2024 International Conference on Intelligent Computing and Sustainable Innovations in Technology (IC-SIT) | 979-8-3503-6917-5/24/$31.00 ©2024 IEEE | DOI: 10.1109/IC-SIT63503.2024.10862342

Early Detection of Neurodevelopmental Disorders: Quantifying Autism Behavioral Markers with Computer Vision and Artificial Intelligence

Raksheet Jain
Research Scholar
Aignosis Research Division
Jaipur, Rajasthan 302021, India
i.m.raksheet@gmail.com

Divyansh Mangal
Research Scholar
Aignosis Research Division
Jaipur, Rajasthan 302021, India
divyanshdec14@gmail.com

***Abstract*—Autism spectrum disorder (ASD) is traditionally diagnosed through clinical observation and standardized tests, processes that are time-consuming and require expert intervention. Early detection is crucial for effective intervention, yet current methods often delay diagnosis, particularly in resource-limited settings. This study presents a scalable, non-invasive method for early autism detection using standard webcam technology to measure biomarkers associated with ASD. The system captures and analyzes eye-tracking data, head movements, and behavioral responses during a controlled 4-minute video presentation. Data is processed through a series of carefully selected machine learning models, with the most advanced model—utilizing a Convolutional Neural Network (CNN) with ResNet layers—achieving an 91% accuracy rate. Our pilot study, involving 147 children, resulted in the creation of a proprietary dataset, supporting the robustness of this method.**

***Index Terms*—Autism Spectrum Disorder (ASD), Early Detection, Non-invasive Screening, Eye-Tracking Data, Machine Learning Models, Convolutional Neural Network (CNN), ResNet Layers, Behavioral Analysis, Artificial Intelligence, Computer Vision.**

I. Introduction

Autism spectrum disorder (ASD) is a neurodevelopmental condition characterized by challenges in social interaction, communication, and repetitive behaviors. ASD affects 1 in 68 children globally, and in India, where 25 million children are born each year, approximately 10% are diagnosed with developmental conditions, including autism. The scarcity of developmental pediatricians, with only 1 specialist available per 500,000 children, exacerbates the challenge of early detection and intervention.

Current diagnostic methods primarily rely on questionnaires and clinical observations, which can be subjective and influenced by social stigma or a lack of parental awareness of the child's behaviors. These limitations often lead to delays in diagnosis, resulting in missed opportunities for early intervention during critical periods of neuroplasticity in a child's development. To address these challenges, we, Divyansh Mangal and Raksheet Jain, have developed a scalable, non-invasive autism detection method leveraging standard webcam technology combined with advanced AI-based analysis. This approach is designed to be accessible, cost-effective, and suitable for mass-scale deployment, particularly in resource-limited settings.

Observational behaviour analysis has been pivotal in understanding and identifying the early signs of neurodevelopmental disorders, particularly Autism Spectrum Disorder (ASD). Tools such as the Autism Diagnostic Observational Schedule (ADOS) are widely regarded as the gold standard for diagnosing ASD, relying on structured observational coding to capture behaviours that are indicative of the disorder. Similarly, the Autism Observational Scale for Infants (AOSI) plays a crucial role in identifying early risk markers in younger children, further emphasizing the importance of observational assessments in the early detection of ASD.

The advent of eye-tracking technology has significantly advanced our understanding of these early behavioural markers. Eye tracking enables the precise measurement of where and how long a child looks at specific stimuli, as well as their gaze patterns in response to social cues. Children with ASD often exhibit atypical visual attention patterns, such as reduced gaze toward faces and difficulties maintaining eye contact, which are crucial for social interaction and communication.

Eye-tracking studies have also uncovered that children with ASD may have delayed or diminished responses when presented with competing visual stimuli. This challenge in disengaging from one stimulus to focus on another is a characteristic feature of ASD, and eye-tracking technology allows for the detailed analysis of these subtle but important differences in behavior. By providing quantitative data on visual attention and social interaction, eye tracking is emerging as a powerful tool for the early detection, diagnosis, and monitoring of ASD.

