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标题: Diagnosing autism in children using nonlinear dynamics of EEG signals and fuzzy extreme learning machines with feature optimization

作者: Wang, X (Wang, Xin);Liu, H (Liu, Han);Zhu, YR (Zhu, Yuer);Zhang, H (Zhang, Hao)

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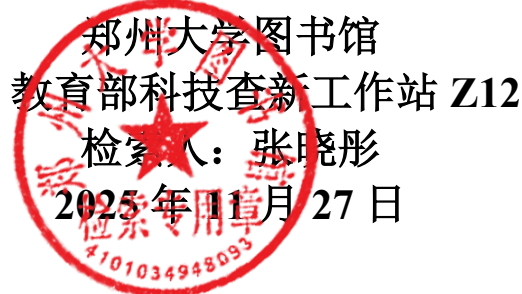
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第 1 条, 共 1 条

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摘要: Autism is a complex psychiatric condition that needs to be diagnosed early using more objective techniques. Hence, many researchers have turned to diagnosing autism by analyzing EEG signals. However, a comprehensive framework for this has not yet been introduced, and there is room for improvement. In this study, to increase the precision of autism diagnosis from EEG signals, a new framework is introduced that includes the steps of data preprocessing, extraction of nonlinear features from EEG time series, optimization of extracted features using an innovative technique based on GA and DBSCAN algorithms, feature reduction using the LASSO technique, and classification using a fuzzy ELM classifier. This study presents a feature optimization technique that leverages a genetic algorithm informed by clustering principles. Rather than relying on random selection for forming the new generation, the approach incorporates clustering during the fitness evaluation phase to identify and exclude outliers from advancing to the next generation. The recommended scheme was examined on two EEG databases. Using only 14-channel EEG data, it was able to achieve 96.81% accuracy, 95.16% sensitivity, 97.73% specificity, and a 96.42% F1-score for autism detection using database A, as well as 97.64% accuracy, 96.55% sensitivity, 98.49% specificity, and a 97.51% F1-score using database B. This framework outperformed existing methods on two EEG databases. The practical use of low-channel systems suggests potential for real-world clinical deployment, enabling scalable and cost-effective screening. This study underscores the potential of using nonlinear dynamics of EEG signals alongside fuzzy ELM for diagnosing autism in children.

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地址: [Wang, Xin; Zhu, Yuer; Zhang, Hao] North Henan Med Univ, Coll Intelligent Med Engn, Xinxiang, Peoples R China;[Liu, Han] Xian Univ Technol, Coll Automat & Informat Engn, Xian, Peoples R China

通讯作者地址: [Wang, Xin] (corresponding author), North Henan Med Univ, Coll Intelligent Med Engn, Xinxiang, Peoples R China

电子邮件地址: 18710965012@163.com

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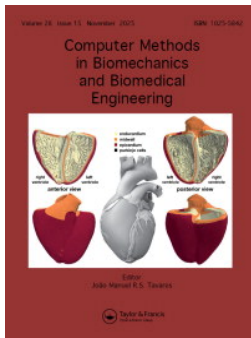
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# Diagnosing autism in children using nonlinear dynamics of EEG signals and fuzzy extreme learning machines with feature optimization

Xin Wang<sup>a</sup>, Han Liu<sup>b</sup>, Yuer Zhu<sup>a</sup> and Hao Zhang<sup>a</sup>

<sup>a</sup>College of Intelligent Medical Engineering, North Henan Medical University, Xinxiang, China; <sup>b</sup>College of Automation and Information Engineering, Xi'an University of Technology, Xi'an, China

## ABSTRACT

Autism is a complex psychiatric condition that needs to be diagnosed early using more objective techniques. Hence, many researchers have turned to diagnosing autism by analyzing EEG signals. However, a comprehensive framework for this has not yet been introduced, and there is room for improvement. In this study, to increase the precision of autism diagnosis from EEG signals, a new framework is introduced that includes the steps of data preprocessing, extraction of nonlinear features from EEG time series, optimization of extracted features using an innovative technique based on GA and DBSCAN algorithms, feature reduction using the LASSO technique, and classification using a fuzzy ELM classifier. This study presents a feature optimization technique that leverages a genetic algorithm informed by clustering principles. Rather than relying on random selection for forming the new generation, the approach incorporates clustering during the fitness evaluation phase to identify and exclude outliers from advancing to the next generation. The recommended scheme was examined on two EEG databases. Using only 14-channel EEG data, it was able to achieve 96.81% accuracy, 95.16% sensitivity, 97.73% specificity, and a 96.42% F1-score for autism detection using database A, as well as 97.64% accuracy, 96.55% sensitivity, 98.49% specificity, and a 97.51% F1-score using database B. This framework outperformed existing methods on two EEG databases. The practical use of low-channel systems suggests potential for real-world clinical deployment, enabling scalable and cost-effective screening. This study underscores the potential of using nonlinear dynamics of EEG signals alongside fuzzy ELM for diagnosing autism in children.

## ARTICLE HISTORY

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## Introduction

Autism is an intricate psychiatric condition marked by significant hurdles in executive functioning, social interactions, typical behaviors, cognitive processing, and daily life activities (Zarafshan et al., 2016). The incidence of autism has recently surged dramatically, impacting a growing number of individuals globally (Mohammadi et al. 2019; 2019; Talepasand et al. 2019). Mental health professionals, such as psychiatrists and psychologists, often encounter autism not as a single definitive condition but as a range of biological and behavioral manifestations (Yousefi et al. 2015; Zarafshan et al. 2019). This variability prompts healthcare providers to utilize diverse screening tools for diagnosis and individual therapists to adopt tailored treatment strategies for each patient (Khaleghi et al. 2020). However, many current diagnostic and screening methods tend to be subjective. Research indicates a pressing need for the establishment of

objective diagnosis techniques for autism (Ali et al. 2022). For instance, a recent review discussed diverse biomarkers, including hormonal indicators, as potential reliable measures for diagnosing autism (Ratajczak 2011). Additionally, a systematic review explored the role of AI in autism diagnosis, relying on validated instruments like the Autism Diagnostic Observation Schedule (ADOS) and the Autism Diagnostic Interview-Revised (ADI-R) (Song et al. 2019). Another study highlighted the effectiveness of combining eye-tracking technology with machine learning (ML) to advance objective and early autism diagnosis (Kollias et al. 2021). Lai et al. introduced a diagnostic approach using automated retinal image analysis paired with ML, achieving a high accuracy rate of 97.4% (Lai et al. 2020). Similarly, Zhao et al. developed an automatic system analyzing movement patterns during motor tasks using ML, reporting a precision of 88.37% for autism diagnosis (Zhao et al. 2019). Consequently, the literature reveals a global

effort among researchers to create objective diagnostic methods for autism through various psychological, biological, and physiological data.

