Received: 7 September 2019 | Revised: 19 January 2020 | Accepted: 1 April 2020
DOI: 10.1111/exsy.12562

ORIGINAL ARTICLE

Expert Systems WILEY

Assessing the importance of autistic attributes for autism screening

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Abstract

Autistic Spectrum Disorder (ASD) is a cognitive disease which leads to the loss of linguistic, communicative, cognitive, and social skills and abilities. Patients with ASD have diverse troubles such as sleeping problems. The role of genetic and environmental factors is of great importance in its pathophysiology. Early diagnosis provides an improved overall mental health of the patients. This study aimed to identify the important attributes for the best detection of this disorder in children, adolescents and adults. To achieve this aim, Recursive Feature Elimination and Stability Selection methods that consider important attributes for target class were proposed. The attributes collected from autism screening methods and other attributes such as age and gender were examined for the disease. The results verified the combining of feature selection method and machine learning algorithm within the frame of accuracy, sensitivity and specificity evaluation metrics.

KEYWORDS

autistic spectrum disorder, importance of autistic attributes, machine learning, recursive feature elimination, stability selection

1 | INTRODUCTION

Autistic Spectrum Disorder (ASD) is a cognitive disease which leads to loss of linguistic, communicative, cognitive, and social skills and abilities (Thabtah, 2019). It describes a vast continuum of associated cognitive and neurobehavioral deficits (Swaiman et al., 2017). Overall mental health of the child increases via early diagnosis of this disease (Bekerom, 2017) which shows different symptoms in the first 3 years of children (Shivakumar & Yamini, 2017). Children and adolescents with ASD have sleeping problems (Cortesi et al., 2010). ASD changes the mirror neuron activity and reduces the brain connectivity in patients. The genetic and environmental factors are of great importance for its pathophysiology (Fakhoury, 2015).

Recently, the researchers have used several machine learning techniques for the diagnosis of this disease in a short time. For example, Bekerom examined the performances of machine learning algorithms in order to identify a set of co-occurring conditions that prove to be predictive of ASD. They firstly separated the dataset into two classes, ASD and non-ASD. Then, ASD data were separated into three classes. So, outcome variable has four classes; no ASD, mild ASD, moderate ASD and severe ASD. Machine learning algorithms used in their studies were successful for two classes but were not sufficient for four classes (Bekerom, 2017). Cortesi et al. demonstrated that sleeping problems, particularly insomnia, are substantial risk factors for children and adolescents with ASD (Cortesi et al., 2010). Fakhoury described the principal behavioral and cognitive features of ASD, and demonstrated the main points involved ASD pathophysiology and its some of the most considerable markers (Fakhoury, 2015). Thabtah discussed the advantages and disadvantages of recent machine learning studies in ASD classification. The author handled out the essential steps in order to develop the intelligent diagnostic tools using machine learning. Moreover, the author focused on the reliability of ASD screening tools using the Diagnostic and Statistical Manual of Mental

Disorders-IV (Thabtah, 2017). Wall et al. used machine learning techniques in order to examine the answers given by individuals with autism and healthy. The accuracy value of 99.9% is obtained on the 7 out of the 93 questions. Then, the accuracy of this 7-question was investigated for two datasets. One of these collected from Simons Foundation has 1,654 individuals with autism. The other one collected from Boston Autism Consortium has 322 individuals with autism. The authors obtained approximately 100% statistical accuracy for both datasets (Wall et al., 2012). In another study, Bohm et al. investigated the ASD situations for twins and non-twin siblings (Bohm et al., 2013). Yates and Couteur presented an assessment framework for professionals who encounter a child with a suspected ASD (Yates & Le Couteur, 2016). Cepedello et al. examined the psychopathology of children with ASD. The children from 6 to 16 years draw a visionary family, a human figure or a free drawing. At least, one of these three criteria, social shortage, communication complexity, and limited interests, was detected in most of the drawings of ASD children (Cepedello et al., 2017). Sharma et al. discussed social dialog disorder and restricted interests and iterative behaviors for the diagnosis of ASD (Sharma et al., 2018). Posar and Visconti demonstrated the major features of sensorial failures and the respective influences in order to tackle with several signs and symptoms of ASD. They inferred that a typical sensorial reactiveness of subjects with ASD may be important factor to understand several abnormal behaviors of subjects with ASD (Posar & Visconti, 2018). Schlebusch and Dada examined the cognitive appraisal measurements for childhood disability. The answers of 180 parents who completed the *Family Impact of Childhood Disability Scale* indicated that the participating families were affected positively or negatively from their child with ASD (Schlebusch & Dada, 2018). Finally, Thabtah et al. proposed variable analysis which is a computational intelligence method to determine the important attributes for the ASD (Thabtah et al., 2018).

