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Embedded Feature Importance with Threshold-based Selection for Optimal Feature Subset in Autism Screening

Ainie Hayati Noruzman[1,*], Ngahzaifa Abd Ghani[2], Nor Saradatul Akmar Zulkifli[2], Essam Alhroob[3]

1 Department of Information and Communication Technology, Polytechnic Sultan Idris Shah, Sg. Lang, 45100 Sungai Ayer Tawar, Selangor, Malaysia
2 Faculty of Computing, College of Computing and Applied Sciences, University Malaysia Pahang Al-Sultan Abdullah, 26600 Pekan, Pahang, Malaysia
2 Faculty of Information Technology, Department of Cybersecurity, Isra University, Amman, Jordan

ABSTRACT

The early detection of autism spectrum disorders (ASD) in children poses significant challenges due to the dynamic and progressive nature of the symptoms. To The current screening process involves a lengthy and costly series of questions covering various aspects of a child's development. To address this issue, we adopt the embedded feature selection method based on random forest and threshold-based to produce a simplified version questionnaire for Autism screening. The objective of this paper is to identify the most crucial and effective features from the Quantitative Checklist for Autism in Toddlers (Q-CHAT) by combining the strengths of threshold filtering and embedded random forest feature importance. This integration allows us to significantly reduce the number of screening questions while maintaining reliable and accurate results. Our proposed method yields a streamlined alternative to traditional screening, extracting eight important features that achieves an impressive 96% accuracy performance. This promising approach holds the potential to revolutionize early detection and intervention programs for toddlers with autism, ultimately leading to improved outcomes.

Keywords:
Threshold-based filter; embedded features importance; random forest; feature selection; QCHAT; autism screening

1. Introduction

Autism Spectrum Disorder (ASD) is a complex condition characterized by challenges in social behavior, communication, language, and repetitive behaviors. Accurate detection of autism is crucial for timely intervention and support. Currently, there are two primary approaches used to identify autism which is screening and comprehensive diagnosis as mentioned by Alonso-Esteban and Alcantud-Marín [1]. Notably, screening serves as the first step taken by medical professionals to diagnose ASD disorder according to Organization for Autism Research (OAR) [2] and Filipek *et al.*, [3].

Screening for ASD involves the use of questionnaire-based instruments to assess various indicators such as communication skills, body language, motor movements, cognitive abilities, and

* *Corresponding author.*
E-mail address: ainie_hayati@psis.edu.my

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behavioral patterns. Medical professionals administer these screening tools to collect information and calculate cut-off scores based on the responses provided by parents or caregivers. The most used screening tools are the Child Behavior Checklist (CBCL), Autism Behavior Checklist (ABC), Autism Spectrum Quotient (ASQ), Childhood Autism Rating Scale (CARS), and many others. However, according to Thabtah [4], conventional screening tools often involve lengthy questionnaires that need to be completed by parents, caregivers, or medical professionals. These questionnaires can be time-consuming and burdensome, especially for parents who then will be required to carefully observe and report on their child's behaviors, which can be a time-intensive process as mentioned by Hyman *et al.,* [5]. For instance, a previous study by Wilson [6], indicates that the CBCL contains 100 items in which careful observation is required prior to answering. Therefore, identifying a small yet influential set of variables in the screening process is necessary for reducing the tedious process and speeding up referrals for patients, and using machine learning could be a potential option as suggested by Wall *et al.*, [7] and Thabtah [8] to improve the accuracy and efficiency of autism detection. The application of machine learning extends beyond healthcare domain, with notable examples such as works by Din *et al.,* [9] who have created a machine learning applications for Non-Revenue Water Management. These studies demonstrate the immense potential of machine learning across various domains. As for the future, the application of machine learning is expected to become an increasingly promising technology with multiple fields and industries.

