2021 International Conference on Frontiers of Information Technology (FIT) | 978-1-6654-0830-1/21/$31.00 ©2021 IEEE | DOI: 10.1109/FIT53504.2021.00063

Predictive Analysis of Autism Spectrum Disorder (ASD) using Machine Learning

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***Abstract*—Autism Spectrum Disorder (ASD) is a severe condition related to brain development that impairs communication and interaction with others. It is a ”developmental disorder” because symptoms generally appear in the first two years of life or later. Till that age, children behave pretty similar to typically developing individuals. Tracking the symptoms leading to autism is challenging because of the wide variation in the type and severity of the disorder. One of the pitfalls is that many countries, including Pakistan, do not track or report their autism cases. In this paper, we have shown how we performed predictive analysis after collecting data from the only government-run Child Psychiatry Department in Pakistan, Mayo Hospital, Lahore. We also collected data from a private school made explicitly for children with autism in Lahore. Data of a total of 100 autistic children under the age of 12 was collected. To avoid any class imbalance problem, we also collected data of 100 healthy children. After performing various machine learning algorithms on our data, our model managed to classify children with autism with an accuracy of 95%. To the best of our knowledge, no such work has been done regarding autism in Pakistan before. This research aims to create a supervised machine learning model that can classify ASD individuals in much less time and effort compared to currently practiced diagnostic procedures and help us visualize common causes leading up to it so that appropriate lifestyle changes can be made accordingly. In the future, the number of records can be increased, and accuracy can be maximized even further. Our model can be used by various physicians and parents of children with ASD for early prediction and for visualizing common causes leading up to it.**

***Index Terms*—autism, autism spectrum disorder, machine learning, predictive analysis, ASD**

1. Introduction

Classification of ASD and finding out the major reasons causing autism is a difficult and time-consuming task. If we talk about South Asia, unfortunately, no reliable epidemiological data on the prevalence of autism exists. Roughly speaking, more than 5 million children have been affected by autism spectrum disorder [1].

, However, as the amount of data is growing faster each day, the possibilities and results of health informatics are also improving. Machine learning algorithms, including algorithms for classification and text analysis, are pretty effective for diagnosing ASD [2]. They can help us to determine which features are useful for prognosis information [3]. They can serve as a vital tool in improving ASD screenings [4]. ML can significantly speed up the screening time [5]. It is of immense importance when it comes to investigating the highly prevalent and heterogeneous syndrome of autism spectrum disorder [6]. It is challenging to detect most important, mildly affecting and trivial symptoms of ASD [7]. Several screening methods are in practice for the detection of ASD such as Autism Diagnostic Observation Schedule-Generic (ADOS) [8]. Integration of neuroimaging tools can be of tremendous significance [9].

FMRI has been proved to be an essential input for autism detection [10]. EEG and ERP data can be helpful as well [11]. Haar wavelet transform can be used for extracting features. Then Naive Bayes classification algorithm can be used for determining whether a person has any ASD risk genes or not [12] [13].

Semi-supervised machine learning can also be considered a feasible approach when we have complex data [3]. Reinforcement Learning (RL) is used in developing a therapeutic system for autistic children [14]. Active machine learning (AML) techniques can be used when we have less labeled data [15]. Sparsifying machine learning models can also provide improved stability over previous models and also minimize the time complexity of autism detection [16]. The use of sparse logistic regression has also shown that endophenotype of ASD occurs in unaffected siblings of individuals with ASD [17]. IoT-based systems can be used for earlier detection of ASD using ML, and DL-based algorithms [18]. Factors such as IgA and VFGM genes have also been utilized for ASD classification [19]. The content of the image and response of the viewer can be utilized as well [20]. Connecting electrodes

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DOI 10.1109/FIT53504.2021.00063

with the scalp area and getting signals have been proved to be very effective [21]. Coronavirus has also caused extreme adverse impact on ASD individuals who are already vulnerable sector of the society [22].

