Machine Learning Approaches in Bioengineering for Biosignal Processing

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***Abstract*—This survey paper offers a comprehensive review of the recent advances and applications of Machine Learning (ML) approaches in the interdisciplinary field of bioengineering, specifically in the realm of biosignal processing. Biosignals, including electroencephalograms (EEG), electrocardiograms (ECG), and electromyograms (EMG), are inherently complex, presenting significant challenges such as noise, artifacts, variability, and nonlinearity in their processing. However, ML has shown promise in overcoming these hurdles, enabling the extraction of useful features and insights from these signals. The paper outlines how ML is leveraged for processing, analyzing, classifying, and interpreting biosignals for various applications, such as diagnosis, monitoring, rehabilitation, and brain-computer interfaces. Additionally, it discusses the ongoing challenges and potential future directions of ML applications in this field. Through this review, we aim to highlight the critical role of ML in enabling adaptive, personalized, and intelligent systems that interact with biosignals in real-time, with potential implications for improving patient outcomes in various medical conditions.**

***Index Terms*—machine learning, bioengineering, biosignal processing, electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), bioelectrical signals, signal processing, supervised learning, unsupervised learning, reinforcement learning, cross validation**

I. Introduction

Machine learning (ML), a subfield of artificial intelligence, empowers computers to glean insights from data and make inferences without the need for specific programming [1]. It has found extensive applications across a spectrum of science and engineering fields, including but not limited to computer vision, natural language processing, robotics, and bioengineering. [2]. Bioengineering is an interdisciplinary field that applies engineering principles and methods to biological systems and problems, such as bioprocesses, biomaterials, biosensors, and biomedicine [3]. Biosignal processing is the application of signal processing techniques to analyze and interpret biomedical signals that are generated by physiological activities [4]. Biosignals can be measured from various sources, such as neural activity, cardiac rhythm, muscle movement, and other biological events. Biosignals are signals that originate from living organisms and reflect their physiological states and functions, such as electroencephalogram (EEG), electrocardiogram (ECG), and electromyogram (EMG) [5] as can be observed in Fig. 1. Biosignal processing is important for understanding the underlying mechanisms and functions of biological systems, as well as for diagnosing and monitoring various diseases and disorders. Biosignals are capable of furnishing pertinent information concerning the health condition, behavioral patterns, and responses of either an individual or a collective population. For instance, ECG can be used to detect cardiac arrhythmias [6], EEG can be used to assess brain activity and cognitive states [7], and EMG can be used to evaluate muscle function and fatigue [8].

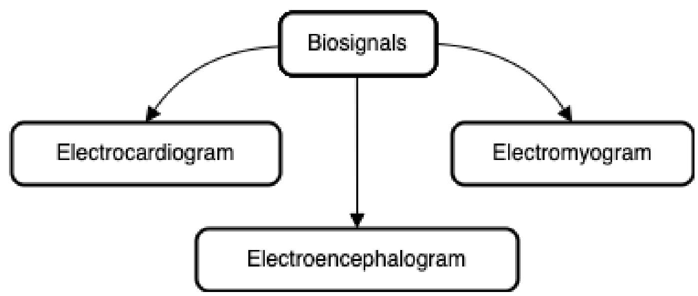

Fig. 1: Overview of the three main types of biosignals: EEG, ECG, and EMG.

Machine learning can provide powerful tools for bioengineering to analyze complex and high-dimensional data, optimize processes and systems, and discover new knowledge and insights [9]. Machine learning can be effective in biosignal processing for several reasons. First, machine learning can handle complex and noisy data that are often encountered in biosignal processing [10]. Second, machine learning can discover hidden patterns and features that are not obvious or known beforehand [11]. Third, machine learning can adapt to changing conditions and environments that may affect biosignal acquisition and analysis [12]. Machine learning can be applied to various aspects of biosignal processing, such as signal enhancement, feature extraction, classification, clustering, regression, and prediction [13]. Some of the recent advances and applications of machine learning approaches in bioengineering for biosignal processing are reviewed in this survey paper.

EEG, ECG, and EMG represent instances of bioelectrical signals that can be quantified and observed in living organisms [14]. EEG is the electrical activity of the brain that reflects the cognitive and emotional states of a person [15]. ECG is the electrical activity of the heart that reflects the cardiac function and rhythm [16]. EMG is the electrical activity of the muscles that reflects the neuromuscular function and movement [17]. These biosignals can provide valuable information for diagnosis, prognosis, treatment, and prevention of various diseases and disorders, such as epilepsy, stroke, cardiac arrhythmia, Parkinson's disease, and depression [18]. However, biosignal processing faces many challenges, such as noise, artifacts, variability, complexity, and nonlinearity [19]. Machine learning approaches are important in bioengineering because they can overcome these challenges and extract useful features, patterns, and insights from biosignals. Machine learning can also enable adaptive, personalized, and intelligent systems that can interact with biosignals in real time and provide feedback, guidance, or intervention [20]. Machine learning has been applied to various tasks and applications of biosignal processing in bioengineering, such as classification, clustering, regression, dimensionality reduction, feature selection, feature extraction, signal enhancement, signal segmentation, signal synthesis, signal fusion, signal interpretation, and signal visualization [21]. Some of the most prominent and recent machine learning approaches in bioengineering for biosignal processing will be reviewed in this survey paper. The focus is on how machine learning can be used for the processing, analysis, classification, and interpretation of biosignals for various purposes, including diagnosis, monitoring, rehabilitation, and brain-computer interfaces. Some of the challenges and future directions of machine learning for biosignal processing in bioengineering are also discussed.

II. Applications of Machine Learning for Biosignal Processing

A. *Electroencephalogram (EEG)*

One of the most promising and challenging applications of biosignal processing in bioengineering is EEG-based machine learning [22]. Example of an EEG signal can be observed in Fig. 2. EEG-based machine learning aims to use machine learning algorithms to extract information from EEG signals and use it for various purposes, such as brain-computer interface (BCI), emotion recognition, cognitive state assessment, and neurological disorder diagnosis [15], [23]. EEG-based machine learning can be useful for enhancing human capabilities, improving quality of life, and providing novel solutions for medical and health problems. Nonetheless, machine learning centered around EEG encounters a multitude of challenges, encompassing low signal-to-noise ratio, substantial inter-subject and intra-subject variability, non-stationarity of signals, and ethical considerations [23], [24]. Therefore, EEG-based machine learning requires careful design and implementation of data acquisition, preprocessing, feature extraction, dimensionality reduction, classification, and evaluation methods [23]. In this survey paper, we will review some of the recent advances and applications of EEG-based machine learning in bioengineering.

