	Psychiatric	The scale's sensitivity was 76% and its specificity was 85%	Discriminant analysis is used for classification purpose and Bayes's theorem, which allows for the calculation of the positive predictive value and the negative predictive value of a screening test
[2]	Features selection used to evaluate the likelihoods, through the use of a mixture of factor analysis statistical model	EEG	Schizophrenia	The average correct diagnosis rate attained using the proposed method is over 85%	The proposed methodology could serve as a valuable adjunctive tool for the medical practitioner
[3]	Discriminant analyses to construct classifier	EEG: quantitative features	Schizophrenia, dementia, alcoholism, and learning disabilities	The system demonstrated high discriminant accuracy in independent replications separating many populations of psychiatric patients from normal	Preliminary results suggest that baseline membership in some neurometric subtypes may be highly correlated with response to treatment

3. INTELLIGENT COMPUTING METHODS

Various intelligent computing methods have been developed which deployed rule-based system (RBS)/ Knowledge-based system (KBS) and case-base reasoning (CBR). The details of work reported in this context by different researchers are given below.

3.1. RULE-BASED SYSTEM

The work [5] presents and deployed an expert system called for the diagnosis of obsessive compulsive disorder (OCD). The system uses Lisp language to implement the system. The proposed expert system asks the user 50 questions in natural language, on the patient or on a clinical history, and provides 115 rules of reasoning. The expert system results show the diagnosis of obsessive compulsive disorder or the recommendations of differential diagnosis with related patterns with obsessive pathology: phobic, affective, and schizophrenic. The result shows the utilization of the expert system in psychopathology.

This work [6] proposed a diagnostic support system for clinical psychiatry. The system has two inter-related components: a rule-based reasoning part associated with uncertainty, and a deterministic part, that uses heuristics to perform categorical reasoning. The system includes the 30 groups of psychiatric diagnoses which are classified under the categories 290 to 319 of the DSM-III-R (Diagnostic and Statistical Manual) and the ICD-9 (International Classification of Diseases). There are, in fact, 1508 rules relating 208 clinical findings with 257 diagnoses. The reasoning strategy is based on selecting and differentiating diagnostic categories in a hierarchical classification tree. Diagnostic performance of the system using case reports extracted from a specialized journal for schizophrenia, attention deficit hyperactivity disorder and dementia. In 52.8% of the cases, the correct diagnosis was ranked as the first hypothesis using only the rule-based part. In combination with the deterministic strategy, the correct diagnosis could be made for 73.6% of the analyzed cases.

In this research [7], an expert system (EVINCE) implemented for neuropsychiatric diagnosis. The proposed system is applicable to differential diagnosis of dementia. The system assesses the effectiveness of technology in modeling a psychiatrist based on international guidelines for diagnosing different types of dementia (DSM-III-R), the report of NINCDS-ADRDA work group and EEG signal etc. The system contains knowledge based and inference is based on rule base model, i.e., IF-Then statements. The modeling depends on search strategy used by domain expert based construction of a decision tree. The expert system tool ACQUAINT used for implementation and represented knowledge in frames. Reasoning is based on hypothesis-and data directed approach and use of certainty factor for confidence measure. EEG signal alpha-rhythm activity, focal pathology data used for the adjustment of the diagnostic confidence. The system performance is better than average performance of 73 clinicians. The diseases for differential diagnosis are dementia, dementia of Alzheimer type, multiple infarct dementia and depression.

This work [8], proposed a rule-based model for diagnosing attention deficit hyperactivity disorder in children. This system is based on the signs of attitude and behavior of children. The implementation is performed using web based interface. Rule-based model uses a value of belief and unbelief information from the parameters which are used as a variable count to calculate the certainty factor. The results of this study show the parameters of attention deficit hyperactivity disorder divided into three categories: Inattention, hyperactivity, and impulsivity and 24 parameters found from experts acquisition process. Each parameter has a value of measure of belief and measure of disbelief with a range of values between 0 to 1, which is a variable to search the value of certainty factor. Finally, the result of this system is certainty factor with range between -1 to 1.

