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RESEARCH ARTICLE

Machine Learning Algorithms for Epilepsy Detection Based on Published EEG Databases: A Systematic Review

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ABSTRACT Epilepsy is the only neurological condition for which electroencephalography (EEG) is the primary diagnostic and important prognostic clinical tool. However, the manual inspection of EEG signals is a time-consuming procedure for neurologists. Thus, intense research has been made on creating machine learning methodologies for automated epilepsy detection. Also, many research or medical facilities have published databases of epileptic EEG signals to accommodate this research effort. The vast number of studies concerning epilepsy detection with EEG makes this systematic review necessary. It presents a detailed evaluation of the signal processing and classification methodologies employed on the different databases and provides valuable insights for future work. 190 studies were included in this systematic review according to the PRISMA guidelines, acquired from a systematic literature search in PubMed, Scopus, ScienceDirect and IEEE Xplore on 1st May 2021. Studies were examined based on the Signal Transformation technique, classification methodology and database for evaluation. Along with other findings, the increasing tendency to employ Convolutional Neural Networks that use a combination of Time-Frequency decomposition methodology images is noticed.

INDEX TERMS Database, detection, EEG, epilepsy, machine learning, signal transformation, systematic review.

I. INTRODUCTION

Epilepsy is a concerning neurological dysfunction as it affects more than 70 million people worldwide according to the World Health Organization [1] and is caused by abnormal electrical discharges of the cortical neurons that are called seizures [2]. Usually, anti-epileptic drugs are prescribed to epileptic patients, which reduce or eliminate the seizure onset, after its initial diagnosis. Although many imaging tools have been used for the detection of epilepsy, like Magnetic Resonance Imaging (MRI), Functional-MRI, PET-scan and others, electroencephalogram (EEG) is recognized to be the main diagnostic tool for the detection of epileptic seizures, because the epileptiform discharges can be observed on an EEG recording and distinguished from the normal neural activity. However, EEG detection requires well-trained and experienced medical personnel. The clinical presentation of a person suffering from seizures is usually typical; however,

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a differential diagnosis is often a challenge for neurologists, in order to avoid misdiagnosis and ineffective treatment (e.g. in cases of narcolepsy).

Prolonged timeseries of EEG data (sometimes lasting several hours) may need to be examined from an experienced neurologist for the visual detection of epileptic waveforms, being a laborious and time-consuming endeavor. Thus, the complexity of seizures and the significant size of the population suffering from epilepsy drives research efforts to continuously develop new applications for the automatic detection of seizures, to assist the work of physicians [3]. Research teams around the world have applied and developed signal processing techniques and machine learning algorithms, attempting to study and detect abnormal spikes, spike waves and spike-wave complexes in the interictal EEG recordings [4]. In the process, research has expanded to detect the early signs of seizure onset to predict an impending episode [5]. With the optimization of Time-Frequency (TF) analysis techniques and the advent of Deep Learning, the interest of the scientific community in the automatic diagnosis of epilepsy has increased dramatically [6].

Although research efforts on automatic epilepsy detection with EEG have been published since the 80's decade, there is an exponential growth of the number of published papers in the last decade. The majority of these studies acquire a collection of EEG recordings of subjects with epilepsy and healthy subjects and propose a methodology that employs different signal processing and feature extraction techniques along with traditional Machine Learning algorithms or elaborate new ones, trying to train a system that automatically classifies an EEG time window as epileptic or not. Research teams focusing on processing, algorithmic or computational issues, found it difficult to contribute to this field in isolation, since clinical recordings, thus cooperation with a medical organization, are required. As a result, multiple epilepsy EEG databases have been published online to assist in the development of automatic seizure detection protocols. Thus, most experimental studies usually rely on published databases rather than performing their own data acquisitions.

The vast number of existing studies in this area, renders the proposition of an unconventional methodology difficult as it requires extensive literature exploration. Also, the selection of the proper published DB or combination of databases for the evaluation of the methodology is of crucial importance for the robustness of the research. So, there is eminent need of a systematic review that incorporates all the latest advances and methods of automated EEG epilepsy detection. Such a review is useful to researchers that work on proposing novel ideas in this area.

This systematic review of the literature focuses on the study of methodologies that have been proposed during recent years for the automatic detection of seizures as well as the grouping and analysis of the respective EEG databases. Since the EEG is the main tool for detecting abnormal cortical patterns of neural activity in epileptic seizures, it is only reasonable that there are thousands of published studies that analyze the EEG in epilepsy, and the analysis of all these studies goes beyond the scope of this review. Therefore, the systematic research is focused on recent bibliographic data, of the last 5 years. The purpose of this study is to summarize the EEG-based epilepsy detection research that has taken place over the last 5 years and to provide a useful guideline for future researchers about the selection of the database (DB) and the proposition of the detection pipeline.

II. MATERIALS AND METHODS

This section describes the methodology that was applied for the study selection, the screening process, the eligibility evaluation, and finally the process for the analysis of the included studies. Every step of this methodology follows in detail the provisions of the PRISMA protocol. Details of the protocol for this systematic review were registered on PROSPERO and can be accessed via the PROSPERO ID that is CRD42022365313.

The search was limited to explore recent studies that focus exclusively on machine learning methodologies for automated epilepsy detection of EEG recordings from published databases. The protocol for the systematic search of bibliographic records follows the guidelines of the PRISMA report [7]. The literature review is carried out collecting evidence from the most well-known and comprehensive electronic libraries of scientific articles: Elsevier's Scopus, IEEE Xplore, Elsevier's ScienceDirect and MEDLINE PubMed. For the literature review, studies containing the keywords "EEG" and "epilepsy" or "seizure" and "detection" in the title or the summary or the keywords of the article were searched, while excluding studies that included the keywords "animal" or "mouse" or "mice" in their title or summary or keywords. The research and retrieval of the results was carried out on the 1st of May 2022, aiming to examine studies that focus on the detection of seizures with machine learning algorithms. In total, 3975 records were found from all 4 search engines. Using the built-in engine search tools, 1006 conference papers or posters were removed. From the 2969 records left, 1454 duplicates were found and disposed, using the Rayyan software. 10 more publications were excluded as being errata/corrigenda. Next, by using the Rayyan capabilities for multiple independent reviewers, 3 independent reviewers performed the appropriateness evaluation of the 1505 records. 1272 papers were excluded (see exclusion criteria below), as well as 43 theoretical studies such as systematic reviews, books and book chapters of nonexperimental studies. Finally, the 190 papers left (which were published during the last 5 years) were included in this review.

The final goal is to select studies that apply machine learning algorithms to EEG records, in order to detect seizures. So, in the final stage, and based on the criteria applied, the following categories of experimental studies are detected and removed:

1. Studies that study epilepsy in animals and were not excluded from the query in the first research (rats, pigs, dogs, sheep, mammals)
2. Studies that study epilepsy at a microscopic level (chromosomes/genes/proteins)
3. Studies that do not analyze merely EEG data (e.g. EEG, TMS-EEG, MEG, Positron emission tomography, MRI/CT scan, Electromyography, video-EEG)
4. Studies that study epilepsy as an association with other diseases or neurological conditions (e.g. encephalitis, schizophrenia, dementia, Autism Spectrum Disorder, brain disorders, trauma, bleeding, tumors, multiple sclerosis, psychogenic non epileptic seizures, heart conditions etc.)
5. Pharmacological studies that study the effect of antiepileptic drugs on EEG
6. Surgical treatment of epileptic seizures studies
7. Studies that study the implementation of devices and systems for the detection of seizures
8. Studies for seizure prediction
9. Case studies
10. Epilepsy studies on newborns and children
11. Studies that do not apply machine learning algorithms to EEG data (Socio-cultural aspects of epilepsy, differences between types of epilepsy, therapeutic approaches, keto diet, neurostimulation, quality of life and behavior-psychology assessment studies)
12. EEG analysis studies not in resting state (patients in a coma, hyperventilation, visual stimulus, sleep studies)
13. Studies that study the removal of noise/interferences from EEG
14. Inaccessible studies (invalid Digital Object Identifier, inability to find and/or obtain the study)
15. High Frequency Oscillations (HFO) analysis studies
16. Patient specific for seizure detection studies
17. Studies for source localization of seizures without performing detection
18. Studies on non-real clinical data (Surrogate/synthetic data)
19. Studies for EEG montage or sampling frequency in epilepsy
20. Studies for neuron connectivity in epilepsy
21. Studies that don't propose a certain methodology but focus on the comparison of existing algorithms

Particularly, the exact procedure was as follows. Initially, for each study, Title, Abstract, Methodology (and if needed, Discussion) were read by 3 independent researchers to clarify the objective and the methodology of the paper. If the study applied to one or more of the aforementioned criteria, the reviewer marked it as excluded in the Rayyan platform, marking the exclusion reason. After the exclusion process was completed for every reviewer, the individual selections were made public for the 3 reviewers and conflicts were marked automatically. Every conflict was resolved by having the 3 reviewers read the whole study and come to agreement. After the exclusion process was finished, the ''studies to include'' were extracted from the Rayyan platform as.RIS format and transferred to the Mendeley Reference Manager environment. There, the studies were divided into subfolders based on what published DB they were using. The folders were: Bonn, CHB-MIT, Freiburg, Other DB, Multiple DB. Then, each researcher made use of a data extraction sheet (in Microsoft Excel) to report the main aspects of the experimental papers. In particular, these aspects were: 1) the DB used and the number of recordings, 2) the preprocessing or signal transform methodology, 3) the feature extraction methodology, 4) the classification methodology, along with possible feature selection or dimensionality reduction techniques applied, 5) the problem they evaluated their methodology on (for example ictal-interictal) and 6) the performance results reported.

Finally, for the data synthesis step of this systematic review, the following results have been extracted: 1) Popularity of each DB (percentage of studies using it). 2) Popularity of type of signal transform used: Frequency domain, Time-Frequency domain or No Transform. No Transform has been further analyzed as Time-domain (if statistical features are extracted), Non-Linear (if a Non-Linear transform is employed), or Raw Signal (if the original signal is fed to a Neural Network). 3) Regarding the TF studies only: Popularity of specific TF decomposition (e.g. Discrete Wavelet Transform). 4) Popularity of classification algorithm applied. 5) Accuracy comparison of the classification algorithms for each different classification problem. 5) Comparison of methodologies used in the 2017-2019 period and in the 2020-2022 period. Fig. 1 illustrates the research methodology, in the form of a diagram.

Then, the final articles were divided into 4 categories according to the DB they used (Fig. 2). In the literature, methodologies are presented that have been applied mainly on the DB of the University of Bonn (Bonn DB) [8], on the DB of the Children's Hospital of Boston - Massachusetts Institute of Technology (CHB-MIT DB) [9] or on other databases such as the Epilepsy Center of the University of Freiburg (Freiburg DB) [10].

III. RESULTS

To detect epilepsy and to differentiate the activity associated with epileptic seizures, several milestone databases have been published, which are widely used by research teams for the application of methodological approaches. Specifically, the most well-known DB is Bonn DB. This DB concerns a short-term scalp and intracranial EEGs parts of physiological activity by individuals without seizures and EEGs segments of recordings of interictal and ictal activity of individuals that suffer from seizures. Another well-established DB is the CHB-MIT DB, which includes long lasting, multi-channel, scalp EEGs recordings of children that suffer from epilepsy. Moreover, the Freiburg DB contains scalp and intracranial EEG recordings of epileptic individuals, during periods of

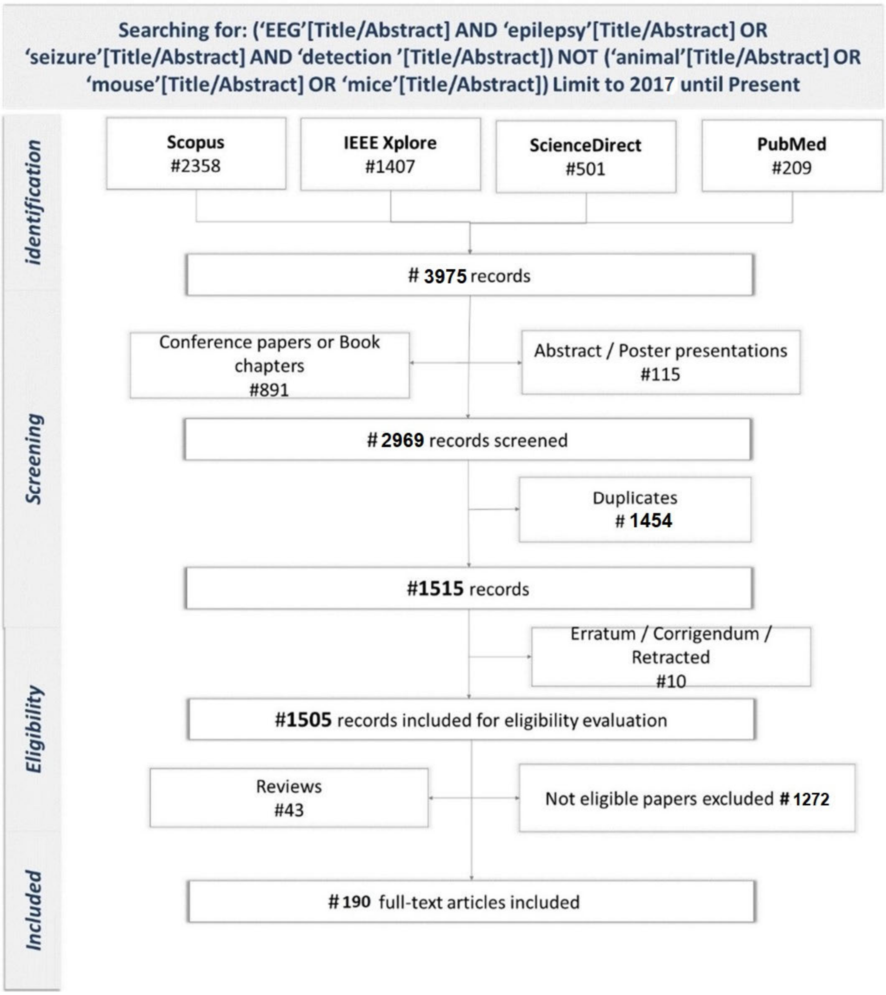

FIGURE 1. Systematic review flowchart according to PRISMA statement.

