Opportunities and Challenges in Deep Learning Methods on Electrocardiogram Data: A Systematic Review

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ABSTRACT

Background: Electrocardiogram (ECG) is one of the most commonly used diagnostic tools in medicine and healthcare. Deep learning methods have achieved promising results predictive healthcare tasks using ECG signals.
Objective: This paper conducts a systematic review of deep learning methods on ECG data from both model and application perspectives.
Methods: We extracted papers that deploy deep learning (deep neural networks) models on ECG data that published between January 1st 2010 and February 29th 2020 from Google Scholar, PubMed, and DBLP. We then analyze them in three aspects, including task, model, and data. Last we discuss open challenges and unsolved problems in this area.
Results: The total number of papers is 191; among them, 108 papers are published after the year 2019. Almost all kinds of common deep learning architectures have been used in ECG analytics tasks like disease detection/classification, annotation/localization, sleep staging, biometric human identification, denoising, and so on.
Conclusion: The number of works about deep learning on Electrocardiogram data is growing explosively in recent years. Indeed, these works have achieved a far better performance in terms of accuracy. However, there are some new challenges and problems like interpretability, scalability, efficiency, which need to be addressed and paid more attention. Moreover, it is also worth investigating by discovering new interesting applications from both the dataset view and the method view.
Significance: This paper summarizes existing deep learning methods on modeling ECG data from multiple views while also point out existing challenges and problems while it can become a potential research direction in the future.

1. Introduction

Electrocardiogram (ECG/EKG) is one of the most commonly used non-invasive diagnostic tool that records physiological activities of heart over a period of time. ECG can help diagnose many cardiovascular abnormalities such as premature contractions of atria (PAC) or ventricles (PVC), atrial fibrillation (AF), myocardial infarction (MI), and congestive heart failure (CHF). In recent years, we have witnessed a rapid development of portable ECG monitors in the medical area such as Holter [125], and wearable devices in healthcare areas such as Apple Watch. Consequently, the amount of ECG data grows rapidly so that human Cardiologists are inadequate for analyzing them. Thus how to analyze ECG data automatically and accurately has become a hot research topic for many years. Moreover, many new emerging applications, such as biometric human identification, sleep staging, can also be implemented based on ECG data.

Traditionally, automatic ECG analysis relies on diagnostic golden rules. As shown in the top of Figure 1, it is a two-stages method that firstly required human experts to engineering useful features from raw ECG data, which we called

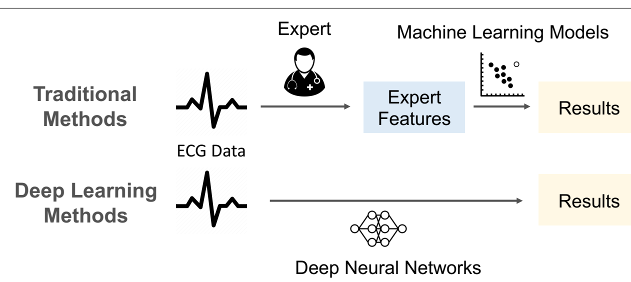

Figure 1: Comparison between traditional methods and deep learning methods.

"Expert Features", then deployed decision rules or other machine learning methods for the final results. Concretely, expert features can be categorized [68] into statistical features (such as heart rate variability [19], sample entropy [3], coefficient of variation and density histograms [168] et al), frequency domain features [147, 103], and time-domain features (such as Philips 12-lead ECG Algorithm [135]). In the implementation, expert features are automatically extracted via computer-based algorithms. However, they are still insufficient since they are limited by data quality and human experts' knowledge [153, 157, 50] .

Recently, deep learning methods have achieved promising results in many application areas such as speech recogni-

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tion, computer vision, and natural language processing [86]. The main advantage of deep learning methods is that they do not require an explicit feature extraction step by human experts, as shown in the bottom of Figure 1. This feature extraction step is done automatically and implicitly by deep learning models due to their powerful data learning abilities and flexible processing architectures. Some studies have experimentally shown that deep learning features are more informative than expert features on ECG data [66, 68]. The performance of deep learning methods is also better than traditional methods on many ECG analysis tasks such as disease detection [30], sleep staging [42], etc.

Although some papers have reviewed machine learning methods on ECG [118] (year 2019), cardiac arrhythmia detection using deep learning [132] (year 2019), deep learning methods on ECG [131] (year 2018), there are no systematic reviews focusing on deep learning methods which we consider them as a promising way to mine the ECG data. Thus, we feel it's amenable and necessary to conduct a systematic review of existing deep learning methods on ECG data from the perspective of the model architecture and their application task. Challenges and problems of current research status are discussed, which, we believe, will give some inspiration and insights for future work.

2. Method

2.1. Search Strategy

In order to conduct a comprehensive review, we searched papers that deployed deep learning methods (deep neural network networks) on ECG data from Google Scholar, PubMed and Digital Bibliography & Library Project (DBLP) from Jan 1 2010 to Feb 29 2020 .

The following general search term were compiled for each database: ("electrocardiogram" OR "electrocardiology" OR "electrocardiography" OR "ECG" OR "EKG" OR "arrhythmia") AND ("deep learning" OR "deep neural network" OR "deep neural networks" OR "convolutional neural network" OR "cnn" OR "recurrent neural network" OR "rnn" OR "long short term memory" OR "lstm" OR "autoencoder" OR "deep belief network" OR "dbn"). All keywords are case insensitive.

To avoid missing papers that not explicitly mentioned the above keywords in title, we expand our search to **all fields in the article**. Note that a vast majority of unrelated papers would more or less mention the above keywords in their introduction part or related work part, which yields a large initial set of papers.

