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TOPOLOGICAL DATA ANALYSIS IN EEG SIGNAL PROCESSING: A REVIEW

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Abstract: Electroencephalogram (EEG) is a non-invasive technique that measures the brain's electrical activity from the cerebral cortex. EEG has been adopted in many studies for disease diagnosis, brain state recognition, and perception evaluation due to its high temporal resolution and low cost. Conventional data analysis methods such as traditional statistics and machine learning, suffer from several limitations, including being sensitive to artifacts when applied to EEG signal processing. As an alternative to these approaches, topological data analysis (TDA) enhances the EEG analysis by focusing on the robust topological invariants in EEG data. The rapid development of the TDA method generates a variety of studies with different TDA-based EEG processing pipelines tailored to diverse research objectives. A comprehensive review of these studies is necessary to serve as a guide for practitioners to gain deeper insight into EEG processing with TDA. This review also identifies the strengths, weaknesses, and future directions of TDA in EEG studies.

Keywords: electroencephalogram; topological data analysis; persistent homology; signal processing; machine learning.

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1. INTRODUCTION

Recent advancements in digital technologies prompt the exponential growth of data size and dimensionality in the biomedical domain. Processing and analyzing this vast amount of data is becoming increasingly important to serve various purposes, such as clinical diagnosis and brain-computer interface (BCI) development. Common examples of biomedical data include electroencephalograms (EEGs), electrocardiograms, electromyograms, and functional magnetic resonance imaging. Among them, EEG has attracted more attention due to its non-invasive nature and other appealing features, such as high temporal resolution, simplicity, portability, and low cost [1]. Widely adopted in neurological research, EEG has supported various applications, including the detection of motor imagery [2], classification of schizophrenia [3], and emotion recognition [4].

EEG is a brain imaging technique that records electrical activity from the cerebral cortex using electrodes placed on the scalp [5]. This non-invasive method offers real-time insights into brain function, making it valuable for studying cognitive processes and understanding neurological disorders [6]. EEG signals reflect different brain rhythms, such as theta, delta, alpha, beta, and gamma, each associated with specific functional states [7]. Studying the subtle changes in these frequency patterns facilitates the identification of neurological abnormalities or neuronal responses to external stimuli.

EEG signal analysis typically involves preprocessing raw signals using filtering or denoising techniques, extracting key features through feature engineering, and applying machine learning models or statistical tests for disease diagnosis or brain state recognition [8]. The rapid development of machine learning (ML) and deep learning (DL) technology, such as the decision tree classifier and neural network [9], has revolutionized the study of EEG. However, the signal-to-noise ratio, non-stationarity, high dimensionality, and limited size of EEG data remain challenging, obstructing the ML and DL models from delivering optimal performance [10].

To address these issues, a powerful method known as topological data analysis (TDA) has been rigorously studied by many researchers. TDA is a relatively new field that draws on concepts from algebraic topology and computational geometry to analyze data [11]. It is grounded in the idea that data has an underlying shape, and this shape holds meaningful insights [12]. TDA offers various tools, including the Mapper and persistent homology, for productive data analysis. TDA's adaptability has been demonstrated across diverse fields, including biomedical signal processing, economics [13], and networking [14]. As a data-driven method, TDA excels at capturing both topological and geometric structures in complex, high-dimensional datasets while also offering robustness to noise and small perturbations [15].

Despite the increasing use of TDA in EEG research, there is still a lack of introductory reviews that outline TDA pipelines for EEG processing, which could guide researchers unfamiliar with the field. The existing reviews primarily focus on the TDA applications and performance in a broader field rather than the TDA framework in EEG analysis [16–19] or provide detailed EEG processing steps without incorporating TDA [20]. There is only one mini-review on the application of TDA in EEG processing conducted by Xu et al. [21] in 2021. Furthermore, the TDA application has evolved rapidly over the past few years, and it is crucial to recognize the latest TDA developments to ensure the full potential of TDA in EEG studies is utilized. Thus, this review addresses that gap by identifying recent TDA applications in EEG processing, outlining standard methodological pipelines, and highlighting emerging trends.

This review aims to make the following contributions:

1. It provides a comprehensive overview of the TDA-based EEG signal processing framework introduced in different works.
2. It explores the cutting-edge TDA techniques proposed in the most recent EEG studies.
3. It highlights prevalent TDA tools, TDA strengths and limitations, and outlines future directions to help researchers identify gaps and effectively apply TDA in their studies.

In the following sections, section 2 presents a more detailed description of EEG signal processing, topological data analysis, and persistent homology. Section 3 summarizes recent studies of TDA applications in EEG signal processing. Lastly, section 4 highlights the tools, strengths, limitations, and future directions of TDA-based EEG analysis.

2. Background

2.1 EEG signal processing

In general, EEG signal processing consists of four main stages: collection, preprocessing, feature engineering, and signal analysis, as shown in Figure 1. EEG signals are first recorded from the brain using either invasive or noninvasive methods [20]. Invasive techniques involve surgically implanting electrodes into the cerebral cortex or other brain areas. In contrast, noninvasive approaches use sensors placed on the scalp and do not require any surgical intervention. Between these two options, noninvasive methods are the preferred choice.

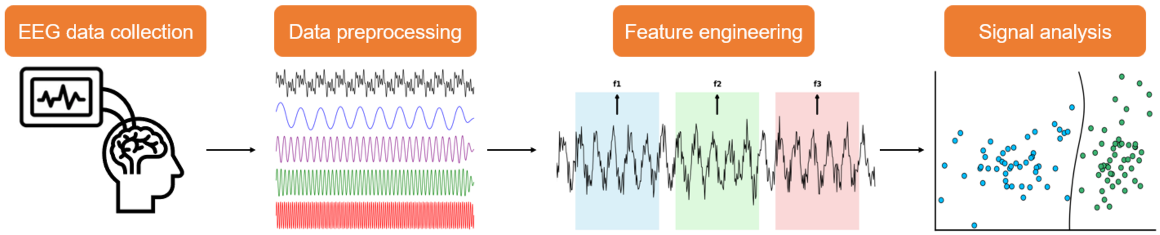

FIGURE 1. EEG signal processing steps.

EEG signals, due to their low amplitude and high temporal variability, are highly prone to external interference, such as eye blinks, muscle activity, and involuntary movements. Thus, it is necessary to eliminate noise and artifacts through preprocessing and appropriate filtering to obtain cleaner EEG signals for reliable feature extraction and classification [22]. Common noise reduction approaches include high-pass filters, low-pass filters, bandpass filters, notch filters, and Butterworth filters [23]. Besides artifact removal through filtering, EEG signals are often segmented into suitable time windows for subsequent analysis.

