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Development of an Interactive Dashboard for Analyzing Autism Spectrum Disorder (ASD) Data using Machine Learning

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Abstract: Autism Spectrum Disorder (ASD) is a neuro developmental disorder that affects a person’s ability to communicate and interact with others for rest of the life. It affects a person’s comprehension and social interactions. Furthermore, people with ASD experience a wide range of symptoms, including difficulties while interacting with others, repeated behaviors, and an inability to function successfully in other areas of everyday life. Autism can be diagnosed at any age and is referred to as a “behavioral disorder” since symptoms usually appear in the life’s first two years. The majority of individuals are unfamiliar with the illness and so don’t know whether or not a person is disordered. Rather than aiding the sufferer, this typically leads to his or her isolation from society. The problem with ASD starts in childhood and extends into adolescence and adulthood. In this paper, we studied 25 research articles on autism spectrum disorder (ASD) prediction using machine learning techniques. The data and findings of those publications using various approaches and algorithms are analyzed. Techniques are primarily assessed using four publicly accessible non-clinically ASD datasets. We found that support vector machine (SVM) and Convolutional Neural Network (CNN) provides most accurate results compare to other techniques. Therefore, we developed an interactive dashboard using Tableau and Python to analyze Autism data.

Index Terms: Autism, CNN, SVM, Machine Learning, Data Mining, Tableau, python.

1. Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder characterized by difficulties interacting with others and communicating socially [1]. Sometimes detecting Autism is difficult to detect, from the physicians point. Dr. Mark Hyman says that “*Autism is not a genetic brain disorder but a systematic body disorder that affects the brain*” [2]. A person with ASD may have a wide range of demanding behavior. The most severe form of ASD is detected in the first two years of life, but it can also occur later. This condition can manifest itself in a variety of ways in adults, from severe symptoms to minor difficulties. The autism spectrum illness is part of a group of five childhood-onset disorders known as Pervasive Developmental Disorders (PDD). This is classified as a complicated neurological condition [3]. It is a communication problem that also has an impact on one’s actions. Figure 1 shows prevalence of ASD around the world.

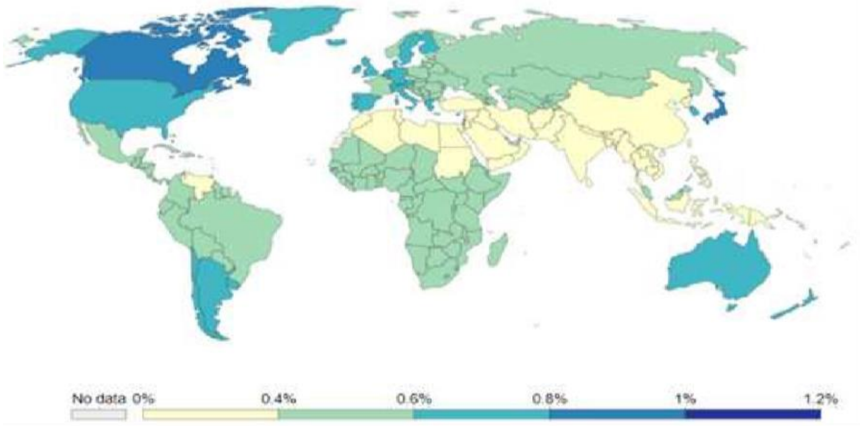

Fig.1. Global Prevalence of Autism [4]

A person with ASD may experience a variety of symptoms. ASD can range in severity from mild to severe, depending on the symptoms [5]. However, there are several disorders that have ASD-like characteristics such as Attention hyperactivity disorder (ADHD) [6]. Social engagement becomes very difficult for a child with ADHD. In comparison to females, males are more affected by ASD. Research shows that genetic factors play an important role in the development of this disease [7]. Scientists have yet to discover the true causes of ASD. People with Asperger’s syndrome (which is similar to autism) have average or above-average intelligence [7]. Low birth weight, having an ASD sibling, and having elderly parents increase someone’s risk of developing ASD [7]. Clinical diagnosis of ASD is expensive and time-consuming [8]. It is not diagnosed by a medical test but through observations and that takes long time. Sometimes, diagnosis may also not be accurate. Data analytics and machine learning algorithms can help a healthcare professional to detect Autism quicker with high accuracy. We have used several machine learning algorithms and shown accuracy calculation to detect Autism. Also, we have developed an analytical tool (dashboard) to analyze and visualize data interactively. In this article, we reviewed several papers to identify machine learning’s impact on ASD Detection, performance of existing machine learning models that detect ASD traits and identifying trends and patterns by data analysis. As we mentioned earlier, there are existence of ASD detection applications, but they are not connected to any dashboard. A dashboard can easily clear one’s point of view about ASD.

