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A Machine Learning Approach to Predict Autism Spectrum Disorder

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***Abstract*—In present day Autism Spectrum Disorder (ASD) is gaining its momentum faster than ever. Detecting autism traits through screening tests is very expensive and time consuming. With the advancement of artificial intelligence and machine learning (ML), autism can be predicted at quite early stage. Though number of studies have been carried out using different techniques, these studies didn't provide any definitive conclusion about predicting autism traits in terms of different age groups. Therefore this paper aims to propose an effective prediction model based on ML technique and to develop a mobile application for predicting ASD for people of any age. As outcomes of this research, an autism prediction model was developed by merging Random Forest-CART (Classification and Regression Trees) and Random Forest-ID3 (Iterative Dichotomiser 3) and also a mobile application was developed based on the proposed prediction model. The proposed model was evaluated with AQ-10 dataset and 250 real dataset collected from people with and without autistic traits. The evaluation results showed that the proposed prediction model provide better results in terms of accuracy, specificity, sensitivity, precision and false positive rate (FPR) for both kinds of datasets.**

***Keywords*—machine learning, AQ-10 dataset, random forest, CART, ID3, ASD**

I. Introduction

Autism spectrum disorder is a neurodevelopmental disorder that affects a person's interaction, communication and learning skills. Although diagnosis of autism can be done at any age, its symptoms generally appear in the first two years of life and develops through time [1]. Autism patients face different types of challenges such as difficulties with concentration, learning disabilities, mental health problems such as anxiety, depression etc, motor difficulties, sensory problems and many others.

Current explosion rate of autism around the world is numerous and it is increasing at a very high rate. According to WHO [2], about 1 out of every 160 children has ASD. Some people with this disorder can live independently, while others require life-long care and support.

Diagnosis of autism requires significant amount of time and cost. Earlier detection of autism can come to a great help by prescribing patients with proper medication at an early stage. It can prevent the patient's condition from deteriorating further and would help to reduce long term costs associated with delayed diagnosis. Thus a time efficient, accurate and easy screening test tool is very much required which would predict autism traits in an individual and identify whether or not they require 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 could effectively predict autism traits of an individual of any age. In other words, this work focuses on developing an autism screening application for predicting the ASD traits among people of age groups 4-11 years, 12-17 years and for people of age 18 and more.

The rest of the paper is organized as follows. Section II discusses the related researches previously done in this area. Section III presents the research methodology. Detailed implementation of the proposed system is discussed in Section IV and the implemented system is evaluated in Section V. Section VI briey discusses how the proposed algorithm was merged into a mobile application. Finally, Section VII concludes the paper by highlighting the research contributions, research limitations and future plans to extend this work.

II. Literature Review

This section briefly presents the works related to the prediction techniques of ASD. Efficacy of ML is quite commendable in predicting different types of diseases based on syndrome. For example, in [3] Cruz et al tried to diagnose cancer using ML while in [4] Khan et al used ML to predict if a person is diabetic or not. Wall et al [5] used Alternating Decision Tree (ADTree) for reducing the screening time and faster detection of ASD traits. They used Autism Diagnostic Interview, Revised (ADI-R) method and achieved high level of accuracy with a data of 891 individuals. But the test was limited within the age of 5 to 17 and failed to predict ASD for different age groups (children, adolescent and adults).

Bone et al [6] applied ML for the same purpose and used support vector machine (SVM) to obtain 89.2% sensitivity and 59% specificity. Their research included 1264 individuals with ASD and 462 individuals with NON-ASD traits. However due to wide range of age (4-55 years) their research was not accepted for people of all age group as screening approach. Allison et al [7] used 'Red Flags' tool for screening ASD with Autism Spectrum Quotient for children and adult, then shortlisted them to AQ-10 with more than 90% accuracy. Thabtah [8] compared the previous works on ML algorithms

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for prediction of autism traits, while Hauck and Kliewer [9] tried to identify relatively more important screening questions for ADOS (Autism Diagnostic Observation Schedule) and ADI-R (Autism Diagnostic Interview Revised) screening methods and found that ADI-R and ADOS screening test can work better when they are combined together.

Bekerom [10] used several ML techniques including naive bayes, SVM and random forest algorithm to determine ASD traits in children like developmental delay, obesity, less physical activity and compared those results. Wall et al [11] worked on classifying autism with short screening test and validation and found that ADTree and the functional tree had performed well with high sensitivity, specificity and accuracy. Heinsfeld [12] applied deep learning algorithm and neural network to identify ASD patients using large brain imaging dataset from the Autism Imaging Data Exchange (ABIDE I) and achieved a mean classification accuracy of 70% with an accuracy range of 66% to 71%. The SVM classifier achieved mean accuracy of 65% ; while the Random Forest classifier achieved mean accuracy of 63% .

