Volume 9, Special Issue No. 1, February 2018

ISBN: 978-93-5300-455-2

International Journal of Advanced Research in Computer Science

(ISSN: 0976-5697)

RESEARCH PAPER

Available Online at www.ijarcs.info

ICRACC 2018 (23rd–24th February 2018)

ENSEMBLE-OF-CLASSIFIERS APPROACH FOR DIAGNOSIS OF PERVASIVE DEVELOPMENTAL DISORDERS USING PSYCHO-METRIC PROFILES OF CHILDREN

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ABSTRACT

Maintaining good health, mentally and physically, is important at every stage of life from childhood to adulthood to live a long and healthy life. But, due to various factors mental health problems have become common today than cancer, diabetes or heart disease. The onset of mental illness starts typically in the early stages of life i.e. infancy or childhood. The diagnosis of the onset of mental illness by the professionals is a complicated task as many factors are involved. An attempt has been made in this research to diagnose the early onset of pervasive developmental disorders from the psycho-metric profiles of children maintained by the psychologist. An ensemble-of-classifiers approach was used for the diagnosis. Individual classifier's balanced accuracies are used for weighing the classifiers and a final decision was made by averaging their predictions. This ensemble approach provided accuracy from 91% to 97%. Hence, this classifier may be used as an additional tool by the psychologists to diagnose the pervasive developmental disorder.

Keywords: Ensemble, Diagnosis, Pervasive Developmental Disorder, Weighted Average, Fuzzy Clustering

I. INTRODUCTION

Pervasive Developmental Disorders (PDD) refers to a group of conditions that involves delays in the development of many basic skills, ability to socialize with others, to communicate and to imagination. Children with these disorders are often confused in their thinking and generally have problems understanding the world around them. Typically, the disorder incepts before 3 years of age. So, it is difficult to diagnose the disorder. According to National Institute of Mental Health (NIMH), the symptoms of PDD include problems with communicating and interacting with others; unusual play with toys and other objects; difficulty with changes in routine or familiar surroundings; and repetitive body movements or behaviour patterns; little or inconsistent eye contact; failing to respond to someone calling their name. Other difficulties include sleep problems, digestion problems and irritability. But, the children may have above-average intelligence, ability to learn through visuals and audios, excellent mathematical and scientific knowledge, the ability to learn in detail and remember for long periods of time. The research suggested that genes and environment play important roles in the development of PDD. The PDD may first be identified by doctors in infants and toddlers by observing the child's behaviour and development. Diagnosing PDD in adults is not easy as the symptoms can overlap with symptoms of other mental health disorders such as schizophrenia or Attention Deficit Hyperactivity Disorder. Family history of PDD, premature or early birth with low birth weight may also have an impact in the development of PDD.

As the scientists do not know the exact causes of PDD and as the factors causing the mental health problems are overlapping, the diagnosis of PDD has become very difficult. Early diagnosis and treatment for PDD with proper care can reduce individual's difficulties and help them to learn new skills and make the most of their strengths. Although PDD is not curable, its symptoms can be addressed with appropriate interventions and many children with the disorder can be educated and integrated into community life.

The need for early identification has become more urgent by the accumulating evidence that intensive early intervention in optimal educational settings results in improved outcomes in speech and intellectual performance. For many years it was believed that individuals with PDD were not interested in human contact. They remain so aloof that it requires a great deal of effort to get a response. At the other end of the spectrum there are individuals who greatly enjoy and initiate social interaction, including hugging their parents and other shows of affection. Many children with the disorder may be restless because of an impairment of their imaginative and social skills. They do not know how to play with their toys and with other children meaningfully [1].

This research has made an attempt to diagnose the early onset of PDD using the psycho-metric profiles of children maintained by the psychologists. Machine learning techniques play a key role in predicting the mental health problems. Ensemble-of-classifiers approach is used to increase the predictive performance of individual classifiers.

I. RELATED WORK

A number of research works are going on in implementing machine learning techniques for predicting mental health problems. Nowadays, ensemble of classifiers is used to overcome the weaknesses of individual classifiers. The table 1 gives a sample list of ensemble of classifiers used for diagnosing the mental disorders.

