

# Early Prediction of Autism Spectrum Disorder by Computational Approaches to fMRI Analysis with Early Learning Technique

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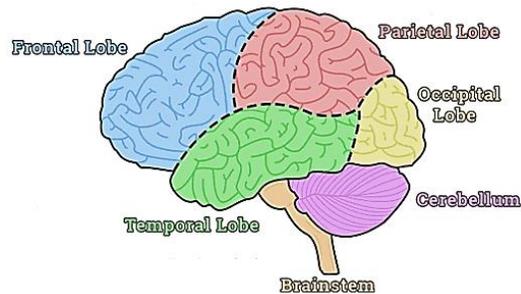
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**Abstract-** The neuro imaging developmental classification studies are undergone with small amount of samples from the brain activity samples. It promises the inspiring complications in high dimensional data analysis. Autism prediction methodologies are based on behavioral function alone previously which provides good precision but repossession will be unfortunate. We address those problems for early prediction of autism with neural development modern techniques and compared with older. Moreover, visualization of brain activities is quite important in neuro imaging. We believe in better visualization and classification of neuro images in early month captures and appended of Mullen Scales of Early Learning (MSEL). Functional magnetic resonance imaging (fMRI) is one of the controlling tools for measuring non-invasively measure brain activity and it provides with good resolution. For high resolution of brain activity, fMRI gives better than electro encephalon graph (EEG). Visualization of brain activity very clearly is first step to recognize the faults of autism. We have taken into the account for predicting in early Autism Spectrum Disorder (ASD) with help of multiple behavioral activities and development measures using machine learning algorithm. The prediction methods are examined with mostly many prediction methods start to examine the neuro imaging with ultra-high risk factors. The prediction of ASD is moderate accuracy in 14 month development measures from multiple time points. In this proposed work, Mullen early prediction is appended for early prediction and it is examined with computational approach to fMRI analysis with adaptive functioning classifier for machine learning algorithm. This proposed algorithm provides improved version of classification in machine languages with MSEL and high accuracy with conservative methods.

**Keywords:** *deep learning, fMRI, Autism Spectrum Disorder*

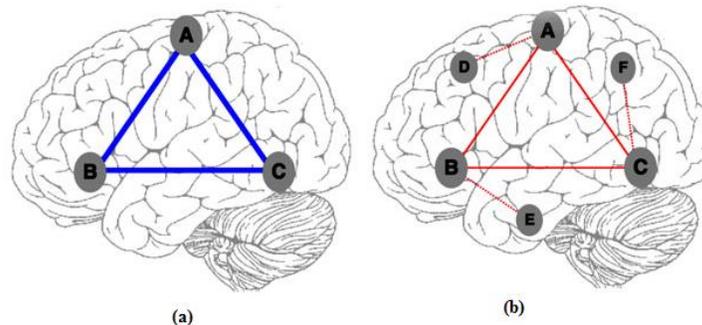
## 1. INTRODUCTION

One of the complex organs in the human body is brain which connects with almost all the organs through many veins and nerves (1). Mainly it divides with some parts as follows, frontal lobe, parietal lobe, occipital lobe, temporal lobe and cerebellum. It is shown in figure 1 in below.



**Figure 1** Human Brain with primary parts division

Dissociation of neural in the brain and behavior development leads to inability to the human is called autism. The autism symptoms may vary child to child. But the symptoms of autism can be detected after 12 to 18 months. It is very hard to detect before this period of children (2). The autism person has problem with verbal and nonverbal communication; hence there is absence of their eye contact with us. The autism brain contains face processing networks is very weaker. The treatment will be more effective and it's curable sometimes if autism is detected as early as possible. The over connectivity of the nerves in brain says autistic function as shows in figure 2.



**Figure 2** (a) Normal brain typical connectivity (b) Autistic brain connectivity

Recently, clinical laboratory categories an identifying in early the autism spectrum disorder is a top priority. Infant at high risk in an early age stage, the brain will be in developing stage before core autism signs in behavioral or in the biological mark have emerged. There is possible to alter the early intervention strategies (3, 4, 5).