Liu [13] examined whether if face scanning patterns could be potentially useful to identify children with ASD by adopting ML algorithm to analyze an eye movement dataset for the classification purpose. This study showed an accuracy of 88.51%; specificity 86.21%; sensitivity 93.10%; AUC 89.63%. Bone et al [14] analyzed the previous works of Wall et al [11] and Kosmicki et al [15] to identify the issues in conceptual problem formation, methodological implementation and interpretation and reproduced the result using their ML approach.

From the literature review it is evident that, though a number of researches have been carried out in this field but the researchers did not come to a decisive conclusion on using the ML approach to generalize autism screening test tool in terms of the age groups. Different tools and techniques have been adapted before for autism screening tests, but none in the form of app based solution for different age groups.

III. Research Methodology

The research was carried out in five phases: Data collection, Data synthesization, Developing the prediction model, Evaluating the prediction model and Developing a mobile application. The phases are briefly discussed in the following sub-sections:

A. Data Collection

To develop an effective predictive model, AQ-10 dataset was used which consists of three different datasets based on AQ-10 screening tool questions [16]. These three datasets contain data of age groups of 4-11 years (child), 12-16 years (adolescent) and lastly ages of 18 or more (adult). AQ-10 or Autism Spectrum Quotient tool is used to identify whether an individual should be referred for a comprehensive autism assessment. AQ-10 screening questions focus on different domains such as- attention to detail, attention switching, communication, imagination and social interaction. Scoring method of the questions is that only 1 point can be scored for each of the 10 questions. User may score 0 or 1 point on each question based on their answer [17]. Datasets of child, adolescent and adult contain 292, 104 and 704 instances respectively. Each of the three datasets contains twenty-one attributes which are a mix of numerical and categorical data, that includes: Age, Gender, Ethnicity, If born with Jundice, Family member with PDD, Who is completing the test, Country of Residence, Used the screening app before, Screening method type, Question 1-10, Result and Class.

B. Data Synthesization

The collected data were synthesized to remove irrelevant features. For example, the ID column was irreverent to develop a prediction model, thus it was removed. To handle null values, listwise deletion technique was applied where a particular observation was deleted if it had one or more missing values. Then to extract unnecessary features from the dataset, decision tree algorithm was used. Results showed dropping ‘relation’, ‘age desc’, ‘used app before’ and ‘age’ columns would result in more accurate classification and so those columns were dropped. Summary of the synthesized datasets are shown in Table I.

C. Developing the Prediction Model

To generate prediction of autism traits, algorithms had been developed and their accuracy were tested. After attaining results from various types of supervised learning like Linear Regression, SVM, Naive Bayes; Random Forest was found to be highly feasible with higher accuracy than the other algorithms. So, Random Forest (CART) was proposed for implementing the ASD predictive system. Further modifications were made to the algorithm to attain even better results.

D. Evaluating the Prediction Model

The proposed predictive model was tested with the AQ-10 dataset and data collected from real-world in terms of the accuracy, specificity, precision, sensitivity and false positive rate. For the AQ-10 dataset, leave-one-out technique was also applied to check effectiveness of the proposed model. Again, to validate the proposed model almost 100 data of ASD cases were collected from an institute of special education for the people with special needs and 150 data of Non-ASD cases were collected through field visit to different schools and shopping malls, using both printed forms and online forms. In later case, the online questionnaires were distributed through social media and email to different administrative and teaching communities.

E. Developing a Mobile Application

Finally, a mobile application was developed for the use of general mass. By answering a set of closed ended questions, user will get a result of having or not having autism traits.

TABLE I
SUMMARY OF THE DATASET

Age Group	Total Cleaned Instances	% of Male-Female	Average Age
4-11 years	248	70.16% male, 29.84% female	6.43 years
12-16 years	98	50% male, 50% female	14.13 years
18 and more	608	52.7% male, 47.3% female	29.63 years

IV. DEVELOPING THE PREDICTION MODEL

At first 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, Random Forest-CART classifier was modified to get improved results by merging it along with 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 Decision Tree-CART classifier was selected to create the prediction model. At the beginning, the tree root consists of whole dataset. Then 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. Sequential attribute selection method is resolved by Gini Impurity and Information Gain (IG) as shown in equation 1 and 2. Attribute with maximum IG will be chosen first to split data.