One of the main challenges of EEG signal processing is the high dimensionality and variability of the data, which requires efficient feature extraction and selection methods. Feature extraction aims to transform the raw EEG signals into a lower-dimensional and more informative representation, while feature selection aims to select the most relevant features for a specific task. Prominent feature extraction methodologies for EEG encompass Wavelet Transform, Fourier Transform, Empirical Mode Decomposition, and Hilbert-Huang Transform. Some common feature selection methods for EEG include mutual information, Fisher score, relief algorithm, and genetic algorithm [26]. Another challenge of EEG signal processing is the classification of different EEG patterns, such as normal or abnormal, awake or asleep, attentive or distracted, and so on. Classification is a type of supervised learning task wherein a specific label is assigned to an input, taking into account a predetermined set of categories. Within the realm of EEG analysis, numerous well-known classification algorithms have been employed, such as the support vector machine (SVM), K-nearest neighbor (KNN), decision tree, random forest, and artificial neural network (ANN). Through the utilization of labeled EEG data during the training phase, these algorithms can acquire knowledge and subsequently make predictions about the class or category of novel EEG data [27]. A recent trend in EEG signal processing is the use of deep learning techniques, which are a subset of machine learning that use multiple layers of nonlinear transformations to learn complex and hierarchical features from data. Deep learning has exhibited exemplary efficacy across diverse fields including computer vision, natural language processing, and speech

Fig. 2: Example of an electroencephalogram (EEG) signals of a person with epileptic disorder [25].

recognition. Additionally, its application to EEG analysis holds the potential to surmount certain constraints inherent in conventional machine learning approaches, such as the reliance on manually engineered features, shallow architectures, and linear models. Some examples of deep learning models for EEG include convolutional neural network (CNN), recurrent neural network (RNN), long short-term memory (LSTM), gated recurrent unit (GRU), and deep belief network (DBN). These models can learn high-level and abstract features from raw or preprocessed EEG signals and achieve state-of-the-art results in various EEG tasks [26], [28], [29].

Machine learning is a powerful tool for EEG signal processing in bioengineering that can provide insights into the brain dynamics and functions. Machine learning can also enable new applications and innovations that leverage the potential of EEG as a noninvasive and portable modality for brain monitoring and stimulation.

B. Electrocardiogram (ECG)

One of the most common and important biosignals is the electrocardiogram (ECG), which measures the electrical activity of the heart and reflects its physiological and pathological conditions [30]. Example of an ECG signal can be observed in Fig. 3. Machine learning can be applied to ECG signals for various purposes, such as classification, diagnosis, prediction, and analysis of cardiac diseases and arrhythmias [31].

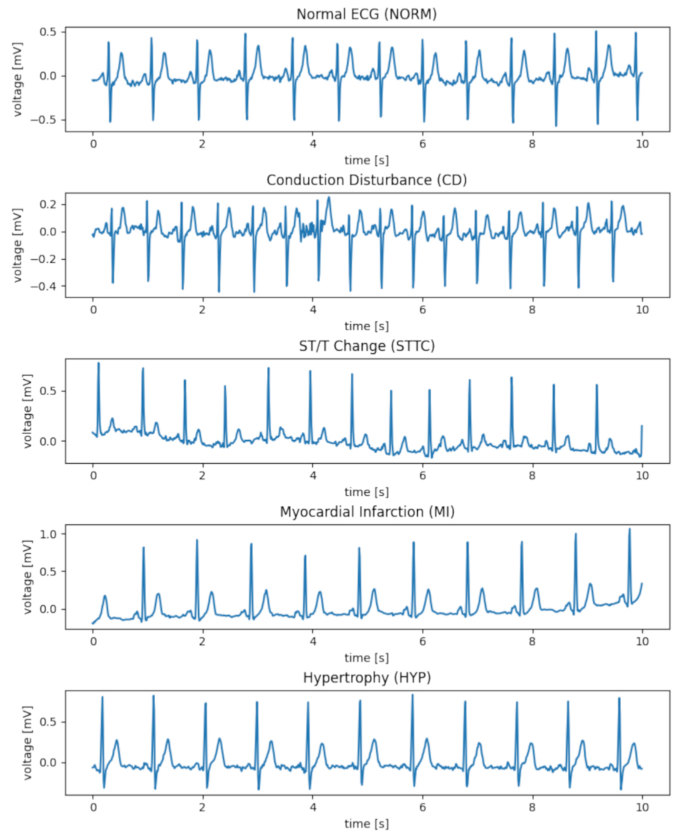

Fig. 3: Examples of the following electrocardiogram (ECG) signals: NORM—normal ECG, CD—myocardial infarction, STTC—ST/T change, MI—conduction disturbance, HYP—hypertrophy [32].

ECG signal classification is the task of assigning a label to an ECG segment or beat based on its morphology or rhythm. This can help in detecting and identifying different types of cardiac abnormalities, such as myocardial infarction, ventricular fibrillation, atrial fibrillation, and so on [33]. Machine learning techniques can improve the accuracy and efficiency of ECG classification by automatically extracting relevant features from the raw signals and learning complex patterns from large and diverse datasets. Some of the machine learning techniques that have been used for ECG classification are support vector machines, k-nearest neighbors, decision trees, random forests, naive Bayes, neural networks, and deep learning [34].

Deep learning, a subset of machine learning, employs multiple strata of nonlinear transformations in order to learn hierarchical representations of data. Deep learning has shown remarkable performance in various domains, such as computer vision, natural language processing, speech recognition, and so on. Deep learning can also be applied to ECG signals for classification and other tasks, such as denoising, segmentation, compression, and generation. Some of the deep learning models that have been used for ECG signals are convolutional neural networks (CNNs), recurrent neural networks (RNNs), autoencoders (AEs), capsule networks (CapsNets), and generative adversarial networks (GANs) [35]. Machine learning can also be used for ECG diagnosis and prediction, which are more challenging tasks than classification. ECG diagnosis is the task of inferring the underlying cause or condition of a cardiac abnormality from the ECG signals. ECG prediction is the task of forecasting the future state or outcome of a cardiac event or disease from the ECG signals. Machine learning can help in these tasks by finding hidden associations and causal relationships between the ECG features and the clinical variables. Some of the machine learning techniques that have been used for ECG diagnosis and prediction are logistic regression, linear discriminant analysis, quadratic discriminant analysis, Bayesian networks, hidden Markov models, and reinforcement learning [36]. Machine learning can also be used for ECG analysis, which is the task of extracting meaningful information or insights from the ECG signals. Machine learning can help in this task by discovering novel patterns, trends, anomalies, or clusters in the ECG data. Some of the machine learning techniques that have been used for ECG analysis are principal component analysis, independent component analysis, wavelet transform, Fourier transform, empirical mode decomposition, and manifold learning [37].

