Journal of Theoretical and Applied Information Technology
15th May 2022. Vol.100. No 9

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ADAPTIVE WHALE OPTIMIZATION BASED SUPPORT VECTOR MACHINE FOR PREDICTION OF AUTISM SPECTRUM DISORDER

S. MALATHI[1], Dr. D. KANNAN[2]

[1]Research Scholar, Department of Computer Science, Pollachi College of Arts and Science, India
[2]Research Supervisor & Professor in Computer Science, Principal, Pollachi College of Arts and Science, India
E-mail: [1]malathisubramaniam.75@gmail.com, [2]kd.khannan@gmail.com

ABSTRACT

Autism Spectrum Disorder (ASD) is a prominent form of neurological disorder that impairs a person's ability to engage socially and interact effectively with others. ASD is also characterised by a tendency toward repetitive and restricted behaviours. The costs associated with autism can rise during the time it takes to get a diagnosis and begin treatment, but many of these expenditures are long-term and will remain with a person throughout their lives. Optimization and machine learning methods have been used in many different industries and professions in an effort to improve results.In this paper, an bioinspired optimization-based classifier namely Adaptive Whale Optimization based Support Vector Machine (AWO-SVM) is proposed for precisely detect ASD. AWO-SVM performs classification after optimization phase gets complete. AWO-SVM involves three different phases namely Exploitation Phase, Exploration Phase, and Classification Phase. Each phase of AWO-SVM plays a major role to predict ASD more accurately. The metrics "accuracy" and "F-Measure" are used to evaluate AWO-SVM on three distinct ASD screening datasets. When AWO-SVM results are compared to those of other classifiers, it is clear that AWO-SVM is superior in terms of accuracy in predicting ASD.
Keywords: *Autism, ASD, Optimization, Classification, Whale, SVM*

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a term currently used to describe a neurodevelopmental disorder marked by difficulties in reciprocal social communication and a predisposition to engage in repeated, stereotyped behaviour patterns, interests, and activities. There are many similarities between autism and other neurodevelopmental diseases. The aetiology is believed to be multi-factorial, with boys outnumbering females and the fundamental traits present in early life[1]. Changes in the clinical presentation might arise due to changes in the environment or co-occurring disorders. Early preschool years are often marked by a lack of verbal, cognitive, or social development in many people with ASD who have this condition. Primary behavioural symptoms tend to improve over time, although some behaviours may linger and create a longer-term problem. As a result of these and other factors, many people affected have difficulty with essential everyday functions such as motor coordination, balance, and sleep and issues with their mental health and actions that put others in danger[2], [3].

Clinical signs of ASD can take several forms, with varying degrees of delay or immaturity coexisting with the onset of more atypical behavioural patterns. Problems with joint attention, lack of eye contact, lack of social purpose in interacting with others, and imitative social play can all be signs of autism's early social communication symptoms. More evident symptoms of ASD include (i) motor stereotypies, (ii) lining up of items, (iii) lack of interest in other children, and (iv) difficulty in playing collaborated manner, which become more apparent with time. The other primary symptoms of ASD are: (i) difficulties communicating, (ii) lack of empathy, and (iii) inflexible thinking styles emerge. ASD symptoms can be seen as exaggerating typical developmental delays. In contrast, other symptoms are distinct and rarely seen in typical children's development[4], [5].

Journal of Theoretical and Applied Information Technology
15th May 2022. Vol.100. No 9

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Early diagnosis and treatment are critical in reducing the symptoms of ASD and improving the quality of life for people living with ASD. Although there is no medical test for autism, it becomes mandatory to diagnose ASD as early as possible. An individual with ASD can't typically tell whether they have specific symptoms related to ASD. Parents and teachers will often see signs of autism in their children as they become older and begin attending school[6]. That's when a special education team from the school evaluates the student's ASD symptoms. It was recommended that these youngsters see their primary care physician for necessary testing by the health care staff in school. Adults have a more challenging time detecting ASD symptoms than older children and adolescents since specific ASD symptoms overlap with other mental health conditions. A child's behavioral alterations are more accessible to spot at six months of age via observation than with autism-specific brain imaging that can only be detected at two years of age[7].

