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In the Direction of an All-encompassing Comparison for Autism Diagnosis Using Assembles

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Abstract: Abstract: Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that affects social communication and behavioral patterns. Accurate and early diagnosis of ASD remains an important research challenge in medical data analysis and machine learning. While many previous studies have focused on individual (base) classifiers, the effectiveness of ensemble learning techniques for ASD diagnosis requires further investigation. In this study, a comprehensive comparative analysis of ensemble methods is conducted using the Adult Autism dataset obtained from the UCI Machine Learning Repository. The preprocessing stage includes handling missing values using the KNN imputation method and reducing the impact of outliers to improve data quality. Subsequently, four ensemble techniques, namely Bagging, Boosting, Voting, and Stacking, are applied and evaluated using WEKA and RapidMiner data mining tools. The performance of the proposed framework is assessed using Accuracy, Precision, Recall, and F1-score metrics. Experimental results demonstrate that ensemble learning methods provide highly competitive classification performance and outperform several corresponding base classifiers on the investigated dataset. The findings highlight the effectiveness of combining preprocessing techniques with ensemble learning approaches for improving ASD diagnosis and prediction.

Keywords: Data Mining; Pre-processing; Autism Spectrum Disorder (ASD) ; Ensemble Learning.

1. Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that affects social communication, interaction patterns, and behavior. It can be identified during early childhood and may continue throughout adolescence and adulthood. ASD presents with varying levels of severity and characteristics among individuals, making accurate diagnosis an important challenge for healthcare professionals and researchers. In recent years, machine learning and data mining techniques have attracted significant attention for improving the early detection and diagnosis of ASD through data-driven approaches.

We examine the literature on autism from 2010 to 2021. The most difficult aspects of the autism dataset are missing values and classification accuracy. The authors proposed a model in 2020 that accurately predicts autism. They investigated how to extract data and determine whether a patient has autism in order to validate the AC association classification. 97% of the results were the highest [1]. Additionally, the authors offered a method and a technique for both developing and predicting autism. They made predictions quickly and produced better outcomes. A study on a social care solution for infants that develops and predicts positive outcomes has been presented. Additionally, they investigated and discovered early autism disorders in children and worked to enhance, elevate, and forecast more quickly [2]. The authors presented a proposal in 2021 to enhance classification and forecast the condition of autism spectrum disorder, which weakens the body, consumes nerve cells, and destroys the patient's mind. In their article, they presented a better outcome than the overabundance of the work. The values obtained by the current authors are identical to this value. Their Support Vector Machine (SVM) work had a 97% accuracy rate. It indicates that we perform better when using more than seven algorithms and recording all 100% of the results.

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In order to diagnose the autism dataset, the current authors proposed a comparison using ensemble tech niques in conjunction with preprocessing methods. The dataset in question is downloaded from the UCI repository. For data mining tasks, two tools called WEKA and Rapid Miner are used to produce better results than their competitors. Preprocessing methods were applied in the initial phase to deal with miss ing values and identify outliers. Ensemble classifiers like voting, stacking, bagging, and boosting are us ed during the classification phase. Stacking produced the highest accuracy rate of 99%. After that, we e mployed algorithms without a preprocessing phase. Bagging yielded the highest accuracy rate of 97%. The obtained results were then compared with Rapid Miner tools using the WEKA tools. The accuracy rate was 100% in every experiment. Our tests verified that the results were better than those from earlie r studies. Because of this, our work's reliance on ensemble algorithms proved to be incredibly successfu l and offered great predictions for enhancing classification performance in this situation. The primary is sues with the applied data were resolved and compensated for. The mean was used to estimate the locati on of the missing values. Similarly, the K nearest neighbor (KNN) method is used to detect outliers. Th e wonderful and good-enough surpasses all expectations in order to solve these issues.

2. Literature Overview

Numerous studies have proposed predicting the diagnosis of autism in the years 2010–2021. Here, we summarized a few important works. Using two data mining tools, Rapid Miner and WEKA, the current authors employed ensemble algorithms, such as boosting, bagging, stacking, and voting, which produced good results and outperformed peers because it predicted 100% accuracy on the applied dataset for autism disease.

In order to address the needs of children with autism, authors presented a virtual presence stereoscopic game in 2010. On average individuals with autism, their initial test yielded positive results [4]. Additionally, other authors suggested a way to improve classification and prediction performance. This method of examining the relationship between behavioral factors and highly prevalent autism was proposed. They used this method to improve autism prediction outcomes. Additionally, they used examinations and patient profiles from two Thai hospitals. [5]

In 2011, a year later, the authors suggested a way to forecast better outcomes and show favorable outcomes that were superior to the work that had been presented. They persisted and put a lot of effort into putting forth a proposal to validate an enhanced approach for autism. This technique uses a well-known robot that has been programmed to identify the impacted child and determine whether to respond favorably or unfavorably. They predicted favorable outcomes., and the accuracy reached 94%, whereas this value was less than the results that we obtained from the current paper, an accuracy of 100%. The results proved that some children are affected positively and some negatively [6].

Screen Mobile Computers (TSMC) were proposed by authors in 2012 as a treatment for autism disorders. Since the TSMC device teaches children with autism to exercise, gain experience, and develop their neurological and mental abilities, the authors suggested a laptop computer with a touch screen. These writers' experiences with autism development and prediction. It seems that our work is superior to all prior work in terms of improving classification performance, and it is more accurate overall [7].

