

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

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**Abstract—Objective:** To conduct a systematic review of deep learning methods on Electrocardiogram (ECG) data from the perspective of model architecture and their application task.

**Methods:** First, we extensively searched papers deploying deep learning (deep neural network networks) on Electrocardiogram data that published between January 1st 2010 and September 30th 2019 from Google Scholar, PubMed and DBLP. Then we analyze them in three aspects including task, model and data. Finally, we conclude unresolved challenges and problems that existing models can not handle well.

**Results:** The total number of papers is 124, among them 97 papers are published after in recent two years. 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 achieve a far more 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 to investigate 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 can become potential research direction in the future.

**Index Terms**—deep learning, deep neural network(s), Electrocardiogram (ECG/EKG), a systematic review.

## I. INTRODUCTION

Electrocardiogram (ECG/EKG) is 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 monitor in medical area such as Holter [1], and wearable devices in healthcare area 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 an hot research topic for many years. Moreover,

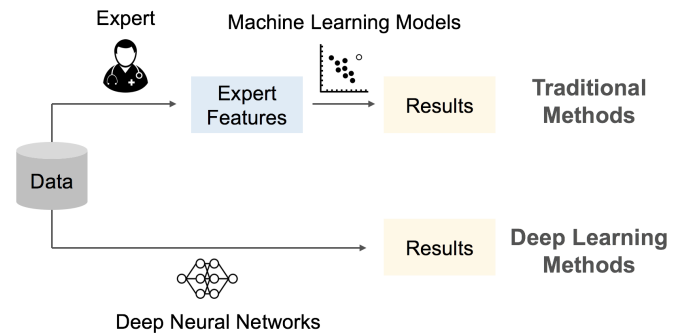


Fig. 1. Comparison between traditional methods and deep learning methods.

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 which firstly required extracting *expert features* from raw ECG data, then deployed decision rules or other machine learning methods for the final results. The feature extraction step is mostly done by human experts. Hence, it is labor intensive and limited [2], [3], [4].

Recently, deep learning methods have achieved promising results on many data analytic applications such as speech recognition, image classification, computer vision, and natural language processing [5]. The main difference between deep learning methods and traditional methods is that they don't 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 [6], [7]. The performance of deep learning methods are also better than traditional methods on many ECG analysis tasks such as disease detection [8], sleep staging [9] and so on.

Although some papers have reviewed deep learning methods

on cardiovascular images [10], or more general Cardiology [11], 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 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 the future work.

## II. METHOD

### A. Literature Search and Selection

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 DBLP from January 1st 2010 to September 30th 2019. The searched keywords are a combination of “deep learning”, “deep neural network”, “deep neural networks” and “Electrocardiogram”, “ECG”, “EKG”. We listed the search results of paper source as follows:

- **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), Biomedical Signal Process and Control, Computing in Cardiology (CinC), Physiological Measurement (PMEA), Computers in Biology and Medicine, IEEE Journal of Biomedical and Health Informatics
- **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 (NIPS), International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), 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.
- **Interdisciplinary:** Nature Scientific Reports, PLoS One, IEEE Access.

The framework of literature search and selection is shown in Figure 2. It is a two-stages method including search and selection. To avoid missing papers that not explicitly mentioned their method in title, or named their method as some other names without above keywords. We expand our search field to “anywhere in the article”, then manually filter out papers that don't use deep learning from them. Notice that a large majority of unrelated papers would more or less mention above keywords in their introduction part, related work part and so on. Thus, we result in the final list of deep learning papers

(124 papers) on ECG would be much less than initial search (727 papers).

### B. Literature 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 networks (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) but whether they include traditional expert features or integrate expert knowledge in building the deep model.
- **Data:** the statistics of data includes (1) the size of dataset, both number of samples and duration of each sample, (2) sampling frequency, and (3) number of channels (number of electrode leads).

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

## III. RESULTS

We include 124 papers in analysis, from 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. Notice that 97 papers (about 78%) are published after 2018, 65 papers come from medical information and biomedical engineering community, while only 20 papers (about 16%) come from artificial intelligence and data mining community. In the rest of Results section, we will discuss more details from aspects of task, model and data.