Machine learning is a powerful tool for ECG signal processing that can enhance the understanding and diagnosis of cardiac diseases and arrhythmias. Machine learning can also enable new applications and innovations in bioengineering for biosignal processing.

C. Electromyogram (EMG)

Electromyography (EMG) is a technique that measures the electrical activity of muscles and nerves. Example of an EMG signal can be observed in Fig. 4. EMG signals can be used to infer the intention and state of the human body, and thus enable various human-machine interaction (HMI) applications [38]. Machine learning can help to extract meaningful features from EMG signals, and to build models that can recognize patterns, predict outcomes, and generate feedback.

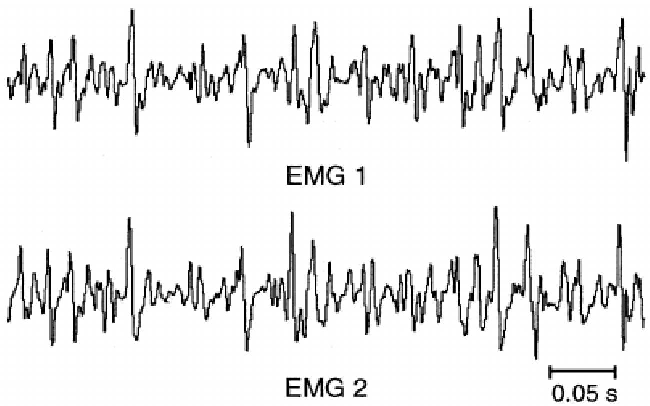

Fig. 4: Examples of electromyogram (EMG) signals.

One of the machine learning applications of EMG is to detect preterm birth indications. Preterm birth is a serious complication that affects millions of pregnant women and newborns worldwide. EMG signals from the uterine muscles can provide information about the contraction patterns and the risk of preterm labor. Machine learning can help to analyze the EMG signals and identify features that are related to preterm birth indications, such as frequency, duration, amplitude, and synchronization of contractions. Machine learning can also help to classify the EMG signals into different categories, such as normal, threatened, or imminent preterm labor. This can help to provide early diagnosis and intervention for preterm birth prevention [39]. Machine learning applications of EMG are not limited to medical domains. They can also be used for entertainment, education, rehabilitation, gaming, and robotics. For example, machine learning can help to create virtual or augmented reality environments that respond to the user's gestures and emotions based on EMG signals [40]. Machine learning can also help to design prosthetic limbs or exoskeletons that can mimic the natural movements and sensations of the human body based on EMG signals. Machine learning can also help to develop intelligent interfaces that can adapt to the user's preferences and needs based on EMG signals.

Machine learning applications of EMG are promising and challenging. They require high-quality data collection, preprocessing, feature extraction, model selection, training, testing, and evaluation. They also face issues such as noise, variability, nonlinearity, dimensionality, and generalization of EMG signals [41]. Therefore, machine learning applications of EMG need to consider the characteristics of the EMG signals, the specific tasks and scenarios, and the user's feedback and satisfaction.

III. Machine Learning Methods for Biosignal Processing

Biosignal processing involves various tasks such as classification, regression, clustering, dimensionality reduction, and generation of synthetic data. Contingent on the accessibility and characteristics of the data, as well as the intended results, various machine learning methodologies may be employed [42]. In this section, three main categories of machine learning methods for biosignal processing and their applications will be reviewed: supervised learning, unsupervised learning, and reinforcement learning. These machine learning methods can be observed in Fig. 5. Supervised learning methods use labeled data to learn a mapping from inputs to outputs, such as predicting a disease diagnosis from an ECG signal [43]. Unsupervised learning methods use unlabeled data to discover hidden patterns or structures in the data, such as grouping similar EEG signals into clusters or reducing the dimensionality of high-dimensional biosignals [44]. Reinforcement learning methods use feedback from the environment to learn an optimal policy or action for a given state, such as controlling a prosthetic limb using EMG signals [45]. For each category, we will introduce some of the most popular and effective methods and their advantages and limitations, as well as some case studies and applications in biosignal processing. Moreover, we will discuss the evaluation and validation of machine learning models in biosignal processing, which are essential steps to ensure the reliability and generalizability of the results.

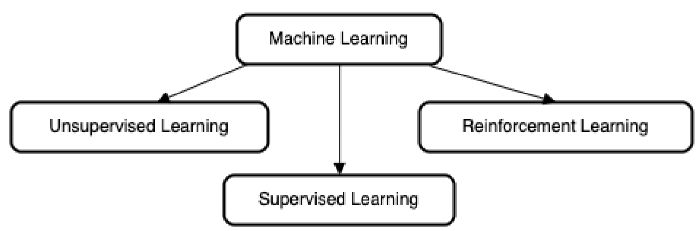

Fig. 5: Diagram illustrating the three principal machine learning methods.

A. Supervised Learning Methods for Biosignal Processing

Supervised learning methods are machine learning techniques that learn from labeled data and make predictions based on the learned model [46]. Some of the supervised learning methods that have been applied to biosignal processing, such as support vector machines (SVM), neural networks, K-Nearest neighbors, and random forests [47], as it can be observed from Fig. 6. Additionally, case studies and applications of each method will be discussed.