1.1 Problem Statement

ASD can be diagnosed in children, adolescents, and adults using the tools that are now available. There are classifiers for adolescent ASD, child ASD, and adult ASD, but no standard classifier is available in common for all three types of ASD. Increased field observations and data analysis are the only ways to handle better what it's like to be autistic. Machine learning models that employ medical data may be used to develop predictions and observations that can lead to improved solutions for detecting ASD at the earliest possible time with higher accuracy in ASD prediction.

1.2 Motivation

ASD affects a large percentage of youngsters. Initial diagnosis is often achievable, but the most significant bottleneck is due to the subjective and arduous nature of the initial stages of the process. That's why getting an ASD diagnosis takes, on average, 13 to 15 months from when someone first believes they have it. Diagnoses take a long time to come to fruition, and demand for visits to pediatric clinics is outpacing the capacity of the nation's facilities. Increased expense in providing treatment for ASD affected persons and a prolonged time for recovery from ASD are the core contents that motivated this research work.

1.3 Objective

This research attempts to build a classification system that uses a bio-inspired optimization technique to improve the accuracy of ASD diagnosis.

1.4 Organization of the Paper

The present portion of the study provides an overview of ASD and concludes with a discussion of the problem description, motivation, and purpose of the research. The next section goes into detail on the relevant literature. Section 3 focuses on the suggested ASD classification classifier. The dataset used to evaluate the proposed classifier is described in detail in Section 4. Using the metrics in this section, we may compare the proposed classifier to the current classifiers. A discussion of the findings is in Section 6, and a look into the future appears in Section 7.

2. LITERATURE REVIEW

"Bayesian and Free-Energy Technique"[8] is proposed to construct ASDs and examine the imbalance in brain inhibitory control. Neuronal networks are used to mimic the disorder's symptoms and build the network's design leading to better classification of ASD. "Operational Taxonomic Units (OTUs)"[9] is incorporated in the prediction model of autism. There will be a better understanding of ASD's changing microbiota due to classification and prediction-oriented research. The findings were based on changes to the microbiome, which may be used to diagnose illness in its early stages. "Fixel Based Analysis Framework (FBAF)"[10] is applied in Magnetic Resonance Imaging to acquire the exact characteristics of ASD persons. To find features employed in the Linear SVM classifier, the microstructure of white matter was verified, and feature-based estimations were used in the same. This technique's usefulness has been demonstrated by comparison to other methods. "Classification and feature extraction based on electroencephalography"[11] is suggested for quantifying brain abnormalities. Non-linear approaches were introduced after pre-processing, and an inability to communicate was discovered. Classifying the characteristics and proving their effectiveness helps anticipate the accuracy of the classification. "Ensemble classifier SVM-ANN"[12] is proposed for children with ASD who have poor sleep quality. Asleep quality estimator and a prediction model are used to gather and estimate sleep characteristics that assist more in predicting ASD. This classification model helps in calculating accuracy and demonstrating efficiency.

"Application of Deep Learning Technique"[13] examines individuals e-health records for the presence of neurological and mental illnesses. Deep learning strategies are applied for increased accuracy. Performance metrics are used to compare the results from qualitative analysis to the results from deep learning and machine learning approaches."Hierarchical GCN (hi-GCN)"[14]was applied to learn graph properties for developing the graph neural network, and neurological diseases were identified. It is possible to estimate the classifier's accuracy and diagnose its malfunction to determine its performance. There is an increase in precision due to the data being collected. "Dynamic Functional Connectome Analysis"[15] was proposed to diagnose schizophrenia conditions, a type of ASD that makes people abnormally interpret reality. Using the windowing approach, functional connectivity states and the overlap disorder were examined. The functioning connection is studied and classified with ASD to demonstrate its efficacy."Modified Grasshopper Optimization Algorithm (MGOA)"[16] has been developed for early detection and diagnosis of autistic condition. Prediction accuracy is assessed using the Random Forest classifier, and it was found that the assessment using SVM has a minor performance."Feature Aspect Classification"[17] aimed to categorize the whole-brain characteristics of ASD-affected children. For more accurate predictions, more priority is given to ASD patterns. The categorization scores for various network types are computed, and the classification is performed.

