SEMARAK ILMU PUBLISHING

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Developing an Artificial Intelligence Based Model for Autism Spectrum Disorder Detection in Children

Chitta Hrudaya Neeharika[1,*], Yeklur Mohammed Riyazuddin[1]

[1] Dept of CSE, School of Technology, GITAM (Deemed to be University), Hyderabad, 502329, Telengana, India

ARTICLE INFO

Article history:
Received 22 March 2023
Received in revised form 7 June 2023
Accepted 19 July 2023
Available online 30 August 2023

Keywords:
Machine Learning; autism spectrum disorder; feature selection; connectivity; diffusion

ABSTRACT

Sensory difficulties, such as an over or under responsiveness to noises, smells, or touch, are frequently present in individuals with Autism Spectrum Disease (ASD), a neurodevelopmental disorder. The condition's primary cause is hereditary, however early diagnosis and therapy can assist. Traditional clinical procedures may be expensive and time consuming, but in current history, deep learning based sophisticated diagnosis has emerged to supplement them. The goal of this study is to streamline the diagnostic procedure by identifying the most important characteristics and automating them using existing classification methods. We have looked at datasets including toddlers, kids, teens, and adults with autism spectrum disorder. To find the highest performing classification and feature set for these four ASD datasets, we compared state-of-the-art categorization and feature selection methods. Across datasets of toddlers, kids, teens, and adults, our experiments reveal that the multilayer perceptron (MLP) classifier achieves 100% accuracy with the fewest possible features. We also determine that the proposed feature selection approach ranks the most important characteristics the highest across all four ASD datasets.

1. Introduction

A neurobiological disease, autism spectrum disorder (ASD) impacts both speech and social abilities. Numerous ideas and theories have been offered as to the origin of ASD, but the disorder's causes remain unclear [1]. According to the available evidence, this is a complicated or multifactorial illness, in which the combined impact of genetic and environmental factors on symptom manifestation are significant. Diverse researchers have proposed different explanations for the underlying causes of ASD symptoms, with some pointing to structural or connection abnormalities and others to a more pliable defect that links different levels of brain activity to the accomplishment of different activities.

Several MRI-based modalities have been used to investigate the various anomalies associated with ASD. These include (i) structural MRI (sMRI) for investigating morphological structures, (ii)

* *Corresponding author.*
E-mail address: hrudayaneeharika@gmail.com

https://doi.org/10.37934/araset.32.1.5772

functional MRI (fMRI) for investigating activity of the brain, and (iii) dispersion quaternion tomography for investigating brain connectivity. Using DTI as a diagnostic tool for ASD is the topic of this paper. Although the Autism Morphological Observation Schedule (ADOS) is the current standard for diagnosing autism, this study proposes a computer-aided method that may help obtaining early-stage non-subjective diagnosis [2].

DTI's ability to analyse the white matter's structural connections has garnered a lot of interest over the past two decades (WM). The axonal organisation might offer a wealth of information, but traditional MRI methods lacked the resolution and contrast to capture this. To our relief, DTI has made this possible thanks to the information revealed by the contrast in its diffusion anisotropy [3]. Because water molecules diffuse more easily in the direction of the neuronal strands than in the perpendicular direction, axonal direction may be determined using DTI.

A water molecule's diffusion in DTI is measured in at least six fixed directions, from which diffusion in any other direction may be deduced. Graphically, this is typically depicted as an ellipsoid, and technically, it is represented by a 3×3-matrix known as the diffusion tensor. Marginal anisotropy (FA), axial dielectric constant, radial dielectric constant, and mean diffusivity are only a few of the properties that may be calculated from the diffusion tensor (MD). Refractive index in WM tracts may be characterised by a number of distinct properties, some of which can be extracted from the aforementioned data [4].

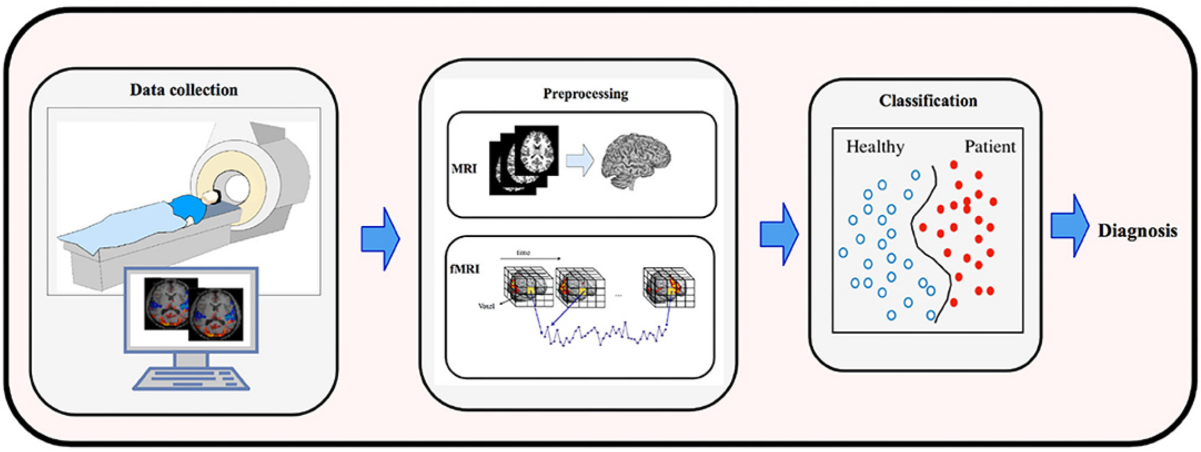

Fig. 1. Overview of Autism Disorder detection process with machine learning

The rising global incidence of autism spectrum disorder (ASD) and the associated diagnostic lag and outlay of resources have substantial economic consequences. The long-term expenditures associated with a delayed diagnosis of ASD can be reduced if the disorder is diagnosed and treated early, benefiting both the patient and the healthcare service provider. Alternatively, the conventional clinical procedures, such as the Autism Diagnostic Interview Revised (ADIR) and the Autism Diagnostic Observation Schedule Revised (ADOS-R), are laborious and time consuming [5].

Children who are excessively young and have speech delays score around 35% of the overall ADI-R questions since the verbal parts cannot be answered appropriately for the patient. Furthermore, it takes a qualified examiner anywhere from 30 min to 1 hour to conduct a discussion with a care taker, making the process tedious and prone to data loss. However, ADOS-ability R's to diagnose autism spectrum disorder is dependent on how well the scoring of the questions is quantified. Furthermore, there is a risk that children with other clinical illnesses will be overclassified if this method is used. Overview of Autism Disorder detection process with machine learning is depicted in Figure 1.

Consequently, there is a critical need for a rapid, simple, and widely available ASD screening tool that can reliably determine if a patient with a given measurable trait has ASD and advise persons as to whether they should seek a formal medical assessment. Currently, there are only a few of datasets accessible (e.g., AGRE, National Database of Autism Research (NDAR), and Boston Autism Consortium) that are tied to clinical diagnosis that is largely genetic in origin (AC).

These days, machine learning is used to diagnose a wide range of illnesses, from depression to autism spectrum disorders. By increasing diagnostic precision and decreasing diagnostic time, machine learning approaches can speed up patient treatment. The process of making a diagnosis is analogous to a classification job in machine learning since it requires determining which class (ASD, No-ASD) an input instance belongs to. In this study, we use a number of classification methods to enhance the outcomes of ASD case detection across all four datasets. There has been a steady rise in the incidence of ASD over the past few decades.

