

MACHINE LEARNING MODEL FOR AUTISM PREDICTION IN TODDLERS

M. SYAMALA SAI SREE¹, G SANJANA², SEJAL KADAM², K NANDHINI², M. VAISHNAVI²

¹Assistant Professor, Department of Information Technology, Mallareddy Engineering College for Women, (UGC-Autonomous), Hyderabad, India, syamalamallubhotla71@gmail.com.

²Student, Department of Information Technology, Mallareddy Engineering College for Women, (UGC-Autonomous), Hyderabad, India.

Abstract

Autism Spectrum Disorder (ASD), commonly referred to as "autism," is a psychiatric condition that affects a person's linguistic, cognitive, and social abilities. It's a prevalent disorder, with approximately 1 in every 54 births being diagnosed with ASD, and about 1% of the global population living with it. Unfortunately, despite its prevalence, the cause and cure for autism remain unknown, posing significant challenges to parents who suspect their child might have ASD. Early diagnosis of autism is crucial for a child's development, but it can be incredibly tough since symptoms manifest as the child grows. Typically, diagnostic tests conducted on children between the ages of 2 to 3 years are less reliable than those performed on children aged 4 to 5 years. This creates a worrying situation because early diagnosis is vital for autistic individuals to reach their developmental milestones successfully. Autism is often characterized by difficulties in social interaction and communication, making it challenging to diagnose accurately even with advanced tools like the ADOS and ADI. This work addresses the concerns surrounding autism diagnosis by focusing on improving the diagnostic pipeline. It involves training and testing machine learning models i.e., Random Forest with Standard scaler using an autism spectrum disorder dataset to identify the most significant indicators of autism in toddlers. The goal is to develop a quantitative approach to aid in early screening and subsequent treatment, as timely intervention can help mitigate long-term symptoms associated with autism. By leveraging machine learning, this work aims to provide valuable insights into diagnosing autism effectively and facilitating better support for individuals with ASD and their families.

1. Introduction

Autism spectrum disorder (ASD) is a developmental disorder that involves persistent challenges in social interaction, speech and nonverbal communication, and restricted and repetitive behaviours. In the USA, the prevalence of ASD has increased substantially in the past two decades, with an estimate of every 1 in 44 children to be identified with ASD by age 8 in 2016 [1]. Although there exist evidence-based interventions which improve core symptoms in children with ASD, many children with ASD still experience long-term challenges with daily life, education and employment [2]. Early diagnosis is the key to early intervention for improving the long-term outcomes of children with ASD. However, despite the growing evidence shows that accurate and stable diagnoses can be made by 2 years, in real-world settings, the median age of ASD diagnosis is 50 months. To improve early diagnosis, the American Academy of Paediatrics (AAP) has recommended universal screening among all children at 18-month and 24-month well-child visits in the primary care settings using the Modified Checklist for Autism in Toddlers (M-CHAT) [3], a questionnaire that assesses children's behaviour for toddlers. However, growing evidence has shown that using M-CHAT alone may not yield sufficient accuracy in detecting ASD cases, with a sensitivity below 40% and a positive predictive value (PPV) under 20% [4, 5]. In addition to ASD-specific behavioural questionnaires, general clinical and healthcare records may also contain meaningful signals to differentiate the ASD

risks among very young children. Studies have found that children with ASD are oftentimes accompanied by certain symptoms and medical issues such as gastrointestinal problems, infections and feeding problems. This implies that past diagnosis and healthcare encounter information, commonly available from health insurance claims or Electronic Healthcare Record (EHR), could potentially be used for ASD risk prediction. In fact, medical claims and EHR data have been widely used in the health informatics literature for identifying disease-specific early phenotypes even before the hallmark symptoms start to manifest, such as for chronic diseases like heart failures, diabetes and Alzheimer's disease [6].

2. Literature Survey

This section explains previous studies that use machine learning-based approaches to detect and predict the autism spectrum disorder. The main motive is to analyze and find some limitations to propose a new, better, and improved machine-learning based approach for autism spectrum disorder prediction. Automated algorithms for disease detection are being deeply studied for usage in healthcare. Graph theory and machine learning algorithms were used. For each age range being examined, the pipeline automatically selected 10 biomarkers. In discriminating between ASD and HC, measures of centrality are the most operational [8]. The study [9] used a neural network-based feature selection method from teacher-student which was suggested to have the most discriminating features and applied different classification algorithms. The results are compared with the already presented methods at the overall and site level. The authors in [10] also utilize the neural network to acquire the distributions of PCD for the classification of ASD as it has far more hyper parameters that make the model extra versatile. Payabvash et al. [11] used computer leaning algorithms to classify children with autism based on tissue connectivity metrics, hence, observed decreased connectome edge density in the longitudinal white matter tracts. It illustrated the viability of it in identifying children with ASD, connectome-based machine-learning algorithms.