"Development of ASD database for painting"[18] is proposed to identify ASD among growing children. An autistic child's traits are observed and classified using a classifier that has undergone training.Cognitive subtypes are identified using "Functional Random Forest (FRF)"[19], and the closeness of each task is quantified. To determine differences in the brain system across groups, RS-fMRI is used. Subgroups and system performance are used to gauge the system's overall effectiveness."Genetics of Neurodevelopmental Disorders (NDD)"[20] is employed to locate genes and biological processes, such as cell cycle, synapse function, metabolism, and chromosomal groupings. An early stage of the brain's development may be recognized, and the expressed genes can be extracted. Gene datasets are used to diagnose the illness and provide findings."Machine Learning method"[21] proposed improving classification accuracy. This method uses an autoencoder tool to choose the data. Classifiers and feature patterns for autistic illness features are taught to increase the approach's performance."Fuzzy Rule-Based Method"[22] is proposed to classify the co-morbid variables of ASD, and the symptoms related to it are distinguished. The neurodevelopmental disorder is diagnosed and detected by supplying the co-morbidities for diagnosis and detection. Optimization strategies [23]–[28] are applied in different domains to achieve better results and it is started being used in ASD prediction also.

"Autism Diagnostic Observation Schedule (ADOS)"[29] is applied to compute the multimodal behaviour descriptor of ASD and assess the feature's behaviour. The classifier's accuracy is calculated when determining specificbehavioural syndromes. Computed and assessed performance characteristics are analyzed are appropriate classification."Linear and Non-Linear Features"[30] is proposed to utilize EEG data in selecting the features for the exact prediction of ASD. The Density-based clustering approach was used to cluster linear and non-linear characteristics. Based on the classifier findings, features were classified using SVM and K-Nearest-Neighbour."Phenotyping Strategy"[31] is proposed to determine whether or not a kid has ASD syndrome. In addition, the concerns and solutions to these hurdles were examined and described. This strategy identifies the biological underpinnings and the heterogeneity of various neuropsychiatric disorders."Machine Learning for Asperger's Syndrome" (MLAS) [32] is proposed to determine who is most likely to have an ASD based on a person's mental and non-mental health. Risk scores and odd ratios are computed using confidence intervals for diagnostic purposes."Intelligent Fuzzy Logic Agent System (IFLAS)"[33]was developed to detect signs of ASD among individuals. By carefully simulating the fuzzy system, diagnosis is made where doctors even struggle tremendously. Performance is enhanced by incorporating machine learning.

3. ADAPTIVE WHALE OPTIMIZATION BASED SUPPORT VECTOR MACHINE

Adaptive Whale Optimization based Support Vector Machine (AWO-SVM) is an novel metaheuristic algorithm that simulates humpback whale foraging behavior. Humpback whales search for krill or tiny fish adjacent to the surface via swimming in the area between blowing characteristic bubbles and diminishing circle. The algorithm's first part included prey encircling and using a spiral bubble-net assaulting mechanism; the second phase, exploitation, included searching for prey at random (i.e., exploration phase). Each phase's mathematical model is discussed in depth in the following subsections. To produce random numbers, this research work uses uniform distribution.

3.1 Exploitation Phase

To begin the process of hunting, encircling is initially performed by humpback whales. Eqn.(1) and Eqn.(2) mathematically represent this behavior.

$$G = \left|U.\overrightarrow{P^*}(f) - \vec{P}(f)\right| \quad (1)$$

$$\vec{P}(f+1) = \overrightarrow{P^*}(t) - \vec{D}.\mathrm{G} \quad (2)$$

where f represents the iteration count of the current phase. P^* represents the acceptable solution that has been found thus far. P indicates the vector position. $||$ represents absolute value, . denotes the product operation that is carried out element by element. Aside from that, the coefficient vectors D and U are determined in the same way as in Eqn.(3) and Eqn.(4).

$$\vec{D} = 2\vec{d}.\vec{b} - \vec{d} \quad (3)$$

$$\vec{U} = 2.\vec{b} \quad (4)$$

While iteration is performed in exploration and exploitation phases, the value of d declines linearly from 2 to 0 overtime, while b is produced at random with uniform distribution within the range [0,1]. Search agents (i.e., humpback whales) adjust their locations following the best-identified prey (i.e., solution) according to Eqn.(2). The values of D and U vectors may be adjusted to regulate where a whale can be found in the vicinity of its prey.According to Eqn.(5), the behavior of shrinking encircling can be achieved by lowering the value of b in Eqn.(3).

