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OPTIMIZED EEG SIGNAL PROCESSING AND FEATURE SELECTION FOR AUTISM SPECTRUM DISORDER CLASSIFICATION

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Abstract
Autism Spectrum Disorder is a neurological disorder linked to brain development that impacts facial features. An extensive and intricate neurodevelopmental disorder, ASD first appeared in early childhood. For healthcare professionals to treat and care for patients in a timely and appropriate manner, early recognition of ASD is essential. Many machine learning algorithms have been explored to investigate the viability of diagnosing autism. But finding accurate and timely ways to identify autism is still quite difficult. To improve autism identification accuracy while reducing time consumption, a new method termed Radial Adaptive Feature Projection based Generalized Emphasis Boost Classification (RAFP-GEBC) is presented. The primary goal of the RAFP-GEBC technique is to increase the accuracy of autism identification by means of effective processing. In order to identify autism spectrum disorder, this technique uses EEG signals from a dataset and includes pre-processing, feature selection, and classification. The Radial Basis Kernel Adaptive Stromberg Wavelet Filtering approach is used in the pre-processing stage. Input EEG signals are cleaned, transformed, and arranged into an appropriate manner using this technology. EEG signals are broken down into discrete frequency components, and noise is removed from each component in turn. Contingency Correlative Projection Pursuit Regression is then used in the feature identification process. The most pertinent and instructive characteristics are found through this procedure to ensure an appropriate classification of autism. The suggested RAFP-GEBC technique's feature selection cuts down on the amount of time needed for autism identification. The time needed to detect autism is decreased by the GEBC approach. In conclusion, the Generalized Learning Vector Quantized Emphasis Boost method is used to classify data with distorted features. By using an ensemble machine learning technique called "boosting," classification results are strengthened and patients with and without autism can be distinguished with the least amount of error. As a result, the RAFP-GEBC method delivers precise and error-free autism identification. Numerous factors are experimentally evaluated by many people. According to qualitative study, the RAFP-GEBC strategy outperforms other approaches in the detection of autism.

Keywords:
Autism Detection, Electroencephalogram (EEG) signals, Radial Basis Kernel Adaptive Strömberg Wavelet Filtering technique, Contingency Correlative Projection Pursuit Regression, Generalized Learning Vector Quantized Emphasis Boost Technique

1. INTRODUCTION

ASD is widespread situation which is usually noticeable at children around the age of 3 years old. Early identification of autism is crucial for an accurate diagnosis of this disorder. Electroencephalogram (EEG) signals are highly significant in the diagnosis of ASD, as they compute electrical actions created through huge amounts of neurons. Various methods have been developed for recognition of ASD by EEG signals. A multimodal diagnosis framework, referred to as the Stacked Denoising Autoencoder (MMSDAE), was developed in [1] to recognize ASD at children by utilizing permutation of electroencephalogram (EEG) and ET information. However, it was found that more efficient aspects combined through ASD were not efficiently selected using advanced processing methods. A unique classification system called SVM polynomial was developed [2] for autism detection, achieving the highest accuracy. However, reducing the time consumption for autism detection remains a significant challenge.

The classification of normal and autistic children based on brain signals was carried out in [3] using a support vector machine (SVM). However, the algorithm's performance did not improve the accuracy during the evaluation process. Hybrid lightweight deep feature extractor was developed in [4] to enhance the classification performance of ASD detection using a large EEG dataset. But premature recognition of autism at clinical setting was not conducted.

Machine learning techniques were developed in [5] to enhance precision and minimize the time required for diagnosing ASD. However, these techniques did not improve the robustness and overall performance of the system. An efficient framework was developed in [6] for assessment of different ML methods to enhance premature recognition of ASD with Feature Scaling (FS) strategies.

A hybrid fusion approach was introduced in [7] for enhancing detection efficiency as well as minimizing costs. However, detection models did not minimize the occurrence of ASD. A novel method was designed in [8] for automatic identification of autism depending on functional brain information. But the more robust methodology was not considered. ML basis of approach was developed for the automatic recognition of ASD, utilizing feature extraction to enhance recognition accuracy. However, the accuracy of ASD detection did not improve. The Common Spatial Pattern (CSP) technique was developed in [10] for diagnosis of autism as well as epilepsy disorders. However, the technique did not achieve perfect classification.

