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EEG Analysis in Benign Epilepsy with Centro-Temporal Spikes: A Comprehensive Review

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Abstract

The electroencephalogram (EEG) methods of analysis for the diagnosis of Benign Epilepsy with Centrotemporal Spikes (BECTS) are reviewed. The focus is on the procedures reported in scientific literature for EEG analysis and diagnosis in BECTS because some recent and potential applications of artificial intelligence (AI) aiming to enhance the diagnostic accuracy and time reduction process, support to be the next step for advancing our knowledge of the electrical nuclei sources and dynamics of energy distribution through scalp in patients suffering epilepsy. The advantages of AI classification techniques have an increasing publication rate in specialist literature, with no clear agreement in methodology. Hence, a better comprehension of procedures, arguments and achievements is needed. For reaching this goal 1) we review the background knowledge of clinical characteristics of BECTS; 2) analyze the results and advantages of computational processing methods for source and connectivity analysis of EEG in BECTS; finally, 3) we explore the IA methods published in specialized journals for BECTS analysis. In conclusion, we argue in favor of a combined use of *a priori* information that is the base of the clinical visual analysis of EEG as a potential feature to be included in AI methods for classification of epileptiform graphoelements in EEG in BECTS diagnosis.

Keywords: BECTS; IES; clinical EEG; epilepsy; EEG source analysis; network functional analysis

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1. Introduction

Benign Epilepsy with Centrotemporal Spikes (BECTS) is the most common pediatric epilepsy syndrome.

Benign Rolandic Epilepsy with Centrotemporal Spikes (BRECTS), also known as rolandic epilepsy (RE), Benign Epilepsy with Centrotemporal Spikes (BECTS), Benign Childhood Epilepsy with Centrotemporal Spikes (BCECTS), and recently Self-limited Epilepsy with Centrotemporal Spikes (SeLECTS) [1], is the most common form of epilepsy syndrome in children [2].

Benign Epilepsy with Centrotemporal Spikes (BECTS hereafter) is classified as an idiopathic focal epilepsy syndrome of childhood, meaning that it occurs in developmentally and neurologically normal children and is presumed to be genetic and age-dependent, with no underlying structural brain lesions [3]. However, structural and functional abnormalities have been reported. The genetic basis is thought to be polygenic and complex, but it is inherited as an autosomal dominant trait, possibly associated with specific genes such as *GRIN2A*, and linked to chromosome 15q14. This genetic determination is linked to hereditary impairment of brain maturation [4].

BECTS accounts for approximately 8–25% of all childhood epilepsy cases. The overall incidence is 10–20/100,000 in children aged 3–15 years. The age of onset ranges from 1 to 14 years, with a peak onset typically around 7–8 years. This condition typically exhibits male predominance. The sex ratio was 60:40 (boys to girls). The disease is characterized by a tendency to start at a certain age and disappear spontaneously before adolescence, with complete recovery of clinical symptoms typically occurring at the age of 15 years. While 15% of children may have only a single seizure, 85% may experience recurrent seizures for several years [5]. This favorable prognosis led to the term "benign." Despite the term "benign," BECTS is frequently associated with neuropsychological deficits, leading to debate regarding its classification [6]. An increasing number of reports suggest a "not so benign" outcome, showing atypical evolution of the disease. A subset of patients may evolve into a less "benign" course, called atypical BECTS (or malignant rolandic epilepsy), characterized by high seizure frequencies, different seizure types, cognitive problems, and potentially Continuous Spike and Waves During Sleep (CSWS) on EEG [7]. A young age at seizure onset is associated with a high risk of evolving into atypical BECTS. However, many recent studies have reported persistent cognitive and behavioral difficulties, leading to the alternative, more recent term, Self-limited Epilepsy with Centrotemporal Spikes (SeLECTS) [8].

Seizures are characterized by being focal, relatively infrequent, and usually brief (lasting 1–3 minutes). They are predominantly nocturnal (occurring during sleep). Symptoms are generally unilateral, often starting as somatosensory and motor symptoms, mainly involving the orofacial region, including facial twitching and stiffness, tingling or numbness of the face and throat, drooling, and hypersalivation. Speech arrest is a characteristic symptom. Seizures can spread and occasionally involve both sides, manifesting as generalized shaking, stiffening, and loss of consciousness [5].

