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EEG Feature Engineering Methods-A Comprehensive Review

R. John Martin

Faculty of Computer Science & Information Technology, Jazan University, KSA

Abstract: Today, the primary topic of discussion in the signal processing domain is the analysis of non-stationary and non-linear signal data. The use of biomedical equipment generates enormous amounts of physiological data that can be analyzed and used for clinical diagnosis. Manual inference of specific decisions from such signals is laborious due to artifacts and the time-series nature of the data, particularly for electroencephalography (EEG) signals. As a result, it is critical to employ appropriate methods for signal analysis. The purpose of this survey is to gain an understanding of the various techniques used to process EEG signal data in epileptic seizure detection frameworks. A variety of classification and regression frameworks based on machine learning have been reviewed. This systematic review will adhere to the PRISMA guidelines. This survey uncovered several significant findings.

Keywords: DWT, EEG, Feature Engineering, Feature Extraction, Feature Selection, Signal Processing, Time-frequency,

Nomenclature

Abbreviations	Descriptions
CWT	Continuous Wavelet Transform
SVD	Single Valued Decomposition
ICA	Independent Component Analysis
MRA	Multiresolution Analysis
KSE	Kolmogorov–Sinai entropy
ApEn	Approximate Entropy
EMD	Empirical Mode Decomposition
SEN	Spectral Entropy
DWT	Discrete Wavelet Transform
REN	Renyi's Entropy
PhEn	Phase Entropy
WPD	Wavelet Packet Decomposition
PCA	Principal Component Analysis
WE	Wavelet Entropy
FE	Fuzzy Entropy
TE	Tsalli's Entropy
PE	Permutation Entropy
IMF	Intrinsic Mode Functions
SPWVD	Smoothed Pseudo-Wigner-Ville Distribution
EMD	Empirical Mode Decomposition
PSR	Phase-Space Reconstruction
SampEn	Sample Entropy
LPF	Low-Pass Filter
MODWT	Maximal Overlap DWT
DTCWT	Dual Dual-Tree Complex Wavelet Transform
ARM	Auto -Regressive Method
LBDWT	Lifting Based DWT
WT	Wavelet Transform
EM	Eigenvector Methods
TFD	Time-Frequency Distributions
RQAEn	Recurrence Quantification Analysis Entropy
HOS	Higher Order Spectra
FFT	Fast Flourier Transform
EA	Envelop Analysis
STLmax	Short-Term Maximum Lyapunov

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DistEn	Distribution Entropy
PSD	Power Spectral Density
ST	Stockwell Transform
DNN	Deep Neural Network
MWT	Multi-Wavelet Transform
SampEn	Sample Entropy
FD	Fractal Dimension
PE	Permutation Entropy
CCOV	Cross-Covariance Technique
ApEn	Approximate Entropy
MAD	Median Absolute Deviation
IQR	Inter-quartile range
CNN	Convolutional Neural Networks
DT-CWT	Dual-Tree Complex Wavelet Transform
MFDFA	Multi-fractal Detrended Fluctuation Analysis
OLS	Orthogonal Least Squares
DCT	Discrete Cosine Transformation
LNDP	Local Neighbour Descriptive Pattern
SRS	Simple Random Sampling
1D-LGP	One-dimensional Local Gradient Pattern
MWT	Multi-Wavelet Transform
TFD	Time-Frequency Distribution
AAR	Adaptive Auto Regression
1D-LBP	one-dimensional Local Binary Pattern
HHT	Hilbert-Huang transform
P. t-SNE	Parametric t-Distributed Stochastic Neighbor Embedding
TFD	Time-Frequency Distribution
AR	Autoregressive Coefficients
HSA	Hilbert Spectral Analysis
IApEn	Improved Approximate Entropy
SFS	Sequential Feature Selection
CBFS	Correlation-Based Feature Selection

