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Detection of Autism Spectrum Disorder (ASD) using Machine Learning Techniques: A Review

Mamata V. Lohar[1] and Suvarna S. Chorage[2]
[1]Research Scholar, Dept. of E&TC, AISSMS Institute of Information Technology, Pune-01
[2]Professor, Dept. of E&TC, Bharati Vidyapeeth's College of Engineering for Women, Pune-43

Abstract

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder described as a set of conditions identified by different challenges like speech, social skills, non-verbal communication, and repetitive behaviors. ASD depends on the factor of gender. The similarities and weaknesses in autistic children and adults are distinct. The irreversible loss is observed if ASD is not detected at earlier stage. Hence there is a need for automated techniques for early and accurate detection. There are many developments in current research in the field of biomarkers for risk assessment, diagnosis and tracking of disease progression. Machine learning used in health care has made enhancements in diagnosis by processing and analysis of the huge amount of data. Present research work focuses on automated methods of identification to diagnose ASD accurately. Fusion method is used to combine any number of instruments, allowing data from various reliable sources to be fused, all within an objective framework that can be converted to the desired metric. Preprocessing techniques can be streamlined to incorporate techniques for data fusion to minimize ambiguity in feature evaluation. For carrying out the research, 153 autism controls and 157 typical subjects of sMRI and fMRI for each is selected from Autism Brain Imaging Data Exchange (ABIDE). This paper presents the overview of recent studies in the semi-or fully-automatic computer-aided diagnosis of ASD and compares the parameters visualized as methods applied, classes considered, features used, criteria of assessment and results obtained. This paper also reveals the classification between ASD and TC subjects for sMRI and fMRI using the K-NN classifier for different feature sets. Using feature optimization and fusion of sMRI and fMRI images, classification efficiency can be enhanced.

Keywords: *Autism Spectrum Disorder (ASD), Automatic Classification, Feature Extraction, Image Fusion, Machine Learning Techniques, Typical Controls (TC).*

1. Introduction

ASD is a condition of neurodevelopment which adversely affects people's entire lives. The main signs of ASD are lack of public contact and communication, patterns of repeated behavior, attitudes and actions, etc. Although ASD is seen at an early stage of development, certain defects and behavioral patterns may not be identified as symptoms unless in significant steps they impact the life of the child. Functional weaknesses differ from individual to individual with ASD and may change over time as well. For children till 18 months of age, signs of ASD are usually diagnosed. But with that, ASD may not be noticed until the school year, if the infant has minimal speech delay. The diagnosis is usually made in such situations where children have issues with peers or interactivity with them. The physicians used various methods and strategies in combination with diagnostic tools for the treatment of ASD. The method of classification is used for diagnosis in most of these studies.

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1.1. Types of ASD

ASD is a group of developmental cognitive disorders with symptoms that include both social and communication difficulties. Autism Spectrum Conditions (ASC) is distinguished by language, cognitive control, developmental disabilities as well as limited or repetitive behaviors. ASDs are a brain development irregularity and functions that arise over the first three years of life. Numerous etiologies, including genetic factors, are known to have autism. A number of studies found a related medical disorder (e.g. tuberous sclerosis) in 10-37% of cases. There are five diagnostic categories of ASD as shown in Figure 1.

