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Autism Disorder Diagnosis Enhancement Using Adaptive Ranking Features and Machine Learning Classifiers

Heba Ahmed Jassim [1], Maysam Kadhim [2], Hafsa Amer Jasim [3], Zahraa Khduair Taha [4]

[1]Computer Engineering Department, Al-Iraqia University, Baghdad, Iraq
Email: hiba.a.jasim@aliraqia.edu.iq

[2] Communication Engineering, Sumer University, Nasiriya, Iraq
Email: maysm.kadhim@uos.edu.iq

[3]Electrical Engineering Department, Baghdad University, Baghdad, Iraq
Email: h.jasim@coeng.uobaghdad.edu.iq

[4]College of Graduate Studies, Universiti Tenaga Nasional, Kajang, Malaysia
Email: PE21268@student.uniten.edu.my

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Abstract

Autism is a disorder of brain function that can appear in children younger than two years and affects their communication and learning. The incidence of Autism in children has been increasing, and at the same time, numerous schemes have been proposed for its diagnosis. However, the researchers continue to face challenges in the early and accurate diagnosis of Autism. Early and accurate detection of autism allows doctors to determine the severity of the disease and begin appropriate treatment protocols to develop communication skills in children. This paper proposes feature ranking methods integrated with four classifiers for the accurate diagnosis of autism. Multiple experiments are conducted by integrating ranking features methods (chi-square, Anova-F, and chi2-yates) with Decision Tree (DT), Multi-layer perceptron (MLP), NaiveBayes Bernoulli (NB), and Support Vector Machine –Radial Basis Function (SVM-RBF) classifiers to achieve accurate early detection. The feature ranking is applied with five sets (5, 10, 20, 40, and 46), and each set is individually evaluated to assess its contribution to autism diagnosis. The best diagnosis model (chi2-yates-based SVM-RBF) has achieved 0.971611, 0.94797, and 0.997335 for the accuracy, F1-score, and ROC-AUC, respectively. The proposed framework would be effective in helping therapists in early detection and selecting suitable treatment for autism.

Keywords: Autism disorders, Classifiers, Feature Ranking, Machine Learning. Deep Learning.

I. Introduction

Autism spectrum disorder (ASD) is a neurological condition that affects brain function, social communication, and behavior, characterized by repetition [1]. This disorder is described as a spectrum because each individual shows different symptoms, and the severity of the disorder varies significantly among individuals. In 1943, Leo Kanner made the first attempt to describe ASD, connecting the symptoms of the disorder to sociodemographic characteristics such as age, sex and Pregnancy complications [2]. Multiple factors have contributed to the growing prevalence of ASD, including unhealthy habits, food with low nutritional value, lifestyle, genetic factors, and increased pollution, resulting in a rising number of children affected by ASD [3] [4]. The number of children diagnosed with ASD has increased since 1980, and ASD diagnosis has traditionally relied on questionnaire-based techniques. However, these techniques are time-consuming, efforts and lack accuracy; therefore, there is a need to adaptive methods for diagnosis. Many researchers have employed machine learning (ML) and artificial intelligence (AI) techniques to early predict and target the level of ASD. However, there is a limitation of considerable research that thoroughly explores the contribution of each feature in the diagnostic process [4] [5].

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Recently, much attention has been given to using ranking features for effective selection and representation of the signal. Ranking features are always robust tools to select important features that contribute well in various applications because they extract relevant features and reduce redundant features [6].

In this work, the proposed framework attempted to address these limitations and fill gaps by measuring the contribution of each feature in the dataset. The proposed framework consists of four phases: the first is a preprocessing step to clean and transform data into a suitable form; the second phase is filling missing values; and the class weight and ranking features are applied. Finally, multiple classifiers are applied after ranking features with different sizes of features.

