Fuzzy Logic for Neonatal EEG Analysis: A Systematic Review

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Abstract: Machine learning has advanced in healthcare, aiding diagnostics, treatment, and monitoring. In neonatal health, it helps to classify and predict conditions such as hypoxic-ischemic encephalopathy, which requires early detection. Thus, EEG pattern analysis is key in improving the neonatal prognosis. In this work, we present a systematic review of the literature to identify strategies currently employed to classify and predict neonatal EEG patterns using fuzzy logic. Fuzzy logic is particularly valuable for handling uncertainties in biological signals and improving interpretability. Five studies were selected and analyzed, focusing on applying fuzzy systems to detect epileptic events. The reviewed studies highlight techniques involving EEG data, emphasizing the role of fuzzy logic in advancing the understanding and management of neonatal neurological conditions, contributing to the state of the art in this critical field.

1 INTRODUCTION

Perinatal asphyxia is one of the leading causes of neonatal mortality, which can lead to hypoxic-ischemic encephalopathy (HIE), a severe condition that affects approximately 20 out of every 1,000 live births in low- and middle-income countries (Abate et al., 2021). HIE compromises the brain to varying degrees, often triggering epileptic seizures within the first hours of life. These events not only indicate the presence of brain injuries but also reflect the severity of neurological impairment (Zhou et al., 2021). Subclinical seizures are difficult to detect without continuous EEG monitoring and represent a significant risk due to the potential for cumulative neurological damage. In these cases, continuous EEG monitoring is essential for early seizure detection, allowing timely clinical interventions that can improve the neonatal prognosis (Glass and Shellhaas, 2019).

In the context of HIE, neonatal epilepsy is a critical neurological condition whose early detection is challenging, as it requires constant monitoring of brain activity signals. Epileptic events and changes in the background patterns of electroencephalography (EEG) signals are valuable indicators of neurological impairment, which can help predict long-term sequelae or immediate life-threatening risks (Toet and Lemmers, 2009; Wikström et al., 2012). Although conventional electroencephalography facilitates the identification of these conditions, the manual interpretation of these signals is complex and time-consuming, requiring the continuous presence of specialists for enhanced, real-time analysis (Wu et al., 2019).

To overcome this limitation, recent research has focused on automating the analysis of these signals by developing algorithms that automatically detect epileptic seizures and classify EEG background patterns in newborns (Wu et al., 2019; Montazeri et al., 2021). These algorithms provide significant support for early diagnosis, enabling rapid and precise in-

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terventions that can mitigate long-term neurological damage (Abbasi et al., 2017). Furthermore, automation allows for the expanded use of EEG in environments where specialists are limited, such as remote areas or smaller hospitals (Pavel et al., 2020).

Among the promising approaches for improving these automated systems is applying fuzzy logic (Abbasi et al., 2014). By handling uncertainties and variabilities inherent in biological signals, fuzzy logic enables a more flexible and robust classification of EEG data (Güler and Übeyli, 2005; Abbasi et al., 2014; Pavel et al., 2020). This flexibility is essential, as these signals frequently present subtle and continuous variations, which are difficult to categorize using traditional binary systems (Wu et al., 2019; Montazeri et al., 2021). Thus, fuzzy logic applied to neonatal monitoring can potentially increase sensitivity and specificity in detecting epileptic events and classifying background patterns, providing a more adaptable and precise tool that allows specialists to better understand and diagnose clinical conditions.

In this context, fuzzy logic stands out for its high explainability in classification systems, thanks to the use of "IF-THEN" rules formulated in language close to human reasoning and the intuitive representation of concepts through linguistic variables. This approach allows clear traceability of how inputs influence outputs, facilitating the interpretation of results by specialists. In applications such as EEG analysis, fuzzy logic enables incorporating heuristic or empirical knowledge, such as known patterns of brain activity, ensuring greater transparency and reliability in the decision-making process (Zadeh, 1996; Ross, 2010).

