A Survey of Advanced Classification and Feature Extraction Techniques Across Various Autism Data Sources

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Abstract: Autism, often known as autism spectrum disorder (ASD), is characterized by a range of neurodevelopmental difficulties that impact behavior, social relationships, and communication. Early diagnosis is crucial to provide timely interventions and promote the best possible developmental outcomes. Although well-established, traditional methods such as behavioral tests, neuropsychological assessments, and clinical facial feature analysis are often limited by societal stigma, expense, and accessibility. In recent years, artificial intelligence (AI) has emerged as a transformative tool. AI utilizes advanced algorithms to analyze a variety of data modalities, including speech patterns, kinematic data, facial photographs, and magnetic resonance imaging (MRI), in order to diagnose ASD. Each modality offers unique insights: kinematic investigations show anomalies in movement patterns, face image analysis reveals minor phenotypic indicators, speech analysis shows aberrant prosody, and MRI records neurostructural and functional problems. By accurately extracting information from these modalities, deep learning approaches enhance diagnostic efficiency and precision. However, challenges remain, such as the need for diverse datasets to build robust models, potential algorithmic biases, and ethical concerns regarding the use of private biometric data. This paper provides a comprehensive review of feature extraction methods across various data modalities, emphasising how they might be included into AI frameworks for the detection of ASD. It emphasizes the potential of multimodal AI systems to revolutionize autism diagnosis and their responsible implementation in clinical practice by analyzing the advantages, limitations, and future directions of these approaches.

1 INTRODUCTION

People with autism spectrum disorder (ASD), a complicated neurological condition, face challenges across various domains, including communication, social interaction, and environmental awareness. Common symptoms exhibited by individuals with autism include repetitive behaviors, restricted interests, and heightened sensitivity to sensory inputs. These traits may manifest as difficulty interpreting facial emotions, body language, and social norms. While autism is typically diagnosed in childhood, its impact extends into adulthood. With the correct support and early interventions, people with autism can lead more fulfilling lives and achieve better integration into society.

Traditionally, behavioral observation and diagnostic instruments like the DSM (Diagnostic and Statistical Manual of Mental Disorders) or the Autism Diagnostic Observation Schedule (ADOS) have been used to identify autism through behavioral observation. While effective, these methods are time-consuming and require specialized expertise. New approaches to early and accurate autism identification have been made possible by recent developments in artificial intelligence (AI). Techniques such as machine learning (ML) and deep learning (DL) have been employed to analyze speech patterns, kinematic behaviors, and facial expressions. Support vector machines (SVMs) and convolutional neural networks

(CNNs) are stand out for their ability to precisely classify and identify characteristics linked to ASD.

One of the most promising methods for detecting ASD is facial image analysis. According to research,

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CNNs are able to recognise subtle differences in autistic people's emotional reactions and facial expressions. Simultaneously, magnetic resonance imaging (MRI) has proven invaluable a useful technique for investigating brain abnormalities and connection patterns linked to ASD. Diffusion tensor imaging (DTI) and functional magnetic resonance imaging (fMRI) have enable detailed analysis of brain networks and their abnormalities in autistic people in great detail. By identifying abnormal patterns of gaze and visual attention often observed in individuals with ASD, eye-tracking technology have significantly enhanced diagnostic capabilities.

Beyond imaging, multimodal approaches offer a comprehensive view of autism by integrating information from multiple sources, such as kinematic analysis, MRI scans, and facial expressions. Kinematic investigations, for example, have shown motor biomarkers that are suggestive of ASD, such as repeated motions. Distinct prosodic and intonational features that differentiate individuals with ASD from neurotypical populations have been identified through speech analysis, especially with CNNs. Enables a more robust and accurate diagnostic framework by integrating these many data sources.

With an emphasis on developments in ML and DL methodologies and their application to image and video data, this paper methodically examines ASD detection techniques. The study looks at important indications like:

- The accuracy of biological and behavioral biomarkers for early identification of ASD.
- The effect on diagnostic accuracy of multimodal data integration that combines eye tracking, MRI, and facial imaging.
- How sophisticated AI models, such as CNNs and transformers, enhance the categorisation and identification of symptoms of ASD in actual clinical situations.

The articles were selected based on strict eligibility criteria. They were (i) written in English, (ii) focused on image or video data, (iii) related to autism in human populations, and (iv) utilized deep learning- based techniques for feature extraction or classification. Using keywords like autism spectrum disorder, ASD detection, deep learning, and federated learning, the search method includes queries across major databases like PubMed, Scopus, Springer Link, IEEE Xplore, and Google Scholar. This rigorous approach ensures that the review highlights the latest and most relevant advancements.

There are six sections in our paper. An introduction comes first, and then a thorough literature review. We then discuss related research, introduce the databases we used, then a discussion, and wrap up with a summary of findings and future research directions.

2 LITERATURE REVIW

2.1 History and Definition

The term "autism" was initially introduced by a Swiss psychiatrist to describe symptoms associated with schizophrenia, characterizing it as a form of childlike thought aimed at escaping reality through fantasies and hallucinations (Bleuler, E., 2012). Later, the term gained prominence through the work of Harris, J. (2018), who introduced it into psychiatric classification, describing it as a condition marked by social disengagement and communication difficulties, which he termed "Autistic Affective Contact Disorder".

Kanner's work on autism led to significant debate regarding its classification. Initially, autism was considered an early form of schizophrenia and was classified as a psychosis in children in subsequent diagnostic manuals. Over time, similarities between autism and schizophrenia were noted, especially in 2210 cases where individuals with autism exhibited symptoms of schizophrenia (Canitano, R., 2017).

As understanding of autism improved, research began to differentiate it from schizophrenia based on symptomatic variations, family histories, and treatment responses. This evolution led to the inclusion of autism in diagnostic classifications (Kolvin, I., 1971).

The classification of autism continued to evolve, with the term "Pervasive Developmental Disorders" (PDD) being used to refer to autism-like disorders. Specific diagnostic criteria for these disorders were later established (Sprock, J., 2014). The DSM-IV categorized PDD-NOS into several disorders, including Autism, Rett syndrome, Childhood Disintegrative Disorder, Asperger disorder, and Unspecified PDD (PDD-NOS) (Lewis, G., 1996).

The most recent revisions consolidated various autistic disorders under the term "Autism Spectrum Disorder" (ASD), recognizing the continuity of symptoms and severity observed in individuals with autism.

The primary behavioral and sensory markers commonly seen in kids with autism spectrum disorders are depicted in Figure 1.

