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Autism Spectrum Disorder Detection Using Machine Learning

Priya Gyanchandani[1], Gaurav Shrivastava[2]

[1]Research Scholar, [2]Associate Professor
Sanjeev Agarwal Global Educational University, Bhopal

***Abstract*— autism spectrum disorder (ASD) is a neurodevelopmental disorder characterized by a variety of behavioral and social problems that can be effectively managed through intervention and support if diagnosed early. However, early diagnosis of autism spectrum disorders is still very difficult. Current diagnostic methods often involve lengthy and expensive tests, including clinical examinations and interviews, making them impractical for large-scale screening. The aim of this study is to use a noninvasive and cost-effective method to solve important problems in identifying autism spectrum disorders in childhood. This study focuses on the potential of facial features (key features of a person's face) as an indicator of autism spectrum disorders. These studies highlight the need for a comprehensive, multidisciplinary approach to autism diagnosis that involves clinicians, researchers, data scientists, and the autism movement to improve early identification and support of individuals on the autism spectrum. This article focuses on machine learning for ASD diagnosis. It includes SVM, DT, RF, KNN, clustering and other methods.**

***Keywords*— autism spectrum disorder, machine learning, early detection, SVM, RF, DT**

I. INTRODUCTİON

The Autism Society of America defines autism as “a lifelong developmental disorder that affects how a person communicates and interacts with others and how they experience the world around them” [14]. Estimates of the global prevalence of autism vary but reach 1% of the total population and more in some countries [11]. Russell et al. (2014) [32] estimated the prevalence of primary school age children in the United Kingdom to be 1.7%. The number of autism diagnoses is increasing.

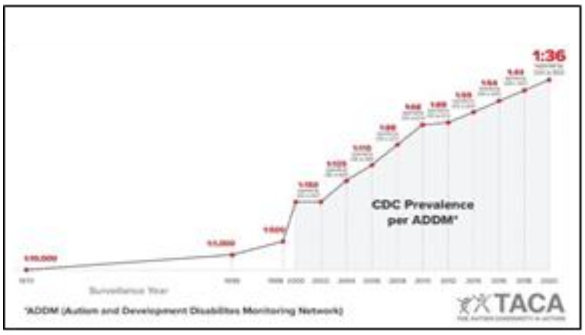

Fig-1. Autism diagnoses have increased in prevalence [32]

Lickham et al. [15] found that over 90% of a sample of children with autism experienced “paresthesias” and “sensory symptoms” in a variety of senses, particularly touch and smell/taste. Living with autism spectrum disorder (ASD) places a heavy burden on patients and their families. According to AutismSpeaks, autism spectrum disorder (ASD) costs the average family $60,000 a year. Studies of facial anthropometric characteristics of people with ASD and typically developing (TD) individuals have shown significant differences between the two groups, such as interpupillary distance, good ears, strabismus, and head circumference.] These results support the use of machine learning techniques to classify ASD and TD individuals based on anthropometric characteristics to facilitate ASD diagnosis. Although autism spectrum disorder is a lifelong condition, research shows that early diagnosis and appropriate treatment can improve a person's long-term outcomes [10] [28]. According to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [7], people diagnosed with autism may have problems in their relationships with others, speech disorders, abnormal behavior, and lack of capital to do every day at home.

School, work or similar events. Considering the increasing number of patients with ASD and the associated costs of diagnosis and treatment, it is important to develop reliable, easy- to-use and cost-effective screening tools [27]. This disease has many complications and requires careful and timely intervention. The primary symptoms include issues with social interactions, issues in communication, habitual interests and repetitive behaviors [13].

Over the years, significant research efforts have been dedicated to exploring the application of machine learning techniques in the proposed research domain.

II. LİTERATURE REVİEW

Over the years, significant research efforts have been dedicated to exploring the application of machine learning techniques in the proposed research domain. These studies have contributed to advancing our understanding of the disease and have paved the way for more accurate and efficient diagnostic approaches. The following is a brief review of the key findings and notable contributions made in this field.