$$d = 2 - f\frac{2}{Mxm\_Iter} \quad (5)$$

where f represents the count of iteration and Mxm_Iter indicates the count of maximum iterations that are allowed. In order to simulate the path that is spiral in shape, distance that exist between best-known search agent (P^*) and general-search agent (P) is utilized and calculation is performed. Eqn.(6) is applied to identify the position of search agent in spiral shape.

$$\vec{P}(f+1) = \acute{G}.h^{vz}.\cos(2\pi z) + \vec{P_*}(f) \quad (6)$$

where $\acute{G}$ is computed as $\left|\vec{P}^*(t) - \vec{P}(t)\right|$and it denotes the presence of distance between prey (i.e., so far identified best solution) and whale s. The formation of spiral shape dependent on logarithmic value is defined by the constant v. Spiral-shaped path and shrinking encircling mechanisms are modelled with an assumption. That is, they both have 50% probability in getting selected for the optimization process as mentioned in Eqn.(7).

$$\vec{P}(f+1) = \begin{cases} Shrinking\ Encircling\ \ if(0.5 > m) \\ Spiral - shaped\ path\ \ if(0.5 \le m) \end{cases} \quad (7)$$

where $m$represents a random number that falls in [0,1].

3.2 Exploration Phase

To increase the search space for exploration in AWO-SVM, agent of random-search is selected for providing guidance instead of simply providing update for the best search agent identified so far. Use of a random vector d with random values higher or lesser than 1 forces the search agent to shift away from the search agent that is identified so-far. Eqn.(8) and Eqn.(9) can be used to represent this mechanism quantitatively.

$$\vec{G} = \left|\vec{U}.\overrightarrow{P_{rand}} - \vec{P}\right| \quad (8)$$

$$\vec{P}(f+1) = \overrightarrow{\vec{P}_{rand}} - \vec{D}.\vec{G} \quad (9)$$

where$\overrightarrow{P_{rand}}$ represent a randomly selected whale that is selected from the current population.

3.3 Classification Phase

A machine learning approach based on the premise of reducing structural risk and statistical learning theory is the Support Vector Machine (SVM) classification strategy AWO-SVM is primarily concerned with transforming data into a high-dimensional space. It uses hyper-planes to classify data, which have a greater margin of error. Eqn.(10) is the mathematical representation of AWO-SVM.

$$f = \min \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{t} e_i \quad (10)$$

Subject to $y_i(\omega . q(x_i)) + b) \geq (1 - e_i)$,
where $e_i \geq 0, i = 1,2, \ldots l$

where $x_i \in R^n$ denotes training sample and $y_i \in \{-1, +1\}$ is the corresponding label of a class, ϕ is the map of nonlinear transformations that the data related to higher dimensional features space, ω indicates normal vector of bounding plane, b is the bias based value, $e_i \geq 0, i = 1,2, \ldots l$ represents the slack variables, and C is the parameter used for calculating the penalty. Instead, to solve the above-mentioned optimization-based classification problem, it is much better to resolve the problem in dual:

$$\min_{\alpha} \frac{1}{2}\sum_{a=1}^{l}\sum_{b=1}^{l} y_a y_b \alpha_a \alpha_b k(x_a x_b) - \sum_{b=1}^{l} \alpha_b \quad (11)$$

$sub.to \sum_{a=1}^{l} y_a \alpha_i = 0$, where $0 \leq \alpha_i \leq C, a = 1,2, \ldots, l$

where $k(x_a x_b) = q(x_a).q(x_b)$ indicates the kernel function.

Decision function is mathematically expressed as Eqn.(12).

$$\mathrm{f(x)} = \mathrm{sign}\left(\sum_{\mathrm{x_a} \in \mathrm{SV}} \mathrm{y_a} \alpha_\mathrm{a}^* \mathrm{k(x, x_a)} + \mathrm{c}\right) (12)$$

where α_a^* represents the optimal solution for the research problem considered in Eqn.(10).

4. DATASET

For testing proposed classifier performance towards predicting ASD, this research work used three datasets (ASD Screening Dataset for Adults, Children, and Adolescents), [34], [35]. Each dataset contains twenty-one attributes. The Adults dataset has 704 cases, Children contains 292 instances, and Adolescents contains 104 instances. Description of 20 common features present in the 3 dataset are provided in Table 1.

