Iranian Journal of Operations Research
Vol. 17, No. 1, 2026, pp. 55-68

Intelligent Growing SOM-Based Approach for Modeling Brain Patterns in Autism Spectrum Disorder

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Autism Spectrum Disorder is characterized by atypical brain function and altered neural organization. This study introduces an unsupervised, interpretable framework based on Growing Self-Organizing Maps (GSOM) to model structural brain patterns in individuals with ASD using the ABIDE I T1-weighted structural MRI dataset. Discriminative features, including wavelet coefficients, entropy measures, intensity histograms, and edge-based descriptors, are extracted from brain images to characterize structural variations. GSOM adaptively expands its topology in response to the data distribution, enabling robust representation of complex and heterogeneous brain patterns without requiring labels during training. Class labels are used only in the evaluation stage to assess the discriminative power of the learned clusters. The proposed framework achieves an overall classification accuracy of 94.2%, outperforming fixed-topology self-organizing models in terms of cluster separability and structural representation. Sensitivity analysis further shows that model performance is most affected by the selection of wavelet- and entropy-based features, whereas moderate changes in the GSOM growth-related parameters have limited impact on classification accuracy. These results highlight the potential of GSOM as a reliable and interpretable tool for ASD brain pattern analysis.

***Keywords**: Autism Spectrum Disorder; Brain Modeling; Growing Self-Organizing Map; Neuroimaging.*

1. Introduction

Autism Spectrum Disorder[2] is a neurodevelopmental condition characterized by impairments in social interaction, communication, and behavioral flexibility. It originates in early childhood and persists throughout the lifespan, significantly affecting cognitive and neural development. Numerous studies have reported that ASD is associated with atypical brain function and altered neural organization, which can be observed through different neuroimaging modalities such as electroencephalography[3], functional magnetic resonance imaging, and positron emission tomography [20,24].

Early and accurate identification of ASD plays a crucial role in improving intervention outcomes and supporting developmental planning. Consequently, a wide range of computational and machine learning approaches have been proposed to assist ASD diagnosis using neuroimaging data [25]. Most of these methods rely on supervised classification models that aim to distinguish individuals with ASD from typically developing controls based on extracted features. While such approaches often report high classification accuracy, they mainly focus on decision performance and provide limited insight into the underlying structure and organization of brain activity.

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[2] ASD
[3] EEG

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In recent years, increasing attention has been directed toward brain modeling rather than mere classification. Brain modeling aims to represent the intrinsic structure of neural patterns and to reveal meaningful differences in brain organization between ASD and control groups. However, relatively few studies have explored unsupervised and adaptive modeling techniques capable of capturing the complex and heterogeneous nature of ASD-related brain data [23]. Fixed-topology neural networks, including conventional Self-Organizing Maps[4], may not adequately adapt to the varying distribution and dimensionality of neuroimaging features.

Growing Self-Organizing Maps[5] provide an extension to classical SOM by enabling dynamic network growth based on data complexity. This adaptive behavior allows GSOM to model complex data distributions more effectively and to produce interpretable topological representations [18]. Despite their advantages, GSOM-based approaches have been less frequently applied to brain modeling in ASD, particularly using large-scale public neuroimaging datasets.

In this paper, an adaptive GSOM-based model is proposed for brain modeling and analysis of individuals with Autism Spectrum Disorder. Neuroimaging data from the ABIDE I dataset is utilized, and multiple discriminative features, including wavelet-based features, entropy measures, intensity histograms, and edge-based descriptors, are extracted from brain images. By leveraging the self-organizing and growing capabilities of GSOM, the proposed model aims to model brain patterns and reveal structural differences between ASD and control groups rather than focusing solely on classification accuracy.

The main contributions of this study are summarized as follows:1-Proposing an unsupervised GSOM-based model for adaptive brain modeling in ASD, 2-Employing multi-level feature extraction to capture complementary characteristics of brain images, 3-Modeling and analyzing structural differences between ASD and typically developing individuals using self-organized maps, 4-Evaluating the effectiveness of GSOM on large-scale ABIDE neuroimaging datasets.

The results demonstrate that adaptive self-organizing models such as GSOM can provide meaningful insights into brain pattern organization in ASD and serve as an effective alternative to fixed-topology neural networks.

2. Related Work

Research on Autism Spectrum Disorder has increasingly focused on identifying neurophysiological and behavioral patterns that distinguish affected individuals from typically developing controls. Various signal processing and machine learning techniques have been employed using modalities such as EEG, speech signals, behavioral features, and neuroimaging data.