Previous research has indicated that ASD symptoms appear at a young age, however there is a large lag between the onset of symptoms and diagnosis. According to the results of a study, the average age of a child when they were diagnosed with ASD was 4.4 years, although the average diagnostic delay was 1.5 years. The diagnosis of ASD can be improved via early intervention; however, toddlers with ASD who are not diagnosed until later in life will miss out on this window of opportunity. Children's ability to respond to their names is an important social skill. The RTN has a crucial recognition role in how we think about and connect with other people [6].

Children as young as four to six months show signs of RTN, suggesting that it is ingrained in their personality. Toddlers who are typically developing (TD) show a strong preference for hearing their own names, especially when their moms use them. Evaluation of RTN may be effective in advance identification and detection of ASD because of its importance in the growth of social skills. Toddlers with autism spectrum disorder have been demonstrated to have a lower RTN through many lines of evidence [7].

A prospective research that looked at RTN trends from 6 to 24 months indicated that children who didn't reply to their names frequently throughout the second year of life were at a higher risk for ASD and other developmental delays. Conclusions Early childhood inability to RTN may be a crucial sign of developmental problems. The revised questionnaire for autism in children and the autism diagnostic observation schedule are only two examples of the many screening and diagnostic tools that have made RTN a central component (ADOS).

Only the parent's report or schedule is used in studies of reduced RTN, although the more precise approach of quantization is little understood. Existing methods for screening for autism spectrum disorder rely heavily on scale screening tools like the Modified Checklist for Autism in Toddlers and the Interpersonal Communication Survey based on parent report, despite their subjectivity, length of administration, and inefficiency.

Machine learning has emerged as a possible option for ASD screening and diagnosis in light of the limitations of more conventional approaches. With the use of search techniques, AI, and mathematical modelling, machine learning seeks to build forecasting analytics from the datasets. Decision tree methods used in data processing are one type of machine learning algorithm utilised as an intelligent way with low human involvement to detect ASD. Using a basic upper-limb reach-to-drop test, researchers have employed machine learning to discriminate ASD from TD children, and the resulting model demonstrated an accuracy rate of 96.7%, suggesting that machine learning might be a viable classification and discriminating tool in the diagnosis of ASD [8].

In a recent study, Achenie *et al.*, [19] showed that the machine learning approach was just as accurate as the M-CHAT with follow-up questions in diagnosing ASD while using less items. Based on the findings, machine learning shows promise as a method for adopting computerized, efficient scoring in ASD diagnosis. A multimodal predictive model is a more sophisticated kind of machine learning that combines generic machine learning principles with behavioural analytic techniques to carry out in-depth computer analysis of multimodal audio-visual data for the purpose of early autism screening.

MMLS can improve our knowledge of ASD and may lay a firmer groundwork for advance identification and detection by extracting important information and constructing complicated models that transcend human ability in evaluating massive datasets. Our best information suggests that doctors are still the primary source for diagnosing toddlers with ASD, and that this process often involves extensive behavioural observations and narrative history gathering. Clinicians also face significant hurdles in the areas of ASD screening and diagnosis.

Few researches have looked at the discrepancy in RTN amongst ASD and non-ASD groups, and even less is known about whether MMLS could improve upon or replace the function of clinicians in the screening and detection of ASD. Our major goal in employing the MMLS was to examine the RTN gap between toddlers with ASD and non-ASD. Our goal is to examine whether or not using a machine-based technique to assessing RTN works for ASD prediction is possible.

This paper has the following research contributions:

- We examine the characteristics of four different ASD data sets (those including children, adolescents, and adults) and look for links between demographic details and ASD occurrences.
- In this work, we investigate state-of-the-art feature selection techniques and isolate the one that yields the best results across all four ASD datasets.
- Our research demonstrates that by selecting the right features, the ASD performance comparison may be dramatically enhanced.
- Using four different datasets for individuals with ASD, we evaluate the performance of the state-of-the-art classification methods and determine the best classification model.

2. Literature Survey

To investigate the hypothesis, Vasa *et al.*, [9] surveyed recent findings on ASD's structural and functional connectivity. They pointed out the contrasting findings and the numerous confounding variables in the existing literature. A major factor in the pathogenesis of autism spectrum disease is believed to be disruptions in connection (ASD). This theory was initially put out by Belmonte *et al.*, [9] who developed a model in which decreased information transmission in the brains of people with ASD was regarded as a result of local overconnectivity and long-range-underconnectivity.

The concept of disturbed connectivity states that the inability of the brain to incorporate complex cognitive activities is a result of weakened functional connections between different areas of the brain. Studies by Brock *et al.*, [20] which found a lack of gamma-band EEG synchronisation in patients with underconnectivity, were fundamental to Belmonte's explanation. By connecting the significance of gamma band behavior to the glutamatergic equilibrium of brain activity, Rippon *et al.*, [21] developed the idea into the "impaired connection" theory of autism.

Observations of the laminar organisation in neuropathological specimens lend support to the disturbed connection theory, which suggests a link between this phenomenon and the excitable inhibitory balance in the brain's cortex. Researchers claim that a bias in brain connections has developed due to a change in cell size. DTI was used to compare ASD and TD groups regarding WM structural integrity, both with and without adjusting for age and IQ. Whether or not the adjustment was applied, those with ASD were shown to have considerably greater MD across the board in white matter regions of the brain.

FA was also found to be reduced in the bilateral upper and lower transverse fasciculi and the left corona zona pellucida in those with ASD, although this difference largely vanished after controlling for age and IQ. This led them to conclude that ASD has a higher kurtosis of the fractional anisotropy distribution. In their recent review article, Travers *et al.*, [22] systematically analysed 52 DTI investigations that were conducted on individuals with ASD and WM integrity between 2003 and 2012. Multiple brain areas were shown to have decreased FA and elevated MD in ASD patients, corresponding with poor WM integrity, as revealed in the analysis of these research [10].

Some areas, including the posterior portion showed more uniform results than others. Compound entropy, average diffusion coefficient, longitudinal permeability, and tangential friction coefficient are four DTI metrics that Kuno *et al.*, [23] correlated with ASD quotient scores (AQ). Previous research has already shown that those with OCD and autistic characteristics have differences in some white matter tracts. Their findings showed that autistic characteristics may account for some of the WM variance seen in people with OCD. Although machine learning has been used extensively in brain research, and DTI brain investigations in particular, for quite some time, there are still relatively few articles that focus on utilising DTI to classify or characterise autism spectrum disorder.

To differentiate between ASD and TD, Zhang *et al.*, [24] utilised a whole-brain white matter connectivity study using several classifiers and diffusion MRI tractography. In addition to edge density imaging to analyse the structural connectome, Payabvash *et al.*, [25] employed DTI measurements such as component anisotropic, mean diffusion coefficient (MD), as well as radial diffusivity (RD). He made use of support vector machines, random forests, neural networks, and bayesian Networks (NB). Contour intensity tomography, which has been applied to both the cerebral cortex and the subcortical grey matter, may be thought of as a three-dimensional spatial manifestation of the connectomes' edges.