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

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

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

- 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 'BUILD 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(TrueRows and FalseRows) with respect to the feature with max information gain [Line 10].
- 'BUILD 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].

Algorithm 1 Decision Tree CART Classifier

1: $features \leftarrow \{AQ - 10\ questions, gender, inheritance\}$
2: $classes \leftarrow \{yes(autistic\ traits), no(no\ autistic\ traits)\}$
3: **procedure** BUILD TREE($rows$)
4: **for** each possible features **do**
5: calculate max gain
6: **end for**
7: **if** $max\ gain\ = 0$ **then**
8: **return** leaf
9: **end if**
10: $TrueRows, FalseRows \leftarrow Partition(rows)$
11: $TrueBranch \leftarrow Build\ Tree(TrueRows)$
12: $FalseBranch \leftarrow Build\ Tree(FalseRows)$
13: **return** $DecisionNode(TrueBranch, FalseBranch)$
14:
15: **procedure** CLASSIFY(row,$node$)
16: **if** $node$ = $leaf$ **then**
17: **return** $node.predictions$
18: **else**
19: $Iterate\_Tree$
20: **end if**

B. Prediction model based on Random Forest-CART

In a random forest, each node is split using the best among a subset of predictors randomly chosen. This somewhat counter intuitive strategy turns out to perform very well compared to many other 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]. 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 'p' number of decision trees of the forest, 'BUILD TREE' function is called 'p' times and the generated trees are stored in 'tree_array' [Line 4-9].
- Each decision tree is generated for 'n' 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 merged 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

Algorithm 2 Random Forest CART Classifier

```
Same as Line 1-13 of Algorithm 1
procedure BUILD FOREST(rows,p,train_ratio)
tree_array ← [ ]
while p ≠ 0 do
    train ← random(train_ratio * len(rows))
    tree ← BUILD TREE(train)
    tree_array.append(tree)
    p ← p − 1
end while
return tree_array

procedure CLASSIFY(row, tree_array[ ], p)
i ← 0, vote_yes ← 0, vote_no ← 0
while i ≠ p do
    tree ← tree_array(i)
    node ← root(tree)
    if node = leaf then
        if leaf.prediction = “Yes” then
            vote_yes ← vote_yes + 1
        else if leaf.prediction = “No” then
            vote_no ← vote_no + 1
        end if
    else
        Iterate_tree
    end if
    i ← i + 1
end while
return vote_yes > vote_no
```

Algorithm 3 Merged Random Forest Classifier

```
1: features ← {AQ10 questions, gender, inheritance}
2: classes ← {yes(autistic traits), no(no autistic traits)}
3: procedure BUILD TREE ID3(rows)
4: for each possible features do
5:     calculate max gain
6: end for
7: if max gain = 0 then
8:     return leaf
9: end if
10: TrueRows , FalseRows ← Partition(rows)
11: TrueBranch ← Build Tree ID3(TrueRows)
12: FalseBranch ← Build Tree ID3(FalseRows)
13: return DecisionNode(TrueBranch, FalseBranch)
14:
15: procedure BUILD TREE CART(rows)
16: for each possible features do
17:     calculate max gain
18: end for
19: if max gain = 0 then
20:     return leaf
21: end if
22: TrueRows , FalseRows ← Partition(rows)
23: TrueBranch ← Build Tree CART(TrueRows)
24: FalseBranch ← Build Tree CART(FalseRows)
25: return DecisionNode(TrueBranch, FalseBranch)
26:
27: procedure BUILD FOREST(rows, p, train_ratio)
28: tree_array ← [ ]
29: while p ≠ 0 do
30:     train ← random(train_ratio * len(rows))
31:     tree1 ← BUILD TREE ID3(train)
32:     tree2 ← BUILD TREE CART(train)
33:     tree_array.append(tree1)
34:     tree_array.append(tree2)
35:     p ← p − 1
36: end while
37: return tree_array
38:
39: procedure CLASSIFY(row, tree_array[ ], p)
40: i ← 0, vote_yes ← 0, vote_no ← 0
41: while i ≠ p 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_no
```

and classifying test data. Difference of it from Algorithm 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 overfitting and thus further reduces error compared to Algorithm 2. The process is described in details below:

- To construct a merged random forest classifier, BUILD FOREST function is called and ‘p’ number of ID3 trees and ‘p’ 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 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 a 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 autistic traits) or else we’ll classify test data as “No"(No autistic traits) [Line 39-55].

