Frontiers in Health Informatics www.healthinformaticsjournal.com
ISSN-Online: 2676-7104
2024; Vol 13: Issue 2 Open Access

A Robust Autism Brain MRI Classification with GLCM Features and Machine Learning

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Article Info

Article type:

Research

Article History:

Received: 2024-03-21

Revised: 2024-05-26

Accepted: 2024-06-20

Keywords:

Autism, Brain MRI, fMRI, Feature extraction, Extra Tree (ET), Gray Level Co-occurrence Matrix (GLCM), Light Gradient Boosting Machine (LGBM), Random Forest (RF), sMRI

ABSTRACT

A new robust classification method for analyzing magnetic response images is provided here as a result of the significance of the automated and accurate classification of brain magnetic resonance imaging (MRI] images. Feature extraction, feature selection, and classification are the three stages that make up the system that has been suggested. When we want to extract features from brain sMRI and fMRI, we utilize a technique called Gray Level Co-occurrence Matrix (GLCM), and then we apply recursive feature elimination to choose the most meaningful features. The classifier's goal is to classify subjects' brain sMRI and fMRI as typical (normal) or autistic. A classification with a success of 91.40% accuracy for Child Database, 87.69% for Adolescents Database and 84.12% for Adults database is obtained by Light GBM classifier for sMRI. The Random Forest gives maximum accuracy for Child and Adult database and Light Gradient Boosting Machine gives maximum accuracy for Adolescents database of fMRI. Similarly, a classification with a success of 76.4% and 74% accuracy for Child and Adults database is obtained by Random Forest and 74.29% for adolescents' database with Light GBM for fMRI database. A robust and efficient technique that minimizes the computational complexity for classification between autism and typical (normal) MRI pictures is the result of the suggested method, which, in comparison to many other recent efforts, results in a robust and efficient strategy.

1.INTRODUCTION

In the present era, computer technology has become an indispensable tool across various medical disciplines, such as cancer research, heart conditions, gastrointestinal disorders, and brain diseases. Over the past few decades, there has been a growing recognition of the significance of computer-assisted diagnosis (CAD) [1] within intelligent healthcare systems. Magnetic resonance imaging (MRI), a safe and painless non-invasive method, is employed to assess the human body, particularly the brain. To enhance the precision of automatically categorizing MRI images for disease identification without human intervention, there is a pressing need, given the vital importance of accurate diagnosis and treatment for brain pathologies.

There is a lot of difficulty involved in the process of automatically classifying MRI into normal and pathological groups in CAD. The primary reason for the difficulty in understanding the brain image is the requirement for the rapid integration of detection techniques that have a high degree of precision. A two-step method is required in order to identify any abnormalities that may be present in brain pictures. Initially, the atypical magnetic resonance pictures of the brain are categorized into a number of different groups (image classification). This is done because the strategy for diagnosis differs depending on the type of irregularity being examined. Additionally, the irregular part (image segmentation) is removed to conduct volumetric analysis that will check the success rate of treatment of the patient.

The diagnosis of autism spectrum disorder (ASD) in a timely and accurate manner is one of the most critical aspects in the treatment of those who have been diagnosed with this illness. The term "autism spectrum disorder" (ASD) refers to a neurodevelopmental condition that is characterized by a wide range of impairments. These impairments can be identified by a variety of challenges, including difficulties in managing with interactions, repeated behaviors, voice, and nonverbal communication. ASD is commonly referred to as ASD. ASD focuses on the gender component. There are significant differences and disadvantages between the autistic children and adults. The permanent failure is found if earlier step ASD is not identified. Therefore, automated methods are needed for precise and early identification. Modern biomarker research has also advanced in terms of risk assessment, diagnosis, and tracking the disorder's course. Machine learning used in healthcare has made predictive advances by storing and interpreting the large volume of data.