Fig.2. Word Cloud of Autism [8]

2. Background

Several researchers have identified symptoms for ASD [9]. Inappropriate facial expressions, gestures, and visual communication, avoiding eye contact or using facial expressions that do not correspond to the message he or she is trying to convey are the key symptoms to establish ASD [10]. People with ASD usually have no interest in sharing common interests or accomplishments with others. They hesitate to have conversation with others [11]. There are other symptoms such as unusual facial expression, anger, and delay in the emergence of social relationships. Researchers are working hard to find a computer-aided detection system to detect ASD at early stage but to be found one. In this section, we have compared results from previous research on computer-aided detection of ASD. We searched for articles were using keywords such as *Autism Spectrum Disorder, ASD, ASD diagnosis, ASD detection Using machine learning", Data mining techniques to diagnose ASD, Supervised machine models to detect ASD*. Figure 3 shows the common symptoms of Autism [12].

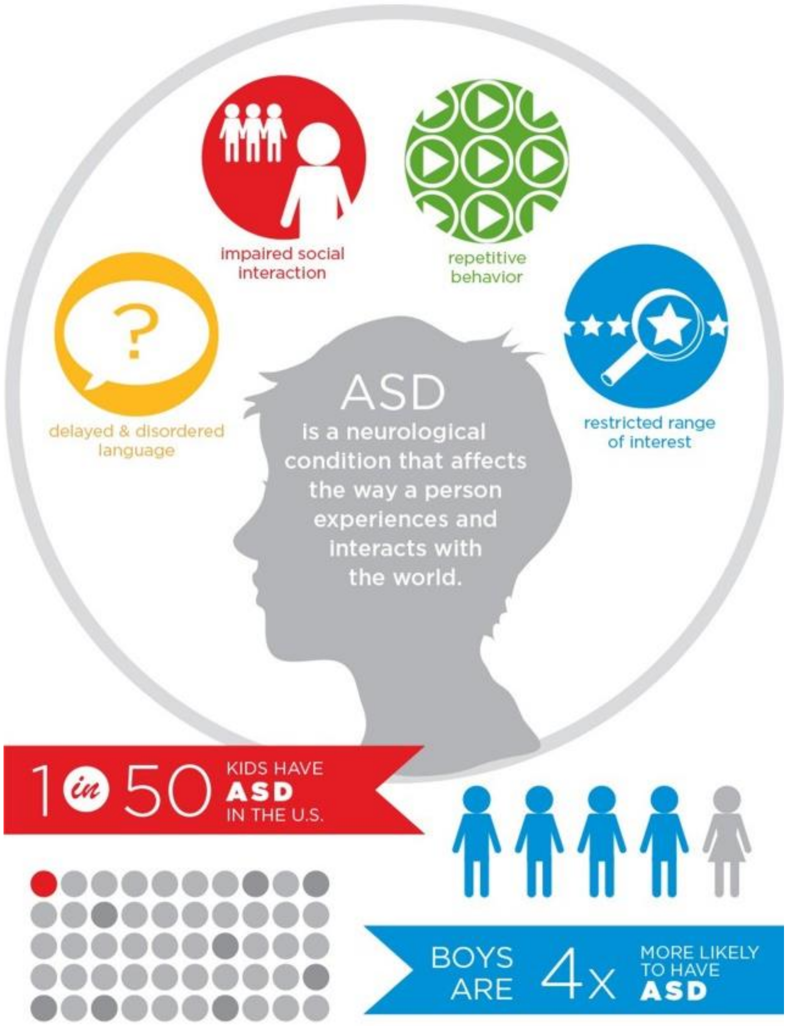

Fig.3. Autism Spectrum in USA [12]

In [13], data collection is done for different age groups such as toddlers, children, adolescents, and adults. For toddlers, Support Vector Machine (SVM) provides high accuracy com-pare to other algorithms. Adaboost shows the best result for children and adult dataset. A Sine function for toddlers and the z-score for children and adolescent datasets were the feature alterations that produced the best classifications.

In [14], concept about the types of ASD are shown. They also mentioned about how ASD child is being helped by tools and techniques. They have taken 100 samples for doing their research. Weka has been used here. A decision tree has been provided for visualization including the decision rules. But they have mentioned only one classification technique but they supposed to mention some other techniques also. They have not mentioned about the number of attributes they have used and the performance measures are also missing here.

In [15], logistic regression, Random Forest, K Nearest Neighbor are applied on 704 sample with 20 features. Using the hamming distance method with 5- fold cross validation, the performance is evaluated. There was no indication of any suitable algorithm proposed by the authors.

In [16], researcher use with J48, Multilayer Perception (MLP), Naïve bayes (NB) and Bayesian Network algorithm (BN). Weka is used for analysis. Total 704 instances with 21 at-tributes of adult dataset have been used. MLP is found the best method in their comparison. Figure 4 shows performance analysis. Only J48 and MLP is labeled here rest of two are not labeled. But they have not mentioned that they are only working with adult data set in the title.

