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Intelligent Information Systems for Predicting, Autism Disorder: A survey

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Abstract **– Autism spectrum disorder (ASD), is a well-known mental disorder that affects a person's abilities for social communication. The importance of early diagnosis prompted researchers to use several machine learning-based techniques. With the aidof machine learning methods like Support Vector Machines, Random Forests, NaiveBayes, K-nearest Neighbors, and many more, several analyses are carried out to predict autism meltdowns. This study provides a comprehensive evaluation of studiesusing algorithms for data analysis and classification, as well as machine learning, to predict ASD. The surveys are compiled from the internet and consider more than 80 study studies. In the end, 41 research publications met the requirements for this investigation. The major objective of this study is to identify and separate the machinelearning trends in the ASD literature, point out important research trends in the fieldof machine learning, and guide researchers interested in developing the fundamentals of predicting ASD data. This survey will serve as a manual for future scholars that are interested in the topic of foretelling ASD meltdowns.**

Keywords **– Autism Spectrum Disorder, Intelligent Information Systems, Machine Learning, Data Analysis and Classification.**

I. INTRODUCTION

Aneurological abnormality that interferes with normal development and has an impact on a person’s behaviour is known as autism spectrum disorder (ASD). Most of the time, this developmental disorder restricts social engagement and communication behaviours. Centers for Disease Control and Prevention (2018) produced a report claiming that 1 in 60 children have an autism spectrum disorder (ASD), and that the prevalence of diagnosed ASD patients is four times higher in male patients than in female patients, according to one analytical study [1]. Unfortunately, there is no permanent cure for ASD, but spotting meltdowns or otherissues in the early stages of medical care [2] or [3] is still a difficult effort that has animpact since it helps others understand and not be afraid. This review paper reviewsthe machine learning techniques that will allow researchers to acquire the notion andelaborate the future study in this area of predicting ASD meltdowns in order to throwmore light on these troubling difficulties. In addition, we expect that by emphasizing the novel approaches as much as possible in this review paper, future researchers would be helped in identifying unexplored territories from various machine learningapproaches to mental health diseases.

The key contributions of the paper are as follows:

1. To identify and distinguish the development of machine learning techniquesin the literature on ASD.
2. To learn different machine learning methods and evaluate the outcomes based on their precision and flexibility.
3. To identify some fresh problems for next research topics in the field of ASDmeltdown predicting.

II. Background

Recent research has demonstrated that subclinical autistic traits of parents amplify the effects of deleterious mutations in the causation of autism spectrum disorder (ASD) in their offspring. Here, we examined the extent to which two neurodevelopmental traits that are non-specific to ASD-inattention/hyperactivity and motor coordination-might contribute to ASD recurrence in siblings of ASD probands.

As the candidates for discriminating indicators of ASD, the following factors wereselected from various studies. These were patients' backgrounds (Age, gender, education level, marital history, living alone, physical diseases [15, 16] and family history of mood disorders [17]), age of onset for psychiatric comorbidity, and past history affecting social function and adjustment (school non-attendance [18-20], bullied experience [21-23], psychotic-like experiences [6, 24, 25], conduct problems [26, 27], suicide-related behaviors [24, 28] and interpersonal friction at work/ school [29]). These variables can be easily asked by clinicians without information from parents of the patients. Presence or absence of these variables were confirmed by simply answering either "yes" or "no" by patients. For bullied experience, we askedsuch questions like "Have you ever been bullied during your school days? For example, being frequently targeted or routinely harassed in any way?". For interpersonal friction at work/ school, we asked questions like "Have you everexperienced interpersonal problems at work/school? For example, having a quarrel or an interpersonal conflict with colleague or your boss?".

III. Related Work

Mamun et al. [16] have introduced AutiLife: a medical service monitoring framework for autistic centers within a 5G mobile network with the use of Machine Learning, taking into account all possible scenarios. The suggested monitoring system looked at WBNA and 5G to enable perceptive devices (Instruments and sensors) that are suitable for capturing signals and information about human well-being. Additionally, the study ordered all collected data and signal data that was captured using various methods using an ML algorithm (SVM).