Beyond autism, DTI imaging has been used to classify a wide range of other neurological illnesses, including Alzheimer's, dyslexia, epilepsy, and auditory processing impairments. FA and MD mean prices per ROI demonstrated diagnostic predictive potential with 80% accuracy in a research including 40ASD and 35TD individuals [11]. Another study with the goal of autism categorization employed the form of white matter lines implanted in the posterior portion of the corpus callosum, and it was successful up to 75% of the time. The integrity of WM connection was utilised to make a diagnosis of autism in 38 well-balanced newborn groups.

We introduce a new feature representation that makes use of micro-structural strong correlations among different brain areas, as opposed to the traditional methods of using raw voxel qualities of a foreordained ROI, non-preserving image compression of input data utilising PCA, PLS, or convolutional, or summarization values of ROIs/brain regions, including mean. Comparable studies have also found that neither the inadequate and the over-connectivity of the component adequately explains the differences seen in the ASD group. There have been various attempts to discover autism-related abnormalities using imaging, but as of yet there is no reliable computer assisted diagnostic (CAD) system that can both predict a diagnosis of autism spectrum disorder and identify brain WM regions that most correlate with autism [12].

Because of this, DTI has been proposed as a means of creating a comprehensive automated diagnosis system for ASD that can aid clinicians in early subject identification, sub-type identification, and a better understanding of influenced brain regions that may aid in the development of individualised treatment plans. The application of machine learning research on home video has been proposed to reduce diagnostic time and improve accuracy by Tariq *et al.*, [26] Machine learning classifiers optimised for sparsity, interpretability, and accuracy have been built by analysing item-level data from two widely used diagnostic equipment. There are 162 two-minute home movies of children with and without ASD, and the authors have explored eight machine learning algorithms to apply to these films.

Additionally, eight distinct machine learning models for identifying ASD employ thirty behavioural indicators (such as eye contact, sociable grin, etc.), which have been evaluated by video raters via a mobile web site. Employing cross-validation assessment and additional independent validation from prior work, the result demonstrates that 94% accuracy is attained across all cases. The procedure is time-consuming since a video must be produced and evaluated using a set of 30 questions. Alternatively, we employ an approach that requires simply a mobile app from which users may choose the correct responses to 10 questions based on indicators of autism spectrum disorder.

In addition, enhanced analysis predicated on a lesser set of variables might vastly enhance ASD detection efficiency. Andrea *et al*., [27] examined the use of video gesture in the diagnosis of ASD. Using video recordings of well-adjusted, healthy youngsters completing the simple task of grabbing a bottle, the authors have constructed a control group for their experiment. They achieve high accuracy in distinguishing ASD patients from non-ASD cases by analysing only the video clips exhibiting the gripping movement with a recurrent deep neural network. All videos are cut into 15-frame chunks and run through the full model, which returns a binary vector with the likelihood of ASD or No-ASD for each frame, as is the case in that study [13].

During the learning process, each clip is handled separately. Accuracy in each test is determined by adding up the probability for each frame in a movie and averaging the results. However, once the model score reaches a threshold of 0.9, its predictive power begins to decline. The findings corroborate the notion that correct results may be obtained quickly using feature tagging of home films utilising machine learning categorization of autism [14]. After some time, McNamara *et al*., [15] also categorize the same dataset using Decision Tree and arbitrary forest classifiers while considering enhanced data pre-processing, in which the authors eliminate least significant characteristics and records with missing values.

The comparative findings between these classifiers reveal that the random forest yields higher accuracy for the version-1 adult ASD dataset. Studying the v1 child ASD dataset using the same methods, Hossain *et al*., [28] deployed 27 benchmark classifiers. When it comes to identifying cases of autism spectrum disorder (ASD) in children, they have also discovered that the sequential minimal optimization (SMO) classifier is the most effective [28]. Furthermore, the most important characteristics for diagnosing autism in children were also determined. IoT is one of the future internet techniques that is focused on the provision of services and modifying the implementation of technologies [16-18].

3. The Proposed System

Our approach to ASD case detection is briefly outlined below and is depicted graphically in Figure 2. Before diving into in-depth analysis and categorization, we do a thorough data-preparation in the Data preprocessing and analysis phase. There are not many blanks in the ASD databases. Some of the qualities (such as who has used the app previously or has finished the exam) represent meta-information and have nothing to do with autism spectrum disorder. Therefore, cleaning and preprocessing the datasets is required prior to classification. We use several different categorization strategies in our benchmarking effort.

In this research, we used all four ASD datasets to test 27 different categorization strategies, assessing their efficacy with accuracy and measure by 10-fold cross validation. At last, we pick the best eight classifiers to take a closer look at. If every attribute in a dataset is used for classification, accuracy might suffer. Additionally, training a model with fewer characteristics requires less infrastructure (memory and processing power). Here, we rank attributes/features to get the best combination of characteristics for maximum accuracy.

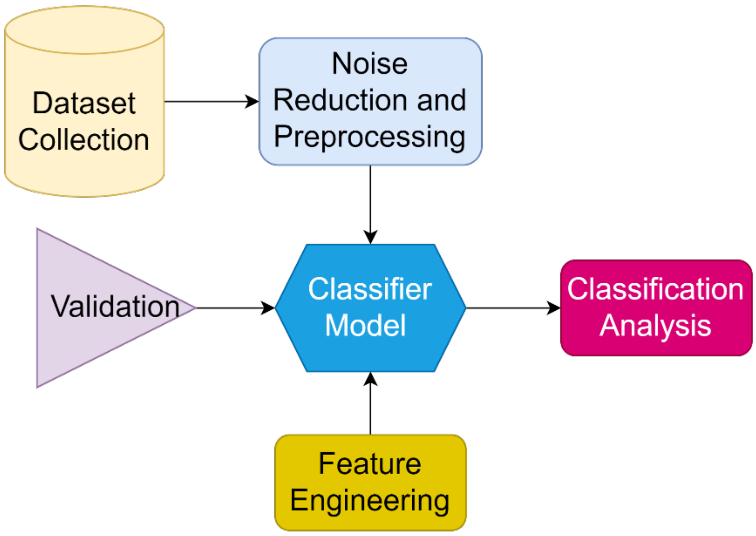

Fig. 2. Proposed System architecture

Data preprocessing in ASD (Autism Spectrum Disorder) datasets involves several steps to ensure the quality and suitability of the data for analysis. Here are the data preprocessing steps followed for ASD datasets:

1. Data Cleaning: This step involves handling missing values, outliers, and noise in the dataset. Missing values can be filled in using imputation techniques, outliers can be identified and treated or removed, and noise can be reduced or eliminated using smoothing or filtering methods.

2. Feature Selection/Extraction: In this step, relevant features or variables that are most informative for the analysis are selected or extracted from the dataset. This helps reduce dimensionality and focus on the most significant aspects of the data. Feature extraction techniques such as Principal Component Analysis (PCA) or feature selection methods like information gain or correlation analysis can be used.

3. Normalization/Scaling: Normalization or scaling ensures that the data is on a consistent scale and prevents certain features from dominating the analysis due to differences in their ranges. Common techniques include min-max scaling, z-score normalization, or robust scaling.

4. Handling Categorical Variables: If the dataset contains categorical variables, they need to be encoded into numerical values for analysis. This can be done using techniques like one-hot encoding or label encoding.

5. Balancing the Dataset: Imbalanced datasets can be a challenge in ASD research, where the number of samples in one class outweighs the others. Techniques such as oversampling,

undersampling, or synthetic data generation can be used to balance the dataset and ensure equal representation of different classes.