After preprocessing, various features are extracted from the artifact-free EEG data. Typically, features extracted in EEG signal analysis can involve time-domain features, frequency-domain features, time-frequency-domain features, or nonlinear features [24]. Time-domain features, such as the Hjorth parameters, summarize signal distribution but lack frequency-specific information. Conversely, transforming signals from the time domain to the frequency domain enables the extraction of frequency-specific features, such as the power spectral density. Time-frequency domain methods, such as wavelet transform, are powerful in analyzing the signal's non-stationarity and capturing accurate time and frequency information [25]. Meanwhile, nonlinear features, such as the entropy measures, quantify the chaotic and complex nature of EEG activity.

The extracted features are then fed into ML or DL models for different signal analysis tasks, including classification, clustering, and pattern recognition. Among these tasks, EEG signal classification emerged as the most common task that groups signals into distinct classes based on their discriminating properties, facilitating effective disease detection and brain state recognition. A variety of approaches, ranging from statistical and ML methods to DL techniques, can be applied. The accuracy and efficiency of classification largely depend on both the quality and quantity of features obtained during preprocessing [26].

2.2 Topological data analysis

TDA is an emerging method that applies concepts from topology, the mathematical study of shape and space, to analyze data. Topology explores both local and global properties of objects that remain unchanged under continuous deformations such as stretching, bending, or twisting but not under transformations like cutting or gluing [27]. For instance, a donut and a torus are considered the same or topologically equivalent because they each contain one hole. Such features, known as topological invariants (e.g., the number of holes or cavities), are preserved across all equivalent topological spaces.

The properties of topology, such as coordinate invariance, deformation invariance, and compressed representations, make TDA superior in analyzing complex and high-dimensional data [17]. Topological features are coordinate invariant, implying that the intrinsic topology of the shape of the dataset stays identical across different coordinate systems that represent the data. Topological features are also deformation invariant, which means that they are not affected by small deformations performed on the data. TDA also produces a compressed topological representation of the complex data shape that effectively reveals hidden structures and relationships within the data.

The application of TDA involves defining a metric space (e.g., Euclidean metric) for the input data and building a nested family of simplicial complexes on top of it. A simplicial complex is a combinatorial structure made up of vertices, edges, triangles, tetrahedra, and their higher-dimensional analogs (i.e., k-dimensional simplex), assembled in a specific way to represent the shape of the data [28]. Figure 2 illustrates an example of a simplicial complex and its k-dimensional complex. Homology, a fundamental invariant in topology that examines holes or voids across different dimensions in a topological space, is used to quantify the topological features within the simplicial complexes [29]. We primarily focus on persistent homology in this review as it is a foundational method in TDA and is widely adopted in recent EEG studies.

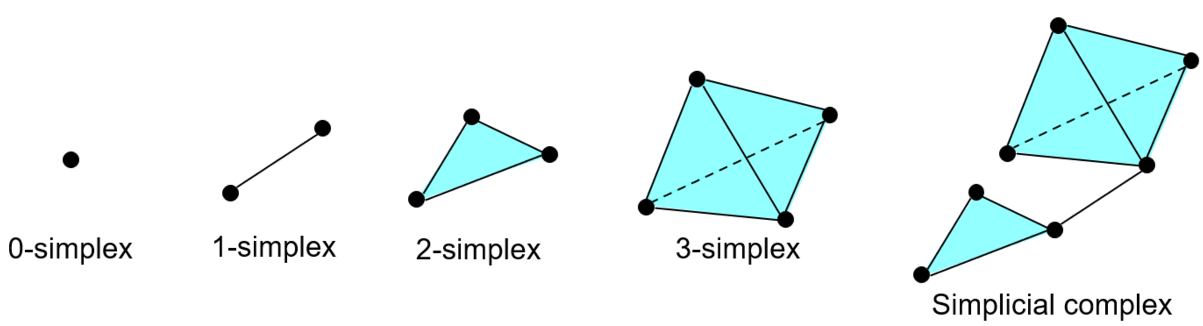

FIGURE 2. Example of simplicial complex and k-simplex.

2.3 Persistent homology

Persistent homology (PH) is a powerful tool for capturing and encoding multiscale topological features of nested simplicial complexes and topological spaces. PH analyses point clouds or functions, generating information about the emergence (or birth) and disappearance (or death) of topological features (homology classes) through visualizations like persistence diagrams (PDs) or barcodes (PBs). Long-persisting homology classes detected over a wide range of spatial scales reflect meaningful structures in the underlying space, distinguishing them from noise or sampling artifacts [30].

The computation of PH starts with performing filtration on the input data representation to construct nested simplicial complexes [31]. Filtration is achieved by varying a scale parameter on the data, creating structures such as Rips and Čech complexes [32], and allowing for the tracking of the birth and death of topological features (e.g., connected components, loops, and holes). Filtration can be considered the most pivotal step in PH computation, as it enables multiscale analysis of the data by adjusting a scale parameter. The effectiveness of PH heavily depends on the choice of this scale parameter, which directly impacts the resolution and quality of the extracted topological features.

After constructing the filtration, the evolution of topological features is recorded and shown in a PD or PB. Features with longer lifetimes are depicted as points further from the diagonal line in a PD, or as longer bars in a PB, while shorter-lived features appear closer to the diagonal or as shorter bars. Statistical measures of these features' lifespans are commonly utilized in ML analysis. Besides the conventional statistical metrics, the topological similarities between the PDs can be evaluated using two distance measures: the Wasserstein distance and the Bottleneck distance. Wasserstein distance measures the total distance between each matched pair of points in the diagrams, while Bottleneck distance considers the maximum distance between the matching points [33].

PDs capture key structural information from complex data and serve as valuable features for machine learning and deep learning tasks. However, it is challenging to directly apply PDs to ML models because their variable number of points conflicts with the fixed-size input required by most ML algorithms [34]. Hence, it is necessary to transform them into functional summaries or vector formats, such as the persistence landscape [35], image [36], and silhouette [37], that align with ML input requirements. The choice of vectorization method depends on the properties of input data and the specific goals of the analysis.

3. TDA In EEG Processing

TDA is widely utilized in EEG signal analysis due to its ability to capture intricate signal properties that act as strong biomarkers for disease diagnosis. To underscore its significance in EEG applications, we perform an exhaustive review of TDA-based methods in EEG signal processing. We conducted a comprehensive literature search across PubMed, Scopus, Web of Science, and Google Scholar databases using the keywords (topological data analysis, TDA) AND (electroencephalogram, EEG).

