Exploring Cutting-Edge Developments in Deep Learning for Biomedical Signal Processing

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***Abstract*—Biomedical condition monitoring devices are progressing quickly by incorporating cost-effective and non-invasive sensors to track vital signs, record medical circumstances, and deliver meaningful responses. These sophisticated innovations rely on breakthrough technology to provide intelligent platforms for health monitoring, quick illness recognition, and precise treatment. Biomedical signal processing determines patterns of signals and serves as the backbone for reliable applications, medical diagnostics, and research. Deep Learning (DL) methods have brought significant innovation in biomedical signal processing, leading to the transformation of the health sector and medical diagnostics. This article covers an entire range of technical innovations evolved for DL-based biomedical signal processing where different modalities have been considered, including Electrocardiography (ECG), Electromyography (EMG), and Electroencephalography (EEG). A vast amount of biomedical data in various forms is available, and DL concepts are required to extract and model this data in order to identify hidden complex patterns that can be utilized to improve the diagnosis, prognosis, and personalized treatment of diseases in an individual. The nature of this developing topic certainly gives rise to a number of challenges. First, the application of sensitive and noisy time series data requires truly robust models. Second, many inferences made at the bedside must have interpretability by design. Third, the field will require that processing be performed in real-time if used for therapeutic interventions. We systematically evaluate these challenges and highlight areas where continued research is needed. The general expansion of DL technologies into the biomedical domain gives rise to novel concerns about accountability and transparency of algorithmic decision-making, a subject which we briefly touch upon as well.**

Keywords*—Biomedical signal processing; health monitoring; deep learning; electrocardiography; electromyography; electroencephalography

I. Introduction

Changing signals provide critical insights regarding the entities that produce them [1]. Advances in technologies such as IoT, machine learning, and Wireless Sensor Networks (WSN) have significantly enhanced the ability to interpret these signals, particularly in fields like biomedicine, where mechanisms change over time as their underlying characteristics continually evolve [2, 3]. These alterations can be abrupt, where the internal properties of the system change gradually over time, or gradual, where the internal properties change slowly over time [4]. The signals from these systems are also time-varying in nature, and their time-varying aspects can unveil the dynamics of these systems [5]. Heart rate variations under stress or pitch changes of a vocalist during a song, for example, show a time-dependent change in the Instantaneous Frequency (IF) of the signal [6]. Similarly, fluctuations in the system's response intensity are linked to changes in the Instantaneous Amplitude (IA). Furthermore, the nature of the vibrations might undergo alteration. The integration of these many sources of variability results in intricate patterns in the temporal progression of the signal.

Biomedical signals are acquired from different levels of the body, such as cellular, organ, and molecular levels. Biomedical signal processing comes from many modalities like EEG for tracking brain electrical activity, ECG for tracking heart electrical activity, EMG for tracking the noise signals of muscle, and electroretinogram and electroneurogram for tracking the electrical activities of the eye [7]. Biomedical signals are first used to diagnose or identify certain physiological and pathological conditions. Moreover, these signals are used in the healthcare industry to examine biological systems [8]. This objective is to remove noise from signals, extract features, accurately recognize signal models, reduce dimensionality for dysfunctional or crucial functions, and anticipate future pathological and functional events by applying AI models.

Typically, EEG signal processing and interpretation were generally carried out using a hierarchical process consisting of four main stages. First, a raw EEG signal was pre-processed to filter out noise and artifacts to improve the signal quality for further analysis. Following pre-processing, useful information should be obtained from the processed signal [9]. Mainly, this step involves techniques such as time-frequency analysis or spectral analysis to determine the features indicative of the different patterns of brain activity. After the features had been extracted, they were subjected to a feature selection method. This step involved selecting fewer extracted features in the next steps of the analysis to make the information more discriminative and to improve computational complexity.

Feature selection techniques such as Principal Component Analysis (PCA) and wavelet transform were frequently employed to identify the most discriminative features for classification or diagnosis. Then, the extracted features were subjected to diagnostic tests for disease diagnosis or for the identification of diverse functional states of the brain [10]. This stage usually involved the use of machine learning models and statistical tests to identify abnormal EEG patterns or patterns indicative of various neurological disorders. To learn complex structures present in EEG data and to help in the accurate classification or prediction task, machine learning algorithms such as Support Vector Machines (SVM), Artificial Neural Networks (ANNs) were employed [11].

Classical signal processing methods are widely used in biomedical signal analysis, providing robust tools for feature extraction, denoising, and signal classification [12]. The information obtained using approaches like Fourier transforms, wavelet analysis, and statistical methods has also led to more insight into many physiological functions and the detection of abnormalities. The complexity and time variations of biomedical signals, however, pose a serious challenge for classical signal processing methods in particular for the non-linear and nonstationary nature of the signals.

The emergence of Deep Learning (DL) has revolutionized biomedical signal processing by providing the capability to automatically learn hierarchical features from raw data with little human intervention [13, 14]. DL models, including Generative Adversarial Networks (GANs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs), have achieved remarkable performance in a wide range of applications, such as extracting ECG arrhythmias, brain-computer interface based on EEG signals, and noise suppression in EMG signals [15, 16]. The turning point in the DL era encourages researchers to gradually shift from expert-designed feature engineering to data-driven end-to-end learning, leading to more precise, efficient, and flexible analysis of biological signals [17]. Table I provides a comparison of our study with previous related survey studies. In summary, the main contributions of this work are:

- Presenting a thorough overview of current advancements in DL techniques applied to biomedical signal processing;
- Reviewing and analyzing the existing DL architectures utilized in processing various biomedical signals;
- Identifying and discussing the challenges inherent in applying DL to biomedical signal analysis, such as noise handling, interpretability, and real-time processing requirements;
- Exploring emerging trends, future directions, and potential opportunities for interdisciplinary collaboration in advancing the field of DL for biomedical signal processing.

