ASD Detection in Males Using MRI- An Age-group Based Study

S. Vigneshwaran, S. Suresh, B. S. Mahanand and N. Sundararajan

***Abstract*—This paper presents an automatic, non-invasive method for detecting Autism Spectrum Disorders (ASD) among males using structural Magnetic Resonance Imaging. Whole brain Voxel Based Morphometry (VBM) analysis is first used to identify the brain regions that are affected for ASD patients and gray matter probability in these regions are used as features for classification. In contrast to existing studies which are small in scale, this paper presents a large scale study using the publicly available dataset from Autism Brain Imaging Data Exchange. Taking a cue from genetic studies which indicate that ASD manifests differently among males and females, this paper considers males only. Even among males, this study shows that better classification accuracy can be achieved by considering adult and adolescent males separately. By using a Metacognitive Radial basis Function Network classifier, classification accuracy of 59.73%, 61.49% and 70.41% is achieved when considering all males, adolescent males and adult males respectively. This is about (5 to 10%) higher than Support Vector Machine classifier which is commonly used in literature for this problem and about (6 to 15%) higher than Naive Bayes classifier. It is also found that all three classifiers perform better when considering adult and adolescent males separately instead of considering all males together underscoring the need to consider different age-groups separately for ASD detection. VBM analysis indicates that the precentral gyrus, motor cortex, medial frontal gyrus and the paracentral lobule areas are possibly affected for adolescent males with ASD while the superior frontal gyrus and the frontal eye fields areas are possibly affected for adult males with ASD.**

I. Introduction

Autism Spectrum Disorder (ASD), is a developmental disorder that is characterized by impaired social communication, social reciprocity and repetitive stereotyped behavior. It is relatively common, affecting 1 in 68 children [1]. Apart from the behavioral conditions, ASD is also known to impact motor function, attention and other cognitive domains [2], [3], [4]. ASD is diagnosed traditionally based on criteria evaluated from standardized behavioral tests and also anecdotal information on past behavior. The Autism Diagnostic Observation Schedule [5] and the Autism Diagnostic Interview [6] are considered the gold-standard among traditional diagnostic methods. These methods depend heavily on the skill of the examiner, availability of an informant and the accuracy of the information provided. Due to these human factors, they are error-prone, invasive and unreliable. Traditional methods are also unable to point out the biological factors that are responsible for a particular ASD related condition in a subject, since many factors can lead to the same behavioral phenotype [7]. Hence, brain imaging based methods are being studied as an alternate way of detecting ASD, since the procedure is non-invasive, automatic and is also capable of providing insights into the underlying brain structure and composition responsible for different behavioral conditions. Magnetic Resonance Imaging (MRI) is the most important brain imaging procedure that provides accurate information about the shape and volume of the brain.

Initial analyses of MR images were mostly region specific approaches. A survey of the various studies on the effect of ASD on different parts of the brain is available in [8]. Areas around the frontal cortex like middle frontal gyrus, inferior frontal gyrus and medial orbito frontal cortex have been reported to show regional differences in gray matter composition. Volumetric differences in gray matter have been reported around the superior temporal sulcus, inferior parietal lobule, cingulate and fusiform gyrus. Similarly, the cerebellum area is reported to show some regional differences in white matter composition. Higher volume of white matter has been reported in the outer zones of all lobes with the frontal lobe showing a clear predominance. However, no clear bio-markers have been identified so far. Whole brain MRI based analysis for ASD detection has been studied in recent works such as [9], [10] and both these methods have attempted to use Voxel-Based morphometry (VBM) to compare the amount of gray matter or white matter between the normal subjects and ASD patients. The features that are extracted from VBM are directly used to build classifiers. In [9], both gray matter and white matter composition of 44 male adults were studied and it was found that gray matter offers better accuracy (81%) than white matter (68%). In [10] only gray matter was used to classify ASD in 76 female children. Since, gray matter is responsible for cognitive functions of the brain, in this paper we have tried to use gray matter alone to classify ASD patients from healthy controls.