Table I Literature Review on Ensemble of Classifiers in Mental health diagnosis

Sl.No.	*Year*	*Authors*	*Ensemble Technique used*	*Mental disorders diagnosed*
1	2007	Shen, Jess J. et al. [2]	Ensemble of three clustering methods	Three subtypes of PDD, namely Autism, PDD-NOS and Asperger's Syndrome

2	2012	Lin Manhua et al. [3]	Ensemble of Weak classifiers on subset of patches of brain images	Alzheimer's Disease with Mild Cognitive Impairment
3	2014	Farhan S. et al. [4]	Ensemble of SVM, MLP and J48 classifiers	Alzheimer's Disease
4	2014	Lebedev et al. [5]	Random Forest Ensemble technique	Alzheimer's Disease
5	2015	Gok et al. [6]	Ensemble of k-Nearest Neighbour Algorithms	Parkinson's Disease
6	2015	B. Ojeme et al. [7]	Ensemble of Bayesian Networks, Back Propagation Multi Layer Perceptron, Support Vector Machines, k-Nearest Neighbour algorithm and Fuzzy Logic	Depressive Disorders
7	2015	T. Latkowski et al. [8]	Ensemble using Rndom Forest	Autism Disorder
8	2016	Iftikhar M.A. and Idris A. [9]	Ensemble classification with SVM	Alzheimer's Disease with Mild Cognitive Impairment
9	2016	Husain et al. [10]	Random Forest ensembles	General Anxiety Disorder
10	2016	Ortiz et al. [11]	Ensemble deep learning architectures	Alzheimer's Disease
11	2016	Zhang et al. [12]	Multi-edit nearest neighbour and Ensemble Learning algorithm	Parkinson's Disease
12	2016	Vyskovsky et al. [13]	Random subspace ensemble method with Multi Layer Perceptron and SVM	Schizophrenia
13	2016	Z.A. Benselama et al. [14]	Ensemble of Sequential Minimization Optimization (SMO) algorithm, Random Forest and Feature-subspace aggregating approach (Feating)	Autism disordered speech
14	2017	Li et al. [15]	Combined Random Forest, SVM and Extreme Learning Machine algorithm	Parkinson's Disease
15	2017	Armananzas R. et al. [16]	Ensemble of different machine learning algorithms	Alzheimer's Disease
16	2017	Abou-Warda H. et al. [17]	Random Forest ensemble	Mental Disorders and Drug Abuse
17	2017	Lee E.S. [18]	Stacking based ensemble classifier of Logistic Regression, Decision Tree, Neural Networks, SVM and Naive Bayes networks	Depression

The sample list shows that a number of research works are going on in diagnosing the mental disorders like Alzheimer's, Parkinson's, Schizophrenia, Depressive disorders, etc. But, only a few attempts have been made to diagnose the mental health problems of children. This article has made an attempt to diagnose the Pervasive Developmental Disorder problem of children effectively using machine learning techniques. If the problem is diagnosed at an early stage, the intervention can be made and proper treatments can be provided to enhance the life of children.

Here, the classification models have been combined to reduce the model errors. Ensemble of classifiers is just like getting the advice of various experts and making a final decision based on the experts' opinions. Some of the advantages of ensemble classification are:

- Less noisy than single classification model.
- No room for over-fitting.
- Improvement in predictive accuracy.

II. MATERIALS AND METHODS

A. *Dataset and its features*

The dataset consisting of one hundred and thirteen psychometric profiles of children was collected from a clinical psychologist. The profiles are maintained by the psychologist in semi-structured text document format and these data are converted into attribute relation file format (.arff). The attributes considered important by the professionals were selected from the profile. This reduces sparseness of data. The name, address and other personal details that identify the child were excluded due to ethical reasons. The data were pre-processed in many ways. For example, numeric data like 'age' were converted into categorical data with four categories namely Infant, Early Childhood, Middle Childhood and Adolescent Childhood. The attributes whose values were missing, were filled with default values as prescribed by the psychologist. 46 attributes were represented from the psycho-metric profiles of children.