1. Introduction

When it comes to studying neuronal dynamics in the human brain, the EEG is a typical neuroimaging tool that clinicians utilize every day. Recent technological breakthroughs have made possible dense arrays of cranial electrodes, which have broadened the reach of EEG recording. Manual analysis of these signals is strenuous because of the artifacts and time-series nature of the data. Due to its direct influence on a classifier's performance, effective feature engineering from relevant EEG data is critical for improving the efficiency of performance evaluations. Furthermore, highly relevant features improve classification performance, and consequently, feature extraction has emerged as the most crucial stage in the categorization of EEG data. Several researchers looked into using quantitative EEG to assess brain activity during cognitive tasks. The data was verified employing time and frequency domain properties like entropy, power spectrum, autoregressive coefficients, and statistical features.

Feature Engineering is the process of cleaning the data inputs and identifying appropriate features related to a data set in order to get optimum performance from the machine learning frameworks. The first phase of feature engineering is preprocessing. In signal processing applications, the input signal needs to be cleaned by denoising it through the different stages of preprocessing.

The second stage of feature engineering is feature extraction and feature selection. In any classification or regression problem, the data set that contains valuable information is considered a significant input and given to the system for making decisions. In some problems, feature extraction need not be a separate procedure: the classifier itself can induct whichever features are necessary for classification. Nevertheless, there are solid reasons why feature engineering is required during classification [1]. In machine learning problems, the complexity relies on the number of dimensions of input data, and the size of the data sample. To minimize the memory and complexity, it is appropriate to minimize the dimensionality of input data. Feature engineering is a significant step if input data is decided to be inappropriate. Dimension reduction is necessary for simpler models as they are more robust on small datasets. It is more convenient for analyzing the information by visualizing it with fewer dimensions. Feature extraction is a process to find a new set of k dimensions which are integrations of the original D dimensions. In feature selection, we decided to find d of the D dimensions that contain more appropriate information and discard the remaining (D − d) dimensions. This procedure is generally referred feature dimension reduction.

The following sections of this paper provide a comprehensive survey of existing literature on various feature engineering methods for EEG signal analysis, particularly for epileptic seizure prediction and detection problems. Section two of this paper briefly discusses the commonly used signal processing approaches. Section three provides an extensive literature review on EEG feature engineering. Section four discusses the important facts about the review and the concluding remarks.

2. Signal Processing Methods

Presently, different techniques are utilized to analyze changes in the non-stationary EEG signals for event detection or prediction. Most the EEG signals processing techniques come under four extensive types: (i) time domain, (ii) frequency domain, (iii) time-frequency domain, and (iv) nonlinear techniques.

2.1 Time Domain Approaches

Time domain methods are used to extract signal features with qualitative information such as amplitude, regularity, and synchronicity. The statistical components like mean average value, variance, and variability change in the EEG signal over time with a suitable window length. In time domain analysis, the regularity of the signal is characterized by the use of an autocorrelation function. The autocorrelation factor for epileptic EEG signals is not always strong due to heavy variations during a seizure, that is during seizure activity, regularity increases, and the signal will be oscillatory.

Estimating the synchronicity of signals obtained from various electrodes is yet another use of time domain analysis. The measure of synchronicity with the information of how alike the signals are to each other is computed with the linear cross-correlation of two different EEG signals by phase locking. Therefore, time domain features are amplitude dependent. In time-domain-based analysis, discrete-time sequences of EEG epochs are obtained through histograms to detect EEG seizures.

The limitation of using time-domain features is that they only provide spatial information without addressing temporal information. As the EEG signals are non-stationary, uncertain oscillations are common during seizure activity. Hence, it is necessary to add a frequency component to classify seizures.

2.2 Frequency Domain Methods

In EEG signal analysis, frequency measurement is utilized to recognize the occurrence of the events at a specified time, as EEG is a non-stationary signal that consists of events at different frequencies. If all the related features of an EEG signal are estimated and analyzed in frequency, subsequently it is called frequency domain analysis. Generally, PSD has utilized the frequency domain feature. PSD also has some disadvantages in that it cannot isolate the time at which the frequency of interest occurs [2]. PSD is a significant tool to observe local stationary behavior and obtain the time-evolving nature of EEG. Therefore, it gives static and dynamic measures of the EEG signal to a certain extent. PSD alone is not adequate for seizure detection; the time domain features such as synchronicity, periodicity, and average energy are also analyzed.

