# Unsupervised ECG Analysis: A Review

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***Abstract*—Electrocardiography is the gold standard technique for detecting abnormal heart conditions. Automatic detection of electrocardiogram (ECG) abnormalities helps clinicians analyze the large amount of data produced daily by cardiac monitors. As the number of abnormal ECG samples with cardiologist-supplied labels required to train supervised machine learning models is limited, there is a growing need for unsupervised learning methods for ECG analysis. Unsupervised learning aims to partition ECG samples into distinct abnormality classes without cardiologist-supplied labels–a process referred to as ECG clustering. In addition to abnormality detection, ECG clustering has recently discovered inter and intra-individual patterns that reveal valuable information about the whole body and mind, such as emotions, mental disorders, and metabolic levels. ECG clustering can also resolve specific challenges facing supervised learning systems, such as the imbalanced data problem, and can enhance biometric systems. While several reviews exist on supervised ECG systems, a comprehensive review of unsupervised ECG analysis techniques is still lacking. This study reviews ECG clustering techniques developed mainly in the last decade. The focus will be on recent machine learning and deep learning algorithms and their practical applications. We critically review and compare these techniques, discuss their applications and limitations, and provide future research directions. This review provides further insights into ECG clustering and presents the necessary information required to adopt the appropriate algorithm for a specific application.**

***Index Terms*—Electrocardiogram (ECG), machine learning, unsupervised learning, clustering, deep learning.**

## I. Introduction

An ELECTROCARDIOGRAM (ECG) depicts the electrical activity of the heart. It is routinely recorded in intensive care units as well as in ambulatory and wearable monitors, producing a large amount of data every day. Numerous systems based on supervised machine learning have been developed using ECG datasets with cardiologist-supplied labels to classify heartbeats into normal and several abnormality classes [1]–[5]. However, cardiologists can only analyze and label a small subset of the massive ECG data to indicate common cardiac abnormalities. Moreover, most labeled ECG datasets are acquired in controlled settings, such as hospitals and clinics, and contain very limited samples compared to the wide variety of ECG patterns that may occur in different physiological and pathophysiological conditions. For example, patterns in ECG data acquired from individuals experiencing stress or suffering from diabetes mellitus are shown to differ from those acquired in normal conditions [6], [7]. As such, several unsupervised learning methods have recently been proposed to analyze ECG data without the need for cardiologist-supplied labels – a process referred to as *ECG clustering*.

The need for unsupervised ECG analysis is, however, not only derived from the lack of cardiologist-supplied labels. There exist inter and intra-patient ECG patterns and structures that, if discovered, can further reveal valuable information about the cardiovascular system and the whole body and mind. Discovering such relationships can reveal complex mechanisms and significant biomarkers of various health conditions as well as the state of the mind and body and ultimately guide physicians with refined treatment decisions. Notably, visual identification of these patterns is impossible due to their complexity and the high volume of data. These patterns, however, can be automatically identified by clustering techniques. For example, ECG clustering has helped researchers, especially in the field of psychophysiology, discover hidden ECG patterns that correlate with different emotional states, such as sadness and emotional stress [6], brain disorders, such as epilepsy [8], and other conditions such as drowsiness [9]. ECG clustering has also enabled researchers to discover distinct cardiac abnormalities and metabolic levels among patients with various health conditions, including diabetes mellitus [7], nocturnal hypoglycemia [10], embolic stroke [11], and atherosclerosis [12].

In addition to their application as a part of a broader *knowledge discovery* system, clustering techniques, in particular deep learning-based unsupervised methods, such as autoencoders [13], [14] and generative adversarial networks [15], have also been employed to overcome some challenges facing ECG supervised learning systems by resolving the imbalanced data problem [16] and low-level automation of patient-specific ECG classifiers [17]–[19]. Moreover, ECG clustering has been utilized in biometric authentication [20]–[23], ECG

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segmentation [24], [25], and fetal ECG extraction from abdominal ECG [26].

To date, several studies have reviewed supervised ECG analysis techniques [2]–[4], [27]–[30]. However, to the best of the authors' knowledge, this work is the first to provide a comprehensive and critical review of unsupervised ECG analysis systems. In this work, we review the clinical/medical applications of unsupervised ECG analysis systems and related machine learning methods – from traditional models to the more recent deep learning models – employed by such systems. To conduct a comprehensive review, we searched several platforms, including IEEEXplore, ScienceDirect, Google Scholar, Scopus, and PubMed database, and mostly selected studies published during the last decade in prestigious journals and conferences ranked by well-known citation indices, such as Science Citation Index. We discuss these state-of-the-art studies, compare them, outline their limitations, and provide future directions. This will enable researchers to conveniently reach the desired information and choose the appropriate algorithm for their specific application.

## II. ECG Clustering

The typical pipeline for ECG clustering comprises of several data preparation and preprocessing steps before applying the clustering algorithm. In this section, we briefly review the data preparation techniques required for efficient clustering of ECG data including denoising, segmentation, and feature engineering. We will then extensively review the conventional and the state-of-the-art clustering algorithms including deep learning methods and provide a critical comparison.

### A. Data Preparation for ECG Clustering

Methods used for denoising, segmentation, and feature engineering mostly overlap with those used in supervised learning systems. Here we briefly introduce these techniques particularly those tailored for ECG clustering. The interested reader is referred to [2]–[4] for more details.

***1) Denoising and Artifact Removal:*** This step aims to reduce the distorting effects of the patient's breathing, skin stretching, power line interference, and muscle contraction. ECG denoising systems are typically based on moving average filters, frequency-selective filters, Wiener filters, adaptive filters, and discrete wavelet transform [31]. Further information about ECG denoising methods can be found in [31].

***2) Segmentation:*** The denoised ECG signal is usually segmented into quasi-periodic units by automatically identifying the heartbeats. A heartbeat is comprised of several electrical waves, called P, QRS, and T, which represent the depolarization (contraction) and repolarization (relaxation) of the heart chambers, namely atria and ventricles [32].

Most ECG clustering studies detect the peak of the QRS complex, called the R peak, across the signal and consider the interval between two consecutive R peaks, i.e., the whole cardiac cycle, as the segmentation unit. There are very few studies that have considered other characteristic points of the ECG signal for segmentation [33]–[35]. Given that the abnormal morphologies of PR, ST, and TP segments of an ECG cycle can indicate common cardiac disorders, such as myocardial ischemia, hypokalemia, and atrial fibrillation [32], incorporating other ECG characteristic points in segmentation could improve the clustering results. Instead of identifying cardiac cycles across the ECG signal, some studies divide the signal into fixed-time intervals without identifying any characteristic points [36], [37]. There also exist a few ECG clustering methods that do not perform segmentation [38], [39]. These methods directly extract features from the ECG signal without identifying any physiological characteristic points.

***3) Feature Engineering:*** This step aims to obtain the most informative features of ECG segments that facilitate the downstream unsupervised learning task. Here, we briefly introduce conventional ECG feature engineering methods. More recent deep learning approaches are presented in Section I-C.

Expert physicians often examine the time and amplitude features of P, QRS, and T waves to diagnose heart disease. However, cardiac abnormalities may not always be visible in time domain. [40]. Frequency information of the ECG signal obtained by power spectral analysis and time-frequency analyzes, such as wavelet transform, can fill this gap. In wavelet transform, the correlations between the input ECG and a set of finite-duration functions, called wavelets, are considered as ECG features [36], [41]. For further details about time-domain, voltage-domain, and frequency-domain feature engineering methods, interested readers can refer to the following sources [3], [4], [29], [30].

Recently, nature-inspired population-based optimization methods, such as Firefly and particle swarm optimization, have been also used for feature engineering [42], [43]. These methods search for features that result in the best classification or clustering performance in a vast population of possible features. For example, Kora [42] viewed each point on the ECG signal as a possible feature. Using the Firefly algorithm, she searched for the points that maximize the accuracy of the neural network employed to classify ECG segments into normal and myocardial infarction classes. For more information about nature-inspired feature engineering methods, we refer the reader to the following sources [44]–[46].

Segmented units of ECG are lastly clustered into groups; each group contains segments whose corresponding feature vectors are more similar to each other than those in other groups according to a predefined similarity metric.

