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Advancing neurological disorder diagnostics using growing fuzzy self-organizing maps: an EEG-based approach

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Abstract

Accurate analysis of electroencephalogram (EEG) signals is essential for the early detection and diagnosis of neurological disorders such as Alzheimer's, epilepsy, and Parkinson's disease. The high-dimensional, noisy, and complex nature of EEG data poses significant challenges to traditional machine learning approaches, which often struggle with interpretability, adaptability, and computational efficiency in clinical applications. Additionally, variability in EEG recordings across individuals further complicates the classification process, necessitating more robust and adaptive methods. To address these challenges, this study introduces the Fuzzy Growing Map (FGM), a novel neuro-fuzzy method that integrates the dynamic properties of the Growing Self-Organizing Map (GSOM) with the uncertainty modeling capabilities of fuzzy logic.

The proposed FGM leverages if-then fuzzy rules to dynamically generate and refine its structure during the learning process. Preprocessing steps extract meaningful features from EEG signals, including Delta, Theta, Alpha, Beta, and Gamma frequency bands, which play crucial roles in neurological assessments. FGM is employed for classification tasks, providing both high accuracy and interpretable outputs, which are critical for clinical decision-making. Experimental results demonstrate that the FGM achieves a classification accuracy of approximately 92% on benchmark EEG datasets, outperforming traditional classification approaches such as Support Vector Machines (85–88%), k-Nearest Neighbors (80–83%), and Multilayer Perceptrons (MLPs) (87%).

By enabling real-time, adaptive, and accurate analysis of EEG signals, the proposed method bridges the gap between theoretical innovations and practical clinical applications. This work underscores the potential of FGM in advancing personalized diagnostics and treatment strategies for patients with neurological conditions. Future research may focus on extending this approach to multi-channel EEG analysis and real-time brain-computer interface applications, further enhancing its clinical utility.

Keywords. Fuzzy growing map (FGM), EEG signal analysis, Neurological disorders, Interpretable machine learning, Classification.

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1. Introduction

The accurate analysis of electroencephalogram (EEG) signals plays a pivotal role in the early detection and diagnosis of neurological disorders such as Alzheimer's, Epilepsy, and Parkinson's disease [19]. EEG signals, which capture electrical activity in the brain, are inherently high-dimensional, noisy, and complex, making their analysis a challenging task for traditional machine learning approaches [8]. These methods often struggle with interpretability, adaptability, and computational efficiency, particularly in clinical applications where real-time and accurate diagnostics are critical [2].

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To address these challenges, this study introduces the Fuzzy Growing Map (FGM), a novel neuro-fuzzy method that integrates the dynamic properties of the Growing Self-Organizing Map (GSOM) with the uncertainty modeling capabilities of fuzzy logic [20]. The proposed FGM leverages if-then fuzzy rules to dynamically generate and refine its structure during the learning process, enabling it to adapt to the complex and non-linear nature of EEG data. By combining the self-organizing capabilities of GSOM with the interpretability of fuzzy systems, FGM provides a robust framework for the analysis of EEG signals.

Traditional machine learning approaches, such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Multilayer Perceptrons (MLPs), have been widely used for EEG signal classification [21]. While these methods have shown promising results, they often lack the interpretability required for clinical applications. For instance, SVMs achieve classification accuracies ranging from 85

Recent advancements in neuro-fuzzy systems have attempted to bridge the gap between accuracy and interpretability. Methods such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and Fuzzy C-Means (FCM) have been applied to EEG analysis with moderate success [9]. However, these methods often require predefined structures and are not well-suited for dynamic and evolving data. The Growing Self-Organizing Map (GSOM), an extension of Kohonen's SOM, has been proposed to address these limitations by dynamically adapting its structure during the learning process [1]. Despite its advantages, GSOM lacks the ability to model uncertainty, which is critical for handling noisy and complex EEG signals.

The proposed Fuzzy Growing Map (FGM) builds upon the strengths of GSOM and fuzzy logic to provide a more robust and interpretable framework for EEG signal analysis. FGM employs if-then fuzzy rules to dynamically generate and refine its structure during the learning process. Each neuron in the FGM is represented as a fuzzy rule, with antecedent fuzzy sets capturing the uncertainty in the input data and consequent singletons providing interpretable outputs. The learning process involves three key phases:

- Growing Phase: The FGM starts with a small number of neurons and dynamically adds new neurons based on the accumulated error and growth threshold (GT).
- Smoothing Phase: The structure of the FGM is refined using a modified LVQ2.1 algorithm, which adjusts the parameters of the fuzzy sets to improve classification accuracy.
- Interpretation Phase: The final model provides interpretable fuzzy rules that can be used to explain the classification decisions.