The rest of the paper is organized as follows. Section II offers a concise overview of biomedical signal processing fundamentals and the associated challenges. Section III presents an in-depth discussion of DL techniques developed for biomedical signal processing. In Section IV, we scrutinize the potential opportunities and existing challenges encountered in using DL for biomedical signals. Furthermore, in Section V, emerging trends and future research directions are presented for better comprehension and advanced research in this domain. Finally, Section VI provides a conclusion, overviews the contribution of DL to the field of biomedical signal processing, and hypothesizes future research opportunities.

TABLE I. COMPARISON OF OUR STUDY WITH PREVIOUS SURVEYS

Study	Methodology	Contribution
[21]	Comparative evaluation of feature selection and classification techniques for brain-computer interface	Offers insights into the effectiveness of different methods for feature selection and classification in brain-computer interface systems
[22]	Review of DL and ML in big data	Provides an overview of the evolution, concepts, and integration of DL and ML in big data analytics, categorizing and synthesizing their potential applications
[23]	Survey of DL in physiological signal analysis	Conducts a detailed study to comprehend, categorize, and compare key parameters of DL approaches in physiological signal analysis, offering insights into their applications and performance
[24]	Review of DL techniques for audio signal processing	Examines DL techniques applied to audio signal processing, identifying key models, challenges, and future directions in the field
[25]	Literature survey on ECG signal analysis	Describes traditional and advanced techniques for ECG signal analysis, discussing challenges, limitations, and future research directions in the field
Our Study	Reviews current advancements in DL techniques for biomedical signal processing, focusing on EEG signals	Provides a comprehensive overview of DL techniques for EEG signal analysis, identifies challenges, and explores future directions for interdisciplinary collaboration

II. BACKGROUNDS

The biomedical signaling modalities incorporate multiple physiological signals that reflect the functioning of different systems of the human body [18]. The signals are tabulated in Table II. ECG, EMG and EEG are some of the most popular examples of body signals providing various types of information about physiological or pathological processes in the human body [19]. ECG signals are the heart's electrical activity over time. ECG measures can check for heart rhythm, conduction abnormalities, ischemia, infarction, and more. These signals are necessary indicators for diagnosing heart failure, myocardial infarction, arrhythmias, etc. ECG can also monitor the heart as an indicator of infectious disease, trauma, and metabolic anomalies that affect the heart in the body. EMG captures electrical signals produced when muscles are activated. It is used in many medical settings like neurology, orthopedics, sports medicine, physical therapy, and other related healthcare providers. The EMG signal is smoothly propagated throughout the body and can provide valuable information on some of the most deadly disorders humans have faced [20]. EEG is an electrophysiological monitoring method used to monitor the electrical activity of the brain. With EEG, voltage fluctuations around the scalp are measured in relation to electrical activity in the brain and waves that occur in a variety of forms and frequencies. From the determined EEG signals it is possible to diagnose neurological problems like epilepsy, tracking anesthesia depth during surgery, etc. Additionally, these measures can reveal other brain-related illnesses like Parkinson's, Alzheimer's, and sleep disorders.

TABLE II. OVERVIEW OF BIOMEDICAL SIGNAL MODALITIES

Modality	Description	Clinical applications
ECG	Measures heart's electrical activity over time	Detection of arrhythmias, ischemia, myocardial infarction
EMG	Captures electrical activity caused by muscle contractions	Diagnosis of neuromuscular disorders, rehabilitation guidance
EEG	Records brain electrical activity	Diagnosis of epilepsy, monitoring during surgery, studying brain disorders

Each biomedical signal type contributes to a different aspect of health and disease, thus offering different information [26]. ECGs are used to illustrate heart conditions. EMG signals are associated with the neuromuscular system, while EEG signals may be used to diagnose neurological conditions [27]. Hence, each signal type is related to a different medical specialty [28]. Moreover, not only is the potential of each signal type in isolation vast, but also, by combining the information from multiple sources, a comprehensive view of the patient's state can be achieved. This, in turn, can personalize the offered treatment. Over the years, advances in signal processing technology and machine learning algorithms have also greatly increased the utility of these signals for the clinician [29]. These technological improvements have led to more accurate diagnostics, prognostics, and personalized treatment plans. Biomedical signal types have the potential to transform and enhance medical treatment as the technology improves.

Advancements in DL, detailed in Table III, have revolutionized biomedical signal processing. DL is an instance of machine learning that uses ANNs with several layers to acquire hierarchical representations of input autonomously. DL models have an advantage over typical machine learning methods because they can extract important characteristics directly from raw data without the need for manually produced features [30]. Deep learning models are able to adapt themselves to very complex and high-dimensional data, such as biomedical signals. DL is currently used for denoising, feature extraction, classification, and segmentation of biomedical signals [31]. For example, CNNs are highly effective in automatically learning spatial and temporal features from biomedical signals such as ECGs and EEGs, enabling accurate classification of abnormal patterns indicative of various cardiac arrhythmias or neurological disorders. Likewise, RNNs can learn temporal dependencies in sequence data and are widely used in time-series prediction and signal segmentation in biomedical signals. Moreover, GANs have been exploited for signal augmentation and generation thereby increasing the availability of annotated data in large amounts for training DL models and their generalization.