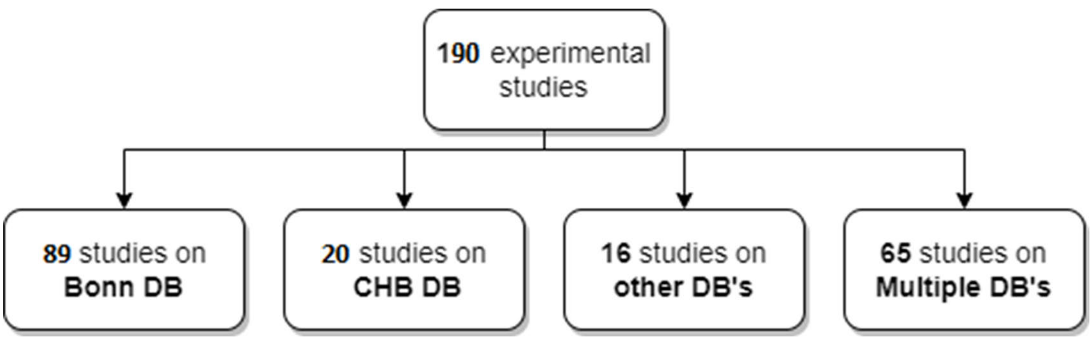

FIGURE 2. Separation of experimental studies according to the database (DB) that has been used.

absence of seizures and during periods of seizures. Last but not least, other databases such as Bern-Barcelona DB or Temple University DB are quality EEG databases with epileptic recordings, that are still gaining popularity among the researchers.

In most studies, signal processing techniques are applied to one of these databases. The proposed methodologies are based on:

- *Time Analysis (Statistical Features)*
- *Frequency Analysis (Fast Fourier Transform)*
- *TF Analysis (Short-time Fourier Transform, Wavelet Transform, Empirical Decomposition Method, etc.)*
- *Nonlinear analysis*
- *Analysis without signal processing technique.*

The last category mainly includes studies that apply deep learning algorithms and do not process the signal to extract features, rather that they use the recordings in their initial form. The next step for every study is to apply a Machine Learning scheme for the detection of epileptic discharges. The classification problem that studies try to solve differs for each research (ictal-interictal or ictal-preictal-interictal or seizure-non seizure etc.).

This study is structured as follows. The Results section briefly analyses the methodologies used based on the DB they are tested. For each DB, the methodologies are further divided based on the signal processing technique they are using. After every DB section, a table presenting all the studies mentioned along with the signal transformation performed, the classification methodology and the problem solved is presented. In the final part of the Results, the methodologies that use multiple databases to evaluate their performance are summarized. Next, the Discussion section summarizes the results and presents statistics regarding the choice of DB, the combination of databases as well as the techniques used, in an attempt to clearly illustrate the trends and provide future directions. Furthermore, the studies are divided in 2 subgroups, one containing the studies of 2017-2019 and one containing the studies of 2020-2022 and the differences of the methodologies most used are discussed. Finally, a brief comparison between this review and other EEG epilepsy related reviews is performed.

A. DATABASE OF BONN'S UNIVERSITY (BONN DB)

The University of Bonn EEG Database (Bonn DB) [8] consists of five subsets of EEG recordings that are distinguished by the capital letters A, B, C, D, E, which refer to signals beginning with the letters Z, O, N, F and S. From this point and for the rest of the paper, to keep up with the international literature, the names of the sets will be the same as the names of the signals and we will analyze the subsets Z, O, N, F and S. These sets are formed by EEG recordings, taken from five healthy volunteers and five people with epilepsy. Each group consists of 100 single channel recordings with 23.6 seconds duration (signal length 4096 samples). The sampling frequency of the data is 173.61 Hz and any kind of interference due to muscle activity or eye movement, were isolated and removed by the DB owners, after visual inspection.

Sets Z and O consist of scalp EEG segments that were obtained from healthy volunteers, who at the time of the recording were relaxed, sitting, with their eyes closed and open, correspondingly. EEG recordings were obtained using surface electrodes, placed, according to the 10-20 International Electrode Placement System. The N, F and S subsets consist of intracranial EEGs, taken from five epileptic patients, during presurgical examination. More specifically, the N subset includes parts of interictal intracranial EEG recordings originating from the epileptic zone of the opposite hemisphere, while the subset O includes parts of interictal intracranial EEG recordings obtained from the epileptic zone. The S subset includes 100 intracranial EEG recordings, obtained from the epileptogenic zone during epileptic activity. The epileptogenic zone was the hippocampus and no further patient data is provided.

1) TIME DOMAIN ANALYSIS

Time domain analysis involves techniques for processing and extracting features using statistical analysis methods or parametric methods that calculate statistical features directly from the signal. Such features are mean, standard deviation, interquartile range, kurtosis, skewness, energy and more. Time domain features is the simpler form of features used in every signal analysis methodology and do not require a transformation of the signal. However, more often than not, statistical features are used in combination with frequency or TF features.

Saini et al. [11] proposed a methodology that exports 15 statistical characteristics from Bonn DB recordings. Specifically, 300 EEG segments were used from the Z, F, S groups and the minimum value of amplitude, the maximum value of amplitude, the average value, the median, the standard deviation, the energy, the coefficients of curvature and the asymmetry, the entropy, the fluctuation, the transit rate of zero and the coefficient of variation were calculated. Then, a Neural Network classifier using the Particle Swarm Optimization algorithm achieved a 99.30% Classification accuracy (ACC) for the Z-F-S classification problem. Also, other studies such as the research of Eltrass et al. [12] have also relied on similar features such as the energy of the signal as a feature for training a Quantized Kernel Least Mean Square classifier.

In another case study of extracting features from the time domain [13], Sharmila et al. examined linear features from Bonn's DB. Specifically, the wavelength, the transit rate of zero, the number of slope sign changes, the standard deviation, the average value and the average power for 14 classification problems, were calculated. The effectiveness of the methodology was tested with the SVM and the Bayes Simplified classifier for many combinations of features and after comparing the classification results, the best results of ACC, Sensitivity (SENS) and Specificity (SPEC) that were reported were achieved with the SVM classifier. Yet, another study that used only statistical features in an SVM classifier (AdaBoost Least-Square SVM) was published by Al-Hadeethi et al. [14]. They achieved 99% classification ACC in the ZONF-S problem.

Kabir et al. [15] used the K-means clustering algorithm to group the Bonn DB EEG data according to the pattern similarity. Then, they calculated statistical characteristics (average value, standard deviation, maximum and minimum value, intra-quadratic range, coefficients of curvature and asymmetry) to form the characteristic vector that was given as an input to three classifiers. The SVM had the best results for all 4 classification problems (Z-S, O-S, N-S, F-S) with ACC scores ranging from 93.13% to 100%. Zeng et al. [16] used a Gray Recurrence Plot to explore the recursive properties of the time series dynamics of the epileptic EEG signal. Then they trained a dense convolution Neural Network (GRP-Dnet) and outperformed other methodologies achieving 100% ACC in the ZONF-S classification problem.

2) FREQUENCY DOMAIN ANALYSIS

Fourier analysis is the technique that transforms the signal from the time domain to the frequency domain and has been vastly used during the recent decades, for the frequency analysis of EEG signals. Discrete Fourier Transform (DFT) or Fast Fourier Transform (FFT) are both implementations of the Fourier transform principles and can be employed to perform analysis in the frequency domain.

Gupta et al. [17] proposed a methodology that uses Fourier series and Bessel functions, in order to analyze EEG signals and extract the 5 key brain rhythms, from which the Weighted multiscale Renyi Permutation Entropy was then calculated. Then, they evaluated 3 machine learning algorithms in 7 classification problems (Z-S, O-S, F-S, N-S, NF-S, ZONF-S and Z-N-S). The SVM achieved the best performance with 10-fold cross-validation, reaching ACC of over 97% for all classification problems. Na et al. [18] proposed a methodology that classified EEG signals which were transformed by DFT via a KNN classifier and achieved ACC of 99.4% in the ZONF-S problem. Pal et al [19], Polat et al [20] and Wang et al. [21], used the FFT to extract spectral energy features and trained different classifiers. The first and the third research used a KNN algorithm achieving 99.73% ACC in the Z-N-S problem and 99% ACC in the Z-F-S problem, respectively. The second research used the SVM classifier achieving 82.5% ACC in the Z-O-N-F-S problem. Li et al. [22] examined a Time-Varying Autoregressive Model (TVAR) for the classification of EEG signals of seizures. For the autoregressive model, which is based on radial basis functions (RBF), the Power Spectral Density was calculated for the 5 EEG rhythms and then the SVM algorithm was trained for the classification of the 4 categorization problems Z-S, F-S, N-S and NF-S. Using the 10-fold cross validation, ACC scores achieved were equal to 100%, 99.80%, 97.60% and 98.73%, respectively.

An alternative technique based on the Fourier Transform (Masking and Check-in based Feature Extraction Technique - MCFET) was presented in [23]. Choubey et al. calculated the variation, the Signal-to-Noise Ratio and the standard deviation from the frequency bands and trained the kNN algorithm in the problems F-S, ZF-S, ONF-F, Z-S, N-S. The results reached ACC scores over 97% for all classification problems.

According to De la O Serna et al. [24] "the basic problem of the DFT, in dealing with dense spectral components, is that it distorts amplitude and phase". Thus, the DFT is accurate on signals with constant amplitude, frequency and phase. So, the Discrete Taylor-Fourier Transform (DTFT) was proposed, which substitutes each DFT constant coefficient by a Taylor polynomial that are referred to as O-splines. In another paper of the same author [25] regarding epilepsy classification, the DTFT was employed for the transformation of the signal in the frequency domain and a SVM classifier was trained that achieved 94.88% ACC in the ZO-NF-S problem.

Lastly, Mathur et al. [26] proposed a methodology that used the Ramanujan Periodic Subspace (RPS) to extract the periodic information of the signal. They calculated the energy of each projection of the RPS of each non-overlapping epoch of the epileptic and non-epileptic signals and trained an SVM classifier that achieved ACC = 99.5% in the Z vs S problem, ACC = 98.6% in the O-S, ACC = 98% in the N-S and ACC = 97.5% in the F-S problem.

3) TIME-FREQUENCY DOMAIN ANALYSIS

Several Time-Frequency analysis methods have been proposed for epilepsy detection such as Short-Time Fourier Transform, Wavelet Analysis, Empirical Mode Decomposition, to name just few, aiming to extract the frequency content of the signals and then calculate linear and/or non-linear features. Time-Frequency analysis methods can analyze better the dynamic behavior of brain signals and capture the subtle changes in EEG waves. Time-Frequency analysis provides a signal representation both in temporal and in spectral domain. Thus, it can better characterize the dynamics of the EEG signal and provide a thorough interpretation of the neurophysiological mechanisms [27].

a: SHORT-TIME FOURIER TRANSFORM

The Short-time Fourier Transform (STFT) is the evolution of the Fourier Transform and implements a Fourier Transform in a rolling window to analyze the signal simultaneously in the field of frequency and time. Different approaches to STFT, are proposed by Li et al. [28], Yildiz et al. [29], Nogay et al. [30] and Mandhouj et al. [31] who all used STFT to represent EEG data in phase and amplitude images. Then, the first study applied image analysis techniques, where phase and amplitude images were divided into blocks and a binary number is extracted for each part. The results with SVM for 8 classification problems (Z-S, O-S, N-S, F-S, NF-S, ZONF-S, ZO-NFS, Z-F-S, ZO-NF-S) showed high percentages of ACC, SENS and Specialty that reached 100% for Z-S, O-S, N-S, F-S. The second and third study applied transfer learning (alexnet, resnet-18, etc) and Convolutional Neural Networks (CNN) respectively and achieved 100% classification ACC in the ZO-NF-S problem. The last study also applied CNN and achieved ACC = 98.88%, SENS 98.33%, SPEC = 100% in the ZO-S problem. Jana et al. [32] also proposed a STFT approach with a SVM classifier and obtained ACC = 97.63%, SENS = 98.38%, SPEC = 94.67% in the ZONF-S problem.

b: WAVELET ANALYSIS

Discrete Wavelet Transform (DWT) is the TF method used in most of the TF Analysis studies. Wavelet Transform is a method that analyzes the signal at a TF level and uses mathematical functions to detect abrupt signal transitions, such as epileptic spikes. In recent years, various research teams have shown increasing preference, among other techniques, with DWT showing significant advantages in both frequency and time domain.

The main idea behind DWT is that a signal can be expressed as a linear combination of a set of functions, obtained by shifting and expanding a single function, called mother wavelet [33]. The mother wavelet uses the wavelet and the scaling function as band-pass filters, in order to decompose the signal into high and low frequency subbands. The resulting low frequency signal is further divided into high and low frequency subbands, while this process is repeated, until the whole signal is decomposed. The low frequency factors are called Approximation coefficients (cA) and those of high frequencies are called Detail coefficients (cD). The number of decomposition levels, as well as the appropriate mother wavelet, is very important and is selected based on the sampling frequency and the data that are analyzed.

In a recent study, Sharmila et al. [34], applied a 5 level DWT and calculated the Approximate entropy and the Shannon entropy for each frequency subband. Then, the SVM algorithm was trained for 15 different classification problems with 50% of the data used as testing set and 50% as training set and achieved high ACC in most of the problems. The same team of researchers in their next study [32] calculated the average of the absolute values of the coefficients, the standard deviation and the power for each subband, after applying the 5-level DWT, only for signals of the Z-S groups. Linear Discriminant Analysis was applied as a feature reduction technique and then various traditional classifiers were trained. The k-Nearest Neighbors classifier provided the highest classification performance among them (ACC, SENS, SPEC: 100%). Aliyu et al [35], Lee et al. [36], Oinam et al. [37], and Mardini et al. [38] also proposed methodologies that used the DWT to extract features for the classification, and each study used a different classification approach. Aliyu and Oinam employed Neural Network approaches (Long Short Term Memory and Multilayer Perceptron, respectively), while Lee and Mardini used more conventional Machine Learning techniques such as Hidden Markov Model and Naïve Bayes classifier. Sujatha et al [39] extracted the approximate entropy and statistical features, using the DWT and trained an SVM classifier, achieving 96.5% ACC in the ZONF-S problem.

Another method of detecting ictal seizures signals from simple linear features is proposed by Chiang et al [40]. The authors applied 5-level DWT and extracted statistical features of the EEG signals. The best characteristics were selected based on the information gain. A Petri network was trained and the classification performance was evaluated by 10-fold cross validation achieving 93.80% ACC for the ZO-NFS problem and 98.60% ACC for the ZONF-S problem.

In another DWT-based study, Chen et al. [41] used only groups F and S and employed a 6-level DWT transform. Then they calculated nonlinear entropy characteristics, such as Approximate Entropy, Spectral entropy, Fuzzy entropy, Permutation entropy, Sample entropy, Shannon entropy and Conditional entropy. The same approach was followed by Zhou et al. [42]. Then, the first study used only the characteristics from the low frequency coefficients D3, D4, D5, A5 and the one factor Variance analysis to select the 18 best characteristics. Detection of the epileptic EEG segments achieved up to 99.50% ACC with the Least-square Support Vector Machines (LS-SVM) algorithm. The second study used a Radial Basis Function (RBF) NN and achieved ACC = 96.3% and ACC = 78.4% in the ZO-NFS and Z-O-N-F-S problems respectively.

Wang et al. [43] applied a 5-level DWT and calculated the mean energy value and the standard deviation of the transformed signal. The Gradient Boosting algorithm was trained for 9 different classification problems and achieved ACC over 93% for all of them. In a similar study [44], Akut et al. applied a 5-level DWT and trained an 11 level Convolutional Neural Network (CNN) based on the low-frequency D3, D4, D5 and A5 wavelet factors. The methodology achieved 100% ACC, SPEC and SENS of the detection of the epileptic group (ZONF-S) and 99.40% ACC for the separation of healthy, epileptic not experiencing a seizure and epileptic experiencing a seizure (ZO-NF-S).