### A. Task

1) *Disease Detection:* The goal of developing a deep learning model for disease detection is to map the input ECG/EKG data to the output disease target via multiple layers of neural networks. For instance, convolutional neural networks is applied on ECG/EKG signals for automated detection of cardiac arrhythmias (e.g., atrial flutter, supraventricular tachyarrhythmia, T Ventricular trigeminy, etc.) [18], [47], [14]. The atrial fibrillation (AF) detection can be regarded as a special case of cardiac arrhythmia detection task, where all non-AF rhythms are grouped together [81], [104], [93]. In [32], [16], a deep learning technique is introduced to monitor ST change in ECG/EKG data.

In [53] and [91], convolutional neural networks was applied to automate the detection of the Myocardial Infarction

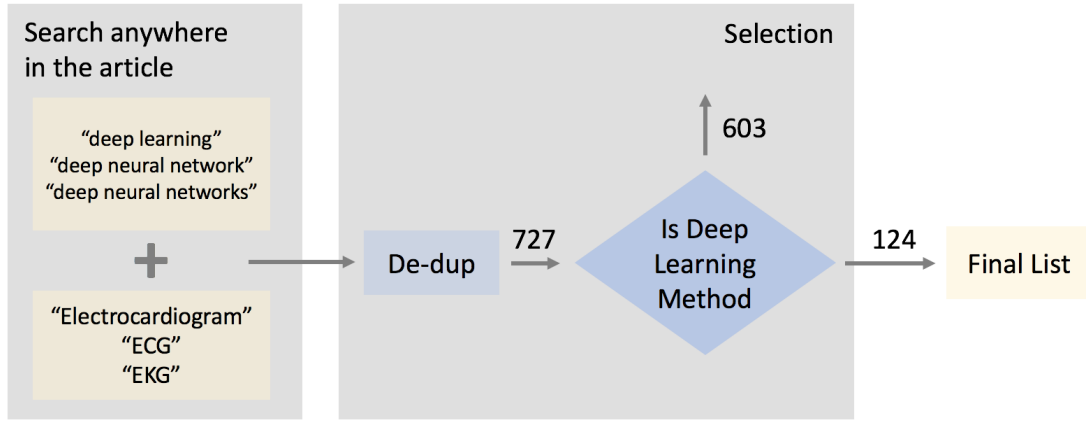


Fig. 2. Framework of literature search and selection.