II. Literature Review

Behavioral analysis is a cornerstone of identifying early risk markers for neurodevelopmental disorders, including Autism Spectrum Disorder (ASD). Traditionally, this process has heavily relied on the expertise of medical practitioners and specialists who are trained to administer specific tasks designed to elicit behaviors indicative of ASD. These specialists then manually code and interpret the observed behaviors, a process that is subjective and limited by the granularity achievable through human observation. Retrospective analysis, where specialists might review behaviors frame-by-frame, is particularly burdensome and lacks scalability, especially in large-scale studies aimed at discovering or refining behavioral risk markers or in longitudinal studies.

With advancements in technology, new tools have emerged to assist in the automatic and semi-automatic coding of behaviors in infants and toddlers. Eye-tracking technology has been particularly impactful, allowing for the automatic coding of gaze behaviors at a much finer scale than is possible with manual observation. This has led to novel insights into the development of ASD, such as decreased attention to eye and mouth regions of faces and impaired oculomotor control. However, despite these advancements, standard eye-tracking systems remain constrained, specialized, and expensive, limiting their availability and reach.

Recent research has shown promise in the use of automatic behavioral coding in less constrained settings, such as schools and homes. For example, researchers have developed tools and datasets to evaluate social and communicative behaviors relevant to child-adult interactions, and have also explored automatic encoding of motor movements during mother-infant interactions to assess the quality of these interactions. Additionally, there has been progress in augmenting visual attention tasks in infants using just a single consumer-grade camera, automating the coding of head movements while watching social and nonsocial stimuli, and monitoring facial expression imitation during child-robot interactions.

In response to the need for accessible and low-cost solutions, our interdisciplinary team has developed a self-contained mobile application that uses movie stimuli to elicit and quantify specific ASD-related behavioral responses in toddlers. This application is designed to function without additional hardware, making it especially valuable for middle and low-resource communities where access to ASD specialists is limited. The mobile application uses the front-facing camera to capture the toddler's responses to stimuli, and these responses are automatically coded using computer vision analysis tools. This approach not only enhances accessibility but also allows for behavioral monitoring in more naturalistic environments, such as the home.

Our application focuses on eliciting behaviors associated with early risk markers of ASD, such as orienting to name calls, social referencing, and social smiling. These behaviors are automatically coded and validated against hand-coded data from specialists, demonstrating that our system can reliably measure engagement, name-call responses, and emotional reactions in both ASD and non-ASD toddlers.

This work is part of a broader effort to develop low-cost, automatic, and quantitative tools that can be used by researchers, schools, and potentially caregivers at home to identify toddlers at risk for ASD and other developmental disorders. The framework we have developed is not passive but actively engages the child, eliciting behaviors through short, entertaining movie stimuli. This closed-loop, self-contained system offers a much higher signal-to-noise ratio compared to passive monitoring systems, providing more valuable and interpretable data for early ASD detection.

Mengwen Liu et al. analyzed the F-Score for three different models, ultimately finding that Support Vector Machine (SVM) outperformed the other two algorithms with a score of 0.071. The SVM model was trained using unigrams proposed by manually developed ontologies. While SVM proved effective in classification, the study highlighted the potential biases introduced by relying on manually developed ontologies. The comparison with Naive Bayes (NB) and Bayesian Logistic Regression (BLR) provided valuable insights into the strengths and limitations of different machine learning approaches in diagnosing Autism Spectrum Disorder (ASD) [2].

Gerardo Noriega et al. investigated the connectivity between various brain regions to differentiate ASD subjects with severe behavior issues from those with milder issues. Their study demonstrated distinct connectivity patterns between the groups, highlighting differences that could aid in the diagnosis of ASD. However, the study was limited by its focus on high-functioning male subjects, which could restrict the generalizability of the findings. The time-correlation approach used in this research allowed for an in-depth analysis of brain connectivity, but the specificity of the study sample raised concerns about its broader applicability to all ASD cases [3].