In analyzing the features from the VBM, multi-variate methods are preferred against the mass-univariate methods [11] making a strong case for machine learning based approaches. In the literature, ASD classification studies have been conducted using VBM detected features and Support Vector Machine (SVM) classifier [9], [12], [10]. Recently a 'Projection Based Learning Metacognitive Radial Basis Function Network'(PBL-McRBFN) was proposed [13], [14], [15] for Parkinson's disease detection effectively and have been shown to perform better than SVM. It has also been applied to many bio-medical applications [16], [17], [18], [19], [20]. PBL-McRBFN used the concept of meta-cognition

Vigneshwaran and Sundaram Suresh are with the School of Computer Engineering, Nanyang Technological University, Singapore (email: vigneshw1, ssundaram@ntu.edu.sg).

N.Sundararajan is with the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore (email: ensundara@ntu.edu.sg).

B. S. Mahanand is with the Department of Information Science and Engineering, Sri Jayachamarajendra College of Engineering, Mysore, India (email: bsmahanand@sjce.ac.in).

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from learning psychology area to select the samples based on the information content in them instead of using all the samples.

Based on recent epidemiological studies [2], it is estimated that the incidence of ASD is at least 5 times higher in males than in females. Also, recent genetic studies [21] suggest a 'female protective model' in the manifestation of ASD. This is motivating researchers to analyze females and males separately. Even prior to this discovery, [9] have done ASD classification studies by recruiting male subjects only. However, it is based on a limited and proprietary data obtained from 44 male subjects (22 - normal, 22 -ASD). The age distribution of the dataset is also in a narrow range (18-42, with mean 22 and Standard deviation of 7), which does not allow us to study the impact of age on ASD classification accuracy. Due to the limited data available, the testing strategies such as leave-two-out cross-validation etc have been used which normally produce high accuracy numbers but far from reality. Recently, the Autism Brain Imaging Data Exchange [22] consortium has publicly released a large dataset consisting of MRI volumes obtained from various locations to enable large scale investigation of ASD from MRI. In [23], a limited part of this dataset contributed by New York University was used to evaluate the performance of the PBL-McRBFN for ASD classification. The results indicated better performance than conventional classification algorithms such as SVM, Naive Bayes classifier, decision trees and nearest neighbor classifier. However this work used only a limited portion of the dataset and did not consider and age or gender specific studies. Hence, this paper attempts to study the ASD detection problem for males specifically, based on the complete ABIDE dataset which contains diverse phenotypic factors of age, location etc. The paper also studies the impact of classification accuracy, when performing age-group based feature extraction and classification steps. In the simulation studies a stricter criteria for evaluating the classification models is employed by using only 75% of the data are used for training while the remaining 25% of the data are used for testing.

The VBM analysis of MRI from all the males of the ABIDE dataset show difference in the gray matter, composition in the Caudate, Premotor Cortex, Supplementary Motor Cortex and the Medial Frontal Gyrus regions of the brain. It was also found that the PBL-McRBFN is able to achieve about 4% higher accuracy than the popular SVM. Since ASD is a developmental disorder, age might have different effects on the brain development and hence this paper attempts to investigate the accuracy of ASD classification when considering three different subsets of males, viz adults only (age $\geq$ 18), adolescents (age $<$ 18) and the full set of males (regardless of age). It is shown that different features are obtained for adults and adolescents in males when performing VBM analysis and hence different regions of the brain needs to be considered for these two groups. It is shown that the overall ASD classification accuracy can be improved by about 10% by performing separate feature extraction and building separate classification model for adults. But the same strategy does not significantly improve the classification performance for adolescents.

This paper is structured as follows: Section 2 briefly describes the dataset used, the framework of the proposed method, the feature extraction process using VBM and the working principle of the PBL-McRBFN classifier. Section 3 describes the experiments done in this study using the PBL-McRBFN classifier and compared with other classification methods such as the SVM and the Naive bayes classifier. Section 4 summarizes the conclusion from this study.

II. Materials and Methods

The broad framework used for ASD detection among males is presented in Fig 1. The structural MRI scans belonging to males are first obtained from the ABIDE dataset. These MRI scans are analyzed using VBM, to identify the voxels that show significant differences in gray matter composition between ASD patients and normal persons. From these voxels, the gray matter probability is taken as the features and arranged in lexical order to obtain the feature vector. These feature vectors are used to train the PBL-McRBFN classifier, which effectively learns the decision boundary in feature space, that can separate ASD patients and normal persons.

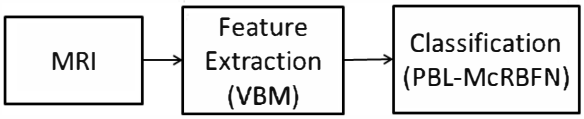


Fig. 1: Framework for ASD detection in males

A. Materials and Image Acquisition

The MRI data is obtained from the publicly available ABIDE [22] dataset. The demographics of males in this dataset are summarized in Table I.