In an experiment suggested by Yu et al. [17], cortical thickness was used to determine the ASD symptoms of participants, and Support Vector Machine and ENet penalized linear regression were used (SVR). With 156 individuals ranging in age from 8 to 40, the study was done. SVR was found to work with the identical calculation statement of the provided input data after being compared to the SVM approach. The results were seen to exhibit an upgraded and better correlation score beyond various sites, which indicated a remarkable potential of Machine learning in predicting the symptoms of ASD, despite the output being extended and in a continual manner.

A dataset named 2008 Georgia ADDM data was used by Xiao et al. [18] to test an RF classifier. From a total stock of 5396 children, categories for both ASD and TD were warped using a bag-of-words approach with TfIDF weighting, and from there, 601 children were found to have ASD syndrome and 561 were determined to have TD syndrome. Later, using the Georgia ADDM data from 2010, the categorization model was checked once more. The authors pointed out that these machine learning techniques can be used to identify and diversify kids who make careful note of the necessary conditions. However, the model should be viewed more as a filter than as a technique for absolute classification, according to the author.

A novel intelligence-sharing pattern was put forth by Song et al. [19] that masked individual data that was bot-

-h responsive and unstable. The study also recommended linear variance analysis as a simple way for keyword separation (LVA). SVM was the technique applied in this filtration procedure. The study's findings offer hope for employing text mining to safeguard private health information transmitted over the Internet.

Machine learning algorithms developed on multi parametric MRI data were put to the test by Zhou et al. [20] to identify ASD. Cross validation was used in the research of estimation bias to reduce classification error [58-101]. These findings suggested that identifying ASD may benefit from machine learning techniques using multi-parametric MRI data. Moreover, Particular characteristics were connected with conclusions of behavioural analysis that can also demonstrate effectiveness in keeping an eye on symptoms covering time.

Omar et al. [21] carried out a different investigation in which machine learning methods were used to create a prediction model. 250 actual datasets from different age groups with and without features from the autism spectrum disorder syndrome were included in the study. Three different random forest algorithms, including the Random Forest Iterative Dichotomiser and the Random Forest Classification, were connected for that purpose. At the end, accuracy results of 92.26% and 97.10% were displayed.

Sharma et al [22]'s analysis of various machine learning models used to predict autism features was done after many researchers used those models to distinguish child diseases from ASD. In order to evaluate each classifier's effectiveness and accuracy, the study was applied to a variety of classifiers, including KNN, LMT, Random Forest, Naive Bayes, LDA, Decision Tree, and many more. SVM has demonstrated the greatest results among all machine learning models, with an efficiency of 98.27%.

Another work by Zhan et al. [23] used non-presumptive neuroimaging in humans and mammals to categories the neurological study area in response to DSM-5 analysis and sizable amounts of intensity of syndrome. Additionally, it evaluated if the classifiers' functional relationships with the ASD and OCD symptomatic domain were typically combined. The paper introduced two novel machine learning methods in a simple and clear manner.

Two machine learning methods were developed by Abbas et al. [24], the first of which was based on a parent-adolescent questionnaire and the second of which was based on home cell phone footage. Both of these systems significantly outperformed the current ASD prognosis models.

Misman et al. [25] offered a technique in which the primary goal of the study was to employ DNN, including an ASD screening dataset, and deploy a supervised deep-learning algorithm with the hope of creating a methodology which can accurately identify and classify cases of ASD. To study ASD illnesses, the DNN and SVM model was developed. With the use of the model, validation and training data were needed and adjusted, and outcome estimation was used to gauge how effective the method was.

A consistent classification accuracy of machine learning approaches that was attained with population models with less than 100 participants was proposed by Arbabshirani et al. [26]. Studies only yielded higher classification accuracy when there were dozens of participants, and the accuracy was discovered to be above 90%. When data is gathered from several parts and in circumstances involving a bigger population, classification accuracy degrades automatically.

