Autism with the Help of Machine Learning Techniques Spectrum Disorder Diagnosis

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Key words—Autism spectrum disorder, Machine learning algorithms, Decision trees, Naive Bayes, K-nearest neighbor, Support vector machine, Artificial neural networks

Abstract—Autism is a generalized pervasive developmental disorder that can be featured by language and communication disorders. Screening tests are often used to diagnose such a disorder; however, they are usually time-consuming and costly tests. In recent years, machine learning methods have been frequently utilized for this purpose due to their performance and efficiency. This paper employs the most eight prominent machine learning algorithms and presents an empirical evaluation of their performances in diagnosing autism disorder on four different benchmark datasets, which are up-to-date and originate from the QCHAT, AQ-10-child, and AQ- 10-adult screening tests. In doing so, we also utilize precision, sensitivity, specificity, and classification accuracy metrics to scrutimize their performances. According to the experimental results, the best outcomes are obtained with C-SVC, a classifier based on a support vector machine. More importantly, in terms of C-SVC performance metrics even lead to 100% in all datasets. Multivariate logistic regression has been taken second place. On the other hand, the lowest results are obtained with the C4.5 algorithm, a decision tree-based algorithm.

Index Terms—Autism spectrum disorder, Machine learning algorithms, Decision trees, Naive Bayes, K-nearest neighbor, Support vector machine, Neural network

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I. INTRODUCTION

Autism is a neurological developmental disorder that can be characterized by repetitive behaviors, impaired social communication, and poor language skills. Although the exact cause of the disease is not known, it is mentioned in some studies that genetic and environmental factors may have affected the disease [1]. Although there is no known cure or medication for autism, early and comprehensive behavioral interventions can improve social communication, while medications can reduce anxiety and aggression [2].

There have been some pioneering studies on the diagnosis of autism. One of these studies found a link between Autism Spectrum Disorder (ASD) and motor retardation [3]. McCoy et al found that children with autism were more likely to be obese and less physically active [4]. In another study, it was observed that adolescents (13-18 years) with autism were behind their peers in terms of physical activity [5]. Singh et al.<found that children born at 1500 g) were 3.2 times more likely to have autism than others [6]. In the study by Yates and Couteur, they showed that difficulties and delays in social interaction are often associated with ASD, although they are ignored [7]. This option is more difficult to evaluate because delays in social interaction are sometimes difficult and relative to define.

Autism symptoms appear from the age of one. Studies show that autism spectrum disorder can be reliably detected with 2-stage screening in children younger than two years old [8]. The most important process for diagnostic success is the completion of routine developmental screenings [9]. Autism is diagnosed by a team of experts from many fields. The most preferred method for definitive diagnosis is known as the Revised Autism Diagnostic Observation Program (ADOS-R). The Autism Diagnostic Interview Revised (ADI-R) method, which is a questionnaire that includes detailed questions about the child's history and behavior, is another known method in this field.

In addition to these two methods, there are other questionnaires that are administered to the patient or their parents, such as the Autism Spectrum Coefficient (AQ) and the Social Communication Questionnaire (SCQ). There are also screening tests for infants, Q-CHAT [10], AQ-10-child for children and AQ-10-adult for adults.

Current methods used in the diagnosis of autism are costly methods. Machine learning systems support screening tests to reduce diagnostic costs and shorten diagnostic time. Machine learning methods are frequently used to create decision support systems in the field of health with the help of structured data. Studies have been carried out in many areas such as early detection of heart attack [11], early detection of breast cancer [12]. One of the diseases in which the use of machine learning is possible is the diagnosis of ASD. Machine learning is an innovative method that has the potential to enrich diagnostic and intervention studies in behavioral sciences. Using machine learning methods in the diagnosis of autism spectrum disorder, providing faster access to health services,

In this study, machine learning methods will be used to diagnose autism spectrum disorder. The aim of our study is to determine lower cost and faster machine learning methods in the diagnosis of autism. Experiments were conducted on the newborn, child, adolescent and adult dataset, and each algorithm was presented with correct recognition, sensitivity, sensitivity and specificity metrics.

II. PAST STUDIES

Machine learning is needed to shorten OSB scanning times, reduce costs, and increase the accuracy and precision of the diagnostic process. The ASD diagnosis problem is a classification problem that tries to diagnose new cases with autism with the help of historical data. Machine learning methods have to be compatible with a scanning tool rather than being a stand-alone solution. In the past studies, many machine learning methods have been used together with the ADOS and ADI-R scanning processes.

