Identifying Autism Spectrum Disorder Classification using Hybrid Machine Learning Techniques

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ABSTRACT: A person's adaptive functioning is impacted by neurodevelopmental spectrum disorders consisting of autism spectrum disorder (ASD), including communication and social interactions. ASD's severity and prolonged effects can be avoided with an early diagnosis. Intelligent diagnosis based on machine learning is recognized in recent years to help with the time-consuming and expensive traditional clinical procedures. An identifying autism spectrum disorder classification using hybrid machine learning (ML) techniques are presented in this paper. In hybrid machine learning, the classifications of decision tree (DT) and logistic regression (LR) are used. Through utilizing the hybrid ML technique and the SURF (speeded up robust features) strategy for feature extraction, the purpose of this study is to differentiate between normal and autistic faces. One hundred samples of normal faces and one hundred samples of autistic faces were gathered from Medan's special schools and used in this study. The result indicates that the Hybrid ML technique provides good performance in terms of Accuracy (98%), precision (97%) and Recall (98%) in classifying autistic and normal.

KEYWORDS: Hybrid machine learning, autism spectrum disorder, Decision Tree (DT), SURF feature detection, and Logistic Regression (LR).

I. INTRODUCTION

Verbal-nonverbal communication difficulties are the primary symptom of the neurological disorder known as ASD, social interactions, and repetitive activities [1]. One out of every 68 children in the US has ASD, based on recent centers for disease control and prevention research. The majority of ASD diagnoses have been made in children ages 2, while later Diagnoses may be made in children based on the severity and complexity of the symptoms [2]. Environmental factors or any genetic connection that impacts not only the neurological system but also the overall social and cognitive capacities of both adults and children is usually the cause of its development. Its symptoms vary widely in both intensity and extent [3]. Obsessive interests, repetitive mannerisms, and trouble communicating, especially in social situations, are common symptoms of the diseases. There isn't a medical test method for diagnosing autism [4]. symptoms that are typically identified by observation. Parents and instructors typically recognize symptoms in older people and adolescents who attend school. To identify ASD, psychologists and other healthcare for children professionals must perform an thorough evaluation and several tests [5].

In order to improve a person's overall quality of life, early identification and treatment of ASD are essential because they help to lessen symptoms [6]. However, diagnosing ASD can take a lot of crucial time because it cannot be accurately identified by focusing only on the behaviors of children or adults [7]. ASD is directly caused by a number of disease types; for example, genetic disorders and environmental risk factors are important factors to ASD. The school's special education team then evaluates the symptoms [8]. For the necessary testing, the school team recommended that these children see a doctor. Compared to older children and adolescents, adults have a much harder time recognizing symptoms because some of them may overlap with those of other mental health conditions. Compared to autism-specific brain imaging, which can detect behavioral changes in a child after years of age, since behavioral changes in children can be seen early in life, they are simple to identify through observation [9].

In the past few years, several studies have been conducted using different Machine Learning (ML) techniques to rapidly evaluate and diagnose ASD as well as various diseases like diabetes, stroke, and heart failure [10]. ASD models can be trained more accurately and in less time due to machine learning (ML) [11]. To speed up the entire diagnostic procedure and make essential therapies more accessible to families, for the quick and accurate evaluation of ASD risk, machine learning techniques are important [12]. In order to prevent the prolonged effects of autism in both adults and children, a number of machine learning classification algorithms can be utilized for early autism prediction [13]. Identifying autism spectrum disorder classification using hybrid ML techniques are presented in this paper. Improving diagnosis accuracy and speeding up diagnosis is the main goal of using machine learning techniques to enable faster access to health care. Logistic Regression (LR) and Decision Tree (DT) classifications are used in this hybrid ML technique. Finally, using data from ASD, they conduct extensive experiments and comparisons

The following is the format for the rest of the paper. In Section II, the literature survey is presented; Section III presents the proposed identifying autism spectrum disorder classification using hybrid machine learning techniques. Section IV analyzes the detailed result analysis and discusses the comparative results. At last, Section V concludes the observations and findings.