Support Vector Machines (SVM) are a type of supervised learning method that can perform classification and regression tasks by finding an optimal hyperplane that separates the data

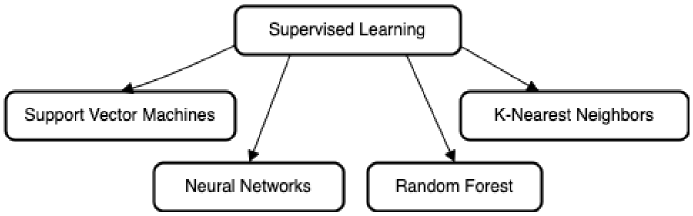

Fig. 6: Diagram illustrating the four supervised learning methods used in biosignal processing.

into different classes or predicts the output value [48].Support Vector Machines (SVM) are capable of managing nonlinear and high-dimensional data through the utilization of kernel functions, which project the data into a higher-dimensional feature space. SVM have been widely used for biosignal processing, especially for classification problems, such as ECG arrhythmia detection [49], EEG emotion recognition [50], and EMG gesture recognition [51]. SVM have several advantages, such as high accuracy, robustness to noise and outliers, and flexibility in choosing kernels [52]. However, SVM also have some limitations, such as high computational complexity, difficulty in choosing optimal parameters, and lack of interpretability. An illustration of how SVM algorithm works can be observed in Fig. 7.

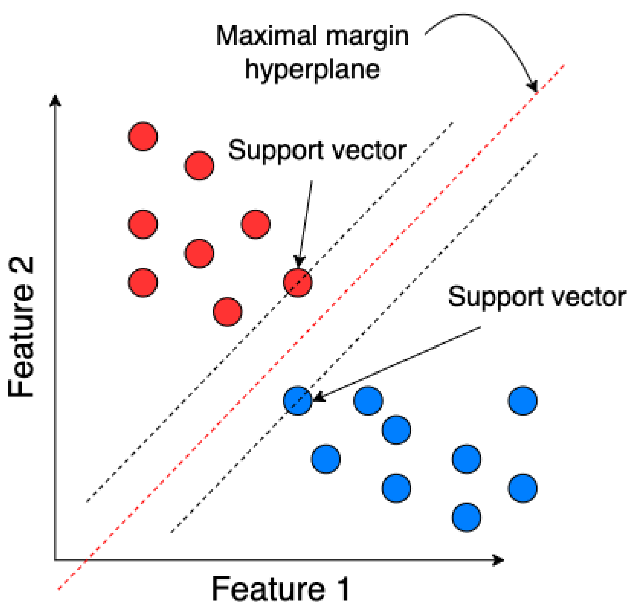

Fig. 7: Illustration of the Support Vector Machines (SVM) algorithm. It shows data points classified into two categories, separated by a maximal margin hyperplane. Additionally, the support vectors, which are the data points closest to the hyperplane from each category, are highlighted. This demonstrates the SVM's process of creating a decision boundary and classifying new data from input to output.

Neural networks are a type of supervised learning method that can perform classification and regression tasks by mimicking the structure and function of biological neurons [53]. Neural networks can handle nonlinear and high-dimensional data by using multiple layers of interconnected nodes that can learn complex features and patterns from the data. Neural networks have been extensively applied to biosignal processing, especially for classification problems, such as ECG arrhythmia detection [54], EEG seizure detection [55], and EMG prosthesis control [56]. Neural networks have several advantages, such as high accuracy, adaptability, and parallel processing. However, neural networks also have some disadvantages, such as high computational cost, overfitting, and lack of interpretability [57]. An illustration of how neural network works can be observed in Fig. 8.

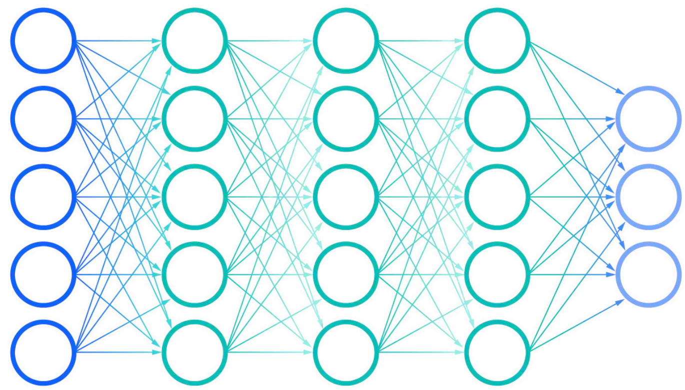

Fig. 8: Illustration of a basic neural network. It shows interconnected layers: an input layer for receiving data, hidden layers for processing data via weighted connections and activation functions, and an output layer for producing final results, highlighting the flow of data from input to output [58].

K-nearest neighbors (KNN) are a type of supervised learning method that can perform classification and regression tasks by finding the k closest data points to a given query point and assigning the majority class label or the average output value [59]. KNN can handle nonlinear and high-dimensional data by using different distance metrics and feature weighting schemes. KNN have been applied to biosignal processing, especially for classification problems, such as ECG heartbeat classification [60], EEG brain-computer interface [61], and EMG hand gesture recognition [62]. KNN have several advantages, such as simplicity, interpretability, and low training cost. However, KNN also have some disadvantages, such as high prediction cost, sensitivity to noise and outliers, and difficulty in choosing optimal parameters. An illustration of how KNN algorithm works can be observed in Fig. 9.

Random forests are a type of supervised learning method that can perform classification and regression tasks by combining multiple decision trees into an ensemble [63]. Random forests can handle nonlinear and high-dimensional data by using random sampling and feature selection techniques to create diverse and uncorrelated trees. Random forests have

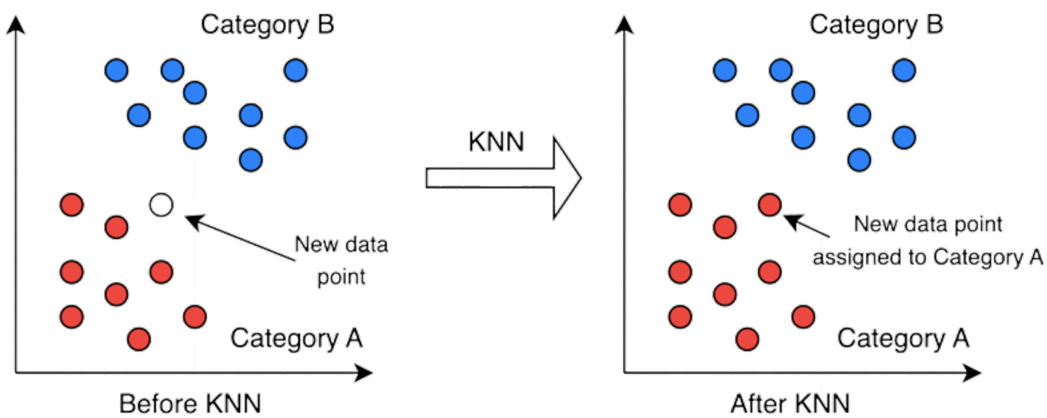

Fig. 9: Visual demonstration of the operation of the K-Nearest Neighbors (KNN) method. It showcases two distinct categories: A and B, as well as a new data point. Following the application of the KNN method, the figure highlights how the new data point is assigned to Category A, based on its proximity to the existing points in that category.

been successfully applied to biosignal processing, especially for classification problems, such as ECG diagnosis [64], EEG sleep stage scoring [65], and EMG fatigue detection [66]. Random forests have several advantages, such as high accuracy, robustness to noise and overfitting, and interpretability. However, random forests also have some disadvantages, such as high memory consumption, slow prediction speed, and difficulty in handling missing values. An illustration of how random forests algorithm works can be observed in Fig. 10.