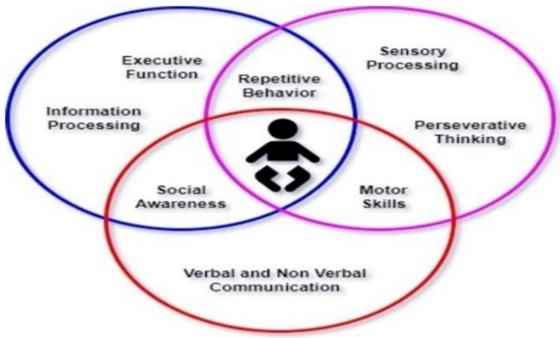

Figure 1: Typical Behavioral and Sensory Indicators of Autism in Children.

Individuals with neurodevelopmental disorders, such as autism and related conditions, may experience notable deficits in their cognitive, social, emotional, and behavioral development. Among these conditions, Rett syndrome, formerly thought to be a subtype of autism spectrum disorder (ASD), is now recognized as a distinct condition due to its genetic origin, although it still shares some clinical similarities with autism. Williams syndrome, a rare genetic disorder, is distinguished by characteristic facial features and mild to moderate intellectual disability. The most common hereditary cause of intellectual disability, fragile X syndrome, often manifests as autism and is widely examined in relation to ASD. Due to the wide range of ASD symptoms, most autism research does not typically focus on a single subtype.

Nonetheless, certain forms of autism, such as high-functioning autism (formerly referred to as Asperger's syndrome), are the topic of more focused investigations, with an emphasis on those with normal or above-average intelligence but notable social challenges. The characteristics of the autism spectrum are also shared by other conditions, such as Prader-Willi syndrome, which is marked by eating disorders and moderate to severe intellectual handicap, and Angelman syndrome, which is recognized for its happy demeanor and motor issues. Additionally, some research emphasizes the variability of autism by accounting for the range of clinical symptoms within the spectrum. Finally, Smith-Magenis syndrome, which is marked by obsessive-compulsive behaviors and sleep disturbances is frequently studied in relation to emotion recognition technologies, especially in studies on the machine learning-based identification of autistic features.

Individuals with autism spectrum disorders (ASD) often stand out due to significant differences in their social interactions, particularly through facial expressions and non-verbal behaviors. These differences, although subtle, play a key role in communication and the interpretation of emotions. Indeed, individuals with autism tend to display more neutral facial expressions, with a limited use of visual cues to express or interpret emotions, which complicates their identification. Thus, the observation of facial expressions and eye movements becomes a critical tool for understanding and diagnosing the early signs of ASD. The face features of two child groups are contrasted in Figure 2. Typical eye movements, normal face symmetry, and unambiguous facial expressions are characteristics of children without autism spectrum disease (ASD). Children with ASD, on the other hand, exhibit clear distinctions, including less coordinated facial expression patterns, aberrant gaze fixation, and diminished emotional intensity.

Figure 2: The differences in facial features between children without autism in the first row and children with autism in the second row.

2.2 Related Work General Context of Autism

Numerous methods including neurological, behavioral, and physiological indicators are used in autism screening procedures. Analysing the structure and traits of the face is made possible by facial features and landmarks, which are frequently used in conjunction with the examination of facial expressions to find subtle clues of emotional variations. An objective and engaging way to measure behavioral reactions is through robot-evaluated systems. While methods like gaze analysis and eye tracking aid in the understanding of social interaction patterns, neurophysiological signals like electroencephalograms (EEGs) offer information on brain activity.

Simultaneously, standardized questionnaires and thorough behavioral monitoring continue to be essential components of clinical diagnostics. Action analysis systems that interpret movements and social interactions, as well as smartphone applications that enable quick and easy detection, are examples of technological developments. Last but not least, neurological tests like brain MRIs provide a biological perspective by detecting anatomical or functional changes in the brain linked to autism spectrum disorders. These methods, which are frequently combined, improve diagnosis speed and accuracy while opening the door to customised solutions.

Autism detection in children has traditionally relied on careful observation of their behavior and comparison with established developmental reference tools. These tools include the Statistical Manual of Mental Disorders (SMD), the Autism Diagnostic Observation Schedule (ADOS) (Lord et al., 2000), the Autism Diagnostic Interview (ADI) (Lord et al., 1994), the Autism Observation Scale Infant (AOSI) (Bryson et al., 2008), the Autism Spectrum Screening Questionnaire (ASSQ) (Ehlers et al., 1999), the Children's Asperger Syndrome Test (CAST) (Williams et al., 2005), and the .DSM-5 (Edition et al., 2013). This process of comparison and measurement requires considerable time and effort.

In recent years, artificial intelligence (AI) has become increasingly important in various applications, particularly in the early detection and diagnosis of autism spectrum disorders (ASD). AI refers to the simulation of human cognition and problem-solving through intelligent systems. At the core of AI is ML which extracts information from input databases using image preprocessing techniques. The data is then classified or ranked using either supervised or unsupervised learning methods. Supervised learning employs classifiers such as support vector machines (SVMs), random forests, and traditional neural networks to categorize data based on labeled input-output pairs.

In the medical field, deep learning (DL), a subset of machine learning, is gaining popularity. Convolutional neural networks (CNNs) are the most commonly used deep learning networks. There are fully connected and include multiple convolutional layers to perform tasks such as feature extraction and classification. Conversely, unsupervised learning does not rely on labeled input-output pairs, instead, it classifies data based on patterns within the input data itself.

2.3 Related Work

Recent advances in deep learning and machine learning have transformed different fields such as natural language processing (NLP) (Gasmi et al., 2023, 2024), (Mezghani et al., 2024) and medical diagnostic practice (Mezghani et al., 2024), offering tools that are both accurate, fast and capable mainly in autism detection. Several different techniques used to identify autism, and each one significantly advances the diagnosis. Techniques like Diffusion Tensor Imaging (DTI) and structural MRI (sMRI), which examine brain connectivity and structure, as well as functional MRI (fMRI), which uses BOLD methodologies to emphasize activity and functional connectivity, have significantly advanced the use of MRI (Magnetic Resonance Imaging). The brain in different cognitive states can be examined thanks to these technologies. Finding brain biomarkers from MRI and EEG data has been significantly enhanced by ML and DL techniques. For instance, Pan et al. (2021) used graph convolutional networks (GCN) with an accuracy of 87.62%, whereas Yang et al. (2019) used ASSDL on MRI data and obtained an accuracy of 98.2%. The efficiency of these strategies is demonstrated by multimodal approaches, such as those explored by Tang et al. (2020) and cutting-edge techniques like the Deep Belief Network (DBN) optimised by the Adam War Strategy (AWSO) which obtained 92.4% accuracy on the ABIDE dataset. Furthermore, Park et al. (2023) created a model integrating residual CNN and Bi-LSTM with self-attention, which achieved 97.6% on ABIDE-I, whereas Wen et al. (2022) employed multi-view GCNs to reach an accuracy of 69.3%.

