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Utilizing Deep Learning Methods for Heart Defect Identification via Electrocardiogram (ECG): A Literature Review

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Abstract: In recent years the application of Deep Learning is widely used in various fields of science, such as in the military, agriculture, health and even in other fields. In the field of health many studies use deep learning, especially related to heart disorders. Identification and detection of heart defects that are widely used are by using an electrocardiogram (ECG). Research related to ECG and the application of deep learning methods is very interesting for researchers, because researchers trace that there are still few studies that focus on researching related to it. This article aims to explain the trend of ECG research using deep learning approaches in recent years. We reviewed journals with the keyword title "ECG Deep Learning" and published from 2016 to October 2023. The articles that have been obtained are then classified based on the most frequently discussed topics including: data sets, pre-processing, feature extraction, and classification/identification methods. The approach used by some researchers is mostly to get the best results from the use of deep learning methods. This article will provide further explanation of the most widely used algorithms for ECG research with a deep learning approach. Of the deep learning methods used, almost 84% use the Convolutional Neural Network method. In this article, critical aspects of ECG research can be carried out in the future, namely the use of data in the form of other data from ECG, and the use of deep learning is a very big opportunity for researchers in the future.

Keywords: electrocardiogram, deep learning, dataset, pre-processing, identification

1. Introduction

In recent decades research on the heart has been rife. Some researchers are competing to present the results of their research related to this. There are even media reporting that in data released by WHO in 2021, deaths from heart disease reached 17.8 million deaths or one in three deaths in the world each year caused by heart disease [1]**.** To reduce the risk of death as equalized, in this case it is very important early that we can analyze and predict heart disease [2]. To obtain information related to heart abnormalities, various ways are done, one of which uses an electrocardiogram (ECG). ECG is the most common cardiological procedure to monitor the heart's electrical activity noninvasively [3]. As stated by [4] currently the method of disease identification is to analyze ECG, which is a medical

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monitoring technology that records heart activity. ECG signals, as one of the most important vital signs, can provide information related to indications of many heart-related diseases [5]. ECG is one simple test that can be used and utilized to evaluate the patient's heart rhythm and electrical activity [6].

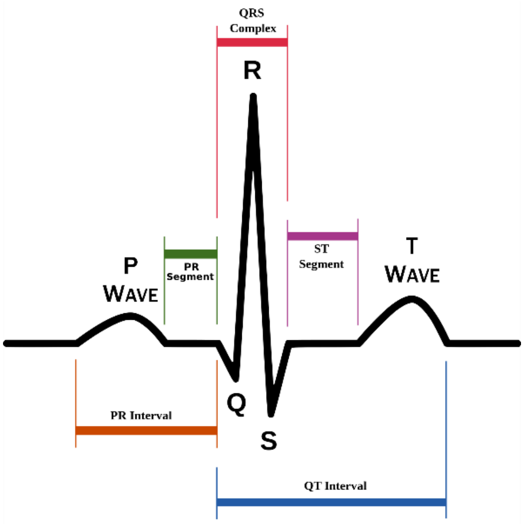

Figure 1. Examples of ECG waves & description of each peak [7]

Analyzing ECG results is usually done by a heart-related expert. Careful analysis of ECG signals can provide invaluable knowledge about cardiac activity [8]. So far, ECG readings are still done manually. Manual ECG signal analysis is not enough to quickly identify abnormalities in heart rhythm [9]. It would even be helpful if ECG diagnosis could be done automatically for clinical use [10]. Especially now that the latest technology and methods have a lot of findings related to this. It is even associated with the latest methods that can help analyze ECG such as the application of artificial intelligence (AI). Artificial intelligence and machine learning are used in a variety of healthcare-related applications [11]. In addition to machine learning (which is part of AI) in recent years there have also been deep learning methods.

Deep Learning algorithms will be very helpful in analyzing health, especially the ECG. Even lately there have been a lot of ECG studies that use this method. Deep learning is currently one of the preferred ways researchers are in healthcare applications, coupled with the emergence of powerful parallel computing hardware and big data technologies [12]. Recently deep learning has been widely used in processing ECG signals, which has previously been used extensively in image processing and other domains with great success [13]. This study tried to review the literature related to ECG using a deep learning approach within eight years (2016-October 2023). With this literature review, it is hoped that it can obtain a road map related to future researches.