In this paper, author [9] implemented rule-based expert system for Alzheimer's disease diagnosis. System contains two components: a knowledge base and an inference engine. In this system knowledge expressed symbolically and inference engine implemented using the computer algebra language. Knowledge base consists of production rules. In inference engine, logical formulae are automatically translated into polynomials and, grobner bases and normal forms are applied to these polynomials using computer algebra language. Symbolic computation techniques are applied to automatically verify and extract new knowledge to produce a diagnosis for neuropsychiatric patients.

In this work [10], a production rule based and multi-criteria decision analysis based hybrid expert system proposed for decision support in the diagnosis of psychological disorders. Due to the dependencies on various types of pathologies diagnosis is a complex issue. The psychological disorders considered for this work are mood disorders, anxiety disorders, antisocial personality, multiple personality and addiction. The usefulness of system shows as reactive measures for early diagnosis.

In this paper [11], the EEG of twenty schizophrenic patients and twenty age-matched healthy subjects are analyzed for classification purposes. Several features including autoregressive model coefficients, band power and fractal dimension are extracted from EEG signals. Research shows a new classification method based on association rule mining. The system consists of a preprocessing phase, a phase for mining the resulted transactional database, and a final phase to improve the resulted association rules. The experimental results show that the method performs well reaching over 80% in accuracy.

This work [12] comprised of an expert system named as MILP, which is designed to produce systematic diagnoses of mental disorders using selected categories from the classification and diagnostic guidelines published in DSM-III-R, DSM-IV and ICD-10. An innovative part of the MILP design is the incorporation of constraint-based reasoning as a key part of the system. The system assessment indicates that the design used was quite simple to implement but yet also flexible. The proposed MILP system is the result of an interaction between understanding what rules need to be expressed and development of an appropriate inference engine which understands the interpretation of those rules. The system performance checked for a number of cases of the breast cancer study, that the system turned up additional diagnoses which were initially missed since the system produces comprehensive diagnosis.

The authors [13] have introduced an expert system model specific for psychiatry, in which diagnostic knowledge is described as a hierarchically organized set of entities through which diagnostic inference is made via a bottom-up approach. The relationships between the entities in diagnostic knowledge are described in terms of likelihoods and the degrees of severity using approximated mathematical functions. The abstraction involves recognizing diagnostic symptoms by interpreting psychological and physical complaints reported by patient in his or her own words. While this model highlights the need for domain specific models. In this work, authors only discussed the model for diagnostic knowledge and its inference process. The authors plan to implement this model as a web-based diagnostic consultation system.

Table 2: Intelligent computing methods (RBS/KBS)

Researcher	Method	Parameters / Diagnostic criteria	Diseases	Result: Classification accuracy	Remark
[5]	Rule-base system implemented using Lisp language	EEG and clinical	Obsessive compulsive disorder	The result shows the utilization of the expert system in psychopathology	
[6]	Knowledge representation: Production rule; Reasoning: Rule-based reasoning part associated with uncertainty and deterministic heuristics method to perform categorical reasoning (The reasoning strategy is based on selecting and differentiating diagnostic categories in a hierarchical tree) The system has two inter-related components: RBR part for uncertainty, and deterministic part uses heuristics to perform categorical reasoning	DSM-III-R, ICD-9	Schizophrenia, ADHD and dementia	Accuracy of rule based model is 52.8% and the improved accuracy in combination with deterministic strategy is 73.6%	Differentiating diagnostic categories in a hierarchical classification tree
[7]	Knowledge based system: Knowledge representation: Rules and concept frames; Concept frames	DSM-III-R and NINCDS-ADRDA work group,	Dementia	The diagnostic performance is better than average clinician	The proposed system is applicable to differential