In a brain, autism neural function is affected easily in cerebral cortex, amygdala, basal gandla, corpus callosum and cerebellum. Also we can estimate in those parts with mullen scale parameters. Usually, amygdala region in brain is responsible for aggressive behavior. Also hippocampus contains the nerves system that remembering recent events and information. Mainly, those areas are started to affect for autistic parameters. We believed this logic and bio marked in those places for early prediction of autism behavior. We succeed it too.

## 2. RELATED WORKS

Vaishali R et al investigate the optimum behavior sets for autism which consists of 21 features getting from UCI machine learning. It says that possible to achieve better accuracy with less number of features (6). Fadi thabatah et al has come across machine learning method with ASD screening model. They highlight the problems that arise in DSM manuals and solve (7). Mohamed shanavas et at propose the research idea to detect the autism problems and stages of autism with a help of SVM in the neural networks. Also they show students behavior and their social interaction (8). J.A. Kosmickil et al study on evaluation of clinical assessment of ASD with different machine learning approach. They are evaluating in their paper with those 28 behaviors parameters from module, and calculated ASD risk with good accuracy (9). Suman raj et al investigated detection of ASD using different techniques of machine

learning approaches. It clinically proves high accuracy than exist methods (3). Li B, et al proposes the imitation method in machine learning algorithm. Here discriminative test conditions are investigated with kinetic parameters on the adolescent dataset. Also, consideration of kinetic parameters for detection of autism, the sensitivity rate is high compared to others (10). Arbabshirani et al studies focus that in order to predict individual outcome of ASD, uses behavioral measure alone. They emphasis was depends on theory that by identifying infants at risk at early age when brain is growing up. The linear regression method is very efficient when linear progression between input and output (11).

Most of the works are done and detected ASD and it gives different accuracy and sensitivity levels. These works miscarries in early prediction of ASD in all. The prediction algorithm is Mullen scales of early learning and fMRI analysis and FC to detect autistic behavior in child. In this work, comparing linear regression with Mullen scales of early learning prediction and approaches for scaling up advanced fMRI analysis for model analysis.

### ***Motivation***

The early diagnosis or intervention of ASD is quite challenging task in clinical field. Generally, “autism is a lifelong developmental disability”. It is degenerative an irreversible process during the young age or early stage of disorder and when their brain plasticity is much more that easier to prevent ASD. So the detection of ASD is not providing perfect solution for their life. With the intention of avert, naming the children as “autistic” in their community and for the rest of their lives. This reason is the motivation of this research article. Mostly many researchers are showing decrease in brain connectivity between default node and network node in brain bio marks.

## **3. ORGANIZATION OF THE RESEARCH**

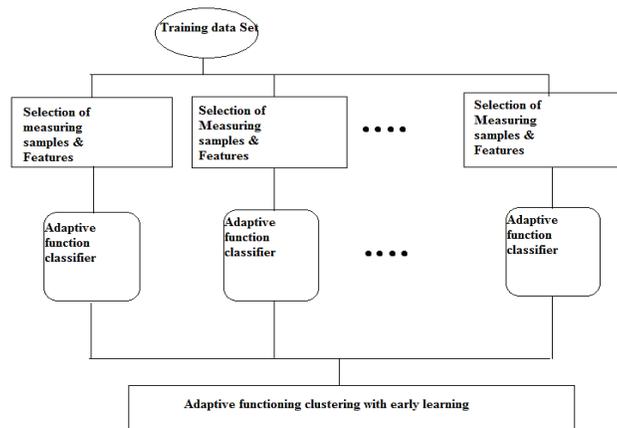
This research article covers introduction, related work, and motivation, theoretical analyses for early prediction for autism, results and discussion, conclusion in a row.

## **4. THEORETICAL ANALYSES**

Functional magnetic resonance imaging (fMRI) is one of the standard tools is to characterize the brain function in health and disease (12, 13, 14, 15). We can understand that how ASD exhibits functionally in the successive interval. Using fMRI data, we can early predict autism behavior function with the help of detecting sensitive and particular biomarkers for ASD (4, 5). There are lots of studies to understand and predict the specific biomarkers for ASD due to local functional or operational brain abnormalities in ASD (16). Our research suggests that there can be found relevant markers for ASD whereas irregularities in the brain function connectivity with the help of functional connectivity.