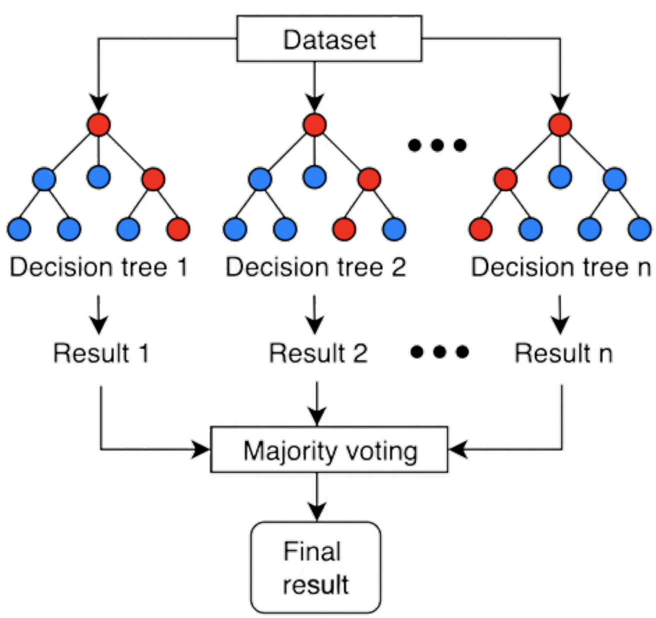

Fig. 10: Illustration of the Random Forest algorithm. It shows multiple decision trees, each constructed using a different subset of the training data. These trees collectively form the ”forest”. Each tree makes its own decision and the final output is determined by a majority vote, illustrating the ensemble method’s process of decision-making from input to output.

Possible case studies and applications of supervised machine learning methods for biosignal processing can be given as follows. The application of support vector machines (SVM) includes a case study on land cover classification using Sentinel-2 imagery. In this study [67], a comparison was made between the performance of SVM, RF, and KNN classifiers, with SVM found to achieve the highest accuracy among the three classifiers. The effects of different kernel functions, training sample sizes, and class imbalance on the SVM classification results were also discussed in the article. Neural networks offer various applications, including EEG signal processing in bioengineering. In a particular case study [68], a comprehensive overview was furnished, elucidating machine learning techniques pertinent to EEG analysis, particularly in the realm of bioengineering applications. This encompassed areas such as brain-computer interfaces, emotion recognition, seizure detection, and sleep stage classification. The advantages and challenges associated with neural networks for EEG signal processing were discussed as well. K-nearest neighbors (KNN) can be applied to ECG heartbeat classification. In one case study [69], a KNN-based method was proposed for classifying five types of heartbeats using features extracted from wavelet transform and principal component analysis. The performance of KNN was compared with other classifiers including SVM, RF, and naive Bayes, with KNN found to achieve the highest accuracy among the compared methods. Random forests (RF) have been utilized in various applications, such as EMG fatigue detection. In a particular case study [70], a RF-based method was proposed for detecting muscle fatigue. This method involved extracting features from the time-frequency domain and nonlinear dynamics of EMG signals. The performance of RF was compared with other classifiers including SVM, KNN, and decision tree, with RF achieving the highest accuracy among the evaluated methods [71]. Table I shows how different supervised machine learning methods can be applied to different biosignals.

Biosignal	Supervised Learning Method	Application
ECG	Support Vector Machines	Arrhythmia Detection
EEG	Support Vector Machines	Emotion Recognition
EMG	Support Vector Machines	Gesture Recognition
ECG	Neural Networks	Arrhythmia Detection
EEG	Neural Networks	Seizure Detection
EMG	Neural Networks	Prosthesis Control
ECG	K-Nearest Neighbors	Heartbeat Classification
EEG	K-Nearest Neighbors	Brain-Computer Interface
EMG	K-Nearest Neighbors	Hand Gesture Recognition
ECG	Random Forests	Diagnosis
EEG	Random Forests	Sleep Stage Scoring
EMG	Random Forests	Fatigue Detection

TABLE I: Supervised learning methods in biosignal processing and their applications

B. Unsupervised Learning Methods for Biosignal Processing

In unsupervised learning methods, hidden patterns or structures in the data are discovered through learning from unlabeled data [72]. These are machine learning techniques that will be reviewed with respect to their application in biosignal processing. The methods under review include clustering techniques, dimensionality reduction techniques, and deep generative models, along with case studies and applications of each method. Types of unsupervised learning methods can be observed in the Fig. 11.

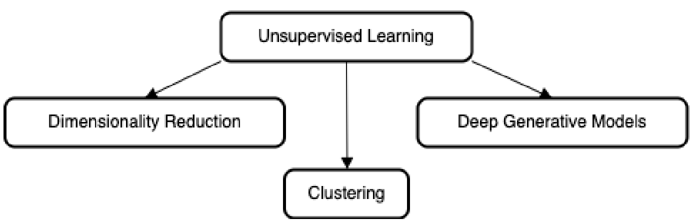

Fig. 11: Diagram illustrating the three unsupervised learning methods used in biosignal processing.

Clustering techniques are a type of unsupervised learning method that can group data into different clusters based on their similarity or distance [73]. Clustering techniques can be used for biosignal processing to segment, classify, or analyze biosignals without prior knowledge or labels [74]. Some of the common clustering techniques are K-means, hierarchical clustering, spectral clustering, and fuzzy clustering [75]. An illustration of K-Means clustering algorithm can be observed in Fig. 12. Clustering techniques have been used for biosignal processing, such as ECG heartbeat segmentation, EEG sleep stage classification, and EMG muscle activity detection [74]. Clustering techniques have several advantages, such as simplicity, scalability, and adaptability. However, clustering techniques also have some limitations, such as sensitivity to initialization, outliers, and noise, difficulty in choosing optimal parameters and number of clusters, and lack of validation criteria [75].