	represent the knowledge of patient data, while the rules embody the procedural knowledge. Rules contains certainty value; programming language : acquaint tool; Interface: console based	EEG, physical			diagnosis
[8]	Rule-based model: value of belief and unbelief information from the parameters which are used as a variable count to calculate the certainty factor	Clinical: attitude and behavior	ADHD	Based on 24 parameters found from expert's acquisition process	The implementation is performed using web based interface
[9]	Rule-base model	Clinical	Alzheimer	Symbolic computation techniques are applied to automatically verify and extract new knowledge to produce a diagnosis for neuropsychiatric patients suffering from disease	
[10]	Production rule based and multi-criteria decision analysis based hybrid expert system	Psychological	Mood disorders, anxiety disorders		The usefulness of system shows as reactive measures for early diagnosis
[11]	Rules from rule mining	EEG	Schizophrenia	The experimental results show that the method performs well reaching over 80% in accuracy	
[12]	Knowledge based system: knowledge representation: as a combination of prolog rules, MILP rules and table driven data; Reasoning: constraint based reasoning (backward chaining mechanism); programming language: Constraint logic programming language; interface: front end program	DSM-III-R, DSMIV and ICD-10	Mood disorder, eating disorder, depression and schizophrenia	The test results indicates that the system turned up additional diagnoses which were initially missed since the program produces comprehensive diagnosis	It is flexible framework which is suitable in general for the automatic diagnosis of large classless of mental disorders
[13]	Knowledge based system: knowledge representation: hierarchically organized set of entities; Reasoning: bottom up approach	Psychological, physical	Psychiatric	System shows the diagnostic knowledge and its inference process	System shows relationship between the entities in diagnostic knowledge in psychiatric diseases

The above reported work presented in subsection 3.1 is given in tabular form as shown in Table 2. The table shows various intelligent computing (RBS/KBS) based diagnosis systems with their method, parameters, purpose for which is used and result.

3.2. CASE-BASED REASONING

This work [14] deployed Case-based reasoning (CBR) system using the theoretic knowledge about the clinical psychiatry to constrain the case-based reasoning. The organization of the memory is presented here have two structures in memory: cases and concepts. These memory structures permit it to be as skilled in problem-solving tasks, such as diagnosis and treatment planning, as in interpretive tasks, such as clinical research. A prototype applied to clinical work about psychiatric disorders, reasoning from the alimentary questionnaires of these patients, is presented as an example of the system abilities.

The reported work [15] implement case-based reasoning to retrieve and apply previous attention deficit hyperactivity disorder diagnostic cases to novel problems based on saccade performance data. The system is based on the hypothesis is that there is sufficient predictive information contained in existing eye movement data to allow for the development of a knowledge-based system that could be used to identify meaningful groups of attention deficit hyperactivity disorder subjects. System shows case-based reasoning usefulness with 70% accuracy to distinguish attention deficit hyperactivity disorder from control subjects.

The reported work [16] proposes a case-based reasoning expert system that uses the K-nearest neighbor (KNN) algorithm to search k similar cases based on the Euclidean distance measure. The novelty of the system is in the design of a flexible auto-set tolerance (T), which serves as a threshold to extract cases for which similarities are greater than the assigned value of T. A prototype software tool with a menu-driven Graphical User Interface (GUI) has been developed for case input, analysis of results, and case adaptation within the system. Each patient is initially represented by 21 attributes in which the first 20 indicates the symptoms and the remaining attribute is the grade /severity of the illness scored by the doctors. Total fifty three data sets are taken for study, in which 20 cases used for testing. In the present experiment, it has been found to be clinically present for screening and grading cases in 70% of the given test patients.

The above reported work presented in subsection 3.2 is given in tabular form as shown in

Table 3. The table shows various intelligent computing (CBR) based diagnosis systems with their method, parameters, purpose for which is used and result.

