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LAGRANGIAN MATCHED FILTER WITH REGRESSIVE PERCETRON DEEP CLASSIFIER FOR AUTISM DISORDER DETECTION WITH EEG SIGNALS

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Abstract

People through ASD frequently contain cognitive disabilities. Efficient association among distinct brain regions is indispensable for ordinary cognition. Electro Encephalo Graphy (EEG) has extensively utilized at neurological disease recognition. Preceding studies on identifying ASD through EEG information centered on time domain, channel and spatial associated aspects. Mainly these studies not preserved the essential information while performing dimensionality reduction. However, such approaches may result in compromising accuracy and increasing training time. To resolve this issue, Deep Belief Network Classification technique for identifying ASD through EEG information using Lagrangian Matched Filter with Truncated Regressive Piecewise Perceptron (LMF-TRPP). The proposed LMF-TRPP method is split asone input layer, three hidden layers and one output layer for carry out autism spectrum detection with EEG signals. Initially, the samples gathered from EEG signals database are provided as input via input layer. To eliminate noise (such as muscle activity in the head, blinking) from the raw input EEG signals, Lagrangian Matched Filter denoising model is carried out in the first hidden layer. Following which relevant features are selected in the second hidden layer by applying Truncated Tobit Regressive Feature Selection model. By selecting this feature selection model aids in minimizing dimensionality while preserving the essential information for accurate classification. Finally Perceptron Piecewise Classification process is modeled in the third hidden layer for performing efficient classification as autism EEG signal or non-autism EEG signal with selected relevant features. Experimental outcomes demonstrated LMF-TRPP technique attained better result compared through two ASD detection techniques that has favorable potentiality to impart an accurate diagnosis to assist clinicians. In conclusion, this work highlights the effectiveness of Deep Belief Network Classification in EEG signal processing, offering valuable contributions with improved precision and computationally efficient for additional precise neurological disease classification as well as diagnosis.

Keywords: Autism Spectrum Disorder, Electro Encephalo Graphy, Deep Belief Network, Lagrangian Matched Filter, Truncated Tobit Regression, Perceptron Piecewise Classification.

1. Introduction

ASD is untimely outbreak neuro improvement disorder. Distinguishing indicators of ASD encompass social deficit, troubles while interaction and regular activities which severely obstruct person's regular life as well as daily chores. Frequency of ASD continuously grown over precedent decades.

In real-time diagnosis for neurological brain chaos employing DL and EEG signal called, Real Time Diagnostic Decision Support Model (RT-NeuroDDSM) was proposed. First to extract high level features, channel and spatial attention network was employed. Following which the valuable features were provided as input to achieve good classification results. Also to select inherent features, modified normative fish swarm (MNFS) algorithm was used and finally detection was made by applying hinging hyperplane neural network (HHNN). This in turn improved overall classification accuracy. Despite improvements observed in overall classification accuracy the noise ratio involved in analyzing neurological brain disorders was not focused. To address on this aspect, Lagrangian Matched Filter denoising model is used that in turn by eliminating outlier aids in improving PSNR.

A fusion of CNN and LSTM, was presented and executed. On the basis of functional association the method achieved improved classification accuracy. Nevertheless, the precision and misclassification involved in ASD diagnosis was not concentrated. To focus on this aspect Perceptron Piecewise Classification process is presented that assists in honing optimal decision boundary, therefore reducing misclassification and improving precision to a greater extent.

Ascertaining ASD at children is demanding because of its difficulty as well as heterogeneity nature. Right now, mainly succeeding techniques specially based on solitary modality through restrained information and regularly cannot achieve satisfactory result. To mention this issue, two-step multimodal FL and fusion method employing deep learning technique, called, SDAE was presented.

Here the fusion model employed both electroencephalogram and ET information. By applying this fusion model for SDAE in turn improved overall accuracy. Nevertheless, such method using data augmentation may basis contamination. To resolve this issue, new technique for identifying ASD using combined network called, CNN-LSTM was proposed. With the application of this combined network in turn aided in improving classification accuracy.

ASD is ordinary neuro developmental disorder as well as to ensure effective therapy early diagnosis is indispensable. EEG signals contain manifested to sound biomarkers for ASD diagnosing. Extorting well constructed associative EEG signal patterns assists to make certain ASD diagnostic robustness. In, hybrid graph CN structure named Rest-HGCN employing relaxing-position EEG signals to obtain models of brain associative among ordinary children as well as ASD patients was proposed. By extracting discriminative graph features assisted in improving the overall accuracy.

An overall performance analysis for recognition of ASD as of EEG was investigated. However, owing to difficulty as well as variety of ASD symptoms, still accuracy gets compromised. To address this gap a fusion of pre-processing technique and ASD detection using Wavelet Scattering Transform and Deep Learning was proposed with improved accuracy. A systematic review of DL based ASD detection in EEG signals was elaborated.

The heightening prevalence of ASD has evolution of premature diagnostic methods progressively pivotal. ASD give rise to notable issues at early recognition, calling for inventive methods for precise recognition. Hybrid Convolutional Recurrent Neural Networks was proposed on the basis of cognitive and behavioral phenotypes to increase the accuracy of ASD detection. A systematic review of DL techniques for ASD detection using EEG according to the body parts was presented.

In a novel method using ML methods trained on a variegated dataset was presented. Here, CNN architectures like, ResNet50, Inception V3 and MobileNetV2 adapted for ASD detection was proposed. In addition, a multimodal concatenation method combining image aspects through behavioral scores to boost prognostic result was presented with improved detection accuracy. However, with the identification of high data leakage results in overfitting and overestimation. To address on this research gap, a survey of majority deep neural network techniques was investigated. A case study for ASD detection using multi-layer perceptron-based attention measure was designed. This in turn aided in obtaining quantifiable information to strengthen the insight of therapist.

Nevertheless, because of its extremely varied indicators as well as convoluted nature, ASD analytics persists to demanding issue as far as researchers are concerned. An intelligent system employing Artificial Gorilla Troops Optimizer (GTO) was presented with the intent of detecting ASD. This in turn aided in minimizing cross-entropy loss function considerably. Yet another method to improve sensitivity in addition to accuracy employing FWHT and single-dimensional (CNN) was proposed. By combining these two techniques more promising performance was ensured.

DL through EEG analysis is an encouraging sector of investigate for ASD detection nonetheless is emerging. Previous to extensively utilized at healthcare facility, demands contain requirement for handling constraints, optimize filter parameters, handling censored data, identifying relevant features, enhancing methods for accuracy as well as consistency, mentioning variability at EEG signals. In spite of these issues, EEG signals present favorable opportunities to boost premature recognition of ASD.

1.1 Contributing remarks

(a) EEG-based DBN solution, combining Lagrangian Matched Filter denoising, Truncated Tobit Regressive Feature Selection and Perceptron Piecewise Classification process is introduced for superior accuracy and effectiveness at ASD diagnosis.

(b) Result of proposed method was reinforced through de-noising as of raw EEG signals by Lagrangian Matched Filter denoising model in the first hidden layer, therefore improving overall PSNR.

(c) Autism detection accuracy as well as time was improved by ascertaining the location and most relevant EEG frequency bands. Moreover, feature vectors were selected using Truncated Tobit Regressive-based Feature Selection model. This model makes it possible to segregate the most informative channels and frequency ranges more accurately and employs minimum storage capability to sustain parsed coefficients, therefore reducing time considerably.

(d) To design Perceptron Piecewise Classification for ascertaining more complex patterns in EEG signals selected data that a single linear boundary or standard perceptron cannot efficiently. This leads to improved precision and better generalization.

1.2 Structure of the work

Rest of this manuscript proceeds as follows. Section 2 describes literature as well as related works in the area of ASD diagnosis. Section 3 details the proposed method, Deep Belief Network Classification ASD detection called, Lagrangian Matched Filter with Truncated Regressive Piecewise Perceptron (LMF-TRPP) using EEG data for ASD detection. Section 4 presents the case study and inferences following which the results of evaluation experiments along with detailed discussion is included in Section 5. Finally, Section 6 summarizes the manuscript.

2. Literature review

Precedent decade has noted sizeable elevation in the pervasiveness of ASD featured by deficiencies in social communication and restrictive behaviors. Hence, a primary cornerstone for the field has been to emphasize ASD earlier detection and subsequent intervention of ASD. A fusion of machine learning (ML) techniques was employed to disclose discriminatory patterns into autism pathophysiology. Yet another method combining Pearson correlation coefficient with support vector machine (SVM) was designed. This in turn facilitated earlier identification of ASD. A systematic review on DL techniques for early ASD prediction was presented with improved accuracy and precision.

ASD being neurological as well as improve mental disorder initiates in premature childhood as well as continues all over individual life. Both genetic and environmental aspects influence autism. Some of the probable characteristics are communication issues, restricted behavior, social interaction deficiency and so on. A novel student’s T-test as well as Marginal Fisher study were used in [19] that in turn uniquely developed progress an ASD index, therefore yielding highest classification accuracy. Yet another data driven method for early ASD detection using EEG signals was proposed in [20] with improved sensitivity and specificity.