The main work focuses on automatic recognition approaches for correctly diagnosing ASD from typical controls. The majority of research for classifying sMRI and fMRI is focused on pattern recognition techniques, where the challenge is to extract useful features, frequently using Digital Wavelet Transformation (DWT) [24, 25, 26] or Co-occurrences Matrix [27]. To extract features, the Gray Level Co-occurrences Matrix (GLCM), published in [27,21] is employed. Comparatively speaking, GLCM is less computationally complex than other techniques like the wavelet transform. This paper's primary goal is to extract useful features using GLCM for autism brain classification from typical (normal) brain [27, 30]. To carry out the research, the database is divided into 3 groups on the basis of their age such as Child (2-10 years), Adolescents (11-16 years) and Adults (>16 yrs) of sMRI and fMRI for each is selected from Autism Brain Imaging Data Exchange (ABIDE). By transforming the original feature space into a smaller subspace, feature reduction techniques shrink the original feature space. The recursive feature elimination technique yields the optimized features. The process of classification makes use of a wide variety of machine learning algorithms, including but not limited to Gradient Boosting, Ridge, LDA, QDA, Random Forest, Extra Tree classifier, Random Forest, SVM, Naive Bayes, Random Forest, Decision Tree, Logistic Regression, Adaboost, Gradient Boosting, Ridge, and many others. Among these, Random Forest, Extra Tree classifier, and Light Gradient Boosting Machine produced the greatest results for fundamental feature extraction, which is utilized for the diagnosis of autism spectrum condition [33, 34]. The Random Forest ensemble's output class is determined by taking the average of the classes that are produced by each decision tree in the ensemble. An ensemble strategy is utilized, and its success is contingent upon the reduction of the total error term's variance. A decision tree is a straightforward classifier that splits the input space into more homogenous groups in an iterative manner by utilizing fundamental notions of decision-making. An ensemble learning technique known as the Extra Tree classifier is a method that combines the results of several de-correlated decision trees into a "forest" in order to arrive at a classification result. Using decision trees as its foundation, the LightGBM is a gradient boosting framework that improves the performance of the model while simultaneously reducing the amount of memory it uses. The proposed method produces a more accurate and dependable automatic categorization of sMRI and fMRI TC/ASD brain pictures by utilizing a powerful classifier and an efficient feature extraction tool [33, 34]. These classification algorithms would divide sMRI and fMRI images into TC and ASD images based on a number of characteristics, such as Accuracy, AUC, Recall, Precision, F1 Score, Kappa, MCC, etc. The age-wise classification of ASD and TC yielded very good results. The architecture of this document is as given: Section 2 provides a brief description of our approach, which involves a database, feature extraction, and feature selection. Techniques for classification are presented in Section 3. A comparison and explanation of the classification results are given in Section 4. This paper is concluded in Section 5.

2.METHODOLOGY

Gray Level Co-occurrence Matrix (GLCM), Extra Tree Classifier (ET), Random Forest (RF), and Light Gradient Boosting Machine (LGBM) are the techniques that form the foundation of the suggested method, which is depicted above in Figure 3. There are three stages that make up this process: the stage of feature extraction, the stage of feature selection, and the stage of categorization. The classification stage makes use of these classifiers, which split the population into two categories: typical (normal) and autism.

2.1 Database: -

The sMRI and fMRI Images are obtained from the Autism Brain Imaging Data Exchange Studies (ABIDE) database. It contains again 3 types of images namely axial, coronal and sagittal images. From these 3 images, we have selected axial images for the classification. These images are T1 weighted.

(a)sMRI TC (b) sMRI ASD (c) fMRI TC (d) fMRI ASD

Fig 1: - sMRI and fMRI images from ABIDE Database[34]

The TABLE I shows the age-wise database used for classification [34].

TABLE I

ABIDE DATABASE

Sr. No.	Age Group	Number of Samples sMRI and fMRI	
		Autism	Controls
1	Child (2-10 yrs)	279	346
2	Adolescents (11-16 yrs)	870	958
3	Adults (>16 yrs)	1094	1174

2.2 GLCM Feature Extraction: -

The consistency of colors and patterns in an object or image, such as in bricks, school uniforms, sand, pebbles, grass, etc., is referred to as texture. To classify objects in a picture based on texture, we should search for the consistent distribution of colors and patterns on the object's surface. Haralick An image's texture can be quantified using texture. Haralick created textural characteristics in 1973. The main concept in calculating Haralick Texture characteristics is the Gray Level Co-occurrence Matrix, or GLCM [21,28].