On the other hand, Deep Neural Networks, while extremely effective in complex scenarios, operate as "black boxes", making it difficult to interpret their decisions due to the high complexity of the models. Despite advancements in explanation methods, these mechanisms still lack the simplicity and clarity provided by fuzzy logic. Thus, while neural networks are preferable for tasks requiring high performance with large volumes of data, fuzzy logic is more suitable in contexts where interpretability and decision reliability are essential (Samek, 2017).

In this scenario, this paper presents a systematic review of algorithm-based approaches for the detection of epileptic events and classification of neonatal EEG background patterns, focusing on methodologies that integrate fuzzy logic to enhance the accuracy, explainability, reliability, and adaptability of these algorithms in order to improve clinical interventions.

The remainder of the paper is structured into four sections. Section 2 outlines the definition and steps involved in conducting a systematic review. Section 3 details the methodology employed to perform the systematic research and discusses each stage. Section 4 presents the results, while the final section offers the conclusions drawn from this study.

2 SYSTEMATIC REVIEW

The systematic literature review (SLR) is a rigorous and structured method widely used to synthesize scientific evidence on a specific research question. Unlike traditional reviews, this approach adopts a transparent, replicable, and protocol-driven process, minimizing biases and enhancing the reliability of conclusions (Higgins et al., 2019; Liberati et al., 2009). Recognized as the gold standard in evidence-based practice, systematic reviews are extensively employed in fields such as health, education, and social sciences, which are essential in informing science-based practices (Kitchenham, 2004; Gough et al., 2017).

A SLR follows a rigorous methodology that ensures its standardization and scientific validity. To conduct a systematic review, it is essential to establish a research protocol consisting of four main steps. The first step involves formulating the research questions the review aims to answer, providing a clear direction for the study. In the second step, the search strategy is defined, including selecting databases and search terms to identify and retrieve relevant articles. The third step establishes the inclusion and exclusion criteria for the studies, while the fourth and final step determines the data to be extracted, how the studies will be characterized, and the methods for synthesizing and analyzing the data (Keele et al., 2007; Liberati et al., 2009; Gough et al., 2017; Bramer et al., 2018; Higgins et al., 2019).

The main advantage of a systematic review is its well-defined methodology, which greatly reduces the risk of bias in the results. This approach ensures that articles are not selectively chosen to align with the author's personal viewpoint, promoting a more balanced and objective synthesis of the literature (Liberati et al., 2009).

3 METHODOLOGY

The methodology employed for conducting the systematic review adhered to the approach outlined by Keele *et al.* (2007) and is summarized in the flowchart shown in Figure 1. This flowchart illustrates the progression of the process, during which articles identified through searches are systematically excluded from the scope of the study. A detailed discussion of