Currently, most prevailing materials and methods chiefly based on a solitary modality through restrained information as well as regularly cannot achieve satisfactory result. To mention on this facet, stacked denoising auto encoder along with typical DL algorithm in [21], therefore ensuring accurate diagnosis to clinicians. However error was not considered. To focus on this facet, a maximum mean discrepancy method was proposed that in turn not only reduced root mean square error but also improved accuracy considerably. However there requires intention diagnostic mechanism which increases accuracy as using lesser of EEG channel. To concentrate on this research gap, an optimal frequency band was employed using SVM and radial basis kernel.

An ensemble of ML and DL algorithms for classifying EEG signals with the motive of ASD detection was presented. Here, by employing Band power and Shannon entropy along with SVM and CNN advanced the potential for accurate diagnosis and classification of neurological disease with improved accuracy. However efficient detection of feature play major role in disease detection. With this objective multi-domain feature fusion and selection method was presented that in turn optimized detection of features. Consequently, the accuracy of ASD detection was found to be improved. A plethora of innovative visual signal analysis employing CNN was investigated. A review of EEG signals for ASD detection was presented. New EEG motor imagery classification method through superior accuracy employing Harmony Search Algorithm was proposed. By utilizing this algorithm resulted in the accuracy rate to a greater extent

3. Materials and Methods

The pipeline of the proposed Deep Belief Network Classification ASD detection called, Lagrangian Matched Filter with Truncated Regressive Piecewise Perceptron (LMF-TRPP) using EEG data is shown in figure 1, using data from EEG dataset. It aims to obtain EEG signals to enhance ASD identification performance via Deep Belief Network Classification by means of five five layers.

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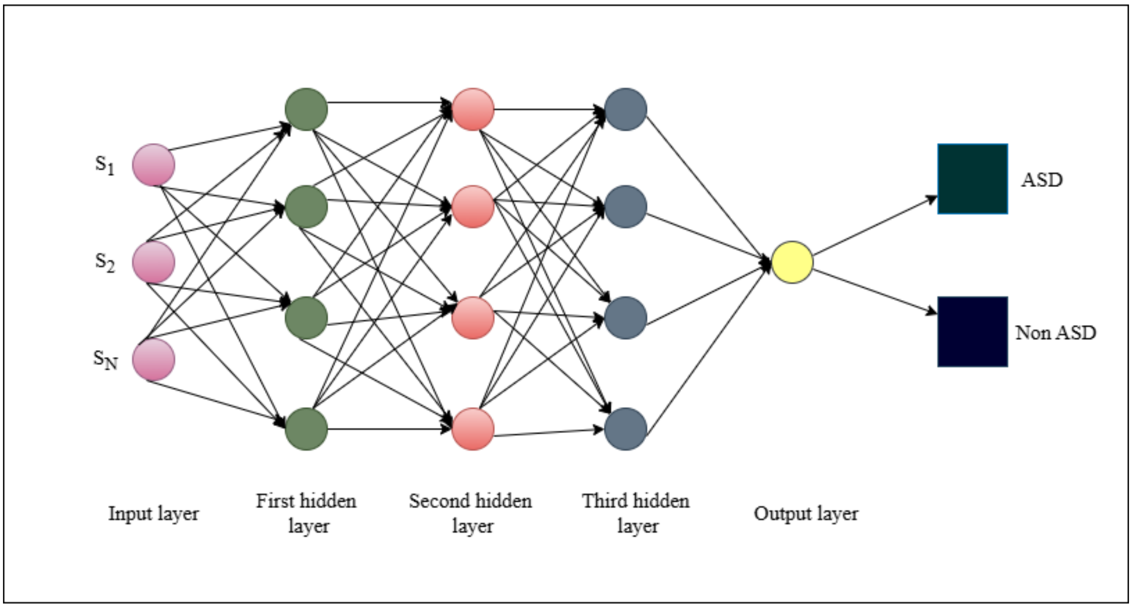

Figure 1 Block diagram Lagrangian Matched Filter with Truncated Regressive Piecewise Perceptron (LMF-TRPP) based Deep Belief Network Classification ASD detection

In figure 1, proposed LMF-TRPP technique mainly contain four sequential steps are performed via different layers. Initially, EEG data is acquired (i.e. in input layer) and pre-processed (i.e. in first hidden layer) using Lagrangian Matched Filter denoising model to eliminate unconnected noise signals. Subsequently, in feature selection (i.e. in the second hidden layer), we selected typical features from pre-processed sample signals, which contain wealthy however superfluous diagnosis data associated to ASD. In feature selection, a feature selection model employing Truncated Tobit Regression is developed to study valuable EEG as of first feature set as well as additional fuse learned information for last categorization among ASD and non-ASD. Finally, to classify (i.e. in the third hidden layer) between ASD and non-ASD Perceptron Piecewise Classification process is applied. This in turn aids in capturing the characteristics of EEG and enhancing overall recognition result that is estimated during relative study.

3.1 Data Collection and Data Acquisition

EEG signals dataset employed in our work is collected from the URL https://figshare.shef.ac.uk/articles/dataset/EEG_Data_for_Electrophysiological_signatures_of_brain_aging_in_autism_spectrum_disorder_/16840351. The EEG signals dataset was attained as of before published EEG study [30] including 56 participants in the age range between 18 and 68. Also the participants involved in the process consented to sharing data for secondary analysis. The prototype which created information was 2.5 minutes or 15 seconds periods of eyes closed relaxing.

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Table 1 EEG signals database description

S. No	Features	Description
1	Age range	18.08 – 68.33
2	Cognitive measurements	Matrix reasoning
3	ASD assessments	SRS
	EEG Acquisition	
4	Number of electrodes	6
5	System	BioSemi Active Two System
6	Sampling rate	2048Hz
7	Impedances	25KΩ
8	Recording length	2.5 minutes

Brainwaves are categorized to five frequency bands. These five frequency bands are related to distinct consciousness state and brain activity. It is calculated in Hertz (Hz). Table 2 lists perception into the definite frequency bands and their power variations.

Table 2 EEG band and its corresponding Frequency band

S. No	EEG Band	Frequency band
1	Delta 'Δ'	'$0.5 - 4\ Hz$'
2	Theta 'θ'	'$4 - 8\ Hz$'
3	Alpha 'α'	'$8 - 13\ Hz$'
4	Beta 'β'	'$13 - 30\ Hz$'
5	Gamma 'γ'	'$30 - 100\ Hz$'

With aid of the above table the individuals with ASD can be analyzed, such as higher power in theta and alpha frequency bands or variability of the EEG signal [29], denoting sensory hypersensitivity.

3.2 Lagrangian Matched Filter Denoise-based Pre-processing

To enhance the quality of EEG signals, Lagrangian Matched Filter denoising model is applied as pre-processing technique in the first hidden layer. This pre-processing technique involve preparing raw EEG signals by eliminating noise (such as muscle activity in the head, blinking), removing artifacts. This in turn aids in enhancing its practicability for analysis and classification. Lagrangian Matched Filter denoising model as pre-processing technique in our work uses a matched filter optimized with Lagrangian multiplier to enhance signal-to-noise ratio (SNR). Figure 2 shows the block diagram of Lagrangian Matched Filter Denoise-based Pre-processing model.

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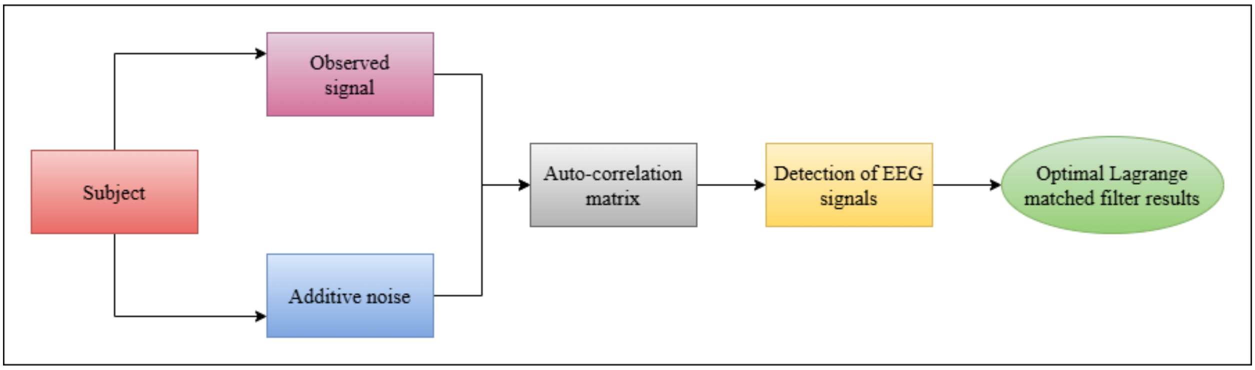

Figure 2 Block diagram of Lagrangian Matched Filter Denoise-based Pre-processing method