At the next study, Alzami et al. [45] proposed an Adaptive Hybrid Feature Selection Based Classifier (AHFSE) for detecting epilepsy. Firstly, they applied a 4 level DWT with a db4 mother wavelet. Then statistical features and non-linear features such as the sample entropy and the fractal dimension were extracted. Various feature selection techniques were tested for 8 classification problems (Z-S, O-S, N-S, F-S, NF-S, ZONF-S, Z-F-S, ZO-NF-S) and the proposed AHFSE classifier achieved a Classification ACC of over 96% in all of the problems. In another study, Zubair et al. [46] extracted band energies, spike rhythmicity, relative spike amplitude and spectral entropy from the DWT and trained a CatBoost classifier, achieving 97% ACC in the ZONF-S problem.

An enhanced methodology of DWT with optimal equilateral wavelet filter bank (OEWFB) has been proposed by Ashokkumar et al. [47]. The OEWFB novelty is that is designed with the objective of frequency spread reduction. In this work, they extracted entropy features (Fuzzy, Renyis and Kraskov) and by using multiple machine learning algorithms they achieved ZONF-S ACC up to 99.4%

Often, DWT is combined with other preprocessing and feature extraction methodologies, in order to provide the classifier in the next step with a wider variety of features. For example, Amin et al. [48] employed DWT along with Arithmetic coding, and trained multiple classifiers (SVM, MLP, KNN). Jang et al. [49] combined DWT with Phase-Space Reconstruction (PSR) algorithm, and Molla et al. [50] used it along with Graph Eigen Decomposition (GED). Lastly, Radman et al. [51] combined DWT, Fast Fourier Transoform and statistical, time domain features to extract a complete feature vector to be fed in a Random Forest Classifier that achieved ACC = 99.33%, SENS = 98.33%, SPEC = 98.88% in the ZO-NF-S problem. Ashokkumar et al. [52] proposed a methodology that combined Fractional S-transform with 4-level DWT and extracted entropy features to train a deep CNN. Zeng et al. [53] combined Intrinsic Time-Scale Decomposition, DWT and PSR for the feature extraction procedure, and trained a MLP that achieved 94% ACC in the Z-O-N-F-S problem

An extension of the Continuous Wavelet Transform, the Stockwell Transform (Stockwell - S-Transform) was used by Chatterjee et al. [54]. The authors implemented the Stockwell Transform and calculated the standard deviation and energy from each period. The SVM and kNN algorithms were tested for their performance in the Z-S and F-S classification problems. The best performance (ACC, SPEC, SENS: 100% for the Z-S and ACC: 99.25% SPEC 100% and SENS 98.85% for the F-S) appeared with the kNN algorithm. Furthermore, Baykara et al. [55] also employed the Stockwell Transform and obtained entropy features and Perservals energy, achieving ACC 90%, SENS 95%, SPEC 82% in the ZO-NF-S problem with an Extreme Learning Machine (ELM) classifier.

Zhao et al. [56] proposed a methodology based on the Stationary Wavelet Transform (SWT) and the Hilbert-Huang Transform for the calculation of instantaneous energy. SWT is a special case of Wavelet Transform, during which at each subsequent level the signal is not altered as in DWT but remains as at the beginning of the transform, changing the filters each time. In this study, a 4-level SWT was employed, and then entropy features (Spectral entropy, Renyi entropy, Approximate entropy), coefficient of variation, spectral characteristics (spectral flux) and spectral flatness, the mean value and the Shannon entropy for the characterization of instantaneous energy were calculated. A Kruskal-Wallis test evaluated the characteristics as a feature selection step. For the detection, the performance of 5 algorithms was examined, and a Back-Propagation Neural Network (BPNN) achieved the best ACC results (over 93%).

In another study [57], Amorim et al. performed 3 signal transformation techniques, Wavelet Transform, Shearlet Transform and Curvelet Transform, in all the EEGs of Bonn DB. For the application of the Curvelet and the Shearlet Transform, the EEG signals (4097 samples) were converted to 64 $\times$ 64 pixel images. Then they calculated statistical characteristics and power coefficients in each zone, as well as the ratio of the absolute mean values of neighboring zones. Then, the Principal Component Analysis and Linear Discriminant Analysis techniques were applied for dimensionality reduction and the performance of SVM, Random Forests and kNN was examined. EEG data sets consisting of epileptic and non-epileptic data were randomly separated with 60% of the data being used as training set and 40%, as test set. The best classification results for the 5-class problem (Z-O-N-F-S) were achieved with the Curvelet Transform and the Random Forests classifier with ACC 81.50%, SPEC 81.70% and SENS 81.50%.

An enhanced Wavelet TF transformation is the Wavelet Packet Decomposition (WPD). WPD is a Wavelet Transform that uses multiple filters at each level of transform, analyzing both the coefficients of detail and approximation, creating a signal decomposition tree in frequency sub-bands [33]. In the study presented by Liu et al. [58] the WPD was employed, and the EEG signals were analyzed in 8 frequency bands and then, the energy, the entropy for each frequency band as well as other time-domain characteristics were calculated. The feature vector trained an Extreme Learning Machine (ELM) Feedforward Neural Network, for the Z-S and Z-F-S problems. The results for the two classification problems, in terms of ACC, reached 97.70% and 96.50% respectively. Ari et al. [59] also extracted the dispersion entropy using a WPD and trained an SVM classifier, obtaining 99.53% ACC in the Z-O-N-F-S problem. Other machine learning approaches that have been used along WPD (regarding the Bonn DB) are Graph-Based ELM [60] and TSK fuzzy system [61]. A modified version of the Wavelet Transform namely Scattering Transform was employed by Jiang et al. [62] and achieved 99.87% ACC with a SVM classifier in the ZO-NF-S problem.

A different version of Wavelet Transform is the Tunable Q-factor Wavelet Transform (TQWT). TQWT is a Wavelet Transform configuration that utilizes the Q factor and a series of variable band's width filters [63]. The factor Q of a pulse expresses the ratio of the central frequency of the pulse to its bandwidth. Sharma et al. [64] analyzed the 16-level TQWT to decompose the signal into frequency bands. Then, the Higuchi Fractal Dimension (HFD) was calculated for each zone, forming the feature vector for the LS-SVM classifier and achieving classification ACC over 98.50%. Similar to the study [64], Sharaf et al. [65] used TQWT to decompose EEG sections into frequency bands. Chaotic, frequency and statistical characteristics, from each frequency band were calculated. At the same time, the contrast, the correlation, the energy and the homogeneity of the TQWT transformed EEG images were extracted. Afterwards a Firefly Optimization Algorithm was applied to reduce the vector of the features, that were fed to a Random Forest classifier. The Classification ACC for the ZO-NF-S problem reached 99%. Lastly, Ashokummar et al. [66] used TQWT to extract the approximate entropy and train an Extreme learning adaptive neuro-Fuzzy Inference System (EXL-ANFIS) that achieved 99.72% ACC in the ZO-NF-S problem.

The importance for the selection of frequency bands and their impact on the classification of epileptic activity has been also studied by Tsipouras [67]. First, DWT of different decomposition levels with variable bandwidth was applied. The recordings were divided into frequency bands, from which the energy of the individual bands, the ratio of the energy of each frequency band to the total energy and the spectral entropy were calculated. The classification ACC, using the algorithm of Random Forests, reached 91.20% for the Z-O-N-F-S problem and 98.80% for the ZO-NF-S problem.

A study analyzing Bonn DB EEG signals, using Wavelet Analysis, employed evolutionary algorithms in the epileptic signal detection methodology. Bandil et al. [68] used EEG recordings only from groups Z, F, S from Bonn DB. They applied the 5-level Discrete Wavelet Transform and calculated a number of characteristics such as energy, entropy characteristics, statistical characteristics and morphological characteristics based on a self-regression model. Then a Genetic Algorithm (GA) for feature vector optimization was proposed and the final characteristics were fed to an NN algorithm, achieving 99% Classification ACC for the Z-F-S problem. A quite similar approach (DWT, GA for feature selection, entropy characteristics) was employed by Omidvar et al. [69] and achieved ACC = 98.7% SENS = 97.5%, SPEC = 100% in the ZO-NF-S problem.

Another variation of Wavelet Decomposition is Empirical Wavelet Transform (EWT). The main idea behind EWT is to extract the different modes of a signal by designing an appropriate wavelet filter bank [70] and was first proposed at 2013. Anuragi et al. [71] used EWT to perform EEG signal decomposition and feature extraction which was then feeded to an Extra Trees classifier and achieved ACC = 99.33%, F1 = 99% in the Z-N-S and ACC = 97.8%, F1 = 97% in the ZO-NF-S problem.

c: EMPIRICAL MODE DECOMPOSITION

The Empirical Mode Decomposition (EMD) is another TF method that creates a set of Intrinsic Mode Functions (IMFs), from which, via the Hilbert-Huang transform, the instantaneous amplitude and frequency [72] are calculated. Biju et al. [72] used all the EEG data from the Bonn DB and applied the EMD transform. Characteristics of Energy, Entropy (e.g. Approximate Entropy), were calculated and fed to an Adaptive Neuro-Fuzzy System (ANFIS) reaching a percentage of ACC, SENS and SPEC equal to 100%.

Mahjoub et al. [73] presented a complete study of EEG analysis techniques. Specifically, they studied the characteristics of the signal as extracted from the untreated signal, from the 3-level TQWT and the EMD, both for the entire length of the signal and for periods of 1000, 2000, 3000 and 4000 points, without overlap. The SVM algorithm was trained with the method of 5-fold cross-validation for 6 classification problems (Z-S, O-S, F-S, N-S, NF-S and ZONF-S). The best results were obtained using the second IMFs of the Empirical Decomposition Method with periods of 3000 points, reaching high ACC scores of over 98%, for all problems. In addition, equally high percentages of detection ACC were observed via untreated data with periods of 1000 points, as well as with the third and fourth subband of TQWT with a window of 4000 samples.

Sharma et al. [74] proposed an alternative approach of calculating local minima and maxima in the Hilbert-Huang Transform, the iterative filtering. In this study, the IMFs were extracted by repeated filtration and entropy characteristics (such as Shannon entropy) were calculated from different window lengths, in order to form 5 classification problems (ZO-NF-S, Z-N-S, Z-S, ZONF-S, F-S). The classification ACC reached over 96% with the Random Forests algorithm and the 10-fold cross-validation method for all classification problems.

A methodology based on EMD and Artificial Neural Networks was presented by Mahjoub et al [73]. Amplitude and frequency features were extracted from the first 4 IMFs, via the Hilbert-Huang Transform. Then the most important characteristics of the 5 subsets (Z, O, N, F, S) were inserted in an Artificial Neural Networks classifier (based on statistical evaluation). The classification ACC for Z-O-N-F-S reached 87.20%. EMD was also implemented in the study [75] by Mert and Akan. The energy, extracted from the IMFs was used as a feature for classification and their methodology achieved ACC scores 97.89%, 83.68%, 96.39%, and 93.00% for the problems Z-S, O-S, N-S and F-S respectively. Yet another study that used Neural Networks along with complete ensemble EMD was published by Singh et al. [76] and achieved 98.7% ACC in the ZO-NF-S problem. Lastly, Hassan et al. [77] proposed a complete ensemble EMD with adaptive noise methodology that used the AdaBoost ensemble classifier with decision trees for the weak classifiers and achieved 97.6% ACC in the ZO-NF-S problem and 99.2% ACC in the ZONF-S problem.

Another EMD based methodology that applies the Grasshopper Optimization Algorithm was presented by Singh et al. [78]. 10 non-linear and 3 morphological features were extracted from the IMF's and five machine learning algorithms were tested individually after hyperparameter optimization with the Grasshopper Optimization Algorithm. Finally, an ensemble method was proposed consisted of these 5 algorithms. Bari et al. [79] proposed a methodology that used EMD with normalized IMF's and trained a Quadratic discriminant analysis (QDA) classifier, achieving ACC = 99%, SENS = 98.5%, SPEC = 100% on the NF-S problem.

Another TF decomposition namely Intrinsic Time-scale Decomposition (ITD) was presented by Yang et al. [80]. This method decomposes a time series into Proper Rotation Components (PRC). From the PRC's the instantaneous amplitude and frequency, the mean value, the standard deviation and coefficients of curvature and asymmetry were calculated. The resulting feature vector was used to train a Neural Network for 17 classification problems and the ACC scores ranged from 98.67% to 100%.

Finally, a new signal decomposition technique that is called Variational Mode Decomposition (VMD) has been utilized by Sukriti et al. [81]. VMD decomposes a multi-component signal in a set of bandlimited and quasi-orthogonal modes, which are less sensitive to noise compared to the EMD. Sukriti et al, extracted kurtosis and bandwidth features using the VMD and trained a Random Forest classifier that achieved ACC = 98.2%, SENS = 99.7%, SPEC = 98.7% in the ZO-NF-S problem.

d: NON-LINEAR ANALYSIS

This category includes studies with methodologies based on the extraction of non-linear characteristics, such as entropy or Fractal Dimensions.

Li et al. [82] calculated Fuzzy Entropy and Entropy from different window lengths and achieved 93% ACC for the separation of normal from epileptic data (ZO-NFS) and 91% for the separation of interictal/ictal period (NF-S) with a QDA Classifier. In another study, Mohammadpoory et al. [83] suggest a Visibility Graph based methodology, a simple approach for representing signals in a graph and they use the

Weighted Visibility Graph Entropy (WVGE) to characterize the weighted visibility graph and distinguish data into normal (Z), epileptic (F) and ictal (S) periods. A Decision Tree classifier achieved ACC of 97%.

Furthermore, Detrended Fluctuation Analysis (DFA) is yet another non-linear technique widely used for noise signal analysis [84], [85]. Bose et al. [85] applied a non-linear method namely the Multifractal Detrended Fluctuation Analysis (MDFA). According to the methodology, 14 characteristics including the Hurst exponent are extracted, from the multifractal spectrum and the optimal characteristics based on the Kruskal-Wallis test are used to train an SVM classifier. The classification results are expressed with ACC, SENS and SPEC for the four classification problems (ZO-S, NF-S, ZO-NF, ZONF-S) all exceeding 95%. Lahmiri et al. [86] also DFA and the Hurst exponent and trained a kNN algorithm with ACC reaching 100% for the NF-S classification problem.

Rizal et al. [87] used the Higuchi method to estimate HFD from 300 EEG signals of Bonn DB and the features obtained were used as input to an SVM classifier. The proposed methodology provided high percentages of classification ACC (98%). Brari et al. [88] also calculated the Higuchi Fractal Dimension of the signal and trained a KNN classifier, achieving 97.28% ACC in the ZO-NF-S problem.