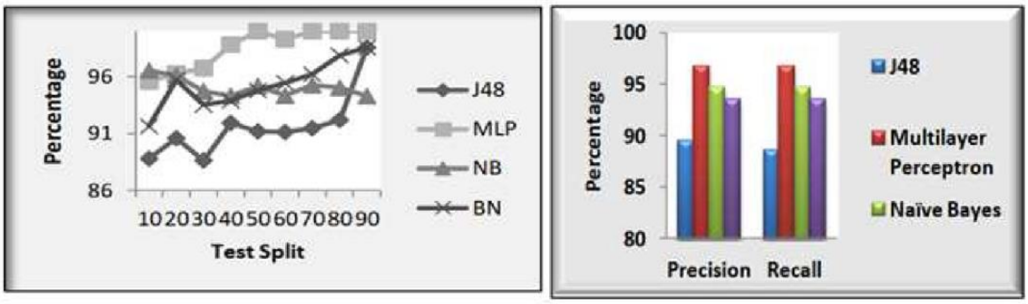

Fig.4. Performance of MLP, J48, NB and BN classifiers [16]

In [17], difference between ASD and ADHD is shown by the authors. As both of them have similar type of symptoms. They have used 2975 instances with 65 features. Among them 2275 are ASD case and 150 are ADHD. Decision tree, Random Forest, Logistic Regression, Support Vector Classification, Linear discriminant analysis, Categorical Lasso algorithms have been used in this paper. Support Vector Machine was found the best classifier. 10-fold cross validation was used here but the age of the participants was not mentioned. For performance measurement they have only used accuracy and ROC curve. Figure 6 shows the results below.

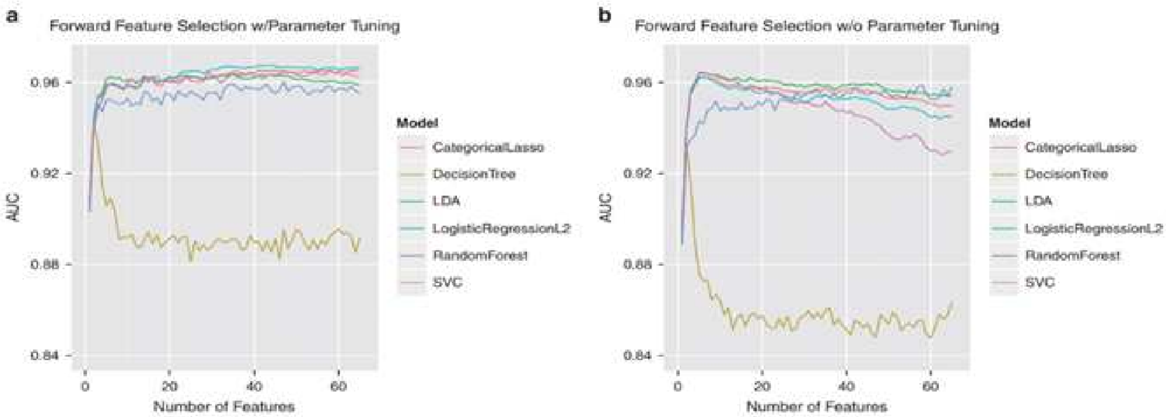

Fig.5. Forward feature selections with parameter tuning (a) without parameter tuning(b) [17]