II. Related Work

In this section, the most important and latest research on ASD is discussed. Radočaj and Martinović [7] introduced CNN- and transformer-based architectures to classify the emotions of autistic children. The transformer model outperformed the CNN in terms of accuracy and F1-score, achieving an accuracy of 0.7484 and an F1-score of 0.7048. Mittal, Malik and Rana [8] proposed an Improved Convolutional Neural Network (I-CNN) to classify children as having ASD or not ASD within the age range of 1 to 10 years. Nogay and Adeli [9] explored the diagnosis of ASD by studying the impact of gender and age range. The proposed method outperformed other techniques—AlexNet, GoogleNet, ResNet-18, and SqueezeNet—in terms of accuracy. Singh et al. [10] designed and implemented a robotic system to support individuals with ASD. The research addressed the issue of high cost and implemented a robot for general use. The framework was evaluated by psychologists and robotics specialists to assess its acceptance among children. Lenker et al. employed Principal Component Analysis (PCA) to identify autism-related dimensions in children and to classify them into distinct clusters, taking age, gender and intelligence quotient (IQ) into account. The findings reveal statistical heterogeneity in ASD based on sleep–wake disturbances, highlighting the need for further research to address issues with nighttime sleep and morning wakefulness [11]. In [12], Alutaibi, Sharma, and Khan employed reinforcement learning for ASD detection and provided advice to patients through a two-phase deep learning approach. In the first phase, features were extracted and optimized using advanced multiscale statistical techniques. In the second phase, Capsule DenseNet++ was applied to classify the optimized features, enhancing the representation of data. Finally, a lifestyle recommendation system was implemented by using the Proximal Policy Optimization (PPO) technique. Sujana and Augustine used Explainable Artificial Intelligence (XAI) to identify areas of impairment and diagnose ASD from state functional magnetic resonance imaging (sMRI) images. Additionally, the degree of brain impairment was estimated using the pointing game score algorithm, which identifies regions associated with children's cognitive function [13]. In [14], Sujana and Augustine proposed a hybrid deep learning approach to improve ASD detection by integrating region of interest (ROI) time-series data with functional connectivity (FC) maps. The results demonstrate that the proposed method outperforms state-of-the-art algorithms. In [15], Wang et al. proposed a hybrid model that combines Long Short-Term Memory (LSTM) networks with an attention mechanism to enhance the early identification of autism. Moreover, a residual block with channel attention was integrated to fuse features, prevent network deterioration, and ensure a light model architecture. Leroy et al. developed a model based on the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) to label unstructured clinical text as either “ASD” or “no ASD". The proposed model demonstrated superior performance compared to other studies that used other ML models [16]. Abdullah et. Al proposed an innovative approach that leverages Attention-based Bidirectional Long Short-Term Memory (BiLSTM) networks alongside CNN with an additional BiLSTM-Attention mechanism to classify autism disorder. The study also employed the Autism Brain Imaging Data Exchange (ABIDE) dataset to analyze resting-state functional magnetic resonance imaging (rs-fMRI) data and phenotypic information. The proposed model significantly improves performance of model [17].

III. Methodology

The model consists of three phases: first, Data identification and preprocessing; after that, the second phase, feature ranking using various techniques; and finally, classification of ASD was performed using different ML methods. The diagram of the proposed model is demonstrated in Figure 1.

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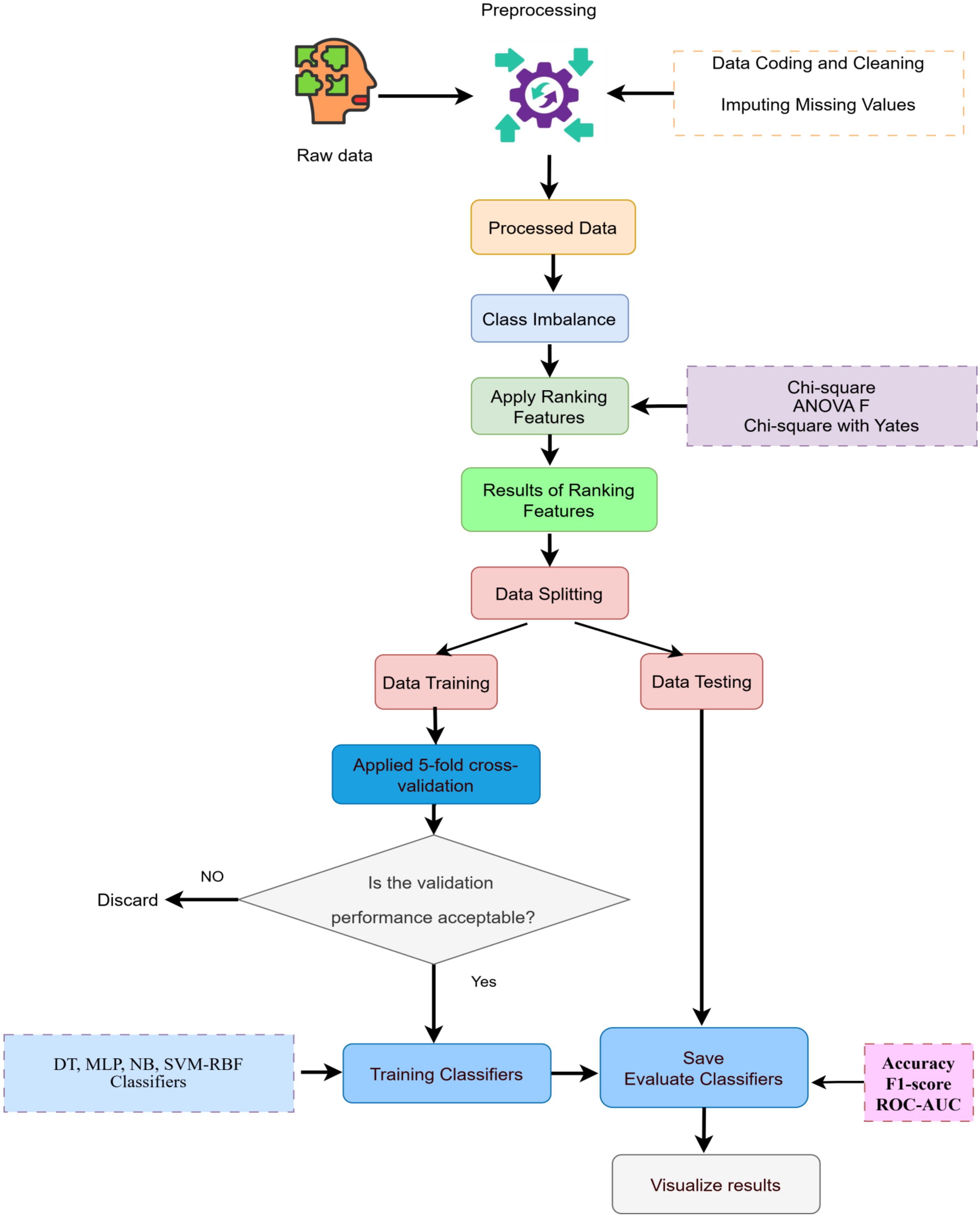