TABLE III. DEEP LEARNING TECHNIQUES FOR BIOMEDICAL SIGNAL PROCESSING

DL technique	Description	Applications
CNN	Learns spatial and temporal features from signals	Classification of cardiac arrhythmias and neurological disorders
RNN	Captures temporal patterns in sequential data	Time-series prediction and signal segmentation
GAN	Augments data and improves generalization performance	Signal augmentation and data synthesis

DL in biomedical signal processing is not limited to diagnostic applications and can also be expanded to personalized medicine, monitoring in real-time, and therapeutic interventions. As an example, a recently reported study demonstrates the capability of DL models to analyze time-evolving data streams from wearable sensors to monitor disease progressions and recognize critical events in a patient with chronic illness such as heart failure or epilepsy [32]. In addition, DL-based predictive models can assist clinicians with more accurately identifying high-risk patient sub-cohorts that are susceptible to specific complications or adverse effects and subsequently administer timely and accurate preventive measures [33]. Alternatively, DL-based methods have been integrated into medical devices and e-health platforms to facilitate real-time processing and analysis of biomedical signals at the patient's bedside, thereby expediting clinical decision-making and personalizing the patient care pathway. In conclusion, DL technology may greatly advance the field of biomedical signal processing by offering a mechanism by which a larger amount of useful information can be extracted from complex physiological data, in turn potentially improving the broader population of patient's health outcomes.

The use of DL in biomedical signal processing has several key strengths that have the potential to transform medical care. First, DL models have successfully discovered multiple levels of abstraction from raw data without utilizing handcrafted feature extraction and selection. This is especially significant in biomedical signal processing, as the processed signals are usually complex and contain subtle information that could be difficult to apprehend with conventional methods. Another advantage of deep learning is that it can take full advantage of large-scale datasets to extract high-level discriminative features, which can be beneficial for more reliable and robust biomedical signal classification, detection, localization, and segmentation. DL can handle multiple types of signals, such as ECGs, EEGs, and EMGs, and can therefore be applied across a wide variety of clinical scenarios. Additionally, machine learning allows such models to become more accurate as they are given more data to learn from, and since it is constantly updated, they can become more accurate.

Yet, DL has not been spared from issues in utilizing it with biomedical signals. First, DL models are often regarded as black boxes due to their complex architectures and non-linear transformations, which may result in hidden representations or obscure representations of the underlying decisions performed by the model, hence reducing the confidence and interpretability of these models in clinical practice as opposed to interpretable models like LRA. This might be risky given the higher level of trust in transparently interpretable models such as LRA in the clinical domain. Second, biomedical signals are inevitably noisy, with artifacts and noise as well as intersubject and intrasubject variability, which may pose challenges to the generalization of DL models and may further reduce their reliability. More broadly, the generalization and reliability of DL methods across different patient populations and clinical scenarios is an ongoing grave concern. Moreover, for the successful utilization of DL in healthcare, several ethical considerations, such as algorithmic bias, privacy and security of data, development, and use of DL models, must be systematically addressed. Developing methods to meet these key challenges will require novel approaches based on the collaboration of interdisciplinary teams, combined with rigorous validation of methods, theory, and algorithms, leading to the design of interpretative and reliable learning algorithms aligned with the distinctive requirements of biomedical signal processing.

III. DL Techniques for Biomedical Signal Processing

In the biomedical signal processing domain, DL algorithms exhibit versatility across four primary categories: deep supervised, unsupervised, reinforcement learning, and hybrid algorithms, each offering unique approaches to tackle distinct challenges in signal analysis. As shown in Fig. 1 and summarized in Table IV, these categories span a range of methods, from supervised models that use labeled data to learn predictive rules to unsupervised models that discover patterns in data without any supervision and hybrid models that incorporate features of both. There can be a plethora of architectures and frameworks within every category of biomedical signal processing. For example, CNNs are usually used for capturing spatial features from ECGs, while RNNs are efficient in modeling temporal sequences from EEGs. Furthermore, there can be more explorations of NNs that simulate GANs for data augmentation and generation, and so on. These models find extensive applications in many tasks, such as signal denoising, feature extraction, classification, and segmentation, as tabulated in Table V, which in turn enhance the diagnostics, monitoring, and therapeutics in healthcare. The subsequent sections will provide brief explanations for each category, which will include methods, tasks, and utility in the emerging area of biomedical signal processing.

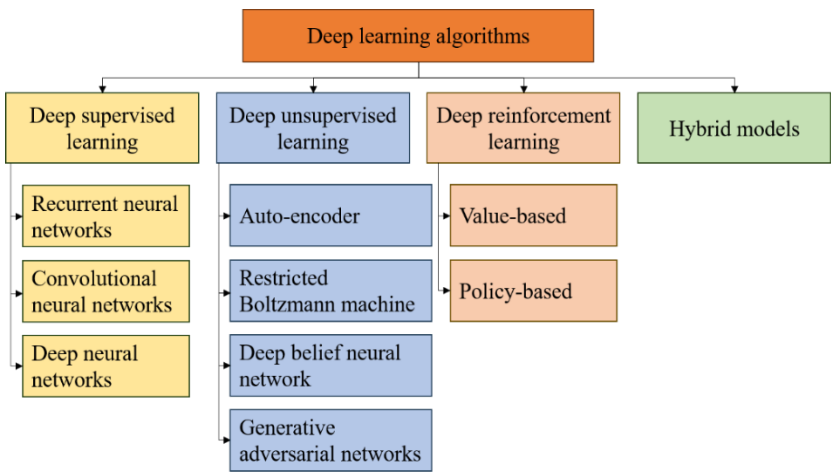

Fig. 1. DL algorithms in biomedical signal processing.