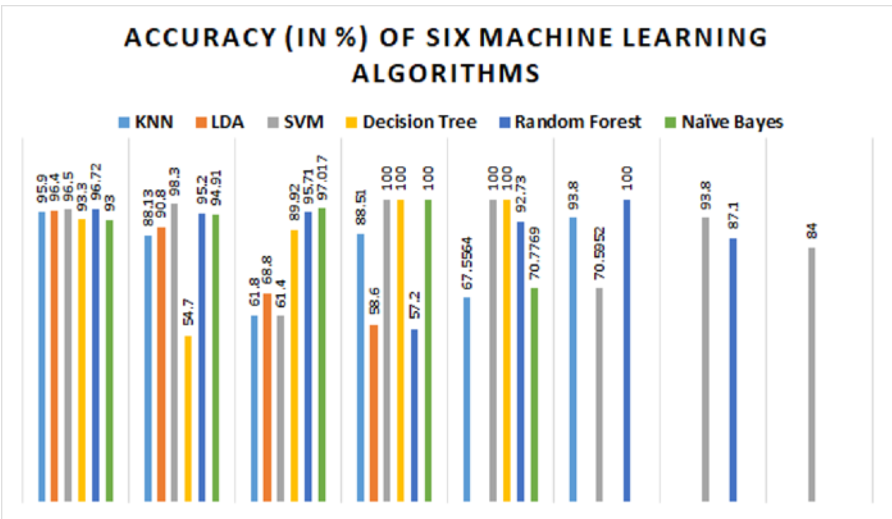

Fig.6. Accuracy of machine learning algorithms for ASD detection

In [18], they have measured performance of Naïve bayes, Support Vector machine (SVM), logistic regression, KNN, Neural Network, Convolutional Neural Network (CNN) algorithms. 292 instances with 21 attributes of child dataset were selected, 704 instances with 21 attribute of adult dataset and 104 instances with 21 attribute of adolescence dataset. Visualization of finding was done very nicely. The highest accuracy was found in SVM and CNN. For our research, we have studied 25 articles related to machine learning algorithms to identify ASD. We have summarized the accuracy of ASD detection using different machine learning algorithms and shown in figure 4. We have seen that machine learning techniques such as Logistic Regression, Artificial Neural Network (ANN) and CART models were used to detect ASD but the accuracy scores are very low for those techniques. For example, in [16], the accuracy was 69.16% using CART. The age of the ASD patients was not stated in this study. Only accuracy and the ROC curve were used to gauge performance, if other approaches were employed, it would be apparent which one was the best. There was not a model diagram or a process diagram here. ASD types are not addressed in this article.

In [19], The algorithms Naive Bayes, Support Vector Machine, logistic regression, KNN, Neural Network, and Convolutional Neural Network were used. This study employed 292 instances with 21 attributes from the child dataset, 704 instances with 21 attributes from the adult dataset, and 104 instances with 21 attributes from the adolescence dataset. The data had been analyzed using Python. A schematic of the process flow was provided. The visualization of the discovery is well done. SVM and CNN outperformed the other algorithms in terms of accuracy. Figure 7 shows the accuracy of SVM and CNN.

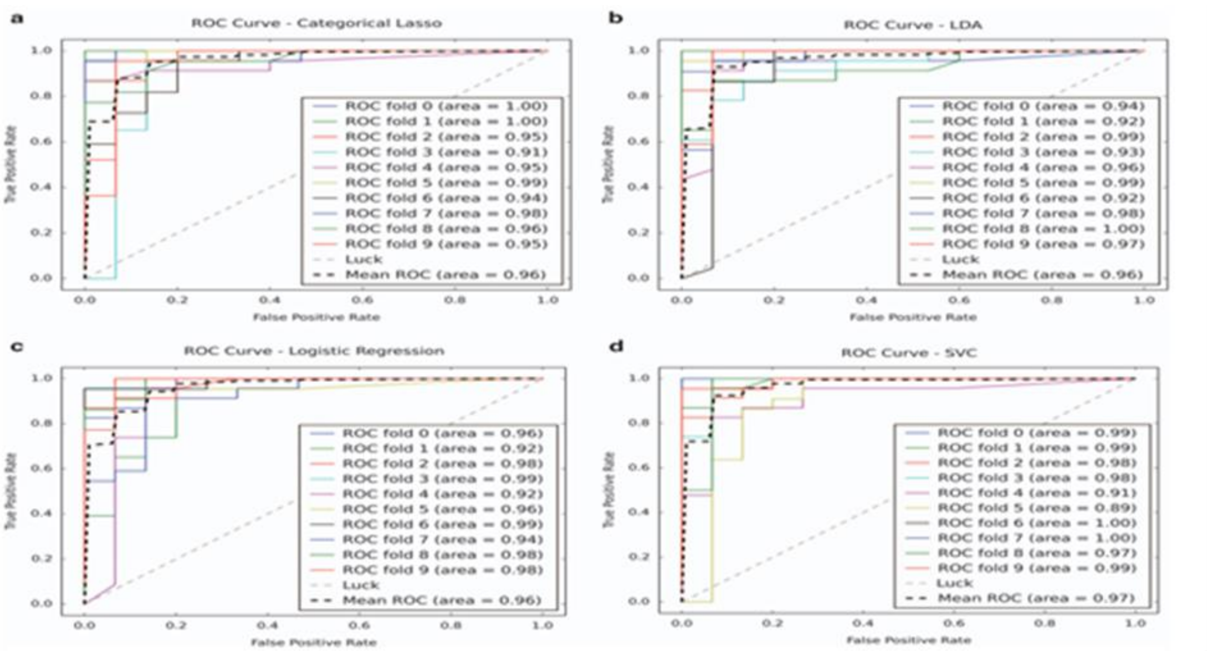

Fig.7. ROC Curves of Top-performed Algorithms [19]

In [20], the Random Forest algorithm was used. A dataset of 704 samples with 21 attributes was utilized, which was a dataset of adults. The number of samples in this dataset was reduced to 699 instances with 19 attributes after the duplicate data was removed. The data was gathered from the machine learning repository at UCI. The 80:20 rule was used in this case. However, there was no workflow diagram here. Though the goal was to reduce the cost of ASD diagnosis, the rate of reduction was not specified. It was claimed that medicine can be utilized to help ASD patients better their condition. However, no mention was made of how it would be applied to them or what would encourage them to do so. The many forms of ASD were also not highlighted.