Table 1: Feature Details

Feature Id	Feature Description
1	Age
2	Gender
3	Ethnicity
4	Jaundice history
5	Pervasive Development Disorders with Family member
6	Who is completing the test
7	Country
8	Whether user have used screening App e
9	Screening Method Type
10 – 19	Answers of 10 questions related to ASD s
20	Screening Score

5. PERFORMANCE METRICS

In order to calculate performance metrics, four variables are utilized:

- True Positive (TruPos): Precise finding of ASD presence
- False Positive (FalPos): Imprecise finding of ASD presence
- True Negative (TruNeg): Precise finding of ASD absence
- False Negative (FalNeg): Imprecise finding of ASD absence

5.1 Classification Accuracy

Classification Accuracy is used to gauge the effectiveness of classifier and it measures how accurate the classifier act in making predictions. Classification Accuracy is mathematically expressed in Eqn.(13).

$$\text{Classification Accuracy} = \frac{\text{TruPos} + \text{TruNeg}}{\text{TruPos} + \text{TruNeg} + \text{FalPos} + \text{FalNeg}} \quad (13)$$

5.2 F-Measure

F-Measure is a better way to quantify instances that were erroneously categorized, and it is the harmonic mean of Precision and Recall. It is mathematically expressed in Eqn.(14).

$$\mathrm{F-Measure} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (14)$$

6. RESULTS AND DISCUSSION

6.1 Classification Accuracy Analysis

Figure 1 compares the classification accuracy attained by the proposed classification algorithm AWO-SVM against existing classification algorithms, namely MLAS and

Journal of Theoretical and Applied Information Technology
15th May 2022. Vol.100. No 9

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

IFLAS. The X-axis is marked with ASD Screening Datasets, namely Adult, Child, and Adolescent, and the Y-axis is marked with accuracy in percentage. From Figure 1, it is clear to understand that the AWO-SVM has attained better classification accuracy than MLAS and IFLAS. Optimization in AWO-SVM leads to a way to attain better accuracy where MLAS and IFLAS simply focus on classification. Exploitation phase of AWO-SVM assist the classification phase to predict ASD more accurately than MLAS and IFLAS. Numerical result values of Figure 1 is provided in Table 1 for better understanding.

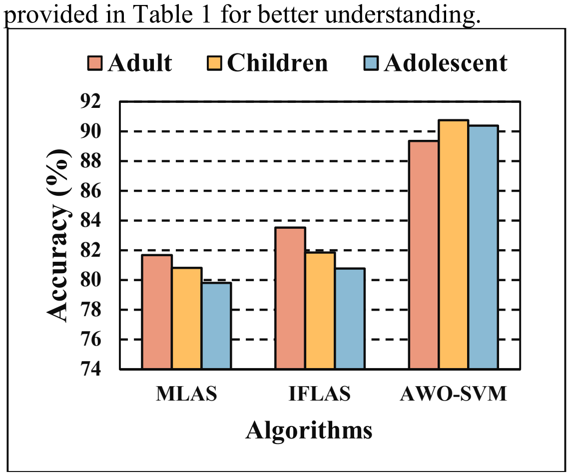

Fig 1. Classification Accuracy Vs Algorithms

Table 1. Result Values of Classication Analysis

Algorithms / Dataset	MLAS	IFLAS	AWO-SVM
Adult	81.676	83.523	89.347
Children	80.822	81.849	90.753
Adolescent	79.808	80.769	90.385

6.2 F-Measure Analysis

Figure 2 compares the f-measure accuracy attained by the proposed classification algorithm AWO-SVM against existing classification algorithms, namely MLAS and IFLAS. The X-axis is marked with ASD Screening Datasets, namely Adult, Child, and Adolescent, and the Y-axis is marked with f-measure in percentage. As illustrated in Figure 2, AWO-SVM has a higher f-measure than MLAS and IFLAS.Unlike the MLAS and IFLAS, AWO-SVM optimization leads to an improved f-measure. AWO-SVM has a higher f-measure than MLAS and IFLAS due to the process used during the exploration phase.Table 2 provides the numerical results of Figure 2 for better comprehension.

