



# AUTISM SPECTRUM DISORDER SCREENING: PREDICTION WITH MACHINE LEARNING MODELS

<sup>1</sup>Kruthi C H, <sup>2</sup>Tejashwini H N, <sup>3</sup>Poojitha G S, <sup>4</sup>Shree Lakshmi H S, <sup>5</sup>Shobha Chandra K

<sup>1,2,3,4</sup>Student, <sup>5</sup>Assistant Professor

<sup>1, 2, 3, 4, 5</sup>Computer Science and Engineering,

<sup>1, 2, 3, 4, 5</sup>Malnad College of Engineering, Hassan, Karnataka, India

**Abstract:** In present day Autism Spectrum Disorder (ASD) is gaining its momentum quicker than ever. Discerning autism traits through screening tests is incredibly expensive and time-consuming. With the advance of Artificial Intelligence, Computing and Machine Learning (ML), autism can be predicted at quite an early stage. Though a number of studies are meted out using completely different techniques, these studies didn't give any definitive conclusion regarding predicting autism traits in terms of various age groups. Therefore, this paper aims to propose a decent prediction model supported by ML technique and develop a user interface for predicting ASD for people of any age. As outcomes of this analysis, an autism prediction model was developed by merging Random Forest-CART (Classification and Regression Trees) and Random Forest-ID3 and conjointly an interface was developed based on the proposed prediction model. The proposed model was evaluated with AQ-10 screening tool and real data sets collected from people with and without autistic traits. The analysis results showed that the proposed prediction model provided better results in terms of accuracy, specificity, sensitivity, precision and false positive rate (FPR) for the data set.

**Keywords - AQ-10 dataset, random forest, CART, ID3, Machine learning, ASD , User Interface.**

## I. INTRODUCTION

### 1.1 Autism Spectrum Disorder

Autism spectrum disorder is a serious developmental disorder that impairs the ability to communicate and interactions. Though identification of autism is done at any age, its symptoms typically seem to appear within the initial 2 years of life and develop through time. Autism patients face different types of challenges like difficulties with concentration, learning disabilities, mental state issues like anxiety, depression etc., motor difficulties, sensory problems and plenty of others. Autism spectrum disorder is controlled if found at an early stage by advising individuals with the correct medication. This might prevent the patient's condition from getting worse and would decrease long-term costs related to delayed diagnosis. So an effective, accurate and simple screening check tool is highly needed which might detect the traits of a person and acknowledge whether the person requires thorough autism syndrome assessment or not. In this paper we have a tendency to use machine learning to find out a group of conditions that are put together to be predictive of autism spectrum disorder. This can be vastly useful to physicians, helping them to notice autism spectrum disorder at a really early stage. The current explosion rate of autism around the world is various, and it's increasing at a really high rate. According to WHO, 1 out of each 160 children has ASD. Some individuals with this disorder can live independently, whereas others need life-long care and support. Earlier detection of autism will come back to an excellent facilitate by prescribing patients with the correct medication at an early stage. It will stop the patient's condition from deteriorating and would help to reduce long-term costs associated with delayed diagnosis. Thus, a time-efficient, accurate and simple screening test tool is very much required which might predict autism traits in an individual and identify whether they need comprehensive autism assessment. The objective of this work is to propose an autism prediction model using ML techniques and to develop a mobile application that would effectively predict autism traits of an individual of any age.

### 1.2 Autism Spectrum Quotient-10 (AQ-10)

The AQ is a self-administrated ASD screening tool developed beside different behavioral scientists, for distinguishing autism and other Neurodevelopmental symptoms in adults with an average level of intelligence. The AQ questionnaire form consists of fifty completely different questions covering the areas of social skills, attention shift, imagination, communication and attention to detail. The AQ test is available online, and every question has four possible responses (definitely agree, slightly agree, slightly disagree, and definitely disagree). The reckoning on that final score is calculated.