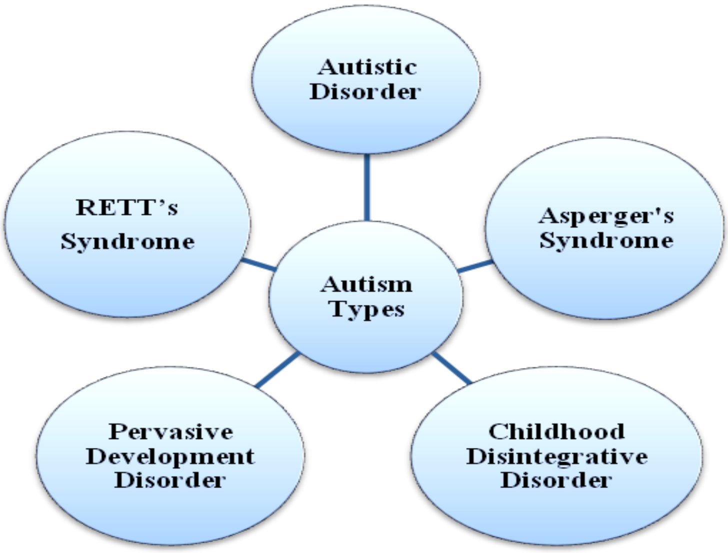

Figure 1. Types of Autism

The defects in the social and interpersonal fields of autistic behavior were maintained and present before the age of three years. A small type of activity is likely to occur in the patient. Speech deferment is Autism's main feature. Autism people may also have an logical disability. Sustained cognitive deficits may occur in Asperger's syndrome, but impairments in the speech field are not as severe and language usually improves at a typical age. In the very young child, the abnormalities become less evident and become more obvious when the adult is in school. Individuals with the disorder of Asperger may have an average or higher IQ. This condition is more widespread in males (13:1), but in females, it might be underdiagnosed.

Pervasive Development Disorder (PDD) is referred to as normal autism; PPNOS can be identified if a child does not meet the diagnosis criteria but demonstrates significant and widespread deficiency in meticulous behaviors. Often known as Atypical Autism is the PDD-NOS. For boys more affected than girls, the CDD is extremely rare. Following an average of 2-4 years of normal growth, but usually before age 10, the children who are diagnosed with CDD begin to lose skills and show signs of ASD. Children with Childhood Disintegrative Disorder may not be able to take on in conversations with others or may use nonverbal forms of communication such as actions, smiles, or drowsy, and may lose interest in winning with peers in other social situations.

1.2. Signs and Symptoms of ASD

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The signs and symptoms of ASD comprise issues with social relations skills, voice, and communication in every child and adult. ASDs are assessed based on the existence of several symptoms that hamper with the ability of the child to play, talk, make associations, learn, and study.

Table 1 shows the different symptoms of ASD related to common behavior, Speech and language, restricted behavior and play, etc.

Table 1. Autism Symptoms

Common Behavior Symptoms	**Speech and Language Related Symptoms**	**Restricted Behavior and Play Related Symptoms**
• Unusual or incorrect visual communication, movements and facial expressions (e.g. avoiding contact with the eyes or facial expressions that do not suit what they say). • Lack of interest in individuals or expressing experiences or successes (e.g. painting, pointing to a bird). • Improbable to approach or seek social dealings; considers itself detached and held in reserve; prefers being alone. • Challenges and difficulties in interpreting the thoughts, reactions and nonverbal signs of a person. • Touching resistance.	• postponement in learning how to talk • Talk in an unusual voice tone or with a peculiar regularity or high pitch. • Words or phrases repeated over and over. • Difficulty to start a spoken language or to keep it going. • Trouble in communicating wishes or desires. • Does not interpret simple statements or questions. • Taking too virtually the same thing, ignoring irony, sarcasm, and satire.	• Movements of the repetitive body (hand undulation, rolling, spinning); constant motion. • Obsessive devotion to unusual items. • Concern with a meticulous topic of interest, usually with numbers or signs (maps, license plates, sports statistics). • For sameness, order, and habits, a strong desire. Get upset by changes in routine or climate. • Illness, odd behavior, or strange ways of walking. • Attentive to rotating objects, moving items or toy components (e.g. spinning wheels on a motor vehicle instead of fidgeting with the entire vehicle).

Medical imaging plays an important role in many aspects of medical diagnosis and therapy in the current time of technological development. For correct medical analysis and therapy, it needs more accurate images with much more details and information. Medical image fusion is one of the solutions in a single image to obtain both high spatial and high spectral data. Multimodal medical image fusion greatly improves the quality of the fused image. Previous studies on autism have been performed in several imaging modalities such as Structural MRI (sMRI), Functional MRI (fMRI), and Diffusion Tensor Imaging (DTI). Modality fusion will be performed to get more detailed brain scans to help better understand and analyze ASD.