The authors in [12] conclude that the data may be used to establish diagnostic biomarkers for the progression of autism spectrum disorders and to distinguish those with the condition in the general population. Wang et al. [13] proposed an ASD identification approach which focuses on multi-atlas deep feature representation and ensemble learning technique. In study [14], the multimodal automated disease classification system uses two types of activation maps to predict whether the person is healthy or has autism. It was able to achieve 74% accuracy. Rakić et al. [15] suggested a technique which is based on a system composed of autoencoders and multilayer perceptron. Because of a multimodal approach that included a set of structural and functional data classification classifiers, the highest classification precision was 85.06%. In study [16], advanced deep-learning algorithms are proposed where HPC solutions can increase the accuracy and time of broad fMRI data analysis significantly. Thomas et al. [17] introduced a novel analysis technique to identify changes in population dynamics in functional networks under ASD. They have also introduced machine learning algorithms to predict the class of patients with ASD and normal controls by using only population trend quality metrics as functions. The limitation of this approach is that the outcomes of the classification are highly dependent on the threshold parameter T . Another problem is that despite age variations in the experimental samples, the same spatial normalization design was used for all subjects. The authors in ref [18] proposed a collection of new features based on MRI images using machine learning algorithms to diagnose ASD which achieved 77.7% accuracy using the LDA approach.

Yin et al. [19] developed deep learning methods from functional brain networks built with brain functional magnetic resonance imaging (fMRI) data for the diagnosis of ASD. Another study [20]

used a graph-based classification approach which yields better results, but missing values are not handled and data normalization is not applied. A previous study [21] analyzes and works on brain networks which are inherent. It is deduced that ASD may be caused due to the aberrant mechanisms. The underlying individual variations in ASD symptom severity may be dysfunction in SN and visual systems and associated processes. A multichannel deep attention neural network called DANN was proposed in [22] in which mechanism-based learning with attention achieved a precision of 0.732. However, this study is limited because the selected cohort is in the population of teenagers and young adults, and hence, restricting the generalizability of the model since the diagnosis of ASD was carried out much earlier. Alvarez-Jimenez et al. [23] presented a multiscale descriptor to classify brain regions and recognize those with discrepancies between groups using a 2D representation and the curvelet transform. With regards to the state-of-the-art methods, including those focused on deep learning, it is shown to be successful. The study [24] suggested a novel architecture using CNN which has to identify autism and monitor patients using RS-fMRI data. This study concludes that through structural MRI images, 3D convolutionary neural networks can also be used to distinguish healthy subjects and patients with autism. Sherkatghanad et al. [25] suggested a CNN architecture. The mean accuracy of the presented model which used 234 test data is 70.2% but no feature selection technique was utilized. The authors in [26] suggest the ANN algorithm for multisite data and also shares the importance of network connectivity for classification was linked to verbal communication deficits in autism. The study [27] utilizes deep neural network and atlases for classification and acquired the accuracy of 78.07% on real data and 79.13% on augmented data.

3. Proposed System Design

Activity diagrams are graphical representations of Workflows of stepwise activities and actions with support for choice, iteration, and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.

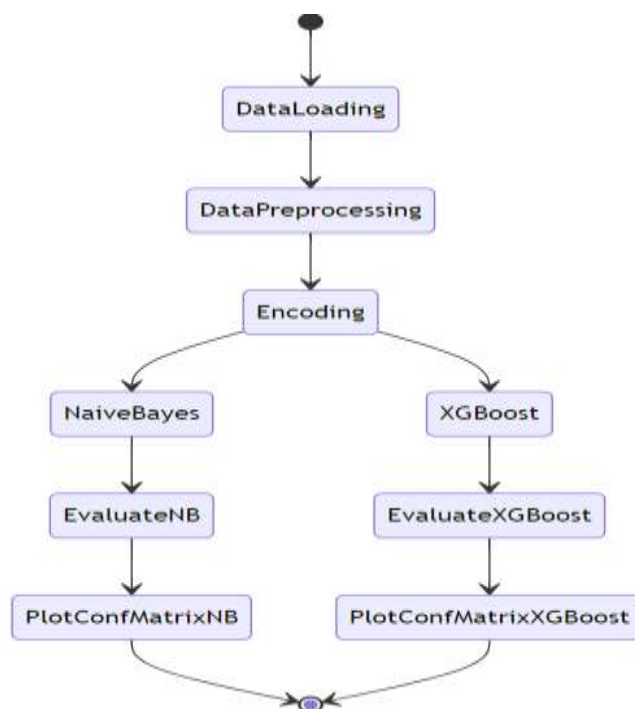


Figure 1. Proposed system design.