The final score will vary from 0 to 50, and a higher score indicates the raised level of autistic symptoms. A recent study on the validity of the AQ advised that a cut-off score of 32 would optimize the validity of screening for adults during a clinical setting. Later, a pair of completely different versions of AQ were launched to cover adolescents and children. AQ-Child may be a parent-

administered questionnaire form specially designed for children aged 4–11 years, whereas AQ adolescent is meant for teenagers aged 12–15 years. All versions of AQ contain 50 unique items and take about 20–30 minutes to complete.

To make it less complicated and less time-consuming [7], presented a compressed version of the original AQ adult, adolescent and children version called AQ-10 adult, AQ-10 adolescent and AQ-10 children. Although AQ-10 is shorter than the original version, its predictive power is just like the original AQ version. The queries of AQ-10 even have four possible responses, definitely or undoubtedly agree, slightly agree, slightly disagree, and definitely disagree. The screening rule usually considers one point per question. That's to mention, a point is allotted if the answer is either slightly agree or definitely/undoubtedly agree for questions 1, 7, 8, and 10. Additionally, it is appropriate if the user's responses to questions 2, 3, 4, 5, 6, and 9 are either slightly or definitely disagree. The overall score is then calculated employing a handcrafted diagnosis rule and anyone who scores above the threshold, i.e., edge of six, is taken into account to possess autism and other alternative connected impairments.

Table 1.1: AQ-10

No.	Attribute Name	Data Type	Description
1	Question 1 Answer	Binary (0, 1)	I often notice small sounds when others do not
2	Question 2 Answer	Binary (0, 1)	I usually concentrate more on the whole picture, rather than the small details
3	Question 3 Answer	Binary (0, 1)	I find it easy to do more than one thing at once
4	Question 4 Answer	Binary (0, 1)	If there is an interruption, I can switch back to what I was doing very quickly
5	Question 5 Answer	Binary (0, 1)	I find it easy to read between the lines when someone is talking to me
6	Question 6 Answer	Binary (0, 1)	I know how to tell if someone listening to me is getting bored
7	Question 7 Answer	Binary (0, 1)	When I'm reading a story, I find it difficult to work out the character's intentions
8	Question 8 Answer	Binary (0, 1)	I like to collect information about categories of things (e.g. types of cars, types of bird, types of train, types of plant, etc)
9	Question 9 Answer	Binary (0, 1)	I find it easy to work out what someone is thinking or feeling just by looking at their face
10	Question 10 Answer	Binary (0, 1)	I find it difficult to work out people's intentions

## II. LITERATURE SURVEY

This section shortly presents the works associated with the prediction techniques of ASD. Effectivity of ML is sort of commendable in predicting differing types of diseases supported autism disorder. As an example, in [3] J. A. Cruz tried to diagnose cancer mistreatment ML whereas in [4] N. S. Khan, used ML to predict if an individual is diabetic or not. D. P. Wall [5] used Alternating Decision Tree (ADTree) for reducing the screening time and quicker detection of ASD traits. They used the Diagnostic Interview, Revised (ADI-R) methodology and achieved a high level of accuracy with dataset of 891 people. However, the check was restricted at intervals from the age of five to seventeen and did not predict ASD for various age teams (children, adolescents and adults). D. Bone[6] applied ML for constant purpose and used support vector machine (SVM) to get eighty-nine% sensitivity and fifty-nine specificity. Their analysis enclosed 1264 people with ASD and 462 people with NON-ASD traits. But because of wide selection of ages (4-55 years), their analysis wasn't accepted for folks of all ages limit as a screening approach.

C. Allison [7] used 'Red Flags' tool for screening ASD with Autism Spectrum Quotient for kids and adults, then shortlisted them to AQ-10 with over ninety-nine percent accuracy. F. Thabtah [8] compared the previous works on ML algorithms for prediction of autism syndrome traits, whereas F. Hauck and N. Kliewer [9] tried to spot comparatively additional necessary screening queries for ADOS (Autism Diagnostic Observation Schedule) and ADI-R (Autism Diagnostic Interview Revised) screening ways and located that ADI-R and ADOS screening check will work higher. B. van den Bekerom [10] used many Machine Learning techniques as well as naive Bayes, SVM and random forest to check ASD traits in kids like biological process delay, obesity, less physical activity and compared those results.