Using deep learning techniques, Patnam et al. [27] suggested a method to create a system that can recognize d-

-ifferent types of behaviour, alerting the parents or caregivers so they may quickly bring any problematic circumstances under control. The study also conducted functional testing by supplying the deep neural network with chosen actions performed by five people. In the end, the study's accuracy rate in all scenarios was 92%, which indicated that the technology could be used in real- time.

In a different study, Mayor et al. [28] examined the literature on ASD and examined neuroimaging data in an effort to create screening tools to identify ASD meltdowns. The research's approaches have produced a terrific opportunity to find high accuracy and perform better. The study was entirely supported by video, neuroimaging, and electronic health data.

A text mining technique called aAutMinera was developed by Gong et al. [29] to examine the ins and outs of ASD genes. The goal of the project was to compile 9276 abstracts related to the topic of autistic spectrum disorder into a dataset using PubMedas E-Utilities. The study also came to the conclusion that AutMiner can be utilised for genetic screening to detect ASD meltdowns.

Later, using Association principles, Gong et al [30] carried on his previous work. ASD-related genes were selected by the author from 16,869 publication abstracts. Association rules were used with both candidate genes and genes that had already been discovered. This study also emphasises the potential of text classification for future gene discovery prediction in ASD meltdowns.

Lehr et al. [31] reported another study on neural networks that was able to demonstrate improved performance in simple linear regression. The study, however, ran into a problem because it was unable to decipher the centralised parameters used by neural networks.

Using various classification algorithms, Bennett et al [32] investigated if any type of personal blogs could quickly analyse any data from the Autism Spectrum Quotient (AQ; Baron-Cohen et al [33]). In the meantime, using the Naive Bayes Classifier with LIWC dimension selection, an accuracy of 90.9% was discovered for males. On the other hand, the Naive Bayes algorithm with 3G models was used to determine an accuracy of 88.7% for female participants. The study indicated that the detection of ASD cases within the field of machine learning has a bright future.

A decision tree was utilised by Hyde et al. [34] to test a novel method of ASD prediction using employment power. The suggested model was successful in determining the prevalence of ASD among all employers who had been hired, and it specifically demonstrated an accuracy rate of 75% and 82% that suggests a high likelihood of foreseeing ASD meltdowns.

In order to extract properties from fMRI data, Ahmed et al. [35] construct a model that combines the Restricted Boltzmann Machine (RBM) and the Support Vector Machine. The results of the grid-search cross-validation show how well the schemed framework identifies the meltdowns ASD. The analyses reveal that in the long - term, a combination of RBM and SVM techniques could be utilized to detect any kinds of ASD meltdowns.

A Logistic Regression model was put forth in a different study by Rane et al. [36] in order to develop an Open Source-based classifier for predicting ASD meltdowns. A total of 539 samples were taken from the ABIDE database. In the final stage, over-fitting was essentially eliminated using LASSO regression and 5-fold cross-val-

-idation, yielding an accuracy of 62%.

The study conducted by Wall and colleagues attracted notice after Bone et al. [37] identified a methodological issue (Wall et al. [38]). The authors designed various tests to mimic the results of the ADTree technique developed by Wall and colleagues, which makes use of enormous amounts of data and more consistent patterns of cognitive and affective facts. These attempts fell short of the accuracy criteria established by the authors for the lower ADI-R and ADOS classifiers.

Another author, Caly et al. [39], discussed a classifier that primarily sought to decrease erroneous ASD tracking while also attempting to maintain a high actual ASD prediction rate. The study included a number of characteristics, including as sex, maternal CMV vaccination, temperature differential, maternal family history, and more.

A novice model for the ASSDL algorithm for the diagnosis of ASD was put forth by Yang et al. [40]. In order to diagnose ASD, the author proposed ASSDL as the first semi-supervised dictionary learning (FSSDL) method. ASSDL outperformed competing approaches, resulting in a strong correlation between implementing the discrimination of labelled data and predicting the categories from unlabeled samples.