V. Evaluating the Prediction Model

AQ-10 dataset and data collected from real-world were used to evaluate the proposed predictive model in terms of accuracy,

Performance Parameters	AQ-10 DATASET									REAL DATASET								
	Existing Model Based on Decision Tree – CART			Existing Model Based on Random Forest-CART			Proposed Model (Random Forest- CART + Random Forest -ID3)			Existing Model Based on Decision Tree – CART			Existing Model Based on Random Forest- CART			Proposed Model (Random Forest- CART + Random Forest -ID3)		
	Child	Adolescent	Adult	Child	Adolescent	Adult	Child	Adolescent	Adult	Child	Adolescent	Adult	Child	Adolescent	Adult	Child	Adolescent	Adult
Accuracy	89.92	73.47	88.32	91.70	92.73	96.91	92.26	93.78	97.10	75.04	75.89	83.10	76.92	77.47	84.32	77.26	79.78	85.10
Specificity	89.34	69.44	89.95	88.18	82.95	96.92	88.52	84.60	97.11	72.57	69.6	81.11	74.3	71.27	83.95	75.34	71.6	84.11
Sensitivity	90.47	75.81	84.44	95.72	98.4	96.87	96.52	98.60	97.07	78.4	80.7	80.07	80.4	82.81	81.44	81.52	82.6	82.07
Precision	89.76	81.03	77.94	87.73	89.85	90.07	88.09	90.82	90.54	71.03	71.82	82.94	72.76	73.03	83.96	73.09	73.82	84.54
FPR	10.66	30.55	10.04	12.82	18.05	4.07	12.48	16.40	3.88	30.40	33.20	12.87	18.66	16.40	9.02	14.48	13.40	6.88

Fig. 1. Results of implemented prediction models

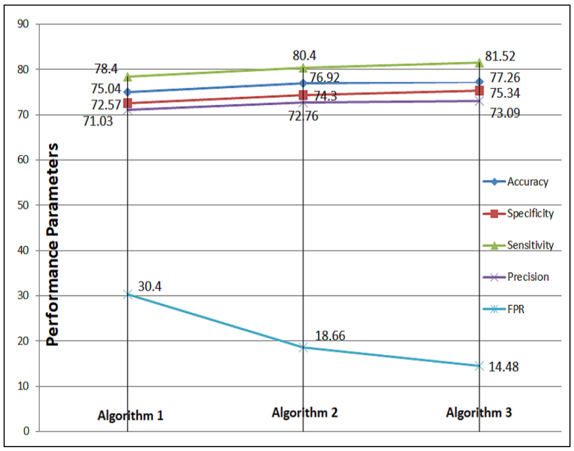

Fig. 2. Comparison of performance parameters on AQ-10 dataset of child

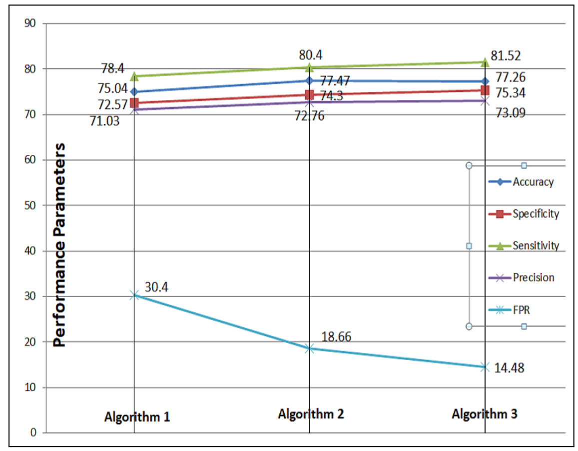

Fig. 3. Comparison of performance parameters on real dataset of child

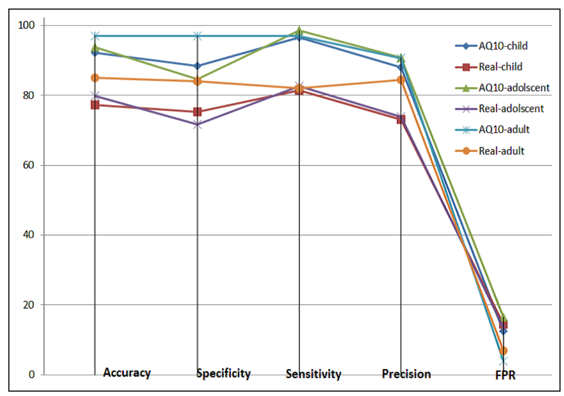

Fig. 4. Comparison of performance parameters of AQ-10 and real dataset

specificity, precision; sensitivity and false positive rate. The developed predictive model could be used to suggest non-diagnosed individuals on possible autism traits. The model would suggest a person from two possible categories: (a) YES (User has possible autism traits and requires comprehensive autism assessment), and (b) NO (User does not have autism traits). Based on the parameters stated above, implemented algorithms were tested for 3 different age groups (child, adolescent and adult) and their results were compared.