D. Wall[11] worked on classifying syndrome with short screening check and validation and located that ADTree and the purposeful tree had also performed well with high sensitivity, specificity and accuracy. A. S. Heinsfeld [12] applied deep learning formula Associate in Nursing neural network to spot ASD patients mistreatment of a giant brain imaging dataset from the ABIDE I and achieved a mean classification accuracy of seventieth with an accuracy vary of sixty-six to seventy-one. The SVM classifier achieved mean accuracy of 65%; whereas the Random Forest classifier achieved mean accuracy of sixty-three.

### III. METHODOLOGY

➤ **Data Collection:** The data needed for the disorder prediction are the heterogeneous genomes that vary from every individual. The syndrome may be a heterogeneous Neurodevelopmental syndrome. It involves complicated biological science, etiology, deoxyribonucleic acid and genes. It's an oversized knowledge set with the complicated genetic structure that ought to be handled to eliminate the crying and inconsistent data. The dataset gift within the variety of AQ ten datasets developed the mistreatment of the disorder spectrum tool. The AQ ten datasets is split into three varieties supported the age. 1) Child-AQ dataset (4-10 years), 2) Adolescent-AQ 10 dataset (11-17 years) and 3) Adult-AQ ten (Adults 18+ years).

➤ **Data Preprocessing:** The Preprocessing of genetic information includes the following:

1. **Data Transformation:**

Normalization: scaling the values to a selected range.

Aggregation: distribution probabilistic values to the genes.

Construction: replacement or adding new genes inferred by the prevailing genes.

2. **Data Reduction:** Searching for a lower-dimensional house which will best represent the data. Removing the irrelevant information from the order dataset. Sampling can be accustomed to alter the method of classification using a small dataset.

3. **Applying algorithm:** At first, the Decision Tree-CART algorithm was implemented to predict autism traits in an individual. For further improvement, Random Forest-CART was implemented and better results were obtained. Finally, the Random Forest-CART classifier was modified to get improved results by merging it along with the Random Forest-ID3 classifier.

The three algorithms consecutively used to implement the system are discussed below:

A. Prediction model based on Decision Tree-CART

Initially, the Decision Tree-CART classifier was selected to create the prediction model. In the beginning, the tree root consists of the whole dataset. Then the data would be split using the best feature. The splitting process will continue recursively until a node consists of data of a unique label class. The sequential attribute selection method is resolved by Gini Impurity and Information Gain (IG) as shown in equation 1 and 2. Attributes with maximum IG will be chosen first to split data.

$$\text{Gini}(\text{data}) = 1 - \sum_{i \in \text{unique\_classes}} P(i)^2 \quad (1)$$

$$\text{InfoGain}(\text{data}, \text{featureX}) = \text{Gini}(\text{data}) - \sum_{i \in \text{featureX}} \text{AvgGini}(i) \quad (2)$$

Algorithm 1 : Decision Tree CART Classifier

```

1: features ← {AQ 10 questions, gender, inheritance}
2: classes ← {yes (autistic traits), no (no autistic traits)}
3: procedure BUILDING A TREE (rows)
4: for every possible feature do
5: calculate max gain
6: end for
7: if max gain = 0 then
8: return leaf
9: end if
10: True Rows, False Rows ← Partition(rows)
11: True Branch ← Building a Tree (True Rows)
12: False Branch ← Building a Tree (False Rows)
13: return DecisionNode (True Branch, False Branch)
14:
15: procedure CLASSIFY (row, node)
16: if node = leaf then
17: return node. Predictions
18: else
19: Iterate_tree
20: end if

```

Algorithm used here [Algorithm 1] can be split into two phases: building a decision tree [line number 3-13] and classifying test data using tree [line number 15-20].