### ***Mullen scale of early learning***

Figure 3 shows design of our proposed algorithm that adaptive functioning classifier will done after selected measuring samples and features. Those features are clustered and predicted with Mullen scale early learning. The scale function is measuring from cognitive functioning and provides score for overall intelligence for infants and preschool- age children. The overall intelligence is estimating by this composite score.



**Figure 3** Overview of design of proposed study

The fMRI connectivity is the useful biomarkers for ASD though in the complex connectivity relation of different parts of the brain. Also fMRI connectivity involves in good very complicated pattern of changes in biomarks system in brain (17, 18, 19). Functional MRI data collected from ABIDE data set. This data set needs preprocessing procedure to analysis and classification purpose due to some variance of signal due to noise environment and physiological disturbance like sudden respiration, hand motions etc. Sometimes non neural variability will be occurred during the process (20, 21). To rectify those problems, blind deconvolution method can be carried out in this process. Initially, in order to make mean zero normalization of every ROI, preprocess should be done. In every pair of ROIs, FC will be computed and it gives us connectivity matrix to perform graphs for each subject. In order to differentiate between two groups of features these ROI approach is used. The Functional Connectivity (FC) analyses used to synchronize ROIs. The complex network constructed with graphs from FC. The data is divided into group or individual by linear model for statistical analyses (22).

This complex network measures are used to identify the node or vertex for machine learning classification. This identification has contained that inclusive of node degrees, node strengths, clustering co efficient, centrality of node and edge both as well (23,36). The centrality of edges provides the number of all shortest paths between the given nodes. These nodes are divides further in the network and named as modules. The form of degree centrality can be limited the module degree. Inside the module connection of individual nodes are measured by harmonizing participation coefficient (HPC). This CPC will facilitate the functional segregation and integration to do clustering for classification in the complex network (24, 36). This clustering of brain region ROIs will be measured in the given networks. There is a calculation of the average clustering co-efficient of the node in the network (25, 26).

The clustering construction is necessary to compute in the complex network for optimization purpose. With the intention of maximize the intra ROI links and reduces the connection between localize nodes; the clustering construction is being constructed. There are classified into low and high degree vertices. Our proposed technique is clustering the coefficients in the entire graph with the help of transforming regularization (TR) method. This combined version of clustering and segregation of inter and intra community nodes called integration. The calculation of average distance between the vertices is defined as;

$$A_{dv} = \frac{1}{N} \sum_{n=1}^N X(n) \cdot \frac{1}{|V(G)| - 1} \cdot \sum_{v \neq w} d(v, w)$$

Where N is Number of vertex and every vertex  $v \in V(G)$

In a complex network, the calculation of correlation coefficient between the nodes in the community is necessary for measuring the resilience of it. In order to measure the assort coefficient function for the network, the

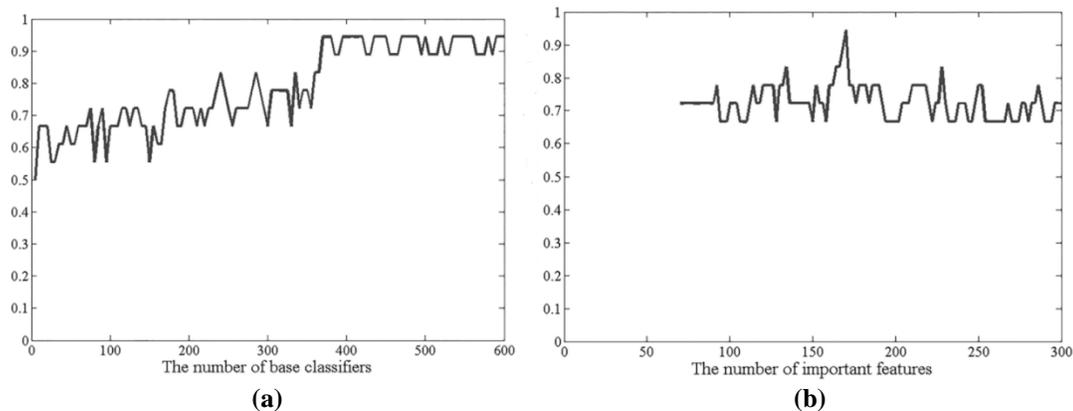
resilience factor calculation is essential. In our proposed algorithm, the input data is splitting into two which is known as training and testing data. The training data can be clustering the features  $F$  in to “ $n$ ” clusters by  $k$  means algorithm. There is a computation of performance of every cluster. After computation of performance of every cluster, remove 20% of clusters with assigned scores (27). The remaining features are shifted into single community region. This will be evaluated classification accuracy with the testing data. This is the process known as SVM classification (21, 28, 29, 30).