In this study, the author focused on the determination of the best attributes for ASD by utilizing Recursive Feature Elimination (RFE) and Stability Selection (SS) methods on the child, adolescent and adult datasets. Answers to the questions below were sought using these methods.

1 Are the best attributes selected?
2 Do the attributes selected contribute to classification?
3 Which method is more successful?

To compare the performance of SS and RFE for the ASD classification problem, the subset of the attributes chosen by these methods were sent to the machine learning algorithms. When compared to the study presented by Thabtah et al. (2018), this study consists of different feature selection methods.

The rest of this paper, which is aimed to determine the important attributes for the ASD, is structured as follows. Section 2 describes materials and methods. Section 3 offers the experiments and results. Section 4 discusses the results and compares them with the studies in the literature. Finally, Section 5 concludes the study.

2 | MATERIAL AND METHODS

2.1 | Datasets

The datasets, Child, Adolescent and Adult, used in this study were collected from the University of California Irvine machine learning repository. Child, Adolescent and Adult datasets consist of 292, 104 and 704 instances, respectively. Each instance has 20 attributes which are sequentially presented in Table 1.

First 10 attributes in all datasets are the answers of questions (A1-A10). These questions provided by https://www.autismresearchcentre.com/arc_tests have three versions; AQ-10 Child version, AQ-10 Adolescent version and AQ-10 Adult version.

1 AQ-10 Child version is a guideline for parents. This form is used in order to complete the information about children aged 4–11 years with suspected autism without learning disability.
2 AQ-10 Adolescent version is a guideline for parents. This form is used in order to complete the information about teenager aged 12–16 with suspected autism without learning disability.
3 AQ-10 Adult version is a guideline for adults with suspected autism and without learning disability.

Attribute 11, screening score, can be between 0 and 10. Only one point can be scored for each question. If the individual score is more than 6 out of 10, he/she is considered as a specialist diagnostic assessment.

Table 1 Attributes and their descriptions

Attribute number	Attribute name	Values
1–10	Answers of questions (1–10)	Binary {0,1}
11	Screening score	Numeric values {0…0}
12	age	Number (years)
13	gender	String{male, female}
14	ethnicity	String {Others, Middle Eastern, White-European, Black, South Asian, Asian, Pasifika, Hispanic, Turkish, Latino}
15	Born with jaundice	String {no, yes}
16	Family member with Pervasive Development Disorder	String {no, yes}
17	Country of residence	String {Jordan, “United States”, Egypt, “United Kingdom”, Bahrain, Austria, Kuwait, “United Arab Emirates”, Europe, Malta, Bulgaria, “South Africa”, India, Afghanistan, Georgia, “New Zealand”, Syria, Iraq, Australia, “Saudi Arabia”, Armenia, Turkey, Pakistan, Canada, Oman, Brazil, “South Korea”, “Costa Rica”, Sweden, Philippines, Malaysia, Argentina, Japan, Bangladesh, Qatar, Ireland, Romania, Netherlands, Lebanon, Germany, Latvia, Russia, Italy, China, Nigeria, “U.S. Outlying Islands”, Nepal, Mexico, “Isle of Man”, Libya, Ghana, Bhutan}
18	Used app before	String{no, yes}
19	Relation (Who is completing the test)	String {Parent, Self, Relative, Health care professional}
20	Class (ASD)	String {no, yes}

2.2 | Attribute selection

Attribute selection, which is an important step for machine learning, presents the best attributes for target class. Determining of the significance of an attribute is very important for any disease. Researchers use the best attributes in order to build the best model for the diagnose of any disease. SS and RFE methods were explained below briefly.