TABLE I: Demographic information of males in the ABIDE dataset

	Healthy Persons	ASD Patients
Adults- (>18yrs)	159	141
Adolescents- (<18yrs)	292	308
Total	451	449

B. Feature Extraction using VBM

Voxel based morphometry [24] is an automatic image analysis approach for identifying the differences in brain composition between two sets of MRI scans (Eg. ASD patients and normal persons). In order to identify significant differences between the two groups of persons, the following steps need to be performed: spatial normalization, segmentation, smoothing and statistical analysis. Tissue segmentation, bias correction and image registration are combined in a

single general model [25] in the unified segmentation step. A 10 mm full-width at half-maximum isotropic Gaussian kernel is then used for smoothing the segmented and registered gray matter images. A simple two-sample t-test is used for statistical testing, to compare the whole brain gray matter composition between normal persons and ASD patients, with and gray matter volume as the covariate. The resulting maximum intensity projection, highlights the regions that show significant differences in gray matter between ASD patients and normal persons. For each MRI scan, the voxel locations of significant regions in the MIP is used as a mask to extract the features (gray matter tissue probability values) and arranged linearly in lexical order to be used as an input to the classifier.

C. Projection Based Learning Meta-cognitive Radial Basis Function Network Classifier

The PBL-McRBFN [13] is a RBF neural network that employs meta-cognitive sequential learning strategies. Whenever a data is presented to the network, it first evaluates the amount of novel information present in it and then chooses one of the four courses of action, viz *Sample deletion*- for very little new knowledge, *Neuron addition*- for significant new knowledge, *Parameter update*- for little new knowledge and *sample reserve*- for future use. These strategies avoid over training and results in better approximation of the decision boundary. The PBL algorithm is an analytical method to determine the weights of the RBF network such that iterative tuning can be avoided. More details on the PBL-McRBFN can be found in [13] and it has been applied to various classification problems.

III. Experimental Results

In this section, the problem of detecting ASD among males using MRI is studied experimentally. The steps involved in extracting the features from the MRI data are provided in detail. Apart from considering all the males in the ABIDE dataset together, age-wise studies are done by performing feature extraction separately for adolescent males (age < 18 years) and adult males (age ≥ 18 years). Based on the VBM based feature extraction, the regions in the brain that are affected for the different age groups are identified. Finally, classification performance for ASD detection among males is evaluated for the PBL-McRBFN classifier and compared with the well known SVM and Naive Bayes classifiers.

A. Feature extraction

The ABIDE dataset consists of MRI volumes from 900 male subjects, of which 451 are normal persons and 449 are ASD patients. VBM analysis is used to extract features from these MRI scans. In this paper, VBM analysis was performed using the Statistical Parametric Map (SPM) software package [26].

The output of VBM analysis is the maximum intensity projection (MIP), which is a map that highlights the voxels that show significant difference in the composition of the brain. In order to study the impact of age, three separate VBM analysis experiments were performed,

- Case A: MRI from all males put together.
- Case B: Considering MRI from adolescent males (age < 18) only.
- Case C: Considering MRI from adult males (age ≥ 18) only.

The significant regions that are identified from VBM analysis can be used for feature extraction directly for future testing samples by skipping the statistical testing step. The results of the VBM analysis for the three cases are provided and discussed below. For each case, the maximum intensity projection, the location of significant voxels and the number of features obtained are given.

1) Case A: Considering all males: In this case, all the MRI scans belonging to males in the ABIDE dataset are taken and a VBM analysis is done on this whole set. The maximum intensity projections (P<0.001) of areas that show significant differences in the gray matter density between normal persons and ASD patients are obtained by following the VBM steps mentioned earlier. A three-dimensional volume-rendering is then performed to spatially locate the brain regions obtained from maximum intensity projection. These results are presented in Fig 2. Within Fig 2, Fig 2a, 2b and 2c present the sagittal, coronal and axial views of the brain respectively. In Fig 2a, subfigure (i) shows the MIP, where the significant regions are highlighted in black. The corresponding three-dimensional volume-rendered display is shown in subfigures (ii) and (iii) which are the views from the right side and the left side of the brain respectively. In the subfigures (ii) and (iii), the affected areas are highlighted in red. Similarly, in Fig 2b, the subfigure (i) represents the MIP and the subfigures (ii) and (iii) represent three-dimensional volume- rendered display as viewed from the front and back of the brain respectively. In Fig 2c, subfigures (ii) and (iii) represent the three-dimensional volume- rendered display in axial view from the bottom and the top of the brain respectively.

