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Early Autism Diagnosis: Machine Learning Models and Their Effectiveness

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Abstract

Diagnosis is of utmost importance for timely intervention and support. However, traditional diagnosis methods, which are based on subjective assessment, are delayed. This project explores the role that machine learning techniques might play in enhancing the accuracy and effectiveness of ASD detection. Several state-of-the-art classification algorithms were benchmarked using a dataset from Kaggle. Logistic Regression, XG Boost, Random Forest, Decision Tree, and Gradient Boosting were taken into consideration. Other performance measures, in terms of accuracy, F1-score, and precision, were considered. The results showed that XG Boost was the best model, because this one had the most precision and reliability of ASD prediction. The research signifies the potential of AI and ML technologies for the betterment of the diagnostic process and provides a robust and timely tool for early detection of ASD. Conclusions and recommendations of the study strongly emphasize the necessity of approaches that integrate multidisciplinary and ethical considerations for responsible translation into clinical practice.

Keywords: Autism spectrum disorder (ASD), Machine learning, Modalities, ADOS, XG Boost, Precision, Accuracy, Confusion Matrix, F1 Score.

INTRODUCTION

It is critical to diagnose ASD in youth as soon as possible to provide the right kind of assistance and mediation[2], [3].

An increasing number of people are interested in applying artificial intelligence techniques, machine learning techniques, Robotics, Gaming etc. to enhance the precision and proficiency of ASD localization since traditional diagnostic methods rely on subjective assessment learning to delay intervention in diagnostics and provide timely support and improvement. There is also another term referred to as ADHD, which means that the individual has trouble paying attention and has impulsive behaviour. This study's foundation is due to the growing incidence of ASD and the need for trustworthy, impartial analytical tools and differentiate it from ADHD.

These methods could provide a solution wherein it would be easy to detect ASD at the correct time as the cases of ASD are increasing globally, emphasizing the need for effective diagnostic approaches. In the research and implementation, various machine learning models in order the identify the most effective and having highest accuracy for the detection of ASD. Methods involving AI and ML provide higher accuracy in comparison to traditional methods for detection which are way to lengthy and cause delays in the process. One more disadvantage of traditional methods is that they don't consider all the factors/

symptoms of ASD which may lead to misdiagnosis[4]. On the other hand, AI and ML technologies provide promising solutions for enhancing ASD detection by analyzing large datasets and considering all the factors/symptoms that play a crucial role. These technologies have the potential to streamline the diagnostic process, leading to increased accuracy and timely detection. To utilize these resources and technologies, various feasibility studies also need to be carried out such as their cost-effectiveness, whether the relevant data is available, computational cost and ethical/legal considerations. As Technology is advancing, different AI, ML, Gaming, Robotics and Brain Neuroimaging models have made advancements in this field [6]. The overall focus is to improve and expand the useability of these technologies economically, technically, and financially. Our focus is to build a platform where the parents or guardian can take an assessment at home without thinking about cultural, or social factors and based on the results they can visit a healthcare service at the earliest, alongside providing a platform for building the cognitive skills of the child. In the research part finding out how each factor plays an crucial role in ASD and which machine learning model provides highest accuracy. AI and ML technologies for ASD detection provide promising avenues for improving diagnostic accuracy, reducing delays in detecting and overall helping in enhancing the quality of life of the individual suffering from ASD, by analyzing a diverse number of datasets and identifying patterns and characteristics. These technologies can in turn lead to meeting the needs of everyone. All the motives can be completed only when all the financial, technical, and ethical factors are met together in turn ensuring the successful implementation of these technologies in clinical practices[9], [12], [14], [16].