AQ-10 datasets were used to calculate performance parameters of the implemented algorithms following the Leave-One-Out Technique. In this technique, while predicting an instance, all other data except that instance will be used as training data. The results of each parameter for each implemented prediction model are shown in Figure 1 while Figure 2 represents the performance of algorithms for AQ-10 dataset of child.

The results showed that the proposed prediction model provides better results comparing to the other two existing models for each of the performance parameter; while the Random Forest (CART) showed better results comparing to the Decision Tree (CART) for each group of participants. Again, the proposed prediction model showed better results for the Adults followed by the Adolescent. Similar result was found in case of Random Forest (CART).

The models were also tested using the 250 collected real dataset, while AQ-10 datasets of child, adolescent and adult were used to train the prediction models. The prediction results for real dataset are presented in Figure 1. Figure 3 represents performance of algorithms for real dataset of child.

The accuracy, specificity, sensitivity, precision of real dataset are lower compared to the AQ10 dataset while it's FPR is higher than AQ-10 dataset (see Figure 4). Real dataset shows comaparitively less performance as the prediction models were trained using the AQ-10 dataset and as the real data were collected through survey, respondents may not be enough sincere to provide accurate information.

VI. Developing the Mobile Application

The proposed Merged Random Forest algorithm was integrated in a screening android application with the help of

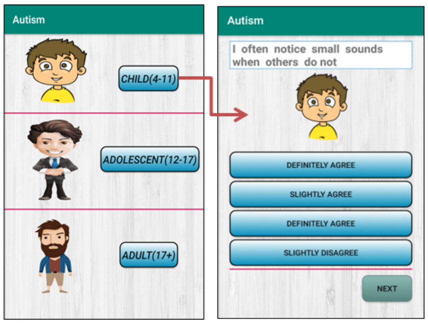

Fig. 5. User interface of ASD Screening application

Amazon Web Service (AWS). Using AWS, an API was created to call from the android app. Home screen and a transition from home screen of the application is showed in Fig. 5. The application was divided for 3 different age groups. Different questions were used for different age groups based on the three AQ-10 screening tool versions. Based on the answer of all the questions the application showed whether or not the user has autism traits.

VII. Discussions and Conclusions

A. Research Contributions

This research provides threefold outcome: firstly, a prediction model was developed to predict autism traits. Using the AQ-10 dataset, the proposed model can predict autism with 92.26%, 93.78%, and 97.10% accuracy in case of child, adolescent and adult persons, respectively. This result showed better performance comparing to the other existing approach of screening autism like [6], [7], and [8]. Moreover, the proposed model can predict autism traits for different age groups, while many other existing approaches (like [5]) missed this feature. The results showed marginal performance in terms of accuracy (77% to 85%) for real dataset. The main reason behind this marginal result was the insufficient number of real dataset.

Secondly, this research provides a comparative view among different ML approach in terms of their performance. The results showed that Random Forest-CART showed better performance than the Decision Tree-CART algorithm, while the proposed (merging Random Forest-CART and Random Forest-ID3) algorithm provide better performance comparing to both the Random Forest-CART and Decision Tree-CART algorithm.

Finally, a user-friendly mobile application has been developed for end users based on the proposed prediction model so that any individual can use the application to predict the autism traits easily. This outcome indicated an extension of many other existing work, since most of the existing works mainly focus on developing and comparing the performance of prediction model or techniques and did not expend to develop any mobile application for end users.

In sum, the outcome of this research provides an effective and efficient approach to detect autism traits for different age groups. Since diagnosing the autism traits is quite a costly and lengthy process, it's often delayed because of the difficulty of detecting autism in children and adolescents. With the help of autism screening application, an individual can be guided at an early stage that will prevent the situation from getting any worse and reduce costs associated with delayed diagnosis.

B. Limitations and Future Work

The primary limitation of the study is lack of sufficiently large data to train the prediction model. Another limitation is that, the screening application is not designed for age group below 3 years as open source data was not available that age group. Our future work will focus to collect more data from various sources and to improve 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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