IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received October 10, 2019, accepted October 30, 2019, date of publication November 11, 2019, date of current version November 27, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2952609

Machine Learning-Based Models for Early Stage Detection of Autism Spectrum Disorders

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ABSTRACT Autism Spectrum Disorder (ASD) is a group of neurodevelopmental disabilities that are not curable but may be ameliorated by early interventions. We gathered early-detected ASD datasets relating to toddlers, children, adolescents and adults, and applied several feature transformation methods, including log, Z-score and sine functions to these datasets. Various classification techniques were then implemented with these transformed ASD datasets and assessed for their performance. We found SVM showed the best performance for the toddler dataset, while Adaboost gave the best results for the children dataset, Glmboost for the adolescent and Adaboost for the adult datasets. The feature transformations resulting in the best classifications was sine function for toddler and Z-score for children and adolescent datasets. After these analyses, several feature selection techniques were used with these Z-score-transformed datasets to identify the significant ASD risk factors for the toddler, child, adolescent and adult subjects. The results of these analytical approaches indicate that, when appropriately optimised, machine learning methods can provide good predictions of ASD status. This suggests that it may possible to apply these models for the detection of ASD in its early stages.

INDEX TERMS ASD, AQ-10 tools, classifier, FT, FST, prediction model.

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a category of neurodevelopmental disabilities that include autism proper and Asperger's syndrome. ASD cannot be cured but its early detection is desirable as it allows more effective mitigating treatment. However, ASD is very difficult to detect and diagnose by conventional behavioural studies. ASD is most often identified at around two years of age but can be later, depending on the severity of the symptoms. While there are a number of clinical tools to detect ASD as early as possible, in practice these involve onerous diagnostic processes that are not often used unless there is a strong suspicion or high risk of ASD development. Allison *et al.* [1] proposed a short quantitative checklist that can be used at several stages of the life of a patient, including toddlers, children, adolescents and young adults. Later, Thabtah *et al.* [2] developed a mobile phone application named ASDTests based on Q-CHAT and AQ-10 tools that help in the detection of ASD at early stage as possible. They also gathered ASD data using these mobile apps and uploaded this data into Kaggle and the University of California-Irvine (UCI) Machine Learning (ML) repository as open source dataset.

There have been a number of studies that have attempted to detect and diagnose ASD using a variety of ML techniques. Thabtah and Peebles [3] proposed a Rules-based ML (RML) to assess the ASD traits and found that RML enables classifiers to increase its performance. Satu *et al.* [4] demonstrated individual significant features of normal and autistic children in Bangladesh using Tree-based classifiers. Abbas *et al.* [5] combined ADI-R and ADOS ML methods into a single assessment and applied feature encoding techniques to overcome the scarcity, sparsity and data imbalance problems. In addition, another study by Thabtah *et al.* [2]

The associate editor coordinating the review of this manuscript and approving it for publication was Li He.

TABLE 1. Features description.

Feature	Type	Description
Age	Number	toddlers (month), children, adolescent, and adults(year)
Gender	String	Male or Female
Ethnicity	String	List of common ethnicities in text format
Born with jaundice	Boolean	Whether the case was born with jaundice
Family member with PDD	Boolean	Whether any immediate family member has a PDD
Who is completing the test	String	Parent, self, caregiver, medical staff, clinician, etc.
Country of residence	String	List of countries in text format
Used the screening app before	Boolean	Whether the user has used a screening app
Screening Method Type	Integer	The type of screening methods chosen based on age category
A1: Response of Q1	Binary	See Table 2 for details Q1
A2: Response of Q2	Binary	See Table 2 for details Q2
A3: Response of Q3	Binary	See Table 2 for details Q3
A4: Response of Q4	Binary	See Table 2 for details Q4
A5: Response of Q5	Binary	See Table 2 for details Q5
A6: Response of Q6	Binary	See Table 2 for details Q6
A7: Response of Q7	Binary	See Table 2 for details Q7
A8: Response of Q8	Binary	See Table 2 for details Q8
A9: Response of Q9	Binary	See Table 2 for details Q9
A10: Response of Q10	Binary	See Table 2 for details Q10
Scoring Result	Integer	See Table 2 for details
ASD	Boolean	toddlers,children,adolescent or adults diagnosed with ASD

proposed a computational intelligence (CI) method called Variable Analysis (VA) which showed feature-to-class and feature-to-feature correlations and used support vector machine (SVM), decision tree (DT) and logistic regression (LR) for robust ASD diagnoses and prognoses [6]–[9]. Duda *et al.* [10] analyzed ASD data with different classifiers and found that 5 out of 65 features were sufficient to distinguish ASD from attention deficit hyperactivity disorder (ADHD). Besides this, Goh *et al.* [11] analysed typically developed (TD) (N = 19) and ASD (N = 11) patients, where a correlation-based feature selection (CFS) was used to evaluate the importance of features. In 2015, Crippa *et al.* [12] analysed ASD and TD children and identified 15 preschool ASD from them using only 7 features. However, they suggested that cluster analysis might better capture complex features predicting an ASD phenotype and heterogeneity.

In this work, we gathered ASD datasets relating to studies of ASD characteristics in toddlers, children, adolescents and adults from the Kaggle and UCI ML repository [2]. Several feature transformation (FT) methods were applied to these datasets which converted them into a suitable format for these analyses. Different classifiers were then applied to these transformed datasets and we identified well performing ML approaches. In addition, we also explored how data transformation may improve the performance of classifiers. Several feature selection techniques (FST) were then applied to these transformed datasets to determine which classifiers gave the best results in prioritising ASD risk factors in toddlers, children, adolescents and adults. Thus, these studies indicate that ML can be utilized to determine ASD risk factors. In addition, we determined which were the best ML models to explore the predictive risk factors of ASD, finding that while several ML methods performed well the best performers differed for the type of dataset used.

II. MATERIALS AND METHODS

A. DATA

In 2012, Allison *et al.* [1], reduced the number of items of Q-CHAT and AQ tools to 10 rather than 50 using a discriminant index (DI) approach. It was split into five areas including attention to detail, attention switching, communication, imagination and social skills. Thabtah *et al.* [2] developed ASDTests app which is used Q-CHAT-10 and AQ-10 tools (AQ-10 Child, AQ-10 Adolescent and AQ-10 Adult) for screening and identifying ASD risk factors. This app calculates a score, which ranges from 0 to 10, with a final individual score of more than 6 out of 10 indicates a positive prediction of ASD. Each item is assigned values from 1 to 10. We collected N = 2009 records from Kaggle and UCI ML repository where ASDTests was used to aggregate datasets [13]–[16]. These contained datasets for toddlers (N = 1054), children

TABLE 2. Details of variables mapping.

Variable	QCHAT-10 Features (18-36 months)	AQ-10-Child Features (4-11 years)	AQ-10-Adolescent (12-15 years)	AQ-10-Adult Features (16 and older)
Q1	Does your child look at you when you call his/her name?	S/he often notices small sounds when others do not	S/he notices patterns in things all the time	I often notice small sounds when others do not
Q2	How easy is it for you to get eye contact with your child?	S/he usually concentrates more on the whole picture rather than the small details	S/he usually concentrates more on the whole picture rather than the small details	I usually concentrate more on the whole picture rather than the small details
Q3	Does your child point to indicate that s/he wants something?	In a social group, s/he can easily keep track of several different people's conversation	In a social group, s/he can easily keep track of several different people's conversations	I find it easy to do more than one thing at once
Q4	Does your child point to share interest with you?	S/he finds it easy to go back and forth between different activities	If there is an interruption, s/he can switch back to what s/he was doing very quickly	If there is an interruption, I can switch back to what I was doing very quickly
Q5	Does your child pretend?	S/he doesn't know how to keep a conversation going with his/her peers	S/he frequently finds that s/he doesn't know how to keep a conversation going	I find it easy to read between the lines when someone is talking to me
Q6	Does your child follow where you're looking?	S/he is good at social chit-chat	S/he is good at social chit-chat	I know how to tell if someone listening to me is getting bored
Q7	If you or someone else in the family is visibly upset, does your child show signs of wanting to comfort them?	When s/he is read a story, s/he finds it difficult to work out the character's intentions or feelings	When s/he was younger, s/he used to enjoy playing games involving pretending with other children	When I'm reading a story I find it difficult to work out the character's intentions
Q8	Would you describe your child's first words as:	When s/he was in preschool, s/he used to enjoy playing pretending games with otherchildren	S/he finds it difficult to imagine what it would belike to be someone else	I like to collect information about categories of things
Q9	Does your child use simple gestures?	S/he finds it easy to work out what someone is thinking or feeling just by looking at their face	S/he finds social situations easy	I find it easy to work out what someone is thinking or feeling just by looking at their face
Q10	Does your child stare at nothing with no apparent purpose?	S/he finds it hard to make new friends	S/he finds it hard to make new friends	I find it difficult to work out people's intention

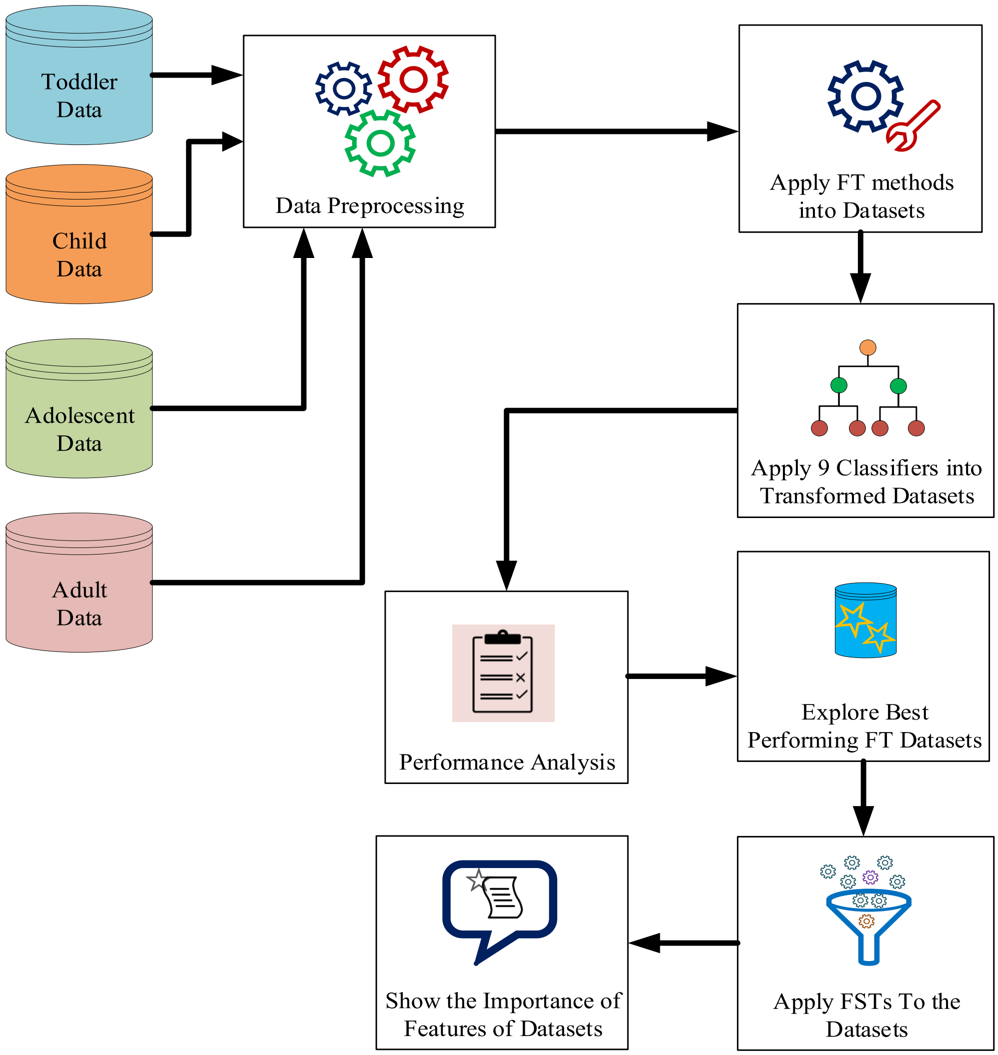


FIGURE 1. Pipeline to detect ASD at early stage.