2. Related Work

Parikh et al. [23] used some limited personal data from the ABIDE I Database. Standard screening tools such as M-CHAT have also been converted to different languages such as Bangla which can elevate healthcare systems [24]. These apps can serve as a reliable source for early detection of autism [25]. A novel machine learning model proposed by Gok produced better results than previous standalone models [13]. Omar created one such mobile application and classified their data set based on different age groups [26]. Thabtah made one app for screening autistic children. [27]. He later proposed a new machine learning model called Rules-Machine Learning that detected autistic traits with higher accuracy, sensitivity, harmonic mean, and specificity compared to other models. His model also provides rules that allowed domain experts to understand the reasons behind the classification [28].

Upper limb movements can also be used in early diagnosis of ASD [29]. There are several models for this purpose. One such model uses Linear Discriminant Analysis (LDA) to elicit the features and Support Vector Machines(Support Vector Machines) for classification of thirty children, including 15 autistic and 15 non-autistic children. This model achieved an optimal sortation accuracy of 100 percent and the average accuracy of 93.8% [30]. Face recognition patterns can be used to identify ASD in children using machine learning [31]. Head movements such as head rotation rate has also been successfully used to identify autistic individuals using machine learning algorithms such as decision tree classifier [32].Severity of the autism spectrum disorder can also be analyzed using neuroimages of the humans and non-human primates [33]. Machine learning can also help us to determine whether the underlying person has some other disorder in addition to ASD, such as ADHD (Attention Deficit Hyperactivity Disorder) [34]. Other techniques such as Graph Theory are also used in combination with Machine Learning to identify ASD [35]. However, in this paper, we will stick to ML algorithms only. It is because machine learning is considered as an effective approach for not only early diagnosis of ASD but also for assessing the level of it's severity [36].

3. Data Collection Method

One of the biggest hurdles of this endeavor was to collect data. The only government-run child psychiatry department is at Mayo Hospital, Lahore. There, an average of 2 patients visit the department daily, sometimes, not even that. Even in that department, no such reasonable measures have been taken to store data in any format. So data had to be collected from scratch. For this purpose, we prepared a questionnaire both in complicated form and soft form. The data in the soft form was collected via Google form.

The questionnaire in hard form, and this version of the form was used while collecting data from a privately run school for autistic children in Lahore. After getting a count of 100 children (all under the age of 10) with autism spectrum disorder, the data was downloaded from Google form to CSV format.

To ensure that our model is trained without any class imbalance problem, we collected data of 100 healthy children as well.

Fig. 1 shows the visualization of the whole data plotted in python from subfigure (a) to (u). It plots the total count along the y-axis of each subfigure, while the division of the whole dataset, based on the last column of our dataset called "ASD diagnosed," which states "yes" in case of data of autistic individuals and "no" in case of non-autistic individuals, is given along x-axis.

Multiple histograms are used to show gender-wise (a), age-wise (b), and birth-order-wise (c) distribution of our dataset. All other columns such as mothers with normal pregnancy (d) and delivery (e), count of prematurely born individuals (f), and history of someone in the immediate family with any cognitive disability (g) are also shown. Oxygen deficiency right after birth is also counted (t). To see the impact of ASD on physical health, we can see results of the columns such as (h) to (l), where we see the count of individuals with their age when they started walking (h), said their first words (k) individuals who were wrongly considered deaf (i) or were sensitive to music (j) and lights (l) in their early years respectively as it is a predictive analysis so we can also see the pre-birth behavior of the parents, such as their educational backgrounds (n) (o), miscarriage history of the mothers (m), the inclination of the mothers towards getting vaccinated (p), taking anti-depressants (r), history of parents either smoking (q) or being alcoholic (s). Count of the individuals who were rocked in their cribs can also be seen (u).

3.1. Input Features

A simple questionnaire comprising a total of 21 questions was made. TABLE I shows the input features of the questionnaire and how the answers are represented.

3.2. Data Encoding

During the process of data formatting, the goal was to represent the final data in the form of 0s and 1s. The questions which had only two options to choose the answers from were easy to encode in the form of 0s and 1s. All other questions which had more than two possible options to choose the answer from were transformed using one-hot encoding. With one-hot encoding, a single column with multiple choices gets split into multiple columns where the size of the newly formed columns is the number of possible choices for that particular column.