The age of the children ranged from 2 years to 16 years and there were 20 girl children and 93 boy children. 18 children had Autism Spectrum Disorder (ASD) and the rest 95 children did not have ASD. A glimpse of psycho-metric data as given by the psychologist is shown in Figure 1.

Age: 6 years 3 months
Pregnancy Complications: None
Type of labour: Induced
Birth Weight: 3.5 kgs
Type of Delivery: Caesarean
Complications: None
Developmental milestones
Started walking at: 1 year
Single words developed by: 3 years
Full sentences developed by: Not yet developed
Seizures: Absent
Therapy/intervention done so far and current treatment/medication: Speech therapy for a year, but no marked improvement could be seen.
Academic performance: Below Average
Relationship Formation:
Home: Staying in joint family. Prefers to be alone. Clinging and demands attention from mother. Doesn't show interest in socialising with relatives. Does not help at home.
School: Ignores presence of teachers and does not interact
Peers: Has no friends. Prefers to be alone
Child management techniques generally adopted at home:
Only mother is able to discipline the child
Interests/Hobbies: Cycling, arranging toys

Figure 1: Glimpse of the data as given by the psychologist

The semi-structured data was converted into tabular format i.e. .arff format, as in Table II.

Table II: Glimpse of dataset in .arff format

Academic Performance	*Affectionate to Others*	*Age*	*Being alone*	*Food Habits*	*Bowel Movement*	*Demands Attention of others*	*Autism Spectrum Disorder (ASD)*
BA	Y	A	Y	I	R	Y	N
BA	Y	A	N	R	I	Y	N
A	Y	A	N	I	R	Y	N
A	Y	M	Y	I	R	N	N
BA	Y	M	N	R	R	N	N
A	Y	A	Y	R	R	N	N
A	Y	A	N	R	R	N	N
A	Y	M	N	R	R	N	N
A	Y	A	Y	I	R	N	N
A	Y	E	Y	R	I	Y	Y
A	Y	M	Y	I	R	N	N
A	Y	M	Y	I	R	Y	N
A	Y	M	N	R	R	Y	N
A	Y	I	N	I	I	N	N
A	Y	A	Y	R	R	N	N
A	Y	I	Y	R	R	Y	N
A	Y	I	Y	R	I	Y	N
BA	Y	A	Y	R	R	N	N

Note: A-Average; BA-Below Average; Y-Yes; N-No; I-Irregular; R-Regular

B. Feature Selection

Recursive Feature Elimination (RFE) method was applied to remove the attributes which are of less importance. Out of 46 features, 25 features were extracted and the experiment was done on the full feature set as well as on the reduced feature set. The details of the features are:

The Recursive Feature Elimination (RFE) algorithm was used to eliminate the less important features for the particular study. The twenty-five features that were extracted for diagnosing the ASD are mentioned below:

$$F_{RFE} = \{ F_1, F_3, F_5, F_7, F_8, F_{10}, F_{11}, F_{13}, F_{14}, F_{15}, F_{21}, F_{24}, F_{27}, F_{28}, F_{30}, F_{37}, F_{38}, F_{39}, F_{40}, F_{41}, F_{42}, F_{43}, F_{44}, F_{45}, F_{46}\}$$

C. Methodology

The methodology, using ensemble of classifiers, proposed in [19] was used for the early diagnosis of Pervasive Developmental Disorder. The methodology for diagnosing PDD using ensemble of classifiers has been shown in Figure 2. After final diagnosis is made, the ensemble model has been evaluated on various measures like Sensitivity, Specificity, Kappa-statistic value and Balanced Accuracy.