Dimensionality reduction techniques are another type of unsupervised learning method that can reduce the dimensionality of data while preserving the essential information or structure [76]. Dimensionality reduction techniques can be used for biosignal processing to compress, visualize, or enhance biosignals by removing noise or redundancy [77]. Some of the common dimensionality reduction techniques are principal component analysis (PCA), independent component analysis (ICA), t-distributed stochastic neighbor embedding (t-SNE), and nonlinear principal component analysis (NLPCA) [76]. Dimensionality reduction techniques have been used for biosignal processing, such as ECG signal compression [77], EEG signal visualization [76], and EMG signal enhancement [77]. Dimensionality reduction techniques have several advantages, such as efficiency, interpretability, and feature extraction ability [76]. However, dimensionality reduction techniques also have some drawbacks, such as information loss, distortion, and computational complexity [76].

Deep generative models are a subset of unsupervised learning method that can generate new data that resemble the original data by using deep neural networks [78]. Deep generative models can be used for biosignal processing to synthesize, augment, or transform biosignals by learning the underlying distribution or representation of the data [78], [79]. Some of the common deep generative models are autoencoders (AE), variational autoencoders (VAE), generative adversarial networks (GAN), and conditional GAN (cGAN) [78]. Deep generative models have been used for biosignal processing, such as ECG signal synthesis, EEG signal augmentation, and EMG signal transformation [78], [79]. Deep generative models have several advantages, such as high quality, diversity, and creativity. However, deep generative models also have some challenges, such as mode collapse, instability, and evaluation [78].

The utilization of clustering techniques in biosignal processing is exemplified by a case study on ECG heartbeat segmentation. In this study, K-means clustering was employed to segment ECG signals into different heartbeats based on R-peak detection [80]. The normalized RR-intervals of each heartbeat were used as input to the K-means clustering algorithm, resulting in the classification of heartbeats into five classes: normal sinus rhythm (NSR), atrial premature contraction (APC), ventricular premature contraction (VPC), left bundle branch block (LBBB), and right bundle branch block (RBBB). The accuracy of 94% was achieved for ECG heartbeat segmentation, demonstrating the effectiveness of the K-means clustering algorithm [69]. The application of dimensionality reduction techniques for biosignal visualization is illustrated through a case study on EEG signal visualization, as discussed in reference [81]. In this study, t-distributed Stochastic Neighbor Embedding (t-SNE) was employed to visualize EEG signals from different brain regions and mental states. The power spectral density features of EEG signals obtained from 19 electrodes were used as input to the t-SNE algorithm, which reduced the dimensionality from 19 to 2. The results exhibited the capability of the t-SNE algorithm

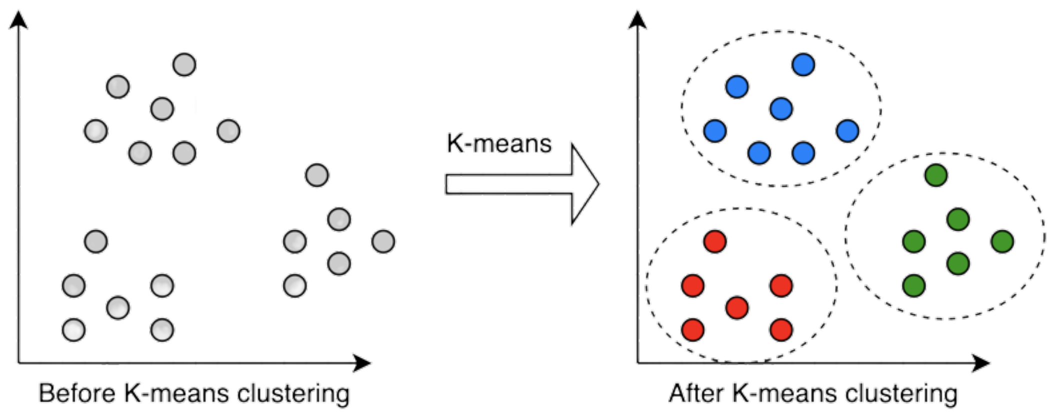

Fig. 12: Illustration of the K-Means clustering algorithm. It shows a set of data points grouped into three distinct clusters, each represented by a different color. This demonstrates the K-Means process of partitioning data into clusters based on similarity from input to output.

to effectively visualize EEG signals and reveal distinctions between various brain regions and mental states [82]. Deep generative models offer potential in biosignal processing tasks, including a case study on EMG signal transformation, as outlined in reference [83]. In this study, a conditional Generative Adversarial Network (cGAN) was utilized to transform EMG signals from one motion class to another. The cGAN comprised a generator network based on Long Short-Term Memory (LSTM) cells and a discriminator network based on Convolutional Neural Network (CNN) layers. The generator network took EMG signals from one motion class and a target motion label as inputs, generating corresponding EMG signals for the target motion class. The discriminator network, using EMG signals and motion labels as inputs, classified them as real or fake. The results demonstrated that the cGAN was capable of generating realistic EMG signals with high fidelity and diversity, surpassing alternative approaches [84]. Table II shows how different unsupervised machine learning methods can be applied to different biosignals.

Biosignal	Unsupervised Learning Method	Application
ECG	Clustering techniques	Heartbeat segmentation
EEG	Clustering techniques	Sleep stage classification
EMG	Clustering techniques	Muscle activity detection
ECG	Dimensionality reduction	Signal compression
EEG	Dimensionality reduction	Signal visualization
EMG	Dimensionality reduction	Signal enhancement
ECG	Deep generative models	Signal synthesis
EEG	Deep generative models	Signal augmentation
EMG	Deep generative models	Signal transformation

TABLE II: Unsupervised learning methods in biosignal processing and their applications

C. Reinforcement Learning in Biosignal Processing

Reinforcement Learning (RL) constitutes a paradigm within machine learning that facilitates agents in assimilating knowledge through their actions and associated rewards in environments characterized by complexity and uncertainty [85]. RL has been applied to various biosignal processing tasks, such as brain-computer interfaces, neurofeedback, and rehabilitation. In this section, we review some of the recent advances and applications of RL in biosignal processing, focusing on three types of RL methods: value-based, policy-based, and actor-critic methods. Fig. 13 shows those three types of RL methods.