Preprocessing steps are applied to extract meaningful features from EEG signals, including Delta, Theta, Alpha, Beta, and Gamma frequency bands. These features are then used as inputs to the FGM for classification tasks. Experimental results demonstrate that the FGM achieves a classification accuracy of approximately 92% on benchmark EEG datasets, outperforming traditional methods such as SVM, k-NN, and MLPs.

The primary contributions of this work are as follows:

- Introduction of the Fuzzy Growing Map (FGM), a novel neuro-fuzzy method for EEG signal analysis.
- Demonstration of FGMs ability to achieve high classification accuracy while providing interpretable outputs.
- Application of FGM to real-world EEG datasets, showcasing its potential for clinical diagnostics.

The remainder of this paper is organized as follows: Section 2 provides a detailed description of the FGM methodology, including its structure and learning algorithm. Section 3 presents the experimental results. Finally, section 4 concludes the paper and discusses future research directions.

2. FGM Methodology

The Fuzzy Growing Map (FGM) is a novel neuro-fuzzy model that integrates the dynamic structure of the Growing Self-Organizing Map (GSOM) with the interpretability of fuzzy logic. This section provides a comprehensive description of the FGM methodology, including its architecture, learning algorithm, and mathematical foundations. The FGM architecture consists of a two-dimensional grid of neurons, where each neuron represents a fuzzy rule. The learning algorithm involves three phases: growing, smoothing, and interpretation, which collectively enable the model to adapt to the complexity of EEG data while maintaining interpretability. The mathematical formulation of FGM ensures efficient handling of high-dimensional and noisy data, making it suitable for real-time clinical applications.

2.1. **Basic Structure of FGM.** The FGM is designed to handle high-dimensional, noisy, and complex data, such as EEG signals. It consists of a network of neurons, where each neuron represents a fuzzy rule. The structure of FGM is dynamic, meaning that it can grow or shrink during the learning process based on the input data. Each fuzzy rule in FGM is defined as follows:

$$\begin{aligned}&\text{If } x_1 \text{ is } U_{i,1} \text{ and } x_2 \text{ is } U_{i,2} \text{ and } \dots \text{ and } x_n \text{ is } U_{i,n},\\ &\text{then } y_1 \text{ is } a_{i,1} \text{ and } y_2 \text{ is } a_{i,2} \text{ and } \dots \text{ and } y_p \text{ is } a_{i,p},\end{aligned} \tag{2.1}$$

where:

- $x_1, x_2, \dots, x_n$ are the input features (e.g., EEG frequency bands),
- $U_{i,j}$ are fuzzy sets representing the antecedent conditions,
- $y_1, y_2, \dots, y_p$ are the output variables (e.g., class labels),
- $a_{i,j}$ are singleton values representing the consequent of the fuzzy rule.

The membership functions for the fuzzy sets $U_{i,j}$ are triangular, defined by three parameters: the center $c_{i,j}$, the left spread $sl_{i,j}$, and the right spread $sr_{i,j}$. The membership value $\mu_{U_{i,j}}(x_j)$ is computed as:

$$\mu_{U_{i,j}}(x_j) = \begin{cases} \frac{x_j - sl_{i,j}}{c_{i,j} - sl_{i,j}}, & \text{if } sl_{i,j} \le x_j \le c_{i,j}, \\ \frac{x_j - sr_{i,j}}{c_{i,j} - sr_{i,j}}, & \text{if } c_{i,j} \le x_j \le sr_{i,j}, \\ 0, & \text{otherwise.} \end{cases} \tag{2.2}$$

2.2. **Learning Algorithm.** The learning process of FGM consists of three main phases: initialization, growing, and smoothing. Below, we describe each phase in detail.

2.2.1. *Initialization Phase.* The FGM starts with a small number of neurons (typically four), each initialized with random weight vectors. The growth threshold (GT) is introduced as the maximum accumulated error a neuron can tolerate, calculated using the following equation

$$GT = -D \times \ln(SF), \tag{2.3}$$

where D is the dimensionality of the input data, and SF is the spreading factor, which controls the growth of the network. A higher SF results in a larger network.