The followed steps are given below:

- Initially best features were selected to construct the decision tree [Line 1] and the class labels were segregated [Line 2]
- To construct a decision tree, training data is called from the 'BUILDING A TREE' function [Line 3]
- Then each feature from data is iterated and the feature with max IG is identified [Line 4-6]
- If max IG equals zero then that means the class labels of that portion of data is pure and will return as leaf nodes [Line 7-9]
- If max IG is not equal to zero then the data will be split into two portions (True Rows and False Rows) with respect to the feature with max information gain [Line 10]

- 'BUILDING A TREE' function will run recursively on both portions of the data [Line 11-12] and the two branches will form a decision node or rule [Line 13]
- Finally after the decision tree is constructed, test data is classified using it. The tree is iterated using the feature values. When tree reaches a leaf node then it will classify the test data with the leaf's prediction [Line 15-20]

#### B. Prediction model based on Random Forest-CART

In a random forest, every node is split using the best and most effective among a subset of predictors randomly chosen. This somewhat counter-intuitive strategy turns out to perform very well and fine compared to several different classifiers, including discriminant analysis, support vector machines and neural networks, and is robust against over-fitting [18]. To make the predictive model more accurate, Random Forest-CART classifier [Algorithm 2] was implemented. Here also the algorithm can be split into two phases: generating random forest [line number 1-10] and classifying test data [line number 12-28].

Algorithm 2: Random Forest CART Classifier

1 Algorithm 1

2: procedure BUILDING A FOREST (rows, x, train ratio)

3: tree\_array  $\leftarrow$  [ ]

4: while  $x \neq 0$  do

5: train  $\leftarrow$  random (train ratio \* len(rows))

6: tree  $\leftarrow$  BUILDING A TREE (train)

7: tree\_array. Append(tree)

8:  $x \leftarrow x - 1$

9: end while

10: return tree\_array

11:

12: procedure CLASSIFY (row, tree\_array [ ], x)

13:  $i \leftarrow 0$ , vote\_yes  $\leftarrow 0$ , vote\_no  $\leftarrow 0$

14: while  $i \neq x$  do

15: tree  $\leftarrow$  tree\_array(i)

16: node  $\leftarrow$  root(tree)

17: if node = leaf then

18: if leaf. Prediction = "Yes" then

19: vote\_yes  $\leftarrow$  vote\_yes + 1

20: else if leaf. Prediction = "No" then

21: vote\_no  $\leftarrow$  vote\_no + 1

22: end if

23: else

24: Iterate\_tree

25: end if

26:  $i \leftarrow i + 1$

27: end while

28: return vote\_yes > vote\_no

Classification using the random forest has been done following the steps below:

- At first, an array named 'tree\_array' is initialized as null to store the decision trees [Line 3]
- Then to generate 'x' number of decision trees of the forest, 'BUILDING A TREE' function is called 'x' time and the generated trees are stored in 'tree\_array' [Line 4-9]
- Each decision tree is generated for 'i' number of random attributes. Construction of decision tree procedure is same as described in Line 1-13 of Algorithm 1
- Finally, to classify a test data, votes are taken from each decision tree of the random forest. If majority of votes are "Yes" then we'll classify test data as "Yes"(Probable autistic traits) or else we'll classify test data as "No"(No autistic traits) [Line 12-28]

#### C. Prediction model based on merging Random Forest-CART and Random Forest-ID3

In order to improve the performance, a prediction model is proposed that merges the concept of random forest- CART with the concept of random forest ID3 [Algorithm 3]. The algorithm for the proposed prediction model can be split into two phases like before: generating the merged random forest and classifying test data. Difference from 2 is that here randomness is increased more by generating and adding ID3 decision trees to the random forest [In line 3-13]. Algorithm 3 tends to work better than Algorithm 2 because addition of ID3 decision trees limits over-fitting and thus further reduces error compared to Algorithm 2.