4. Methodologies

A total of 9 algorithms were used for this classification problem. Different techniques were used for analyzing the

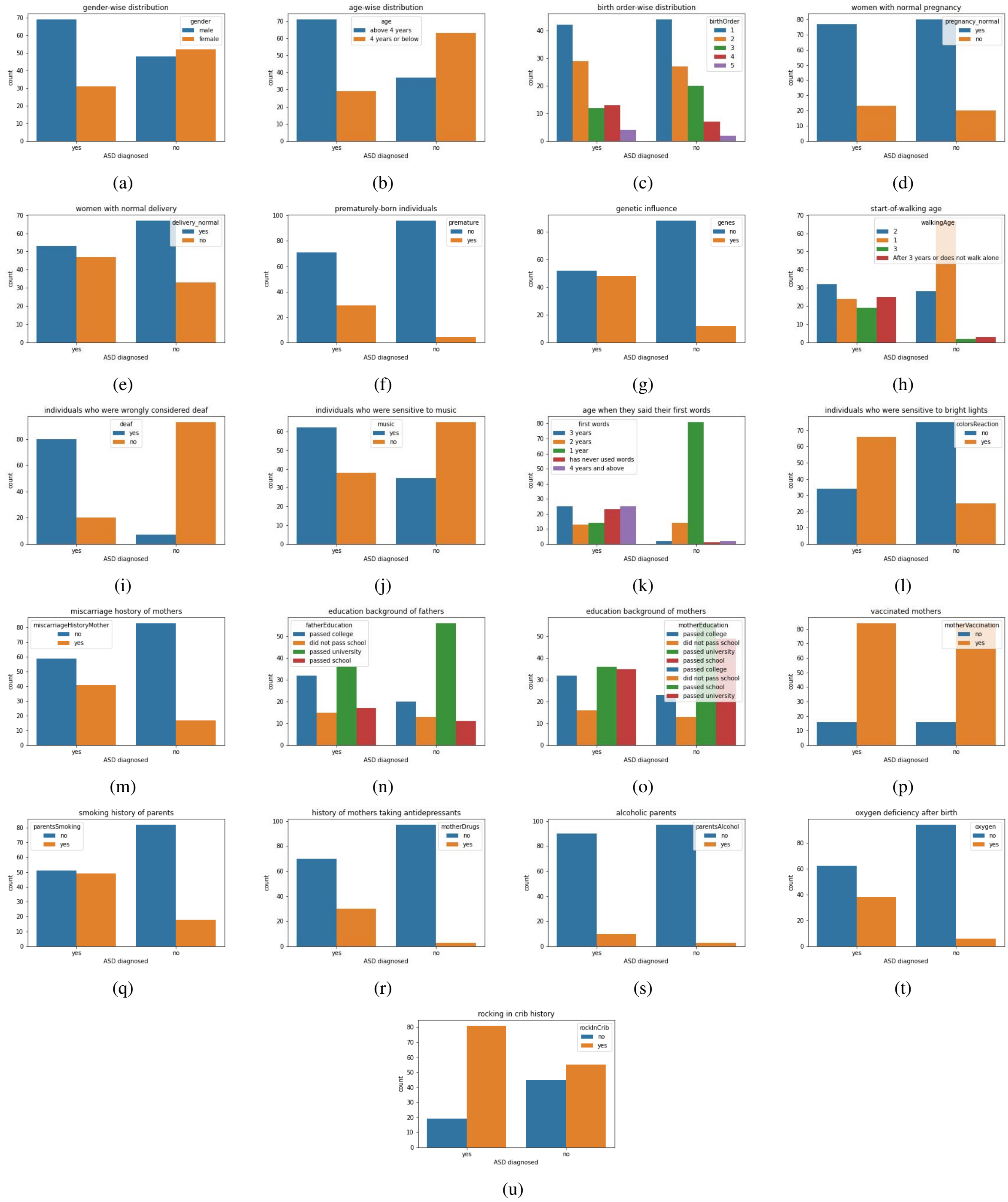

Fig. 1: A visualization of the collected data.

TABLE I: Features collected and their descriptions.