TABLE II

GLCM FEATURES AND FORMULAE [21]

Sr. No.	Features	Formulae
1	Energy (ASM)	E = $\sum_{i=1}^{m-1}\sum_{j=1}^{n-1}(p(i,j))^2$
2	Contrast	C= $\sum_{i=1}^{m-1}\sum_{j=1}^{n-1}(i-j)^2 p(i,j)$
3	Correlation	CO = $\frac{\sum_i\sum_j(i*j)p(i,j)-(\mu x*\mu y)}{(\sigma x*\sigma y)}$
4	Variance	V= $\frac{1}{m*n}\sum_{i=1}^{m}\sum_{j=1}^{n}(I(i,j)-\mu)^2$
5	Inverse Difference Moment	IDM = $\sum_{i=1}^{m-1}\sum_{j=1}^{n-1}\frac{1}{1+(j-1)^2}p(i,j)$
6	Sum Average	SA=$\sum_{i=2}^{2N} i * Px + y\ (i)$
7	Sum Variance	SV= $\sum_{i=2}^{2N}(i-SE)^2 Px - y(i)$
8	Sum Entropy	SE= $-\sum_{i=2}^{2N} Px + y(i) \log\{Px + y(i)\}$
9	Entropy	S = $\sum_{i=1}^{m-1}\sum_{j=1}^{n-1}p(i,j)\log(P(i,j))$
10	Difference Variance	$DV = \sum_i (i-u)^2 p_{x-y}(i)$ Where $p_{x-y}(k) = (k = \|i-j\|)\sum_{i=1}^{Ng}\sum_{j=1}^{Ng}p(i,j)$
11	Difference	DE=

	Entropy	$-\sum_{i=0}^{N-1} Px-y(i)\log\{Px-y(i)\}$
12	Information Measure of Correlation	$IMC=\frac{H_{XY}-H_{XY1}}{\max\{H_X,H_Y\}}$ $H_{XY}=-\sum_i\sum_j p(i,j)\log(P(i,j))$ $H_{XY1}=-\sum_i\sum_j p(i,j)\log\{Px(i)Py(j)\}$ H_X and H_Y are Entropies of Px and Py
13	Maximal Correlation Coefficient	(Second largest Eigen value of Q)^0.5

The Gray Level Co-occurrence Matrix (GLCM) analyses images utilizing the adjacency concept. The basic principle is that it continuously captures all pairs of neighboring pixel values that appear in an image. The GLCM structure is shown in the image below.

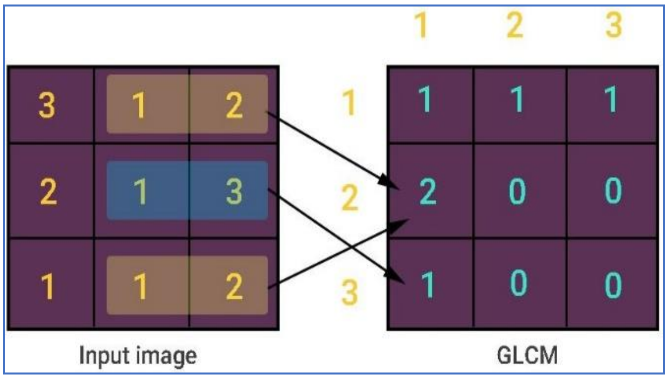


Fig 2: - Gray Level Co-occurrence Matrix (GLCM) [21]

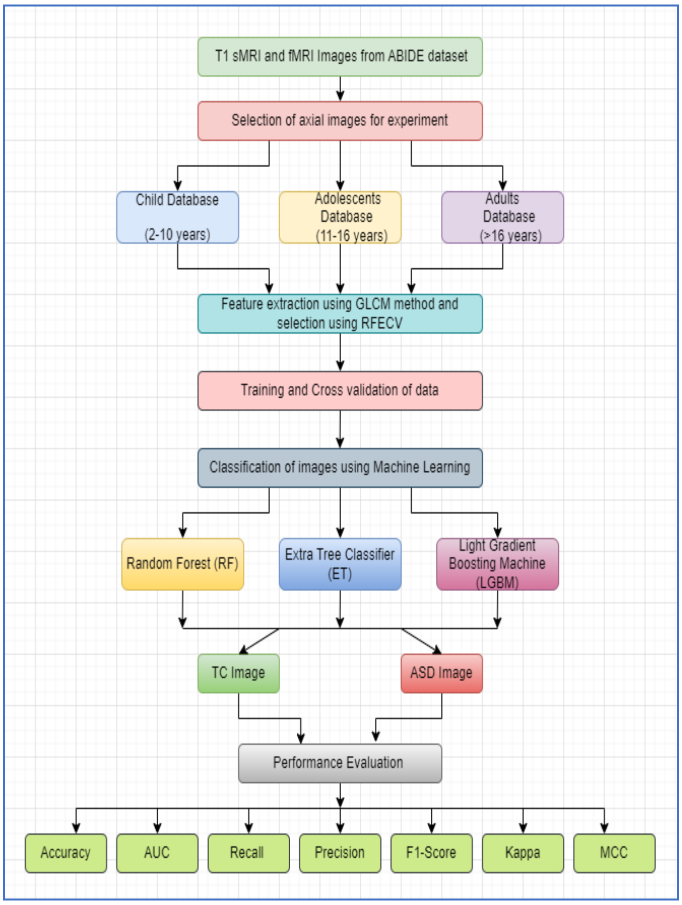
Since gray-level pixel values 1 and 2 appear twice in the aforementioned image, GLCM counts them as two. However, because pixel values 1 and 3 only appear once in the image, GLCM counts them as one. Of course, we have just considered the calculation of adjacency from left to right. Since there are actually four different types of adjacency, four GLCM matrices are created for a single image. The next four categories of adjacency are listed. 1. Left-to-Right 2. Top-to-Bottom 3. Top-Left-to-Right-Bottom 4. Top-Right-to-Bottom-Left. 4. Right-to-Left at the top. Thirteen textural features that are based on statistical theory are generated from the four GLCM matrices [33,34].