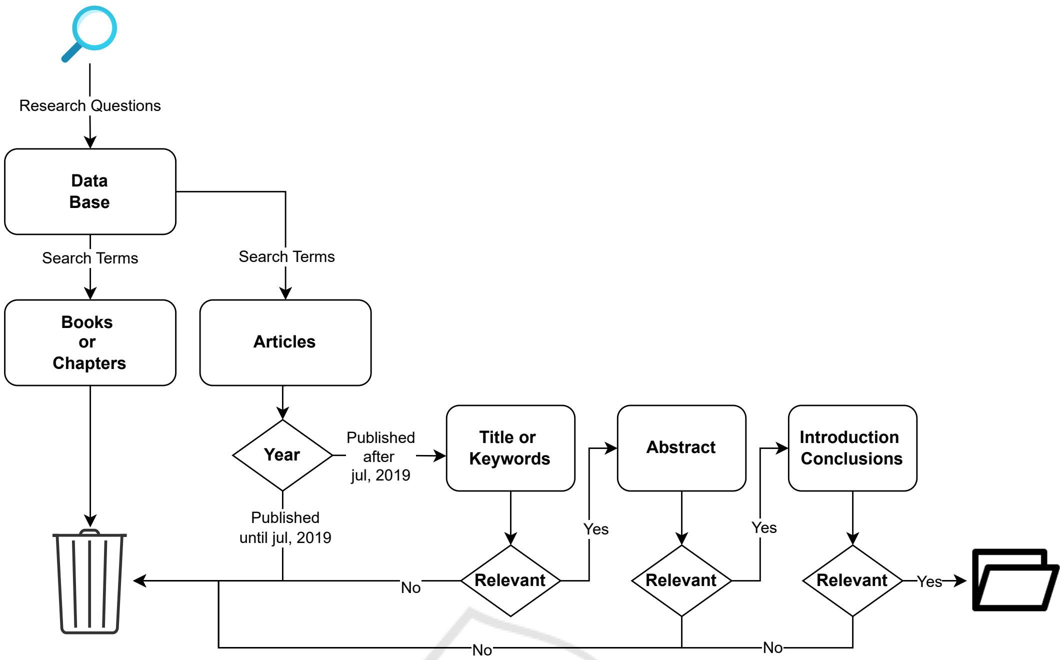

Figure 1: Flowchart of the theoretical review methodology.

the criteria adopted for each of the four key stages of the systematic review process follows in subsections 3.1, 3.2, 3.3, 3.4 and 3.5.

3.1 Research Questions

The first step in conducting a systematic review involves defining the research questions that must be answered. These questions guide the development of search terms and keyword combinations used in database searches. Based on the problem discussed in the Introduction, four research questions were formulated as follows:

Q1. Which predictive methods are applied to classify background patterns in neonatal EEG signals?

Q2. Which computational approaches detect epileptic and subclinical seizures in neonatal EEG signals?

Q3. Which techniques are applied to identify sleep-wake states in neonatal EEG signals?

Q4. Which methodologies have expert systems employed to diagnose encephalopathies in newborns shortly after birth?

It is important to note that for each planned study, only fuzzy logic approaches were reviewed, as the research aims to assess their applicability in predicting neonatal encephalopathy using biomarkers derived from electroencephalography recordings.

3.2 Search Terms

To define the search terms for composing the query string, a preliminary analysis of each term was conducted using the Google Scholar database, as it is diverse and indexes articles and works from various sources. The study considered only the last 5 years (2020–2024). It was progressively conducted (see Table 1 for indexes k=1 to k=17) to identify the best terms for the composition of the query string as the number of articles returned increased. The combination of search terms and the number of articles returned for each composition are described in Table 1. Finally, the conjunction ‘AND’ and the term ‘fuzzy’ were added to the end of the query string that yielded most of the results (see k=17 in Table 1) to limit the search to articles that use prediction methods based on fuzzy logic.

3.3 Data Bases

The *Google Scholar* database can be a useful tool for exploring broad and preliminary literature or for assisting in developing the query string. However, due to its lack of quality control, limited precision, and difficulty in filtering results, it is not the best option as a primary source for systematic reviews. Therefore, specialized databases (DB) such as *ACM Digital Library*, *EI Compendex*, *IEEE Xplore*, *Web of Science*, *PubMed*, *ScienceDirect*, *Scopus*, and *SpringerLink*

Table 1: Keyword combinations used to construct the search string and the respective number of articles returned.

K	Combination	Articles returned
1	(“baby”) AND (“electroencephalogram”)	4440
2	(“preterm”) AND (“electroencephalogram”)	4840
3	(“newborn”) AND (“electroencephalogram”)	6940
4	(“neonatal”) AND (“electroencephalogram”)	12200
5	(“preterm” OR “baby”) AND (“electroencephalogram”)	8090
6	(“preterm” OR “newborn”) AND (“electroencephalogram”)	9130
7	(“baby” OR “newborn”) AND (“electroencephalogram”)	9700
8	(“preterm” OR “neonatal”) AND (“electroencephalogram”)	13400
9	(“neonatal” OR “baby”) AND (“electroencephalogram”)	14300
10	(“neonatal” OR “newborn”) AND (“electroencephalogram”)	14400
11	(“neonatal” OR “newborn” OR “baby” OR “preterm”) AND (“electroencephalogram”)	16200
12	(“neonatal” OR “newborn” OR “baby” OR “preterm”) AND (“electroencephalography”)	16400
13	(“neonatal” OR “newborn” OR “baby” OR “preterm”) AND (“EEG”)	20900
14	(“neonatal” OR “newborn” OR “baby” OR “preterm”) AND (“EEG” OR “electroencephalogram”)	22500
15	(“neonatal” OR “newborn” OR “baby” OR “preterm”) AND (“EEG” OR “electroencephalography”)	23100
16	(“neonatal” OR “newborn” OR “baby” OR “preterm”) AND (“EEG” OR “electroencephalography” OR “electroencephalogram”)	26000
17	(query string presented in k=16) AND (“fuzzy”)	2730

were selected, as they collectively provide a more robust, reliable, and structured approach for conducting systematic reviews.