Feature	Type	Description
Q1	String	Gender of a child? Male or Female
Q2	Number	Age of the child?
Q3	Number	Birth order of child?
Q4	Boolean	Was mother's pregnancy normal?
Q5	Boolean	Was mother's delivery normal?
Q6	Boolean	Is there anyone else in the immediate family with some cognitive disability (related to the brain)?
Q7	Boolean	Was the birth premature?
Q8	Boolean	Was the child given oxygen in the first month?
Q9	Boolean	Did the child rock in his crib as a baby?
Q10	Boolean	Did you ever expect the child was nearly deaf?
Q11	Boolean	Was there a time when the child insisted on listening to some certain music?
Q12	Number	At what age did the child learn to walk alone?
Q13	Number	At what age did the child say their first words?
Q14	Boolean	During the first year, did the child react to bright lights, bright colors, or unusual sounds?
Q15	String	Father's highest educational level?
Q16	String	Mother's highest educational level?
Q17	Boolean	Did the mother got vaccinated during pregnancy with the child?
Q18	Boolean	Has the mother gotten any history of miscarriage?
Q19	Boolean	Did any of the parents smoked during pregnancy with the child?
Q20	Boolean	Did the mother take any anti-depressants during pregnancy?
Q21	Boolean	Were any of the parents taking any drugs such as alcohol etc., during or before pregnancy?

results. The models were evaluated on the basis of their accuracies, and a confusion matrix was used to calculate sensitivities and specificities for each model.

A. Naive Bayes Algorithm (GNB)

Based on Bayes Theorem, it is used primarily in classification problems. It is one of the most simple and fast classification algorithms which works on the basis of probabilities.

B. K-Nearest Neighbour (KNN)

Also known as a lazy-learner algorithm it sorts each incoming point in a group or cluster based on the similarity against each group. It then performs an action on the whole data at the time of classification.

C. Logistic Regression Classifier (LR)

It is used to classify objects based on their probability of similarity to the possible outcome. The probable value can lie between 0 and 1 hence forming an 'S' shaped curve.

D. Decision Tree Classification Algorithm (DTC)

It works in a tree-like manner where features are represented through nodes, decision rules through branches, and outcomes through leaves.

E. Random Forest Classifier (RFC)

It is based on the principle of having multiple decision trees and improving the final accuracy by taking an average of the accuracy of all decision trees.

F. Support Vector Machine Classifier (SVM)

It works on the principle of dividing the whole plane into n dimensions based on some extreme points. A boundary separates all points on the basis of their similarity to extreme points. The boundary that helps us to make the best decision is called a hyperplane.

G. AdaBoost Classifier (ABC)

It adapts according to the situation as it re-assigns the weights to the incorrectly classifying instances.

H. Gradient Boosting Classifier

It chooses a weak hypothesis again and again that leads in the negative gradient direction. It thus optimizes the cost function through this technique.

I. XGB Classifier

It works on the principle of gradient boosting. It uses a parallel tree boosting technique to produce fast and accurate results.

5. Model Configurations

Primarily, three techniques were used for feature selection. SelectKBest, Variance Threshold and SelectFromModel.

I. Feature Selection

In feature selection, only those columns or features are considered important that have the most impact on the classification process.

A. SelectKBest

SelectKBest uses a score function to calculate scores of all features and then keeps only 'k' best features based on the highest scores and discards all others. We used k=17 as it gave the best results.

B. Variance

In this technique, a threshold value for training features will be set, and all columns that have variance less than that threshold value will be removed. We set our threshold value to 0.8, which means if 80 percent of our data in a particular feature is the same, then that column will be discarded as it will not help in the classification process.

C. SelectFromModel

In this case, the threshold value is selected based on important weights. When profit is set to true, feature selection is done using fit and transform, and the model is meta transformed.

II. Train Test Split

For each model, whole data was split at an 80/20 ratio with training data set to 80 percent and testing data set to 20 percent of the whole data.