Meanwhile, electroencephalography (EEG) is a type of electrophysiological data that has garnered significant interest from investigators. It has been examined through diverse approaches to create objective techniques for diagnosing autism (Brihadiswaran et al. 2019). EEG reflects the electrical activity patterns of neurons across various regions of the brain, offering valuable insights into brain function under both normal and pathological conditions (Khaleghi et al. 2023; 2024). Therefore, numerous researchers have investigated EEGs and examined the signals from individuals with autism (Bosetti et al. 2024). Some of these studies have used traditional ML methods to diagnose autism from EEG data. For instance, Bosl et al. employed a mix of nonlinear EEG analysis and various ML methods, successfully achieving a screening precision of 95% for pediatric populations at risk for autism (Bosl et al. 2018). Similarly, Haputhanthri et al. derived statistical features from wavelet analysis deployed to the EEG signals of autistic children, attaining a diagnostic precision of 93% (Haputhanthri et al. 2019). Pham et al. utilized the bispectrum method from higher-order spectra on EEG signals, achieving an impressive precision of 98.7% in autism diagnosis by employing a probabilistic neural network (Pham et al. 2020). Alotaibi and Maharatna developed a classification system for EEGs that relies on functional connectivity features derived from graph theory, using a cubic SVM. This approach resulted in a precision of 95.8% for diagnosing autism (Alotaibi and Maharatna 2021).

On the other hand, some other studies have focused on new DL methods. For instance, Baygin et al. implemented a hybrid approach for feature extraction that integrated one-dimensional local binary patterns with deep features derived from spectrogram images created through the short-time Fourier transform. Their outcomes, evaluated using a 10-fold cross-validation method, demonstrated that they could distinguish children with autism by deploying an SVM, achieving a precision of 96.44% (Baygin et al. 2021). Radhakrishnan et al. assessed various deep learning (DL) schemes for diagnosing autism based on EEG signals, and their approach yielded a mean precision of 81% (Radhakrishnan et al. 2021). Menaka et al. assessed the performance of pre-trained CNNs such as VGG16, AlexNet, and ResNet50 based on cepstral coefficients attributes of EEGs and reported 90% accuracy for autism detection (Menaka

et al. 2024). Xu et al. introduced an EEG-based system drawing on functional connectivity feature maps and a hybrid deep CNN-LSTM model and achieved 81% accuracy for autism diagnosis (Xu et al. 2024). However, DL techniques for classifying autism through EEG signals come with several drawbacks. One major challenge is the requirement for large amounts of labeled data, which can be difficult to attain in the healthcare domain due to privacy concerns and the need for expert annotation. Additionally, these schemes often operate as black boxes, making it challenging to interpret their decision-making processes, which can hinder clinicians' trust in the outcomes. Their computational demands are also significant, necessitating powerful hardware for training and inference, which can be cost-prohibitive. Furthermore, there is a risk of overfitting, especially when working with smaller databases, leading to schemes that perform well on training data but fail to generalize to unseen cases.

Among the traditional techniques, the effectiveness of classification, specifically regarding accuracy and the time required to assess that accuracy, largely relies on the methods used for feature engineering. This includes factors such as the kinds of features chosen, the number of features selected, and the techniques applied for feature optimization. In addition to the globally optimal solutions discussed in the literature (Aljalal et al. 2024; Holm et al. 2024; Houssein et al. 2024), there are optimization approaches that specifically target feature optimization in EEG applications. While these techniques have enhanced the precision of classification systems, there remains significant room for further improvement. Optimization algorithms aim to identify the most effective solutions within a reasonable timeframe. In this study, Genetic Algorithms (GA) are utilized specifically for optimizing features in EEG classification of autism. Both feature optimization and the classification phase play crucial roles in developing a reliable CAD system. Considering the complex and uncertain nature of EEG data, a fuzzy extreme learning machine (ELM) is utilized in the classification phase. This research primarily tries to enhance the performance of autistic EEG detection regarding accuracy. To achieve this objective, a clustering-oriented GA approach is recommended for feature enhancement.

While previous studies have demonstrated the utility of nonlinear EEG features (e.g. entropy, fractal dimensions) for autism diagnosis, critical limitations remain unresolved: (1) lack of robust feature optimization techniques to handle high-dimensional,

noisy EEG data; (2) reliance on conventional classifiers (e.g. SVM) that struggle with the inherent uncertainty and variability of neurodevelopmental disorder biomarkers; and (3) limited emphasis on clinically feasible low-channel systems for real-world deployment. This study bridges these gaps by introducing a clustering-informed genetic algorithm (GA-DBSCAN) for feature optimization, coupled with a fuzzy ELM classifier to manage signal uncertainty, while achieving high accuracy using only 14-channel EEG—a practical setup for clinical settings.

## Methods

In this section, the methodology used to diagnose autism from EEG signals is fully explained. Figure 1 displays the whole flow of the recommended scheme, which includes the steps of data preprocessing, extraction of nonlinear features from EEG time series, optimization of extracted features using an innovative technique based on GA and DBSCAN algorithms, feature reduction using the LASSO technique, and classification using a fuzzy ELM classifier. The details of each of these stages are explained below.

### EEG databases

**Database A.** This database was collected by researchers from a private psychiatric clinic. The EEG data were collected by the research team from a sample of 42 children diagnosed with autism (boy:girl = 32:10, mean age  $8.21 \pm 1.80$  years) and 42 typically developing children (boy:girl = 28:14, mean age  $8.54 \pm 1.63$  years). The ages of the participants ranged from 5 to 11 years, and all autism diagnoses were made by qualified clinicians according to DSM-5 criteria. Enrollment of participants took place in a psychiatric clinic. The exploration adhered to the ethical principles outlined in the Declaration of Helsinki as well as current Good Clinical Practice standards. During the initial contact, both the project goals and an overview were communicated to the participants and their parents. Those who consented to join the exploration received all relevant information before

providing written informed consent. The subjects' information was treated confidentially and used solely for research purposes. EEG recordings for each participant were conducted in a single session lasting between 8 and 20 min in a resting state with eyes open. Due to the challenges associated with working with autistic individuals and capturing EEG data while they are awake, the exploration employed the Emotiv Epoch headset. This wireless EEG device facilitated easier signal acquisition from autistic participants. The Emotiv Epoch headset utilizes Bluetooth technology for seamless data transmission. It is equipped with 14 electrodes under the 10–20 international system (Figure 2) and includes DRL/CMS reference electrodes located at P4/P3. With a sampling rate of 128 Hz, the device minimizes electrode impedance by using saline solution and alcohol pads. Recording of the EEG data was performed using Emotive software.

**Database B.** This EEG database was acquired from (Askari et al. 2018), which is not publicly available. The research sample of this database included a total of 89 autism participants, comprising 53 boys and 36 girls, all aged between 5 and 12 years. Additionally, 94 healthy control participants, consisting of 61 boys and 33 girls within the same age range, were also selected for comparison. The average age of the children with autism was  $9.7 \pm 2.3$  years, while the control group had an average age of  $9.3 \pm 1.9$  years. Similar to our study, EEG recordings were performed for each participant over 8–20 min in a resting state with eyes open using the Emotiv Epoch headset device. More details about this database can be found in (Askari et al. 2018).