In the automated system, the critical step is the classification of images. The main goal is to distinguish the various unusual clinical images based on the optimum set of features. Image classification is one of the pattern recognition system sub-categories in which an input image is

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classified into any of the pre-defined classes. Because of the rapid developments in medical imaging technology, it is now possible to acquire high resolution and a more concise definition of the anatomies and functions of humans. This design facilitates research in the field of clinical image analysis. An automatic classification system for ASD detection integrates the anatomical and functional information of the brain. There are various tools available to diagnose autism early, but they are costly, time-intensive, and sometimes predictive value poor. Machine learning can be a low cost, fast and easy method to identify and classify medical objects that perform better than most commonly used standardized tools. Many machine learning techniques are used for classification, such as K-NN, SVM, Naïve Bayes, PCA, ICA, LDA, ANN, Random Forest, Decision Tree, Fuzzy Method, Deep Learning, etc., giving the best results for feature extraction of ASD diagnostics.

ASD is a community of distinct identifiable early childhood developmental disabilities. At present, ASD is diagnosed mainly by assessing a child's behavioral and mental capacity. This diagnosis of conduct can be subjective, time-consuming, and inconclusive, does not provide an understanding of the underlying etiology, and is not appropriate for early detection. The accuracy of the abnormality detection technique must be considerably high because the treatment planning is based on this identification [1].

The children having age from 4-11 years, Osman Altay et al. [2] used the classification approach in diagnosing ASD. For identification, the algorithms Linear Discriminant Analysis (LDA) and K-Nearest Neighbor (K-NN) are used. At the precision cost, the LDA algorithm yields a better result than the K-NN algorithm. Fatiha Nur et al. [3] compared the quality of different classification methods such as K-Nearest Neighbors, Naive Bayes, Random Forest, and Radial Basis Function Network, on UCI 2017 Autistic Spectrum Disorder Screening Results for Children and Random Forest has better classification outcomes. Nicha C. Dvornek et al. [4] introduced a variety of methodologies to combine phenotypic data with rsfMRI into a single deep learning system for ASD classification. Dingan Liao et al. [5] proposed a new model for the objective and automated identification of autism disorders and normal subjects based on community structure and deep learning, which would give greater accuracy than traditional methods.

O. Dekhil et al. [6] proposed a new autism diagnostic CAD model by fusion of anatomical and functional information from sMRI and fMRI. The CAD model was applied to 47 subjects and demonstrated a high accuracy of 94.74 % overall distinction between autism and normally developing brains. It also included local brain region assessment, which will classify subjects to the autism spectrum and help practitioners to provide specific care for people with autism. Yun Jiao et al. [7] described autism classification using several cortical measures derived from SBM and comparing the results of classification between these mixture features. We found curvature offers only limited information on the thickness of the predictive model of ASD and their findings indicated that patients with ASD may have more irregular cortical thickness than cortical curvature. Anibal Sólon Heinsfeld et al. [8] studied functional communication patterns that classify ASD patients objectively from functional brain imaging information and attempted to expose the neural structures that originated from the classification. Researchers also defined the brain areas that most contributed to separating ASD from typically developing controls according to the concept of deep learning.

Daniel Bone et al. [9] have produced algorithms that are more effective than existing algorithms, adjustable (sensitivity and specificity can be weighted differently) and more reliable.

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Results from ADI-R and SRS ML-based fusion were reported and presented with a screener algorithm below (above) age 10 that achieved sensitivity of 89.2 % (86.7%) and specificity of 59.0 % (53.4 %) with only five codes of conduct. Yan Jin et al. [10] demonstrated the feasibility of using machine learning methods to classify high-risk ASD infants as early as six months after birth, based on the finding that white matter (WM) tract and whole-brain integration ASD-induced defects have already started to occur within 24 months of birth. They proposed a new multi-kernel support vector machine classification system using connectivity features obtained from WM communication networks that achieve an accuracy of 76 % and an area of 0.80 under the receiver operating characteristic curve (AUC) compared to 70 % accuracy and 70 % AUC given by the best single-scale parameter network.

The paper is structured as follows: The symptoms, types, and effect of ASD are presented in section 1, Methodology for computer-aided diagnosis of ASD is discussed in section 2, section 3 gives a comparison of ASD detection using Machine Learning Techniques, experimentation and results for ASD VS TC classification with forward feature selection using K-NN is presented in section 4 followed by conclusion in section 5.

2. Methodology for Classification of ASD

2.1. Methodology

The general procedure for the diagnosis of ASD as a classification problem is described in Figure 2. The ASD cases and controls are selected from the diagnostic tool. The preprocessing like sampling, noise removal, feature extraction, and selection is done. The processed data is given to the detective model of ASD classification using machine learning techniques. The prediction results are then tested and verified.