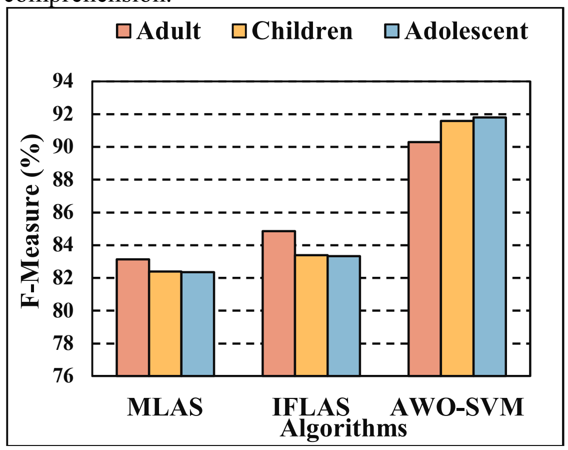

Fig 2. F-Measure Vs Algorithms

Table 2. Result Values of F-Measure Analysis

Algorithms / Dataset	MLAS	IFLAS	AWO-SVM
Adult	83.137	84.856	90.298
Children	82.390	83.386	91.589
Adolescent	82.353	83.333	91.803

7. CONCLUSION

Autism spectrum disorder (ASD) is a developmental disability characterised by difficulties in social interaction, verbal communication, and behavioural expression. They might be small, moderate, or serious. The cost of detecting and treating ASD is significantly higher than that of other disorders. In order to better diagnose ASD, an adaptive whale optimization-based support vector machine (AWO-SVM) has been proposed in this paper. Three different phases of AWO-SVM play a significant role in achieving better classification accuracy. AWO-SVM is evaluated with three different ASD screening datasets. Two benchmark performance metrics is used to measure the results of AWO-SVM against existing classifiers namely MLAS and IFLAS. Averagely AWO-SVM has achieved 90.162% of accuracy where MLAS and IFLAS has achieved

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

80.769% and 82.047% respectively. To improve classification accuracy even more in the future, this research work plans to use a combination of bioinspired optimization and machine learning methodologies.

REFERENCES

[1] S. Ali *et al.*, "An Adaptive Multi-Robot Therapy for Improving Joint Attention and Imitation of ASD Children," *IEEE Access*, vol. 7, pp. 81808–81825, 2019, doi: 10.1109/ACCESS.2019.2923678.

[2] T. Wu *et al.*, "Potential of gut microbiome for detection of autism spectrum disorder," *Microb. Pathog.*, vol. 149, p. 104568, 2020, doi: https://doi.org/10.1016/j.micpath.2020.104568.

[3] M. Sakishita, C. Ogawa, K. J. Tsuchiya, T. Iwabuchi, T. Kishimoto, and Y. Kano, "Autism Spectrum Disorderâ€™s Severity Prediction Model Using Utterance Features for Automatic Diagnosis Support," in *Studies in Computational Intelligence*, vol. 843, Springer Verlag, 2020, pp. 83–95.

[4] H. Kalantarian, K. Jedoui, P. Washington, and D. P. Wall, "A Mobile Game for Automatic Emotion-Labeling of Images," *IEEE Trans. Games*, vol. 12, no. 2, pp. 213–218, 2020, doi: 10.1109/TG.2018.2877325.

[5] A. Liang *et al.*, "Whole-Head Magnetoencephalogram and Its Application in Developmental Communication Disorders Research: A Review," *IEEE Access*, vol. 9, pp. 42515–42532, 2021, doi: 10.1109/ACCESS.2021.3063054.

[6] M. Oliveira, M. Guebert, and P. Nohama, "TEACCH Methodology-Based Web System to Support Learning for Children with Autism," *IEEE Lat. Am. Trans.*, vol. 16, no. 11, pp. 2698–2705, 2018, doi: 10.1109/TLA.2018.8795110.

[7] C. Shulman, A. Esler, M. J. Morrier, and C. E. Rice, "Diagnosis of Autism Spectrum Disorder Across the Lifespan," *Psychiatr. Clin. North Am.*, vol. 43, no. 4, pp. 583–603, 2020, doi: https://doi.org/10.1016/j.psc.2020.08.001.

[8] P. Lanillos, D. Oliva, A. Philippsen, Y. Yamashita, Y. Nagai, and G. Cheng, "A review on neural network models of schizophrenia and autism spectrum disorder," *Neural Networks*, vol. 122, pp. 338–363, 2020, doi: https://doi.org/10.1016/j.neunet.2019.10.014.