(N = 248), adolescents (N = 98) and adults (N = 609). The datasets represent 319 (30.26%) female and 735 (69.73%) male in toddlers, 74 (29.83%) female and 174 (70.16%) male in child, 49 (50%) female and 49 (50%) male in adolescent and 288 (47.29%) female and 321 (52.70%) male in adult. Table 1 & 2 show a brief feature description of the different datasets used in this study.

B. METHODS

The datasets employed contained noisy, missing, and unwanted records which were replaced by mean values. In addition, different categorical features were encoded by corresponding integer values. Thus, different FT methods were used to reduce skewness, spread equality, linear and additive relationship of ASD datasets. Some common methods such as Log, Z-score and Sine FT methods were applied in these datasets (see details in Table 3). 250 classifiers were applied in these transformed datasets and found that 80 of them worked well. Those classifiers which showed accuracies below 70% have been omitted. Then, 9 of them which are Adaboost, FDA, C5.0, LDA, MDA, PDA, SVM and CART were finally selected. Figure 1 indicates sequential steps how to we analyzed and explored risk factors of ASD. Brief discussions on the classifiers are represented here:

TABLE 3. Brief description of different FT methods.

FTs	Details	Formula
Logarithmic	It converts excessively skewed density into a near Gaussian density [17].	$y = c\log_b(1+x)$
ZScore	It is used for converting different features into the range of -1 to 1 value.	$z = \frac{x-\mu}{\sigma}$
Sine	It transforms instances into the sine value in the interval 0 to 2π	$F_k = \sum_{j=1}^{N-1} f_j \sin\left(\frac{\pi jk}{N}\right)$

TABLE 4. Evaluation metrics.

Metrics	Details	Formula
Accuracy	This is the proportion of the sum of TP and TN divided by total number of population [30]	$Acc. = (\frac{TP+TN}{TP+FN+FP+TN})$
Kappa Statistics	This measures inter rater agreement from observed and expected accuracy for qualitative features [31].	$K_p = 1 - \frac{1-p_o}{1-p_e}$
AUROC	Two parameters are considered inclxperiuding the True Positive Rate (TPR) or sensitivity and 1-False Positive Rate (FPR) or specificity to measured the average area under the ROC for all possible orderings [32].	$TRP = \frac{TP}{TP+FN}$ $FPR = \frac{FP}{FP+TN}$
Sensitivity	This describes the proportion of the true positives versus all the predicted positives [6]	$Sens. = (\frac{TP}{TP+FN})$
Specificity	It calculates by the proportion of the true negatives versus all the predicted negatives [6]	$Spec. = 1 - (\frac{FP}{FP+TN})$
Logloss	This metric is used to evaluate the performance of the ML algorithms [33].	$L_g = \frac{-\sum_{y=1}^{j}\sum_{x=1}^{n} f(x,y) log(p(x,y))}{n}$

TABLE 5. Brief description of different FSTs.

FST	Abbreviation	Details	Formula
Correlation based Feature Subset Selection	CFSSE	It evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them [32].	$F_s = \frac{N_{*ra}}{N+N(N-1)r_n}$
Gain Ratio based Attribute Evaluation	GRAE	It justifies the worth of a feature by measuring the gain ratio with respect to the class [34].	$GR(C, A) = (H(C)_H(C\|A))/H(A)$
Info Gain based Attribute Evaluation	IGAE	It investigates the worth of a feature by measuring the information gain with respect to the class [34].	$IG(C, A) = (H(C)_H(C\|A))$
ReliefF based Attribute Evaluation	RFAE	It evaluates the worth of an attribute by repeatedly sampling an instance and considering the value of the given attribute for the nearest instance of the same and different class [35].	$R_x = P(\text{diff } X\|\text{ diff } class)$ $-P(\text{diff } X\|\text{ same } class)$

- **Adaboost:** This is a boosted classification tree based algorithm which reduces misclassification errors by iterating algorithms [18]. It can also handle missing records, and boosts multiple classifiers which can perform better. Let (x_1, y_1) be considered as the initial and (x_m, y_m) as m^{th} training instances. Then, it considered all weights

TABLE 6. Accuracy of different classifiers.

			C1	C2	C3	C4	C5	C6	C7	C8	C9
Toddlers	FT1	Median	**99.06**	95.28	97.13	97.62	96.70	97.13	96.70	98.58	95.24
		Mean	98.49	95.26	96.97	97.44	96.12	95.92	96.12	**98.77**	95.16
		Max.	**100.00**	98.10	99.05	**100.00**	98.10	98.11	98.10	**100.00**	99.06
	FT2	Median	**99.06**	95.72	97.17	97.62	96.70	95.26	96.70	**99.06**	95.24
		Mean	98.49	95.36	97.25	97.44	96.21	94.70	96.21	**98.67**	95.16
		Max.	**100.00**	98.08	**100.00**	**100.00**	98.10	99.04	98.10	**100.00**	99.06
	FT3	Median	98.58	95.28	98.10	97.62	95.75	95.25	95.75	**99.05**	96.15
		Mean	98.49	94.88	97.25	97.44	95.35	94.88	95.36	**98.77**	95.16
		Max.	**100.00**	97.14	99.05	**100.00**	98.10	97.17	98.10	**100.00**	98.11
Child	FT1	Median	96.08	96.00	96.00	98.00	**100.00**	95.92	**100.00**	96.00	92.00
		Mean	**97.20**	94.83	95.97	96.83	96.83	94.43	96.83	95.93	92.35
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT2	Median	96.08	96.00	96.00	98.00	**100.00**	92.15	**100.00**	96.08	92.00
		Mean	**97.20**	94.83	95.57	96.83	96.83	93.91	96.83	96.35	92.35
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT3	Median	96.00	95.92	95.92	**98.00**	95.92	96.00	95.92	96.00	92.23
		Mean	**97.17**	95.61	94.33	96.83	94.81	95.17	94.81	95.18	92.30
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
Adolescent	FT1	Median	90.00	90.00	90.00	90.00	**95.00**	90.00	**95.00**	90.00	90.00
		Mean	92.78	90.89	91.89	92.89	92.78	92.89	**93.89**	90.78	84.78
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT2	Median	90.00	90.00	**95.00**	90.00	**95.00**	90.00	**95.00**	90.00	90.00
		Mean	92.78	91.89	92.89	**93.89**	93.78	91.78	93.78	90.78	85.78
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT3	Median	**90.00**	**90.00**	**90.00**	**90.00**	**90.00**	89.44	**90.00**	**90.00**	**90.00**
		Mean	91.89	86.67	89.89	**92.89**	92.78	89.78	92.78	90.00	85.89
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
Adult	FT1	Median	**98.36**	94.22	96.69	96.72	95.87	95.08	96.69	96.72	92.57
		Mean	**98.36**	94.42	96.39	96.55	95.40	94.74	95.73	96.88	92.94
		Max.	**100.00**	96.72	**100.00**	98.36	96.72	96.72	98.36	98.36	96.72
	FT2	Median	**98.36**	94.22	96.72	96.72	96.69	95.90	96.69	97.54	92.57
		Mean	**98.36**	94.25	96.22	96.55	95.57	95.07	95.57	97.37	92.94
		Max.	**100.00**	96.72	**100.00**	98.36	96.72	98.36	96.72	98.36	96.72
	FT3	Median	**97.53**	95.04	95.87	96.72	95.87	95.87	95.87	**97.53**	94.26
		Mean	**97.70**	94.91	95.73	96.55	95.57	95.40	95.57	97.37	94.25
		Max.	**100.00**	98.36	98.36	98.36	96.72	96.72	96.72	98.36	98.36

of sample $D_1(i) = \frac{1}{m}$ for $i = 1, \ldots\ldots, m$, where D is declared as weights of samples for i^{th} training sample. Afterwards, it trains weak learners using a distribution of D_t and gets the hypothesis as:

$$h_t : X \in \{-1, 1\} \tag{1}$$

Then choose $\alpha_t \in R$ where α is defined as weight for this classifier. It selects Z_t as normalized factor and D_{t+1} as a distribution to update weight.

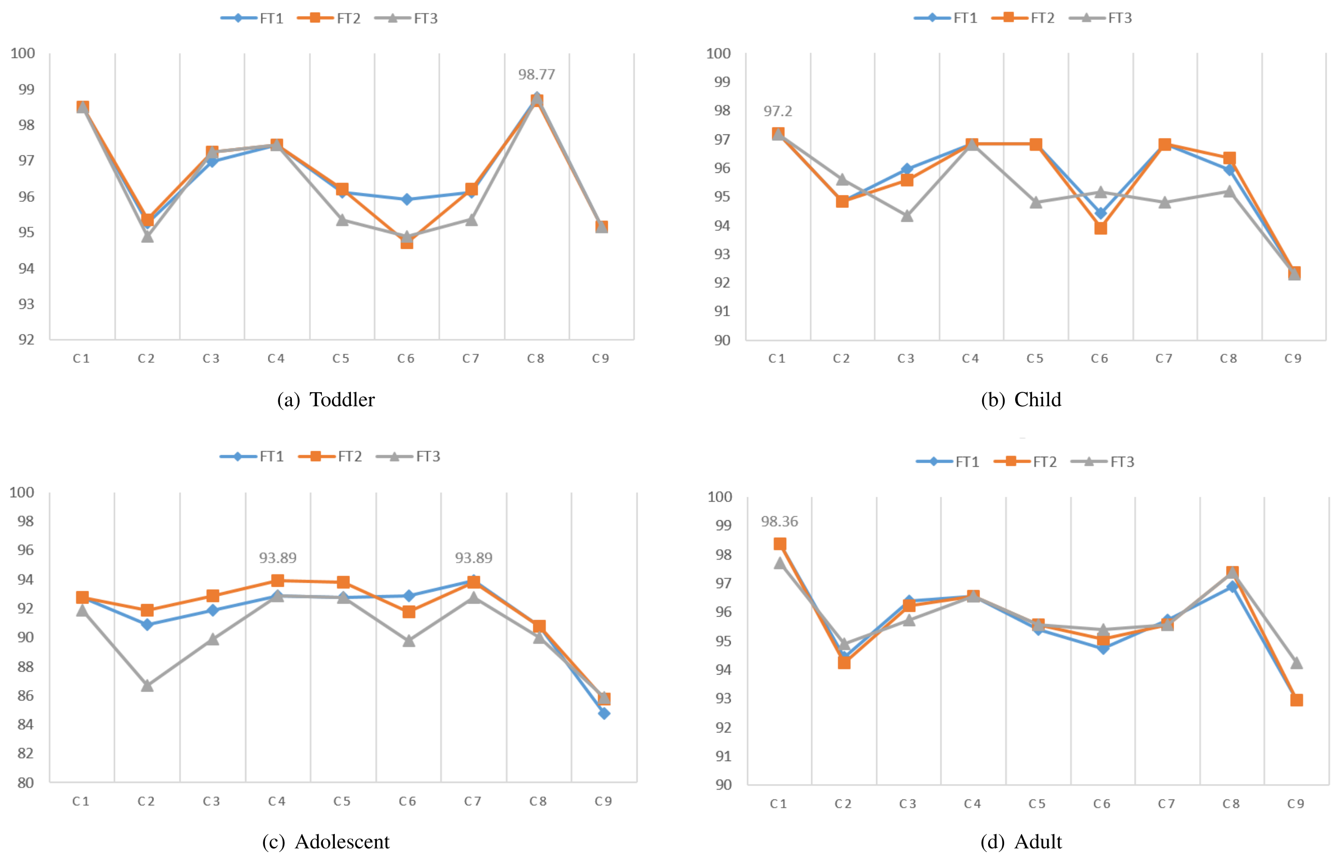
$$D_{t+1}(i) = \frac{D_t(i)e^{-\alpha_t y_i h_t(x_i)}}{Z_t} \tag{2}$$

Then the produced classifier model is:

$$D_{t+1}(i) = sign(\sum_{t=1}^{T} a_t h_t(x)) \tag{3}$$

- **Flexible Discriminant Analysis (FDA):** FDA [19] is used as a generalized bagging cross validation approach to prune this model. Pruning is an overfitting prevention method which mutually obtains linear score functions as discriminant variables and classifies into the nearest class centroid is:

$$\eta_l(x) = x^T(\beta_l) \tag{4}$$



(a) Toddler

(b) Child

(c) Adolescent

(d) Adult

FIGURE 2. Accuracy of different classifiers.

