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A Discrete Congruence Levenberg–Marquardt Deep Convoluted Neural Learning Classifier for the Automatic Detection of Autism Spectrum Disorder

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Abstract: Autism spectrum disorder is a condition that affects around one out of every 54 children. Many studies have identified abnormalities in electroencephalography (EEG) signals for ASD diagnosis. The early and accurate identification of autism poses a substantial difficulty. The detection accuracy needs to be significantly boosted and the computational complexity reduced. The discrete congruence Levenberg-Marquardt deep convoluted neural learning classification (DCLMDCNLC) approach is introduced to address these issues in this work. The goal of the DCLMDCNLC approach is to perform automated ASD diagnosis at an early stage with higher accuracy and less time complexity. The DCLMDCNLC technique is applied to EEG signals through pre-processing, feature selection, and data classification. Discrete global threshold wavelet-transform-based pre-processing is carried out for EEG signal decomposition to remove unwanted noise. After that congruence correlation feature selection is carried out using the DCLMDCNLC technique with denoised signals to perform further processing. Finally, piecewise regression data analysis is carried out using the DCLMDCNLC technique for accurate autism detection with higher accuracy. An experimental assessment of the DCLMDCNLC technique is simulated, and the technique is validated using the EEG dataset for autism detection. Compared with traditional approaches, the DCLMDCNLC technique improves the accurate diagnosis of autism by 65%, the precision by 15%, the recall by 17%, the rate of errors by 77%, and the autism detection time by 35%.

Keywords: autism spectrum disorder, electroencephalography, congruence correlative feature selection, discrete global threshold wavelet transform, piecewise regressive data analysis

1. Introduction

Autism is a neurobiological condition that involves limited and repeated behavioral characteristics in tandem with an absence of an interpersonal nature, social interactions, and interpersonal communication abilities. Autism is associated with various levels of disability and functionality, spanning from high functionality (HF) to minimal functionality (LF). Autism affects social skills, communication, and individual behavior. It is identified through different behavioral characteristics, and different autism spectrum disorders (ASDs) are widely recognized based on the severity level. A recommender model with multi-classification was introduced by Shinde and Patil [1] to increase prediction accuracy. Though the accuracy was improved, the designed model did not minimize the time complexity.

To assist trained medical professionals in diagnosing autism, the response-to-instruction (RTI) protocol was developed by Liu et al. [2], employing vision-based advances in technology. The correlation between toddlers' emotional characteristics and their surroundings has been utilized to examine autism-related signs. However, the f-score was not improved by the RTI protocol. A stress monitoring system was introduced by Tomczak et al. [3] for individuals with ASDs in educational institutions. However, the ASD detection accuracy was not improved by the designed system. A machine learning technique was introduced by Thapa et al. [4] to categorize individuals under the DSM-IV using minimal data inputs. Though the accuracy level was improved, the f-score was not enhanced by this technique.

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Enhanced by federated learning, the convolutional neural network and long short-term memory CNN-LSTM (FCNN-LSTM) approach was initially developed by Lakhan et al. [5] to detect ASD among children. The FCNN-LSTM methodology was created within a decentralized computational architecture. Regional labs have employed the FCNN-LSTM methodology to validate dataset information, but the degree of precision could be further improved. ResNet101 was used with a bidirectional gated recurrent unit (Bi-GRU) to develop a distinctive hybrid ensemble approach [6]. For ASD and its identification and classification, a model called ResNet has also been employed, but it has not been possible to improve the recall metric of this model.

An sMRI classification architecture was introduced by Mishra and Pati [7] for ASD detection with a data augmentation approach. The designed framework employed an ensemble model by combining a deep convolutional neural network (DCNN model) with diverse optimizers. Unfortunately, the framework's architectural structure failed to minimize the computation required. A comprehensive framework was released in the word of RethikumariAmma and Ranjana [8] to identify patients who have ASD through mining relevant features. The designed model increased the pre-processed image efficiency for categorizing neuron patterns. Nevertheless, extensive modeling failed to improve the accuracy level.

According to Mazumdar et al. [9], a unique technique was created by employing information collected through the tracking of eyes along with machine learning. The distinctive features of the visuals were examined to identify possible behaviors, including objects that contribute to image retention. However, the error rate was not minimized by the designed approach. The brain hemodynamic responses of neurotypical adults and those with spectrum disorders were discussed by Charpentier et al. [10]. The responses were investigated using the oddball model to identify brain responses with different saliency levels and emotional content. However, the time complexity was not minimized.

The problems associated with models in the existing literature include low ASD detection accuracy, low precision, low recall, low f-scores, increased error rates, increased computational costs, increased computational complexity, and higher ASD detection times. The discrete congruence Levenberg–Marquardt deep convoluted neural learning classification (DCLMDCNLC) technique is introduced here to address these issues.