### B. Clustering Algorithms

Essential to clustering is the similarity (or dissimilarity) metric used to measure the distance between two ECG segments. Among various existing similarity metrics, Euclidean distance, cosine coefficient, and dynamic time-warped distance [47] are the three widely used metrics in ECG clustering. The first two are typically used to measure the similarity between ECG units expressed as temporal and morphological features or wavelet coefficients. Dynamic time warping is a method that measures the similarity between two time series, which may vary in length. Here, we briefly describe conventional clustering algorithms

TABLE I
SUMMARY OF CLUSTERING ALGORITHMS USED IN REVIEWED STUDIES AND THEIR PROS AND CONS. BASED ON ANALYSIS CONDUCTED BY XU AND TIAN [47]

| Algorithm | Pros | Cons | Studies |
|---|---|---|---|
| Deep Embedding Network | Easier to implement than other deep architectures. Suitable for high dimensional feature space. Suitable for handling noise and oulier. Finds arbitrary shape clusters. | A priori knowledge about number of clusters is required. Sensitive to the choice of clustering loss function. High computational cost. | [67] |
| Variational Deep Embedding | Capable to generate samples from obtained clusters. Suitable for high dimensional feature space. Suitable for handling noise and oulier. Finds arbitrary shape clusters. | A priori knowledge about number of clusters is required. High computational cost. | [74] |
| K-means | Easy to implement. Easily adapts to new examples. Very low time complexity (linear in the size of ECG samples). | A priori knowledge about number of clusters is required. Sensitive to noise and outlier. Not suitable for non-convex shape clusters. | [8], [33], [35], [74], [78]–[87] |
| Fuzzy c-means | Handles overlapped clusters. Handles noise and outlier. | A priori knowledge about number of clusters is required. Computationally more expensive than K-means. | [35], [39], [83], [88]–[95], [95] |
| Affinity propagation | A priori knowledge about number of clusters is not required. | Low scalability. Sensitive to noise and outlier. Computationally more expensive than K-means. | [96] |
| Max-Min | Easy to implement. Easily adapts to new examples. Low time complexity (linear in the size of ECG samples). | A priori knowledge about number of clusters is required. Sensitive to noise and outlier. | [97] |
| Gaussian Mixture Models | Handles overlapped clusters. Suitable for handling noise and outlier. | A priori knowledge about number of clusters is required. High time complexity. | [8], [36], [37], [98] |
| Maximum Margin Clustering | Suitable for high dimensional feature space. Suitable for handling noise and outlier. Handles overlapped clusters. | A priori knowledge about number of clusters is required. High time complexity. Low scalability. Sensitive to the choice of kernel. | [34] |
| Swarm Intelligence | A priori knowledge about number of clusters is not required. Mostly avoids local optimal. | High time complexity. Low scalability. | [41], [60], [61] |
| Spectral clustering | Suitable for high dimensional feature space. Suitable for handling noise and oulier. Finds arbitrary shape clusters. | A priori knowledge about number of clusters is required. High time complexity. | [56] |
| DBSCAN | A priori knowledge about number of clusters is not required. Suitable for handling noise and oulier. Finds arbitrary shape clusters. | Sensitive to the choice of hyper-parameters. Not Suitable for data spaces with uneven density (imbalance clusters). | [8], [9], [99] |
| Self-Organizing Map | Provides an interpretable organization of clusters in a 2-dimensional grid. | A priori knowledge about number of clusters is required. High time complexity. | [100]–[102] |
| Hierarchical Clustering | Provides hierarchical relationship among clusters. Handles noise and outliers. Finds arbitrary shape clusters. A priori knowledge about number of clusters is not required | High time complexity. | [83], [85], [86], [86], [103] |
| Permutation distribution clustering | Specifically designed for clustering time-series data. | High time complexity. High space complexity for storing permutation distribution of ECGs. | [66] |

$n$ and $k$ denote number of samples and number of clusters, respectively.

employed for ECG clustering. Recent deep learning-based clustering algorithms are described in Section I-C. The strengths and limitations of the presented algorithms in ECG analysis are discussed in Section I-D and summarized in Table I.

***1) Centroid-Based Clustering:*** Centroid-based clustering techniques separate ECG segments into groups based on their similarity to the *centroids* of these groups. A centroid is viewed as the representative segment of its corresponding group. *K-means* is the most well-known centroid-based clustering algorithm that considers the cluster centroid as the average of the ECG segments (or their feature vectors) in that cluster. Variations of K-means used in unsupervised ECG analysis are *Fuzzy C-means* [48], *Affinity propagation* [49], and *Max-Min* clustering [50]. These algorithms differ from each other based on how they obtain the centroids. For example, Affinity propagation obtains the centroids by exchanging messages carrying the similarity between ECG segments. Centroid-based clustering algorithms are typically easy-to-implement and incur a low computational cost. However, they are not generally suitable for handling noise, outliers, and high-dimensional feature spaces.

***2) Hierarchical Clustering:*** Hierarchical clustering considers each ECG segment as an individual cluster and merges the most similar clusters until only one cluster is left (which comprises the entire dataset). Compared to the centroid-based clustering algorithms, hierarchical clustering algorithms typically incur a higher computational cost; however, the uniqueness of these methods is the resulting dendrogram that visualizes the hierarchical relationships between clusters, which can facilitate the interpretation by physicians [51].

***3) Distribution-Based Clustering:*** This group of clustering algorithms aims to find the probability of ECG segments belonging to the clusters. Gaussian mixture model (GMM) is a well-known distribution-based clustering algorithm widely employed by the reviewed studies [36], [37]. GMM assumes that several Gaussian distributions generate ECG segments; that is, each cluster is defined by the mean and the standard deviation around the mean of a Gaussian distribution. Dirichlet Process GMM is a variation of GMM that does not require the initial number of clusters (i.e., Gaussian components within the data space)[52]. DPGMM automatically learns the number of clusters through a variational Bayesian inference, an iterative algorithm that estimates the prior distribution of clusters. Distribution-based clustering algorithms are suitable for handling noise and outliers, but they typically incur a high computational cost. Notably, DPGMM incurs higher computational cost that GMM.

***4) Density-Based Clustering:*** Density is often defined as the number of data points within some predefined radius. Density-based clustering considers clusters as regions with higher density within the data space. DBSCAN [53] and self-organizing map [54] are well-known density-based clustering algorithms that have been used for ECG clustering. DBSCAN considers a region as a cluster if its density exceeds a predefined threshold. It can effectively handle noise and outliers; however, the resulting clusters are heavily dependent on the choice of the radius and threshold. A self-organizing map (SOM) is a type of neural network that maps the input segments into a two-dimensional grid, with the assumption that there exists specific topology among the ECG segments. The resulting grid is bent and twisted toward regions of high density [54]. SOM provides an interpretable organization of clusters in a 2-dimensional grid; however, it incurs a high computational cost.

***5) Spectral Clustering:*** Spectral clustering transforms the clustering problem into a graph partitioning problem [55], where the goal is to partition a graph into subgraphs such that the sum of the weights of the edges connecting the subgraphs is minimized. In ECG clustering, ECG segments are viewed as nodes, and similarity between them are represented as the weights of edges connecting the nodes [56]. Spectral clustering can effectively handle high-dimensional feature spaces, but incurs high computational and space costs [47].

***6) Clustering Based on Swarm Intelligence:*** Swarm intelligence models the clustering problem as an optimization task, where the goal is to maximize the overall similarity between ECG segments within the clusters. For example, in the ant colony clustering algorithm [57], a population of *ants* randomly moves from one ECG segment to another and assigns a value (i.e., pheromone) to the segments based on their similarity. Clusters are then identified as the segments whose similarity values exceed a pre-defined threshold. Particle swarm optimization [58] and artificial bee colony [59] are other swarm intelligence-based clustering algorithms employed for ECG clustering [41], [60], [61]. Clustering algorithms based on swarm intelligence can avoid the local optimum when searching for the best cluster solution, promising high-quality clusters. However, due to the stochastic nature of these algorithms, they often incur a high computational cost, especially in large-scale datasets.

***7) Maximum Margin Clustering:*** Maximum margin clustering (MMC) [62] takes the advantage of support vector machines (SVMs) to perform clustering over unlabeled data. In particular, it finds a set of labels for ECG segments to maximize the margin obtained by running the SVM on the labeled segments. The main drawback of MMC is its computationally expensive steps to solve its non-convex integer problem [34].

***8) Ensemble Clustering:*** In ensemble clustering, results from multiple runs of one or several clustering algorithms are integrated to achieve a consensus clusters that are better fits to the data than the one obtained by individual clustering algorithms. For example, Abawajy *et al.* [38] integrated the results of K-means and GMM for ECG clustering, while Aidos *et al.* [63] constructed an ensemble of 200 runs of K-means with various values for $K$.

***9) Permutation Distribution Clustering:*** This algorithm was developed specifically for clustering time-series to find similarity in time-series based on differences in their *permutation distribution*. This is achieved by counting the frequency of distinct order patterns in an embedding of the time-series [64].