In order to enhance the classifier's performance, authors proposed a new model in 2019. They employed machine learning (ML) under supervision. Using algorithms like SVM, boosting, and decision trees, their study sought to achieve high accuracy. In order to improve prediction and fill in the missing values, they also worked with these algorithms. Their experiments produced good results during these procedures. The best results were 97.1, 97, 98, and 0.98% for accuracy, precision, recall, and F1, respectively. Although their experiments yielded good results, our work in this paper is superior and provides good values to predict well on the autism data [14].

In order to predict the best outcomes for autism spectrum disorder, authors proposed machine learning algorithms in 2020 and employed the AdaBoost algorithm. The corresponding values for accuracy, recall, and F1 were 97, 95, and 95.98%. These results are deemed acceptable, but the results transferred by the current authors are high and have a better prediction than the other results because they demonstrate that

they use ensemble algorithms in this current paper to significantly improve the performance of classification and autism prediction. By combining learning and vision-based examination as a method of transformation to follow autism at early ages in the eye examination, the results are excellent in predicting autism and they accelerated the detection of autism [15].
In 2020, the authors worked on the French version of RAADS-R and proposed psychological verification pertaining to each injured person's psychological state. About 105 of the 305 adult cases of autism were found to be free of intellectual disability, brain abnormalities, or subconscious mind damage. from 95%, since this makes it impossible for them to use their experience to psychologically resist. In order to predict the best outcomes for autism and enhance classifier performance, they found a way to assist physicians with this technique [16].

In order to work with autism data, authors introduced a technology in 2021. To enhance its performance, they used the SVM algorithm to better handle and forecast such data.
Recent studies have demonstrated the growing importance of advanced machine learning and artificial intelligence techniques for Autism Spectrum Disorder (ASD) diagnosis. Farooq et al. (2023) applied machine learning models for ASD detection in both children and adults and reported promising classification performance using predictive learning approaches [17]. In another study, Ali et al. (2023) proposed a comprehensive machine learning framework for personalized classification of ASD behavioral severity, demonstrating the effectiveness of data-driven approaches for autism assessment [18]. Furthermore, Alves et al. (2023) utilized functional brain networks combined with machine learning techniques for ASD diagnosis and achieved encouraging classification results based on neuroimaging data [19]. More recently, Aldrees et al. (2024) introduced a data-centric framework incorporating feature selection and Explainable Artificial Intelligence (XAI) for ASD prediction, highlighting the importance of model interpretability in clinical applications [20]. Similarly, Jeon et al. (2024) integrated machine learning and explainable AI techniques to provide reliable and transparent autism diagnosis for pediatric patients, emphasizing both predictive accuracy and decision transparency [21]. These recent developments indicate a clear research trend toward explainable AI, advanced machine learning models, and intelligent diagnostic systems for ASD detection.
They worked on it using the Python programming language, and SVM produced satisfactory and good results. They put the three datasets for adults, kids, and teenagers in a separate group and saw an improvement in their performance. 95% of the results were accurate [1].
After reviewing numerous studies, we discovered that our work produced the best results when employing ensemble techniques with pre-treatment using the two programs WEKA and Rapid Miner. It demonstrated the highest accuracy of 100% using our applied methods, which is a good outcome for improving the classification performance and significantly predicting autism spectrum disorder.

3. Methodolgy

This section provides the necessary background and references to calculate external blast loading. Although there is uncertainty in predicting the size, type, and location of the explosive, calculation of blast loads is essential in the design of blast-resistant structures as shown in Figure 1.

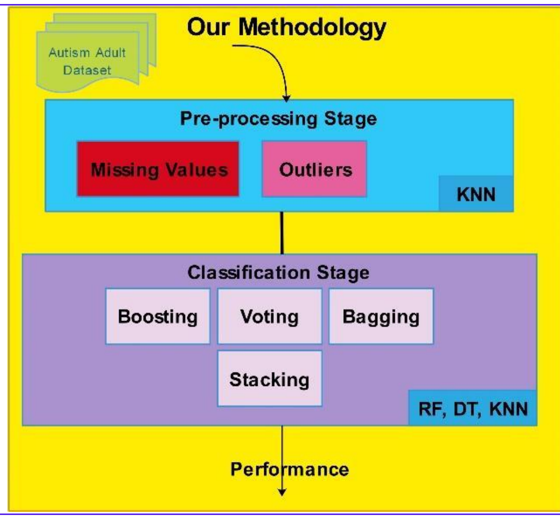

Fig. 1.The proposed methodology in two Data Mining tools

3.1 Dataset Description

The dataset used in this study is the Adult Autism dataset obtained from the UCI Machine Learning Repository. It consists of 704 instances and 21 attributes related to behavioral and demographic features used for ASD screening. The dataset includes both categorical and numerical variables and contains missing values that require preprocessing before model training.

3.2 Data Preprocessing

In the preprocessing stage, missing values were handled using the K-Nearest Neighbors (KNN) imputation method to improve data consistency and completeness. Outliers were also identified and treated to reduce their impact on model performance and enhance data quality. These prepr ocessing steps were applied to ensure better separability between classes and improve the reliab ility of classification results.

3.2 Classification Methods

The classification phase is based on ensemble learning techniques, which include Bagging, Boosting, Voting, and Stacking. These methods combine multiple base classifiers to improve predictive performance and reduce model variance and bias. The base classifiers used in the experiments include Decision Tree (DT), Random Forest (RF), and K-Nearest Neighbors (KNN). For the stacking approach, the outputs of base models are combined using a meta-classifier to generate the final prediction.