From Fig 2, it can be observed the lateral ventricle, caudate, premotor cortex, supplementary motor cortex and the medial frontal gyrus regions of the brain, show significant difference in gray matter composition for ASD patients. From these voxel locations, the gray matter tissue probabilities are taken as the features resulting in 645 features for each MRI scan.

In the following subsections, the same VBM analysis procedure is performed exclusively on MRI scans from adolescent males and adult males separately. The aim of such a separate study is to see if different regions in the brain are affected for adolescents as compared to adults. ASD is a considered a developmental disorder, where in the symptoms get milder with age as the subject may develop some coping strategies. The maximum intensity projections (P<0.001) of significant areas with changes in gray matter density between normal persons and ASD patients for Case A, Case B and Case C are obtained from the VBM analysis shown in Fig 3.

This figure provides a comparison of the maximum intensity projections for the three cases from the three basic views. The sagittal, coronal and axial views of the MIP are presented in the figures 3a, 3b and 3c respectively and within each of these, the subfigures, (i), (ii) and (iii) correspond to Case A, Case B and Case C respectively. The affected regions and the number of features are discussed in the following subsections.

2) Case B: ASD detection for adolescent males (Age <18 years): In this case, all the MRI scans belonging to adolescent males (< 18 years) in the ABIDE dataset are considered separately for VBM analysis. The MIP for this case can be found in the second column of Fig 3. From this figure, it can be seen that the precentral gyrus, paracentral lobule, medial frontal gyrus, primary somatosensory cortex, primary motor cortex, premotor cortex and supplementary motor cortex regions are affected for adolescent males. The VBM analysis of MRI from adolescent males resulted in 2699 morphometric features.

3) Case C: ASD detection for adult males (Age >=18 years): In this case, the MRI scans from the male adults (Age >=18 years) in the ABIDE dataset are considered separately. VBM analysis is performed as done in the sections III-A1 and III-A2 in order to identify the brain regions that show significant differences in the gray matter composition for adult males suffering from ASD. The maximum intensity projections (P<0.001) for this case is shown in the third column of Fig. 3. From Fig 3, it can be seen that the superior frontal gyrus, frontal eye fields areas are affected for adult males. 132 morphometric features are obtained by considering the gray matter probability in these areas.

B. Observations on VBM analysis for ASD in males

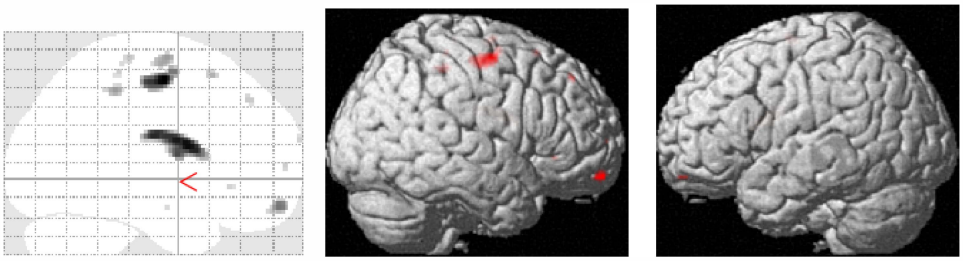
The observations from VBM analysis on different age-groups have been summarized in Table II. When considering all the males in the dataset (Case A), the pre-motor cortex, supplementary motor cortex, caudate and the medial frontal gyrus regions are the areas identified by VBM. This has considerable overlap with the regions identified for adolescent males (Case B) where the motor cortex, medial frontal gyrus and the paracentral lobule regions are identified by VBM. The motor cortex area is responsible for planning, control and execution of movement. It is also responsible for understanding the actions of others by internally imitating the actions. ASD patients experience difficulty in interpreting basic social cues such as pointing at objects, etc. Thus the motor cortex region seem to be consistent with this symptom. In the literature, [27] have also noted dysfunction of the mirror neuron system among ASD patients. [28] have also observed that simple finger movements induce some atypical activation pattern in the motor cortex region for ASD patients. However, for adults (Case C), these regions do not seem to be significantly affected. Adults show activation in entirely different regions of the brain such as the superior frontal gyrus and the frontal eye fields area. These regions are responsible for self-awareness and control of visual attention etc.