Another non-linear methodology widely used is Recurrence Quantification Analysis (RQA). Gao et al. [89] used non-linear features such as RQA and approximate entropy and trained a Convolutional Neural Network achieving ACC = 99.26%, SENS = 98.84%, SPEC = 99.26% in the ZO-NFS problem.

Goshvarpour et al. [90] proposed a methodology that quantifies the self-similarity of the EEG signal by creating a variation of a Poincare plot, the lagged Poincare plot. Then, they trained a KNN classifier and achieved ACC = 96%, SPEC = 99.48%, SENS = 95.19% in the Z-F-S problem.

Zhang et al. [60] proposed a methodology that used a TF modification of the Wavelet Transform called Frequency Slice Wavelet Transform (FSWT) to explore the non-linearity of the EEG signal extracting features such as Fuzzy entropy and Higuchi Fractal Dimension and trained a t-distributed stochastic neighbor embedding (t-SNE) system to perform classification in the Z-O-N-F-S problem with achieved ACC = 93.62%

e: ANALYSIS WITHOUT SIGNAL PROCESSING TECHNIQUE

Principal Component Analysis (PCA) is a dimensionality reduction technique, for enhancing the classification efficiency. Three variants of PCA are used in the studies [91], [92] by Jaiswal et al. The researchers propose alternative approaches to extracting features from the total of Bonn DB, based on PCA and are called "Global modular PCA - GModPCA" [91], subpattern based PCA - SpPCA and cross-subpattern correlation-based PCA - SubXPCA [92]. The SVM algorithm is trained in many classification problems (Z-S, O-S, N-S, F-S, ZO-S, NF-S, ZONF-S) and achieves classification ACC of over 94% for all cases.

In recent years, interest for studies based on deep learning architectures, with application especially on Convolutional NN, has been increasing. A common element of deep learning methodologies is that they use the entire non processed signal and do not calculate specific characteristics. To distinguish healthy EEGs from pathological EEGs before and during a seizure, Acharya et al. [93] proposed a 13-level CNN. The entire duration of the EEGs was used from the O,F,S groups. The methodology for the 3-class problem, achieved an ACC of 88.67%, SPEC 90% and SENS 95%. The advances in the computational performance is the main reason for the increase in popularity of raw signal methodologies the latest years. These systems usually take advantage of a series of convolution blocks to perform the feature extraction process [94], [95], [96], [97], [98]. However, other NN architectures that do not rely on a convolution block have also been used taking raw signal as input for the epilepsy detection [99].

Similarly, Hussein et al. [100], proposed a model that combines Deep Learning in a feedback neural network architecture (Deep Neural Network Long Short-term Memory Network (LSTM)). In this study, each EEG signal is initially divided into smaller, non-overlapping periods, of 2 points. Periods are then given as an input to the LSTM level, which is used to learn high-level representations of EEG signals. The output of the LSTM level is provided as an input to a fully connected level to find the most powerful EEG characteristics, associated with seizures. Finally, a softmax layer activation function is utilized to generate predictions for each class. The proposed model achieved 100% ACC, SPEC and SENS for the three Z-S, Z-N-S and Z-O-N-F-S classification problems.

Table 1 and Table 2 present the studies that validated their methodology using the Bonn DB. Table 1 contains the studies of 2017-2019 and Table 2 contains the studies of 2020-2022.

B. CHILDREN'S HOSPITAL OF BOSTON BASE – MASSACHUSETTS INSTITUTE OF TECHNOLOGY (CHB-MIT)

The second most used EEG DB is an open access DB provided by Children's Hospital of Boston - Massachusetts Institute of Technology (CHB-MIT) [9]. The DB includes long, continuous, multi-channel recordings, recorded from the scalp of 24 people with drug-resistant seizures. For each participant 9 to 42 consecutive.edf files with EEG data are provided and the interval of seizures is recorded. EEG signals were recorded with 256 Hz sampling rate with a 16-bit analog-to-digital converter. In total the DB includes 664.edf files, 140 EEG records and 198 seizures. The DB also includes the demographic characteristics of the patients. The 24th person was added to the DB after its initial publication and the information about his gender and age is not available. Of the 23 remaining, 22 are individual patients, while subject 21 is subject 1 at a recording time of 1.5 years. Of the 22 patients, 5 were men, aged 3 to 22 years, while the rest 17 patients were women, aged between 1.5 and 19 years.

TABLE 1. Studies validated on the bonn database published in 2017-2019.

Author	Year	Signal Transform	Feature Extraction	Classification	Classification Problem	Results
Akut et al.[44]	2019	Time-Frequency	DWT	CNN	ZO-NF-S	ACC=99.4%, SENS=98.5%, SPEC=99.45%
Alzami et al.[45]	2019	Time-Frequency	DWT	Adaptive Hybrid Feature Sel.-Based Classifier	ZO-NF-S	ACC=96%, SENS=96.53%, SPEC=98.93%
Attia et al.[158]	2019	Non-Linear	Autoregressive Model, Firefly optimazation	SVM	Z-N Z-F O-N	ACC=96%, ACC=95%, ACC=94%
Bandil and Wadhwani [68]	2019	Time-Frequency	DWT, Entropy features	ANN	Z-F-S	ACC=99%
Chen et al. [41]	2019	Time-Frequency	DWT, Entropy features	LS-SVM	F-S	ACC=99.5%, SENS=100%, SPEC=99.4%
Chiang et al. [40]	2019	Time-Frequency	DWT, Fuzzy entropy	Petri-Net	ZO-NFS	ACC=93.8%
Gupta and Pachori [17]	2019	Frequency	DFT, Renyi entropy	LS-SVM	ZONF-S Z-N-S	ACC=98.6%, ACC=97.3%
Hussein et al. [100]	2019	Raw Signal		LSTM	Z-O-N-F-S	ACC=100%
Li et al. [28]	2019	Time-Frequency	STFT spectogram, scalogram	SVM	ZO-NF-S	ACC=99.6%, SENS=99.33%, SPEC=100%
Mahjoub et al. [73]	2019	Time-Frequency	EMD	SVM	ZONF-S	ACC=97%, SENS=90.62%, SPEC=98.59%
Zhao et al. [56]	2019	Time-Frequency	Stationary WT, Entropy features	Back-Propagation NN	ZO-NF-S	ACC=93.3%, SENS=96.67%, SPEC=96.67%
Singh et al. [78]	2019	Time-Frequency	EMD	Ensemble classifier with grasshopper optimization	ZO-NF-S	ACC=99.2%
Tsipouras et al. [67]	2019	Time-Frequency	DWT, Entropy features	Random Forests	Z-O-N-F-S ZO-NF-S	ACC=91.2%, ACC=98.8%
Wang et al. [43]	2019	Time-Frequency	DWT	Gradient Boosting with Grid Search optimizer	ZONF-S ZO-NF-S	ACC=98.4%, ACC=96.5%
Yang et al. [80]	2019	Time-Frequency	Intrinsic Time-scale Decomposition	ANN	ZO-NF-S Z-N-S	ACC=99.5%, ACC=99.67%
Bose et al. [85]	2018	Non-Linear	multifractal detrended fluctuation analysis	SVM	ZO-NF	ACC=96.25%, SENS=95.44%, SPEC=97.06%
Choubey et al. [23]	2018	Frequency	FFT	KNN	ZF-S	ACC=97%, SENS=98%, SPEC=97%
Kabir et al. [15]	2018	Time domain	K-means clustering, statistical features	SVM	Z-S, O-S	ACC=98.13%, ACC=97.75%
Lahmiri et al. [86]	2018	Non-Linear	multifractal detrended fluctuation analysis, Hurst exponent	KNN	NF-S	ACC=100%
Li et al. [82]	2018	Non-Linear	Fuzzy entropy, Dispersion Entropy	Quadratic Discriminant Classifier	ZONF-S	ACC=92.8%, SENS=90.67%, SPEC=96%
Mert and Akan [75]		Time-Frequency	EMD	Not reported	Z-S, F-S, O-S	ACC=97.89%, ACC=93%, ACC=83.68%
Saini et al. [11]	2018	Time domain	Statistical and Entropy Features	ANN	Z-F-S	ACC=99.3%, SENS=99.02%, SPEC=99.34%
Sharaf et al. [65]	2018	Time-Frequency	TQWT, chaotic features	Firefly optimization, Random Forest	ZO-NF-S	ACC=99%, SENS=98%, SPEC=97%
Sharma et al. [74]	2018	Time-Frequency	EMD, Entropy	Random Forests	ZO-NF-S	ACC=98%, SENS=97.8%, SPEC=99%
Sharmila and Geethanjali [13]	2018	Time Domain	Slope sign changes and Statistical features	SVM	ZONF-S	ACC=95.15%, SENS=81.23%, SPEC=96.6%
Acharya et al. [93]	2017	Time Domain	Z-score normalization	CNN	O-F-S	ACC=88.67%, SENS=95%, SPEC=90%
Amorim et al. [57]	2017	Time-Frequency	DWT, Shearlet & Contourlet transforms	Random Forests	Z-O-N-F-S, Z-S	ACC=88.67%, ACC=100%

TABLE 1. *(Continued.)* **Studies validated on the bonn database published in 2017-2019.**

Biju et al. [72]	2017	Time-Frequency	EMD	Adaptive Neuro-Fuzzy Neural Network	ZO-S	ACC=100%
Chatterjee et al. [54], [91]	2017	Time-Frequency	Stockwell Trasform	SVM, kNN	Z-S, F-S	ACC=100%, ACC=99.25%
Jaiswal et al. [91]	2017	Time Domain	GModPCA	SVM	ZO-S NF-S ZONF-S	ACC=99.66%, ACC=95.8%, ACC=97.17%
Jaiswal et al. [92]	2018	Time Domain	SubXPCA	SVM	Z-N-F, ZO-NF-S, Z-O-N-F-S	ACC=97.2%, ACC=97.43%, ACC=94.6%
Liu et al. [58]	2017	Time-Frequency	WPD, energy, entropy, kurtosis	ELM	Z-S, Z-F-S	ACC=97.7%, ACC=96.5%
Li et al. [22]	2017	Frequency	PSD, Autoregressive Model	SVM	NF-S	ACC=98.73%, SENS=98%, SPEC=99.1%
Mohammadpoory et al. [83]	2017	Non-Linear	Weighted Visibility Graph Entropy	Decision Trees	Z-F-S	ACC=97%
Sharma et al. [64]	2017	Time-Frequency	TQWT	LS-SVM	ZO-S, ZO-NF, ZONF-S	ACC=99.67% ACC=98.5% ACC=99.6%
Sharmila et al. [34]	2018	Time-Frequency	DWT, shannon entropy	SVM	ZONF-S, NF-S	ACC=78%, ACC=88%
Sharmila et al. [159]	2017	Time-Frequency	DWT	kNN	Z-S	ACC=100%

However, it is pointed out that it consists mostly of pediatric cases and 3 marginal pediatric cases (older than 16 years) that mainly fall into the category of adults.

1) TIME DOMAIN ANALYSIS

A study based on Time domain analysis was presented by Hu et al. [101] In this study, the authors employed Local Mean Decomposition and trained a Bidirectional LSTM, achieving performance of G-mean 92.66% SENS = 93.61%, SPEC = 91.85% in the ictal-interictal problem. Time domain characteristics (no signal transformation in Frequency or TF domain) were also extracted by Quintero-Rincón et al. [102] and Siddiqui et al. [103]. Finally, Zhao et al. [104] proposed a methodology that employs Pearson Correlation for the feature extraction step and fed a Linear Graph Convolution Network and achieved ACC = 99.3%, SENS = 99.43%, SPEC = 98.82%, F1 = 98.73% in the ictal-interictal problem.

2) FREQUENCY DOMAIN ANALYSIS

A study focusing on channel selection and reducing the dimension of the vector characteristics by a non-linear method, to increase detection ACC, is presented by Birjandtalab et al. [105]. EEG recordings from the 23 patients of the CHB-MIT DB were divided into 10-second epochs, from which the Spectral Power Density was calculated for the 5 basic EEG rhythms, for each of the 23 channels. Then they applied feature selection based on the Random Forests algorithm to select the appropriate channels, by limiting spatial information to the 3 best channels. To further limit the selected features, the non-linear technique that is called t-distributed Stochastic Neighbor Embedding (tSNE) was applied for the final representation of the selected features, in a 2-dimensional space. In this way, 2 characteristics were selected for each section of 10 seconds. Finally, a kNN classifier was employed for the seizure-non seizure problem achieving SENS equal to 80.87%.

Mansouri et al. [106] proposed a methodology for the detection of seizures. In their methodology, EEG recordings are divided into 10 seconds epochs with a 5-second overlap and the Fast Fourier Transform (FFT) is applied to extract the power for the 5 EEG rhythms. A threshold function is then applied for the initial separation of the pathological sections. In order to study the transition from the preictal to the ictal period, they created a network of distances, based on the Euclidean distance between the coefficients of the Fourier Transform, corresponding to the high band of the rhythm c. The distance network models the synchronization of brain activity and the diffusion of a seizure in the brain. A network of correlations is then created, between the channels. The original methodology was applied to EEG recordings from 18 patients and provided a SENS rate of 83%.

Zhang et al. [107] proposed a methodology employing DFT and extracting band energies that they fed in an Attention Network AttVGGNet, to achieve ACC = 95.6%, SENS = 94.7%, SPEC = 94.1%, Recall = 89.3%, Precision = 78.1% in the ictal-interictal classification problem. Akbarian et al. [108] combined DFT with effective brain connectivity measures to feed an Autoencoder Neural Network and achieved ACC = 97.91% SENS = 97.65%, SPEC = 98.06% in the same problem.

An approach using CNN to reduce the vector of characteristics is presented by Tian et al. [109]. The methodology initially separates the EEG recordings from 23 cases of the CHB-MIT DB in 1 second periods and uses FFT and WPD to calculate the time, frequency, and TF characteristics. The characteristics are then inserted into a Convergent Neural Network, which reduces the dimension of the vector characteristics and isolates the characteristics with the best classification ability. The classification model is based on a TSK

TABLE 2. Studies validated on the bonn database published in 2020-2022.