3.4 Experimental Tools

The experiments were conducted using two widely used data mining tools: WEKA and RapidMiner. These tools were selected due to their strong support for machine learning algorithms and ensemble methods, as well as their ability to perform preprocessing and evaluation tasks efficiently.

3.5 Performance Evaluation

The performance of all models was evaluated using standard classification metrics, including Accuracy, Precision, Recall, and F1-score. These metrics provide a comprehensive assessment of model performance in terms of correctness, completeness, and balance between precision and recall.The overall framework is designed to provide a fair comparison between different ensemble learning techniques under the same experimental conditions.

We have applied evaluation parameters such as accuracy, precision, recall, and F1. These procedures were calculated and implemented through these formulas and the requirements in Table 1

Table 1. Evaluation parameters

Parameter	Equation
Accuracy	$\frac{TP+TN}{P+N}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{P}$
F1	$\frac{2 \times precision \times recall}{precision \times recall}$

4. Experimental Setup

To ensure a systematic evaluation of the proposed framework, the Adult Autism dataset obtained from the UCI Machine Learning Repository was used. The dataset contains 704 instances and 21 attributes related to autism spectrum disorder (ASD) screening and diagnosis. Prior to classification, data preprocessing was performed to address missing values using the K-Nearest Neighbors (KNN) imputation method with (k = 10). Outliers were also identified and treated to improve data quality and reduce their influence on the classification process.

The experimental evaluation was conducted using both RapidMiner and WEKA data mining tools. Ensemble learning techniques, including Bagging, Boosting, Voting, and Stacking, were applied in combination with commonly used machine learning classifiers such as Decision Tree (DT), Random Forest (RF), and K-Nearest Neighbors (KNN). For the stacking approach, the predictions generated by the base classifiers were combined to produce the final classification output.

The performance of the proposed framework was evaluated using Accuracy, Precision, Recall, and F1-score metrics. The experiments were performed under identical data processing conditions to ensure a fair comparison among the investigated ensemble methods. This setup enabled the assessment of the impact of preprocessing and ensemble learning techniques on autism classification performance.

4.1 Experiment I

In the first experiment, we looked at how the autism data set was affected by collection techniques without any pre-processing. We used ensemble algorithms such as voting, bagging, boosting, and stacking. We used Rapid Mine to apply these algorithms. While the accuracy of stacking was 100%, the highest accuracy of voting, bagging, and boosting was 97.16%. As a result, the stacking process outperforms the other algorithms and enhances classification performance using ensembles without requiring Rapid Miner pre-processing. With bagging, voting, and boosting, the best accuracy, precision, recall, and F1 were 97.16, 96.9, 95.84, and 96.36%, respectively. The stacking value is the highest value among these values.

Accuracy, precision, recall, and F1 all reached 100% in every measurement. These outcomes are the best available for enhancing classifier and prediction performance overall. The best results using ensembles without pre-processing in combination with KNN and RF via Rapid Miner Tool are displayed in Table 2.

Table 2 indicates that the ensemble results with stacking, bagging, voting, and boosting without pre-processing demonstrated a strong predictor of significantly enhancing the classification performance for the adult autism spectrum data. 97% was the highest accuracy. By utilizing positive outcomes for forecasting and performance enhancement.

Table 2 The results obtained using ensembles without pre-processing in combination with KNN and RF using the Rapid Miner Tool

Method	Precision	Recall	Accuracy	F1
Bagging	96.9%	95.84%	97.16%	96.36%
Boosting	96.9%	95.84%	97.16%	96.36%
Voting	96.9%	95.84%	97.16%	96.36%
Stacking	100%	100%	100%	100%

4.2.Experiment II

In the second experiment, we attempted to use ensemble techniques on the adult autism data without any pre-processing. The findings showed a strong and unique prediction for enhancing performance. Because it will provide good predictions with bagging, boosting, voting, and stacking, accuracy, precision, recall, and F1 reached a high rate of 100%, which is regarded as the best. Table 3 displays the measurement values that we used with Rapid Miner's aggregation algorithms, and it did a fantastic job surpassing its peers and prior experiences.

Table 3. The obtained results through ensembles without pre-processing in conjunction with DT And Random Forest (RF) through Rapid Miner Tool

Method	Precision	Recall	Accuracy	F1
Bagging	100%	100%	100%	100%
Boosting	100%	100%	100%	100%
Voting	100%	100%	100%	100%
Stacking	100%	100%	100%	100%

4.3. Experiment III

In the third experiment, we investigate the pre-processing effects of ensemble approaches on the autism dataset. We employed ensemble algorithms with a pre-processing step on the autism dataset. To forecast better results, we employed algorithms like stacking, boosting, voting, and bagging. The accuracy of bagging, stacking, boosting, and voting was attained when we applied these algorithms using the Rapid Miner tool. Accuracy, recall, precision, and F1 all attained 100% in the ensemble with pre-processing. This method produced 100% recall as shown in Table3, accuracy, precision, and F1. When it comes to improving the classifier's performance and producing a significant prediction, these are the best results.