In healthcare, applications using machines learning have been developed for early detection. Previous works by Pillai *et al.,*[10] used machine learning classifiers algorithms to predict early diagnosis of stomach cancer. Similarly, machine learning techniques can be applied to other healthcare domains such as detecting autism. In this study, we focus on the use of machine learning, particularly feature selection, for autism detection. According to Thabtah *et al.,* [11], feature selection involves finding the most meaningful attributes or characteristics that can help distinguish between individuals with autism and vice versa. These attributes could include behavioral traits, communication patterns, or medical history, among others. However, a previous study by Bone *et al.,*[12] states that existing feature selection methods often focus only on the feature space without considering feature importance or the weighting process or may overlook the interactions or dependencies between features and may not capture the full complexity of the data.

To address these limitations, this study's aim is to propose an embedded random forest feature importance with threshold-based selection to determine the most important features and selecting the most effective features in the ASD screening tool. These methods can help in the early detection and diagnosis of ASD by identifying the most important features associated with autism accordance to Wolff *et al.,* [13]. The key contribution of this study is to identify the important ASD features which can offers advantages such as effective feature selection, time efficiency, accessibility, and accurate results, thus assisting healthcare professionals in identifying individuals with ASD symptoms who may require further examination.

1.1 Embedded Random Forest Feature Importance with Threshold-Based Selection Approach (ERFFIT-bSA)

The ERFFIT-bSA is an approach that combines the Random Forest model and a threshold value to determine the importance of each feature. The Random Forest model developed by Breiman [14] is a supervised model that uses an ensemble learning method for classification, regression, and other tasks that works by constructing many decision trees at training time and outputs of the class is the mode of the classes or the mean prediction of each tree according to Alsagri and Ykhlef [15]. The embedded random forest feature importance measures the importance of each feature in the Random Forest model. It provides insights into which features have the most influence on the model's predictions. It works by evaluating each feature to the reduction based on the Gini impurity. Each of the features will have its score and then be ranked from highest to lowest where the highest score is considered the most important feature and gives better interpretability of data and model. Recently, studies by Fontana *et al.,* [16], Rodríguez-Pérez and Bajorath [17] and Alduailij *et al.,* [18] have found that the random forest feature importance has widely been used in numerous different applications promising results proven to provide reliable and accurate feature importance rating while according to Prasetiyowati *et al.*, [19] the threshold acts as a filter approach in feature selection, where the top-ranked features are selected based on their relevance to the data's intrinsic characteristics. This method improves the speed and prediction accuracy of the random forest model as stated by Wang *et al.,* [20]. By combining these two concepts, we can identify the optimal subset of features where that narrows down the feature set and focuses on the most relevant features, improving model interpretability, reducing computational complexity, and potentially enhancing prediction accuracy.

2. Methodology

In this section, the ERFFIT-bSA methodology is employed to investigate optimal feature selection using threshold and features selected from Q-CHAT10 are depicted in Figure 1.