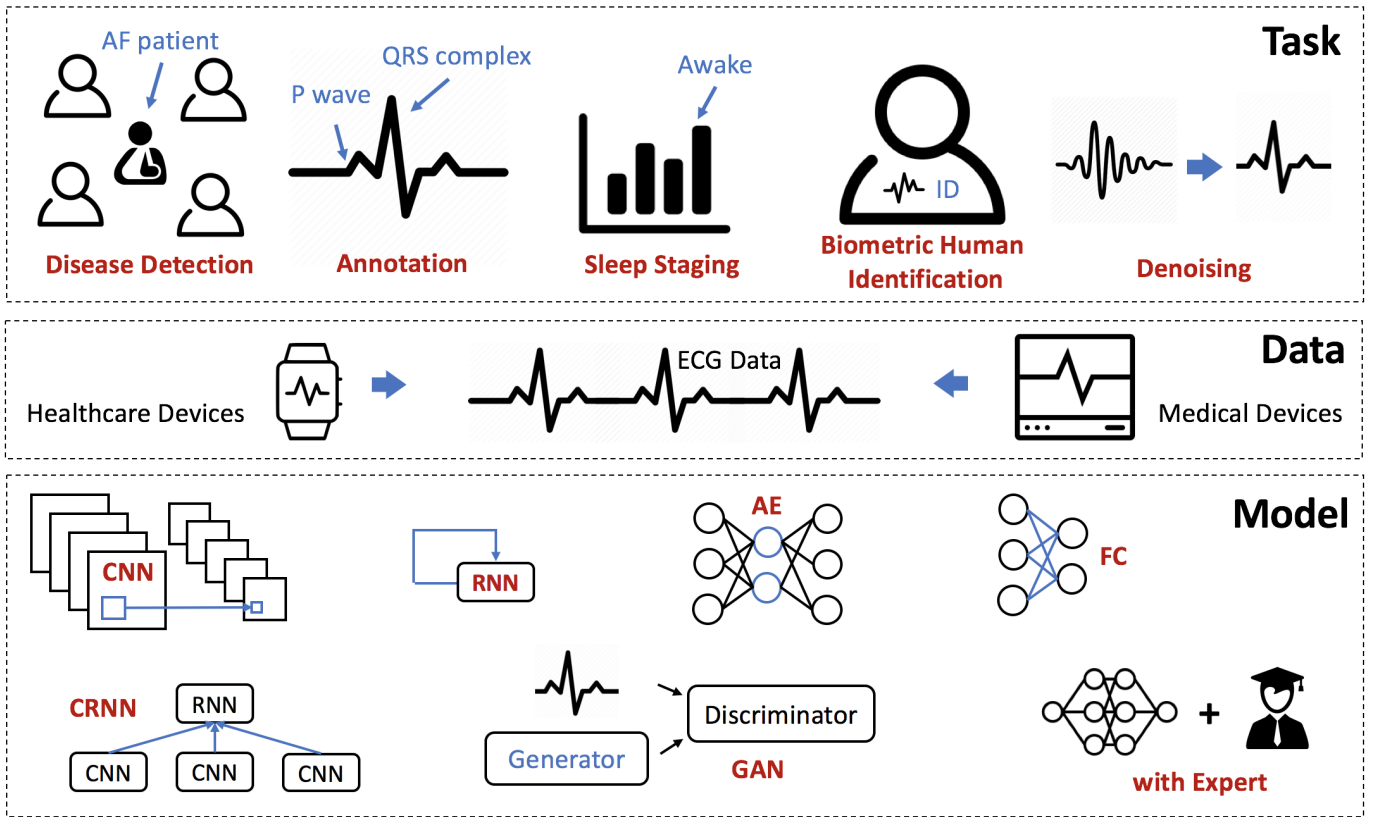


Fig. 3. An overview of the analysis from aspects of task, model and data.

and Congestive Heart Failure respectively. Some studies include data from multiple modalities (e.g., ECG, transthoracic echocardiogram [15]), and support both binary classification (e.g., patients with paroxysmal atrial fibrillation or Healthy [55]), multi-class classification (e.g., detection of acute cognitive stress detection [31], decompensation of patients detection [131]) and multi-task classification (e.g., detection of prevalent hypertension, sleep apnea, and diabetes [89]).

2) *Annotation or Localization*: Annotation and localization of specific waves (e.g., QRS, P-wave) in ECG/EKG signals is of great importance to cardiologists in order to help them diagnosing cardiac disease such as atrial fibrillation. Most studies

which applied deep learning method to ECG/EKG annotation or localization focus on using deep learning method for the QRS detection, P-wave detection, localization of ventricular tachycardia, localization of origins of premature ventricular, as well as for the discovering of the patterns of ECG/EKG.

Autoencoder (AE) [114] and recurrent neural network (RNN) [85] are employed to automatically detecting the exit of ventricular tachycardia from 12-lead electrocardiogram. [62], [63] and [64] focused instead on the annotation of 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.

	Disease Detection	Anotation or Localization	Sleep Staging	Biometric Human Identification	Denoising	Others
CNN	[12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [30], [31], [32], [33], [34], [35], [6], [36], [37], [38], [39], [40], [41], [7], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59]	[60], [61], [62], [63], [64]	[65], [66]	[67], [68], [69], [70]	[71], [72]	[73], [74], [75]
RNN	[76], [24], [25], [77], [78], [79], [80], [81], [82], [83]	[84], [85], [86]	[87]	N.A.	[88]	N.A.
CRNN	[89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], [101], [102], [103], [104], [105], [106]	N.A.	N.A.	N.A.	N.A.	[107], [108], [109], [110]
AE	[111], [76], [112], [113]	[85], [114]	[115]	N.A.	[71], [116], [88]	[117]
GAN	[103]	N.A.	N.A.	N.A.	[118]	[108], [119]
With Expert Features	[21], [6], [37], [38], [78], [41], [7], [81], [47], [56]	N.A.	N.A.	[68]	[72]	N.A.
FC & Others	[120], [121], [122], [123], [124], [125], [126], [127]	[128]	N.A.	[129]	N.A.	[130]