Table 3. The obtained results through ensembles with pre-processing in conjunction with DT And RF through Rapid Miner Tool

Method	Precision	Recall	Accuracy	F1
Bagging	100%	100%	100%	100%
Boosting	100%	100%	100%	100%
Voting	100%	100%	100%	100%
Stacking	100%	100%	100%	100%

4.4.Experiment IV

In the fourth experiment, we check the methods of aggregation. We applied the ensemble algorithms with pre-processing on the adult autism data. We conducted other experiments. In this experiment, we applied the ensemble algorithms that include bagging, boosting, voting, and stacking with pre-processing in conjunction with KNN, RF using the Rapid Miner tool. The highest results were obtained with bagging, Adaboost, and voting. The precision, recall, accuracy, and F1 were 96.9, 95.84, and 97.16, 96.36%, respectively. The stacking algorithm showed the best results and in all its measurements was 100%. It indicates that stacking will predict better than others and give better results to improve the classification performance with the autism data for adults that we work on in this article. Table 4 shows the highest results using ensembles with pre-processing in conjunction with KNN And RF through Rapid Miner Tool.

Table 4 The obtained results through ensembles with pre-processing in conjunction with KNN And RF through Rapid Miner Tool

Method	Precision	Recall	Accuracy	F1
Bagging	96.9%	95.84%	97.16%	96.36%
Boosting	96.9%	95.84%	97.16%	96.36%
Voting	96.9%	95.84%	97.16%	96.36%
Stacking	100%	100%	100%	100%

4.5.Experiment V

We will use the WEKA tool to confirm the ensemble algorithms' application in the fifth section. Reinforcement, bagging, boosting, voting, and stacking were among the aggregation techniques we used in our work. One of the best outcomes from the results we extracted using the Rapid Miner tool was 100% accuracy across all algorithms. The accuracy, precision, recall, and F1 measurements all reached 100%, as shown in Table 5. These outcomes from using the WEKA are good; you can anticipate what will happen, and it is important to enhance the classification's performance. Two programs have been used for this in order to improve outcomes and provide good values that are more predictive.

Table 5 .The obtained results through ensembles with pre-processing with WEKA tool

Method	Precision	Recall	Accuracy	F1
Bagging	100%	100%	100%	100%
Boosting	100%	100%	100%	100%
Voting	100%	100%	100%	100%
Stacking	100%	100%	100%	100%

4.6.Discussions

Two data mining tools were used in this article. Both Rapid Miner version 9 and WEKA versions 3.5 and 8 were used to process the data and apply algorithms for a set of autistic patient records. We used the ensemble algorithms, which include voting, stacking, bagging, and boosting. Additionally, these aggregates were employed with the DT, KNN, and RF. The two tools assess how these algorithms are implemented both with and without pre-processing. When these algorithms were used with pre-processing, they produced excellent outcomes for every combination of bagging. It produced excellent results, with an estimated 100% success rate. Additionally, we used the Rapid Miner tool to apply these algorithms without pre-processing, which produced good results, estimated, 97.16% and 100%, respectively. Additionally, four crucial evaluation metrics—recall, accuracy, precision, and F1—were employed. The accuracy of the results obtained through ensembles without pre-processing with KNN and

RF with Rapid Miner is equal to the number of real positives over the total number of positives, true, and false negatives. These algorithms were used, and the outcomes with bagging, boosting, voting, and stacking are shown in the Table 6 below. With bagging, voting, and boosting, we obtained good results estimated at 97.16, 97.16, and 97.16%, respectively.

The achievement of 100% classification performance in several experiments may be attributed to the characteristics of the Adult Autism dataset used in this study. The dataset contains a relatively limited number of instances (704 records) and a set of highly informative screening features that are strongly correlated with the target class. Furthermore, the preprocessing stage, including KNN-based imputation for missing values and the treatment of outliers, improved data quality and enhanced class separability.

In addition, ensemble learning methods such as Stacking, Bagging, Boosting, and Voting are designed to combine the strengths of multiple classifiers, which can substantially improve predictive performance when the dataset exhibits clear decision boundaries. The obtained results suggest that the selected features provide strong discriminatory information for autism classification, enabling ensemble models to achieve very high predictive accuracy.

Nevertheless, the perfect performance achieved in some experiments should be interpreted with caution. Such results may be influenced by the relatively small size of the dataset, the strong predictive power of the selected attributes, and the characteristics of the data distribution. Although no evidence of intentional data leakage was observed during the experiments, exceptionally high performance may indicate potential risks of overfitting that should be carefully considered. Therefore, future work will evaluate the proposed approach using larger and more diverse datasets and employ more extensive validation procedures to further assess the robustness, generalization capability, and practical applicability of the developed models.

The results were also presented with stacking amounting to 100%, as Table 2 demonstrates. The results obtained using ensembles without pre-processing using DT and RF with Rapid Miner, where the ensemble algorithms, such as bagging,. The third Table, which displays the four measures of bagging, boosting, voting, and stacking, was created using ensembles with pre-processing, DT, and RF with Rapid Miner. The results showed good predictions for an improvement in autism. The total of the four measurements in the Table was 100%. The results in the fourth Table were obtained using ensembles with pre-processing and KNN and RF with Rapid Miner, where we employed ensemble algorithms such as voting, stacking, bagging, and boosting. When these algorithms were used with pre-processing and KNN and RF algorithms, the results were 95.84, 97.16, and 96.36%, which are thought to be the best values when all measurements are stacked by 100%., the outcomes of ensembles using WEKA pre-processing. The ensemble algorithms were used in conjunction with pre-processing for bagging, boosting, voting, and stacking. With this program, the predictions were greatly fulfilled. The accuracy, precision, recall, and F1 measurements in the Table all had values that were 100%. The outcomes are useful for making accurate predictions and obtaining high-quality values to enhance classification performance. A comparison between our best results and other works is presented in Figure 2. The ROC curves derived from the classifications are displayed in Figures 3 through 12. Using ensemble algorithms such as boosting, bagging, voting, and stacking with DT, RF, and KNN, we extracted the results and obtained a good performance in autism classification and prediction. The ROC for the best classification of the current author ensembles without pre-processing is displayed in Figures 3 to 7, while the ROC for the best classification of the current author ensembles with pre-processing is displayed in Figures 8 to 12.