Figure 1: The Structure Diagram for Proposed Framework

A. Preprocessing

Data preprocessing is an essential step to clean and transform data into a suitable format. It also enhances data representation and ensures consistency for the next stage. The preprocessing steps depend on many factors, such as the number of features, the dataset size, and the significance of the information it contains. This phase consists of two steps: Data Coding and Cleaning and Imputing Missing Values.

B. Data Coding and Cleaning

The dataset is checked for missing values and invalid symbols before classifier training begins. This step is essential to remove invalid entries or irrelevant columns. Additionally, text and mixed-type columns are converted to numerical form to prepare the data for the next stage. This Invalid Sample and Irrelevant or Meta Columns are illustrated in Table I.

TABLE I. TABLE TYPE STYLES

Category	Column Name	Invalid Sample / Example	Reason / Description
Columns with Invalid Symbols	ethnicity	'?'	Represents missing or unknown data — should be replaced with NaN before imputation
	relation	'?'	Represents missing or unknown data — should be replaced with NaN before imputation
Irrelevant / Meta Columns	austim	—	Possible data leakage (directly indicates autism condition)
	result	—	Possible data leakage or meta information (screening outcome)
	age_desc	—	Constant value column — provides no variation or predictive value

C. Imputing Missing Values

There are some null values or missing values in the autism dataset employed in this research. The percentage of null values is shown in Figure 2, demonstrating the proportions of both missing and existing values. The null values can be handled using various techniques, such as the mean or a random value.

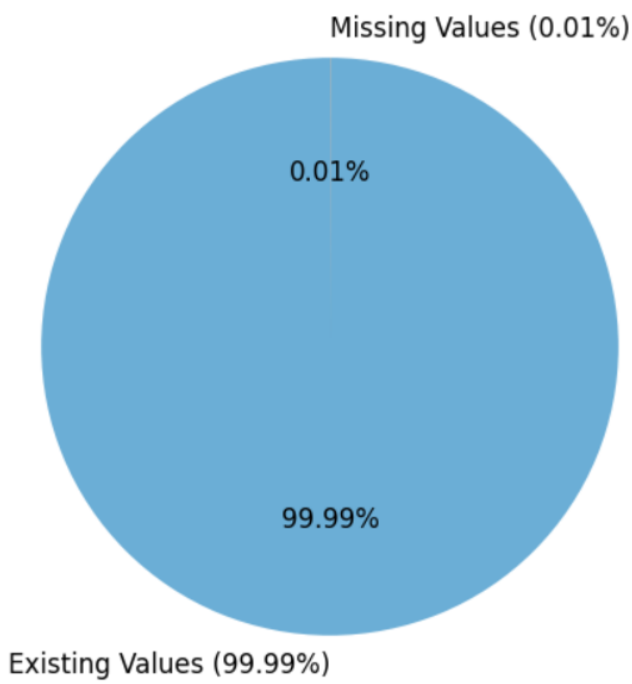

Figure 2: Percentage of Missing Values vs. Existing Values

D. Class Imbalance

Class weight is a technique for capturing by assigning a higher weight to the minority class through a training model. The primary aim of Class weight is to encourage the model is more learning from the underrepresented classes, and this method is beneficial in

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case of significant class imbalance, and the cost of learning varies across classes [18]. It also improves the model's performance across all classes and reduces bias toward dominant classes, weighted of classes are defined by Equation (1).

$$W_c = \frac{n}{K*n_c} \tag{1}$$

Let W_c is the weight for class c, n_c is the number of samples in class c, n is the total number of training samples and K is the total number of classes

For binary classification, the weighted loss function of the classifier is defined as follows by Equation (2):

$$l = -\sum_{i=1}^{n} w_{y_i}(y_i \log(\hat{p}_i) + (1-y_i)\log(1-\hat{p}_i)) \tag{2}$$

Where l is the total losses, y_i is actual output for sample i and $\hat{p}_i$is the predicted probability of ASD.

E. Ranking features

Ranking features is an important step to determine whether they are relevant or irrelevant and to assess their predictive power and explanatory power alongside the training of the model. The objective of feature selection is to reduce computation cost, prevent overfitting, and improve training efficiency by selecting the most valuable features, particularly in datasets with rich features [19].

Chi-square, ANOVA-F, and CHI2-YATES are used to rank features and extract relevant features that enter the second stage. This step aims to reduce the dimensionality of the dataset into uncorrelated features and to select the most informative features that contribute to autism prediction. Each method generates a different set of features, and their effectiveness in producing accurate results varies. Moreover, feature selection before training is essential in ML, as it improves model learning and reduces cost computation.

F. Classifiers

Different classifiers are used to diagnose ASD after generating informative features. DT, MLP, NB, and SVM-RBF classifiers are among the five classifiers employed to evaluate the effectiveness of feature selection and to enhance diagnosis and prediction.