II. LITERATURE SURVEY

In [14] combines eye tracking (ET) and electroencephalogram (EEG) data to investigate both external behavior and internal neurophysiological features at the same time, and proposes a novel multimodal diagnostic approach for identifying children with ASD. In order to improve identification performance, in a latent feature space, complementarity and connections between behavior and neurophysiological modality can be automatically detected by our multimodal identification approach. Additionally, it can generate useful feature representations with enhanced generalization and discriminability. Our proposed strategy outperformed a simple feature-level fusion method and two unimodal approaches based on experimental data.

In [15] provide an approach for detecting ASD based on scanpaths, which uses continuous dynamic changes in gaze distribution to identify the atypical visual pattern of ASD. Four sequence features that reflect changes are extracted from scanpaths, and the differences in feature space and gaze behavior patterns between ASD and typical development (TD) are investigated using two similarity measures: multimatch and dynamic time warping (DTW). According to the results of the experiment, for machine learning, the long short-term memory (LSTM) network performs better than traditional techniques.

In [16] presents a two-phase method. The first phase uses a variety of machine learning models, such as an ensemble of XGBoost and random forest classifiers that have a 94% accuracy rate in identifying ASD. The study's second phase examines the physical, verbal, and behavioral performance of children with ASD in order to determine the best teaching strategies. By using machine learning to improve accuracy in meeting their specific needs, this research seeks to provide personalized educational approaches for people with ASD.

In [17] suggest a system that uses an embodied agent and a social interaction with virtual reality, particularly a shopping experience which helps in autism spectrum disorder screening. Behavioral reactions during this routine interaction are monitored and reported. Using machine learning techniques, they investigate this behavior by correctly classifying participants from a sample of autistic people in comparison to a control sample of people with normal development, indicating the feasibility of the method.

In [18] investigates in a virtual classroom simulation, social and nonsocial visual cues have an impact on the attention of children with ASD and children who are typically developing (TD).. A set of attention tests were provided to 46 participants, utilizing visual stimuli as target stimuli, both social and nonsocial. The results demonstrate the fact that children with ASD perform on attention activities and how eye-gaze tests may be used to detect attention problems in these children.

In [19], It is suggested that subtypes of ASD can be identified from normal controls (NC) using the non-oscillatory brain connectivity technique. By eliminating the non-oscillatory connection from the BOLD functional magnetic resonance imaging (rs-fMRI) signal, three subtypes of ASD are distinguished from NC: autism disorder (ATD), pervasive developmental disorder-not other specific (PDD) and asperger's disorder (APD). Multiclass accuracy is 88.9%, whereas binary classification accuracy is 98.6%, 97.2%, and 97.2% for ATD vs. NC, APD vs. NC, and PDD vs. NC, respectively.

In [20] provide a useful framework for assessing different ML methods for the early identification of ASD. Our research studies use datasets from common ASD people, including adolescents, toddlers, adults, and children. For toddlers and children, respectively, AB had the highest accuracy rate of 99.25% and 97.95% in predicting ASD, and an analysis of the results of experiments of different classifiers on feature-scaled ASD datasets showed that LDA identified ASD with the highest accuracy of 97.12% for adolescents and 99.03% for adults. These thorough experimental analyses show that accurate ML method, when predicting ASD in people of different ages, improvement can be extremely significant.

In [21] provide a low-rank representation decomposition (maLRR) multi-site adaption framework for functional MRI (fMRI)-based ASD identification. Data from the target domain is used to decrease data heterogeneity between the two domains, while data from the source domains are represented linearly in the common space. They tested the suggested approach for identifying ASD using both synthetic and actual multi-site fMRI data. Our approach outperforms a number of state-of-the-art domain adaptation techniques, according to the results.

In [22] suggest new methods to the autism brain imaging data exchange (ABIDE) dataset for the classification of multi-site autism. They introducing tangent pearson embedding, a novel second-order functional connectivity (FC) metric, to extract better features for classification. Our investigation shows that the categorization accuracy is 73%. 1) At the 5% level, there is statistically significant relationship between site and FC features, and 2) By reducing their site dependence, second-order features obtained from neuroimaging data can surpass state-of-the-art (SOTA) classification results.