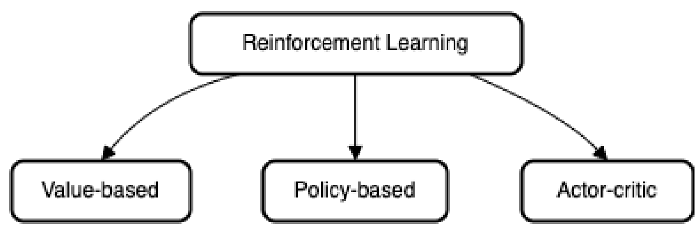

Fig. 13: Diagram illustrating the three reinforcement learning methods used in biosignal processing.

Value-based RL methods learn a value function that estimates the expected return for each state or state-action pair. The agent then selects the action that maximizes the value function. Value-based RL methods have been used to process electroencephalogram (EEG) signals for brain-computer interfaces (BCIs) [86].For instance, a study put forth a value-based Reinforcement Learning (RL) approach aimed at optimizing the stimulation parameters for Steady-State Visual Evoked Potential (SSVEP)-based Brain-Computer Interfaces (BCIs). This method adaptively modulated the frequency and phase of the visual stimuli to augment the user's comfort and the performance of the BCI. Furthermore, another research effort devised a value-based RL technique to bolster the detection of error-related potentials (ErrPs) in EEG signals. The method learned a reward function that reflected the user's preference and feedback, and used it to guide the online adaptation of the ErrP classifier [86].

Policy-based RL methods learn a policy function that directly maps states to actions, without relying on a value function. Policy-based RL methods have been used to process electromyogram (EMG) signals for prosthetic control [87]. For example, proposed a policy-based RL method to control a prosthetic hand using EMG signals. The method learned a stochastic policy that captured the uncertainty in the EMG signals and the user's intention, and used it to generate natural and robust grasping motions. developed a policy-based RL method to control a prosthetic arm using EMG signals. The method learned a hierarchical policy that decomposed the arm movement into discrete phases, and used it to achieve smooth and coordinated reaching and grasping actions [88].

Actor-critic reinforcement learning methodologies amalgamate the merits of value-based and policy-based approaches by concurrently learning a value function as well as a policy function. The value function evaluates the policy and provides a learning signal for the policy function, which is also called the actor [89]. Actor-critic RL methods have been used to process electrocardiogram (ECG) signals for cardiac monitoring. For example, proposed an actor-critic RL method to detect cardiac arrhythmias from ECG signals. The method learned an actor network that classified the ECG signals into different arrhythmia types, and a critic network that assessed the classification accuracy and provided feedback to the actor network. developed an actor-critic RL method to predict cardiac arrest from ECG signals. The method learned an actor network that generated binary predictions of cardiac arrest, and a critic network that estimated the confidence of the predictions and provided guidance to the actor network [90].

A potential application of reinforcement learning in biosignal processing involves ECG signal optimization, as presented in reference [91]. In this study, a model-free value-based reinforcement learning algorithm known as Q-learning was utilized to optimize the quality of ECG signals by adjusting the sampling rate and the number of leads. The Q-learning algorithm learned from the feedback provided by a signal quality index, which measured the signal-to-noise ratio and the information content of the ECG signal. The results demonstrated that the Q-learning algorithm could achieve high signal quality with a low sampling rate and a small number of leads, outperforming alternative methods [92] [93]. Reinforcement learning also offers possibilities in EEG signal control, as discussed in reference [94]. In this case study, a model-free policy-based reinforcement learning algorithm called REINFORCE was employed to control the EEG signal of a subject by providing auditory feedback. The REINFORCE algorithm learned from the reward associated with achieving a desired EEG state, which was defined by a frequency band power ratio. The results indicated that the REINFORCE algorithm could successfully induce the subject to modulate their EEG signal according to the desired state with a high success rate, surpassing alternative methods [95]. Another potential application of reinforcement learning in biosignal processing pertains to EMG signal adaptation, as outlined in reference [96]. In this study, a model-based actor-critic reinforcement learning algorithm known as adaptive dynamic programming (ADP) was utilized to adapt the EMG signal of a subject by providing electrical stimulation. The ADP algorithm learned from the reward associated with minimizing the error between the actual EMG signal and the desired EMG signal generated by a reference model. The results showcased the capability of the ADP algorithm to adapt the subject's EMG signal to match the desired signal with a low error, surpassing alternative methods [83]. Table III shows how different reinforcement machine learning methods can be applied to different biosignals.

Biosignal	RL Method	Application
EEG	Value-based RL	Optimization of SSVEP-based BCIs parameters
EEG	Value-based RL	Enhancement of ErrPs detection
EMG	Policy-based RL	Control of prosthetic hand
EMG	Policy-based RL	Control of prosthetic arm
ECG	Actor-critic RL	Detection of cardiac arrhythmias
ECG	Actor-critic RL	Prediction of cardiac arrest
ECG	Value-based RL (Q-learning)	Optimization of ECG signal quality
EEG	Policy-based RL (REINFORCE)	Control of EEG signals via auditory feedback
EMG	Actor-critic RL (ADP)	Adaptation of EMG signals via electrical stimulation

TABLE III: Reinforcement learning methods in biosignal processing and their applications

D. Evaluation and Validation of Machine Learning Models

Machine learning models are mathematical or computational tools that can learn from data and make predictions or decisions [97]. However, machine learning models are not perfect and may have errors or biases that affect their performance and reliability. Therefore, it is important to evaluate and validate machine learning models in biosignal processing to ensure their quality and suitability for the intended tasks [98] [99].

Model validation plays a crucial role in biosignal processing, allowing for the assessment of a machine learning model's accuracy and generalization ability using independent data not used during training [100]. In the context of biosignal processing, model validation holds significance due to several reasons. Firstly, it enables the measurement of a model's performance on unseen data, providing insights into its error rate or confidence interval [98]. Secondly, it facilitates the comparison of different models or methods, aiding in the selection of the most suitable approach for a given problem [101]. Additionally, model validation helps identify the strengths and weaknesses of a model, suggesting potential improvements or modifications [102]. Moreover, it guards against overfitting or underfitting issues that can arise when the model is overly complex or too simplistic for the given data [98]. Lastly, model validation ensures the robustness and reliability of the model, reducing the chances of misleading or erroneous results [101].