Simultaneously, the examination of emotions and facial expressions provides a non-invasive way to identify abnormal patterns linked to ASD. The integration of neural networks and machine learning techniques has been made easier by the challenges that people with ASD have when it comes to expressing and recognising their emotions. Wu et al. (2021) investigated head movements and facial points via OpenFace, while Hassouneh et al. (2020) classified emotions with an accuracy of 87.25% using LSTM-convolutional models. In order to enhance emotional recognition, Cai et al., (2022) more recently included attention techniques. Accuracy ranges from 84% to 96% thanks to these efforts, which combine face dynamics, gazes, and emotional shifts with models like VGG19, MobileNet, and Vision Transformers (ViT). Notably, the ViTASD-L model was presented by Cao et al. (2023) and achieved 94.5% accuracy on the Piosenka dataset. Last but not least, privacy-preserving strategies that use federated learning, as those by Shamseddine et al. (2022), integrate behavioral and facial characteristics while guaranteeing the security of personal information.

Emerging techniques include eye tracking, which examines gaze patterns to identify ASD early. The accuracy of techniques developed by Atyabi et al.

(2023) and Wei et al. (2021) that combine temporal and spatial information has surpassed that of earlier approaches. Similarly, to enhance categorisation, Liaqat et al. (2021) and Wloka et al. (2017) employed synthetic saccade models. Another potential technique is kinematic analysis, which uses motor impairments as biomarkers.

While Prakash et al. (2023) utilised R-CNN models to study joint attention tasks and achieved 93.4% accuracy, Zhao et al. (2019) employed KNN to analyse hand movements with an accuracy of 86.7%. YOLO-V5 and DeepSORT were coupled by Ali et al. (2022) to track and categorise motions. Lastly, speech and language-based detection looks at linguistic and prosodic abnormalities that are commonly seen in kids with ASD. With models like CNNs (Ashwini et al., 2023) and SVMs (Nakai et al., 2017), these studies take advantage of voice spectrograms and linguistic data, exhibiting great accuracy in this area because of machine learning.

3 FEATURE EXTRACTION

3.1 Feature Extraction for Facial Recognition

Two primary types of facial features those linked to emotion recognition and those related to eye movement analysis are crucial in diagnosing autism. Finding distinguishing characteristics in facial expressions is essential in the field of emotion recognition in order to identify emotional states like happiness, sadness, or anger. For instance, Banire et al. (2021) used the iMotions software to extract 34 face landmarks and utilized those cues to create geometric features based on Euclidean distance estimates. Conditional Local Neural Field (CLNF) models have been utilised in several studies, including those by Leo et al. (2018) and Del Coco et al. (2017), to automatically analyse the facial expressions of children with autism spectrum disorders (ASD).In order to support the prediction of behaviours associated with autism, sophisticated techniques like OpenFace (Wu et al., 2021) make it easier to extract key points, action units (AU), head positions, and gaze orientations. Furthermore, by extracting pertinent features, pre-trained convolutional neural networks like AlexNet, MobileNet, and Vision Transformers (ViT) (Slimani et al., 2024) have demonstrated efficacy in automatically segmenting and classifying facial images. Furthermore, techniques like gesture analysis and thermal imaging have been used to distinguish children with ASD from those with typical development (TD).

Gaze-related traits, which frequently show abnormalities in children with ASD, offer important hints for early identification. By combining the temporal and spatial aspects of eye movements, Atyabi et al. (2023) improved this method and enhanced classification performance. The accuracy of this study was further enhanced by Wei et al. (2021) by integrating spatiotemporal data from gaze trajectories.

Other cutting-edge studies, such as those by Liaqat et al. (2021) and De Belen et al. (2021), have either analyzed fixation sequences to find anomalies or converted eye-tracking data into visual representations. Additionally, recent research has concentrated on emotional states like boredom or dissatisfaction or on dynamic social interactions, including head movements and eye contact (Chong et al., 2017).

A schematic of models for autism detection that concentrate on feature extraction from facial images is shown in Figure 3.

3.2 Feature Extraction for Kinematic Analysis

Certain motor biomarkers can help diagnose autism spectrum disorders (ASD) more precisely. Attention problems are often linked to complex motor,

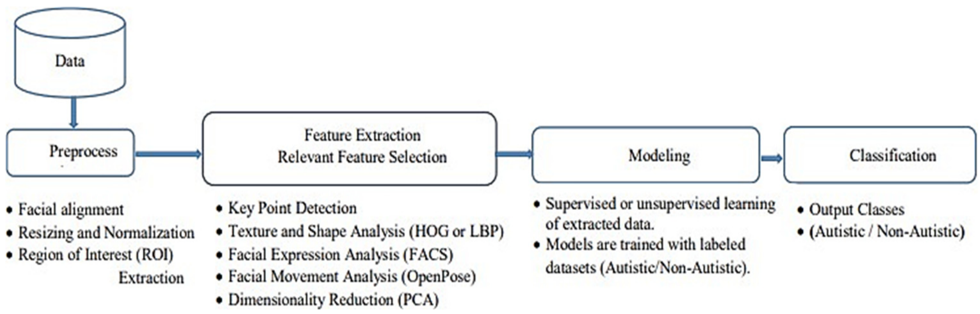

Figure 3: Diagram of models for autism detection.

patterns including head motions, arm flapping, finger trembling, and body shaking. Children with autism may exhibit repetitive behaviors, such as shaking their heads. Currently, motor deficits are considered associated characteristics that lend credence to the ASD diagnosis. According to recent studies, a better comprehension of the motor deficits associated with ASD could lead to for novel approaches to diagnosis and treatment.

Patients with ASD can be differentiated from those with typical development (TD) using kinematic data. 20 kinematic features were derived from hand gestures using kinematic analysis in a study with 16 participants with ASD and 14 with TD (Li et al., 2017). Eight noteworthy characteristics were found when these parameters were tested using the Naive Bayes approach. Four methods were tested: Support Vector Machine (SVM, both RBF and linear), Random Forest, Decision Tree, and Naive Bayes. SVM and Naive Bayes fared better than the other algorithms, according to the results, with the linear SVM showing the best results with 86.7% accuracy, 87.5% specificity, and 85.7% sensitivity.