All proposed models, including feature selection techniques and classifiers, are evaluated using comprehensive performance metrics.

IV. DATASET

The dataset consists of 704 people who filled out a form for ASD. The dataset is collected based on a questionnaire (10 binary questions) about social behavior and contact with others. These features are commonly used to diagnose ASD. Records are collected from adults aged 18 years or older and include information on age, gender, ethnicity, country of residence, and relation (self, parent). There are 512 cases of normal cases, and 189 cases of ASD, which is demonstrated in Figure 3.

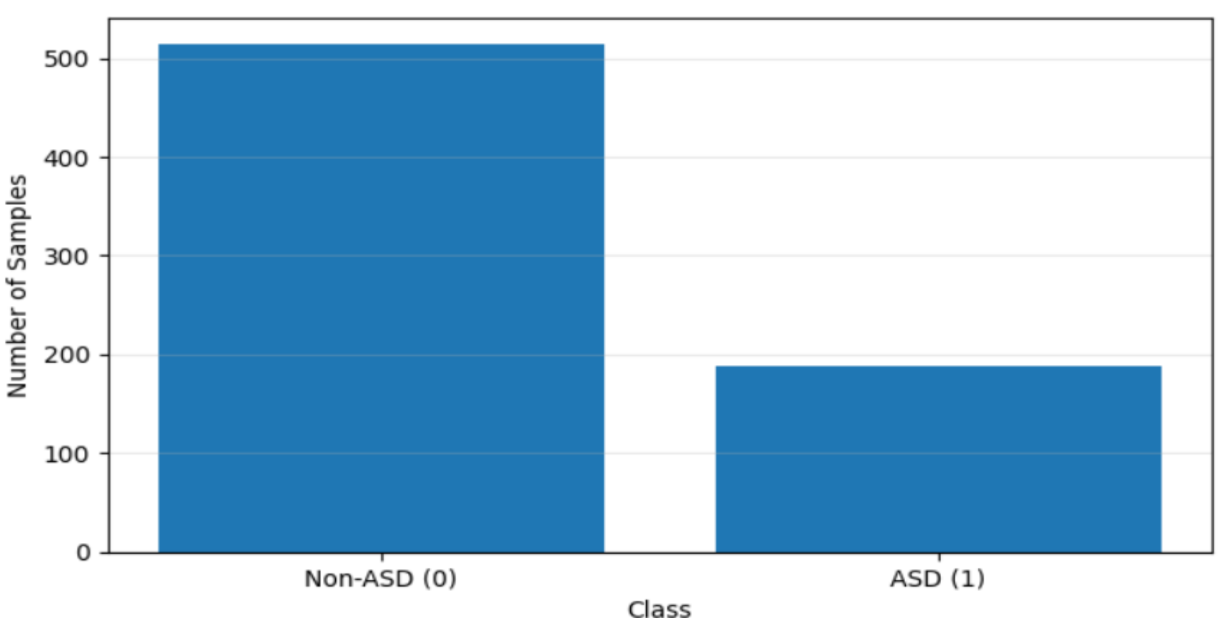

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Figure 3: Number of samples for the normal case and ASD case

V. EXPERIMENT SETUP

All experiments were designed and run on the Kaggle platform. Kaggle provides thousands of datasets in different fields, and it provides different libraries like TensorFlow, Keras, and PyTorch, which help in implementation. The code is operated on the GPU-T4 x2. k-fold cross-validation was used to evaluate the proposed framework that combines feature ranking with ML classifiers. 5-fold cross-validation was chosen to divide the dataset; 4 folds are used for training and the rest for testing. Multiple performance metrics are used, such as the mean and standard deviation for accuracy, F1-score, and ROC-AUC across 5 folds.

Data link: https://www.kaggle.com/datasets/andrewmvd/autism-screening-on-adults

VI. RESULT

A. Ranking Features for different schemes

The framework is proposed to enhance ASD diagnosis by selecting the most relevant features. Ranking Features method, combined with a classifier, assigns a score to each feature and evaluates its contribution to the classifier's ability to detect Autism. Table II shows the feature rank using chi-square; different values like p-values, effect sizes (phi coefficient), and support are measured to select the relevant 20 features. The results demonstrate that A9, A6, A5, A4, A3, A7, ethnicity, A10, and A2 have high chi-square, the smallest p-value with a phi effect more than 0.05, and a large number of components contribute to each sample.

The results showed that ANOVA F achieved high scores for A9, A6, A5, A4, A3, A10, A7 ethnicity White-European and A2, which slightly differed from chi-square, with very low p-values and a strong phi effect. Table III demonstrates rank features using ANOVA-F.

Finally, CHI2-YATES presents performance by reaching perfect phi-effect while preserving a lower p-value. The results are shown in Table IV.