2.2. Study Selection

We only include published peer-reviewed papers but excluding pre-prints. Particularly, we consider papers from the following journals/conferences:

- **Medical Information and Biomedical Engineering (MI & BME)** : Circulation, Journal of the American College of Cardiology (JACC), Nature Medicine, Nature Biomedical Engineering, American Medical Informatics Association (AMIA), Journal of American Medical Informatics Association (JAMIA), Journal of American Biomedical Informatics (JBI), Transactions on Biomedical Engineering (TBME), Computers in Biology and Medicine (CBM), Biomedical Signal Procession and Control, Computing in Cardiology (CinC), Physiological Measurement (PMEA), IEEE Journal of Biomedical and Health Informatics, Computer Methods and Programs in Biomedicine, Journal of Electrocardiology, International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).
- **Artificial Intelligence and Data Mining (AI & DM)**: Nature Machine Intelligence, ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD), AAAI Conference on Artificial Intelligence (AAAI), International Joint Conference on Artificial Intelligence (IJCAI), Neural Information Processing Systems (NeurIPS), IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE Transactions on Neural Networks and Learning Systems (TNNLS), IEEE Transactions on Knowledge and Data Engineering (TKDE), IEEE Transactions on Cybernetics, Neurocomputing, Knowledge-Based System, Expert Systems with Applications, Pattern Recognition Letters.
- **Interdisciplinary Area**: Nature Scientific Reports, PLoS One, IEEE Access.

The process of literature search and selection is shown in Figure 2. It is a four-stages method including identification, screening, eligibility, and included.

The number of papers results in the identification step is 1,621. Then, after removing duplicates, the number of papers is 1,224. Next, the paper eligibility assessment was done from coarse to fine by two independent reviewers - one reviewer first screen titles and abstracts, another reviewer then reading full-text. The excluding criteria are: 1) not in English, 2) Not focus on ECG data, 3) Not deep learning methods, 4) No quantitative evaluations. As a result, 928 papers excluded by screening, 105 papers excluded by full-text assessment. Finally, we result in a list of 191 papers from the initial 1,621 papers.

2.3. Data Extraction and Analysis

For each paper, we analyze them in the following three aspects:

- **Task**: the targeted application tasks include: (1) disease detection, e.g. specific diseases like atrial fibrillation, myocardial infarction, congestive heart failure, ST elevation, or general diagnostic arrhythmia, (2) annotation or localization, e.g. QRS complex annotation, P wave annotation, localizing the origin of ventricular activation, (3) sleep staging, (4) biometric human identification, (5) denoising, and (6) the Others.
- **Model**: deep model architectures include (1) convolutional neural networks (CNN), (2) recurrent neural net-

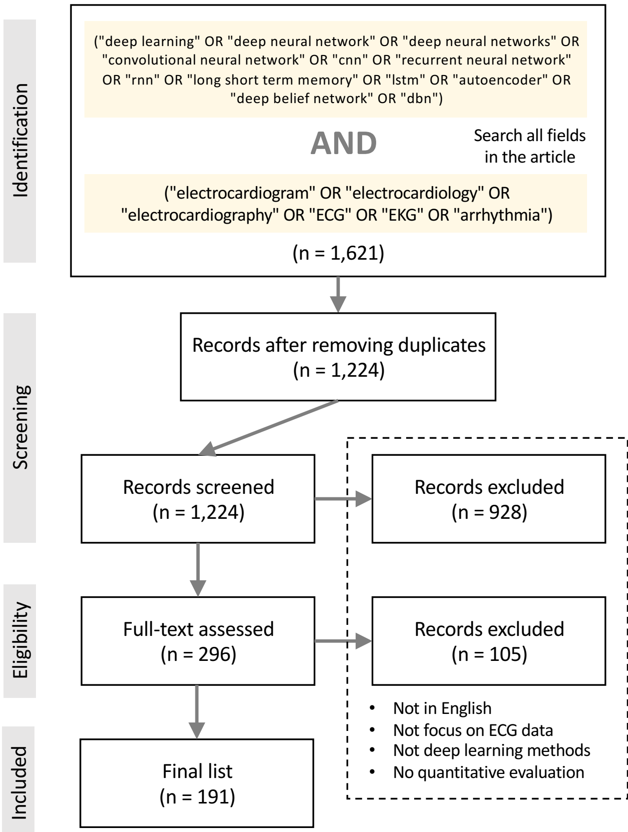

Figure 2: Framework of literature search and selection.

works (RNN), (3) combination of CNN and RNN (CRNN), (4) autoencoders (AE), (5) generative adversarial networks (GAN), (6) fully connected neural networks (FC) and others. Moreover, we also identify (7) whether they include traditional expert features or integrate expert knowledge in building the deep model.

- **Data**: the statistics of data include (1) the size of the dataset, (2) number of channels (number of electrode leads), (3) duration, (4) annotations, (5) sources, (6) collected year, (7) number of used papers.

We summarize all papers from the perspective of Models and Tasks, as shown in Figure 3. Finally, we conclude the challenges and problems that existing models can not handle well.

3. Results

We include 191 papers in the survey, and will analyze them from the aspects of task, model, and data. An overview of the analysis is shown in Figure 3. An overall statistics of these papers is shown in Figure 4. Among them, 108 papers (about 57%) were published after 2019, 112 papers come from medical information and biomedical engineering community, while only 25 papers (about 13%) come from artificial intelligence and data mining community. We will update detailed summarization of each paper on GitHub `https://github.com/hsd1503/DL-ECG-Review`.