In [21], LDA and KNN models were used for ASD prediction. The dataset in this dataset comes from the University of California, Irvine. There were 292 samples and 19 attributes in all. A total of 141 samples were tested for ASD. As stated in the title, it was a child dataset. For performance testing, they used the 70:30 rule. The Euclidian distance formula was utilized for KKN. Here the confusion matrix was given. LDA outperformed the other two algorithms. However, no visual depiction was provided, and it was also unclear how they are encouraged to complete the task. The flowchart is missing. ASD types were not addressed in this article.

In [22], the researcher used an 851-sample with six attributes. There were 430 non-ASD patients and 421 ASD patients among them. The following algorithms were used: Decision tree, Majority model, Random Forest, SVM(Linear), SVM(Non-Linear), Confidence model, Logistic regression, K-Nearest neighbor, and Neural Network. K-fold cross-validation was used in this case. However, there is no visual representation of the findings. The study was based on an adult dataset that was never revealed. The flowchart for the workflow is missing. The many forms of ASD are also not discussed. There had not been much published about the symptoms.

In [23], machine learning methods were used to predict ASD in different age groups. A smartphone application was developed by researchers that utilize machine learning to predict ASD. The major focus was on creating an autism screening app for adults aged 4 to 11, 12 to 17, and 18 and above to predict ASD. Data gathering, data synthetization, building the prediction model, evaluating the prediction model, and developing a mobile application were the five steps of this study. The optimal algorithm for building the mobile app was utilized after data collecting and synthetization. After obtaining results from several supervised learning methods such as Linear Regression, SVM, Naive Bayes, and

Random Forest, it was discovered that the Random Forest was extremely viable and accurate. But the issue is that they did not demonstrate any results and did not explain why the random forest is the best option for their mobile app. They utilized 248 samples for the (4-11) year group, 98 instances for the (12-16) year group, and 608 instances for the 18 and more year group after cleaning the data to train the machine. To train a machine, this data set is relatively little. A computer cannot adequately learn with such a little dataset. The application, on the other hand, was not created for children under the age of four. The app may be more useful if it included contained statistics for children under the age of four.

In [24], Researchers used a data set from the University of California at Irvine's repository to try to predict ASD using WEKA tools' supervised learning algorithms. It did not adequately describe the data set. As a result, it was unclear which age groups or types of people this research was successful for. The accuracy and some mistakes were listed, but no mention was made of where the test set was obtained.

In [25], the algorithms utilized in the study were Decision Tree, Support Vector Machine, Random Forest, and Naive Bayes. The data was divided into two sections. 70% of the data is used for training, whereas 30% is used for testing. The proposed algorithms were tested on the data set and proved to be 100 percent accurate in every case. However, the models were not validated using unknown data. If the recommended accuracy for the models were measured using unknown data, this research might be more successful.

In [26], To predict ASD, researchers utilized machine learning techniques such as LDA (Linear Discriminate Analysis), Naive Bayes (NB), Regression Trees (Cart), K – Nearest-Neighbor (KNN), Linear Regression (LR), and Support Vector Machine (SVM). The Euclidean distance calculation formula was chosen for KKN. Here, a dataset of 702 instances with 19attributes from an adult dataset was employed. It was retrieved from the University of California at Irvine's repository. For assessing the performance of the models, the 70:30 rule was used. Among the algorithms used, LDA outperformed the others. Each model's correctness had been provided for explanation. It would be easier to determine which algorithm was the best if certain additional factors were taken into account. The workflow diagram was not mentioned. Types of ASD were also absent. It should have been indicated earlier that an adult dataset was utilized, which was mentioned last in the conclusion section.

In [27], Only the words in the children's assessments were utilized to predict whether they met the case criteria for ASD using eight supervised learning algorithms. The algorithms' performance was evaluated using classification accuracy, F1 score, and the number of positive calls over ten random train-test splits of the data, evaluating their potential applicability for surveillance. Two of the algorithms that obtained above 87 percent accuracy were random forest and support vector machine with Naive Bayes features (NB-SVM). The number of false negatives produced by this NB-SVM was significantly greater ($P = 0.027$) than the number of false positives. The random forest outperformed more recently developed models like the NB-SVM and neural network, as well as providing reliable prevalence estimates. NB-SVM may not be a viable choice for usage in a fully automated surveillance workflow due to the increased false negatives. This type of machine learning method, in general, produces varied outcomes and accuracy for persons of various ages. Only children's data from the Georgia ADDM site was used in this study. Using various data sets for different age groups might make this research more successful. A total of ten train test cycles were used in this study. Where the total dataset was randomly split into 57 percent training, 13 percent validation, and 30 percent test sets for each cycle. These test sets were used to assess its performance once it had been trained. They may utilize a test set from a variety of data sets to see how well these algorithms work when dealing with unknown data.