Then, the flexible Mahalanobis distance of a test point x to k^{th} class is defined by:

$$ASR = \frac{1}{N}\sum_{l=1}^{L}[\sum_{i=1}^{N}[\theta_l(g_i) - {x_i}^T\beta_l)^2] \tag{5}$$

where the $\theta_l(g)$ is identified for scores and β_l is selected for the maps to minimize the average residual. This leads to reduced memory during training. The cross validation process is used to give a reliable estimate of the predictive accuracy of the model. The estimation of generalized Cross-Validation is:

$$min_\alpha GCV(\alpha) = n^{-1}\frac{\sum_{i=1}^{n}(Y_{-i} - g(t_i))^2}{(1-n^{-1}trA(\alpha))^2} \tag{6}$$

- **Decision Tree (C5.0):** C5.0 is an improved version of C4.5 which is the divide and conquer recursive method [20]. It solves fitting, error pruning and also robust to the noise and missing data. When C5.0 is worked, it uses entropy E of a sample for measuring purity which can be expressed as:

$$P(e) = \sum_{i}^{N}(\frac{(p_i + n_i)}{(p+n)}).I(p_i, n_i) \tag{7}$$

where p is the number of positive records, n is the number of negative records and $I(p, n)$ is the entropy of function [21].

- **Boosted Generalized Linear Model (Glmboost):** Glmboost is a univariate generalized component-wise classifier to adjust with linear models. It can fit generalized linear models with $x = (x_1, \ldots, x_p)$ and (conditional) expectation μ that can represent as [22]:

$$g(\mu) = \beta_0 + \beta_1 x_1 + \ldots\ldots\ldots + \beta_p x_p \tag{8}$$

where the expectation of the response $\mu = E(y|x)$, g is indicated as the link function and β is defined as parameters.

- **Linear Discriminant Analysis (LDA):** LDA [23] is used as a classification and dimensional reduction approach by exploring a linear combination of features. We considered that there are k classes and n training samples which are defined as $\{x_1, \ldots x_n\}$ with classes $z_i \in \{1, \ldots, k\}$. The prior probability a_k is assumed to display a Gaussian distribution $\phi(x|\mu_k, \sum)$ in each class. The model estimation is then defined by:

$$a_k = \frac{\sum_{i=1}^{n} I(z_i = k)}{n} \tag{9}$$

TABLE 7. Kappa statistics of different classifiers.

			C1	C2	C3	C4	C5	C6	C7	C8	C9
Toddlers	FT1	Median	**97.80**	89.27	93.26	94.51	92.52	93.20	92.52	96.69	89.05
		Mean	96.45	89.20	92.80	94.06	91.07	90.61	91.07	**97.08**	88.53
		Max.	**100.00**	95.58	97.73	**100.00**	95.58	95.67	95.58	**100.00**	97.82
	FT2	Median	**97.80**	90.20	93.29	94.51	92.52	88.82	92.52	**97.80**	89.05
		Mean	96.45	89.39	93.48	94.06	91.28	87.31	91.28	**96.83**	88.53
		Max.	**100.00**	95.41	**100.00**	**100.00**	95.58	97.76	95.58	**100.00**	97.82
	FT3	Median	96.69	89.09	95.51	94.51	90.26	89.12	90.26	**97.79**	91.05
		Mean	96.46	88.33	93.48	94.06	89.41	88.30	89.40	**97.10**	88.63
		Max.	**100.00**	93.32	97.77	**100.00**	95.58	93.56	95.58	**100.00**	95.60
Child	FT1	Median	92.16	91.96	92.01	96.01	**100.00**	91.81	**100.00**	91.99	84.03
		Mean	**94.41**	89.68	91.94	93.67	93.68	88.86	93.68	91.86	84.67
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT2	Median	92.16	91.96	92.01	96.01	100.00	84.29	**100.00**	92.16	84.03
		Mean	**94.41**	89.68	91.15	93.67	93.67	87.83	93.67	92.70	84.67
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT3	Median	92.01	91.81	91.81	**96.01**	91.81	91.99	91.81	91.96	84.44
		Mean	**94.34**	91.24	88.69	93.67	89.64	90.35	89.64	90.37	84.54
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
Adolescent	FT1	Median	78.26	78.26	79.13	78.26	**89.13**	79.13	**89.13**	78.26	75.97
		Mean	83.67	79.41	81.57	83.99	83.48	84.54	**86.17**	79.31	65.39
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT2	Median	78.26	78.26	**90.00**	78.26	89.13	78.26	89.13	78.26	75.97
		Mean	83.67	81.78	84.35	**86.37**	85.85	82.41	85.85	79.31	67.98
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT3	Median	**78.26**	75.30	**78.26**	**78.26**	**78.26**	77.59	**78.26**	78.26	77.59
		Mean	81.62	70.01	77.65	**83.99**	83.86	77.56	83.86	77.17	68.25
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
Adult	FT1	Median	**95.99**	86.55	91.83	91.99	90.26	87.97	91.96	91.99	82.41
		Mean	**96.02**	86.78	91.12	91.64	89.00	87.35	89.74	92.35	83.25
		Max.	**100.00**	92.12	**100.00**	96.12	92.37	92.37	96.12	96.12	92.12
	FT2	Median	**95.99**	86.55	91.96	91.99	91.96	90.11	91.96	94.06	82.41
		Mean	**96.02**	86.37	90.75	91.64	89.36	87.75	89.36	93.58	83.25
		Max.	**100.00**	92.12	**100.00**	96.12	92.37	96.12	92.37	96.12	92.12
	FT3	Median	**94.17**	87.94	90.08	91.99	90.08	90.26	90.08	**94.17**	86.30
		Mean	**94.39**	87.87	89.54	91.64	89.37	88.99	89.37	93.61	86.11
		Max.	**100.00**	96.12	95.99	96.12	92.37	92.37	92.37	96.12	95.99

$$\mu_k = \frac{\sum_{i=1}^{n} x_i l(z_i = k)}{\sum_{i=1}^{n} l(z_i = k)} \tag{10}$$

$$\sum = \frac{\sum_{i=1}^{n}(x_i - \mu_{z_i})(x_i - \mu_{z_i})^T}{n} \tag{11}$$

This classifier uses Bayes theorem to estimate the probability.

- **Mixture Discriminant Analysis (MDA):** It is considered as an extension of LDA which is generated based on mixed models of classification to obtain a density estimation for each class. In this model, a single Gaussian distribution is too restricted to generate a class. For class k, the within-class density is [24]:

$$f_k(x) = \sum_{r=1}^{R_k} \pi_{kr} \phi(x|\mu_{kr}, \sum) \tag{12}$$

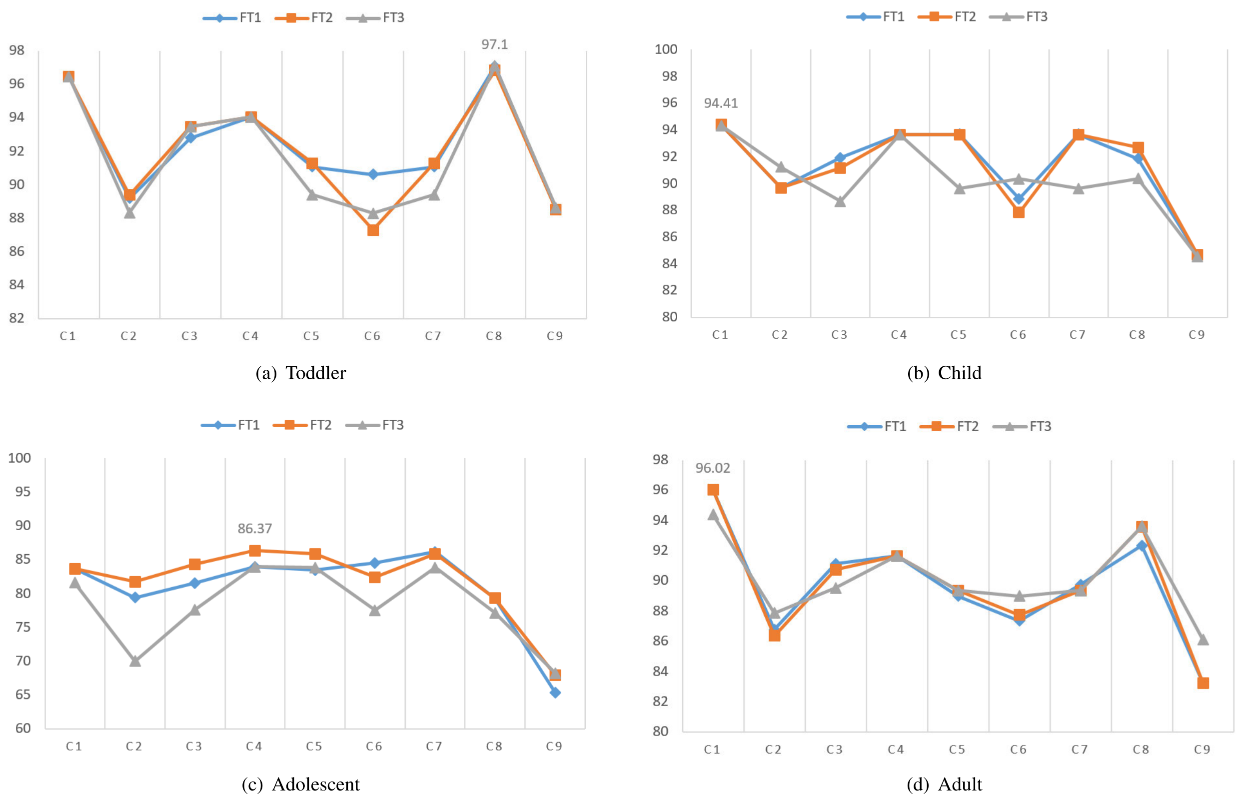
and the overall model is:

$$P(X = x, Z = k) = a_k f_k(x) = a_k \sum_{r=1}^{R_k} \pi_{kr} \phi(x|\mu_{kr}, \sum) \tag{13}$$

where a_k is the proportion of training samples in class k.