In figure 2, Lagrangian Matched Filter Denoise-based Pre-processing is split into two parts, namely, detection of EEG signals and optimization using Lagrangian multiplier. The Matched Filter denoising model here represents a correlation value. On one hand a peak in the correlation value denotes the presence of known signal and vice versa. The peak location denotes the EEG signals' arrival time. Let us consider the observed signal '$ObsS$' consisting of the desirable signal 'S' and the additive noise 'ϵ' as given below.

$$ObsS = S + \epsilon \qquad (1)$$

With the above observed signal and desirable signal let us moreover define auto-correlation matrix of noise. Auto-correlation matrix of noise is defined in such a way that the complex square is equal to its own conjugate transpose. To be more specific the frequency bands in the '$i - th\ time\ instance$' and '$j - th\ activity$' is equal to the complex conjugate of the frequency band in the '$j - th\ activity$ and '$i - th\ time\ instance$' recorded by a single electrode. This is mathematically stated as given below.

$$ACM_{\epsilon} = Exp\{\epsilon\epsilon^{H}\} \qquad (2)$$

From the above equation (2), 'ϵ^{H}', represent the conjugate transpose of additive noise 'ϵ' with 'Exp' representing the expectation. Now let us denote the output 'Out' referring to the inner product of filter and the observed EEG signal, then the detection of EEG signals is mathematically stated as given below.

$$Out = \sum h^{H} S + h^{H} + \epsilon \qquad (3)$$

Then according to the optimization factor using Lagrangian multiplier, SNR is defined to be ratio of output power due to desired signal to output power due to the additive noise as given below.

$$SNR = \frac{|Out_S|^2}{Exp\{|Out_{\epsilon}|^2\}} \qquad (4)$$

Finally, the optimal Lagrange matched filter results eliminating noise (such as muscle activity in the head, blinking), removing artifacts is mathematically represented as given below.

$$h = \frac{1}{\sqrt{S^{H} ACM_{\epsilon}^{-1} S}} ACM_{\epsilon}^{-1} S \qquad (5)$$

From the above equation results (5) the normalized denoise filter results are obtained for further processing. The pseudo code representation of Lagrangian Matched Filter Denoise-based Pre-processing is given below.

Input: Dataset 'DS', EEG Signals (samples) '$S = \{S_1, S_2, \dots, S_N\}$'
Output: noise removed pre-processed EEG signals 'h'
1: **Initialize** '$N = 56$', '$\epsilon = 0.25$' 2: **Begin** 3: **For** each Dataset 'DS' with EEG Signals (samples) 'S' **//Detection of EEG Signals using auto-correlation matrix** 4: Formulate observed signal via desirable signal and additive noise according to (1) 5: Evaluate auto-correlation matrix according to (2) 6: Detect EEG signals according to (3)

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//Optimization using Lagrangian multiplier
7: Evaluate signal-to-noise ratio via Lagrangian multiplier according to (4)
8: Measure optimal Lagrange matched filter results according to (5)
9: **Return** pre-processed EEG signals 'h'
10: **End for**
11: **End**

Algorithm 1 Lagrangian Matched Filter Denoise-based Pre-processing

As shown in the above algorithm the Lagrangian Matched Filter Denoise-based Pre-processing is split into two parts, namely, auto-correlation matrix-based EEG signal detection and Lagrangian optimized matched filter results. The purpose behind the use of this denoising model is while eliminating the noisy to target distinct features in EEG data that are assumed to be contrasting in individuals with autism should be not considered as noise. For example, while performing Lagrangian Matched Filter denoising model with the EEG signals in our work specific temporal patterns can be amplified that are thought to be associated with autistic traits. This in turn aids in improving the overall peak signal-to-noise ratio extensively.

3.3 Truncated Tobit Regressive-based Feature Selection in EEG signal analysis

As far as Brain Computer Interfaces are concerned, in Deep Belief Network to recognize motor imagery tasks, feature selection has to be employed in ascertaining the location and most relevant EEG frequency bands for accurate ASD disease detection. Discarding redundant and irrelevant features from the pre-processed EEG signals can speed up model training and minimize overfitting. For example, certain frequency bands (e.g., theta and alpha) are known to be associated with motor activity and feature selection could help segregate the most informative channels and frequency ranges for optimal performance. In this work, Truncated Tobit Regression is used for feature selection, as it is appropriate for reshaping the feature for accurate ASD detection in the second hidden layer. By selecting this feature selection model aids in minimizing dimensionality while preserving the essential information for accurate classification. Figure 3 shows the block diagram of Truncated Tobit Regression-based feature selection for EEG signals.

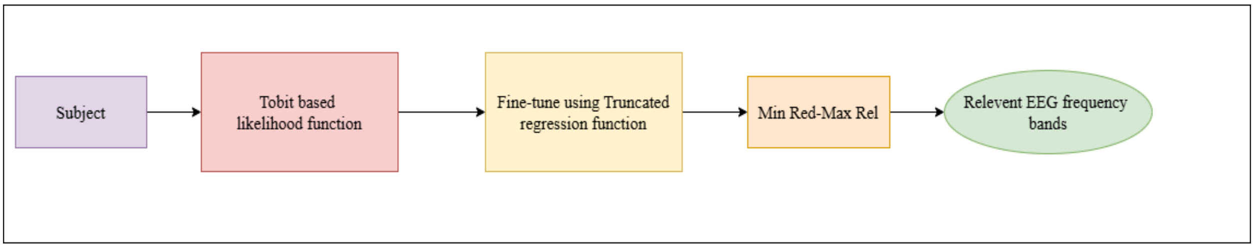

Figure 3 Block diagram of Truncated Tobit Regression-based feature selection for EEG signals.

As shown in the above figure the Truncated Tobit Regression-based feature selection for EEG signals is used to select relevant subset of all available features that not only results in a small dimensionality of classification problem but also minimizes the noise. The Truncated Tobit Regression-based feature selection concentrates on the association between features or feature subset 'FS' (i.e. smaller, pre-processed EEG samples denoised from original dataset) and the target class 'C' (i.e. category or group than an EEG signals belongs to, either autism EEG signals [AS] or non-autism EEG signals [NAS]) that is inclined to necessitate redundant features, influencing the learning accuracy (i.e. autism detection accuracy) in a computationally efficient manner (i.e. autism detection time). In order to achieve these results we initially applied likelihood function using Tobit as given below.

$$Ind(h) = \begin{cases} 0, if\ h \le h_L \\ 1, if\ h > h_L \end{cases} \quad (6)$$

From the above equation (6) 'Ind' represents an indicator function for modeling likelihood function for the corresponding pre-processed EEG signals 'h' with respect to lower limit 'L'. Moreover let us consider 'Φ' as cumulative distribution function (i.e. probability that a pre-processed sample signals, power in a frequency band

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be less than or equal to a given value) and 'φ' as the normal probability density function respectively (i.e. pre-processed sample signals in a resting state). Next, the Truncated Regression function employed in our work fine-tunes the above likelihood function to reflect the fact that the pre-processed sample signals with 'n' observations is not representative of the overall population. This is mathematically represented as given below.

$$\zeta(FS,C) = \prod_{i=1}^{n} \left(\frac{1}{\sigma}\varphi\left(\frac{h_i - S_i FS}{\sigma}\right)\right)^{Ind(h_i)} \left(1 - \Phi\left(\frac{S_i FS - h_L}{\sigma}\right)\right)^{1-Ind(h_i)} \quad (7)$$

Finally with the above likelihood functions result (7) minimal-redundancy maximal-relevance (MinRed-MaxRel) to conduct feature selection. The MinRed-MaxRel addresses the issue by measuring both redundancy occurring in feature and relevancy in a simultaneous fashion. The MaxRel '$MaxRel$' with the intent of maximizing relevance of feature subset 'FS' to the class 'C' is mathematically represented as given below.

$$MaxRel\ (FS,C) = \frac{1}{FS|}\sum r(F_i,C) \quad (8)$$

From the above equation (8) '$r(F_i,C)$' denotes the relevance of a feature 'F_i' with respect to class 'C'. On the other hand feature redundancy is represented on the basis of pair wise feature dependence between features. If two relevant features of pre-processed EEG signals are found to be highly dependent on each other, then the class discrimination would not change if one of the features are eliminated and vice versa. With this hypothesis, minimum redundancy '' is employed in selecting a feature subset 'FS' of mutually exclusively features '(F_i,F_j)'. Then the redundancy of a feature subset is mathematically represented as given below.

$$MinRed(FS,C) = \frac{1}{|S|^2}\sum r(F_i,F_j) \quad (9)$$

$$FS = \left(MaxRel\ (FS,C) \cup MinRed(FS,C)\right) \quad (10)$$

From the above equations (8) and (9) the objective remains in designing simple operator maximizing 'Rel' and minimizing 'Red' with varying number of features. Finally these varying features (i.e. relevant features selected 'FS') are validated using Perceptron Piecewise Classification in the following sub-sections for ASD detection. The pseudo code representation of Truncated Tobit Regression-based feature selection for EEG signals is given below.