Xia-an Bi et al. employed Support Vector Machine (SVM) techniques to identify abnormal brain regions, achieving an impressive accuracy rate of 96.8. Their research revealed significant differences in the brains of individuals with ASD compared to healthy controls (HC), with these differences varying across different ages. The study's reliance on SVM proved highly effective in classification, yet it also highlighted the complexity of brain development and the potential challenges in differentiating ASD from HC due to age-related variations [11].

Noor B et al. explored the effects of medication use during pregnancy on the development of ASD, analyzing the presence of protein-protein interactions between genes. The study suggested a potential link between prenatal medication and the development of ASD. However, one limitation of the study was its inability to accurately identify which specific gene caused ASD. The research utilized various tools, including cytogenetic analysis, association linkage analysis studies, copy number variation (CNV), and DNA microarray analysis, which provided valuable insights into potential prenatal factors influencing ASD, but also underscored the challenges in pinpointing the exact genetic causes [12].

Roberto Munoz et al. focused on differentiating ASD children from healthy controls based on their performance in specific tasks. The study successfully identified distinctions between the two groups, but its conclusions were limited by the small sample size of ASD participants. The user-centered design of the application used in the study was innovative, offering a promising approach to ASD diagnosis, though the small sample size raised concerns about the study's overall robustness and the generalizability of its findings [13].

979-8-3503-6917-5/24/$31.00 ©2024 IEEE

Khalid Al-jabery et al. conducted a study focusing on IQ scores in ASD patients, forming three clusters using multivariate discriminant analysis. The study reported an IQ mean score of 81.83 but was limited by its focus on a specific patient population within a particular geographic area. The use of the Expectation Maximization algorithm provided a robust method for clustering, but the localized focus of the study may limit the applicability of its findings to a broader population [14].

Mohd AzJar Miskam et al. utilized a humanoid robot, the NAO Robot, to capture nine emotion gestures in ASD children. The study received a positive response, with a 70.9 good rating from surveys, yet the small sample size of 17 participants limited the statistical power of the findings. While the use of humanoid robots in ASD diagnosis represents a promising new approach, larger studies are needed to validate these initial results and to explore the full potential of robot-assisted interventions in ASD [15].

III. Dataset

This dataset was meticulously gathered using eye-tracking technology to capture a range of critical behavioral metrics. The dataset includes head movements, eye gaze patterns, and preferences between geometric shapes and social cues.

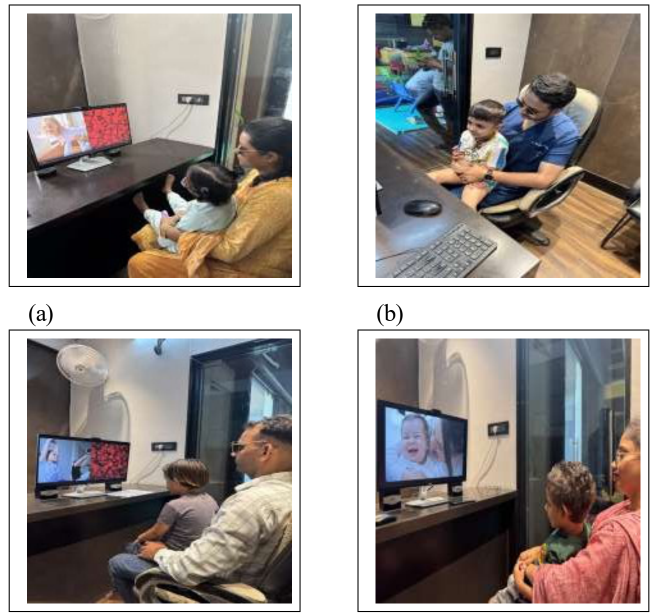
The eye-tracking data were collected in a controlled environment where children were exposed to a series of video stimuli designed to elicit specific responses related to joint attention, social interaction, and visual preference. These responses were recorded as time-series data, providing a comprehensive view of each child's behavior over time.