3.1. Task

3.1.1. Disease Detection

The goal of developing a deep learning model for disease detection is to map the input ECG data to the output disease target via multiple layers of neural networks. For instance, the detection of cardiac arrhythmias (e.g., atrial flutter, supraventricular tachyarrhythmia, ventricular trigeminy, etc.) [57] is one of the most characteristic tasks to apply deep learning model on ECG signals for cardiac arrhythmias detection. The AF detection can be regarded as a special case of cardiac arrhythmia detection task, where all non-AF rhythms are grouped [169, 225]. Moreover, a deep learning technique is introduced to monitor ST change in ECG data [130]. In [110] and [177], convolutional neural networks were applied to automate the detection of the Myocardial Infarction and Congestive Heart Failure, respectively.

From the perspective of the amount of classification results, multiple modalities (e.g., ECG, transthoracic echocardiogram [8]) are employed for binary classification task (e.g.,patients with paroxysmal atrial fibrillation or Healthy [139]), multi-class classification task (e.g., detection of acute cognitive stress detection [61], decompensation of patients detection [201]) and multi-task classification task (e.g., detection of prevalent hypertension, sleep apnea, and diabetes [170]).

3.1.2. Localization or Annotation

Localization and annotation of specific waves in ECG signals are of great importance to cardiologists in order to help them in diagnosing cardiac diseases such as atrial fibrillation. For instance, AE [51] and RNN [52] are employed to automatically localize the exit of ventricular tachycardia from the 12-lead electrocardiogram. Some studies focused instead on the localization of origins of premature ventricular [203], as well as for the Myocardial Infarction [216].

Most studies that applied deep learning methods to ECG annotation focus on using deep learning methods for the annotation of the fetal QRS complex (detecting the Q-wave, R-wave, and S-wave and calculating the heart rate), which is critical to determine various arrhythmias, from the MIT-BIH arrhythmia dataset [90]. Some studies use the QT database (QTDB) on PhysioNet [46] to explore ways of other types of annotating ECG waves, including P-wave [134], T-wave annotation [10], etc.

3.1.3. Sleep Staging

Understanding sleep is critical for the whole healthcare system, as sleep is a key ingredient to our well-being. Sleep disorder may lead to catastrophes in personal medicine or public health [115]. In [94], sparse autoencoder (SAE) and Hidden Markov model (HMM) are combined to detect obstructive sleep apnea (OSA) using the PhysioNet challenge 2000 dataset. Convolutional Neural Network is used to detect the OSA instead of the SAE-HMM method [115].

In addition to the OSA detection, CNN-based deep learning architecture is also employed for multi-class classification of obstructive sleep apnea and hypopnea (OSAH) [172], which is the most common sleep-related breathing disorder,

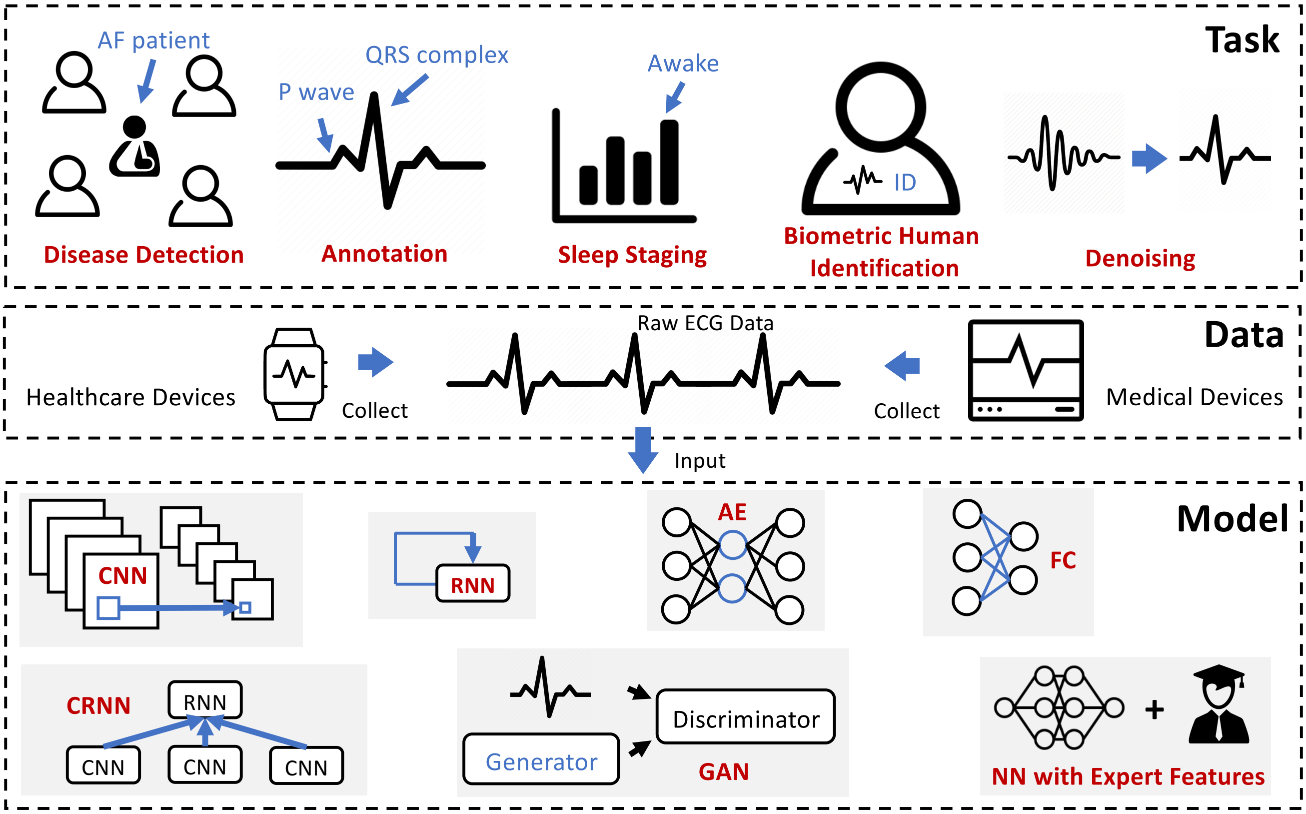

Figure 3: An overview of the analysis from aspects of task, model and data.