Input: Dataset 'DS', EEG Signals (samples) '$S = \{S_1, S_2, \dots, S_N\}$'
Output: Accurate and computationally-efficient relevant EEG frequency bands 'FS'
1: **Initialize** '$N = 56$', pre-processed EEG signals 'h', lower limit '$L = 0$', feature subset 'FS', target class 'C' 2: **Begin** 3: **For** each Dataset 'DS' with pre-processed EEG signals 'h' 4: Model likelihood function using Tobit according to (6) 5: Model Truncated Regression function to fine-tunes the likelihood function with 'n' observations according to (7) 6: Formulate MaxRel '$MaxRel$' with the intent of maximizing relevance of feature subset 'FS' according to (8) 7: Formulate MinRed '$MinRed$' with the intent of minimizing relevance of feature subset 'FS' according to (9) 8: **Return** relevant EEG frequency bands 'FS' 9: **End for** 10: **End**

Algorithm 2 Truncated Tobit Regression-based feature selection for EEG signals

As given in the above algorithm, the relevant EEG frequency bands for EEG signals are modeled by combining the Truncated Regression results to the Tobit model. Initially the pre-processed EEG signals are focused to likelihood function for each subject using Tobit model. Following which pre-processed EEG signals focused to likelihood function for distinct subjects using Truncated Regression. This in turn aids in minimizing the autism detection time involved in selecting frequency bands. Finally, minimal-redundancy maximal-relevance is applied to select relevant EEG frequency bands, therefore improving autism detection accuracy.

3.4 Perceptron Piecewise Classification

Classificcation of EEG signals for differentiating between Autism Spectrum Disorder (ASD) and non-ASD individuals encompasses ascertaining distinct frequency bands and patterns within EEG data. Researchers have ascertained from the above literature that individuals with ASD may evince perceptible EEG characteristics. This may be, like increased activity in three distinct frequency bands, delta, theta and beta bands whereas decreased frequency band in alpha respectively. This distinct frequency bands and patterns, combined with Perceptron Piecewise Classification in the third layer aid in ASD diagnosis. Figure 4 shows the block diagram of Perceptron Piecewise Classification for ASD diagnosis.

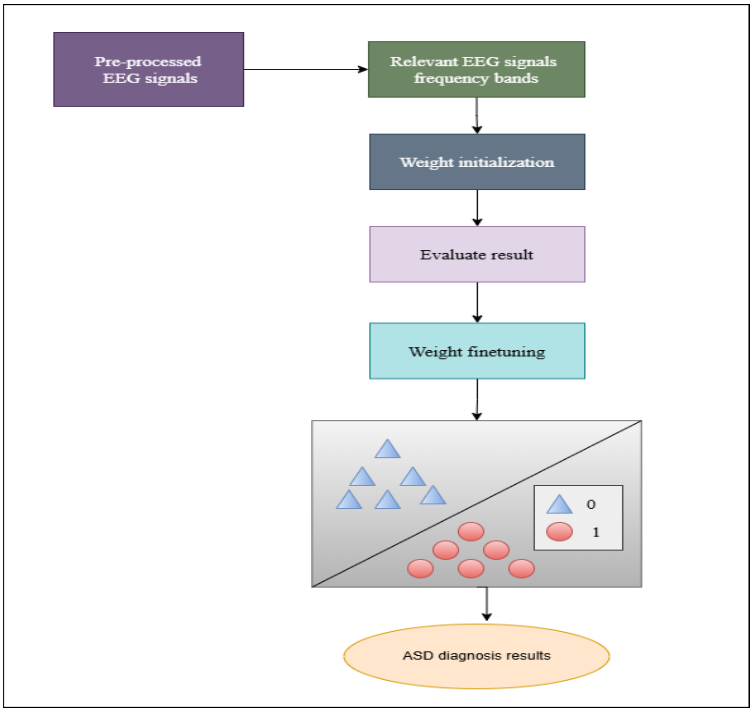

Figure 4 Block diagram of Perceptron Piecewise Classification for ASD diagnosis

As shown in the above figure, initially the weights 'w' are initialized to '0'. Following which for each training pre-processed features selected EEG signals '$S \in h(FS)$', the output results 'Res' are measured and accordingly the weights are fine-tuned. The output results 'Res' here denotes the class label predicted as either ASD or non-ASD as given below.

$$output = g(Res) \quad (11)$$

Following which the fine-tuning of weight is modeled based on the initialized weight structured '$w_j = w_j + \Delta w_j$' as given below.

$$\Delta w_j = \eta(Act^i - Pred^i)S_j^i (12)$$

From the above equation (12), the value for fine-tuning of weight 'Δw_j', is obtained according to the learning rate 'η', actual class label 'Act^i' and the predicted class label '$Pred^i$' with respect to the EEG signals 'S_j^i'. Then, according to two dimension results, i.e. ASD or non-ASD, two hypotheses are said to exist. On one hand, in case when the perceptron predicts class label accurately weights abide unchanged and on the other hand, in case of wrong prediction the weights are being influenced towards the positive or negative target (i.e. actual) class. This is mathematically formulated as given below.

$$Res = \begin{cases} \eta(-1^i - -1^i)S_j^i = 0, \eta(1^i - 1^i)S_j^i = 0\ , Correct\ prediction \\ \eta(-1^i - -1^i)S_j^i = \eta(2)S_j^i, \eta(-1^i - 1^i)S_j^i = \eta(-2)S_j^i, Wrong\ prediction \end{cases} \quad (13)$$

From the above equation results (13) are obtained and accordingly the ASD or non-ASD prediction results are obtained. With the increased activity in three distinct frequency bands, delta, theta and beta bands represent the presence of ASD and on the other hand with decreased frequency band in alpha represent the absence

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of ASD (i.e. non-ASD). The pseudo code representation of Perceptron Piecewise Classification for ASD diagnosis is given below.

Input: Dataset 'DS', EEG Signals (samples) '$S = \{S_1, S_2, \dots, S_N\}$'
Output: Optimal decision results

Initialize '$N = 56$', pre-processed EEG signals 'h', relevant EEG frequency bands 'FS', '$w = 0$', '$\eta = 0.5$'
Begin
For each Dataset 'DS' with pre-processed EEG signals 'h' and relevant EEG frequency bands 'FS'
Formulate the output according to (11)
Model fine-tuning of weight according to (12)
Formulate results according to (13)
Return results
End for
End

Algorithm 3 Perceptron Piecewise Classification for ASD diagnosis

As given in the above algorithm with the objective of improving the precision and recall factor along with the minimization of classified samples, the pre-processed and feature selected EEG samples are provided as input. Following which the weight and learning rate is initialized. Next, a binary hypotheses result is generated employing Perceptron Piecewise classifier and accordingly weights are fine-tuned. The main advantage of using Perceptron Piecewise classifier for ASD diagnosis is that, efficient fine-tuning of weights are performed therefore ensuring optimal decision boundary between ASD and non-ASD in a precise manner.

4. Case study and inferences

In this section case analysis of robust ASD diagnosis using EEG dataset are simulated by applying Lagrangian Matched Filter with Truncated Regressive Piecewise Perceptron (LMF-TRPP) method. Figure 5 given below provides the sample EEG signals of subject 1 for ASD diagnosis (left) along with the denoising results (right).