The major contributions of RAFP-GEBC technique are listed below.

- A novel technique, RAFP-GEBC is introduced to enhance the accuracy of autism disease detection through preprocessing, feature selection, and classification.
- To minimize the detection time for autism, the Radial Basis Kernel Adaptive Strömberg Wavelet.
- Filtering techniques are used to eradicate noise as of EEG signals. Wavelet transform is utilized for decomposing EEG signals to various frequency subbands and effectively reduces noise. Additionally, a congruence correlative piecewise regression approach has been developed to identify significant features from these frequency subbands.
- To develop an algorithm called Generalized Learning Vector Quantized Emphasis Boosting for accurately

diagnosing the autism using the Canberra distance measure. In order to minimize errors, a damped least squares approach is developed, which leads to improved classification results.

- Extensive simulation results reveal that the proposed RAFP-GEBC technique achieves better autism detection compared to existing methods

The structure of the manuscript is as follows: The literature review is explained in Section 2. The third section applies the RAFP-GEBC technique. The detailed experimental setup and dataset description are presented in Section 4. Section 5 explains performance outcomes. Lastly, Section 6 provides conclusions.

2. LITERATURE REVIEW

A novel dynamic filtering approach and Recurrent Neural Networks (RNNs) employing Gated Recurrent Units (GRUs) were developed in [11] for the detection of neurological disorders based on EEG data. However, the detection process incurred longer processing times. In [12], various classification techniques were developed to enhance the accuracy of ASD detection. However, a more robust ASD detection algorithm was not developed.

A recommender method with multiple classifiers was introduced in [13] to improve accuracy of ASD recognition. However, this technique did not succeed in minimizing the processing time. A cross-sectional analysis of children with premature diagnosis program for ASD was developed in [14] using electroencephalography signals. Robust technique for premature diagnosis of ASD as of EEG signals using density-based clustering was developed in [15]. However, efficient classifiers were not designed to enhance the diagnosis process.

IoT-basis of solutions uses ML and DL methods were developed in [16] to identify the ASD as well as improve lives of patients. New CNNPL approach was developed in [17] for categorizing brain functional networks in order to diagnose ASD. A Graph Attention Network was developed in [18] for ASD prediction.

A Temporal Coherency Deep Features model as well as an SVM Classifier was developed [19] for recognition of ASD. However, classifier did not provide precise classifications. The paper introduced a Bayesian multilevel model for ASD detection in [20]. However, the model did not succeed in minimizing the error rate of ASD detection.

3. METHODOLOGY

ASD is kind of neurodevelopmental disorder distinguished through disruptions at verbal as well as nonverbal activities, symptoms such as stereotyped behaviors, and so on . These symptoms typically emerge previous to age of three years aged children's. Then, it is vital to recognize the disorder as premature as possible to improve the child's behavioral outcomes. However, accurately detecting autism spectrum disorder with high precision is challenging. The proposed RAFP-GEBC technique is used for detecting autism spectrum disorder with higher accuracy and minimum time.

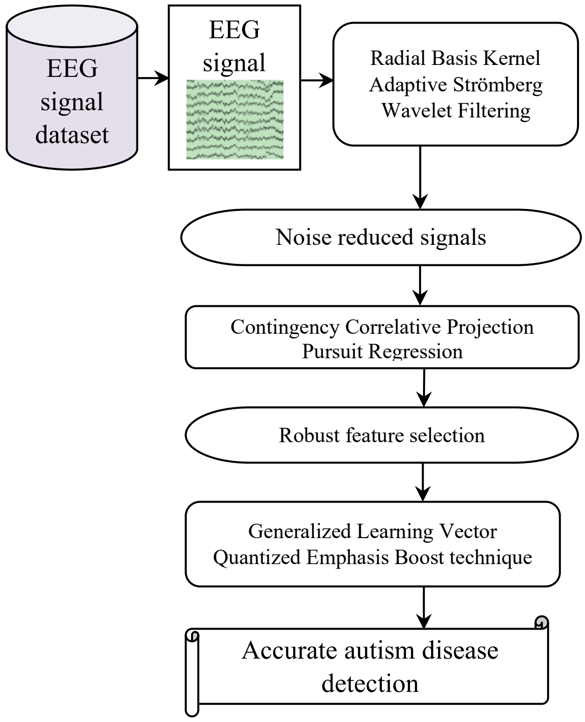

Fig.1. RAFP-GEBC technique's architecture

The Fig.1 illustrates the structural design of RAFP-GEBC method, designed to enhance accuracy of autism disease detection. Initially, it involves processing a set of EEG signals, denoted as $S_1, S_2, S_3 \ldots S_n$ corresponding to individual subjects $U_1, U_2, U_3 \ldots U_n$. The RAFP-GEBC technique comprises three key stages namely preprocessing, feature selection, and classification.