The combination of “The Least Absolute Shrinkage and Selection Operator (Lasso)” and its successive regressions select a small subset of features in dataset in order to explain the output variable (Mordelet et al., 2013). SS, and also known as Randomized Lasso method introduced by Meinshausen and Bühlmann (2010) presents knowledge about the attributes for outcome variable. It presents consistent variable selection even if the necessary conditions are not provided (Mordelet et al., 2013).

RFE method (Guyon et al., 2002) selects the best attributes by using the iterative procedure below:

1 Design of the classification model.
2 Calculating of the ranking criterion for all features.
3 Removing of the feature having the smallest score.

3 | EXPERIMENTS AND RESULTS

First, some samples which consist of incomplete values (? or None) were removed from all raw datasets. Therefore, Child, Adolescent and Adult datasets include 248, 98 and 609 instances, respectively. Also, the categorical data such as no/yes, m/f (male/female) were transformed into 0/1 categorical values. For example, Middle Eastern, White-European, Black, Jordan and United States data for Country of residence attribute were transformed to categorical values in digit. As can be seen in Figure 1, the number of instances with ASD and without ASD in the Children dataset is approximately the same. I can say that the number of instances in the Adolescent dataset is very low. And, the number of instances with non-ASD is much higher than the number of instances with ASD in the Adult dataset.

After the datasets were shuffled, the best attributes were derived by SS and RFE feature selection methods which compute the importance of attributes for the target class. Table 2 presents the results obtained by RFE method on the datasets. According to the results obtained;

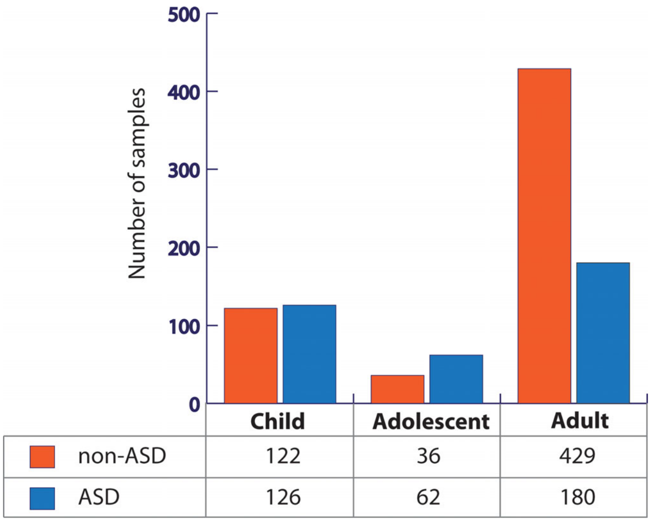


Figure 1 The statistical information about the datasets

Table 2 Attribute importance results obtained by RFE method

		Attribute importance		
Number	Attribute	Child dataset	Adolescent dataset	Adult dataset
1	Question 1	False	False	True
2	Question 2	True	False	True
3	Question 3	False	False	True
4	Question 4	True	False	True
5	Question 5	True	False	False
6	Question 6	True	False	True
7	Question 7	False	False	True
8	Question 8	False	True	True
9	Question 9	False	True	True
10	Question 10	True	False	True
11	Screening score	True	True	True
12	age	False	False	False
13	gender	False	False	True
14	ethnicity	False	False	False
15	Born with jaundice	True	False	True
16	Family member with Pervasive Development Disorder	True	True	True
17	Country of residence	False	False	False
18	Used the app before	True	True	False
19	Relation (Who is completing the test)	False	False	True

1 *Questions*: 2,4,5,6 and 10, *Attributes*: “Screening score”, “born with jaundice”, “Family member with Pervasive Development Disorder” and “used the app before” were found important for the Child dataset. So, the number of important attributes is 9.
2 *Questions*: 8 and 9, *Attributes*: “screening score,” “family member with pervasive development disorder” and “used the screening app before” were found important for the Adolescent dataset. So, the number of important attributes is 5.
3 *Questions*: 1,2,3,4,6,7,8,9 and 10, *Attributes*: “screening score,” “gender,” “born with jaundice,” “family member with pervasive development disorder” and “relation” were found important for the Adult dataset. So, the number of important attributes is 14.