In [23] introducing DeepTSK, a multi-output takagi-sugeno-kang (MO-TSK) fuzzy inference system (FIS) for composite feature learning is integrated with a deep belief network (DBN) for ASD classification in a single network to create an interpretable ASD classifier. To evaluate the proposed DeepTSK, datasets collected from three locations in the Autism Brain Imaging Data Exchange (ABIDE) database were utilized. The efficiency of the suggested approach was demonstrated by the results of the experiment, and the discriminate functional connectivity's (FC) are displayed by an analysis of the Deep MO-TSK's resulting parameters.

In [24] examined the use of four physiological measures to identify that children with ASD respond autonomically to both positive and negative stimuli. Temperature, skin conductance, respiration, and while fifteen children with ASD saw standard images that are known to produce different levels of arousal (low and high intensity) and valence (positive and negative), ECG readings were taken. It was determined which affective states were started by stimuli with high and low arousal or positive and negative valence using an ensemble of classifiers with average accuracies that were near to or higher than 80%. These results indicate that it may be possible to use physiological cues to objectively identify affective states in people with ASD.

In [25], In this study, a novel approach for the clinical validation and diagnosis of ASD is proposed: response to name (RTN). Together with clinical partners, the RTN approach is created, and new gaze estimation is created to validate the behavior that is diagnostic of ASD. According to these experiment results, with an average classification score of 92.7%, the suggested RTN approach performs effectively, demonstrating beyond any possibility that early ASD screening might be automated using the motion protocol-based approach.

III. Identifying Autism Spectrum Disorder classification using Hybrid ML

Figure 1 demonstrates the procedure for identifying autism spectrum disorder classification using hybrid machine learning techniques.

A smart phone camera was used to directly collect the dataset for this study from several special schools (SLB) in the city of Medan. Data samples for the trial included 100 samples of faces with autism and 100 samples of faces without autism. The data are divided into training and testing groups so that a model may be evaluated. It is predicted that this approach will produce more accurate and reliable model evaluation results.

We begin with a thorough preparation of the data before beginning an extensive examination and classification. Metadata or a small number of images with missing values may be included in the collected data. Thus, before to performing classification, the datasets must be cleaned or preprocessed.

Using every feature or feature in a dataset may result in a decrease in classification accuracy. Furthermore, training a model requires less time and memory when there are less attributes. Therefore, the feature engineering process determines the best combination of the most important features that provides the highest accuracy.

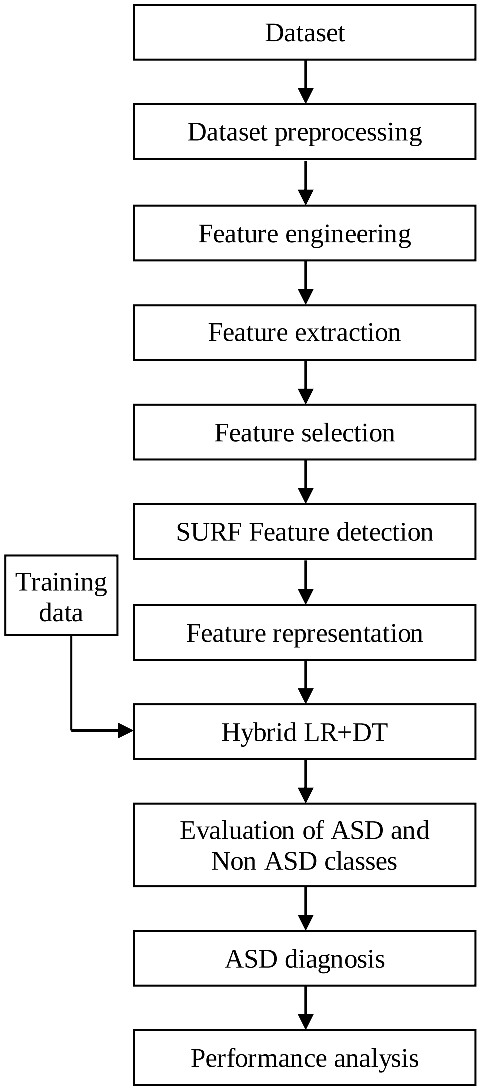

Figure 1. Identifying Autism Spectrum Disorder classification using Hybrid ML

They have used a feature selection technique before classification, the key features can be found and the number of features and dimensionality reduced. In our work, they utilize a feature selection process known as recursive feature elimination, or RFE. In a four-fold cross-validation experiment, the RFE is used to identify and extract important features from the train sets. To avoid overfitting over the small dataset, the test sets are randomly selected for validation.