TABLE IV. Overview of Deep Learning Categories for Biomedical Signal Processing

Deep learning category	Description	Examples
Deep supervised learning	Utilizes labeled data to train models for accurate predictions	DNNs, CNNs, and RNNs
Deep unsupervised learning	Extracts meaningful representations from unlabeled data	Autoencoders, RBMs, DBNs, and GANs
Deep reinforcement learning	Learns optimal behavior through interaction with the environment	Value-based, policy-based, and model-based methods
Hybrid deep learning	Combines elements of different DL architectures for enhanced performance	Combination of CNNs and RNNs and CNNs with attention mechanisms

TABLE V. Examples of Deep Learning Models for Biomedical Signal Processing

Deep learning model	Description	Applications
DNN	Models complex relationships within high-dimensional data	Signal classification and prediction tasks
CNN	Captures spatial dependencies in signals	Image-based tasks (ECG, EEG) and signal classification
RNN	Models temporal dynamics and sequential dependencies	Time-series forecasting and sequential pattern recognition
Autoencoders	Learns compact representations of input data	Dimensionality reduction and anomaly detection
GAN	Generates realistic samples from a given distribution	Data augmentation and synthesis

A. Deep Supervised Learning

Deep supervised learning-based models represent a cornerstone in biomedical signal processing, leveraging labeled training datasets to learn discriminative features and make accurate predictions. These models operate by iteratively adjusting network parameters, often referred to as weights, to minimize a predefined loss function, effectively optimizing the model's performance. Among the supervised DL category, three pivotal architectures have emerged as particularly effective for processing biomedical signals: DNNs, CNNs, and RNNs, as depicted in Fig. 2. DNNs offer a robust framework for modeling complex relationships within high-dimensional data, making them well-suited for tasks such as signal classification and prediction. CNNs excel in capturing spatial dependencies in signals, enabling precise feature extraction from images or sequential data, such as ECGs and EEGs. Meanwhile, RNNs specialize in modeling temporal dynamics and sequential dependencies, which is crucial for tasks like time-series forecasting and sequential pattern recognition, particularly in signals with temporal structures like EEGs and EMGs. These deep supervised learning models constitute foundational tools in biomedical signal processing, facilitating accurate diagnosis, prognosis, and personalized treatment strategies for a wide range of medical conditions.

B. Deep Unsupervised Learning

Deep unsupervised learning models have emerged as a prominent branch within the realm of DL, offering compelling solutions for tasks requiring minimal labeled data. These models, as depicted in Fig. 3, encompass a variety of architectures designed to extract meaningful representations from unlabeled datasets, thereby enabling effective feature learning and data-driven insights. One prevalent category of deep unsupervised models is autoencoders, which aim to learn a compact representation of input data by encoding it into a lower-dimensional latent space and then reconstructing the original data from this representation.

Restricted Boltzmann machines (RBMs) provide another powerful framework for unsupervised feature learning, leveraging energy-based probabilistic models to capture complex dependencies in data. Deep Belief Networks (DBNs) extend upon RBMs by stacking multiple layers of generative models, facilitating hierarchical representation learning. Moreover, GANs have garnered significant attention for their ability to generate realistic samples from a given distribution by training a generator network to produce data that is indistinguishable from authentic samples while simultaneously training a discriminator network to distinguish between actual and generated samples. These diverse deep unsupervised learning models offer versatile solutions for tasks such as data augmentation, dimensionality reduction, and anomaly detection in biomedical signal processing, thereby expanding the repertoire of techniques available to researchers and practitioners in the field.

C. Deep Reinforcement Learning

Reinforcement learning (RL) emerges as a transformative paradigm within the domain of biomedical signal processing, offering a dynamic framework for decision-making in complex environments to maximize cumulative rewards [34]. Unlike conventional supervised learning methods, RL operates in interactive settings, enabling agents to autonomously learn optimal behavior through iterative exploration and exploitation of the environment. In the context of biomedical signal processing, RL finds applications in adaptive treatment strategies, optimal medical device settings, and personalized healthcare interventions. Particularly pertinent is RL's capability to facilitate agent learning in environments where comprehensive prior knowledge is lacking or limited.

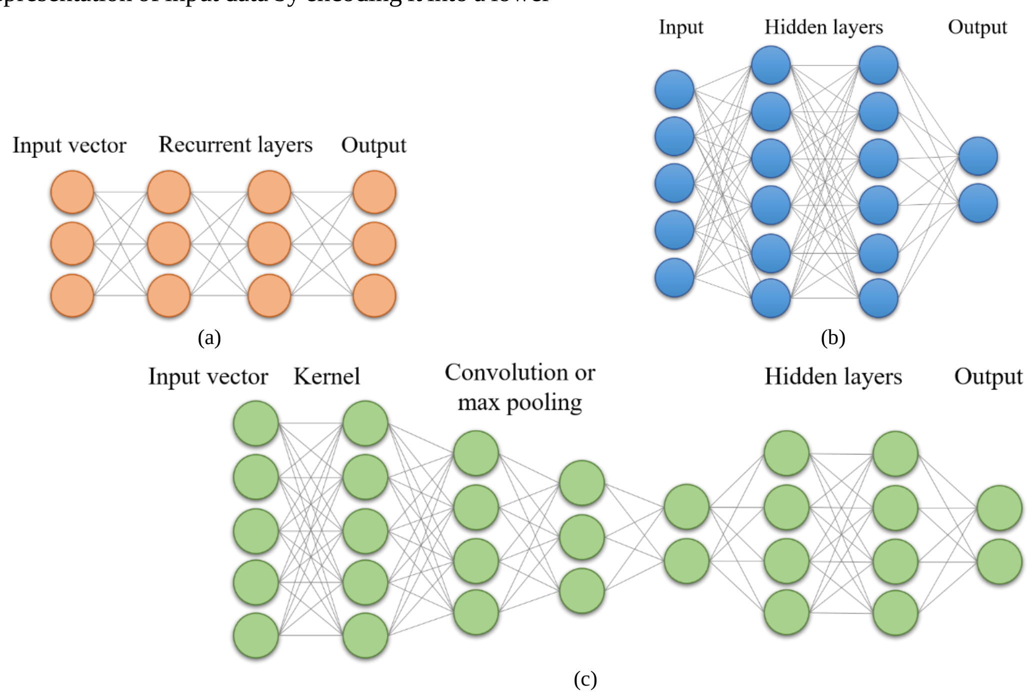

Fig. 2. Deep supervised learning architectures in biomedical signal processing: RNN (a), DNN (b), CNN (c).