Early studies primarily investigated spectral and connectivity characteristics of brain signals in individuals with ASD. For instance, Arkoha et al. analyzed high-frequency power spectra in autistic and healthy children and reported reduced hemispheric correlation, particularly in the left hemisphere associated with speech processing [3]. Their findings highlighted abnormal neural synchronization patterns in ASD and motivated further exploration of frequency-based brain features.

Several supervised learning approaches have been proposed for ASD detection using EEG and signal-based features. In [15], a combination of Fast Fourier Transform[6] features and Fisher Linear Discriminant classification was applied, achieving a detection accuracy of approximately 80%. Similarly, discrete signal transforms such as the Discrete Sine Transform were utilized in conjunction with artificial neural networks to simplify feature representation and reduce computational

[4] SOM
[5] GSOM
[6] FFT

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complexity [9]. These approaches demonstrated the potential of machine learning for ASD detection but relied heavily on fixed feature representations and supervised classifiers.

Beyond EEG-based methods, speech and behavioral signal analysis has also been explored for early ASD diagnosis. Santos et al. employed acoustic and pre-linguistic vocal features combined with Support Vector Machines[7] and neural networks, reporting high detection rates exceeding 97% in controlled experimental settings [4,12]. Kakaha et al. proposed a multi-kernel learning model to weight and optimize a large set of vocal features, improving classification performance by jointly learning decision boundaries and feature importance [7]. Although these methods achieved promising results, they focused mainly on classification accuracy and did not address structural modeling of neural or brain patterns.

Other studies investigated hybrid and soft-computing approaches for ASD assessment. Neuro-fuzzy systems were applied to analyze social, communicative, motor, and behavioral parameters, emphasizing the importance of multi-dimensional input features in ASD severity estimation [17, 26]. Data mining techniques were also explored, where decision trees demonstrated competitive performance compared to other classifiers in distinguishing autistic individuals from healthy subjects [21]. These studies further confirmed the effectiveness of intelligent systems for ASD analysis but were limited by their reliance on predefined structures and supervised learning paradigms.

Despite the demonstrated success of artificial neural networks and machine learning techniques, existing research largely emphasizes diagnostic performance rather than adaptive brain modeling. As noted in previous reviews [5, 22, 27, 42], fixed-topology neural networks may struggle to capture the heterogeneous and complex nature of ASD-related brain data. Moreover, limited attention has been given to unsupervised and self-organizing models capable of revealing intrinsic data structures.

In contrast, self-organizing neural networks offer an interpretable and data-driven approach for modeling complex patterns. However, conventional Self-Organizing Maps employ a fixed structure that may not adequately adapt to varying data distributions. This limitation motivates the use of Growing Self-Organizing Maps, which dynamically expand their topology based on data complexity. Although GSOM has shown advantages in modeling high-dimensional data, its application to brain modeling and neuroimaging-based ASD analysis remains relatively underexplored. This research addresses this gap by proposing a GSOM-based adaptive model for modeling and analyzing brain patterns in individuals with ASD using MRI data from large-scale public datasets.

2.1. Research Gap and Contributions

Despite the growing body of research on Autism Spectrum Disorder using neuroimaging and machine learning techniques, several important gaps remain in the literature. First, many existing studies have primarily focused on supervised classification frameworks, which often depend heavily on labeled data and are mainly optimized for predictive accuracy rather than for understanding the intrinsic structural organization of brain patterns. While such methods can provide strong classification results, they may offer limited interpretability regarding how structural heterogeneity in ASD is represented.

Second, conventional clustering and self-organizing methods commonly rely on fixed network topologies, which may not be sufficiently flexible to capture the complexity and variability of structural MRI data in ASD populations. Given the heterogeneous nature of ASD-related brain alterations, a more adaptive representation mechanism is needed to model subtle and nonuniform structural differences across subjects.

[7] SVM

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Third, although structural MRI has been widely used in ASD studies, relatively limited attention has been given to unsupervised and topology-adaptive approaches that can simultaneously provide meaningful pattern discovery, visualization, and discriminative representation without requiring label-dependent learning during the training stage. To address these gaps, this study proposes an unsupervised and interpretable framework based on Growing Self-Organizing Maps for structural brain pattern analysis in ASD. The significance and novelty of this study can be summarized as follows:

1. An adaptive unsupervised framework is introduced for modeling ASD-related structural brain patterns without relying on labeled supervision during training.
2. GSOM is employed instead of fixed-topology self-organizing networks, enabling the model to dynamically expand according to the intrinsic distribution and complexity of the data.
3. A comprehensive structural feature representation is constructed using wavelet coefficients, entropy-based measures, intensity histograms, and edge descriptors to characterize brain morphology more effectively.
4. The proposed framework emphasizes interpretability and robustness, making it suitable not only for discrimination between ASD and control groups but also for exploratory analysis of heterogeneous brain structures.
5. Sensitivity analysis is incorporated to evaluate the influence of feature groups and model parameters, providing additional insight into the stability and practical reliability of the proposed method.