2. Clinical Characteristics of BECTS

2.1. Diagnosis of BECTS

Clinical and Behavioral Assessment

The initial diagnosis of BECTS is fundamentally based on clinical findings and is typically supported by clinical routine EEG [9,10]. Diagnosis requires fulfilling criteria established by the International League Against Epilepsy (ILAE), including a typical age of onset, characteristic seizure semiology (sensorimotor seizures, often orofacial), a normal neurological examination, and the absence of brain lesions on MRI [9–11]. Furthermore, detailed clinical profiles could be collected, including demographic details, family history, associated systemic diseases, and the semiology of seizures (frequency, duration, and relationship to sleep), by interviewing primary caregivers, guardians/witnesses, and sometimes using home videos [12]. Additionally, given the recognized cognitive deficits associated with BECTS, neuropsychological assessments and intelligence tests are critical for comprehensive diagnosis and monitoring [7,9].

2.2. Electrophysiological Assessment Techniques

Electroencephalography (EEG) is the essential diagnostic tool, defining the hallmark of centrotemporal spikes (CTS), which relies on characteristic findings from the EEG [10]. Assuming EEG signals like serial time varying in BECTS, the obvious visual observation of changes at online recording represents the common clinical practice [13]. To improve diagnostic accuracy, EEG recordings must include awake and sleep recordings, especially non-Rapid Eye Movement (non-REM) sleep recordings, because CTS are typically activated by drowsiness and non-REM sleep (Stage N2 sleep) [14]. Hence, the most common analysis for BECTS diagnosis is the presence, location (unilateral/bilateral), frequency, and morphology (diphasic/triphasic patterns) of the centrotemporal spikes visually observed in routine EEG [9,15]. In the absence of obvious spikes, it is a challenge for clinicians to get accurate information from underlying cortical rhythms and network dynamics that BECTS pathology can reveal and pose a challenge to current AI techniques to localize and predict the features of seizures into ongoing recordings [16,17].

This challenge increases if patients have no record or visual manifestation of motor seizure, mioclonic or astatic changes to correlate with EEG data. Only after the observation of ictal or interictal events in the EEG recording, a common analysis tool for this diagnosis is the spectral analysis. Spectral analysis consists of the decomposition of raw EEG into power spectrum of the energy distributed through the scalp, assuming the accurate sensing of the synchronized post-synaptic potentials of several neurons [18] for detecting interictal sleep spindle observed during EEG to measure paroxysm amplitude, duration, and density and the high-frequency oscillations (HFOs about 80–250 Hz) or ripples on top of rolandic spikes.

Spectral Power Analysis decomposes relative and absolute spectral power of resting-state EEG rhythms or bands (typically split in delta 1-4, theta 4-8, alpha 8-12, beta 12-30 and gamma <30 Hz.) in the geometric source space of the scalp [18] to identify regions of abnormal activity (e.g., increased power in theta, alpha, and beta bands in the right centrotemporal areas, and decreased power in frontal/occipital lobes) [19]. Also, analysis of beta band power (14.9–30 Hz) in the sensorimotor cortex (the seizure onset zone) during sleep, measured using high-density EEG and source localization, is explored as a potential dynamic physiological biomarker of BECTS status [20].

The spectral analysis depicted in graphical spectrograms or in brain topographical maps are useful for clinicians to corroborate the visual analysis of paroxysm; the reduction of ictal or interictal changes in the EEG after pharmacology therapy, or the changes due to brain development. This procedure is enriched when prolonged recordings (4-6 hours of recordings), supported by video observations of clinical characteristics of epileptic seizures, are utilized by physicians [14]. This process of diagnosis, however, is altered if no seizure is observed, despite cognitive, behavioral or emotional, and EEG paroxysmal observations. Hence, this analysis procedure is biased by clinical experience, the software used for frequency decomposition and the ability to use it; as well as the techniques for preprocessing (rejecting muscular artifacts, eye blinking, teeth clenching or neck tension**)** the signal that the user knows, and the software performance.