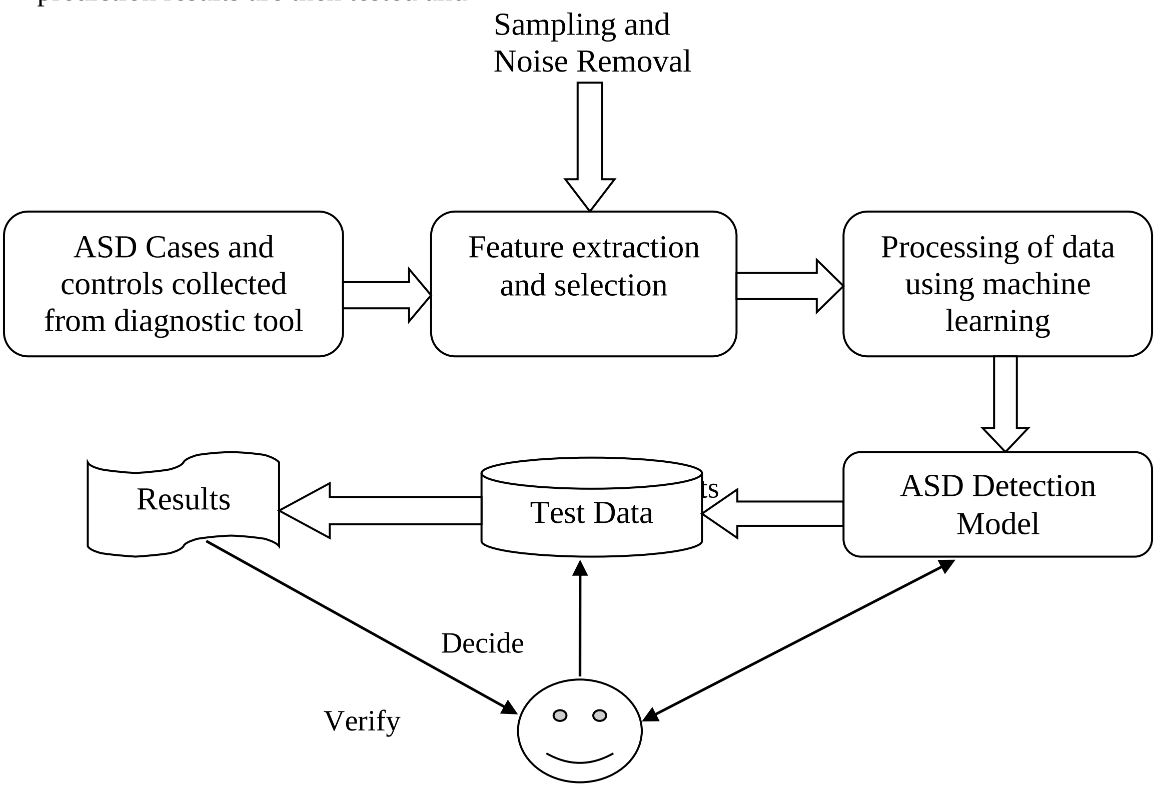

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Figure 2. Methodology for detection of ASD

2.2. Feature Extraction and Selection

In machine learning applications one of the most important tasks is data preprocessing. The data that are collected for training in the machine learning tasks are not appropriate for the training purposes initially. This needs to be analyzed to make the data usable for such applications. Processing includes techniques for noise identification and management of missing data. Pre-processing of data is carried out to prepare the data for input into processes of machine learning and mining. It includes transforming the data to improve their reliability and hence the efficiency of the algorithms in machine learning, such as predictive accuracy and reduced learning time. One of the tasks of data pre-processing is the collection of features in which only some of the features are chosen and used in the learning algorithm's training process. The goal is to find the best possible subset of features, which increases the learning algorithm's efficiency. Features in a dataset can be relevant i.e. the features that have an influence on the output or irrelevant i.e. the features that have no effect on the output. Thus feature selection involves identifying the relevant features and using them in the machine learning application and ignoring the rest of the features with little or no predictive information. The choice of features is therefore very critical techniques that need to be developed to find an appropriate subset of features from the original features superset. The features chosen for ASD detection are based on physical characteristics such as shape and size [18], Statistical features [5,21], textural analysis features, asymmetry based features, Questionnaires[2,3,24], Phenotypic features [4,8,22], Acoustic features [19,20], Demographic features [11], Eye gaze features [11,15], Correlation-based features [9,13] etc. Reduction of dimensionality is the conversion of high-dimensional data into a significant representation of compact dimensionality. To treat this information properly, it needs to reduce its dimensionality. The dimensionality curse dictates that the dimensionality of pattern representation should be kept as small as possible by a model developer. A small but important collection of features simplifies the representation of the pattern as well as the classifiers based on the representation selected. In addition, if the numbers of training samples are minimum, a less number of features will mitigate the curse of dimensionality. The extraction and selection of features are two important steps in the creation of an appropriate pattern representation.