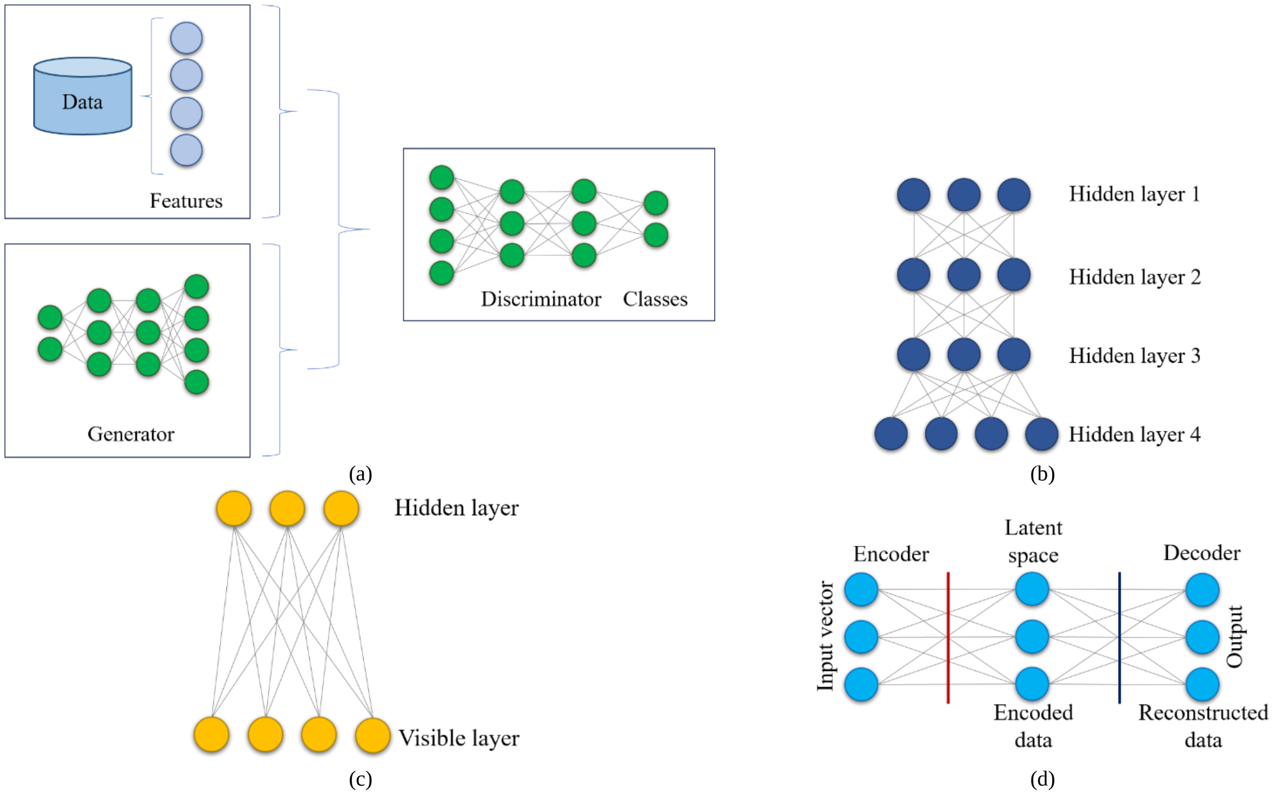

Fig. 3. Deep unsupervised learning architectures in biomedical signal processing: GAN (a), DBNN (b), RBM (c), auto-encoder (d).

At the core of RL lies the iterative interaction between an agent and its environment. The agent perceives the current state, selects actions based on its policy, and receives feedback in the form of rewards, indicating the efficacy of the chosen actions in transitioning to new states. This feedback loop enables the agent to refine its decision-making strategy over time, with the aim of maximizing cumulative rewards. Notably, RL does not necessitate detailed mathematical models of the underlying system for optimal control. Instead, the agent treats the biomedical signal processing environment as a black box and optimizes its policy through continuous interaction and adaptation.

By leveraging RL techniques, biomedical signal processing agents can autonomously learn to navigate complex decision spaces, optimizing treatment regimens and medical device settings to enhance patient outcomes. Despite challenges related to scalability in large-scale networks, RL remains a powerful and versatile approach for learning optimal behavior in biomedical signal processing environments, offering promising avenues for innovation and advancement in healthcare delivery.

Deep Reinforcement Learning (DRL) harnesses the capabilities of deep neural networks to enhance learning efficiency and algorithm performance, as depicted in Fig. 4. By leveraging deep neural networks, DRL enables the agent to learn and adapt its decision-making policy within the environment effectively. The deep neural network serves as a fundamental component of the agent, maintaining an internal representation of the policy that dictates the agent's actions based on the observed state of the environment. This integration of deep neural networks facilitates rapid learning and improved performance, which is crucial for real-time decision-making and adaptive control in biomedical signal processing applications.