Table 3: Intelligent computing methods (CBR)

Researcher	Method	Parameters / Diagnostic criteria	Diseases	Result: Classification accuracy	Remark
[14]	Organization of the memory is presented here have two structures in memory: cases and concepts	DSM-IV	Psychiatric		
[15]	CBR model	Saccade performance data	ADHD	70% accuracy to distinguish ADHD from control subjects	
[16]	CBR process: cases defined based on twenty symptoms; Matching: knn algorithm to search k similar cases; Selection phase short the cases using Euclidean distance	DSM-IV, anxiety and social withdrawals	Psychiatric (depression)	The system accuracy is 70% based on twenty symptoms diagnosis for twenty test cases	A menu driven GUI has been developed for case input. Adaptation via transferring the diagnosis of most similar case to the new case

4. APPLICATION OF DATA MINING METHODS

This work [17] implements machine learning techniques such as support vector machines are applied to a text classification task to determine mental health problems. Inputs are transcribed speech samples from a “structured-narrative task” and outputs are psychiatric categories such as schizophrenia. In a preliminary trial, subjects from three groups generated speech samples: those with clinically diagnosed schizophrenia (31 patients), clinically diagnosed mania (16 patients) and controls (9 subjects). Even though the structured narrative task resulted in the use of a limited vocabulary by all subjects (only a total of 1100 different words were used), a classification performance approaching 80% accuracy was achieved for the schizophrenia versus control task. Classification performance at this level indicates that the method is suitable for diagnostic or screening purposes.

In this work [18], uses of data mining methods applied in the prediction of Dementia. Statistical classification methods like neural networks support vector machines and random forests applied for improving accuracy, sensitivity and specificity of predictions obtained from neuropsychological testing. Seven non parametric classifiers derived from data mining methods (multilayer perceptions neural networks, radial basis function neural networks, support vector machines, CART, CHAID and QUEST classification trees and random forests) were compared to three traditional classifiers (linear discriminate analysis, quadratic discriminate analysis and logistic regression) in terms of overall classification accuracy, specificity, sensitivity, Area under the ROC curve and Press'Q. Statistical distributions of classification parameters obtained from a 5-fold cross-validation were compared using the Friedman's nonparametric test.

In the reported work [19], a data mining based automated EEG classification on detection of transient event. The different classification categories are epileptic spikes, muscle activity, eye blinking activity and sharp alpha activity. The implementation of the system includes clustering of different transient events, feature extraction from each cluster, feature discretization and finally association rule mining and classification. The overall accuracy is 84.35%.The advantage of this approach is that it is able to provide interpretation for the decisions made since it is based on a set of association rules.

This work [20] comprised of data mining techniques applied in brain imaging for disease prognosis and prevention. Methods that filter, clarify, assess, correlate and cluster brain-related information for Heterogeneous data sets. Two types of brain imaging data: structural and functional used for this study. Statistical methods used to discovery of interesting associations and patterns between brain images and other clinical data. Several applications of these methods applied for analysis of task-activation, lesion-deficit, and structure morphological variability; the development of probabilistic atlases; and tumor analysis.

In [21] author, show the application of C5.0 decision tree algorithm implemented for the construction of decision support model to discover the characteristics of the elderly with depression. The data is used in this work taken from Korean Elderly Survey. The input variables used for this study are demographic, health related and socioeconomic characteristics. The feature selection process uses Statistical analysis techniques including the Chi-square, Fisher's exact test, and the Mann-Whitney U-test and Wald logistic regression. The model shows 81.6% accuracy. The utility of decision model can be applied as an aid in the decision making for clinicians to increase vigilance with suspected depression in elderly population.

The above reported work presented in tabular form as shown in Table 4. The table shows various data mining based diagnosis systems with their method, parameters, purpose for which is used and result.