1.1. Contributions of this paper

The main contributions of this article are as follows:

1) The DCLMDCNLC technique is introduced to perform automated ASD diagnosis at initial stage with better accuracy and minimum time complexity.
2) A Discrete global threshold wavelet-transform-based pre-processing is designed in DCLMDCNLC technique for EEG signal decomposition to eliminate the unwanted noise.
3) A congruence correlative feature selection is performed to DCLMDCNLC technique with denoised signals for relevant feature selection to perform further processing.
4) Piecewise regressive data analysis is employed to accurate classification of subjects into autism and non-autism classes.
5) The performance of pre-processing and feature selection steps leads to a reduction in the amount of time required for performing ASD diagnosis.
6) Finally, an experimental examination is implemented to compare DCLMDCNLC technique with existing methods by different performance metrics.

1.2. Structure of the manuscript

Manuscript is structured to various sections. Literature review that is related in autism screening is presented in Section 2. Section 3 describes the proposed DCLMDCNLC model through pre-processing, feature extraction, and classification processes for autism detection. Section 4 provides the experimental scenario with the dataset description. Performance analyses as well as discussion are explained in Section 4. Finally, Section 5 concludes the article.

2. Related Works

The diagnosis of ASD is essential for medical professionals to be able to give patients prompt and appropriate care. A combination of behavioral and architectural MRI findings was employed by Rakić et al. [11] to classify individuals with autism spectrum disorder. Authors used function as a connection pattern among cortical regions for architectural processing pipelines with a volumetric existence of cerebral gray matter quantities inside the central nervous system. In the work of Parui et al. [12], an approach was presented to generate a functioning interconnectivity network by employing the resting state of a functioning magnetic resonance imaging (RS-fMRI) dataset. Regional connection to the network was determined using time intervals of fMRI data.

A multiple logistic regression model with various corrections was introduced by Belica et al. [13] for a log-transformed plasma G-CSF concentration with increased child risk of autism. The G-CSF model was examined alongside different activities of the immune system. Genetic defects in the chromosomes of children with autism were discussed by Al-Awadi et al. [14] through particular probes identified using the Fluorescence in situ hybridization (FISH) technique. The design clarified methods of diagnosing cytogenetic deflection among autistic patients using karyotyping and the FISH technique.

A patient with ASD was identified by Bhandage et al. [15] through Adam war strategy optimization (AWSO) based on a deep belief network (DBN). An AWSO algorithm was introduced by combining the Adam optimizer with war strategy optimization (WAO). However, the precision level of this approach still needs to be improved. Among the significant biomarkers in children, the total amount of sialic acid (SA) along with anti-ganglioside M1 connected to (anti-GM1) IgG antibody responses was investigated by Ashaat et al. [16]. SA was used to identify the ASD diagnostic yield and its correlation with autism severity. However, the computation cost was not minimized.

CSF has been used to identify the optimal control group of neurological individuals suffering from arterial hypertension and ASD [17]. The different kinds of cytokine from CSF have been determined using an electromagnetic bead multiplexed immunoassay. Despite this, the degree level of the CSF approach still needs to be reduced [18]. The use of a deep neural network (DNN) has been described as a potential alternative approach to evaluating ADOS rating systems. Convolutional neural network (CNN) technology has been implemented to achieve higher-quality results. Fortunately, the deep neural network (DNN) method could reduce the amount of complexity.

A new multiple model termed a Kalman-like filter was introduced by Puli and Kushki [19] to combine heart rate and accelerometry signals. However, the method employed failed to lower computational expenses. An outlier identification method was also developed to diagnose autism using structural magnetic resonance imaging (sMRI) [20]. However, the designed outlier detection approach still needs improved precision.

An automated method was designed by Guo [21] to examine the visual indications of autism using pictures captured of individuals with ASD. The manual inspection of photos inspired the approach. Though the developed technique had an enhanced degree of accuracy, the amount of computing power required remained the same. Based on Hasan et al. [22], an efficient framework was developed to evaluate numerous methods using machine learning (ML) for autism spectrum disorder detection. ASD risk indicators were determined and prioritized by their respective values.

Autonomic response detection was carried out by Sarabadani et al. [23], employing children's favorable and detrimental stimuli to determine the presence of ASD. However, the error rate was not minimized by the automatic detection system. The visual processing variation among individuals with high-functioning autism and those without it was investigated by Yaneva et al. [24] with eye-tracking technology. However, the detection accuracy of this approach still needs to be improved.

Variable frequency complex demodulation (VFCDM), an unprecedented resolution time-frequency spectral technique, was developed by Posada-Quintero et al. [25] to decompose ERG waveforms. The decomposition was carried out with signal flash strengths to classify ASD. However, the accuracy level could be further improved. A deep neural network (DL)-based framework for recognizing individuals with ASD was put forward by Shin et al. [26]. Writing with hands patterns have been observed using functional near-infrared spectroscopy (fNIR) data. However, the recall was not improved by this DL-based algorithm.

In the research of Ma et al. [27], we constructed a multi-scale dynamic graph learning (MDGL) method capable of gathering spatiotemporal dynamic rs-fMRI data representations to identify neurological conditions. The level of accuracy still needs to be further improved. Based on the research of Huang et al. [28], an effective federation multi-task learning (MTL) structure built around functional magnetic resonance imaging (MRI) was demonstrated to be capable of recognizing various linked mental health conditions. Still, there has been no improvement in computational challenges.