In the preprocessing phase, the EEG signals undergo decomposition using the Radial Basis Kernel Adaptive Strömberg Wavelet Filtering technique. This decomposition separates the signals into different frequency sub-bands and eliminates noise artifacts. Subsequently, output of filtering procedure is input to Contingency Correlative Projection Pursuit Regression technique to select significant features while discarding irrelevant ones from the frequency sub-bands. Finally, for accurate autism disease detection, the technique employs the Generalized Learning Vector Quantization Emphasis Boost technique as a classifier.

3.1 DATA ACQUISITION AND PREPROCESSING

EEG signals used for autism detection were acquired using the Biosemi Active system. The original EEG recordings were converted into an executable file format using EEGLAB. The EEG recordings were collected from 28 individuals with autism and 28 without autism, ranging in age as of 18 to 68 years. The recordings were taken through a 2.5-minute (150-second) period of eyes-closed resting and involved the use of 64 electrodes. Additionally, the sampling rate was set at 2048 Hz.

Signal preprocessing is fundamental step which includes manipulating, transforming, cleaning raw signals to enhance their quality for further analysis. The proposed RAFP-GEBC technique uses the Radial Basis Kernel Adaptive Strömberg Wavelet Filtering technique. Filtering technique is used to remove unwanted noise or artifacts from the signals. This includes applying filters to remove frequency components that are not of interest.

The Strömberg wavelet transform is a smooth orthonormal wavelet transform that gives adequate data for analysis as well as synthesis of original EEG signal. Strömberg wavelet transform decomposes the signals into different sub-blocks for accurate verification. The transformation process of the image decomposition is expressed as follows,

$$T = 2^{\frac{i}{2}} r^n (2^i t - m) \tag{1}$$

where T, indicates a wavelet transform at a time 't', 'i', 'm' denotes an integer, r^n denotes a Strömberg wavelet of order 'n'.

The proposed method selects the frequency domain for pre-processing and analyzing EEG signals. Examining EEG signals in time area is challenging due to frequent presence of noise caused by various factors. This noise often has a different frequency than regular brainwaves, making it more detectable in the frequency domain. As a result, the decomposition of EEG signals to different frequency sub-bands. Designed decomposition process gets the required frequency ranges

Table.1 decomposition of sub-bands

S. No	Frequency sub-bands	Threshold for frequency
1	Delta	0 - 4 Hz
2	Theta	4 - 8 Hz
3	Alpha	8 - 12 Hz
4	Beta	12 - 30 Hz
5	Gamma	> 30 Hz

Each frequency band includes a distinct type of threshold for frequency ranges as shown in Table.1. Radial Basis Kernel Adaptive filtering technique is applied for analyzing the given subbands to identify which ones contain noise and it removed while preserving the signal.

Apply appropriate filters to remove noise from the noisy subbands.

$$F = \exp\left(-0.5 \times \frac{|F_r - F_t|}{d^2} \right) \tag{2}$$

where, F denotes an output of filtering technique, F_r indicates a frequency if subband, F_t indicates a threshold frequency range, d indicates a deviation. The frequency ranges of subbands that deviate from the threshold are considered noisy. These noisy frequency components are then removed. Finally, quality-enhanced signals are obtained to increase disease detection accuracy with minimal time. The algorithm for radial basis kernel adaptive Strömberg wavelet filtering is provided below.