2. Methods

Several studies related to ECG have been published a lot in the past few decades. Based on searches obtained by researchers and also conducted by [14], ECG-related research has previously been conducted by [15]. While the use of Deep Learning in identifying heart abnormalities using ECG obtained by researchers was first carried out by [16]. Then the following year there was also a study by [17]. After that, many researchers conducted ECG research using deep learning.

In this study, researchers tried to conduct research in terms of literature studies related to electrocardiogram (ECG). Researchers began to search literature studies related to journals that discuss ECG and used deep learning methods. The search was conducted on several publication database sites published from 2016 to October 2023 with the keyword "ECG Deep Learning", and was limited to the field of Computer Science.

A search of documents related to this study obtained 73 articles that the researchers obtained. Then the next stage of 73 articles was selected based on the appropriate criteria, 45 articles were obtained (ECG using deep learning methods) (Table 1).

Table 1. Article search

No.	Search	Information
1	73 articles	collected articles
2	45 articles	appropriate articles (ECG using deep learning methods)

The next step is for researchers to analyze articles based on the classification that has been set at the beginning.

3. Results & Discussion

Previous studies that have been conducted related to the use of ECG based on deep learning methods were analyzed. The analysis in this section will be divided into three sub-section stages, namely pre-processing, feature extraction and classification. As well as systematically focused on 45 journals starting from 2016 to October 2023.

3.1 Dataset

Before analyzing the three stages (Pre-processing, extraction, characteristics, and classification), researchers first analyze the source of data collection. From the analysis of data collection based on the criteria that have been obtained can be grouped into five data collection sources, namely PhysioNet, The China Physiological Signal Challenge (CPSC) 2018, UK Biobank, ASCERTAIN Dataset, and there are also independent data collection.

3.1.1 PhysioNet

Some researchers who often conduct ECG-related research mostly use datasets from PhysioNet. Judging from its website, PhysioNet which is under the auspices of the National Institutes of Health (NIH) and established since 1999 is one of the research resources for Physiological Signals (*Research Resource for Complex Physiologic Signals*). Its main objective is to catalyze research and education in the biomedical field, by offering free access to physiological and clinical databases. Computing in Cardiology conference, as well as annual series of challenges activities that are often carried out by PhysioNet. PhysioNet is managed by members of the MIT Laboratory for Computational Physiology. Many databases provided by PhysioNet include MIT-BIH, Europe ST-Database, Fantasia Database, St-Petersburg, Creighton University database (CUDB), PTB diagnostic ECG database, and others.

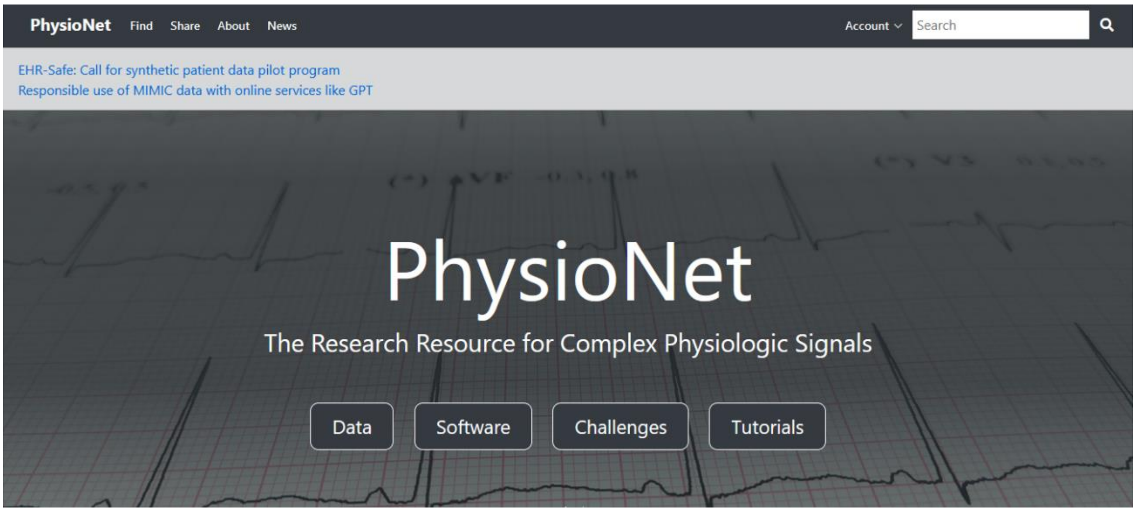

Figure 2. PhysioNet [18]

3.1.2 The China Physiological Signal Challenge (CPSC) 2018

The China Physiological Signal Challenge (CPSC) 2018 seeks to contribute a more comprehensive database. CPSC 2018 aims to encourage the development of algorithms to identify rhythmic/morphological abnormalities from 12-lead ECGs. The data used in CPSC 2018 included one normal ECG type and eight abnormal types. CPSC 2018 is China's first physiological signaling challenge, aiming to provide a platform for open-access data and algorithms to analyze physiological signals, and in doing so promote open-source research patterns for the detection and prediction of cardiovascular abnormalities in China. The practical goal is to identify rhythm/morphological abnormalities from a 12-lead ECG, lasting a few seconds to tens of seconds [19].