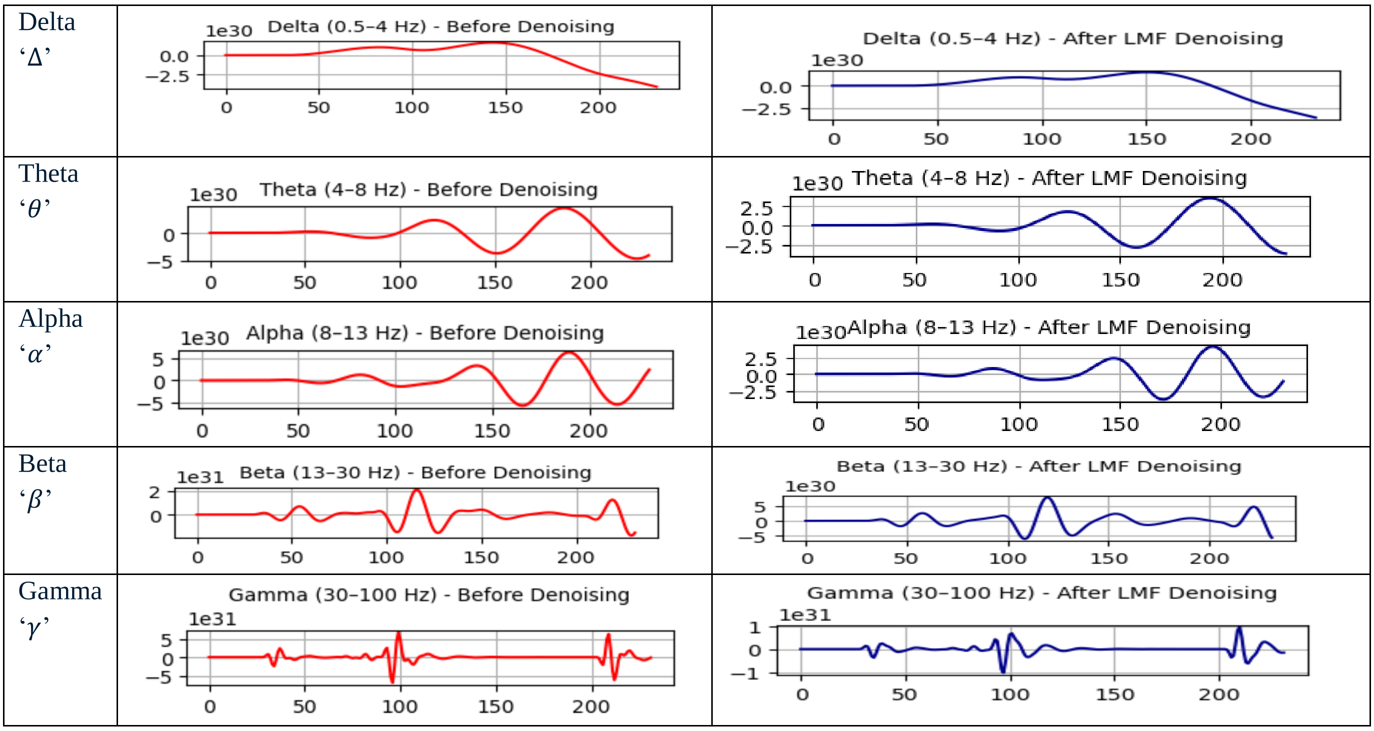

Figure 5 Denoised results of Subject 1 after applying Lagrangian Matched Filter Denoise-based Pre-processing

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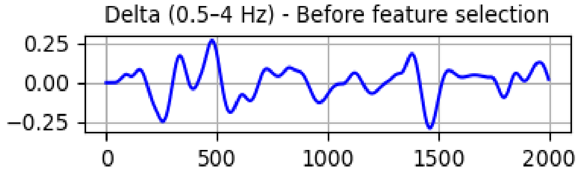
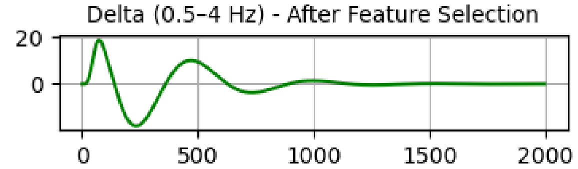
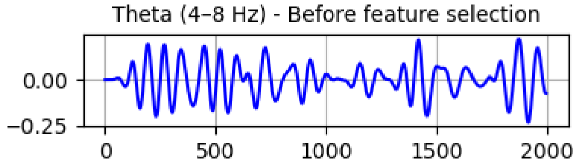
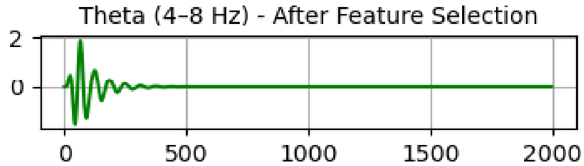
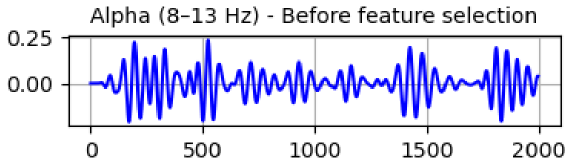
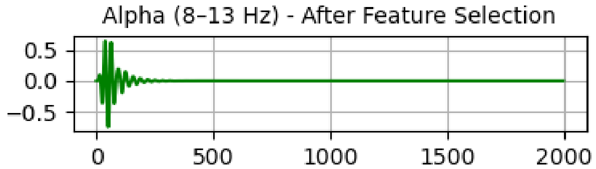
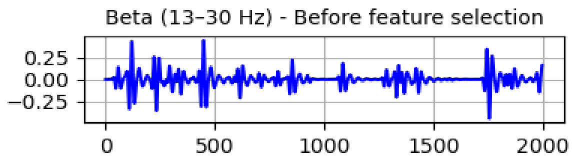
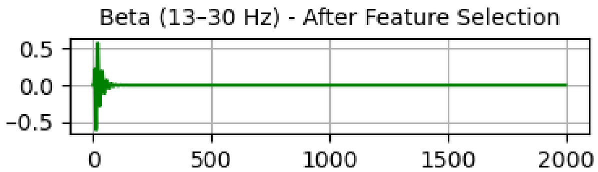
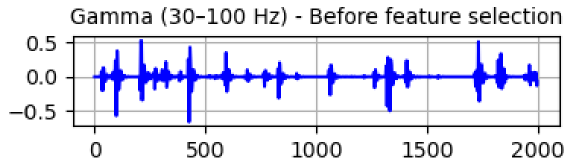
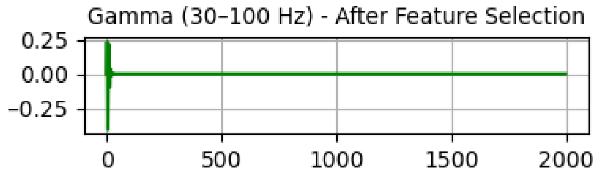
The above figure provides the results of applying Lagrangian Matched Filter Denoise-based Pre-processing to the sample EEG signals of subject 1. For the above sample results matched filter optimized with Lagrangian multiplier to enhance signal-to-noise ratio. This in assisted in enhancing entire PSNR. With pre-processed EEG signals as input are focused to feature selection process for with the objective of ascertaining location and the most relevant EEG frequency bands. Figure 6 shows the relevant EEG frequency band results of subject 1.

Figure 6 Relevant EEG frequency band results of Subject 1 after applying

EEG Band	Before Truncated Tobit Regressive-based Feature Selection EEG signals	After Truncated Tobit Regressive-based Feature SelectionEEG signals
Delta ‘Δ’		
Theta ‘θ’		
Alpha ‘α’		
Beta ‘β’		
Gamma ‘γ’		

Truncated Tobit Regression-based FS

In figure 6 ,by applying Truncated Tobit Regression-based feature selection to the pre-processed EEG signals separates the most informative channels and frequency ranges for optimal performance. This in turn reduces the training time and by preserving the essential information using Truncated Regression along with Tobit function in turn aids in improving the autism detection accuracy. Finally, the relevant frequency bands selected

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were subjected to Perceptron Piecewise Classification for ASD diagnosis. Here according to the variations in frequency bands the classess of ASD or non-ASD is outputted as diagnosed results. By applying Perceptron Piecewise Classifier to the relevant selected frequency bands accurately fine-tunes the weight. This in turn ensure optimal decision boundary between ASD and non-ASD in a precise manner. The quantitative analysis of LMF-TRPP for ASD diagnosis with EEG signals is provided in the following sub-sections.

5. Experimental Setup and Discussion

The proposed Deep Belief Network Classification method for detecting ASD with EEG data using Lagrangian Matched Filter with Truncated Regressive Piecewise Perceptron (LMF-TRPP) for ASD diagnosis with EEG signals is evaluated employing Python. Outcomes are compared with existing Real Time Diagnostic Decision Support Model (RT-NeuroDDSM) [1] and CNN-LSTM [2]. Moreover the results are analyzed and validated on five metrics. Moreover, for estimation, highest number of samples is considered as 50. Also to ensure fair comparison between result of LMF-TRPP through the Real Time Diagnostic Decision Support Model (RT-NeuroDDSM) [1] and CNN-LSTM same samples as of above mentioned database is employed.

5.1 Performance analysis of PSNR

As far as EEG signals are considered, PSNR is utilized in quantifying signal quality. It also states the ratio of maximum possible signal power to corrupting noise power. It aids in estimating how well desired EEG signal stands out from noise. Also a higher PSNR represents a better signal quality with less noise and vice versa.

$$PSNR = 10 \log 10 \left[\frac{P_{signal}}{P_{noise}}\right] \quad (14)$$

From the above equation (14) the peak signal-to-noise ratio 'PSNR' is measured based on the signal power 'P_{signal}' and noise power 'P_{noise}' respectively. It is calculated in decibels (dB). Table 3 illustrates performance of PSNR when employing the proposed LMF-TRPP method. In comparison to the existing two methods, RT-NeuroDDSM [1] and CNN-LSTM [2], LMF-TRPP method exhibits an improvement in performance with this denoising factor.