As one example, a stress-related monitoring technique can recognize neurological conditions by employing EEG data [29]. Convolutional neural networks, also called CNNs, have been utilized in conjunction with the framework created for classifying medical conditions. Nevertheless, no particular system has succeeded in decreasing the ASD identification time. A machine learning structure was designed by Jacob et al. [30] that depends on automated hyperparameter optimization and was employed to rank the nonclinical markers for autism. Despite an increase in accuracy, the time complexity remained the same.

3. Methodology

ASD is an intricate neuro-developmental disease. An EEG records the electrical activity of the brain, with electrodes affixed to the scalp to capture electrical impulses of different frequencies used by neurons for communication. In this work, DCLMDCNLC technique aims to perform automated ASD diagnosis at an early stage with higher accuracy and less time complexity. The ASD diagnosis process is categorized into pre-processing, feature selection, and data classification, as shown in Figure 1.

The suggested architecture diagram in Figure 1 shows the DCLMDCNLC technique used to classify the EEG signals automatically. The DCLMDCNLC approach utilizes the Biosemi Active system to obtain the EEG signals for performing ASD diagnosis. The EEG LAB transforms the original EEG recordings into an executable file format. EEG recordings were taken from people with ages ranging from 18 to 68 years old, 28 people with autism and 28 people without. Electrode that actively participates in the electrochemical reaction is known as active electrode. It takes part in the reactions that take place in the electrolyte to conduct the electricity. Both oxidation and reduction reactions can occur in active electrodes. By using 64 electrodes, the recording duration was set to a 2.5-min (150-s) resting period with the eyes closed. The EEG time series epoch was sampled at 2048 Hz. To achieve good temporal precision, the original signal was sampled 2048 times per. The input EEG signalsMath input errorwere collected from the input dataset D. After that, the input signals were pre-processed to remove the unwanted noise and enhance the signal quality. Next, feature extraction was performed to extract the relevant features. With the extracted features, the signals were correctly classified within a minimum time. Finally, data classification was carried out to categorize the signal as a non-autism or autism signal with selected noise-reduced signals. A detailed explanation of the DCLMDCNLC technique is given in the following subsections.

3.1. DCLMDCNLC technique

EEG signals have modest amplitudes and can be polluted by noise. The noise in EEG signals must be eliminated for a proper analysis. In this work, the DCLMDCNLC technique is implemented to perform efficient ASD diagnosis through the data classification process. With the help of the DCLMDCNLC technique, the autism detection accuracy increases with a minimal error rate. The main objective of neural learning is to reduce the dimensionality with minimum time consumption for performing the required tasks. Figure 2 shows a schematic diagram of the deep convolutional neural learning classifier.

The classifier includes different layers: the input layer, the output layer, and at least one hidden layer for efficient data classification. The hidden layers are considered following layers with small units termed artificial neurons for analyzing the input signals. The synapses are the connection points between neurons in a particular layer. In the DCLMDCNLC technique, the input layer collects the EEG signals and is considered an input. After that, the EEG signals are passed to the hidden layers for future processing (i.e., signal classification). The three hidden layers are the convolutional, max-pooling, and fully connected layers. The final classifier output comes from the output layer. Initially, the input layer obtains several EEG signals $S_1, S_2, S_3, \ldots S_n$. The input layer $Int(t)$ is given as

$$Int(t) = \left[\sum_{i=1}^{n} S_{\mathrm{i}} * we_{inp}\right] + B. \tag{1}$$

In Equation (1), S_i represents the EEG signals, B represents the bias, and we_{inp} symbolizes the weight in the input layer. After that, the input layer is sent to hidden layer 1 (i.e., the convolutional layer), where the data pre-processing is carried out.

The deep neural network is a convolutional layer where most of the computations are carried out. The convolutional layer applies a mathematical operation to the incoming signal. With a collection of weights and input signals, it describes the linear mathematical process of convolution.

1) **Signal pre-processing**

In the convolutional layer, signal pre-processing is carried out using the DCLMDCNLC technique to reduce the noise without signal distortion. The goal of signal pre-processing in ASD diagnosis is primarily noise removal. A discrete wavelet transform (DWT) is