3.4 Exclusion/Inclusion Criteria

Exclusion Criteria (EC) are defined as factors that, while meeting the inclusion criteria, possess additional characteristics that may hinder the study's success or lead to the inclusion of irrelevant or unnecessary information. These criteria are designed to ensure the study remains focused and reliable. The EC considered in this study were:

- EC1: Books and book chapters, as the focus is on identifying recent developments by researchers rather than exploring the concepts and definitions related to the subject discussed in the work;
- EC2: Articles published before July 2019, as the goal is to focus on the most recent developments and studies being conducted by scholars and researchers;
- EC3: Articles that do not incorporate electroencephalography or electrocorticography (ECoG) signals in their methodology, as the focus of this systematic review is on the utilization of brain-derived signals to assess the clinical status of newborn patients;
- EC4: Articles that did not demonstrate the use of fuzzy logic in the methodology for analyzing EEG signals.

Inclusion Criteria (IC) are defined as the main characteristics of the population or research being conducted. ICs are used to answer the research questions and are presented below:

- Title and Keywords: Does the article title reflect the application of expert systems for predicting or classifying neurological disorders in newborns using electroencephalography (EEG) signal analysis? Do the keywords of the article include electroencephalography or terms related to this context, suggesting that the article likely involves the analysis of such signals?
- Abstract: Does the article discuss the application of fuzzy systems for monitoring and predicting epileptic seizures in EEG signals? Does the study discuss the application of the fuzzy system for classifying background patterns in EEG signals? Does the study present a fuzzy system for classifying the sleep-wake cycle in EEG signals? Does the study present an expert system for monitoring and diagnosis based on fuzzy logic?
- Introduction and Conclusion: Are the study's objectives clearly defined? Does it propose using fuzzy logic to predict or classify electroencephalography (EEG) exams? Does the article report that the designed system can be applied to the neonatal population?

3.5 Selecting Works

After the inclusion and exclusion criteria were defined, the study was conducted using specialized databases (see section 3.4) and managed with the Parsifal software. The first step consisted of performing a search based on the defined research terms (see k = 17 in Table 1) across all selected databases, initially without applying any exclusion criteria.

Subsequently, the articles were imported into Parsifal, where duplicate studies were identified and removed. Duplicates were eliminated by retaining only the articles from the database with the most records.

After the removal of duplicate studies (RDS), the exclusion criteria were applied as follows: the publication date of the retrieved articles (EC2) and the type of publication, specifically excluding books and book chapters (EC1).

After applying criteria EC1 and EC2, the remaining articles were evaluated based on EC3, which excluded studies that did not incorporate EEG signals in their methodology. This evaluation was performed by analyzing each article's title and keywords.

Following the evaluation of the titles and keywords of the articles, EC4 was applied by analyzing the abstracts to determine whether the methodology employed included fuzzy logic. Thirty-one articles remained after applying this exclusion step.

Finally, the last step was to analyze the 31 remaining articles to determine whether they addressed the questions defined by the inclusion criteria. Initially, each article's title and keywords were evaluated. If the title did not meet the established criteria, the article was discarded. However, if the title and keywords complied with the criteria, the analysis proceeded to the article's abstract. If the abstract met the inclusion criteria, the introduction and conclusion of the article were then evaluated to confirm its acceptance.

The described process is summarized in Table 2, which presents the total number of articles retrieved from each digital library at each study stage. Figure 2, in turn, summarizes the number of articles excluded during the application of the inclusion and exclusion criteria adopted in this systematic review.