To enhance the robustness and reliability of our dataset, the collected data were labeled using the Indian Scale for Assessment of Autism (ISAA), a standardized tool widely recognized for its effectiveness in diagnosing ASD in the Indian context. The dataset comprises data from 147 children, allowing us to train and validate our proprietary model effectively.

IV. Methodology

A. Data Collection

- **Participant Setup:** A total of 147 children, aged 1.5 to 6 years, participated in the study. The testing was conducted in a quiet, controlled environment with minimal distractions, ensuring that the data captured was as accurate and untainted as possible. Each child was seated facing a standard webcam placed at eye level to ensure consistent data capture. The children were asked to watch a 4-minute video designed to engage them in tasks related to joint attention, social interaction, and response to stimuli.
- **Video Modules:** The video content was carefully curated to include audio-visual prompts designed to elicit differential responses between ASD children and typically developing (TD) children. These prompts were selected based on existing literature and expert consultations to highlight behavioral and attention-related differences critical for ASD detection. The prompts included stimuli such as moving objects, facial expressions, and auditory cues like the child's name being called. In parallel, the webcam continuously recorded real-time responses throughout the video, capturing eye movements, gaze patterns, and facial expressions. This data was then used to extract various features and derive multiple biomarkers for ASD, forming the basis of our machine learning models.



(a) (b) (c) (d)

Fig. 1: Date collection process

(a) Eye Tracking (b) Head Tracking
(c) Pattern Preference (d) Facial Recognition

B. Data Extraction Process

The data extraction process was pivotal in transforming the raw inputs into meaningful features that could be utilized by our AI models. The process involved the following key steps:

- **Raw Data Collection:** The data collected from the webcam was initially stored in a raw CSV format, which is inherently time series data. This dataset included metrics such as gaze direction, head translation (movement along the X, Y, and Z axes), and the actual video feed of the child. The time series nature of the data allowed us to track changes in these metrics over time, which is crucial for understanding the dynamic aspects of a child's behavior during the screening.
- **Biomarker Extraction:** After the initial data collection, we extracted additional biomarkers using existing AI models like DeepFace. This model performed facial analysis, detecting and quantifying expressions indicative of ASD. We then integrated this data with gaze and head translation metrics, creating a comprehensive behavioral profile. Additionally, time-dependent graphs were generated to map the child's attention levels and social cue

979-8-3503-6917-5/24/$31.00 ©2024 IEEE

responsiveness, highlighting any posture or movement abnormalities.

- **Image Derivation for Computer Vision Models:** Key images were derived from the time series data, representing significant moments during the screening. These images were processed using Convolutional Neural Networks (CNNs) to extract both spatial and temporal features, capturing the progression of the child's reactions over time.
- **Feature Construction:** The features constructed included simple metrics (such as gaze fixation duration) and complex, derived features (such as the ratio of attentive to inattentive moments). These features were designed to encapsulate the behavioral patterns observed, enhancing the model's ability to distinguish between ASD and TD groups.

C. Pre-Processing Data

- **Data Cleaning:** Ensuring the quality and reliability of the dataset was crucial. Missing data points were identified and either replaced with contextually appropriate values or removed to prevent bias. Duplicate entries and outliers were also removed to maintain data integrity.
- **Feature Encoding:** The raw eye-tracking data and behavioral responses were encoded into numerical values, ensuring that the most relevant features were preserved for model training.
- **Dataset Split:** The dataset was divided into 75% for training, 15% for development (used for hyperparameter tuning), and 10% for testing, ensuring robust evaluation.

V. AI Model Implementation and Results

A. Model Selection and Equations

We selected machine learning models based on their ability to balance accuracy, interpretability, and computational efficiency. Below are the models used, along with their defining equations:

- **Support Vector Machines (SVM):** SVM finds the hyperplane that maximizes the margin between different classes:

$$f(x) = \mathrm{sign}(w \cdot x + b)$$

where w is the weight vector and b is the bias. SVM is effective in high-dimensional spaces but may struggle with non-linear relationships.