TABLE I  
SUMMARY OF PAPERS FROM THE PERSPECTIVE OF MODELS AND TASKS.

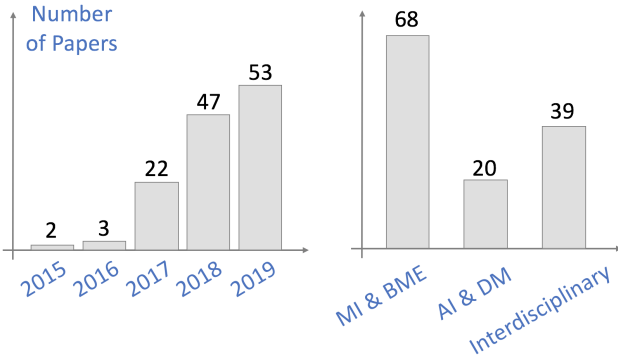


Fig. 4. Overall statistics of all 124 papers.

Some studies use the QT database (QTDB) on PhysioNet to explored ways of other types of annotating ECG/EKG waves, including P-wave [86], [84], T-wave annotation [84], etc.

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 [66]. In [115], sparse autoencoder (SAE) and Hidden Markov model (HMM) are combined together to detect the 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 [66].

To automatically identify the sleep stage, LSTM network is employed for [87] 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. In [65], convolutional neural network (CNN) based deep learning architecture is employed for multi-class classification of obstructive sleep apnea and hypopnea (OSAH), which is the most common sleep-related

breathing disorder, using single-lead electrocardiogram (ECG) recordings.

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 human identification (ID) is a promising technology for automatic and accurate individual recognition using various body sensor data, such as heart rate, temperature and activity. For example, [70] proposes a novel ECG biometric authentication system that incorporates generalized S-transformation (GST) and CNN techniques. Zhang *et al.* built a multiresolution convolutional neural network (MCNN) based biometric human identification system [67] and evaluated their system using eight dataset from PhysioNet [132] including CEBSD, WECG, FANTASIA, NSRDB, STDB, MITDB, AFDB, VFDB and showed better performance using CNN than existing systems.

A secure multimodal biometric system that uses convolution neural network (CNN) and Q-Gaussian multi support vector machine (QG-MSVM) based on a different level fusion is employed [68]. Moreover, PTB Diagnostic dataset (containing 549 15-channels ECG records from 290 subjects) [133] and CYBHi dataset (containing 65 subjects with an average age between 21.64 and 40.56 years) [134] are used to evaluate the proposed method. [69] present an ECG biometric authentication method based on parallel multi-scale one-dimensional residual network, which can improve the generalization ability of the method on different ECG signals sampled in the different environment for the matching task. In [129], the features are extracted by the principal component analysis network (PCANet) and then using a robust EigenECG network (REECGNet) based on time-frequency representations of ECGs for personal identification.

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. [72] addresses this issue by proposing a noise rejection method based on the combination of modified frequency slice wavelet transform (MFSWT) and convolutional neural network (CNN). Generative adversarial method is employed for ECG signals de-noising and evaluates the quality of de-noised signals against SVM algorithm. [118]

Xiong *et al.* [116] and Chiang *et al.* [71] propose a denoising auto-encoders (DAEs) and Fully convolutional network (FCN) based DAE method respectively for ECG signal denoising which are evaluated on ECG signals from the bench-marker MIT-BIH Arrhythmia Database and the noises come from the MIT-BIH noise stress test database. In [88], bidirectional recurrent denoising auto-encoder (BRDAE) is used, and the evaluation results on MIMIC-III database indicate that it promises values beyond traditional denoising method by providing PPG feature accentuation for pulse waveform analysis.