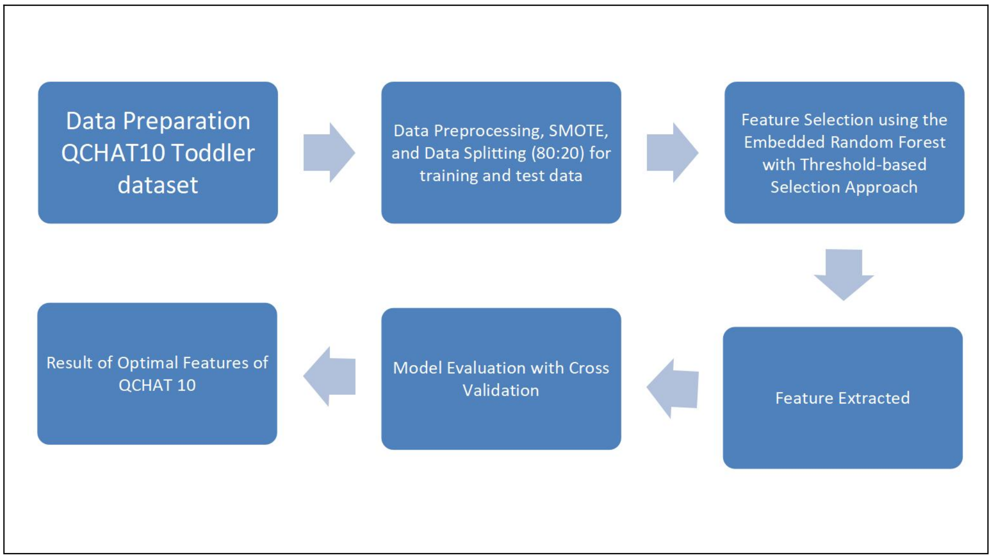

Fig. 1. The ERFFIT-bSA methodology

2.1 Data Preparation

This study examines on the Quantitative Checklist for Autism in Toddlers (Q-CHAT10), which was developed by Allison *et al.,*[21] comprising 10 items commonly used to assess autistic traits. The Q-CHAT10 dataset, sourced from Kaggle, an open-source platform, was created by Thabtah [22] for screening autism in toddlers.

The dataset's attributes descriptions are summarized in Table 1, providing a detailed overview of the questions. The Q-CHAT10 dataset consists of 1054 instances with 19 features, including 18 as input attributes and one is a class label indicating the presence of ASD. The dataset also shows an imbalance of class labels with 728 instances labeled as "Yes ASD" and 326 instances label as "No ASD". The attributes A1 through A10 are questions related to behavioral traits and individual characteristics based on symptoms of autism. These questions are indexed to correspond with the questions in the original Q-CHAT225 as developed by Allison *et al.,* [23]. Each of these items is scored on a five-point Likert scale, ranging from 0 to 4, with higher scores indicating more autistic traits.

The Q-CHAT10 score is calculated as a summative score, with a maximum score of 10 to determine whether an ASD is present. A cutoff score of 3 to 10 is considered a 'red flag' and suggests that further professional diagnostic evaluation is needed Allison *et al.,* [24]. This scoring system is crucial for early detection and intervention in children showing signs of autism.

Table 1
QCHAT10 attributes descriptions

No	Domain	Attributes
1	Does your child look at you when you call his/her name?	A1
2	How easy is it for you to get eye contact with your child?	A2
3	Does your child point to indicate that s/he wants something? (e,g., a toy that is out of reach)	A3
4	Does your child point to share an interest with you? (e.g., pointing at an interesting sight)	A4
5	Does your child pretend? (e.g., care for dolls, talk on a toy phone)	A5
6	Does your child follow where you are looking?	A6
7	If you or someone else in the family is visibly upset, does your child show signs of wanting to comfort them? (e.g., stroking hair, hugging them)	A7
8	Would you describe your child's first words as a typical	A8
9	Does your child use simple gestures?	A9
10	Does your child stare at nothing with no apparent purpose?	A10
11	Case No	case no
12	Age Mons	age
13	Q-Chat-10 score	Score
14	Sex	gender
15	Ethnicity	Ethnicity
16	Born with Jaundice	Jaundice
17	Family member with ASD history	Family member with ASD history
18	Who is completing the test	Who completing the test
19	Class (ASD)	target

2.1 Data Pre-Processing

Label encoder transformation is required for all categorical features except case number and age. Case number and Q-Chat-10 score features were removed to determine which questions in the questionnaire were most important to contribute to the best performance of the model. Because the dataset is not balanced and has no missing values, the Synthetic Minority Oversampling Technique (SMOTE) was applied. After equalization, the data set was normalized so that each column had a mean of zero and a standard deviation of one. Then, the data set was split into 80% training data and 20% test data. All preprocessing and data analysis were performed in Google collaborative open-source software with Python 3.6 using scikit-learn.

2.3 Feature Selection Based on Embedded Random Forest Feature Importance with Threshold-based Selection Approach (ERFFIT-bSA)

In our experiments, the ERFFIT-bSA model uses the Random Forest model which is the tree-based algorithm. The Random Forest model use the Gini Index calculation, where *Pi* is the probability of an object being classified to a particular class, *j* represents the Yes ASD and No ASD class and *i* represent the ratio of total number of observations in nodes based on the Random Forest model as represented in Eq. (1).

$$Gini = 1 - \sum_{i=1}^{j} (Pi)^2 \tag{1}$$

During the training process, the score for each feature is calculated and the model adjusts the internal parameters to assign the feature score and determine the feature's importance. The feature score corresponds to the threshold for deciding which features to keep and which to discard. The threshold serves as a filter-based statistical method whereby it is a straightforward and fast method since it can operate independently with or without involving any machine learning algorithms.