Authors	Year	Signal Transform	Feature Extraction	Classification	Classification Problem	Results
Al-Hadeethi et al. [14]	2020	Time domain	Statistical Features	adaboost LS-SVM	All combinations	ACC=99%
Aliyu et al. [35]	2021	Time-Frequency	DWT	LSTM	ZONF-S	ACC=99%
Amin et al. [48]	2020	Time-Frequency	DWT + Arithmetic Coding	SVM, KNN, MLP	Z-S, ZONF-S	ACC=100%
Anuragi et al. [71]	2022	Time-Frequency	EWT	Extra Trees	Z-N-S, ZO-NF-S	ACC=99.33%, ACC=97.8%,
Arı et al. [59]	2020	Time-Frequency	WPD + dispersion entropy	SVM	Z-O-N-F-S	ACC=99,53%
Ashokkumar et al. [52]	2021	Time-Frequency	DWT, Fractional S-transform, Entropy	Deep CNN	NF-S	ACC= 99.7% , SENS = 97.71%, SPEC= 98.7%
Ashokkumar et al. [47]	2020	Time-Frequency	Optimal equilateral wavelet filter bank, Fuzzy, Renyi and Kraskov entropy	Gaussian SVM	ZONF-S NF-S	ACC=99.4% ACC=98.6%
Ashokkumar et al. [66]	2020	Time-Frequency	Q-Tuned Wavelet Transform, Approximate entropy	Extreme learning adaptive neuro-Fuzzy Inference System	ZO-NF-S	ACC=99.72%
Bari et al. [79]	2020	Time-Frequency	EMD with normalized Intristic Mode Function	Quadratic discriminant analysis (QDA)	NF-S	ACC=99%, SENS=98.5%, SPEC=100%
Baykara et al. [55]	2021	Time-Frequency	Stockwell Transform, entropies and Perservals energy	ELM	ZO-NF-S	ACC=90%, SENS=95%, SPEC=82%
Brari et al. [88]	2021	Non-Linear	Higuchi Fractal Dimension	KNN	ZO-NF-S	ACC=97.28%
De La O Serna et al. [25]	2020	Frequency domain	Taylor-Fourier Filter Bank with O-Splines	SVM	ZO-NF-S	ACC=94.88%
Eltrass et al. [12]	2021	Time domain	Energy of signal	Quantized Kernel Least Mean Square	Z-O-N-F-S	ACC=97.88%, SENS=98.8%, SPEC=97.65%
Gao et al. [89]	2020	Non-Linear	Approximate Entropy, Recurrence Quantification Analysis	CNN	ZO-NFS	ACC=99.26%, SENS=98.84%, SPEC=99.26%
Goshvarpour et al. [90]	2020	Non-Linear	Lagged Poincare Plot	KNN	Z-F-S	ACC=96%, SPEC=99.48%, SENS=95.19%
Gu et al. [160]	2021	Raw Signal	-	Hierarchical discriminative sparse representation classifier	Z-O-N-F-S	ACC=98.8%
Hassan et al. [77]	2020	Time-Frequency	Complete Ensemble EMD with adaptive noise	AdaBoost	ZO-NF-S ZONF-S	ACC=97.6% ACC=99.2%
Jana et al. [32]	2021	Time-Frequency	STFT	SVM	ZONF-S	ACC=97.63%, SENS=98.38%, SPEC=94.67%
Jang et al. [49]	2020	Time-Frequency	DWT and Phase-Space Reconstruction	Neural Network with weighted fuzzy membership (NEWFM)	Z-S	ACC=97.5%, SENS=95%, SPEC=100%
Jiang et al. [62]	2020	Time-Frequency	Scattering Transform, Fuzzy entropy, Log Energy entropy	SVM	ZO-NF-S	ACC=99.87%
Lee et al. [36]	2020	Time-Frequency	DWT	Hidden Markov Model	ZONF-S	ACC=99.54%, SENS=99.51% SPEC = 98.6%
Li et al. [61]	2021	Time-Frequency	STFT, WPD, KPCA	TSK fuzzy system	ZO-NFS	ACC=98.67%
Lian et al. [94]	2020	Raw Signal	_	CNN	Z-S	ACC= 99.84%, SENS= 99.5%, SPEC=99.6%
Ma et al. [95]	2021	Raw Signal	_	CNN + RCNN		ACC=100%, SPEC=100%, SENS 100%
Mandhouj et al. [31]	2021	Time-Frequency	STFT spectogram	CNN	ZO-S	ACC: 98.88%, SENS 98.33%, SPEC=100%
Mardini et al. [38]	2020	Time-Frequency	DWT	Naïve Bayes	ZONF-S	ACC=99.3%
Mathur et al. [26]	2021	Frequency domain	Ramanujan periodic subspace (RPS), energy of the projection	SVM	Z-S O-S N-S F-S	ACC= 99.5%, ACC= 98.6%, ACC= 98% ACC= 97.5%

TABLE 2. ***(Continued.)*** **Studies validated on the bonn database published in 2020-2022.**

Molla et al. [50]	2020	Time-Frequency	DWT, Graph Eigen Decomposition (GED)	Feed-Forward NN	ZONF-S	ACC=99.39%
Na et al. [18]	2021	Frequency domain	DFT	KNN	ZONF-S	ACC=99.4%
Nogay et al. [30]	2021	Time-Frequency	STFT spectogram	CNN + ALEXNET	ZO-NF-S	ACC=100%
Oinam et al. [37]	2020	Time-Frequency	DWT	MLP trained with hybrid PSO, GSA	ZF-S F-S	ACC=95.33% ACC=93%
Omidvar et al. [69]	2021	Time-Frequency	DWT, entropy	SVM, MLP with GA for feature selection	ZO-NF-S	ACC=98.7% SENS=97.5%, SPEC=100%
Pal et al. [19]	2021	Frequency domain	FFT, Bubble entropy	KNN	Z-N-S	ACC=99.73%
Polat et al. [20]	2020	Frequency domain + Time domain	FFT + time features	SVM	Z-O-N-F-S	ACC=82.5%
Radman et al. [51]	2021	Time-Frequency	DWT + FFT + time features	Random Forest	ZO-NF-S	ACC= 99.33%, Sens = 98.33%, SPEC=98.88%
Shekokar et al. [99]	2022	Raw Signal	-	LSTM	Z-S	ACC=99.5%
Singh et al. [76]	2021	Time-Frequency	Complete Ensemble EMD, dispersion entropy	MLP	ZO-NF-S	ACC=98.7%
Sujatha et al. [39]	2020	Time-Frequency	DWT, Approximate entropy, Statistical features	SVM	ZONF-S	ACC=96.5%
Sukriti et al. [81]	2021	Time-Frequency	Variational Mode Decomposition (VMD)	Random Forest	ZO-NF-S	ACC=98.2%, SENS=99.7%, SPEC=98.7%
Wang et al. [21]	2020	Frequency domain	FFT	weighted kNN	Z-F-S	ACC=99%
Woodbright et al. [96]	2021	Raw Signal		CNN	ZONF-S	ACC= 98.65%, SENS=96.29%, SPEC=99.25%
Yildiz et al. [29]	2021	Time-Frequency	STFT spectogram, scalogram	CNN, alexnet, resnet-18, googlenet	ZO-NF-S	ACC=100%
Zeng et al. [16]	2021	Time domain	Gray Recurrence Plot	DenseNet NN	ZONF-S	ACC=100%
Zeng et al. [53]	2020	Time-Frequency	Intrinsic Time-Scale Decomposition, DWT, PSR	MLP	Z-O-N-F-S	ACC=94%
Zhang et al. [97]	2020	Raw Signal		CNN with Multi-Scale Non-Local Layer	Z-O-N-F-S	ACC=94.01%, F1=89.46%
Zhang et al. [161]	2021	Time-Frequency, Non Linear	Frequency slice WT (FSWT), Fuzzy entropy, Higuchi FD	t-distributed stochastic neighbor embedding (t-SNE)	Z-O-N-F-S	ACC=93.62%
Zhao et al. [98]	2020	Raw Signal		CNN	ZO-NF-S Z-O-N-F-S	ACC=96.73% ACC=93.55%
Zhou et al. [42]	2020	Time-Frequency	DWT, entropy features	RBF NN	ZO-NFS Z-O-N-F-S	ACC=96.3% ACC=78.4%
Zhou et al. [162]	2021	Time-Frequency	WPD	Graph-Based ELM	ZONF-S	ACC=94.8%
Zubair et al. [46]	2021	Time-Frequency	DWT, Spike Rhythmicity, Relative Spike Amplitude, Spectral entropy	CatBoost	ZONF-S	ACC=97%
Dehuri et al. [163]	2022	Time-Frequency	DWT	SVD-ELM	Z-O-N-F-S	ACC=95%

fuzzy system and achieves percentages of ACC, SENS and SPEC equal to 98.30%, 96.70% and 99.10% respectively.

3) TIME-FREQUENCY DOMAIN ANALYSIS

a: SHORT-TIME FOURIER TRANSFORM

Short-Time Fourier Transform has been used in a few EEG-based epilepsy detection studies. Cao et al. [110] proposed a methodology based on spectral characteristics for the training of a CNN. They applied STFT to calculate the spectrum amplitude from frequency subbands and then used a 2-level CNN, to select and fuse the characteristics that trained an ELM neural network. The validation of the methodology was done in the total of CHB-MIT for 3 problems: ictal/interictal, ictal/interictal/preictal and ictal/interictal/preictal status 1/preictal status 2/preictal status 3 achieving high classification rhythms (99.33%, 98.62% and 87.95 respectively). Gabr et al. [111] extracted spectrogram and scalogram images from the STFT and trained a CNN that achieved 97% ACC in the ictal-preictal-interictal problem. Similar methodologies were proposed by Nasiri et al. [112] and Zhang et al. [113], who they proposed CNN methodologies that classified images obtained from STFT. Nasiri et al. achieved ictal-interictal ACC = 91.71%, SENS = 91.09%,

TABLE 3. Studies validated on the CHB-MIT database published in 2017-2019.

Author	Year	Signal Transform	Feature Extraction	Classification	Classification Problem	Results
Cao et al.[110]	2019	Time-Frequency	STFT	CNN, ELM	a) seizure/non-seizure, b) preictal/ ictal/ interictal	a) ACC=99.33%, b) ACC=98.62%
Harpale et al.[118]	2018	Time-Frequency	Time domain features+ FFT features + Pattern Adapted WT	Fuzzy classifier	ictal-interictal	ACC=96.02% SPEC=94.5%
Mansouri et al.[106]	2019	Frequency	FFT, band power	Assosiation Network	seizure/non-seizure	SENS=83%
Tian et al.[109]	2019	Time-Frequency	WPD, FFT	TSK fuzzy system	seizure/non-seizure	ACC=98.3%, SENS=96.7%, SPEC=99.1%
Birjandtalab et al.[105]	2017	Frequency	FFT, band power	kNN	seizure/non-seizure	SENS=80.87%, F-score=56.23%
Ibrahim et al.[116]	2017	Time-Frequency	DWT, Shannon entropy	kNN	seizure/non-seizure	SENS=94.5%, FDR=1.14/h

SPEC = 94.73% using the leave-one-subject-out cross validation method. Zhang et al, achieved ictal-interictal ACC = 97.75% Recall = 98.44%, Precision = 97.47%.

b: WAVELET ANALYSIS

In a DWT-based study [114], Ahmad et al. used a new signal analysis method, originally proposed in the study "Invariant Scattering Convolution Networks" [115] by Bruna and Mallat, to extract characteristics from EEG recordings and detect abnormalities to identify seizure regions. The method is based on the Scattering Transform, the basic idea of which is to connect the Wavelet Transform to CNN. The researchers applied the technique to EEG data from 24 patients from the CHB-MIT DB and they examined several window sizes with lengths of 32, 64, 128, 256, 512 and 1024 points, concluding that the best window length was 2 seconds (512 points), with 50% coverage. The unsupervised classification method managed to classify 180 of the 197 seizures correctly (ACC: 91.40%).

Similarly, Ibrahim et al. [116] proposed a methodology based on the DWT, the Shannon entropy and the k-nearest neighbors algorithm. Specifically, the DWT analyzes the signal into individual frequencies and Shannon entropy and the standard deviation are calculated for each frequency and for the whole spectrum. The vector characteristics is provided as an input to a kNN classifier for seizure detection. The methodology was applied to EEG recordings from 10 patients from CHB-MIT with 55 seizures and 570 hours of analysis in total and had a SENS of 94.50%.

Recently, Mouleeshuwarapprabu et al. [117] employed the DWT and achieved ACC = 95.6%, SENS = 94.7%, SPEC = 94.1%, Recall = 89.3%, Precision = 78.1% at the ictal-interictal problem using a Nonlinear Vector Decomposed Neural Network. In another work, Harpale et al. [118] proposed an adaptive method using Pattern WT to feed a Fuzzy classifier and achieved ACC = 96.02% SPEC = 94.5% in the ictal-interictal problem. Khan et al. [119] combined the DWT with the LDA classifier for the same problem achieving ACC = 99.6%, SENS = 99.8%. Different TF methodologies such as DWT and EMD have also been combined in studies for enhanced feature extraction [120], [121].

Table 3 and Table 4 present the studies that validated their methodology using the CHB-MIT DB. Table 3 contains the studies of 2017-2019 and Table 4 contains the studies of 2020-2022.

C. EPILEPSY CENTER OF UNIVERSITY OF FREIBURG (FREIBURG DB)

The DB from the Epilepsy Center of the University of Freiburg (Freiburg DB) [10] includes continuous long-term EEG recordings taken from 21 patients (8 men aged 13-47 years, 13 women aged 10-50 years) suffering from drug resistant focal epilepsy. Each EEG recording is taken from six intracranial channels, three focal and three non-focal electrodes, sampled at 256Hz.

EEG data are divided into ictal (providing the beginning and the end of epileptic activity), preictal and interictal activity. At least 24 hours of continuous interictal EEG activity has been recorded for each patient. For each patient two to five seizure episodes are recorded, lasting from a few seconds to a few minutes (from 4.21 to 1071.5 seconds), composing a set of data of 88 seizures, 509 hours of interictal activity and 199 hours of preictal and ictal activity.

On this basis, a clear distinction is made between ictal and interictal activity for each of the patients. The recordings during a seizure, include at least 50 minutes of preictal activity. Although the DB is no longer accessible and can only be accessed through the EPILEPSIAE project [10], it is one of the most complete accessible EEG databases with long-lasting recordings and it has been used in the past extensively by research teams worldwide. In recent years, only a few research papers that test their methodologies on this DB have been proposed.

Ma et al. [122] applied Dictionary Learning and Sparse Representation algorithms to classify ictal and interictal data. According to the proposed methodology, the Freiburg DB EEG recordings are cut into 4-second periods and a 5-level

TABLE 4. Studies validated on the CHB-MIT database published in 2020-2022.