6. Data Splitting: The dataset is typically divided into training, validation, and testing subsets. The training set is used to train the model, the validation set helps tune hyperparameters, and the testing set evaluates the final model's performance. The ratio of the splits may vary depending on the dataset size and specific requirements.

We employ five standard feature ranking methods to evaluate and contrast their results, ultimately selecting the one that produced reliable attribute rankings across all four ASD datasets. We then compare the top eight classifiers' accuracy over the ideal set of qualities and select the best one. If the patient has a positive result for ASD during the categorization process, then additional medical evaluation and therapy are required. As a result, correct categorization is crucial for minimising false positives and maximising efficacy.

With the suggested feature engineering, the multilayer perceptron (MLP) classifier beats state-of-the-art results on all four ASD datasets, achieving 100% accuracy when considering the top ten features. In general, the ASD datasets we've utilised have 23 characteristics, with the exception of the toddler dataset, which only has 18. There are ten categorical variables and ten binary features across all datasets, including gender, race/ethnicity, jaundice status, autism spectrum disorder (ASD) status in the family, place of residence, and ASD classification.

Age and screen score or outcomes are only two examples of the two number variables present in each of these datasets. We discovered that the toddler ASD dataset lacked five attributes: the person who took the test (user), the reason for taking the screening, whether or not the app had been used previously, the user's place of origin, and the user's native language. Screening questions in the child and adolescent datasets are identical, whereas those in the toddler and adult datasets vary.

We have included all ASD dataset questions in chronological order across four age groups: childhood, adolescence, adulthood, and infancy. During data collection, the responses to these questions are used to determine the class value. When the sum of the AQ-10's method scores is less than 7 the class value "No" is assigned. If the answer is "Yes," then the person is considered to have autism spectrum disorder. To the contrary, the minimum acceptable score in the toddler dataset is 4.

Therefore, in this scenario, if the patient has a total score of less than 4, they are diagnosed with ASD. Here we see how many cases of ASD there are, as well as how many cases there are that do not fall under the ASD umbrella. This diagram depicts the gender-based distribution of classes across the four ASD datasets used in the analysis. Here, we see that the child and adolescent datasets are balanced with respect to the overall number of ASD cases and/or gender distribution, but the toddler and adult datasets are not. We remove instances with missing values from datasets to simplify our model and enhance classification accuracy.

Next, we do pre-processing on the datasets by eliminating meta information qualities that are unrelated to autism spectrum disorder. So, if this characteristic is used in the classification process, the result of the target variable is known to the classification algorithm in advance. This is why this property is ignored in the statistical analysis. We settle on 16 attributes across the child, teen, and adult datasets, and 15 attributes across the toddler dataset. We have ranked the qualities of four ASD datasets using five widely used feature choices techniques, including Information gain, Chi-square test, Pearson correlation, One-R, and Releif F.

We investigate the efficacy of feature selection methods by examining feature ranking and applying it to ASD datasets. Answers to questions A1–A10 provide us with information about characteristics that are known to be important in determining whether or not a child has ASD. In addition, the results of the demographic questionnaires contribute very little to the process of diagnosing ASD. Based on our analysis of the five feature selection approaches, we conclude that the Relief F attribute selection method provides the greatest results across the four ASD datasets, and is also able to rank features ahead of the demographic attributes.

We analyse the traits' efficacy in spotting ASD patients by counting how often they appear in each of four ASD datasets. Each group's first column shows the attribute's score of '1' when the ASD case is 'yes' (lower portion) and 'no' (higher portion), while the second column shows the score of '0' when the ASD case is 'yes' (bottom portion) and 'no' (upper portion). In the first and second columns, we evaluate whether or not the trait provides a higher rate of success in recognising ASD patients. We find that the Relief F feature rating is consistent with our own rankings of these features across all four datasets. To determine the minimum set of features required for optimal accuracy, we employ the Relief F feature selection approach. We assess the efficacy of eight different classifiers and examine their effectiveness as the number of characteristics increases in descending order of importance. Adding more characteristics seems to improve accuracy.

For most classifiers, this limit is reached when there are ten characteristics in total. After that point, accuracy is roughly the same for toddlers, children, and adults, although it decreases significantly for adolescents when more traits are added. As a result, we can claim that all the traits are the most important ones for making a correct ASD diagnosis. We observe that both MLP and Logistic Regression (LR) classifiers achieve 100% accuracy for the top ten attributes (the bare minimum), but that MLP's accuracy remains constant (i.e., 100%) for the toddler, child, and adult datasets as the number of attributes increases, while LR performance declines after the minimal attribute point. As an added bonus, the decline in LR performance for the teenage sample is more than that of MLP. That's why we claim MLP is superior to LR and the other seven classifiers we tested it against.

4. Results and Discussion

We evaluate the predictive power of this study in relation to the current state of the art. Previous studies rely heavily on the Autism Spectrum Disorder dataset. Perhaps Baranwal *et al*.,[29] recently looked at ways to reduce features while maintaining high accuracy. According to our research, Thabtah *et al*., [30] only used the logistic regression classifier on the version 2 adult and adolescent datasets. In order to determine which characteristics were most important, the authors used a combination of chi-squared and information gain feature ranking algorithms, resulting in a 99% accuracy rate for the teen dataset and a 97.58% success rate for the adult dataset. UCI ML repository, which is both secure and open to the public, is where we compiled our data on children with ASD. There are 292 cases and 21 attributes in the dataset.

In ASD (Autism Spectrum Disorder) detection research, the hypothesis typically revolves around identifying specific characteristics or patterns in data that can distinguish individuals with ASD from those without ASD. The hypothesis may vary depending on the specific research study. In our research, We use the hypothesis as Machine learning algorithms can effectively classify individuals as ASD or neurotypical based on specific features or data patterns. This hypothesis explores the potential of using machine learning techniques to analyze various types of data, such as behavioral data, genetic data, or brain imaging data, to develop accurate classification models for ASD detection.

Table 1
Performance analysis

Performance Measure	Decision Tree	Random Forest	Proposed Approach
Accuracy	88.65	92.56	93.6
Specificity	85.45	86	91.25
Sensitivity	90.25	89.56	92.65
Precision	89.54	80.54	90.05
FPR	11.25	12.56	9.35

We have tried five different approaches for ranking features, involving chi-squared and information gain, and discovered that Relief F feature ranking helps us get the best results (a perfect classification rate). Down addition, we have methodically chosen the best classifier (out of a collection of 27 benchmark classifiers), found the best feature ranking approach (out of five notable methods), and zeroed in on the smallest number of characteristics necessary for optimal accuracy. In addition, we have utilised all four ASD datasets, version 2.

Given that we conducted this study using version-2 of the dataset, any comparisons we make will have to be with other studies that employed the same dataset, such as Thabtah *et al.*, [31]. Although this is the case, we have included version-1 related research in our analysis to give a comprehensive perspective of the detection performance for ASD. This article is the first to use the Toddler Autism Spectrum Disorders Dataset, and the results reveal that it performs better than the state-of-the-art studies on ASD identification. The initial purpose of this research was to evaluate the use of AI in ASD screening programmes for young children.

The findings suggest that the automated system can code behaviours just as well as humans. The current research looked at how RTN develops in toddlers with autism spectrum disorder (ASD), Tourette syndrome (TD), and TD. Toddlers with ASD had a lower rate of RTN call compared to the non-ASD group. Automatic participant ratings have been an improvement over manual scoring in video-based research because of their greater reliability. Overall, the software was fairly accurate (92%), suggesting that MMLS can properly reflect the real performance of various children in RTN operations. In particular, the evaluation approach used by the evaluator yielded the best accuracy for toddlers with TD. In Figure 3, Performance analysis with proposed approach has been shown.