2.3 Time-frequency Domain Methods

Though time domain analysis provides better spatial information, it falls short in terms of frequency content information that is needed for EEG analysis for classification. In frequency domain analysis, the temporal information can be obtained only subsequent to windowing the functions that are absent in the time-domain analysis of the EEG signals. As EEG signals are non-stationary, selecting a window size is a challenging task in frequency analysis. These difficulties could be solved through time-frequency EEG signals analysis by wavelet analysis.

In the biomedical signal processing field, the wavelet domain approach to EEG analysis is extensively exploited, particularly for seizure detection and prediction. CWT, DWT, WPD, and other variants of wavelet transform methods have evolved over the last few decades for EEG analysis. Both stationary and non-stationary signals can be transformed using the wavelet transform. In EEG analysis, DWT works well for MRA and noise filtering.

2.4 Nonlinear Methods

Many other signal processing approaches are used other than time, frequency, and time-frequency methods for EEG analysis of epileptic seizures. The more popular approaches include EMD, SVD, ICA, and PCA. PCA & ICA are the two commonly used feature selection methods through dimensionality reduction.

3. EEG Feature Engineering

The efficiency of any machine learning system is influenced by feature engineering. Data preprocessing, feature extraction, and feature selection are the three most important phases of feature engineering. The researchers use a variety of approaches for data preprocessing, including wavelet denoising. Three domain approaches are commonly utilized to extract features from EEG signal data: time domain, frequency domain, and time-frequency domain (wavelet domain).

3.1 Feature Extraction and Feature Selection

EEG signals are observed as time-series signals in the time domain, and based on that statistical features are extracted for classification. As the frequency module is missing in time-domain feature extraction, some have adopted frequency domain feature extraction methods too in their issues like the one reported by Chunchu et al. [3]. Numerous researchers have used spectral analysis by taking the assumption that EEG signals are stationary. EEG signals are typically non-stationary time-series signals and will present only time domain and frequency domain information. Afterward, researchers augmented that the frequency module might vary over time in EEG. Therefore, the time-frequency method (wavelet method) for feature extraction is recommended to accommodate time and frequency information.

According to Lina Wang et al. [4] and D. Gajic et al. [5], multi-domain nonlinear feature set provides more effective classification performance than individual domain feature sets. DWT-based feature engineering had been used in their works. Moreover, DWT threshold denoising is used to preprocess the EEG signal data. Subsequently, MRA of feature extraction is adopted for extracting features in the wavelet domain. In another EEG-based application proposed by Ming-ai Li et al. [6] adaptive feature extraction technique is used which is based on WPD and SE-isomap. WPD is also used in combination with PCA for feature engineering, for an epileptic seizure classification work proposed by U.R Acharya et al. [7].

Acharya et al. reviewed [8] various feature extraction methods based on wavelet transform and entropies. In another work by Acharya *et al.* [9] different entropy-based features are extracted for EEG classification problems. They include KSE, ApEn, SampEn, SEN, REN, PE, TE, FE, WE, Normalized Bispectrum Entropy (S1, S2), PhEn and RQAEn. Malihe Sabeti et al. [10] also adopted entropy-based feature extraction methods for their EEG classification problem of schizophrenic and control patients. HOSand Entropy-based nonlinear features are used in another problem brought by Acharya et al. [11] for seizure detection.

Various frequency domain and wavelet domain feature engineering methods such as FFT, TFD, EM, WT, and ARM are detailed by Amjed et al. [12]. The applicability and suitability are studied and concluded that the methods are based on the signals to be analyzed for the specific purpose.