3. Computational Methods for EEG Analysis

3.1. Source Localization and Connectivity Analysis

To move beyond the visual interpretation of surface EEG and understand the widespread network abnormalities, some methods are utilized. These analysis techniques are computational based and aimed at taking advantage of spectral analysis decomposition of raw EEG, to obtain integrated and complex information of brain activity. These techniques can be grouped into two main analytic processes: 1) Source localization and 2) Functional network analysis.

3.1.1. Source Location by Dipoles

The concept of the dipole source is fundamental to the non-invasive localization of brain activity, particularly epileptic activity in EEG. A dipole represents the Equivalent Current Dipole (ECD), being an idealized representation of a localized electrical current source within the brain.

Definition

The main task of EEG Source Localization (ESL) is to solve the inverse problem, that is, to determine the location, orientation, and strength of electrical sources (dipoles) inside the brain based on potential fields measured at the scalp [21].

A dipole source is characterized by three parameters: 1) Location: Defined by Cartesian coordinates (*x,y,z*) is expressed relative to the midline (zero point) of the axes, where +1 or -1 represents the far end of the model sphere. In spherical coordinates, the eccentricity (radial distance from the center of the head) is a key parameter used to describe the depth of the source. 2) Orientation: Defined by vectors (n_x, n_y, n_z being fractions of ±1) is crucial because it defines the direction of current flow and whether the source is tangential (parallel to the cortical surface, often found in sulci/fissures) or radial (perpendicular to the cortical surface, often found at gyral crowns). 3) Amplitude/Strength (Amp): The current strength or electrogenesis of the dipole [22].

Dipole Modeling Algorithms

Dipole analysis relies on choosing appropriate constraints (mathematical assumptions) on the source distribution to solve the ill-posed inverse problem [23].

There exist two main strategies for modeling, assuming a single, small focal source that generates the measured field. It is often used for analyzing high-amplitude, monomorphic spikes, and it is called Single Equivalent Current Dipole (SECD). The second strategy consists in assuming a sequential fitting strategy with multiple equivalent dipoles (e.g., up to three) where dipoles have fixed location and orientation, and their time-varying activity is analyzed via source waveforms. This procedure is called Multiple Source Analysis (MSA) [24].

Different iterative algorithms constrain the dipole fitting in time. Among these are 1) Fixed Equivalent (Coherent) Algorithm by which location and orientation are fixed across the spike interval, but amplitude changes at each time point. 2) Rotating Algorithm (ROT-NR), that by means of the best fit at each time point, fixes the location of the dipole, and in case of non-linear series, has been proven to statistically identify the non-regularized (NR) rotating dipole. 3) Moving Algorithm regularized (MOV-R) uses the best fit for each time point in parameters of orientation and amplitudes in cases of sources that are discreet with minimal propagation. 4) Regional Dipole Source (RDS) consists of three orthogonal dipoles at a single location, fitted to obtain an appreciate the major equivalent source location explaining the 3D current flow [23,25]

The quality of a dipole model is quantified by comparing the predicted field to the measured field [26]. Two main techniques are commonly used, 1) the residual deviation, by using the least square approach, represents the percentage of unexplained variance; the model takes for granted as non-acceptable explanation if the percentage is more than 10% [27]. 2) By taking the percentage of variance explained ≥ 95% or the correlation ≥ 98 the goodness of fit model accepts the dipole localization [23–25,28,29].

3.2. Functional Network Analysis

Functional network analysis involves mathematically assessing the interdependence of electrical activity between localized brain regions (sources), which means that it is generally constructed at the source level [30].

The main approaches to network analysis of EEG are: 1) Correlation, meaning the construction of a functional whole-brain network through the statistical index measurement of correlation and directionality between source pairs, is performed on the signals (waveforms) from virtual sensors located at specific brain sources. A correlation factor is derived by averaging the signals of these two sources. 2) Through Phase Synchronization, where a parameter of the phase leads and lags between two-time courses to detect changes in phase synchronization, it is possible to measure the weighted phase lag index. 3) Threshold estimation of significant connections, considering the t-values (Tp) of correlation factor (R) according to the number of connected data points (dipoles), is used to determine the functional connectivity of dipoles [31].

By applying these correlation techniques to represent functional connectivity, assessing the balance between functional integration and segregation within connectomes, Graph Theory analysis supports a small-world feature of brain function; in the case of epilepsy, this feature is disrupted [10].