Using machine learning techniques such as SVM, LDA, Decision Tree, Random Forest, and K-Nearest Neighbors (KNN), Zhao et al. (2019) enhanced the diagnosis of ASD. Twenty-five children with high-functioning autism and twenty-three typically developing children participated in the study and completed a variety of motor tasks. As markers of limited kinematic properties, the researchers computed the entropy and range of 95% of the motion's amplitude, speed, and acceleration. With 88.37% precision, 91.3% specificity, 85% sensitivity, and an area under the curve (AUC) of 0.8815, the KNN approach (k = 1) outperformed the other five classifiers in terms of classification accuracy.

An important development in the assessment of autism was the creation of the Autism Diagnostic Observation Schedule (ADOS) by Lord et al. (2006). This method looks for behavioral indicators of autism by utilising unstructured observation tasks to look at how kids react to various situations.

3.3 Feature Extraction for MRI

A key tool in the research of autism spectrum disorder (ASD) is MRI, which provides unmatched insights into the structure and function of the brain and enables the identification of neurological biomarkers linked to the disorder.

Both structural and functional neuroimaging data have been widely used in recent studies on the diagnosis of autism spectrum disorder (ASD), and feature extraction is essential to processing and interpreting these datasets for machine learning applications. Structural imaging techniques, such as diffusion tensor imaging (DTI) (Travers, 2012) and sMRI (Dekhil, O., 2020) are two structural methods that reveal anomalies linked to ASD by shedding light on brain connectivity and morphology. By using blood oxygenation level-dependent (BOLD) approaches to analyse brain activity and functional connectivity, functional magnetic resonance imaging (fMRI) enhances these investigations. Researchers may examine how the brain functions in different cognitive states using both task-based and resting-state fMRI (rsfMRI).

The diagnosis of ASD has greatly improved with the use of ML algorithms in conjunction with neuroimaging data. For example, BOLD signals can yield valuable information when functional MRI is used in conjunction with methods like the General Linear Model (GLM) and Independent Component Analysis (ICA). Furthermore, the application of ML and DL techniques to EEG and MRI signals makes it easier to identify biomarkers linked to ASD, including regional cortical thickness, grey matter volume, and white matter (WM) volume. Studies like Yang et al. (2019), which used ASSDL methods to obtain a 98.2% accuracy on MRI data, and Pan et al. (2021), which claimed an 87.62% accuracy with graph convolutional networks (GCNs), serve as examples of these developments.

Researchers improve the accuracy and dependability of diagnosing ASD by customising feature extraction methods to the unique properties of MRI data, illustrating the interaction between cutting-edge imaging technology and complex computational methods.

3.4 Feature Extraction for Speech and Language

Many children with autism spectrum disorder (ASD) struggle greatly with speech and language comprehension, which frequently leads to ongoing communication problems or no communication at all after the age of two. These children may repeat words or phrases without completely understanding their meaning, and their voices may have an odd pitch or rhythm when they do talk. A toddler may count from one to five several times during a conversation that has nothing to do with numbers, demonstrating how speech can occasionally seem divorced from conversational context. Many autistic children also display echolalia, which is the immediate or delayed repetition of previously heard words or phrases, frequently accompanied by irrelevant enquiries. Some autistic kids start conversations with cliches, even with people they know, while others sing, talk too much, or have a robotic voice. Another prevalent trait is repetitive speech patterns.

These abnormal speech and language characteristics linked to ASD have motivated researchers to investigate machine learning (ML) methods for assessment and classification, with encouraging outcomes. Using 24 fundamental frequency (F0)-based variables to measure pitch, Nakai et al. (2017) used a Support Vector Machine (SVM) to analyse single-syllable utterances in both neurotypical (NT) and autistic participants, outperforming traditional speech-language pathologists in terms of accuracy.

In a similar vein, Hauser et al. (2019) classified ASD in people between the ages of 18 and 50 using a linear regression model with 123 audio features, with a weighted accuracy of 0.83. SVMs were used by Lau et al. (2022) to examine intonation and rhythmic patterns in English and Cantonese speech, finding that rhythmic features were only important in English.

Advanced approaches like Random Forests and Convolutional Neural Networks (CNNs) have significantly enhanced classification performance beyond conventional machine learning techniques. A CNN trained on spectrograms improved accuracy to 0.79. Plank et al. (2023) achieved a balanced accuracy of 0.76 by using L2-regularized SVMs on phonetic data that was extracted using the Praat tool. By training SVM models on transcripts that contained a variety of language variables from both NT and autistic children, Ashwini et al. (2023) were able to reach an impressive accuracy of 0.94.

Liu et al. (2022) extended this study by looking into transformer-based models to find linguistic patterns unique to ASD. The study used written transcripts of adult conversations captured during collaborative tasks and discovered that transformer models performed noticeably worse for participants with ASD than for those without ASD, indicating a difficulty in representing the aberrant language of autistic people. This disparity was ascribed to biases in the training data, which were mostly drawn from online and news sources and did not accurately represent the distinct social-linguistic techniques used by people with ASD.

These results highlight how machine learning and deep learning techniques can be used to identify and decipher the complex speech and language traits of ASD, opening the door to more precise and non-invasive diagnostic instruments.

3.5 A Multimodal Approach for Enhanced Feature Extraction

People with ASD have abnormal gaze patterns, such as avoiding eye contact and having different joint attention in social situations, in addition to neurological abnormalities. The direct measurement of gaze behaviors and directed visual activities is made possible by eye-tracking technology (ET), which has been extensively employed in research on attention allocation in individuals with ASD. According to Nakano et al., (2010), for instance, children with ASD spend less time observing faces and social interactions than children who are normally developing. Using an ET dataset, Liu et al., (2016) created a machine learning framework that could classify children with ASD and TD with up to 88.51% accuracy.

In research on ASD, electroencephalogram (EEG) and ET have been used separately to find useful biomarkers and create diagnostic models with cutting-edge machine learning techniques. However, it is challenging to make a reliable diagnosis using only unimodal data, like EEG or ET, because ASD is complex and heterogeneous, showing up at both the behavioral and cellular levels. Despite having different viewpoints while ET captures behavioral information and EEG reflects neurophysiological activity these two modalities provide rich and complementing data on ASD. However, it can be difficult to directly identify the underlying correlations and complementarities due to the diversity of the data.