Overall, the main contribution of this work lies in presenting a robust and interpretable GSOM-based structural MRI framework that extends beyond conventional classification-oriented studies and offers a more adaptive way to model complex brain patterns in ASD.

3. Materials and Methods

In this study, an unsupervised and adaptive learning model is employed to model brain patterns associated with Autism Spectrum Disorder using neuroimaging data. The proposed methodology is designed to capture the intrinsic structure of high-dimensional brain features and to provide an interpretable representation of differences between ASD and typically developing individuals. Instead of relying solely on supervised classifiers, the focus is placed on brain modeling and structural analysis, which allows a deeper exploration of data organization beyond binary decision boundaries [14].

The core of the proposed approach is based on Growing Self-Organizing Maps, an extension of conventional Self-Organizing Maps that dynamically adapts its topology according to data complexity. Neuroimaging data derived from the ABIDE I is first preprocessed, followed by the extraction of complementary features capturing spatial, statistical, and textural characteristics of brain images. These features are then used to train the GSOM model, which incrementally grows and organizes its map structure to reflect the underlying distribution of the data.

The selection of GSOM is motivated by several key considerations. First, ASD-related brain data are inherently heterogeneous and high-dimensional, making fixed-topology models less effective in capturing complex patterns. Unlike classical SOM, GSOM automatically adjusts the number of nodes and network structure during training, enabling a more flexible and data-driven representation. Second, GSOM provides an interpretable topological map, which facilitates visualization and qualitative analysis of brain pattern organization, an important advantage in neuroimaging studies where model transparency is desirable.

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Furthermore, the unsupervised nature of GSOM reduces dependence on labeled data and mitigates potential bias introduced by class imbalance or annotation variability. This property is particularly relevant when working with large-scale public datasets such as ABIDE, where data heterogeneity across acquisition sites can affect supervised learning performance. By combining adaptive learning with self-organization, the proposed model offers an effective balance between modeling capability, interpretability, and robustness.

Overall, the adopted methodology enables adaptive brain modeling and structural comparison between ASD and control groups, providing a flexible alternative to fixed-structure neural networks and conventional classification-oriented approaches. The flowchart illustrating the main stages of the proposed method is presented below.

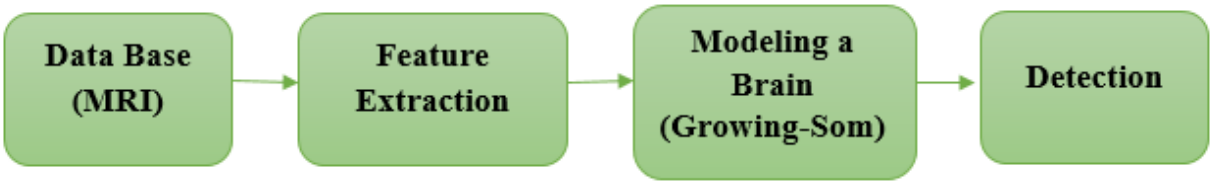

Figure 1. Flowchart of Proposed model

3.1. Dataset Description

Neuroimaging data used in this study is obtained from publicly available dataset, including ABIDE I, which provide structural MRI scans of individuals diagnosed with ASD and typically developing control subjects. These datasets are widely used in autism research due to their multi-site nature and standardized acquisition protocols.

The inclusion of data from multiple acquisition sites introduces variability in imaging conditions; therefore, careful preprocessing and robust modeling techniques are required to ensure reliable brain representation. The datasets include subjects from both ASD and control groups, enabling comparative modeling of brain structures.

3.2. Data Preprocessing

Prior to feature extraction, MRI images undergo a preprocessing stage to improve data quality and ensure consistency across samples. This stage includes noise reduction, intensity normalization, and resizing of images to a unified spatial resolution. Preprocessing is performed to minimize the effect of acquisition-related artifacts and to enhance the discriminative characteristics of brain structures. The preprocessed images are then used as inputs for feature extraction, ensuring that subsequent modeling stages are driven by meaningful and standardized representations [5].

3.3. Feature Extraction

To capture complementary characteristics of brain images, a multi-feature extraction strategy is employed. Each feature group is designed to describe a specific aspect of the MRI data, including frequency content, statistical complexity, spatial distribution, and structural boundaries.

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3.3.1. Wavelet Transform Features

Wavelet transform is applied to MRI images to analyze brain structures at multiple spatial resolutions. This transform decomposes the image into different frequency sub-bands, enabling the extraction of both coarse and fine-grained structural information. Wavelet-based features are particularly effective in representing localized variations in brain tissue patterns. The discrete wavelet transform that is used here is based on formula (1):

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k] \quad (1)$$

where x denotes the input signal and g represents the impulse response of the low-pass filter. This process is repeated up to four decomposition levels [19].