LITERATURE SURVEY

A lot of methods are being used to detect ASD with the intervention of Scientific Software. In the Research it was found that various technologies like Machine learning Techniques, Brain Neuroimaging data, Wearable devices, Robotics, Characteristics and consequences of computer-based games on children having ASD and Face Expression Recognition using Deep Learning from Video Games are being studied by people and various pros and cons have been developed based on each study and findings [13]. Talking about the Scientific ways, talking about machine learning techniques- it is being used in various ways to enhance the diagnosis of ASD, Scientists have used feature selection in conjunction with under-sampling to distinguish between autism and ADHD patients. ASD detecting metrics were based on brain activity, which used an approach like Artificial Neural Network (ANN). Some of the research took into consideration the Brain neuroimaging data [19]. It selected six personal traits from the Autism Brain Imaging Data Exchange (ABIDE) database and used a cross-validation technique to train and test the machine-learning models using data from 851 subjects. Patients who had ASD or not were segregated using this. A special AI-based system was also utilized for monitoring, helping, and assisting ASD sufferers in the process of dealing with the COVID-19 epidemic. To identify ASD, wearable technology with sensors has also been used by researchers. Such tools can be helpful for people in increasing their social and emotional intelligence. Model outlining involves a great variety of methods and tools, including structural, neural networks, machine learning, deep learning, transfer learning, and IOT, to identify ASDs. The application of these methods has identified ASD in both adults and children with a fair degree of accuracy. Robotics is not only crucial in the identification of ASD and its consequences but is also very crucial in instructing and training children with ASD. It works on improving a variety of areas, including developing communication and social skills and improving verbal and non-verbal expressiveness and cognitive skills. Although it’s a new and emerging topic of robot-based intervention for autism education and therapy. It holds potential benefits but also challenges associated with its implementation, which include technical complexities, cost considerations and the need for an individualized approach tailored to the unique needs of the child. This requires interdisciplinary collaboration with ongoing research to optimize the effectiveness and accessibility of robot-assisted therapy. An approach was identified for classifying the literature was produced. The overall result indicated that the use of virtual reality can be used to support social skills and video modelling can be used to promote the development of emotional skills in children with ASD [10]. It was revealed that discussing the effectiveness of computer-based games on affecting children's cognitive deficits was useless; despite the high number of sessions, the effectiveness of the game was not discovered. The target group was considered because some children are vulnerable and performing a specific task can cause disturbance to them. It was found as a result that the amount of rehabilitation sessions involving repeating games was not enough to help the victims of ASD. One of the other ways that we tried to distinguish between images of facial expressions and patients' behaviour was by training a model with CNN when children are playing video games, which in our study were capturing pictures of their behaviour and faces. Other parameters are lack of pain, inability to control your eyes properly, unable to recognize gestures, inadequate response to sounds etc. Overall, these technologies provide promise for improving the detection but a lot of intervention is required until it is used for the detection of an individual. These tools once well-established can help individuals and doctors to overcome the challenges [11]. However, keeping in consideration to address the ethical and technical aspects to ensure the responsible and effective use of these technologies in clinical practice. Examining existing agreements and writing on (ASD) using Artificial intelligence, Machine Learning, Games, Robotics, and Neuroimaging brains reveals several significant advances, but also highlights fundamental gaps and areas for further investigation. Despite the victories in the field of AI & ML, ASD is a heterogeneous disorder with a wide range of symptoms [7]. It struggles to capture the diversity of ASD presentations accurately- making software which can adapt to the whole diversity of features requires a lot of effort and is a complex task. One more disadvantage/ Problem encountered using this is that AI/ ML models use a single type of data, whereas integrating multiple models can actually enhance the accuracy. Talking about the other models that are available is Robotics but one of the main concerns Is about the lack of standard protocols and methodologies for using Robotics in ASD detection and might have to struggle between the complexity of social reactions that are relevant for the detection of ASD, also the person dealing with ASD are sensory sensitive and interaction with such an advanced robotics technology can be very overwhelming for the individual having ASD and the high cost of developing robots limits its accessibility to people. Gaming also have played a significant role in identifying whether a patient has ASD or not according to the studies [18]. It is important to ensure that the gaming elements are made specifically considering the challenges to capture ASD related behaviors and characteristics but It is often said that the game based assessment can lack generalization to real world situations. Although brain imaging gives insight into the composition and functioning of the brain, which is important,, but there are certain gaps in this model that arise and have been noticed- The brain development and neuroimaging patterns change with age , making it difficult to apply a constant diagnostic criterial across all developmental stages, and also the limited availability of large-scale, diverse neuroimaging datasets for robust model development and validation and thus challenges arising to convert the neurological findings into practical and clinically relevant diagnostic tools for routine use. Addressing these gaps requires research, collaboration and advancements in AI, ML, Games, Robotics and Brain Neuroimaging [19-23]. In conclusion continuous efforts are required to refine existing techniques, develop standardized protocols, and enhance accessibility to innovate technologies for individuals with ASD. Table 1 indicates the Summary of the literature covered in this study.