After that, this data can be utilized for classification, where objects or patterns in images can be found and categorized using the SURF approach. When features are collected from images, the SURF (Speeded Up Robust Feature) approach goes through a unique procedure to help in identifying differentiating visual characteristics. Areas of importance in the image are highlighted by the marked coordinate points, which improves the study and interpretation of features that have been retrieved.

In order to choose relevant features for classification, feature representation is an essential component of our classification framework. A discriminative (excellent) characteristic should be as sensitive to intra-group variances as possible while maximizing the statistical difference between participants from various groups.

In the next step, a new framework called hybrid ML technique is used to identify samples of autistic faces and normal faces. Logistic Regression (LR) and Decision Tree (DT) classifications are used in this hybrid ML technique. The binary dependent variables are analyzed using LR, a regression method. With a dependent variable range of 0 to 1, LR is a probability measure that shows the expectation that an event, like voting, will occur. In logistic regression, the chances are converted using the log it formula, which are calculated by dividing the probability of failure by the likelihood of success.

A decision tree is a model that resembles a tree and provides a tool for decision support by visually displaying decisions together with their possible costs, effects, and outcomes. From there, choosing the best courses of action is as simple as comparing and evaluating the "branches".

In the next step, ASD and Non ASD classes are evaluated using this hybrid model. The patient must receive additional medical diagnosis and any required treatments if the categorization provides a positive result for ASD. The categorization model's performance and effectiveness are evaluated using performance evaluation metrics. Accuracy, Precision and Recall are used performance parameters.

IV. RESULT ANALYSIS

This section assesses the performance of the provided identifying autism spectrum disorder classification with hybrid machine learning technique. A smartphone camera was used to directly collect the dataset for this study from several special schools (SLB) in the city of Medan. Data samples included 100 samples of normal faces and 100 samples of faces with autism. 70% of the data sample is utilized for training, and 30% is used for testing. To determine how well a categorization model is working or to reach a goal, performance measurement is essential. The classification model's performance and effectiveness on the test dataset is evaluated using performance evaluation indicators. The appropriate metrics, such as Accuracy, Precision, and Recall, must be chosen in order to evaluate model performance. These metrics are calculated using particular formulas.

Accuracy: The ratio of accurately identified predicted to all predictions is known as accuracy. Equation 1 represents the Accuracy parameter.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \dots \dots (1)$$

Precision: The accuracy of positive predictions is measured by the ratio of true positives to the total observed positives. It can be expressed as in equation 2,

$$Precision = \frac{TP}{TP + FP} \dots \dots (2)$$

Recall/Sensitivity: When all test results are positive, the percentage of samples that are truly positive is referred to as the true positive rate. Recall can be expressed in equation 3.

$$Recall = \frac{TP}{TP + FN} \dots \dots \dots (3)$$

True Positive (TP): The person with ASD was accurately diagnosed with the disorder.
True Negative (TN): The prediction that the person did not have ASD was accurate.
False Positive (FP): The person who does not have ASD gets incorrectly diagnosed
False Negative (FN): It is incorrectly stated that the person with ASD does not have disorder.

Table 1 represents the comparative performance analysis for described model of Identifying autism spectrum disorder classification using hybrid machine learning technique (LR+DT) and Autism Spectrum Disorder detection model using Adaboost technique in terms of Accuracy, Precision and Recall parameters.

Table 1. Comparative performance analysis

Parameters	ASD identification models	
	LR+DT	Adaboost
Accuracy	98	90
Precision	97	91
Recall	98	91

The accuracy parameter for the provided ASD identification model using the Hybrid Machine Learning Technique (LR+DT) and the ASD detection using the Adaboost technique is compared in Figure 2. With a percentage value on the Y-axis and models on the X-axis, the graph shows that the model in question is more accurate than the others.