2.3 Feature Selection: -

Elimination of Recursive characteristics The process of selecting the most advantageous characteristics is known as cross validation. Through the utilization of recursive feature elimination Cross-Validation (RFECV), this is accomplished by deleting 0 to N features, where N is the total number of features. This approach is a feature selection method that selects the most appropriate subset of features for the estimator that is provided. The model's cross-validation score is then used to determine which subset is the most representative of the whole. Recursive feature removal involves refitting a model with N features removed, leaving out the weakest features each time. The coef_ or feature_importances_attribute of the fitted model indicates which characteristics are the weakest. This process is done until all N features have been removed. The visualization displays trends in feature reduction and depicts the score in relation to each subset. If the feature removal CV score is flat, the model might not have enough features. When the score gradually declines from the optimal number of features to a low value as the number of features deleted increases, the curve is perfect [34].

2.4 Block Diagram: -

Figure 3 depicts the block architecture for the categorization of autism spectrum disorder (ASD) and transgender (TC) utilizing various machine learning techniques, including the extraction and selection of GLCM features through the use of Recursive Feature Elimination Cross Validation (RFECV).



MCC: - Matthews correlation coefficient, TC: - Typical Control, ASD: - Autism Spectrum Disorder, GLCM: - Grey Level Co-occurrence Matrix, RFECV: -Recursive Feature Elimination Cross Validation)

Fig 3: Block Schematic of ASD Detection using different Machine Learning Algorithms

3.CLASSIFICATION TECHNIQUES

3.1 Random Forest (RF): -

Random Forest is an ensemble of decision trees, and the output class of Random Forest is determined by the mode type of the unique output class of each decision tree. The reduction of the variance of the general error term is the basis for this ensemble approach, which is dependent on the variance. The primary objective of RF is to reduce the overall error of the ensemble by reducing the variance term while simultaneously preserving a consistent bias. This form of variance minimization can be accomplished by multiplying the classifiers that have a significant variance or the classifiers that have decision trees. The decision trees' ability to eliminate errors through comparison improves with increasing complexity or lack of correlation. The term 'Random Forest' refers to the way RF infuses randomness into the tree-building process in order to differentiate amongst decision trees. First, data processing is used to apply randomization, and then, decision trees are built using this technique. Each tree is trained using a copy of bootstrapped data that was gathered by random sampling and replacement in the source data. Because of this, the decision trees have some degree of randomness because they have several bootstrap replicas.

3.2 Extra Tree (ET): -

The output of several de-correlated decision trees gathered in a "forest" is combined via an ensemble learning method known as Extremely Randomized Trees Classifiers (or Extra Trees Classifiers) to provide a single classification result. The only conceptual distinction between the forest and a Random Forest Classifier is in the construction of the decision trees. The original training sample is used to build each decision tree in the Extra Trees Forest. Subsequently, each tree receives a random sample of k features from the feature-set at each test node. Its task is to determine which feature in the feature-set is the best fit for partitioning the data according to a given mathematical criterion (typically the Gini Index). Many de-correlated decision trees are devloped as a result of this random feature selection procedure. The normalized total reduction in the mathematical criteria used in the feature of split decision (or the Gini Index if the Gini Index is used in the construction of the forest) is computed for each feature during the construction of the forest in order to perform feature selection using the above forest structure. The feature's Gini Importance is denoted by this value. The user ranks each feature according to its Gini Importance and then selects the top k attributes that most appeal to them [16].