Figure 1
Architecture diagram of proposed DCLMDCNLC technique

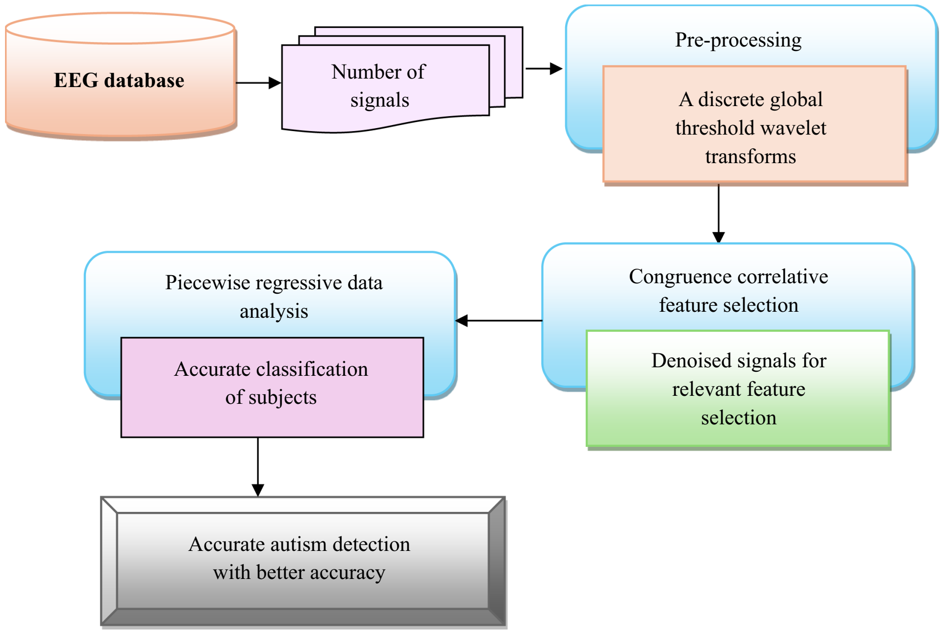


Figure 2
Structural diagram of the deep convolutional neural learning classifier

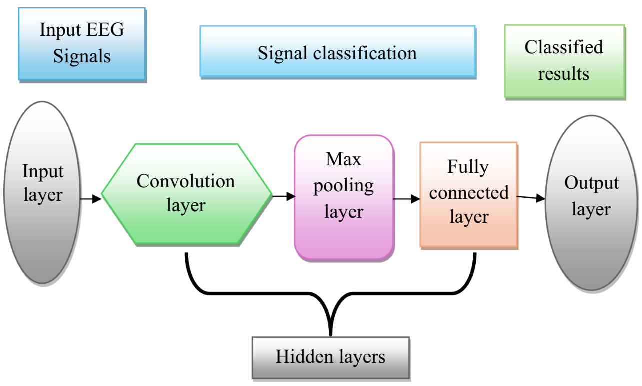
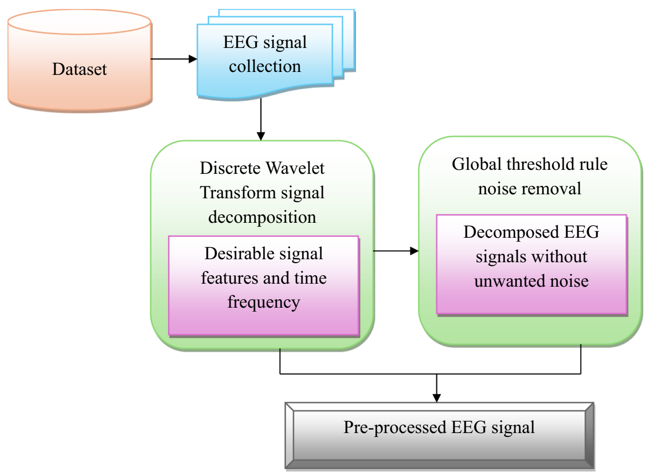


Figure 3
Flow process of the discrete global threshold wavelet transform



used for the EEG signal decomposition to preserve desirable signal features. The wavelet transform describes the EEG signals in the time-frequency domain. The DWT decomposes the EEG signal into different sub-bands in the time-frequency scale plane to obtain denoised signals. A discrete global threshold wavelet transforms (DGTWT)-based pre-processing model is introduced in the DCLMDCNLC technique to obtain the decomposed EEG signals without unwanted noise. Figure 3 illustrates the flow process of the DGTWT-based pre-processing model.

As illustrated in Figure 3, the DCLMDCNLC technique initially partitions the EEG signal into five different sub-bands with a DWT. The five sub-bands are the delta sub-band ($0-4$ Hz), the theta sub-band ($4-8$ Hz), the alpha sub-band ($8-12$ Hz), the beta sub-band ($12-30$ Hz), and the gamma sub-band (> 30 Hz). The coefficients of the decomposed signals are thresholds based on the global threshold rule for removing noise in the signal. The mathematical expression for the global threshold rule is:

$$GT^r = \hat{m}^2 \log N. \tag{2}$$

With the above threshold rule, further processing for autism detection is performed. The algorithmic representation of the discrete global threshold wavelet transforms for pre-processing the input signal is provided below in Algorithm 1.

Algorithm 1 DGTWT-based pre-processing
Input: EEG Signals **Output**: Noise-reduced signals (NRS) **Start** 1: **For** each EEG signal 2: Decompose the input EEG signals into five different sets 3: **For** each frequency sub-band 4: Apply the global threshold rule 5: Return noise-reduced signals 6: **End for** 7: **End for** **End**

Algorithm 1 clarifies the DGTWT-based pre-processing step to obtain the noise-reduced (i.e., pre-processed) signals. Initially, the DWT is used to perform the signal decomposition. After that, global threshold rule is applied in DCLMDCNLC technique to attain a pre-processed signal by removing the noise from the decomposed signal. Finally, the pre-processed signal is obtained for the EEG signal analysis.