Table 3 Experimental results for PSNR using LMF-TRPP, RT-NeuroDDSM [1] and CNN-LSTM [2]

EEG sample size (MB)	Peak signal to noise ratio (dB)		
	LMF-TRPP	RT-NeuroDDSM [1]	CNN-LSTM [2]
17.5	32.35	25.15	17.45
15.63	38.15	31.25	28.35
17.19	35.45	28.45	35.15
18.75	40.25	33.15	30.45
16.25	45.35	38.55	35.15

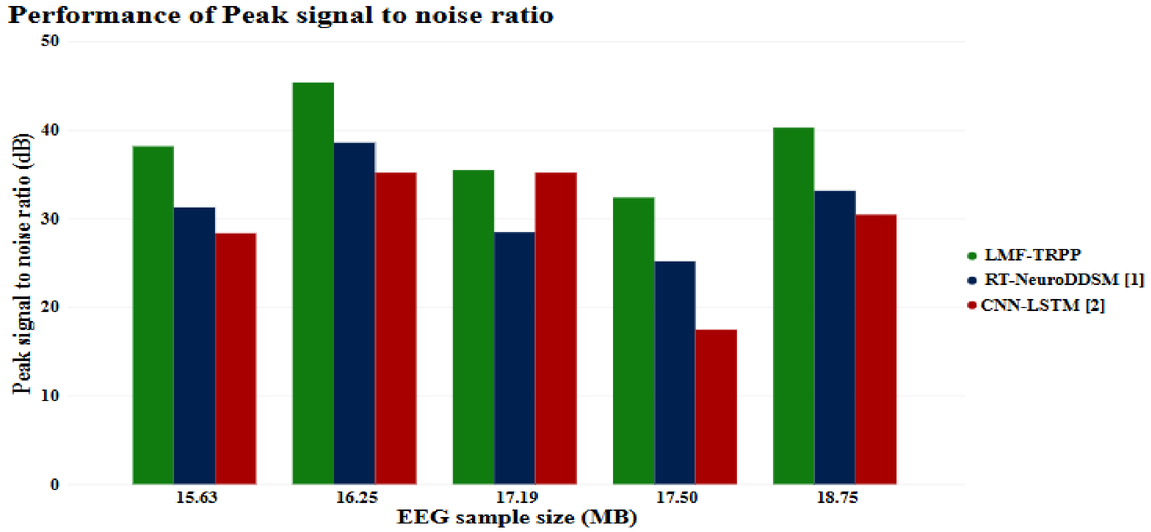

Figure 7 PSNR versus EEG sample size

Figure 7 shows graphical depiction of PSNR using LMF-TRPP, RT-NeuroDDSM [1] and CNN-LSTM [2]. The horizontal axis in the above figure represents the EEG sample size of five different subjects. Also to ensure fair comparison similar subjects and sample size were applied to all the three methods. The values were substituted in equation (14) and accordingly the values recorded in the above table. The recorded values were plotted in the vertical axis. From the above figure the PSNR using the proposed LMF-TRPP method was found to be comparatively better than [1] and [2]. The main advantage of employing Lagrangian Matched Filter denoising model as pre-processing technique in the first hidden layer of Deep Belief Network Classification for ASD detection in EEG signals is its ability to improve PSNR in the presence of additive noise. This signifies that it can obtain EEG signals in a reliable fashion from noisy environments. With this the overall PSNR using proposed LMF-TRPP method was enhanced by 19% and 24% than the [1], [2].

5.2 Performance analysis of autism detection time

Autism detection time or training time refers to time utilized at autism diagnosis. While performing autism diagnosis a small amount of time is consumed while doing pre-processing and selecting of relevant features. This is referred to as autism detection time or simply training time. This is measured as given below.

$$ADT = \sum_{i=1}^{N} S_i * Time\ (AD) \qquad (15)$$

From the above equation (15) autism detection time 'ADT' or training time is calculated depend on EEG samples provided as input 'S_i' and the time consumed in diagnosis autism '$Time\ (AD)$'. It is calculated in milliseconds (ms). Table 4 provides autism detection time performance when employing LMF-TRPP method. Upon comparison to existing two methods, RT-NeuroDDSM [1] and CNN-LSTM [2], LMF-TRPP method exhibits an improvement in performance with this autism denoising or training time.

Table 4 Experimental results for autism detection time using LMF-TRPP, RT-NeuroDDSM [1] and CNN-LSTM [2]

Number of subjects	Autism detection time (ms)		
	LMF-TRPP	RT-NeuroDDSM [1]	CNN-LSTM [2]
10	15	18	20
20	17.35	22.35	25.35
30	20	25.15	28.55
40	22.45	27.35	30.15
50	25	30.45	33.55

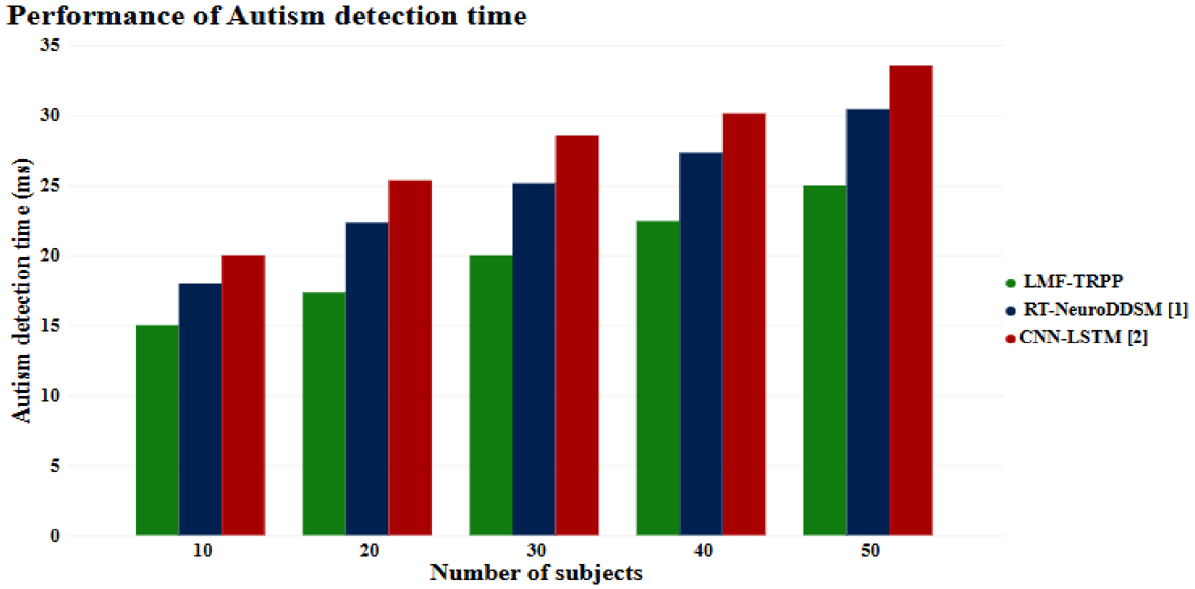

Figure 8 Autism detection time versus number of subjects

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Figure 8 shows graphical depiction of autism detection time or simply the training time involved in ASD detection process. From figure 8, x-axis denotes number of subjects ranging between 10 and 50 and on the other hand, the y-axis represents ADT calculated in milliseconds (ms). Two hypotheses can be made from the above experimental analyses. First, increasing the number of subjects caused an increase in the training time. Second, though increasing number of subjects also resulted in the increased training time, however, the performance metric was found to be reduced using LMF-TRPP method upon comparison to [1] and [2]. This is because by applying Truncated Tobit Regression-based feature selection for EEG signals first, results in dimensionality reduction and also preserves essential information for accurate classification. Also using, Truncated Regression and Tobit function separately assists in eliminating redundant and irrelevant features from pre-processed EEG signal output. This in turn speed up model training and minimize overfitting, therefore reducing the overall autism detection time using LMF-TRPP technique by 24% and 38% than the [1],[2].

5.3 Precision, recall and autism detection accuracy

Precision is referred as percentage of EEG samples forecasted as positive which truly positive. On one hand superior precision result denotes additional precise positive class forecasts and vice versa. This precision is mathematically represented as given below.

$$Pre = \frac{TP}{TP+FP} \quad (16)$$

From the above equation (16) the precision 'Pre' results are arrived at based on TP and FP respectively. Recall refers to ratio of every positive EEG samples properly forecasted to actual positive EEG samples. To be more specific, superior recall value denotes potentiality to obtain additional positive class samples as of overall positive samples. It is mathematically represented as given below.

$$Rec = \frac{TP}{TP+FN} \quad (17)$$

From the above equation (17) the recall 'Rec' results are arrived at on the basis of the true positive rate 'TP' and false negative rate 'FN' respectively. Accuracy or autism detection accuracy computes ratio of correct forecast in proportionate to total number of EEG samples. To be more specific a higher ratio denotes better performance. This autism detection accuracy is mathematically formulated as given below.

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \quad (18)$$

Finally, from the above equation (18), autism detection accuracy or simply accuracy is calculated depend on 'TP' and 'FN', 'FP' and 'TN' respectively. Finally, Table 5 given below provides precision, recall and accuracy performance employing the proposed LMF-TRPP, [1] and [2]. Upon comparison to existing two methods, RT-NeuroDDSM [1] and CNN-LSTM [2], LMF-TRPP method exhibits an improvement in performance with this precision, recall and accuracy factors.