### *C. Clustering With Deep Learning*

Deep learning-based clustering algorithms have recently attracted much attention and have achieved superior performance than the conventional machine learning algorithms in numerous tasks [65]. The primary advantage of these algorithms over conventional clustering algorithms is that they bypass the conventional feature engineering step and automatically learn the best set of features for clustering. Deep learning-based clustering methods are categorized into three groups based on their architecture [65]: (1) autoencoders, (2) feed-forward networks, and (3) deep generative models. For each group, we present the current advances in ECG clustering and introduce state-of-the-art algorithms that can potentially be employed to further enhance ECG clustering.

***1) Deep Autoencoders:*** An auto-encoder comprises an *encoder*, a neural network that transforms the input data to a low-dimension feature vector, followed by a *decoder*, a neural network that reconstructs the original input from this low-dimensional feature vector. The encoder and decoder are trained simultaneously to minimize a *reconstruction* loss: the difference between the original input and the decoded output.

Deep clustering network [13] and deep embedding network [14] are two popular autoencoder-based clustering algorithms that have been used for ECG analysis [66]–[68]. The idea behind these algorithms is to impose a clustering loss in addition to the reconstruction loss while training the network. In the deep clustering network, K-means loss is imposed, while in the deep embedding network, two constraints, namely, locality preserving and group sparsity are imposed to preserve the local structure of the data and diagonalize the affinity of representations. Some applications of these algorithms are further reviewed in Section II-A.

***2) Deep Feed-Forward Networks:*** This group of algorithms only incorporates the clustering loss to train the deep network. The network architecture can be fully connected, convolutional, or a combination of both. The weights of the networks can be initialized randomly or fine-tuned using restricted Boltzmann machines on a pre-trained network [69]. Deep adaptive

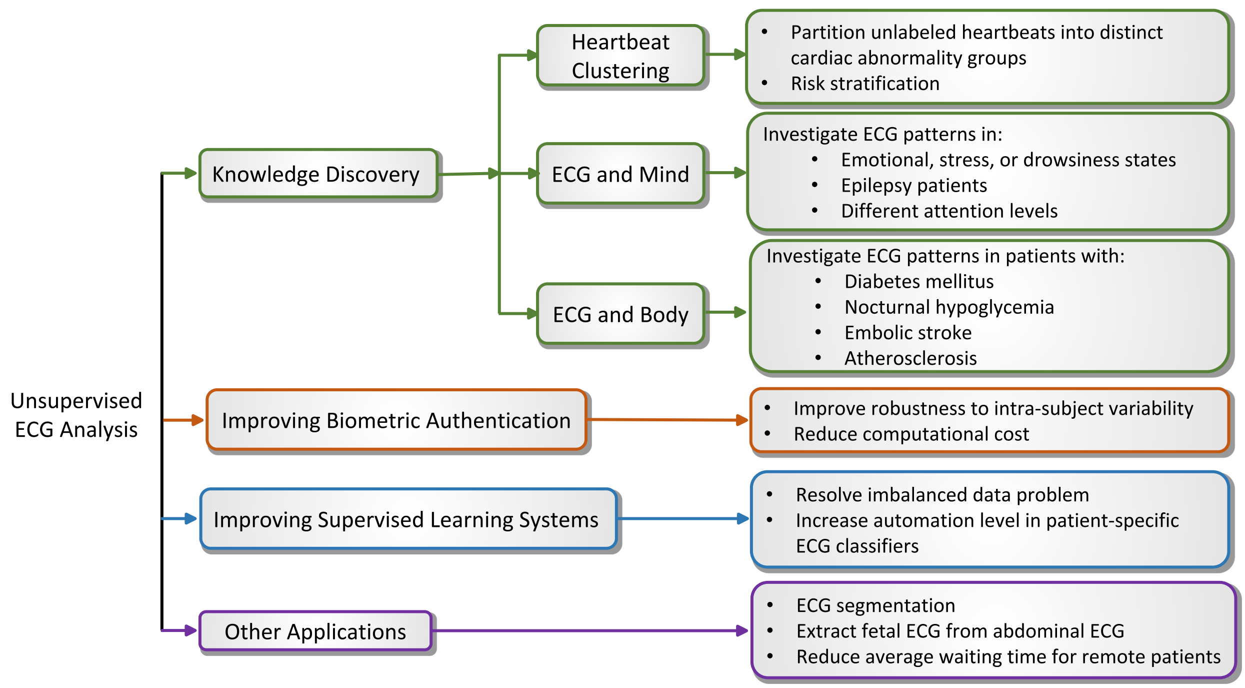


Fig. 1. Overview of unsupervised ECG analysis applications.

clustering (DAC) [70] is a popular deep feed-forward clustering network. It is a one-layer convolutional neural network (CNN) trained using a binary pairwise classification approach. In short, the input sample is first mapped into a one-hot encoded vector using the CNN. The cosine distance between all pairs of samples is then calculated. As the ground-truth similarities are unknown, an adaptive learning algorithm called self-paced latent variable learning [71] is adopted to train the weights of the CNN based on the estimated similarities. DAC was originally proposed for image clustering and achieved superior performance over several challenging image datasets. With some modifications to its CNN architecture, DAC can be adopted for ECG analysis, accounting for a possible future direction.

***3) Deep Generative Models:*** Variational autoencoders (VAEs) [72] and generative adversarial networks [15] are the most popular deep generative models in recent years. VAEs enforce the latent representation learned by the autoencoder to follow a predefined distribution, which is typically a mixture of Gaussians. Variational deep embedding [73] is a VAE-based clustering algorithm that has been employed for ECG analysis [74]. This algorithm can be viewed as a deep learning version of the conventional GMM clustering algorithm, where the feature space is automatically learned.

Generative adversarial networks (GANs) aim to generate a set of fake data based on the ground-truth such that the fake data distribution is similar to that of the ground truth. In short, a GAN comprises two submodules: (1) generator, $G$, generating fake data, and (2) discriminator, $D$, distinguishing the fake data generated by $G$ from the ground-truth. Sets of parameters in $G$ and $D$ are learned such that the Nash equilibrium in the min-max game between the generator and discriminator is achieved.

CatGAN [75] is a popular clustering algorithm based on the GAN. It enforces the discriminator to classify the training data into a predefined number of classes (instead of only fake and real) while having low confidence in classifying samples generated by generator. ClusterGAN is a variation of CatGAN that has recently shown superior performance in different clustering tasks over many other deep learning-based clustering algorithms [76]. As these algorithms have not been employed for ECG analysis, their applications in ECG analysis can form a possible future direction.

In addition to clustering, deep generative-based algorithms can learn to generate new samples from the obtained clusters. Recently, several studies adopted GANs to generate new heartbeats for tackling imbalanced data problems, one of the long-lasting challenges in supervised ECG abnormality classification [18], [19]. In Section II-E, we will discuss applications of these methods.

### *D. Comparison of Clustering Algorithms for ECG Analysis*

Table I compares different ECG clustering algorithms.

The ability of a clustering algorithm to handle noise and outliers is an important factor in ECG clustering as outliers exist in most publicly available ECG datasets and can adversely affect the structure of the resulting clusters.

The time complexity of a clustering algorithm is another important factor. For applications that real-time analysis of ECG is vital (e.g., in ICU settings), a clustering algorithm incurring high computational cost may be an infeasible choice even though the resulting clusters may be of high quality. K-means, Fuzzy

TABLE II
SUMMARY OF STATE-OF-THE-ART HEARTBEAT CLUSTERING METHODS ALONG WITH THEIR REPORTED PERFORMANCES

| Ref. | Clustering | Dataset | # of Test ECGs | # of Abnormality Classes | # of Clusters | Performance |
|---|---|---|---|---|---|---|
| [102] | Self-Organizing Map | MIT-BIH | 48 | 16 | 25 | 98.5% accuracy |
| [97] | Max-Min | MIT-BIH | 48 | 6 | Auto | 98.6% accuracy |
| [96] | Affinity Propagation | MIT-BIH | 48 | 15 | 15 | 98.4% accuracy |
| [81] | K-means + SVD | MIT-BIH | 48 | 4 | 4 | **99.98% accuracy** |
| [60] | Ant Colony | MIT-BIH | 32 | 6 | 6 | 94.4% sensitivity |
| [34] | Maximum Margin Clustering | MIT-BIH | 7 | 5 | 5 | 95.9% accuracy |
| [36] | Tensorization + Gaussian Mixture Model | CTAD | 2 | 2 | 2 | 0.93 Jaccard coefficient |
| [37] | Symbolization + Gaussian Mixture Model | PTB | 10 | 10 | 10 | 94.4% accuracy; 0.97 NMI |
| [66] | Autoencoder + Permutation Distribution | UCR | 200 | 2 | 2 | 80.6% accuracy; 0.31 Silhouette coefficient |
| [74] | Variational Deep Embedding | BIDMC | 500 | 5 | 5 | 96.0% accuracy |

C-means, and Max-Min algorithms incur a low computational cost; however, their ability to handle outliers is lower than more computationally expensive algorithms such as DBSCAN, GMMs, hierarchical, spectral, and deep learning-based clustering. Among these algorithms, DBSCAN incurs the lowest computational cost, although it is sensitive to the choice of its hyper-parameters (the radius of the neighborhood and the minimum number of points in a neighborhood). Moreover, DBSCAN is not suitable for data spaces where the inherent density of clusters is uneven.