2) **Feature selection process**

After the signal pre-processing, the second hidden layer (i.e., the max-pooling layer) performs feature extraction. Using the estimation of neuron activity, the max-pooling layer determines the correlation measure. The correlation measure is a measure of the similarity that determines the relationship between the EEG signals and features. The congruence correlation function is formulated in the DCLMDCNLC technique as

$$CF_{Cong} = \frac{\sum S_{tr} * S_{ts}}{\sqrt{\sum {S_{tr}}^2 \sum {S_{ts}}^2}}. \quad (3)$$

In Equation (3), CF_{Cong} is the congruence correlation function, S_{tr} is the set of training EEG signal samples, and S_{ts} represents the testing data samples. $\sum S_{tr} * S_{ts}$ is the sum of the product of the paired score of two EEG signal samples. $\sum {S_{tr}}^2$ indicates the square of the d score of the training signals S_{tr}. $\sum {S_{ts}}^2$ symbolizes the squared score of the testing signals.

The outcomes of CF_{Cong} are obtained from values between 0 and 1. *0* indicates that the features are not similar and 1 indicates that the features are identical, which corresponds to the EEG signals being classified as typical or indicative of autism. When the result is 0, there is no correlation between the two signal samples. Similarly, when the test result value is 1, there is a correlation between the two signal samples. The max-pooling layer results are passed to the third hidden layer (i.e., the fully connected layer) that minimizes the dimensions by combining the input at one layer and transforming it into the next layer.

3) **Classification process**

The correlation results CF_{Cong} are considered an input to the fully connected layer. The fully connected layer reduces the dimensions of the output by detecting the correlated results depending on the threshold value with the help of piecewise regression analysis. The piecewise regression analysis partitions the independent EEG signal that represents a different relationship between region features. It is formulated as

$$PRA = \begin{cases} CF_{Cong} > th;\ Selectcorrelationresults \\ CF_{Cong} < th;\ Discarded \end{cases}. \quad (4)$$

In Equation (4), PRA is the piecewise regression analysis result. When the correlation exceeds the threshold, it is selected for signal classification. Otherwise, the correlation results are discarded. The output of the fully connected layer categorizes the EEG signal as a standard signal or an autism signal. The output layer uses a softplus activation function to perform the signal classification. It is formulated as

$$S_{AF} = \log\left[1 + e^{MP}\right]. \quad (5)$$

Using Equation (5), the softplus activation function S_{AF} attains positive results. Then, the signal can be accurately classified into specific classes. The error is then determined as

$$ER = [Act\ (S_{AF}) - S_{AF}]^2. \quad (6)$$

Using Equation (6), ER is estimated, where $Act\ (S_{AF})$ denotes the actual outcome and S_{AF} represents the output predicted by the activation function. The Levenberg–Marquardt method is applied in the DCLMDCNLC technique to detect the minimum loss. It is formulated as

$$LM = arg \min ER. \quad (7)$$

In Equation (7), LM denotes the output of the Levenberg–Marquardt method. Therefore, the final classification results are obtained at the output layer with higher accuracy and a lower error rate.

Using the above algorithm, the DCLMDCNLC technique efficiently performs ASD diagnoses by accurately determining whether the data is typical or indicative of autism with minimal error. The ASD detection accuracy is improved, as the error involved in the data classification is minimized to ensure effective ASD diagnosis.

Algorithm 2 Discrete congruence Levenberg–Marquardt deep convoluted neural learning classification
Input: Database, EEG Signals **Output**: ensure effective ASD diagnosis **Start** **Step 1**: Initialize the number of EEG signals$S_1,\ S_2, S_3 \ldots .S_n$ Step 2: **For each** EEG signal **Step 3:** Remove the noisy pixels through pre-processing **Step 7:** Measure the congruence correlation between pixels **Step 12:** Perform the feature extraction **Step 13:** Extract the color, texture, and intensity features Step 14**: End for** Step 15**: For each image** **Step 16:** Apply the softmax plus activation function **Step 17: if** ($S_{AF} > th$), **then** **Step 18:** Signal is classified as autism class Step 19**: Else** **Step 20**: Image is classified as non-autism class Step 21: **End if** Step 22**: End for** **End**

4. Experimental Settings

Simulations of the proposed DCLMDCNLC technique and the existing recommender model with multi-classification [1], a response-to-instruction (RTI) protocol [2], a stress monitoring system [3], and a machine learning technique [4] are implemented in

Java. To detect autism in both children and adolescents, two datasets are used from the electrophysiological signatures of brain aging in autism spectrum disorder dataset. EEG signals for 56 different subjects are taken from the first dataset. The observations were gathered from 28 individuals with an autism spectrum disorder diagnosis and 28 people without the disorder. The latter were used as neurotypical regulates and varied in age between 18 and 68. The results were achieved using a 2.5-min (150-s) eyes-closed resting paradigm. The dataset is split into 80% of training dataset and 20% of testing dataset. Five metrics are used to assess the performance of different diagnosis methods:

1) The autism detection accuracy
2) The autism detection time
3) Precision
4) Recall
5) The error rate

The metrics are examined with the help of table and graph representations.

4.1. The autism detection accuracy

The autism detection accuracy is the number of signals or subjects correctly detected to have autism. The autism detection accuracy is measured in terms of a percentage (%). It is formulated as

$$AD_{Acc} = \left[\frac{T_p + F_p}{T_p + F_p + T_n + F_n} \right] * 100. \quad (8)$$

From Equation (8), the autism detection accuracy AD_{Acc} can be determined. T_p represents true positive, F_p represents false positive, T_n represents true negative, and F_n represents false negative.