Author	Year	Signal Transform	Feature Extraction	Classification	Classification Problem	Results
Gabr et al.[111]	2020	Time-Frequency	STFT spectogram, scalogram	CNN	ictal-preictal-interictal	ACC=97%
Mouleesh-uwarapprabu et al.[117]	2020	Time-Frequency	DWT	Nonlinear Vector Decomposed NN	ictal-interictal	ACC=95.6%, SENS=94.7%, SPEC=94.1%, Recall=89.3%, Precision=78.1%
Zhang et al.[107]	2020	Frequency Domain	DFT, band energies	Attention Network AttVGGNet	ictal-interictal	ACC=95.6%, SENS=94.7%, SPEC=94.1%, Recall=89.3%, Precision=78.1%
Khan et al.[119]	2020	Time-Frequency	DWT	LDA	ictal-interictal	ACC=99.6%, SENS=99.8%
Akbarian et al.[108]	2020	Frequency Domain	DFT, effective brain connectivity	Autoencoder NN	ictal-interictal	ACC=97.91% SENS=97.65%, SPEC=98.06%
Zeng et al.[120]	2021	Time-Frequency	EWT + DWT	kNN	ictal-interictal	ACC=99.77%, SENS=99.88%, SPEC=99.88
Zhao et al.[104]	2021	Raw Signal	Pearson Correlation	Linear graph Convolution Network	ictal-interictal	ACC=99.3%, SENS=99.43%, SPEC=98.82%, F1=98.73%
Nasiri et al.[112]	2021	Time-Frequency	STFT	CNN	ictal-interictal	ACC=91.71%, SENS=91.09%, SPEC=94.73%
Zhang et al.[113]	2020	Time-Frequency	STFT	deep CNN, ImageNet	ictal-interictal	ACC= 97.75% Recall=98.44%, Precision=97.47%
Hu et al.[101]	2020	Time Domain	Local Mean Decomposition	Bidirectional LSTM	ictal-interictal	G-mean 92.66% SENS=93.61%, SPEC=91.85%
Slimen et al.[121]	2020	Time-Frequency	EMD, DWT, dual-tree complete WT (DTCWT)	LDA	ictal-interictal	ACC=100%
Quintero-Rincón et al.[102]	2020	Time Domain	R-square value, RMS	Random Forests	ictal-interictal	ACC=94.1%, TPR=92% TNR=96%
Siddiqui et al.[103]	2020	Time Domain + Non Linear	Statistical + Entropy Features	Random Forests,	ictal-interictal	ACC=66%, Recall= 83.01%
Bhandari et al. [164]	2022	Time-Frequency	STFT+DWT	Modified Tunicate Swarm, LSTM	ictal-interictal	ACC= 96.87%, SENS=98.7%, PREC=97.98%

DWT is applied, the high frequency coefficients (>32 Hz) are removed and the signal is reconstructed. Zhan et al. [123] utilized DWT along with Fourier Transform and a Convolution Block for feature extraction and trained a Fuzzy C-means classifier achieving ACC = 89.75%, SENS = 85.52% in the ictal-interictal problem. Mu et al. [124] combined DWT with a Graph-regularized non-negative matrix factorization for 21 patients with intracable focal epilepsy and trained a Bayesian LDA classifier achieving ACC = 98.16%, SENS = 93.2%, SPEC = 98.16% in the same problem.

1) NON-LINEAR ANALYSIS

Mu et al. [125] employed the bispectrum analysis, to study the relationship between different frequencies from different channels and from different regions of the brain. The methodology analyzed EEG data from 19 patients, with 78 seizures from Freiburg DB. Nonlinear characteristics, such as entropy characteristics, they were calculated from the bispectrum analysis and used as the input vector in an SVM classifier to separate ictal from interictal activity. Classification results showed high percentages of ACC (96.80%), SENS (95.80%) and SPEC (96.70%).

D. OTHER DATABASES OF EEG EPILEPSY RECORDINGS

In addition to the 3 most widely used EEG databases that were analyzed in detection methodologies, several research teams have applied their methodologies to new EEG databases. Some of these databases are openly accessible (Bern-Barcelona, Temple University Hospital), while others involve clinical EEG recordings that are not available through their studies.

The Bern-Barcelona EEG DB [126] was published in 2012 by a team of researchers who published the Bonn DB and includes 7,500 intracranial recordings from 5 people with drug-resistant, temporal epilepsy. The 20-second recordings originate from 2 electrodes (one focal and one non-focal) and have been sampled at 512 Hz. In studies [127], [128], [129] they apply time domain analysis along with a self-regression model [127], TF analysis with TQWT [129], EMD [130], or Non-Linear analysis with Higuchi Fractal Dimension [131] for the detection of seizures or the separation of focal/non-focal EEG activity.

A more extensive DB was published in 2016 by I.Obeyd and J. Picone with clinical recordings from Temple University Hospital (TUH-EEG Corpus) [132]. The TUH-EEG Corpus is a DB is still being renewed and contains the most long-time, pathological EEG recordings, thus being the most suitable for deep learning methodologies. It includes 16,986 pathological EEG recordings from different time periods, from 10,874 patients, some of whom suffer from seizures. In 2018, the DB was published exclusively for epilepsy cases [133] containing 315 patients with a total of 822 sessions of 20 minutes, of which 280 sessions contain 10 different types of epileptic seizures. The signals were received from 19 recording channels and the majority has been recorded at 256 Hz. In TUH-EEG Corpus research teams mainly applied TF analysis studies with DWT [134], [135], [136], [137], or Wavelet Packet Decomposition [138], analysis in the frequency domain [139], and CNN application [140], in order to detect the seizure activity and to separate the types of epilepsy. The size of the DB and the number of different logs is suitable for deep learning methodologies.

The rest of the studies have analyzed recordings from fewer patients. In the literature, EEG data have been used from the following databases/clinics:

- *Neurology and Sleep Center, New Delhi (NCS)*
- *Peking University People's Hospital (PUPH)*
- *Institute of Neuroscience, Ramaiah Memorial Hospital, India (RMCH)*
- *Department of Neurology, Epilepsy Center, Zhejiang University (INeuro)*
- *KU Leuven dataset*
- *MIT-BIH Arrhythmia DB (MIH Arrhythmia)* [141]
- *All India Institutes of Medical Sciences (AIIMS)*
- *Department of Clinical Neurophysiology, Maastricht (MUMC)*
- *Karunya Institute of Technology and Sciences (KITS)*
- *pone_pat dataset*
- *European Epilepsy DB (EPILEPSIAE)*

Briefly, NCS DB consists of EEG signals recorded from 10 epileptic subjects with a 16-electrode, 200 Hz sampling rate system, divided in three categories: ictal, interictal and preictal. PUPH DB consists of EEG signals of 7 epileptic subjects with a 256 Hz sampling rate. KU Leuven DB consists of EEG recordings of 22 subjects with 22 electrodes during ictal, interictal and preictal states. AIIMS DB contains 20-minute signals from 13 epilepsy patients recorded from a 32-channel EEG system, with 256 Hz sampling rate. MUMC DB consists of 40 routine EEG recordings obtained at the intensive care unit with a 19-electrode setting and 250 Hz sampling rate. KITS DB consists of 258 normal, generalized and focal epileptic EEG signals, recorded with 256 Hz sampling rate and a 16-channel setting. Pone_pat DB consists of ECG and EEG of 15 epileptic patients, with 512 Hz sampling rate. Finally, the EPILEPSIAE DB contains scalp EEG recordings of 217 patients and intracranial EEG recordings from 58 patients from 3 different epilepsy centers that have been recorded during long-term presurgical monitoring.

Also, datasets from other clinics (published or not) that are used in studies together with the well-established datasets of Bonn, CHB-MIT, Freiburg and TUH are briefly mentioned in the next paragraph.

E. DATABASE COMBINATION

Methodological approaches for detecting epileptic activity have, also, been applied to more than one DB, that usually being to two of the three known EEG databases (Bonn DB, Freiburg DB, CHB-MIT), along with the NSC. By doing so, researchers attempt to ensure the generalization of the approach they propose and at the same time, to check and compare the effectiveness of their method with other methodologies.

In most of the studies the methodology is applied to the short-term EEG sections of Bonn DB and to the pediatric, long-time EEG recordings of the CHB-MIT DB. In recent experimental studies, the methodologies apply TF Analysis, either with Wavelet Transform [142], [143], [144], [145], or with EMD [146], [147], Non-linear Analysis [148], or they use the signal directly without processing and with deep learning algorithms [149], aiming at detecting epileptic activity.

More complex methodologies are applied to the studies that are evaluated on the CHB-MIT and Freiburg DB databases [150], [151]. CNN neural networks have been used in a methodology that processes signals directly from long-time recordings from CHB-MIT and Freiburg DB databases, achieving ACC rhythms of over 95% for three classification problems [150].

The research revealed only one seizure detection methodology, applied to EEG data from Bonn DB, Freiburg DB and CHB-MIT [152]. Initially the EEG recordings were split into 4-second periods, then a 5-level DWT (db4) is applied, and the Local Binary Patterns (LBP) are calculated to characterize the seizures episodes. Then a collaborative learning framework is created with SVM algorithms, based on the Easy Ensemble, for the classification of seizures and non-seizure that are not balanced. Finally, a multi-level decision fusion algorithm is proposed. Classification ACC reached 95% for Freiburg DB and CHB-MIT for the separation of ictal/interictal condition.

In addition, some researchers have studied the performance of their methodology on one or two of the epileptic EEG databases and on EEG data collected from a clinical environment (custom database). Table 6 contains all the methodologies that were tested on data from multiple databases.

IV. DISCUSSION

In this systematic review, we have analyzed studies published between 2017 and 2022 (May) that propose a methodology

TABLE 5. Studies that examine other databases.

Authors	Database	Date	Category of Features	Feature Extraction	Classification	Classification Problem	Results
Zeng et al.[165]	PUPH	2017	Non-Linear	Permutation Entropy	QDA	ictal-preictal-interictal	ACC=90.3%
Gao et al. [127]	Bern-Barcelona	2018	Time-Domain	Statistical Features	Autoregressive Linear Model	Seizure-Non seizure	F1= 93.75%
Zhang & Yang et al. [134]	TUH	2018	Frequency, Non-Linear	FFT, Statistical Features, Fractal Dimension	SVM	ictal-interictal	ACC=99.4%
Sriraam et al. [166]	RMH	2018	Non-Linear	Teager Energy	MLP	ictal-interictal	SENS=94.38%, SPEC=98.25%,
Ma *et al.* [122]	Freiburg	2019	Time-Frequency	DWT	Dictionary Learning	ictal-interictal	ACC=98.5%, SENS=93.39%, SPEC=98.51%
Mahmoodian *et al.*[125]	Freiburg	2019	Frequency, Non-Linear	FFT, Cross-bispectrum Analysis	SVM	seizure- non seizure	ACC=96.8%, SENS=95.8%, SPEC=96.7%
Alhussein et al.[140]	TUH	2019	Raw Signal	-	CNN, Transfer Learning	ictal-interictal	ACC=87.96%
Zhang et al.[135]	TUH	2020	Time-Frequency	DWT	CNN	ictal-interictal	SENS=70.98%, SPEC=73.17%
Sharma et al. [136]	TUH	2020	Time-Frequency	DWT, minimized orthogonal wavelet filter bank, Fuzzy entropy, Fractal Dimension	SVM	ictal-interictal	ACC=79.34%
Iešmantas et al. [139]	TUH	2020	Frequency Domain	Phase-Locking Value	CNN	ictal-interictal	ACC=74%
Zhan et al. [123]	Freiburg	2020	Time-Frequency	DWT, Fourier Transform, Convolution Block	Fuzzy C-means (FCM)	ictal-interictal	ACC=89.75%, SENS=85.52%
Tuncer et al. [138]	TUH	2021	Time-Frequency	WPD, Chaotic one-dimensional local binary pattern (CLBP)	SVM	ictal-interictal	ACC=96.23%, PREC=96.92%, Recall=95.01%, F1=95.93%
Priyasad et al. [167]	TUH	2021	Raw-Signal	Attentive Feature Fusion	deep CNN	ictal-interictal	F1 score=96.7%
Lu et al. [131]	Bern-Barcelona	2021	Non-Linear	Sample Entropy, Higuchi Fractal Dimension	SVM	ictal-interictal	PREC 88%, Recall 79%, F1= 81%
Mu et al. [124]	Freiburg	2021	Time-Frequency	DWT + Graph-regularized non-negative matrix factorization (GNMF)	Bayesian linear discriminant analysis (BLDA)	ictal-interictal	ACC=98.16%, SENS=93.2%, SPEC=98.16%
Hadiyoso et al. [168]	NSC	2021	Non-Linear	Spectral Entropy, Katz & Sevcik Fractal Dimension	Naïve Bayes	Ictal- Preictal-Interictal	ACC= 85.3%, SPEC= 92.7% SENS=85.3%

for automated, Machine Learning epilepsy detection using EEG recordings from published databases that are available to the public, either as open source or by paying. 190 studies were found that meet the eligibility criteria. From these 190 studies, 125 studies were tested with EEG recordings from only one DB, while in the remaining 65 studies the methodology was evaluated on more than one database (multi-DB).

Even though different methodological approaches are proposed, a common basic structure is followed in most of them as represented in Fig. 3. First, the preprocessing step takes place (or is already performed in the DB recordings), where the EEG signals are filtered, and an artifact rejection methodology is performed/applied. In this step, the bandwidth is limited and only frequencies with scientific interest to the EEG interpretation are allowed, that being usually in the range of [0.5-45] Hz. Also, in most studies the recordings are segmented into fixed length time-windows, either after evaluating the optimal window length or arbitrarily. Next, a signal transformation (Frequency or TF or Non-Linear) may or may not take place by employing well established methodologies such as FFT or DWT and the signal is usually divided to the 5 EEG rhythms namely Alpha, Beta, Gamma, Theta, Delta (or some other study specific division). Following, the feature extraction step takes place where the feature vector is created. The feature vector may include features from more than one domain (Time, Frequency, TF or Non-Linear). Some studies also employ multiple TF transformations (such as DWT along with STFT) and perform the feature extraction step on all of them. Next, a feature selection methodology is performed where the feature vector is reduced to the most effective characteristics for classification or transformed with a vector transformation such as Principal Component Analysis (PCA). Finally, the proposed Machine Learning algorithm is trained for one or more classification problems. The performance results obtained from a validation technique such as k-fold cross validation or leave-one-patient-out validation [153] are then reported.

The scope of this study is to provide a systematic overview of the methodologies and the databases used in the last 5 years, to facilitate as a reference point for researchers that plan on proposing a new methodology for epilepsy detection.

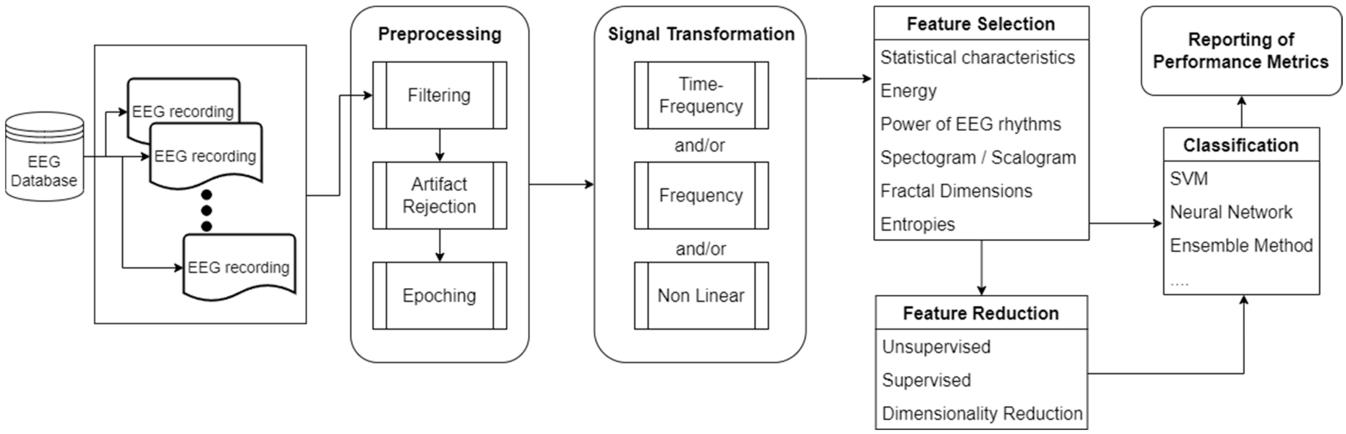

FIGURE 3. **Basic structure of electroencephalography (EEG)-based epilepsy detection methodologies.**

In the following paragraphs, issues regarding the selected signal transformation methodology and the selected classifier methodology will be discussed and percentage measures will be presented. Furthermore, an analysis regarding the studies with multiple databases will be performed and insights about which databases are most commonly combined together will be provided. Next, observations about specific DB characteristics that should be noted from researchers for future studies will be presented. Finally, a brief comparison of this systematic review with other related reviews regarding epilepsy will be performed and the limitations of this methodology will be discussed.