For epileptic seizure detection, numerous EEG classification issues use wavelet domain feature extraction techniques. Umut Orhan et al. [13] and Reza et al. [14] were taking up the DWT technique to attain diverse frequency sub-bands and subsequently statistical features are derived for their EEG classification works. DWT-based wavelet coefficients like mean, energy, variance, and different entropies were utilized subsequent to four to eight-level signal decompositions to detect epileptic seizures as stated in several kinds of literature [15-23]. Another problem put forth by Benzy et al. [24] to find the depth of anesthesia also used DWT-based features for EEG classification. Some other works reported in recently exploited diverse variants of DWT like LBDWT [25], DTCW [26], and MODWT to extract features and to claim their advantage in classification accuracy. Elif Derya Ubeyli [27] utilized DWT-based feature engineering to compare several neural network-based EEG classification approaches. Mrigank Sharad et al. [28] presented another variant of DWT referred simplified LPF-only-DWT for epileptic seizure detection problems.

In a recent work proposed by Tzimourta et al. [29] and claimed that DWT is contributing well to their classification method with SVM. The two alike works of literature put forth by Sharmila et al. [30] and Kavita Mahajan et al. [31] have also used DWT-based feature extraction by decomposing the signals into various sub-bands. According to Sang-Hong Lee et al. [32], DWT-based signal processing in integration with PSR worked fine for the classification of EEG signals.

Time-frequency analysis utilizing the SPWVD technique of feature extraction is used for the classification of EEG signals in the work presented by Tzallas et al. [33]. Rajeev Sharma et al. [34] used EMD and the Phase-Space Reconstruction method of extracting features using IMF for applying to various classifiers.

Also, Rafik Djemili et al. [35] inducted the EMD method to decompose the signals into several IMFs for epileptic seizure detection.

Yang li et al. [36][37][38] recommended a multi-scale wavelet basis function for representing high-resolution time-frequency analysis of EEG signals and subsequently used the OLS approach assisted by the mutual information principle for sparse model selection and parameter estimation.

Oliver Foust et al. [39] reviewed various feature engineering paradigms and concluded that wavelet transform is the ideal paradigm for analyzing time-varying EEG signals to find the time and frequency location of the abnormalities. They compared CWT and DWT methods of feature extraction and recommended that DWT is superior to CWT.

Bose R et al. [40] adopted the MFDFA method of feature extraction by considering nonlinear, chaotic, and noisy time series EEG signals. In the recent work reported by Md. Kamurul et al. [41] used statistical features such as average energy, approximate entropy, and the mean and standard deviation for the classification work to detect epileptic seizures. Similar work done by Husain Sheik et al. [42] used DWT as a tool for preprocessing the EEG signals by signal decomposition and extracted Energy, Covariance IQR, and MAD as features.

The two similar works reported by Gopika Gopan et al.[43][44] and another reported by Bhuvaneshwari et al. [45], used various time domain statistical features such as energy, variance, entropy, median absolute deviation, interquartile range, kurtosis, skewness, and linear prediction coefficient. Khorshidtalab et al. [46] also used time domain statistical features for their motor imagery classification problem by analyzing EEG signals. In a work proposed by Vangelis Sakkalis et al. [47], nonlinear statistical features were derived for EEG signal analysis. Arunkumar N et al. [48] used ApEn, SampEn, and Reyni's entropy as features for classifying focal and nonfocal EEG signals.

Peng li et al. [49] used SampEn and DistEn for signal analysis. They also compared the performance of SampEn and DistEn through classification and concluded that DistEn outperformed than SampEn. Sharenreddy et al. [50] used MWTbased ApEn as a feature for EEG classification and further enhanced it by applying IApEn algorithm. Hasan Ocak [51] also inducted DWT-based ApEn and used it as a deciding factor for an epileptic seizure.