### Data preprocessing

After obtaining the signals, a trained operator, under the guidance of a neurologist, selected EEG segments that were free from artifacts, particularly those related to visual and motion disturbances as well as electromyogram interference. Initially, the goal was to isolate five-second-long EEG segments without artifacts, but this proved challenging in numerous samples. As a

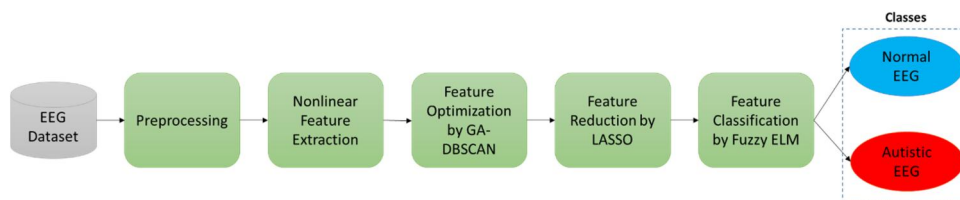
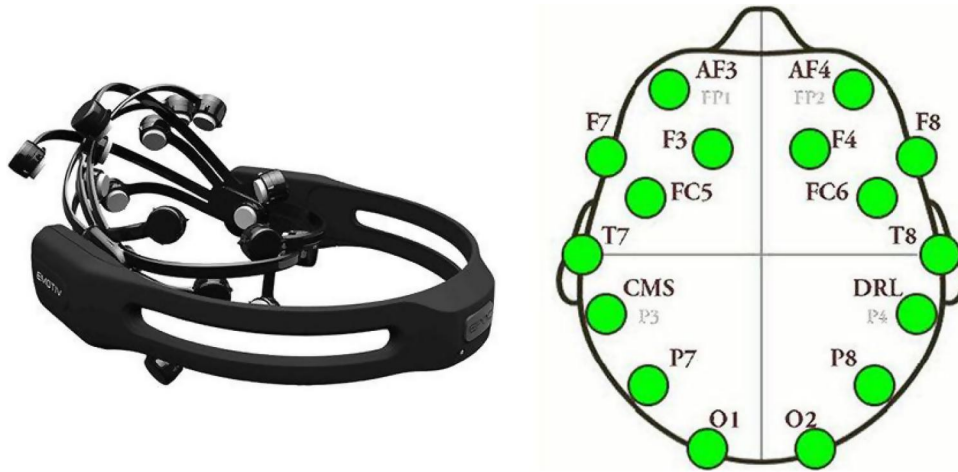


Figure 1. Overall flow of the recommended scheme for autism detection from EEG.



**Figure 2.** The emotiv poch device for EEG recording and the electrode positions.

result, the analyses relied on two-second segments for both the autism and control groups. Ultimately, each group provided 60 artifact-free epochs for analysis. The use of 2-second EEG epochs in this study was motivated by the need to balance signal quality with practical constraints in pediatric autism research. While longer epochs theoretically provide more stable estimates of neural activity, they are highly susceptible to motion artifacts and myogenic noise—a critical concern when working with children, particularly those with autism who may exhibit involuntary movements or difficulty remaining still. While 2-second epochs improve artifact rejection, they may truncate slower frequency neural oscillations (e.g. delta/theta bands) and reduce the reliability of long-range connectivity measures. However, nonlinear features used in this study are less sensitive to epoch length than linear metrics, as they capture signal complexity rather than sustained periodic activity. Moreover, shorter epochs yield more trials per subject, enhancing statistical robustness for group-level analyses, albeit at the cost of potentially overlooking longer-duration neurodynamic patterns.

The EEG data were processed on a personal computer, with all electrode information organized as an array. A converter program in MATLAB version R2015 facilitated the reading of data from 14 electrodes. The signals underwent preprocessing to eliminate artifacts and reduce AC power interference. Furthermore, a band-pass Hamming window with a finite duration and cut-off frequencies ranging from 0.1 to 60 Hz was applied using MATLAB software.

### Nonlinear feature extraction

This phase is crucial for the creation of an automated diagnostic system. In this study, we employed

nonlinear techniques, specifically the largest Lyapunov exponent (LLE) (Kutepov et al. 2020), detrended fluctuation analysis (DFA) (Mesquita et al. 2021), Katz and Higuchi fractal dimension (FD1 and FD2) (Jacob et al. 2019), permutation entropy (PE) (Balani et al. 2024), bispectrum phase entropy (BPE) (Bouafif 2021), Hurst exponent (HE) (Córdova 2022), sample entropy (SamE) and approximate entropy (ApEN) (Pallathadka et al. 2024), differential entropy (DE) (Lu 2024), Lempel-Ziv complexity (LZC) (Zarafshan et al., 2016), fuzzy entropy (FEN) and Sure entropy (SEN) (Catherine Joy et al. 2022), normalized bispectral squared entropies (BSE1 and BSE2), normalized bispectral entropy (BSE3) (Nævra et al. 2023), and recurrence plot features including entropy (ENT), recurrence rate (RR), determinism (DET), laminarity (LAM), and trapping time (TT) (Runnova et al. 2021).

### Feature optimization

The methodology for applying EEG classification to autism involves an innovative integration of GA and the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm to optimize feature selection from EEG data. This section explains the GA-DBSCAN algorithm recommended for feature optimization in this work. The recommended approach introduces a novel twist to the conventional GA by reimagining the selection process used for parent candidates during crossover and mutation phases. Rather than relying on random selection, we utilize a density-based clustering technique. In this framework, similar data objects are grouped into clusters, while those with low similarity to any cluster are classified as outliers. This clustering approach serves a dual function. Firstly, by selecting the parental population exclusively from within these clusters, we ensure that

only relevant and similar individuals contribute to the next generation, which enhances the quality of the genetic operations. Secondly, the outliers are actively replaced by newly generated individuals during each iteration, maintaining evolutionary pressure to refine and enhance the overall population. This strategy not only curtails the impact of irrelevant or dissimilar data points but also promotes the continuous improvement of the population's genetic diversity and fitness. The details of the GA-DBSCAN are further delineated in [Algorithm 1](#), showcasing its innovative design and operational mechanics. This methodology aims to bolster the efficiency of EEG classification for autism by leveraging the strengths of clustering and evolutionary strategies in tandem.

---

**Algorithm 1.** GA-DBSCAN feature optimization

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Input: Database  $S = (x_1, x_2, \dots, x_n, y)$ ,  
 $m$  = Chromosome length (feature set size),  
 $Pop$  = Population,  $Popsize$  = Population size,  
 $P_m$  = Mutation probability,  $P_c$  = Crossover probability,  $N$  = Number of classes (2).