3.1 XGBoost Classifier

XGBoost is an optimized distributed gradient boosting library designed for efficient and scalable training of machine learning models. It is an ensemble learning method that combines the predictions of multiple weak models to produce a stronger prediction. XGBoost stands for “Extreme Gradient Boosting” and it has become one of the most popular and widely used machine learning algorithms due to its ability to handle large datasets and its ability to achieve state-of-the-art performance in many machine learning tasks such as classification and regression. One of the key features of XGBoost is its efficient handling of missing values, which allows it to handle real-world data with missing values without requiring significant pre-processing. Additionally, XGBoost has built-in support for parallel processing, making it possible to train models on large datasets in a reasonable amount of time. XGBoost can be used in a variety of applications, including recommendation systems, and click-through rate prediction, among others. It is also highly customizable and allows for fine-tuning of various model parameters to optimize performance.

4. Results and description

This dataset contains information about various attributes of individuals, including demographic information (age, gender, ethnicity), medical history (jaundice), family history of ASD, and assessment scores (Q-CHAT-10) used to predict the presence of ASD traits. The "Class/ASD Traits" column appears to be the target variable used for classification purposes, indicating whether the individual exhibits ASD traits or not.

Case_No	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	Age_Mons	Qchat-10-Score	Sex	Ethnicity	Jaundice	Family_mem_with_ASD	Who completed the test	Class/ASD Traits
0	1	0	0	0	0	0	1	1	0	1	28	3	f	middle eastern	yes	no	family member	No
1	2	1	1	0	0	0	1	1	0	0	36	4	m	White European	yes	no	family member	Yes
2	3	1	0	0	0	0	0	1	1	0	36	4	m	middle eastern	yes	no	family member	Yes
3	4	1	1	1	1	1	1	1	1	1	24	10	m	Hispanic	no	no	family member	Yes
4	5	1	1	0	1	1	1	1	1	1	20	9	f	White European	no	yes	family member	Yes
...
1049	1050	0	0	0	0	0	0	0	0	0	24	1	f	White European	no	yes	family member	No
1050	1051	0	0	1	1	1	0	1	0	1	12	5	m	black	yes	no	family member	Yes
1051	1052	1	0	1	1	1	1	1	1	1	18	5	m	middle eastern	yes	no	family member	Yes
1052	1053	1	0	0	0	0	0	0	1	0	19	3	m	White European	no	yes	family member	No
1053	1054	1	1	0	0	1	1	0	1	1	24	6	m	asian	yes	yes	family member	Yes

1054 rows x 19 columns

Figure 2: Sample dataset used for classification of ASD.