A mobile app called “PandaSays” was suggested by Popescu et al. [41] to help children with autism, their families, and teachers improve their communication abilities. The software uses machine learning for label identification and object recognition. Different machine learning techniques, including PART (a partial decision tree based on the separate-and-conquer technique), SMO (sequence minimal optimization algorithm), Logistic-R, Naive Bayes, IBk, and J48, were favored for predicting the experiment.

In order to estimate autism symptoms in patients of all ages, Omar et al. [42] looked at conventional tree-based machine learning approaches and presented a novel tree-based machine learning model. According to the intended use of the research, two distinct tree-based ML techniques were used to develop prediction models of autism that were tested on. The study found that the merged random classifier models exceed conventional tree-based machine learning techniques.

In the framework of unsupervised learning, Liang et al. [43] suggested a method based on unlabeled data that is used to learn how to recognise slow-changing classifying self-stimulatory behaviour traits. In comparison to the most recent state result (73.6%), the study's findings were successful, with a 98.3% accuracy rate.

A method for choosing the best result and defining ASD was developed by Chowdhury et al. The study investigated the performance of various machine learning classifiers using a particular dataset. The study preferred SVM to delve deeper into the dataset. The investigation also found that the best algorithm and classifier for anything connected to the healthcare dataset is the SVM Gaussian Radial Basis kernel.

Brain tissue-specific Functional Relational Network (FRN), created by Duda et al. [45], uses machine learning techniques to predict the genomic activation of autism-related genes, including CTCF (11-zinc finger protein encoded gene), BRAF (serine and threonine kinase protein encoded gene), CHD7 (Chromodomain Helicase DNA 7), CHD8 (Chromodomain Helicase DNA 8), NTRK1 (Neurotrophic (Phosphatase and Tensin Homolog). The number of distinct genes with a strong likelihood of increasing the risk of ASD is suggested by this model. For their investigation, the authors in this case used microarray data from GEO (Gene Expression Omnibus).

Introducing a preprocessing technique for delineating data objects was Pancerz et al. [46]. Evaluation sheets are a part of the preprocessing activities to create classifiers and clean the training data from ASD. By calculating the consistency factor and splitting the set of all training instances into subsets of specific cases and boundary cases, they divided the technique into two parts. This document includes 70 instances in which each subject was assessed using questions grouped into 17 categories and 300 qualities. Each attribute has four values: 0 (not performed), 25 (done with physical assistance), 50 (performed with verbal assistance or demonstration), and 100 (finished without assistance).

ASD sufferers also have difficulty recognizing and distinguishing their vocal identities. Lin et al. [47] shown in their article how people with ASD may identify vocal identity. Three experiments were used as examples in their study: a familiarity test, a vocal identity recognition experiment, and a gender discrimination experiment.

It is impossible to calculate the combined impact of features that have been evaluated individually using traditional feature selection approaches due to their dependence and redundancy. Teng et al. [49] used an adaptive feature selection technique in these situations to assess the cumulative effect of various subsets on the overall feature space. This method was based on binary particle swarm optimization in a V-shape.

By identifying only a basic subset of behavioral traits, Levy et al. [25] reduced the number of features. They successfully distinguished between ASD and non-ASD occurrences during the ADOS investigation. By using score sheets for ADOS module 2 (ASD, 1319; non-ASD, 70) and module 3 in particular, they were able to refine their preliminary study and create a sparse system with a stronger capacity to generalise to the clinical population (ASD, 2870; non-ASD, 273). For their investigation, they employed datasets from the Simons Variation in Individuals Project (Simons VIP), AGRE, SSC, and Boston AC.