Output: Best fitness and optimal feature set

Initialize algorithm parameters

Load normalized database  $S$

Separate each class from database  $S$

For  $i = 1$  to  $M$ , do

    For  $j = 1$  to  $Popsize$  of  $N_i$ , do

$P_c = 0.9$  (initialize  $P_c$ ) and  $P_m = 0.1$  (initialize  $P_m$ )

$NewPopsize = Popsize$

$Eps = (0.01-0.1) \times \text{breath of } N_i$  (adjust the  $Eps$ )  
 for DBSCAN

$K = \log(m)$  (calculate the parameter  $K$  for DBSCAN)

        Apply DBSCAN on  $Pop$

        Detect outliers

        Select parent1 and parent2 from non-outliers with the same gender

        If  $P_c < 0.9$

            Do Crossover

            Replace the outliers with newly generated children from the  $Pop$  generation

        Select parent3 from non-outliers

        If  $P_m < 0.1$

            do Mutation

            Replace the outliers with newly generated children

        End For

$Newpop = Pop$  (update the existing population)

End For

Return the optimized feature set of database  $S$

---

Initially, the system loads a database containing normalized features and segregates it into distinct autism and control classes. The starting population is derived from a single class. Subsequently, the DBSCAN clustering technique is utilized to identify outliers within the data. Following this, parents for the processes of crossover and mutation are chosen exclusively from the non-outlier group. To maintain the integrity of gender-specific information, it is ensured that both selected parents are of the same gender. The algorithm allows for single-point crossover to occur with a probability of 0.9 and mutation to take place with a probability of 0.1. In the subsequent phase, the previously identified outliers are substituted with newly generated offspring that share the same gender. This entire cycle is repeated until the predetermined stopping criteria are satisfied and both classes have been processed. The criteria for halting the optimization process are set to double the database size, which is found to yield optimal outcomes. During each iteration, new outliers are identified, and non-outliers are chosen to participate in the crossover and mutation steps. While the resulting feature set is optimized, further dimensionality reduction is necessary to streamline the database.

The GA-DBSCAN parameters—including the DBSCAN neighborhood radius ( $Eps$ ) and minimum points ( $K$ )—were carefully selected through an empirical optimization process to balance clustering sensitivity with computational efficiency. Let  $\text{breath of } N_i$  denote the range of feature values in class  $N_i$ , calculated as:

$$\text{breath}(N_i) = \max_{x \in N_i}(\text{norm}(x)) - \min_{x \in N_i}(\text{norm}(x)) \quad (2)$$

Where  $\text{norm}(x)$  is min-max normalized feature vector  $x$ . For  $Eps$ , we adopted an adaptive approach, setting it to  $(0.01-0.1) \times$  the feature value range after normalization, ensuring scalability across datasets:

$$Eps = \alpha \cdot \text{breath}(N_i), \alpha \in [0.01, 0.1] \quad (2)$$

Scaling to the feature value range ensures adaptation to dataset-specific variability while avoiding arbitrary thresholds. The  $\alpha$  range was empirically optimized to balance cluster granularity and outlier rejection. The minimum points  $K$  was defined as  $\log(m)$ , where  $m$  is the feature set size, a heuristic derived from density-based clustering literature to avoid overfitting while retaining meaningful clusters.

### Feature reduction

The feature set has been refined, yet it remains extensive, with a total of 294 features (21 features  $\times$  14 channels). This necessitates the use of an effective dimensionality reduction technique. The high dimensionality of EEG data—resulting from multiple channels, time points, and extracted features—poses a significant challenge for machine learning classifiers, often leading to overfitting and reduced generalizability, which carries the risk of overwhelming the classifier with redundant or noisy predictors. Of the various methods available, such as PCA (Principal Component Analysis), we chose to implement the LASSO (Least Absolute Shrinkage and Selection Operator) algorithm. LASSO not only reduces dimensionality by selecting a subset of significant features but also provides interpretable outcomes, which is important in understanding the underlying signals associated with autism. It helps in obtaining sparse solutions, which is useful when dealing with high-dimensional EEG data, as it can highlight the most relevant features that contribute to classification. It can also handle multicollinearity (where features are correlated) more effectively than some other methods, which is often a concern with EEG data. Following the optimization procedure facilitated by our suggested GA-DBSCAN, we applied LASSO to the optimized feature set. The resulting reduced feature set includes 20 features (which is about 1/5-1/10 of the number of subjects), which were subsequently utilized in the classification phase.

### Fuzzy ELM

The ELM was initially introduced for single-hidden-layer feedforward neural networks (SLFNs) and later expanded to encompass generalized SLFNs that do not require a neuron-like hidden layer. In the ELM framework, the input weights for SLFNs are selected randomly without the need for iterative adjustments, while the output weights are computed analytically (Wang et al. 2022). This approach enables ELM to train substantially faster—up to a thousand times quicker—than conventional iterative SLFN methods. Nonetheless, traditional ELM cannot handle imbalanced and weighted classification scenarios. Thus, in this work, a new technique called fuzzy ELM (FELM) is introduced, which incorporates fuzzy membership for each input within the ELM framework, allowing different inputs to contribute variably to the learning of output weights. This innovative approach proves beneficial for real-world classification tasks by

effectively addressing issues involving varying weights. Unlike traditional learning methods, ELM aims to lower the training error and the norm of the output weights:

$$\text{minimize: } \sum_{i=1}^N \|\beta h(x_i) - t_i\|, \quad \text{minimize: } \|\beta\| \quad (1)$$

In this context,  $\beta$  represents the output weight connecting the  $i$ -th hidden node to the output node, while  $h(x_i)$  signifies the output vector from the hidden layer based on the input  $x_i$ , and  $t_i$  is the label associated with  $x_i$ . As noted in reference (Santiago et al. 2021), for feedforward neural networks, achieving a lower training error is correlated with better generalization performance when the weight norms are minimized. Consequently, the implementation of ELM utilizes the minimal norm least squares approach:

$$\beta = \bar{H}T \quad (2)$$

$\bar{H}$  signifies the Moore-Penrose generalized inverse of matrix  $H$ , and  $T = [t_1, \dots, t_N]^T$ . If  $HH^T$  is non-singular, then  $\bar{H} = H^T(HH^T)^{-1}$ .