	Disease Detection	Anotation or Localization	Sleep Staging	Biometric Identification	Denoising	Others
CNN	[78, 80, 208, 110, 1, 66, 197, 5, 187, 149, 102, 43, 79, 139, 192, 188, 207, 7, 41, 47, 99, 212, 97, 133, 196, 137, 163, 76, 164, 124, 191, 150, 18, 74, 155, 31, 62, 185, 70, 63, 189, 165, 92, 91, 61, 21, 130, 100, 160, 8, 57, 95, 68, 126, 174, 220, 156, 223, 13, 16, 85, 186, 58, 166, 71, 127, 173, 59, 55]	[203, 20, 222, 25, 210, 90, 53, 75, 171, 162, 73]	[115, 172, 35]	[215, 221, 54, 26, 29, 83, 217, 65, 98]	[219, 27, 39, 40]	[152, 9, 117, 11, 156, 6, 204, 158]
RNN	[114, 154, 205, 23, 169, 143, 108, 224, 24, 31, 62, 175, 96, 45, 216, 198, 151]	[10, 134, 52]	[184, 35]	N.A.	[140]	[60]
CRNN	[227, 182, 170, 12, 37, 167, 128, 142, 159, 183, 193, 4, 107, 121, 177, 178, 67, 225, 136, 72, 180, 206, 93, 194, 2, 218, 109, 122, 101]	[211]	N.A.	[111]	N.A.	[34, 144, 201, 49, 226, 138]
AE	[36, 190, 175, 214, 206]	[52, 51]	[94]	N.A.	[27, 195]	[44, 209]
GAN	[178, 45, 223]	N.A.	N.A.	N.A.	[176]	[87, 226, 204, 60, 158]
NN with Expert Features	[66, 5, 187, 114, 43, 47, 70, 96, 169, 76, 68, 151, 123, 202, 93, 85, 58]	N.A.	N.A.	[54]	[219]	N.A.
FC & Others	[199, 200, 116, 129, 113, 77, 38, 123, 202]	N.A.	[35]	[89]	N.A.	[213, 82]

Table 1
Summary of papers from the perspective of models and tasks.

using single-lead ECG recordings. Some studies focused on sleep stage identification other than OSA detection. For example, the LSTM network is employed for [184] from a multi-channel physiological signals dataset (EEG, EOG, and EMG signals), which is collected from the sleep disorders diagnosis center of Xijing Hospital, Fourth Military Medical University.

3.1.4. Human Identification

With the rapid development of information technology, body sensor networks are reshaping people's daily lives, especially in smart health applications. Biometric-based hu-

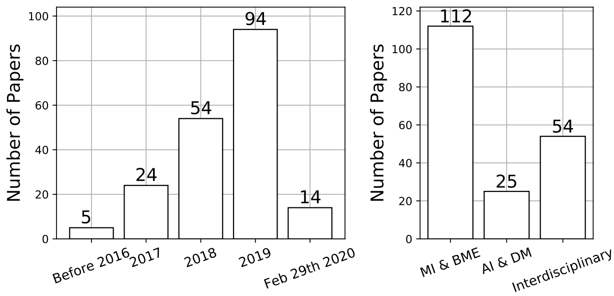

Figure 4: Overall statistics of all papers.

man identification (ID) is a promising technology for automatic and accurate individual recognition using various body sensor data, such as heart rate, temperature, and activity. Zhang et al. built a CNN-based biometric human identification system and evaluated their system using eight datasets from PhysioNet, including CEBSDB, WECG, FANTASIA, NSRDB, STDB, MITDB, AFDB, VFDB and showed better performance using CNN than existing systems. Similarly, PTB Diagnostic dataset (containing 549 15-channels ECG records from 290 subjects) [83] and CYBHi dataset (containing 65 subjects with an average age between 21.64 and 40.56 years old) [54] are used to evaluate the CNN-based biometric human identification method.

Some studies combine CNN and other approaches. Zhao et al. proposed a novel ECG biometric authentication system that incorporates generalized S-transformation (GST) and CNN techniques. A secure multimodal biometric system that uses CNN and Q-Gaussian multi-support vector machine (QG-MSVM) based on a different level fusion is employed in [54].

Besides, the residual network is employed to present an ECG biometric authentication method, which can improve the generalization ability of the method on different ECG signals sampled in the different environments for the matching task [29]. In [89], the features are extracted by the principal component analysis network (PCANet) and then a robust Eigen ECG network (REECGNet) is used on time-frequency representations of ECGs for personal identification. Gated Recurrent Unit (GRU) based method in a bidirectional manner is proposed for human identification from ECG [111].

3.1.5. Denoising

The ECG signals acquisition process is often accompanied by a large amount of noise, which will seriously affect the doctor's diagnosis of patients, especially in the telemedicine environment. In [40], the encoder-decoder convolutional neural network, which is one of the most commonly used techniques, is employed for ECG denoising. Similarly, Xiong et al. and Chiang et al. propose a Fully convolutional network (FCN) based denoising auto-encoder (DAE) method, respectively, for ECG signal denoising. In [88], bidirectional recurrent denoising auto-encoder (BRDAE) is used by providing PPG feature accentuation for pulse waveform analysis.

Moreover, GAN is employed to accumulate knowledge on the distribution of ECG noise continuously through the minimax game between the generator and the discriminator, and the quality of de-noised signals is evaluated against the SVM algorithm [176]. Zhao et al. addresses this issue by proposing a noise rejection method based on the combination of the modified frequency slice wavelet transform (MFSWT) and CNN.