To address this challenge, multimodal fusion emerges as a promising solution. This approach, which has garnered increasing interest in the medical field, has been applied not only to the diagnosis of ASD but also to other diseases such as Parkinson's, Alzheimer's, and depression. For example, Alexandru et al., (2018) integrated EEG, fMRI, and DTI data to characterize the autistic brain, while Mash et al., (2020) explored the relationships between fMRI and EEG in spontaneous brain activity related to ASD. Recent work, such as that of Vasquez-Correa et al., (2019), has shown that the fusion of multimodal data can fully exploit the strengths of each modality while compensating for their weaknesses, resulting in improved diagnostic performance. Han et al., (2022) combine electroencephalogram (EEG) and eye-tracking data (ET) to present a novel multimodal diagnostic approach for detecting autism spectrum disorders (ASD) in children. Stacking denoising autoencoders (SDAE) are used in this method to learn and fuse features from both modalities.

This approach, which was tested on a dataset that included 40 children with ASD and 50 normally developing (TD) children, shows how neurophysiological (EEG) and behavioral (ET) perspectives complement each other. It achieved an overall accuracy of 95.56%, with a sensitivity of 92.5% and a specificity of 98%. When compared to unimodal and basic techniques, the experimental findings demonstrate a substantial improvement, with multimodal fusion enabling better separation of ASD/TD groups.

A diagram showing the various deep learning (DL) techniques examined in this review is shown in Figure 4.

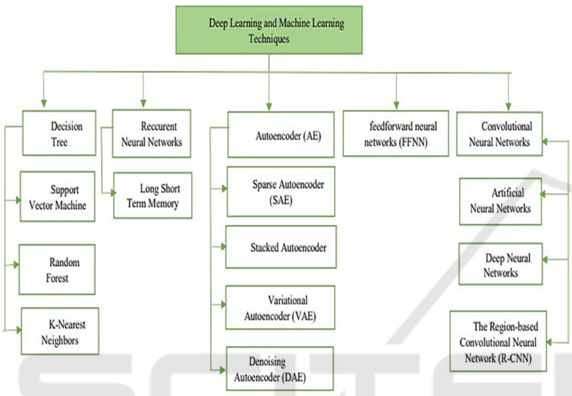

Figure 4: Diagram of diferents DL/ML-based approaches considered in this review.

4 DATASETS

In this part, we examine in depth the different databases public and private that are crucial to autism research, emphasising their content, unique features, and contributions to the development of autism spectrum detection and analysis methods.

4.1 MRI Datasets

Significant disparities between people with ASD and neurotypical participants can be identified thanks to magnetic resonance imaging (MRI), a non-invasive technique that creates three-dimensional anatomical pictures. The Autism Brain Imaging Data Exchange (ABIDE) (Di Martino et al., 2014, 2017) has collected structural and functional brain imaging data from labs worldwide in order to better understand the neurological underpinnings of autism. Two significant collections that are the outcome of this effort are ABIDE I and ABIDE II. The initial version of ABIDE I, which was released in 2014, combined information from 17 different countries, comprising 1,112 resting-state functional MRI (rs-fMRI) recordings with 539 participants with ASD and 573 neurotypical people between the ages of 7 and 64. A more varied sample, consisting of 1,044 records, including 487 participants with ASD and 593 neurotypical people, was added to the collection by ABIDE II in 2017. Researchers can use these databases as a useful resource to investigate the neurological underpinnings of autism.

4.2 Visual Datasets

1Face and eye tracking datasets are essential for identifying autism. Eye movement data from 28 children (with ASD and TD) was gathered using the Tobii T120 eye tracker from 300 different visual stimuli and is included in the Saliency4ASD (Duan et al., 2019b). Chong et al. (2017) annotated 2 million video images of 100 youngsters interacting with adults to identify gaze, while Carette et al. (2018) created a set of 547 photos translating dynamic eye movements. In terms of facial data, Shukla et al. (2017) gathered 1,126 facial images labelled by age and gender, and Leo et al. (2018b) gathered videos of 17 kids displaying a range of emotions. Lastly, with 2,540 training images and a standardised reference protocol, the Autism Facial Image Dataset (AFID) (Piosenka, 2021) continues to be the only publicly available database devoted to autism research using facial images. These varied datasets provide a valuable foundation for developing more precise and reliable diagnostic tools. Once more, Rani, (2019) gathered 25 pictures of people with ASD with four different emotions (angry, neutral, sad, and cheerful) from various online sources for their study.

4.3 Skeleton Datasets

The 2D/3D coordinates of the human joints make up skeleton data. 136 participants with evenly dispersed ASD and TD were included in a video collection of social interaction created by Kojovic et al. (2021). Later, they use OpenPose to extract the essential elements from videos (Cao et al., 2017).

4.4 Multi Modal Datasets

Simple but frequently constrained by noisy data and poor accuracy are unimodal systems, which employ a single feature or modality to identify or assess autism spectrum disorders (ASD) (Uddin et al., 2017). Multi-modal data, which combines multiple sensor and feature kinds, has been introduced to address these issues. For instance, 128 children between the ages of 5 and 12 participated in 152 hours of multi-modal interactions (audio, depth, and video) through robot or adult-assisted activities in the De-Enigma dataset (Shen et al., 2018). Similar to this, the DREAM dataset (Billing et al., 2020) records 300 hours of robot-assisted therapy for 61 children with autism. 3D skeletons and metadata (such as age, gender, and diagnosis) are extracted using RGB and RGBD cameras. Additional datasets include those of Zunino et al. (2018), which consists of 1,837 recordings of 40 children (autistic and neurotypical) doing gestures in particular tasks, and Cai et al. (2022), which examines videos of 57 children with ASD and 25 neurotypical children based on facial and movement traits. Finally, to categorise repetitive behaviors like spinning or flapping of the arms, the SSBD (Rajagopalan et al., 2013) gathers 75 videos from public platforms. The diagnosis of ASD and behavioural analysis are made more accurate and diverse by using multi-modal datasets.

5 DISCUSSION

The various feature extraction techniques used to diagnose autism spectrum disorder (ASD)—including facial recognition, kinematic analysis, MRI, speech a n d language, multimodal data, and others—emphasize how difficult it is to capture the complex character of ASD. With machine learning techniques like SVM and KNN attaining noteworthy classification accuracies of up to 88.37% (Zhao et al., 2019), kinematic analysis reveals motor biomarkers. However, small sample sizes highlight the necessity for more datasets to improve generalisation. With sophisticated approaches like graph convolutional networks reaching accuracies over 98%, MRI techniques that make use of diffusion tensor imaging (DTI) and functional MRI (fMRI) offer vital insights into structural and functional abnormalities (Pan et al., 2021). Similar to this, despite difficulties with cultural heterogeneity and data biases, machine learning methods such as CNNs can achieve up to 94% accuracy in speech and language feature extraction, revealing linguistic patterns unique to ASD (Ashwini et al., 2023). Although integration complexity is still a problem, multimodal approaches such as merging EEG and eye-tracking data have shown greater diagnostic performance, with fusion techniques obtaining accuracies of 95.56% (Junxia et al., 2022). In the meantime, facial recognition leverages sophisticated deep learning models like Vision Transformers and tools like iMotions to improve diagnostic accuracy by analysing eye movements and emotions. Even though these approaches have a lot of potential, issues with scalability and accessibility, as well as ethical concerns about data protection, need to be addressed. In order to increase the precision and dependability of ASD diagnosis, these findings collectively highlight the necessity of interdisciplinary cooperation and the creation of strong, affordable, and morally sound multimodal diagnostic frameworks.