Table 1. Literature Review- Summarized view

Authors	**Paper Key findings**	**Modalities**	**Reference**
Kelly et al.	Uses DSM-5 criteria for active monitoring of ASD Presence among children aged 8 and 4 years, using a two-phase methodology of record reviews and clinician assessments. It calculates co-occurring intellectual disability rates, analyzes early identification metrics like median age for evaluation and diagnosis	The Modalities in the paper include early routine screening and other developmental concerns and intervention strategies for improving developmental outcomes, monitoring trends in prevalence and early identification and providing resources like milestone tracker.	[8]
Maarten et al.	A meta-analysis of 35 studies from 35 countries including subgroup analysis for children below the age of 10 revealed a mean age of diagnosis to be 43.18 months. The results underline the importance of continued efforts toward global diagnosis at early stage and treatment of Autism Spectrum Disorder.	Employed a quantitative research modality, utilizing systematic review and meta-analysis technique. This method involved rigorous collection, synthesis and statistical analysis of data from multiple studies to derive meaningful conclusions about the mean age at diagnosis of ASD. The study also incorporated qualitative elements such as literature review and quality assessment to enhance the overall validity and reliability of the findings.	[5]
Wafaa et al.	Developmental monitoring, genetic conditions analysis such as fragile X- syndrome or tuberous sclerosis. Genes associated with ASD risk and studying gene environment interactions brain regions like the amygdala, cerebellum and nucleus acumens may show differences. Deficiencies in nutrients is also tested.	Systematic approach, complexities of ASD, Potential causes, brain abnormalities, diagnosis. Emphasizing genetic and environmental influences, brain structure abnormalizes and diagnostic criteria	[15]

Susan et al.	Identifies the core symptoms such as deficits in social communication and restrictive behaviors, are outlined, emphasizing the behavioral basis of diagnosis. Talks about the crucial role of primary care provided.	Emphasizes the critical role of primary care providers for identifying and supporting children with ASD, need for culture sensitive approaches, significance of recognizing developmental regression and necessity of comprehensive evaluation	[17]
Catherin et al.	Variations in symptoms and onset, delves into the diagnostic criteria of ASD as outlined in DSM-IV/ ICD-10, research on genetics, familial risk. Examines neuropathological findings such as structural MRI findings, neurobiology of social behavior and animal models used in ASD.	Neuropathological findings, abnormalities in brain regions like the cerebellum and limbic structures, neurobiological aspects. Animal models of autism such as medial temporal lobe lesions in macaque monkeys to elucidate behavioral parallels with human ASD.	[20]
Shiqi et al.	Delves into the multifaceted nature of ASD, genetic architecture and synaptic irregularities, genetic predispositions including mutation in genes like NRXN and NLGN. Shows a notable gender disparity, with boys being more commonly affected than girls	Diverse Modalities including impaired social communication skills in social interaction. Cognitive and intellectual differences are common, ranging from average to above average intelligence and intellectual disabilities	[13]
Scott et al.	The Study predicted ASD using textual evaluations. Classifiers used LDA, LSA, NB, SVM, NB-SVM and neural networks. Result: Random forest and NB-SVM achieve highest accuracy and prevalence estimation	Compares the performance of algorithms. Modalities investigated include document classification methods, Feature engineering techniques such as bag-of-words models and hyperparameter optimization strategies. Evaluates algorithm on basis of Accuracy, F1 score and prevalence estimates across multiple train-test splits of data	[10]
Rahman et al.	Social interaction metrics, includes frequency of initiating interaction and maintaining eye contact, along with behavioral patterns such as repetitive behaviors and sensory sensitivities are key indications. ADOS and AQ assessment tools help in evaluating.	Intervention results in progress of language skills and therapy utilization coupled with demographic factors like age and family history.	[7]

WORKING MODEL

This starts by removing noise from the data, dropping missing values and outliers and encoding categorical features,. Feature design is used to extract the most useful features from the whole dataset. It reduces the dimensions of the data to make it faster and more efficient in the training process. After preprocessing the dataset, classification algorithms such as logistic regression and naïve byes.The accuracy of each classifier is calculated and compared. In addition, F1 scores and precision values were calculated to develop a better model with the one which has the highest results. If a classifier performs well, its training accuracy surpasses its testing accuracy. A model that is considered best will be classified and applied for further model training. Figure 1 illustrates the overall functionality