Additionally, an approach for measuring the effective connectivity of the directional connectivity patterns and causal relationship is the Dynamic Causal Modeling (DCM). This method identifies the initiation and propagation of electrical activity to identify the causal influence between regions. It uses a Bayesian modeling scheme with competing hypotheses, such as Forward (F), Backward (B), and Forward-Backward (FB) models, to determine which model best explains the data [15].

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3.3. Dipole Source and Functional Connectivity in BECTS

Source Localization in BECTS

Dipole analysis is critical for electrophisologically characterizing EEG signals of various focal epilepsies based on the location, stability, and orientation of the spike sources [9].

In BECTS, the typical electrophysiological hallmark is a single tangential dipole traversing the central sulcus; this is consistent with the location and orientation in the rolandic region, often in the precentral gyrus or deep in the rolandic fissure (central sulcus). The dipole is typically tangential (horizontal) to the scalp surface, oriented with the positive pole directed frontally/anteriorly and the negative pole directed centro-temporally/posteriorly. The localization often corresponds to the face or hand area, but sometimes it reaches the leg area of the sensorimotor cortex [33,34].

Also, spikes in BECTS are stable in time. The dipoles from individual spikes are often clustered and stable for prolonged periods in individuals' life, which is a distinguishing hallmark among epilepsies. This stability is characteristic of BECTS compared to other focal epilepsies [34].

However, sometimes patients exhibit a more posterior dipole location. This feature of the dipole orientation has been reported in poor seizure control or cognitive deficits in BECTS. This characteristic is also exhibited in Panayiotopoulos syndrome, in which source localization sometimes suggests the calcarine sulcus and parieto-occipital areas.

In this context, averaging multiple spikes enhances the Signal-to-Noise Ratio and improves the stability and reliability of dipole analysis [15,24,34].

Altered Functional Networks in BECTS

On the other hand, DCM analysis has demonstrated that the central region (the source of epileptic activity) acts as the major driver of the brain network during interictal discharges (IEDs) in BECTS [36].

The sources highlight significant disorganization in the functional networks of children with BECTS, which is associated with cognitive deficits [10].

These functional changes in BECTS include complex functional connectivity changes, including small-world network impairment, meaning that brain networks in BECTS are less organized, shifting towards a more random network topology [34].

In frontal cortex, both unilateral and bilateral IEDs types of patients show increased frontal cortex connectivity, suggesting altered activity in the frontal cortex during interictal periods [10,34]. Also, in resting-state EEG, increased functional connectivity (hypercoupled state) has been detected among areas involved in sensory-motor integration, specifically the cingulate gyrus, superior and medial frontal gyri, and paracentral lobule, in the delta (0.5–3.0 Hz), theta (3.5–7.0 Hz), and alpha1 (7.5–10.0 Hz) frequency bands in patients with BECTS [37–39]. Additionally, high-frequency oscillations (HFOs, 50–250 Hz) have been reported in BECTS; the rate of pathological epileptic HFOs during NREM sleep is related to epilepsy severity [9,34,39]. Finally, the IES causes remote desynchronization in low frequencies (delta and theta) in frontal, temporal, and occipital networks [9]. This distant desynchronization is suggested to be a potential substrate for the functional disruption and network reorganization that leads to transient cognitive impairment (TCI) [9,34].

4. AI Methods for BECTS Analysis

An increasing amount of research involving AI, including methods for detecting IEDs within EEG recordings, populates scientific literature nowadays. According to a recent paper, these methods can be classified into four categories: 1) Rule-Based methods, using ad hoc processing steps for signals; 2) Machine Learning (ML) methods, which create employ or combine supervised or unsupervised algorithms to classify signals, allowing the machine to learn the classification process; 3) Deep Learning (DL) methods which, by creating layers of ML processes, execute the classification; and 4) Hybrid Methods, emerging from the combination of the categories above [40].

In this section, following the aforementioned categories, we explore the relevant literature for detecting and classifying IEDs from EEG recordings.

4.1. Rule-Based Methods for BECTS

Rule-based methods for analyzing BECTS typically involve implementing strict predefined criteria, filters, and thresholds derived from established neurophysiological knowledge. These methods are essential for initial spike identification, noise removal, and data preprocessing before inputting them into sophisticated ML classifiers.