In this method, each of the features is iterated through a range of predefined threshold values, starting from a minimum value of 0.01 and increasing until reaching a maximum value of 0.09. The minimum value was chosen based on the nature of the problem, starting with a low threshold to observe the behaviour of the features until the maximum threshold was reached, indicating the optimal features. The range of 0.01-0.09 is used to determine the distribution of feature score, which reflects the number of selected features whose important score exceeds or equals the threshold, i.e., they are considered important and selected. In this way, we can determine the optimal set of important features for classification analysis. Eq. (2) summarizes the selection process, where *selected features* represent the set of features that meet the threshold criterion and are selected. The *importance(feature)* refers to the importance score assigned to a specific feature, and the *threshold* represents the minimum importance score required for a feature to be considered relevant and included in the selected features set.

$$\textit{selected features} = \{\textit{feature} \mid \textit{importance(feature)} \geq \textit{threshold}\} \tag{2}$$

2.4 Model Evaluation

Model evaluation is the most important part of validating the model's efficiency. Without model evaluation results, the model could be meaningless with no scientific significance. In this study, the Random Forest classifier is used for model classification performance. The Receiver Operating Characteristic (ROC) curves and the Area Under Curve (AUC) were used to assess the predictive power of the ERFFIT-bSA model. The comprehensive performance of this model was evaluated using an ROC curve that was constructed based on the true positive rate (sensitivity) and false positive rate (specificity) and use four combinations of features depicted in Eq. (3), (4), (5) and (6) which are accuracy, precision, recall and f-score where score measurement indicate TP is true positive where the number of toddlers which predicted autistic and correctly positive autistic traits, TN is true negative, indicating that the number of toddlers which predicted autistic and correctly negative having autistic traits, the false positives (FP), indicating that the total number of toddlers which predicted autistic when they actually have no autistic traits , and the false negatives (FN), indicating that the totals number of toddlers which predicted is no autistic when it actually have autistic traits.

- Accuracy indicates the correctness between prediction with overall instances in dataset.

$$\frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

- Precision is to measure the accuracy of the positive predictions made by a model, relative to all the positive predictions it made.

$$\frac{TP}{FP+TP} \tag{4}$$

- Recall is to measures the proportion of true positive predictions to all actual positive instances in the dataset.

$$\frac{TP}{FN+TP} \tag{5}$$

- F-Score is to measure balanced that considers both false positives and false negatives made by a model.

$$\frac{2X(PRECISON\ X\ RECALL)}{(PRECISION+RECALL)} \tag{6}$$

3. Results

Our study aimed to optimize the QCHAT 10 screening tool for ASD traits by reducing the number of questions while maintaining or improving accuracy. Therefore, this study is focused exclusively on the questions posed to the participants ('A1' to 'A10') for the autism screening process. The demographic features, namely gender, family member with ASD history, who is completing the test, age, ethnicity, and jaundice were not considered for selection as part of the feature set. For that reason, the analysis and findings presented here solely pertain to the questionnaire-based features ('A1' to 'A10') only so that the investigation is concentrated on the questions posed in the screening questionnaire. This approach allows for a more focused and precise assessment of the specific elements directly associated with autism screening, without effects from demographic attributes.

3.1 Features Selected by ERFFIT-bSA

Table 2 shows the results on features selected during feature selection process. We aimed to find the most effective questions for screening autism traits (ASD). Among the QCHAT 10, we found that eight questions demonstrated the highest accuracy in identifying ASD traits (A1, A2, A4, A5, A6, A7, A8, and A9). Focusing on these specific questions allowed us to streamline the screening process and make the tool more efficient in identifying ASD traits. From the results obtained in Table 2, it can be summarized that as the threshold increases, less relevant features are excluded, resulting in a more concise feature subset for the model's predictive performance. The selection process effectively narrows down the feature set, focusing on the most relevant features for the autism screening task while optimizing the model's accuracy.