3.1.6. Others

The CNN used in the other types of the studies are mainly including emotion detection [152], drug assessment [9], data compression [213], transfer learning in ECG classification from human to horse [173], etc. The combination of CNN and LSTM is used to learn long-term dependencies (e.g., classifying pulsed rhythm (PR) or pulseless electrical activity (PEA) [34], detecting hypoglycemic events in healthy individuals [138], predicting needs for urgent revascularization [49], classifying the driver stress level[144], etc.). A combination of CNN and hidden Markov models are used to segment the ECG into standard component waveforms and intervals [171].

Besides, AE [44] is used for reconstruction and analysis of biomedical signals. GAN is employed for Electrocardiogram generation [226], synthesis [87], as well as the anomaly beat detection [223]. In the reviewed articles, some method studies the use of deep neural networks to deal with the raw ECG waveform data for future risk prediction (e.g., assess the risk of future cardiac disease [117], sudden cardiac arrest risk prediction [156], mortality prediction [141], physiological measure of health prediction [6] etc.).

3.2. Model

3.2.1. CNN

CNN is a class of deep neural networks widely applied for image classification, natural language processing, and signal analysis. It can automatically extract hierarchical patterns in data using stacked learnable small filters or kernels, which means it requires little pre-processing compared to hand-engineered features. A typical CNN is composed of convolutional layers followed by batch normalization layer, non-linear activation layer, dropout layer, pooling layer in the first stages, and classification layers like fully connected layers in the subsequent stages as done in [57]. In some works, support vector machine, boosting classifier tree, and RNN can also be the alternatives for fully connected layers to summarize the global feature from CNN. CNNs have proved to achieve superior performance and compute fast due to its shared-weights architecture and ability of parallelization.

Two types of CNN are commonly used for ECG classification, namely, 1-D CNN and 2-D CNN. In detail, 1-D CNN works by applying the kernel along temporal dimension on the raw ECG data, while 2-D CNN is usually done on the transformed ECG data such as distance distribution matrix by entropy calculation [99], gray-level co-occurrence matrix (GLCM) [165] or combined feature like morphology, RR intervals, and beat-to-beat correlation [92]. But there is some contradiction when it comes to multi-head ECG or

ECG time-frequency spectrogram extracted by wavelet transform, fast Fourier transform (FFT), and short-term Fourier transform (STFT). Some work like [70] directly applied 2D-CNN on it, but the problem is the different frequency resolutions, meaning that most signal characteristics are reflected by intra-component patterns, not inter-component behaviors. To handle this problem, shared 1-D CNN is used in [78, 110], and multi-scale 1-D CNN is similarily used in [215] for biometric human identification.

In addition, 2-D CNN can be done on a one-head ECG signal treated as an image. In this case, pre-trained ResNet, DenseNet, and Inception-Net on ImageNet dataset [32] can be fine-tuned on an ECG dataset for heartbeat disease detection [185] and examining ST changes [178]. Particularly for Localization tasks such as QRS detection, a fully convolutional network with larger kernel size can be applied on an ECG image to squeeze the image's height size to 1 and keep the output length the same as the input to get the QRS window label [90].

Some advanced techniques, like the atrous spatial pyramid pooling (ASPP) module is used to exploit multi-scale features from ECG. Moreover, active learning [189], data augmentation [178, 225] can be incorporated into the CNN framework to tackle the imbalance problem and further improve the accuracy.

3.2.2. RNN

RNN is a type of neural network naturally designed to model sequential data, such as time series, event sequences, and natural language. It works in the way where the output from the previous step is fed as input to the current step. By iteratively updating the hidden state and memory, it is capable of remembering information in sequence order.

In particular, for ECG data, RNN is a preferred choice for both capturing the temporal dependency and handling varied length input. GRU/LSTM, Bidirectional-LSTM (BiLSTM) are commonly used RNN variants that tackle one critical problem called vanishing gradient caused by vanilla RNN. Two small LSTMs [151] are employed to combine raw ECG features and wavelet transformed features for continuous and real-time execution on wearable devices. In [96], attention mechanism is equipped to BiLSTM for improving performance and interpretability by visualizing the attention weight.

3.2.3. CRNN

CRNN, as the name suggests, is composed of CNN and RNN modules introduced above. It is a preferred architecture to handle long ECG signals with varied sequence length and multi-channel input. 1-D CNN [62] or 2-D CNN [159] is applied to ECG segments for extracting the local features, then RNN summarizes the local features along time dimension to get the global features.

DeepHeart [12] follows the CRNN framework for cardiovascular risk prediction on heart rate sequences extracted from ECG, and utilized an auto-encoder model (see Sec. 3.2.4) to initialize model weights which achieved better performance. Besides, to provide interpretable diagnosis, MINA [67] incorporates CRNN with a multi-level attention mechanism with beat-level, rhythm-level, and frequency-level expert features based on medical domain knowledge.

3.2.4. AE

AE is a type of neural network composed of an encoder module and a decoder module to learn embeddings in an unsupervised manner. The goal of the AE is to learn a reduced dimension representation by the encoder while the decoder tries to reconstruct from the representation as close as the original input. There are three commonly used varients of AE, namely, Denoising autoencoder (DAE), Sparse autoencoder (SAE), and Contractive autoencoder (CAE). DAEs take a partially corrupted input and are trained to recover the original undistorted input, while SAE and CAE utilize different regularization methods like KL-divergence and Frobenius norm of the Jacobian matrix, to learn more robust representations.