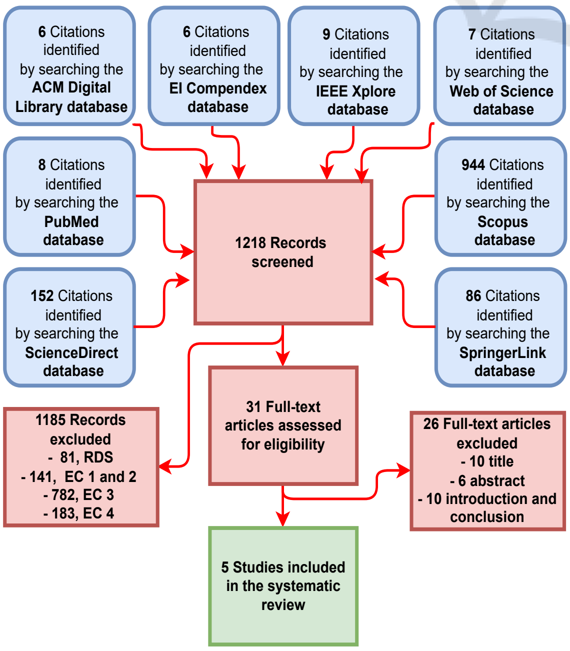

Figure 2: PRISMA Flow Diagram.

Table 2: Total articles returned for each of the described steps.

Databases	Initial	RDS	EC1 EC2	EC3	EC4	IC
ACM Digital Library	6	0	0	0	0	0
EI Compendex	6	2	2	1	0	0
IEEE Xplorer	9	6	6	6	1	0
Web of Science	7	7	7	6	5	4
PubMed	8	0	0	0	0	0
ScienceDirect	152	134	94	22	1	0
Scopus	944	911	841	166	24	1
SpringerLink	86	77	46	13	0	0
Total	1218	1137	996	214	31	5

After applying all inclusion criteria, five articles based on the established research questions were selected (briefly discussed in Sect. 4), with information detailed in Table 3.

4 RESULTS

In this section, each of the five selected articles is briefly presented, highlighting the questions they address and their main points.

Before starting this analysis, a word cloud was created based on the frequency of keywords found in each article's titles, abstracts, introductions, and conclusions. This approach allowed for a more detailed examination of the central concepts discussed in the selected articles.

In constructing the word cloud presented in Figure 3, the most frequently appearing keywords in the selected sections were considered. The most cited terms are displayed in the figure with larger font sizes, while less frequently cited terms across the set of articles are shown with proportionally smaller font sizes. This visualization facilitates the identification of the most relevant concepts discussed in the analyzed articles.

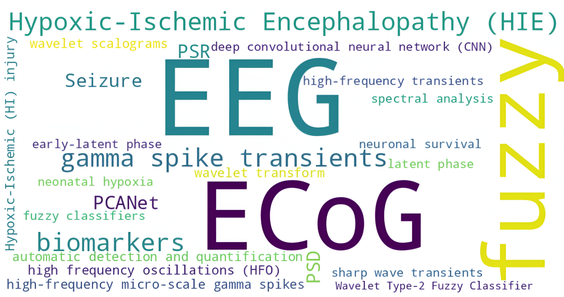

Figure 3: Word cloud assembled from selected articles.

Thus, it can be concluded that the most frequent words precisely define the scope of this study, namely, the terms used in the queries. Additionally, terms such as "ECoG" and "Hypoxic-Ischemic En-

Table 3: Summary of key characteristics and findings of selected studies.