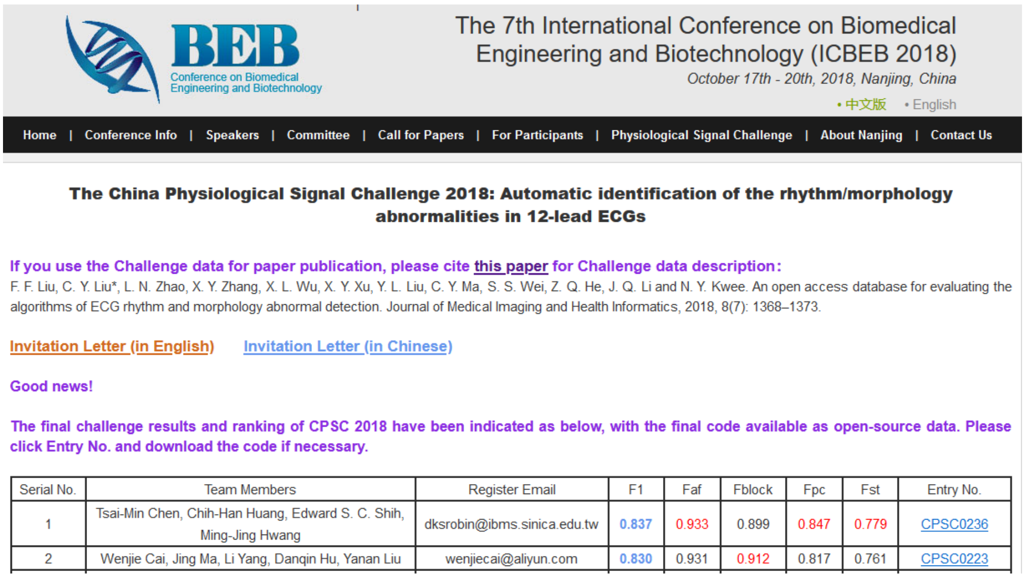

Figure 3. CPSC 2018 [20]

3.1.3 UK Biobank

The UK Biobank is a large-scale biomedical database and research resource, containing genetic and health information from half a million UK participants. The regularly developed database is supplemented with additional data and is globally accessible to researchers who have been approved to conduct important research into the most common and life-threatening diseases for society. It is hoped that this can be a major contributor to the progress of modern medicine and medicine, and can produce several scientific discoveries that are very useful for improving human health.

Figure 4. UK Biobank [21]

3.1.4 ASCERTAIN Dataset

Referring to its website, ASCERTAIN Dataset presents multimodal database for implicit personality and affect recognition using commercial physiological sensors. To their knowledge, ASCERTAIN is the first database to link a person's personality traits and emotional state through physiological responses. ASCERTAIN contains five large personality scales and emotional self-assessments of 58 users along with Electroencephalogram (EEG), Electrocardiogram (ECG), Galvanic Skin Response (GSR) and synchronously recorded facial activity data, recorded using off-the-shelf sensors while viewing affective film clips.

Figure 5. Website ASCERTAIN Dataset [22]

3.1.5 DREAMER

DREAMER database as explained by [23], is a multimodal database consisting of electroencephalogram (EEG) and electrocardiogram (ECG) signals recorded during elicitation through audio-visual stimuli. Signals from 23 participants were recorded simultaneously with participants' self-assessments of their affective states. The outline of his research is based on EEG and ECG-based features, which were established through classification experiments using the SVM method. The results of this study show quite good prospects by using devices at a low cost. The proposed database will be publicly available. Researchers who have used the DREAMER database are [24].

3.1.6 Independent

The point of independent purpose here is that they are primarily researchers in that the collection of data for their research is done independently Table 2 shows some studies that took the data independently.