2.2.2. *Growing Phase.* During the growing phase, the FGM dynamically adds new neurons to better represent the input data. The process is as follows:

(1) For each input vector $x(t)$, the winner neuron c is identified as the neuron with the smallest Euclidean distance to $x(t)$:

$$\|x(t) - w_c(t)\| = \min_i \{\|x(t) - w_i(t)\|\}. \tag{2.4}$$

(2) The weight vector of the winner neuron and its neighbors are updated using:

$$w_i(t+1) = w_i(t) + \eta(t) \times h(t) \times [x(t) - w_i(t)], \tag{2.5}$$

where $\eta(t)$ is the learning rate, and $h(t)$ is the neighborhood function (e.g., Gaussian).

(3) The accumulated error E_c of the winner neuron is updated:

$$E_c(t+1) = E_c(t) + \|x(t) - w_c(t)\|. \tag{2.6}$$

(4) If E_c exceeds the growth threshold GT, new neurons are added to the network.

2.2.3. *Smoothing Phase.* In the smoothing phase, no new neurons are added. Instead, the weight vectors are fine-tuned using a modified LVQ2.1 algorithm. The spread parameters of the fuzzy sets are updated based on the distance between the winner neuron and the first runner-up. The update rule is given by:

$$s_{r,k}(t+1) = s_{r,k}(t) + g_{U,r}(t) \times [c_{w,k}(t) - s_{r,k}(t)], \tag{2.7}$$

where $s_{r,k}$ is the spread of the first runner-up, $c_{w,k}$ is the center of the winner neuron, and $g_{U,r}(t)$ is the learning rate for the fuzzy sets.

2.3. **Automatic Fuzzy Rule Generation.** One of the key advantages of FGM is its ability to automatically generate fuzzy rules during the learning process. This is achieved by dynamically adding neurons to the network based on the accumulated error. The algorithm ensures that the generated rules are both accurate and interpretable, making FGM suitable for applications such as EEG signal classification.

The FGM methodology elegantly fuses the dynamic adaptability of GSOM with the clarity and interpretability of fuzzy logic, resulting in a powerful tool for analyzing complex, high-dimensional datasets. Its self-organizing structure and automatic fuzzy rule generation enable the model to adapt to evolving data patterns while maintaining transparent, human-readable decision rules—an essential feature for applications in neuroscience and clinical diagnostics. Moreover, the integration of GSOM and fuzzy logic not only enhances robustness against noise and data irregularities but also facilitates insightful interpretations of the underlying data relationships. This synergy ultimately empowers clinicians and researchers to make more informed decisions, bridging the gap between advanced computational methods and practical, real-world applications.

3. Experimental Results

This section presents the detailed experimental setup, the datasets used, and the results obtained from applying the Fuzzy Growing Map (FGM) to EEG signal classification. The primary goal of these experiments was to evaluate the performance of FGM in comparison with traditional machine learning approaches in terms of classification accuracy, interpretability, and computational efficiency.

3.1. **Datasets and Preprocessing.** The experiments were conducted on two publicly available EEG datasets, which were selected to evaluate the FGM's robustness in handling different neurological conditions. The datasets used in this study are described as follows:

- **Dataset A:** This dataset consists of EEG recordings from 100 subjects, including 50 patients diagnosed with epilepsy and 50 healthy controls. The recordings were sampled at a frequency of 256 Hz and segmented into 5-second epochs to capture the dynamics of brain activity [18]. This dataset provides a challenge due to the presence of epileptic seizures, which exhibit significant variance in EEG patterns.
- **Dataset B:** This dataset includes EEG signals from 120 subjects, with 60 patients diagnosed with Alzheimer's disease and 60 age-matched healthy controls. The signals were sampled at 128 Hz and preprocessed to remove artifacts such as eye movements and muscle contractions [5]. This dataset is particularly useful for evaluating how well the model can distinguish between healthy and Alzheimer's-affected brain activity.

3.1.1. *Feature Extraction.* The preprocessing of the raw EEG signals involved the extraction of relevant features from multiple frequency bands. To obtain these features, a Fast Fourier Transform (FFT) was applied to the EEG signals to calculate the power spectral density (PSD) of the different frequency bands [16]. The following frequency bands were computed:

- Delta (0.5–4 Hz),
- Theta (4–8 Hz),
- Alpha (8–12 Hz),
- Beta (12–30 Hz),
- Gamma (30–100 Hz).