Based on our review, we have chosen to build an automatic dashboard. For this, a toddler dataset with 1054 occurrences and 19 characteristics was used.

3. Methodology

The practice of methodically applying statistical and/or logical approaches to explain and demonstrate, compress, and recap, and assess data is known as data analysis. Analytic techniques allow inferential conclusions to be drawn from data while differentiating the signal (the event of interest) from the noise (statistical fluctuations) contained in the data. Most of the time, in data analysis data is acquired continuously and almost simultaneously analyzed in real time. During the data collection phase researchers usually look for patterns in observations.

Data Collection

The dataset used in this research was collected from Kaggle [28]. The dataset was proposed, as its included relevant aspects from toddler autism screenings that may be used for future study, particularly in defining autistic traits and enhancing the categorization of ASD patients. This dataset contains ten behavioral traits (Q-Chat-10) as well as additional individual characteristics that have been found very effective to ASD detection [28].

The dataset had 1054 instances and 19 attributes including the class variable without any missing values. The names, types and descriptions of the attributes are shown in Table 1 and 2.

Table 1. ASD Dataset Attributes

Feature	Type	Description
A1	Binary (0, 1)	The answer code of the question based on the screening method used
A2	Binary (0, 1)	The answer code of the question based on the screening method used
A3	Binary (0, 1)	The answer code of the question based on the screening method used
A4	Binary (0, 1)	The answer code of the question based on the screening method used
A5	Binary (0, 1)	The answer code of the question based on the screening method used
A6	Binary (0, 1)	The answer code of the question based on the screening method used
A7	Binary (0, 1)	The answer code of the question based on the screening method used
A8	Binary (0, 1)	The answer code of the question based on the screening method used
A9	Binary (0, 1)	The answer code of the question based on the screening method used
A10	Binary (0, 1)	The answer code of the question based on the screening method used
Age_Mons	Number	Toddlers (months)
Qchat-10-Score	Number	1-10 (Less than or equal 3 no ASD traits; > 3 ASD traits)
Sex	Character	Male or Female
Ethnicity	String	List of common ethnicities in text format
Jaundice	Boolean (yes or no)	Whether the case was born with jaundice
Family_mem_with_ASD	Boolean (yes or no)	Whether any immediate family member has a PDD
Who is completing the test	String	Parent, self, caregiver, medical staff, clinician, etc.
Class/ASD Traits	String	ASD traits or No ASD traits (automatically assigned by the ASDTests app). (Yes / No)

Table 2. Dataset Description

Variable in Dataset	Corresponding Questions
A1	Does your child look at you when you call his/her name?
A2	How easy is it for you to get eye contact with your child?
A3	Does your child point to indicate that s/he wants something? (e.g. a toy that is out of reach)
A4	Does your child point to share interest with you? (e.g. pointing at an interesting sight)
A5	Does your child pretend? (e.g. care for dolls, talk on a toy phone)
A6	Does your child follow where you're looking?
A7	If you or someone else in the family is visibly upset, does your child show signs of wan9ng to comfort them? (e.g. stroking hair, hugging them)
A8	Would you describe your child's first words as:
A9	Does your child use simple gestures? (e.g. wave goodbye)
A10	Does your child stare at nothing with no apparent purpose?

Data Preprocessing

We began by cleaning the data; we did not need to eliminate any instances because there were no undesired observations in the dataset, such as duplicate or irrelevant observations. However, we had deleted several attributes and conducted the analysis with seven attributes. After that data transformation process started. In this stage, we converted Sex from nominal to numerical, Ethnicity from categorical to numerical, Jaundice, Family_mem_with_ASD and Class/ASD Traits from Boolean to numerical.

4. Design of an Interactive Dashboard for Data Analysis

In this section, we have shown our developed dashboard (designed using Tableau) for ASD data analysis. By using this dashboard, one can easily analyze data. The current design allows user to visualize results in numeric and graphical format. Figure 8 shows the dashboard developed to analyze ASD data.

5. Result and Analysis

In this section, data analysis using the dashboard is shown. Our design allows user to visualize the data more interactively. Features such as ASD Rates per Ethnicity, Heat Map, Total ASD Counts, Impact of Family Member, ASD Traits vs. No ASD Traits, ASD in Different Ethnicity and ASD based on gender can be observed by using our dashboard. Figure 6 shows the flow chart of dashboard development process. We have created a dashboard, which will eventually be linked to an app in future. We also looked at several research papers and determined that the SVM and CNN are the best-scoring machine learning algorithms for ASD identification. As a result, we use these algorithms.