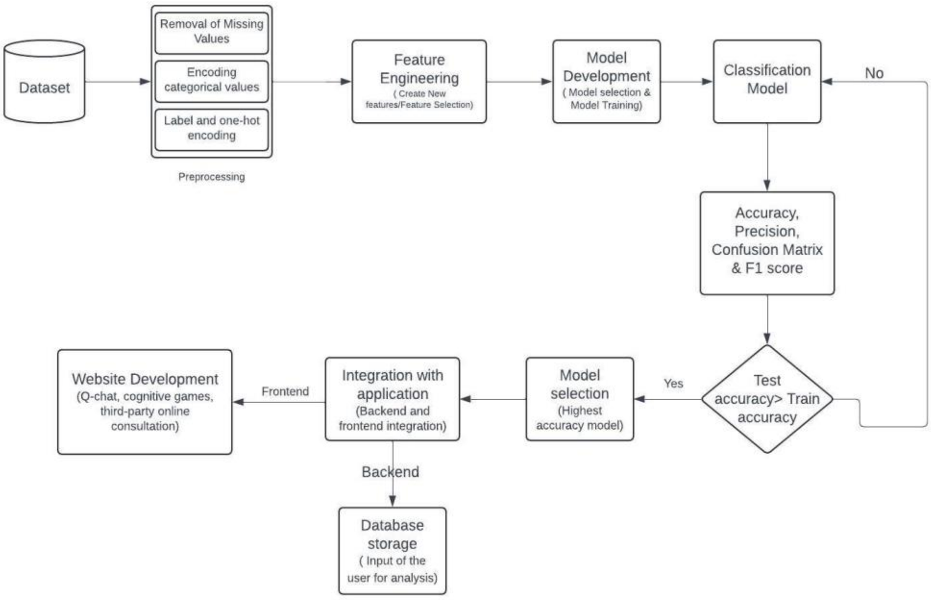

Figure 1. Architecture of the suggested system

METHODOLOGY

documentation

The data contains attributes that are binary, continuous, and category; the dataset was sourced from Kaggle. [1]. It has 1054 instances and 18 class attributes. The dataset is pre-processed before training the model. It helps in removal of raw or noisy data and helps in accurate analysis and training. The non-contributing attributes were removed so that there is no errors in the results. Additionally, the dataset is checked for any null values, which might create inconsistencies. Next, one hot encoding and label encoding will be applied to the data. When there are more than two classes in a field, the label encoding seems to be ineffective; thus, the field receives one hot encoding.

Categorization

The dataset now undergoes training and testing in 80% and 20% scenario. This random splitting of data helps in determining whether a model is suffering from underfitting or overfitting. When a models training error is low and testing error is high, it is said that the model is suffering from overfitting. Conversely, when training error is high and testing error is low, it is said that the model is suffering from underfitting. A well-designed model should not exhibit both of these situations.. The next was applying Machine learning models, we applied Logistic Regression, XG Boost Classifier, Random Forest classifier, Decision Tree classifier and Gradient Boost Classifier.

Logistic Regression (LR)

Logistic regression is a statistical technique where one or more predictor variables are used to estimate the likelihood of a binary result. Logistic regression models the chance of a dependent variable falling into one of two categories, while linear regression predicts continuous values. This approach uses maximum likelihood to estimate the parameters of a logistic model. It is frequently utilized in health, finance, and social sciences to perform tasks like as illness prediction, credit scoring, and consumer segmentation. Logistic regression is favored for its simplicity, interpretability, and efficacy in binary classification issues.

XG Boost Classifier

Extreme Gradient Boosting, more simply called XGBoost, is a high-performance machine learning technique applied to both classification and regression problems. It is actually an implementation of gradient boosting that makes the model faster and more accurate through certain ways. These include the processing that makes it parallel, hence faster; trimming of trees to retain only those features thought to be important; and dealing with missing data points to ensure that quality information is not compromised. XGBoost creates a collection of decision trees where each new tree corrects errors made by previous ones—therefore, the model structure evolves iteratively. This method really is effective when applied on structured or tabular data since it is proven stable even when handling large amounts of complex, interrelated datasets: hence it has won many machine learning competitions.