To determine the optimal features, we used a threshold plot, which helped us identify the best threshold value for feature selection. This process is executed parallelly where the model iterates over all features, and for each feature, it checks if the importance score of that feature is greater than or equal to the specified threshold. If the condition is true, the feature is added to the selected features set. As a result, the selected features set contains only the features with important scores meeting the specified threshold condition.

Table 2
Feature selection results for ERFFIT-bSA model

Threshold	Selected Features	Number of Features	Not Selected Features
0.01	'A1', 'A2', 'A3', 'A4', 'A5', 'A6', 'A7','A8', 'A9', 'A10', 'Age_Mons','Ethnicity', 'Jaundice'	14	Family member with ASD history, who is completing the test
0.02	'A1', 'A2', 'A3', 'A4', 'A5', 'A6','A7', 'A8', 'A9', 'A10', 'Age_Mons', 'Ethnicity'	12	Gender, family member with ASD history, who is completing the test
0.03	'A1', 'A2', 'A4', 'A5', 'A6', 'A7', 'A8','A9', 'Age_Mons','Ethnicity'	11	A3, A10, gender, family member with ASD history, who is completing the test
0.04	'A1', 'A2', 'A4', 'A5', 'A6', 'A7', 'A8', 'A9	8	A3, A10, gender, family member with ASD history, who is completing the test, age, ethnicity, jaundice
0.05	**'A1', 'A2', 'A4', 'A5', 'A6', 'A7','A8','A9**	**8**	**A3, A10, gender, family member with ASD history, who is completing the test, age, ethnicity, jaundice**
0.06	'A2', 'A4', 'A5', 'A6', 'A7', 'A9'	6	A1, A3, A8, A10, gender, family member with ASD history, who is completing the test, age, ethnicity, jaundice
0.07	'A2', 'A4', 'A5', 'A6', 'A7', 'A9'	6	A1, A3, A8, A10, gender, family member with ASD history, who is completing the test, age, ethnicity, jaundice
0.08	'A2', 'A4', 'A5', 'A6', 'A7', 'A9	6	A1, A3, A8, A10, gender, family member with ASD history, who is completing the test, age, ethnicity, jaundice
0.09	'A4', 'A5', 'A6', 'A7', 'A9'	5	A1, A2, A3, A8, A10, gender, family member with ASD history, who is completing the test, age, ethnicity, jaundice

Figure 2 shows the results of iterating through different threshold values from 0.01 to 0.09. The plot establishes threshold values with the number of selected features at each threshold indicating that as the threshold increases, the number of selected features gradually decreases, indicating that higher thresholds lead to a smaller number of important features selection process. While Figure 3 shows the threshold 0.05 represent with the red dashed line and gives eight important features using ERFFIT-bSA model indicating that these eight features are the most influential in predicting ASD and enhancing the efficiency and effectiveness of early detection methods.

We validated this threshold by plotting the number of selected features with cross-validation AUC. The plotted number begins with 14 features and the graphs show a gradual decrease in the number of selected features until it reaches the optimal threshold of 0.05 indicating the selection of eight features with high accuracy as shown in Figure 4.