Hadi Ratham et al. [52] used a time domain feature extraction method called SRS and used the SFS technique to choose the features by reducing the feature dimensions. In order to study various wavelet families for EEG classification, Tapan Ghanthi et al [53] used DWT as a tool for extracting features. EEG classification problems for brain disorders suggested by Shen et al. [54] and Yatindra Kumar et al. [55] used DWT as a signal preprocessing tool and subsequently, wavelet-based statistical and entropy features were used for high-performance classifiers. Md Mursalin et al. [56] offered a new approach to feature selection calledCBFS after performing MRAof EEG signals using DWT. The CBFS is further improved by using a modified algorithm. Najumnisssa et al. [57] adopted MRAof feature extraction using 8-level DWT for epileptic seizure detection issues.

Multi-wavelet-based feature engineering is now popular and used with many recent classification problems. Ling Guo et al. [58] proposed a multi-wavelet with various scaling and wavelet functions for feature engineering. They used orthogonal, symmetric, and short support simultaneously in their classification problem. Abeg Kumar Jaiswal et al. [59] introduced two different approaches for extracting features namely LNDP)and 1D-LGP. Sunil Kumar et al. [60] used the 1D-LBP method of feature extraction.

In the work proposed by Ahmed [61], it is noticed that time domain statistical features were used for classification. Similarly, Mohammad Zavid Parvez et al. [62] reported that the statistical features of DCT, DCT-DWT, SVD, and IMF were used for the classification. Khushnandan Rai et al. [63] also utilized the EMD technique of feature engineering for the classification of focal and non-focal EEG signals. Another work proposed by Varun Joshi et al. [64] used the FLP method for deriving coefficients for discriminating EEG signals. Feature vectors were extracted by using the bilinear TFD method in the research work presented by Marcus et al. [65]. Antika et al. [66] used the AAR algorithm for an EEG classification problem for recognizing cognitive states. For a wavelet-based neural network classification problem proposed by Zaritha et al. [67] as well as Omerhodzic et al. [68], DWT-based features coefficients were computed through MRA analysis. Wei-Yen Hsu [69] adopted the CWT method of MRA analysis for extracting features for his motor imagery classification problem. Panda et al. [70] adopted a 5-level decomposition of DWT for MRA of feature engineering in epileptic detection problems.

For a hypnosis susceptibility estimation problem using EEG signals, distinguishable features were extracted using fractal dimension, AR wavelet entropy, and band power according to Elahi et al. [71]. A similar approach is also used in an EEG classification problem of schizophrenic and control participants by Sabeti et al. [72]. The windowing method of making non-stationary time-series signals into smaller one-second windows is applied in the above two works. Sheik et al. [73] proposed a new approach in feature engineering called HHT which contains EMD and HSA for feature selection. According to Shouyi Wang et al. [74], feature extraction by estimating the chaotic factor STLmax exponent performed well for seizure prediction.

Mehran et al. [75] used the wavelet packet analysis method to decompose the signal data to extract the features and further optimized it through PCA. James R Williamson et al. [76] proposed a multivariate analysis of multichannel EEG data for extracting features for epileptic seizure detection. Hunyadi et al. [77] brought a novel approach by integrating multichannel EEG data to derive a feature-channel matrix. SVD is also used to extract features in this work. For an EEG spike detector problem, Edras Pacola et al. [78] used a combination of DWT and various statistical descriptors in the form of a multivariate matrix of features.

Dynamic PCA using the non-overlapping moving window method of feature engineering has been adopted by Shengkun Xie et al. [79] to bring out the best classification framework. S M Shafiul Alam et al. [80] [81] used the EMD domain for computing statistical and chaotic features such as skewness, kurtosis, variance, and largest Lyapunov exponent, correlation dimension, and approximate entropy for EEG signal classification. The energy feature is calculated in the EMD domain for an EEG classification problem reported by Lorena Orosco et al. [82] too. Rui P. Costa et al. [83] exercised their classification problem with statistical, wavelet transform, and nonlinear system dynamics approach for extracting features. In a review work done by Jasmin Kevric and Abdulhamit Subasi [84], EMD, DWT, and WPD were used for efficacy assessment for motor imagery problems by analyzing EEG signals. These three methods are subjected to assessment by Emina Alickovic, Jasmin Kevric, and Abdulhamit Subasi [85] for epileptic seizure detection problems. In both problems, WPD is suggested by the authors.