- **Decision Trees:** Decision Trees split data into subsets based on the value of features:

$$I(p) = -\sum_{i=1} p_i \log_2(p_i)$$

where $I(p)$ is the impurity of a node, p_i is the probability of class i, and c is the number of classes. Decision Trees are easy to interpret but prone to overfitting.

- **Random Forests:** Random Forests combine multiple decision trees to improve accuracy:

$$\hat{y} = \frac{1}{T}\sum_{t=1} h_t(x)$$

where T is the number of trees, $h_t(x)$ is the prediction of the t-th tree. Random Forests reduce overfitting but require more computational power.

- **K-Nearest Neighbors (KNN):** KNN classifies data points based on the majority class among its k nearest neighbors:

$$y = \mathrm{mode}\{y_i : x_i \in N_k(x)\}$$

where $N_k(x)$ is the set of k nearest neighbors of x. KNN is simple but computationally intensive.

- **Artificial Neural Networks (ANN):** ANN models consist of layers of interconnected neurons:

$$a^{(l)} = g(W^{(l)}a^{(l-1)} + b^{(l)})$$

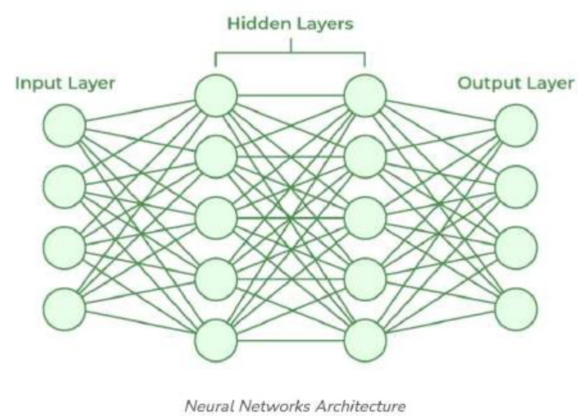
where $W^{(l)}$ and $b^{(l)}$ are the weights and biases for layer l, and g is the activation function. ANN captures non-linear relationships but requires careful hyperparameter tuning.

- **Convolutional Neural Networks (CNN) with ResNet:** CNNs are effective for image data, with ResNet addressing vanishing gradients:

$$y = x + F(x, \{W_i\})$$

where x is the input, $F(x, \{W_i\})$ is the residual mapping, and W_i are the weights. ResNet enables deeper networks, improving feature extraction.

VI. Architecture of the Model



The model we developed for diagnosing Autism in children is based on an Artificial Neural Network (ANN). ANN models are particularly well-suited when a transient body of experimental data exists, but a compatible theoretical framework for developing predictive relationships is not available. ANNs excel in handling large volumes of input data and processing complex, non-linear relationships between inputs and outputs.

979-8-3503-6917-5/24/$31.00 ©2024 IEEE

The ANN model consists of three primary layers: the input layer, hidden layers, and the output layer. Each layer in the ANN contains nodes known as neurons. These neurons process the input values, which are connected to hidden nodes through weighing factors. During the training phase, these weighing factors help determine the output values produced by the hidden nodes. The weighing factors simulate the strength of neural connections, and each hidden node can be biased by an activation signal, which causes it to generate an output only when the combined input signals exceed a pre-set threshold.

A. Comparative Analysis

The performance of each model was evaluated using key metrics, including accuracy, sensitivity, specificity, and F1-Score. The CNN with ResNet layers consistently scored the highest, particularly excelling in sensitivity and specificity.

TABLE I: Biomarkers Extracted

Biomarker	Description
Gaze Fixation	Duration and stability of eye contact with specific objects or faces.
Head Translation	Movements along X, Y, Z axes.
Facial Emotion Recognition	Detected emotional responses using DeepFace.
Social Cue Responsiveness	Time-dependent graphs of recognition and response to social cues.
Posture and Movement Anomalies	Detection of abnormal postures and movements.
Temporal Gaze Patterns	Analysis of gaze shifts over time.
Facial Expression Variability	Variability in facial expressions.
Derived Image Features	Key images processed using CNN.