#### **Importance of higher classification accuracy**

For early prediction, the classification and computational approach should be effective. Due to getting the higher classification accuracy, our functional MRI data should be rich for cognitive neuroscience. Many modified progression will be considered to yield for early diagnosis from the conservative methods. The process modifies by often involving concrete and improves the visual perception. Then manipulate the model localizing model variables in the brain; after locate the variables appropriately and it is estimate parameters independently of behaviors like errors and loss (31, 32, 33). This behavior is red and computed decision variables step to final stage. It provides better result compared to the fMRI analysis. The fMRI data will be combined in group by mean value at each vertex by the cross validation (34). Additionally, finding the most important voxels for the classifier, the evolutionary algorithm is used in which different voxel clusters are used to train and evaluate the classifier (35).

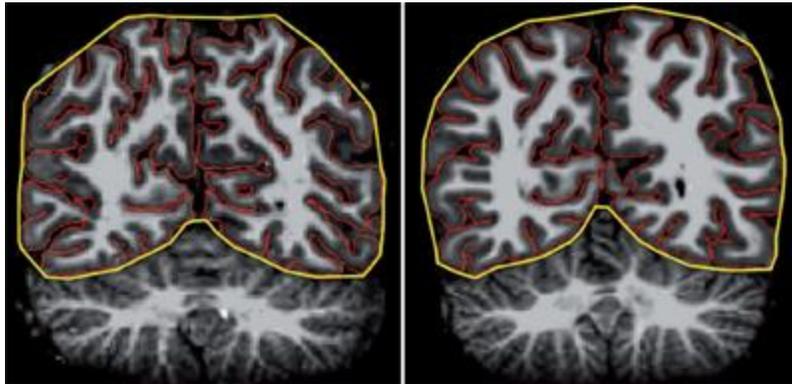
## **5. RESULTS AND DISCUSSIONS**

In Classifiers, our proposed study shows great performance in accuracy level which is showed in figure 4 (a) & (b). The vertical axis in (a) figure is that accuracy of our proposed study. Moreover, the accuracy is measured with important features shown in the graph.



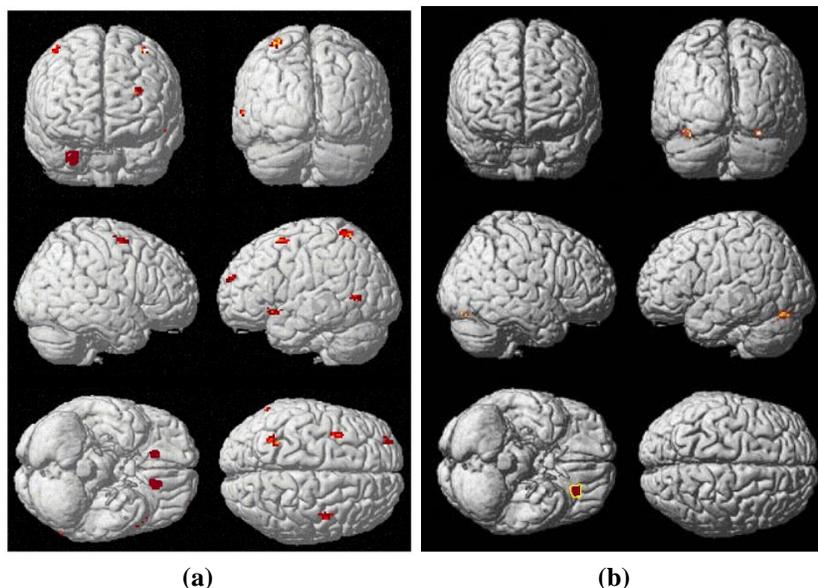
**Figure 4 (a) & (b)** Our proposed method accuracy between base classifiers & important features