3.3 Light Gradient Boosting Machine (LGBM): -

A gradient boosting framework that is founded on decision trees, LightGBM is able to increase model performance while simultaneously reducing the amount of memory that is used. LightGBM divides the tree leaf-wise, in contrast to earlier boosting algorithms that developed trees level-by-level before moving on to the next level. In order to grow, it chooses the leaf that has seen the highest delta loss. In comparison to the level-wise approach, the leaf-wise technique suffers from a lower amount of loss because the leaf is fixed. There is a possibility that the complexity of the model will increase as a consequence of the growth of the tree in a leaf-wise manner, which may also lead to overfitting in limited data.

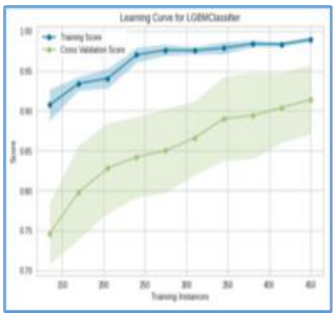
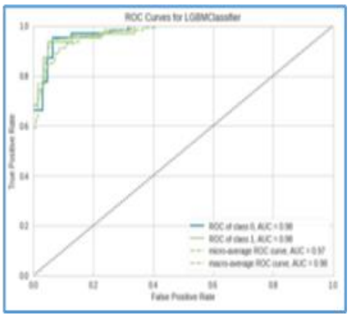
1. Experimental Results Comparison

For the purpose of classifying ASD from TC, axial sMRI and fMRI pictures are chosen from the Autism Brain Imaging Data Exchange (ABIDE). Three age groups—children (2–10 years old), adolescents (11–16 years old), and adults (>16 years old) are separated within the database. The training phase makes use of each image's feature vectors and class labels. With angles θ = 0°, 45°, 90°, and 135°, and a distance of d = 1, the Gray Level Co-occurrence Matrix (GLCM) is used to extract the feature vectors for each image. The ASM, Contrast, Correlation, variance, Inverse Difference Moment, Sum Average, Sum Variance, Sum Entropy, Entropy, Difference Variance, Difference Entropy, Information Measure of Correlation, and Maximal Correlation Coefficient are the Haralick features that are determined from each image. The effectiveness of various classification algorithms is assessed and contrasted through the use of several metrics, such as MCC, F1 Score, AUC, Accuracy, Recall, and Precision. To enhance the classification performance for every age group, hyper-parameter adjustment is carried out [33, 34].

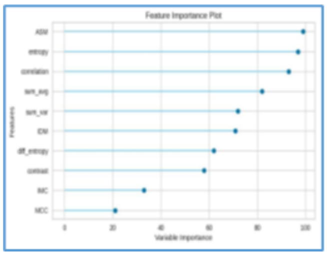
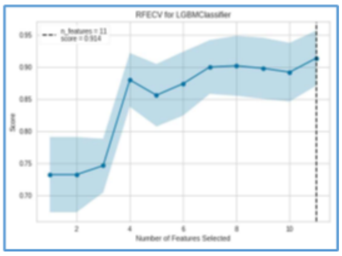
TABLE III

ASD vs TC Classification Results for sMRI with Parameter Tuning

Classifier	Extra Tree Classifier			Random Forest			Light GBM		
Parameters	Child (2-10 yrs)	Adolescents (11-16 yrs)	Adults (>16 yrs)	Child (2-10 yrs)	Adolescents (11-16 yrs)	Adults (>16 yrs)	Child (2-10yrs)	Adolescents (11-16 yrs)	Adults (>16 yrs)
Accuracy	0.91	0.8043	0.6212	0.896	0.8584	0.6428	0.914	0.8769	0.8412
AUC	0.9784	0.8946	0.6853	0.9642	0.934	0.7014	0.9641	0.9405	0.9153
Recall	0.9256	0.8483	0.5464	0.9505	0.8993	0.6181	0.9289	0.9059	0.8674
Prec.	0.9169	0.7929	0.6598	0.8782	0.8422	0.665	0.9208	0.8672	0.8333
F1	0.92	0.8188	0.5973	0.9117	0.8693	0.64	0.9241	0.8855	0.8493
Kappa	0.8169	0.6065	0.2459	0.7857	0.7151	0.2865	0.8248	0.7526	0.6817
MCC	0.8201	0.6098	0.2499	0.7931	0.7182	0.2878	0.8267	0.7547	0.6837