Table 3:Features collected from the psycho-metric profiles of children

S.No.	**Feature Name**	**S.No.**	Feature Name
F_1	Academic Performance	F_{24}	Moody
F_2	Affectionate	F_{25}	Has nightmares
F_3	Age	F_{26}	Mother had pregnancy complication
F_4	Aloof	F_{27}	Reading skill
F_5	Anxious	F_{28}	Completes school-work
F_6	Appetite	F_{29}	Has Seizures
F_7	Arithmetic Skill	F_{30}	Gender
F_8	Attention level	F_{31}	Sleeping Habit
F_9	Bowel Movement	F_{32}	Attracted to spinning objects
F_{10}	Concentration level	F_{33}	Stubborn
F_{11}	Demands attention of parents	F_{34}	Temper tantrums
F_{12}	Developmental delay	F_{35}	Under any medication
F_{13}	Distracted	F_{36}	Underactive
F_{14}	Maintains Eye-contact	F_{37}	Unusually loud
F_{15}	Psychiatric problem in family history	F_{38}	Whines/Screams
F_{16}	Fearful	F_{39}	Writing skill
F_{17}	Fidgets	F_{40}	Intelligence level
F_{18}	Fights with siblings/friends	F_{41}	Behavioural Emotional Problem
F_{19}	Friendly with elder children	F_{42}	Anxiety/Depression symptoms
F_{20}	Number of friends	F_{43}	Social/Language/Communication Deficit
F_{21}	Impulsive	F_{44}	Autism
F_{22}	Independent	F_{45}	Attention Deficit Hyperactivity Disorder
F_{23}	Listening skill	F_{46}	Pervasive Developmental Disorder

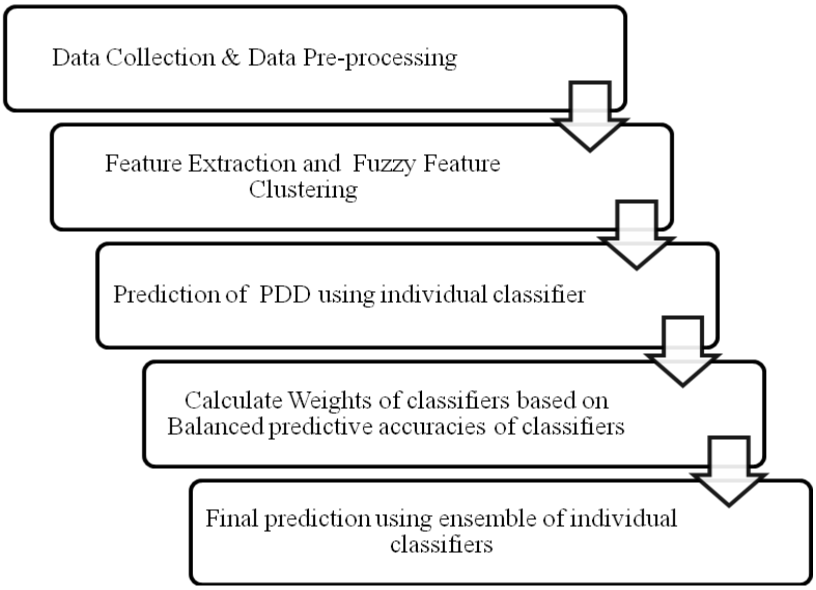

Figure 2: Ensemble methodology for diagnosing PDD

III. MODEL EVALUATION

The ensemble of classifier model had been evaluated on various measures like Sensitivity, Specificity, Kappa-value and Balanced Accuracy. Repeated *k*-fold cross validation is used to test the strength of the ensemble model. The comparisons were made on four models. The first two models used K-Medoids clustering method to cluster the features. The first model used full feature set and the second model used reduced feature set. The third and fourth models used K-Medoids fuzzy clustering method with full and reduced feature sets.

A. *Performance Evaluation*

A confusion matrix, also known as error matrix, was constructed to evaluate the performance of a machine learning model. In the present study, the sensitivity, specificity, kappa-value and balanced accuracy measures were calculated, from the confusion matrix, to evaluate the performance of the ensemble model. Table 4 shows the confusion matrix for diagnosing the PDD.