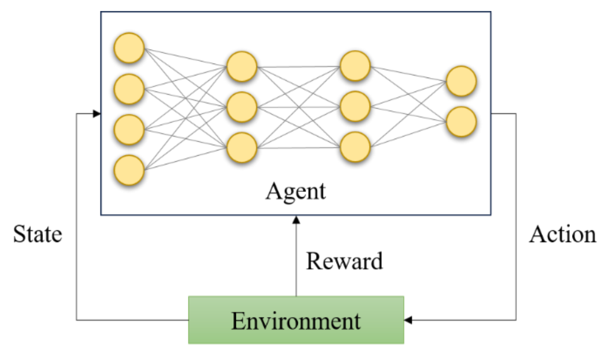

Fig. 4. Deep reinforcement learning in biomedical signal processing.

DRL methodologies in biomedical signal processing can be broadly categorized into three main approaches: value-based, policy-based, and model-based methods. Value-based methods focus on estimating the value or expected return of different actions in a given state, allowing the agent to select actions that maximize long-term rewards. Policy-based methods, on the other hand, directly parameterize the agent's policy and learn to optimize it through gradient-based methods without explicitly estimating the value function. Model-based methods incorporate a learned model of the environmental dynamics to guide decision-making, enabling the agent to plan and anticipate the consequences of its actions. Each of these DRL methods offers unique advantages and trade-offs, depending on the specific requirements and characteristics of the biomedical signal processing task at hand. Overall, DRL holds significant promise for advancing the field of biomedical signal processing, offering efficient and adaptive solutions for a wide range of clinical applications.

D. Hybrid DL

DL models exhibit a spectrum of strengths and weaknesses concerning hyperparameter tuning and data exploration, as highlighted in previous research. These weaknesses may impede their efficacy across various applications. However, each DL model possesses unique characteristics that render it efficient for specific tasks. To address these shortcomings and leverage the strengths of individual DL models, hybrid DL models have been proposed. These hybrids combine elements of different DL architectures to mitigate weaknesses and enhance performance for specific applications.

Among these hybrid models, CNNs and RNNs stand out as widely utilized and versatile frameworks with high applicability and potentiality. CNNs excel in extracting spatial features from data, making them particularly suited for tasks involving images or sequential data, such as ECGs and EEGs. On the other hand, RNNs specialize in capturing temporal dependencies in sequential data, making them practical for time-series analysis and sequential pattern recognition, essential in fields like speech recognition and natural language processing. By combining the strengths of CNNs and RNNs, hybrid DL models can tackle a broader range of challenges and offer more robust solutions in biomedical signal processing and other domains. However, the selection and design of hybrid models depend on the specific requirements and characteristics of the application, highlighting the importance of tailored approaches in leveraging the full potential of DL in real-world scenarios.

IV. DISCUSSION

In classification tasks, assessing the performance of DL models necessitates the utilization of various metrics to accurately evaluate their effectiveness in classifying data. These metrics offer insights into different facets of the model's performance and aid in determining its efficacy in data classification [35]. Commonly employed metrics for evaluating DL models in classification tasks encompass accuracy, precision, recall, F1-score, area under the receiver operating characteristics curve, false alarm ratio, and misdetection ratio [36].

Accuracy: This metric is primarily utilized in classification problems to quantify the correct predictions made by a DL model. It is calculated as depicted in Eq. (1), where T_P represents true positives, T_N denotes true negatives, F_P signifies false positives, and F_N indicates false negatives.

$$A = \frac{T_N + T_P}{F_N + F_P + T_N + T_P} \times 100 \quad (1)$$

Precision: Precision pertains to the ratio of true positives to the total number of positive predictions, encompassing both true positive and false positive instances. It can be expressed mathematically by Eq. (2).

$$P = \frac{T_P}{T_P + F_P} \times 100 \quad (2)$$

Recall (detection rate): This metric evaluates the proportion of positive samples correctly classified relative to the total number of positive samples. It is quantified according to Eq. (3), thereby indicating the model's proficiency in classifying positive samples, among others.

$$R = \frac{T_P}{T_P + F_N} \times 100 \quad (3)$$

F1-Score: Derived from the precision and recall of the test, the F1-Score integrates both metrics to provide a balanced measure of a model's performance as follows.

$$F = \frac{2T_P}{2T_P + F_N + F_P} \times 100 \quad (4)$$

Area under the receiver operating characteristics curve (AUC): AUC is a pivotal metric in classification problems, offering insights into the model's performance. The Receiver Operating Characteristic (ROC) curve illustrates the trade-off between sensitivity and specificity in DL models. The AUC value, ranging from 0 to 1, signifies the model's discriminative ability, with higher values indicative of superior performance. It is computed using Eq. (5), where *x* represents the varying AUC parameter.

$$AUC = \int_{x=0}^{1} \frac{T_P}{T_P + F_N}\left(\left(\frac{F_P}{F_P + T_N}\right)^{-1}(x)\right)dx \quad (5)$$

False alarm ratio: Also known as the false positive rate, this metric quantifies the likelihood of a false alarm being triggered, wherein a positive result is generated when the actual value is negative. It can be calculated by Eq. (6).

$$FAR = \frac{F_P}{T_N + F_P} \times 100 \quad (6)$$

Misdetection ratio: This metric signifies the percentage of misclassified samples, highlighting instances where the model fails to detect the correct class. It is expressed as the percentage of samples that remain undetected, as demonstrated in Eq. (7).

$$MR = \frac{F_N}{T_P + F_N} \times 100 \quad (7)$$

In the domain of biomedical signal processing, learning strategies encompass a range of techniques tailored to address the unique challenges and requirements of analyzing physiological data. These strategies comprise online learning, federated learning, and transfer learning, each offering distinct advantages and applications in biomedical signal analysis, as summarized in Table VI.