Stacked DAE [190], SAE [209, 214], and CAE [195] are widely used for ECG denoising purpose, since ECG signals are prone to be contaminated by various kinds of noise, such as baseline wandering, electrode contact noise and motion artifacts, which may lead to wrong interpretation. In practice, the crux of the matter comes to the choice of the encoder and decoder modules. As introduced in Sec. 3.2.1, 3.2.2, 3.2.3, CNN, RNN, and CRNN would be pairwise combined. [27] utilized the fully convolutional networks as the encoder and decoder while [84] used BiLSTM. To further improve the classification performance, [44, 143, 206] simultaneously carried out the reconstruction and classification procedure. For instance, [206] utilized a 1-D CNN autoencoder to firstly compress large-sized ECG signals with a minimum loss, then an LSTM takes the compressed signals to automatically recognize arrhythmias.

3.2.5. GAN

GAN is a class of neural network framework invented by Ian Goodfellow et. al [48]. This generative model consists of two models: a generative model G that captures the data distribution of the training dataset from a latent representation, and a discriminative model D that distinguishes the probability that a sample produced by the generator from the true data distribution. These two models are trained iteratively to conduct a minimax game.

GAN applications have increased rapidly, especially in areas like image generation [17] and language generation [104]. Recently, it has been applied to tackle the imbalanced-data challenge remaining in ECG data. To name a few, [178] proposed an abnormality detection model for ECG signals based on a CRNN framework and using GAN composed of multiple 1-D CNN to do data augmentation which shows high performance for class-imbalanced dataset. [185] utilized GAN to de-noising the ECG and [226] proposed GAN composed of a BiLSTM (generator) and CNN (discriminator) to generate synthetic ECG data to tackle the problem that a large volume of labeled clinical data is required to train a deep learning model. Similarly, PGAN [45] is proposed to perform personalized ECG classification where subject-specific labeled data is sparse and needed. Here, GAN is optimized with a specialized loss function and learns to synthetically generate personalized ECG signals of different arrhythmias.

3.2.6. *NN with Expert Features*

ENCASE [66] suggests that the expert features can be divided into three categories: 1) Statistical features includes count, mean, maximum, minimum, and so on. 2) Signal procession features that transform ECG data from the time domain to frequency domain, including Fast Fourier Transform (FFT), Wavelet Transform (WT), Shannon entropy, and so on. 3) Medical Features based on medical domain knowledge, for example, features based on P,Q,R,S and T waves, sample entropy, coefficient of variation and density histograms (CDF), and so on.

All the methods mentioned above could benefit a lot from the expert features, although extra efforts are needed to extract them compared to the raw morphological features as the input to Deep Neural Networks (DNN). Nowadays, ensemble methods [66, 70, 187] combine expert features with raw morphological features and incorporate the random forests, boosting tree models with DNN are the state-of-the-art method as far as we know.

3.2.7. *FC & Others*

Some works rely on the FC for disease detection and classification [38, 77], especially for extremely short ECG like only 10-RR-interval [77]. Stacked Restricted Boltzmann machines, a generative stochastic deep neural network, are also used on raw ECG data combined with beat alignment processing to classify heartbeat types [199].

Other works borrow ideas from the computer vision area. To name a few, U-net [148], stemming from the fully convolutional network and consisting of a contracting path and an expansive path is widely used in image segmentation task. [129] proposed a modified U-net to handle varied length ECG for classification and R-peak detection. PCANet [22], an image classification model working with the help of cascaded principal component analysis (PCA), binary hashing, and blockwise histograms, is modified for biometric human identification task in non-stationary ECG noise environment [89]. But its effect remains to be evaluated with the state-of-the-arts baselines introduced in the above sections.

3.3. Data

Most of the works (150 out of 191) used open-source datasets, which makes it easier for follow-up works and reproduction. A summary of the top-10 frequently used open-

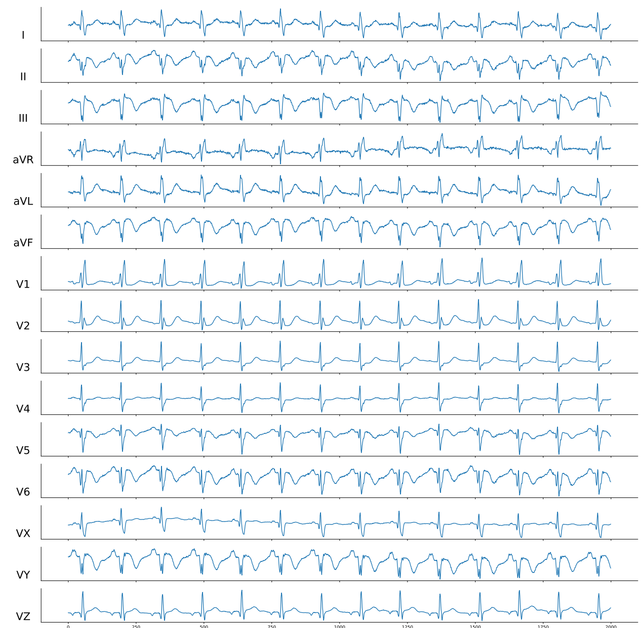

Figure 5: Example of 15-lead ECG data collected from medical devices. The figure shows 10 seconds 15-lead ECG of Myocardial Infarction patient from PTB Diagnostic ECG Database.