2.3. Machine Learning Techniques used for Classification

Machine learning approaches provide automated, efficient and effective classification models for the ASD problem as they use a combination of computer science and mathematical methods. Researchers have recently applied a variety of different machine learning techniques to the ASD classification e.g. K-NN [2, 3, 13, 15, 17, 21, 25], SVM [7-10, 13-20, 22-26], Naïve Bayes [3, 13, 17, 25, 26], LDA [2, 24], ANN [4, 15, 16, 21], Random Forest [1, 3, 8, 13, 17, 18, 26], Fuzzy Technique [7], Deep Learning [5,8], Decision Trees [11, 13, 15, 23, 24], Rule classifiers [11, 17, 25], etc. ASD detection is considered a standard classification problem in machine learning where a model is built on the basis of cases and controls previously categorized. The new case detection type (ASD, Non-ASD (TC)) can then be defined using these methods.

3. Comparison on ASD Detection Using Machine Learning Techniques

Several research papers are reported in the literature with different approaches to classifying

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ASD. Table 2 provides a comprehensive overview of classifier types, modality used, various stages of ASD, the number of samples, extracted features, classification results etc. used to detect abnormalities.

Table 2. Comparison of ASD Detection using Machine Learning Techniques

Classifier Used	Modality	No of Samples	Features	Accuracy
RF, GBM [1]	MRI	Total 876= 417 (367 Males, 50 Females) ASD +459 (382 Males, 77 Females) Typically Developing Children	White matter, Gray matter, cerebrospinal fluid, total intracranial volume	Accuracy= 60% AUC=61%
LDA, K-NN [2]	Questionnaire	292 Samples = 141 ASD+151 Non ASD (4-11Yrs)	19 Different attribute/ Questions	LDA= 90.80 %
NB, K-NN, RBFN, RF [3]	Questionnaire	244 Samples	21 Different attribute/ Questions	Author= 100%
NN [4]	rsfMRI	529 Autism, 571 typical controls	Phenotypic features e.g. Age, Sex, Handedness, Full IQ, Eye status	DNN= 70.1 %
Deep Learning [5]	rsfMRI	Total | ASD | NC 38 | 19 | 19 110 | 55 | 55 35 | 13 | 22	NMI matrix, Pearson matrix	NMI= 59.09% (D2 Dataset)
MDN [6]	sMRI, fMRI	47subjects = (22 autistic (20 Males, 2 Females) +25 controls (all males))	Cerebral cortex, cerebral white Matter	Modality Fusion=94.7%
SVM, FT, LMT [7]	MRI	22 ASD Children, 16 Normal Children	Cortical thicknesses, mean curvature, Gaussian curvature, folding index, curvature index	FT, LMT= 76%
DNN, SVM, RF [8]	rsfMRI, sMRI	505 ASD individuals, 530 typical controls	Phenotypic features e.g. Age, Sex, Handedness, Full IQ, Eye status	DNN= 70%
MLCV, SVM [9]	Questionnaire	1264 ASD, 462 non-ASD	Correlation-based Features	ML Fusion= 89.2%
SVM	MRI	40 High-Risk Infants	White Matter	SVM= 76%