TABLE II: VBM detected regions for different age-groups

Age-group	**Identified regions**	**Functionality**
Case A: All males	Premotor cortex, Supplementary motor cortex	Planning, spatial and sensory guidance of movement. Understanding the actions of others. Control of movement.
	Medial frontal gyrus	Executive functions, Decision making.
	Lateral Ventricle	Conduction of fluild through the brain
	Caudate	Spatial, Pnemonic processing, directed movements. Goal directed action, memory, learning, language, sleep.
Case B: Adolescent males	Precentral gyrus, Primary somatosensory cortex, Primary motor cortex, Premotor cortex and Supplementary motor cortex	Planning, spatial and sensory guidance of movement. Understanding the actions of others. Somatic sensation, visual stimuli, and movement planning.
	Medial frontal gyrus	Executive functions, Decision making.
	Paracentral lobule	Motor and sensory innervations of the contralateral lower extremity. Regulation of physiological function such as defecation and micturition.
Case C: Adult males	Superior frontal gyrus	Self-awareness in coordination with sensory system, Laughter.
	Frontal eye fields	Control of visual attention and eye movements.

However, different age groups show activations for different sub-regions within the motor cortex. For example, only the premotor cortex and supplementary motor cortex sub-regions show activiation when the comple set (Case A) is considered, but when for adolescents age group, additional areas such as the somatosensory cortex are also affected.

From these VBM identified regions, the gray matter probabilities are taken as the features which are then used by the different classifiers for ASD detection. It can be noted that the number of features obtained for each of the cases considered in sections III-A1, III-A2 and III-A3 are different. These features are then used for classification purposes which is described in the next section.

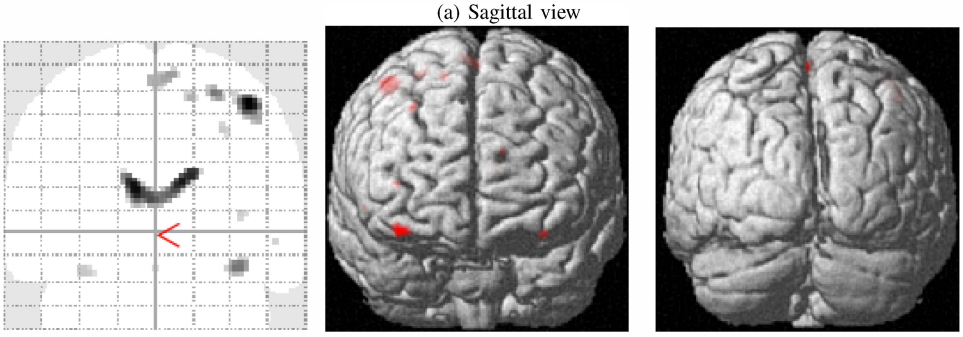


(i) Maximum intensity projection-regions of the brain that show significant difference in gray matter.

(ii) 3-dimensional volume-rendered display of significant difference in gray matter (Right).

(iii) 3-dimensional volume-rendered display of significant difference in gray matter (Left).

(a) Sagittal view

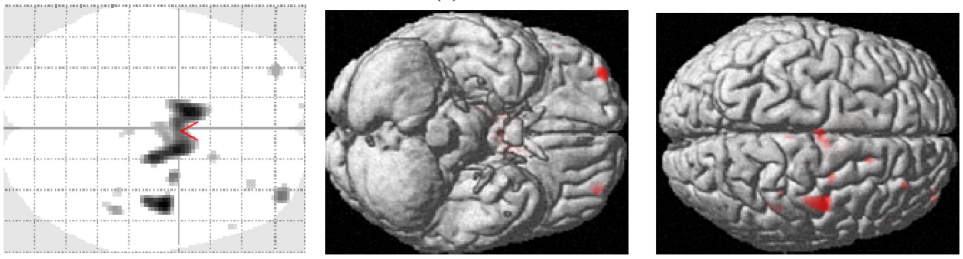


(i) Maximum intensity projection-regions of the brain that show significant difference in gray matter.

(ii) 3-dimensional volume-rendered display of significant difference in gray matter (Front).