3.3.2. Entropy-Based Features

Entropy measures are used to quantify the complexity and randomness of brain image textures. Higher entropy values generally indicate increased structural variability, while lower values correspond to more homogeneous regions. These features provide statistical insight into the distribution of intensity patterns across brain regions. In this study, entropy is computed using Equation (2) [11, 16].

$$H(X) := -\sum_{x \in \mathcal{X}} p(x) \log p(x) = \mathbb{E}[-\log p(x)] \quad (2)$$

3.3.3. Histogram Features

Histogram-based features are extracted to represent the global intensity distribution of MRI images. These features capture overall brightness and contrast variations and provide a compact statistical summary of image content.

3.3.4. Edge Features Using Canny Operator

The Canny edge detection algorithm is employed to identify structural boundaries within brain images. Edge-based features emphasize anatomical contours and transitions between different tissue types, contributing to the structural modeling capability of the proposed model. The extracted features from all groups are concatenated to form a high-dimensional feature vector representing each brain image [28].

3.4. Brain Modeling Using Growing Self-Organizing Maps

To model the intrinsic structure of brain feature vectors, a Growing Self-Organizing Map is utilized. GSOM is an unsupervised neural network that extends the classical SOM by allowing dynamic growth of its topology during training. Unlike fixed-size SOMs, GSOM adapts the number of neurons based on data complexity, enabling more flexible and accurate representation of heterogeneous brain patterns.

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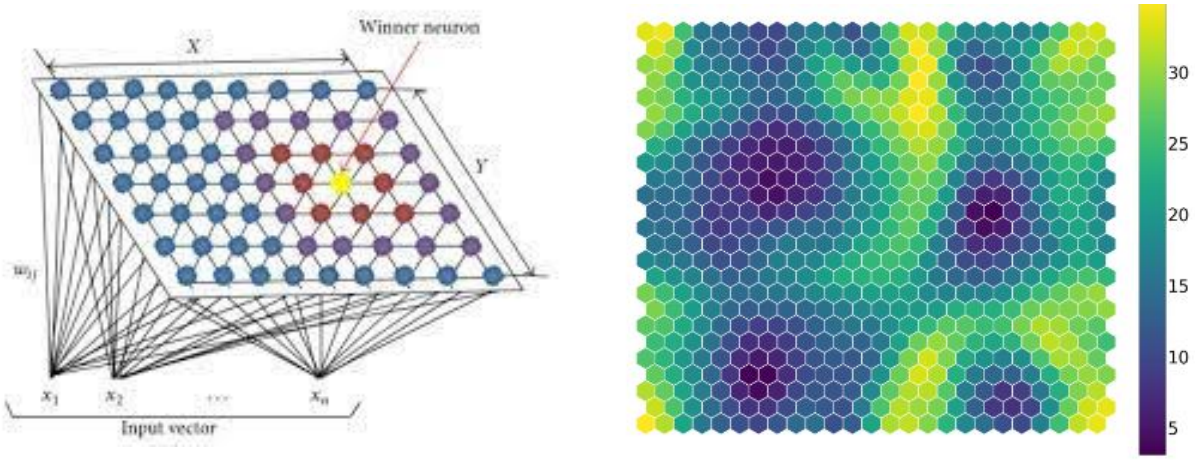
The GSOM was trained in a fully unsupervised manner using MRI-derived features, without incorporating diagnostic labels. After training, each subject was mapped to its Best Matching Unit on the GSOM map. The learning process of GSOM is based on competitive and cooperative mechanisms. For each input feature vector, the neuron with the minimum distance to the input is selected as the Best Matching Unit. The weights of the BMU and its neighboring neurons are updated to move closer to the input vector. When accumulated quantization error exceeds a predefined growth threshold, new neurons are added to the network, allowing the map to expand adaptively. This adaptive behavior enables GSOM to capture both global and local structural variations in brain data, making it suitable for modeling ASD-related heterogeneity [10, 13].

The proposed model is based on a two-layer self-organizing Kohonen network, where each layer initially consists of 200 neurons, and the layers are allowed to grow incrementally up to 300 neurons. All neurons compete with each other in a competitive learning process based on a feature-distance criterion. Figure 2 illustrates the schematic of a single layer of the employed self-organizing neural network as well as the overall network architecture used in this study



(a) (b)

Figure 2. The architecture of self-organizing neural network

The training process of the self-organizing map is performed iteratively through the following steps:

Table 1. Training process

1. Each input sample is sequentially presented to the network.
2. The distance between the input feature vector and the weight vector of all neurons is computed.
3. The neuron with the minimum distance to the input vector is identified as the Best Matching Unit (BMU).
4. The weight vector of the winning neuron is updated according to Equation (3).

$$W_J^{t+1} = W_J^t + \eta \cdot (x - W_J^t) \quad (3)$$

The weight vectors of neurons located in the neighborhood of the winning neuron

$$W_N^{t+1} = W_N^t + \theta \cdot \eta \cdot (x - W_N^t) \quad (4)$$

are updated based on Equation (4).