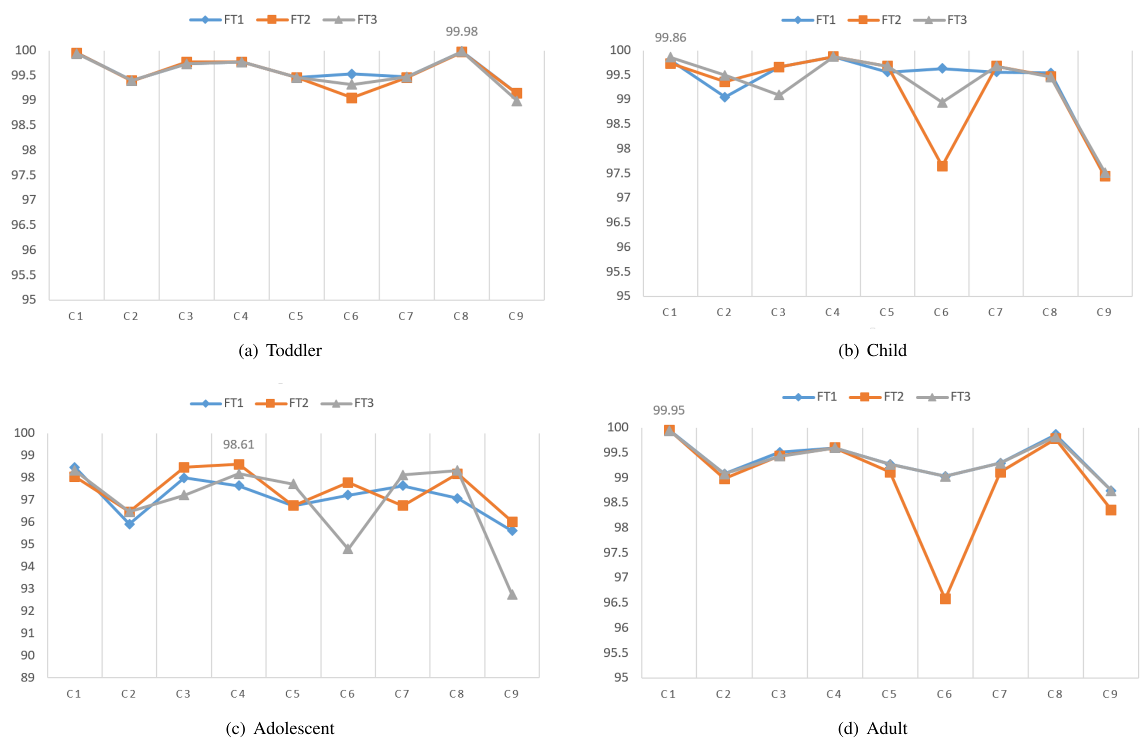
- **Penalized Discriminant Analysis (PDA):** PDA is a nonparametric statistical classifier which is developed by Hastieet *et al.* [25] to improve the performance of LDA. It shows linear combinations and contribution of predictors by generating discriminative rules [26]. If X is considered as a predictor with the basis of expansion $h(X)$, then the penalized Mahalanobis distance is given by:

$$P(x, \mu) = (h(x) - h(\mu))^T \left(\sum w + \lambda\Omega\right)^{-1} (h(x) - h(\mu)) \tag{14}$$



(a) Toddler
(b) Child
(c) Adolescent
(d) Adult

FIGURE 3. **Kappa statistics of different classifiers.**



(a) Toddler
(b) Child
(c) Adolescent
(d) Adult

FIGURE 4. **AUROC of different classifiers.**

TABLE 8. AUROC of different classifiers.

			C1	C2	C3	C4	C5	C6	C7	C8	C9
Toddlers	FT1	Median	99.98	99.58	99.81	99.81	99.67	99.75	99.67	**100.00**	99.48
		Mean	99.95	99.40	99.74	99.77	99.46	99.53	99.47	**99.98**	99.14
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	99.96	**100.00**	**100.00**	99.88
	FT2	Median	99.98	99.54	99.79	99.81	99.68	99.02	99.68	**100.00**	99.42
		Mean	99.95	99.39	99.77	99.77	99.46	99.05	99.46	**99.97**	99.14
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	99.38	**100.00**	**100.00**	99.88
	FT3	Median	99.98	99.58	99.81	99.81	99.67	99.56	99.67	**100.00**	99.48
		Mean	99.94	99.40	99.73	99.77	99.46	99.32	99.47	**99.98**	98.99
		Max.	**100.00**	99.91	**100.00**	**100.00**	99.91	99.96	99.91	**100.00**	99.64
Child	FT1	Median	**100.00**	99.65	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	97.62
		Mean	99.79	99.05	99.66	**99.87**	99.56	99.63	99.56	99.54	97.44
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT2	Median	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	98.66	**100.00**	**100.00**	97.62
		Mean	99.73	99.36	99.66	**99.87**	99.68	97.65	99.68	99.47	97.44
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT3	Median	**100.00**	**100.00**	99.31	**100.00**	**100.00**	99.65	**100.00**	**100.00**	98.26
		Mean	99.86	99.49	99.bf09	99.87	99.68	98.94	99.68	99.46	97.52
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
Adolescent	FT1	Median	**100.00**	97.92	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	98.96
		Mean	**98.47**	95.91	98.00	97.64	96.75	97.22	97.64	97.08	95.62
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT2	Median	**100.00**	97.92	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	98.96
		Mean	98.06	96.47	98.47	**98.61**	96.75	97.78	96.75	98.19	96.03
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT3	Median	**100.00**	95.83	**100.00**	**100.00**	**100.00**	95.83	**100.00**	**100.00**	91.07
		Mean	**98.33**	96.47	97.22	98.19	97.72	94.80	98.13	**98.33**	92.75
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
Adult	FT1	Median	**100.00**	98.95	99.74	99.74	99.16	99.03	99.16	99.87	98.64
		Mean	**99.95**	99.08	99.51	99.60	99.27	99.03	99.29	99.86	98.74
		Max.	**100.00**	99.87	**100.00**		99.74	99.74	99.87	**100.00**	99.74
	FT2	Median	**100.00**	98.90	99.48	99.74	99.10	98.26	99.10	99.81	98.40
		Mean	**99.95**	98.98	99.44	99.60	99.11	96.58	99.11	99.78	98.36
		Max.	**100.00**	99.74	**100.00**	**100.00**	99.74	99.87	99.74	**100.00**	99.42
	FT3	Median	**100.00**	98.95	99.42	99.74	99.16	99.02	99.16	99.87	98.64
		Mean	**99.94**	99.08	99.43	99.60	99.27	99.03	99.29	99.82	98.74
		Max.	**100.00**	99.87	**100.00**	**100.00**	99.74	99.74	99.87	**100.00**	99.74

where $\sum w$ is called within class covariance matrix of the derived variable $h(x_i)$. Using a penalized metric, this classification subspace is decomposed into:

$$\max u^T \sum u \text{ subject to } u^T(\sum + \lambda\Omega)u = 1$$

- **Support Vector Machine (SVM):** SVM is an algorithm which is used to classify both linear and nonlinear data. It works well with high dimensional data using non-linear mapping. It explores an optimal separating hyperplane (decision boundary) of one class to another. When a radial basis function is used as a kernel, SVM automatically determines centres, weights and threshold, and minimizes an upper bound of expected test error [27], [28]. If we consider a radial basis function based SVM, then it is defined as:

$$k(x, x') = exp(-\frac{\|x - x'\|^2}{2\sigma^2}) \tag{15}$$

$\|x - x'\|^2$ is identified as the squared euclidean distance between the two feature vectors and σ is a free parameter.

- **Classification and Regression Trees (CART):** This is used to explain decision trees algorithms for classification and regression learning tasks. Various bootstrap aggregated (Bagging) techniques are used which involves fitting CART to the bootstrap sample with replacement of the original sample size, repeated several times. Bagged CART is implemented using the "ipred" package in R [29].

TABLE 9. Sensitivity of different classifiers.

			C1	C2	C3	C4	C5	C6	C7	C8	C9
Toddler	FT1	Median	96.88	96.92	95.41	96.97	98.48	96.88	98.48	**100.00**	93.84
		Mean	95.72	96.02	94.18	96.95	96.64	95.39	96.65	**99.39**	92.05
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	96.97
	FT2	Median	96.88	96.92	95.41	96.97	**100.00**	90.63	**100.00**	**100.00**	92.42
		Mean	95.42	96.02	94.50	96.95	96.64	89.27	96.64	**99.08**	91.12
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	96.97	**100.00**	**100.00**	**100.00**
	FT3	Median	96.88	96.92	95.41	96.97	98.48	96.88	98.48	**100.00**	93.84
		Mean	95.72	96.02	94.18	96.95	96.64	95.39	96.65	**99.39**	92.05
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	96.97
Child	FT1	Median	**100.00**	91.67	96.15	**100.00**	**100.00**	95.83	**100.00**	**100.00**	91.67
		Mean	**97.56**	92.82	95.13	96.09	96.09	91.99	96.09	94.23	92.69
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT2	Median	**100.00**	91.67	**100.00**	**100.00**	**100.00**	91.67	**100.00**	**100.00**	91.67
		Mean	**97.56**	92.82	95.96	96.09	95.26	93.46	95.26	95.00	92.69
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT3	Median	**100.00**	95.83	96.15	**100.00**	91.67	88.14	91.67	**100.00**	91.99
		Mean	**98.40**	93.65	95.06	96.09	92.76	89.49	92.76	95.06	91.03
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
Adolescent	FT1	Median	75.00	75.00	75.00	75.00	87.50	**100.00**	**100.00**	**100.00**	75.00
		Mean	80.83	78.33	77.50	81.67	83.33	89.17	86.67	**97.50**	68.33
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT2	Median	75.00	75.00	**100.00**	87.50	87.50	**100.00**	87.50	**100.00**	75.00
		Mean	80.83	80.83	**89.17**	86.67	85.83	**89.17**	85.83	**89.17**	70.83
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT3	Median	87.50	70.83	87.50	87.50	**100.00**	87.50	**100.00**	**100.00**	75.00
		Mean	79.17	75.00	84.17	84.17	**86.67**	84.17	**86.67**	**86.67**	74.17
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
Adult	FT1	Median	**100.00**	97.65	97.67	97.67	96.51	96.51	95.35	97.67	95.35
		Mean	**99.07**	95.81	98.14	98.14	96.74	96.51	96.51	97.90	96.27
		Max.	**100.00**	97.67	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT2	Median	**100.00**	96.48	98.84	97.67	97.67	94.19	97.67	97.67	94.19
		Mean	**99.30**	95.11	98.13	98.14	96.74	94.87	96.74	98.13	94.41
		Max.	**100.00**	97.67	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT3	Median	**100.00**	97.65	97.67	97.67	96.51	96.51	95.35	97.67	95.35
		Mean	**99.07**	95.81	98.14	98.14	96.74	96.51	96.51	97.90	96.27
		Max.	**100.00**	97.67	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**

A number of evaluation metrics such as accuracy, kappa statistics, AUROC, sensitivity, specificity and logloss were considered in order to represent the outcomes of different classifiers and compare their performance based on these metrics. The metrics were represented by calculating the true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values (see details in Table 4). After evaluation, we explored the best classifiers which can represent the highest outcomes for all datasets. We also investigated these datasets to determine which different classifiers give the best results in these analyses.

