Classification and Detection of ECG Arrhythmia and Myocardial Infarction Using Deep Learning: A Review

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Abstract

Recently, DL (Deep Learning) becomes the focus study for researchers in wide and various applications such as; healthcare, where early detection can play an important and vital role in diagnosing abnormal (pathological) conditions through an electrocardiogram (ECG). In the current study, an extensive presentation was given on the modern techniques that have been applied in the ECG device, which have been introduced to classify heart rhythms and identify disturbances in it precisely in the infraction of the myocardial. To enter the method that defines the biological systems of vision, studies have been studied and reviewed that specifically describe the Convolutional Neural Network (CNN). Also, researches and studies related to the subject have been summarized from several aspects, the most important of which are according to the sequence: collecting data and application areas, in addition to planning the form and content of the model and the type of data that is entered, and then evaluating the performance.

Keywords

ECG Signal Detection, Myocardial Infarction (MI), Arrhythmia, Deep Learning (DL), Convolutional Neural Network (CNN).

Introduction

The heart is the main responsible for the blood circulation inside the human body through contraction and diastole, like the heart, and through the arteries, pumps blood to all parts of the body, and any narrowing or blockage in the arteries may lead to a failure in blood circulation (Sahoo et al., 2020). Among the diseases and the well-known problems of the heart is the irregularity of the pulse (which is called arrhythmia), and heart rhythm problems range from tolerable to causing death (Sodmann et al., 2018). An important clinical procedure for heart problems, early diagnosis of tachycardia is considered a priority that saves the lives of many heart patients. The tachycardia and electrocardiogram (ECG) screening chart are common, well-known, and important methods of initial diagnosis to heart inefficiency. The electrocardiogram consists of 12 points, and the recording takes place over a time interval of 10 seconds, and as needed, the ECG recordings may range from several hours to several days, and the cardiologist identifies this need, analyzes, and makes the myocardial infarction (MI), cardiovascular (CVDs), and heart diseases and diagnose them (Sodmann et al., 2018). The ECG device records all signals that reflect the activity of the heart and identifies abnormal ones; however, it is very difficult to determine and interpret the ECG circuit's signals because of its duration and its amplitude is small (Benjamin et al., 2018). The examination requires technicians and continuous training for the staff of the ECG device, and with time the process becomes costly and routine for those working on it (Acharya et al., 2017). To assist the specialists in diagnosing through analyzing data and charts, it is possible to improve devices with the help of automated computers diagnosis systems (CADs). Sometimes, as a result of an error or anomaly in the ECG system, the error may cause false symptoms of heart disease such as hypotension, persistent ventricular tachycardia, rapid atrial fibrillation. The diseases mentioned above require immediate treatment and are considered very dangerous and threatening human life, and by analyzing the ECG diagram, which can be monitored automatically or manually, important information about the state of the heart can be observed. Manual diagnosis is very difficult due to the different shapes in the ECG chart, for this reason, the automatic diagnostic system is considered successful and crucial instrumentation (ECG) in the classification and diagnosis of heart disease. And by applying the ECG device to heart patients, many of them can be diagnosed, including myocardial infarction, arrhythmia, and ischemic heart disease (M. A. Serhani et al., 2020). In 2018, Benjamin and his coworkers (Benjamin et al., 2018) indicate, and cording to a statistical study achieved in 2016, that CVD (Cardiovascular Disease) is the leading death cause for around 31% of all of the world. In addition to the ECG diagram, specialists also rely on clinical examinations as well as the patient's medical history to establish an accurate medical diagnosis of cardiovascular diseases. Then the specialists, according to the medical standards and classifications, analyze the information, interpret the results and reach the diagnosis. Given the simplicity and low cost of the ECG device, it is considered one of the familiar, well-known, and most widespread methods of detecting and diagnosis arrhythmias. Given the large quantities of daily checks that technicians perform using the ECG device, and to reach an accurate and fast diagnosis, deep learning is adopted and mixed with traditional machine learning (Benjamin et al., 2018). Figure 1 shows a sample of the electrocardiogram.