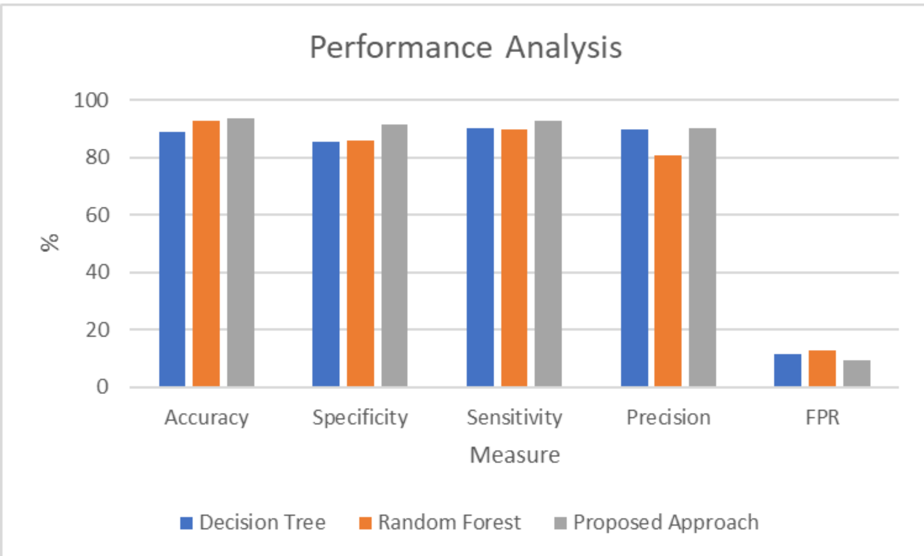

Fig. 3. Performance analysis with proposed approach

Toddlers with TD are more cooperative and adapt more quickly to new settings, which may explain why they outperform the other two different groups. Because of this, we were able to record their behaviours with greater precision. However, hyperactive performance and increased erratic behaviour were common among children with ASD, which may make it harder to assess behavioural data. The new study employed multimodal information to analyse behavioural data, which made the findings more trustworthy than those of prior studies on the automated identification of RTN.

Our data showed that children with ASD were much more likely to ignore their name being called than toddlers without ASD. Using computer vision analysis, a recent study found that children with ASD replied to their names substantially less frequently than kids without the disorder (CVA). Our findings agree with those from the CVA, which revealed that autistic children who did orient to name call had a longer delay before turning their head. The hypothesis of support is associated and social cognition in ASD helps to explain the attenuated reaction.

Autism spectrum disorder was a severe case of low social drive, as proposed by the idea. Toddlers with ASD may have a lower reaction rate and longer response latency to name call because of difficulties in social orienting and social reward, while shorter response length time may be due to difficulties in social maintenance. Moreover, children with ASD may be less receptive to social stimulations like name call if they have narrow patterns of interest. There is conclusive proof that social cognition is linked to successful social interactions. Young children with ASD may have trouble understanding social contexts due to deficiencies in social cognition.

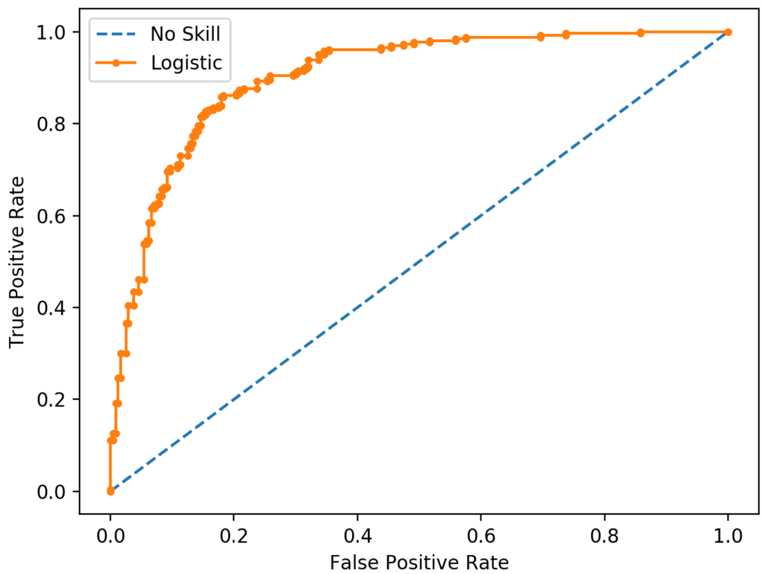

Fig. 4. ROC analysis

Therefore, children with ASD did not know they were supposed to respond to the name call, did not know how to respond, and often did not even comprehend that the name call was directed at them. It's also likely that children with ASD have trouble paying attention to sounds around them, which might explain the low reaction rate. Researchers found that people with ASD have unusual auditory object processing, which may help explain the disorder's impact on their ability to communicate. Children with ASD benefit greatly from early intervention, but these interventions are less effective if they are delayed due to a lack of appropriate identification and diagnosis. Figure 4 shows ROC analysis in the proposed training model.

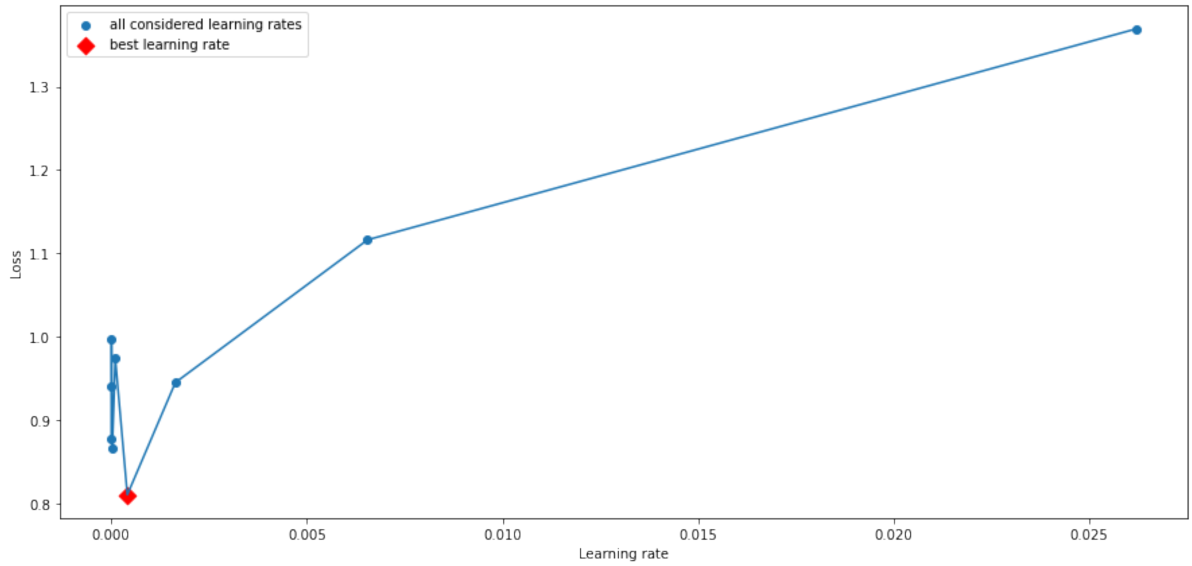

Fig. 5. Loss analysis during learning process

Children with ASD have less of a chance of succeeding if they don't start receiving help until they're well into elementary school. Because it can recognise ASD in kids as young as 2 years old, machine learning offers a novel method for screening and diagnosing autism spectrum disorder. As an added bonus, this machine learning can be implemented easily and without risk. A computerised coding course eliminates human subjectivity in evaluation. Loss analysis during learning process is shown in Figure 5.