In practical classification scenarios, the impact of training instances should vary based on their different weights. Thus, a collection  $S$  of labeled training samples, each accompanied by corresponding fuzzy membership values, is introduced:

$$S = (x_1, t_1, s_1), \dots, (x_N, t_N, s_N) \quad (3)$$

Every training sample  $x_i$  has a label  $t_i$  and a fuzzy membership  $\sigma \leq s_i \leq 1$ , where  $\sigma > 0$ . The fuzzy membership  $s_i$  reflects how strongly the corresponding sample  $x_i$  belongs to a particular class, while  $\frac{1}{2}\|\xi_i\|$  serves as an error metric. Consequently,  $\frac{1}{2}s_i\|\xi_i\|$  represents a weighted error measure. This leads to the formulation of the classification challenge for the constrained-optimal-based fuzzy ELM as follows:

$$\begin{aligned} \text{minimize: } L_{FELM} &= \frac{1}{2}\|\beta\|^2 + C\frac{1}{2}\sum_{i=1}^N s_i\|\xi_i\|^2, \\ \text{subject to: } h(x_i)\beta &= t_i^T - \xi_i^T \end{aligned} \quad (4)$$

where  $i = 1, \dots, N$ . According to the KKT theorem, training a fuzzy ELM can be seen as solving the corresponding dual optimization problem, which is expressed as follows:

$$\begin{aligned} L_{FELM} &= \frac{1}{2}\|\beta\|^2 + C\frac{1}{2}\sum_{i=1}^N s_i\|\xi_i\|^2 \\ &\quad - \sum_{i=1}^N \sum_{j=1}^m \alpha_{i,j}(h(x_i)\beta_j - t_{i,j} + \xi_{i,j}) \end{aligned} \quad (5)$$

The optimality conditions related to the KKT can be articulated as:

$$\frac{\partial L_{FELM}}{\partial \beta_j} = 0 \rightarrow \beta_j = \sum_{i=1}^N \alpha_{i,j} h(x_i)^T \rightarrow \beta = H^T \alpha \quad (6)$$

$$\frac{\partial L_{FELM}}{\partial \xi_i} = 0 \rightarrow \alpha_i = C s_i \xi_i \quad (7)$$

$$\frac{\partial L_{FELM}}{\partial \alpha_i} = 0 \rightarrow h(x_i) \beta - T_i^T + \xi_i^T = 0 \quad (8)$$

By incorporating (6) and (7) into (8), the equations can be rewritten in an equivalent form as:

$$\left( \frac{S}{C} + HH^T \right) \alpha = T, \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix} \text{ and} \quad (9)$$

$$S = \begin{bmatrix} \frac{1}{s_1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 1 & \cdots & \frac{1}{s_N} \end{bmatrix}_{N \times N}$$

From (9) and (12):

$$\beta = H^T \left( \frac{S}{C} + HH^T \right)^{-1} T \quad (10)$$

As a result, inputs that utilize varying fuzzy matrices can impact the learning of the output weights  $\beta$  in different ways. Consequently, the output function of the FELM classifier is expressed as:

$$f(x) = h(x) \beta = h(x) H^T \left( \frac{S}{C} + HH^T \right)^{-1} T \quad (11)$$

In the case of binary classification tasks, the FELM requires just a single output node, with the decision function being:

$$f(x) = \text{sign} \left( h(x) H^T \left( \frac{S}{C} + HH^T \right)^{-1} T \right) \quad (12)$$

In scenarios with  $m$  classes, the predicted class label for a testing instance corresponds to the index of the output node that produces the highest value:

$$\text{label}(x) = \arg \max_{j \in [1, \dots, m]} f_j(x) \quad (13)$$

## Outcomes and discussion

Here, we analyze the efficiency of the presented approach for distinguishing between autism and the control group based on resting-state EEG data. In addition, we compare our outcomes with other reference techniques as presented in previous literature. The efficiency of our recommended model is recognized by two EEG databases. During the training phase, a 5-fold cross-validation approach was adopted to enhance the robustness of the outcomes, and multiple performance metrics were employed for evaluation. The primary metric assessed was accuracy, which gauges the scheme's performance in distinguishing between autism and normal classifications. Additionally, sensitivity and specificity were calculated to evaluate the scheme's capability in accurately identifying samples within each category. The F1-score, which reflects the harmonic mean of sensitivity and specificity, provides a nuanced view of the scheme's overall effectiveness. All the codes and experiments were administered through MATLAB 2015 on a laptop with a 2.20 GHz Core i7-8750 processor and 16 GB RAM. For the GA-DBSCAN algorithm, as shown in Algorithm 1,  $P_m$  and  $P_c$ , as the probabilities for mutation and crossover, respectively, were set at 0.1 and 0.9. In fuzzy ELM, the sigmoid function is utilized for feature mapping, with its parameters being generated at random.

Figure 3 displays the outcomes of feature reduction via LASSO. This technique selects optimized features

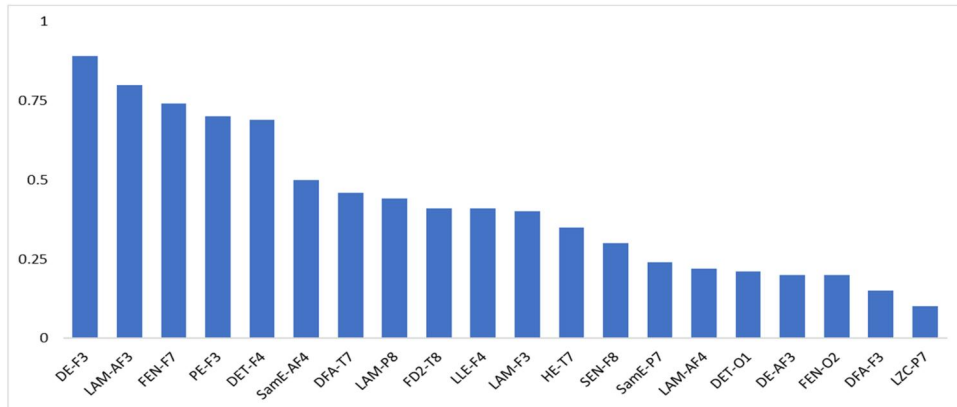


Figure 3. Selected nonlinear EEG features using the LASSO technique for autism detection.

from the GA-DBSCAN algorithm by applying an L1 regularization penalty, which drives some coefficients to zero, effectively eliminating unimportant variables. 20 selected features by LASSO are shown in Figure 3. As can be seen, 60% (12/20) of the selected nonlinear features are from the frontal region of the head. This finding is consistent with previous research showing that the frontal cortex is affected by autism (Fetit et al. 2021; Milovanovic and Grujicic 2021). The frontal cortex is responsible for executive function, impulse control, and decision-making, and disruption in it can affect social behavior and communication, which is one of the core symptoms of autism (Vakilzadeh et al. 2024). Irregular frontal nonlinear dynamics may contribute to sensory processing abnormalities and repetitive behaviors, as the pre-frontal cortex modulates top-down regulation of sensory input and habit formation. Furthermore, selected features are from both hemispheres. Research indicates that both hemispheres of the brain can be influenced in children with autism, although some research highlights distinct differences in how each hemisphere is affected. The right hemisphere, linked to spatial processing and social understanding, tends to display more significant irregularities in autistic individuals, especially in areas that handle emotions and social engagement. Conversely, the left hemisphere, which plays a crucial role in language and logical thinking, may also show differences that impact communication abilities (Lamanna and Meldolesi 2024).