Where W, N, t and ŋ denote weight, number of neurons, times and learning rate.

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By repeating these steps for all input samples over multiple iterations, the network gradually converges to an optimal configuration in which each neuron represents a specific region of the input feature space. When MRI images are provided to the proposed neural network during training, an adaptive growth mechanism is employed. Specifically, 100 additional neurons are incrementally added to the network, allowing the model to better represent data complexity and improve structural discrimination. This adaptive behavior enhances the modeling capability of the network when handling heterogeneous brain patterns associated with ASD.

Although the proposed model is primarily designed for brain modeling, the resulting map organization allows indirect evaluation of group separability. Distinct clustering tendencies observed on the GSOM indicate meaningful structural differences between the two groups.

4. Experimental Results

The proposed model is evaluated using structural MRI data obtained from the ABIDE I dataset. The model was implemented by Python. All experiments are conducted under identical conditions to ensure fair comparison. Feature vectors extracted from MRI images are used as inputs to the GSOM model.

Although the proposed model is primarily designed for brain modeling, quantitative evaluation is performed to assess its discriminative capability. Standard performance metrics, including accuracy, sensitivity, and specificity, are employed to provide an objective assessment of group separability [87, 88].

$$Accuracy = (TP + TN) / N \quad (5)$$

$$precision = TP/(TP + FP) \quad (6)$$

$$recall = TP/(TP + FN) \quad (7)$$

In the above formulations, TP and TN denote the numbers of true positive and true negative samples that are correctly classified, respectively. FP and FN represent the numbers of false positive and false negative samples that are incorrectly classified. N indicates the total number of samples.

To validate the proposed model, k-fold cross-validation is employed with **k = 10**. In this procedure, the dataset is partitioned into *k* subsets, where in each iteration one subset is used for validation and the remaining $k - 1$ subsets are used for training. This process is repeated *k* times such that each sample is used exactly once for validation and once for training.

In the proposed model, the evaluation criteria are based on the aggregation of the number of neurons within different regions, expressed in terms of percentage. Initially, the entire self-organizing network is partitioned into 12 distinct regions, as illustrated below.

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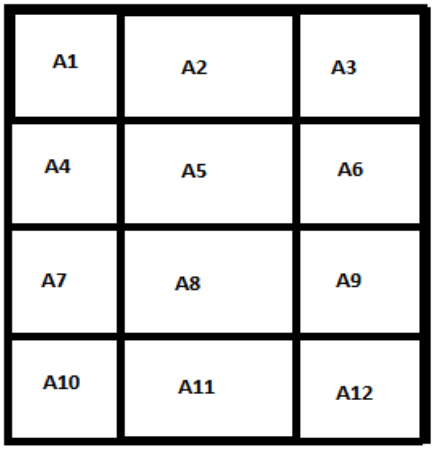

Figure 3. The considered regions of brain

Following this partitioning, the neuron density distribution within each region is calculated. The resulting percentages reflect the structural organization learned by the GSOM and provide insight into how the network allocates representational resources across different map areas.

Table 2. Percentage distribution of neurons across map regions

Region	Percentage (%)
A1	20
A2	18
A3	20
A4	3
A5	15
A6	2
A7	1
A8	10
A9	2
A10	3
A11	2
A12	4

The observed distribution indicates that regions A1, A2, A3, and A5 contain the highest neuron densities, suggesting that these areas correspond to more complex or information-rich representations in the learned brain model. In contrast, regions with low neuron density represent less activated or less discriminative structural patterns. Importantly, this region-based aggregation enables

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interpretation of the GSOM topology, which is a key advantage over conventional black-box classification models.

For evaluation purposes, a post-hoc labeling strategy was employed. Each GSOM neuron was assigned a class label (ASD or healthy control) based on the majority class of training subjects mapped to that neuron. Test subjects inherited the label of their corresponding BMU, allowing classification performance to be assessed. To further validate the effectiveness of the proposed GSOM-based model, its performance is compared with several widely used intelligent methods, including Support Vector Machines[8], Multilayer Perceptrons[9], and Cellular Neural Networks[10]. All methods are evaluated under identical experimental conditions.