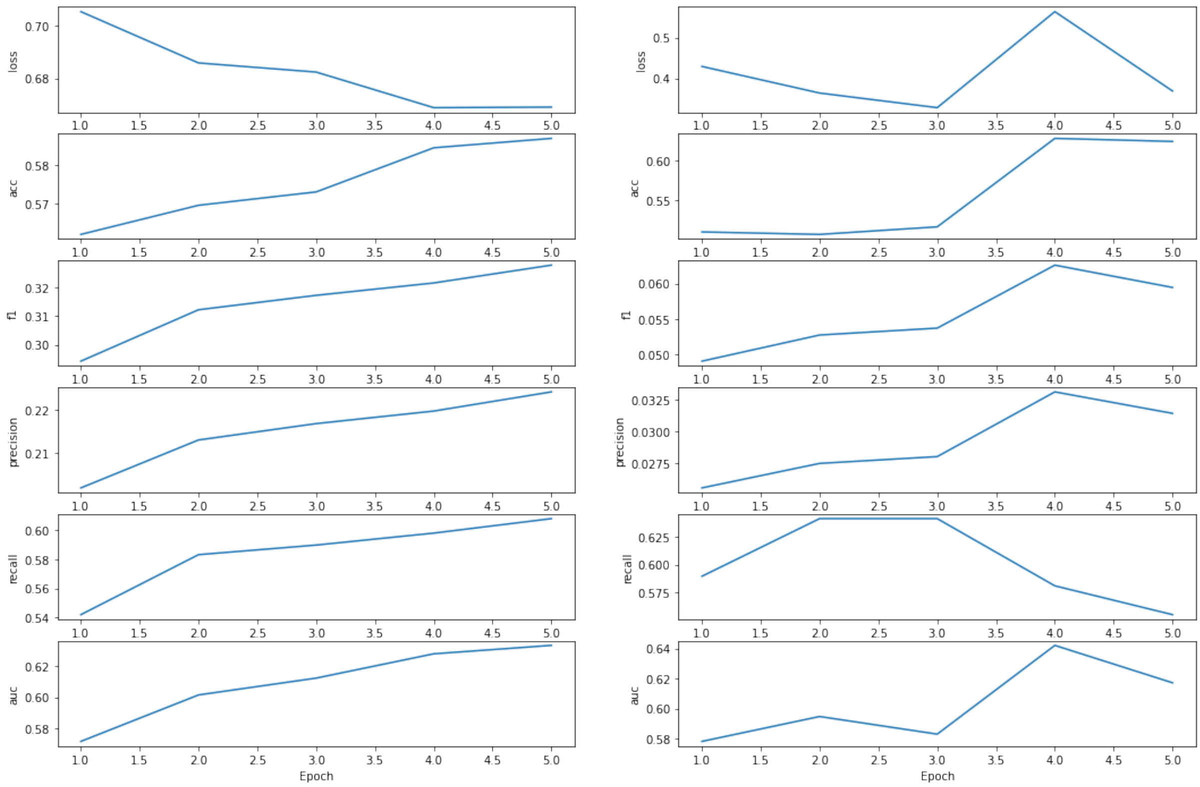

Fig. 6. Performance Progression

As this study shown, there is little to no difference in accuracy between machine and human diagnosis of ASD. Based on the aforementioned data, it appears that computers and humans performed similarly when tasked with behaviour coding. This study has major repercussions for the early screening and diagnosis of ASD through the use of an artificial intelligence test system. The current technique for screening and predicting ASD mostly depends on a scale assessment and an anecdotal diagnosis by doctors, both of which lack objective instruments. An additional way for accurately and dependably analysing toddler behaviour may be provided by the current study's unique approach to categorising behavioural data objectively and intelligently. Figure 6 shows the performance progression of the proposed system.

In the present work, we have looked at the potential of applying machine learning for early screening of ASD as a standard paradigm. MMLS has the potential to reduce the time and effort needed for ASD screening and diagnosis in this context. In addition, it may provide kids who have to wait a long time for a full medical evaluation an opportunity to be recognised sooner in places where medical resources are few. There are still a number of caveats to our research. Firstly, the study is cross-sectional, although the growth of toddlers' social skills is an ongoing process. The ability of a society cannot be gauged by its performance at a single moment in time.

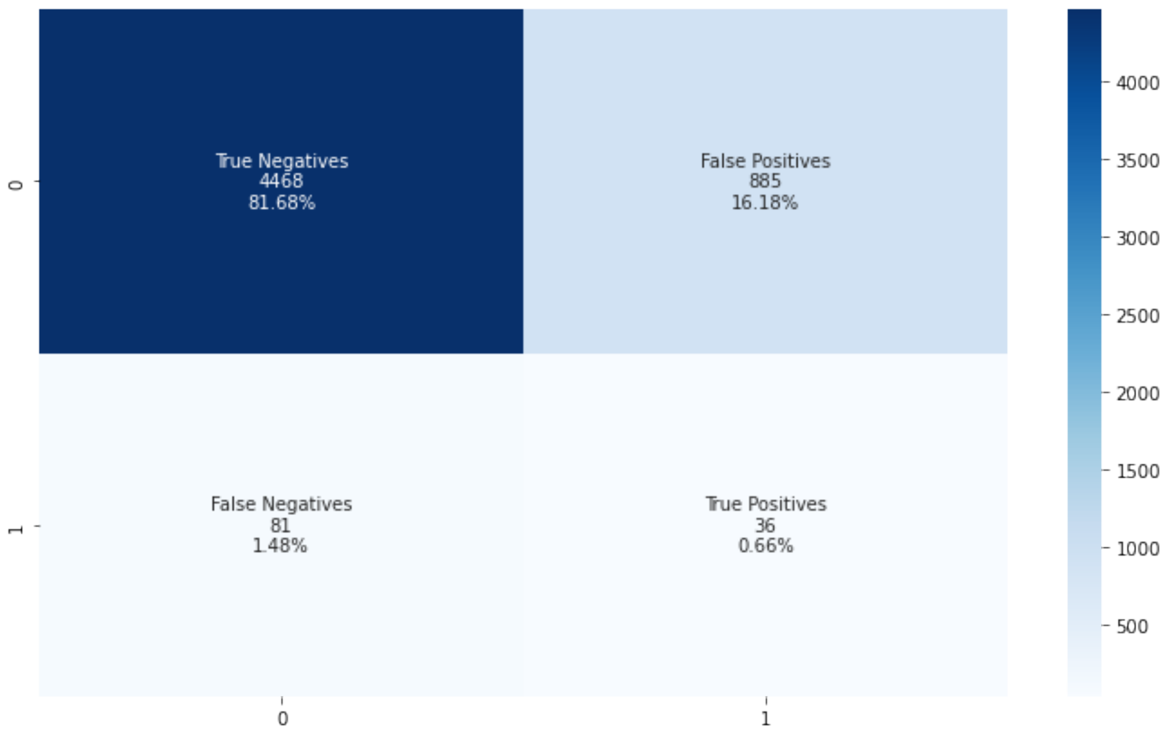

Fig. 7. Confusion Matrix

Because the experiment was carried out in a semi-structured context and the kids were required to sit in a prescribed posture, this might have an impact on the toddlers' behavioural performance in a more natural setting, and therefore our rating method may have missed some relevant data. Third, ASD can't be predicted by using RTN alone. A prospective technique, incorporating a bigger sample size and longitudinal follow-up, should be designed as the next step in future study. Confusion matrix has been depicted in Figure 7. A single symptom like RTN detection is not adequate for ASD identification, and machine learning is not as reliable as a human observer. Multiple social markers of autism spectrum disorder should be included in further research. For RTN to be effective, it must be conducted in a free-play setting, where the participants' actions will be more realistic and in keeping with ecological validity.