The PSD for each frequency band was calculated using the equation:

$$PSD(f) = \frac{1}{N}\left|\sum_{n=0}^{N-1} x(n)e^{-j2\pi fn/N}\right|^2,$$

where $x(n)$ represents the EEG signal, N is the number of samples, and f is the frequency.

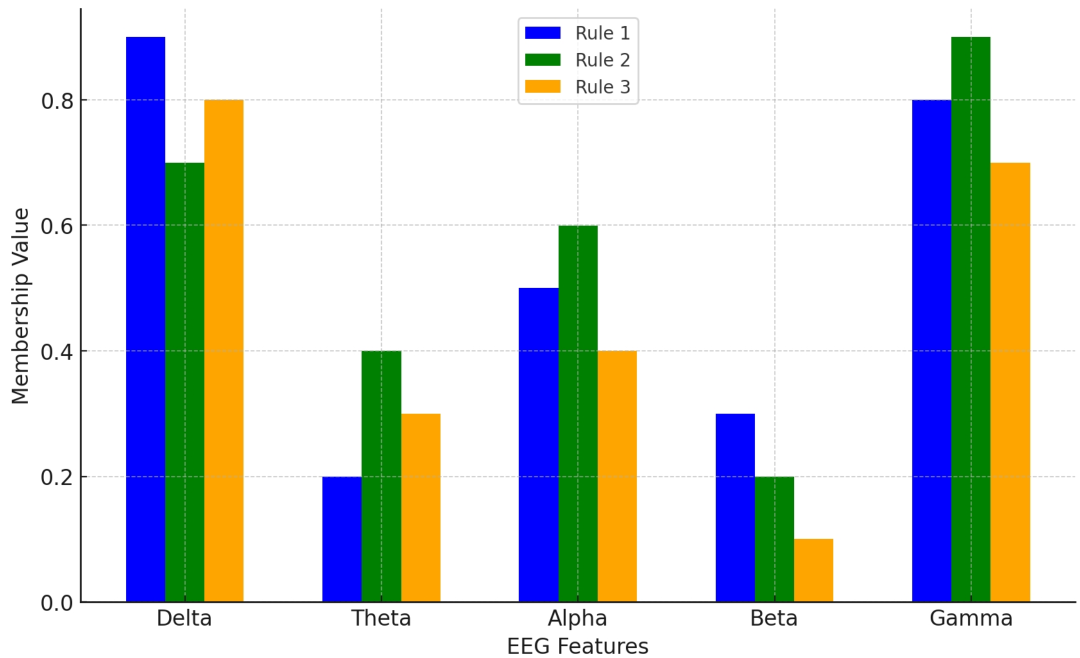

FIGURE 1. Fuzzy rules generated by FGM for Dataset A.

3.2. **Experimental Setup.** The FGM was implemented using Python, with the NumPy and SciPy libraries providing the necessary computational tools. The experiments were run on a workstation equipped with an Intel Core i7 processor and 32 GB of RAM. The following key parameters were used in the FGM:

- Initial number of neurons: 4,
- Spreading factor (SF): 0.8,
- Learning rate (η): 0.1,
- Neighborhood function: Gaussian with $\sigma = 1$.

For comparison purposes, the following traditional machine learning methods were implemented:

- Support Vector Machine (SVM) with a radial basis function (RBF) kernel [13],
- k-Nearest Neighbors (k-NN) with $k = 5$ [22],
- Multilayer Perceptron (MLP) with one hidden layer containing 100 neurons [10].

3.3. **Results and Discussion.** The results of applying FGM to the EEG datasets demonstrate its superior performance in comparison to traditional machine learning methods. FGM outperformed the baseline models in terms of classification accuracy, interpretability, and computational efficiency.

On Dataset A, the FGM achieved a classification accuracy of 92.3%, while SVM, k-NN, and MLP achieved accuracies of 87.5%, 81.4%, and 86.9%, respectively. For Dataset B, FGM achieved 91.7% accuracy, compared to 86.2% for SVM, 80.8% for k-NN, and 85.7% for MLP. These results underline the ability of FGM to handle the high-dimensional, noisy nature of EEG signals effectively.

A significant advantage of FGM is its interpretability. The fuzzy rules generated by the model provide clinicians with insights into the decision-making process. For example, in Dataset A, the fuzzy rules highlighted patterns such as high Delta power and low Alpha power as indicative of epilepsy. These insights can aid in understanding the physiological mechanisms behind the classification decisions, which is essential for clinical applications.