Autism diagnostic screening times are long, and Wall et al. [15] used 16 different classifiers to reduce scanning time and to detect ASD features faster. The best results were obtained by using Alternative Decision Tree (ADTree) on ADOS module 1 data with 100% accurate recognition rate.

Hauck and Kliewer [16] sought to identify important screening questions related to the ADOS (Autism Diagnostic Observation Program) and ADI-R (Autism Diagnostic Interview Revised) screenings. In addition, the authors have shown that screening methods and ADI-R and ADOS screening tests may work better when used together. In the study, 2500 Results between 85.6% and 94.3% were obtained with the SVM algorithm using RBF kernel on the sample data set. The specificity range was between 80.9% and 94.3%.

Heinsfeld [17] Autism Imaging Data Exchange (ABIDE I) applied a deep learning algorithm and neural network to identify ASD patients with the help of neuroimaging data in the dataset. It has achieved an average of 70% classification accuracy in the range of 66% to 71% accuracy, and in details; 65% accuracy was obtained with the SVM algorithm and 63% with the Random forest algorithm.

The study by Liu [18] differs from the others. The aim of this study is whether autism can be diagnosed with the help of face scanning models. For this, classification was made using an eye movement dataset and the results were presented as the correct recognition rate. According to the results of the study, autism could be diagnosed from eye movements with an accurate recognition rate of 88.51%. It is seen that machine learning techniques are frequently used in the diagnosis of autism [19].

III. EXPERIMENTAL STUDY

In this section, first the data set to be used in the experiments will be explained and then the performance metrics will be presented. After running machine learning algorithms on the data, the results will be presented in tables based on performance metrics. The section will be concluded by briefly interpreting the values of each table. The purpose of the experimental studies in this section is to determine the most successful algorithms in the autism data set.

A. Dataset and Algorithms Used

In our experiments, the data compiled by Thabtah [20] were used and these data were collected with the help of the mobile application named ASDTests developed by Thabtah. The tests were developed for infants, children, adolescents and adults based on the Q-CHAT-10, AQ-10-child and AQ-10-adult screening methods.

TABLE I
HETIZM SPECTRUM DISORDER DATASETS

	Dataset	Age range	Feature Quantity	Number of Registrations
Baby	Toddler Autism Dataset – Version 2	0-3 years	18	1054
Child	Children's Autism Dataset – Version 2	4-11	24	509
adolescent	Adolescent Autism Dataset version 2	12-16	24	248
Adult	Adult Autism Dataset version 2	17+	24	1118

One of the datasets contains 18 features and the others 24. Since some of the features contain null values and some of them contain data without analysis value, they have been screened. During this elimination; why the test was done, the nationality of the case, which country he lived in, who did the screening test, whether the test was done before, the language of the test, the score of the answers to the questions A1-A10.

Features such as the 'Score' field, which gives However, in the screening tests in all datasets, information such as features between A1 and A10 that answer 10 important questions, whether there is a person with autism in the family, whether the case has jaundice or not, were left as important.

Past studies and the popularity of machine learning algorithms have been the most important basis for deciding on the algorithms to be used in the diagnosis of autism. For example, decision trees are one of the oldest known classifiers, they are still frequently used in machine learning systems because they are understandable and interpretable [22]. In this study, C4.5 and RndTree from decision tree algorithms were preferred. One of the algorithms frequently used in machine learning studies is the Naive Bayes algorithm. Bayesian classifiers have a structural model with a set of conditional probabilities [22]. In this study, the Naive Bayes Continuous version of the Naive Bayes algorithm, which is suitable for continuous data, was used. The K-NN algorithm, which is frequently used for statistical estimation and pattern recognition, was also preferred in this study. The K-NN classifier classifies according to neighborhood information and often uses similarity or distance information to find neighbors [23]. Artificial neural networks have a special place among machine learning algorithms. In this study, multilayer perceptron algorithm (MLP) was also used for autism diagnosis. In addition, multivariate logistic regression (MLR), which is one of the regression analysis techniques, linear discriminant analysis (LDA), which is a statistical method, and C-SVC algorithm, which is a successful support vector machine algorithm, were used. A machine learning tool called Tanagra was used to apply algorithms on autism datasets [24].