Algorithm 3 : Merged Random Forest Classifier

1: features  $\leftarrow$  {AQ-10 questions, gender, inheritance}

2: classes  $\leftarrow$  {yes (autistic traits), no (no autistic traits)}

3: procedure BUILDING TREE ID3(rows)

4: for every possible feature do

5: calculate the max gain

6: end for

7: if max gain = 0 then

8: return leaf

9: end if

10: True Rows, False Rows  $\leftarrow$  Partition(rows)

11: True Branch  $\leftarrow$  Building Tree ID3(True Rows)

12: False Branch  $\leftarrow$  Building Tree ID3(False Rows)

13: return Decision Node (True Branch, False Branch)

14:



```

15: procedure BUILDING TREE CART (rows)
16: for all possible features do
17: calculate the max gain
18: end for
19: if max gain = 0 then
20: return leaf
21: end if
22: True Rows, False Rows ← Partition(rows)
23: True Branch ← Building Tree CART (True Rows)
24: False Branch ← Building Tree CART (False Rows)
25: return Decision Node (True Branch, False Branch)
26:
27: procedure BUILDING FOREST (rows, x, train_ratio)
28: tree_array ← [ ]
29: while x ≠ do
30: train ← random (train_ratio * Len(rows))
31: tree1 ← BUILDING TREE ID3(train)
32: tree2 ← BUILDING TREE CART (train)
33: tree_array. Append(tree1)
34: tree_array. Append(tree2)
35: x ← x - 1
36: end while
37: return tree_array
38:
39: procedure CLASSIFY (row, tree_array[ ], x)
40: i ← 0, vote_yes ← 0, vote_no ← 0
41: while i x≠ do
42: tree ← tree_array(i)
43: node ← root(tree)
44: if node = leaf then
45: if leaf. Prediction = "Yes" then
46: vote_yes ← vote_yes + 1
47: else if leaf. Prediction = "No" then
48: vote_no ← vote_no + 1
49: end if
50: else
51: Iterate_tree
52: end if
53: i ← i + 1
54: end while
55: return vote_yes > vote_n

```

The process is described in details below:

- To construct a merged random forest classifier, the BUILDING FOREST function is called and 'x' number of ID3 trees and 'x' number of CART trees are generated. The trees are then stored in tree\_array [Line 27-37]
- Construction criteria of ID3 trees [Line 3-13] and CART trees [Line 15-25] are the same as Algorithm 1. Difference between ID3 and CART is that, in ID3 decision trees' IG is calculated from entropy while in CART decision trees' IG is calculated from gini impurity
- Finally to classify the test data, votes were taken from each decision tree of the merged random forest. If majority of votes are "Yes" then we'll classify test data as "Yes" (Probable ASD traits) or else we will classify test as "No" (No ASD traits) [Line 39-55]

#### ➤ Developing User Interface

We have used a flask framework to design the front end. Syntax such apps. The route is used to connect html pages. Separate html pages contain the design layout of the web page. Designing web pages is done using normal HTML tags. The session was kept active using a secret key. After running the algorithm, we have come to the conclusion that random forest base has 98% accuracy.

#### IV. SYSTEM ARCHITECTURE

The project is distributed in four totally different steps, finally the Data Collection, second the Data Synthesization, third the Developing the prediction model, and also the fourth Evaluating the prediction model.