Roozbeh Zarei et al. [86] inducted a robust feature extraction method by combining PCA and CCOV to obtain discriminating features from EEG. Mingyang Li et al. [87] brought a new approach to feature engineering for automatic EEG detection in the wavelet domain called DT-CWT. After decomposition, several nonlinear features such as Hurst exponent (H), FD, and PE were extracted for classification. Xiao-Wei Wang et al. [88] used Octave wavelet decomposition of feature extraction for an emotional detection problem through EEG signals. Ming-ai Li et al. [89] proposed yet another approach of feature engineering by DWT and P. t-SNE for processing motor imagery EEG.

Hashem Kalbkhani et al. [90] have employed ST for feature engineering in their seizure detection problem. ST covers the time-frequency analysis of wavelets and overcomes the shortcomings of this domain. Paulo Amorim et al. [91] proposed a technique to feature extraction from EEG signals by introducing Shearlet and Contourlet Transforms. In this approach, EEG signals are decomposed into diverse sub-bands utilizing these transforms, and the features selected from time-frequency coefficients are used for classification.

Ozan Kocadagli et al. [92] used DWT for signal decomposition into different bandwidths for extracting distinct features for seizure detection problems. In this work, fuzzy relations are used to reduce the dimensionality of data. Mingyang Li et al. [93] brought a new approach to extracting significant features by EEG signal decomposition for epileptic classification using DWT in combination with EA.

John Martin et al. [97] [103] used a DWT-based feature engineering approach in their epileptic seizure detection framework. It is claimed that the machine learning-based framework outperformed previously reported benchmark works. Time-frequency-based feature engineering is applied for an EEG classification model using deep learning proposed by K. M. Hassan et al [98] and reported that the model resulted in superior results.

An award-winning seizure detection work was proposed by C. Chatzichristos *et al*. [99] and used wavelet-based an innovative EEG processing approach. The framework was implemented using a deep neural network. According to Md. Faizul Bar et al. [100], an automated seizure detection approach on the basis of statistical and spectral features of max normalized IMFs generated using complete ensemble EMD with adaptive noise method has been developed and tested.

Another DNN-based seizure detection model put forth by Kemal Akyol et al. [101] used a time-frequency-based feature engineering method and showcased superior performance. M. Radman et al. [102] adopted time-frequency-based feature extraction for a classification model of epileptic seizure detection, where they used DSET-based feature fusion to enhance feature selection confidence.

G. Jaffino et al. [104] adopted DWT-based MRA analysis for a seizure detection framework using deep learning-based classification. This method's analysis uses a real-time database and yields 93.4 percent precision. Ravi, S. et al. [105] used a nonlinear method of obtaining EEG frames to detect abnormalities in the EEG. A CNN approach was trained for the real-time identification of epileptic seizures.