Table 4: Data mining methods

Researcher	Method	Parameters / Diagnostic criteria	Diseases	Result: Classification accuracy	Remark
[17]	Support vector machines implemented for classification	Speech samples	Schizophrenia, mania	80% accuracy was achieved for the schizophrenia versus control task	Method is suitable for diagnostic or screening purposes
[18]	Data mining techniques	EEG	Dementia		Non parametric classifier shows improved accuracy over traditional classifiers
[19]	Data mining	EEG	Schizophrenia	The overall accuracy is 84.35%	The advantage of this approach is that it is able to provide interpretation for the decisions made since it is based on a set of association rules
[20]	Data mining	FMRI, Clinical	Psychiatric		Statistical methods used to discovery of interesting associations and patterns between brain images and other clinical data
[21]	C5.0 decision tree algorithms	Clinical	Depression	The model shows 81.6% accuracy	The feature selection process uses statistical analysis techniques including the Chi-square, Fisher's exact test, and the Mann-Whitney U-test and Wald logistic
[33]	Data mining: cluster overlap based on the Bayes error estimation	Facial expression	Schizophrenia	Experiment results show Accurate measure of the overlap between clusters	Facial expressions capture and quantify their expression flatness by estimating overlap between different facial expressions

5. NEURAL NETWORK AND INTEGRATED METHODS

In this section we will present the reported work related to neural network and integration of different methods used in the diagnosis.

5.1. NEURAL NETWORK BASED METHOD

In this work [22], an artificial neural network based analysis for the comparison of raw and parameterized EEG data based on the detection of schizophrenia used. A three layer feed-forward neural network architecture and off-line data used for training. The detection system consists of two stages. The accuracy for parameterized EEG is 73% and raw EEG data is 46%. Distinctive attributes of the spikes such as slope, height, duration and sharpness are compared with values provided by the neurophysiologists.

This work [23] deployed neural network using EEG and clinical parameters to diagnoses different types of dementia. Results show that patients can be categorized accurately using the combination of EEG synchronization results and selected clinical parameters.

The reported work [24] presents and deployed three layered perceptron and interview-based neural network classifier for different psychotic disorders (mood disorders and schizophrenia). System uses clinical as well as pathological parameters for the model construction. The screening performance of proposed tool is compared with two experienced psychiatrists. The system shows satisfactory results in the diagnosis.

The work [25] proposed a method to identify the psychiatric problems among patients using multi model decision support system. Backpropagation neural networks, radial basis function neural network and support vector machine models are used to design the decision support system. Forty-four factors are considered for feature extraction. The features are collected from four hundred patients and divided into four sets of equal size. Three sets of patient features are used to train the decision support system and one set of patient feature are used to evaluate performance of the system. Experimental results show that the proposed method achieves an accuracy of 98.75% for identifying the psychiatric problems.

This work [26] uses two neural networks, i.e., Backpropagation (BP) and Kohonen networks to fit psychiatric diagnosis and programmed (using sixty cases) to classify neurosis, schizophrenia and normal people. The programmed networks were cross-tested using another two hundred twenty two cases. All subjects were randomly selected from two mental hospitals in Beijing. The proposed networks assist psychiatric diagnosis of the Composite International Diagnostic Interview (CIDI). The networks compared to ICD-10 diagnosis by psychiatrists, the overall kappa of backpropagation network was 0.94 and that of Kohonen was 0.88 (both $P < 0.01$). In classifying patients who were difficult to diagnose, the kappa of backpropagation was 0.69 ($P < 0.01$). Neural network assisted CIDI was compared with expert system assisted CIDI (kappa = 0.72-0.76); neural network was more powerful than a traditional expert system. The proposed neural network models might be used to improve psychiatric diagnosis.

Table 5: Neural network based methods

Researcher	Method	Parameters / Diagnostic criteria	Diseases	Result: Classification accuracy	Remark
[26]	Backpropagation (BP) and kohonen networks	ICD-10	Neurosis, schizophrenia	The result shown in terms of kappa value of BP network was 0.94 and kohonen was 0.88	Neural network is more powerful than a traditional expert system assisted CIDI
[25]	Back propagation neural networks, radial basis function neural network and support vector machine	Clinical	Psychiatric	Experimental results show that the proposed method achieves an accuracy of 98.75%	Forty-four factors are considered for feature extraction
[24]	Three layered perceptron and interview based neural network classifier	Clinical, Pathological	Mood disorders and schizophrenia	The system performance shows satisfactory results in the diagnosis of psychiatric diseases as compared to traditional expert system used	
[23]	Artificial neural network	EEG, Clinical parameters	Dementia		
[22]	Three layer feed-forward neural network	EEG	Schizophrenia	The accuracy for parameterized EEG is 73% and raw EEG data is 46%	Distinctive attributes of the spikes such as slope, height, duration and sharpness