TABLE II: Model Performance Metrics

Model	Acc (%)	Sens (%)	Spec (%)	F1 (%)
SVM	72	71	73	72
Decision Trees	68	65	70	67
Random Forests	77	75	79	77
KNN	70	69	71	70
ANN	78	76	79	77
CNN with ResNet	91	87	85	86

VII. Discussion

A. Implications of Our Findings

The 86 accuracy achieved by our CNN model with ResNet layers is a significant step forward in early autism detection. This high accuracy suggests that our methodology can reliably identify ASD at a very early stage, critical for improving outcomes through early intervention. The use of AI not only streamlines the diagnostic process but also reduces reliance on specialized expertise, making the detection process more objective and less prone to error. This advancement highlights the potential of AI and computer vision technologies in non-invasive diagnosis, which could revolutionize pediatric healthcare.

B. Scalability and Accessibility

A major advantage of our system is its scalability and accessibility. By using standard webcam technology, our diagnostic tool can be deployed in various settings, including rural healthcare centers, without the need for expensive equipment or specialized training. This makes it feasible to implement large-scale screening programs, particularly in resource-constrained environments. The system's ability to bridge the gap between diagnosis and intervention could have profound public health implications, especially in developing countries with limited access to specialized healthcare services.

C. Ongoing Research and Future Directions

Our promising initial results lay the groundwork for further research. Future efforts will focus on integrating additional ASD biomarkers, expanding the dataset to include diverse populations, and exploring multimodal approaches that combine audio analysis, physiological measurements, and parent-reported outcomes. These enhancements aim to improve the model's sensitivity, specificity, and generalizability, ensuring it remains effective across various demographic groups and developmental stages.

D. Potential for Broader Application

While focused on ASD, our technology has the potential to be adapted for other neurological and developmental disorders, such as ADHD and learning disabilities. The flexibility to train models on different datasets makes it possible to develop a comprehensive diagnostic suite for multiple conditions. This adaptability is particularly valuable in pediatric healthcare, where early diagnosis and intervention are crucial for positive long-term outcomes.

VIII. Conclusion

A. Summary

This research introduces a novel approach to early ASD detection using standard webcam technology and AI models. With an accuracy rate of 86, our system demonstrates its potential as a reliable and scalable tool for early diagnosis, especially in resource-limited settings. The successful application of CNNs with ResNet layers illustrates the transformative potential of AI in pediatric healthcare.

B. Future Work

Future research will focus on refining our AI models, integrating additional diagnostic tools, and expanding our dataset to improve accuracy and generalizability. Collaborations with healthcare providers and policymakers will be key to scaling up this technology for widespread adoption.

C. Call to Action

Given the global rise in ASD prevalence and the importance of early intervention, we urge the medical community, policymakers, and developers to support and adopt our AI-based diagnostic system. By integrating this technology into public health initiatives, we can make early ASD screening

979-8-3503-6917-5/24/$31.00 ©2024 IEEE

accessible to all children, improving outcomes and reducing the long-term burden on families and healthcare systems. We invite collaboration to help realize this vision.

REFERENCES

[1] C. Lord, et al., "Autism from 2 to 9 years of age," *Arch. Gen. Psychiatry*, vol. 63, pp. 694–701, 2006.

[2] Mengwen Liu, Yuan An, and Xiaohua Hu, Debra Langer, Craig Newschaffer, and Lindsay Shea, "An Evaluation of Identification of Suspected Autism Spectrum Disorder (ASD) Cases in Early Intervention (EI) Records", IEEE Xplorer, 2013.

[3] Gerardo Noriega, "Restricted, Repetitive, and Stereotypical Patterns of Behavior in Autism – an fMRI Perspective", IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2018.

[4] T. Eslami, F. Almuqhim, J. S. Raiker, and F. Saeed, "Machine Learning Methods for Diagnosing Autism Spectrum Disorder and Attention-Deficit/Hyperactivity Disorder Using Functional and Structural MRI: A Survey," 2021.