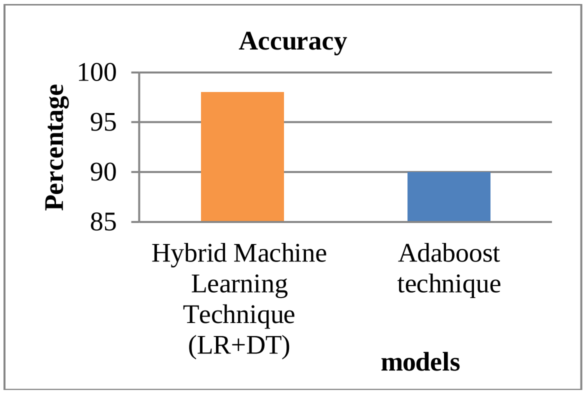

Figure 2. Accuracy parameter comparative analysis

Precision parameter comparative analysis is represented in below Figure 3 for ASD detection models using Hybrid Machine Learning Technique (LR+DT) and Adaboost technique. When compared to other models, the precision of the stated model is shown to be high. Y-axis represents the percentage value and X-axis represents models.

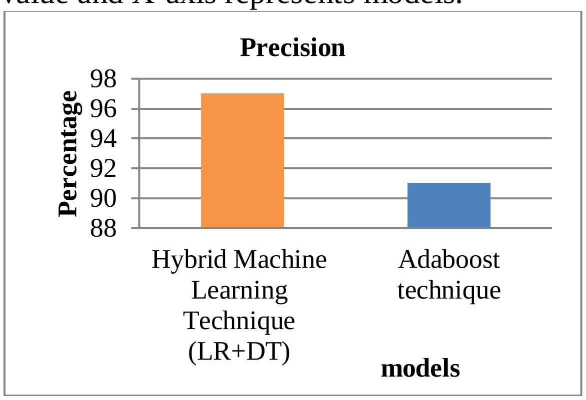

Figure 3. Precision parameter comparative analysis

Comparative Recall value is represented in Figure 4 for ASD detection models using Hybrid Machine Learning Technique (LR+DT) and Adaboost technique. Recall value of described model is efficient in percentage than other models. In this graph, Y-axis represents the percentage value and X-axis represents models.

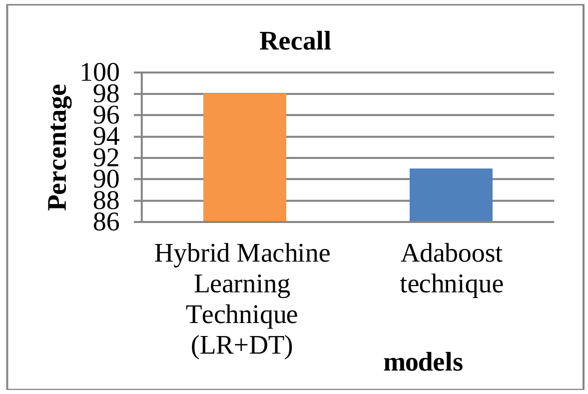

Figure 2. Recall parameter comparative analysis

According to the examination of the total results, the presented model achieves the efficient parameter values of 98% accuracy, 97% precision, and 98% recall. The accuracy of the current study is competitive. As a result, this paper provides significantly to the identification of autism spectrum disorder utilizing the hybrid ML Technique.

V. CONCLUSION

An identifying autism spectrum disorder classification using hybrid machine learning techniques is described in this paper. One of the many ways that ASD, a neurodevelopmental disease, impacts people is through limited, repetitive behaviors, communication difficulties, and social interaction impairments. For those with ASD, enhancing outcomes requires early recognition and intervention. A small number of Medan's SLBs provided the dataset directly. Logistic Regression (LR) and Decision Tree (DT) classifications are used in this hybrid ML technique. Accuracy, Precision and Recall are used performance parameters. According to the examination of the overall results, the presented model achieves the efficient parameter values of 98% accuracy, 97% precision, and 98% recall. The accuracy of the current study is competitive. As a result, this paper provides significantly to the identification of autism spectrum disorder utilizing the hybrid ML Technique. Additionally, the study can be expanded to include uses beyond ASD prediction, like personalized treatment, emotion detection, and mental health screening.