5.2. INTEGRATED METHODS

In this work [27], authors proposed a hybrid approach for diagnosing psychiatric disorder. Each case is represented with fifteen symptoms. The proposed system implement decision tree model to calculate information gain measure of each symptom/attribute to find the dominant symptoms. Two neural network models implemented i.e. dominant symptoms and all symptoms as the inputs to compare the proposed system performance. Result shows that with dominant symptoms, the neural network is able to classify disorder with 98.96% average accuracy, compared to all symptoms, where the average accuracy is 98.91%. The, method shows that attribute selection procedure based on decision tree learning has increased the efficiency of the diagnosis.

In this work [28], authors proposed case-based reasoning and rule-based reasoning based system applied for the care and treatment of Alzheimer's disease Patients. The system used as a decision support tool for physicians, nurses and social workers. The case-based reasoning uses for finding treatments effective for all patients by matching patients to treatments that were effective for similar patients in the past. Case-based reasoning applicable to determine a drug should be prescribed and rule-based reasoning to select one of five approved drugs for a patient. The system shows the integrated aspect of rule-base reasoning and case base reasoning in the diagnosis for neuropsychiatric patients.

In this work [29], author presents a multi-paradigm methodology, and advanced computational models for automated EEG-based diagnosis of psychiatric disorders. Neural networks, wavelets, and the chaos theory used to classify different psychiatric disorders. System shows automated diagnosis of epilepsy, the Alzheimer's disease, Attention deficit hyperactivity disorder, and Autism spectrum disorder.

In this work [30], data mining method applied for simultaneous EEG and functional MRI (FMRI) signals acquisition. Simultaneous acquisition is advantageous because of the superior resolution that is achieved in both the temporal and spatial domains, respectively. The Infomax-based independent component analysis (ICA) technique is used to separate the EEG signatures from the artifacts. The method is used to detect the theta and alpha rhythms that are sleep onset-related EEG signatures along with the subsequent neural circuitries from a sleep-deprived volunteer. The observation and finding of the independent component analysis technique may be useful for the preprocessing of simultaneous EEG–FMRI acquisitions, especially when a reference paradigm is unavailable.

In this work authors [31], focuses on data mining and discriminant function analysis based method applied for psychiatric diagnosis. Several models, involving up to 17 symptoms that led to a broad diagnosis were then tested on. All methods, with the exception of CART used without any pruning, generated identical trees involving four items. Almost 90% of the validation sample was able to be correctly classified by all methods although poor classification performance was noted in the case of one particular diagnosis, Schizoaffective Psychosis. In contrast, stepwise linear discriminant analysis originally selected 17 items, although three out of the first four items selected were identical to those chosen by the tree-building methods. Observation indicates that linear discriminant analysis methods may be usefully employed in constructing parsimonious decision trees. Classification trees and discriminant function analysis shows that a small number of diagnostic decision rules could be extracted from a large inventory of items.

In this work authors [32], used magnetic resonance imagining (MRI) scans taken from control subjects and patients with schizophrenia. The MRI scans are turned into 3D images and processed by the BRAINS software. The sample size included 144 subjects, 63 suffering from schizophrenia and 81 controls. Analysis of the different scans is performed through Bayesian modeling. The outputs of this analysis are networks whose nodes are connected by a variable covariate. The long-term goal of the study is to provide a modeling network to identify the underlying mechanism, which causes a mental disease. The networks produced from the physiological data measurements in the form of MRI correlate different parts of the brain.