Regarding the Signal Transformation step, TF methodologies are far more popular among the examined studies, with 59.84% of them employing a TF transformation. According to Morales et al. [27] TF advantage over other EEG methods is their interpretability because they provide more direct information about the neurophysiological mechanisms of the EEG data. Also, the capability of most TF decompositions to transform the time domain signal to image makes them suitable to be used along CNN implementations. The TF that is most used is the DWT, which is used in the 43.8% of the TF methodologies alone, as well as on the majority of the studies that employ multiple TF transforms (being 13.7%). The more sophisticated Empirical Mode Decomposition comes second, with usage percentage of 13.7% while the STFT comes third with 12.3%. An interesting observation can be made regarding the methodologies that employ a combination of TF methodologies, that being the increase in the population of them. Specifically, while only 7.1% of the TF related studies employed a combination of TF during 2017-2019, this percentage has been significantly increased during 2020-2022, reaching 17.8%. This indicates the continuous effort of research teams to propose more elaborate schemes for better epilepsy detection. Last but not least, another observation that can be made by comparing the percentages of 2017-2019 and 2020-2022 is that the Raw-Signal methodologies have been increased significantly. Specifically, 2 studies (4.1%) proposed a Raw-Signal scheme in the former timeline while 9 studies (8.9%) proposed one in the latter timeline. The reason behind this, is the increased computational power that modern computer systems have, especially regarding GPU performances, that make able to operate complex Convolutional Neural Networks which take as input Raw-Signal data and transform them using 1-D convolutional layers. Fig. 4 represents a chart of the popularity of the Signal Transformation methodologies.

Regarding the Classification step, 50% of the classifiers used in the previous 5 years were traditional Machine Learning classifiers (meaning SVM, kNN, Naïve Bayes etc, excluding Random Forests), with SVM being the most popular one, being employed in 24% of the total studies (the best performing classifier was reported for studies that examined multiple classifiers). Neural Networks were used in 40% of the total studies with CNN being by far the most used implementation. A detailed graph containing the popularity of each classifier is presented in Fig. 5. However, when comparing the 2017-2019 and 2020-2022 percentages (Fig. 6), it can be observed that the usage of Neural Networks has been doubled (25% to 50%), making them the most used classifier the last 2 years, that are still gaining popularity. As mentioned in the previous paragraph, one reason of this change is the increase in computational power. Finally, the least employed category of Machine Learning algorithms in the EEG epilepsy detection is the Ensemble learning. Only 10% of the studies proposed an ensemble algorithm such as Random Forests, Gradient Boosting or Extra Trees.

Regarding the classification performance of each algorithm, it was evident that a direct comparison is impossible for multiple reasons: a) the lack of a universal dataset for every study. Even in studies conducted on the same DB, the selection of EEG signals or subjects differs. b) The fact that each study examines a different classification problem (i.e., studies on the Bonn DB evaluate any combination of Z-O-N-F-S). c) Methodology flaws may exist in some studies (such as overfitting), thus reporting higher performance

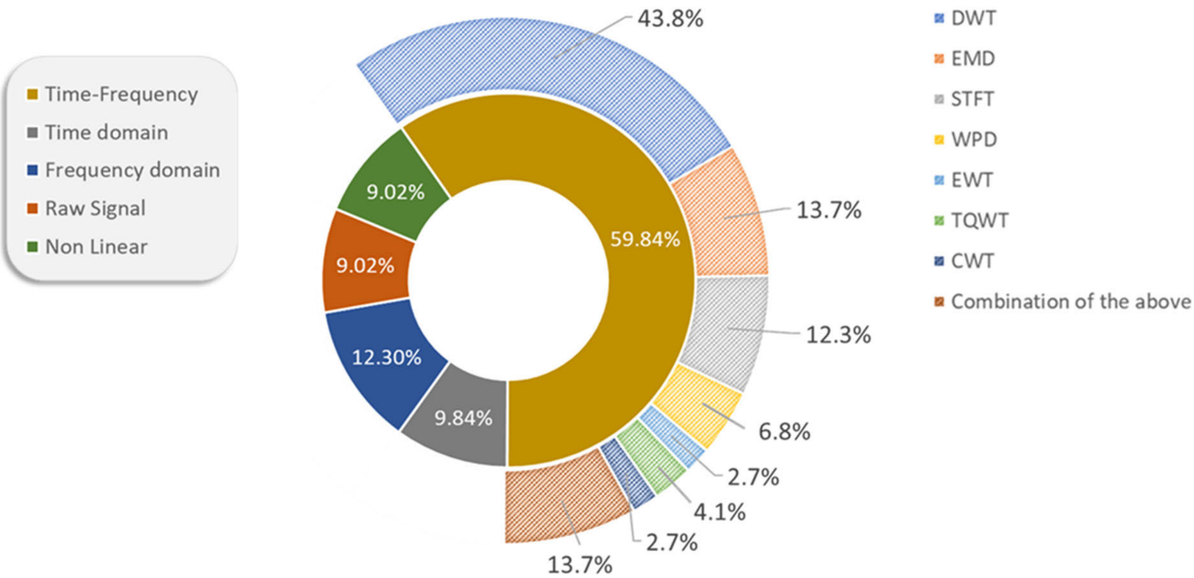

FIGURE 4. Signal processing techniques that are applied in the reviewed methodologies.

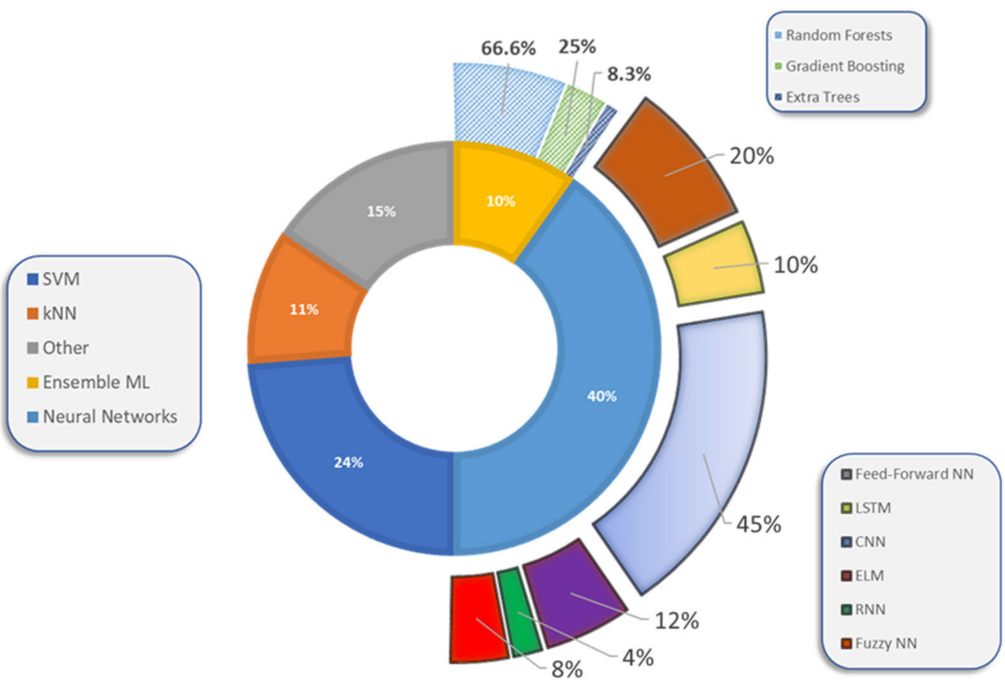

FIGURE 5. Machine learning algorithms that are applied in the reviewed methodologies.

scores. d) Lack of an adequate number of studies with a standard classifier, database and problem so that a rigorous statistical evaluation of the classifier's differences in performance can be made.

Having mentioned all these constraints, a comparison of the average accuracy scores for each algorithm is made in Fig. 7., which is divided into three sub-figures, each containing the average accuracy scores of a different DB. For Bonn DB, studies have been divided into three categories: Healthy-Interictal-Ictal, Seizure Detection and Healthy-Interictal. For CHB DB and Other DB figures, a single Seizure Detection category has been explored. It should also be noted that CNN has been examined separately from Neural Network studies due to its significance, as examined in Fig. 5. Also, algorithms employed in less than two papers were not included in this evaluation. As observed,

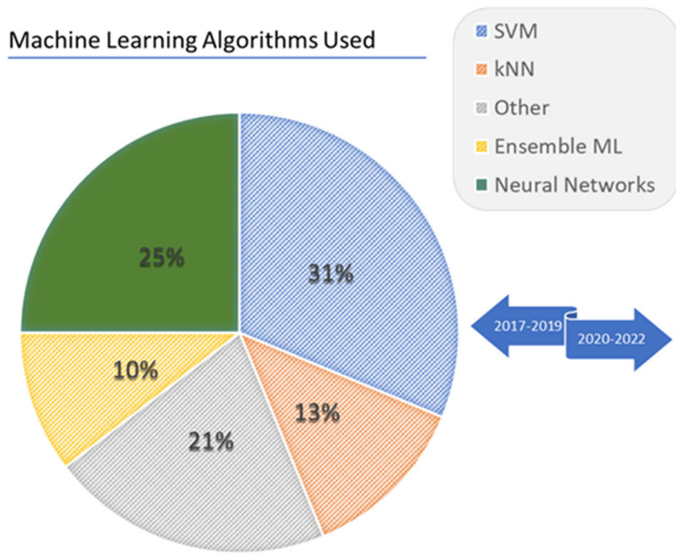

FIGURE 6. Comparison of machine learning methodologies used in the 2017-2019 and the 2020-2022 period.

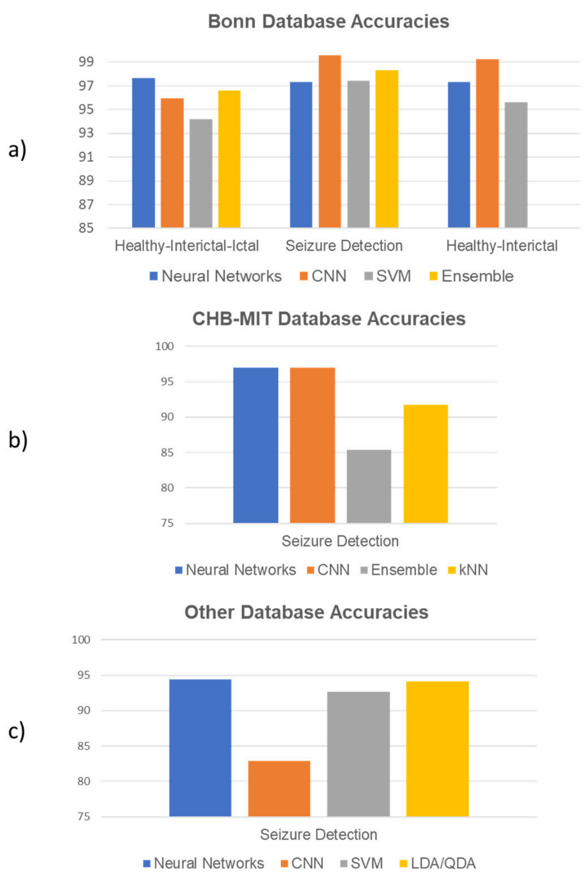

FIGURE 7. Average accuracies of different classifiers for each database. Bonn DB studies are divided into 3 categories namely Healthy-Ictal-Interictal, Seizure Detection and Healthy-Interictal. Convolutional Neural Networks (CNN) is considered a different category from neural networks.

CNN implementations achieved higher accuracies for Seizure Detection and Healthy-Interictal problems in Bonn DB and CHB DB. Also, Neural-Network implementations achieved higher performance in the Healthy-Ictal-Interictal Bonn DB problem and Seizure Detection CHB and Other DB problems.

With regard to the popularity of the available databases, the DB of Bonn is by far the most examined DB. 46.8% of the studies evaluate their methodologies using only the Bonn DB. Also, 72.31% of the studies that examine multiple databases make use of the Bonn EEG recordings. In total, 71.5% of the studies used the Bonn recordings. The usability and immediate availability of the DB, makes Bonn DB the main base for the study of epileptic activity, during the ictal and interictal period. A significant percentage of methodologies have been applied to CHB-MIT long-time recordings, while Freiburg DB, once one of the first choices of researchers, is no longer preferred, possibly because it is no longer accessible for free. A detailed overview of the databases used in the studies that were examined in this review can be found in Fig. 8. The left side of Fig. 8 represents how the studies are divided based on what DB they use. The right side is only about studies examining multiple databases. Each bar represents the percentage of the multiple-DB studies that use a certain DB.

Fig. 9 represents a chord diagram in which the thickness of a chord between DB A and B is proportionate to the percentage of studies that examined EEG recordings from both A and B. The strong connection between Bonn and CHB-MIT DB's can be noted, since 47.7% of the multiple DB studies contain the combination Bonn & CHB-MIT databases. Also, the combination of Bonn DB and Neurology Sleep Center DB is also notable, since 13.8% of the multiple DB's studies employ it. Finally, the combination of Freiburg DB and CHB-MIT DB at 9.2% is the biggest collaborative DB scheme that does not include Bonn DB. Table 7 represents the percentage of multiple DB studies at which the DB at x axis and the DB at y axis are combined.