A brief description of steps is given below:

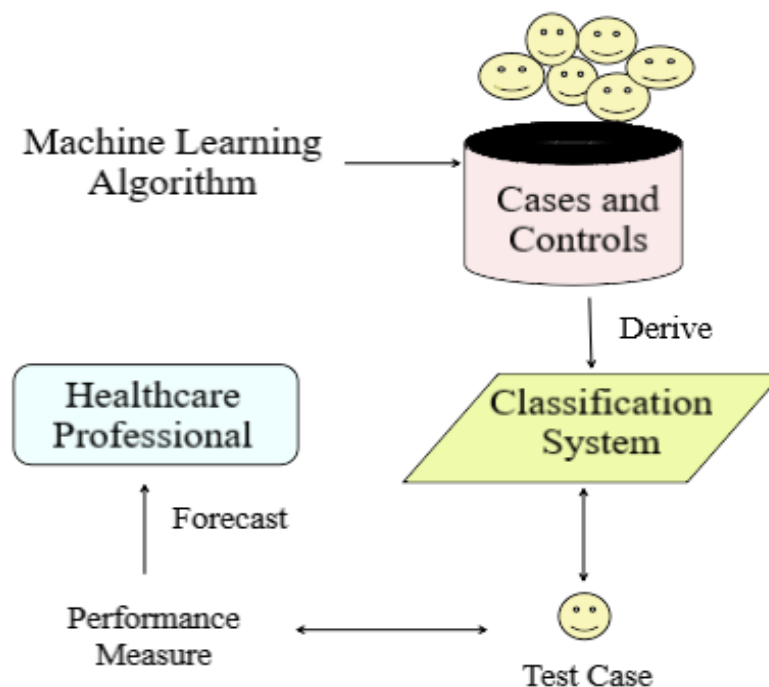


Figure 4.1 System Architecture

The analysis was distributed in four phases: Data collection, Data synthesization, Developing the prediction model, Evaluating the prediction model. The phases area unit briefly mentioned within the following sub-sections:

- A. Data collection
- B. Data Synthesization
- C. Developing the Prediction Model
- D. Evaluating the Prediction Model

#### A. Data collection

To develop an efficient prophetic model, AQ-10 dataset was used that consists of dataset supported AQ-10 screening tool queries. These 3 information sets contain data of age teams of 4-11 years (child), 12-16 years (adolescent) and last ages of eighteen or additional (adult). AQ-10 or syndrome verbal description Quotient tool is employed to spot whether or not a personal should be referred for a comprehensive syndrome assessment. AQ-10 screening queries specialize in totally different domains such as attention to detail, attention switch, communication, imagination and social interaction. The evaluation technique of the questions is that only one purpose will be scored for every of the ten questions. Users might score zero or one purpose on every question based mostly on their answer. Datasets of kids, adolescent and adult contain 292, 104 and 704 instances severally. The datasets contain twenty-one attributes that area a mixture of numerical and categorical information that include Age, Gender, Ethnicity, If born with Jaundice, family members with autism, Who is finishing the test, Country of residence, used the screening app before, Screening technique kind, Question 1-10, Result and others.

#### B. Data Synthesization

The collected information was synthesized to get rid of extraneous features. As an example, the ID column was irreverent to develop a prediction model, so it was removed. To handle null values, a list-wise deletion technique was applied wherever a specific observation was deleted if it had one or additional missing values. Then to extract spare options from the dataset, a decision tree algorithmic program was used. Results showed dropping 'age desc', 'relation', 'age' and 'app used before' columns would result in more correct classification, and then those columns were dropped.

#### C. Developing the Prediction Model

To generate prediction of syndrome traits, algorithms had been developed and their accuracy were tested. Once obtaining results from varied varieties of supervised learning like SVM, Naive Bayes; Random Forest was found to be extremely possible with higher accuracy than the opposite algorithms. So, Random Forest (CART) was planned for implementing the ASD proposed system. Any modifications were created to the algorithmic program to realize even higher results.

#### D. Evaluating the Prediction Model

The planned proposed model was tested with the AQ- 10 and data collected from the real-world in terms of the accuracy, specificity, precision, sensitivity and false positive rate. For the AQ-10 dataset, the leave-one-out technique was additionally applied to ascertain the effectiveness of the planned model.