Table 2. Independent data retrieval

Year	Author	Collect Data
2022	[25]	The ECG is 12-lead 10 seconds long
2023	[26]	ECG data were obtained from hospital A and randomly separated into training sets (70%), development sets (15%) for hyper parameter tuning, and finally for test sets (15%). All ECG data obtained from hospital B were used for the test set.
2023	[27]	The 12-lead ECG database data for arrhythmia research was obtained from Chapman University and Shaoxing People's Hospital
2023	[28]	The ECGs collected came from patients with at least one echocardiogram recorded at 3 hospitals from 2 continents (Keio University Hospital, Brigham and Women's Hospital, and Dokkyo Medical University Saitama Center).

3.2 Pre-processing

The first stage that is often done in pattern recognition research is the Pre-processing stage. In this literature review, the use of deep learning using ECG case studies mostly uses pre-processing stages. While in this pre-processing stage, from 45 journals used in this study, there are several methods used at this pre-processing stage (Table 3).

Table 3. Use of pre-processing

Year	Author	Pre-Processing
2018	[29]	Binary Image
2019	[13]	Wavelet
2020	[30]	Filtering & Segmentation
2020	[31]	DWT
2021	[4]	Wavelet self-adaptive threshold denoising
2021	[32]	Binary Images
2022	[33]	Segment beat
2022	[25]	Filtering
2022	[34]	✓ Normalization ✓ Filtering ✓ Segmentation
2023	[27]	Converted to grayscale and binary

2023	[11]	Grey-scaled spectrogram
2023	[35]	Baseline Wandering
2023	[36]	Peak Detection
2023	[37]	Wavelet (db6)
2023	[28]	Binary Image
2023	[24]	DWT

3.3 Feature Extraction

The second stage is characteristic extraction. In research that uses deep learning, most rarely use the stages of trait extraction, because deep learning already includes the stages of characteristic extraction (Figure 6). However, there are several studies that still use or still include the stages of extraction of this characteristic with different methods.

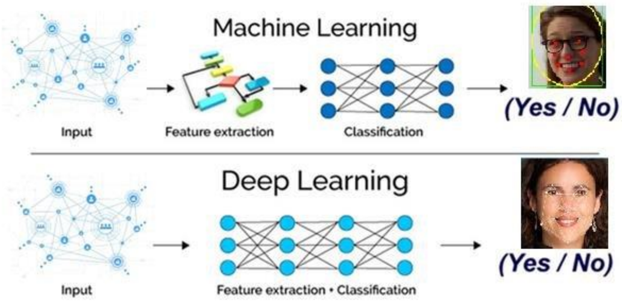

Figure 6. The Difference Between Machine Learning and Deep Learning [38]

Literature review at the trait extraction stage in this study, almost 17% of the papers used the trait extraction stage. Table 4 shows some researchers who used the trait extraction stages.

Table 4. Feature extraction method

Year	Author	Feature Extraction
2020	[31]	Segmentation
2020	[39]	✓ Log-spectrogram ✓ Mel-spectrogram ✓ Spectrogram ✓ MFCC (Mel Frequency Cepstral Coefficient) ✓ Scalogram
2021	[40]	Continuous Wavelet Transform (CWT)
2021	[2]	Welch dan Discrete Fourier Transform
2021	[32]	CNN
2022	[33]	Spectral Analysis
2022	[41]	DWT (sym4-level 4)
2023	[35]	Continuous Wavelet transform

3.4 Identification & Performance

At this last stage, most of the research is related to classification or identification. The stages of classification or identification in this study all use deep learning methods. Among the methods used are mostly using CNN Convolution Neural Network (CNN) and several other deep learning methods. The use of the method chosen is usually based on the use of data to be used.

In addition to the selection of methods, at this stage will also usually look for performance from the research being developed. Researchers in terms of performance search that are often used include accuracy, sensitivity and specificity [14]. Confusion Matrix is used to find the level of accuracy, sensitivity and specificity, some even use precision [42]. The application of the Confusion Matrix method is one that is used to obtain evaluation results based on matrix tables [43]. Research related to ECG from the above research through a deep learning approach can be presented in table 5.