Table 6. A comparison among the obtained results through ensemble s with pre-processing and other works

Works	Precision	Recall	Accuracy	F1
[13]	76%	42%	76%	54.1%
[14]	97%	95%	100%	95.98%
[15]	97%	98%	97.1%	98%
The best results of t he current study	100%	100%	100%	100%

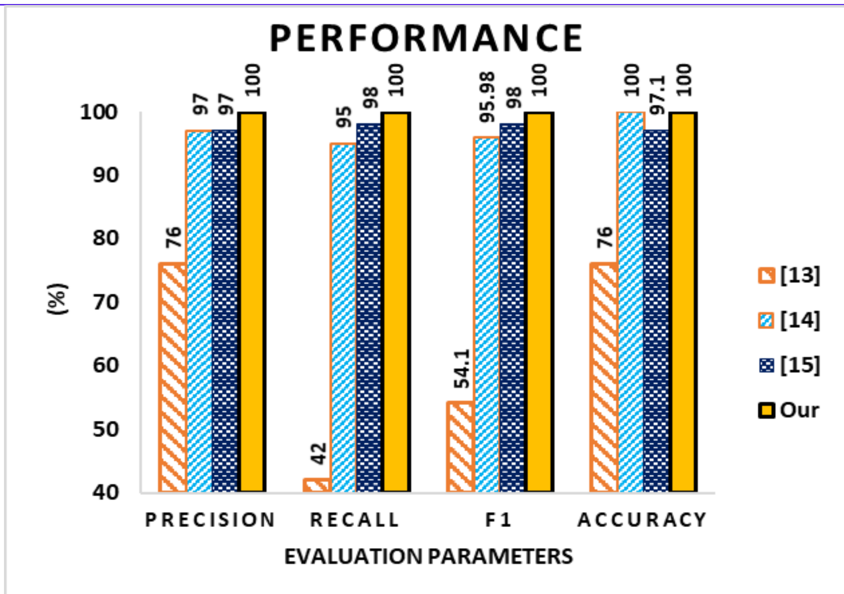

Fig. 2. A comparison among our best results and other works