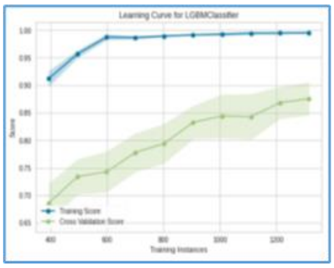
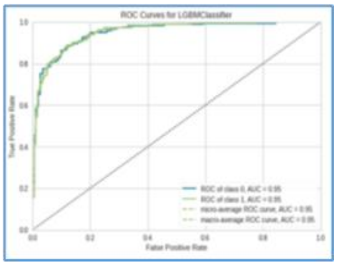



(4.a) Learning Curve *(4.b) ROC Curve*

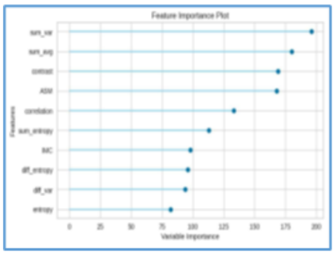
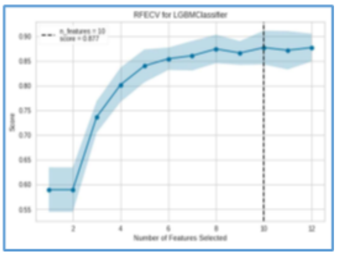



(4.c) Feature Importance Plot *(4.d) RFECV Plot*

Fig 4: Inference Graphs for sMRI Child Database

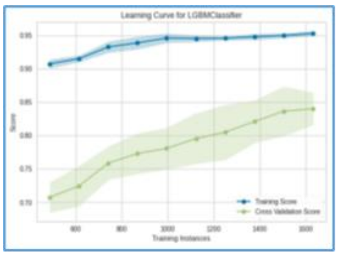
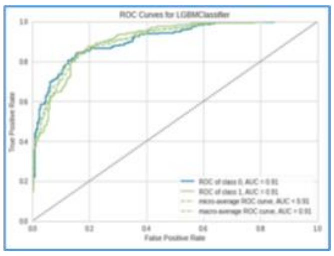



(5.a) Learning Curve *(5.b)ROC Curve*

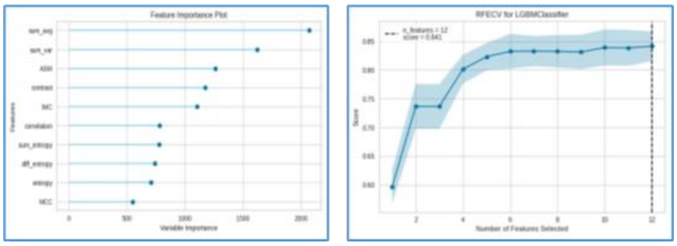



(5.c) Feature Importance Plot *(5.d) RFECV Plot*

Fig 5: Inference Graphs for sMRI Adolescents Database

(6.a) Learning Curve *(6.b)ROC Curve*



(6.c) Feature Importance Plot *(6.d)RFECV Plot*

Fig 6: Inference Graphs for sMRI Adults Database

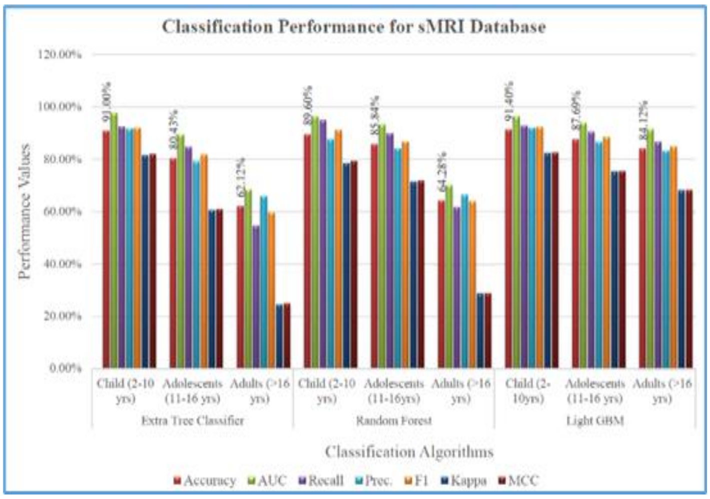
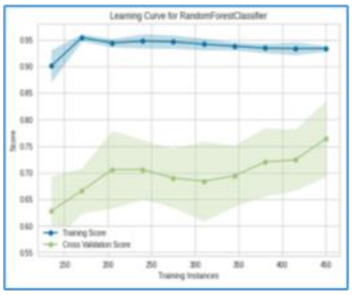