All these machine learning models aim to provide intelligent systems to assist the neurophysiologists' task in the

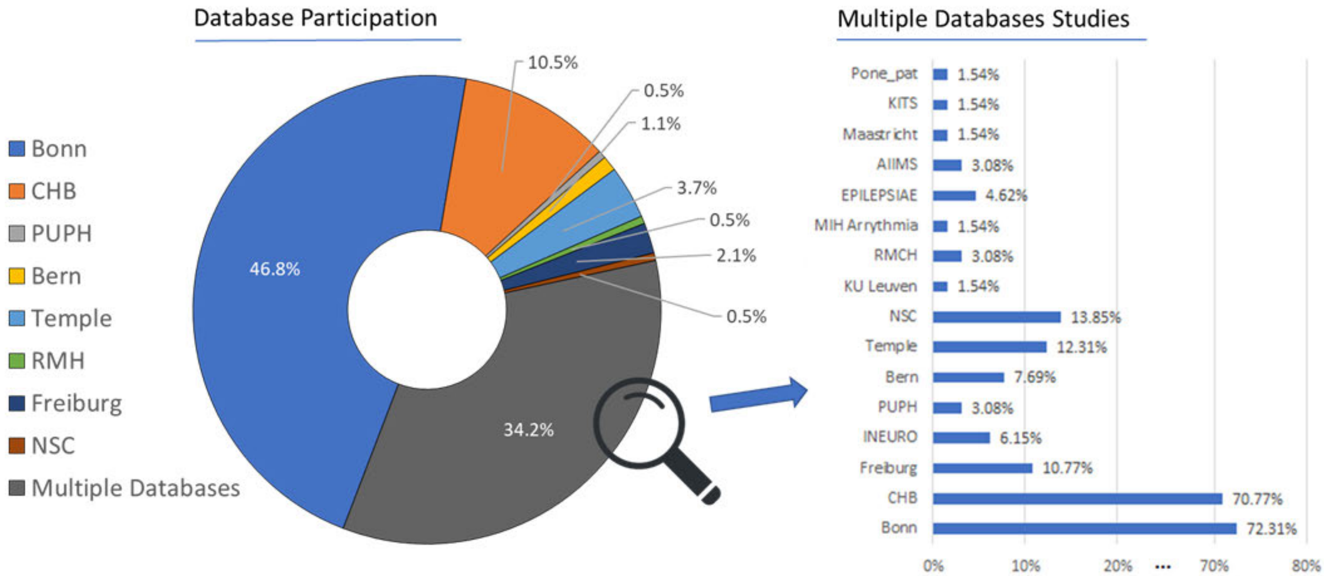

FIGURE 8. Left: Pie chart containing the employment percentages of each database in the reviewed studies. Right: Regarding the "Multiple Databases" studies, this bar chart represents the percentage of studies that examined a certain database.

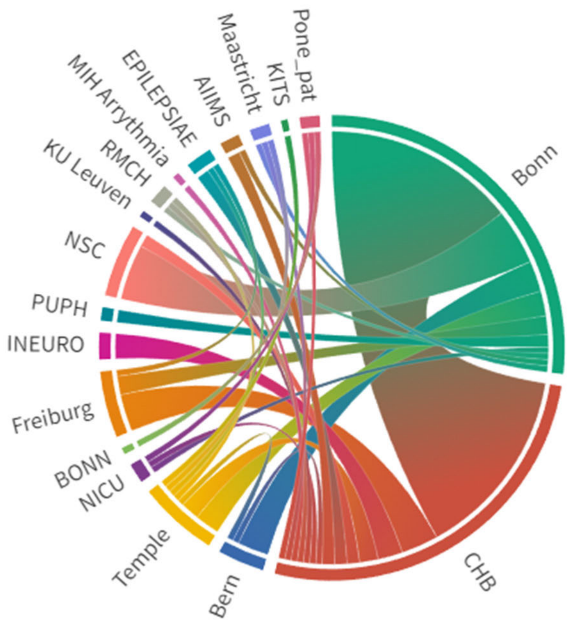

FIGURE 9. Chord diagram representing which databases are co-examined in the studies that examine multiple databases.

diagnosis of the life-threating epilepsy. Since there in no intelligence without learning, a crucial aspect of these potential systems is on which data the machine learning models are trained on. The Bonn DB database is an extremely limited database of about 3,5 hours recordings in total, consisting of both scalp (i.e. sets Z, O) and intracranial (i.e. sets N, F, S) EEG recordings. Undoubtedly, the electrical activity of the brain obtained from the scalp and the one recorded directly from the exposed brain region is totally different. Algorithms trained on such data pose the greatest risk of profound errors in the quality of the ML model and later on the development of the system. Furthermore, the CHB-MIT DB consists of EEG recordings from both pediatric and adult cases. It goes without saying that there are significant differences in brain maturation among pediatric and adult cases and at least 4 subjects of the CHB-MIT DB (Patients 4, 15, 18, 19) do not meet age criteria to be considered pediatric cases. Thus, the inclusion of the EEG data of these subjects in groups with adult EEG recordings may mislead the classification results. Taking all the above into account, it is of significant importance machine learning models applied in all aspects of medicine to be aligned with the medical problem their dealing with and not just present a ML model that may provide the highest classification results but have no actual impact on the medical problem.

A variety of comprehensive review papers have been presented during the 2021-2022 timeline exploring Machine Learning EEG Epilepsy detection and recent advances on the field. These studies are summarized in Table 8. None of the mentioned studies have followed a PRISMA-based review methodology to systematically evaluate EEG-based studies that perform epilepsy detection. A brief report of the results and limitations of these studies is presented in the following paragraph.

Saminu et al. [154] limited their years of coverage to 2016-2021 and focused on methodologies taking advantage of Computer Aided Devices that perform classification based on EEG and/or MRI signals. However, this review was not systematic and was focused only on the classification

TABLE 6. Studies that examine multiple databases.

Author	Year	Databases
Chen et al.[142]	2017	Bonn, PUPH
Solaija et al.[169]	2018	CHB-MIT, KU Leuven
Raghu et al. [170]	2018	Temple, RMCH
Kumar et al. [130]	2019	Bonn, Bern
Jiang et al. [137]	2019	Temple, Bonn
Raghu et al. [171]	2019	Bonn, RMCH, CHB-MIT
Al Ghayab et al.[172]	2019	Bonn, Bern
Bilal et al. [173]	2019	Bonn, NSC
Pandey et al. [174]	2019	CHB-MIT, MIH Arrythmia
Wu et al. [175]	2019	CHB-MIT, INeuro
Truong et al. [151]	2019	CHB-MIT, Freiburg, EPILEPSIAE
Gómez et al. [176]	2020	CHB-MIT, EPILEPSIAE
Sameer et al. [177]	2020	Bonn, NSC
Lian et al. [178]	2020	Bonn, Freiburg
Zhou et al. [179]	2020	Bonn, NSC
Ansari et al. [180]	2020	CHB-MIT, Bonn, AIIMS
Raghu et al. [181]	2020	CHB-MIT, Bonn, TUH, MUMC
Abiyev et al. [182]	2020	CHB-MIT, Bonn
Ayodele et al. [183]	2020	CHB, Temple
George et al. [184]	2020	KITS, Temple
Li et al. [185]	2020	Bonn, CHB, Freiburg
Li et al. [186]	2020	CHB-MIT, Bonn, Temple
Rout et al. [187]	2020	Bonn, NSC
Wu et al. [188]	2020	CHB-MIT, Bonn
Kiranmayi et al. [189]	2020	Bonn, custom
Zhang et al. [190]	2020	Bonn, NSC
Dash et al. [191]	2020	CHB-MIT, AIIMS, Custom
Jiang et al. [192]	2020	CHB-MIT, Bonn
Liu et al. [193]	2020	Temple, EPILEPSIAE
Lyu et al. [194]	2021	CHB-MIT, Custom
Anuragi et al. [195]	2021	CHB-MIT, Bonn
Supriya et al. [196]	2021	Bern, Bonn
Panda et al. [197]	2021	Bonn, NSC
Xiong et al. [198]	2021	CHB-MIT, Bonn
Shankar et al. [199]	2021	CHB-MIT, Bonn
Shariat et al. [200]	2021	CHB-MIT, Custom
He et al. [201]	2021	CHB-MIT, Bonn, Pone_pat
Liu et al. [202]	2021	CHB-MIT, Bonn
Jiang et al. [203]	2021	CHB-MIT, Bonn
Glory et al. [204]	2021	CHB-MIT, Bonn
Wang et al. [205]	2021	Bonn, NSC
Hu et al. [206]	2021	CHB-MIT, INeuro
Praveena et al. [207]	2021	Bern, Bonn, Temple
Peng et al. [208]	2021	CHB-MIT, Bonn, NSC
Aayesha et al. [209]	2021	CHB-MIT, Bonn
Hu et al. [210]	2021	CHB-MIT, INeuro
Li et al. [211]	2021	CHB-MIT, Bonn

TABLE 6. *(Continued.)* Studies that examine multiple databases.

Zarei et al. [212]	2021	CHB-MIT, Bonn, NSC
Sahani et al. [213]	2021	CHB-MIT, Bonn
Rafiammal et al. [214]	2021	CHB-MIT, Bern, Bonn
Cao et al. [215]	2021	CHB-MIT, INeuro
Huang et al. [216]	2021	Bonn, CHB-MIT
Chen et al. [142]	2017	Bonn, CHB-MIT
Jiang et al. [143]	2019	Bonn, CHB-MIT
Wang et al. [144]	2017	Bonn, CHB-MIT
Yuan et al. [145]	2018	Bonn, CHB-MIT
Lu et al. [146]	2018	Bonn, CHB-MIT
Hussain et al. [147]	2019	Bonn, CHB-MIT
Zhang et al. [148]	2019	Bonn, CHB-MIT
Abdelhameed et al. [149]	2019	Bonn, CHB-MIT
Zhou et al. [150]	2018	CHB, Freiburg
Yu et al. [217]	2019	CHB, Freiburg
Sun et al. [152]	2019	Bonn, CHB-MIT, Freiburg
Fu et al. [218]	2019	Bonn, PUPH

algorithm usage percentages of the studies. Ahmad et al. [155] published a systematic review, wherein no specific search methodology was mentioned, and the years of coverage were not reported. The authors focused on ML/DL methodologies for EEG epilepsy detection but no exclusion criteria was reported. The study was not adequately explained and many conclusions about comparisons of performance metrics between classifiers were vague due to lack of information. In another review, Praveena et al. [156] presented a short non-systematic review focusing solely on studies applying Deep Learning for EEG epilepsy detection. Moreover, Supriya et al. [157] published a review that focuses on EEG epilepsy detection studies that employ Graph Theory schemes such as Visibility Graph, Time Series Complex Network and others. Lastly, Rasheed et al. [1] published a review of the methodologies for automated prediction of seizures and provided a timeline since the beginning of EEG epilepsy prediction methodologies in 1970, also commenting on the pitfalls of ML prediction methodologies.

The advantage of our review over other recently published related reviews is that we systematically collected, analyzed and evaluated experimental studies following the PRISMA statement, providing useful insights for every stage of the creation of an original methodology for EEG-based epilepsy detection. Specifically, we present a detailed comparison of public DB's regarding their characteristics, their percentage of employment on other studies and the combination between them. Furthermore, we provide a detailed examination of the Signal Transformation and Feature Extraction steps, evaluating which is used most and how these tendencies changed after 2020. Likewise, we evaluate the Classification Step,

TABLE 7. Each cell represents the percentage of studies that used axis x & axis y combination of databases, from the total of multiple database studies.

	Bonn	CHB-MIT	Freiburg	Bern	Temple	Upenn	Pone_pat
CHB-MIT	47.7%	--	--	--	--	--	--
Freiburg	4.6%	9.2%	--	--	--	--	--
INEURO		5.9%		--	--	--	--
PUPH	3.1%			--	--	--	--
Bern	7.8%	1.5%		--	--	--	--
Temple	6.2%	4.6%		1.5%	--	--	--
NSC	13.8%	3.1%				--	--
KU Leuven		1.5%				--	--
RMCH	1.5%	1.5%			1.5%	--	--
MIH Arr.		1.5%				--	--
Mayo Clinic		1.5%	1.5%			1.5%	--
EPILEPSIAE		3.1%	1.5%		1.5%		--
AIIMS	1.5%	3.1%					--
Maastricht	1.5%	1.5%			1.5%		--
KITS					1.5%		--
Pone_pat	1.5%	1.5%					--

TABLE 8. A comparison of recent related review papers exploring EEG-based epilepsy detection studies.

Author	Year	Search Methodology	Years of Coverage	Inclusion Criteria / Focus
Saminu et al. [154]	2022	Not Reported	2016-2021	Computed Aided Devices, EEG or MRI,
Ahmad et al. [155]	2022	Not Reported	Not Reported	EEG, Epilepsy, Deep Learning/ Machine Learning, Further inclusion or exclusion criteria are not reported
Praveena et al. [156]	2021	Not Reported	Not Reported	EEG, Epilepsy, Deep Learning
Supriya et al. [157]	2021	Not Reported	Not Reported	Graph Theory, EEG, Epilepsy
Rasheed et al. [1]	2020	Not Reported	1970-2019	EEG, Epilepsy, Deep Learning/ Machine Learning, prediction, Focus on discussion of Machine Learning pitfalls
This study	**2022**	**PRISMA**	**2017-2022**	**EEG, Epilepsy, Detection, Machine Learning, Published DB Focused**

providing details and visualizations about the increase in popularity of the Neural Networks during the recent years.

In this point, it is important to mention the limitations of this review. Firstly, the large number of studies examined (190) made difficult to evaluate individually each implementation, so a detailed analysis of each pipeline was not performed, but instead they were examined in a more general format of distinct steps as presented in Tables 1-5. Furthermore, a systematic evaluation of different classifier performances cannot be performed due to multiple reasons already mentioned, so the comparison of accuracy scores performed in this study is clearly indicative and should not be taken for granted for the selection of the best methodology. Lastly, the large number of studies existing on the EEG epilepsy detection topic, obliged us to evaluate studies from a limited timeline (2017-2022), thus not being able to effectively track the methodology trends during time.

V. CONCLUSION

A systematic review of the published methodologies of the last 5 years for automatic EEG epilepsy detection using Machine Learning has been presented in this study. This review is meant to be read by researchers in the EEG epilepsy detection area that need to fill the literature gap regarding the proposed methodologies of the latest years. The study focused on the Signal Transformation methodologies and the Classification Algorithms applied and evaluated which is prevailing during the latest years. Furthermore, detailed comparison and evaluation of the published epileptic EEG databases has been performed. The PRISMA guidelines have been focused during the review process. This review concluded on the following observations: 1) the future on automatic epilepsy detection lies on methodologies that employ a combination of Time-Frequency transformations to produce images and feed CNN classifiers, as well as on methodologies that employ Neural Networks on raw EEG signal. Also, CNN seems to outperform other classifiers regarding the Seizure Detection and Healthy-Interictal problems. 2) the most popular database is Bonn DB, however more databases such as Neurology and Sleep Center DB, Freiburg DB, Temple DB provide more appropriate EEG recordings (meaning no combination of scalp EEG and intracranial EEG) for classification tasks and are increasingly employed in combination with the most well-established Bonn and CHB-MIT databases. 3) limitations regarding each DB exist and are presented shortly in the Discussion section.

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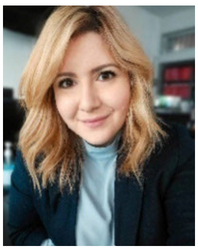

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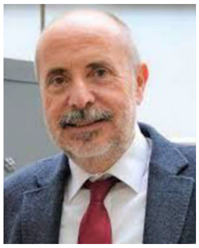

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