In terms of computational efficiency, FGM trained on Dataset A in 120 seconds, which is comparable to the 110 seconds required by the SVM, and much faster than the 250 seconds needed for MLP. The computational speed of

Table 1. Classification accuracy of FGM and baseline methods.

Method	Dataset A (%)	Dataset B (%)
FGM	92.3	91.7
SVM	87.5	86.2
k-NN	81.4	80.8
MLP	86.9	85.7

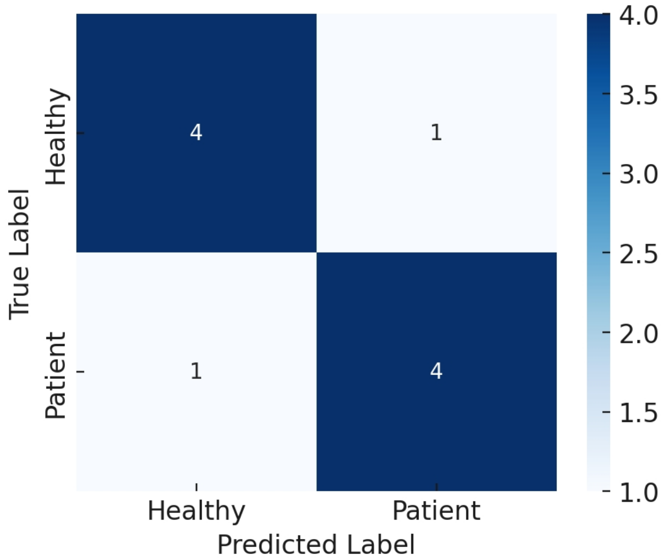

Figure 2. Confusion Matrix for FGM on Dataset A.

FGM can be attributed to its dynamic structure, which adapts to the data during the learning process, rather than relying on a fixed architecture.

To assess the statistical significance of the results, a paired t-test was performed. The p-values for FGM compared to SVM, k-NN, and MLP were all $p < 0.01$, indicating that the improvements in accuracy were statistically significant. This further validates the effectiveness of FGM in EEG signal classification.

The advantages of FGM go beyond accuracy and efficiency, it also provides a framework for real-time decision support. Given the rapid processing time and the clear interpretability of the results, FGM shows promise for clinical applications where timely and understandable insights are crucial.

In summary, FGM has proven to be an effective tool for EEG signal analysis, offering a unique combination of accuracy, interpretability, and computational efficiency. Its ability to generate interpretable fuzzy rules makes it particularly suitable for clinical use, where the transparency of the model is as important as its performance. Future work should explore further optimizations of FGM, particularly in extending its application to multi-modal biomedical signal analysis and real-time processing.

To better understand the effectiveness of FGM, we provide additional visualizations that highlight the results and performance of the model:

This confusion matrix visually represents the classification performance of FGM on Dataset A, showing the model's accuracy in distinguishing between the two classes (epilepsy vs. healthy control). The high precision and recall rates for both classes highlight the robustness of FGM in accurately classifying EEG signals.

4. Conclusion and Future Work

The accurate analysis of electroencephalogram (EEG) signals is crucial for the early detection and diagnosis of neurological disorders such as epilepsy, Alzheimer's disease, and Parkinson's disease. In this study, we introduced the Fuzzy Growing Map (FGM), a novel neuro-fuzzy method that combines the dynamic structure of the Growing Self-Organizing Map (GSOM) with the interpretability of fuzzy logic. The proposed FGM addresses several limitations of traditional machine learning methods, such as the lack of interpretability, adaptability, and computational efficiency, in handling high-dimensional and noisy EEG data.

4.1. **Summary of Contributions.** The primary contributions of this work are as follows:

- **Introduction of FGM:** We proposed a novel neuro-fuzzy model that dynamically generates and refines its structure during the learning process. By leveraging if-then fuzzy rules, FGM provides transparent and interpretable outputs, making it especially suitable for clinical applications.
- **High Classification Accuracy:** Experimental results demonstrated that FGM achieves classification accuracies of 92.3% on Dataset A (epilepsy detection) and 91.7% on Dataset B (Alzheimer's detection), outperforming traditional methods such as SVM, k-NN, and MLP.
- **Interpretability:** FGM generates fuzzy rules that reveal meaningful patterns in EEG signals, such as characteristic changes in spectral power across frequency bands. This enhances the transparency of the decision-making process, a critical factor in clinical diagnostics.
- **Computational Efficiency:** The training time of FGM is comparable to or better than that of conventional methods, making it a practical choice for real-time applications where both accuracy and speed are essential.