TABLE II. 20 TOP FEATURES USING CHI-SQUARE

Rank	Feature	χ^2 Value	p-value	Phi Effect
A5 Score	101.7959	6.15E-24	0.380258	351
A9 Score	192.2833	1.01E-43	0.522618	228
A6 Score	176.6881	2.56E-40	0.500977	200
A4 Score	78.40121	8.41E-19	0.333714	349
Country (United Arab Emirates)	22.45012	2.16E-06	0.178576	82
Country (Sri Lanka)	5.137864	0.023409	0.085429	14
A3 Score	74.31658	6.65E-18	0.324905	322
A10 Score	44.6796	2.32E-11	0.251923	404
A1 Score	17.36211	3.09E-05	0.157042	508
Country (Jordan)	12.21393	0.000474	0.131717	47
Country (Canada)	12.11077	0.000501	0.131159	15
A7_Score	50.63585	1.11E-12	0.26819	294
Country (India)	15.58538	7.89E-05	0.14879	81
Ethnicity (Middle Eastern)	15.43342	8.55E-05	0.148062	92
A2 Score	37.32905	9.98E-10	0.23027	319
Ethnicity (White European)	47.14591	6.59E-12	0.258783	233
Ethnicity (Asian)	6.282673	0.012192	0.094468	36
Ethnicity (Pacifica)	2.094224	0.147857	0.054541	12
Ethnicity (Unknown)	14.59973	0.000133	0.144008	95
Relation (Unknown)	14.59973	0.000133	0.144008	95

ISSN: 2710-2165

TABLE III. 20 TOP FEATURES USING ANOVA F

Rank	Feature	ANOVA F value	p-value	Phi Effect
A9 Score	475.7666	6.27e-81	0.6356	228
A6 Score	378.9507	8.01e-68	0.5921	200
A5 Score	284.4728	7.72e-54	0.5370	351
A4 Score	198.9801	5.80e-40	0.4699	349
A3 Score	169.5582	7.11e-35	0.4411	322
A10 Score	122.8460	2.02e-26	0.3859	404
A7 Score	98.9146	6.82e-22	0.3514	294
Ethnicity (White European)	78.0845	7.86e-18	0.3164	233
A2 Score	75.3730	2.71e-17	0.3114	319
A1 Score	68.2285	7.24e-16	0.2976	508
A8 Score	41.8372	1.86e-10	0.2372	457
Country (United States)	28.6118	1.20e-07	0.1979	113
Country (United Arab Emirates)	26.2864	3.81e-07	0.1900	82
Ethnicity (Middle Eastern)	18.1610	2.31e-05	0.1588	92
Country (India)	18.0123	2.49e-05	0.1582	81
ethnicity	17.2426	3.69e-05	0.1548	95
relation	17.2426	3.69e-05	0.1548	95
Ethnicity (Asian)	14.7971	1.31e-04	0.1437	123
Country (Jordan)	13.2977	2.85e-04	0.1363	47

TABLE IV. 20 TOP FEATURES USING CHI²-YATES

Rank	Feature	CHI²-Yates Value	p-value	Phi Effect
A9 Score	281.3289	3.85e-63	0.6322	228
A6 Score	243.8488	5.70e-55	0.5885	200
A5 Score	200.5988	1.55e-45	0.5338	351
A4 Score	153.3636	3.19e-35	0.4667	349
A3 Score	134.9698	3.35e-31	0.4379	322
A10 Score	103.0945	3.20e-24	0.3827	404
A7 Score	85.3449	2.51e-20	0.3482	294
Ethnicity (White European)	68.9596	1.01e-16	0.3130	233
A2 Score	66.8546	2.92e-16	0.3082	319
A1 Score	60.8725	6.09e-15	0.2941	508
A8 Score	38.4832	5.52e-10	0.2338	457
Country (United States)	26.3666	2.82e-07	0.1935	113
Country (United Arab Emirates)	24.0910	9.19e-07	0.1850	82
Ethnicity (Middle Eastern)	16.7062	4.36e-05	0.1540	92
Country (India)	16.5110	4.84e-05	0.1531	81
ethnicity	15.8701	6.78e-05	0.1501	95
relation	15.8701	6.78e-05	0.1501	95
Ethnicity (Asian)	13.6917	2.15e-04	0.1395	123
Country (Jordan)	11.8841	5.66e-04	0.1299	47
Country (Canada)	10.3894	1.27e-03	0.1215	15

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B. Classification Performance for Proposed Framework

The experimental results are reported in Table V, summarizing the mean and standard deviation of the performance of different classifiers with different numbers of features (K=5, 10, 20, 40, and 46), across k-fold cross-validation.

MLP and NB achieve excellent results, with accuracy values of 0.947437 and 0.947447, respectively, and F1-score values of 0.904897 and 0.902851 at 20 selected features, along with low standard deviation and high ROC-AUC. While high performance trends are reached for the chi-based SVM-BRF classifier, with the corresponding accuracy, F1-score, and ROC–AUC values at 20 features.

A clear performance variation for ANOFA-F across different classifiers and numbers of features is demonstrated in Table VI. The DT classifier records high accuracy, F1 score, and ROC-AUC at k=10, while NB achieves even higher accuracy, F1 score, and ROC-AUC than DT at the same number of features. The SVM-RBF classifier reaches slightly higher accuracy than the MLP at the same number of features, with low standard deviation in both accuracy and f1-score. MLP and SVM-RBF need to include more features to attain excellent results in terms of accuracy, F1-score, and ROC-AUC.