6) *Others*: The convolutional neural network (CNN) used in the other types of the studies are mainly including emotion detection [75], and drug assessment [74], data compression [130], etc. In addition to the CNN, Long Short-Term Memory (LSTM) is used to learn long-term dependencies. For instance, [109] use the combination of CNN and LSTM to detect pulse and classify an organized ECG into pulsed rhythm (PR) or pulseless electrical activity (PEA). In [107] and [110], the combination of CNN and LSTM method is employed, respectively, to predict needs for urgent revascularization and classify the driver stress level.

Besides combination of CNN and LSTM, [108] formulated Electrocardiogram generation as a sequential data generation problem using generative adversarial network (GAN). V-lead ECG signals is synthesized from limb leads using an R-peak aligned generative adversarial network (GAN) to [119]. In the reviewed articles, some method study the use of Residual Network (ResNet) to deal the raw ECG/EKG waveform data to assess the risk of future cardiac disease. [73] Risk scores derived from an ECG/EKG measurement do not depend on patient history and can be more generally applicable to new patients, patients with missing health information, or patients from clinically underserved populations. Gogna *et al.* [117] propose a semi-supervised stacked label consistent auto-encoder (AE) for reconstruction and analysis of biomedical signals.

## B. Model

1) *CNN*: Convolutional neural network (CNN) is a class of deep neural networks widely applied for image classification, natural language processing and signal analysis. It can automatically extract hierarchical pattern 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 few stages and classification layers like fully connected layers in the subsequent stages as done in [14]. 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 CNNs. 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 [20], gray-level co-occurrence matrix (GLCM) [27] or combined feature like morphology, RR intervals and beat-to-beat correlation [30]. But there is some contradiction when it comes to multi-head ECG or ECG time-frequency spectrograms extracted by wavelet transform, fast Fourier transform (FFT) and short-term Fourier transform (STFT). Some work like [21] 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 [53] and multi-scale 1-D CNN is similarly used in [67] for biometric human identification.

In addition, 2-D CNN can be done on an one-head ECG signal treated as a image. In this case, pre-trained ResNet, DenseNet and Inception-Net on ImageNet can be fine-tuned on a ECG dataset for heart beat problems detection [28] or examining ST changes [103]. Particularly for Localization task such as QRS detection, fully convolutional network (FCN) with larger kernel size can be applied on a ECG image to squeeze the image' height size to 1 and keep the output length same as input to get the QRS window label [64].

Some advanced techniques like atrous spatial pyramid pooling (ASPP) module is used to exploit multi-scale features from ECG. Moreover, active learning [23], data augmentation [103], [104] can be incorporated into the CNN framework to tackle the imbalance problem and further improve the accuracy.

2) *RNN*: Recurrent Neural Network(RNN) is a type of neural network naturally designed to model sequential data, such as time series, event sequences and natural language text. It works in the way where the output from previous step are fed as input to the current step. By iteratively updating the hidden state and memory, it is capable to remember 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 which tackles one critical problem called vanishing gradient caused by vanilla RNN. In [77], attention mechanism is combined with BiLSTM to provide performance gain and interpretability by visualizing the attention weight.

3) *CRNN*: CRNN, as the name suggests, is composed of CNN and RNN modules introduced above. It's a preferred choice to handle long ECG signal with varied sequence length and multi-channel input. 1-D CNN [24] or 2-D CNN [106] is applied on segments of ECG to extract the local feature followed by BiLSTM to summarize the multiple segments feature long time dimension as the global feature for classification.

DeepHeart [92] follows the CRNN framework for cardiovascular risk prediction, and utilized an auto-encoder model(see Sec. III-B4) to initialize model weights which achieved better performance. In order to provide interpretability for diagnosis decision, recently a model called MINA [93] incorporates CRNN with multi-level attention model where beat, rhythm and frequency-level domain knowledge is extracted and different attentions are learned.