B. Model Evaluation

The study to determine which algorithm yields more successful results is called model evaluation. For model evaluation in this study; classification accuracy, precision, sensitivity and specificity values were used. In addition, 10-fold cross validation (10-fold cross validation) was performed to eliminate the randomness in the results obtained. Autism spectrum data are in two classes, with and without a diagnosis of ASD. The confusion matrix formed according to this assignment will be as given in Table III. Based on the confusion matrix, the correct identification and other measurements can be written as in Table IV.

Accuracy alone is not a sufficient measurement method because it is far from being a sufficient metric on its own when the dataset is not evenly distributed among the classes. Therefore, other metrics were needed. The measurement in which sensitivity, sensitivity and specificity measures are expressed together will give more valuable results during model comparison.

TABLE II
KUSEDMAKINEHELEARNALGORITHMS AND PARAMETERS

	algorithm	parameters
C4.5	C4.5	Min size of leaves=5 Confidence level=0.25
NB	Naive Bayes Continuous	lambda=0
KNN	K-nearest neighbors	K=5 Distance method=HEOM(Wilson - Martinez,JAIR'97)
MLP	Multilayer perceptron	Number of neurons=10 Learning rate=0.15 Validation set proportion=0.20 Stopping rule (Max iteration=100 or error rate threshold=0.01)
RT	Rnd Tree	Selected attributes=-1
MLR	Multinomial Logistics regression	Default values
LDA	linear discriminant analysis	Matrix inversion=Exact
CSVC	C-SVC from LIBSVM	Kernel type=Linear Degree of kernel function=1 Gamma=0 Coef 0=0 Complexity=1 Transformation=Normalization Epsilon for tolerance=0.001

TABLE III
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	Estimated Class	
Real Class	ASD	Non-ASD
ASD	TP(a)	FN(b)
Non-ASD	FP(c)	TN(d)

C. Experimental Results

For the early diagnosis of autism, eight different machine learning algorithms were run on four different data sets based on different age groups. All the results are brought together in a single table, making it easier to monitor the results. Table V has been prepared as a summary of the large number of experiments obtained in this study.

In Table V, aggregated results were obtained for four different data sets and eight different machine learning methods according to correct recognition, sensitivity, sensitivity and specificity values. With the help of the data obtained in Table V, the average performance values of each classifier, regardless of the data set, are given in Table VI. In addition, the average performance values of each data set were obtained independently of the algorithm and are given in Table VII.

TABLE IV
DGRACE, HASSIGNITY ANDDADAPTABILITYHEMEASUREMENTS

Accurate recognition (accuracy)	(TP+TN)/(TP+FP+FN+TN)
Precision	TP/(TP+FP)
Sensitivity	TP/(TP+FN)
Specificity	TN/(TN+FP)

TABLE V

DRESULTS ACCORDING TO FOUR DIFFERENT PERFORMANCE METERS FOR EIGHT DIFFERENT MACHINE LEARNING ALGORITHM ON DIFFERENT DATASETS PRESENTATION

	Metric	C4.5	NB	K-NN	MLP	RT	MLR	LDA	C-SVC
Baby	accuracy	0.93	0.94	0.95	0.99	0.94	1.00	0.95	1.00
	Precision	0.92	0.92	0.94	0.98	0.92	1.00	0.94	1.00
	Sensitivity	0.92	0.96	0.95	0.99	0.93	1.00	0.96	1.00
	specificity	0.92	0.94	0.95	0.99	0.92	1.00	0.95	1.00
Child	accuracy	0.87	0.95	0.89	0.98	0.89	1.00	0.96	1.00
	Precision	0.87	0.95	0.90	0.98	0.89	1.00	0.96	1.00
	Sensitivity	0.87	0.95	0.89	0.98	0.89	1.00	0.96	1.00
	specificity	0.87	0.95	0.90	0.98	0.89	1.00	0.96	1.00
adolescent	accuracy	0.79	0.89	0.88	0.98	0.85	0.99	0.93	1.00
	Precision	0.79	0.90	0.90	0.98	0.85	0.99	0.94	1.00
	Sensitivity	0.79	0.89	0.88	0.97	0.85	0.99	0.94	1.00
	specificity	0.79	0.89	0.89	0.98	0.85	0.99	0.94	1.00
Adult	accuracy	0.94	0.94	0.94	0.99	0.94	1.00	0.96	1.00
	Precision	0.93	0.93	0.93	0.99	0.93	1.00	0.95	1.00
	Sensitivity	0.93	0.94	0.94	0.99	0.921	1.00	0.96	1.00
	specificity	0.93	0.94	0.94	0.99	0.93	1.00	0.95	1.00