Table 3. Performance comparison of different methods

Method	Accuracy (%)	Precision (%)	Recall (%)
SVM	69.2	70.9	73.3
MLP	59.7	57.3	64.1
Cellular NN [2]	85.8	82.7	78.3
Proposed GSOM-based method	**94.2**	**91.2**	**92.4**

As shown in Table 3, the proposed GSOM-based method achieves the highest performance across all evaluation metrics. Among the comparative approaches, Cellular Neural Networks demonstrate the second-best performance, while the MLP exhibits the weakest results.

Here, the performance of the proposed model is evaluated using different numbers of neurons at various stages of the experiment. The objective is to analyze the impact of network size on the accuracy, precision, and recall of autism detection. Figure 4 illustrates the classification accuracy achieved with different neuron counts. As observed, the accuracy improves as the number of neurons increases, indicating that a larger network capacity enables more effective representation of complex brain patterns.

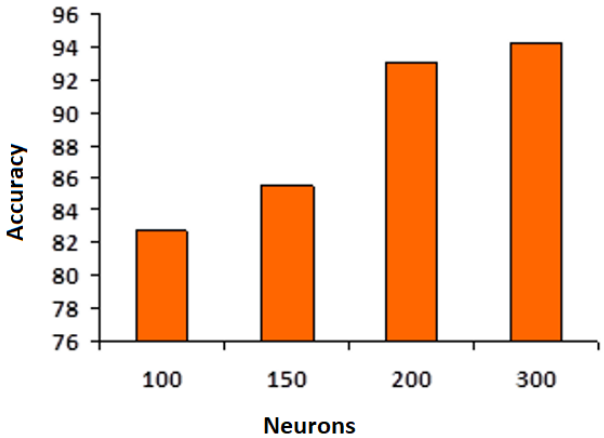

Figure 4. Accuracy across different numbers of neurons

[8] SVM
[9] MLP
[10] CNN

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Figure 5 presents the precision of the proposed method under different neuron configurations. The results show a similar trend, where increasing the number of neurons leads to more reliable detection performance.

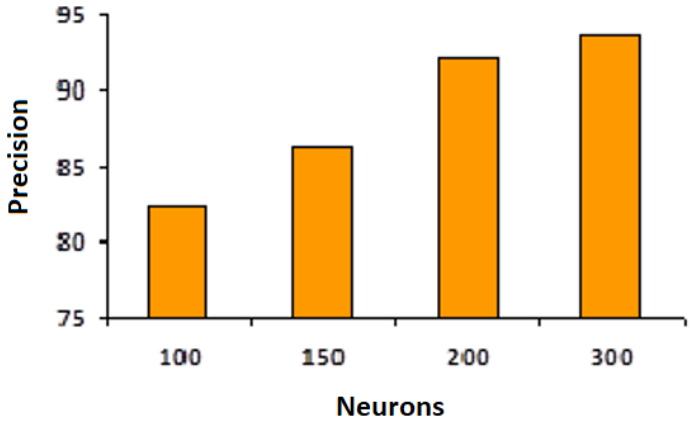

Figure 5. Precision across different numbers of neurons

In addition, Figure 6 depicts the recall values obtained for different neuron counts. The proposed method demonstrates improved recall as the number of neurons increases, reflecting enhanced sensitivity in identifying ASD samples.

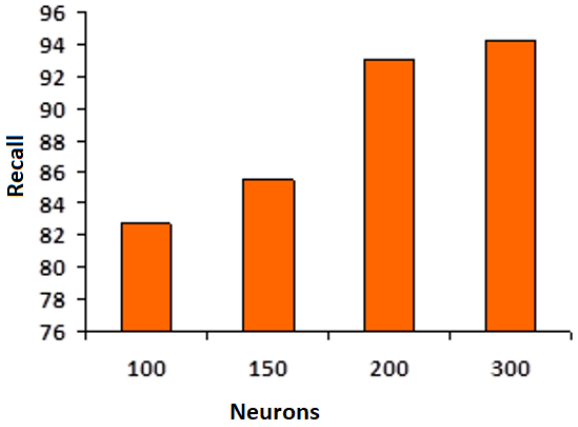

Figure 6. Recall across different numbers of neurons

Overall, the experimental results indicate that the proposed model achieves its best performance with 300 neurons**.** Nevertheless, it should be noted that the optimal number of neurons can be further determined using dedicated optimization techniques, which may lead to improved efficiency while maintaining high performance. The effect of applying Principal Component Analysis[11] on the performance of the proposed model is evaluated and is shown in table 4. PCA is employed as a dimensionality reduction technique to investigate whether reducing feature dimensionality influences the modeling capability of the GSOM.