[5] R. Sreedasyam, A. Rao, N. Sachidanandan, N. Sampath, and S. K. Vasudevan, "Aarya—A kinesthetic companion for children with autism spectrum disorder," *J. Intell. Fuzzy Syst.*, vol. 32, no. 4, pp. 2971-2976, Mar. 2017.

[6] K.-F. Kollias, C. K. Syriopoulou-Delli, P. Sarigiannidis, and G. F. Fragulis, "The contribution of machine learning and eye-tracking technology in autism spectrum disorder research: A systematic review," *Electronics*, vol. 10, no. 23, pp. 2982, Nov. 2021.

[7] M. D. Hossain, M. A. Kabir, A. Anwar, and M. Z. Islam, "Detecting autism spectrum disorder using machine learning techniques," *Health Inf. Sci. Syst.*, vol. 9, no. 1, pp. 1-13, Dec. 2021.

[8] S. P. Abirami, G. Kousalya, and R. Karthick, "Identification and exploration of facial expression in children with ASD in a contactless environment," *J. Intell. Fuzzy Syst.*, vol. 36, no. 3, pp. 2033-2042, Mar. 2019.

[9] C. Allison, B. Auyeung, and S. Baron-Cohen, "Toward brief 'red flags' for autism screening: The short autism spectrum quotient and the short quantitative checklist in 1000 cases and 3000 controls," *J. Amer. Acad. Child Adolescent Psychiatry*, vol. 51, no. 2, pp. 202-212, 2012.

[10] J. Peral, D. Gil, S. Rotbei, S. Amador, M. Guerrero, and H. Moradi, "A machine learning and integration based architecture for cognitive disorder detection used for early autism screening," *Electronics*, vol. 9, no. 3, 2020.

[11] Xia-an Bi, Yingchao Liu, Qi Sun, Xianhao Luo, Haiyan Tan, Jie Chen, Nianyin Zeng, "The Genetic-Evolutionary Random Support Vector Machine Cluster Analysis in Autism Spectrum Disorder", IEEE Access, Vol:7, PP no: 30527 - 30535, March 2019.

[12] Noor B. Almandil, Deem N. Alkuroud, Sayed AbdulAzeez, Abdulla AlSulaiman, Abdelhamid Elaissari, and J. Francis Borgio, "Environmental and Genetic Factors in Autism Spectrum Disorders: Special Emphasis on Data from Arabian Studies", International Journal of Environmental Research and Public Health, Vol:16, Feb 2019.

[13] Roberto Munoz, Claudio Morales, Rodolfo Villarroel, Á ngeles Quezada, Victor Hugo C. De Albuquerq, "Developing a Software That Supports the Improvement of the Theory of Mind in Children With Autism Spectrum Disorder", IEEE Access, Vol:7, PP no: 7948 - 7956, December 2018.

[14] Khalid Al-jabery, Tayo Obafemi-Ajayi, Gayla R. Olbricht, T. Nicole Takahashi, Stephen Kanne, Donald Wunsch, "Ensemble Statistical and Subspace Clustering Model for Analysis of Autism Spectrum Disorder Phenotypes", IEEE Xplorer, 2016.

[15] Mohd Azfar Miskam; Syamimi Shamsuddin; Hanafiah Yussof; Ilmi Mohd Ariffin; Abdul Rahman Omar, "A questionnaire-based survey: Therapist's response on emotions gestures using humanoid robot for autism" IEEE Xplorer International Symposium on Micro-NanoMechatronics and Human Science (MHS), 2015.

[16] M. D. Hossain, M. A. Kabir, A. Anwar, and M. Z. Islam, "Detecting Autism Spectrum Disorder using Machine Learning-An Experimental Analysis on Toddler," *Child and Adult Adults*, 2020.

[17] N. Gabbay-Dizdar, M. Ilan, G. Meiri, M. Faroy, A. Michaelovski, H. Flusser, et al., "Early diagnosis of autism in the community is associated with marked improvement in social symptoms within 1-2 years," *Autism*, SAGE Publications Ltd, vol. 26, no. 6, pp. 1353-1363, Aug. 2022.