Table 5 Experimental results for precision, recall and accuracy using LMF-TRPP, RT-NeuroDDSM [1] and CNN-LSTM [2]

Number of subjects	Precision			Recall			Accuracy		
	LMF-TRPP	RT-NeuroDDSM [1]	CNN-LSTM [2]	LMF-TRPP	RT-NeuroDDSM [1]	CNN-LSTM [2]	LMF-TRPP	RT-NeuroDDSM [1]	CNN-LSTM [2]
10	0.95	0.92	0.88	0.97	0.87	0.82	0.97	0.92	0.86
20	0.93	0.85	0.81	0.95	0.85	0.8	0.95	0.9	0.84
30	0.96	0.92	0.88	0.96	0.92	0.88	0.93	0.86	0.8
40	0.95	0.87	0.88	0.97	0.87	0.82	0.94	0.89	0.83
50	0.92	0.84	0.74	0.93	0.83	0.78	0.95	0.9	0.84

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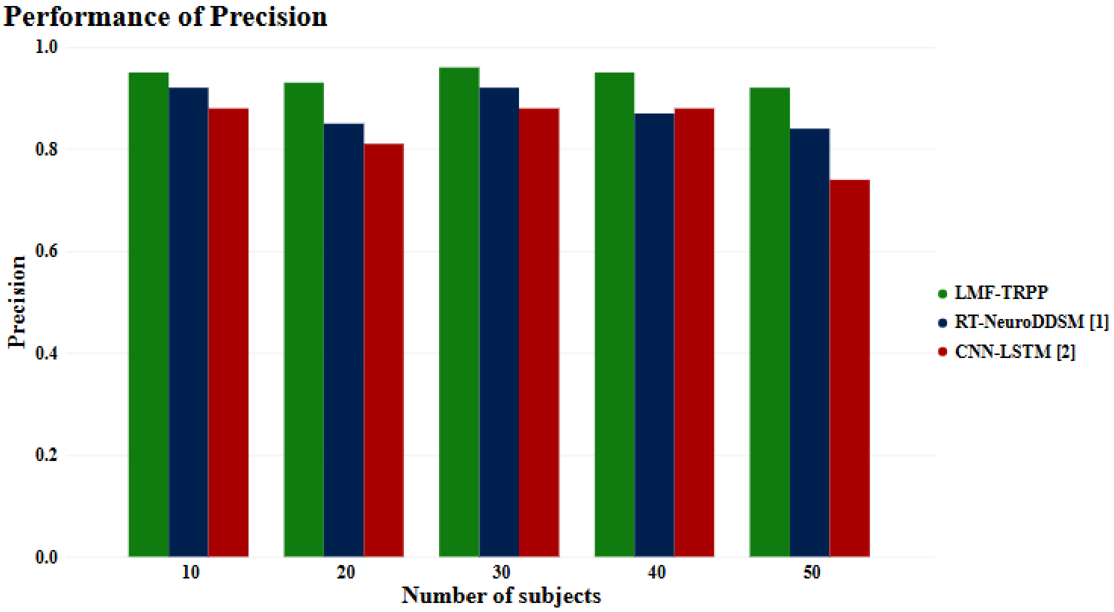

Figure 9 Precision versus number of subjects

Figure 9 illustrates graphical depiction of precision with fifty dissimilar subjects performed over 5 iterations for three methods, RT-NeuroDDSM [1] and CNN-LSTM [2] and LMF-TRPP. From the above graphical representation increasing the number of subjects did not had any influence of precision results. This is evident from the 20 subjects where the precision using the three methods where the precision was observed to be 0.93, 0.85 and 0.81 whereas for 30 subjects it was found to be 0.96, 0.92 and 0.88. Second, the precision results of proposed LMF-TRPP method was found to be better than [1] and [2].

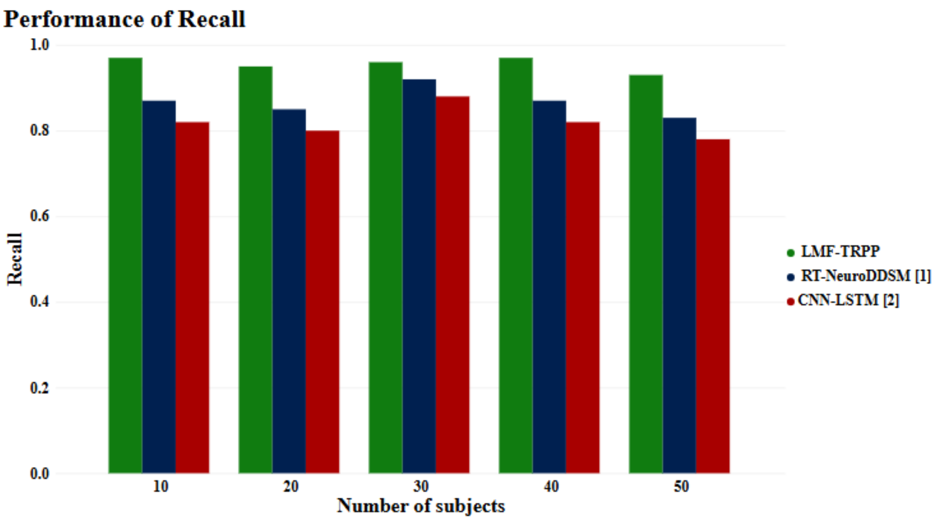

Figure 10 Recall versus number of subjects

Figure 10 depicts graphical depiction of recall rate observed for fifty dissimilar subjects performed over 5 iterations for three methods, RT-NeuroDDSM [1] and CNN-LSTM [2] and LMF-TRPP. From the above graphical representation recall rate were observed to be in the decreasing trend for the first two iterations, whereas

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for the rest of two iterations it was observed to be increase in all the three methods. However, simulations results showed comparatively better results when applied with proposed LMF-TRPP method upon comparison to [1] and [2].

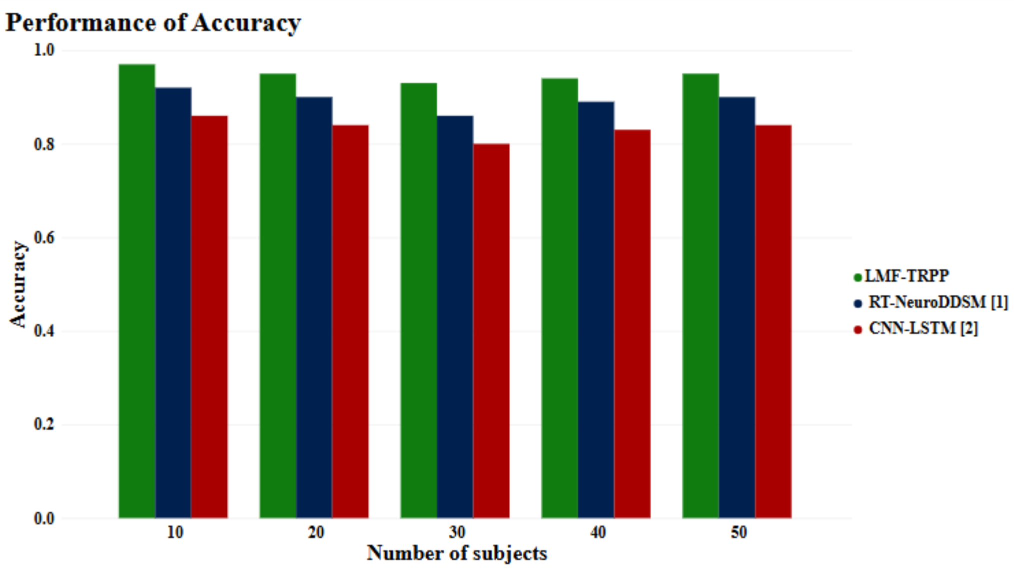

Figure 11 Accuracy versus number of subjects

Finally, figure 11 given above illustrates the accuracy rate upon comparison to 50 different subjects using the three methods, RT-NeuroDDSM [1] and CNN-LSTM [2] and LMF-TRPP. Though for the first three iterations the accuracy rate was observed to be in the decreasing trend, however for the rest of two iterations it was observed in the increasing trend. Also comparative analysis saw better results for proposed LMF-TRPP technique upon comparison to [1], [2]. Cause behind improvements of three performance metrics, precision, recall and accuracy could be contributed to application of Perceptron Piecewise Classification in the third layer for ASD diagnosis. Here, a binary hypotheses result were initially generated using Perceptron Piecewise classifier and fine-tuning of weights were done. This in turn assisted in improving TP, so enhancing entire precision by LMF-TRPP by 7% and 11% than the [1], [2]. Next, by fine-tuning of weights in efficient manner in turn ensured optimal decision boundary between ASD and non-ASD, therefore minimizing the false negative rate. This in turn resulted in the improvement of recall with LMF-TRPP by 9% and 14% than the [1],[2]. Finally, the distinct frequency bands and patterns generated, combined with Perceptron Piecewise Classification in the third layer aid in ASD diagnosis, so enhancing entire accuracy with LMF-TRPP by 6% and 12% than the [1],[2].

6. Conclusion

Early ASD diagnosis is pivotal to make certain that the patient get timely interferences to notably enhance their development and quality of life. In this work a robust and accuracy ASD diagnosis method to ensure early detection employing Deep Belief Network Classification method for detecting ASD with EEG data using Lagrangian Matched Filter with Truncated Regressive Piecewise Perceptron (LMF-TRPP) is proposed. With the preprocessing section being analytical and is simple using denoising and artifact removal via Lagrangian Matched Filter Denoise-based Pre-processing aids in improving the PSNR significantly. Obtained pre-processed results are fed into the Truncated Tobit Regression-based feature selection for EEG signals for segregate the most informative channels and frequency ranges for optimal performance. Finally, with the aid of the results learnt in the feature selection process, Perceptron Piecewise Classifier is applied for early and accurate diagnosis. Quantitative study and validation validate LMF-TRPP technique was improved than conventional methods, in PSNR, training time, precision, recall , Acc.