We restricted our search to the studies published from 2022 onward to trace the developments of TDA in this domain following the work by Xu et al. [21]. We then inspect the title and abstract of the resulting publications and omit the redundant and irrelevant studies. After this filtering procedure, only 32 publications were considered relevant to our review aims. These selected publications and their applied methods are summarized in Table 1. It is apparent from Table 1 that the use of TDA-based approaches in detecting neurological disorders from EEG signals is the primary focus of the articles reviewed in this study. These neurological disorders include Parkinson's, depression, and Alzheimer's disease.

Table 1. Summary of the TDA-based EEG studies and their applied methods ordered by publication date under different domains.

Domain	Authors and year of publication	Methods			
		Preprocessing	Embedding	Statistical analysis	Others
Clinical diagnosis	Cai et al., 2025 [68]	ICA	TDE		k-PDTM, MKDE
	Jolin, 2025 [49]	FFT			
	Prantzalos et al., 2025 [78]				Few-shot learning
	Sathyanarayana et al., 2025 [60]		Functional connectivity embedding	permutation test	
	El-Yaagoubi et al., 2024 [74]	SW	TDE		HFD
	Goodarzi et al., 2024 [72]	PCA	TDE		
	Kang et al., 2024 [40]	PCC, ICA, SW			grid search
	Poetto & Duch, 2024 [52]	PCC, STFT	TDE		SelectKBest
	Reddy et al., 2024 [46]	Voronoi tessellation		paired t-test	
	Reddy & Reddy, 2024 [58]	PCA, graph mapping		paired t-test	
	Rutkowski et al., 2024 [70]			Wilcoxon rank-sum tests	UMAP, t-SNE
	Zhen et al., 2024 [51]	Visibility graph			RFE

	El-Yaagoubi et al., 2023 [56]	Coherence matrix			
	Flammer, 2023 [39]	PCA, DyCA, SW			
	Kwessi, 2023 [45]	ISOMAP, LEIM, FastICA, KRR, t-SNE	TDE	permutation test	
	Prantzalos et al., 2023 [92]				NIC and MaTiLDA platform
	Upadhyaya et al., 2023 [42]				SMOTE, grid search
	Wang et al., 2023 [41]	SW			
Cognitive recognition	Turkeš et al., 2025 [57]	Recurrence plot, PCC, CNN			
	Gaurav et al., 2024 [69]	SW	TDE		
	Gupta et al., 2024 [73]	FastICA	TDE		
	Zheng et al., 2024 [55]	HHT			RFE
	Ferrà et al., 2023 [44]	ICA, PCA			RFE
	Yan et al., 2023 [75]	PCC, SW			
	Yan et al., 2022 [62]	SW	TDE		
Perception	Liu et al., 2024b [71]				Grey model
	Ni et al., 2023 [38]	Hilbert transform, PCA			
Signal processing	Zheng et al., 2023 [54]	HHT	TDE		RFE
	Ameneyro et al., 2022 [65]		Quantum delay embedding		
	Billings et al., 2022 [64]	PCC	TDE, direct embedding		
	Guo et al., 2022 [61]	PCC			
	Yin & Wang, 2022 [67]	PCC, normalized mutual information, cross correlation			

TDE = Time delay embedding, SW = Sliding window, PSR = Phase space reconstruction, NIC = Neuro-Integrative Connectivity

EEG signal processing with TDA methods involves multiple steps, including signal preprocessing, feature engineering (which includes both feature extraction and selection), and signal analysis. A large variety of evolving methods can be employed in each of these steps to facilitate and enhance the TDA application and performance. Figure 3 gives a brief overview of the commonly used techniques in each EEG processing step. We will discuss these steps in more detail in the following subsection.

It is worth mentioning that we found the segmentation (i.e., one of the preprocessing steps) and feature selection are less often implemented in EEG processing, as indicated in Table 2. The possible reasons for such observations include researchers generally working with small data and/or feature sizes to reduce computational costs. Besides, Table 2 also indicates relatively more works are analyzing public datasets, such as the popular OpenNeuro and Bonn datasets, compared to analyzing private datasets. This indirectly suggests that access to more publicly available datasets may enhance the credibility and reproducibility of EEG studies.