Despite the progress made in the identification of ASD in children using AI-based models, there are still certain drawbacks and limits to be aware of. These drawbacks are as follows:

Artificial intelligence (AI) models may not be able to generalise adequately to new populations or contexts if they were only trained on a small subset of data. The model's efficacy may shift if it's used with kids from diverse socioeconomic backgrounds or cultural traditions. In order to guarantee the model's generalizability, vast and varied training data is required. Many deep learning models used for ASD diagnosis operate in mysterious ways, making it difficult to ascertain how and why they arrived at their conclusions. Clinicians, carers, and parents who need interpretability and openness in decision-making may be less likely to trust and accept a system that lacks explainability. Privacy, consent, and data security are all areas where the use of AI models for ASD detection might go wrong. When dealing with minors, it is especially important to respect their right to privacy and not collect or store any information that might identify them without their consent. There should be stringent safeguards in place to prevent data breaches and guarantee adherence to moral principles. Biases in the training data might affect the results of AI models. A model may have biassed behaviour during prediction or classification if the training data is not representative or contains biases. For underrepresented groups or minorities in particular, this might lead to erroneous or biassed conclusions.

The effectiveness of AI models is highly dependent on both the quality and amount of the data utilised in their training. The model's precision and dependability might be compromised by a lack of necessary data. It might be difficult to collect big and varied datasets with high-quality annotations, which can reduce the model's accuracy. Expertise in AI model development, training, and interpretation is needed for autism spectrum disorder (ASD) identification. In order to properly implement and evaluate the model's results, clinicians and experts will require familiarity with AI approaches. This can be a problem when trying to implement it in a context with limited resources or a clinical environment. To ensure the appropriate and ethical use of AI in ASD detection, it is essential to solve these drawbacks by continuous study, data gathering, algorithm improvement, and the participation of interdisciplinary teams. Before incorporating AI models into clinical practise, it is important to rigorously examine and validate their performance, taking into account their limits and potential biases.

5. Conclusion

Here, we have studied data from four different ASD cohorts, including children, adolescents, and adults. For the purpose of deriving fewer features from ASD datasets while keeping competitive performance, we employ the five most prevalent feature selection approaches. For the best results, we recommend using the Relief F feature selection technique. In our experimental setting, we use a variety of categorization methods after gradually increasing the number of attributes. Utilizing our methodology and approach, we discover that MLP is the most effective classifier. This study's biggest flaw is its limited data sample size. Our long-term goal is to increase performance by collecting huge datasets and using deep learning approaches that jointly conduct feature evaluation and classification. In addition, we hope to build a more accurate ASD identification method by analysing brain signals (such as EEG) and correlating them with AQ-based research. In conclusion, we found that MMLS successfully identified ASD children from the control group and provided correct quantification of behaviours throughout RTN procedures. This innovative technology has the potential to offer a cost-effective means of screening and diagnosing toddlers with ASD at an early age.

References

[1] Parlett-Pelleriti, Chelsea M., Elizabeth Stevens, Dennis Dixon, and Erik J. Linstead. "Applications of unsupervised machine learning in autism spectrum disorder research: a review." *Review Journal of Autism and Developmental Disorders* (2022): 1-16. https://doi.org/10.1007/s40489-021-00299-y

[2] Minissi, Maria Eleonora, Irene Alice Chicchi Giglioli, Fabrizia Mantovani, and Mariano Alcaniz Raya. "Assessment of the autism spectrum disorder based on machine learning and social visual attention: A systematic review." *Journal of Autism and Developmental Disorders* 52, no. 5 (2022): 2187-2202. https://doi.org/10.1007/s10803-021-05106-5

[3] Alqaysi, M. E., A. S. Albahri, and Rula A. Hamid. "Diagnosis-based hybridization of multimedical tests and sociodemographic characteristics of autism spectrum disorder using artificial intelligence and machine learning techniques: a systematic review." *International Journal of Telemedicine and Applications* 2022 (2022). https://doi.org/10.1155/2022/3551528

[4] Ahmed, Zeyad AT, Theyazn HH Aldhyani, Mukti E. Jadhav, Mohammed Y. Alzahrani, Mohammad Eid Alzahrani, Maha M. Althobaiti, Fawaz Alassery, Ahmed Alshaflut, Nouf Matar Alzahrani, and Ali Mansour Al-Madani. "Facial features detection system to identify children with autism spectrum disorder: deep learning models." *Computational and Mathematical Methods in Medicine* 2022 (2022). https://doi.org/10.1155/2022/3941049

[5] Ahmed, Ibrahim Abdulrab, Ebrahim Mohammed Senan, Taha H. Rassem, Mohammed AH Ali, Hamzeh Salameh Ahmad Shatnawi, Salwa Mutahar Alwazer, and Mohammed Alshahrani. "Eye tracking-based diagnosis and early detection of autism spectrum disorder using machine learning and deep learning techniques." *Electronics* 11, no. 4 (2022): 530. https://doi.org/10.3390/electronics11040530

[6] Kohli, Manu, Arpan Kumar Kar, Anjali Bangalore, and Prathosh Ap. "Machine learning-based ABA treatment recommendation and personalization for autism spectrum disorder: an exploratory study." *Brain Informatics* 9, no. 1 (2022): 1-25. https://doi.org/10.1186/s40708-022-00164-6

[7] Alsaade, Fawaz Waselallah, and Mohammed Saeed Alzahrani. "Classification and detection of autism spectrum disorder based on deep learning algorithms." *Computational Intelligence and Neuroscience* 2022 (2022). https://doi.org/10.1155/2022/8709145

[8] Bala, Mousumi, Mohammad Hanif Ali, Md Shahriare Satu, Khondokar Fida Hasan, and Mohammad Ali Moni. "Efficient machine learning models for early stage detection of autism spectrum disorder." *Algorithms* 15, no. 5 (2022): 166. https://doi.org/10.3390/a15050166

[9] Zhu, Feng-lei, Shi-huan Wang, Wen-bo Liu, Hui-lin Zhu, Ming Li, and Xiao-bing Zou. "A multimodal machine learning system in early screening for toddlers with autism spectrum disorders based on the response to name." *Frontiers in Psychiatry* 14 (2023): 1039293. https://doi.org/10.3389/fpsyt.2023.1039293