Algorithm 1: Radial Basis Kernel Adaptive Strömberg Wavelet Filtering

Input: Database, number of EEG signals $S_1, S_2, S_3 \dots . S_n$
Output: Preprocessed signals

Begin
Step 1: Collect the number of EEG signals $S_1, S_2, S_3 \dots S_n$
Step 2: For each signal S_i
Step 3: Apply transformation T using Eq.(1)
Step 4: Decompose signals into different frequency sub- bands
Step 5: for each sub band
Step 6: Apply the filtering process using Eq. (2)
Step 7: Find noisy frequency components
Step 8: Remove the noisy components
Step 9: **Return** (Noise reduced EEG signal)
Step 10: End for
Step 11: End for
End

Algorithm 1, given above, illustrates the various steps involved in processing a signal. Initially, EEG signals are collected from the dataset. Subsequently, the Strömberg Wavelet transform is employed to decompose input signal to distinct frequency sub-bands. After signal decomposition, the radial basis kernel adaptive filtering technique is applied to identify and eliminate noisy frequency components. Consequently, noise-reduced EEG signals are obtained for more accurate disease detection while minimizing time.

3.2 CONTINGENCY CORRELATIVE PROJECTION PURSUIT REGRESSION BASIS OF FEATURE SELECTION

After signal preprocessing, feature selection step is involved for selecting the most relevant and informative features from the EEG signal to enhance accuracy of a categorization method designed for identifying individuals with autism. Removing the irrelevant features reduces the dimensionality and making it easier to evaluate machine learning models.

The proposed RAFP-GEBC technique uses the contingency correlative projection pursuit regression for choosing significant aspects. Projection pursuit regression is ML method which involves finding more relevant aspects by measuring relationship using contingency correlation. Contingency correlative coefficient is a measure of association for two variables.

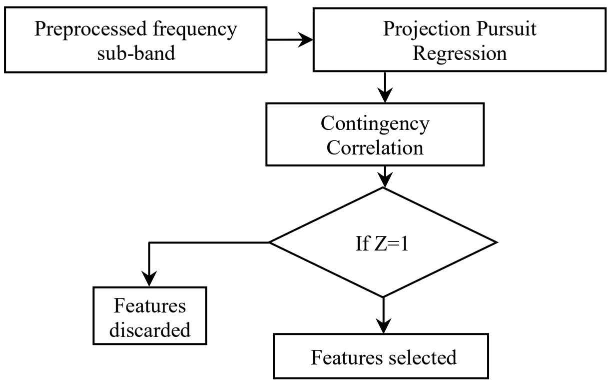

Fig.2. Flow process of contingency correlative projection pursuit regression based feature selection

The Fig.2 illustrates procedure of contingency correlative projection pursuit regression for choosing significant aspects from dataset. The regression function considers the preprocessed EEG signal as an input. It is used to find the most informative features for autism detection.

Let us assume number of features $f_1, f_2, f_3 \dots f_n$ in each sub-band of the preprocessed EEG signal. Projection pursuit maps the significant features into lower-dimensional space as given below.

$$f(x): f_T \rightarrow f_s \tag{3}$$

where, $f(x)$ indicates a projection function used to project the significant features (f_s) from the total set 'f_T'. The significant features are identified through contingency correlation function.

$$Z = \frac{|f_i - f_j|^2}{n} \tag{4}$$

From Eq.(5), Z denotes a Contingency correlative coefficient is referred as mean square of the variation among the features f_i and f_j. The output of the coefficient returns a value between −1 and +1. A coefficient of +1 represents a positive correlation i.e. linear dependency between the features, 0 implies that there is no dependency between the features and −1 indicates negative correlation.

$$Z = \begin{cases} +1, & \text{Positive correlation} \\ 0, & \text{No correlation} \\ -1, & \text{Negative correlation} \end{cases} \tag{5}$$

A feature is selected if the correlation coefficient provides '+1'. A feature is discarded if the correlation coefficient provides '-1' or 0. Every time the correlation is evaluated, the negative and no correlation features are discarded from further processing. The pseudo code representation of contingency correlative projection pursuit regression-based feature selection is given below.