Finding arbitrary (i.e., non-convex) shaped clusters and handling high-dimensional feature spaces are other important factors in choosing an effective clustering algorithm for ECG analysis. Although distance-based clustering algorithms, such as K-means, mostly find clusters of convex shapes, clusters are likely in arbitrary shapes in an ECG dataset. Density-based and deep learning-based clustering algorithms can effectively find non-convex shaped clusters but with a higher computational cost than distance-based clustering algorithms.

Feature spaces in ECG analysis are typically high-dimensional as many features are often extracted from ECGs, while the number of training ECG samples is typically limited. Graph-based and deep learning-based clustering algorithms; however, they typically incur a higher computational cost. Deep learning-based algorithms, in particular, are significantly more effective in handling high-dimensional data than conventional algorithms; however, deep learning methods require large amounts of data for training.

In addition to the above considerations, some clustering algorithms provide unique features for visualization. For example, hierarchical clustering provides dendrograms visualizing the hierarchical relationships between clusters, and self-organizing maps provide a 2-dimensional grid that visualizes some specific topologies within the dataset. For further information about clustering algorithms and their pros and cons, we refer the reader to [47], [65], [77].

## III. APPLICATIONS

We have categorized unsupervised ECG analysis studies, introduced to date, into six application fields, as shown in Fig. 1. The most developed application is heartbeat clustering that provides a succinct yet comprehensible organization of heartbeats within large amounts of ECG data. The most recent and innovative line of research aims to discover relationships between the cardiovascular system and the whole body and mind. Unsupervised ECG analysis has also been used to improve the performance of supervised abnormality detection and ECG-based authentication systems.

### A. Heartbeat Clustering

Heartbeat clustering aims to partition heartbeats across the ECG signal into groups representing distinct abnormalities or events. A summary of state-of-the-art heartbeat clustering methods is provided in Table II.

The effectiveness of heartbeat clustering systems is typically measured over ECG datasets with cardiologist-supplied labels. Each resulting cluster is expected to contain heartbeats belonging to only one label. Classification metrics, such as accuracy and sensitivity, and similarity metrics, such as Jaccard coefficient [103] and normalized mutual information (NMI) [104] are widely used as success measures. The Jaccard coefficient and NMI range from 0 to 1, where a high value indicates that identified clusters match well with ground-truth labels. Silhouette score [105] is another widely-used measure that does not require the ground-truth clusters. Silhouette measures the similarity of a sample to its cluster with respect to the other clusters, and ranges from -1 to 1, where a high value indicates that the sample is well-matched with its cluster and well separated from other clusters.

The datasets used for the evaluation of ECG clustering methods include MIT-BIH Arrhythmia [106], Physikalisch-Technische Bundesanstalt (PTB) [107], St.-Petersburg Institute of Cardiological Technics 12-lead Arrhythmia (CTAD) [1], UCR Arrhythmia [108], and BIDMC Congestive Heart Failure [109] datasets, among which MIT-BIH Arrhythmia is the most frequently used set.

One of the first and effective heartbeat clustering systems was designed by Lagerholm *et al.* [101]. They partitioned QRS complexes represented as wavelet coefficients into 25 clusters using a self-organizing map and achieved a high accuracy (98.5%) over MIT-BIH. The motivation behind using SOM was to provide a neighborhood map (as in a 2-dimensional grid) that preserves some topological information within the dataset, which can ultimately facilitate the interpretation by cardiologists.

Extensive research have focused on improving the ECG clustering accuracy by employing various clustering and optimization techniques, such as ant colony clustering [60], bee colony clustering [41], maximum margin clustering [34], Gaussian mixture models [36], hierarchical clustering [37], K-means [80], affinity propagation [95], and deep auto-encoder networks [67]. Among these, the clustering system proposed by Balouchestani and Krishnan [80] achieved the highest accuracy over the MIT-BIH dataset (99.98%). They devised a system based on K-means, compressed sensing theory, and K-singular value decomposition to partition heartbeats into five groups corresponding to normal, supra-ventricular ectopic, ventricular ectopic, fusion, and unclassifiable beats.

The ECG datasets used in these studies are relatively small to train deep learning models. Nevertheless, a few studies have recently adopted deep learning to cluster heartbeats within these datasets. Wachowiak *et al.* [67] trained a deep embedding network [14] over MIT-BIH with different initial number of clusters. The clustering result with the best silhouette score separated different abnormal beats into distinct clusters; however, the normal beats were equally spread over several clusters. Notably, this can be attributed to imbalanced classes within MIT-BIH, where normal beats constitute almost 75% of labeled beats in MIT-BIH. In another study, Thinsungnoen *et al.* [66] employed a genetic algorithm to obtain the optimal number of neurons in a 2-layer autoencoder. They trained the network over the UCR dataset containing 200 ECGs classified as normal or abnormal. The learned feature space was then clustered by the permutation distribution clustering algorithm which resulted in 80.6% overall accuracy. Most recently, Pereira *et al.* [74] trained a variational deep embedding network [73] over a subset of the BIDMC dataset comprising 4500 beats classified into normal class and four abnormality classes. Their evaluation over 500 test beats presented an overall accuracy of 96.0%. Although these deep learning-based studies achieved promising results, there is still a significant need for more advanced clustering algorithms that can automatically handle imbalanced data problem without the need for preprocessing algorithms and expert analysis. For this purpose, deep generative-based algorithms, such as ClusterGAN [76], that can learn to generate new samples from the minority clusters can further be investigated. Future work should also focus on the application of deep learning-based clustering algorithms over large public ECG datasets, such as those collected by Zheng *et al.* [110] and Wagner *et al.* [111].

From the clinical point of view, Syed *et al.* [96] performed an innovative ECG clustering via symbolization. They transformed the ECG signal into a symbolic string by clustering heartbeats using the Max-Min clustering algorithm [50] and assigning symbols to each identified cluster. Over the reduced symbolic representation of the signal, they then searched for subsequences of increased entropy representing irregular activities. In one case, their method detected a sequence with an ectopic atrial rhythm that had gone unnoticed by an expert cardiologist. Syed *et al.* further extended their work for risk stratification using hierarchical clustering [113]. Risk stratification aims to identify groups of patients within the post-acute coronary syndrome population with an elevated risk of death despite receiving similar treatment. In their method, two clusters that were most similar to each other were merged until the similarity between clusters being merged diminished. Once the merging stopped, all patients falling out of the largest cluster were identified at an elevated risk. They tested their framework over ambulatory ECGs acquired from 686 patients, and successfully found patients at an elevated risk of major adverse cardiac events 90 days after their acute coronary syndrome treatment. Similar to Syed *et al.*, Wang *et al.* [37] aimed to obtain a symbolized representation of the ECG signal using K-means. They partitioned the symbolic ECGs into ten clusters using Gaussian mixture models. Their study reached an accuracy of 94.4% over a subset of the PTB dataset containing ten multi-channel ECGs classified into ten abnormality classes.

One of the standard clinical protocols for monitoring heart is via the 12-lead ECG that records the electrical activity via electrodes attached to 10 different positions on the patient's body [32]. To obtain features from the 12-lead ECG, it is common to concatenate features extracted from each lead. However, such a representation is often unable to preserve the relative positions of the 12 signals. To overcome this problem, He *et al.* [36] used a technique called *Tensor decomposition*. First, the ECG recorded via each lead was represented as its wavelet coefficients: $W \in R^{V \times L}$, where $V$ and $L$ denote the number of leads and number of wavelet coefficients, respectively. Using tensorization, $W$ was then decomposed to $W' \in R^{I_1 \times I_2 \times I_3}$, where $I_1, I_2$, and $I_3$ represent the recorded signal, sampling time, and wavelet frequency sub-band, respectively. They partitioned the tensor representation of 12-lead ECGs into two clusters, corresponding to normal and abnormal ECGs, using Gaussian mixture models. Their system reached a high Jaccard coefficient of 0.93 over a subset of the CTAD dataset containing two 30-minute 12-lead ECG recordings.