Table IV : Confusion Matrix

	Diagnosis made by the psychologists		
	Total Population	***With ASD***	***Without ASD***
Prediction made by the model	With ASD	True Positive (TP)	False Positive (FP)
	Without ASD	False Negative (FN)	True Negative (TN)

a. *Sensitivity*

Sensitivity, also called as true positive rate, recall or probability of detection, is a statistical measure that measures the proportion of positives which are correctly identified as positives by the classifier. A high sensitivity value indicates that the model will recognize all children with the disorder by testing positive. The formula for computing sensitivity is:

$$Sensitivity = \frac{\text{Number of true positives (TP)}}{\text{Number of true positives (TP)} + \text{Numberof False Negatives (FN)}}$$

$$= \frac{\text{Number of children predicted with the ASD}}{\text{Total number of children truly affected by the ASD}}$$

b. *Specificity*

Specificity is related to the model's ability to correctly reject the healthy cases without a condition, i.e., it correctly rejects the children without the ASD disorder. It measures the proportion of healthy children known not to have the disorder, will also be tested negative by the model. High specificity value specifies that the model accurately exclude the children with ASD from the children without ASD. The formula for computing specificity is:

$$Specificity = \frac{\text{Number of true negatives (TN)}}{\text{Number of true negatives (TN)} + \text{Numberof False Positives (FP)}}$$

$$= \frac{\text{Number of children predicted without ASD}}{\text{Total number of children truly not affected by the ASD}}$$

c. *Kappa statistic value*

Kappa statistic is a measure of agreement between the predictions and the actual labels. I can also be interpreted as a comparison of the overall accuracy to the expected random chance accuracy. The higher value of kappa statistic is preferred, The formula for calculating kappa statistic measure is :

$$\text{Kappa statistic value} = \frac{\text{Observed Accuracy} - \text{Expected accuracy}}{1 - \text{Expected accuracy}}$$

d. *Balanced Accuracy*

The conventional accuracy is high when the classifier takes advantage of an imbalanced data set and it is purely because of chance. To avoid this for an imbalanced data set, the balanced accuracy is used instead of conventional accuracy. Balanced accuracy is the average accuracy obtained on either class. From the confusion matrix, the balanced accuracy is given by:

$$\text{Balanced Accuracy} = \frac{1}{2}\left(\frac{TP}{P} + \frac{TN}{N}\right)$$

If the classification model performs equally well on either class, the balanced accuracy reduces to the conventional accuracy.

B. Results

The model has been evaluated on four measures Sensitivity, Specificity, Kappa Statistics Values and Balanced Accuracies and a comparison has been made between ensemble of classifiers using majority voting and ensemble of classifiers using Weighted Average. The values have been given in Table 5 and a graphical representation has been made in Figure 3.

Table V: Predictive performance of Ensemble of Classifiers

	Sensitivity		*Specificity*		*Kappa-Value*		*Balanced Accuracy*	
Attribute Set	***Majority Voting***	***Weighted Average***	***Majority Voting***	***Weighted Average***	***Majority Voting***	***Weighted Average***	***Majority Voting***	***Weighted Average***
K-Medoids Clustered - Full	0.96	0.96	0.45	0.88	0.48	0.79	0.71	0.92
K-Medoids Clustered - Reduced	0.96	0.94	0.27	1.00	0.29	0.81	0.61	0.97
Fuzzy K-Medoids Clustered - Full	0.93	0.94	0.73	0.88	0.66	0.74	0.83	0.91
Fuzzy K-Medoids Clustered - Reduced	0.94	0.94	0.88	1.00	0.74	0.81	0.91	0.97