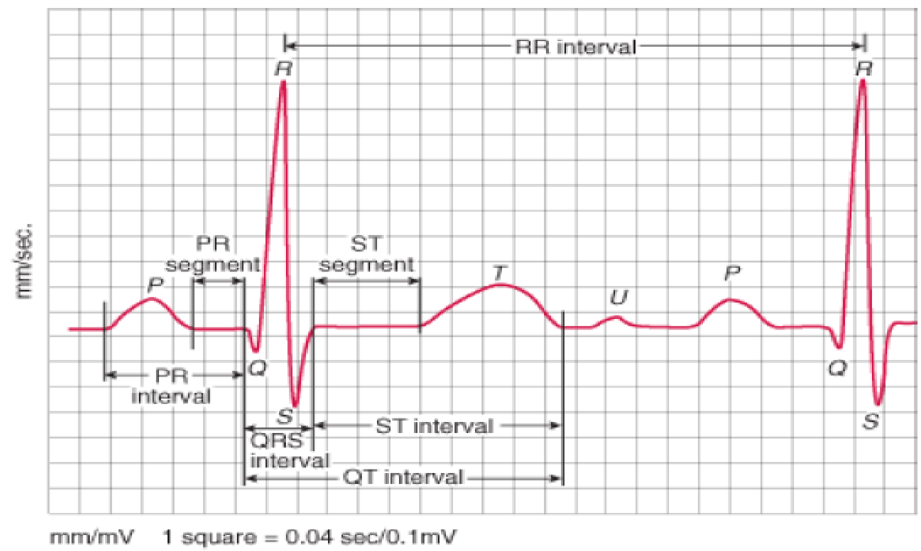

Figure 1 Electrocardiogram (Fakheraldin Y. et. al 2020)

The (DNN) has been introduced, 'used and developed in the classification' and prediction in the task of diagnosis of a wide variety of different medical fields. Deep neural network systems, which have been recently applied to the ECG device to improve its quality, reduce the cost for identifying arrhythmias. Despite this, depending on ECG is facing difficulties and challenges in diagnosing and classifying myocardial infarction and tachycardia (Z.Ebrahimi et al., 2020). Figure 2(a) shows a diagram of machine learning while figure 2(b) shows a diagram of deep learning methods and clearly shows the data feeding into the network structure in addition to the low-level processing of the network that consists of many hidden layers, as the data inside the deep network is automatically selected and classified, it differs from machine learning. Algorithms based on deep learning performed outstandingly on different standard datasets. In particular, Convolutional Neural Networks (CNNs) were successfully used to solve and analyze the tasks of complex images for both medical and non-clinical (Parvaneh et al., 2018). In recent years, deep neural networks have been adapted and developed for time-series analysis 1D (Biosignals). In this article, the latest research and results obtained by researchers are discussed regarding methods of detecting cardiac muscle (myocardial) and automatic heart rhythm disorders through applications of deep learning methods.

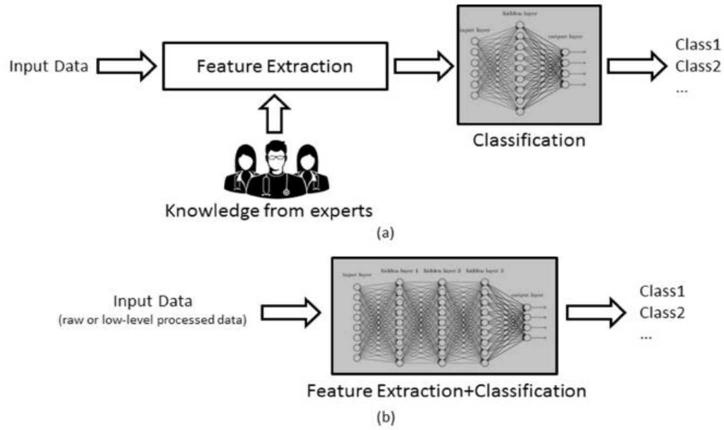

Figure 2 (a): The ML (Machine Learning); (b)The DL (Deep Learning) (S. Parvaneh et al., 2019)