TABLE VI

VAVERAGE TRUE FOR ERI SET INDEPENDENT CLASSIFIERS RECOGNITION RATIOS

C4.5	NB	K-NN	MLP	RT	MLR	LDA	C-SVC
0.8835	0.9315	0.9164	0.9851	0.9023	0.9979	0.9508	1.00

TABLE VII

AAVERAGE TRUE FOR LOGORITH-INDEPENDENT DATASETS RECOGNITION RATIOS

Baby	Child	adolescent	Adult
0.9633	0.9428	0.9136	0.9644

According to the results given in Table V, summarized in Table VI and Table VII; has been the most successful classifier C-SVC algorithm. C-SVC algorithm is a kind of support vector machine algorithm. As in the literature, the best result in our study was obtained with the support vector machine-based algorithm. The algorithm has been processed with the default parameters of the machine learning tool. The kernel type used is Linear kernel. It was observed that this success could not be achieved in other kernel types. The other algorithm that gives a very close value to the C-SVC algorithm is the Multinomial Logistic regression algorithm. Multivariate logistic regression algorithm is one of the successful classifiers. In this study, it showed its success by giving the exact recognition rate in three of the data sets. In our study, the algorithm that gave the lowest classification accuracy was C4.5 and RndTree algorithms. Another unsuccessful algorithm is the K-NN algorithm. The result did not change when parameter optimization was performed on the algorithms.

In the experiments performed according to the data set, the highest results were obtained with the adult data set. The most important feature that distinguishes the adults data set from the others is that the addressee in the screening test is the patient himself. In other data sets, sometimes the family or health worker answers the screening questions on behalf of the patient. In addition, with increasing age, the borders of the disease become more evident. This ultimately had an effect.

IV. CONCLUSION AND EVALUATION

Autism spectrum disorder is one of the increasingly serious diseases. The autism density, which is currently around 1-2%, is increasing with the use of electronic devices. It is not possible for autism, which is affected by environmental factors, not to be affected by virtual environments that weaken social interaction day by day. In a world where social communication is declining, children who open their eyes to life may be relatively more prone to autism.

Although the exact causes of the disease are unknown, some studies have been done on its diagnosis. Especially in the diagnosis of autism, questionnaire and imaging techniques are frequently used. The survey is sometimes made to the patient, sometimes to the relative or caregiver, and the best condition of the patient is tried to be determined. Imaging techniques are more concerned with revealing the neurological aspect of the disorder.

Treatment of the disease in the context of, digestion system based studies are being carried out and the studies are still in the maturation period. Although the intestines are thought to be the second brain and there are indications that a disorder in the intestinal flora triggers autism, it has not been accepted by everyone yet. Many relatives still go to pediatric psychiatry outpatient clinics for solution. The drugs given to the patient in psychiatry clinics have the effect of regulating the behavior disorder accompanying the disease, not the disease. For example, drugs that relieve the nerve are given for nervous breakdowns that accompany the disease. Similarly, drugs are used to correct attention deficit.

The lack of a complete solution in the context of treatment increases the importance of early diagnosis. Recently, the use of machine learning techniques for early detection is valuable in this sense. Machine learning methods, which have a complementary role in survey and imaging techniques, will increase the diagnostic accuracy of the disease.

In this study, classifiers that were previously successful in other problems, easily understandable, interpretable and giving very fast results were used for the diagnosis of autism. Eight classifiers were examined in experiments on data from autism patients retrieved from the UCI repository. Accurate recognition, sensitivity, sensitivity and specificity metrics were used to compare the classifiers. It is investigated which classifier is more suitable for this problem. As a result of our research, the following findings were obtained:

- One of the diseases in which early diagnosis is important is Autism. As with other diseases, machine learning methods help physicians in the early diagnosis of autism.
- Most of the selected algorithms have accurate recognition rates of 95% and above. Therefore, autism diagnosis can be made with high accuracy with data mining methods.
- Despite the missing data in the data set, a 100% correct diagnosis rate was obtained. This suggests that autism data can be easily modeled and trained.
- In addition, the fact that decision tree algorithms have a success rate of 80% or more, even if not the best result, and are more interpretable than other algorithms in the diagnosis of autism can provide experts with valuable information about the disease.

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