Table 1 and Figure 4 show a comparative analysis of the autism detection accuracy for a number of subjects, which varies from 5 to 50. The autism detection accuracy is determined for five different techniques in total. For the 35 subjects, the autism detection accuracy using the proposed DCLMDCNLC technique was 89%, compared to 42%, 47%, 56%, and 63% for the existing methods proposed by Shinde and Patil [1], Liu et al. [2], Tomczak et al. [3] and Thapa et al. [4], respectively. The proposed DCLMDCNLC technique provided superior accuracy to all of the existing methods considered. This is because discrete global threshold wavelet-transform-based pre-processing and congruence correlative feature selection are carried out using the DCLMDCNLC technique with denoised signals for relevant feature selection. The piecewise regressive data analysis resulted in autism detection with higher accuracy. Ten different autism detection accuracy results were attained for other subjects. Compared to the methods proposed by Shinde and Patil [1], Liu et al. [2], Tomczak et al. [3] and Thapa et al. [4], the autism detection accuracy performance of the DCLMDCNLC technique was greater by 91%, 82%, 50%, and 38%, respectively.

4.2. The autism detection time

The autism detection time is the amount of time needed to detect subjects with autism disorder accurately. The autism detection time is measured in terms of milliseconds (ms). It is calculated as

$$AD_{Time} = N * Time \text{ (detecting one subject)}. \quad (9)$$

Using Equation (9), the autism detection time (AD_{Time}) can be measured. N represents the number of subjects and $Time$ (one subject) represents the time needed to analyze a subject.

Figure 4
A graphical representation of the autism detection accuracy of various techniques

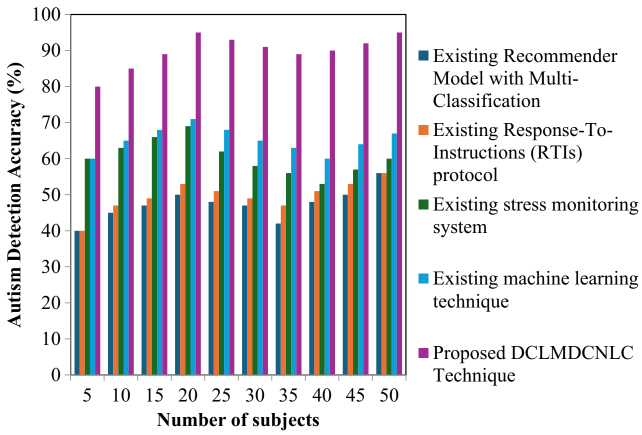


Table 1
Autism detection accuracy results

Number of subjects	Autism Detection Accuracy (%)				
	Existing recommender model with multi-classification	Existing RTI protocol	Existing stress monitoring system	Existing machine learning technique	Proposed DCLMDCNLC technique
5	40	40	60	60	80
10	45	47	63	65	85
15	47	49	66	68	89
20	50	53	69	71	95
25	48	51	62	68	93
30	47	49	58	65	91
35	42	47	56	63	89
40	48	51	53	60	90
45	50	53	57	64	92
50	56	56	60	67	95

Table 2
Autism detection time results

	Autism detection time (ms)				
Number of subjects	**Existing recommended model with multi-classification**	**Existing (RTI) protocol**	**Existing stress monitoring system**	**Existing machine learning technique**	**Proposed DCLMDCNLC technique**
5	35	31	25	20	15
10	39	35	29	22	17
15	43	38	32	25	21
20	47	42	36	28	24
25	51	45	40	30	27
30	55	48	43	33	30
35	59	52	48	36	32
40	62	56	51	39	35
45	66	60	54	43	38
50	70	64	58	47	40

Figure 5
A graphical representation of the autism detection time results

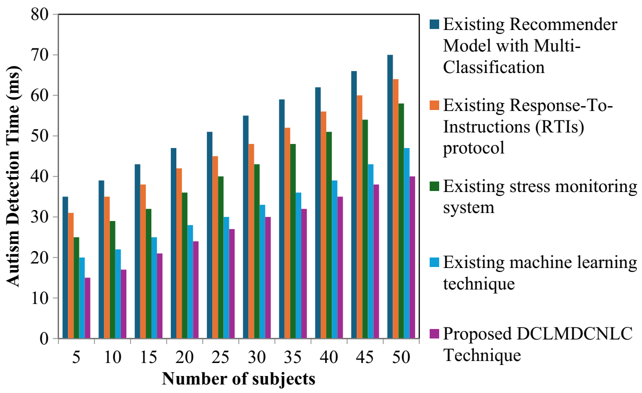


Table 2 and Figure 5 show a comparative analysis of the autism detection time for number of fields ranging from 5 to 50. The autism detection time is computed using the same five techniques as before. For 15 fields, the autism detection times of the proposed DCLMDCNLC technique and the existing methods by Shinde and Patil [1], Liu et al. [2], Tomczak et al. [3] and Thapa et al. [4] were 21, 43, 38, 32, and 25 ms, respectively. The proposed DCLMDCNLC technique provides a shorter autism detection time than the existing autism detection techniques. This is due to the application of the discrete global threshold wavelet transform and the congruence correlative feature selection for pre-processing and relevant feature selection. Subsequently, piecewise regressive data analysis was performed for autism detection with minimum time consumption. As before, ten different autism detection time results were obtained for other subjects. The autism detection time of the DCLMDCNLC technique was 48%, 42%, 34%, and 14% lower than that of the existing methods by Shinde and Patil [1], Liu et al. [2], Tomczak et al. [3] and Thapa et al. [4], respectively.