Algorithm 2: Contingency correlative projection pursuit regression
Input: Preprocessed EEG signal **Output**: Select significant features
Begin **Step 1: For each** preprocessed sub bands **Step 2: for each** features f_i **Step 3: for each** features f_j **Step 4:** Measure the correlation 'Z' **Step 5: If** (Z=+1) **then** **Step 6:** Features are said to be a correlative **Step 7:** Project the correlative features **Step 8: else** **Step 9:** Features are said to be no correlation of negative correlation **Step 10:** Discard the irrelevant features **Step 11:End if** **Step 12: End for** **Step 13: End for** **Step 14: End for** **End**

Algorithm 2 outlines the process of feature selection using Contingency Correlative Projection Pursuit Regression. It involves considering the number of features extracted from sub-bands of EEG signals. Following that, correlations between the features are measured. Features exhibiting positive correlations are projected as significant for autism detection, while the others are discarded. This in turn reduces the time complexity of the autism detection process.

3.3 GENERALIZED LEARNING VECTOR QUANTIZED EMPHASIS BOOST CLASSIFICATION

Finally, classification of autism detection is performed using the generalized learning vector quantized emphasis boosting technique. Boosting is an ensemble machine learning method that strengthens weak classification results, effectively distinguishing between patients with and without autism. A weak classifier provides results that are only slightly correlated with the true classification, while a strong classifier provides the true classification of individuals with and without autism. Therefore, the proposed RAFP-GEBC technique utilizes an ensemble approach to enhance the accuracy of autism detection.

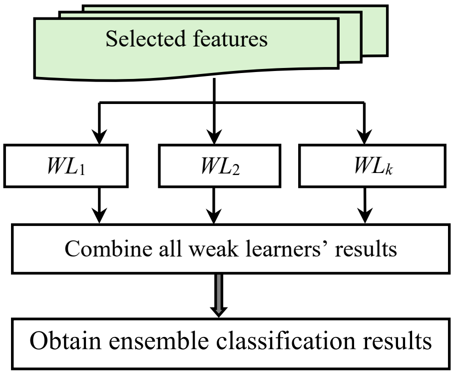

Fig.3. Schematic construction of Generalized Learning Vector Quantized Emphasis Boost

The Fig.3 represents the schematic illustration of generalized learning vector quantized emphasis boost classification through superior accuracy and minimum time utilization. Emphasis boosting method considerers the training set $\{X_i, Y_i\}$ where X_i indicates the selected features i.e. training samples and Y_i indicates the ensemble classification output. First, the ensemble boosting technique constructs k number of weak learners WL_1, WL_2, WL_3,⋯. WL_k, as GLVQ. The GLVQ is type of machine learning algorithm that particularly useful for classification tasks, where the training samples are to assign the predefined categories or classes i.e. 'with autism' and 'without autism'. GLVQ is also inspired by biological models of neural systems and trained its network with two layers, one is the input layer and output layer.

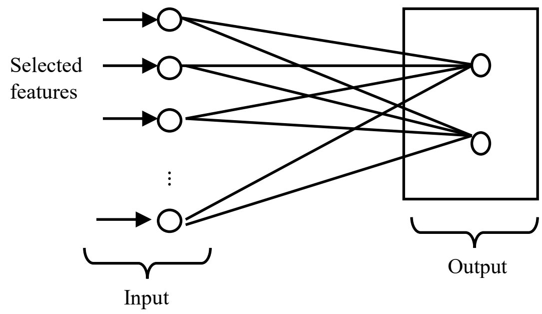

Fig.4. Generalized learning vector quantization

The Fig.4 illustrates the Generalized Learning Vector Quantization (GLVQ) architecture, where the input layer receives the selected features. Each input is attached to nodes. Every connection has dissimilar weights (q_j). Weights of neurons are initialized through arbitrary integer values.

For each input, winning vector is detected based on the shortest distance between the selected features and the disease features.

$$R = \arg\min d(f_s, f_{df}) \tag{6}$$

From Eq.(6), Y denotes an output of distance 'd' between the input features f_s and the disease features f_{df}.

$$d(f_s, f_{df}) = \frac{|f_s - f_{df}|}{|f_s| + |f_{df}|} \tag{7}$$

where, $|f_s|$ and $|f_{df}|$ represents the cardinalities of the two sets (i.e. number of features in each set). The minimum distance between the features is classified as patients with autism. Like this, weak learners categorize patients with and without autism. To obtain the strong classification output, weak classification outcomes are integrated as follows,

$$Y = \sum_{i=1}^{k} R_i \tag{8}$$

where,

Y indicates ensemble classification outcomes,

$\sum_{i=1}^{k} R_i$ represents weak classification result.