Table 1. Summary of published works on EEG feature extraction in various domains

Author (s) [Ref]	Year	Feature Domain(s)	Methods adopted
Subasi et al. [25]	2005	Time-frequency	LBDWT
Subasi [94]	2007	Time-frequency	DWT
Tzallas et al. [33]	2007	Time-Frequency	(SPWVD
Rui P. Costa et al. [83]	2008	Time-frequency,Nonlinear	WT, Correlation dimension
Malihe Sabeti et al. [10]	2009	Time, Nonlinear	Entropies
Elif Derya Ubeyli [27]	2009	Time-frequency	DWT
Hasan Ocak [51]	2009	Time-frequency	DWT, ApEn
Lorena Orosco et al. [82]	2009	Nonlinear	EMD
Ling Guo et al. [58]	2010	Time-frequency	MWT
Panda et al. [70]	2010	Time-frequency	DWT
Umut Orhan et al. [13]	2011	Time-frequency	DWT
Sabeti et al. [72]	2011	Time, Time-frequency, Nonlinear	Statistical
Shengkun Xie et al. [95]	2011	Time-frequency	DWT, PCA
Acharya et al. [7]	2012	Time-frequency	WPD
Acharya et al. [9]	2012	Time, Nonlinear	Entropies
Acharya et al. [11]	2012	Nonlinear	HOS, Entropies
Reza et al. [14]	2012	Time-frequency	DWT
Mrigank Sharad et al. [8]	2012	Time-frequency	LPF-only-DWT
Sheik et al. [42]	2012	Time-frequency	DWT
Yatindra Kumar et al. [55]	2012	Time-frequency	DWT
Najumnisssa et al. [57]	2012	Time-frequency	DWT
Marcus et al. [65]	2012	Nonlinear	Bilinear TFD
Zaritha et al. [67]	2012	Time-frequency	DWT
J. R Williamson et al. [76]	2012	Nonlinear	Multivariate analysis
Hunyadi et al. [77]	2012	Nonlinear	SVD
Khorshidtalab et al. [46]	2013	Time	Statistical
Sharenreddy et al. [50]	2013	Time-frequency	MWT, Entropies
Shen et al. [54]	2013	Time-frequency	DWT
Omerhodzic et al. [68]	2013	Time-frequency	DWT
Elahi et al. [71]	2013	Time, Time-frequency, Nonlinear	Statistical
Shouyi Wang et al. [74]	2013	Nonlinear	STLmax
Shafiul Alam et al. [80]	2013	Nonlinear	EMD - Statistical and chaotic features
Chunchu et al. [3]	2014	Time, Frequency	FFT, DFFT
Osman Salem et al. [15]	2014	Time-frequency	DWT
Dragoljub Gajic et al. [16]	2014	Time-frequency	DWT
Sang-Hong Lee et al. [32]	2014	Time-frequency	DWT with PSR
M. Zavid Parvez et al. [62]	2014	Nonlinear	DCT, SVD-IMF
Varun Joshi et al. [64]	2014	Nonlinear	FLP
Wei-Yen Hsu [69]	2014	Time-frequency	CWT
Xiao-Wei Wang et al. [88]	2014	Frequency, Time-frequency, Non - linear	FFT, Wavelet Decomposition, Statistical
Gajic et al. [5]	2015	Time-frequency, Nonlinear	Statistical, FFT, DWT, EMD-IMF
Benzy VK et al. [24]	2015	Time-frequency	DWT
Musa Peker et al. [26]	2015	Time-frequency	DTCWT
Rajeev Sharma et al. [34]	2015	Nonlinear	EMD-IMF , PSR
Gopika Gopan et al. [43,44]	2015	Time	Statistical
Bhuvaneshwari et al. [45]	2015	Time	Statistical
Sunil Kumar et al. [60]	2015	Nonlinear	1D-LGP
Khushnandan et al [63]	2015	Nonlinear	EMD-IMF
Sharmila et al. [17]	2016	Time-frequency	DWT
Rafik Djemili et al. [35]	2016	Nonlinear	EMD-IMF
Peng li et al. [59]	2016	Time	Entropies
Hadi Ratham et al. [52]	2016	Time	Simple Random Sampling
Ming-ai Li et al. [89]	2016	Time-frequency, Nonlinear	DWT, P. t-SNE
Lina Wang et al. [4]	2017	Time, frequency, Time-frequency, Nonlinear	Statistical, FFT, DWT, EMD-IMF
Ming-ai Li et al. [6]	2017	Time-frequency, Nonlinear	WPD
Ying-Fang La et al. [18]	2017	Time-frequency	DWT
Chandani et al. [22]	2017	Time-frequency	DWT
Tzimourta et al. [29]	2017	Time-frequency	DWT
Sharmila et al. [30]	2017	Time-frequency	DWT
Yang li et al. [36]	2017	Time-frequency	Multi scale wavelet
Pratiher et al. [40]	2017	Nonlinear	MFDFA
Md. Kamurul et al. [41]	2017	Time	Statistical