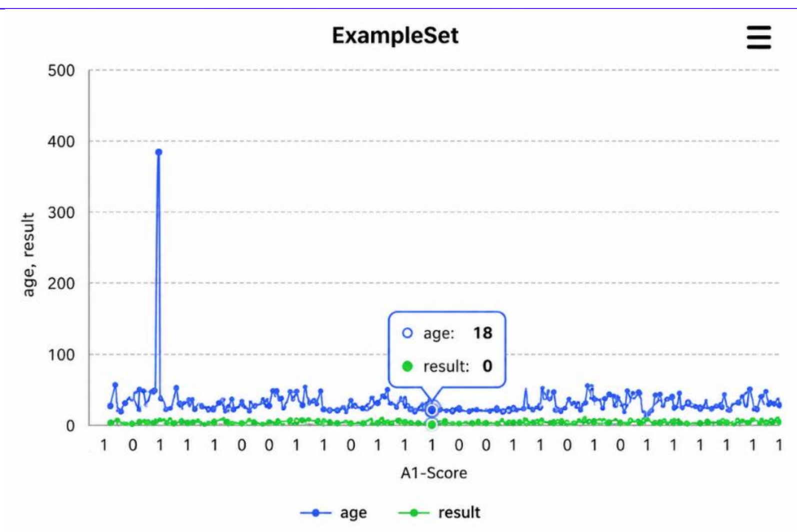

Fig.3.The ROC for the bagging method

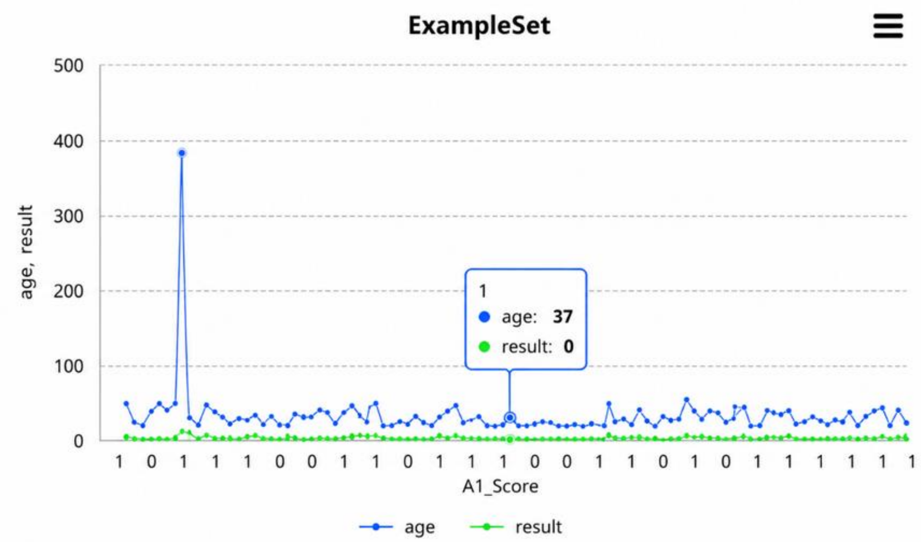

Fig. 4. The ROC for the boosting method

Fig.5. The ROC for KNN

Fig. 6. The ROC for stacking method

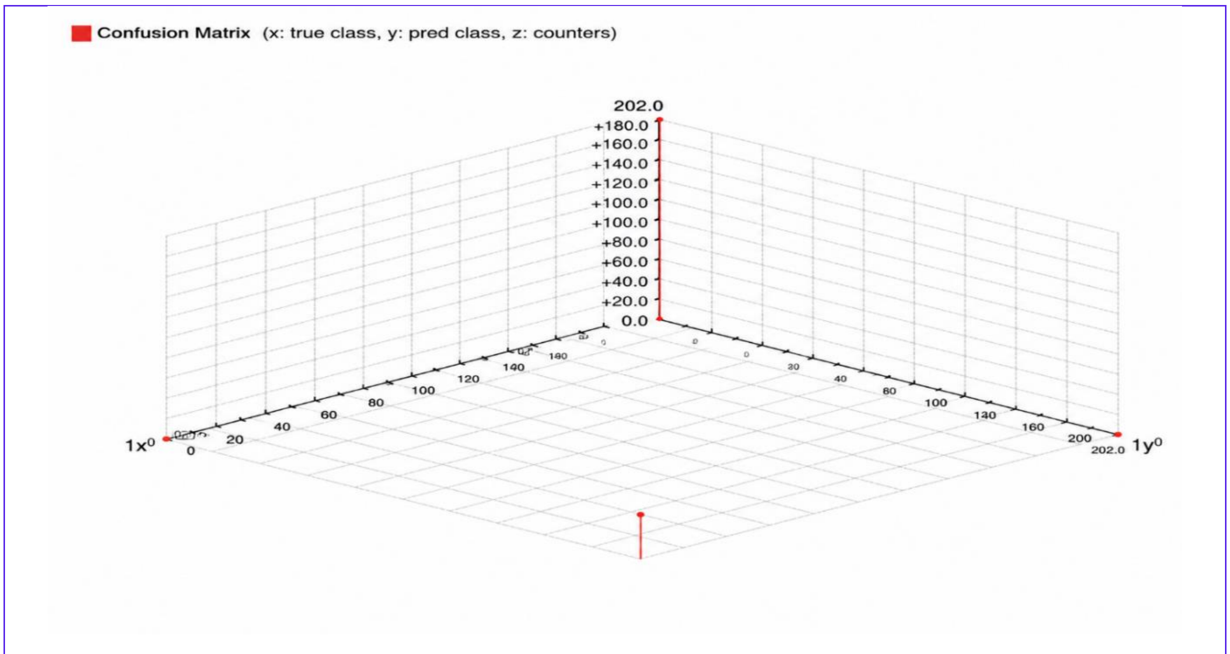

Fig. 7. The confusion Matrix for the stacking method

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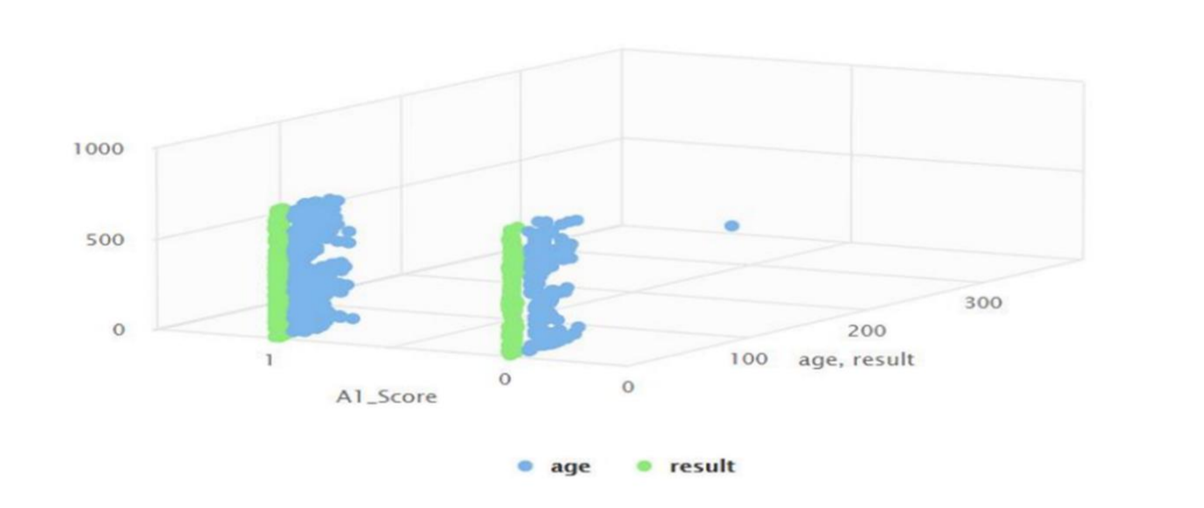