VI. REFERENCES

[1] Y. Zhang *et al.*, "Predicting the Symptom Severity in Autism Spectrum Disorder Based on EEG Metrics," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 1898-1907, 2022, doi: 10.1109/TNSRE.2022.3188564

[2] H. -L. Cao *et al.*, "Robot-Assisted Joint Attention: A Comparative Study Between Children With Autism Spectrum Disorder and Typically Developing Children in Interaction With NAO," in *IEEE Access*, vol. 8, pp. 223325-223334, 2020, doi: 10.1109/ACCESS.2020.3044483.

[3] J. Liu *et al.*, "Early Screening of Autism in Toddlers via Response-To-Instructions Protocol," in *IEEE Transactions on Cybernetics*, vol. 52, no. 5, pp. 3914-3924, May 2022, doi: 10.1109/TCYB.2020.3017866.

[4] M. Eni, I. Dinstein, M. Ilan, I. Menashe, G. Meiri and Y. Zigel, "Estimating Autism Severity in Young Children From Speech Signals Using a Deep Neural Network," in *IEEE Access*, vol. 8, pp. 139489-139500, 2020, doi: 10.1109/ACCESS.2020.3012532.

[5] P. R. K. Babu *et al.*, "Exploring Complexity of Facial Dynamics in Autism Spectrum Disorder," in *IEEE Transactions on Affective Computing*, vol. 14, no. 2, pp. 919-930, 1 April-June 2023, doi: 10.1109/TAFFC.2021.3113876.

[6] J. Li *et al.*, "Appearance-Based Gaze Estimation for ASD Diagnosis," in *IEEE Transactions on Cybernetics*, vol. 52, no. 7, pp. 6504-6517, July 2022, doi: 10.1109/TCYB.2022.3165063.

[7] W. Jung, E. Jeon, E. Kang and H. -I. Suk, "EAG-RS: A Novel Explainability-Guided ROI-Selection Framework for ASD Diagnosis via Inter-Regional Relation Learning," in *IEEE Transactions on Medical Imaging*, vol. 43, no. 4, pp. 1400-1411, April 2024, doi: 10.1109/TMI.2023.3337362.

[8] Z. Zheng *et al.*, "Design of an Autonomous Social Orienting Training System (ASOTS) for Young Children With Autism," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 6, pp. 668-678, June 2017, doi: 10.1109/TNSRE.2016.2598727

[9] M. Kulyabin, P. A. Constable, A. Zhdanov, I. O. Lee, D. A. Thompson and A. Maier, "Attention to the Electroretinogram: Gated Multilayer Perceptron for ASD Classification," in *IEEE Access*, vol. 12, pp. 52352-52362, 2024, doi: 10.1109/ACCESS.2024.3386638.

[10] J. Shin, M. Maniruzzaman, Y. Uchida, M. A. M. Hasan, A. Megumi and A. Yasumura, "Handwriting-Based ADHD Detection for Children Having ASD Using Machine Learning Approaches," in *IEEE Access*, vol. 11, pp. 84974-84984, 2023, doi: 10.1109/ACCESS.2023.3302903

[11] T. Akter *et al.*, "Machine Learning-Based Models for Early Stage Detection of Autism Spectrum Disorders," in *IEEE Access*, vol. 7, pp. 166509-166527, 2019, doi: 10.1109/ACCESS.2019.2952609.

[12] R. Liu, Z. -A. Huang, Y. Hu, Z. Zhu, K. -C. Wong and K. C. Tan, "Spatial–Temporal Co-Attention Learning for Diagnosis of Mental Disorders From Resting-State fMRI Data," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 8, pp. 10591-10605, Aug. 2024, doi: 10.1109/TNNLS.2023.3243000.

[13] Y. Chen *et al.*, "Adversarial Learning Based Node-Edge Graph Attention Networks for Autism Spectrum Disorder Identification," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 6, pp. 7275-7286, June 2024, doi: 10.1109/TNNLS.2022.3154755

[14] J. Han, G. Jiang, G. Ouyang and X. Li, "A Multimodal Approach for Identifying Autism Spectrum Disorders in Children," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp.