For each output, weights are randomly assigned.

$$Y = \sum_{i=1}^{k} R_i * \beta_i \tag{9}$$

where, β_i represents weights. The proposed technique utilizes weighted emphasis function to calculate quadratic errors of classification outcomes obtained by the weak learners,

$$EF = \exp\left[\phi\left((\sum_{i=1}^{k} R_i \, \beta_i - Y)^2 \right) - (1-\phi)\left(\sum_{i=1}^{k} R_i \right)^2 \right] \tag{10}$$

where, EF demonstrates weighted emphasis function, φ denotes weighting constraint (φ=1), Y portrays actual classification outcomes, $\sum_{i=1}^{k} R_i * \beta_i$ denotes forecasted classification results with weight β_i and without weight $\sum_{i=1}^{k} R_i$.

From the Eq.(10), by substituting 'φ' value is 1 and attain final output,

$$EF = \exp\left[(\sum_{i=1}^{k} R_i \, \beta_i - Y)^2 \right] \tag{11}$$

According to estimated error value, weak learner weight obtains updated. By applying a damped least-squares method, the least-squares problem is minimized. Therefore, the sum of the squares of the deviations is minimized.

$$EF = \arg\min\left[\exp\left((\sum_{i=1}^{k} R_i * \beta_i - Y)^2 \right) \right] \tag{12}$$

Finally, the learner results with minimum error are considered as the final strong classified result. Based on the classification results, patients with autism and without autism is correctly detected. The Generalized Learning Vector Quantized Emphasis Boost classification algorithm is given below,

Algorithm 3: Generalized Learning Vector Quantized Emphasis Boost classification
Input: Selected signal features
Output: Improve the autism detection accuracy

Begin
Step 1: **For each** extracted features from the sub-band of the signals
Step 2: Construct 'k' number of weak classifier
Step 3: Measure Canberra distance d (f_s, f_{df})
Step 4: if argmin $d(f_s, f_{df})$ then
Step 5: Classify the input signals or subject with autism
Step 6:else
Step 7: Classify the input signals or subject without autism
Step 8: **End if**
Step 9: End for
Step 10: Combine the set of weak learner results $Y = \sum_{i=1}^{k} R_i$
Step 11: for each weak learner results
Step 12: Initialize the weight β_i
Step 13: Apply the emphasis function
Step 14: Find the learner results with minimum error using Eq.(12)
Step 15: end for
Step 16: Return (accurate autism detection output)
End

Algorithm 3 provided above outlines process of autism detection by Generalized Learning Vector Quantized Emphasis Boost classification technique. This ensemble technique constructs multiple weak learners using the selected features. For each selected feature and disease feature, Generalized Learning Vector Quantization is applied to calculate the Canberra distance. The minimum distance among these features is used to classify input signals or subjects having autism or not having autism. Subsequently, the results from these weak learners are combined, and weight values are initialized. The emphasis function is then applied to compute quadratic error for every weak learner's classification results. Finally, weak learner through minimum error is chosen as final categorization outcome. Based on this classification, autism disease detection is accurately achieved with higher accuracy.

4. EXPERIMENTAL SETUP

Experimental assessments of RAFP-GEBC method as well as conventional MMSDAE [1] SVM polynomial [2] are executed in python by EEG signals dataset collected as of https://figshare.shef.ac.uk/articles/dataset/EEG_Data_for_Electrophysiological_signatures_of_brain_aging_in_autism_spectrum_disorder_/16840351.

The EEG recordings were obtained from 28 autism subjects and 28 normal subjects between age 18 and 68 years. The recording length was set for 2.5-minute (i.e., 150 seconds) period of eyes closed resting employing 64 electrodes. Result of proposed as well as conventional methods is examined with different performance parameters.

4.1 PERFORMANCE COMPARISON

In this section, a performance comparison between the RAFP-GEBC technique and the existing MMSDAE [1] SVM polynomial [2] is conducted using various metrics. Performance of these different parameters is analyzed and presented through tables as well as graphs.

4.1.1 Autism Detection Time:

The time taken by the algorithm to accurately detect autism disorder in subjects is measured by the autism detection time. Consequently, the assessment of the overall time required for autism detection is measured as follows.

$$ADT = \sum_{i=1}^{n} U_i \times T[AD] \tag{13}$$

where *ADT* denotes autism disorder detection time, n represents number of subjects 'U_i', and $T[AD]$ indicates time for detecting the autism for one subject. The overall detection time is calculated in milliseconds (ms).