### B. ECG and State of the Mind

Different states of the mind, emotions, and mental disorders are often associated with the *autonomic nervous system* (ANS). ANS and heart bidirectionally interact with each other through the sinoatrial (SA) node in the heart [8], [113], [114]. The SA node, also known as the heart's pacemaker, generates electrical impulses that stimulate the heart's muscles to contract and pump blood [32]. In recent years, ECG clustering has helped researchers, especially in psychophysiology, discover hidden ECG patterns that correlate with different states of the mind.

TABLE III
SUMMARY OF REVIEWED STUDIES INVESTIGATING RELATIONSHIP BETWEEN ECG DATA AND DIFFERENT STATES OF THE MIND IN TERMS OF THEIR OBJECTIVES AND FINDINGS, ALONG WITH THE EMPLOYED CLUSTERING ALGORITHM

| Ref. | Objective | Biosignal/Modality | Clustering | Findings |
|---|---|---|---|---|
| [98] | Investigate relationship between emotional granularity and cardiorespiratory signals | ECG, ICG | DP-GMM | Higher emotional granularity results in a larger number of clusters of cardiorespiratory signals. |
| [8] | Investigate relationship between ECG and preictal interval in epilepsy patients | ECG | K-means, DBSCAN, and GMM | A cluster of ECGs suggestive of an upcoming seizure in 41% of patients. |
| [9] | Detect driver drowsiness via cluster analysis of wearable ECG | ECG | DBSCAN | Three clusters for each participant driver corresponding to awake, drowsy, and sleep states. |
| [117] | Investigate relationship between ECG acquired from driver's palms and EEG for detecting fatigue driving | ECG, EEG | K-means | Strong correlation between ECG and EEG. ECG can be utilized, instead of EEG, to identify fatigue driving. |
| [87] | Investigate relationship between driver's heart rate, eye blink rate, and fatigue level | ECG, Facial image | K-means | Heart rate, blink rate, and fatigue level under traffic congestion are higher than normal conditions. |
| [86] | Investigate relationship between ECG and EEG during attention-demanding tasks | ECG, EEG | Hierarchical clustering | Strong correlation between ECG and EEG. ECG can help detect different levels of attention. ECG clusters are more separated than EEG clusters. |
| [118] | Investigate ECG features discriminating between joy and sadness during watching movie | ECG, Self-report questionnaires | K-means | Frequency-domain features of ECG are more discriminative than time-domain features in distinguishing joy from sadness. |
| [95] | Investigate effect of negative emotions in emotional stress inducement through ECG clustering | ECG, Self-report questionnaires | Fuzzy C-means | Heart rate is lowest in the cluster of subjects with positive emotion, and is highest in the cluster with negative emotion. |
| [6] | Investigate relationship between demographics, physical activities, cardiorespiratory activities and emotional stress | ECG, ICG, Self-report questionnaires | Mixture modles | Five clusters within 744 participants that differed in autonomic balance and the level of resting systolic blood pressure. Smoking, regular physical exercise, and BMI were unrelated to the clusters. Men were twice as likely to be in clusters with higher resting blood pressure and increased cardiac output when performing the stress-induced task. |
| [120] | Investigate relationship between emotional eating behavior and ECG | ECG, Self-report questionnaires | K-means | Two clusters separating individuals with and without emotional eating behavior. Emotional eating behavior was more common among overweight individuals. Obese individuals show significantly greater high-frequency components in their RR time series. |
| [119] | Detect stress states via ECG clustering | ECG | Ensemble clustering | Subjects with a similar level of stress in the same cluster. |
| [99] | Detect group of firefighter trainees under stress via cluster wearable ECG analysis | ECG | Convolutional auto-encoder, DBSCAN | Two clusters found. One is smaller than the other, which corresponds to those firefighters exhibiting significantly more stress. |

The datasets used in these studies typically consist of ECG and impedance cardiogram (ICG) signals acquired from either healthy individuals under different emotional states or patients with mental disorders. The feature engineering stage relies on the extraction of a combination of ECG and ICG features. Here, rather than evaluating the quality of the resulting clusters, statistical hypothesis tests, such as t-test, are usually performed to measure how relevant ECG (and ICG) features in each cluster are to the state of the mind of individuals in that cluster. Different states of the mind are treated as ground-truth clusters and are identified manually through questionnaires or automatically by clustering electroencephalogram (EEG) signals. As such, metrics that measure the similarity between identified clusters and ground-truth labels, such as NMI [104] and Jaccard coefficient [103], can be used to improve the reliability of these studies.

In this section, we review novel studies in this line of research. A summary of the reviewed studies is provided in Table III. As the reviewed studies targeted different mental states using various private datasets, the clustering techniques are not compared against each other. Nevertheless, we critically review the existing studies in terms of the employed clustering algorithms, feature engineering, and their experimental scheme, and provide future directions.

Most recently, Hoemann *et al.* [97] performed clustering over ambulatory ECG and ICG signals, acquired from 67 participants, to investigate the correlation between the cardiorespiratory activities and emotional granularity. *Emotional granularity* describes an individual's ability to precisely distinguish their emotions. Low levels of emotional granularity have been associated with mental disorders, including schizophrenia, autism, and depression [97]. Hoemann *et al.* employed the Dirichlet process Gaussian mixture model to find the optimum number of clusters within the data. They found that ECG and ICG can be used to identify different levels of emotional granularity.

Leal *et al.* [8] investigated the relationship between time interval features of ECG and preictal interval (i.e., short time before the seizure) in patients with epilepsy via ECG clustering, with the prospect of predicting epileptic seizures early enough to allow the patient to prepare for the upcoming seizure. They performed K-means, DBSCAN, and Gaussian mixture models over time intervals extracted from ECGs of epileptic patients to see if a cluster, clearly separated from others, represented preictal interval. They found that in 41% of the seizures, such a cluster existed and represented an interval of two to nine minutes in advance of the seizure occurrence.

Babaeian and Mozumdar [9] proposed a system to detect driver drowsiness through clustering ECGs collected from wearable devices. They performed density-based clustering over time interval features and found three clusters associated with awake, drowsy, and sleep states.

Carreiras *et al.* [85] aimed to detect the drop of attention in individuals solving challenging math problems through ECG clustering. Detecting attention drop in attention-demanding tasks, such as surgery and piloting, is important because lack of attention in such tasks may be catastrophic. Their work was motivated by the fact that acquiring ECG via wearables is more convenient than acquiring EEG via head-mounted equipment. They performed consensus clustering, consisting of multiple runs of a hierarchical algorithm with different distance metrics, on ECG and EEG signals acquired from 24 subjects while solving math problems. Their results showed a strong correlation between discovered clusters in ECG dataset and those in the EEG dataset, suggesting that ECG can help detect different levels of attention. Another finding revealed that the number of ECG clusters was greater than those discovered in the EEG dataset, which can provide more accurate information for deeper analysis. Similarly, Wang *et al.* [115] showed that the clusters obtained by analyzing ECG acquired from palms of the drivers strongly correlate with the clusters obtained by analyzing EEG. They suggested that the ECG collected from driver's palms can be utilized, instead of the EEG, to identify different levels of driver's attention.

Another application of ECG clustering is emotion detection. The aim is to automatically identify different emotional states, such as joy and sadness, through clustering. Wan-Hui *et al.* [116] found that the frequency-domain features of the ECG signal were more discerning than the time-domain features in distinguishing joy from sadness. Zheng *et al.* [94] employed the fuzzy C-means clustering algorithm to separate ECGs into emotional stress and non-emotional stress clusters, and showed that time interval features played significant roles in distinguishing these two clusters. Medina [117] performed an ensemble clustering, including K-means and spectral clustering, over ECGs acquired from 25 subjects while solving math problems. Their system successfully partitioned subjects with a similar level of stress in the same groups.

In an innovative study, Kupper *et al.* [6] investigated the relationship between emotional stress and cardiorespiratory activities among 744 young adults performing a stress-induced activity involving solving a math problem and speaking in front of two audiences. The ECG and ICG signals were acquired from participants before and during the task. Using distribution-based clustering, they found five clusters of participants that differed in autonomic balance and the level of resting systolic blood pressure. The results also showed that smoking, regular physical exercise, and body mass index (BMI) were unrelated to the clusters. Furthermore, men were twice as likely to be in clusters with higher resting blood pressure and increased cardiac output when performing the stress-induced task.

González-Velázquez *et al.* [118] investigated the relationship between emotional eating behavior and ECG through clustering. They performed K-means (K=2) on ECGs acquired from 52 young adults to partition individuals with and without emotional eating behavior. They found that the emotional eating behavior was more common among overweight individuals (BMI > 85th percentile). Moreover, obese individuals showed significantly greater high-frequency components in their RR time series.