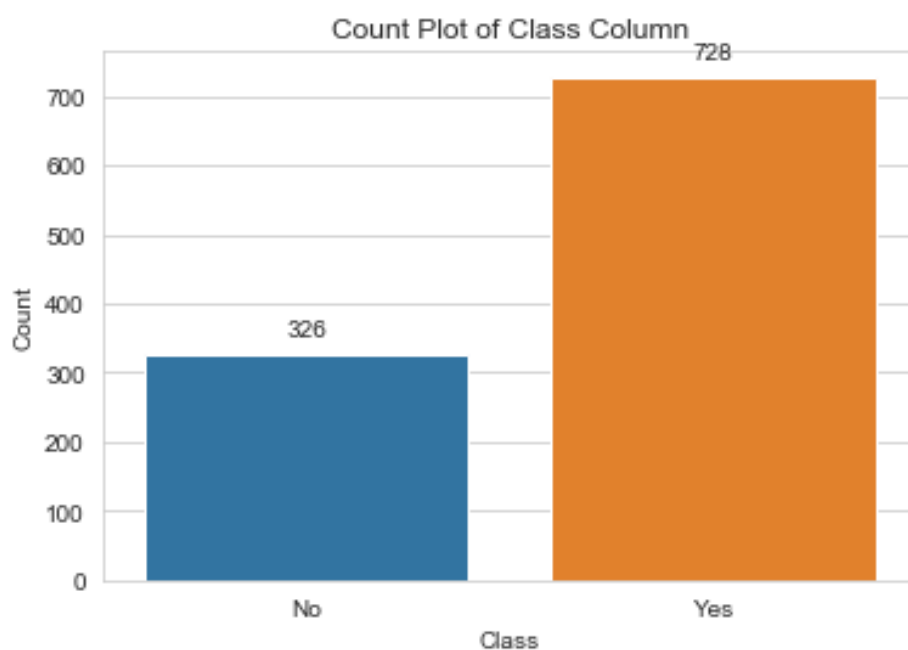


Figure 3: Count plot of class column i.e., Autism or Normal.

Accuracy: 100.00
 Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	68
1	1.00	1.00	1.00	143
accuracy			1.00	211
macro avg	1.00	1.00	1.00	211
weighted avg	1.00	1.00	1.00	211

Figure 4: Obtained accuracy and classification report using XGBoost model.

5. Conclusion

In the analysis of autism prediction in toddlers, the XGBoost model emerges as the superior choice compared to the Naive Bayes model. This assessment is based on various performance metrics and evaluations. Firstly, in terms of accuracy, the XGBoost model demonstrates a notably higher accuracy score when compared to the Naive Bayes model. This suggests that XGBoost excels at correctly classifying cases, a crucial aspect of any predictive model. Secondly, a closer examination of the classification report reinforces the superiority of the XGBoost model. The classification report provides insights into precision, recall, and F1-score values for both classes—likely autism and not autism. The XGBoost model consistently showcases higher values across these metrics, indicating a more balanced and accurate classification of positive and negative cases. Furthermore, the confusion matrix, which offers a detailed breakdown of true positives, true negatives, false positives, and false negatives, reflects better performance by the XGBoost model.

References

[1] Maenner MJ, Shaw KA, Bakian AV, et al. Prevalence and characteristics of autism spectrum disorder among children aged 8 Years - autism and developmental disabilities monitoring network, 11 Sites, United States, 2018. *MMWR Surveill Summ* 2021;70:1–16.

-
- [2] McPheeters ML, Weitlauf A, Vehorn A. U.S. preventive services Task force evidence syntheses, formerly systematic evidence reviews. screening for autism spectrum disorder in young children: a systematic evidence review for the US preventive services Task force. Rockville (MD): Agency for Healthcare Research and Quality (US), 2016
- [3] Lipkin PH, Macias MM, Council on children with disabilities, section on developmental and behavioral pediatrics. Promoting optimal development: identifying infants and young children with developmental disorders through developmental surveillance and screening. *Pediatrics* 2020;145. doi:10.1542/peds.2019-3449.
- [4] Guthrie W, Wallis K, Bennett A, et al. Accuracy of autism screening in a large pediatric network. *Pediatrics* 2019;144.
- [5] Carbone PS, Campbell K, Wilkes J, et al. Primary care autism screening and later autism diagnosis. *Pediatrics* 2020;146. doi:10.1542/peds.2019-2314.
- [6] Park JH, Cho HE, Kim JH, et al. Machine learning prediction of incidence of Alzheimer's disease using large-scale administrative health data. *NPJ Digit Med* 2020;3:46.
- [7] Downs J, Velupillai S, George G, et al. Detection of suicidality in adolescents with autism spectrum disorders: developing a natural language processing approach for use in electronic health records. *AMIA Annu Symp Proc* 2017;2017:641–9
- [8] A. Kazeminejad and R. C. Sotero, "Topological properties of resting-state fMRI functional networks improve machine learning-based autism classification," *Frontiers in Neuroscience*, vol. 12, p. 1018, 2019.
- [9] N. A. Khan, S. A. Waheeb, A. Riaz, and X. Shang, "A three-stage teacher, student neural networks and sequential feed forward selection-based feature selection approach for the classification of autism spectrum disorder," *Brain Sciences*, vol. 10, no. 10, p. 754, 2020.
- [10] M. N. Parikh, H. Li, and L. He, "Enhancing diagnosis of autism with optimized machine learning models and personal characteristic data," *Frontiers in Computational Neuroscience*, vol. 13, no. 9, p. 9, 2019.
- [11] S. Payabvash, E. M. Palacios, J. P. Owen et al., "White matter connectome edge density in children with autism spectrum disorders: potential imaging biomarkers using machine-learning models," *Brain Connectivity*, vol. 9, no. 2, pp. 209–220, 2019.
- [12] R. M. Thomas, S. Gallo, L. Cerliani, P. Zhutovsky, A. El-Gazzar, and G. van Wingen, "Classifying autism spectrum disorder using the temporal statistics of resting-state functional MRI data with 3D convolutional neural networks," *Frontiers in Psychiatry*, vol. 11, p. 440, 2020.
- [13] Y. Wang, J. Wang, F.-X. Wu, R. Hayrat, and J. Liu, "AIMAFE: autism spectrum disorder identification with multi-atlas deep feature representation and ensemble learning," *Journal of Neuroscience Methods*, vol. 343, Article ID 108840, 2020.
- [14] M. Tang, P. Kumar, H. Chen, and A. Shrivastava, "Deep multimodal learning for the diagnosis of autism spectrum disorder," *Journal of Imaging*, vol. 6, no. 6, p. 47, 2020.
- [15] M. Rakić, M. Cabezas, K. Kushibar, A. Oliver, and X. Lladó, "Improving the detection of autism spectrum disorder by combining structural and functional MRI information," *NeuroImage: Clinic*, vol. 25, Article ID 102181, 2020.
-