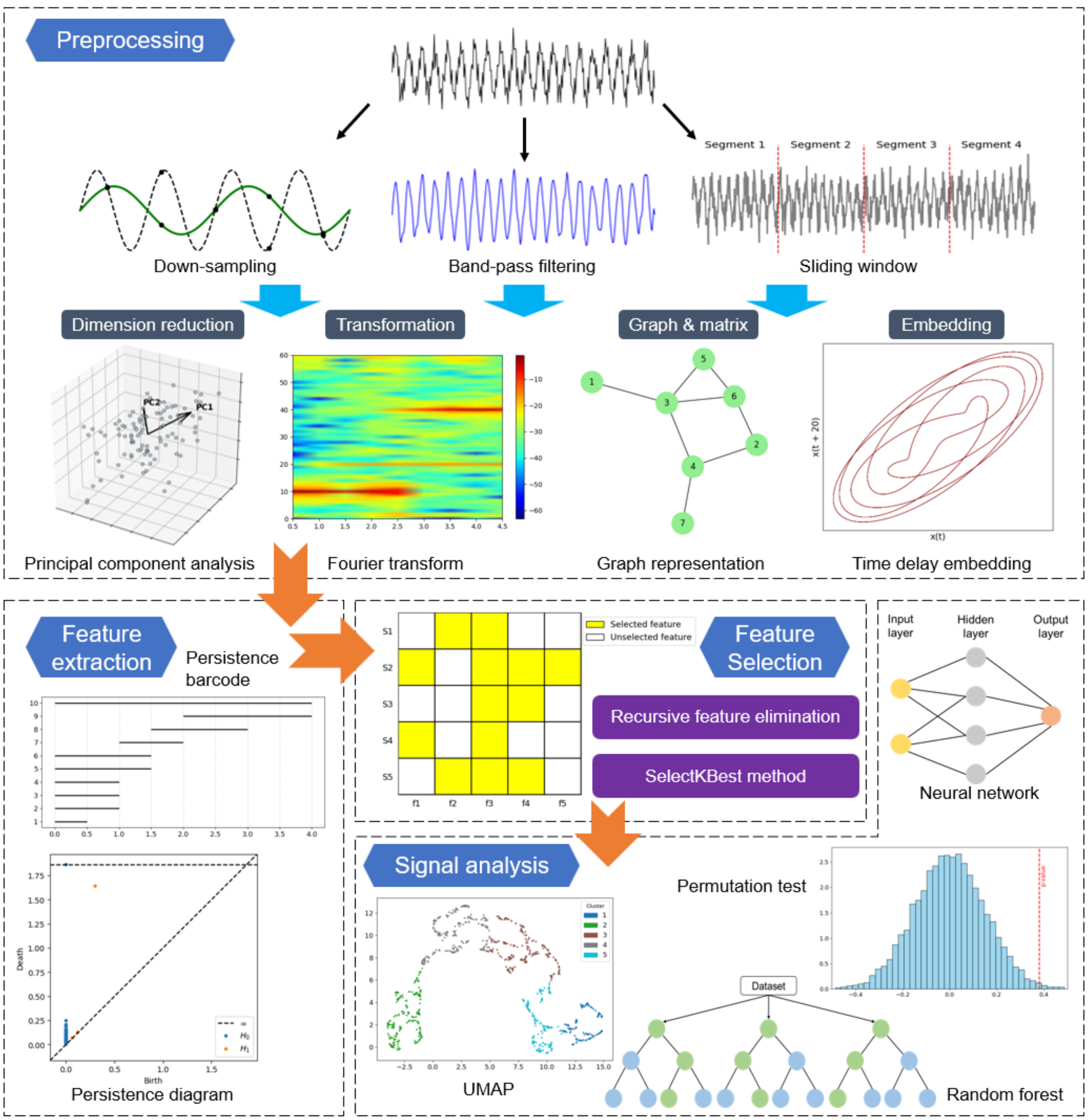

FIGURE 3. Overview of common methods in each EEG processing step.

3.1 Signal preprocessing

Xu et al. [21] noted that standard EEG preprocessing techniques encompass band-pass filtering, down-sampling, and artifact removal. Beyond these, sliding window segmentation, either overlapping [39] or non-overlapping [40], has also been employed to enhance signal characterization or expand sample size for more robust analysis [41]. In the studies by Upadhyaya et al. [42] and Das et al. [43], the authors utilized the synthetic minority oversampling technique (SMOTE) to address class imbalance in the dataset, aiming to mitigate bias and enhance accuracy.

Table 2. Proportion of TDA-based EEG studies that perform segmentation, feature selection, and use public or private datasets in different domains.

Domain	**Segmentation**		**Feature selection**		**Datasets**	
	Yes	**No**	**Yes**	**No**	**Public**	**Private**
Clinical diagnosis	4	14	2	16	14	4
Cognitive recognition	3	4	2	5	5	2
Perception	0	2	0	2	0	2
Signal processing	0	5	1	4	2	3
Count	7	25	5	27	21	11
Percentage	21.87%	78.13%	15.63%	84.37%	65.63%	34.37%

3.1.1 Dimension reduction

Dimensionality reduction is a crucial step in EEG processing. The "curse of dimensionality" is a well-known problem in time series analysis where the algorithm performance declines as data dimensionality increases, even if the method performs well on low-dimensional inputs [18]. To address this issue, various dimension reduction methods are employed to decompose the multivariate EEG signals into lower-dimensional components before PH computation for better results. For example, techniques such as principal component analysis (PCA) and dynamical component analysis (DyCA), which are similar to independent component analysis (ICA), have been utilized in various studies for this purpose [39, 44].

Moreover, Kwessi [45] examined several dimension reduction methods, including isometric feature mapping (ISOMAP), Laplacian Eigenmaps (LEIM), fast ICA, kernel ridge regression (KRR), and t-distributed stochastic neighbor embedding (t-SNE) in his study. Meanwhile, Reddy et al. [46] proposed a novel method called Voronoi tessellation, which reduces the dimensional complexity of EEG signals and improves the EEG classification accuracy when paired with the alpha complex. Researchers can choose from this collection of dimension-reduction methods for their study instead of limiting themselves to standard approaches like ICA and PCA, which have constraints such as the strict assumption [47] and the inability to capture subject variability [48].

3.1.2 Transformation

One of the popular methods in EEG analysis is converting the signals from the time domain to the frequency domain using the Fourier transform, which reveals brainwave power distribution across frequencies. The frequency-based EEG signal representations can then be used to construct simplicial complexes for PH computation [29, 49]. From the reviewed papers, researchers utilized different Fourier transform variants, including the fast Fourier transform (FFT), weighted Fourier transform, and short-time Fourier transform, for diverse purposes. These include signal denoising [50], frequency-based feature extraction [51], and point cloud embedding [52].

Besides the Fourier transform, a method called the Hilbert-Huang transformation (HHT) introduced by Huang et al. [53] has gained attention in recent EEG studies. While the Fourier transform assumes signal stationarity and assigns constant power to each frequency over time [54], EEG signals often exhibit time-varying frequencies and power. To address this, researchers have adopted HHT to generate dynamic time-frequency representations that effectively capture these variations for PH analysis [55].

3.1.3 Graph and matrix

While the Fourier transform emphasizes the frequency components of EEG signals, researchers have also examined their temporal dynamics through coherence matrices [56] and recurrence plots [57]. These representations serve as inputs for PH computation or EEG time domain features, which enhance analysis results when combined with topological features. Moreover, the EEG time series can also be converted into a graph with nodes and edges, enabling the extraction of network features and the generation of simplicial complexes [51, 58].

3.1.4 Embedding

TDA methods typically operate on point clouds embedded in a high-dimensional affine space [59].

To apply these techniques to EEG data, the multivariate time-series signals should first be embedded into a suitable metric space [60]. The most common way for transforming EEG signals into point clouds is through phase space reconstruction via time delay embedding [61, 62]. According to Takens' theorem, an EEG signal can be embedded into an m-dimensional state space with a delay of τ [63], where the resulting topology preserves key characteristics of the original time series.

Besides time delay embedding, Poetto and Duch [52] investigated and compared two more embedding methods, namely the correlation and short time Fourier transform (STFT) embedding. Correlation embedding converts the EEG time series into a distance matrix by computing the pairwise correlation between each pair of signals using Pearson's correlation coefficient (PCC). On the other hand, the STFT embedding captures EEG frequency dynamics by constructing a spectrogram of the EEG using STFT. Similar to correlation embedding, Sathyanarayana et al. [60] introduced functional connectivity embedding that constructs a distance matrix of the EEG based on coherence-derived brain connectivity graphs. Furthermore, Billings et al. [64] and Ameneyro et al. [65] applied directed embedding and quantum delay embedding, which offer high interpretability and computational efficiency, respectively, in their study. This diversity in embedding strategies offers researchers flexibility in tailoring TDA-based EEG analysis to specific needs.

3.2 Feature extraction

Following EEG preprocessing, simplicial complexes are built from signal representations (e.g., embedded point cloud and distance matrix) through different PH filtrations. These complexes are then summarized into PBs or PDs, from which topological features are extracted. For further analysis, PDs can be transformed into functional summaries or vectorized forms. The upcoming subsections outline the different PH filtrations and PD summaries used in EEG analysis.