[9] F. Ye *et al.*, "Comparison of gut microbiota in autism spectrum disorders and neurotypical boys in China: A case-control study," *Synth. Syst. Biotechnol.*, vol. 6, no. 2, pp. 120–126, 2021, doi: https://doi.org/10.1016/j.synbio.2021.03.003.

[10] Z. Zhang and W. Zheng, "The Discriminative Power of White Matter Microstructures for Autism Diagnosis," *IFAC-PapersOnLine*, vol. 53, no. 5, pp. 446–451, 2020, doi: https://doi.org/10.1016/j.ifacol.2021.04.121.

[11] S. Ibrahim, R. Djemal, and A. Alsuwailem, "Electroencephalography (EEG) signal processing for epilepsy and autism spectrum disorder diagnosis," *Biocybern. Biomed. Eng.*, vol. 38, no. 1, pp. 16–26, 2018, doi: https://doi.org/10.1016/j.bbe.2017.08.006.

[12] A. Alivar *et al.*, "Smart bed based daytime behavior prediction in Children with autism spectrum disorder - A Pilot Study," *Med. Eng. Phys.*, vol. 83, pp. 15–25, 2020, doi: https://doi.org/10.1016/j.medengphy.2020.07.004.

[13] M. Quaak, L. van de Mortel, R. M. Thomas, and G. van Wingen, "Deep learning applications for the classification of psychiatric disorders using neuroimaging data: Systematic review and meta-analysis," *NeuroImage Clin.*, vol. 30, p. 102584, 2021, doi: https://doi.org/10.1016/j.nicl.2021.102584.

[14] H. Jiang, P. Cao, M. Xu, J. Yang, and O. Zaiane, "Hi-GCN: A hierarchical graph convolution network for graph embedding learning of brain network and brain disorders prediction," *Comput. Biol. Med.*, vol. 127, p. 104096, 2020, doi: https://doi.org/10.1016/j.compbiomed.2020.104096.

[15] A. Andriamananjara, R. Muntari, and A. Crimi, "Overlaps in brain dynamic functional connectivity between schizophrenia and autism spectrum disorder," *Sci. African*, vol. 2, p. e00019, 2019, doi: https://doi.org/10.1016/j.sciaf.2018.e00019

[16] N. Goel, B. Grover, Anuj, D. Gupta, A. Khanna, and M. Sharma, "Modified Grasshopper Optimization Algorithm for detection of Autism Spectrum Disorder," *Phys. Commun.*, vol. 41, p. 101115, 2020, doi: https://doi.org/10.1016/j.phycom.2020.101115.

[17] H. Chen *et al.*, "Multivariate classification of autism spectrum disorder using frequency-specific resting-state functional connectivity—A multi-center study," *Prog. Neuro-Psychopharmacology Biol. Psychiatry*, vol. 64, pp. 1–9, 2016, doi: https://doi.org/10.1016/j.pnpbp.2015.06.014.

[18] F. Shi *et al.*, "Drawing reveals hallmarks of children with autism," *Displays*, vol. 67, p. 102000, 2021, doi: https://doi.org/10.1016/j.displa.2021.102000.

[19] E. Feczko *et al.*, "Subtyping cognitive profiles in Autism Spectrum Disorder using a Functional Random Forest algorithm," *Neuroimage*, vol. 172, pp. 674–688, 2018, doi: https://doi.org/10.1016/j.neuroimage.2017.12.044.

[20] C. S. Leblond *et al.*, "Operative list of genes associated with autism and neurodevelopmental disorders based on database review," *Mol. Cell. Neurosci.*, vol. 113, p. 103623, 2021, doi: https://doi.org/10.1016/j.mcn.2021.103623.

[21] E. Ferrari *et al.*, "Dealing with confounders and outliers in classification medical studies: The Autism Spectrum Disorders case study," *Artif. Intell. Med.*, vol. 108, p. 101926, 2020, doi: https://doi.org/10.1016/j.artmed.2020.101926.

[22] G. Kaur and D. Kakkar, "Fuzzy Based Integrated Diagnostic System for Neurodevelopmental Disorders," in *2019 6th International Conference on Signal Processing and Integrated Networks (SPIN)*, 2019, pp. 132–136, doi: 10.1109/SPIN.2019.8711674.