We then identified the significant ASD risk factors from these datasets using different FSTs including correlation based feature subset selection (CFSS), gain ratio based attribute evaluation (GRAE), information gain based attribute evaluation (IGAE) and ReliefF based attribute evaluation (RFAE) with ranked search method (see details in Table 5)

III. EXPERIMENTAL RESULTS

In this study, we used the caret package in R for feature manipulation and classification tasks [27]. Three FT methods named Log, Scale and Sine (denoted as FT1, FT2 and FT3) were implemented into toddler, child, adolescent and adult ASD datasets. 250 classifiers were applied to these datasets and Adaboost, FDA, C5.0, Glmboost, LDA, MDA, PDA, SVM and CART (denoted as C1, C2, C3, C4, C5, C6, C7, C8 and C9 respectively) were shown the comparative outcomes and considered them for further evaluation process. Random sampling distribution with three number summary statistics (Median, Mean and Maximum) was used to generate

TABLE 10. Specificity of different classifiers.

			C1	C2	C3	C4	C5	C6	C7	C8	C9
Toddler	FT1	Median	**100.00**	95.18	98.63	97.26	95.89	95.89	95.89	**100.00**	97.24
		Mean	**99.59**	94.93	98.76	97.67	95.89	96.02	95.89	99.32	96.98
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	98.63
	FT2	Median	**100.00**	95.86	98.63	97.26	96.56	97.24	96.56	99.32	96.58
		Mean	**99.59**	95.06	98.35	97.67	96.02	96.57	96.02	99.04	96.98
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	98.63	**100.00**	**100.00**	98.63
	FT3	Median	**100.00**	94.52	98.63	97.26	95.21	95.18	95.21	**100.00**	97.24
		Mean	**99.59**	94.37	98.63	97.67	94.78	94.65	94.78	99.32	96.57
		Max.	**100.00**	97.26	**100.00**	**100.00**	98.61	98.61	98.61	**100.00**	98.63
Child	FT1	Median	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	92.31	92.31
		Mean	96.09	96.92	96.92	**97.69**	**97.69**	96.92	**97.69**	94.49	91.99
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT2	Median	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	96.15	**100.00**	92.31	92.31
		Mean	96.09	96.92	95.32	97.69	**98.46**	94.36	**98.46**	94.49	91.99
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT3	Median	**100.00**	**100.00**	96.15	**100.00**	**100.00**	96.15	**100.00**	**100.00**	96.15
		Mean	96.09	**97.69**	93.78	**97.69**	96.92	95.26	96.92	95.32	93.46
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
Adolescent	FT1	Median	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	84.52	**100.00**
		Mean	96.67	**98.33**	95.24	**98.33**	**98.33**	95.00	**98.33**	81.90	95.48
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT2	Median	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
		Mean	96.67	**98.33**	95.00	**98.33**	**98.33**	93.33	**98.33**	93.33	95.48
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT3	Median	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
		Mean	95.00	93.33	91.90	**98.33**	96.67	93.57	96.67	93.33	93.81
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
Adult	FT1	Median	94.44	94.44	91.67	94.44	94.44	91.67	94.44	**97.22**	88.89
		Mean	**96.11**	92.78	90.00	92.78	92.78	92.78	92.78	**96.11**	89.44
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT2	Median	**94.44**	**94.44**	91.67	**94.44**	**94.44**	86.11	**94.44**	**94.44**	88.89
		Mean	**96.11**	92.22	90.00	92.78	92.78	86.11	92.78	95.00	89.44
		Max.	**100.00**	**100.00**	94.44	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
	FT3	Median	94.44	91.67	86.11	94.44	94.44	91.67	94.44	**97.22**	88.89
		Mean	94.44	92.78	88.89	92.78	92.78	92.78	92.78	**96.11**	89.44
		Max.	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**

experimental results. Accuracy, Kappa Statistics, AUROC, Sensitivity, Specificity and Logloss were used to justify experimental findings. However, we represent Classification Accuracy (see Table 6), Kappa Statistics (see Table 7), AUROC (see Table 8), Sensitivity (see Table 9), Specificity (see Table 10) and Logloss (see Table 11) for classifiers from analysis of different ASD datasets.

A. EXPERIMENTAL ANALYSIS OF ACCURACY

The ASD dataset of toddler, child, adolescent and adult were analyzed by the classifiers and the accuracy of each of these are shown in Table 6. Regarding the accuracy of toddler ASD dataset, the median highest result (99.06%) was calculated by C1 for FT1, C1 and C8 for FT2 respectively. In addition, the mean highest result (98.77%) is generated by C8 for FT1 and FT3. Finally, the maximum highest result (100%) result was calculated by C1, C3, C4 and C8 where C1, C4 and C8 for all FT methods and C3 for FT2 are found in this work. When we evaluated the accuracy of child ASD dataset, the median (100%) highest result was obtained by C5 and C7 for both FT1 and FT2. The mean (97.20%) was also obtained by C1 for FT1 and FT2 respectively. On the other hand, the maximum highest result (100%) was generated by all classifiers and FT methods. Furthermore, when the accuracy of the adolescent is represented, the median highest result (95%) was calculated by C3, C5 and C7 where C5 and C7 for both FT1 and FT2 and C3 for only FT2 have gained this result. Besides this, the mean highest result (93.89%) is generated by C4 and C7 where C7 for FT1 and C4 for FT2 respectively. The maximum highest result (100%) was

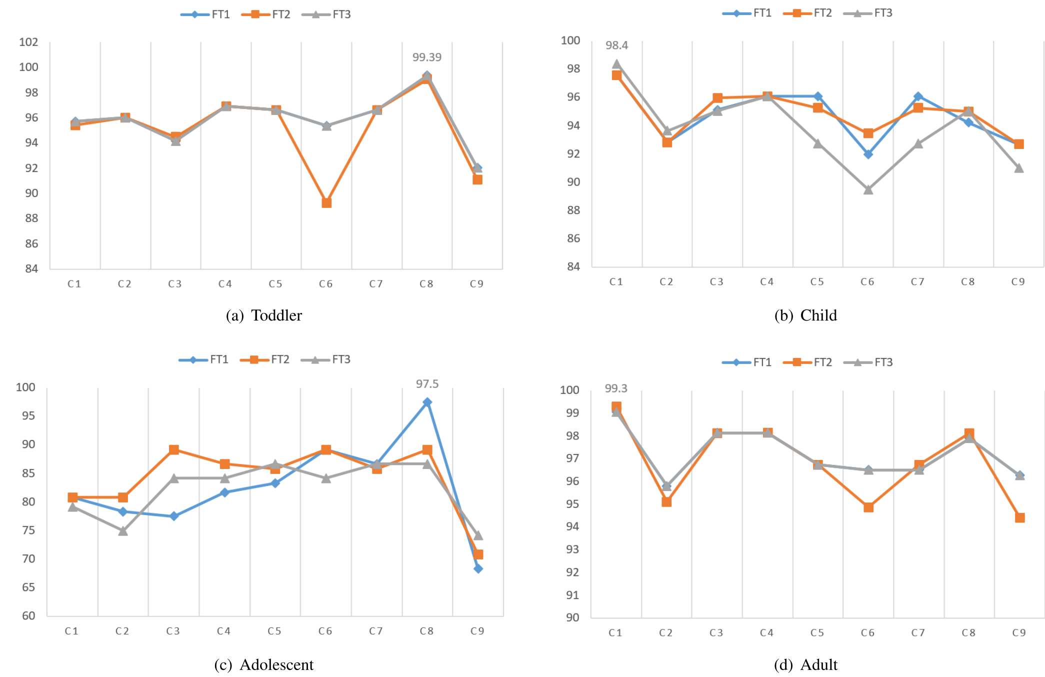
TABLE 11. Logloss of different classifiers.

			C1	C2	C3	C4	C5	C6	C7	C8	C9
Toddler	FT1	Median	4.56	11.14	10.32	16.51	10.36	10.58	10.35	**3.22**	11.78
		Mean	4.87	11.51	10.03	16.96	10.91	10.27	10.89	**3.20**	11.89
		Max.	8.03	16.28	13.36	19.59	15.67	14.79	15.62	**6.19**	16.33
	FT2	Median	4.56	11.24	10.26	16.51	10.30	12.94	10.30	**3.25**	11.84
		Mean	4.87	11.54	9.97	16.96	10.99	13.48	10.98	**3.22**	11.91
		Max.	8.03	16.25	13.09	19.59	15.58	19.54	15.58	**6.07**	16.33
	FT3	Median	4.26	10.75	10.39	16.51	10.09	10.47	10.08	**2.66**	11.47
		Mean	4.84	11.94	9.97	16.96	11.19	11.51	11.19	**3.01**	12.41
		Max.	7.64	16.84	13.49	19.59	15.59	15.74	15.60	**5.53**	17.20
Child	FT1	Median	10.66	13.67	18.29	18.74	9.16	9.33	**9.08**	11.19	21.46
		Mean	**10.22**	14.79	18.63	18.19	11.66	11.67	11.48	12.06	21.57
		Max.	**16.84**	23.10	26.09	24.76	23.87	23.03	22.03	28.08	38.99
	FT2	Median	10.67	13.35	17.05	18.91	9.28	17.20	**9.22**	11.21	21.46
		Mean	**10.42**	14.49	18.43	18.23	11.97	32.32	11.93	12.74	21.76
		Max.	**17.01**	22.73	24.63	24.76	24.87	152.64	24.95	28.86	39.39
	FT3	Median	**9.41**	12.64	21.61	19.11	11.12	15.02	10.94	9.72	20.16
		Mean	**9.62**	14.39	19.99	18.27	12.60	15.36	12.48	12.40	33.99
		Max.	**17.07**	24.24	26.80	24.76	28.95	26.66	28.76	28.26	160.53
Adolescent	FT1	Median	13.55	23.09	25.70	22.95	19.14	23.37	**12.92**	16.16	28.17
		Mean	**15.81**	24.24	28.67	22.53	30.47	32.17	24.20	21.57	31.76
		Max.	35.66	39.72	44.96	**35.36**	77.08	96.82	60.29	53.52	44.09
	FT2	Median	12.60	22.30	25.52	22.51	24.77	**11.97**	24.86	14.85	28.17
		Mean	**16.34**	23.80	27.56	22.26	30.68	26.24	31.02	20.15	31.62
		Max.	38.86	39.93	47.41	**35.72**	73.55	73.56	74.66	50.06	44.09
	FT3	Median	20.35	24.99	26.66	22.80	**17.34**	28.32	19.35	18.01	29.98
		Mean	**20.57**	23.83	29.35	22.09	25.79	44.02	25.65	21.27	34.38
		Max.	45.33	38.02	44.72	**34.06**	72.02	106.77	68.78	43.52	54.93
Adult	FT1	Median	**5.29**	13.29	13.31	16.87	10.84	11.98	10.77	6.52	16.29
		Mean	**5.64**	12.30	13.08	16.76	10.44	11.71	10.39	6.55	15.80
		Max.	**8.84**	14.93	16.05	19.14	13.19	14.99	13.11	9.25	21.53
	FT2	Median	**5.29**	13.29	13.58	16.87	10.71	18.73	10.71	6.87	16.38
		Mean	**5.64**	12.40	13.16	16.76	10.60	36.00	10.60	6.56	15.84
		Max.	8.84	15.52	15.80	19.14	15.57	115.59	15.56	**8.49**	21.53
	FT3	Median	**5.64**	12.55	13.54	16.87	10.79	10.96	10.62	6.79	16.18
		Mean	**6.05**	11.83	13.01	16.76	10.06	11.70	10.02	6.11	15.30
		Max.	10.01	14.38	16.80	19.14	13.79	16.00	13.82	**8.25**	17.95

generated by all classifiers and FT methods. Furthermore, when we observed the accuracy of the adult, the median (98.36%) and mean highest result (98.36%) were generated by C1 for FT1 and FT2 respectively. In addition, the results (100%) are shown by C1 and C3. In this case, C1 for all FT methods and C3 for FT1 and FT2 were performed best results. The average accuracy of different classifiers of toddlers, children, adolescents and adults are shown in figure 2.