The outcomes of Chi-Yates with different feature sizes and different classifiers, including DT, MLP, and SVM-RFB, are shown as in Table VII. When Chi-Yates with k=10 is employed, the DT achieves 0.907609 accuracy, a 0.84227 F1-score, and a 0.92553 ROC-AUC. While MLP with 10 features records 0.957376 accuracy, 0.922522 F1-score, and 0.922522 ROC-AUC. Similarly, NB's strong combined performance at k=10, while at k=20, SVM-RBF achieves competitive results in terms of accuracy, F1-score, and ROC-AUC.

TABLE V. THE EVALUATION OF CHI-SQUARE ACROSS DIFFERENT CLASSIFIERS

model	k	Acc_m	Acc_std	f1_m	f1_std	ROC_AUC_m	ROC_AUC _std
DT	5	0.884954	0.02619126	0.810996	0.034916	0.955515	0.027168
DT	**10**	**0.904772**	**0.039604506**	**0.83577**	**0.064283**	**0.924211**	**0.046435**
DT	20	0.900537	0.026711419	0.831766	0.033193	0.919372	0.018883
DT	40	0.900537	0.037652222	0.829336	0.057072	0.905142	0.034064
DT	46	0.900527	0.0366883	0.8293	0.055396	0.906982	0.029665
MLP	5	0.893465	0.028810651	0.817856	0.041101	0.966305	0.018158
MLP	10	0.936049	0.026659537	0.884037	0.046711	0.981699	0.014177
MLP	**20**	**0.947437**	**0.016354856**	**0.904897**	**0.02945**	**0.99063**	**0.003914**
MLP	40	0.943181	0.026537196	0.898897	0.040785	0.983389	0.007575
MLP	46	0.958774	0.024366305	0.923917	0.044437	0.991675	0.007023
NB	5	0.91617	0.025876322	0.841837	0.046718	0.972164	0.014306
NB	10	0.930365	0.029112845	0.87191	0.05289	0.985025	0.008153
NB	**20**	**0.947447**	**0.012865061**	**0.902851**	**0.019656**	**0.990846**	**0.003813**
NB	40	0.943161	0.016741869	0.895221	0.030415	0.987779	0.006177
NB	46	0.943161	0.01340491	0.894584	0.025303	0.987417	0.006132
SVM_RBF	5	0.890628	0.024853949	0.817484	0.035532	0.939476	0.023704
SVM_RBF	10	0.930365	0.024414368	0.871412	0.041355	0.982954	0.009789
SVM_RBF	**20**	**0.964488**	**0.018081984**	**0.93535**	**0.029563**	**0.996971**	**0.001595**
SVM_RBF	40	0.948845	0.011779635	0.903504	0.022559	0.99306	0.004512
SVM_RBF	46	0.954539	0.020451496	0.914992	0.036223	0.994142	0.003041

TABLE VI. PERFORMANCE OF ANOVA-F ACROSS DIFFERENT CLASSIFIERS

model	k	Acc_m	Acc_std	f1_m	f1_std	ROC_AUC_m	ROC_AUC _std
DT	5	0.884954	0.026191	0.810996	0.034916	0.955515	0.027168
DT	**10**	**0.907609**	**0.038134**	**0.84227**	**0.062204**	**0.92553**	**0.054283**
DT	20	0.896272	0.029687	0.826168	0.036364	0.91845	0.019619
DT	40	0.896282	0.026958	0.822409	0.038793	0.902591	0.022536
DT	46	0.899108	0.038812	0.826479	0.059224	0.905091	0.032226
MLP	5	0.883536	0.029006	0.807945	0.039028	0.96699	0.016412
MLP	10	0.958815	0.023184	0.925505	0.038349	0.993455	0.003726

ISSN: 2710-2165

MLP	**20**	**0.960223**	**0.015553**	**0.927387**	**0.026026**	**0.992605**	**0.002251**
MLP	40	0.953121	0.015555	0.913594	0.028553	0.99109	0.003849
MLP	46	0.945998	0.019276	0.901474	0.032835	0.99133	0.005531
NB	5	0.91617	0.025876	0.841837	0.046718	0.972164	0.014306
NB	**10**	**0.954539**	**0.020451**	**0.915255**	**0.036382**	**0.993283**	**0.003931**
NB	20	0.947437	0.015567	0.902519	0.026875	0.989902	0.004514
NB	40	0.94458	0.014672	0.897381	0.027943	0.987677	0.005972
NB	46	0.943161	0.013405	0.894584	0.025303	0.987417	0.006132
SVM_RBF	5	0.890628	0.024854	0.817484	0.035532	0.939476	0.023704
SVM_RBF	10	0.951672	0.024889	0.907885	0.049151	0.991641	0.005117
SVM_RBF	**20**	**0.967325**	**0.016339**	**0.940193**	**0.027667**	**0.996915**	**0.001703**
SVM_RBF	40	0.954549	0.008061	0.914691	0.015147	0.994868	0.002595
SVM_RBF	46	0.954539	0.020451	0.914992	0.036223	0.994142	0.003041