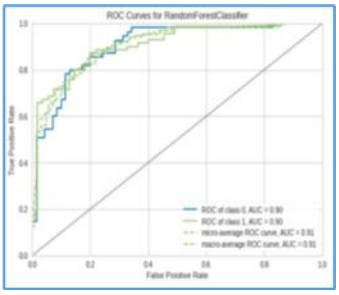
Fig 7: Comparison of ASD vs TC Classification for sMRI Dataset

TABLE IV

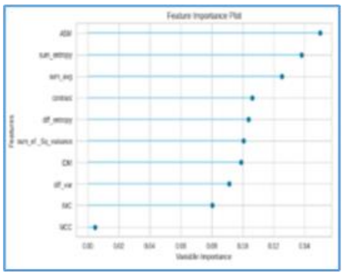
ASD VS TC CLASSIFICATION RESULTS FOR FMRI WITH PARAMETER TUNING

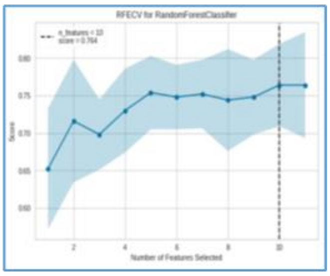
Classifier	Extra Tree Classifier			Random Forest			Light GBM		
Parameters	Child (2-10 yrs)	Adolescents (11-16 yrs)	Adults (>16 yrs)	Child (2-10 yrs)	Adolescents (11-16 yrs)	Adults (>16 yrs)	Child (2-10yrs)	Adolescents (11-16 yrs)	Adults (>16 yrs)
Accuracy	0.7200	0.6436	0.6929	0.7640	0.7312	0.7400	0.7260	0.7429	0.6565
AUC	0.7985	0.7104	0.7762	0.8241	0.8148	0.8069	0.7930	0.8328	0.7115
Recall	0.7104	0.7095	0.6275	0.7858	0.7951	0.6968	0.7931	0.7791	0.6467
Prec.	0.7665	0.6355	0.7399	0.7869	0.7120	0.7625	0.7375	0.7371	0.6767
F1	0.7362	0.6703	0.6778	0.7855	0.7504	0.7272	0.7615	0.7546	0.6606
Kappa	0.4387	0.2851	0.3880	0.5228	0.4607	0.4602	0.4400	0.4846	0.3132
MCC	0.4414	0.2874	0.3940	0.5240	0.4656	0.4633	0.4469	0.4895	0.3142





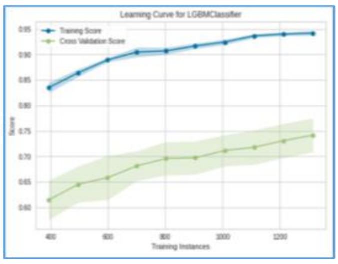
(8.a) Learning Curve *(8.b)ROC Curve*

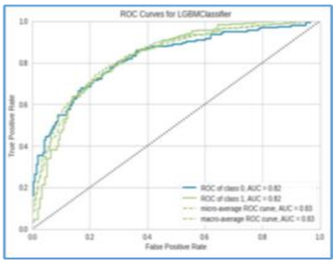




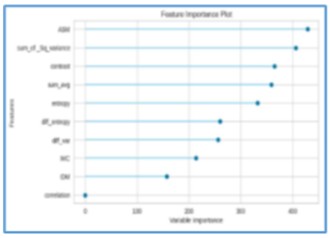
(8.c) Feature Importance Plot *(8.d)RFECV Plot*

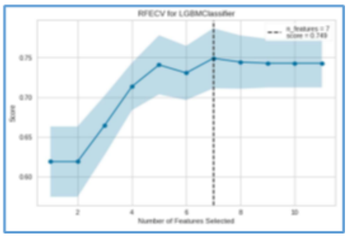
Fig 8: Inference Graphs for fMRI Child Database