TABLE VI. LEARNING STRATEGIES IN BIOMEDICAL SIGNAL PROCESSING

Learning Strategy	Description	Advantages	Applications
Online Learning	Involves continuously updating DL model parameters as new data becomes available, facilitating real-time adaptation to changing signal patterns and dynamic monitoring and interventions for patients.	Real-time adaptation, dynamic monitoring, responsiveness to evolving patterns	Dynamic monitoring of patient health, adaptive interventions, real-time decision-making in healthcare
Transfer Learning	Leverages knowledge from training on one dataset to improve performance on related but different datasets, allowing DL models trained on one type of physiological data to be adapted and applied to similar tasks with different data modalities.	Utilization of existing knowledge, enhanced generalization and efficiency	Generalization across different data modalities, adaptation to new tasks with limited labeled data
Federated Learning	Enables DL models to be trained over distributed data sources while maintaining data privacy, facilitating collaborative model training using data from multiple healthcare institutions without compromising patient privacy.	Data privacy preservation, scalability, reduced computational burden	Collaborative model training across multiple healthcare institutions, robust and generalizable model development

Online learning involves continuously updating the DL model's parameters as new data becomes available. In biomedical signal processing, online learning enables real-time adaptation to changing signal patterns, facilitating dynamic monitoring and adaptive interventions for patients [37]. The purpose of online learning in biomedical signal processing is to optimize the accuracy and adaptability of prediction models by leveraging prior predictions [38]. Contrary to offline or batch machine learning strategies, which necessitate the entire training dataset to be available for training, online learning models operate dynamically, continuously updating their parameters with each new data instance in a sequential stream. This real-time updating process enables online learning models to adapt to evolving patterns and dynamics within biomedical signals swiftly, facilitating dynamic monitoring and responsive interventions for patients.

By iteratively refining their predictive capabilities based on incoming data, online learning models can effectively capture temporal dependencies and subtle changes in signal characteristics, enhancing their ability to provide accurate and timely predictions in clinical settings [39]. Furthermore, the sequential nature of online learning aligns well with the streaming nature of many biomedical signal data sources, enabling seamless integration and analysis of continuous streams of physiological data. Thus, online learning serves as a valuable approach in biomedical signal processing, enabling efficient model adaptation and real-time decision-making in healthcare applications. Through this continual learning process, the online model endeavors to optimize its predictive accuracy and adaptability, ultimately achieving better performance in classifying or predicting outcomes in real-world applications.

Transfer learning leverages knowledge gained from training on one dataset to improve performance on a related but different dataset [40]. In the context of biomedical signal processing, transfer learning allows DL models trained on one type of physiological data (e.g., ECG signals) to be adapted and applied to similar tasks with different data modalities (e.g., EEG signals), thereby enhancing model generalization and efficiency. Training DL models from scratch demands substantial computational resources, memory allocation, and abundant labeled datasets. However, in specific scenarios, the availability of vast annotated datasets is not always feasible or practical. This limitation poses a significant challenge, particularly in domains such as biomedical signal processing, where data acquisition and annotation can be resource-intensive and time-consuming. As a result, researchers often encounter constraints when attempting to develop robust DL models for analyzing biomedical signals. The scarcity of labeled datasets presents a bottleneck in traditional DL approaches, hindering the model's ability to generalize effectively to unseen data and limiting its performance in real-world applications.

Moreover, the computational and memory requirements for training large-scale DL models exacerbate these challenges, making it difficult to deploy them in resource-constrained environments. Alternative strategies such as transfer learning, semi-supervised learning, and unsupervised learning have emerged as promising approaches in biomedical signal processing to address these limitations [41]. These strategies leverage existing knowledge from pre-trained models or exploit unlabeled data to enhance model performance without the need for extensive labeled datasets. By leveraging transfer learning, for instance, researchers can adapt pre-trained models on related tasks or domains to biomedical signal processing tasks, thereby reducing the dependency on large annotated datasets while still achieving competitive performance. Similarly, semi-supervised and unsupervised learning techniques enable the utilization of unlabeled data to augment the training process, facilitating the discovery of underlying patterns and structures within biomedical signals. In transfer learning, a pre-trained neural network, typically trained on an extensive dataset for a related task, serves as the basis for learning new tasks or domains with limited labeled data.

Federated learning enables DL models to be trained over distributed data sources while maintaining data privacy. In biomedical signal processing, federated learning facilitates collaborative model training using data from multiple healthcare institutions, enabling the development of robust and generalizable models without compromising patient privacy [42]. In conventional centralized DL systems, collected data is typically kept on local devices. Centralized DL involves storing user records on a central server and utilizing them for both training and testing functions. However, this centralized approach is not without its limitations. One significant drawback is the requirement for high computational power, as all data processing and model training tasks are performed on the central server. This can lead to scalability issues, mainly when dealing with large datasets or complex DL models, requiring substantial computational resources to achieve acceptable performance.

Furthermore, centralized DL systems may raise concerns regarding security and privacy. Centralizing sensitive user data on a single server increases potential vulnerabilities and unethical access, compromising user privacy and confidentiality. Moreover, compliance with data protection regulations, such as GDPR or HIPAA, becomes more challenging in centralized systems due to the centralized storage and processing of user data. To address these shortcomings, decentralized approaches, such as federated learning, have emerged as promising alternatives. Federated learning enables model training to be performed locally on user devices, with only model updates aggregated on a central server. This distributed method maintains data confidentiality by keeping user data on local devices, reducing the risk of data exposure, and enhancing security. Additionally, federated learning reduces the computational burden on the central server, making it more scalable and efficient for training DL models on decentralized data sources.