The survey taxonomy [9] describes the methods, scan techniques, and features that are based on brain classification for ASD diagnosis. This study looks at the age and number of subjects, features/biomarkers, types of scan modalities, datasets used, preprocessing tools, classification algorithms, and evaluation measures.

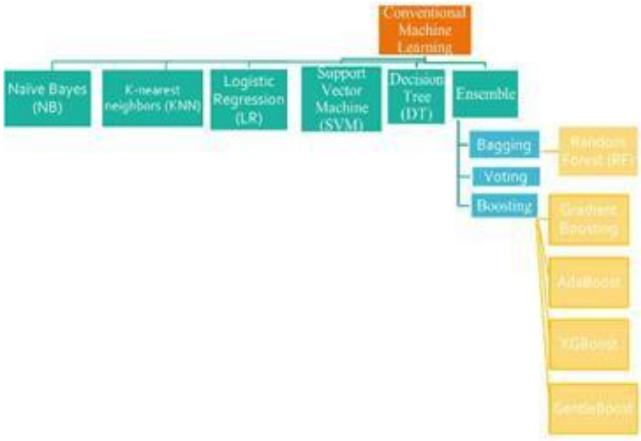

Fig 2. Taxonomy of ASD [9]

Gabriel et al. [16] proposed a computer-aided clinical decision that can distinguish between ASD and TD based on children's facial images captured by a digital camera, thus aiding diagnosis. We defined methods for image acquisition and prioritization, and tested and compared methods for dataset balancing, dimensionality reduction, and classification. The best results were obtained by the SVM classifier with 86.2% accuracy. When the model is prepared based on facial images, it has the potential to facilitate early diagnosis of autism spectrum disorders.

C. Wu et al. [12] proposed a machine learning (ML) method to diagnose autism spectrum disorder (ASD) based on identifying specific behaviors from videos of infants aged 6 to 36 months. They can smile 70% of the time, smile 68% of the time, smile 67% of the time, and make noise 53% of the time.

Vandewouw, Marlee et al. [23] used measures derived from brain activity in the brain to assess heterogeneity between conditions.

Jacob et al. [33] studied CNN models and UCI datasets. They exclude the diversity of ASD. Han, Yu et al. [34] Works on RF, SVM, KNN, CCEA. They use the ABIDE dataset. They achieved over 93% accuracy with KNN.

[4] Evaluated the Autism Brain Imaging Data Exchange (ABIDE) dataset. The ABIDE dataset consists of resting-state functional magnetic resonance imaging (RS-fMRI) and data from 20 different locations. Data are publicly available from the University of California, Irvine (UCI) repository [3].

Kim et al. [8] compared AlexNet, VGG16, and ResNet networks on ImageNet and VGGFace datasets with previous works using two methods: (i) fine-tuning the networks; (ii) using them as feature extractors for SVM classifiers. The best results were obtained using the VGG16 architecture, which was previously trained using images from the VGGFace dataset and used as output for the linear SVM classifier, although the sample size was small (70 images per syndrome, without data augmentation).

Hosseini et al. [25] used the pre-trained MobileNet model, but added three additional layers for optimization: global average and two thick layers of 124 neurons and two neurons, achieving an accuracy of 94.6%. Accuracy

Koushik Ch. and Mir A. I. [5] proposed to find the best way to evaluate ASD according to multiple parameters in various classifications, including support vector machine (SVM) and Gaussian radial kernels. When the ASD information system, which is available to everyone, is used, the results are best and most accurate, reaching 95%.

Research [1] proposed a method that uses visual behavior and eye contact to distinguish children with intellectual disabilities from typically developing individuals.

[35] proposed the use of functional connectivity for autism diagnosis by selecting and interpreting input points. Using EEG- trained support vector machine (SVM) as a diagnostic tool for ASD. Conjoint studies have been defined as the use of functional magnetic resonance imaging to reveal advanced features and diagnose various neurological diseases such as autism, schizophrenia [24].

To diagnose different neurological disorders using EEG data, computer-aided diagnosis using neural networks has been introduced to assist specialists and doctors [24].