3.2.1 Persistent homology filtrations

There are many filtration techniques available in PH for generating simplicial complexes. The Vietoris-Rips (VR) filtration stands out as the most widely adopted method, appearing in nearly 80% of the studies that we reviewed, as shown in Figure 4. Besides VR filtration, Zheng et al. [55] described another filtration called sublevel filtration, which can be applied directly to EEG signals. Despite its advantage in bypassing the preprocessing step [66], we have observed stagnant usage of this filtration in recent studies. This observation may suggest that sublevel filtration fails to capture sufficient geometric structure from EEG signals.

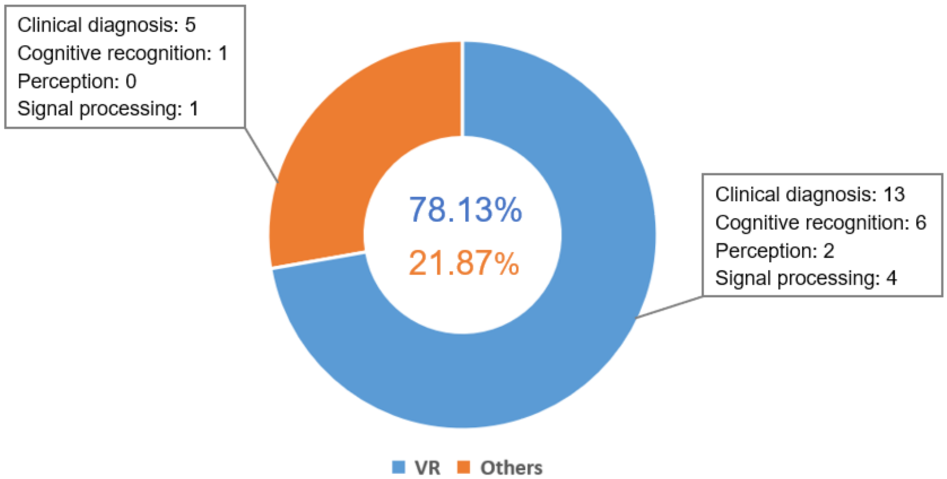

FIGURE 4. Chart summarizing the ratio of studies in different domains that applied VR filtration.

In addition to VR and sublevel filtrations, Turkeš et al. [57] applied rank filtration, a filtration that replaces the scalar values in a distance matrix with their corresponding ordinal ranks. Yin and Wang [67] employed a filtration called gradient filtration that is similar to sublevel filtration, but it enables signal filtration with a threshold oriented in an arbitrary direction. Sticking to VR filtration, Cai et al. [68] proposed two methods, namely the k-power distance to measure (k-PDTM) and multivariate kernel density estimation (MKDE), to refine and merge the embedded point clouds from each EEG channel before constructing PD.

Figure 5 depicts each of the PH filtration applied in recent studies. Figure 5(a) is the PH sublevel set filtration, whereby a horizontal line with increasing value tracks the emergence and merging of connected components from a signal. As discussed, gradient filtration, as shown in Figure 5(b), is just a sublevel set filtration with a threshold line that can examine the signal in different directions. Figure 5(c) shows the process of VR filtration, where the data points are gradually connected along the increasing distance value (blue disks around the black dots), and the emergence of topological shapes is recorded. Differing from VR filtration, edges between data points are added to the simplex based on their rank instead of the distance between the corresponding points, as shown in Figure 5(d) (red and blue edges have the highest and lowest rank).