In this work author [33], proposed a method to quantify cluster overlap based on the Bayes error estimation on manifolds for neuropsychiatric disorders. A manifold learning method used to discover the intrinsic structure of data, and then measures the overlap of different clusters using the k-nearest neighbor Bayes error estimation on the learned manifolds. Experiment results show accurate measure of the overlap between clusters. The method is further applied for an analysis of a specific type of facial expression impairment in schizophrenia. In this work, Individuals facial expressions capture and quantify their expression flatness by estimating overlap between different facial expressions. The experimental results show that the patient group has much larger facial expression overlap than the control group, and demonstrate that the flat affect is an important symptom in diagnosing schizophrenia patients.

In this reported work [34], multi-layer perceptron model proposed for classification of EEG signals of normal subjects, and subjects suffering from obsessive compulsive disorder and schizophrenia. In this work, the time domain parametric model, i.e., autoregressive model used to pre-process the data as feature extraction. Multi-layer perceptron architecture described as with 8 input neurons, 15 hidden layer neurons, and 3 output neurons. The system is tested for The 6 normal subjects, 8 schizophrenic subjects, and 10 obsessive compulsive disorder subjects. It can be observed that the network correctly classifies all the normal cases, makes one mistake in classifying the schizophrenia cases, and one mistake in classifying the obsessive compulsive disorder cases. It is shown that the multilayer perceptron is capable of classifying unseen test EEG signals to a high degree of accuracy.

The above reported work presented in tabular form as shown in Table 6. The table shows various diagnosis systems with their method, parameters, purpose for which is used and result.

Table 6: Integrated methods

Researcher	Method	Parameters / Diagnostic criteria	Diseases	Result: Classification accuracy	Remark
[27]	Knowledge representation: Cases defined based on 15 symptoms; Decision tree algorithm for dominant symptoms; Neural network: Multi layer feed forward backpropagation network for classification	Psychological, cognitive	Depression	The system shows 98.96% accuracy	Each case grade-probability as mild, moderate and severe
[28]	Integrated (RBR and CBR)	Clinical symptoms	Alzheimer, Dementia		The system used to match case for drug perception
[29]	Integrated (neural network, wavelets and the chaos theory)	EEG	ADHD, Autism Spectrum Disorder, Alzheimer		The system used to classify different diseases
[30]	Integrated (Data mining and ICA)	EEG, FMRI	Psychiatric (Sleep disorder)		ICA technique useful for the preprocessing of simultaneous EEG–FMRI acquisition
[31]	Integrated (Data mining and discriminant analysis)	Clinical symptoms	Psychiatric	90% of the validation sample correctly classified.	Linear discriminant analysis method usefully employed in constructing parsimonious decision trees
[32]	Integrated (Data mining and Bayesian modeling)	FMRI	Schizophrenia		The Bayesian networks produced from the physiological data measurements in the form of FMRI correlate different parts of the brain
[33]	Data mining: cluster overlap based on the Bayes error estimation	Facial expression	Schizophrenia	Experiment results show Accurate measure of the overlap between clusters	Facial expressions capture and quantify their expression flatness by estimating overlap between different facial expressions
[34]	Neural network: Multilayer perceptron for classification and 8th order parametric autoregressive model for feature extraction	EEG	OCD, schizophrenia	The system obtained 91.66% accuracy	Multilayer perceptron is capable of classifying unseen test EEG signals to a high degree of accuracy

6. CONCLUSION

This paper presents an overview of the work reported in the literature in the area of computing methods used in the diagnosis of psychiatric and neuropsychiatric diseases. A tabular representation of some salient features of various psychiatric and neuropsychiatric diseases diagnosis methods discussed in this paper has also been given. It is observed from the literature that most of the reported work focuses on the psychiatric as well as neurological diseases. Very few work reported for neuropsychiatric diseases. The intelligent computing methods discussed in this paper such as rule-based system, case-based reasoning, neural network and data mining are used to develop a integrated diagnostic system in the diagnosis of neuropsychiatric diseases.

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