Crippa et al [50]'s classification of ASD children with upper-limb motions between the ages of 2 and 4 years using seven characteristics and supervised machine learning with SVM yielded a 96.7% accuracy rate. The objective of this study was to accurately distinguish TD from ASD by delving into the kinematic analysis of upper- limb movements. Despite the positive outcome, there were a few drawbacks, such as the small sample size (15 children with ASD and 15 with TD). For a specific data set, such as low-functioning and preschool-aged ASD children, SVM performed best; however, it performed poorly for high-functioning ASD patients, adults, and female patients.

Once more, as Vaishali et al. [13] asserted, it is sufficient to distinguish between those with ASD and those without ASD by using only 10 features out of the 21 features in the datasets of autism. For the selection of the best features, the authors suggested using a single-objective binary firefly method based on swarm intelligence. From the University of California Irvine Machine Learning data Repository, they gathered autism datasets (UCI).

Variable analysis (VA), a computational intelligence method suggested by Thabtah et al. [51], significantly reduces the sum of features for ASD screening methods while maintaining levels of sensitivity, specificity, and analytical correctness. They made use of datasets related to the AQ-Child, AQ-Adolescent, and AQ-Adult models. In comparison to most other filtering approaches, VA can choose fewer characteristics from the datasets. This technique reduced the AQ-10 child, adolescent, and adult versions to 8, 8, and 6 characteristics, respectivel-

-y, while maintaining sufficient scores of accuracy, sensitivity, and specificity.

Reaven et al. [52] employed the ADOS and ADI-R, two validated diagnostic instruments known as gold standards. The goal of the study was to determine how well ADOS and ADI-R assessment packages can identify ASD. Algorithms for supervised machine learning have also been applied to ASD classification issues. In supervised learning, a goal variable-the dependent variable-is predicted using an algorithm from the input variables. Otherwise, this target variable would be categorized as a continuous variable.

As an illustration, Hyde et al [53]'s research on autism showed a variety of patterns and the advancement of supervised machine learning approaches. They talked about how this technology supports vast and varied datasets, genetic data, and multidimensional data.

Additionally, Stevens et al. [54] used unsupervised machine learning to identify and examine behavioural characteristics in ASD. The authors mostly used hierarchical clustering and Gaussian mixture models. Through the indications and traits found, this investigation attempted to assess the behavioral aspects of autism and examine the therapy response. Using personal characteristic data, Parikh et al.

Improved and assessed the performance of nine machine learning models to classify ASD (PCD) [30]. By using PCD as an input feature coupled with better machine learning approaches, they improved ASD diagnosis. When paired with external characteristics, such as functional magnetic resonance imaging (fMRI), these models can produce an extra realistic method of diagnosing ASD. The analysis's major disadvantage comes from how the ABIDE data are collected because data from 17 clinical and testing sites were obtained for this work.

Recent clinical and screening machine-learning research in ASD was examined by Thabtah [55]. The analysis revealed the critical concerns that must be addressed and exposed the shortcomings of conventional approaches. Data, diagnostic timing, and feature selection methodology were a few of the problems with machine learning for ASD classification that needed to be addressed.

A new machine learning technique called rule-based machine learning (RML), which distinguishes autistic aspects of positive cases and controls, was also put out by Thabtah et al. in another article [56]. The method offers users knowledge bases and rules that illustrate the key characteristics classified by the methodology. They claimed that the method outperformed other machine learning methods like bagging, boosting, rule induction, and decision trees in terms of predicted accuracy, specificity, harmonic mean, and sensitivity.

Wolfers et al. [57] used a different strategy, such as pattern categorization and stratification. The study includes 57 papers on pattern classification and 19 studies on stratification screened in 635 different studies, respectively. They discovered significant heterogeneity in the studies' pattern classification, with predictions being accurate to the tune of 60% to 98%. The above is explained by, among other things, the wide range of validation techniques employed in different studies, the variability of ASD, sample error, and variations in data quality. Only two replications were noted for the stratification research, and there were fewer studies that indicated external validity.