(iii) 3-dimensional volume-rendered display of significant difference in gray matter (Back).

(b) Coronal view



(i) Maximum intensity projection-regions of the brain that show significant difference in gray matter.

(ii) 3-dimensional volume-rendered display of significant difference in gray matter (Bottom).

(iii) 3-dimensional volume-rendered display of significant difference in gray matter (Top).

(c) Axial view

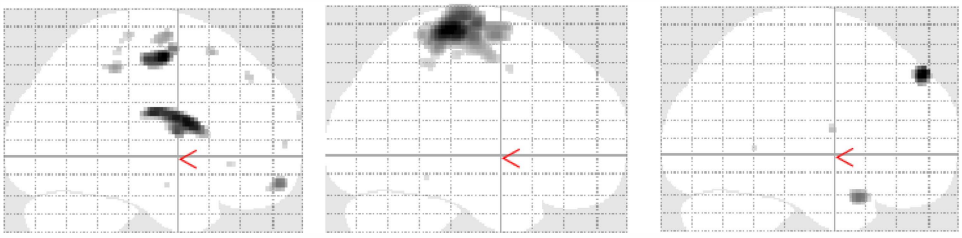
Fig. 2: Brain regions with significant differences in gray matter density in ASD patients, when considering MRI scans of all males in the ABIDE dataset

C. Classification performance comparison

In this section, the performance of PBL-McRBFN classifier is compared with SVM classifier that is commonly used in literature for the ASD detection problem. The classification results are presented for the three age-groups that were considered for VBM analysis, in the same order. For comparison of classification performance, the following classifiers are considered in this study,

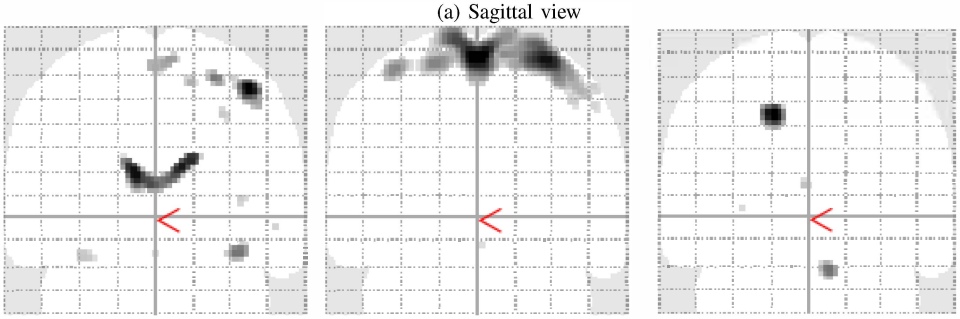
- Support Vector Machine (SVM). This is the most common classifier used in literature. In this study, a Gaussian kernel is chosen for SVM and the parameters of SVM were optimized using the gridsearch method. The LIBSVM [29] is a popular implementation of the SVM with gridsearch method [30] and it has been used in the simulation studies reported in this paper.
- Naive Bayes Classifier (NBayes). This is a simple classifier [31] that assumes that each feature is statistically independent from other features and then uses the Bayes theorem to assign a class label that maximizes the a-posteriori probability. In this study, the naive bayes classifier implemented in the WEKA 3.7 [32] library has been used for simulations.
- PBL-McRBFN classifier [13]. This is a RBF neural network based approach employing meta-cognitive learning principles.

For this study, in each trial, 75% of the samples are chosen randomly as the training set and the rest as testing set. Performance evaluation of the classifier has been done by generating 5 such random trials. All the algorithms were



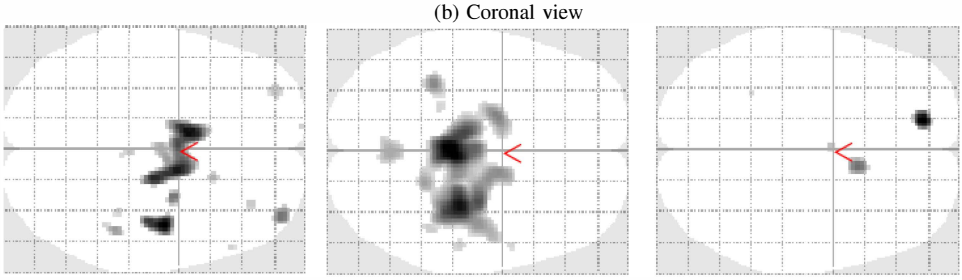
(i) Case A- all males in ABIDE dataset. (ii) Case B- adolescent males in ABIDE dataset. (iii) Case C- adult males in ABIDE dataset.