Table.2. Comparison of ADT

Number of Subjects	Autism detection time (ms)		
	RAFP-GEBC	MMSDAE	SVM polynomial
10	20	25	28
20	26	30	34
30	33	36	39
40	38	40	48
50	41.5	45	50

The Table.2 illustrates a performance comparison of time consumption for autism detection using three different methods: the proposed RAFP-GEBC technique, and the existing methods MMSDAE [1] and SVM polynomial [2]. As shown in Fig.4, the time consumption performance for all methods increases as the number of subjects or EEG signals increases. However, the proposed RAFP-GEBC technique significantly reduces the time than the [1] ,[2]. For instance, in an experiment involving '10' subjects, the autism detection time using the RAFP-GEBC technique was found to be '20ms', while it was '25ms' for [1] and '28ms' for [2]. Similar variations in performance were observed for each method. Average of these comparison results demonstrates which overall performance of autism detection time with RAFP-GEBC method is notably minimized by 11% and 21% than [1], [2]. This is because of the radial basis kernel adaptive Strömberg wavelet filtering-based preprocessing step; it breaks down EEG signals into discrete frequency components and removes noise from each band in a targeted manner. Additionally, a significant feature selection step is employed, involving Contingency Correlative Projection Pursuit Regression, which helps in discarding irrelevant features and selecting only the most important ones, further reducing the time.

4.1.2 Autism Detection Accuracy:

It is quantified by amount of subjects correctly identified as with autism or without autism. The assessment of the autism detection accuracy is expressed as follows.

$$ADA = \frac{(TR_p + FL_p)}{(TR_p + FL_p + TR_n + FL_n)} \times 100 \tag{14}$$

where *ADA* indicates a autism detection accuracy, TR_p indicates true positive, FL_p denotes a false positive, TR_n indicates the true negative, FL_n denotes false negative. The accuracy is calculated in percentage (%).

Table.3. Comparison of autism detection accuracy

Number of Subjects	Autism detection accuracy (%)		
	RAFP-GEBC	MMSDAE	SVM polynomial
10	90	80	70
20	95	85	80
30	93.33	86.66	83.33
40	95	90	85
50	96	92	88

The Table.3 illustrates a comparative analysis of autism detection accuracy versus the number of subjects taken from the dataset. As shown in Fig.6, the autism detection accuracy of the proposed RAFP-GEBC technique has increased. Let's consider the case of 10 subjects in the first iteration. The autism detection accuracy using the RAFP-GEBC technique was found to be 90%, as accuracy of conventional [1] and [2] was 80% and 70%. Correspondingly, dissimilar accuracy outcomes are examined for every three techniques using different numbers of inputs. The overall comparison outcomes confirm which result of autism detection accuracy with the RAFP-GEBC technique has increased by 8% compared to [1] and 16% compared to [2]. This improvement was achieved by applying the Generalized Learning Vector Quantized Emphasis Boost classification technique. This ensemble technique constructs multiple weak learners using the selected features. Generalized Learning Vector Quantization is applied to calculate the Canberra distance between the features, which is then used to classify subjects with autism or without autism. To improve accurate classification, the results of weak learners are combined to minimize errors in final categorization outcome. Depending on this classification, the accuracy of autism disease detection has increased.

4.1.3 Performance Analysis of Precision:

Precision refers to measure of accuracy of classification method. It measures ratio of TR_ppredictions to every positive forecast made through method to number of true positive forecast as well as false positive predictions.

$$PS = \frac{TR_p}{(TR_p + FL_p)} \times 100 \tag{15}$$

where *PS* indicates a Precision, TR_p indicates a true positive, FL_p denotes a false positive.