According to the analysis above, machine learning techniques have recently been applied widely in research on ASD. In order to diagnose ASD, researchers have created predictive models and used machine learning as the most clever methods. Examples include supervised machine learning, unsupervised machine learning, and deep

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learning; in particular, the exceptional performances of Gaussian mixture, hierarchical clustering, RML, and support vector machines, among others. Consequently, machine learning methods for diagnosing ASD are a potential area of study and can increase the precision of predictive models.

As shown in Figure 1, the fundamental form of the classification problem is a binary classification, such as ASD or non-ASD. To be clear, binary classification includes dividing all of the features or data items into two categories in accordance with established classification criteria. For a test case prediction, the possible responses are depicted in this picture. Machine learning algorithms have been utilized in earlier research to make predictions. As a binary classification, a confusion matrix was used [14-16].

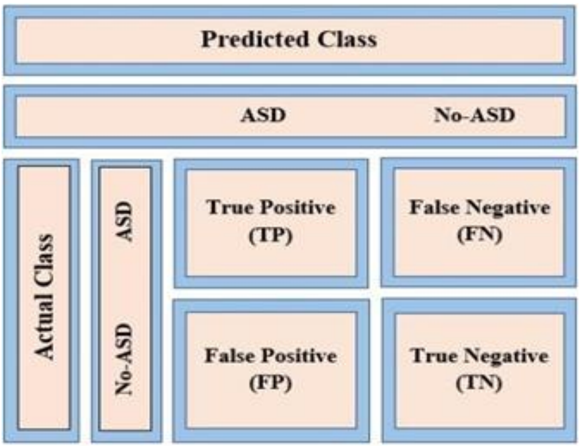

Fig. 1. Confusion matrix for (ASD) classification [30].

ASD diagnosis is a classification issue with several steps. Figure 2 describes the procedure. The cases and controls in this training dataset have already received a diagnosis [35].

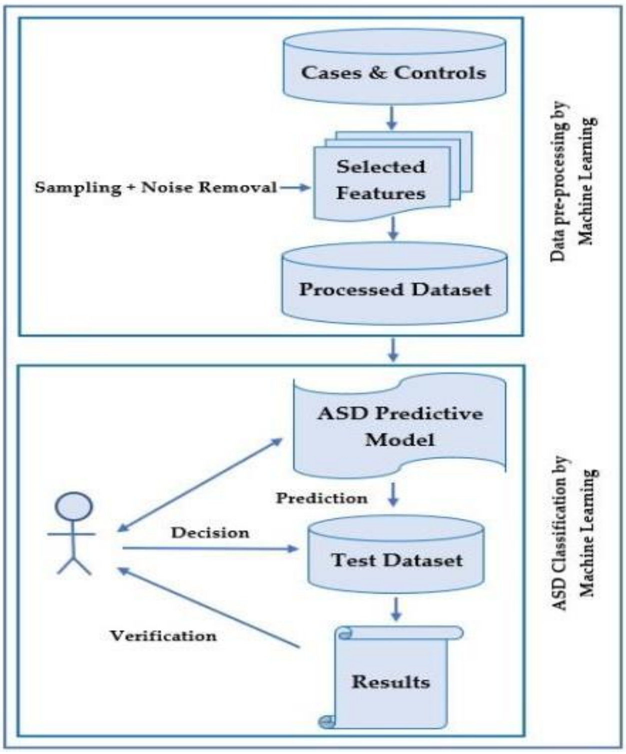

Figure 2. ASD classification with ML [40].

These cases and controls are often produced in a clinic by a diagnostic tool like the ADOS-R or ADI-R. These resources are managed by clinical doctors or psychologists. There is an optional stage where feature selection is conducted by choosing a smaller collection of features to reduce data dimensionality after determining the training dataset.

The method of controlling the computer resources is used and incorporated duringdata management in addition to focusing on the issue and identifying the key ASD aspects. Noise elimination is the next stage, which is optional. Replicated records, missing values, and imbalanced data are all examples of noise. To increase data concerns, numerous research have recently adopted sampling approaches. In binary classification, sampling approaches fall into two broad types. These are methods of under- and over-sampling. Data analysis is used in both methods to modify the class distribution of a dataset. A smaller class's instances are equal to those of other classes'instances through under sampling. The over-sampling method, in contrast, uses samples from a class that is more important until the number of instances is balanced.