(a) Sagittal view



(i) Case A- all males in ABIDE dataset. (ii) Case B- adolescent males in ABIDE dataset. (iii) Case C- adult males in ABIDE dataset.

(b) Coronal view



(i) Case A- all males in ABIDE dataset. (ii) Case B- adolescent males in ABIDE dataset. (iii) Case C- adult males in ABIDE dataset.

(c) Axial view

Fig. 3: Comparison of brain regions affected for different age groups among males in the ABIDE dataset

implemented in MATLAB and the simulations were run on a laptop with Intel Core i7 quad core processor, 2.1 GHz CPU and 16 GB RAM.

1) Case A: Considering all males: In this section, the classification results are presented for the case where MRI belonging to all the males in the ABIDE dataset are analyzed together. The features obtained in section III-A1 was used to build a classification model using PBL-McRBFN classifier and compared with SVM and Naive Bayes classifiers. The overall accuracy, F-measure and the number of neurons used by each of the three classifiers is given in Table III. For each entry, in the table, the mean value obtained over the 5 trials are given first, followed by the standard deviation which is provided within parantheses. From the table, it can be seen that the accuracy and F-measure of PBL-McRBFN and the SVM classifiers are similar (above 97%) during the training phase, but the Naive Bayes classifier gives very low training accuracy of 55.6% and F-measure of 55.2%. However, during the testing phase, it can be seen that PBL-McRBFN is able to achieve slightly better (about 4%) testing accuracy than the popular SVM. Number of neurons needed by PBL-McRBFN is also much lesser than the number of support vectors needed for SVM. The naive Bayes algorithm gives the least testing accuracy, but it is very close to the accuracy of SVM. During testing, PBL-McRBFN is able to achieve about 5% higher F-Measure than the SVM and the F-measure of the Naive Bayes algorithm is about 9% lower than that of PBL-McRBFN.

2) Case B: ASD detection for adolescent males (Age <18 years): Here, the feature vectors obtained in section III-A2 were used to build classification models for ASD detection using the three classifiers mentioned earlier. The classification performance of PBL-McRBFN, SVM and Naive Bayes classifiers for adolescent males are given in Table IV. In this case, it can be seen that the classification accuracy of PBL-McRBFN is slightly higher (by about 2%) than that was achieved in Case A. But the accuracy of SVM is almost the same as that obtained for Case A. Similar to Case A, PBL-

McRBFN and SVM are able to achieve very high accuracy (> 95 %) during the training phase, but their performance is much lower in the testing phase. Here again PBL-McRBFN is able to achieve about 5% higher accuracy in the testing phase than the popular SVM classifier in spite of using much fewer number of neurons than that is needed for SVM. The number of neurons and support vectors are significantly lower than the ones needed by PBL-McRBFN and SVM classifier for Case A, where all the males were considered regardless of age. Thus it can be inferred that considering adolescents separately results in a reduction in the number of neurons or support vectors. The Naive Bayes classifier is able to achieve a marginally better accuracy (by about 0.4%) than SVM classifier when considering adolescents separately, but the F-measure of the Naive Bayes classifier is about 3.5% lower than SVM. The performance of the Naive Bayes classifier has improved by 2% in terms of accuracy and F-measure when compared to Case A.

3) Case C: ASD detection for adult males (Age >=18 years): In this case, ASD classification performance is studied for adult males by using the feature vectors obtained in section III-A3 to build classification models. The overall accuracy and F-measure for the three different classifiers are summarized in Table V. In the training phase PBL-McRBFN is able to achieve the highest accuracy and F-measure, among the three algorithms. The training accuracy of PBL-McRBFN is about the same as was seen for the Cases A and B , but the training accuracy of SVM for this is case is lower than the previous two cases. SVM also uses nearly double the number of support vectors than the number of neurons used by PBL-McRBFN. In the testing phase, it can be observed that PBL-McRBFN classifier is able to much achieve higher accuracy (about 70%) for this age-group than what was observed from the previous two cases. The conventional SVM is also able to achieve much better accuracy than that was achieved in Case A and B, but it is still about 10% lower than the performance of PBL-McRBFN. Thus it can be seen that considering male adults separately significantly improves the classification performance for PBL-McRBFN and SVM. The Naive Bayes classifier does not show any significant change in the classification accuracy for the three cases, however its F-measure for this case is about 5% higher than Case A.