[10] Zhu, Yinghan, Hironori Nakatani, Walid Yassin, Norihide Maikusa, Naohiro Okada, Akira Kunimatsu, Osamu Abe et al. "Application of a machine learning algorithm for structural brain images in chronic schizophrenia to earlier clinical stages of psychosis and autism spectrum disorder: a multiprotocol imaging dataset study." *Schizophrenia Bulletin* 48, no. 3 (2022): 563-574. https://doi.org/10.1093/schbul/sbac030

[11] Zhang, Jin, Fan Feng, Tianyi Han, Xiaoli Gong, and Feng Duan. "Detection of autism spectrum disorder using fMRI functional connectivity with feature selection and deep learning." *Cognitive Computation* (2022): 1-12. https://doi.org/10.1007/s12559-021-09981-z

[12] Pires, Gabriel, Aniana Cruz, Diogo Jesus, Mine Yasemin, Urbano J. Nunes, Teresa Sousa, and Miguel Castelo-Branco. "A new error-monitoring brain–computer interface based on reinforcement learning for people with autism spectrum disorders." *Journal of Neural Engineering* 19, no. 6 (2022): 066032. https://doi.org/10.1088/1741-2552/aca798

[13] Garg, Anupam, Anshu Parashar, Dipto Barman, Sahil Jain, Divya Singhal, Mehedi Masud, and Mohamed Abouhawwash. "Autism spectrum disorder prediction by an explainable deep learning approach." *Computers, Materials & Continua* 71, no. 1 (2022): 1459-1471. https://doi.org/10.32604/cmc.2022.022170

[14] Stember, Joseph, Danielle Stember, Luca Pasquini, Jenabi Merhnaz, Andrei Holodny, and Hrithwik Shalu. "Deep reinforcement learning for fMRI prediction of Autism Spectrum Disorder." *arXiv preprint arXiv:2206.11224* (2022).

[15] Vishal, Vaibhav, Abhishek Singh, Y. Bevish Jinila, S. Prayla Shyry, and J. Jabez. "A comparative analysis of prediction of autism spectrum disorder (ASD) using machine learning." In *2022 6th International Conference on Trends in Electronics and Informatics (ICOEI)*, pp. 1355-1358. IEEE, 2022. https://doi.org/10.1109/ICOEI53556.2022.9777240

[16] Satyanarayana, P., G. Diwakar, B. V. Subbayamma, NV Phani Sai Kumar, M. Arun, and S. Gopalakrishnan. "Comparative analysis of new meta-heuristic-variants for privacy preservation in wireless mobile adhoc networks for IoT applications." *Computer Communications* 198 (2023): 262-281. https://doi.org/10.1016/j.comcom.2022.12.006

[17] Rammo, Fawziya M., and Mohammed N. Al-Hamdani. "Detecting the speaker language using CNN deep learning algorithm." *Iraqi Journal for Computer Science and Mathematics* 3, no. 1 (2022): 43-52. https://doi.org/10.52866/ijcsm.2022.01.01.005

[18] Mohsin, Zainab Rustum. "Investigating the use of an adaptive neuro-fuzzy inference system in software development effort estimation." *Iraqi Journal For Computer Science and Mathematics* 2, no. 2 (2021): 18-24. https://doi.org/10.52866/ijcsm.2021.02.02.003

[19] Achenie, Luke EK, Angela Scarpa, Reina S. Factor, Tao Wang, Diana L. Robins, and D. Scott McCrickard. "A machine learning strategy for autism screening in toddlers." *Journal of developmental and behavioral pediatrics: JDBP* 40, no. 5 (2019): 369. https://doi.org/10.1097/DBP.0000000000000668

[20] Brock, J., C. C. Brown, J. Boucher, and G. Rippon. "The temporal binding deficit hypothesis of autism. Developmentand Psychopathology, 14 (2), 209–224." (2002). https://doi.org/10.1017/S0954579402002018

[21] Rippon, Gina, Jon Brock, Caroline Brown, and Jill Boucher. "Disordered connectivity in the autistic brain: challenges for the 'new psychophysiology'." *International journal of psychophysiology* 63, no. 2 (2007): 164-172. https://doi.org/10.1016/j.ijpsycho.2006.03.012

[22] Travers, Brittany G., Nagesh Adluru, Chad Ennis, Do PM Tromp, Dan Destiche, Sam Doran, Erin D. Bigler, Nicholas Lange, Janet E. Lainhart, and Andrew L. Alexander. "Diffusion tensor imaging in autism spectrum disorder: a review." *Autism Research* 5, no. 5 (2012): 289-313. https://doi.org/10.1002/aur.1243

[23] Kuno-Fujita, Ayaka, Toshiki Iwabuchi, Keisuke Wakusawa, Hiroyuki Ito, Katsuaki Suzuki, Akira Shigetomi, Hirotaka Kosaka, Masatsugu Tsujii, and Kenji J. Tsuchiya. "Sensory processing patterns and fusiform activity during face processing in autism spectrum disorder." *Autism Research* 13, no. 5 (2020): 741-750. https://doi.org/10.1002/aur.2283

[24] Zhang, Fan, Anna Breger, Kang Ik Kevin Cho, Lipeng Ning, Carl-Fredrik Westin, Lauren J. O'Donnell, and Ofer Pasternak. "Deep learning based segmentation of brain tissue from diffusion MRI." *NeuroImage* 233 (2021): 117934. https://doi.org/10.1016/j.neuroimage.2021.117934

[25] Payabvash, Seyedmehdi, Eva M. Palacios, Julia P. Owen, Maxwell B. Wang, Teresa Tavassoli, Molly Gerdes, Anne Brandes-Aitken, Daniel Cuneo, Elysa J. Marco, and Pratik Mukherjee. "White matter connectome edge density in children with autism spectrum disorders: potential imaging biomarkers using machine-learning models." *Brain connectivity* 9, no. 2 (2019): 209-220. https://doi.org/10.1089/brain.2018.0658

[26] Tariq, Osama Bin, Mihai Teodor Lazarescu, Javed Iqbal, and Luciano Lavagno. "Performance of machine learning classifiers for indoor person localization with capacitive sensors." *Ieee Access* 5 (2017): 12913-12926. https://doi.org/10.1109/ACCESS.2017.2721538

[27] D'Andrea, Antonino, Claudio Cappadona, Gianluca La Rosa, and Orazio Pellegrino. "A functional road classification with data mining techniques." *Transport* 29, no. 4 (2014): 419-430. https://doi.org/10.3846/16484142.2014.984329

[28] Hossain, Md Delowar, Muhammad Ashad Kabir, Adnan Anwar, and Md Zahidul Islam. "Detecting autism spectrum disorder using machine learning techniques: An experimental analysis on toddler, child, adolescent and adult datasets." *Health Information Science and Systems* 9 (2021): 1-13. https://doi.org/10.1007/s13755-021-00145-9

[29] Baranwal, Aseem, Kimon Fountoulakis, and Aukosh Jagannath. "Graph convolution for semi-supervised classification: Improved linear separability and out-of-distribution generalization." *arXiv preprint arXiv:2102.06966* (2021).

[30] Thabtah, Fadi, Suhel Hammoud, Firuz Kamalov, and Amanda Gonsalves. "Data imbalance in classification: Experimental evaluation." *Information Sciences* 513 (2020): 429-441. https://doi.org/10.1016/j.ins.2019.11.004

[31] Thabtah, Fadi. "Machine learning in autistic spectrum disorder behavioral research: A review and ways forward." *Informatics for Health and Social Care* 44, no. 3 (2019): 278-297. https://doi.org/10.1080/17538157.2017.1399132