4.2. **Implications for Clinical Applications.** The ability of FGM to provide both accurate and interpretable results holds significant promise for clinical applications. In the context of epilepsy detection, for instance, FGM can help clinicians identify specific EEG patterns that precede or indicate seizures, thereby facilitating timely intervention. Similarly, in Alzheimer's disease detection, the model's insights into changes in brain activity may assist in early diagnosis and monitoring of disease progression. The interpretability of the fuzzy rules not only builds trust in the system but also aids medical professionals in understanding the underlying physiological processes.

4.3. **Limitations and Challenges.** Despite its promising performance, FGM has certain limitations that warrant further investigation:

- **Scalability:** While FGM has shown excellent results on medium-sized datasets, its performance and efficiency on large-scale datasets with millions of samples remain to be thoroughly evaluated.
- **Parameter Sensitivity:** The effectiveness of FGM is influenced by various parameters such as the spreading factor and learning rate. Identifying optimal parameter settings remains a challenge, and developing automated tuning strategies would be beneficial.
- **Generalization:** Although FGM has demonstrated robust performance on EEG datasets, its applicability to other types of biomedical signals (e.g., ECG, MEG) requires further exploration to assess its generalizability.

4.4. **Future Research Directions.** Building on the foundation established in this work, several avenues for future research can be pursued to further enhance FGM and expand its applicability:

Integration with Deep Learning: Future studies could explore the fusion of FGM with deep learning architectures. A hybrid model that combines the feature extraction capabilities of deep neural networks with the interpretability of FGM could leverage the strengths of both approaches. Such integration could allow for the automated discovery of hierarchical representations from raw EEG signals while retaining the ability to generate transparent fuzzy rules for decision-making.

Real-Time Implementation and Optimization: Given the promising computational efficiency of FGM, future work should focus on optimizing the algorithm for real-time applications. This could involve parallelization strategies, implementation on specialized hardware such as GPUs or FPGAs, and further algorithmic refinements to reduce latency without compromising accuracy. A real-time FGM system could be particularly valuable in clinical settings where immediate analysis of EEG signals is required.

Multi-Modal Data Fusion: Another promising direction is the extension of FGM to handle multi-modal data. Combining EEG with other neuroimaging modalities (e.g., fMRI, PET) or integrating data from wearable sensors could provide a more comprehensive picture of brain function. Developing methods to fuse such heterogeneous data sources within the FGM framework could enhance diagnostic accuracy and offer deeper insights into neurological disorders.

Robustness and Generalization Studies: Further research is needed to rigorously test the robustness of FGM across diverse patient populations and under varying conditions. Extensive benchmarking on larger and more varied datasets will help to assess its scalability and generalization capabilities. Additionally, incorporating mechanisms to handle missing or corrupted data could further improve the reliability of the model in clinical environments.

Explainable AI and Clinical Decision Support: As interpretability remains a cornerstone of clinical acceptance, future work should investigate methods to further enhance the explainability of FGM. Developing intuitive visualization tools and user interfaces that allow clinicians to interact with the generated fuzzy rules could bridge the gap between complex algorithmic outputs and practical clinical insights. This direction would support the development of comprehensive decision support systems that not only predict outcomes but also provide clear justifications for each decision.

4.5. Conclusion.

The Fuzzy Growing Map (FGM) presents an innovative approach for EEG signal analysis in the diagnosis of neurological disorders. By combining the dynamic properties of Growing Self-Organizing Maps (GSOM) with the uncertainty modeling capabilities of fuzzy logic, FGM provides a robust model for analyzing EEG signals. The method not only offers high accuracy in noisy and complex data but also generates interpretable fuzzy rules that provide valuable insights into underlying physiological processes.

This study demonstrates that FGM achieves approximately 92% classification accuracy, outperforming traditional methods such as SVM, k-NN, and MLPs. The dynamic structure and adaptability of FGM make it a suitable tool for real-time EEG analysis in clinical environments.

Overall, FGM proves to be an effective and interpretable tool for EEG signal analysis, offering enhanced diagnostic capabilities for neurological disorders.

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