TABLE VII. COMPARISON OF DIFFERENT CLASSIFIERS BASED ON CHI-YATES

model	k	Acc_m	Acc_std	f1_m	f1_std	ROC_AUC_m	ROC_AUC _std
DT	5	0.884954	0.026191	0.810996	0.034916	0.955515	0.027168
DT	**10**	**0.907609**	**0.038134**	**0.84227**	**0.062204**	**0.92553**	**0.054283**
DT	20	0.896272	0.029687	0.826168	0.036364	0.916713	0.017885
DT	40	0.903364	0.032951	0.832894	0.051234	0.908745	0.028986
DT	46	0.896282	0.026958	0.822409	0.038793	0.902744	0.02115
MLP	5	0.884954	0.028929	0.808944	0.039259	0.968624	0.016748
MLP	**10**	**0.957376**	**0.024594**	**0.922522**	**0.043961**	**0.992884**	**0.004808**
MLP	20	0.947386	0.027524	0.904702	0.05102	0.987847	0.008731
MLP	40	0.945988	0.016534	0.898633	0.033711	0.992465	0.004192
MLP	46	0.945957	0.035899	0.903533	0.06253	0.990003	0.009266
NB	5	0.91617	0.025876	0.841837	0.046718	0.972164	0.014306
NB	**10**	**0.954539**	**0.020451**	**0.915255**	**0.036382**	**0.993283**	**0.003931**
NB	20	0.947437	0.015567	0.902519	0.026875	0.989902	0.004514
NB	40	0.94458	0.014672	0.897381	0.027943	0.987779	0.005912
NB	46	0.943161	0.013405	0.894584	0.025303	0.987417	0.006132
SVM_RBF	5	0.890628	0.024854	0.817484	0.035532	0.939476	0.023704
SVM_RBF	10	0.951672	0.024889	0.907885	0.049151	0.991641	0.005117
SVM_RBF	**20**	**0.971611**	**0.018062**	**0.94797**	**0.03057**	**0.997335**	**0.001778**
SVM_RBF	40	0.955968	0.005917	0.917407	0.012905	0.994664	0.003047
SVM_RBF	46	0.954539	0.020451	0.914992	0.036223	0.994142	0.003041

VII. DISCUSSION

The results of ranking features combined with different classifiers are demonstrated in Table 8. In general, the classifier with moderated feature dimensionality outperforms the classifier with low feature dimensionality across all ranking feature techniques. For the three ranking features, SVM-RBF achieved strong performance, with an approximate accuracy improvement of about 4.5%, 1.47, and 9.45 from Naïve Bayes Bernoulli, MLP, and DT. Under Chi-square, classification performance enhances when moving from MLP to Naïve Bayes, Bernoulli and DT, with accuracy rising by 3% and 7%, respectively, and F1-score improvements by roughly 6% and 15%, respectively. The ROC-AUC values remain high across different classifiers, confirming that all ranking features effectively maintain relevant features while reducing irrelevant information. Similarly, the performance of ANOVA-F is maintained for MLP, Naïve Bayes Bernoulli, and SVM-RBF compared with Chi-square and CHI2-YATES, while slightly improving relative to DT.

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Overall, the percentage-based improvements verify that SVM-RBF contributes significantly to the stability and consistency of the model against other classifiers.

In conclusion, the findings indicate that integrating the technique of feature ranking with classifiers results in measurable improvements in accuracy, F1-score, and RUC-AUC, leading to accurate diagnosis of autism.

TABLE VIII. BEST RESULTS FOR EACH CLASSIFIER WITH RESPECT TO FEATURE-RANKING DIMENSION

Ranking	Model	Ranking	Acc_m	Acc_std	f1_m	f1_std	ROC_AUC_m	ROC_AUC _std
Chi-square	DT	10	0.904772	0.039605	0.83577	0.064283	0.924211	0.046435
	MLP	46	0.958774	0.024366	0.923917	0.044437	0.991675	0.007023
	NB	20	0.947447	0.012865	0.902851	0.019656	0.990846	0.003813
	SVM_RBF	20	0.964488	0.018082	0.93535	0.029563	0.996971	0.001595
Anova-F	DT	10	0.907609	0.038134	0.84227	0.062204	0.92553	0.054283
	MLP	20	0.960223	0.015553	0.927387	0.026026	0.992605	0.002251
	NB	10	0.954539	0.020451	0.915255	0.036382	0.993283	0.003931
	SVM_RBF	20	0.967325	0.016339	0.940193	0.027667	0.996915	0.001703
CHI2_YATES	DT	10	0.907609	0.038134	0.84227	0.062204	0.92553	0.054283
	MLP	10	0.957376	0.024594	0.922522	0.043961	0.992884	0.004808
	NB	10	0.954539	0.020451	0.915255	0.036382	0.993283	0.003931
	SVM_RBF	20	0.971611	0.018062	0.94797	0.03057	0.997335	0.001778

VIII. ASSESSMENT OF BIAS AND ETHICAL ASPECTS IN THE PROPOSED SCHEME

In this study, there is bias towards the dataset and modeling process because the ASD dataset is collected from limited samples and at the same time doesn't consider differences in global demographics, age, gender, family genus, etc. These limitations cause the result to be biased towards the overrepresented class.

To mitigate class imbalance, a class-weighting strategy was integrated with cross-validation to assign high weights for underrepresented classes and improve class distribution in each fold, respectively. By using these techniques, the trained and learned model is improved, and bias and overfitting due to imbalanced datasets are reduced; however, demographic bias may remain in the ASD screen dataset. The proposed model helps doctors as a tool for decision assistance, but it is not designed for diagnosing ASD.