[11] PCA

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Table 4. The effect of applying PCA

Method	PCA with	Without PCA
Proposed Model	91.1	92.4
CNN	82.2	85.8

The experimental results show that applying PCA leads to a slight improvement in computational efficiency; however, the overall modeling and discrimination performance does not significantly increase. This observation suggests that the proposed feature extraction process already captures the most informative characteristics of the brain images.

5. Managerial and Practical Implications

Beyond its methodological contribution, the proposed GSOM-based framework provides several practical and managerial insights for healthcare institutions, clinicians, and decision-makers involved in autism assessment. First, the high classification accuracy achieved by the model (94.2%) indicates its potential as a supportive tool for the structural analysis of brain MRI data, which may assist specialists in ASD screening and evaluation processes. Second, the sensitivity analysis showed that wavelet- and entropy-based features have the strongest influence on model performance. This finding is important from a managerial perspective because it suggests that healthcare centers and research teams can prioritize these high-impact features when designing diagnostic support systems, thereby reducing computational burden and improving implementation efficiency. Third, the relative stability of the GSOM framework under moderate parameter variations indicates that the proposed approach does not require highly sensitive parameter tuning. This improves its practicality in real-world environments where technical expertise and computational resources may be limited.

Finally, because the proposed model is unsupervised during the training stage, it can be applied in contexts where fully labeled neuroimaging datasets are not readily available. This characteristic may support more scalable and cost-effective analysis pipelines in clinical and research settings. Overall, the findings suggest that the proposed framework is not only methodologically robust but also practically relevant for supporting data-driven decision-making in ASD-related neuroimaging analysis.

6. Conclusion

This study proposed an unsupervised and interpretable framework based on Growing Self-Organizing Maps for modeling structural brain patterns in individuals with Autism Spectrum Disorder using T1-weighted structural MRI data from the ABIDE I dataset. By extracting discriminative features including wavelet coefficients, entropy measures, intensity histograms, and edge-based descriptors, the proposed model was able to adaptively represent heterogeneous brain structures without relying on labeled supervision during training.

The experimental results demonstrated that the proposed GSOM-based framework achieved an overall classification accuracy of 94.2%, indicating strong discriminative capability between ASD and control groups. Compared with fixed-topology self-organizing approaches, GSOM showed improved flexibility in capturing intrinsic data structures and enhancing cluster separability. Furthermore, sensitivity analysis revealed that wavelet- and entropy-based features had the most

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significant impact on model performance, while moderate variations in GSOM growth-related parameters did not substantially affect classification accuracy, highlighting the robustness of the proposed framework.

Despite these promising findings, several limitations should be acknowledged. First, the evaluation was conducted solely on the ABIDE I dataset, and external validation on independent or multi-site datasets is necessary to assess generalizability. Second, the study relied exclusively on T1-weighted structural MRI data; incorporating multimodal neuroimaging data such as fMRI or DTI may provide complementary information and further enhance model performance. Third, although the model is interpretable compared to many deep learning approaches, feature extraction and preprocessing steps remain computationally demanding.

Future research may focus on validating the proposed framework on larger and more diverse datasets, integrating multimodal neuroimaging information, and exploring hybrid approaches that combine GSOM with advanced representation learning techniques. Additionally, investigating the potential clinical utility of the learned structural patterns for early diagnosis or subtype characterization of ASD represents an important direction for further study. Overall, the results suggest that GSOM provides a robust, adaptive, and interpretable tool for structural brain pattern analysis in ASD and may serve as a valuable alternative to purely classification-oriented methods.

References

[1] Askari, E. (2025), Emotion recognition in Persian texts using an improved transformer model, *Iranian Journal of Operations Research*, 16(1), 136–146.

[2] Askari, E., Setarehdan, S.K., Sheikhani, A., Mohammadi, M.R. and Teshnehlab, M. (2018), Modeling the connections of brain regions in children with autism using cellular neural networks and electroencephalography analysis, *Artificial Intelligence in Medicine*, 89, 40–50.

[3] Bagheri, S., Askari, E. and Motamed, S. (2025), Classification of leukemia using a hybrid approach based on temporal fusion transformer and XG-Boost, *Iranian Journal of Operations Research*, 16(2), 26–38.

[4] Chengwen, L., Edwin, B. and Hong, X. (2017), Association between autistic traits and emotion adaptation to partially occluded faces, *Vision Research*, 133, 21–36.

[5] Demirhan, A. (2018), The effect of feature selection on multivariate pattern analysis of structural brain MR images, *Physica Medica*, 47, 103–111.

[6] Dimond, D. *et al.* (2019), Reduced white matter fiber density in autism spectrum disorder, *Cerebral Cortex*, 29(4), 1778–1788.

[7] Garcia Garcia, M.J., Penichet, V.M.R., Lozano, M.D. and Fernando, A. (2021), Using emotion recognition technologies to teach children with autism spectrum disorder how to identify and express emotions, *Universal Access in the Information Society*.