Table 5. Identification & Performance

Year	Author	Approach	Performance	Data
2016	[16]	CNN	Accuracy: 99,66%	
2017	[17]	CNN	Accuracy: 86 %	
2018	[29]	CNN	Accuracy: 99,1%	PhysioNet
2018	[44]		Accuracy: 96,2 %	PhysioNet
2019	[45]	CNN and BRNN	Accuracy: 87,69%	PhysioNet
2019	[46]	CNN		
2019	[13]	✓ CNN ✓ LSTM		
2020	[47]	✓ CNN ✓ DBN ✓ RNN ✓ LSTM ✓ GRU		✓ PhysioNet ✓ MITDB ✓ PTB
2020	[30]	✓ CNN ✓ LSTM		PhysioNet
2020	[9]	✓ CNN 2D		PhysioNet
2020	[31]	✓ CNN 1D	Accuracy: 99,98% Sensitivity: 99,9% Specificity: 99,89%	✓ PhysioNet ✓ 2018 China Challenge
2020	[12]	✓ CNN ✓ RNN ✓ LSTM ✓ GRU		PhysioNet
2020	[39]	✓ Xception ✓ ResNet ✓ DenseNet		PTB (Physikalisch-Technische Bundesanstalt)-ECG database
2021	[4]	✓ Backpropagation ✓ Random Forest ✓ CNN		PhysioNet

2021	[10]	CNN		China Physiological Signal Challenge (CPSC) 2018
2021	[48]	RNN		PhysioNet
2021	[40]	CNN		PhysioNet
2021	[49]	✓ CNN ✓ LSTM	Accuracy: 95,81%	PhysioNet
2021	[2]	✓ SVM ✓ CNN		PhysioNet
2021	[32]	SVM	Accuracy: 97,6%	PhysioNet
2022	[50]	CNN	Accuracy: 86%	
2022	[51]	✓ CNN-LSTM	Accuracy: 99,92%	
2022	[3]	✓ CNN 1D+MLP ✓ Dense Model ✓ CNN 1D		PhysioNet
2022	[6]	CNN		PhysioNet
2022	[52]	CNN		UK Biobank
2022	[53]	CNN		Independent
2022	[33]	CNN	Accuracy: 99,65% Sensitivity: 98,87% Specificity: 99,85%	PhysioNet
2022	[25]	CNN		Independent
2022	[41]	CNN		PTB-XL database
2022	[34]	CNN	Accuracy: 92%	PhysioNet
2022	[54]	Faster R-CNN		
2023	[27]	CNN		✓ PTB-XL (PTB) ✓ CPSC 2018 ✓ Chapman University and Shaoxing People's Hospital ✓ A cohort study (Tongji)
2023	[11]	ResNet18	Accuracy: 90,8%	PhysioNet
2023	[55]	ResNet		PhysioNet
2023	[56]	CNN 1D		
2023	[35]	CNN	Accuracy: 91,95%	PhysioNet
2023	[57]	CNN	Accuracy: 96,2%	
2023	[58]	✓ CNN ✓ MLP ✓ Transfer Learning.	Accuracy: 90% Accuracy: 87%	

			Accuracy: 93,8%	
2023	[36]	CNN	Accuracy: 98,63% Sensitivity: 92,41% Specificity: 99,06% Precision: 92,86%	PhysioNet
2023	[37]	CNN	Accuracy: 98,69%	PhysioNet
2023	[26]	CNN		Independent
2023	[28]	CNN		✓ United States: Keio University Hospital (KUH) ✓ Brigham and Women's Hospital (BWH) ✓ Dokkyo Medical University Saitama Medical Center (SMC)
2023	[59]	CNN		PhysioNet
2023	[60]	CNN		PhysioNet
2023	[24]	Temporal CNN	Accuracy: 100%	DREAMER

4. Conclusions

Very diverse research related to the discussion of ECG. These studies strive to obtain the best method in their studies. The use of data used in this study from several researchers is also very diverse and varied, ranging from utilizing data banks such as PhysioNet, The China Physiological Signal Challenge (CPSC) 2018, UK Biobank, ASCERTAIN Dataset, and independent where the data is taken directly from patients. The pre-processing stage of 45 journals used 66% used this stage. Including trait extraction are also very diverse methods used such as searching for Segmentation, Continuous Wavelet Transform (CWT), Welch and Discrete Fourier Transform, Spectral Analysis, MFCC (Mel Frequency Cepstral Coefficient), and others. While at the identification stage, all of them use deep learning methods such as convolutional neural network (CNN), bi-directional recurrent neural network (BRNN), Deep Belief Network (DBN), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), and others. Of the deep learning methods used, almost 84% use the CNN (Convolutional Neural Network) method. Future work has great opportunities for research related to electrocardiogram (ECG), one of which is the use of other data that can be extracted characteristics of ECG.

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