The linear regression based algorithms are predicted in coronal slice of scanned image as “autistic” function after computed the feature of thicker cortex and more folds. Even though absence of thicker cortex in frontal lobe of the brain, our proposed algorithm identifying autistics behavior in the image which shown in the figure 5b.



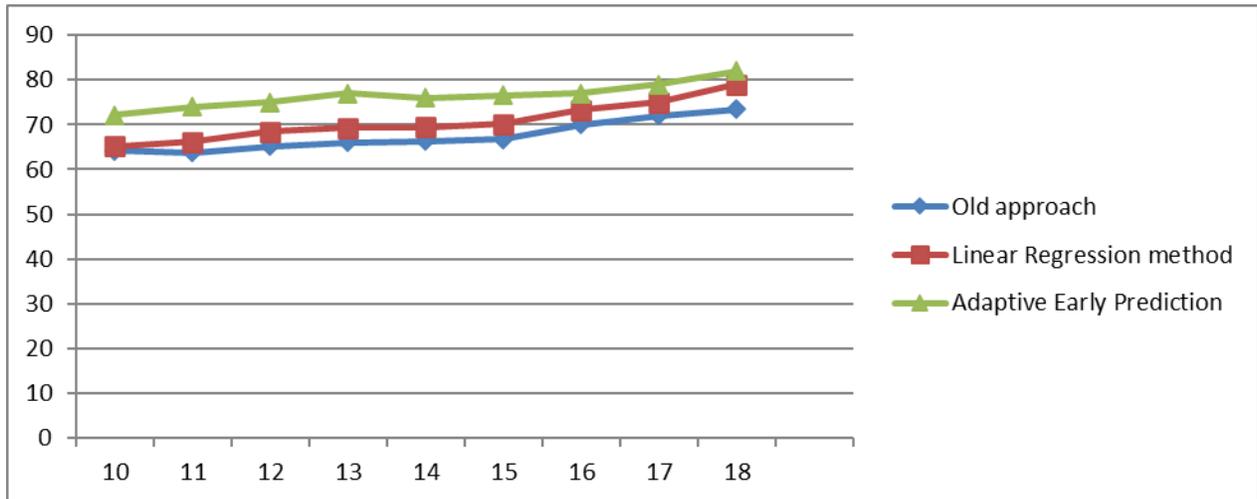
**Figure 5 (a) & (b) Presence of Neural wrinkles in top sliced view of brain**

The autism brain image is having more folds and thicker cortex in its neuro function which is shown in figure 6 (a). The figure 6 (b) tells that our algorithm predicted well autistic function at early stage while other algorithm is unsuccessful.



**Figure 6 (a) Predicted region with normal neuro functioning brain (b) Autism neuro functioning brain**

Due to increase the parameters to predict the autism functioning in the brain nervous which will be responsible for the early prediction of autism. Our method is providing good effects in higher level aspects of cognition as early prediction during decision, valuation, control (DVC) and social interactions. The early prediction results highlight that MSEL is useful technique to assist medical physician to predict autism in a high accuracy. This tool is considering the main parameters receptive and expressive language, visual and fine motor impairments during early stage of children. Our proposed method appears to be sensitive to behavior activities. In the linear regression method, deviates output coefficients when inputs increase more complexity. Our integrated SVM algorithm is suitable and effective in high dimensional space. The sensitivity of the linear regression prediction gradually increases with our proposed study for early prediction which is shown in figure 8. The horizontal axis of figure 8 is from 10<sup>th</sup> month of child. Our proposed study has proved good sensitive in predicting autism in early stages and shown in figure 8.