Random Forest Classifier (RF)

The Random Forest classifier is a model for ensemble learning, mainly used for classification-related tasks. During training a large number of trees are created, where for each tree, it classifies the mode of classes and thus creates trees based on a random subset of data and attributes. By constructing the trees in such a way, the model fosters diversity, which works hand in hand with developing resilience— an added advantage over using decision trees independently: reducing overfitting while ensuring accuracy and stability. Random Forests shine brightly in both categorical and numerical data; they cope well with big datasets, very often full of complexity, because of their simplicity but high performance, which finds frequent use in most cases, owing to its interpretability.

Decision Tree Classifier (DT)

This simple yet effective machine learning method is used for the classification of problems. It divides data into subgroups according to the value of input attributes and gets a decision-tree model as a result. Internal nodes represent the features, while the branches represent the decision rules. The leaf nodes represent outcomes or class labels. Despite simplicity, decision trees are really easy to read and understand visually, thus ideal for understanding or explaining the decision-making processes without any difficulty.

They handle numerical and categorical data and require no strenuous effort in data preparation, although they can be overfitted, but that can be dealt with through measures like pruning.

Gradient Boost Classifier (GBC)

Gradient boosting is a classification-based ensemble learning technique that consists of making a combination of the predictions from several base learners, typically decision trees, to get better improvement. It builds this model in stages, where every new tree focuses on residuals as a means of correcting what previous trees failed at. This strategy iteratively lowers the loss function and increases accuracy. Its superior predictive ability and capability to handle various data forms, whether numeric or categorical, are some of the reasons why gradient boosting has remained popular. Oftentimes it outperforms single models but it requires careful tuning since it is computationally expensive and sensitive to hyperparameters.

RESULTS

Observation

To identify patterns and relations between various aspects, various data visualization has been made.

Figure 2 represents that patients with ASD in most cases do not have their family members with ASD, that means that ASD is not a genetic disease.

Figure 3 shows that the chances of getting affected by ASD is highest at the age of 2 Years in most of the patients. Upon further analysis, some more things were noticed that the males were more prone to ASD than the females, Toddlers having Jaundice are more prone to ASD in comparison to normal toddler