TABLE III: Case A - Classification performance of algorithms, considering all males regardless of age

Algorithm	Training %		Testing %		
	Acc	F_1	Acc	F_1	Neurons
PBL-McRBFN	97.92 (1.85)	97.94 (1.85)	59.73 (1.82)	63.4 (3.5)	395 (15.43)
SVM	99.25 (0.83)	99.25 (0.83)	55.19 (2.6)	58.86 (2.2)	576.2 (123.7)
Naive Bayes	55.58 (1.42)	55.2 (4.68)	54.02 (2.71)	54.87 (2.61)	NA

TABLE IV: Case B - Classification performance of algorithms, considering only adolescent males

Algorithm	Training %		Testing %		
	Acc	F_1	Acc	F_1	Neurons
PBL-McRBFN	98.21 (2.43)	98.22 (2.44)	61.49 (2.46)	63.19 (2.17)	266 (16.09)
SVM	96.46 (4.6)	96.73 (4.22)	55.95 (4.3)	59.97 (5.8)	437 (15.6)
Naive Bayes	65.54 (1.98)	65.63 (1.66)	56.35 (3.08)	56.42 (2.56)	NA

TABLE V: Case C - Classification performance of algorithms, considering only adult males

Algorithm	Training %		Testing %		
	Acc	F_1	Acc	F_1	Neurons
PBL-McRBFN	98.91 (0.89)	98.83 (0.95)	70.41 (3.49)	68.13 (8.48)	136.4 (22.8)
SVM	88.91 (14.9)	87.96 (16.44)	59.45 (1.47)	48.96 (8.55)	203 (22.09)
Naive Bayes	59.1 (2.32)	62.1 (3.7)	55.62 (6.67)	59.66 (5.85)	NA

D. Observations on classification performance:

Based on the classification results presented in section III-C, it can be seen that the classification performance for all the classifiers can be improved by performing separate VBM feature extraction and building separate classifier for adults (Case C) and adolescents (Case B) instead of considering everybody as a single set (Case A). The classifiers are able to achieve their highest classification accuracies for Case C, when considering male adults. For male adolescents (Case B), age-group specific feature extraction and classification does not have any significant impact on the classification accuracy but PBL-McRBFN and SVM use much less number of neurons and support vectors than that was used for Case A. The Naive bayes classifier on the other hand shows a significant improvement in training accuracy and testing F-Measure when using the age-group based classifiers in Cases B and C, than the Case A. For Cases A and B, the PBL-McRBFN outperforms the conventional SVM based approach both in terms of accuracy and in terms of F-measure by about 5%. For Case C, the PBL-McRBFN is able to achieve an significant improvement of about 10% in classification accuracy of the SVM.

IV. Conclusions

This paper has presented an automatic diagnosis method for ASD in males using structural MRI data and a meta-cognitive RBF classifier. A large-scale performance study has been done based on the publicly available ABIDE dataset (449 male ASD patients and 451 male healthy persons). Separate VBM analysis and classification experiments were done by considering all males (Case A), adolescents (Case B, < 18 years) and adults (Case C, >= 18 years). Whole brain VBM analysis indicates that the precentral gyrus, motor

cortex, medial frontal gyrus and the paracentral lobule areas are the most affected regions for adolescent males while the superior frontal gyrus and the frontal eye fields areas are the regions affected for adult males. The cognitive functions of these areas seem to match some of the symptoms observed in ASD patients. During classification, the PBL-McRBFN classifier was able to achieve a modest classification accuracy of 59.73% and an F-measure of 63.4% for Case A. While these numbers may be considered to be low, it is still about 5% higher than the accuracy and F-measure achieved by SVM classifier which is the one that is commonly used in literature for ASD detection. For adolescents, PBL-McRBFN and SVM used significantly lower number of neurons and support vectors than the Case A, but the classification accuracy did not improve significantly. For Adults, all three classifiers showed improvement in classification performance than for the Case A, with PBL-McRBFN showing a significant 10% improvement and SVM showing a 5% improvement. This indicates that better ASD detection can be achieved by considering adults and adolescents separately. The classification performance of PBL-McRBFN was also consistently better than the popular SVM classifier for all the three cases.

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