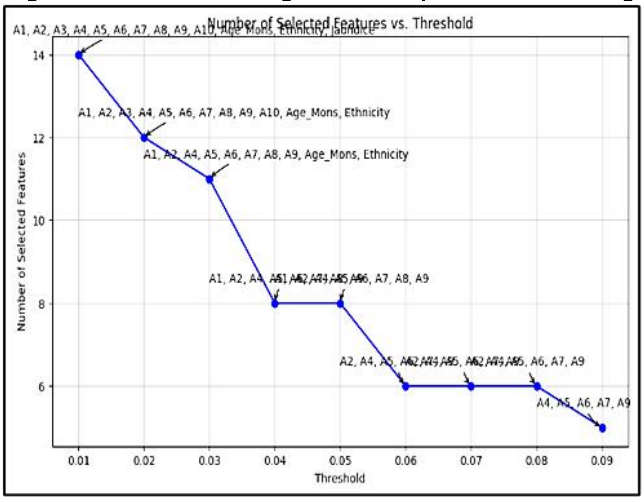

Fig. 2. Number of selected features Vs threshold

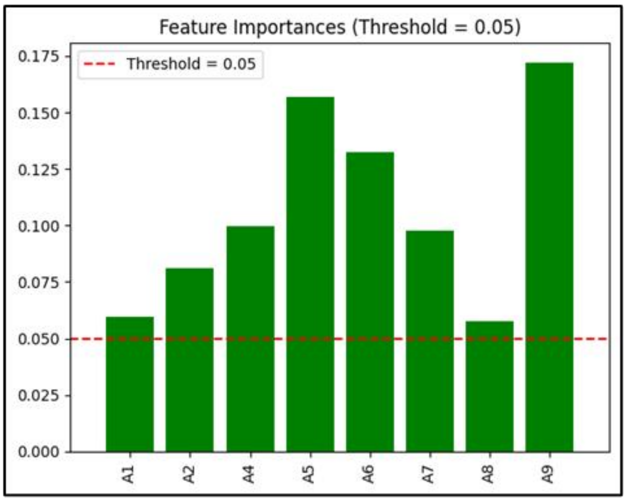

Fig. 3. Features importance of the threshold 0.05

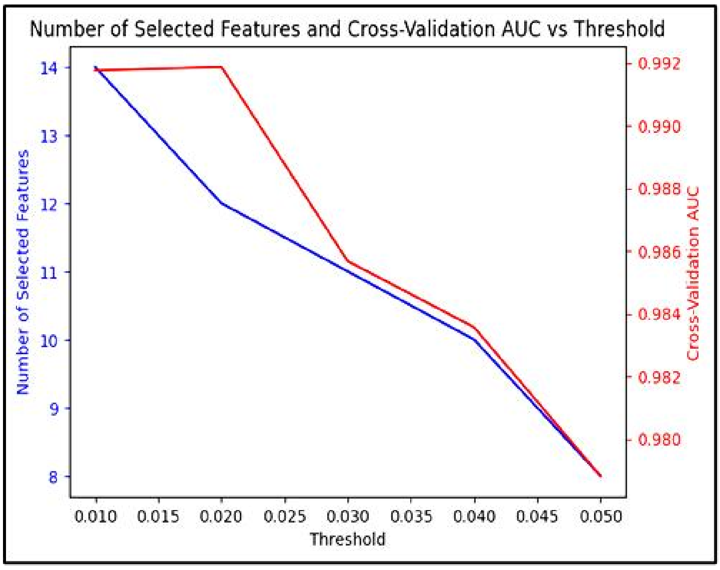

Fig. 4. Number of selected features and cross-validation AUC

3.1.1 Classification performance of ERFFIT-bSA

Table 3 shows the classification performance of ERFFIT-bSA using the QCHAT10 dataset with eight features validated by cross-validation. The model is evaluated by the Random Forest classifier and demonstrated consistently high accuracy from (0.01-0.09) indicated (0.9549 to 0.8956), along with high precision (0.9644 to 0.9192), recall (0.9710 to 0.9317), and F1-score (0.9677 to 0.9254). Overall, the model shows high accuracy precision, recall, and F1-score with more than 94% and exhibits similar performance patterns with a slight distinction in accuracy scores performance across different thresholds.

Figure 5 and Figure 6 depict the (ROC) curves, which illustrate the relationship between the true positive rate (TPR) and the false positive rate (FPR) at different classification thresholds. The Area Under the Curve (AUC) value is a measure of the overall performance of the model. The ROC curves for ERFFIT-bSA demonstrate a perfect classification performance of 100% for all features, while Figure 6, represents the ROC curves and AUC values for selected features, where ERFFIT-bSA exhibits high performance with an AUC of 0.97%. This indicates that by utilizing ERFFIT-bSA model with only selected features, the classifiers still demonstrate high performance, as reflected by their AUC values. Therefore, feature selection can still be beneficial in reducing the dimensionality of the dataset without significantly compromising the classifiers' overall performance.