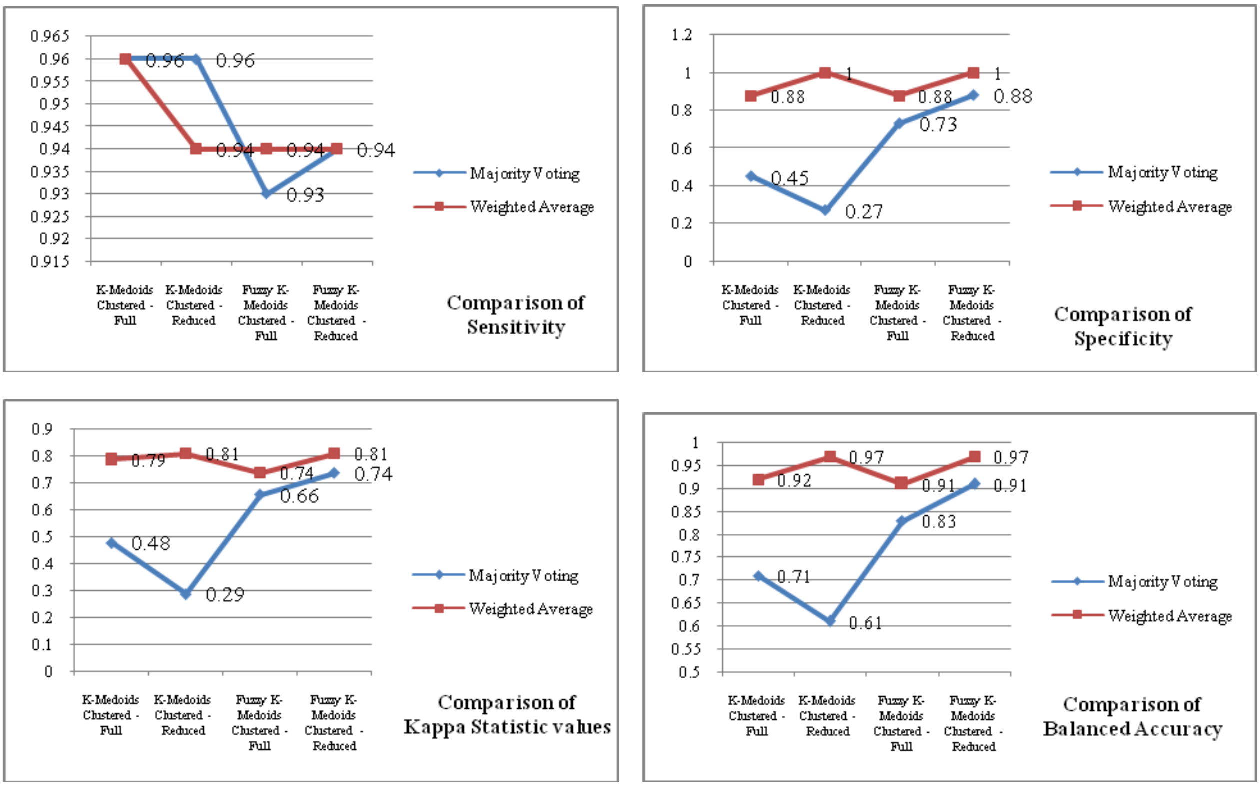

Figure 3: Evaluation of Ensemble of Classifiers

IV. DISCUSSION

The predictive performance of the ensemble of classifiers using Majoirty voting and Weighted average have been shown in Table V. The comparison has been made on full feature set and on the reduced feature set. Two clustering techniques namely *k*-Medoids and Fuzzy *k*-Medoids have been employed to cluster features. The comparison of the ensemble of classifiers shows that Weighted Average based Ensemble of classifiers is effective on various measures like Specificity, Kappa-statistics and Balanced Accuracy. According to sensitivity, there is only a slight difference between the both the methods.

V. CONCLUSION

Mental health is important at every stage of life from childhood to adulthood. Mental health problems have become common today among children. Mental health diagnosis is a challenging task as a number of factors are involved. The onset of mental illness starts typically in the early stages of life i.e. infancy or childhood. This research has attempted to diagnose the early onset of pervasive developmental disorders from the psycho-metric profiles of children maintained by the psychologist. An ensemble-of-classifiers approach was used for the diagnosis. Individual classifier's balanced accuracies are used for weighing the classifiers and a final decision was made by averaging their predictions. This ensemble approach provided accuracy from 91% to 97%. Hence, this classifier may be used as an additional tool by the psychologists to diagnose the pervasive developmental disorder.

VI. ACKNOWLEDGEMENT

We thank Dr. Sangeetha Madhu, Clinical Psychologist, Chennai Institute of Learning and Development (CHILD) Centre, Chennai, for providing data, insight and expertise throughout the study of the research article.

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