V. Future Directions and Opportunities

The area of DL for biomedical signal processing has great potential to improve healthcare delivery, enhance patient satisfaction, and enable discoveries in the future. Some important issues to concentrate on and possible paths to investigate include:

- Interdisciplinary collaboration: Facilitating interdisciplinary cooperation between DL scientists and healthcare, biological, or signal processing experts can produce new solutions specifically fitting the requirements of biomedical signal processing. By combining knowledge from multiple domains, researchers can increase their understanding of complex biological processes. This will result in more generalizable methods for disease diagnosis, health monitoring, and personalized treatment.

- Integration of multi-modal data: Since biomedical data includes a variety of modalities, such as ECG, EEG, EMG, and medical imaging, the integration of these multi-modality signals may offer a unique prospect to exploit interdependencies and improve diagnostic reliability. DL models can agilely harmonize and pool the diverse modalities to discover vital information, which could, in turn, unravel the mysteries behind diverse biological underpinnings.

- Real-time monitoring and intervention: Recent developments in DL algorithms and advances in hardware acceleration technologies make the vision of deploying real-time monitoring systems for continuous health monitoring and early detection of anomalies possible. Such systems have the potential to allow for timely intervention and personalized care plans that all combine into improved care outcomes and reduced healthcare costs.

- Explainable AI and interpretability: Improving the comprehensibility of deep learning models is essential for establishing confidence among physicians and healthcare practitioners. Future research should prioritize the development of explainable AI approaches that provide insights into the decision-making process of DL models. This will allow doctors to comprehend and evaluate model predictions within the framework of clinical practice.

- Continuous learning and adaptation: Implementing mechanisms for constant learning and adaptation within DL models can enhance their ability to respond dynamically to evolving patient conditions and healthcare requirements. By incorporating feedback loops and reinforcement learning techniques, models can continually update and refine their predictions based on new data, enabling proactive interventions and personalized healthcare management.

- Remote monitoring and telehealth: The proliferation of wearable devices and remote monitoring technologies presents opportunities for leveraging DL in telehealth applications. DL models can analyze data from wearable sensors and remote monitoring devices to monitor patient health remotely, detect early warning signs of deterioration, and facilitate virtual consultations with healthcare providers, particularly in underserved or remote areas.

- Patient stratification and precision medicine: DL models may give valuable support to patient stratification and precision medicine by discovering natural clusters of patients with shared attributes in terms of clinical and biological characteristics and by predicting the response to treatment on an individual basis. This patient-specific guidance would allow for the personalization of treatment strategies, thus allowing for maximization of therapeutic benefit while minimizing collateral toxicity, with the ultimate goal of enhancing patient satisfaction.

- Standardization and benchmarking: In this context, standardization of pre-processing enforces the core virtues of reproducibility, comparability, and reliability across studies. This goal can be achieved by sharing standardized datasets, assessment protocols, and benchmarks through community-wide efforts to benefit progress and translational efficacy.

- Domain-specific architectures: Designing domain-specific deep learning architectures based on the unique features of biomedical signal data works in alleviating the model performance and interpretability. For instance, using architecture like RNNs with attention mechanisms in the time-series data or CNNs specifically tailored for medical imaging data instead of raw architectures better captures the complex temporal and spatial patterns existing far more robustly in biomedical signals.

- Multi-task learning: Multi-task learning paradigms, where DL models are trained to accomplish multiple related tasks concurrently by sharing a common input representation, may enable better knowledge transfer across tasks. For example, in biomedical signal processing, multi-task learning may allow models to predict multiple clinical outcomes or physiological parameters at the same time, allowing knowledge to propagate between tasks and hence improving the model's generalization capability.

- Resource-constrained environments: Techniques in deep learning can be extended to address the needs of resource-constrained environments, for instance, those involving low-power devices or the healthcare infrastructure of many developing countries. Therefore, in order to make these cutting-edge healthcare technologies available worldwide, we need more research on lightweight and efficient DL models, data compression, and edge computing so that these can be deployed to resource-constrained settings without compromising on performance and accuracy.
- Integration with Electronic Health Records (EHRs): Integrating DL models with EHRs can help clinicians glean meaningful knowledge from the wealth of clinical data, allowing for predictive analytics, disease surveillance, and decision support. Leveraging data fields of EHRs, DL models can assist with improving clinical decision-making, streamlining administrative tasks, and increasing healthcare operational efficiency.

VI. Conclusion

In this survey, we thoroughly reviewed the DL-based signal processing methods for the processing of biological signals. We covered a wide variety of DL-based models, including deep supervised, deep unsupervised, DRL, and hybrid models. All of these models have unique advantages, characteristics, and applications in biological signal processing. We discussed the drawbacks of conventional signal processing methods and motivated using DL models in biological signal processing, which can learn intrinsic features and automatic optimization independently. We then provided a brief introduction of each biological signal (e.g., ECG, EEG, and EMG) and presented a brief review of their clinical significance. We then put the problem in context by explaining the relevance of signal processing in the healthcare diagnostics and monitoring domain. We also discussed related works and the limitations of using DL with biological signals. The primary challenges to using DL in this context are the need for labeled data, heavy computational requirements, and the non-intuitive nature of the DL model. We also discussed some potential future works and emerging trends that are likely to drive this field, such as the need for collaborative and interdisciplinary investigations, multi-modal data integration, and the ethical concerns of DL for healthcare. We showed the possible ways the DL model could be used for real-time monitoring, telemedicine, and precision medicine, as well as the importance of standardization, benchmark databases, and ethical guidelines to ensure sustainable advances. In addition, we discussed the potential of DL to address global health crises and healthcare disparities, seeing the exciting possibilities of DL to reshape healthcare and individual health.

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