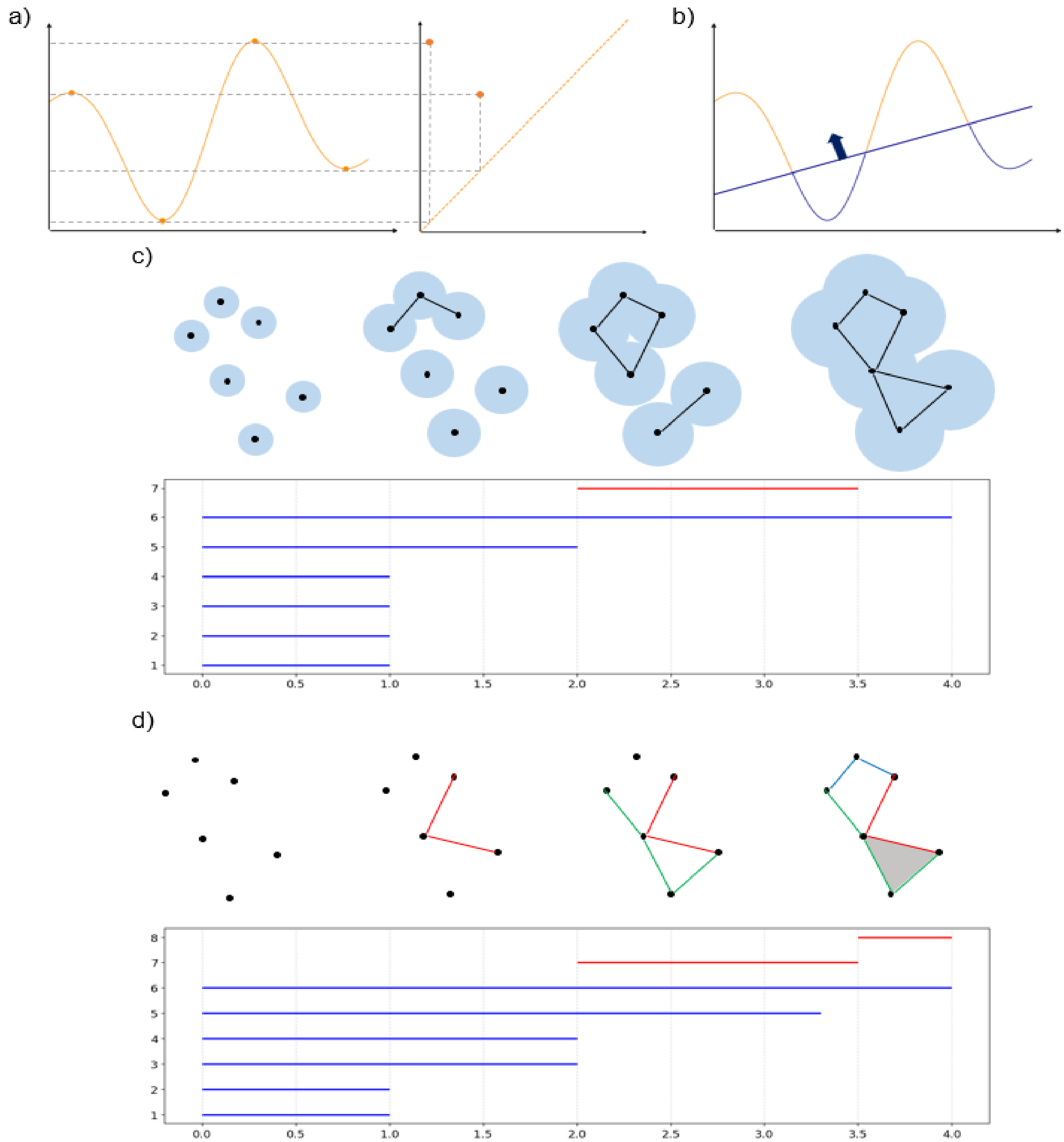

FIGURE 5. Persistent homology (a) sublevel set, (b) gradient, (c) Vietoris-Rips, and (d) rank filtrations.

3.2.2 Persistent homology representations

After applying the PH filtration, PDs are constructed from the filtered simplicial complex, and various topological features can then be extracted from these PDs. The statistical measures, such as the sum, median, and maximum, of the birth and death times of the homology shapes are the most common features utilized in many studies [69, 70]. Besides the statistical metrics, the distances between PDs measured using Wasserstein and Bottleneck distances also provide essential insights into EEG signals [39, 45]. Betti number, which is the number of n-dimensional points that exist in the PD, is another regular feature used in EEG analysis.

Besides PD, recent studies have increasingly adopted features derived from persistence landscapes, silhouettes, images, entropy, and Betti curves [71, 72] to analyze EEG signals. These techniques convert PBs and PDs into vectorized formats, facilitating statistical analysis and machine-learning applications. Figure 6 shows examples of the visualization of these PH representations. In addition, Gupta et al. [73] and Kang et al. [40] employed a heat kernel, a method that transforms the PD into a heatmap, as the topological feature in their study. To enhance TDA-based EEG analysis, several new topological features, such as the persistence curve, amplitude, and ratio, have recently been introduced [70, 74]. These alternative topological features offer additional insights into EEG, enhancing analysis performance when integrated with existing PD features.

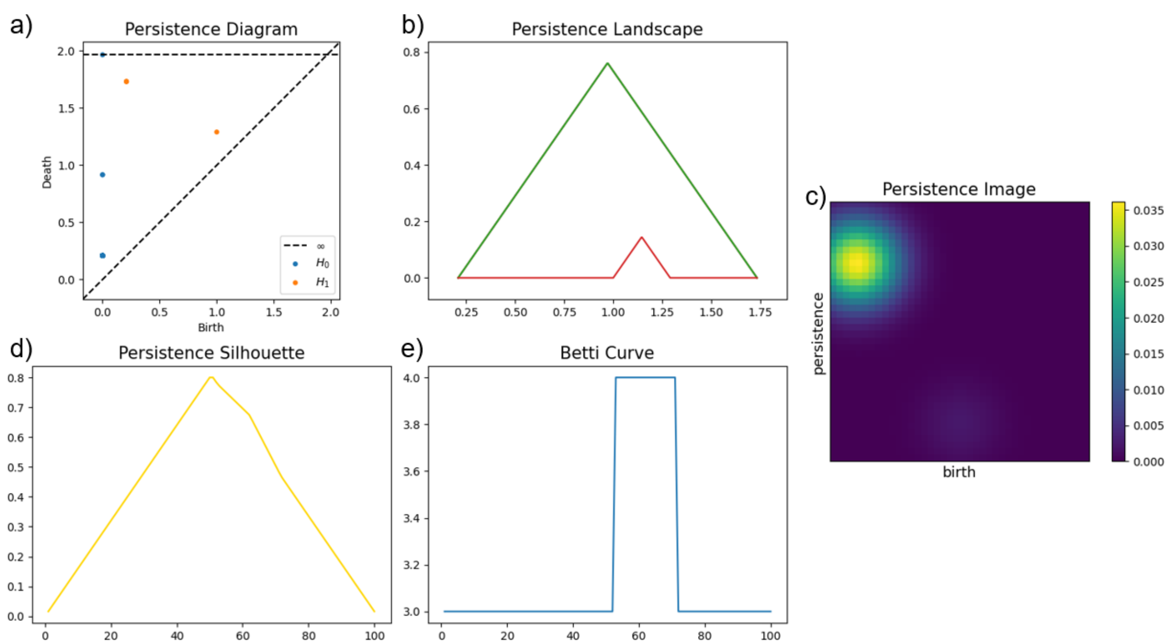

FIGURE 6. Visualizations of persistence (a) diagram, (b) landscape, (c) image, (d) silhouette, and (e) Betti curve.

Among all the above-mentioned PH representations, Figure 7 reveals that PD is most often used by recent studies, followed by persistence landscape and entropy. The combination of PD with other topological and conventional features consistently yields good analysis results, making PD the primary choice in TDA-based EEG analysis despite the underlying challenge of PD analysis with quantitative methods [42]. In contrast, recent studies have shown that the persistence landscape alone achieves excellent performance [62, 75]. Thus, we recommend that researchers incorporate these PH features into their TDA studies.