4.3. Precision

The precision is determined from the number of true positive and false positive subjects. It is calculated in terms of a percentage (%) as

$$Pn = \left(\frac{T_p}{T_p + F_p}\right) * 100. \tag{10}$$

From Equation (10), the precision (Pn) can be determined from the accurate positive data (T_p) and false positive data (F_p).

Table 3 and Figure 6 show a comparative analysis of the precision results for number of subjects varying from 5 to 50. The precision level is determined using the same five techniques as before. For 45 subjects, the precision values of the proposed DCLMDCNLC technique was 96%, compared to 80%, 87%, 92%, and 93% for the existing methods by Shinde and Patil [1], Liu et al. [2], Tomczak et al. [3] and Thapa et al. [4] respectively. The proposed DCLMDCNLC technique increased the precision level over those of all existing methods. This is because of the use of a discrete global threshold wavelet transform to perform pre-processing and congruence correlative feature selection for feature selection. Next, piecewise regressive data analysis was performed for autism detection with a higher precision level. As before, ten different precision results were attained for different number of subjects. The precision was increased using the proposed DCLMDCNLC technique by 27%, 21%, 8%, and 5% compared to the existing methods by Shinde and Patil [1], Liu et al. [2], Tomczak et al. [3] and Thapa et al. [4] respectively.

4.4. Recall

The recall is computed based on the number of true positives and false negative data during autism spectrum detection. It is measured in terms of a percentage (%) and calculated as

$$Re_{call} = \left(\frac{T_p}{T_p + F_n}\right) * 100. \tag{11}$$

Figure 6
A graphical representation of the precision results

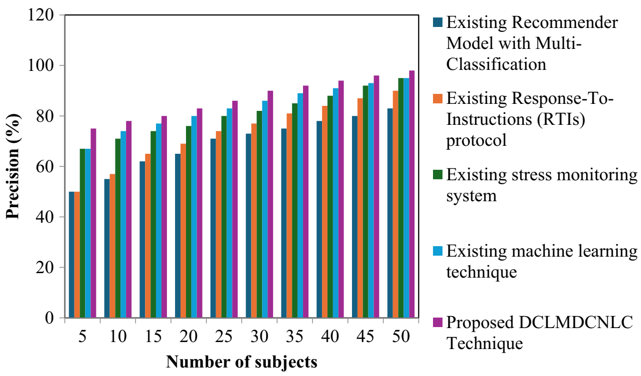


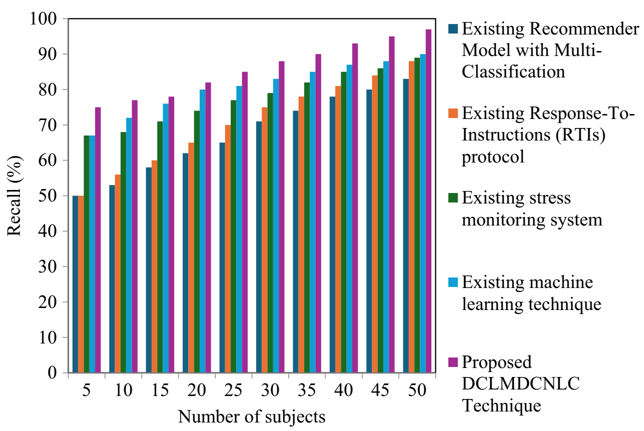
Table 3
Precision results

Number of subjects	Precision (%)				
	Existing recommender model with multi-classification	Existing response-to-instruction (RTI) protocol	Existing stress monitoring system	Existing machine learning technique	Proposed DCLMDCNLC technique
5	50	50	67	67	75
10	55	57	71	74	78
15	62	65	74	77	80
20	65	69	76	80	83
25	71	74	80	83	86
30	73	77	82	86	90
35	75	81	85	89	92
40	78	84	88	91	94
45	80	87	92	93	96
50	83	90	95	95	98

Table 4
The recall results

Number of subjects	Recall (%)				
	Existing recommender model with multi-classification	Existing response-to-instruction (RTI) protocol	Existing stress monitoring system	Existing machine learning technique	Proposed DCLMDCNLC technique
5	50	50	67	67	75
10	53	56	68	72	77
15	58	60	71	76	78
20	62	65	74	80	82
25	65	70	77	81	85
30	71	75	79	83	88
35	74	78	82	85	90
40	78	81	85	87	93
45	80	84	86	88	95
50	83	88	89	90	97

Figure 7
A graphical representation of the recall results



Using Equation (11), a recall (Re_{call}) is computed from the accurate positive data T_p and false negative data F_n.