### 4.2 Designing User Interface

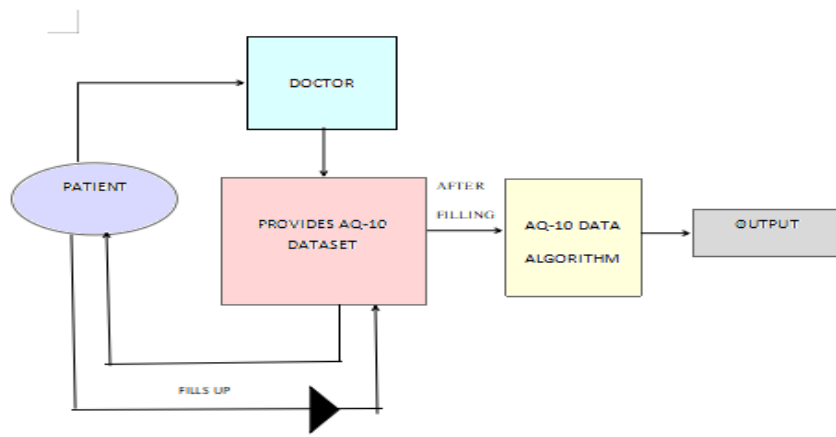


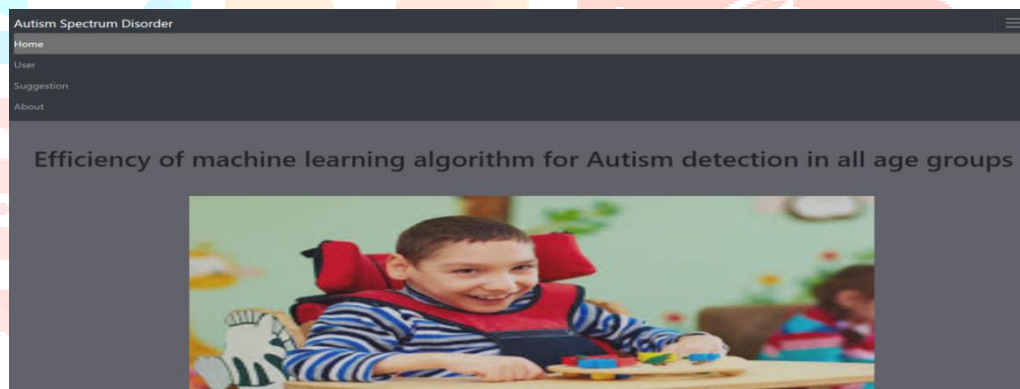
Figure 4.2 UI design

In the process of prediction initially, the patient/user will input the data for AQ10 which has 20 attributes in total, where 10 are general questions and other 10 attributes are personal questions like age, country etc. This is provided by the doctor or any medical assistant. After filling up the data given by the user, several required machine learning algorithms were used to predict whether the patient/user had ASD traits or not.