**Figure 8** Comparison of sensitivity parameters from 10<sup>th</sup> month

## 6. CONCLUSION

The proposed study is aimed well with combination of adaptive functioning classifier and early learning techniques and works well. Since our process is based on high dimensional spaces, it shows the effective work. Also here appropriate kernel function will be hard to choose. The computational approach will address the complexity of theoretical models with less number of empirical data. Our proposed method considers this computational approach that dimension of variation at every voxel. The space will expands widely with the voxel dimension variation. This challenging problem solved by our computational approach which may improve the ability to predict the cognitive signals in earlier. Since we are having less data set our proposed algorithm was suited for the process. In case of analysis the large data; our algorithm has to revise. We were preprocessed our algorithm to perform and handle easy less amount of noisy data set. Our proposed technique is improved process for number of features for each data point exceeds the number of training data samples. The execution time for advanced scaling up fMRI analysis method is greater than model based analysis without Mullen scale of early learning. The revised algorithm has to implement.

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## REFERENCES

- [1] Sarraf, Saman & Sun, Jian. "Advances in Functional Brain Imaging: A Comprehensive Survey for Engineers and Physical Scientists" International Journal of Advanced Research. 4. 640-660. 10.21474/IJAR01/1259. (2016).
- [2] Webb SJ, Jones EJ, Kelly J, Dawson G. "The motivation for very early intervention for infants at high risk for autism spectrum disorders". Int J Speech Lang Pathol. 2014 Feb;16(1):36-42. doi: 10.3109/17549507.2013.861018. PMID: 24410019; PMCID: PMC4141560.
- [3] Suman Raj "Analysis and Detection of Autism Spectrum Disorder Using Machine Learning Techniques" Published in Procedia Computer Science 167:994-1004, January 2020, DOI: [10.1016/j.procs.2020.03.399](https://doi.org/10.1016/j.procs.2020.03.399)

- [4] Lemoine, Lise & Schneider, Benoît, “Autism Spectrum Disorder in French children's literature: an analysis of portrayals of children with autism in the light of the DSM-5” *Research in Autism Spectrum Disorders*. 80. 10.1016/j.rasd.2020.101675. (2020).
- [5] Carrie Cuffman, Kimberly Burkhart, “Constipation prevalence and perceptions: Comparison of children and adolescents with ASD and other developmental-behavioral disorders” *Research in Autism Spectrum Disorders*, Volume 80, 2021, <https://doi.org/10.1016/j.rasd.2020.101710>.
- [6] Vaishali, R., and R. Sasikala. "A machine learning based approach to classify Autism with optimum behaviour sets" (2018) *International Journal of Engineering & Technology* 7(4): 18.
- [7] Fadi Thabtah. (2017). “Autism spectrum disorder screening: machine learning adaptation and DSM-5 fulfillment.” In *Proceedings of the 1st International Conference on Medical and Health Informatics*, pp. 1-6. ACM.
- [8] M. S. Mythili, and AR Mohamed Shanavas. “A study on Autism spectrum disorders using classification techniques”, *International Journal of Soft Computing and Engineering (IJSCE)*, 4: 88-91, (2014)
- [9] J. A. Kosmicki, V. Sochat, M. Duda, and D. P. Wall. (2015) “Searching for a minimal set of behaviors for autism detection through feature selection-based machine learning”, *Translational psychiatry*, 5(2): e514.
- [10] Baihua Li, Arjun Sharma, James Meng, Senthil Purushwalkam, and Emma Gowen. (2017) “Applying machine learning to identify autistic adults using imitation: An exploratory study.” *PloS one*, 12(8): e0182652.
- [11] Arbabshirani, M. R., Plis, S., Sui, J. & Calhoun, V. D. “Single subject prediction of brain disorders in neuroimaging: promises and pitfalls”, *Neuro Image* 145, 137–165 (2017).
- [12] Bi, Xia-an & Jiang, Qin & Sun, Qi & Shu, Qing & Liu, Yingchao.. “Analysis of Alzheimer’s Disease Based on the Random Neural Network Cluster in fMRI” *Frontiers in Neuroinformatics*. 12. 10.3389/fninf.2018.00060. (2018)
- [13] Cohen, Jonathan & Daw, Nathaniel & Engelhardt, Barbara & Hasson, Uri & Li, Kai & Niv, Yael & Norman, Kenneth & Pillow, Jonathan & Ramadge, Peter & Turk-Browne, Nick & Willke, Theodore. “Computational approaches to fMRI analysis” *Nature Neuroscience*. 20. 304. 10.1038/nn.4499.(2017)
- [14] Eklund A, Andersson M, Knutsson H. “fMRI analysis on the GPU-possibilities and challenges” *Comput Methods Programs Biomed*. 2012 Feb;105(2):145-61. doi: 10.1016/j.cmpb.2011.07.007. Epub 2011 Aug 20. PMID: 21862169.
- [15] Bi XA, Shu Q, Sun Q, Xu Q. “Random support vector machine cluster analysis of resting-state fMRI in Alzheimer's disease” *PLoS One*. 2018 Mar 23;13(3):e0194479. doi: 10.1371/journal.pone.0194479. PMID: 29570705; PMCID: PMC5865739.
- [16] Libero LE, DeRamus TP, Lahti AC, Deshpande G, Kana RK. “Multimodal neuroimaging based classification of autism spectrum disorder using anatomical, neurochemical, and white matter correlates” *Cortex*. 2015 May;66:46-59. doi: 10.1016/j.cortex.2015.02.008. Epub 2015 Mar 3. PMID: 25797658; PMCID: PMC4782775.
- [17] Murdaugh DL, Shinkareva SV, Deshpande HR, Wang J, Pennick MR, Kana RK. “Differential deactivation during mentalizing and classification of autism based on default mode network connectivity” *PLoS One*. 2012;7(11):e50064. doi: 10.1371/journal.pone.0050064. Epub 2012 Nov 19. PMID: 23185536; PMCID: PMC3501481.