IX. CONCLUSION

The objective of this study is to design and implement a proposed framework by combining a number of feature ranking techniques with four classifiers to accurately and more reliably diagnose autism. The chi-square, ANOVA-F, and CHI2-YATES are combined with DT, MLP, Naïve Bayes Bernoulli, and SVM-RBF, and each option is evaluated with different feature dimensions in terms of accuracy, F1-score, and ROC-AUC. The results demonstrate that the performance of classifiers can be enhanced by extracting relevant features from the autism dataset. The experimental results demonstrate that by using any one ranking features technique (chi-square, Avona-F, or ch2- YATES) in conjunction with SVM-RBF yields an accuracy of 0.978723, F1-score of 0.96, and a ROC-AUC of 0.996168.

Finally, the findings show that integrating the technique of feature ranking with the classifier results in more reliability and generalization for diagnosing ASD.

A. APPENDIX

TABLE A: LIST OF ABBREVIATIONS AND TERM

Abbreviation	Full Term
ASD	Autism spectrum disorder
ML	Machine Learning
DL	Deep Learning
DT	Decision tree
MLP	Multi-layer perceptron

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NB	NaiveBayes Bernoulli
SVM-RBF	Support Vector Machine –Radial Base Function
AI	Artificial Intelligence
CNN	Convolution Neural Network
ICNN	Improved Convolutional Neural Network
PCA	Principle Component Analysis
IQ	intelligence quotient
PPO	Proximal Policy Optimization
XAI	Explainable Artificial Intelligence (XAI)
sMRI	state functional magnetic resonance imaging
LSTM	Long Short-Term Memory
DSM-5	Diagnostic and Statistical Manual of Mental Disorders
ABIDE	Autism Brain Imaging Data Exchange
Rs-fMRI	resting-state functional magnetic resonance imaging

TABLE A2: SAMPLE OF RANKING FEATURES USING CHI-SQUARE

Feature	F_score	p_value_F	support	phi_effect	a_f1_y1	b_f1_y0	c_f0_y1	d_f0_y0	risk_diff	risk_ratio	odds_ratio	or_95ci_low	or_95ci_high	any_zero_corrected
A9 Score	475.7666	6.27E-81	228	0.635576	154	74	35	441	0.601909	9.185965	26.22162	16.85458	40.79445	FALSE
A6 Score	378.9507	8.01E-68	200	0.592091	137	63	52	452	0.581825	6.639231	18.90232	12.49447	28.59646	FALSE
A5 Score	284.4728	7.72E-54	351	0.537004	178	173	11	342	0.475961	16.27402	31.98949	16.93861	60.41391	FALSE
A4 Score	198.9801	5.80E-40	349	0.469945	167	182	22	333	0.416538	7.721412	13.88886	8.595398	22.4423	FALSE
A3 Score	169.5582	7.11E-35	322	0.441074	155	167	34	348	0.392361	5.408294	9.499824	6.276215	14.37915	FALSE
A10 Score	122.846	2.02E-26	404	0.385917	168	236	21	279	0.345842	5.940594	9.457627	5.819303	15.37069	FALSE
A7 Score	98.91462	6.82E-22	294	0.351429	133	161	56	354	0.315796	3.312075	5.22205	3.630248	7.51183	FALSE
Ethnicity White-European	78.08448	7.86E-18	233	0.316382	109	124	80	391	0.29796	2.754238	4.29627	3.02077	6.110341	FALSE
A2 Score	75.37298	2.71E-17	319	0.311382	134	185	55	330	0.277206	2.940439	4.345946	3.026513	6.240596	FALSE
A1 Score	68.22853	7.24E-16	508	0.297628	178	330	11	185	0.294271	6.243379	9.071625	4.807376	17.11836	FALSE
A8 Score	41.83724	1.86E-10	457	0.237161	158	299	31	216	0.220227	2.754712	3.681951	2.412136	5.620231	FALSE
Country of United States	28.61181	1.20E-07	113	0.197892	53	60	136	455	0.238908	2.038196	2.95527	1.949196	4.480626	FALSE
Country of United Arab Emirates	26.28637	3.81E-07	82	0.189983	3	79	186	436	-0.26245	0.122345	0.089016	0.027749	0.28555	FALSE
Ethnicity Middle Eastern	18.16103	2.31E-05	92	0.158802	8	84	181	431	-0.2088	0.294019	0.226782	0.107586	0.478039	FALSE
Contry of India	18.0123	2.49E-05	81	0.158167	6	75	183	440	-0.21967	0.252176	0.19235	0.082276	0.449689	FALSE
ethnicity	17.24261	3.69E-05	95	0.154833	9	86	180	429	-0.20083	0.320526	0.249419	0.122823	0.506497	FALSE
relation	17.24261	3.69E-05	95	0.154833	9	86	180	429	-0.20083	0.320526	0.249419	0.122823	0.506497	FALSE
Ethnicity Asian	14.79712	0.000131	123	0.143678	16	107	173	408	-0.16768	0.436863	0.352655	0.202523	0.614083	FALSE
Contry of Jordan	13.29771	0.000285	47	0.136347	2	45	187	470	-0.24207	0.149505	0.111705	0.026826	0.465149	FALSE

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