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[10]		(29 Males, 11 Females). 40 Low-Risk Infants (27 Males,13 Female)	Multiscale Connectivity network of element	
RRF, C4.5, DT, PART [11]	Eye Gaze	91 Female, 166 Male (Age 2-132)	Eye Gaze and demographic features like age and gender	PART= 94.7 %
HMM [12]	Behavioral Patterns	4 ASD, 4 Normal Subjects	Self Stimulatory patterns like Hand Flapping, Punching, Drumming, Rocking	Flap = 96%
DT, RF, NB, MP, BN, SVM, K-NN [13]	Centre of Pressure	19 Normal Adults (19-35 yrs), 11 ASD Adults (19-40 yrs)	Correlation-based Features	RF=97.6 %
SVM, ELM [14]	Light sensor, Wireless Bluetooth Sensor	17 High-Risk Infants, 15 Low-Risk Infants (1-3 yrs)	Sub Movements like Reach, Place Duration, etc.	ELM=81.67 %
SVM, K-NN, DT, ANN, Discriminant Analysis [15]	EEG	20 ASD Subjects = 19 Male +1 Female	Eye Gaze, Performance, Psychology, EEG Features	Feature Level Fusion=84.4%
NN, SVM [16]	AMTI force plates	32 Normal Subjects+ 12 ASD Subjects	Gait parameters e.g. temporal-spatial, kinetic and kinematic features	SVM (Poly)= 95.8 %
BN, NB, K-NN, SVM, MP, RF, J48[17]	EEG	16 ASD Teenagers (13-18 Yrs)	Enjoyment, frustration, boredom, behavioral engagement, and difficulty	K-NN= 85.96%
RF, SVM, GBM [18]	sMRI	373 ASD + 361 TDC	Area, Volume, Thickness, Folding Index, Mean and Gauss Curvature	Accuracy= 60%
SVM, GA [19]	Speech Recorder	99 Subjects= 35 ASD +64 Normal Subjects	6373 Acoustic Features like MFCC, PCM, etc.	GA L2 (Test) = 78.6%

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MKL-SVM [20]	Speech Recorder , OpenEAR	20 ASD Children (4-9 yrs), 21 typically developing Children	484 Acoustic Features like MFCC, LPC, etc., 44 Dimensional Acoustic Features,11 Statistical Functions	MKL-SVM= 80.2 %
DWT, Entropy, ANN, K-NN [21]	EEG	9 ASD Children, 10 Normal Children (9-19 yrs)	Statistical Features like mean, SD, Variance and Entropy functions like Shannon entropy	ANN= 99.7%
SVM, BN, RBF, SMO, GT [22]	fMRI, sMRI	127 Children with ASD, 153 age and gender-matched TC	Phenotypic features, Quantitative Imaging features	RBF= 70%
SVM, Elman NN, DT [23]	fMRI	50 ASD, 42 TD Children	Supplementary motor area, the median cingulate and paracingulate gyri, the fusiform gyrus (FG) and the insula (INS).	Elman NN= 84.7 %
DT, RT,SVM, LR,CL, LDA [24]	Questionnaire	2775 ASD, 150 ADHD	Social Responsiveness Scale questions	SVM=96.5 %
SVM, NB, RT, C4.5, CS-CRT, K-NN [25]	rsfMRI	60 ASD Subjects (52 Males, 8 Females), 45 Typically Developing Subjects (38 Males, 7 Females)	Centrality measures namely degree, betweenness, eigenvector and leverage	RT= 88.46 %
SVM, RF, MP, NB [26]	rsfMRI	147 subjects with ASD and 146 healthy controls	Functional connections variability	SVM= 61.1 %

ASD=Autism Spectral Disorder, SVM=Support Vector Machine, K-NN= K- Nearest Neighbor, DT=Decision Tree, NB=Naive Bayes, RF=Random Forest, MP=Multilayer Perceptron, BN=Bayesian Network, ELM= Extreme Learning Machine, LDA= Linear Discriminant Analysis, ANN= Artificial Neural Network, MKL=Multiple Kernel Learning, PCA= Principal Component Analysis, FT= Functional Trees, LMT= Logistic Model Trees, DNN= Deep Neural Network, DWT= Discrete Wavelet Transform, SMO= Sequential Minimal Optimization, RBFN=Radial Basis Function Network , NMI= Normalized Mutual Information.