The sources highlight rule-based methods used primarily in the first two stages of comprehensive automatic classification algorithms: 1) EEG spike detection, which is a principal rule-based method used for automatic spike detection, involves the application of a mathematical morphological filter. This technique is explicitly designed to isolate spikes by filtering out normal brain activity, such as brain rhythms and movement artifacts; the filtering methods is based on the morphological filter by erosion (the elimination of points of sampling frequency SF) and dilation (adding of points of SF); and 2) spike parameter validation which uses two main strategies: one filters according to a structural element defined by two U-shapes to follow the normal signal and capture slow variations in brain activity without cutting into the sharp changes characteristic of EEG spikes; and the second involves adaptation criteria, using time-window analysis or epochs (2,4 5, o 10 s) in the frequency and amplitude of brain rhythms to recalculate within a moving window, allowing the algorithm to adapt to the constantly changing background brain activity of patients EEG [41,42].

Another strategy for spike detection in the rule-based methods is the template method that uses geometric properties and similar measures compared against idealized patterns. In this case, a recorded waveform is contrasted against an idealized template of a a spike to assess its morphological and correlation features. This template is triangular (approximately 300 μV in amplitude, 60 ms in duration). An EEG signal segment is considered a potential spike if and only if the cross-correlation threshold exceeds about 60% and the morphological feature threshold is up 30%. However, since the EEG signal changes continuously, a Normalized Cross-Correlation (NCC) and Morphological Characteristics (MC) are parameters to set an adaptative template, in such a way that surpassing the threshold parameters reveals an IED in patient's EEG [41,43].

After initial detection, which may lead to false positives, a subsequent set of brain physiology rules is commonly applied to validate or eliminate detected candidate spikes (epileptiform discharges, IEDs). This post-processing procedure enhances the specificity of the detection algorithm. The rules require the spike candidate to meet the following conditions: 1) the upward and downward phases of the spike waves must have different signs (if they do not, the spike is considered falsely detected and rejected); 2) the duration of the spike's sharp wave should be between 20 ms and 80 ms, and must not exceed 200 ms; and, 3) the detected spike must occur in at least two neighboring EEG electrodes. Samples that do not conform to the characteristic peak to peak phenomenon are excluded to remove artifacts [41,42]. In essence, these rule-based methods work as strict criteria for ensuring that only signals meeting basic physical and morphological criteria of an epileptiform spike are detected, usually, serving as raw classifier feature for feeding sophisticated machine learning models for final classification based on subtle features.

4.2. Machine Learning Methods for BECTS

ML method are foundational components of intelligent automation techniques applied across various aspects of BECTS analysis, which allow for discrimination between subtle epilepsy types and the optimization of spike detection accuracy.

Several papers report the application of ML methods to BECTS classification. We have extracted the specific procedures from these papers.

Once some rule-based methodology is applied, BECTS classification is performed by comparing patients against diagnosis criteria.

One such procedure involves linear regression and linear discriminant analysis, which are supervised methods for reducing redundant information from original data or samples to detect characteristic information [44]. However, this method achieves less than 60% accuracy, resulting in poor performance. Hence, an Artificial Neural Network (ANN), is preferred, which features an input layer, a single hidden layer, and an output neuron. This methodology is suitable for binary classification, such as distinguishing between two samples (e.g., BECTS spikes vs. structural spikes) and achieved an accuracy rate of up to 75% for BECTS identification. The reliability reached was approximately 72% for EEGs containing 90 or more epileptiform discharges, using a non-overlapping training and testing strategy. Another ML strategy is the Support Vector Machine (SVM), which is a classification method used to solve linearly separable problems in the feature space [45]. Classification of non-linear signals, however, depends on the kernel function selected. When comparing groups of spikes, that a priori belongs to different groups, this selection may fulfill spike selection criteria but result in poor performance in classification between patients with EEG spikes [43].