- [18] Bussu G, Jones EJH, Charman T, Johnson MH, Buitelaar JK; BASIS Team. "Prediction of Autism at 3 Years from Behavioural and Developmental Measures in High-Risk Infants: A Longitudinal Cross-Domain Classifier Analysis" *J Autism Dev Disord.* 2018 Jul;48(7):2418-2433. doi: 10.1007/s10803-018-3509-x. PMID: 29453709; PMCID: PMC5996007.
- [19] Deshpande G, Libero LE, Sreenivasan KR, Deshpande HD, Kana RK. "Identification of neural connectivity signatures of autism using machine learning" *Front Hum Neurosci.* 2013 Oct 17;7:670. doi: 10.3389/fnhum.2013.00670. PMID: 24151458; PMCID: PMC3798048.
- [20] Christensen DL, Bilder DA, Zahorodny W, Pettygrove S, Durkin MS, Fitzgerald RT, Rice C, Kurzius-Spencer M, Baio J, Yeargin-Allsopp M. "Prevalence and Characteristics of Autism Spectrum Disorder Among 4-Year-Old Children in the Autism and Developmental Disabilities Monitoring Network" *J Dev Behav Pediatr.* 2016 Jan;37(1):1-8. doi: 10.1097/DBP.0000000000000235. PMID: 26651088.
- [21] Bi XA, Shu Q, Sun Q, Xu Q. "Random support vector machine cluster analysis of resting-state fMRI in Alzheimer's disease" *PLoS One.* 2018 Mar 23;13(3):e0194479. doi: 10.1371/journal.pone.0194479. PMID: 29570705; PMCID: PMC5865739.
- [22] Siobhan O'Hagan, Caroline Bond, Judith Hebron, "What do we know about home education and autism? A thematic synthesis review", *Research in Autism Spectrum Disorders*, Volume 80,2021,101711, ISSN 1750-9467, <https://doi.org/10.1016/j.rasd.2020.101711>.
- [23] Greenstein D, Malley JD, Weisinger B, Clasen L, Gogtay N. "Using multivariate machine learning methods and structural MRI to classify childhood onset schizophrenia and healthy controls" *Front Psychiatry.* 2012 Jun 1;3:53. doi: 10.3389/fpsy.2012.00053. PMID: 22675310; PMCID: PMC3365783.
- [24] May, Tamara & Yi, Karen & Loveland, Kate & Vollenhoven, Beverley & Williams, Katrina. (2021). "Overlap of autism and conditions associated with atypical sex hormone levels or response: A systematic review and meta-analysis", *Research in Autism Spectrum Disorders.* 80. 101693. 10.1016/j.rasd.2020.101693.
- [25] Xu L, Geng X, He X, Li J, Yu J. "Prediction in Autism by Deep Learning Short-Time Spontaneous Hemodynamic Fluctuations" *Front Neurosci.* 2019 Nov 8;13:1120. doi: 10.3389/fnins.2019.01120. PMID: 31780879; PMCID: PMC6856557.
- [26] Werkman, M.F. & Brouwer, Sandra & Dijkxhoorn, Y.M. & Berckelaer-Onnes, I.A. & Reijneveld, S.A. & Landsman, J.A. & Begeer, Sander. (2020) "The moderating effect of cognitive abilities on the association between sensory processing and emotional and behavioural problems and social participation in autistic individuals", *Research in Autism Spectrum Disorders.* 78. 101663. 10.1016/j.rasd.2020.101663.
- [27] Yousef M, Jung S, Showe LC, Showe MK. "Recursive cluster elimination (RCE) for classification and feature selection from gene expression data" *BMC Bioinformatics.* 2007 May 2;8:144. doi: 10.1186/1471-2105-8-144. PMID: 17474999; PMCID: PMC1877816.
- [28] El-Baz, Ayman. "Machine learning applications to recognize autism and Alzheimer's disease" 10.1088/978-0-7503-1793-1ch1,(2019).