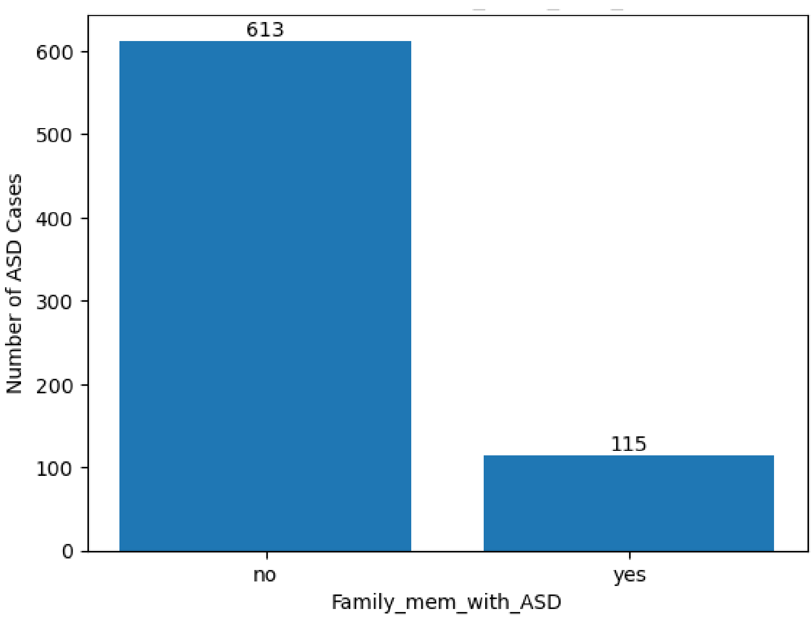

Figure 2. ASD Patients with Family members not having ASD

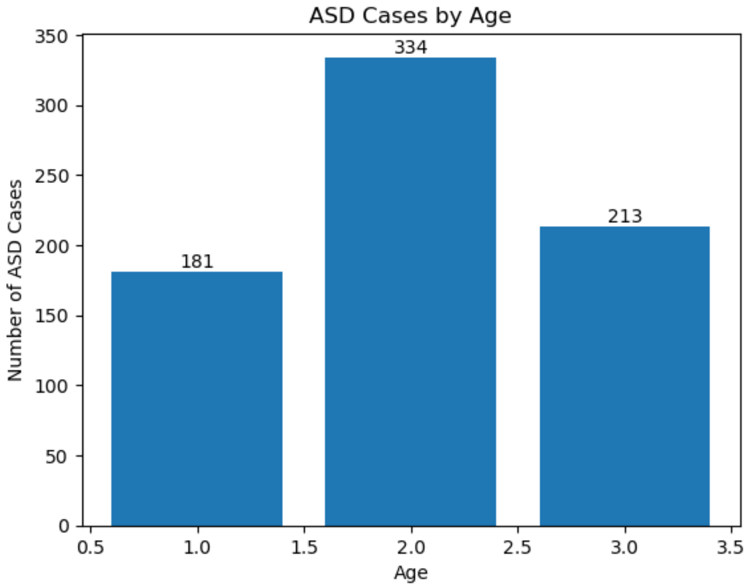

Figure 3. ASD Cases by age

Evaluation Matrix

The confusion matrix is a method for contrasting actual and expected classifications to determine how good a classification model is., providing insights into model accuracy, precision, recall, and overall performance. There are four components to the matrix:

The number of instances where the positive class is correctly predicted by the model.

It represents a count of the instances for which the negative class was correctly predicted by the model.

False positives: This happens when the model makes a Type I error; that is, when it forecasts the positive class wrong.

False negatives: This happens when models make a type 2 error, where they incorrectly predict the negative class.

Several significant component metrics are derived such as

- Accuracy, that is the measure of the overall correctness of the model.
- Precision, which indicates the accuracy of positive Prediction.
- Recall, indicates how proficiently the model is able to detect good examples
- F1 Score, that basically harmonizes precision and recall into a single metric.

Collation of Models

In this study, the following five machine learning models were applied: the gradient boosting classifier (GBC), XG Boost classifier, Random Forest classifier (RF), Decision-Tree classifier (DT), and logistic regression (LR). These models were evaluated on the basis of Accuracy, Confusion Matrix, F1 Score and Precision as shown in Table 2.

Table 2. Comparison of applied machine learning models

	LR	**XG Boost**	**RF**	**DT**	**GBC**
Accuracy	90.48%	99.04%	98.91%	98.50%	98.64%
Confusion matrix	311 33 37	339 5 2 390	339 5 3 389	337 7 4 388	337 7 3 389
F1 Score	0.9	0.99	0.98	0.98	0.98
Precision	0.91	0.99	0.98	0.98	0.98

From the outputs, it is concluded that XG Boost Classifier provides the maximum accuracy and is therefore the best possible model for the dataset used in this study. The same is represented by Figure 4. The overall comparison on basis of Accuracy of Models is shown in Figure 5 that illustrates that the least effective model for the present dataset is decision tree and highest effective model is XG boost.