6 CONCLUSION

Our review of the literature focusses on various feature extraction techniques and highlights important advancements in the field of autism identification. Among the approaches studied are deep learning models, machine learning algorithms, and conventional image processing techniques. The ability of deep learning models to extract important and complex aspects from a range of data, such as eye movements, facial expressions, and brain signals, has made them particularly promising.

However, problems persist in spite of these advancements, particularly in the areas of accuracy, model generalisation, and participant privacy protection. Despite their significance, the size and diversity limitations of the current datasets make it difficult to build robust and inclusive models.

Using techniques like federated learning could be a good solution for further study. This approach would improve the security of sensitive data by allowing models to be trained on decentralised data by utilising information from several sources. Furthermore, the use of multimodal data for example, integrating facial, ocular, and brain signals could significantly improve model performance by capturing complementary information.

By paving the way for more inclusive, secure, and reliable detection systems, these perspectives contribute to our growing understanding and support of autism.

REFERENCES

Alexandru Cociu, B., Das, S., Billeci, L., Jamal, W., Maharatna, K., Calderoni, S., ... & Muratori, F. (2018). Multimodal Functional and Structural Brain Connectivity Analysis in Autism: *A Preliminary Integrated Approach with EEG, fMRI and DTI. arXiv e-prints, arXiv-1801.*

Ali, A., Negin, F., Bremond, F., Thummler, S. (2022). Video-based be- ¨ havior understanding of children for objective diagnosis of autism, in: *VISAPP 2022-International Conference on Computer Vision Theory and Applications.*

Ashwini, B., Narayan, V., Shukla, J. (2023).Semantic and Pragmatic Speech Features for Automatic Assessment of Autism. In *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 1-5). IEEE.*

Atyabi, A., Shic, F., Jiang, J., Foster, C.E., Barney, E., Kim, M., Li, B., Ventola, P., Chen, C.H. (2023). Stratifcation of children with autism spectrum disorder through fusion of temporal information in eye-gaze scan-paths. *ACM Transactions on Knowledge Discovery from Data 17, 1–20.*

Banire, B., Al Thani, D., Qaraqe, M., Mansoor, B., 2021. Face-based attention recognition model for children with autism spectrum disorder. *Journal of Healthcare Informatics Research 5, 420–445.*

Bleuler, E. (2012). *Dementia praecox ou groupe des schizophrénies*. Epel Editions.

Bryson, S. E., Zwaigenbaum, L., McDermott, C., Rombough, V., & Brian, J. (2008). The Autism Observation Scale for Infants: scale development and reliability data. *Journal of autism and developmental disorders*, *38*, 731-738.

Canitano, R., & Pallagrosi, M. (2017). Autism spectrum disorders and schizophrenia spectrum disorders: excitation/inhibition imbalance and developmental trajectories. *Frontiers in psychiatry*, *8*, 69.

Cai, M., Li, M., Xiong, Z., Zhao, P., Li, E., Tang, J., 2022. An advanced deep learning framework for video- based diagnosis of asd, in: *International Conference on Medical Image Computing and Computer- Assisted Intervention, Springer. pp. 434–444.*

Cao, Z., Simon, T., Wei, S.E., Sheikh, Y., 2017. Realtime multiperson 2d pose estimation using part afnity felds, in: *Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 7291– 7299.*

Cao, X., Ye, W., Sizikova, E., Bai, X., Coffee, M., Zeng, H., & Cao, J. (2023). Vitasd: Robust vision transformer baselines for autism spectrum disorder facial diagnosis. In *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing(ICASSP)* (pp. 1-5). IEEE. *Signal Processing (ICASSP)* (pp. 1-5). IEEE.

Carette, R., Elbattah, M., Dequen, G., Guerin, J.L., Cilia, F., 2018. ´ Visualization of eye-tracking patterns in autism spectrum disorder: method and dataset, in*: 2018 Thirteenth International Conference on Digital Information Management (ICDIM), IEEE. pp. 248–253.*

Chong, E., Chanda, K., Ye, Z., Southerland, A., Ruiz, N., Jones, R.M., Rozga, A., Rehg, J.M., 2017. Detecting gaze towards eyes in natural social interactions and its use in child assessment. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies 1, 1–20.*

De Belen, R.A.J., Bednarz, T., Sowmya, A., 2021. Eyexplain autism: interactive system for eye tracking data analysis and deep neural network interpretation for autism spectrum disorder diagnosis, in: *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems, pp. 1–7.*

Dekhil, O., Ali, M., Haweel, R., Elnakib, Y., Ghazal, M., Hajjdiab, H., ... & El-Baz, A. (2020, July). A comprehensive framework for differentiating autism spectrum disorder from neurotypicals by fusing structural MRI and resting state functional MRI. In *Seminars in pediatric neurology* (Vol. 34, p. 100805). WB Saunders

Del Coco, M., Leo, M., Carcagni, P., Spagnolo, P., Luigi Mazzeo, P., Bernava, M., Marino, F., Pioggia, G., Distante, C., 2017. A computer vision based approach for understandingemotional involvements in children with autism spectrum disorders, in: *Proceedings of the IEEE International Conference on Computer Vision Workshops, pp. 1401–1407.*

Di Martino, A., Yan, C.G., Li, Q., Denio, E., Castellanos, F.X., Alaerts, K., Anderson, J.S., Assaf, M., Bookheimer, S.Y., Dapretto, M., et al., 2014. The autism brain imaging data exchange: towards a large-scale evaluation of the intrinsic brain architecture in autism. Molecular psychiatry 19, 659–667.