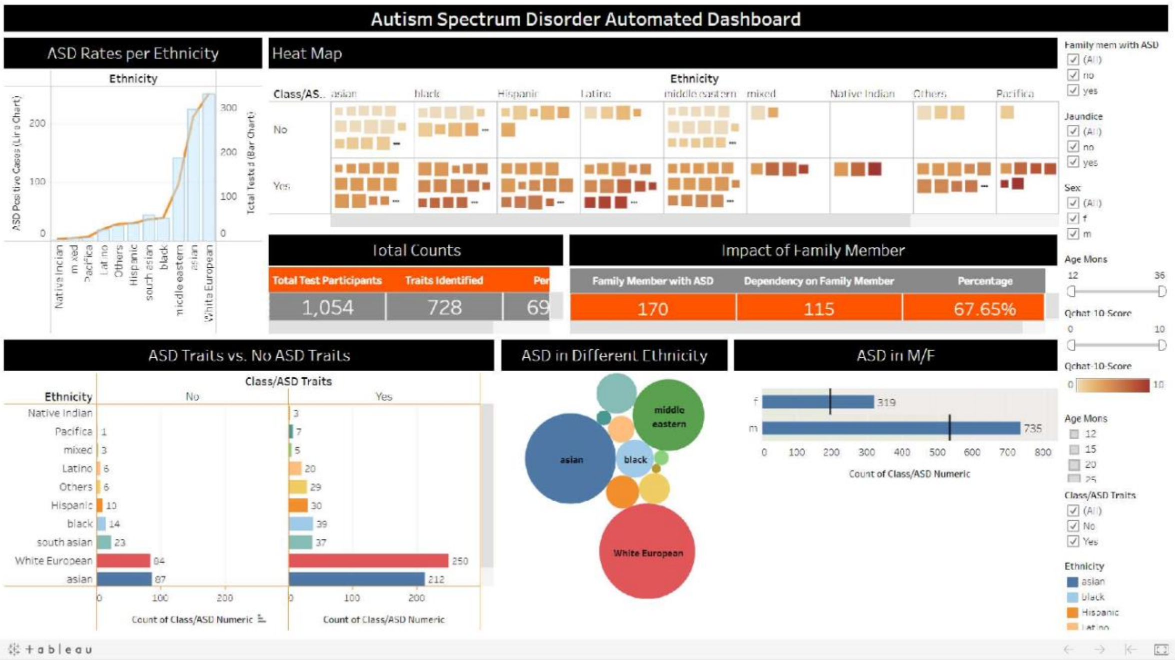

Fig.8. Dashboard for ASD Data Analysis

ASD Rates per Ethnicity:

In this section of the dashboard, we have shown how many participants had taken the ASD test and how many of them exhibited ASD characteristics. The bars in this graph shows the total number of test cases by ethnicity, whereas the line represents the number of persons who participated in this test who exhibited ASD characteristics. Figure 9 shows that the majority of the test cases come from White Europeans, whereas the lowest test cases come from Native Americans. We can also see from this graph that normally when the number of test cases is large, the number of ASD Traits Identified persons is also high. However, this situation is different for South Asians. The overall number of black participants was 53, and 39 of them had ASD traits, the total number of South Asian test participants was 60, with 37 of them having ASD traits.