Arunkumar N et al. [48]	2017	Nonlinear	Entropies
Md Mursalin et al. [56]	2017	Time, Time-frequency	Statistical, DWT, ICFS
Abeg Kumar J et al. [59]	2017	Nonlinear	LNDP, 1D-LGP
Ahmed [61]	2017	Time	Statistical
Edras Pacola et al. [78]	2017	Time-frequency, nonlinear	DWT, Multivariate analysis
Roozbeh Zarei et al. [86]	2017	Nonlinear	PCA, CCOV
Mingyang Li et al. [87]	2017	Time-frequency	DT-CWT
Hashem K et al. [90]	2017	Time-frequency	Stockwell Transform (ST)
Paulo Amorim et al. [91]	2017	Time-frequency	Shearlet and Contourlet Transforms
Ozan Kocadagli et al. [92]	2017	Time-frequency	DWT
Mingyang Li et al. [93]	2017	Time-frequency	DWT, Envelop Analysis (EA)
Yuanfa Wang et al. [96]	2017	Time-frequency	DWT
John Martin R et al. [97]	2018	Time-frequency	DWT
K. M. Hassan et al [98]	2019	Time-frequency	DWT
C. Chatzichristos *et al* [99]	2020	Time-Frequency	Multi-view U-nets
Md. Faizul Bari [100]	2020	Wavelet	EMD, IMF
Kemal Akyol et al.[101]	2020	Time-Frequency	DWT
M. Radman et al.[102]	2021	Time-frequency	Relief-F (RF), CDET, Fisher Score (FS)
John Martin R et al. [103]	2021	Time-frequency	DWT
G. Jaffino et al. [104]	2021	Time-frequency	DWT
Ravi, S et al.[105]	2022	Nonlinear	Recurrence Plots (RP)

Feature dimensionality reduction is the process of optimizing feature vectors for classification. After employing feature extraction methods on various domains such as time, frequency, time-frequency, and non-linear domains, the extracted features are further reduced for classification if necessary. The selection of distinctive features through a feature dimension reduction method is considered a novel idea for achieving high accuracy in classification. In EEG classification problems, different techniques are being utilized to minimize the feature dimensionality as they are associated with high volumes of signal data and to avoid spatial redundancy.

4. Conclusion

The majority of the benchmarking research works chosen for the review are classification frameworks for detecting epileptic seizures using EEG. The wavelet method of feature engineering was used by the majority of the authors, and selected features worked well with classification. Regarding data sets, most of the researchers used Germany's Bonn University Database, few others used the University of Freiburg EEG database, and very few used real-time EEG data. Machine learning-based classification was employed in most of the reported works. In recent works, the tendency for using deep learning for EEG analysis is observed.

While looking at the research methodologies used in the literature listed in Table 1, there are a few things to be noticed from among the EEG classification issues that have been taken up for epileptic seizure detection. (i) The time-frequency domain (wavelet) feature engineering technique has been commonly used for the classification of epileptic seizure detection problems. In the literature, it has been discovered that the time-frequency technique improves classification accuracy more than the time and frequency domain techniques. (ii) For EEG classification problems in seizure detection, DWT and its variants are generally used for time-frequency analysis. (iii) The empirical studies state that the wavelet-based statistical features and entropy-based statistical features were ideal for EEG classification. (iv) In EEG classification of epileptic seizure detection, DWT was largely used for time-frequency domain feature engineering. (v) In most of the tabulated works, researchers used the Daubechies 4 (db4) mother wavelet for MRA analysis. vi) Though machine learning-based classification is common, deep learning-based real-time EEG analysis is state-of-the-art.

This overview paper will be a source of knowledge for prospective researchers in the field of EEG signal processing. Though this review work reveals a number of significant findings, the performance metrics of the experiments are not analyzed due to diversified performance measures used in the classification and regression. This study can be deepened in the future by looking into specific signal processing approaches using real-time EEG.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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