Di Martino, A., O'connor, D., Chen, B., Alaerts, K., Anderson, J.S., Assaf, M., Balsters, J.H., Baxter, L., Beggiato, A., Bernaerts, S., et al., 2017. Enhancing studies of the connectome in autism using the autism brain imaging data exchange ii. *Scientific data 4, 1– 15.*

Duan, H., Zhai, G., Min, X., Che, Z., Fang, Y., Yang, X., Gutierrez, ´ J., Callet, P.L., 2019b. A dataset of eye movements for the children with autism spectrum disorder, in: *Proceedings of the 10th ACM Multimedia Systems Conference, pp. 255–260.*

Edition, F. (2013). Diagnostic and statistical manual of mental disorders. *Am Psychiatric Assoc*, *21*(21), 591-643

Ehlers, S., Gillberg, C., & Wing, L. (1999). A screening questionnaire for Asperger syndrome and other high-functioning autism spectrum disorders in school age children. *Journal of autism and developmental disorders*, *29*, 129-141.

Gasmi, S., Mezghani, A., & Kherallah, M. (2023, December). Arabic Hate Speech Detection on social media using Machine Learning. In *International Conference on Intelligent Systems Design and Applications* (pp. 174-183). Cham: Springer Nature Switzerland.

Gasmi, S., Mezghani, A., & Kherallah, M. (2024). SMOTE for enhancing Tunisian Hate Speech detection on social media with machine learning. *International Journal of Hybrid Intelligent Systems*, *20*(4), 355-368.

Han, J., Jiang, G., Ouyang, G., & Li, X. (2022). A multimodal approach for identifying autism spectrum disorders in children. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *30*, 2003-2011.

Harris, J. (2018). Leo Kanner and autism: a 75-year perspective. *International review of psychiatry*, *30*(1), 3-17.

Hassouneh, A., Mutawa, A. M., & Murugappan, M. (2020). Development of a real-time emotion recognition system using facial expressions and EEG based on machine learning and deep neural network methods. *Informatics in Medicine Unlocked*, *20*, 100372.

Hauser, M., Sariyanidi, E., Tunc, B., Zampella, C., Brodkin, E., Schultz, R. T., & Parish-Morris, J. (2019, June). Using natural conversations to classify autism with limited data: Age matters. In *Proceedings of the Sixth Workshop on Computational Linguistics and Clinical Psychology* (pp. 45-54).

Kojovic, N., Natraj, S., Mohanty, S.P., Maillart, T., Schaer, M., 2021. Using 2d video-based pose estimation for automated prediction of autism spectrum disorders in young children. *Scientific Reports 11, 1–10.*

Kolvin, I. (1971). Studies in the childhood psychoses I. Diagnostic criteria and classification. *The British Journal of Psychiatry*, *118*(545), 381-384.

Lau, J. C., Patel, S., Kang, X., Nayar, K., Martin, G. E., Choy, J., ... & Losh, M. (2022). Cross-linguistic patterns of speech prosodic differences in autism: A machine learning study. *PloS one*, *17*(6), e0269637

Leo, M., Carcagn`ı, P., Distante, C., Spagnolo, P., Mazzeo, P.L., Rosato, A.C., Petrocchi, S., Pellegrino, C., Levante, A., De Lume,` F., et al., 2018b. Computational assessment of facial expression production in asd children. *Sensors 18, 3993*.

Leo, M., Carcagn`ı, P., Del Coco, M., Spagnolo, P., Mazzeo, P.L., Celeste, G., Distante, C., Lecciso, F., Levante, A., Rosato, A.C., et al., 2018a. Towards the automatic assessment of abilities to produce facial expressions: The case study of children with asd, in: *20th Italian National Conference on Photonic Technologies (Fotonica 2018), IET. pp. 1–4.*

Lewis, G. (1996). DSM-IV. Diagnostic and Statistical Manual of Mental Disorders, 4th edn. By the American Psychiatric Association.(Pp. 886;£ 34.95.) APA: Washington, DC. 1994. *Psychological Medicine*, *26*(3), 651-652.

Li, B., Sharma, A., Meng, J., Purushwalkam, S., & Gowen, E. (2017). Applying machine learning to identify autistic adults using imitation: *An exploratory study. PloS one, 12(8), e0182652.*

Liaqat, S., Wu, C., Duggirala, P.R., Cheung, S.c.S., Chuah, C.N., Ozonof, S., Young, G., 2021. Predicting asd diagnosis in children with synthetic and image-based eye gaze data. Signal Processing: *Image Communication 94, 116198.*

Liu, D., Liu, Z., Yang, Q., Huang, Y., & Prud'Hommeaux, E. (2022, October). Evaluating the performance of transformer-based language models for neuroatypical language. In *Proceedings of COLING. International Conference on Computational Linguistics* (Vol. 2022, p. 3412). NIH Public Access.

Liu, W., Li, M., & Yi, L. (2016). Identifying children with autism spectrum disorder based on their face processing abnormality: *A machine learning framework. Autism Research, 9(8), 888-898.*

Lord, C., Risi, S., DiLavore, P. S., Shulman, C., Thurm, A., & Pickles, A. (2006). Autism from 2 to 9 years of age. *Archives of general psychiatry*, *63*(6), 694-701.

Lord, C., Risi, S., Lambrecht, L., Cook, E. H., Leventhal, B. L., DiLavore, P. C., ... & Rutter, M. (2000). The Autism Diagnostic Observation Schedule—Generic: A standard measure of social and communication deficits associated with the spectrum of autism. *Journal of autism and developmental disorders*, *30*, 205-223.

Lord, C., Rutter, M., & Le Couteur, A. (1994). Autism Diagnostic Interview-Revised: a revised version of a diagnostic interview for caregivers of individuals with possible pervasive developmental disorders. *Journal of autism and developmental disorders*, *24*(5), 659-685.

Mash, L. E., Keehn, B., Linke, A. C., Liu, T. T., Helm, J. L., Haist, F., ... & Müller, R. A. (2020). Atypical relationships between spontaneous EEG and fMRI activity in autism. *Brain connectivity*, *10*(1), 18-28.

Mezghani, A., Slimen, S., & Kherallah, M. (2024). Skin Lesions Diagnosis Using ML and DL Classification Models. *International Journal of Computer Information Systems and Industrial Management Applications*, *16*(2), 17-17.

Mezghani, A., Elleuch, M., Gasmi, S., & Kherallah, M. (2024). Toward Arabic social networks unmasking toxicity using machine learning and deep learning models. *International Journal of Intelligent Systems Technologies and Applications*, *22*(3), 260-280.