- [29] assin, W., Nakatani, H., Zhu, Y. et al. "Machine-learning classification using neuroimaging data in schizophrenia, autism, ultra-high risk and first-episode psychosis" *Transl Psychiatry* 10, 278 (2020). <https://doi.org/10.1038/s41398-020-00965-5>
- [30] Rudovic, Ognjen & Lee, Jaeryoung & Dai, Miles & Schuller, Björn & Picard, Rosalind. (2018). "Personalized Machine Learning for Robot Perception of Affect and Engagement in Autism Therapy" *Science*. 3. 10.1126/scirobotics.aao6760.
- [31] Spain, Debbie & Sin, Jacqueline & Linder, Kai & McMahon, Johanna & Happe, Francesca. (2018). "Social anxiety in autism spectrum disorder: A systematic review", *Research in Autism Spectrum Disorders*. 52. 51-68. 10.1016/j.rasd.2018.04.007.
- [32] Mateos-Pérez, José & Dadar, Mahsa & Lacalle-Auriolas, María & Iturria, Yasser & Zeighami, Yashar & Evans, Alan. "Structural neuroimaging as clinical predictor: a review of machine learning applications." (2018)
- [33] Emily McDougal, Deborah M. Riby, Mary Hanley, "Teacher insights into the barriers and facilitators of learning in autism, *Research in Autism Spectrum Disorders*", Volume 79, 2020, 101674, ISSN 1750-9467, <https://doi.org/10.1016/j.rasd.2020.101674>.
- [34] Ismail MM, Keynton RS, Mostapha MM, ElTanboly AH, Casanova MF, Gimel'farb GL, El-Baz A. "Studying Autism Spectrum Disorder with Structural and Diffusion Magnetic Resonance Imaging: A Survey", *Front Hum Neurosci*. 2016 May 11;10:211. doi: 10.3389/fnhum.2016.00211. PMID: 27242476; PMCID: PMC4862981.
- [35] Webb SJ, Jones EJ, Kelly J, Dawson G. "The motivation for very early intervention for infants at high risk for autism spectrum disorders". *Int J Speech Lang Pathol*. 2014 Feb;16(1):36-42. doi: 10.3109/17549507.2013.861018. PMID: 24410019; PMCID: PMC4141560.
- [36] Chaitra, N. & Vijaya, P.A. & Deshpande, Gopikrishna. "Diagnostic prediction of autism spectrum disorder using complex network measures in a machine learning framework" *Biomedical Signal Processing and Control*. 62. 102099. 10.1016/j.bspc.2020.102099. (2020)