Fig.8. The ROC for with bagging with Histogram and Scalter3D charts

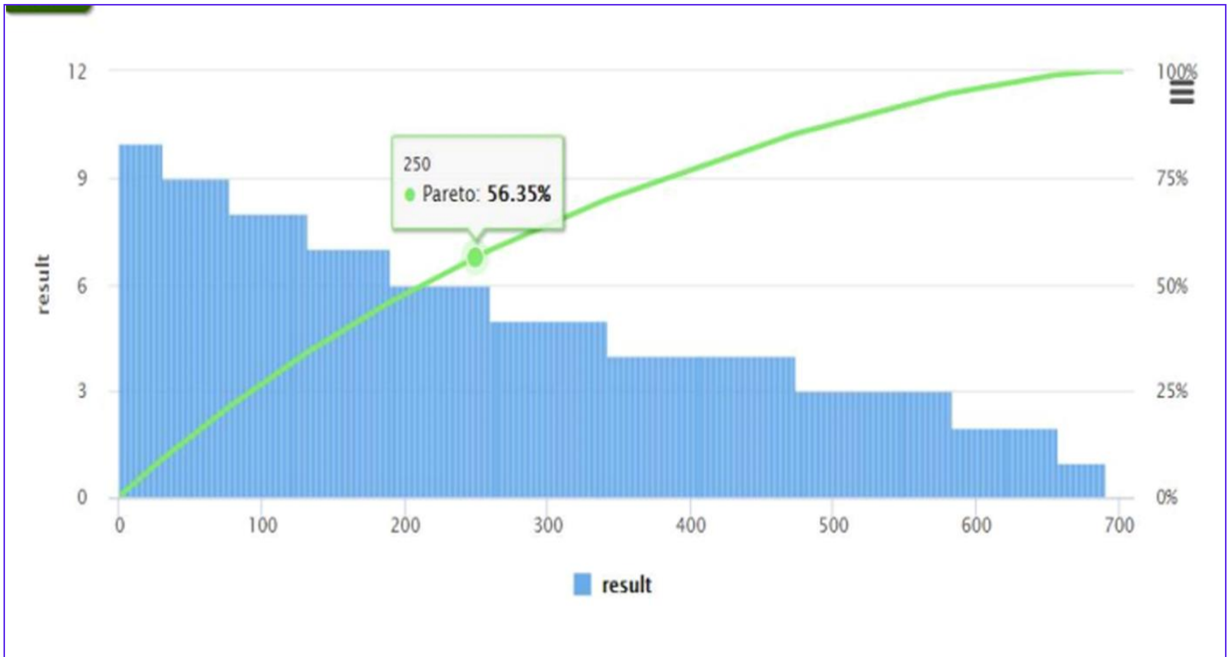

Fig.9. The ROC for boosting with pareto and Histogram charts

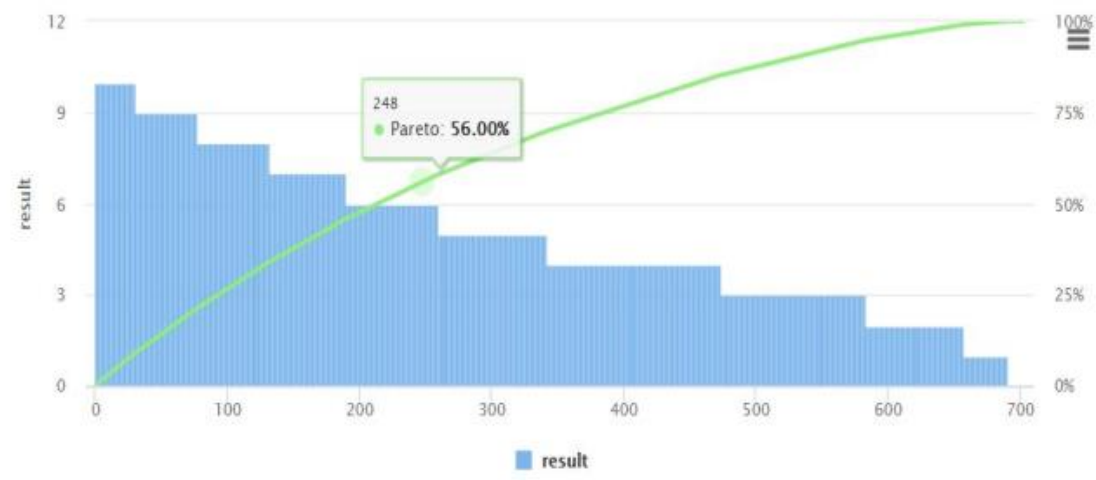

Fig.10.The ROC for stacking method with pareto and scatter/Bubble charts

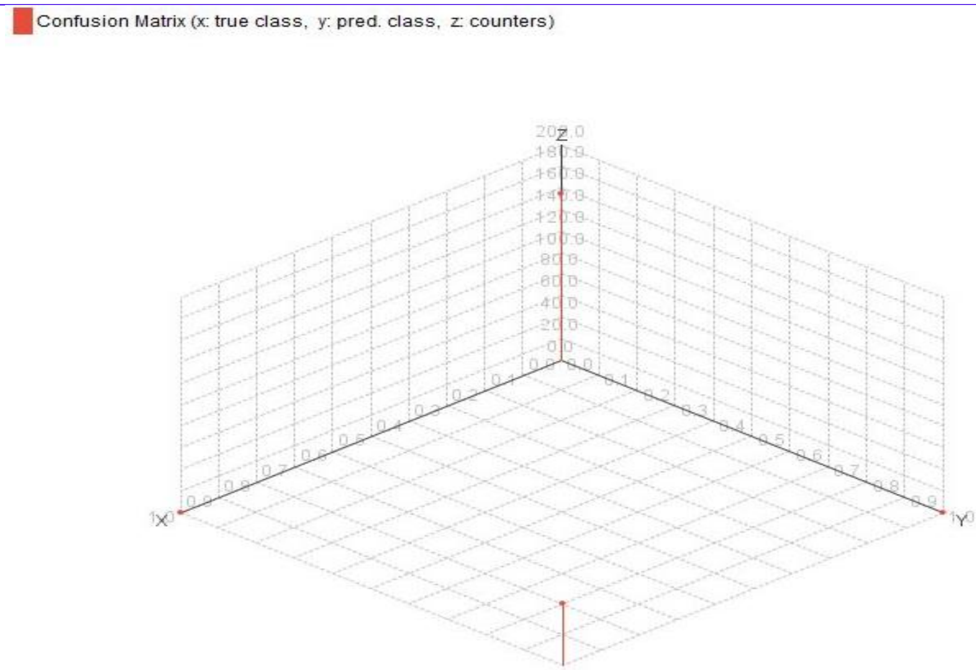

Fig.11. The confusion Matrix for the stacking method

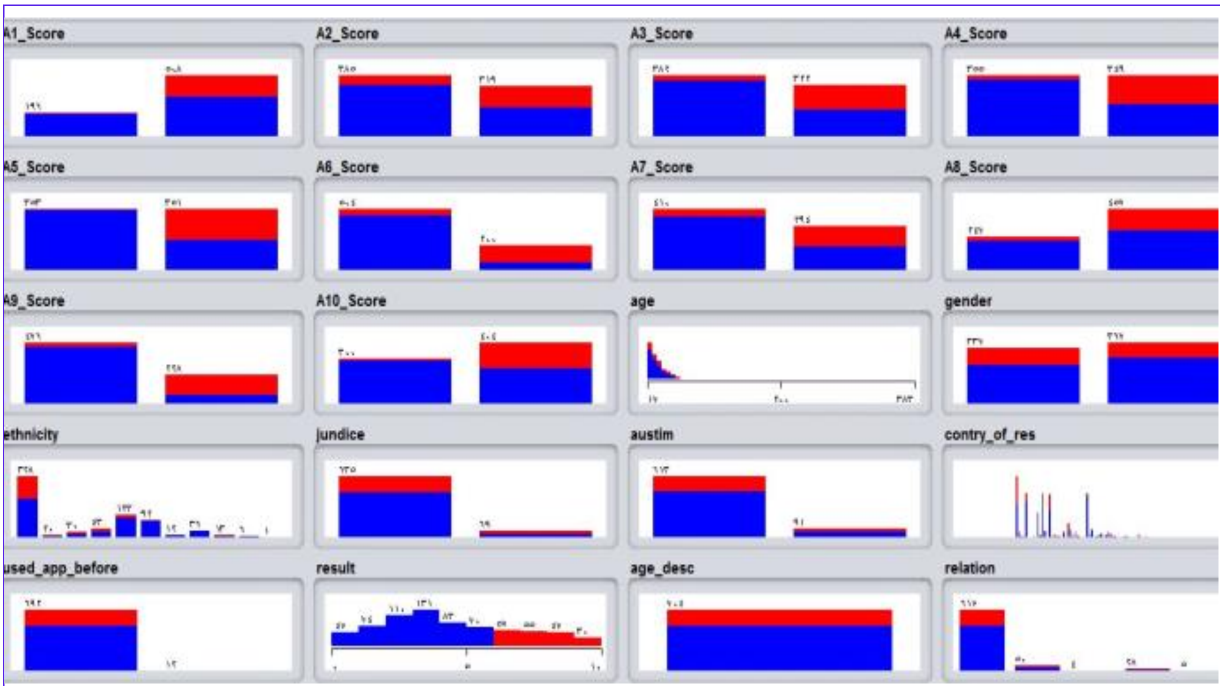

Fig.12. The ROC for the best classification of the current authors (ensembles with pre-processing) in WEKA tool

5. Conclusion

When it comes to its effects on a person's psyche and mind, autism is one of the most common illnesses that affect people. When a child's speech is delayed or unresponsive and we are unable to respond, suspicions about autism arise because some people are mentally and anxiously affected, which affects the extent of their response and understanding because it affects the subconscious mind. We used good methods and produced good results in this article. These methods demonstrated their ability. When DT algorithms and KNN technology were combined with the ensemble algorithm—which includes bagging, boosting, voting, and stacking—the performance of autism classification and prediction was greatly enhanced., and RF. These techniques were applied with two data mining tools with and without pre-processing. Pre-processing in WEKA produced excellent results, with 100% values for every metric. Additionally, all measurements were obtained using the Rapid Miner, and 100% pre-processing was achieved. Additionally, we used the same program without pre-processing, and the results showed an average of 97% for voting, bagging, and AdaBoost, while stacking reached its value of 100% for all measurements. In terms of accuracy, recall, precision, and F, these results demonstrated a good development, a high level, and a wonderful prediction to improve the performance of classification and work on the quick prediction of autism. 1. The proposed technique in this article showed that it is an excellent technique for improving classification performance as well as predicting autism better than business measurement. This method showed great success in terms of the outcomes that we showed in this article. In terms of upcoming projects, we'll work on additional optimization algorithms like the genetic algorithm. We are searching for the best ways to enhance performance and predict autism in a high and excellent way. In the past, we have worked to develop our work and obtain results and a very high future prediction. We have demonstrated the success and quality of our work, and we will continue to demonstrate the success of our work in the future.

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Conflicts of Interest: The authors declare no conflict of interest.

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