[18] M. Mehmood, M. Rizwan, M. Gregus ml, and S. Abbas, "Machine Learning Assisted Cervical Cancer Detection," *Frontiers in Public Health*, vol. 9, 2021.

[19] G. Chanel, S. Pichon, L. Conty, S. Berthoz, C. Chevallier, and J. Gre`zes, "Classification of autistic individuals and controls using cross-task characterization of fMRI activity," *NeuroImage: Clinical*, 2016.

[20] A. A. Abdullah, S. Rijal, and S. R. Dash, "Evaluation on Machine Learning Algorithms for Classification of Autism Spectrum Disorder (ASD)," *Journal of Physics: Conference Series*, vol. 1372, no. 1, p. 012052, 2019.

[21] A. S. Heinsfeld, A. R. Franco, R. C. Craddock, A. Buchweitz, and F. Meneguzzi, "Identification of autism spectrum disorder using deep learning and the ABIDE dataset," *NeuroImage: Clinical*, 2018.

[22] H. S. Nogay and H. Adeli, "Machine learning (ML) for the diagnosis of autism spectrum disorder (ASD) using brain imaging," *Reviews in the Neurosciences*, vol. 31, no. 8, pp. 825-841, 2020.

[23] S. Batsakis, M. Adamou, I. Tachmazidis, S. Jones, S. Titarenko, G. Antoniou, et al., "Data-driven decision support for adult autism diagnosis using machine learning," *Digital*, vol. 2, no. 2, pp. 224-243, 2022.

[24] A. Samuel, "Some studies in machine learning using the game of checkers II: Recent progress," *IBM J. Research and Development*, 1967.

[25] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies Volume 1 (Long and Short Papers)*, Minneapolis, Minnesota: Association for Computational Linguistics, pp. 4171-4186, Jun. 2019.

[26] B. Wingfield, S. Miller, P. Yogarajah, D. Kerr, B. Gardiner, S. Seneviratne, et al., "A predictive model for paediatric autism screening," *Health Informatics Journal*, vol. 26, no. 4, pp. 2538-2553, 2020.

[27] X. Guo et al., "Diagnosing Autism Spectrum Disorder from Brain Resting-State Functional Connectivity Patterns Using a Deep Neural Network with a Novel Feature Selection Method," *Frontiers in Neuroscience*, vol. 11, pp. 460, 2017.

[28] A. Liaw, M. Wiener, et al., "Classification and regression by randomforest," *R News*, vol. 2, no. 3, pp. 18-22, 2002.

[29] F. N. Buyukoflaz and A. Ozturk, "Early autism diagnosis of children with machine learning algorithms," in *2018 26th Signal Processing and Communications Applications Conference (SIU)*, pp. 1-4, 2018.

[30] F. Tabtah, "Autism Spectrum Disorder Screening: Machine Learning Adaptation and DSM-5 Fulfillment," in *Proceedings of the 1st International Conference on Medical and Health Informatics 2017*, Taichung City, Taiwan: ACM, pp. 1-6.

[31] A. S. Albahri, R. A. Hamid, O. S. Albahri, and A. A. Zaidan, "Detection-based prioritisation: framework of multi-laboratory characteristics for asymptomatic COVID-19 carriers based on integrated entropy–TOPSIS methods," *Artificial Intelligence in Medicine*, vol. 111, article 101983, 2021.

[32] R. Chauhan, E. Yafi, "Applicability of classifier to discovery knowledge for future prediction modelling," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, pp. 10347-10362, 2023. DOI: https://doi.org/10.1007/s12652-022-03694-3.

[33] R. Chauhan, N. Gola, and E. Yafi, "An Analytical Approach to Predict the Cardio Vascular Disorder," in *2023 17th International Conference on Ubiquitous Information Management and Communication (IMCOM)*, Seoul, Korea, Republic of, 2023, pp. 1-8, doi: 10.1109/IMCOM56909.2023.10035581.

979-8-3503-6917-5/24/$31.00 ©2024 IEEE