Objectives of the Study

The classification of myocardial infarction and arrhythmia is the aim of this study through a discussion of Deep Learning (DL), and to achieve this, images and diagrams of the most used models of previous research related to CNN (Convolutional Neural Networks) will be presented, where a general introduction to the medical point of view on tachycardia and how to assess the performance of the heart through an ECG was presented in addition to the current charts that are used in conducting an ECG. Among the objectives of the research is also to prepare 'a tabular representation to be used as a source and reference for future purposes for researchers,' and the researches that were mentioned and discussed in this review article were classified according to MI (myocardial infarction) and arrhythmia.

This is the first paper that we are aware of those aims to provide a succinct overview of deep learning applications in biomedical signals. The survey's key goal is four-fold.

1. The first to provide background information on how deep learning algorithms have developed and revolutionized machine learning in recent years.
2. Second, to critically examine the use of deep learning in various biomedical signal analysis applications.
3. And third to provide a detailed review of existing literature.
4. Finally, to explore the research opportunities in the field of study that can serve as a starting point for new researchers to define potential research directions in a succinct manner using deep learning algorithms. We attempted to address the

following research questions in the course of achieving these four goals of the paper:

a) Can DL be the potential to analyze the biomedical ECG signals?
b) How DL can be applied efficiently to analyze different types of ECG biosignals?
c) How accurately does DL detect abnormality patterns in ECG biosignals?
d) To critically examine the use of deep learning in ECG classification of myocardial infarction and arrhythmia are the four aims of this study?

Finally, methods of MI classification and arrhythmias analysis in terms of general inference and performance evaluation, as well as technical problems encountered, will also be discussed during the research review.

DL Techniques

In this part of the article, the researcher will go throw the knowledge from previous studies that refer to deep learning (DL) in terms of how to extract the information, then, guess and predict and eventually making an intelligent decision, and use these data to set the intricate patterns and come to the data of training, the evaluation and comparison between deep neural network system (DNNs) and the techniques of traditional learning as the scalability are large, the difference between them is large in terms of accuracy and data set, in addition to the network size for each one of them. The ineffectiveness, and deficiency of some shallow learning models, such as support vectors machines (SVMs) and decision trees, especially when used in modern applications, as their limitations appear in many respects, including their need for large human labor in addition to the presence of a large number of observations (Loni et al., 2020). Recently, and to improve and develop accuracy in 'deep learning models (DL), several models have been proposed, including the Deep Belief Network (DBN), Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN)', Multilayer Preceptor (MLP), and Convolutional Neural Network (CNN). With the progression of time, the late neural network was developed into the growing neural network which was presented as a new theory of learning. Despite the well-designed and special design of biological signals within the growing neural network, so far, the electrocardiogram has not been classified by applying the robust method (ECG) (Gharehbaghi et al., 2019b). Figures 3 show the diagrams of DBN, RBM, GRU, BRNN, DBN, and LSTM respectively.