4) *AE*: Autoencoder(AE) is a type of neural network composed of an encoder module and a decoder module used to learn hidden embedding in an unsupervised manner. The goal of the AE is to learn a reduced dimension representation by the encoder while the decoder tries to generate from the representation as close as the original data. There are three commonly used variants 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 method like KL-divergence and Frobenius norm of the Jacobian matrix respectively to learn more robust hidden representation for classification.

Stacked DAE [111], SAE [112] and CAE [116] are widely used for ECG denoising purpose, since ECG signals are prone to be contaminated by various kinds of noise, such as baseline wander, electrode contact noise and motion artifacts, which may lead to wrong interpretation. In practise, the crux of the matter comes to the choice of the encoder and decoder module. As readily introduced in Sec. III-B1, III-B2, III-B3, CNN, RNN and CRNN would be pairwise combined. [71] utilized the fully convolutional networks as the encoder and decoder while [135] used BiLSTM. To further improve the classification performance, [117] simultaneously carried out the reconstruction and classification procedure.

5) *GAN*: Generative adversarial network (GAN) is a class of neural network framework invented by Ian Goodfellow et. al [136]. 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 [137] and language generation [138]. Recently, it has been applied to tackle the imbalanced-data challenge remaining in ECG data. To name a few, [103] proposed an abnormality detection model for ECG signals based a CRNN framework and using GAN composed of multiple 1-D CNN to do data augmentation which shows high performance for class-imbalanced dataset. [28] utilized GAN to de-noising the ECG and [108] 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.

6) *With Expert Features*: According to ENCASE [6], the expert features can be divided into three categories: 1) Statisti-

cal features includes count, mean, maximum, minimum and so on. 2) Signal procession features which transform ECG data from 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 [6], [21], [38] take as the input of the expert features combined 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.

7) *FC & Others*: Some works also rely on the fully connected neural networks (FC) to do disease detection and classification [122], [120] especially for extremely short ECG like only 10-RR-interval [120]. Other works borrow ideas from image vision area. To name a few, U-net [139], stemming from the fully convolutional network (FCN) and consisting of a contracting path and an expansive path is widely used in image segmentation task. [124] proposed a modified U-net to handle varied length ECG for classification and R-peak detection. PCANet [140], a image classification model working with the help of cascaded principal component analysis (PCA), binary hashing, and block-wise histograms, is modified for biometric human identification task in nonstationary ECG noise environment [129]. But its effect remains to be evaluated with the state-of-the-arts baselines introduced in above sections.

### C. Data

The datasets can be categorized into two groups: (1) collected from medical devices, and (2) collected from healthcare devices. The biggest difference is that medical devices data have more channels than healthcare devices data, so that it is more informative. However, medical devices data is also much harder to collect, so that the amount of healthcare devices data is much more. Moreover, most of the works (98 out of 124) used open source datasets, which makes it easier for follow-up works and reproducibility.

Concretely, three most frequently used open source datasets are as follows:

- MIT-BIH Arrhythmia Database<sup>1</sup> [141] (MITDB, 39 papers) consists of 48 half hour ECG records from 47 subjects at Boston's Beth Israel Hospital. 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<sup>2</sup> [8] (28 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

<sup>1</sup><https://physionet.org/content/mitdb/1.0.0/>

<sup>2</sup><https://www.physionet.org/content/challenge-2017/1.0.0/>



recordings are normal, 717 recordings are AF, 2557 recordings are others and 46 recordings are noise.

- PTB Diagnostic ECG Database<sup>3</sup> [133] (PTBDB, 8 papers) contains 549 15-channels ECG records from 290 subjects. The sampling rates 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.