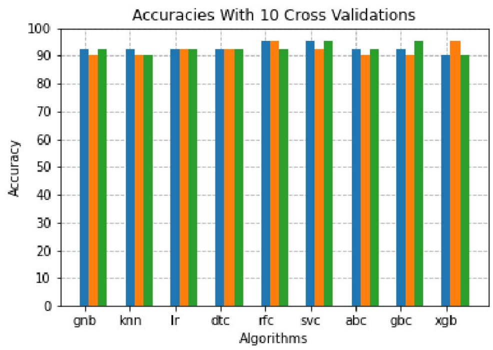

Fig. 2: A histogram is showing accuracies based on the statistical approach of feature selection and machine learning analysis.
Blue bars represent SelectKBest results.
Orange bars represent Variance Threshold results.
Green bars represent SelectFromModel results.

Algorithm	A	B	C
GNB	92.5	90.0	92.5
KNN	92.5	90.0	90.0
LR	92.5	92.5	92.5
DTC	92.5	92.5	92.5
RFC	95.0	95.0	92.5
SVM	95.0	92.0	95.0
ABC	92.5	90.0	92.5
GBC	92.5	90.0	95.0
XGB	90.0	95.0	90.0

TABLE II: Algorithms and their respective accuracies.

6. Results

Fig. 2 gives the detail of all the algorithms used and their results using a histogram.

Algorithms and their respective accuracies with SelectKBest (A), Variance (B) and SelectFromModel (C) techniques are given in TABLE II.

A. *ROC curve*

The models were evaluated on the basis of their accuracies, and a confusion matrix was used to calculate sensitivities and specificities for each model. The values of True Positives (TP), False Negatives (FN), False Positives (FP) and True Negatives (TN) using SelectKBest technique (TABLE III) is also given as it was giving us the maximum values of accuaracies.

Performance measurements were analyzed using ROC curves as they tell us how good our model is in classifying ASD and no ASD. The higher the ROC curve, the better our model is in classification. It is plotted with True Positive Rate along its y-axis and False Positive Rate along its x-axis. A graph closer to the y-axis means the particular model yields better accuracy.

The ROC curve given in Fig. 3 shows Random Forest and Support Vector Machine (SVM) classifiers performing best using the "Select K Best" method. Random Forest and XGB

Algorithm	TP	FN	FP	TN
GNB	20	0	3	17
KNN	20	0	3	17
LR	19	1	2	18
DTC	19	1	2	18
RFC	18	2	0	20
SVM	18	2	0	20
ABC	19	1	2	18
GBC	17	3	0	20
XGB	18	2	2	18

TABLE III: Algorithms and their respective values of the confusion matrices using SelectKBest technique consisting of True Positive (TP), False Negative (FN), False Positive (FP) and True Negative (TN) values.

classifiers are performing best using the "Variance Threshold" method. Support Vector Machine (SVM) and Gradient Boosting using the "Select From Model" method.

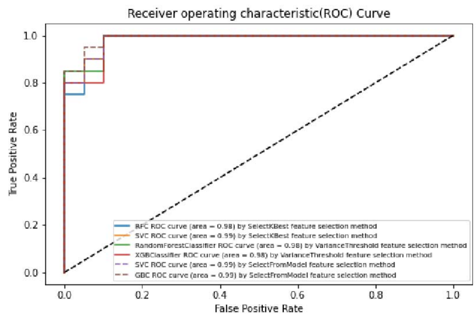

Fig. 3: ROC curve showing that the best performing algorithms are closer to y-axis.

7. Conclusion

After visualizing the data, we put forth the following observations based on the accuracy of our models:

- Autism is quite often found in firstborns and males rather than females.
- Around 50 percent of the children diagnosed with autism had some family member with some cognitive disability so that genes can play an important role as well.
- Physically, it is observed that children with autism develop just like children without autism.
- Most of the children with autism were considered deaf in their early childhood and also reacted to bright lights and loud sounds.
- Most of the mothers were vaccinated during pregnancies and had normal deliveries.
- Almost 50 percent of the parents smoked before giving birth to children with autism.

8 Limitations and Recommendations for Future Work

This dataset can be increased to make our model more reliable. An android/iOS app can be developed and used as a tool by doctors for faster and accurate diagnoses. Historical data should be maintained, and mental health awareness should be raised. A correlation between various traits can be further strengthened in the future with more data. This model should be used with care and under supervision of some professional. This is a local dataset which should not be applied elsewhere in the world without consultation.

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