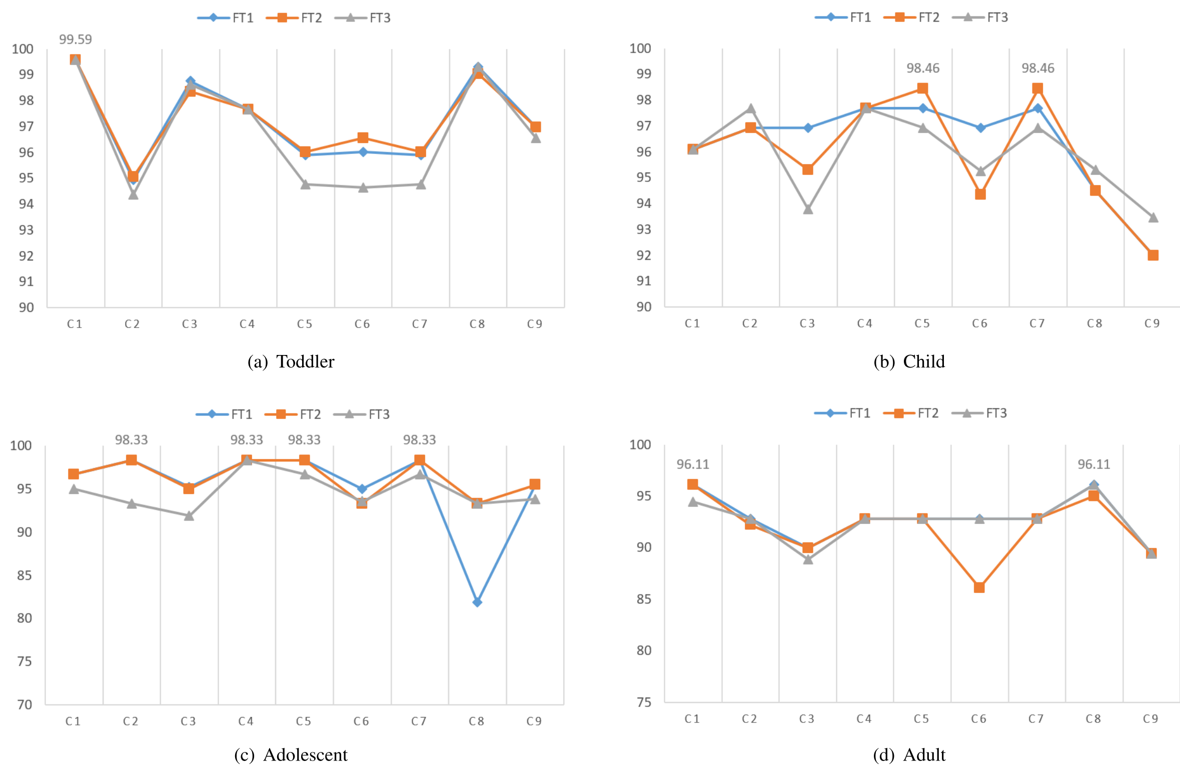
B. EXPERIMENT ANALYSIS OF KAPPA STATISTICS

We examined the experimental results of kappa statistic calculations of the toddler, children, adolescent and adult datasets, shown in Table 7. When we explored the toddlers ASD dataset, the median highest result (97.80%) was seen with C1 and C8 where C1 for FT1 and FT2, and C8 for FT3. The mean highest result (97.10%) was then calculated these findings by C8 for FT3, and the maximum highest result (100%) is seen with C1, C3, C4 and C8. In these cases, C1, C4 and C8 produced a similar result for all classifiers and FT methods, where C3 produced this result for FT2. When the Children ASD dataset was studied, the median highest result (100%) was generated by C5 and C7 and the mean highest result (94.41%) was seen with C1 for FT1 and FT2 respectively. Besides this, when we considered the adolescent



(a) Toddler (b) Child (c) Adolescent (d) Adult

FIGURE 5. Sensitivity of different classifiers.



(a) Toddler (b) Child (c) Adolescent (d) Adult

FIGURE 6. Specificity of different classifiers.

ASD dataset, the median (90.00%) and mean (86.37%) highest results are generated by C3 and C4 for FT2. The maximum (100%) highest result was shown by all classifiers using FT methods. Thereafter, we analyzed the adult ASD dataset, finding that the median (95.99%) and mean (96.02%) highest results were generated using C1 for FT1 and FT2. Lastly,

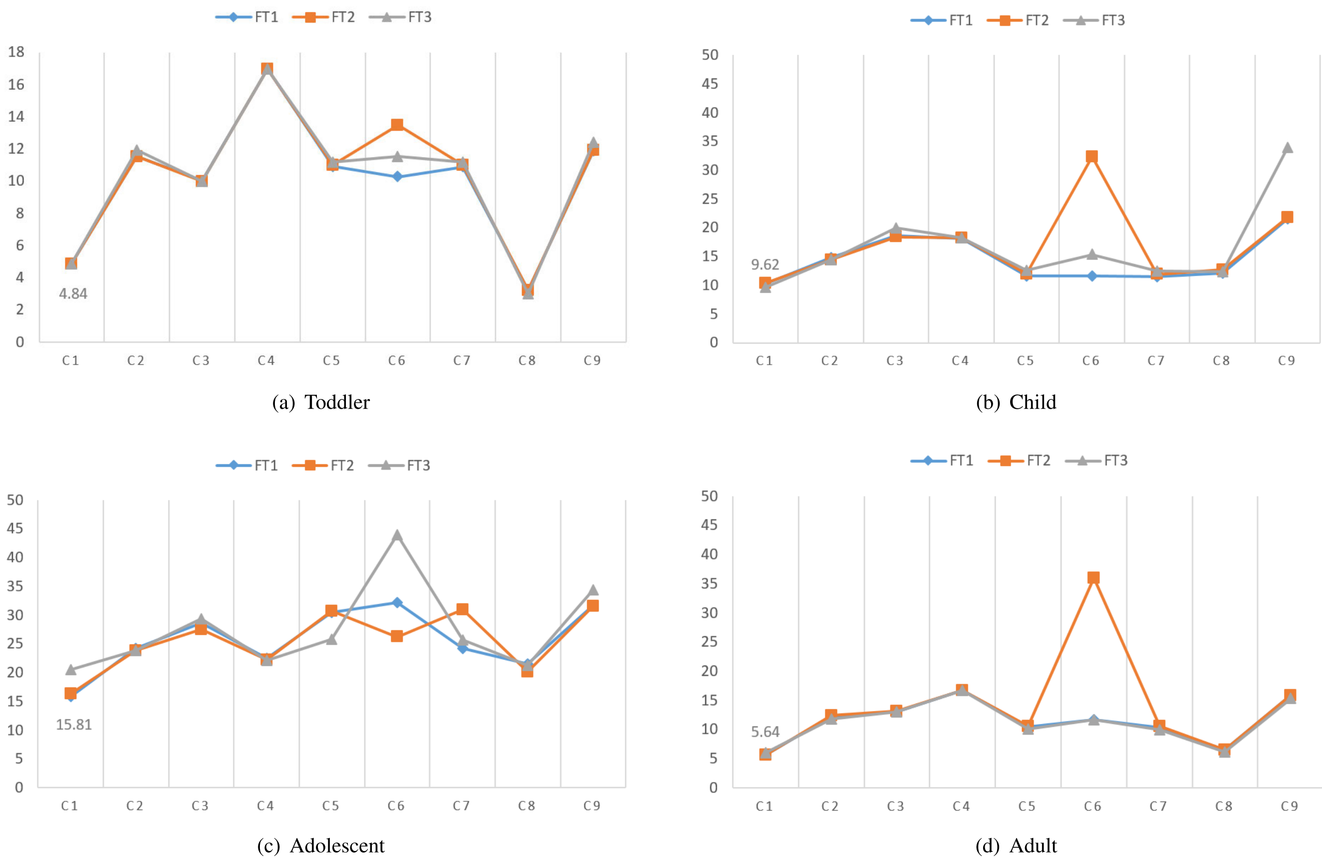


FIGURE 7. **Logloss of different classifiers.**

the maximum highest result (100%) was seen using C1 and C3 where C1 for all FT methods and C3 for FT1 and FT2 gave this outcome. The average kappa statistics of different classifiers of toddler, children, adolescent and adult datasets are shown in figure 3.

C. EXPERIMENTAL ANALYSIS OF AUROC

We analyzed AUROC to assess the predictions made for the toddler, children, adolescent and adult ASD datasets, shown in Table 8. When we investigated the results of the toddler ASD dataset, the median (100%) the highest result is generated by C8 for all FT methods. Then, the mean (99.98%) result was obtained by C8 for FT1 and FT3 methods. Afterward, the maximum (100%) highest result is gained by C1, C3, C4 and C8 for all FT methods, C2, C5 and C7 for FT1 and FT2 respectively. When we evaluated the experimental findings of child ASD dataset, the median highest result (100%) was obtained by C1, C2, C3, C4, C5, C6, C7 and C8 respectively. In this case, C1, C4, C5, C7 and C8 for all FT methods, C2 for FT2 and FT3 as well as C3 for FT1 and FT2 and C6 for FT1 showed these results. This mean (99.87%) and maximum (100%) highest results are generated by C4 and all classifiers and FT methods respectively. When the results of adolescent ASD data were examined, the median (100%) highest result is determined by C1, C3, C4, C5, C6, C7 and C8 where C1, C3, C4, C5, C7 and C8 for all FT methods and C6 for FT1 and FT2 are manipulated this result respectively. Afterward, the mean (98.61%) and the maximum (100%) highest results were calculated by C4 for FT2 and all classifiers and FT methods respectively. When we considered the outcomes of the adult ASD dataset, the median (100%) highest result was produced by C1 for all FT methods. Besides, the mean highest result (99.95%) was generated by C1 for FT1 and FT2. The maximum (100%) highest result was found by C1, C3, C4 and C8 for all FT methods. The average AUROC of different classifiers of toddler, child, adolescent and adult datasets are shown in figure 4.

D. EXPERIMENTAL ANALYSIS OF SENSITIVITY

We explored the sensitivity of toddler, children, adolescent and adult ASD datasets as shown in Table 9. When we analyzed experiment results of the toddler ASD dataset, the median (100%) was obtained by C5, C7 and C8. The mean (99.39%) highest result was obtained using C8 for FT1 and FT3, and the maximum (100%) highest result was seen for all CTs where C1, C2, C3, C4, C5, C7 and C8 for all FT methods, and C6 for FT1 and FT3. Besides this, when we analyzed the outcomes of child ASD dataset, the median (100%) was seen with calculations using C1, C3, C4, C5, C7 and C8. In this case, C1, C4 and C8 for all FT methods, C3 for FT2. C5 and C8 for FT1 and FT2 showed these results. The mean (98.40%) and maximum highest result (100%) was calculated using C1 for FT3 and all classifiers and FT methods.

TABLE 12. Feature ranking.