Study	Methodology	Results	Dataset	Relevance	Fuzzy Logic-based Approach
Liu *et al.* (2024)	Hybrid EEG classification using PCANet, phase space reconstruction (PSR), and power spectral density (PSD). Two-layered classification: F-KNN for initial layer; SVM for second layer (Liu et al., 2024).	Accuracy: 99.4%, Sensitivity: 99.5%, Specificity: 99.75%. Demonstrated potential for neonatal EEG but not validated on neonatal signals.	Non-neonatal (Public)	Addressed Q2 and Q3, highlighting seizure prediction potential without neonatal validation.	Cascade Deep Learning Architecture: Fuzzy K-Nearest Neighbor (F-KNN)
Abbasi *et al.* (2020)	Spectral analysis using Fourier Transform with a Type-1 fuzzy classifier (FFT-Type-1-FLC). Focused on high-frequency spike transients (80-120 Hz) (Abbasi et al., 2020).	Overall performance: 98.87%. Effective in identifying spike transients but limited to specific patterns (e.g., interburst intervals not covered).	Animal (Private)	Addressed Q1 (partially), Q2, and Q4, providing a strong framework for transient detection.	Type-1 Fuzzy Logic Classifiers: - FFT-Type-1-FLC classifier
Abbasi *et al.* (2021)	Scalogram-based CNN (WS-CNN) and fuzzy classifiers (WT-Type-I-FLC and FFT-Type-I-FLC) using CWT for feature extraction. Focused on the identification of post-hypoxic epileptiform EEG spikes (Abbasi et al., 2021).	WS-CNN: Accuracy 99.81%, AUC 1.0. Fuzzy classifiers effective (99.04%, 98.42% accuracy), but CNN outperformed fuzzy systems in robustness.	Animal (Private)	Addressed Q1 (partially), Q2, and Q4, comparing deep learning and fuzzy systems effectively.	Type-1 Fuzzy Logic Classifier: - Wavelet-based fuzzy classifier (WT-Type-1-FLC) - Fast Fourier transform-based Fuzzy classifier (FFT-Type-1-FLC)
Abbasi *et al.* (2019b)	Reverse biorthogonal wavelets (Rbio-WT-Type-1-FLC) for detecting hypoxic-ischemic transients in gamma range (80-120 Hz) (Abbasi et al., 2019b).	Overall performance: 99.78%. Demonstrated biomarkers for HIE diagnosis during latent phase.	Animal (Private)	Addressed Q1 (partially), Q2, and Q4. Significant potential for diagnostic support tools.	Type-1 Fuzzy Classifier: Rbio-Wavelet Type-1 fuzzy classifier (rbio-WT-Type-1-FLC)
Abbasi *et al.* (2019a)	Wavelet-based Type-2 fuzzy classifier (WT-Type-2-FLC) for sharp-wave transients detection post-hypoxic-ischemic insult (Abbasi et al., 2019a).	Identified transients correlated with neuronal preservation during latent phase. Key for therapeutic timing.	Animal (Private)	Fully addressed Q4, focusing on biomarkers and neuroprotective intervention timing.	Type-2 Fuzzy Classifier: Wavelet-based Type-2 fuzzy classifier (WT-Type-2-Fuzzy)

cephalopathy (HIE)" also stand out, even though they were not directly included in the queries, as they are closely related to the overall context of the study. In this context, ECoG represents a brain-derived signal, similar to surface EEG, while HIE refers to a clinical condition associated with the neonatal population.

The analysis included five selected studies, each employing fuzzy logic methodologies to enhance the analysis of neonatal EEG signals. For instance, Liu *et al.* (2020) introduced a hybrid EEG classification model that utilized PCANet, phase space reconstruction (PSR), and power spectral density (PSD) for seizure detection. While the model achieved high accuracy, sensitivity, and specificity, it lacked validation with neonatal datasets. Similarly, Abbasi *et al.* (2020) focused on high-frequency spike transients using Fourier Transform-based spectral analysis and a Type-1 fuzzy classifier (FFT-Type-1-FLC). Their approach demonstrated strong performance in detecting specific EEG patterns but showed limited scope for identifying other pathological background patterns.

A comparative study between fuzzy classifiers and a scalogram-based CNN (WS-CNN) for identifying high-frequency spikes is conducted by Abbasi *et al.* While the fuzzy classifiers demonstrated robust accuracy, the CNN outperformed them regarding robustness and adaptability to morphological variations. In an earlier study, Abbasi *et al.* (2019b) proposed a Type-1 fuzzy classifier based on reverse biorthogonal wavelets (Rbio-WT-Type-1-FLC), designed to detect hypoxic-ischemic transients and identify valuable biomarkers for the early diagnosis of hypoxic-ischemic encephalopathy. Following this same line of research, Abbasi *et al.* (2019a) developed a Type-2 fuzzy classifier (WT-Type-2-FLC) correlating sharp-wave transients with neuronal survival during the latent phase after hypoxic-ischemic insults, highlighting its potential to guide neuroprotective interventions.