Motivated by the success of deep learning techniques, Oskooei *et al.* [98] recently trained a convolutional auto-encoder over RR time series of 100 firefighter trainees to identify the group under significant stress when performing a drill. They applied DBSCAN to the latent representation learned by the auto-encoder and found two clusters – one smaller than the other, corresponding to those firefighters exhibiting significantly more stress. They further showed that the application of K-means for this task was unable to find the group of trainees under stress.

Various statistical hypothesis tests can be used to infer a significant relationship between ECG features and different states of the mind. Most of the reviewed studies used t-test, which assumes that the population follows a normal distribution. However, this assumption needs further validation as the collected datasets are small and may not follow such a distribution. The application of non-parametric tests that do not rely on the normality, such as Friedman test [119] and Spearman's rank correlation [120], can also be further investigated in this application.

Additionally, the ECG feature engineering stage in most studies is limited to RR interval and heart rate. As such, there is an unmet need for investigating the correlation between other ECG features, such as PR and QT intervals and voltage- and frequency-domain features, and different states of the mind. Moreover, the employed clustering algorithms are limited to conventional K-means, hierarchical clustering, Gaussian mixture models, and DBSCAN. In particular, deep learning-based clustering algorithms have not yet been employed for this purpose. Larger datasets are required to develop and train reliable deep learning algorithms capable of discovering the relationship between ECG and different states of the mind.

Lastly, as mentioned earlier, most studies treated different states of the mind, such as different emotions or different levels of mental disorder, as ground-truth clusters. The number of such clusters is required as prior knowledge for most employed clustering algorithms. Few studies, however, employed algorithms that do not require such prior knowledge, such as DP-GMM [52] and DBSCAN [53]. They obtained more ECG clusters than those indicated by the ground truth. An increase in the number of clusters often leads to a better separation between different ECG patterns but makes the interpretation of the clustering results

TABLE IV
SUMMARY OF REVIEWED STUDIES INVESTIGATING RELATIONSHIP BETWEEN ECG DATA AND DIFFERENT STATES OF THE BODY IN TERMS OF THEIR OBJECTIVES AND FINDINGS, ALONG WITH THE EMPLOYED CLUSTERING ALGORITHM

| Ref. | Objective | Modality | Clustering | Findings |
|---|---|---|---|---|
| [123] | Investigate effect of heart rate and blood pressure on predicting orthostatic cardiovascular dysregulation in patients with spinal cord injury | ECG, Blood pressure | Hierarchical clustering | Heart rate, systolic blood pressure, and diastolic blood pressure can effectively identify the prevalence of cardiovascular dysregulation in the SCI population. |
| [7] | Investigate relationship between ECG, diabetes, obesity, hypertension, and the habit of smoking | PTB dataset | K-means | All diabetic patients were partitioned in the same group. Patients with smoking, hypertension, and obesity were spread over all clusters. |
| [124] | Investigate relationship between ECG and physical activity capacity | ECG | Hierarchical clustering, K-means | Four clusters. C1: individuals with high physical work capacity. C2: young individuals with low physical work capacity. C3: old individuals with low physical work capacity and low abdominal fat. C4: old individuals with low physical work capacity and high abdominal fat. |
| [11] | Investigate distinct ECG abnormalities, demographics, metabolic indicators, and the habit of smoking among patients with embolic stroke of undetermined source | ECG, Medical records | Hierarchical clustering | Three clusters. C1: young males with patent foramen ovale and posterior circulation infarct. C2: patients with hypertension, severe stroke, left atrial cardiopathy, and diabetes. C3: smoker patients with dyslipidemia and ipsilateral vulnerable sub-stenotic carotid plaque. |
| [12] | Investigate correlation of heart rate and blood pressure with atherosclerosis disease | ECG, Blood pressure | Ensemble | 16 clusters. Two of them include significantly greater proportion of patients at high risk of atherosclerosis disease. In these two clusters, diabetes, body mass index, and total cholesterol were significantly high. |
| [10] | Detect nocturnal hypoglycemia through ECG | ECG | Auto-encoder, CNN | Obtained an accuracy of 90% over eight subjects experiencing nocturnal hypoglycemia. |

difficult for experts. Future work needs to focus on finding the optimal number of ECG clusters.

### *C. ECG and State of the Body*

This line of research focuses on discovering distinct clinical phenotypes, including ECG abnormalities, blood pressure profile, metabolic indicators, and demographics, among patients with various diseases through clustering. Several studies aim to reveal the underlying mechanisms and significant biomarkers in each subpopulation of patients with similar ECG patterns – which is almost impossible to perform visually.

Datasets used in these studies typically consist of ECG and blood pressure signals acquired from individuals with different conditions such as diabetes, atherosclerosis, embolic stroke, or a chronic habit such as smoking. After clustering ECGs, the dominant ECG pattern in each cluster is determined. Hypothesis tests are then performed to confirm whether such pattern is correlated with the disease (or the severity level of the disease) represented by the cluster. As ground-truth clusters are mostly unknown in this application, metrics that measure inter and intra cluster similarity, such as Silhouette score, can be used to improve the reliability of these analyzes. Here, we review novel studies in this line of research. A summary of the reviewed studies is provided in Table IV.

Wang *et al.* [121] investigated the effect of heart rate and blood pressure on predicting *orthostatic cardiovascular dysregulation* in patients with spinal cord injury. They performed hierarchical clustering over ECG and blood pressure signals acquired from 207 subjects (48 controls) while lying and passively moving into the seated position. The clustering result with the best silhouette score partitioned subjects into eight groups. They found that heart rate and systolic and diastolic blood pressures can effectively identify the prevalence of cardiovascular dysregulation in the spinal cord injury population.

Tseng *et al.* [7] investigated the relationship between ECG, diabetes, obesity, hypertension, and smoking habit. They used ECGs of 268 subjects within the PTB dataset and performed K-means over time interval features to partition the patients into eight groups. The results showed that almost all diabetic patients were partitioned into the same group suggesting a strong association between diabetes and ECG. However, patients with smoking, hypertension, and obesity were spread over all clusters, suggesting a weak correlation between these conditions and time-interval features of ECGs.

Hernandez *et al.* [122] investigated the relationship between ECG and physical activity capacity. ECG was acquired from 67 male participants at resting, cycling, and recovery states. A wearable body composition analyzer recorded the amount of fat stored within the abdominal cavity during the ECG acquisition. They applied hierarchical clustering to time intervals and wavelet extracted features, and, by analyzing the dendrograms, found a four-cluster solution separating the data space appropriately. They next applied K-means (K=4) and discovered the following four groups: (1) individuals with high physical work capacity, (2) young individuals with low physical work capacity, (3) old individuals with low physical work capacity and low to medium abdominal fat, and (4) old individuals with low physical work capacity and high abdominal fat.

Lattanzi *et al.* [11] investigated the association of ECG abnormalities, demographics, metabolic indicators, and the smoking habit among 127 patients with embolic stroke of undetermined source. Cardiac abnormalities identified by a cardiologist, such as atrial fibrillation and hypertension, were used for clustering. They performed hierarchical clustering and found three subpopulations of patients: (1) young males with patent foramen ovale and posterior circulation infarct, (2) patients with hypertension, severe stroke, left atrial cardiopathy, diabetes mellitus, and multiple vascular territories, and (3) smoker patients with dyslipidemia, ipsilateral vulnerable sub-stenotic carotid plaque, and infarct of anterior vascular territory.

Hyun *et al.* [12] investigated the correlation of ECG and blood pressure with *atherosclerosis* disease. They applied consensus clustering over ambulatory ECG and blood pressure signals acquired from 989 patients. They found 16 clusters, out of which two clusters contained a significant proportion of patients at high risk of atherosclerosis. In these two clusters, metabolic indicators, including diabetes, body mass index, and total cholesterol were significantly high. Notably, age was commonly associated with all clusters.

Porumb *et al.* [10] trained a convolutional autoencoder over ECGs acquired from subjects with nocturnal hypoglycemia (low blood glucose level during sleep) to predict the drop of glucose level. They used t-distributed stochastic neighbor embedding [123] method to cluster and visualize the learned latent representations and showed that the autoencoder effectively separated ECGs recorded during low glucose levels from those recorded during normal glucose levels. They fed the latent representation as the input to a convolutional neural network and trained the network over expert-supplied labels to classify the ECG into normal and low glucose levels. Their study obtained an accuracy of 90% over eight subjects experiencing nocturnal hypoglycemia.