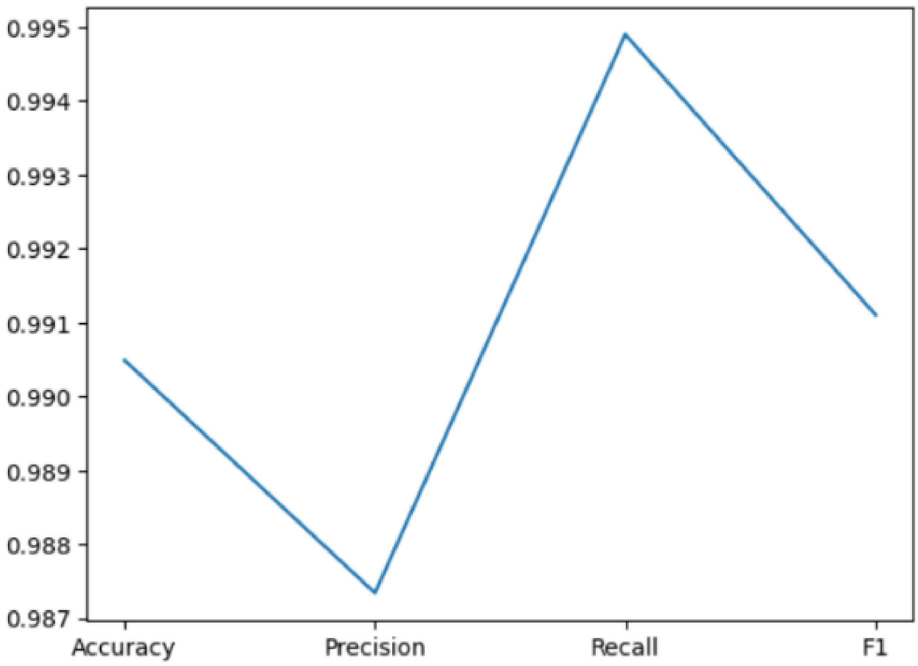

Figure 4. Representation of XG Boost

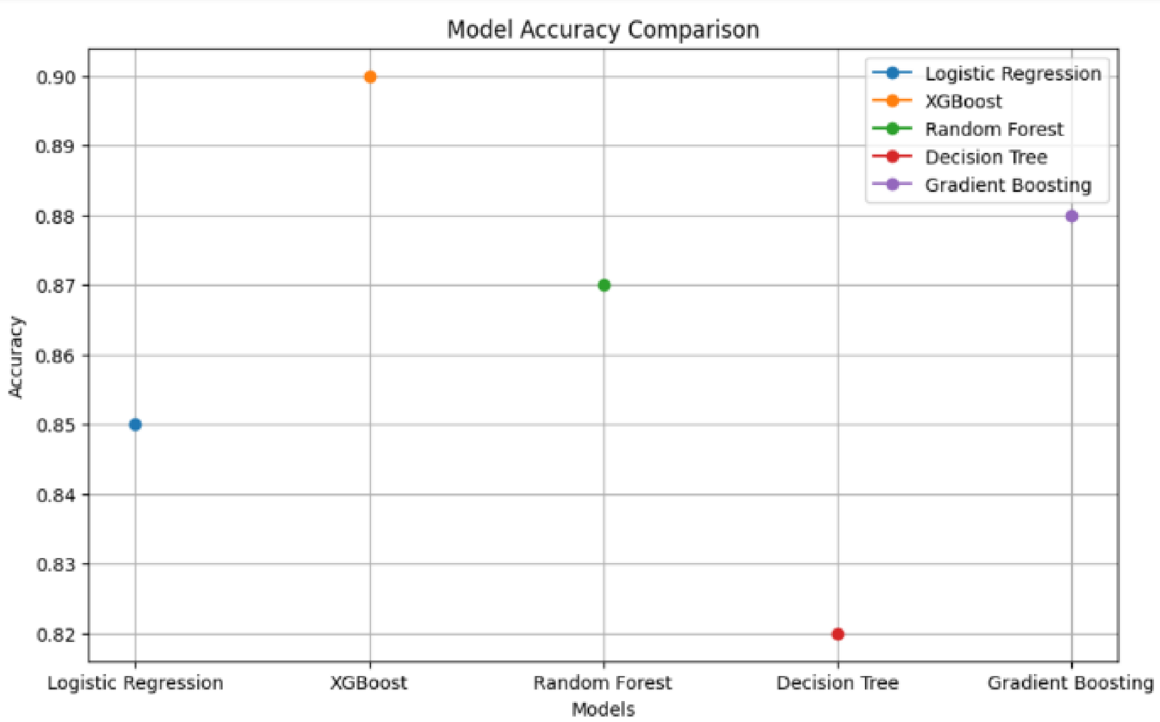

Figure 5. Model Accuracy Comparision

Conclusions

- It shows the application of machine learning techniques to enhance the autism spectrum disorders' identification in children, as traditional methods of diagnostics possess some limitations.
- By applying various classification algorithms like Logistic Regression, XG Boost, Random Forest, Decision Tree, and Gradient Boosting, for finding out the best model for accurate prediction of ASD.
- XG Boost Classifier came out on top in accuracy, precision, and F1 scores, making it a very important tool for the detection of ASD at a early stage
- The work points out that AI and ML technologies can make the process of diagnosis more efficient and effective, guaranteeing interventions in a timely and accurate manner, which is absolutely significant for the enhancement for the patient's quality of life with ASD. Moreover, the integration of multidisciplinary approaches with ethical considerations ensures that such advanced technologies are translated into clinical practice in a effective and responsible way.

Declaration of Interest

The authors declare that there exists no conflict of interest regarding the publication of this manuscript.

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