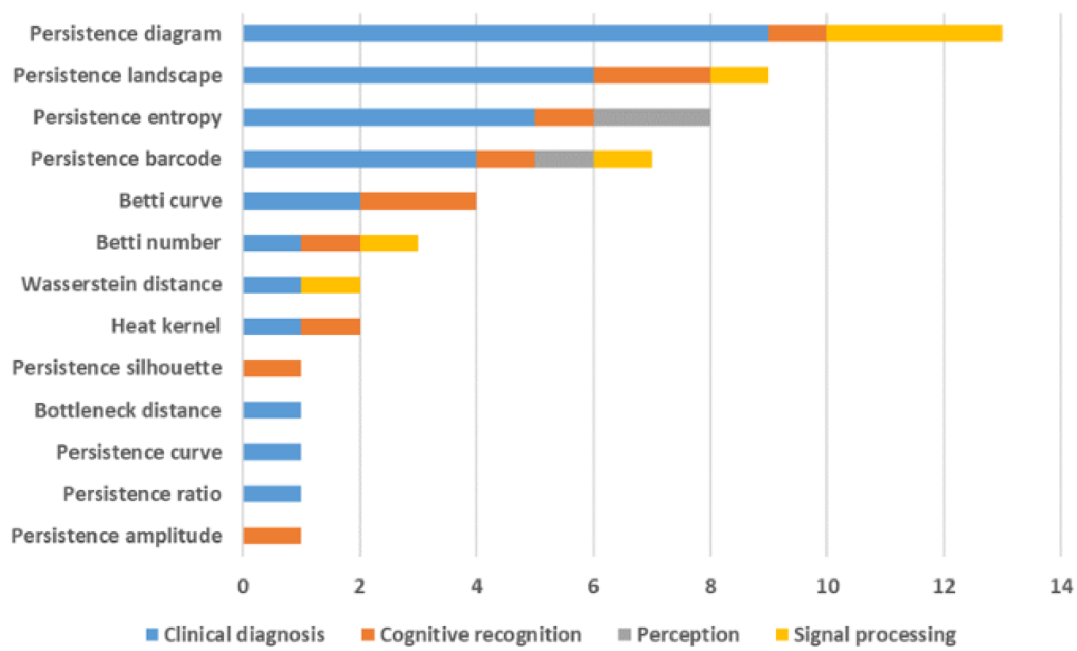

FIGURE 7. Bar chart summarizing the frequency of each PH feature being used in the reviewed EEG studies in different domains.

3.3 Feature selection

Feature selection plays a key role in eliminating redundant or irrelevant features, thereby reducing computational costs and improving analysis results. The feature selection methods that have been employed in the reviewed papers are the recursive feature elimination (RFE) and SelectKBest methods [52, 54]. Instead of applying the feature selection technique, most studies limit their choice of topological features in their analysis or restrict themselves to only one or two homological dimensions to reduce the total number of features.

As discussed in Section 3.2.2, a variety of PH representations exhibit good performance in EEG analysis. These representations generate a large number of features, especially with multidimensional EEG signals from multiple subjects and EEG electrodes. Assumptions on the low impact of certain topological features in the analysis might be inappropriate and could prevent researchers from achieving optimal results. Thus, we recommend applying feature selection techniques in TDA-based EEG analysis to enhance analysis results and reduce model training time, although most studies have excluded this approach.

3.4 Signal analysis

After feature extraction and selection, EEG data are commonly analyzed with ML or DL methods. Logistic regression (LR), support vector machine (SVM), random forest (RF), and k-nearest neighbor (KNN) are some popular classifiers used to classify EEG signals for different tasks (e.g., disease diagnosis). Among these, the RF classifier reported superior performance in several studies [54, 55, 69, 72, 75]. Its ability to handle large datasets, support multi-class classification, and resist overfitting [76] makes it particularly effective for classifying EEG signals using topological features.

The availability of complex and large EEG datasets promotes the use of DL models in recent studies. DL models such as the deep neural network (DNN), graph neural network (GNN), and convolutional neural network (CNN) are frequently applied to distinguish EEG signals with diverse topological properties. Wang et al. [41] employed a new deep-learning algorithm, GoogLeNet, which is known for its high computational efficiency and practicality [77], to classify seizure EEG. Moreover, Prantzalos et al. [78] proposed the application of generative artificial intelligence, the Google Gemini 1.0 Pro-Vision model integrated with the PD for epileptic EEG classification. Despite the unsatisfactory results, their study plays a vital role as a pioneer in combining fast-developing artificial intelligence with topological data analysis in EEG signal processing.

Figure 8 indicates that the SVM and RF are the top two most applied classifiers in recent TDA-based EEG studies. Their robustness and capability in handling nonlinear classification problems lead to consistently superior results, making them popular in various classification tasks [79, 80]. The DNN and GNN models have also been increasingly utilized despite their requirement for a large sample size. With the expanding data availability and computational resources, the use of DL or other advanced classification models is expected to grow exponentially.

Following the EEG classification with topological features, different statistical methods, such as the pairwise permutation test [45, 60] and paired t-test [46], are applied to validate the statistical significance of the features. Rutkowski et al. [70] employed uniform manifold approximation and projection (UMAP) to cluster and visualize the dissimilarities of topological features between normal and mild cognitive impairment EEG in their work. Additionally, the grid search method is employed for hyperparameter tuning of classification models in several studies [40, 42]. Moreover, TDA is often combined with frameworks, such as the novel Higuchi fractal dimension-based (HFD) testing framework introduced by El-Yaagoubi et al. [74], to enhance analysis performance.

4. Discussion

TDA shows significant potential in the realm of EEG signal processing. By leveraging its strength in identifying complex signal properties, TDA enables us to gain deeper insight into EEG, thereby facilitating the use of EEG in various applications, such as diagnosing neurological disorders and advancing BCI technology. However, TDA also suffers from several limitations. As emphasized by the no-free-lunch theorem [81], no single algorithm performs best across all problem types. In the following sections, we discuss commonly used TDA tools, highlight TDA strengths and limitations, and outline future directions for TDA application in signal processing.

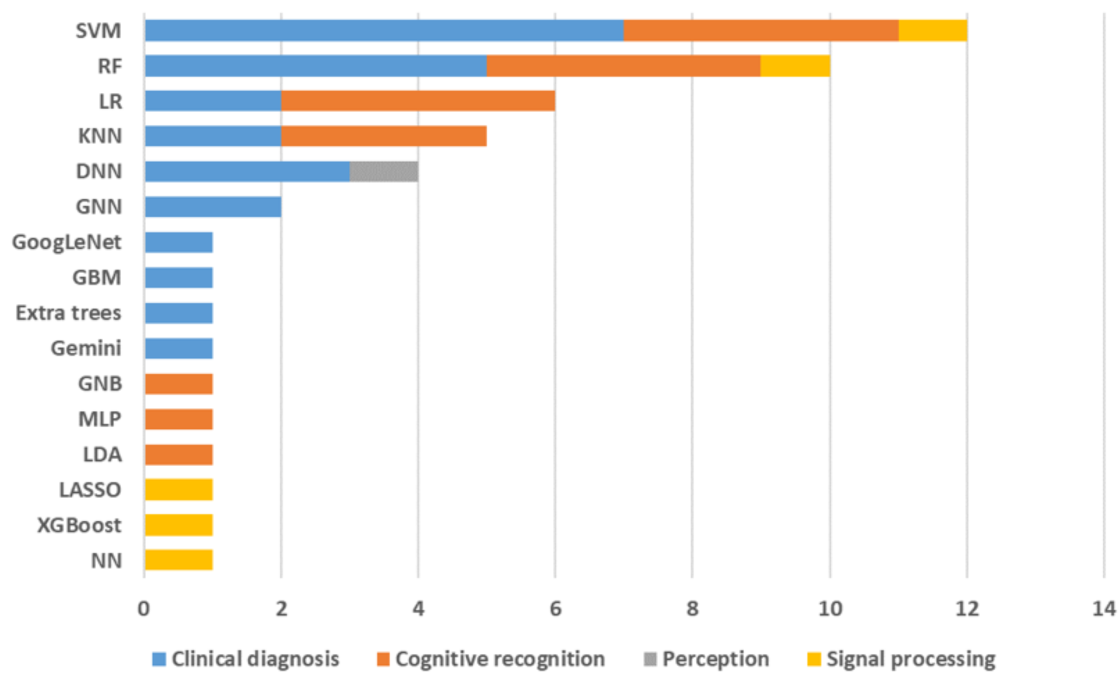

FIGURE 8. Bar chart summarizing the frequency of each classifier being used in the reviewed EEG studies in different domains (GBM = Gradient boosting machine, GNB = Gaussian naive bayes, MLP = Multi-layer perceptron, LDA = Linear discriminant analysis, LASSO = Least absolute shrinkage and selection operator, XGBoost = Extreme gradient boosting, NN = Neural network).