Nakai, Y., Takiguchi, T., Matsui, G., Yamaoka, N., Takada, S. (2017). Detecting abnormal word utterances in children with autism spectrum disorders: machine-learning-based voice analysis versus speech therapists. *Perceptual and motor skills, 124(5), 961- 973.*

Nakano, T., Tanaka, K., Endo, Y., Yamane, Y., Yamamoto, T., Nakano, Y., ... & Kitazawa, S. (2010). Atypical gaze patterns in children and adults with autism spectrum disorders dissociated from developmental changes in gaze behaviour. *Proceedings of the Royal Society B: Biological Sciences*, *277*(1696), 2935-2943.

Pan, L., Liu, J., Shi, M., Wong, C. W., Chan, K. H. K. (2021). Identifying autism spectrum disorder based on individual-aware down-sampling and multimodal learning. *arXiv preprint arXiv:2109.09129.*

Park, K. W., & Cho, S. B. (2023). A residual graph convolutional network with spatio-temporal features for autism classification from fMRI brain images. *Applied Soft Computing*, *142*, 110363.

Piosenka, G., 2021. Detect autism from a facial image.

Plank, I. S., Koehler, J. C., Nelson, A. M., Koutsouleris, N., & Falter-Wagner, C. M. (2023). Automated extraction of speech and turn-taking parameters in autism allows for diagnostic classification using a multivariable prediction model. *Frontiers in Psychiatry*, *14*, 1257569.

Prakash, V.G., Kohli, M., Kohli, S., Prathosh, A., Wadhera, T., Das, D., Panigrahi, D., Kommu, J.V.S. (2023). Computer vision-based assessment of autistic children:

Analyzing interactions, emotions, human pose, and life skills. *IEEE Access.*

Rajagopalan, S., Dhall, A., Goecke, R., 2013. Self-stimulatory behaviours in the wild for autism diagnosis, in: *Proceedings of the IEEE International Conference on Computer Vision Workshops, pp. 755– 761.*

Rani, P., 2019. Emotion detection of autistic children using image processing, in: *2019 Fifth International Conference on Image Information Processing (ICIIP), IEEE. pp. 532–535.*

Shamseddine, H., Otoum, S., & Mourad, A. (2022). A Federated Learning Scheme for Neuro- developmental Disorders: Multi-Aspect ASD Detection. *arXiv preprint arXiv:2211.00643*.

. Shen, J., Ainger, E., Alcorn, A., Dimitrijevic, S.B., Baird, A., Chevalier, P., Cummins, N., Li, J., Marchi, E., Marinoiu, E., et al., 2018. Autism data goes big: A publicly-accessible multi-modal database of child interactions for behavioural and machine learning research, in: *International Society for Autism Research Annual Meeting.*

Shukla, P., Gupta, T., Saini, A., Singh, P., Balasubramanian, R., 2017. A deep learning frame-work for recognizing developmental disorders, in: *2017 IEEE Winter Conference on Applications of Computer Vision (WACV), IEEE. pp. 705–714.*

Slimani, N., Jdey, I., & Kherallah, M. (2024). Improvement of Satellite Image Classification Using Attention-Based Vision Transformer. In *ICAART (3)* (pp. 80-87).

Sprock, J. (2014). DSM-III and DSM-III-R. *The Encyclopedia of Clinical Psychology*, 1-5.

Tang, M., Kumar, P., Chen, H., & Shrivastava, A. (2020). Deep multimodal learning for the diagnosis of autism spectrum disorder. *Journal of Imaging*, *6*(6), 47.

Travers, B. G., Adluru, N., Ennis, C., Tromp, D. P., Destiche, D., Doran, S., ... & Alexander, A. L. (2012). Diffusion tensor imaging in autism spectrum disorder: a review. *Autism Research*, *5*(5), 289-313.

Uddin, M., Muramatsu, D., Kimura, T., Makihara, Y., Yagi, Y., et al., 2017. Multiq: single sensor-based multi-quality multi-modal large-scale biometric score database and its performance evaluation. IPSJ Transactions on Computer Vision and Applications 9, 1–25.

Vásquez-Correa, J. C., Arias-Vergara, T., Orozco-Arroyave, J. R., Eskofier, B., Klucken, J., & Nöth, E. (2018). Multimodal assessment of Parkinson's disease: a deep learning approach. *IEEE journal of biomedical and health informatics*, *23*(4), 1618-1630.

Wei, W., Liu, Z., Huang, L., Wang, Z., Chen, W., Zhang, T., Wang, J., Xu, L. (2021). Identify autism spectrum disorder via dynamic filter and deep spatiotemporal feature extraction. *Signal Processing: Image Communication 94, 116195.*

Wen, G., Cao, P., Bao, H., Yang, W., Zheng, T., Zaiane, O. (2022). Mvs-gcn: A prior brain structure learning-guided multi-view graph convolution network for autism spectrum disorder diagnosis. *Computers in Biology and Medicine 142, 105239.*

Williams, J., Scott, F., Stott, C., Allison, C., Bolton, P., Baron-Cohen, S., & Brayne, C. (2005). The CAST (childhood asperger syndrome test) test accuracy. *Autism*, *9*(1), 45-68.

Wloka, C., Kotseruba, I., Tsotsos, J.K. (2017). Saccade sequence prediction: *Beyond static saliency maps. arXiv preprint arXiv:1711.10959* .

Wu, C., Liaqat, S., Helvaci, H., Chcung, S.c.S., Chuah, C.N., Ozonof, S., Young, G. (2021). Machine learning based autism spectrum disorder detectionfrom videos, in: *2020 IEEE International Conference on E-health Networking, Application & Services (HEALTHCOM), IEEE. pp. 1–6.*

Yang, M., Zhong, Q., Chen, L., Huang, F., Lei, B. (2019). Attention based semi-supervised dictionary learning for diagnosis of autism spectrum disorders. In *2019 IEEE International Conference on Multimedia & Expo Workshops (ICMEW) (pp. 7-12).*

Zhang, B., Zhou, L., Song, S., Chen, L., Jiang, Z., Zhang, J., 2020. Image captioning in chinese and its application for children with autism spectrum disorder, in: Proceedings of the 2020 12th *International Conference on Machine Learning and Computing, pp. 426–432*

Zhao, Z., Zhang, X., Li, W., Hu, X., Qu, X., Cao, X., ... & Lu, J. (2019). Applying machine learning to identify autism with restricted kinematic features. *Ieee Access*, *7*, 157614-157622.

Zunino, A., Morerio, P., Cavallo, A., Ansuini, C., Podda, J., Battaglia, F., Veneselli, E., Becchio, C., Murino, V., 2018. Video gesture analysis for autism spectrum disorder detection, in: *2018 24th international conference on pattern recognition (ICPR), IEEE. pp. 3421–3426.*