Regarding nonlinear features, laminarity (LAM) had the highest frequency among other selected features. Indeed, outcomes showed that laminarity is reduced in children with autism compared to healthy children, suggesting that there may be differences in the regularity and stability of neural activity patterns. A reduction in laminarity in autistic children could indicate impaired or disrupted neural coherence, which may point to atypical neural processing. This lower level of organization might be linked to difficulties in sensory integration, communication, and social interactions, which are commonly observed in autism (Hernández et al. 2023). Essentially, this finding may imply that the autistic brain functions less predictably, reflecting potential challenges in their cognitive and emotional processing. Moreover, reduced DE in frontal channels (F3) aligns with fMRI evidence of hypoactivity in dorsolateral prefrontal cortex during executive tasks in autism, reflecting diminished neural resource allocation. Elevated FEN in left frontal cortex (F7) suggests atypical neural adaptability, consistent

**Table 1.** Performance measures of the recommended approach for autism diagnosis on both EEG databases.

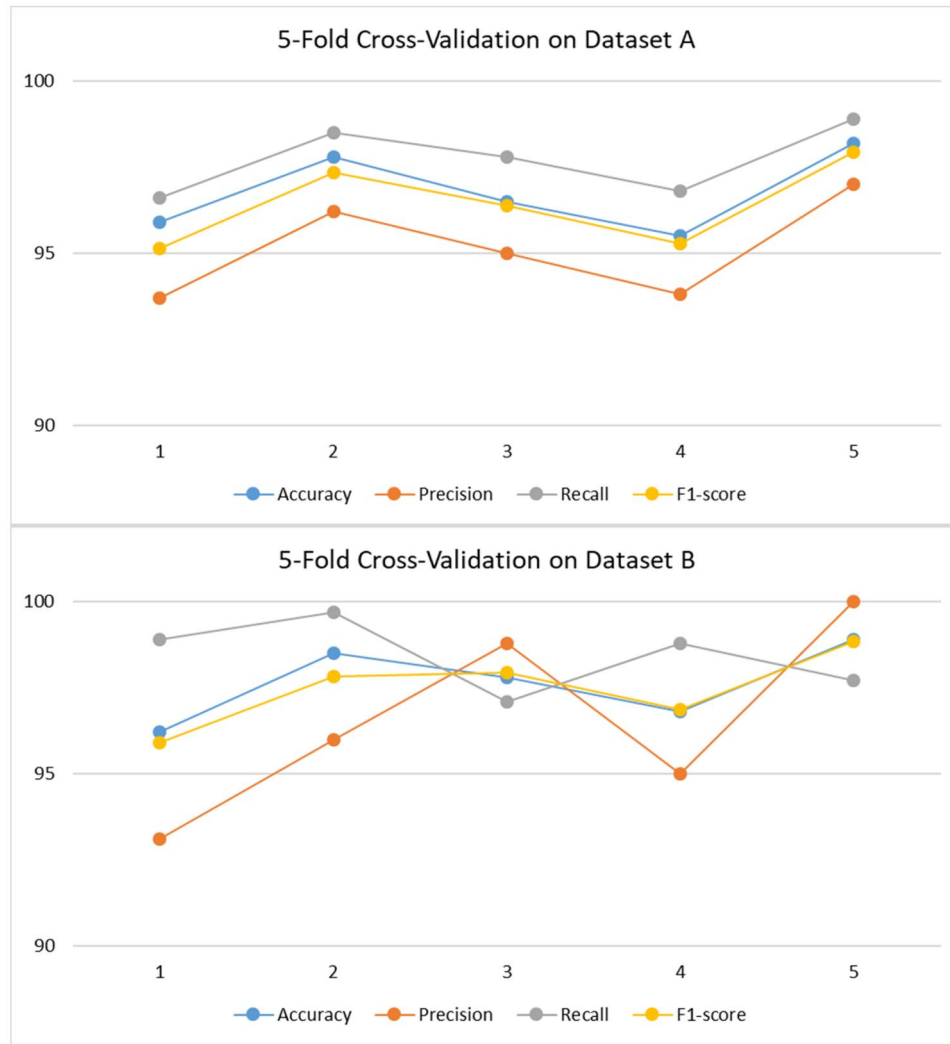
| Database | Accuracy (%) | Sensitivity (%) | Specificity (%) | F1-score (%) |
|----------|--------------|-----------------|-----------------|--------------|
| A        | 96.81        | 95.16           | 97.73           | 96.42        |
| B        | 97.64        | 96.55           | 98.49           | 97.51        |

with theories of impaired predictive coding in autism. This mirrors findings of exaggerated high-frequency oscillations in frontal regions during sensory overload (Hiremath et al. 2021)

Table 1 displays the obtained performance measures for both databases, respectively. Our framework achieved 96.81% accuracy, 95.16% sensitivity, 97.73% specificity, and a 96.42% F1-score for autism detection using Database A, as well as 97.64% accuracy, 96.55% sensitivity, 98.49% specificity, and a 97.51% F1-score using Database B. Figure 4 displays the 5-fold cross-validation results for both databases.

To rigorously assess the generalizability of our framework, we performed cross-database validation—training the model on one dataset and testing it on the other. This stress-test evaluates whether the learned features are robust to variations in data acquisition protocols and cohort characteristics. While such validation often yields lower performance than within-database testing, it provides critical insights into real-world applicability across clinical settings. Table 2 shows the results of this analysis. Cross-database validation revealed an expected performance decline (15–17% lower accuracy than within-database tests), primarily attributed to differences in EEG referencing and cohort severity distributions. Despite this drop, the model retained clinically meaningful accuracy (~80%), with frontal lobe features consistently driving predictions—supporting their neurobiological relevance to ASD. The results highlight that while the framework is portable across sites, optimal deployment requires protocol harmonization or site-specific calibration of parameters like GA-DBSCAN's Eps. This aligns with real-world clinical EEG practices, where vendor-specific adjustments are common. Future work should prioritize multicenter datasets with standardized protocols to bridge this gap.

To examine the efficiency of various components of the recommended scheme, the LASSO feature reduction technique was compared with other existing techniques. For this purpose, PCA, ridge model, Double Input Symmetrical Relevance (DISR), and Minimum Redundancy–Maximum Relevance (MRMR) method were utilized. The entire recommended scheme was fully implemented in this analysis, and each time one of the aforementioned feature selection or reduction techniques was used in



**Figure 4.** Five-fold cross-validation outcomes for both EEG databases.

**Table 2.** Comparison of different feature selection or reduction methods in the recommended scheme for autism diagnosis.

| Validation Scheme      | Accuracy (%) | Sensitivity (%) | Specificity (%) | F1-score (%) |
|------------------------|--------------|-----------------|-----------------|--------------|
| Train on A → Test on B | 82.32 ± 2.11 | 78.10 ± 2.85    | 85.21 ± 1.97    | 80.13 ± 2.38 |
| Train on B → Test on A | 79.80 ± 1.72 | 81.44 ± 2.53    | 77.94 ± 2.23    | 79.50 ± 1.91 |

the scheme. Table 3 displays the obtained findings from this analysis. As shown, LASSO outperforms other techniques, indicating its efficiency in this classification task. LASSO outperformed other feature reduction techniques in this study due to its unique suitability for EEG analysis. By applying L1 regularization, LASSO produced sparse, interpretable solutions that effectively eliminated redundant features while preserving neurophysiologically meaningful biomarkers - particularly important given the high dimensionality and inherent correlations in multi-channel EEG data. Unlike PCA (which obscures feature origins) or Ridge regression (which retains all features), LASSO's selective shrinkage aligned with

known autism-related neural patterns, with 60% of selected features originating from frontal regions consistent with autism pathology. The method's ability to handle multicollinearity while maintaining clinical interpretability made it ideal for deriving actionable biomarkers from complex EEG signals. While LASSO assumes linear relationships, its performance here suggests most discriminative EEG features for autism detection operate within this constraint. Future work could explore nonlinear extensions to capture more complex interactions.