4.3. Deep Learning Methods for BECTS

Deep learning (DL) methods represent a principal source of intelligent automation applied to the analysis and detection of BECTS and related epileptic activity in EEG. DL models are advantageous because they surpass traditional methods that rely on manual features from raw EEG data. Among DL methods, Convolutional Neural Networks (CNNs) outstand because they automatically process spatial and temporal features from raw EEG signals [46]. These models can learn hierarchical structures in natural signals, such as images and audio, and effectively extend this capability to EEG data analysis [47,48]. Some studies have explored CNN-based BECTS features extraction in EEG by applying Adaptive Template Matching (ATM) as a pre-processor. This segments candidate spikes based on the subject's waveform characteristics, resolving the data-overlapping issues inherent in traditional sliding window segmentation. Subsequently, a 1D-CNN architecture, which utilizes three convolutional layers, performs feature extraction and classification with fewer trainable parameters and lower computational demands [47]. The ATM plus CNN scores above 90% accuracy in classification of general forms of spikes [41,48]. On the other hand, by applying deep CNN, it is possible to extract spectral, spatial, and temporal features from raw EEG data, learning the general structure of a seizure that is less sensitive to inter-patient variations. The resulting model, featuring multiple convolutional and pooling layers, demonstrates an accuracy rate of 98.05% and sensitivity of 90.00% [49,50]. This procedure can also be visualized as an effective brain-mapping tool through visualization techniques, such as correlation maps. These maps display the spatial distribution of band-power features (alpha, beta, gamma, and theta) learned by the CNN during classification [50].

A variant of DL called the Recurrent Neural Networks (RNN), specifically Long Short-Term Memory (LSTM) and Bi-directional LSTM (BiLSTM), is critical for analyzing the sequential nature of EEG data, particularly due to its capacity to capture long-range temporal dependencies and mitigate the vanishing gradient problem. A BECTS spike detection algorithm that utilizes a stacked BiLSTM model takes a fusion of three time-domain sequences: the raw EEG signal, Smooth Nonlinear Energy (SNE), and Morphological Characteristics (MC). This methodology has been proven to be an optimal spike detection model, demonstrating superior capability in time-series data learning, and achieving an average score of 88.54% and a sensitivity of 92.04% across patients with BECTS [50].

Additionally, another method employs a weighted fusion strategy to combine multichannel EEG signals, followed by an LSTM detection method to classify spike/non-spike events achieving an average score of 95.74%, sensitivity of 93.94%, and precision of 97.73% [54].

4.4. Hybrid Methods for BECTS

Hybrid methods in the context of BECTS EEG analysis involve combining multiple distinct analytical techniques, often integrating traditional processing methods (such as morphological analysis, feature extraction, or the mathematical filtering described above) with advanced ML or DL models, or fusing different neural network architectures (like CNNs and RNNs). These methodologies are summarized in the following two tables, as much of the information has been detailed in the preceding sections.

Table 1. CNN-Based Hybrid Models.

Hybrid Method	Components & Features	Objective	Performance
ATM + 1D-CNN [41]	Adaptive Template Matching (ATM) (Rule-based pre-processing) + One-Dimensional Convolutional Neural Network (1D-CNN) (DL classifier).	ATM filters candidate spikes based on the subject's waveform to resolve data-overlapping issues. The 1D-CNN performs automatic feature extraction and classification.	Achieved average accuracy of 0.9870, specificity of 1.0000, and sensitivity of 0.9739 on BECTS data.
RF + CNN (Feature Fusion & Selection) [51]	Discrete Wavelet Transform (DWT) (Feature decomposition) + Feature Fusion (combining Approximate Entropy (ApEn), Fuzzy Entropy (FuzzyEn), Sample Entropy (SampEn), and Standard Deviation (STD)) + Random Forest (RF) (Feature selection) + CNN (Classifier).	This method uses DWT for signal decomposition, extracts hybrid nonlinear and time-domain features, uses RF to select the most important features to reduce redundancy, and finally classifies using CNN.	This RF + CNN system achieved a classification accuracy rate of 99.2% after feature selection, demonstrating the effectiveness of combining ML selection with a DL classifier.
EMD-WOG-2DCNN [52]	Empirical Mode Decomposition (EMD) (Feature separation) + Weighted Overlook Graph (WOG) (Signal-to-graph conversion) + Two-Dimensional Convolutional Neural Network (2DCNN) (DL classifier).	EMD separates the high-frequency components (IMFs) which contain the seizure information. WOG converts the time series of these components into an adjacency matrix (a graph representation). The 2DCNN classifies image-like graph representation.	Achieved accuracy exceeding 97.6% in the Rolandic dataset (specifically using IMF1 as the key high-frequency component).