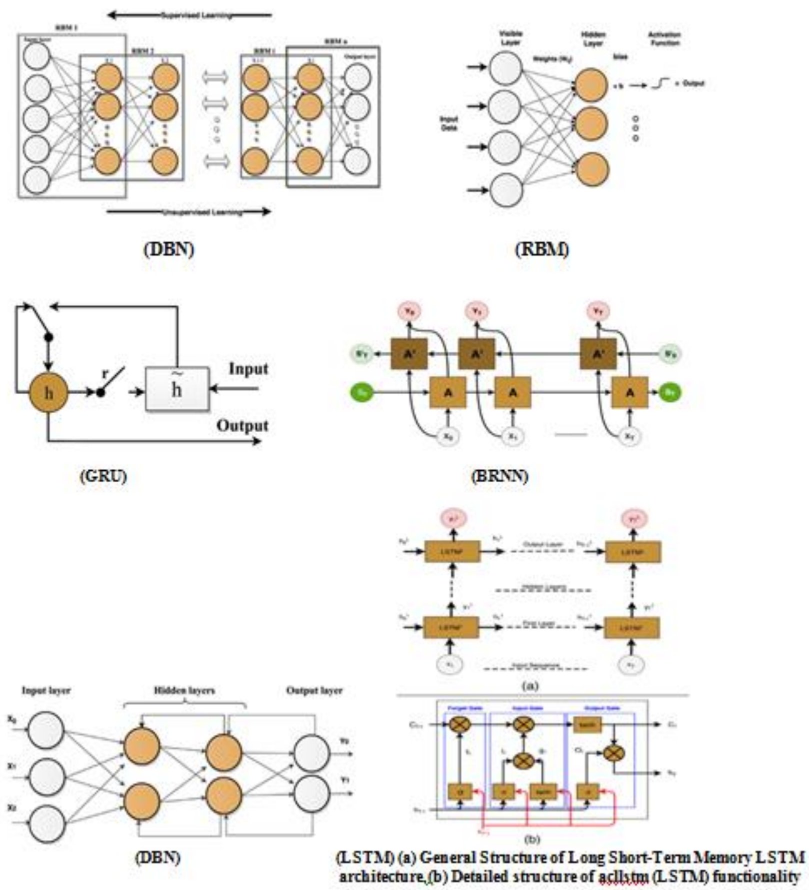

Figure 3 Deep Learning (DL) models (Ebrahimi et al., 2020)

1. CNN (Convolutional Neutral Network)

This type of network (CNN) is considered to be one of the types of architecture DNN (DotNetNuke that uses an architecture model that has three-tier) in which gradient-based algorithm was used in its training. Generally, the CNN system consists of several consecutive layers (normalization, pooling, convolutional, and fully connected layers) that were connected by a certain method called forward feed. The first 3 layers are in charge of features extraction, while the fourth one (fully connected) is responsible for the classification. Figure 4 shows the structural design of CNN which is architecture for the task of classification (Gharehbaghi et al., 2019b), while the popular diversity of the problems of CNN were depicted in table 2. The application of CNN in the medical field has been grown rapidly, in particular in the fields of physiology, and radiology by which the researchers treat the signals of ECG as if they are one-dimensional images (1D) and they applied this in the diagnosis of arrhythmias, and MI via single individual signal which guides to achieve a high-quality of performance the consist of 12 leads (Baloglu, U.B. et al., 2019), and to take the full benefit from 12 leads, it was created what is called

MFB (Multiple Feature Branch) for the one dimensional (1D) for the CNN (Wenhan Liu. et al., 2018). And to enable this, it was proposed the Multi-Lead for the residual neural network, and to capture the significant features through the convolutional Kernel of the 1D layer, a new design was used (the 3 residual blocks) (C. Han. et al.; 2019) The detection of MI was carried out via four leads of the convolutional kernel of the ID, this can be achieved through the sub 2D of the CNN that recognizes the representation of the variety of features. Despite the application of 2D CNN, the operation of the feature map is still based on 1D CNN because the last one is focusing on the single lead which shares, inside the same lead, the convolutional kernel of the 1D, and as a result, using 2D CNN to extract feature in arrhythmias and MI diagnosis is not accurate and required further researches and development, (Lidan Fu. et al.; 2020).