Table.4. Comparison of precision

Number of Subjects	Precision		
	RAFP-GEBC	MMSDAE	SVM polynomial
10	0.88	0.857	0.714
20	1	0.937	0.875
30	0.962	0.92	0.88
40	0.972	0.942	0.909
50	0.978	0.954	0.93

The Table.4 depicts performance outcomes of PSconcerning three different methods: the RAFP-GEBC method, and conventional MMSDAE [1] , SVM polynomial [2]. The precision is improved using the RAFP-GEBC technique that of the existing methods. This enhancement is attained by accurate classification of all subjects into their respective categories (i.e., with autism or without autism). In simulations involving 10 subjects, the precision was observed to be 0.880 when using the RAFP-GEBC technique, whereas it was 0.857 and 0.714 for [1] and [2], respectively. This enhancement in precision results in an improved true positive rate in autism detection, achieved through the application of the quantised emphasis boost classification method is a generalised learning vector.Additionally, the false positive rate in autism detection is minimized using the damped least square method to attain accurate classification results with minimal error. The overall result of the RAFP-GEBC method is then compared to conventional techniques. Comparison reveals that precision increases significantly by 4% and 12% when compared to [1] and [2], respectively.

4.1.4 Performance Analysis of Recall:

Recall is computed as ratio of TR_p (correctly identified subject having autism or not) to sum of TR_p and FL_n. It is also called sensitivity. It is expressed as follows,

$$RL = \frac{TR_p}{(TR_p + FL_n)} \times 100 \tag{16}$$

where RL indicates a recall, TR_p indicates a true positive, FL_n denotes a false positive.

Table.5. Comparison of recall

Number of Subjects	Recall		
	RAFP-GEBC	**MMSDAE**	**SVM polynomial**
10	1	0.857	0.833
20	0.947	0.882	0.875
30	0.962	0.92	0.88
40	0.972	0.942	0.909
50	0.978	0.954	0.930

The Table.5 illustrates the outperformance of recall achieved by applying the RAFP-GEBC technique compared to conventional [1] [2] across varying numbers of subjects. The conclusion drawn from this analysis is that the recall performance is notably higher using the RAFP-GEBC technique compared to [1] and [2]. Let's consider a specific scenario with 10 subjects for conducting experiments. The recall performance results for the proposed RAFP-GEBC technique were found to be 1, as RL values for conventional [1] [2] are 0.857 and 0.833, respectively. When comparing the overall percentages, the RAFP-GEBC technique demonstrated an improvement of 7% and 10% compared to [1] and [2]. This enhancement is attained to ensemble technique's ability to classify subjects with autism and without autism, thus enhancing recall.

4.1.5 Performance Analysis of F1-score:

It is valuable metric for estimating entire result of classification method. It is calculated as average precisions and recall. The F1-score is computed as given below,

$$F1\text{-score} = 2 \times \frac{(PS \times RL)}{(PS + RL)} \times 100 \tag{17}$$

where, F1-score is computed based on precision PS and recall RL.

Table.6. Comparison of F1 -score

Number of Subjects	F1 -score		
	RAFP-GEBC	**MMSDAE**	**SVM polynomial**
10	0.936	0.857	0.768
20	0.972	0.908	0.875
30	0.962	0.92	0.88
40	0.972	0.942	0.909
50	0.978	0.954	0.93

The Table.6 presented above illustrates the graphical representation of F1-scores for various numbers of subjects, ranging from 10 to 50. Examined outcomes denote which F-measure achieved with RAFP-GEBC technique is 0.936, while it is 0.857 when using [1], and 0.768 when using [2]. These results suggest that result of the F-measure is significantly improved when using proposed RAFP-GEBC technique compared to existing methods. The RAFP-GEBC technique increases the precision as well as recall during autism detection, finally resulting in more accurate classifications when employed in an ensemble classifier. Consequently, the F-measure is notably enhanced by 5% compared to [1] and 11% compared to [2].

5. CONCLUSION

Early detection of autism spectrum disorder is important for starting therapy. New RAFP-GEBC method is designed for categorizing autism and normal subjects using EEG signals. The RAFP-GEBC technique begins with preprocessing EEG signals using a wavelet transform-based filtering technique. Subsequently, highly significant features are selected from the obtained sub bands of brain signals based on contingency correlative projection pursuit regression. Using these significant features, effectively and accurately differentiating between subjects with and without autism, the generalised learning vector quantised emphasis boost technique is used. The experimental evaluation is conducted with various parameters. Quantitatively analyzed outcomes demonstrate that RAFP-GEBC technique achieves higher accuracy in autism detection, as well as improved precision, recall, and F1-score, all while requiring less time compared to conventional methods.

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