[23] J. Ramkumar and R. Vadivel, "Performance Modeling of Bio-Inspired Routing Protocols in Cognitive Radio Ad Hoc Network to Reduce End-to-End Delay," *Int. J. Intell. Eng. Syst.*, vol. 12, no. 1, pp. 221–231, 2019, doi: 10.22266/ijies2019.0228.22.

[24] J. Ramkumar and R. Vadivel, "Whale Optimization Routing Protocol for Minimizing Energy Consumption in Cognitive Radio Wireless Sensor Network," *Int. J. Comput. Networks Appl.*, vol. 8, no. 4, doi: 10.22247/ijcna/2021/209711.

[25] J. Ramkumar and R. Vadivel, "Multi-Adaptive Routing Protocol for Internet of Things based Ad-hoc Networks," *Wirel. Pers. Commun.*, pp. 1–23, Apr. 2021, doi: 10.1007/s11277-021-08495-z.

[26] J. Ramkumar and R. Vadivel, "Intelligent Fish Swarm Inspired Protocol (IFSIP) For Dynamic Ideal Routing in Cognitive Radio Ad-Hoc Networks," *Int. J. Comput. Digit. Syst.*, vol. 10, no. 1, pp. 1063–1074, 2020, doi: http://dx.doi.org/10.12785/ijcds/100196.

[27] J. Ramkumar and R. Vadivel, "Improved frog leap inspired protocol (IFLIP) – for routing in cognitive radio ad hoc networks (CRAHN)," *World J. Eng.*, vol. 15, no. 2, pp. 306–311, 2018, doi: 10.1108/WJE-08-2017-0260.

[28] M. Lingaraj, T. N. Sugumar, C. Stanly Felix, and J. Ramkumar, "Query Aware Routing Protocol for Mobility Enabled Wireless Sensor Network," *Int. J. Comput. Networks Appl.*, vol. 8, no. 3, p. 258, Jun. 2021, doi: 10.22247/IJCNA/2021/209192.

[29] C.-P. Chen, S. S.-F. Gau, and C.-C. Lee, "Toward differential diagnosis of autism spectrum disorder using multimodal behavior descriptors and executive functions," *Comput. Speech Lang.*, vol. 56, pp. 17–35, 2019, doi: https://doi.org/10.1016/j.csl.2018.12.003.

[30] D. Abdolzadegan, M. H. Moattar, and M. Ghoshuni, "A robust method for early diagnosis of autism spectrum disorder from EEG signals based on feature selection and DBSCAN method," *Biocybern. Biomed. Eng.*, vol. 40, no. 1, pp. 482–493, 2020, doi: https://doi.org/10.1016/j.bbe.2020.01.008.

[31] M. Jalbrzikowski, "Neuroimaging Phenotypes Associated With Risk and Resilience for Psychosis and Autism Spectrum Disorders in 22q11.2 Microdeletion Syndrome," *Biol. Psychiatry Cogn. Neurosci. Neuroimaging*, vol. 6, no. 2, pp. 211–224, 2021, doi: https://doi.org/10.1016/j.bpsc.2020.08.015.

[32] L. Ejlskov *et al.*, "Prediction of autism risk

from family medical history data using machine learning: a national cohort study from Denmark," *Biol. Psychiatry Glob. Open Sci.*, 2021, doi: https://doi.org/10.1016/j.bpsgos.2021.04.007.

[33] S. Qazi and K. Raza, "Chapter 4 - Fuzzy logic-based hybrid knowledge systems for the detection and diagnosis of childhood autism," H. D. B. T.-H. of D. S. S. for N. D. Jude, Ed. Academic Press, 2021, pp. 55–69.

[34] F. F. Thabtah, "UCI Machine Learning Repository: Autism Screening Adult Data Set," 2017. https://archive.ics.uci.edu/ml/datasets/Autism+Screening+Adult (accessed Jan. 01, 2021).

[35] F. F. Thabtah, "UCI Machine Learning Repository: Autistic Spectrum Disorder Screening Data for Children Data Set," 2017. https://archive.ics.uci.edu/ml/datasets/Autistic+Spectrum+Disorder+Screening+Data+for+Children++ (accessed Jan. 01, 2021).