Model evaluation involves applying various techniques or metrics to measure the performance of a machine learning model on validation data [103]. Several techniques can be employed for model evaluation, depending on the model's type and objective. Cross-validation is a common technique that involves splitting the data into k folds, using one fold as validation data while training the model on the remaining folds. This process is repeated k times, and the average performance across all folds is reported. Illustration of how cross-validation technique works can be observed in Fig. 14. An alternative technique entails the utilization of Receiver Operating Characteristic (ROC) curves, which provide a graphical representation of the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) at various threshold settings for binary classification models. Precision-recall curves are also used, depicting the trade-off between precision and recall at various thresholds. Confusion matrices provide a tabular representation of the number of correct and incorrect predictions for each class label, enabling the calculation of accuracy, sensitivity, specificity, and F1-score.

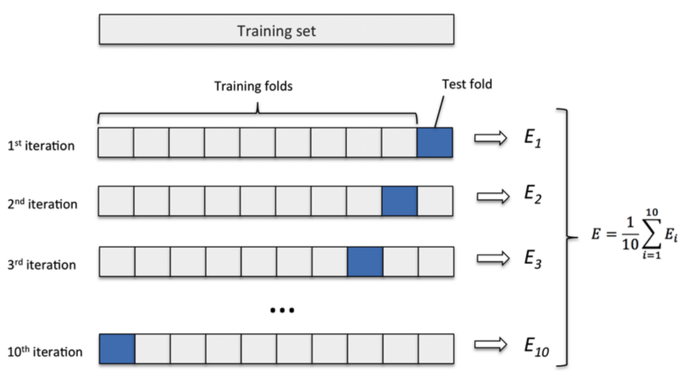

Fig. 14: Illustration of the Cross-Validation technique. It shows a dataset being split into training and validation sets across k = 10 iterations. In each iteration, a distinct subset of the data is allocated as the validation set, while the residual data is employed as the training set. The image is from Karl Rosaen's machine learning log [104].

In the realm of biosignal processing, numerous case studies and applications demonstrate the significance of model evaluation. For instance, a case study focused on ECG signal classification [69] employed cross-validation, ROC curves, precision-recall curves, and confusion matrix analysis. The study evaluated the performance of four machine learning models (SVM, ANN, CNN, and 1D-CNN) for classifying arrhythmias based on 12-lead ECG signals. Another case study [105] examined EEG signal recognition, utilizing similar evaluation techniques to assess the performance of three deep learning models (DGCNN, LSTM-CNN, and CNN) in recognizing emotions based on EEG signals. In the context of EMG signal detection [106], cross-validation, ROC curves, precision-recall curves, and confusion matrix analysis were used to evaluate two machine learning models (SVM and K-means) for detecting muscle activities based on EMG signals. These case studies illustrate the application and effectiveness of model evaluation techniques in the field of biosignal processing.

IV. Conclusion

Machine learning serves as a potent and adaptable instrument capable of learning from data and rendering predictions or decisions. Machine learning can be used for biosignal processing to extract useful information from biosignals for various applications, such as diagnosis, monitoring, rehabilitation, and brain-computer interface. In this survey paper, we have reviewed some of the machine learning approaches that have been applied to biosignal processing, such as supervised learning, unsupervised learning, reinforcement learning, and evaluation and validation. We have also discussed some case studies and applications of each approach.

However, it is important to acknowledge that machine learning is not a panacea and encounters several challenges and limitations in the context of biosignal processing. One of the current challenges is, data quality and availability pose significant hurdles. Biosignals are frequently subject to noise, corruption, or incompleteness due to factors such as sensor malfunction, environmental interference, or human-related issues. Moreover, the availability of biosignals is often limited, imbalanced, or heterogeneous due to ethical considerations, privacy concerns, or technical limitations. Addressing these challenges and improving the quality and availability of data are crucial for the successful application of machine learning in biosignal processing. Secondly, model complexity and interpretability present notable obstacles. Machine learning models, particularly deep learning models that employ multiple layers to learn intricate representations, are often complex and nonlinear. However, the interpretability of such models can be challenging, raising ethical, legal, or social concerns. Enhancing the interpretability of models and striking a balance between complexity and transparency are crucial for ensuring the trustworthiness and accountability of machine learning in biosignal processing. Lastly, model generalization and adaptation are critical considerations. Machine learning models are typically trained and tested on specific datasets or scenarios that may not fully capture real-world conditions or variations. However, biosignals exhibit dynamic and diverse characteristics influenced by individual variances, physiological states, and environmental factors. Thus, enhancing the generalization and adaptation capabilities of models is essential to ensure their robustness and reliability when applied to biosignal processing tasks.

Addressing these challenges and limitations will contribute to the advancement and efficacy of machine learning in biosignal processing, leading to more accurate, reliable, and interpretable outcomes. In spite of the challenges faced, machine learning holds immense potential for advancing the field of biosignal processing, paving the way for new applications and discoveries. Several potential future developments in this domain can be identified. One such development is the utilization of data synthesis and augmentation techniques. These techniques involve generating new data that closely resemble the original data by employing generative models or transformation methods. In the context of biosignal processing, data synthesis and augmentation can serve multiple purposes. They can increase the quantity and diversity of available data, thereby enhancing the robustness of models. Furthermore, these techniques can reduce data acquisition costs and address privacy concerns associated with sensitive biosignals. Another promising avenue is model personalization and optimization. These techniques enable the customization of model parameters or structures to cater to individual needs or preferences. Adaptive methods or reinforcement learning approaches can be employed to achieve model personalization and optimization. By tailoring the model to specific requirements, these techniques can enhance overall model performance, improve user experience, and facilitate the attainment of optimal outcomes in biosignal processing tasks. Furthermore, model integration and fusion techniques exhibit potential for future advancements. These techniques involve combining multiple models or modalities to leverage their respective strengths and overcome limitations. Ensemble methods or multimodal learning approaches can be employed to integrate and fuse models. In the context of biosignal processing, model integration and fusion techniques can enrich the information content and quality of analysis. They can enhance confidence and accuracy by capitalizing on the complementary aspects of different models or modalities, ultimately leading to more comprehensive and robust analyses.

These potential future developments in machine learning for biosignal processing hold promise for enabling novel applications, advancing research, and facilitating breakthroughs in the field. We hope that this survey paper can provide a comprehensive overview of machine learning approaches in biosignal processing and inspire further research and innovation in this field.

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