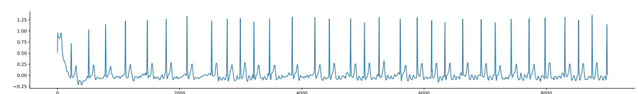

Figure 6: Example of single lead ECG data collected from healthcare devices. The figure shows 30 seconds single lead ECG of AF patient from PhysioNet Computing in Cardiology Challenge 2017 dataset.

source databases is shown in Table 2. In detail, we show the following aspects of each database, which can be used to classify them into further sub-types:

- Sources. Most databases are collected from medical devices, while a few are collected from healthcare devices. The biggest difference is that medical devices data usually have more leads than healthcare devices data so that they are more informative. However, medical devices' data are harder to collect. Healthcare ECG monitor devices like smart hardware and wrist-band are becoming more and more common.
- Number of leads. Standard 12-lead ECG (or even 15-lead ECG) system can observe more abnormalities than single-lead ECG (similar to lead I in 12-lead ECG). For example, posterior wall MI can only be detected in the chest leads (V1-V4), while there is no abnormality in a single lead. Examples of 15-lead ECG from medical devices and single-lead ECG from healthcare devices are shown in Figure 5 and Figure 6, respectively.
- Duration. Short-term ECG (less than several minutes) and long-term ECG complemented each other. Short-term ECG is cheaper, easier to collect. Many cardiac diseases can be detected from short-term ECG so that it is

[1] `https://physionet.org/content/mitdb/1.0.0/`
[2] `https://www.physionet.org/content/challenge-2017/1.0.0/`
[3] `https://physionet.org/content/ptbdb/1.0.0/`
[4] `https://physionet.org/content/afdb/1.0.0/`
[5] `http://2018.icbeb.org/Challenge.html`
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[7] `https://physionet.org/content/nsrdb/1.0.0/`
[8] `https://physionet.org/content/incartdb/1.0.0/`
[9] `https://physionet.org/content/vfdb/1.0.0/`
[10] `https://physionet.org/content/cudb/1.0.0/`

Database	Records	Leads	Duration	Annotations	Source	Year	Papers
MIT-BIH Arrhythmia Database [1]	47	2	30 minutes	Beat Level, rhythm level. (annotations are keeping updating, please refer to https://archive.physionet.org/physiobank/annotations.shtml)	Boston's Beth Israel Hospital	1975-1979	54
PhysioNet/Computing in Cardiology Challenge 2017 [2]	8528 train, 3658 test	1	30 seconds	Rhythm level: normal, AF, other, noise	AliveCor healthcare device	2017	33
PTB Diagnostic ECG Database [3]	549	15	Several minutes	Rhythm level: Myocardial infarction, Cardiomyopathy/Heart failure, Bundle branch block, Dysrhythmia, Myocardial hypertrophy, Valvular heart disease, Myocarditis, Miscellaneous, Healthy controls	National Metrology Institute of Germany	1995	16
MIT-BIH Atrial Fibrillation Database [4]	25	2	10 hours	Rhythm level: AF, atrial flutter (AFL), AV junctional rhythm, and others	Boston's Beth Israel Hospital	1983	8
2018 China Physiological Signal Challenge [5]	6877 train, 2954 test	12	15 seconds	Rhythm level: AF, I-AVB, LBBB, RBBB, PAC, PVC, STD, STE	11 hospitals	2018	7
QT Database [6]	105	2	15 minutes	Onset, peak, and end markers for P, QRS, T, and U waves	Compiled from several existing databases	1997	6
MIT-BIH Normal Sinus Rhythm Database [7]	18	2	24 hours	Beat Level: normal	Boston's Beth Israel Hospital	N.A.	5
St Petersburg INCART 12-lead Arrhythmia Database [8]	75	12	30 minutes	Rhythm level: Acute MI, Transient ischemic attack (angina pectoris), Prior MI, Coronary artery disease with hypertension, Sinus node dysfunction, Supraventricular ectopy, Atrial fibrillation or SVTA, WPW, AV block, Bundle branch block	St. Petersburg Institute of Cardiological Technics	2003	3
MIT-BIH Malignant Ventricular Ectopy Database [9]	22	2	30 minutes	ventricular tachycardia, ventricular flutter, and ventricular fibrillation	Compiled from two separate databases	1986	3
CU Ventricular Tachyarrhythmia Database [10]	35	1	8 minutes	ventricular tachycardia, ventricular flutter, and ventricular fibrillation	Creighton University Cardiac Center	1986	3

Table 2
Summary of databases.

the primary diagnostic tool in the outpatient department. In the meantime, long-term ECG can help to detect occasional diseases like paroxysmal VF, paroxysmal AF, and so on.

- Annotations. Annotations including ECG measurement annotations (Onset, peak, and end markers for P, QRS, T, and U waves), beat level annotations (PVC, PVC, and so on) and rhythm level annotations (covers beat level annotations and others like AF, VF). The annotations require huge efforts of medical experts.

Specifically, the following databases are mostly used by existing papers:

- MIT-BIH Arrhythmia Database [120] (MITDB, 54 papers) consists of 48 half-hour ECG records from 47 subjects at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Center). Each ECG data is an 11-bit resolution over a 10 mV range with a sampling frequency of 360 Hz. This dataset is fully annotated with both beat-level diagnosis and rhythm-level diagnosis.
- PhysioNet/Computing in Cardiology Challenge 2017 [30] (33 papers) contains 8,528 de-identified ECG recordings lasting from 9s to just over 60s and sampled at 300Hz by the AliveCor healthcare device. Among them, 5154 recordings are normal, 717 recordings are AF, 2,557 recordings are others, and 46 recordings are noise. Besides, 3,658 test recordings remain private for scoring. The dataset was collected from healthcare devices.
- PTB Diagnostic ECG Database [15] (PTBDB, 16 papers) contains 549 15-channels ECG records from 290 subjects. The sampling rate is available at up to 10 kHz. Among these subjects, 216 of them have 8 types of heart disease patients, and 52 of them are healthy control, while 22 is unknown.
- MIT-BIH Atrial Fibrillation Database [119] (AFDB, 8 papers) includes 25 ten hours long-term 2-lead ECG recordings sampling at 250 Hz of human subjects with AF (mostly paroxysmal). The original recordings were made at Boston's Beth Israel Hospital using ambulatory ECG recorders with a 0.1 Hz to 40 Hz recording bandwidth.
- 2018 China Physiological Signal Challenge [106] (CPSC, 7 papers) contains 6,877 (3178 female, 3699 male) 12-lead ECG recordings lasting from 6 s to just 60 s, collected from 11 hospitals sampled as 500 Hz. Among them, 918 recordings are normal, 1,098 recordings are AF, 704 recordings are first-degree atrioventricular block, 207 recordings are left bundle branch block (LBBB), 1,695 recordings are right bundle branch block (RBBB), 556 recordings are PAC, 672 recordings are PVC, 825 recordings are ST-segment depression, 202 recordings are ST-segment elevated. Besides, 2,954 test recordings remain private for scoring.