For a more accurate comparison, we performed non-parametric Wilcoxon signed-rank tests (for feature selection comparisons in Table 3) and one-way

**Table 3.** Comparison of different feature selection or reduction methods in the recommended scheme for autism diagnosis.

| Technique | Database | Accuracy (%)  | Sensitivity (%) | Specificity (%) | F1-score (%) | p-Value* | 95% CI Acc.   |
|-----------|----------|---------------|-----------------|-----------------|--------------|----------|---------------|
| LASSO     | A        | 96.81 ± 0.82  | 95.16 ± 1.12    | 97.73 ± 0.91    | 96.42 ± 0.88 | –        | –             |
|           | B        | 97.64 ± 0.102 | 96.55 ± 0.98    | 98.49 ± 1.10    | 97.51 ± 0.90 |          |               |
| PCA       | A        | 86.55 ± 2.31  | 83.27 ± 3.01    | 85.90 ± 2.67    | 84.56 ± 2.45 | <0.001   | [84.21–88.89] |
|           | B        | 87.12 ± 1.85  | 83.31 ± 1.96    | 87.00 ± 1.73    | 85.11 ± 2.00 |          |               |
| Ridge     | A        | 86.10 ± 1.95  | 84.02 ± 2.33    | 86.98 ± 2.11    | 85.47 ± 2.02 | <0.001   | [83.75–88.45] |
|           | B        | 86.92 ± 2.11  | 84.65 ± 1.97    | 87.71 ± 2.74    | 86.15 ± 2.21 |          |               |
| DISR      | A        | 93.45 ± 1.28  | 91.11 ± 1.84    | 94.67 ± 1.42    | 92.85 ± 1.35 | 0.012    | [84.65–89.19] |
|           | B        | 94.50 ± 1.55  | 92.08 ± 1.61    | 95.00 ± 1.38    | 93.51 ± 1.25 |          |               |
| MRMR      | A        | 87.31 ± 1.97  | 85.33 ± 2.45    | 88.82 ± 2.20    | 87.04 ± 2.13 | 0.005    | [85.05–89.57] |
|           | B        | 88.09 ± 2.15  | 86.26 ± 2.70    | 88.34 ± 2.46    | 87.28 ± 1.95 |          |               |

Note. \*Compared to LASSO using Wilcoxon signed-rank test.

**Table 4.** Comparison of different classifiers in the recommended scheme for autism diagnosis.

| Technique | Database | Accuracy (%) | Sensitivity (%) | Specificity (%) | F1-score (%) | p-Value* | 95% CI Acc.   |
|-----------|----------|--------------|-----------------|-----------------|--------------|----------|---------------|
| Fuzzy ELM | A        | 96.81 ± 0.92 | 95.16 ± 0.67    | 97.73 ± 1.00    | 96.42 ± 0.88 | –        | –             |
|           | B        | 97.64 ± 0.75 | 96.55 ± 1.02    | 98.49 ± 0.68    | 97.51 ± 0.72 |          |               |
| ELM       | A        | 93.44 ± 1.34 | 90.17 ± 1.41    | 95.00 ± 1.58    | 92.52 ± 1.37 | 0.021    | [91.58–95.30] |
|           | B        | 93.82 ± 1.15 | 91.74 ± 1.63    | 93.69 ± 1.32    | 92.70 ± 1.21 |          |               |
| SVM       | A        | 94.03 ± 1.28 | 92.23 ± 1.18    | 95.11 ± 0.97    | 93.64 ± 1.05 | 0.042    | [92.25–95.81] |
|           | B        | 94.75 ± 1.03 | 93.00 ± 1.45    | 95.80 ± 1.12    | 94.37 ± 1.08 |          |               |
| LDA       | A        | 90.68 ± 1.10 | 86.39 ± 1.33    | 92.47 ± 1.46    | 89.32 ± 1.29 | 0.007    | [88.35–93.01] |
|           | B        | 92.36 ± 1.42 | 88.05 ± 2.01    | 93.81 ± 1.65    | 90.83 ± 1.85 |          |               |

Note. \* Compared to Fuzzy ELM using ANOVA with Tukey post-hoc.

**Table 5.** Performance of the recommended scheme without feature optimization and feature reduction steps.

| Technique                    | Database | Accuracy (%) | Sensitivity (%) | Specificity (%) | F1-score (%) |
|------------------------------|----------|--------------|-----------------|-----------------|--------------|
| Without feature optimization | A        | 91.52        | 88.97           | 92.62           | 90.75        |
|                              | B        | 93.80        | 92.43           | 94.95           | 93.67        |
| Without feature reduction    | A        | 93.25        | 90.83           | 94.78           | 92.76        |
|                              | B        | 94.41        | 92.00           | 96.07           | 94.00        |

ANOVA with Tukey post-hoc tests (for classifier comparisons in Table 4) to assess statistical significance. Standard deviations were calculated across 5-fold cross-validation runs, and 95% confidence intervals were determined through bootstrap resampling ( $n = 1000$ ). All  $p$ -values were adjusted for multiple comparisons using the Benjamini-Hochberg procedure to control false discovery rate at  $\alpha = 0.05$ .

Furthermore, to evaluate the impact of the fuzzy ELM classifier on the obtained outcomes, popular classifiers (ELM, SVM with linear kernel, and LDA) were used in the classification unit, and the outcomes were compared. The findings of this analysis are summarized in Table 4. As shown, the fuzzy ELM obtains the best classification accuracy over both databases. This outcome highlights the effective use of the fuzzy ELM on complex brain data, indicating the significant potential of this classifier to handle uncertainty and variability in EEG signals, which is crucial given the diverse symptomatology and presentations of autism.

Ablation experiments are a crucial method for evaluating the contribution of different components or features of a model to its overall performance. Table 5 displays the performance of the recommended scheme without feature optimization and

**Table 6.** Computational performance metrics of the proposed framework.

| Pipeline Stage           | Time (sec)    | Hardware Needs      |
|--------------------------|---------------|---------------------|
| Preprocessing            | 45.12 ± 8.02  | CPU (MATLAB/Python) |
| Feature Extraction       | 8.37 ± 1.29   | Parallelizable      |
| LASSO Reduction          | 3.05 ± 0.52   | Low CPU             |
| GA-DBSCAN Optimization   | 9.68 ± 1.81   | Moderate CPU        |
| Fuzzy ELM Classification | 1.34 ± 0.40   | Embedded-friendly   |
| Total Runtime            | 67.56 ± 10.74 | Laptop/Jetson       |

feature reduction steps. As can be seen, all network performance metrics in both databases decrease without these two important steps. This indicates the high importance of optimizing EEG features and selecting the best features before classification.