2003-2011, 2022, doi: 10.1109/TNSRE.2022.3192431.
[15] W. Zhou, M. Yang, J. Tang, J. Wang and B. Hu, "Gaze Patterns in Children With Autism Spectrum Disorder to Emotional Faces: Scanpath and Similarity," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 32, pp. 865-874, 2024, doi: 10.1109/TNSRE.2024.3361935
[16] F. Hajjej, S. Ayouni, M. A. Alohali and M. Maddeh, "Novel Framework for Autism Spectrum Disorder Identification and Tailored Education With Effective Data Mining and Ensemble Learning Techniques," in *IEEE Access*, vol. 12, pp. 35448-35461, 2024, doi: 10.1109/ACCESS.2024.3349988.
[17] M. Robles *et al*., "A Virtual Reality Based System for the Screening and Classification of Autism," in *IEEE Transactions on Visualization and Computer Graphics*, vol. 28, no. 5, pp. 2168-2178, May 2022, doi: 10.1109/TVCG.2022.3150489.
[18] B. Banire, D. Al-Thani, M. Qaraqe, K. Khowaja and B. Mansoor, "The Effects of Visual Stimuli on Attention in Children With Autism Spectrum Disorder: An Eye-Tracking Study," in *IEEE Access*, vol. 8, pp. 225663-225674, 2020, doi: 10.1109/ACCESS.2020.3045042
[19] A. Sadiq, M. I. Al-Hiyali, N. Yahya, T. B. Tang and D. M. Khan, "Non-Oscillatory Connectivity Approach for Classification of Autism Spectrum Disorder Subtypes Using Resting-State fMRI," in *IEEE Access*, vol. 10, pp. 14049-14061, 2022, doi: 10.1109/ACCESS.2022.3146719.
[20] S. M. Mahedy Hasan, M. P. Uddin, M. A. Mamun, M. I. Sharif, A. Ulhaq and G. Krishnamoorthy, "A Machine Learning Framework for Early-Stage Detection of Autism Spectrum Disorders," in *IEEE Access*, vol. 11, pp. 15038-15057, 2023, doi: 10.1109/ACCESS.2022.3232490.
[21] M. Wang, D. Zhang, J. Huang, P. -T. Yap, D. Shen and M. Liu, "Identifying Autism Spectrum Disorder With Multi-Site fMRI via Low-Rank Domain Adaptation," in *IEEE Transactions on Medical Imaging*, vol. 39, no. 3, pp. 644-655, March 2020, doi: 10.1109/TMI.2019.2933160.
[22] M. Kunda, S. Zhou, G. Gong and H. Lu, "Improving Multi-Site Autism Classification via Site-Dependence Minimization and Second-Order Functional Connectivity," in *IEEE Transactions on Medical Imaging*, vol. 42, no. 1, pp. 55-65, Jan. 2023, doi: 10.1109/TMI.2022.3203899.
[23] Z. Lu, J. Wang, R. Mao, M. Lu and J. Shi, "Jointly Composite Feature Learning and Autism Spectrum Disorder Classification Using Deep Multi-Output Takagi-Sugeno-Kang Fuzzy Inference Systems," in *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 20, no. 1, pp. 476-488, 1 Jan.-Feb. 2023, doi: 10.1109/TCBB.2022.3163140
[24] S. Sarabadani, L. C. Schudlo, A. A. Samadani and A. Kushski, "Physiological Detection of Affective States in Children with Autism Spectrum Disorder," in *IEEE Transactions on Affective Computing*, vol. 11, no. 4, pp. 588-600, 1 Oct.-Dec. 2020, doi: 10.1109/TAFFC.2018.2820049
[25] Z. Wang, J. Liu, K. He, Q. Xu, X. Xu and H. Liu, "Screening Early Children With Autism Spectrum Disorder via Response-to-Name Protocol," in *IEEE Transactions on Industrial Informatics*, vol. 17, no. 1, pp. 587-595, Jan. 2021, doi: 10.1109/TII.2019.2958106.