4.1 TDA implementation tools

Based on the reviewed papers, Giotto-tda is the most commonly used tool for TDA implementation. It is a comprehensive and high-performance topological ML toolbox in Python, enabling the computation of various topological features, PH visualization, and time series preprocessing [82]. Another regular TDA tool is the Gudhi, a versatile C++ library that provides advanced algorithms for constructing various types of simplicial complexes, representing their structures, and computing geometric approximations and PH [83].

On the other hand, Ripser and Persim are two Python packages included in the Scikit-tda library that have excellent computational efficiency. Ripser focuses on the construction of VR and sublevel set filtration [84], while Persim extracts topological features by transforming PDs into functional summaries or calculating distances between PDs [85]. JavaPlex [86] is another widely used TDA tool that computes the PH of filtered chain complexes and automatically builds filtrations from geometric data.

4.2 Strengths

TDA exhibits several advantages compared to conventional analysis tools. TDA is capable of uncovering the intrinsic data structure and pattern that has low sensitivity to changes and variations. TDA also excels at identifying cycles (e.g., periodicity) that might be invisible to traditional statistics, especially in nonlinear or nonstationary signals. TDA provides rich topological features that are robust to perturbations and deformations, enhancing the performance of ML and DL models in EEG analysis.

Moreover, Zheng et al. [55] reported that TDA, when applied to multichannel EEG, is robust across subjects and channel counts, maintaining stable performance across three datasets of different sizes. Guo et al. [61] demonstrated that low-dimensional topological features calculated through VR filtration can effectively capture noise, making the PH features nearly equivalent to those derived from noiseless data. All these TDA's strengths make it suitable for analyzing the complex correlation and interdependency of EEG signals.

4.3 Limitations

Like any analytic technique, TDA also has a set of limitations. The most frequently discussed limitation of TDA is its computational complexity. As data dimensionality grows, the calculation of the simplicial complex becomes more intense, making TDA less applicable for researchers with limited computational resources. The second limitation is the parameter tuning. Computing PH involves many choices, such as the filtration threshold and the distance metric. These choices can introduce subjectivity and lead to varying results depending on the parameters selected [73]. Thus, fine-tuning TDA parameters is crucial to reduce the effect of poor parameter choices on the analysis results.

Furthermore, a significant drawback of TDA is its restricted capacity for statistical inference. Standard PH lacks built-in measures of feature significance for effectively comparing and evaluating different topological properties extracted from signal time series. Besides, TDA often suffers from information loss because it focuses on global properties and overlooks subtle localized variations. This issue could drastically impact TDA performance when local transient changes are essential. Although some studies suggested that TDA handles EEG inter-subject variability well, Yan et al. [75] found that individual differences in EEG significantly affect the accuracy of emotion recognition using TDA features. The contradictory finding highlights the importance of signal preprocessing choices and data quality in determining the effectiveness of TDA.

4.4 Future directions

TDA demonstrates substantial potential for future advancements in the field of signal processing. It is noteworthy that PH is not the only tool available in TDA. The Mapper algorithm is another popular TDA tool that is extensively applied in various study domains, including the analysis of COVID-19 time series [87, 88]. Researchers generally employed Mapper for dimension reduction and data visualization. Mapper can be integrated into the TDA-based EEG processing pipeline for data dimensionality reduction or feature distribution visualization.

Next, researchers can work on improving the applicability of TDA in signal processing in different ways. In addition to the existing computational cost issue, many studies emphasize the need to combine features from other domains with nonlinear topological features for optimal performance [68, 89]. The growing number of features exacerbates computational challenges and hinders practitioners from applying TDA. Researchers should examine effective feature selection methods, such as genetic algorithms and sequential backward floating selection [90], that are currently lacking. Furthermore, there is a growing need for improved methods to interpret TDA outputs, either through advanced statistical tests or visualization tools that enhance understanding.

Besides, the development of publicly accessible TDA software or platforms with user-friendly interfaces is crucial to improving the usability of TDA within non-expert communities. The platforms available, such as Brava [91] and MaTiLDA [92], enable users to upload their datasets and easily generate various PH representations for feature extraction. However, most applications exclude the implementation of data preprocessing and TDA feature interpretation. Thus, users still require a basic understanding of signal processing and TDA concepts to harness the applications' potential. Developing software that balances functionality with ease of use would significantly expand TDA's accessibility beyond technical domains.

Lastly, current TDA-based EEG studies mainly focus on detecting neurological disorders, such as attention deficit hyperactivity disorder, epilepsy, and schizophrenia. Only a few studies have examined topics beyond disease, such as recognizing brain states, emotions, and motor imagery. Gaining deeper insights into brain activity through EEG will enhance the development of innovative technologies to assist people, especially those with disabilities, in their daily lives. Moreover, accurate detection of cognitive fatigue and attention facilitates the evolution of safety devices to prevent the happening of fatal accidents. Studying human perception across various contexts can also improve the design and performance of BCI. Thus, researchers can pay more attention to non-clinical EEG applications in their future studies. Overall, TDA-based EEG analysis shows great potential and opportunities, and we hope more researchers engage in advancing this field.

5. Conclusion

In summary, this review provides a clear overview of the TDA-based EEG processing pipeline introduced in recent studies. We discuss each processing step in detail and summarize the methods used. We outline the latest TDA techniques applied in the reviewed studies for EEG processing, including the PH filtrations and vectorization approaches. We summarize the general TDA tools available and the pros and cons of TDA techniques. We recommend further research into effective feature selection methods and the development of user-friendly TDA platforms to enhance the facilitation of TDA. We believe that the application of TDA will continue to grow, and there is much more to discover.

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Conflict of Interests

The authors declare that there is no conflict of interests.

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