Features	Toddlers				Child				Adolescent				Adult			
N	CFSSE	GRAE	IGAE	RFAE	CFSSE	GRAE	IGAE	RFAE	CFSSE	GRAE	IGAE	RFAE	CFSSE	GRAE	IGAE	RFAE
A1	0.5038	0.1930	0.1908	0.2565	0.3583	0.1068	0.0959	0.1859	0.1654	0.0000	0.0000	0.0112	0.2931	0.0903	0.0746	0.1442
A2	0.4635	0.1751	0.1738	0.2965	0.2739	0.0548	0.0548	0.0786	0.1633	0.0000	0.0000	0.1082	0.3351	0.0831	0.0829	0.1997
A3	0.4097	0.1413	0.1373	0.2143	0.4078	0.1573	0.1286	0.1024	0.4375	0.1523	0.1371	0.1857	0.4350	0.1443	0.1441	0.2005
A4	0.5052	0.1994	0.1993	0.2503	0.5683	0.2524	0.2485	0.3044	0.4776	0.1924	0.1634	0.1622	0.4704	0.1766	0.1764	0.2476
A5	0.5633	0.2521	0.2516	0.3007	0.3931	0.1482	0.1193	0.1645	0.5270	0.2560	0.2012	0.2633	0.5507	0.2577	0.2572	0.3947
A6	0.5694	0.2504	0.2462	0.3010	0.4474	0.1793	0.1549	0.1294	0.4274	0.1730	0.1297	0.1276	0.6064	0.2925	0.2603	0.2644
A7	0.5632	0.2453	0.2292	0.2573	0.3374	0.0881	0.0840	0.0980	0.3277	0.0791	0.0790	0.1449	0.3553	0.0932	0.0918	0.2108
A8	0.4272	0.1443	0.1436	0.2649	0.4769	0.1713	0.1711	0.1948	0.4292	0.1405	0.1333	0.2143	0.2462	0.0518	0.0476	0.1414
A9	0.5773	0.2780	0.2779	0.3528	0.4842	0.1773	0.1765	0.1899	0.4545	0.2022	0.1476	0.0745	0.6414	0.3237	0.2998	0.3143
A10	0.1798	0.0237	0.0232	0.1411	0.4295	0.1712	0.1431	0.1863	0.5076	0.2048	0.1866	0.2133	0.3773	0.1185	0.1152	0.1635
age	0.0249	0.0000	0.0000	0.0148	0.0513	0.0000	0.0000	0.0073	0.0914	0.0000	0.0000	0.0082	0.0524	0.0000	0.0000	0.0004
gender	0.1177	0.0110	0.0098	0.0129	0.0281	0.0000	0.0000	-0.0012	0.1693	0.0000	0.0000	0.0571	0.0856	0.0000	0.0000	0.0071
ethnicity	0.0633	0.0271	0.0238	0.0248	0.0087	0.0000	0.0000	0.0039	0.2511	0.0000	0.0000	0.0531	0.2157	0.0571	0.1061	0.0309
born with jaundice	0.0741	0.0000	0.0000	0.0164	0.0002	0.0000	0.0000	-0.0008	0.0643	0.0000	0.0000	0.0531	0.1285	0.0241	0.0110	0.0082
ASD					0.0390	0.0000	0.0000	0.0008	0.0518	0.0000	0.0000	0.0265	0.1649	0.0313	0.0183	-0.0066
contry_of_res					0.0428	0.0000	0.0000	0.0165	0.2816	0.0000	0.0000	0.0626	0.0011	0.0447	0.0992	0.0158
used_app_before					0.0025	0.0000	0.0000	-0.0056	0.1637	0.0000	0.0000	0.0010	0.0579	0.0000	0.0000	0.0025
relation	0.0353	0.0000	0.0000	-0.0010	0.0926	0.0000	0.0000	0.0017	0.0755	0.0000	0.0000	0.0145	0.0282	0.0000	0.0000	0.0003

When we then evaluated the result of adolescent ASD dataset, the median highest result (100%) was seen using C3, C5, C6, C7 and C8 where C3 for FT2, C5 for FT3, C6 for FT1 and FT2 and C7 for FT1 and FT3 and C8 for all FT methods obtained this result. The mean (97.50%) and maximum (100%) highest result are generated by C8 for FT1 and all classifiers and FT methods respectively. Therefore, when we investigated the outcomes of adult ASD dataset, the median (100%) is determined by C1 for all FT methods and mean (99.30%) was also obtained FT2. Finally, the maximum highest result (100%) is analysed by C1, C3, C4, C5, C6, C7, C8 and C9 for all FT methods. The average sensitivity of different classifiers of toddlers, children, adolescents and adults are shown in figure 5.

E. EXPERIMENTAL ANALYSIS OF SPECIFICITY

We explored the specificity of toddlers, children, adolescent and adult ASD dataset that is shown in Table 10. When we investigated the experimental outcomes of the toddler ASD dataset, the median highest result (100%) was produced by C1 and C8 where C1 for all FT methods and C8 for FT1 and FT3 have generated these results. After that, the mean highest result (99.59%) was calculated by C1 classifier for all FT methods. Finally, the maximum highest results (100%) are computed by C1, C2, C3, C4, C5, C6, C7 and C8. In this case, C1, C3, C4 and C8 for all FT methods, C2, C5 and C7 for FT1 and FT2, C6 for FT1 calculated this results respectively. Besides, when the results of the child ASD dataset was explored, the median highest result (100%) was produced from C1 to C8. In this case, C1, C2, C4 and C5 for all FT methods, C3 for FT1 and FT2, C6 for FT1 and C8 for FT3 obtained this result. Therefore, the mean (98.46%) was generated by C5 and C7 for FT2 and the maximum highest result (100%) was also produced by all classifiers and FT methods respectively. Furthermore, when we observed the result of adolescent ASD dataset, the median highest results (100%) were generated by all classifiers except C8 which calculated this result for FT2 and FT3. Furthermore, the mean highest result (98.33%) is generated by C2, C4, C5 and C7 where only C4 for all FT methods and C2, C5 and C7 for FT1 and FT2 produced this outcome. We found that the maximum highest result (100%) was calculated by all classifiers and FT methods. When the findings of the adult ASD dataset was evaluated, the median (97.22%) and mean (96.11%) highest result was generated by C8 for FT1 and FT3 and by C1 and C8 where C1 for FT1 and FT2 and C8 for FT1 and FT3 respectively. Finally, the maximum highest result (100%) was seen with calculations using all classifiers. In this case, only C3 for FT1 and FT3 and other classifiers produced this result for all FT methods. The average specificity of different classifiers of toddlers, children, adolescents and adults are shown in figure 6.

F. EXPERIMENTAL ANALYSIS OF LOGLOSS

If the experimental results of logloss were explored, and the lowest logloss values considered for evaluating the experimental results (see Table 11). When we considered the outcomes of the toddler ASD dataset, the lowest median (2.66%), mean (3.01%) and maximum (5.53%) results were seen with C8 for FT3. Therefore, when the

TABLE 13. **Comparison of our model with the previous studies.**

Dataset	Authors	Acc. (%)	Sens. (%)	Spec. (%)	Kappa (%)	AUROC (%)	Logloss (%)
Toddler	Omar et al.						
	Thabtah et al.						
	Proposed Model	98.77	99.39	99.39	97.10	99.98	3.01
Child	Omar et al.	92.26					
	Thabtah et al.	97.80	98.00	97.35			
	Proposed Model	97.20	98.40	98.46	94.41	99.89	9.62
Adolescent	Omar et al.	93.78					
	Thabtah et al.	94.23	92.20	92.68			
	Proposed Model	93.89	97.50	98.33	89.37	98.61	15.81
Adult	Omar et al.	97.10					
	Thabtah et al.	99.85	99.90	99.70			
	Proposed Model	98.36	99.30	96.11	96.02	99.95	5.64

outcomes of child autism dataset were observed, the lowest median (9.07%), mean (9.62%) and maximum (16.84%) were found using C7 for FT1, C1 for FT3 and C1 for FT1. Then when we observed the results of the adolescent ASD dataset, the median (11.97%), mean (15.81%) and maximum (34.06%) are manipulated by C6 for FT2, C1 for FT1 and C4 for FT3 respectively. When we later explored the results of adult ASD dataset, the lowest median (5.29%), mean (5.64%) is generated by C1 for FT1 and FT2. The lowest maximum (8.25%) was generated by C8 for FT3. The average logloss for different classifiers of toddler, child, adolescent and adult datasets are shown in figure 7.

IV. DISCUSSION AND CONCLUSION

Many researchers have performed studies with ASD datasets, but ASD prediction still needs significant improvement [36], [37]. In our study, we gathered early detection ASD datasets of different stages of life (toddler, child, adolescent and adult) and analyzed results of using a range of different classifiers to explore the significant features of ASD. We found results of 100%, the best prediction possible, for all accuracy metrics in the random sampling distribution of experimental outcomes, but we considered averaged results to compare with previous studies. When we analyzed ASD screening data by applying different FT methods and then implemented classifiers (Adaboost, FDA, C5.0, Glmboost, LDA, MDA, PDA, SVM and CART) into these datasets in R. After this analysis, we explored significant FT methods which produce better performing outcomes than others. When we worked with the top performing 9 different classifiers using ASD screening dataset, the classifiers model predicted ASD with 98.77% (C8), 97.20% (C1), 93.89% (C4), 98.36% (C1) accuracy; 97.10% (C8), 94.41% (C1), 86.37% (C4), 96.02% (C1) kappa statistics; 99.98% (C8), 99.87% (C4), 98.61% (C4), 99.95% (C1) AUROC; 99.39% (C8), 98.40% (C1), 97.50% (C8), 99.30% (C1) sensitivity; 99.59% (C1), 98.46% (C7), 98.33% (C4), 96.11% (C1) specificity; 3.01% (C8), 9.62% (C1), 15.81% (C1), 5.64% (C1) logloss in case of toddlers, children, adolescents and adults respectively. After analyzing them, C8 (SVM) for toddlers, C1 (Adaboost) for children, C4 (Glmboost) for adolescent and C1 (Adaboost) for adults were found to give the best results respectively for any possible ASD feature sets. On the other hand, the classification outcomes of FT2 or ZScore transformed child, adolescent and adult ASD datasets showed the highest performance of any FT methods. In contrast, the classification outcomes of FT3 or Sine transformed toddler dataset also showed the highest performance compared to other FT methods in this experiment. However, we implemented a variety of different FST approaches such as CFSSE, GRAE, IGAE and RFAE into Sine transformed toddler and ZScored transformed child, adolescent and adult datasets to identify and prioritize the significant features of these datasets. In these cases, A9 and A4 were found to be the most significant features for toddler and child datasets, respectively, based on the all FSTs. For the adolescent dataset, A4 was the most significant feature according to all FSTs. Finally, for the adults, A9 was found to be the most significant feature according to CFSSE, GRAE, IGAE and A5 shows as the high ranked significant features according to RFAE. Table 12 is represented the importance of significant features of ZScored transformed datasets.