References

[1] Abdulqader M. Almars, Mahmoud Badawy, Mostafa Elhosseini, "ASD 2-TL* GTO: Autism spectrum disorders detection via transfer learning with gorilla troops optimizer framework", Heliyon, Elsevier, Vol. 9, Nov 2023

[2] Abhilasha Nakra, Manoj Duhan, "Deep neural network with harmony search based optimal feature selection of EEG signals for motor imagery classification", International Journal of Information Technology, Dec 2021

[3] Abigail Dickinson, Shafali Jeste, Elizabeth Milne, "Electrophysiological signatures of brain aging in autism spectrum disorder", HHS Public Access, Mar 2022

[4] Ali Nirabi, Faridah Abd Rahman, Mohamed Hadi Habaebi, Khairul Azami Sidek, Siti Hajar Yusoff, "EEG Signal Analysis for Mental Stress Classification: A Review", Journal of Theoretical and Applied Information Technology, Vol. 100, Oct 2022

[5] Duanyang Yuan, Jingwei Yue, Xuefeng Xiong, Yibi Jiang, Peng Zan, Chunyong Li, "A regression method for EEG-based cross-dataset fatigue detection", Frontiers in Physiology, May 2023

[6] Emel Koc, Habil Kalkan, Semih Bilgen, "Autism Spectrum Disorder Detection by Hybrid Convolutional Recurrent Neural Networks from Structural and Resting State Functional MRI Images", Autism Research and Treatment. Hindawi, Dec 2023

[7] Fleming C. Peck, Laurel J. Gabard-Durnam, Carol L. Wilkinson, William Bosl, Helen Tager-Flusberg, Charles A. Nelson, "Prediction of autism spectrum disorder diagnosis using nonlinear measures of language-related EEG at 6 and 12 months", Journal of Neurodevelopmental Disorders, Springer, Oct 2021

[8] Geo reyBrookshire, Jake Kasper, Nicholas M. Blauch, Yunan Charles Wu, Ryan Glatt, David A. Merrill, Spencer Gerrol, Keith J. Yoder, Colin Quirk, Ché Lucero, "Data leakage in deep learning studies of translation EEG", Frontiers in Neuro Science, May 2024

[9] Guanqing Kong, Shuang Ma, Wei Zhao, Haifeng Wang, Qingxi Fu, Jiuru Wang, "A novel method for optimizing epilepsy detection features through multi domain feature fusion and selection", Frontiers in Computational Neuroscience, Nov 2024

[10] Hanife Go¨ker, "1D-convolutional neural network and fast Walsh Hadamard transform approach for diagnosing autism spectrum disorder", Neural Computing and Applications, Springer, Vol. 37, Apr 2025

[11] José Jaime Esqueda-Elizondo, Reyes Juárez-Ramírez, Enrique Efrén García-Guerrero, Oscar Roberto López-Bonilla, Gilberto Manuel Galindo-Aldana, Laura Jiménez-Beristáin, Alejandra Serrano-Trujillo, Esteban Tlelo-Cuautle, EverardoInzunza-González, "Attention Measurement of an Autism Spectrum Disorder User Using EEGSignals: A Case Study", Mathematical and Computational Applications, MDPI, Oct 2022

[12] Junxia Han, Guoqian Jiang , Member, IEEE, Gaoxiang Ouyang, Xiaoli Li, "A Multimodal Approach for Identifying Autism Spectrum Disorders in Children", IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 30, Nov 2022

[13] Junxia Han, Guoqian Jiang, Gaoxiang Ouyang, Xiaoli Li, "A Multimodal Approach for Identifying Autism Spectrum Disorders in Children", IEEE Transactions on Neural Systems and Rehabilitation Engineering, Volume 30, 2022, Pages 2003 – 2011

[14] Kasturi Barik, Katsumi Watanabe, Joydeep Bhattacharya, Gautam Saha, "A Fusion-Based Machine Learning Approach for Autism Detection in Young Children Using Magnetoencephalography Signals", Springer, Oct 2022
[15] Md. Zasim Uddina, Arif Shahriara, Md. Nadim Mahamood, Fady Alnajjab, Md. Ileas Pramanika, Md Atiqur Rahman Ahad, "Deep learning with image-based autism spectrum disorder analysis: a systematic review", Engineering Applications of Artificial Intelligence, Elsevier, Vol. 127, Jan 2024
[16] Menaka Radhakrishnan, Karthik Ramamurthy, Kaustav Kumar Choudhury, Daehan Won, Thanga Aarthy Manoharan, "Performance Analysis of Deep Learning Models for Detection of Autism Spectrum Disorder from EEG Signals", Traitement du Signal, International Information and Engineering Technology Association, Vol. 38, Jun 2021
[17] Nisreen Said Amer, Samir Brahim Belhaouari, "Exploring new horizons in neuroscience disease detection through innovative visual signal analysis", Scientific Reports, Nature Portfolio, Oct 2024
[18] Noor Kamalal-Qazzaz, Alaa Aldori, Ali K. Buniya, Sawal Hamid Bin Mohd Ali, Siti Anom Ahmad, "Transfer Learning and Hybrid Deep Convolutional Neural Networks Models for Autism Spectrum Disorder Classification From EEG Signals", IEEE Access, Vol. 12, May 2024
[19] Qaysar Mohi ud Din, Anavai K. Jayanthy, "Wavelet Scattering Transform and Deep Learning Networks Based Autism Spectrum Disorder Identification Using EEG Signals", Traitement du Signal, International Information and Engineering Technology Association, Vol. 38, Jun 2021
[20] Ruchi Mittal, R. John Martin, Hamdan Alshehri, Varun Malik, S. B. Goyal and S. L. Swapna "RT-NeuroDDSM: Real-Time EEG-Driven Diagnostic Decision Support Model for Neurological Disorders using Deep Learning", IEEE Access, Volume 12, August 2024, Pages 116711 – 116726 [Real Time Diagnostic Decision Support Model (RT-NeuroDDSM)]
[21] S. Saranya, R.Menaka, "An Explainable Machine Learning Network for Classification of Autism Spectrum Disorder Using Optimal Frequency Band Identification From Brain EEG", IEEE Access, Vol. 13, Feb 2025
[22] Shu Lih Oh, V. Jahmunah, N. Arunkumar, Enas W. Abdulhay, Raj Gururajan, Nahrizul Adib, Edward J. Ciaccio, Kang Hao Cheong, U. Rajendra Acharya, "Complex & Intelligent Systems, Springer, Jun 2021
[23] Souhaila Khalfallah Mehdi Tlija, William Puech, Andkais Bouallegue, "Exploring the Effectiveness of Machine Learning and Deep Learning Techniques for EEG Signal Classification in Neurological Disorders", IEEE Access, Vol. 13, Jan 2025
[24] Suseela Sellamuthu, Sharonrose, "Enhanced Special Needs Assessment: A Multimodal Approach for Autism Prediction", IEEE Access, Vol. 12, Sep 2024
[25] Tian Tanga, Cunbo Lib, Shuhan Zhang, Zhaojin Chen, Lei Yang, Yufeng Mu, Jun Chen, Peng Xu, Dongrui Gao, Fali Li, Baoming Hee, Ye Zhu, "A hybrid graph network model for ASD diagnosis based on resting-state EEG signals", Brain Research Bulletin, Elsevier, Jan 2024
[26] William J. Bos, Helen Tager-Flusberg, Charles A. Nelson, "EEG Analytics for Early Detection of Autism Spectrum Disorder: A data-driven approach", Scientific Reports, May 2018
[27] Yang Ding, Heng Zhang, Ting Qiu, "Deep learning approach to predict autism spectrum disorder: a systematic review and meta-analysis", BMC Psychiatry, Oct 2024
[28] Yongjie Xu, Zengjie Yu, Yisheng Li, Yuehan Liu, Ye Li and Yishan Wang, "Autism spectrum disorder diagnosis with EEG signals using time series maps of brain functional connectivity and a combined CNN–LSTM model", Computer Methods and Programs in Biomedicine, Elsevier, Volume 250, June 2024, Pages 1-10 [convolutional neural network and long short-term memory (CNN-LSTM)]
[29] Yongjie Xua, Zengjie Yua, Yisheng Lia, Yuehan Liua, Ye Lia, Yishan Wanga, "Autism spectrum disorder diagnosis with EEG signals using time series maps of brain functional connectivity and a combined CNN–LSTM model", Computer Methods and Programs in Biomedicine, Elsevier, Jun 2024
[30] Ziqian Yang, Yuyao Zhang, Jiachuan Ning, Xin Wang, Zhihui Wu, "Early Diagnosis of Autism: A Review of Video-Based Motion Analysis and Deep Learning Techniques", IEEE Access, Vol. 13, Jan 2025