These results demonstrated that two items, “Screening score” and “Family member with Pervasive Development Disorder,” were found important in common for the three datasets.

Table 3 presents the results obtained by SS method on the three datasets. According to the results obtained;

Table 3 Attribute importance obtained by SS method

		Attribute importance		
Number	**Attribute**	**Child dataset**	**Adolescent dataset**	**Adult dataset**
1	Question 1	False	True	False
2	Question 2	True	True	False
3	Question 3	True	True	True
4	Question 4	True	True	False
5	Question 5	True	True	True
6	Question 6	True	True	True
7	Question 7	True	True	False
8	Question 8	True	True	True
9	Question 9	True	True	True
10	Question 10	True	True	False
11	Screening score	True	True	True
12	age	False	True	False
13	gender	False	True	False
14	ethnicity	True	True	True
15	Born with jaundice	True	True	False
16	Family member with Pervasive Development Disorder	False	True	False
17	Country of residence	True	True	True
18	Used the app before	True	False	True
19	Relation (Who is completing the test)	True	True	False

1. *Questions*: 2,3,4,5,6,7,8,9 and 10, *Attributes*: "screening score," "ethnicity," "born with jaundice," "country of residence," "used the app before" and "relation" were found important for the Child dataset. So, the number of important attributes is 15.
2. *Questions*: 1,2,3,4,5,6,7,8,9 and 10, *Attributes*: "Screening score," "age," "gender," "ethnicity," "born with jaundice," "family member with pervasive development disorder," "country of residence" and "relation" were found important for the Adolescent dataset. So, the number of important attributes is 18.
3. *Questions*: 3,5,6,8 and 9, *Attributes*: "Screening score," "ethnicity," "country of residence" and "used the app before" were found important for the Adult dataset. So, the number of important attributes is 9.

These results demonstrated that eight items; Questions 3,5,6,8 and 9, Attributes: "score," "ethnicity," "country of residence" and "used the app before" were found important in common for these datasets.

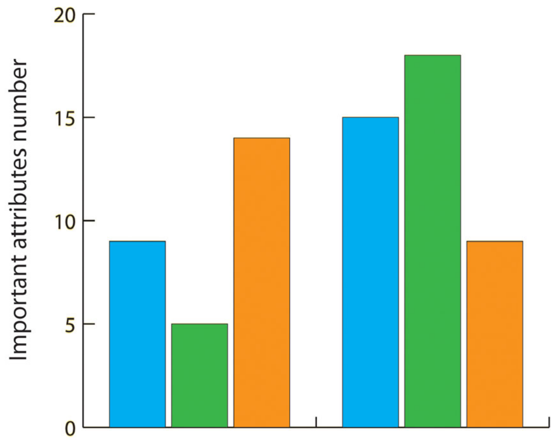
Figure 2 shows the number of important attributes chosen by these methods. Specifically, RFE selected 9, 5, and 14 items from the Child, Adolescent and Adult datasets, respectively. SS method selected 15, 18, and 9 items from the Child, Adolescent and Adult datasets, respectively.

After feature selection phases, all datasets were separated into 70–30% train and test subdatasets respectively. The information about the train and test datasets are as follows:

1. 173 train and 75 instances were reserved as train and test sets, respectively for the Child dataset.
2. 68 and 30 instances were reserved as train and test sets, respectively for the Adolescent dataset.
3. 426 and 183 instances were reserved as train and test sets, respectively for the Adult dataset.

By sending the training data as input to the following the machine learning algorithms, Multilayer Perceptron (MLP), Quadratic Discriminant Analysis (QDA), Random Forest, Support Vector Machine with "rbf" kernel (SVM with "rbf") and SVM with "linear" kernel (SVM with "linear"), training phases were conducted on the original and best attributes datasets for ASD classification. Then, the performances of these algorithms were analysed on the testing data in order to reveal the performances of SS and RFE methods dealing with the ASD.