Oma *et al.* [38] developed an autism prediction model by merging Random Forest-CART (RF-CART) and Random Forest-ID3 (RF-ID3) and their proposed models predicted ASD with 92.26%, 93.78%, and 97.10% accuracy in case of children, adolescents and adults respectively for AQ-10 dataset and 77.26%, 79.78%, and 85.10% accuracy in case of children, adolescents and adults respectively for real dataset. Talabani and Engin [39] applied SVM with four types of kernels into child ASD screening datasets and found their accuracy 95.54%, 100%, 100% and 99.31% respectively in WEKA. Thabtah [40] also used ASD screening dataset for predictive analysis and computed accuracy, sensitivity and specificity rates of classifiers which were generated by NB and LR in WEKA. They got the highest results for LR as 97.94% accuracy, 98% sensitivity, 97.35% specificity for the child, 94.23% accuracy, 92.20% sensitivity, 92.68% specificity for adolescent and 99.85% accuracy, 99.90% sensitivity, 99.70% specificity for adult. However, the analysis with toddlers was not performed in many of the previous studies (see table 13). We also applied various FSTs to the ASD datasets where different classifiers show the best results and some significant features of toddler, child, adolescent and adult datasets were explored and ranked which were not shown properly in the previous studies [2], [38], [39] (see Table 13). In addition, no study has evaluated in detail the early detection based on the ASD datasets, while we used a range of metrics (AUROC, kappa statistics and logloss) to assess this [2], [38], [39] (see Table 13). Moreover, we used different FT methods which further improved the performance of the various classifiers in the four ASD datasets.

In summary, we implemented FT methods in the different stages ASD datasets, and used various classifiers to analyze these transformed data and evaluated performance. We found significant features which are highly predictive for ASD using a range of feature selection and ranking methods. This will improve the ability of physicians to detect ASD at an early stage by using our identified features. Our performance evaluations were demonstrated using a range of accuracy parameters including accuracy. Some of the classifiers did not show consistently good results because while they showed good accuracy, they produced biased results for these datasets. However, the amount of ASD data available was not large enough to fully resolve these matters. In the future, we will identify better the associated limitations of this approach, and analyse more data to improve the detection of ASD and related neurodevelopmental disorders.

REFERENCES

[1] C. Allison, B. Auyeung, and S. Baron-Cohen, "Toward brief 'red flags' for autism screening: The short autism spectrum quotient and the short quantitative checklist in 1,000 cases and 3,000 controls," *J. Amer. Acad. Child Adolescent Psychiatry*, vol. 51, no. 2, pp. 202–212, 2012.

[2] F. Thabtah, F. Kamalov, and K. Rajab, "A new computational intelligence approach to detect autistic features for autism screening," *Int. J. Med. Inform.*, vol. 117, pp. 112–124, Sep. 2018.

[3] F. Thabtah and D. Peebles, "A new machine learning model based on induction of rules for autism detection," *Health Inform. J.*, 2019, Art. no. 1460458218824711, doi: 10.1177/1460458218824711.

[4] M. S. Satu, F. F. Sathi, M. S. Arifen, M. H. Ali, and M. A. Moni, "Early detection of autism by extracting features: A case study in Bangladesh," in *Proc. 1st Int. Conf. Robot., Elect. Signal Process. Techn. (ICREST)*, Jan. 2019, pp. 87–90.

[5] H. Abbas, F. Garberson, E. Glover, and D. P. Wall, "Machine learning approach for early detection of autism by combining questionnaire and home video screening," *J. Amer. Med. Informat. Assoc.*, vol. 25, no. 8, pp. 1000–1007, 2018.

[6] F. Thabtah, "Machine learning in autistic spectrum disorder behavioral research: A review and ways forward," *Informat. Health Social Care*, vol. 44, no. 3, pp. 278–297, 2018.

[7] F. Thabtah, "Autism spectrum disorder screening: Machine learning adaptation and DSM-5 fulfillment," in *Proc. 1st Int. Conf. Med. Health Inform.*, 2017, pp. 1–6.

[8] K. C. Howlader, M. S. Satu, A. Barua, and M. A. Moni, "Mining significant features of diabetes mellitus applying decision trees: A case study in Bangladesh," *bioRxiv*, Nov. 2018, Art. no. 481994.

[9] M. A. Hossain, S. M. S. Islam, J. M. Quinn, F. Huq, and M. A. Moni, "Machine learning and bioinformatics models to identify gene expression patterns of ovarian cancer associated with disease progression and mortality," *J. Biomed. Inform.*, vol. 100, Oct. 2019, Art. no. 103313, doi: 10.1016/j.jbi.2019.103313.

[10] M. Duda, R. Ma, N. Haber, and D. P. Wall, "Use of machine learning for behavioral distinction of autism and ADHD," *Transl. Psychiatry*, vol. 6, no. 2, p. e732, 2016.

[11] K. L. Goh, S. Morris, S. Rosalie, C. Foster, T. Falkmer, and T. Tan, "Typically developed adults and adults with autism spectrum disorder classification using centre of pressure measurements," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Mar. 2016, pp. 844–848.

[12] A. Crippa, C. Salvatore, P. Perego, S. Forti, M. Nobile, M. Molteni, and I. Castiglioni, "Use of machine learning to identify children with autism and their motor abnormalities," *J. Autism Develop. Disorders*, vol. 45, no. 7, pp. 2146–2156, 2015.

[13] *Autism Screening Data for Toddlers*. Accessed: Sep. 10, 2018. [Online]. Available: https://www.kaggle.com/fabdelja/autism-screening-for-toddlers

[14] *UCI Machine Learning Repository: Autistic Spectrum Disorder Screening Data for Children Data Set*. Accessed: Sep. 10, 2018. [Online]. Available: https://archive.ics.uci.edu/ml/datasets/Autistic+Spectrum+Disorder+Screening+Data+for+Children++

[15] *UCI Machine Learning Repository: Autistic Spectrum Disorder Screening Data for Adolescent Data Set*. Accessed: Sep. 10, 2018. [Online]. Available: https://archive.ics.uci.edu/ml/datasets/Autistic+Spectrum+Disorder+Screening+Data+for+Adolescent+++

[16] *UCI Machine Learning Repository: Autism Screening Adult Data Set*. Accessed: Sep. 10, 2018. [Online]. Available: https://archive.ics.uci.edu/ml/datasets/Autism+Screening+Adult

[17] Y. Zhang, J. Wang, and X. Luo, "Probabilistic wind power forecasting based on logarithmic transformation and boundary kernel," *Energy Convers. Manage.*, vol. 96, pp. 440–451, May 2015.

[18] D. Mease, A. J. Wyner, and A. Buja, "Boosted classification trees and class probability/quantile estimation," *J. Mach. Learn. Res.*, vol. 8, pp. 409–439, Mar. 2007.

[19] H. Zhao, L. Fu, Z. Gao, Q. Ye, Z. Yang, and X. Yang, "Flexible nongreedy discriminant subspace feature extraction," *Neural Netw.*, vol. 116, pp. 166–177, Aug. 2019.

[20] T. Bujlow, T. Riaz, and J. M. Pedersen, "A method for classification of network traffic based on C5.0 machine learning algorithm," in *Proc. Int. Conf. Comput., Netw. Commun. (ICNC)*, Jan./Feb. 2012, pp. 237–241.

[21] C. Cong and C. Tsokos, "Theory and applications of decision tree with statistical software," *Age*, vol. 58, p. 250, Jun. 2009.

[22] B. Hofner, A. Mayr, N. Robinzonov, and M. Schmid, "Model-based boosting in R: A hands-on tutorial using the R package mboost," *Comput. Statist.*, vol. 29, nos. 1–2, pp. 3–35, 2014.

[23] A. Arabameri and H. R. Pourghasemi, "Spatial modeling of gully erosion using linear and quadratic discriminant analyses in GIS and R," in *Spatial Modeling in GIS and R for Earth and Environmental Sciences*. Amsterdam, The Netherlands: Elsevier, 2019, pp. 299–321.

[24] T. Hastie and R. Tibshirani, "Discriminant analysis by Gaussian mixtures," *J. Roy. Statist. Soc. B (Methodol.)*, vol. 58, no. 1, pp. 155–176, 1996.

[25] T. Hastie, A. Buja, and R. Tibshirani, "Penalized discriminant analysis," *Ann. Statist.*, vol. 23, no. 1, pp. 73–102, 1995.

[26] B. Yu, M. Ostland, P. Gong, and R. Pu, "Penalized discriminant analysis of *in situ* hyperspectral data for conifer species recognition," *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 5, pp. 2569–2577, Sep. 1999.

[27] M. S. Satu, S. Ahamed, A. Chowdhury, and M. Whaiduzzaman, "Exploring significant family income ranges of career decision difficulties of adolescents in Bangladesh applying regression techniques," in *Proc. Int. Conf. Elect., Comput. Commun. Eng. (ECCE)*, Feb. 2019, pp. 1–6.

[28] S. Huang, N. Cai, P. P. Pacheco, S. Narrandes, Y. Wang, and W. Xu, "Applications of support vector machine (SVM) learning in cancer genomics," *Cancer Genomics Proteomics*, vol. 15, no. 1, pp. 41–51, Jan./Feb. 2018.

[29] B. K. Lee, J. Lessler, and E. A. Stuart, "Improving propensity score weighting using machine learning," *Statist. Med.*, vol. 29, no. 3, pp. 337–346, 2010.

[30] M. S. Satu, T. Akter, and M. J. Uddin, "Performance analysis of classifying localization sites of protein using data mining techniques and artificial neural networks," in *Proc. Int. Conf. Elect., Comput. Commun. Eng. (ECCE)*, Feb. 2017, pp. 860–865.

[31] M. S. Satu, T. Akter, M. S. Arifen, and M. R. Mia, "Predicting accidental locations of Dhaka-Aricha highway in Bangladesh using different data mining techniques," *Int. J. Comput. Appl.*, vol. 165, no. 12, 2017.

[32] M. S. Satu, S. Ahamed, F. Hossain, T. Akter, and D. M. Farid, "Mining traffic accident data of N5 national highway in bangladesh employing decision trees," in *Proc. IEEE Region 10 Humanitarian Technol. Conf. (R10-HTC)*, Dec. 2017, pp. 722–725.

[33] S. Young, T. Abdou, and A. Bener, "Deep super learner: A deep ensemble for classification problems," in *Proc. 31st Can. Conf. Artif. Intell.* Toronto, ON, Canada: Springer, May 2018, pp. 84–95.

[34] M. S. Satu, F. Tasnim, T. Akter, and S. Halder, "Exploring significant heart disease factors based on semi supervised learning algorithms," in *Proc. Int. Conf. Comput., Commun., Chem., Mater. Electron. Eng. (IC4ME2)*, Feb. 2018, pp. 1–4.

[35] R. J. Urbanowicz, M. Meeker, W. La Cava, R. S. Olson, and J. H. Moore, "Relief-based feature selection: Introduction and review," *J. Biomed. Inform.*, vol. 85, pp. 189–203, Sep. 2018.
[36] M. E. Hossain, A. Khan, M. A. Moni, and S. Uddin, "Use of electronic health data for disease prediction: A comprehensive literature review," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, 2019, doi: 10.1109/TCBB.2019.2937862.
[37] M. R. Islam, A. R. M. Kamal, N. Sultana, R. Islam, M. A. Moni, and A. Ulhaq, "Detecting depression using K-nearest neighbors (KNN) classification technique," in *Proc. Int. Conf. Comput., Commun., Chem., Mater. Electron. Eng. (IC4ME2)*, Feb. 2018, pp. 1–4.
[38] K. S. Oma, P. Mondal, N. S. Khan, M. R. K. Rizvi, and M. N. Islam, "A machine learning approach to predict autism spectrum disorder," in *Proc. Int. Conf. Electr., Comput. Commun. Eng. (ECCE)*, Feb. 2019, pp. 1–6.
[39] H. Talabani and E. Avci, "Performance comparison of SVM kernel types on child autism disease database," in *Proc. Int. Conf. Artif. Intell. Data Process. (IDAP)*, Sep. 2018, pp. 1–5.
[40] F. Thabtah, "An accessible and efficient autism screening method for behavioural data and predictive analyses," *Health Informat. J.*, Sep. 2018, Art. no. 1460458218796636.

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