4. Discussion of Opportunities and Challenges

In this section, we will discuss current challenges and problems of deep learning on ECG works. In the meantime, potential opportunities are also identified, along with these challenges and problems.

4.1. Data Collection

As shown in Table 2, we can see that there is no standard about collection procedures - they have varied leads, duration, sources (background of subjects), etc. This problem makes it difficult to fairly compare results among different datasets. Besides, high-quality data and annotations are hard to get, so that many recent works are still using MIT-BIH Arrhythmia Database, which is collected over 40 years ago. The most recent single lead PhysioNet/Computing in Cardiology Challenge 2017 and 12-lead 2018 China Physiological Signal Challenge are really good, but they are both short-term ECG. Researchers will welcome a new collected high-quality long-term ECG with annotations, and it will definitely inspire new innovative studies.

4.2. Interpretability

Deep learning models are often regarded as black-box models because they usually have many model parameters or complex model architecture, which is hard for a human to understand the reason why a certain result is given by the model. This challenge is much severer in medical domain tasks since diagnosis without any explanation is not acceptable by medical experts.

There are a few works noticed enhancing interpretability on ECG deep learning methods. For example, some works [96, 68] explicitly add interpretable expert features on deep learning methods, can use them for partial interpretation. Others using multi-level attention weights [67], or attribution score [164] to show salient maps learned over raw ECG data. There are also several works [159, 68] demonstrate lower dimensional embeddings using t-SNE [112] as interpretation results.

Here, we point out that there are two worth studying directions. The first one is how to interpret a complex deep learning model by a relatively simple model. For example, one can first build a black-box deep learning model for a specific task, then build a separate interpretable simple model which accords with deep learning model's prediction, and interpret the prediction based on the simple model [145, 146]. The second one is how to directly build an interpretable deep model. For example, when designing deep model architecture, one can borrow neuron connection ideas from tree-based model [179], or adding attention mechanism on hidden layers [28, 67], which can be better understood by a human.

4.3. Efficiency

Since deep models are much more complex, it's hard to deploy big models to portable healthcare devices, which is a huge obstacle to applying deep learning models on real-world applications. In this situation, a promising research direction is the model compression technique. For example, knowledge distillation is commonly used to transform a big and powerful model to a simple model with minor accuracy decrease [64]. Also, we can use the quantization, weight sharing, and careful coding of network weights [56] to compress a big model.

4.4. Integration with Traditional Methods

Most of existing deep learning models are trained end-to-end, so it is hard to integrate with traditional expert features based methods once the model finished training [131].

To handle this, there are two research lines to tackle the aforementioned problems. The first one is to use existing expert knowledge to design deep neural network architecture [69]. For example, [67] proposed to guide multi-level attention weights via expert features for modeling ECG. The second one is to regard deep models as feature extractors and explicitly extract latent embeddings from deep learning models. To some extent, NN with expert features methods are working toward this. Then one can easily combine expert features with deep features and build traditional machine learning methods on them.

4.5. Imbalanced Labels

The ECG disease labels are very likely to be a biased distribution since many severe diseases happen rarely, but they are actually much more important. It is hard to train an effective deep learning method with a large number of model parameters on such a small dataset.

There are two ways to handle this problem. The first one is data augmentation such as data preprocessing using the side-and-cut technique, or generating more training dataset using generative models like variational autoencoders (VAE) [33] or GAN [48]. The second one is to design new loss functions like Focal loss [105], or other model training schema like few shot learning [181].

For example, [225] uses skewness-driven dynamic data augmentation to balance the data distribution. [223] and [45] deploy GAN to improve classification and anomaly detection respectively. [74] eliminates the negative effect of imbalanced data from the views of resampling, data feature, and algorithm altogether.

4.6. Multi-modal Data

Currently, most works only consider ECG for analysis; a few works consider joint analyzing with other data sources. For example, [201] predicts ICU patients' moralities based on a combination of interventions, lab tests, vital signs, and ECG. [54] designs a multi-modal biometric authentication system using a fusion of ECG and fingerprint.

With the development of medical devices and healthcare devices, many other vital signs like temperature, respiratory rate, blood pressure can also be collected along with ECG. However, these data are not always synchronized in the timeline, and their sampling frequencies are also varied, so they can be regarded as multi-modal data. It is a potential opportunity to study on how to design a model that is capable of utilizing these multi-modal data simultaneously to improve task performance compared with the model trained on any individual data.

4.7. New Emerging Interdisciplinary Studies

Finally, there remains some innovative new emerging interdisciplinary studies. To name a few: 1) Safe Driving Intensity (SDI) and Cardiac Reaction Time (CRT) assessment from ECG signals [81]. 2) emotion detection from ECG [161]. 3) mammalian ECG analyzing [14]. 4) estimate age and gender from ECG data [6]. The key of achieve above studies is the support of data.

5. Conclusion

In this paper, we systematically reviewed existing deep learning (deep neural network) methods on ECG data from the perspective of model, data, and task. On the one hand, we found that deep learning methods can achieve better performance than traditional methods of ECG modeling. On the other hand, there are still some unresolved challenges and problems with these deep learning methods. Our contribution is twofold: (1) we provide a systematic overview of various deep learning methods that can be employed in real applications for engineers. (2) we highlight some potential research opportunities for researchers.

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