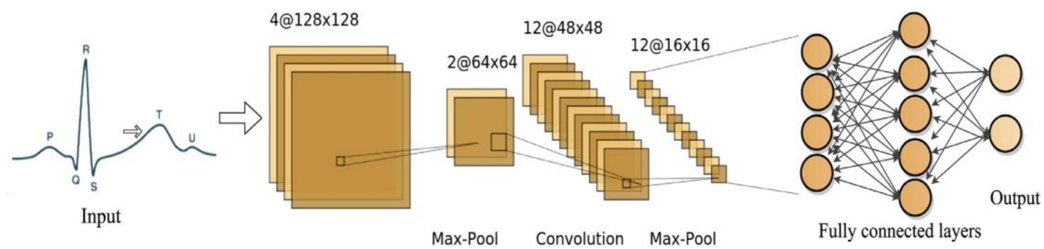

Figure 4 CNN diagram (Z. Ebrahimi, et al, 2020)

Medical Overview and Background

This part of the article will focus on the detection of heart diseases that can be distinguished by the signals of ECG which reflect the status of the patient's heart (Kasper, D. L. et al.; 2018). Generally, the information that is provided by ECG can be classified into two types:

- The first type is related to the cardiologist, by which he can determine the time intervals through adjusting the electrical wave that passes via the heart's electrical conduction system which helps the cardiologist to discover the regular and irregular electrical activities whether they are slow or fast.
- Second, from the outcome of the first step, the cardiologist will be able to distinguish which part of the heart is overworked or too large and diagnose the status of the heart.

Figure 5 shows samples of different heartbeats that reordered by ECG that includes meaningful and important segments of waves such as T-wave (repolarization wave), QRS complex wave (ventral depolarization), and P-wave (atrial depolarization), any signal coming from the patient's heart to the ECG will be analyzed and the signals will reflect the disorder of the neural cells of the heart which diagnosed as arrhythmia.

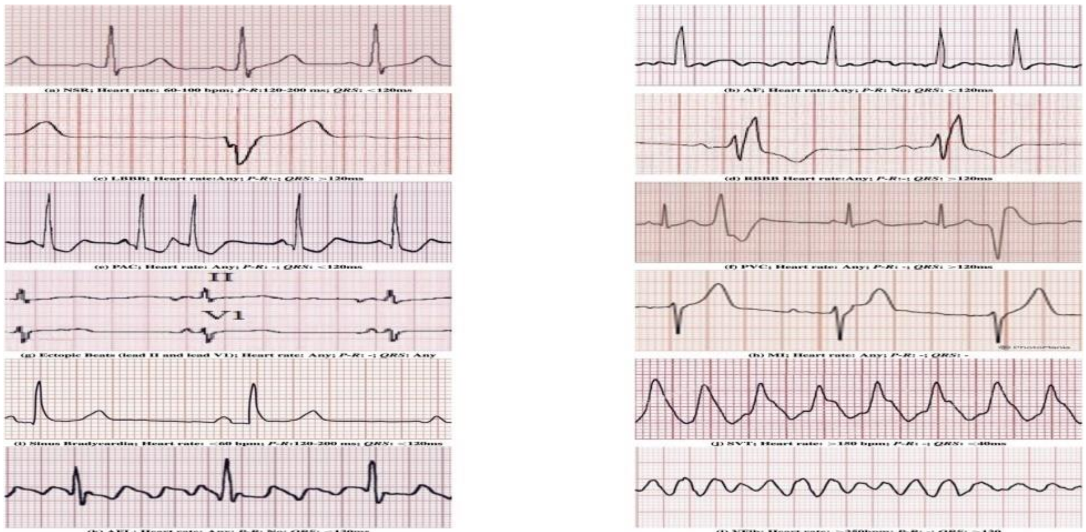

Figure 5 Electrocardiogram of dissimilar arrhythmias: (a)' NSR Normal Sinus Rhythm; (b) AF Atrial Fibrillation; (c) LBBB Left Bundle Branch Block; (d) RBBB (Right Bundle Branch Block); (e) PAC (Premature Atrial Contraction), (f) Premature Ventricular Contraction, (g) Ectopic Beats (illustrating both lead II and lead V1), (h) Myocardial Infarction, (i) Sinus Bradycardia, (j) Atrial or Supraventricular Tachycardia, (k) Atrial Flutter, and (l) Ventricular Fibrillation'(Sahoo et al., 2020)