Table 3
Classification Performance Of ERFFIT-bSA

Threshold	Accuracy	Precision	Recall	F1-Score
0.01	0.9549	0.9644	0.9710	0.9677
0.02	0.9537	0.9691	0.9642	0.9666
0.03	0.9419	0.9605	0.9556	0.9581
0.04	0.9371	0.9479	0.9625	0.9551
0.05	**0.9442**	**0.9576**	**0.9625**	**0.9600**
0.06	0.9371	0.9587	0.9505	0.9546
0.07	0.9181	0.9434	0.9386	0.9410
0.08	0.8956	0.9192	0.9317	0.9254
0.09	0.8956	0.9192	0.9317	0.9254

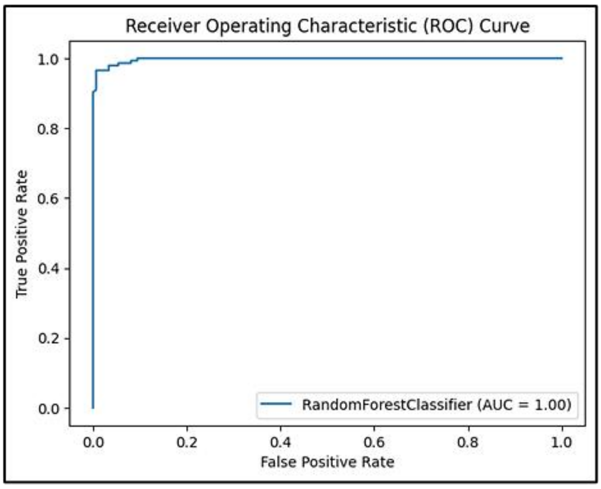

Fig. 5. ROC and AUC all features

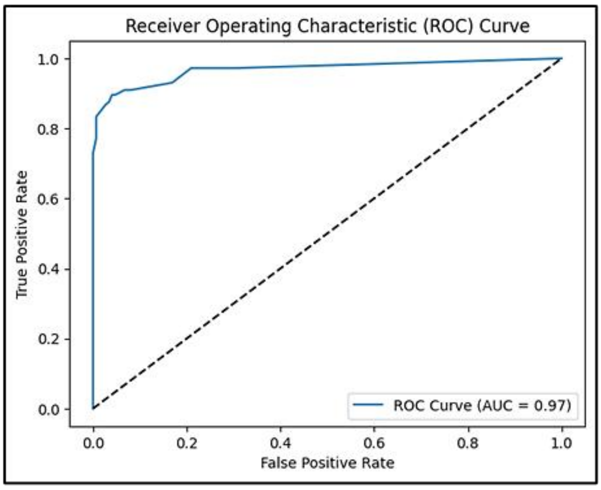

Fig. 6. ROC and AUC eight selected features

4. Conclusions

Overall, our study provides evidence supporting the optimization of the QCHAT 10 screening tool by focusing on the most informative and relevant questions. This paper introduces the Embedded Random Forest Feature Importance with the Threshold-based Selection Approach (ERFFIT-bSA) in the QCHAT 10 ASD screening tool. In our approach, the model is generated on the outputs trained using the ten-fold cross-validation (CV) technique. With the threshold of 0.05, the effective features were selected which have influential and perform predictive analysis. The feature analysis results reported that eight (8) effective features (A1, A2, A4, A5, A6, A7, A8, A9) were chosen and are mainly concerned with communication and social behaviours. With the ROC and AUC of 0.97%, this indicates that the selected features retain significant discriminatory power and contribute to accurate classification. However, our study has a limitation as it exclusively focused on analyzing the QCHAT 10 toddler screening tool. Although our results demonstrate the effectiveness of this tool in identifying autism spectrum disorders (ASD), future research should explore the application of our proposed method to broader datasets as well as the examination of screening tools with a more extensive range of features, such as the QCHAT 25, which consists of 25 question-based screening items. By expanding the scope of the analysis, we can further validate and improve the efficacy of our approach, potentially leading to even more robust and accurate early detection and intervention programs for toddlers with autism. While feature selection is an established machine learning technique, combining Random Forest feature importance with threshold-based selection, as shown in ERFFIT-bSA, offers a novel and creative solution to address ASD screening challenges.

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