Deep learning was proposed using CNN, recurrent neural network RNN, and SVM, a brain perception system that uses facial expressions as biomarkers [2].

Federal Learning (FL) model [18] proposed to diagnose ASD as a neurological disease using patients' specific behaviors and facial features. Hasan et al. [19] found that children's use of facial expressions is important for the diagnosis of autism spectrum disorders because the face is thought to be a reflection of the brain; It is also an easy-to-use and useful tool for the early detection of autism spectrum disorders (ASD) and can also be used as a diagnostic biomarker. This work uses multiple learning transformations available in deep CNNs to identify children with autism based on face detection. They conducted a study on optimization to find the best optimizers and hyperparameters in CNN models to improve prediction accuracy. Transfer learning such as MobileNetV2 and Hybrid VGG19 are used with different learning techniques such as logistic regression, linear support vector machines (linear SVC), random forests, decision trees, gradient boosting, MLPClassifier, and K-based nearest neighbors. The deep learning model was analyzed using Kaggle's mining model dataset containing 2940 images of autistic and non-autistic children. The MobileNetV2 model achieved 92% accuracy in the test cases.

Contribution in the field of ASD detections also shown in table below:

TABLE I. Major Contribution in The Field

Ref. & Year	Method	Dataset	Accuracy
[19], 2023	Transfer Learning	Kaggle	92%
[23], 2023	Clustering	HBN	
[21], 2022	LR, RF, and xgboost		75.5%

[16], 2021	SVM		86.2%
[26], 2021	SVM	ABIDE 1	81%
[31], 2021	RF	NDAR	72%
[5], 2021	SVM	ASD	95%
[12], 2020	ML with balancing	ASD	82%
[17], 2019	DT	Videos	60%

Research into autism diagnosis has made significant progress, but there are still some important areas of research and areas that need further investigation. Some research gaps in autism research include:

Early Diagnosis: Early detection of autism is critical for timely intervention. Research should focus on the development and validation of tools and methods, including behavioral markers and biological markers, to identify autism in infants and children.

Subtypes and heterogeneity: Autism is a spectrum disorder with many different components. Research should address the identification and understanding of different types of mental disorders, including behavioral and genetic factors and their impact on diagnosis and treatment.

Cross-Cultural Validity: Autism presents differently in different cultures, and diagnostic tools may not be universally valid. Research should investigate the cross-cultural validity of existing diagnostic methods and develop cross-cultural assessments. 4. Biomarkers and Imaging: Investigating potential biomarkers and neuroimaging techniques for autism diagnosis is an ongoing research project. Biomarkers may include genetic, metabolic, or neuroimaging markers that provide objective diagnostic information.

Gender Differences: Autism diagnosis is more common in men, and this gender difference may lead to misdiagnosis in women. Research should examine gender-specific diagnoses and tools. 6. Comorbidities and overlapping conditions: Many people with autism also have comorbidities such as attention deficit hyperactivity disorder or anxiety. Research should focus on improving the accuracy of diagnosis in overlapping individuals.

Adult Tests: Most studies and tests are aimed at children. More research is needed on diagnosing and supporting adults with autism, especially those who were not diagnosed in childhood.

Technology and tools: The development of digital and cognitive-based tools for autism diagnosis and treatment is an emerging field. More research is needed to confirm the accuracy and validity of these methods.

Longitudinal Studies: Long-term studies that follow individuals from childhood to adulthood can provide insight into the stability of diagnoses and the impact of early intervention.

Research: Although research is important, research will continue to focus on the development and evaluation of effective interventions and supports for individuals with autism.

III. CONCLUSİON

The paper concludes by summarizing the research findings and their significance in the context of autism diagnosis. It may also suggest future research directions and potential applications. This paper reflects the ongoing efforts to leverage advanced technologies, particularly machine learning and artificial intelligence, in addressing critical healthcare challenges, such as the early identification of neurodevelopmental disorders like Autism Spectrum Disorder. In future more efficient machine learning methods can be developed with optimization and hybridization also.

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