After completing the aforementioned preprocessing processes, ASD cases are classified using machine learning techniques in the following steps. Currently, researchers use software programmes like Weka and R. These software packages require the loading of relevant preprocessed data in order to operate. For data classification, there are several possibilities for using alternative filters and machine learning methods. These kinds of software contain machine learning techniques, which offer more advantages due to the availability of numerous evaluation measures. Users can accomplish their anticipated objectives in this instance, including accuracy, sensitivity, specificity, false positive and false negative rate, processing speed, receiver operating characteristic (ROC), and F-measure.

Therefore, the following is a summary of the necessary conditions for identifyingASD using machine learning techniques:

Stage of preprocessing (first steps):

(i) Select features.

Data balancing methods include missing value handling, sampling, and datasetnoise reduction.

Stage of classification (major actions):

(ii) Input: Include controls and positive cases together with a specific dataset.

(iii) Procedure: Create a diagnostic prediction model for ASDs using embeddedmachine learning classification techniques. A class prediction model for test data is the output.

(iv) An authorized specialist then performs the surgery, confirms the outcome ofthe predicted model, and makes a decision.

IV. Challenges and Limitations

1. Deep learning (DL), which is used to categories diseases in various ways, is one of the main issues in ASD analysis and prediction. However, there is a lackof theoretical and mathematical support for a variety of Deep Learning techniques to explain different Architectures in ASD predictions.

2. The noniterative single hidden layer feed-forward neural network [45], for example, combines fuzzy logic and neural networks to address a number of problems in early ASD prediction and bring about a significant shift in data mining.

3. There are two ways that fuzzy logic models can be utilised to predict ASD meltdowns: first, by improving the precision of the current rating scales, and second, by creating a new rating scale based on a standardized ANN. Patwaryet al. [46] proposed a sound mathematical model to explain how low-fuzzinesssamples affect the learning performance of ASD models.

4. By feeding even minor symptoms into semi-supervised machine learning and an ANN, it may be possible to diagnose ASD early, which could be a game- changer in the early diagnosis of autism spectrum diseases. Using real labelledsamples as validation samples, Patwary et al. [47] developed a straightforwardmethod that should improve the accuracy of predicting various ASD meltdowns of SSL.

5. It would be advantageous to expand the investigation's experimental scope andconduct a theoretical analysis of the pattern this paper has identified. At the moment, a fundamental approach to understanding these features is based on statistical learning theory [48].

V. Discussion

Although still in their infancy, machine learning (ML) techniques such as supervised, semi-supervised, unsupervised, and deep learning (DL) have showed promise in the majority of situations when it comes to diagnosing ASD. This review paper aims to consolidate papers that have examined ASD using machine learning concepts. The most commonly used algorithms were Decision Tree, Naive Bayes, Linear Regression, SVM, and Random Forest, and they were used to investigate cases of concern in an ASD colony, find potential ASD genetic codes, and look at complex relationships between ASD and numerous other facets of ASD. We think there is a good chance that machine learning experts will band together and encourage other researchers to join in the effort to recognize and address this remarkable challenge.

VI. Conclusion

The main objective of our study was to investigate and assess various machine learning methods that might predict autism spectrum disorder (ASD) symptoms under various circumstances. Several machine learning and deep learning techniques were tested in this study to see how well they might identify autism spectrum disorders. Nevertheless, there are a few points brought up in this work that can act as guides for future researchers trying to predict ASD meltdowns. One benefit of machine learning's capacity to handle data is that it might be referenced as a helpful tool while explaining new research. Due to how simple it is to collect and analyse data, machine learning is currently being utilised to treat ASD meltdowns. We have high hopes for future research in the field of ASD meltdown detection and believe that the machine learning models described in this paper can help other researchers create straightforward and practical methods for ASD predictions.

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