Table 3 presents the key characteristics and findings of these studies, detailing their methodologies, results, and specific contributions.

This structured analysis highlights the diverse methodologies employed and their contributions to the field. While the results underscore the potential of fuzzy logic systems, they also reveal critical gaps, particularly the lack of validation in human neonatal datasets and the need to address broader EEG patterns for clinical application.

5 CONCLUSIONS

Machine learning-based methodologies have been widely used to solve problems in the healthcare field. In neonatal contexts, conditions such as hypoxic-ischemic encephalopathies and epileptic events require continuous monitoring and early diagnosis, as they can cause severe neurological damage.

The objective of this study is to identify prediction and classification methodologies based on fuzzy logic applied to the analysis of neonatal EEG signals, focusing on advancements that improve system sensitivity, specificity, and interpretability. To this end, a systematic review was conducted to understand the state-of-the-art techniques used for the detection of epileptic events and background patterns in neonatal EEGs. The review was carried out considering strict inclusion and exclusion criteria to select relevant studies, ensuring the quality and reliability of the results.

Based on the reviewed studies, it was observed that fuzzy logic techniques - such as Type 1 and Type 2 fuzzy classifiers, wavelet-based fuzzy systems, frequency spectrum-based fuzzy systems, and Fuzzy K-Nearest Neighbor (F-KNN) - are widely applied in the detection of epileptic events and the classification of neonatal EEG background patterns. These approaches demonstrate how fuzzy logic improves the sensitivity, specificity, and interpretability of algorithms that process complex biological signals, particularly in challenging contexts such as hypoxic-ischemic encephalopathy. Nonetheless, the validation of these techniques has predominantly been performed on animal models or datasets of adult patients, which presents limitations for their direct application to human neonates. This methodological gap highlights the need for future studies aimed at validating these techniques in real neonatal populations to ensure their clinical relevance.

From this perspective, several aspects remain unexplored, offering opportunities for future research. In this context, none of the selected studies fully address the integration of multiple EEG patterns beyond high-frequency peak transients. Other patterns, such as burst suppression, excessive discontinuity, low-voltage patterns, and inactivity, were not considered in the reviewed studies, despite their clinical importance. Furthermore, the databases used often include EEG signals with limited characteristics or obtained under controlled conditions, which may not represent the broad variability observed in neonatal intensive care units (NICUs). Thus, developing a comprehensive fuzzy system capable of identifying a wider range of background patterns and validating by real clinical data could significantly improve diagnostic accuracy.

Additionally, while the reviewed studies explore conventional fuzzy classifiers, none employed the Adaptive Neuro-Fuzzy Inference System (ANFIS). The use of ANFIS could be a promising solution as it combines the high accuracy of neural networks with the explainability and interpretability of fuzzy logic. Implementing this method would enable the creation of hybrid systems capable of automatically adjusting fuzzy rules based on EEG patterns, thereby enhancing both accuracy and interpretability. Nevertheless, the lack of widely available and specific neonatal EEG databases limits the evaluation of new methods and underscores the need for initiatives to build standardized neonatal clinical repositories. Another possibility would be the integration of real-time monitoring systems based on fuzzy logic, providing continuous feedback to physicians in NICUs, leading to faster and more effective interventions.

Finally, incorporating multimodal data sources — such as oxygen saturation and clinical observations — into fuzzy logic-based systems could offer a more holistic approach to neonatal neurological monitoring, providing robust support for early diagnosis and treatment planning. So, given these gaps, the next step is to develop and implement a comprehensive fuzzy logic-based methodology for neonatal EEG analysis that addresses these unexplored areas. This approach should prioritize validation using real neonatal datasets to ensure greater clinical applicability while aiming to enhance the accuracy, explainability, and adaptability of diagnostic tools, thereby offering more reliable support for clinical interventions and improving outcomes in neonatal care.

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