Table 4 and Figure 7 show a comparative analysis of the recall for number of subjects varying from 5 to 50. The recall level is computed for the same five techniques as before. For 25 subjects, the recall of the proposed DCLMDCNLC technique was 85%, compared to 65%, 70%, 77%, and 81% for the existing methods by Shinde and Patil [1], Liu et al. [2], Tomczak et al. [3] and Thapa et al. [4] respectively. Among the five different autism detection techniques, the proposed DCLMDCNLC technique provides the best recall level. This is due to the application of the wavelet transform for pre-processing and the congruence correlation for feature selection. Piecewise regression was carried out for autism detection with higher recall levels. Consequently, ten different recall results were attained for different number of subjects. The recall was increased using the proposed DCLMDCNLC technique by 29%, 24%, 11%, and 6% compared to the existing methods by Shinde and Patil [1], Liu et al. [2], Tomczak et al. [3] and Thapa et al. [4] respectively.

4.5. Error rate

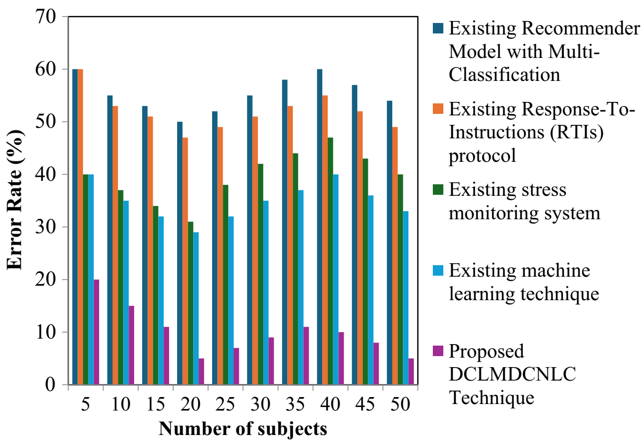
The error rate is the number of signals or subjects incorrectly determined to have autism disorder. The error rate is computed in terms of a percentage (%) as

$$ER_{RA} = \left[\frac{T_n + F_n}{T_p + F_p + T_n + F_n} \right] * 100. \tag{12}$$

Table 5
The error rate results

	Error Rate (%)				
Number of subjects	Existing recommender model with multi-classification	Existing RTI protocol	Existing stress monitoring system	Existing machine learning technique	Proposed DCLMDCNLC technique
5	60	60	40	40	20
10	55	53	37	35	15
15	53	51	34	32	11
20	50	47	31	29	5
25	52	49	38	32	7
30	55	51	42	35	9
35	58	53	44	37	11
40	60	55	47	40	10
45	57	52	43	36	8
50	54	49	40	33	5

Figure 8
A graphical representation of the error rate results



From Equation (12), the error rate (ER_{RA}) can be computed. A lower error rate corresponds to a more efficient method

Table 5 and Figure 8 show a comparative analysis of the error rate for number of subjects varying from 5 to 50.

For 50 subjects, the error rate of the proposed DCLMDCNLC technique was 5%, compared to 54%, 49%, 40%, and 33% for the existing methods by Shinde and Patil [1], Liu et al. [2], Tomczak et al. [3] and Thapa et al. [4] respectively. The proposed DCLMDCNLC technique reduced the error rate compared to existing techniques. This is because of the wavelet transform for pre-processing and the congruence correlation for feature selection. Piecewise regression was carried out for autism detection with a minimal error rate. Ten different error rate results were achieved for other subjects. The error rate was minimized using the proposed DCLMDCNLC technique by 82%, 81%, 74%, and 72% compared to the existing methods by Shinde and Patil [1], Liu et al. [2], Tomczak et al. [3] and Thapa et al. [4] respectively.

5. Conclusion

A novel DCLMDCNLC technique has been applied to perform automated ASD diagnosis at an early stage with higher accuracy. Discrete global threshold wavelet-transform-based pre-processing is carried out for EEG signal decomposition to remove unwanted noise. After that, congruence correlation feature selection is carried out using the DCLMDCNLC technique with denoised signals to perform further processing. Finally, piecewise regression data analysis is carried out using the DCLMDCNLC technique for accurate autism detection with higher accuracy. An experimental assessment of the DCLMDCNLC technique is simulated and the technique is validated using the EEG dataset for autism detection. Compared with traditional approaches, the DCLMDCNLC technique improves the accurate diagnosis of autism by 65%, the precision by 15%, the recall by 17% the rate of errors by 77%, and autism detection time by 35%.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The EEG data that support the findings of this study are openly available at https://orda.shef.ac.uk/articles/dataset/EEG_Data_for_Electrophysiological_signatures_of_brain_aging_in_autism_spectrum_disorder_/16840351.

Author Contribution Statement

Sujatha Krishna: Conceptualization, Methodology, Writing – review & editing. **Rajesh Natarajan:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing, Visualization. **Amalraj Irudayasamy:** Formal analysis, Writing – review & editing. **Gururaj Harinahalli Lokesh:** Validation, Formal analysis, Writing – original draft, Writing – review & editing, Supervision. **Francesco Flammini:** Writing – review & editing, Supervision. **Badria Sulaiman Alfurhood:** Writing – review & editing, Visualization.

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