Others including: MIT-BIH Atrial Fibrillation Database [142] (AFDB, 5 papers), MIT-BIH Normal Sinus Rhythm Database (NSRDB, 4 papers), 2018 China Physiological Signal Challenge<sup>4</sup> [143] (CPSC, 3 papers), QT Database [135] (QTDB, 4 papers), St Petersburg INCART 12-lead Arrhythmia Database (INCARTDB, 3 papers), MIT-BIH Malignant Ventricular Ectopy Database (VFDB, 3 papers), CU Ventricular Tachyarrhythmia Database (CUDB, 3 papers), Medical Information Mart for Intensive Care [144] (MIMIC-III, 2 papers), Congestive Heart Failure RR Interval Database (CHF2DB, 2 papers), AHA Database Sample Excluded Record (AHADB, 2 papers), MIT-BIH Noise Stress Test Database [145] (NSTDB, 2 papers), ECG-ID Database [146] (ECGIDDB, 2 papers), BIDMC Congestive Heart Failure Database [147] (BIDMC, 1 paper), MIT-BIH ST Change Database [148] (STDB, 1 paper), ECG Effects of Ranolazine, Dofetilide, Verapamil, and Quinidine [149] (ECGRDVQ, 1 paper), ECG Effects of Dofetilide, Moxifloxacin, Dofetilide+Mexiletine, Dofetilide+Lidocaine and Moxifloxacin+Diltiazem [150] (ECGDMMLD, 1 paper), Long Term ST Database [151] (LTSTDB, 1 paper), European ST-T Database [152] (EDB, 1 paper), Noninvasive Fetal ECG - The PhysioNet Computing in Cardiology Challenge 2013 (1 paper).

Above ECG dataset without providing link can be found in PhysioNet website<sup>5</sup> [132], or the alternative archived PhysioNet website<sup>6</sup>.

#### IV. 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. Again, we will discuss from the perspective of model, data and task.

From the perspective of model, following three challenges and problems need to be considered:

- **Interpretability.** Deep learning models are often regarded as black box model, because they usually have many model parameters, or complex model architecture, that is hard for 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. To handle with this, two directions are worth studying. 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 is according with deep learning model's prediction, and interpret the prediction based on the simple model [153], [154]. 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 [155], or adding attention mechanism on hidden layers [156], [93], which can be better understood by human.

- **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 model on real world applications. In this situation, a promising research direction is 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 [157]. Also, we can use the quantization, weight sharing, and careful coding of network weights [158] to compress a big model.
- **Integration with expert features.** Most of existing deep learning models are trained end-to-end, so it is hard to integrate with existing expert features or expert knowledge once the model finished training. And, there are two research lines to tackle aforementioned problems. The first one is use domain expert knowledge to design deep neural network architecture [159], [93]. The second one is to regard deep models as feature extractors, coined as deep features [6], [7], and explicitly extract latent embeddings from deep learning models. Then one can easily combine expert features with deep features, and build traditional machine learning methods on them.

Then, from the perspective of model, following two challenges and problems need to be considered:

- **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 amount of model parameters on such a small dataset. There are two ways to handle with this problem. The first one is data augmentation such as data preprocessing using side-and-cut technique, or generating more training dataset using generative models like variational autoencoders (VAE) [160] or GAN [136]. The second one is to design new loss functions like Focal loss [161], or other model training schema like few shot learning [162].
- **Multi-modal data.** Currently, most works only consider ECG for analysis. 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 time line, 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 which is capable of utilizing

<sup>3</sup><https://physionet.org/content/ptbdb/1.0.0/>

<sup>4</sup><http://2018.icbeb.org/Challenge.html>

<sup>5</sup><https://physionet.org>

<sup>6</sup><https://archive.physionet.org>

these multi-modal data simultaneously to improve task performance compared with the model trained on any individual data.

Finally, there remains a lot of interesting and innovative application tasks to be studied, including: mental stress measurement (the electrode is equipped in steering wheel for driver), emotion detection, analyze mammalian ECG [163], create risk scores of out-hospital patients via healthcare devices and so on.

## V. CONCLUSION

In this paper, we systematically reviewed existing deep learning (deep neural network) methods on Electrocardiogram (ECG) data, from the perspective of model, data and task. We found that deep learning methods can also achieve better performance than traditional methods on ECG modeling. However, we also found that these deep learning still face up with some unresolved challenges and problems. This paper can provide an systematic overview of how deep learning methods can be used to solve real applications for engineers, while also point out some potential research opportunities in the future for researchers.

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