- [16] T. Eslami, J. S. Raiker, and F. Saeed, “Explainable and Scalable Machine-Learning Algorithms for Detection of Autism Spectrum Disorder Using fMRI Data,” 2020, <https://arxiv.org/abs/2003.01541>.
- [17] E. E. Thomas Martial, L. Hu, and S. Yuqing, “Characterising and predicting autism spectrum disorder by performing resting-state functional network community pattern analysis,” *Frontiers in Human Neuroscience*, vol. 13, p. 203, 2019.
- [18] S. Mostafa, L. Tang, and F.-X. Wu, “Diagnosis of autism spectrum disorder based on eigenvalues of brain networks,” *IEEE Access*, vol. 7, pp. 128474–128486, 2019.
- [19] W. Yin, S. Mostafa, and F.-x. Wu, “Diagnosis of autism spectrum disorder based on functional brain networks with deep learning,” *Journal of Computational Biology*, vol. 28, no. 2, 2021.
- [20] Z.-A. Huang, Z. Zhu, C. H. Yau, and K. C. Tan, “Identifying autism spectrum disorder from resting-state fMRI using deep belief network,” *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 7, pp. 2847–2861, 2021.
- [21] E. P. K. Pua, P. Thomson, J. Y.-M. Yang, J. M. Craig, G. Ball, and M. Seal, “Individual differences in intrinsic brain networks predict symptom severity in autism spectrum disorders,” *Cerebral Cortex*, vol. 31, no. 1, pp. 681–693, 2021.
- [22] K. Niu, J. Guo, Y. Pan et al., “Multichannel deep attention neural networks for the classification of autism spectrum disorder using neuroimaging and personal characteristic data,” *Complexity*, vol. 2020, Article ID 1357853, 9 pages, 2020.
- [23] C. Alvarez Jimenez, N. Múnera Garzón, M. A. Zuluaga, N. F. Velasco, and E. Romero, “Autism spectrum disorder characterization in children by capturing local regional brain changes in MRI,” *Medical Physics*, vol. 47, no. 1, pp. 119–131, 2020.
- [24] S. Shrivastava, U. Mishra, N. Singh, A. Chandra, and S. Verma, “Control or autism-classification using convolutional neural networks on functional MRI,” in *Proceedings of the 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, pp. 1–6, IEEE, Kharagpur, India, July 2020.
- [25] Z. Sherkatghanad, M. Akhondzadeh, S. Salari et al., “Automated detection of autism spectrum disorder using a convolutional neural network,” *Frontiers in Neuroscience*, vol. 13, 2019.
- [26] M. Ingalthalikar, S. Shinde, A. Karmarkar, A. Rajan, D. Rangaprakash, and G. Deshpande, “Functional connectivity-based prediction of Autism on site harmonized ABIDE dataset,” *IEEE Transactions on Biomedical Engineering*, vol. 68, no. 12, pp. 3628–3637, 2021.
- [27] T. M. Epalle, Y. Song, Z. Liu, and H. Lu, “Multi-atlas classification of autism spectrum disorder with hinge loss trained deep architectures: ABIDE I results,” *Applied Soft Computing*, vol. 107, Article ID 107375, 2021.