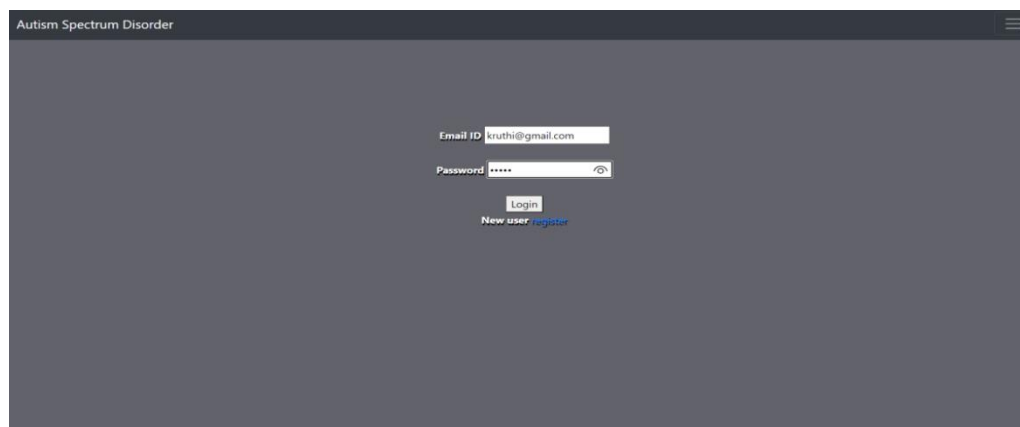
### V. RESULT

The following are the images of user interface where participants can give their AQ-10 scores and other general parameters as input with the help of a medical assistant/ parent/ self, anyone who scores above the threshold of six is considered to have autism according to the National ASD Diagnostic Referral Service, International Classification of Disease (ICD) 10 informed by the ADOS-G and ADI-R assessments for suspected autism.

#### A. Home Page



#### B. Log in Page

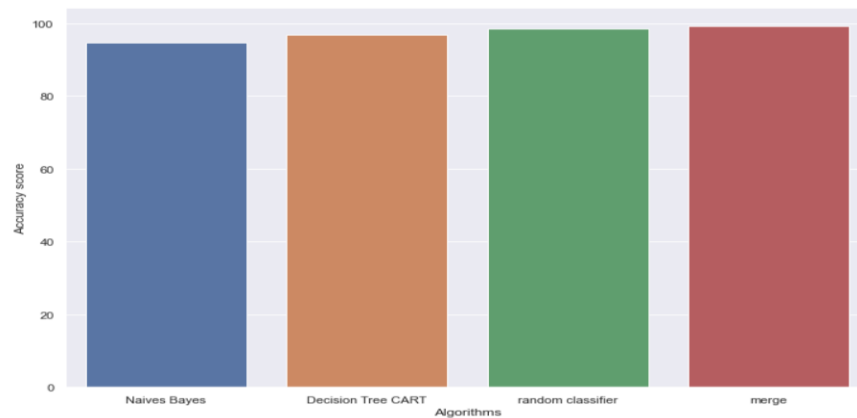


#### C. Accuracy Analysis

The below output shows the comparison of the algorithms used in the existing system and the proposed system. In the bar graph we can see the percentage of Decision Tree CART, Random Forest CART and Merging Random Forest-CART and Random Forest-ID3 are 96.9%, 98.6%, 99.2% respectively. These proposed algorithms are more flexible and accurate than the Naive Bayes which has an accuracy of 94.72%.

```
The accuracy score achieved using Naives Bayes is: 94.72 %
The accuracy score achieved using Decision Tree CART is: 96.9 %
The accuracy score achieved using random classifier is: 98.6 %
The accuracy score achieved using merge is: 99.2 %
```

```
Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x1cd623ea970>
```



## VI. CONCLUSION AND FUTURE WORK

This analysis provides a threefold outcome: Initially, a prediction model was developed to predict autism traits. Using the AQ-10 scores, the suggested model will predict Autism disorder with 99% accuracy by merging CART model in the case of children, adolescents and adults respectively. This result showed better performance scrutiny to the opposite existing approach of screening syndrome. Moreover, the projected model will predict ASD disorder traits for various age groups, while many different existing approaches incomprehensible this feature. Furthermore, this analysis provides a comparative read among different machine learning approaches in terms of their performance. The results showed that Random Forest CART showed higher performance than the Decision Tree-CART algorithmic rule, while the projected (merging Random Forest-CART and Random Forest-ID3) algorithmic rule gives higher performance scrutiny. Finally, an easy user interface has been developed for finished users supporting the projected prediction model in order that a person will use the application to predict the syndrome traits simply. In sum, the end result of this analysis provides a good and efficient approach to sight ASD traits for various age groups. Since designation of the syndrome traits is kind of an expensive and lengthy method, it's usually delayed attributable to the difficulty of detecting the syndrome in children and adolescents.

Our future work will focus on collecting more data from various sources and on improving the proposed machine learning classifier to enhance its accuracy. A user study will also be conducted to evaluate the usability and user experience (UX) of the mobile application.

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