Table 2. RNN/LSTM-Based Hybrid Models.

Hybrid Method	Components & Features	Objective	Performance
Multichannel Weighted Fusion + LSTM/BiLSTM [43]	Waveform feature screening (Rule-based candidate selection) + Weighted Data Fusion (Multichannel	Combines information from multiple EEG channels using a weighted strategy to strengthen the	Achieved an average F1 score of 95.74%, which outperformed other SOTA methods, by efficiently

	fusion based on amplitude, waveform, and distance weights) + Stacked Bi-directional Long Short-Term Memory (BiLSTM) (DL classifier).	spike signal and suppress noise/artifacts. BiLSTM is used as the temporal sequence classifier.	exploiting multichannel information.
Feature Fusion + BiLSTM [53,54]	Feature Extraction (Raw EEG + Smooth Nonlinear Energy (SNE) + Morphological Characteristics (MC)) + SMOTE (Data augmentation) + Stacked BiLSTM (DL classifier).	Fuses multiple time-domain sequence features to enhance signal representation, applies SMOTE to solve the class imbalance problem, and uses BiLSTM for time-series classification.	The stacked BiLSTM trained on fused features (EEG+SNE+MC) was the overall optimal model, achieving an average F1 score of 88.54% and sensitivity of 92.04%.

As can be seen, hybrid approaches highlight the necessity of combining signal processing, feature engineering, and diverse classification methodologies from medical science and neuroscience to address the complexities and non-stationarity inherent in BECTS EEG data.

4. Discussion

The present review has examined the analytical procedures for clinical EEG BECTS diagnosis, ranging from clinical raw EEG observation (qualitative procedure) to computer-assisted techniques, and more recently, AI methods. It has been noted that clinical physicians still rely on the observed behavioral manifestations of seizure (e.g., motor changes), which can lead to false negatives, when BECTS does not produce such symptoms. These limitations in the clinical diagnosis of BECTS have been addressed through computer-assisted methods, and more recently, through AI-assisted methodologies. However, the probable reason why physicians still rely on clinical signs and visual EEG features for the diagnosis of BECTS may be that the computational and mathematical approaches, upon which computer-assisted and AI methods are based, are difficult to develop. Furthermore, when the necessary software is available, it is often not user-friendly.

Conversely, computer-aided and AI methods often exhibit an over-reliance on EEG feature extraction, potentially overlooking clinical markers. This implies that, despite the high reported accuracy rates, a clinical physician may not find correlated alteration in patients diagnosed with BECTS.

A middle ground between these two perspectives might be the incorporation of basic observation and analysis of raw EEG used by clinicians into computer-assisted and AI analysis [55]. This procedure might probably yield better results in concurrent information in both clinical practice and research.

For example, in clinical practice, user-friendly toolboxes for raw EEG data, the video recording of EEG sessions, and the classification of artifacts can mitigate EEG data misinterpretation [56,57]. These issues can be resolved if such factors are investigated and incorporated into spike classification processes (such as in epilepsy). In this context, BECST, because it is a focal form of epilepsy, represents an opportunity for research.

On the other hand, the development of AI methods for BECTS analysis has reached significant milestones in differentiating epilepsy types, automatically detecting spikes, and characterizing functional brain differences; however, a consensus is far from being reached. That is why the future direction of this research must focus heavily on improving robustness, expanding clinical applicability through larger datasets, and refining the feature learning and localization capabilities of the models, by adding for example, data augmentation techniques, which can learn from the own patient raw EEG, applying source model reconstruction that informs the classifiers about the distribution of the spike [58].

Furthermore, to reach a consensus in EEG research, computer-assisted and AI investigations must consider that patients diagnosed with BECTS are in a stage of development. It is crucial to incorporate methodologies tailored to the developing brain [59], as assessed by neuropsychological and intelligence evaluations, incorporating cognitive-developmental features can about the effects of spikes and what classification methods are uncovering.

This *a priori* information may contribute to superior results in EEG-based BECTS diagnosis, improve the comprehension of the condition, and provide scientifically explainable information about epilepsy. Also, as researchers achieve these goals, the effects of therapeutics, either pharmacological, behavioral, or in the field of magnetic stimulation, can be better assessed.

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