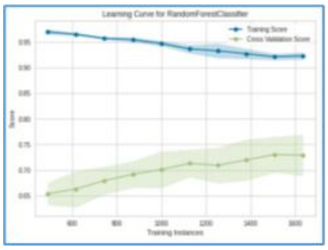
(9.a) Learning Curve *(9.b)ROC Curve*

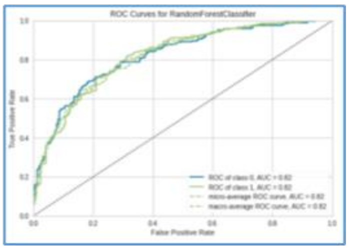




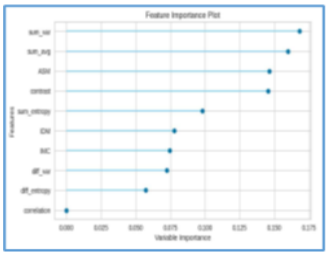
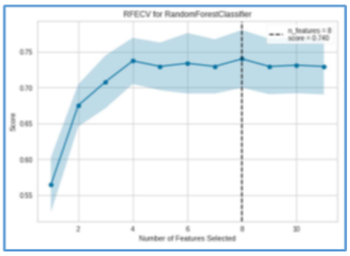
(9.c) Feature Importance Plot *(9.d)RFECV Plot*

Fig 9: Inference Graphs for fMRI Adolescents Database





(10.a) Learning Curve *(10.b)ROC Curve*

(10.c) Feature Importance Plot *(10.d)RFECV Plot*

Fig 10: Inference Graphs for fMRI Adults Database

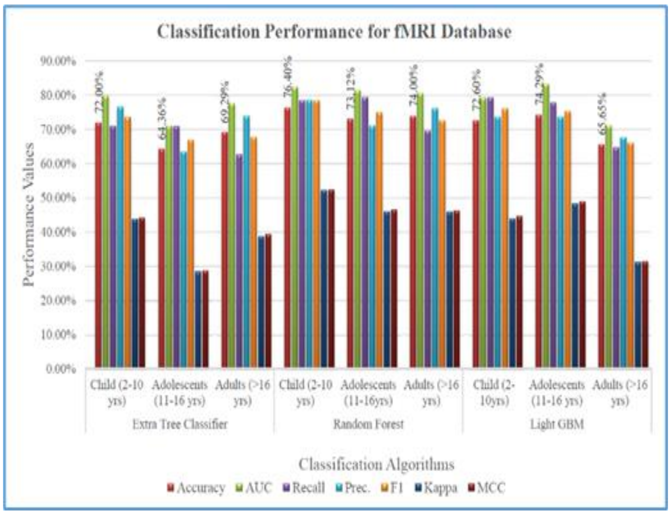


Fig 11: Comparison of ASD vs TC Classification for fMRI Dataset

Following the accumulation of all of these findings, it has been determined that the GLCM approach of texture feature extraction is effective for both the sMRI and fMRI pictures. The feature elimination with cross validation gave better accuracy for optimized features. Grouping of subject on the basis of their ages gives improved classification performance between ASD and TC for both sMRI and fMRI images. Extra Tree Classifier, Random Forest and Light Gradient Boosting Machine gave the best classification performance. Hyper-parameter tuning for these classifiers even more enhanced the classification results. The performance for all machine learning algorithms is validated using K-fold=10 cross validations.

4.CONCLUSION

The goal of this work is to create a medical decision support system that can classify each functional magnetic resonance imaging (fMRI) and structural magnetic resonance imaging (sMRI) scan for autism against typical (normal) brain. This automatic detection system achieves very satisfactory and encouraging results to support the prompt diagnosis of the brain disease known as autism. These results are achieved with the assistance of the Gray Level Co-occurrence Matrix (GLCM), Extra Tree Classifier (ET), Random Forest (RF), and Light Gradient Boosting Machine (LGBM). The methodology that was built in this work is based on applying the efficient image features and utilizing a recursive feature reduction strategy in order to differentiate between autism and normal brain for sMRIs and fMRIs of child, teenager, and adult individuals independently. This was done in order to achieve the goal of identifying autism. The Light Gradient Boosting Machine gives the maximum classification accuracy for all 3 databases of sMRI. Our work produces 91.40% accuracy for Child Database, 87.69% for Adolescents Database and 84.12% for Adults Database for sMRI. The Random Forest gives maximum accuracy for Child and Adult database and Light Gradient Boosting Machine gives maximum accuracy for Adolescents database of fMRI. We got 76.4% and 74% accuracy for Child and Adults respectively and 74.29% for adolescents for fMRI database. Furthermore, since the combined image has the characteristics of both the source images, fMRI and sMRI image fusion can produce even better classification results.

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