This section evaluates the practical feasibility of deploying the proposed framework in real-world clinical settings. It quantifies computational efficiency—a critical factor for adoption—by reporting processing times for each step (preprocessing, feature extraction, optimization, feature reduction, and classification) on standard hardware for a single patient's EEG data from start to finish using this framework. As shown in Table 6, the proposed pipeline achieves clinically feasible processing times ( $67.56 \pm 10.74$  s per subject) while maintaining diagnostic accuracy. Preprocessing

**Table 7.** Features of research focusing on autism diagnosis through EEG analysis and ML techniques.

| Reference                     | Sample                                            | Feature extraction                                                               | Classifier                                           | Accuracy                                   |
|-------------------------------|---------------------------------------------------|----------------------------------------------------------------------------------|------------------------------------------------------|--------------------------------------------|
| (Ahmadlou et al. 2012)        | 9 autistic and 9 healthy children                 | Fuzzy synchronization likelihood                                                 | Enhanced probabilistic neural network                | 95.5%                                      |
| (Sheikhani et al. 2012)       | 17 autistic children and 11 healthy children      | Short-time Fourier transform                                                     | KNN                                                  | 96.4%                                      |
| (Jamal et al. 2014)           | 12 subjects in each autism and normal group       | Brain connectivity                                                               | Linear discriminant analysis (LDA) and SVM           | 94.7%                                      |
| (Eldridge et al. 2014)        | 19 autistic children and 30 healthy children      | Modified multiscale entropy                                                      | SVM, Logistic regression, Naïve Bayes                | 79%                                        |
| (Heunis et al. 2018)          | 7 autistic children and 7 non-autistic children   | Recurrence quantitative analysis                                                 | SVM                                                  | 92.9%                                      |
| (Kang et al. 2018)            | 52 autistic children and 52 non-autistic children | Fast Fourier transform                                                           | SVM                                                  | 91.38%                                     |
| (Haputhanthri et al. 2019)    | 10 autistic children and 5 non-autistic children  | Wavelet analysis                                                                 | Logistic regression, SVM, Naïve Bayes, Random forest | 93%                                        |
| (Baygin et al. 2021)          | 61 autistic subjects and 61 healthy subjects      | One-dimensional local binary pattern and deep features of the spectrogram images | SVM                                                  | 96.44%                                     |
| (Alotaibi and Maharatna 2021) | 12 autistic children and 12 healthy children      | Brain connectivity                                                               | SVM                                                  | 95.8%                                      |
| (Xu and Yang 2023)            | 24 autistic children and 24 healthy children      | Linear and nonlinear analyses                                                    | Self-organizing map                                  | 97.1%                                      |
| Ours                          | Database A and Database B                         | Various nonlinear analyses                                                       | Fuzzy ELM                                            | Database A = 96.81%<br>Database B = 97.64% |

dominates the runtime ( $45.12 \pm 8.02$  sec) due to manual artifact rejection, highlighting an opportunity for optimization through automated methods. LASSO feature reduction provides critical efficiency gains - though adding  $3.05 \pm 0.52$  s, it enables a 14% total speedup by reducing the feature space from 294 to 20 dimensions. This reduction significantly accelerates downstream steps: GA-DBSCAN optimization becomes 50% faster (12→9 sec) and Fuzzy ELM classification requires 40% less memory, enhancing deployability on embedded systems. The complete framework demonstrates practical potential for clinical implementation, particularly when considering its balance of speed (comparable to routine EEG review times) and performance (96–97% accuracy). Future work targeting automated preprocessing could further reduce total runtime to under 20 s.

A simple search in the literature reveals that previous studies have attempted to diagnose autism using EEG signal analysis. Here, the outcomes obtained in previous studies are compared with the findings of the present work. Table 7 summarizes the characteristics and outcomes of these studies in comparison to ours. The table highlights that earlier research employed a variety of methods to extract features from EEGs, ranging from linear frequency analysis to several nonlinear techniques, including fractal dimension and recurrence quantification analysis. Our findings suggest that future investigations should focus on the nonlinear dynamics of EEG signals, as well as the integration and optimization of nonlinear features for diagnosing autism. SVM has emerged as the most

commonly used classifier in these studies for EEG feature classification, which showed worse outcomes compared to the fuzzy ELM classifier recommended in our work. Additionally, some researchers have implemented neural networks, such as probabilistic neural networks and radial basis function networks, for this task. Notably, many studies have achieved autism classification accuracies of 90% or more, indicating the promising potential of this approach for objective autism diagnosis. Nevertheless, several of these studies face significant limitations that may hinder their applicability. Challenges such as small sample sizes, complicated implementation processes, and lower accuracy rates are among these constraints. The sample size, though adequate for preliminary validation, remains relatively small. Larger, multicenter datasets are needed to enhance the generalizability of the findings and account for the heterogeneity of autism across populations. This study utilized 14-channel EEG data to align with portable, clinically accessible devices (e.g. Emotiv Epoc). While this enhances practicality for real-world screening, the limited spatial resolution may overlook localized neural patterns detectable only with high-density EEG systems. Future studies should validate our framework using high-density electrodes (e.g. 64+ channels) to assess generalizability across hardware configurations and confirm whether the selected nonlinear features remain discriminative at finer spatial scales. Combining optimized feature selection with high-density EEG could further refine diagnostic precision while maintaining computational efficiency.

## Conclusion

In the current work, a new feature optimization technique was recommended to be used in combination with LASSO feature reduction and fuzzy ELM classifier for autism diagnosis from EEG. This framework outperformed existing methods on two EEG databases. This study underscores the potential of using nonlinear dynamics of EEG signals alongside fuzzy ELM for diagnosing autism in children. The recommended scheme, characterized by a systematic approach to data preprocessing, innovative feature optimization, and robust classification, presents a significant advancement in neurodevelopmental disorder diagnosis. The integration of GA and DBSCAN for feature optimization, followed by the LASSO technique for reducing dimensionality, enhances the interpretability and efficiency of the classification process. This comprehensive methodology displays promise for not only improving diagnostic accuracy but also facilitating personalized treatment plans based on individual EEG patterns. Future research directions could involve the application of this framework to larger databases and various age groups to further validate its effectiveness. Additionally, exploring other ML techniques in conjunction with our method may yield deeper insights into the subtleties of EEG signal patterns associated with autism. Overall, we believe that our findings contribute valuable knowledge to the ongoing pursuit of innovative diagnostic tools in pediatric neurodevelopmental disorders.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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