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4. Experimentation and Results

For ASD VS TC classification, 153 ASD and 157 TC axial sMRI and fMRI images from Autism Brain Imaging Data Exchange (ABIDE) is selected. The K-NN classification with cross-validation is done using K-fold values 3, 5, 7, 9, 10, 15. In the training phase, feature vectors and class labels of each image are used. The feature vectors are extracted for each image using Gray Level Co-occurrence Matrix (GLCM) calculated for distance d = 1 with angles θ = 0°, 45°, 90°, 135°. Initially Contrast, Correlation, Energy, Homogeneity were chosen as basic features and then added one by one Inverse Difference Moment, Entropy, Symmetrical Feature, Spatial Frequency, Information Measure of Correlation using method of forward selection of features. The performance of K-NN classification is evaluated and compared using different parameters like accuracy, specificity, sensitivity. Forward Selection of features is done to improve classification performance. The sMRI and fMRI are not giving satisfactory results individually for mentioned features. Table 3 shows the classification results with forward selection of features using K-NN classifier.

Table 3. Results for ASD VS TC Classification

K-Fold	No. of Features	Accuracy (%)		Sensitivity (%)		Specificity (%)	
		sMRI	fMRI	sMRI	fMRI	sMRI	fMRI
K=9	4	70.59	70.59	64.17	70.59	76.47	70.59
	5	64.71	70.59	70.59	88.24	58.82	52.94
	6	64.71	67.65	52.94	88.24	76.41	47.06
	7	61.76	67.65	70.59	64.71	52.94	70.59
	8	85.29	67.65	100	70.59	70.59	64.71
	9	76.47	73.53	64.71	64.71	88.24	82.35
K= 15	4	76.19	71.13	100	81.82	54.55	60.00
	5	**85.71**	75.00	70.00	80.00	100	70.00
	6	75.00	75.00	80.00	90.00	70.00	60.00
	7	80.00	75.00	80.00	70.00	80.00	80.00
	8	80.95	80.95	72.73	70.00	90.00	90.91
	9	80.00	**85.71**	90.00	90.91	70.00	80.00

The huge scope for research can be seen from the results as: Classification of brain MR images into ASD or non-ASD (TC) can be carried out for large datasets. Better classification can be obtained with optimization of features to get dimensionality reduction. Classification performance can be improved with the fusion of sMRI and fMRI images. The obtained results can be validated using the feedback received through radiologist.

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5. Conclusion

Manual techniques are too costly and time-consuming to detect presence of ASD. It is necessary to identify the correct classifier for automatic classification, which is acceptable in terms of accuracy and computational speed, and has promising results for the extraction and classification of basic features. This work presents a significant comparison of different Machine Learning techniques for automatic classification of ASD. In this paper, GLCM method is used for feature extraction and forward selection of features is performed for performance improvement. The K-NN classifier gives the maximum accuracy 85.71% for sMRI with 5 features and for fMRI with 9 features for K-fold=15. Further accuracy is decreased or increased as features added. Therefore to improve the accuracy of classification, feature optimization is required. Fusion of sMRI and fMRI images can give better results as fused image is having the qualities of both the source images. Thus with the help of automatic classification and fusion techniques for increased subjects, radiologists and researchers can get better classification results which will improve the accuracy of ASD detection.

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Authors

Mamata Lohar
She is currently pursuing her Ph.D. form AISSMS Institute of Information Technology, Pune, Maharashtra. She has completed her Master's degree in E&TC (Signal Processing) Engineering from P.E.S. Modern College of Engineering, Pune in 2015. Her research interest is in development of Computer-aided Diagnosis (CAD) System using Machine Learning Techniques for neurological disorders.

Suvarna Chorage
She is presently working as a Professor in E&TC Engineering in Bharati Vidyapeeth's College of Engineering for Women, Pune. She is graduated from Mumbai University in E&TC Engineering in 1996 and received her M.E. in E&TC Microwave Engineering in 2003 from Government College of Engineering, Pune. She has received her Ph. D. in Electronics Engineering from Bharati Vidyapeeth University, Pune in 2012. Her research topic is "Investigations and analyses of crosstalk and interference penalties in all optical DWDM systems". She has total 22yrs of experience in teaching. Her subject expertise in radiation and microwave techniques, Signals and systems, digital communication, Information theory and coding techniques, optical fiber communication, mobile communication, software defined radio and machine intelligence. She has published 23 research papers in renowned international journals that includes Elsevier, optical engineering, IEEE explore, national and international conferences.

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