The hierarchical clustering algorithm is widely used in this line of research. This algorithm does not require the initial number of clusters and provides a hierarchical visualization of the resulting clusters. Such visualization can greatly help researchers identify underlying mechanisms and biomarkers in each subpopulation. Self-organizing map [54] and t-distributed stochastic neighbor embedding [123] are other well-known algorithms that provide a two and three-dimensional map to visualize topologies within the data space. As these two algorithms preserve the local and global structure of the data, they are suitable candidates for this application.

Moreover, the clustering algorithms employed by the reviewed studies are limited to K-means and hierarchical clustering. As the collected datasets by these studies are significantly larger than those available publicly (such as MIT-BIH), the application of deep learning-based clustering algorithms can provide further improvement.

Lastly, similar to studies investigating the relationship between ECG and states of the mind, the extracted ECG features are limited to RR interval and heart rate. As such, the application of other time-, voltage-, and frequency-domain features need to be studied.

### *D. ECG-Based Biometric Authentication and Identification*

Biometric authentication is the process of authenticating an individual based on their physical traits – mostly fingerprint and face. Fingerprint and facial patterns are physically exposed and prone to external attacks. ECG-based authentication systems, however, are difficult to deceive as the underlying biometric features of heart electrical activity are concealed [23].

A challenge facing ECG-based authentication systems is intra-subject variability due to the different subject's physical and mental states that can lead to authentication failure. Several studies have aimed to improve the robustness of ECG-based authentication systems to intra-subject variability by cluster analysis. The idea is to partition the subject's ECG (or heartbeats) into clusters, when the subject is under different mental or physical conditions, and use information about the clusters, such as the center of the clusters, as an additional feature for the supervised learning method performing the authentication [20]–[23]. Most studies in this application use their collected ECG dataset recorded under different levels of emotion or stress. Rather than evaluating the quality of the resulting clusters, classification metrics, such as sensitivity, specificity, and F1-score, are used to assess the performance of the downstream supervised authentication task. As ground-truth clusters are mostly unknown in this application, metrics that measure inter and intra cluster similarity, such as Silhouette score, can further be used to improve the reliability of these studies.

As an example of a state-of-the-art study, Zhou *et al.* [23] employed Gaussian mixture models clustering to improve the robustness of their authentication system when the subject is under stress. In particular, they partitioned the subject's ECG into several groups that differed in stress levels. The centers of the clusters, combined with the latent representation of the ECG learned by a convolutional auto-encoder, were fed as the input feature vector to a support vector machine performing authentication. They tested their system over 23 healthy subjects under different stress conditions and achieved an average recognition rate of 95% and an average F1-score of 0.97.

Similar to authentication, biometric identification is the process of identifying an individual based on their physical traits within a database of previously identified templates. ECG-based identification systems typically incur a high computational cost due to cross-matching of the given ECG with all the template ECG signals stored in the database to find a match. Clustering has helped reduce the computational cost of such systems by clustering the template ECG signals. During identification, only the cluster whose centroid is most similar to the given ECG signal is searched. Neehal *et al.* [124] partitioned templates in a database of 50,000 ECGs into five clusters using K-means. Searching only the most similar cluster during identification, they reduced the identification time by 79.26%. Following a similar approach, Sufi *et al.* [125] proposed an ECG-based identification system that worked with compressed ECG data. Compression of ECG data is often required for wireless cardiovascular monitoring. However, decompressing millions of compressed ECG signals is highly time-consuming. To solve this issue, Sufi *et al.* devised a system based on Gaussian mixture models that directly clustered compressed ECG signals within the template ECG database.

The clustering algorithms employed by these studies are mostly limited to K-means and GMM. As such, the application of other clustering algorithms used for ECG clustering, such as DBSCAN [53] and deep learning-based methods, needs to be further investigated. The datasets used by studies focusing on ECG-based authentication are very small ($n < 30$). A much larger ECG dataset recorded under different levels of emotions or stress is needed to further improve the robustness of ECG-based authentication systems to intra-subject variability. The development of clustering algorithms capable of detecting synchrony between ECG and other physiological signals need to be also investigated [126].

### *E. Improving Supervised Abnormality Classification*

In addition to knowledge discovery, clustering and deep learning-based unsupervised techniques can be employed to improve the performance and overcome the challenges of ECG classification systems. The quality of the identified clusters is barely evaluated in this application. Instead, classification metrics, such as sensitivity, specificity, and F1-score, are used to assess the performance of the downstream classification task. Nevertheless, as the ground-truth clusters are known, the classification metrics mentioned above as well as similarity metrics, such as NMI and Jaccard coefficient, can be used to evaluate the performance of the clustering phase and improve the reliability of these studies. The MIT-BIH dataset has been mostly used in this line of research. As this dataset is relatively small, future work should also focus on using larger datasets such as those collected by Zheng *et al.* [110] and Wagner *et al.* [111].

One of the long-lasting challenges in accurately classifying ECG abnormalities is the heavily *imbalanced data* problem as a huge portion of cardiologists-supplied labels in public ECG datasets indicate normal heartbeats. For example, in the MIT-BIH dataset, more than 75% of the labeled heartbeats belong to the normal class, while less than 1% of the beats belong to four abnormality classes, namely, ventricular flutter, nodal escape, atrial premature, and ventricular escape beats. These imbalanced data result in poor performance of classifiers when detecting minority classes. A well-known technique to overcome this problem is *under-sampling*, where samples from the majority class are randomly removed to make the training set balanced [127]. However, this technique may lose relevant information that is essential for the classification task. To reduce information loss during under-sampling, Carrillo-Alarcón *et al.* [16] clustered heartbeats in each majority class within the MIT-BIH dataset using self-organizing maps. They under-sampled the heartbeats that are farthest from the center of their clusters to ensure that the most informative heartbeats are used to train the classifier. Their study reached a high accuracy ($> 99.96\%$) when detecting minority classes. Notably, they used the differential evolution algorithm [128] – a nature-inspired population-based optimization algorithm – to find the optimal number of clusters that resulted in the best classification performance.

Deep learning-based unsupervised techniques have also been used to enhance the automation and performance of abnormality classification systems. Xu *et al.* [129] improved the performance of their deep neural network classifier by initializing the weights in each layer using a greedy unsupervised algorithm. Each hidden layer was viewed as a restricted Boltzmann machine [69] and optimized using the contrastive divergence algorithm [130] – a well-known unsupervised algorithm to train energy-based latent models. The entire network was then fine-tuned by minimizing the cross-entropy loss between the ground-truth labels and the predictions. They evaluated their method over the MIT-BIH dataset using three patient-specific and one patient-independent experiments. Their system reached an accuracy of 93.1%, 94.7%, 99.9% over three individuals within MIT-BIH. Their system generalized well to unseen patients in their patient-independent experiment but with a lower accuracy of 91.8%.

Patient-specific ECG classifiers – trained classifiers that are fine-tuned over the ECG of the given patient – have shown superior performance over classifiers trained on a common ECG pool. Zahi *et al.* [17] showed that re-tuning the classifier over patient-specific normal beats improved the classification performance over MIT-BIH. Despite their superior performance, patient-specific classifiers have a low level of automation as they require a part of the ECG signal to be manually labeled for fine-tuning. To overcome this problem, Zahi *et al.* [17] proposed an unsupervised method to automatically identify normal ECG beats. They clustered heartbeats based on their similarity to their adjacent beats, and identified beats in the cluster exhibiting the highest average similarity as normal. Their deep classifier was then fine-tuned over the identified normal beats. Their system outperformed the patient-independent classifier – especially when detecting two abnormality classes, namely ventricular and supraventricular ectopic beats, where they obtained the high accuracy of 97.4% and 98.6%, respectively.

Recently, generative adversarial networks (GANs) [15] have been also used to improve the automation of patient-specific classifiers. The idea is to utilize the generator in GAN to generate new patient-specific normal beats. Zhou *et al.* [18] used the MIT-BIH dataset augmented with the GAN-generated normal heartbeats for more accurate training and classification on ventricular and supraventricular ectopic beats, and reached an overall accuracy of 97%. Similarly, Golany *et al.* [19] trained a GAN over first few minutes of each patient unlabeled ECG data to generate normal beats. In contrast to Zhou *et al.* [18] that used a convolutional neural network for arrhythmia classification, they used a long short-term memory neural network [131], and achieved similar good performance.

Deep learning-based unsupervised feature extraction techniques have also improved the performance of supervised classification systems when compared with classifiers that use handcrafted features. As an example, Nurmaini *et al.* [68] combined a CNN-based deep auto-encoder as an unsupervised feature extraction technique with a deep neural network for arrhythmia classification. Their system reached a high F1-score of 0.92 over the entire MIT-BIH dataset.