Accuracy, specificity and sensitivity evaluation metrics (Shaikh, 2011) were used in order to evaluate the performance of classifier algorithms. Accuracy given in Equation (1) is the ratio of the number of correctly classified instances to the number of all instances. Sensitivity metric given in Equation (2) is the ratio of the number of correctly diagnosed patients with ASD to the number of all patients with ASD. Specificity metric given in Equation (3) is the ratio of the number of correctly diagnosed patients with non-ASD to the number of all patients with non-ASD.



	RFE	SS
Child	9	15
Adolescent	5	18
Adult	14	9

Figure 2 Number of selected attributes based on the RFE and SS methods

$$\text{Accuracy (Acc)} = \frac{TP + TN}{TP + FN + TN + FP} \quad (1)$$

$$\text{Sensitivity (Sen)} = \frac{TP}{TP + FN} \quad (2)$$

$$\text{Specificity (Spe)} = \frac{TN}{TN + FP} \quad (3)$$

where, TP is the number of patients with ASD correctly classified. TN is the number of patients with non-ASD correctly classified. FP is the number of patients with non-ASD incorrectly classified as ASD. FN is the number of patients with ASD incorrectly classified as non-ASD.

The experimental results and performance measures which were obtained on the testing data are presented in Table 4.

3.1.1. | Effect of RFE method

1 Child dataset: The performances of all classifier algorithms were well improved. Specifically, RF offered the best performance. The accuracy rate of this classifier on the best attributes dataset derived by the RFE method is 100% while this metric is about 92% for the original dataset.
2 Adolescent dataset: Despite the slight drop in accuracy for the MLP algorithm, RFE slightly improved the performances of the QDA and RF algorithms. Also, it well improved the performances of the SVM with "rbf" and SVM with "linear" algorithms. Specifically, RF, SVM with "rbf" and SVM with "linear" algorithms offered the best performance. The accuracy rate of the RF algorithm on the best attributes dataset derived by the RFE method is 100% while this metric is about 97% for the original dataset. The accuracy rates of the SVM with "rbf" and SVM with "linear" algorithms on the best attributes dataset derived by the RFE method are 100% and 100% while the accuracy rates are 77% and 77% for the original dataset.
3 Adult dataset: Despite the slight high in accuracy for the RF algorithm, RFE method well improved the performances of the MLP, QDA, SVM with "rbf" and SVM with "linear" algorithms. Specifically, RF offered the best performance. The accuracy rate of this classifier on the dataset derived by the RFE method is 100% while this metric is 97% for the original dataset.

3.1.2. | Effect of SS method

1 Child dataset: Despite the slight drop in accuracy for the MLP and RF algorithms, it well improved the performances of the QDA, SVM with "rbf" and SVM with "linear" algorithms. Specifically, SS and QDA offered the best performance. The accuracy rate of this classifier on the dataset derived by the SS method is 95% while this metric is 75% for the original dataset.

Table 4 Experimental results on the all, and best attributes derived by feature selection methods

Dataset		The results obtained on the all attributes			The results obtained on the features selected by RFE method			The results obtained on the features selected by SS method		
		Acc	Sen	Spe	Acc	Sen	Spe	Acc	Sen	Spe
Child	MLP	0.84	0.89	0.79	0.92	1.0	0.85	0.81	0.97	0.64
	QDA	0.75	0.86	0.64	0.92	0.94	0.9	0.95	0.92	0.97
	RF	0.92	0.94	0.9	1.0	1.0	1.0	0.91	0.97	0.83
	SVM with “rbf”	0.51	1.0	0.05	0.93	0.86	1.0	0.73	0.49	1.0
	SVM with “linear”	0.51	1.0	0.05	0.93	0.86	1.0	0.73	0.49	1.0
Adolescent	MLP	0.97	0.96	1.0	0.83	0.96	0.43	0.87	0.89	0.83
	QDA	0.87	0.83	1.0	0.9	0.96	0.71	0.9	0.89	0.92
	RF	0.97	0.96	1.0	1.0	1.0	1.0	0.97	1.0	0.92
	SVM with “bf”	0.77	1.0	0.0	1.0	1.0	1.0	0.6	1.0	0.0
	SVM with “linear”	0.77	1.0	0.0	1.0	1.0	1.0	0.6	1.0	0.0
Adult	MLP	0.77	0.0	1.0	0.97	0.98	0.97	0.97	0.93	0.98
	QDA	0.66	0.74	0.64	0.98	0.95	0.99	0.95	0.89	0.97
	RF	0.97	0.95	0.97	1.0	1.0	1.0	1.0	1.0	1.0
	SVM with “rbf”	0.78	0.02	1.0	0.87	0.43	1.0	0.87	0.56	1.0
	SVM with “linear”	0.78	0.02	1.0	0.87	0.43	1.0	0.87	0.56	1.0