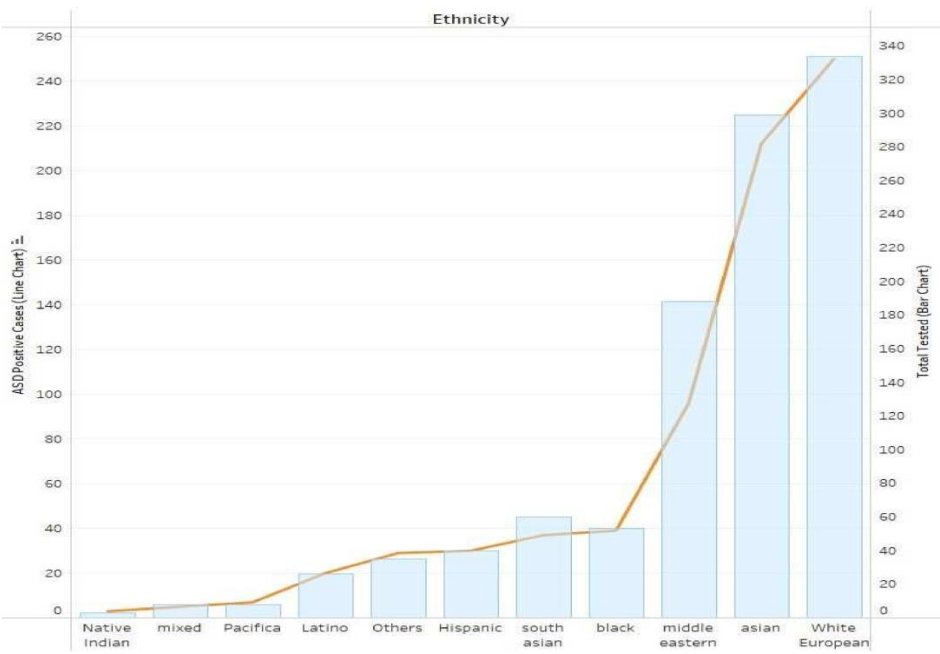

Fig.9. ASD rates per ethnicity

We have summarized the analysis using SVM and CNN in table 3 below

Table 3. ASD Traits In Different Ethnicity

Ethnicity	Test Participants	Traits Identified	%
White European	334	250	74.85%
Asian	299	212	70.90%
Middle Eastern	188	96	51.06%
Black	53	39	73.58%
South Asian	60	37	67.67%
Hispanic	40	30	75.00%
Others	35	29	82.86%
Latino	26	20	76.92%
Pacifica	8	7	87.50%
Mixed	8	5	62.50%
Native Indian	3	3	100%

Heat Map

This graph combines ethnicity, age, and the QChat-10-Score (obtained from the questionnaire). The range of the QChat-10-Score is set as 0 to 10. Figure 10 shows that a greater QChat-10-Score corresponds to a darker hue, and the size of the square corresponds to age. Higher age value is shown by a large square. Each square also signifies a distinct individuality. We have added filters in heat map such as Family Member with ASD, Jaundice, Sex, Age and QChat-10-Score. User can modify these filters in order to see some specific results.

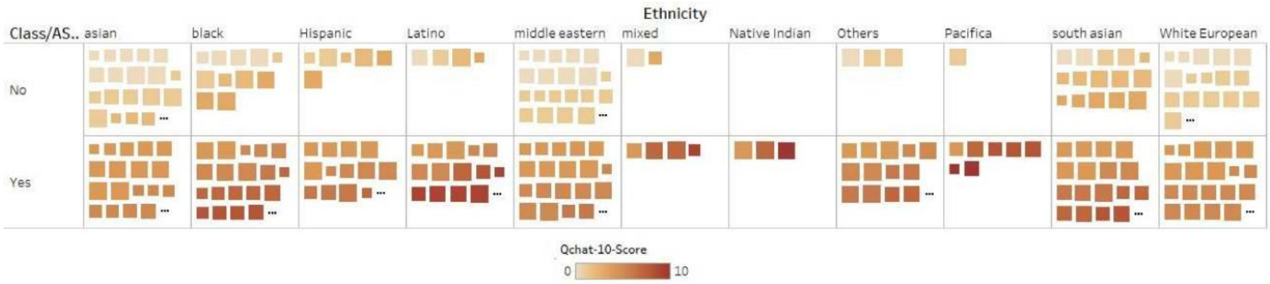

Fig.10. Heat Map of ASD traits

ASD Based on Gender

Here we have shown ASD based on gender. Figure 11 shows that 735 of the participants were male, with 534 of them having ASD traits, and 319 of the participants were female, with 194 having ASD traits.

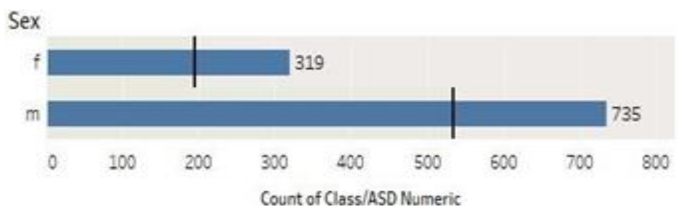

Fig.11. ASD based on gender

6. Conclusion

Early detection is critical since it allows for treatment to begin much sooner. For young children with autism, this implies that the skills they need to realize their full potential are taught at a young age when brain plasticity is much more prominent, and intervention's influence is much broader. The traditional diagnosis of ASD is very costly, and it is very difficult for some families to bear this cost. Using the machine learning technique, we can get rid of this problem. Machine Learning can help to diagnose autism spectrum disorder easily. Such information, if predicted in advance, can provide valuable insights to clinicians, allowing them to tailor their diagnosis and treatment to each patient. It can be very cost-friendly, and it will save lots of time. In this research, we develop a dashboard for ASD data analysis. The development is followed by a comprehensive background study of the topic. From the background, 25 research articles are reviewed. During the review, most common techniques, rules, and tools used by researchers are given the priority. Based on the accuracy, sensitivity, and specificity of supervised machine learning algorithms, we have also provided a table. Our analysis showed that out of 1054 cases the percentages of positives is 70%. Number of males with ASD is higher than females. If we consider the number of participants, then White European are mostly affected with ASD. Early identification of ASD patients can help them become more independent in the future, and the ability of machine learning to process data can help researchers significantly. There is currently no app that is connected to an analytics dashboard for autism prediction. Our dashboard depicts the global condition of autism spectrum disorder (ASD). We aim to link the app in the future, then this dashboard will be useful for further research in the domain of autism research. The app we want to develop based on this research will be able to predict the presence of autism spectrum disorder in human body at early stage, which will drastically lower their treatment costs.

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