Another advantage of combining unsupervised learning with supervised ECG classification is the usage of transfer learning [132]. The idea is to transfer the parameters of a model trained on a large dataset to another model for performing classification over a smaller dataset labeled inaccurately or missing some labels. Weimann *et al.* [133] trained a deep residual network classifier [134] over the Icential11 K dataset [135] – the largest publicly available ECG dataset with 11,000 patients – and fine-tuned their network on Physionet/CinC 2017 dataset [136] for atrial fibrillation detection. Jang *et al.* [137] pre-trained a convolutional autoencoder over more than two million ECG samples. They then fine-tuned their network over another dataset of ten thousand 12-lead ECGs to detect 11 arrhythmia classes and achieved an F1-Score of 0.857.

### F. Other Applications

In addition to the discussed applications, ECG clustering has also been employed in other interesting applications. Xia *et al.* [24] used ECG clustering to improve the accuracy of a QRS detection system. The idea is that lines intercepting pairs of points belonging to QRS regions have a significantly higher absolute slope than lines intercepting any other pairs of points across the ECG. Using K-means, they partitioned all pairs of points across the ECG based on their absolute slope into two clusters. They found that one cluster mainly contains pairs of points belonging to QRS regions. Among these points, the point with maximum amplitude was identified as the R-peak. They achieved a sensitivity of 99.72% and a positive predictivity of 99.80% on R-peak detection over eight records in MIT-BIH. Following a similar idea, in a recent study, Chen *et al.* [25] applied hierarchical clustering to the average amplitude of each pair of points in addition to their slope to partition the points into two clusters: R-wave cluster and non-R-wave cluster. They achieved a sensitivity of 99.89% and a positive predictivity of 99.97% in R-peak detection over MIT-BIH.

Zhou *et al.* [26] extracted fetal QRS complexes from maternal QRS complexes in abdominal ECG through clustering. Notably, fetal ECG acquired from the maternal abdomen is contaminated by maternal heart's activities, fetal brain activities, and various noises such as uterine contraction. Zhou *et al.* proposed that the amplitude of R-S peaks can be a distinctive characteristic to distinguish maternal QRS complexes from that of fetal ECG because the amplitude of R and S peaks in maternal ECG is significantly larger than that in fetal ECG. They applied K-means to pairs of consecutive local maximum-minimum across the ECG and found three clusters. One included R-S peaks belonging to the mother, the other included R-S peaks from the fetal, and the last cluster had non-RS peaks.

Salman *et al.* [138] tried to reduce the average waiting time for remote patients by clustering them into groups that differ in degrees of urgency. They applied fuzzy c-means to the features extracted from ECG and blood pressure signals, and partitioned patients into five groups. The identified clusters corresponded to patients at normal, cold, sick, urgent, and high risk states. They viewed each cluster as a queue and proposed an algorithm that minimized the average waiting time while prioritizing urgent patients.

## IV. Discussion and Future Direction

### A. Deep Learning-Based Clustering and Contrastive Learning

Although the reviewed ECG clustering techniques have reported promising results, there is still a significant need for more advanced algorithms that can automatically handle large amounts of data without the need for preprocessing steps and expert analysis. The primarily advantage of deep learning techniques over traditional machine learning methods is the automatic feature extraction and selection process. Deep learning techniques have shown to outperform the traditional machine learning methods in several complex tasks, such as speech recognition and image classification – to name just a few. Nevertheless, very few studies have focused on employing deep learning for unsupervised ECG analysis. As such, new generation of deep learning algorithms, such as deep adaptive clustering [70] and ClusterGAN [76] (as reviewed in Section I-C) have the potential to be employed in ECG clustering systems.

A disadvantage of deep learning techniques is their lack of interpretability as features are extracted in *black-box*. This becomes an ever more important concern in the ECG analysis as the interest in *how* the results are obtained is no less that what the results are. Future research in this area should focus on interpretability of deep learning techniques for ECG analysis. The adoption of algorithms such as DeepLIFT [139] can be investigated. Given an input, DeepLIFT assigns a contribution score to each neuron in the neural network by back-propagating the activations of neurons from the predicted output to every feature of the input.

In addition to deep learning, the application of contrastive learning in ECG clustering can be further studied. Contrastive learning aims to learn an embedding space where similar data points are closer to each other than dissimilar ones without the need for labeled data. It recently achieved superior performance over several deep learning methods tackling vision and language processing tasks. In ECG analysis, it can be adapted for unsupervised or semi-supervised analysis where cardiologists annotate a small subset of the dataset. Interested readers can refer to [140], [141] for more information.

### B. Unsupervised Analysis of ECG Recorded by Wearable Devices

Wearable ECG monitoring devices have enabled long-term monitoring of elderly patients and patients at risk everywhere, rather than only in specialist settings such as hospitals and clinics. Moreover, as described in Section II, wearable ECG devices have recently enabled researchers to tackle biometric authentication and emotion detection tasks using ECG. Analyzing the ECG recorded by a wearable can be done either on the device itself or in a remote server. The time and space complexity of the clustering method must be within the computational power of the wearable when ECG data are supposed to be analyzed within the device. The reliability of the transmission channel and its latency are important considerations when the ECG data are transmitted to a remote server. Therefore, efficient compression and encryption algorithms are required for optimum and secure transmission of the ECG data [142]–[145].

Besides, the robustness to the noise is of high importance as the wearable devices are more likely to record lower quality ECGs than standard clinical equipment. Even after de-noising, there is no guarantee that the signal is noise-free, because the practical implementation of any de-noising system is known to be imperfect [146]. The use of artifact rejection algorithms is extremely important within this context [147].

The majority of the reviewed methods have been developed and verified on resting-state ECG where the heart rate is typically below 120 beats per minute. However, heart rate may vary significantly in ambulatory settings where subjects are being monitored for long periods of time. Therefore, the robustness of the methods to the heart rate variations is another important consideration. Analyzing ECGs recorded via wearable devices is a recent and emerging field on which very few studies have focused, leaving room for further investigation. Interested readers can refer to the following sources for more information [142]–[145], [148]–[150].

### C. Stream ECG Clustering

The sheer volume of ECG data produced every day is impractical to be stored due to the limited hardware resources. Moreover, real-time monitoring of high-risk patients and the immediate detection of abnormal events is vital. As such, future clustering systems need to handle ECG data arriving continuously – a form of data known as *stream*.

Stream ECG clustering poses several key challenges to traditional clustering systems. First, the ECG should be analyzed in only one pass as storing all the arriving signals is impractical. Second, the clusters can change as new ECGs arrive. Third, cardiac events must be identified in real-time. Notably, all the methods reviewed here handle non-stream ECGs, leaving room for possible future research. Interested readers can refer to the following sources to gain more information about data stream clustering analysis [151]–[155].

### D. Need for Public Databases of ECG Recorded Under Different States of Mind and Body

To date, much effort has been devoted to developing open-access ECG datasets that represent various cardiac abnormalities [1], [111], [112]. Nevertheless, as described in Sections III-B.III-D, studies discovering relationships between ECG and different states of the mind and body, and those developing ECG-based authentication systems use private datasets. This makes the comparison among methods and reproducing their results impossible. To further develop these innovative lines of research, an open-access dataset of ECGs recorded under different mental states, such as stress or mental disorders, and different health conditions, such as diabetes, is needed. Such a database needs to be large enough and balanced in terms of the sex and age of the individuals.

### E. Feature Engineering Based on P, QRS, and T Waves

The majority of the reviewed studies do not use important features of the ECG signal such as P and T waves for feature engineering, while the abnormal morphology of such waves can indicate important cardiac disorders, such as myocardial ischemia, hypokalemia, or atrial fibrillation – to name just a few [32]. Moreover, the R-wave is often assumed to be present in all recorded heartbeats. However, we note that R-wave can be absent in the presence of some abnormalities such as *dextrocardia* [32].

To overcome these problems, researchers can employ state-of-the-art ECG segmentation systems such as those developed by Martinez *et al.* [156] and Bote *et al.* [157]. Such systems can effectively identify P, Q, R, S, and T waves along the ECG, allowing extracting temporal and morphological features of all primary waves.

## V. Conclusion

In this article, we provided a comprehensive and critical review of unsupervised machine learning methods for ECG analysis. The conventional as well the state-of-the-art ECG clustering algorithms were reviewed, and their advantages and disadvantages were thoroughly discussed. We also extensively reviewed various applications of unsupervised ECG analysis, described state-of-the-art studies in each application, outlined their limitations, and provided future directions.

We believe that the reviewed clustering methods in this paper will continue to advance in the context of unsupervised biomedical signal processing and will likely form an important component of ECG monitors in the future.

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