2 Adolescent dataset: Despite the drop in accuracy for the MLP, SVM with “rbf” and SVM with “linear” algorithms, unchanged in accuracy for RF algorithm, and the slight high in accuracy for the QDA algorithm, specifically, RF offered best performance on the dataset obtained by SS method. The accuracy rates of this classifier on the best attributes dataset derived by the SS method, and original dataset are 97% and 97% respectively. One notable result from the adolescent dataset showed that the performance of SS method is quite low. I consider that the limited number of samples and the imbalanced data distribution cause it.

3 Adult dataset: Despite the slight high in accuracy for the RF algorithm, it quite improved the performances of other algorithms. Specifically, RF offered the best performance. The accuracy rate of this classifier on the dataset derived by the SS method is 100% while this metric is 97% for the original dataset.

By comprehensively comparing all models;

1 The RFE-RF and the SS-QDA models presented 100% and 95% accuracies, respectively on the Child dataset. Overall, the RFE-RF model presented good performance in terms of accuracy metric on the Child dataset.

2 The RFE-RF, the RFE-SVM with “rbf”, the RFE-SVM with “linear” and the SS-RF models presented good classification performances with 100%, 100%, 100% and 97% accuracies, respectively on the Adolescent dataset.

3 The RFE-RF and the SS-RF models presented good classification performances with 100% and 100% accuracies, respectively on the Adult dataset.

Since autism is a biological disease, the biological significance of the attributes also was examined. Many studies focused on this subject. For example, Geier et al. examined the biological causes of autism spectrum disorders (Geier et al., 2010). Tordjman et al. indicated that autism is a disorder which is biological and behavioral rhythms (Tordjman et al., 2015). In this context, Table 5 presents the attributes which are important in terms of biological significance.

In the experiments by RFE method, “family member with pervasive development disorder” attribute was found important for all datasets in terms of biological significance. Moreover, as expressed by https://www.autismspeaks.org/pervasive-developmental-disorder-pdd-nos, the terms “pervasive developmental disorders” and “autism spectrum disorders” were often substituted each other by psychologists and psychiatrists in the past. The strong side of the RFE algorithm is that it determined this attribute as important for three datasets. SS method found that this attribute was important only for the Adolescent dataset. “Born with jaundice” attribute was important on two of three datasets by both methods. “Ethnicity” attribute was not found as important by RFE while it was found as important by SS. Along with the attributes chosen by RFE were more effective in machine learning under the same conditions, the author indicates that “ethnicity” has little effect on the disease. The gender attribute was found to be significant only in the Adult dataset by the RFE method, and this attribute was found to be significant only in the Adolescent dataset by SS. Finally, the “age” attribute was also found to be important only by the SS and only in the Adolescent dataset.

Table 5 Examining of the attributes with respect to biological significance

Method	Dataset	Born with jaundice	Family member with pervasive development disorder	Gender	Ethnicity	Age
RFE	Child	√	√			
	Adolescent		√			
	Adult	√	√	√		
SS	Child	√			√	
	Adolescent	√	√	√	√	√
	Adult				√	

Table 6 Comparison of existing methods

Studies	Techniques	Child	Adolescent	Adult
Thabtah et al. (2018)	RIPPER	—	87.30% Sen	82.54% Sen
Demirhan (2018)	k-NN	—	89% Acc 100% Sen 74% Spe	—
	SVM	—	95% Acc 95% Sen 97% Spe	—
	Random Forest	—	100% Acc 100% Sen 100% Spe	—
Al-Diabat (2018)	Fuzzy Unordered Rule Induction	91.35% Acc 91.40% Sen	—	—
Proposed study	*RFE-RF*	100% Acc 100% Sen 100% Spe	—	—
	RFE-RF *RFE-SVM with "linear"* *RFE-SVM with "rbf"*	—	100% Acc 100% Sen 100% Spe	—
	RFE-RF *SS-RF*	—	—	100% Acc 100% Sen 100% Spe