[8] Georges, N., Mhiri, I. and Rekik, I. (2020), Identifying the best data-driven feature selection method for boosting reproducibility in classification tasks, *Pattern Recognition*, 101.

[9] Gordon, A. and Geschwind, D.H. (2020), Human in vitro models for understanding mechanisms of autism spectrum disorder, *Molecular Autism*.

[10] Guo, X., Dominick, K.C., Minai, A.A., Li, H., Erickson, C.A. and Lu, L.J. (2017), Diagnosing autism spectrum disorder from brain resting-state functional connectivity patterns using a deep neural network with a novel feature selection method, *Frontiers in Neuroscience*, 11, 460.

[11] Ha, S., Sohn, I.-J., Kim, N., Sim, H.J. and Cheon, K.-A. (2015), Characteristics of brains in autism spectrum disorder: Structure, function and connectivity across the lifespan, *Experimental Neurobiology*, 24(4), 273–284.

[Downloaded from iors.ir on 2026-11-28]

[12] Ilieva, M., Fex Svenningsen, A., Thorsen, M. and Michel, M.T. (2017), Psychiatry in a dish: Stem cells and brain organoids modeling autism spectrum disorders, *Biological Psychiatry*.
[13] Jahedi, A., Nasamran, C.A., Faires, B., Fan, J. and Müller, R.-A. (2017), Distributed intrinsic functional connectivity patterns predict diagnostic status in large autism cohort, *Brain Connectivity*, 7, 515–525.
[14] Ke, F., Choi, S., Kang, Y.H., Cheon, K.-A. and Lee, S.W. (2020), Exploring the structural and strategic bases of autism spectrum disorders with deep learning, *IEEE Access*, 8, 153341–153352.
[15] Lanillos, P., Daniel, O., Anja, P.H., Yuichi, Y., Yukie, N. and Cheng, G. (2020), A review on neural network models of schizophrenia and autism spectrum disorder, *Neural Networks*, 122, 338–363.
[16] Li, D., Karnath, H.-O. and Xu, X. (2017), Candidate biomarkers in children with autism spectrum disorder: A review of MRI studies, *Neuroscience Bulletin*, 33(2), 219–237.
[17] Lu, M. and Ueno, S. (2013), Calculating the induced electromagnetic fields in real human head by deep transcranial magnetic stimulation, *Proceedings of the IEEE EMBS*, 795–799.
[18] Orekhova, E.V., Stroganova, E.V., Nygren, T.A. *et al.* (2007), Excess of high frequency electroencephalogram oscillations in boys with autism, *Biological Psychiatry*, 62, 1022–1029.
[19] Park, H.R. *et al.* (2017), Nucleus accumbens deep brain stimulation for a patient with self-injurious behavior and autism spectrum disorder, *Acta Neurochirurgica*, 159(1), 137–143.
[20] Plauché Johnson, C. and Myers, S.M. (2007), Identification and evaluation of children with autism spectrum disorders, *Pediatrics*, 120, 1183–1215.
[21] Rossignol, D.A. (2007), Hyperbaric oxygen therapy might improve certain pathophysiological findings in autism, *Medical Hypotheses*, 68(6), 1208–1227.
[22] Shahamat, H. and Abadeh, M.S. (2020), Brain MRI analysis using a deep learning based evolutionary approach, *Neural Networks*.
[23] Sheikhani, A., Behnam, H., Mohammadi, M.R. and Noroozian, M. (2010), Detection of abnormalities for diagnosing children with autism disorders using quantitative electroencephalography analysis, *Journal of Medical Systems*, 957–963.
[24] Sheikhani, A., Behnam, H., Mohammadi, M.R., Noroozian, M. and Mohammadi, M. (2012), Detection of abnormalities for diagnosing children with autism disorders using quantitative electroencephalography, *Journal of Medical Systems*, 36(2), 957–963.
[25] Sheikhani, A., Behnam, H., Noroozian, M. and Mohammadi, M.R. (2019), Abnormalities of quantitative electroencephalography in children with Asperger disorder, *Journal of Autism and Developmental Disorders*, 538–546.
[26] Wennberg, A. and Zetterberg, L.H. (2005), Computer analysis of EEG signals with parametric models, *Proceedings of the IEEE*, 69(4), 451–461.
[27] Xiao, X., Fang, H., Wu, J. *et al.* (2017), Diagnostic model generated by MRI-derived brain features in toddlers with autism spectrum disorder, *Autism Research*, 10, 620–630.
[28] Zhou, T., Ruan, S. and Canu, S. (2019), A review: Deep learning for medical image segmentation using multi-modality fusion, *Array*, 3–4, 100004.

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