4 | DISCUSSION

Results on the public datasets show that the performance of RFE method was superior to the SS method. The important attributes chosen by the RFE method provided an easily understood for not only readers but also biomedical researchers. More importantly, to my knowledge, there exists no study in the literature that unleashes the important attributes by utilizing these methods. Considering the results, the performance of proposed study was compared with other studies in literature and shown in Table 6. Since the datasets used in this study has been released recently, there are very few published studies using these datasets. Demirhan detected the ASD adolescent scan data using SVM, k-nearest neighbors (k-NN) and RF machine learning methods. Although RF presented good performance, there is no information about the significance of the attributes in the paper (Demirhan, 2018). Al-Diabat detected the possibility of autistic traits on the Child dataset using Fuzzy Unordered Rule Induction algorithm and found out that the accuracy and sensitivity values are 91.35% and 91.40%, respectively (Al-Diabat, 2018). For the sake of comparison, the proposed method presented the highest accuracy, sensitivity and specificity by 100%, 100% and 100% on the three datasets. This indicates that proposed method outperformed the studies by Al-Diabat, 2018 and Thabtah et al., 2018.

5 | CONCLUSION

ASD is a mental disorder which causes the linguistic lost, communicative, cognitive, and social skills and abilities. Showing different symptoms and viewed within the first 3 years of children, ASD causes sleeping problems, particularly insomnia for children and adolescents with autism. Also, the role of genetic and environmental factors is of great importance for its pathophysiology. Early diagnosis of this disease provides an improved overall mental health for the patients. Therefore, the studies have been employed on how to improve the ASD detection through the attributes obtained from the patients. In this study, first, the importance of attributes was investigated by utilizing RFE and SS methods. Then, the machine learning algorithms were implemented and compared within the frame of accuracy, sensitivity and specificity metrics in order to address that the best attributes dataset is more successful than all attributes dataset. Experimental results on Child, Adolescent and Adult datasets clearly show that the best attributes can boost up the performance of the learning algorithms. Particularly, RFE method is better than SS method based on accuracy measure for all datasets. This shows us that the feature selection is important in machine learning. It is thought that this study is useful for a real-time ASD scanning tool, and also the field specialists contribute to the literature by evaluating these results.

If the expert systems which show and interpret the features collected from a patient with ASD are not designed, medical doctors can only conclude with their observations on the patients. But, it is not feasible for medical doctors in that not only it is time-consuming, but also it is difficult. For this reason, the field experts need the knowledge of expert systems. With this respect, the author would aim a significant contribution to improve the life of ASD patients. The proposed study could assist the medical doctors in detecting the ASD in their clinical works. Moreover, it is thought that this paper, which provides a number of experimental analyses, with their results discussed, is a valuable for medical doctors and also the members of the biomedical field who need to examine the important attributes for the ASD detection. The proposed study is not only suitable for examining of the ASD patients, but also it could be adopted in developing robust expert systems.

Furthermore, the proposed study could be extended to another feature reduction method called as factor analysis. This method yields fewer factors and thus reduces the number of attributes by gathering the attributes, which are the correlations between the attributes, into a category. In the future, it is planned to use this method in the analysis of ASD data.

ACKNOWLEDGEMENTS

Author would like to thank the Thabtah (2017) for public Autism Screening datasets.

CONFLICT OF INTEREST

The author declares no potential conflict of interest.

AUTHOR CONTRIBUTIONS

Kemal Akyol developed the original idea and the protocol, abstracted and analyzed data, wrote the manuscript, and is the guarantor.

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ENDNOTE

[1] 1. http://archive.ics.uci.edu/ml//datasets/Autistic+Spectrum+Disorder+Screening+Data+for+Children++.

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How to cite this article: Akyol K. Assessing the importance of autistic attributes for autism screening. *Expert Systems*. 2020;e12562. https://doi.org/10.1111/exsy.12562