Database

To remain in the main aspects of the review, most of the studies use the present ECG charts to offer them as an online database, and the main examples are; PTB, MITDB, PhysioNet that has transition stage option among fibrillation (that cause unexpected and sudden death) and VT. The characterization of the waveform to its sinusoidal is achieved without any obvious definition of QRS and T-waves. In general, the signal of ECG has much additional information that is considered as noise which has dissimilar brands. Figure 6 indicates many kinds of signals that are considered as noise in the chart of the ECG which is considered as useless information throughout the reading and explanation of the ECG chart, precisely, the cardiac cycle (Sahoo et al., 2020). However, the adequate signal of the ECG process is very important before examining the electrocardiogram, which highlighted the importance of adaptive filters as well as the averaging to remove them from the ECG chart (Muhammad A. Haroon., 2020).

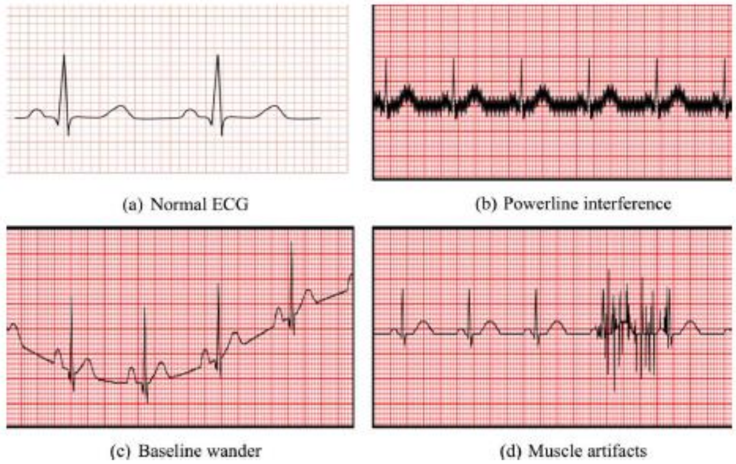

Figure 6 Kind of noises in ECG Electrocardiogram (Sahoo et al., 2020)

Evaluation of Performance

The researches that applied AFDB, PTB, MIT-BIH, CUBD, and PhysicoNet, the performance evaluation was carried out through some approaches:

- Validation with K-Fold: In this approach, (k-1) folds were used in the model of training, and for the evaluating one-fold were used to evaluate the recall, precision, specificity, and the sensitivity, and for metrics of the performance F1-score, dice coefficient, PREmicro, PREmacro and Area under the Curve (AUC). These measures are calculated and applied mathematically in Equation 1 to Equation 10.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, (1)$$

$$F1_{score} = 2 \times \frac{Precision \times \mathrm{Recall}}{Precision \times Recall}, (2)$$

$$Precision = \frac{TP}{TP + FP}, (3)$$

$$Recall = \frac{TP}{TP + TN}, (4)$$

$$Sensitivity = \frac{TP}{TP + FN}, (5)$$

$$Specificity = \frac{TP}{TP + FN}, (6)$$

$$Dice\ Score = \frac{2\,|P \cap GT|}{|P| + |GT|}, (7)$$

$$PRE_{micro} = \frac{TP_1 + \cdots + TP_K}{TP_1 + \cdots + TP_K + FP_1 + \cdots + FP_K}, (1)$$

$$PRE_{macro} = \frac{PRE_1 + \cdots + PRE_K}{K}, (9)$$

$$AUC = \frac{1}{n_{\mathrm{p}}} \sum_{j=1}^{n_p} f_{\mathrm{j}}, \ (2)$$

- where 'TP (true positive) denotes the number of cases that were correctly identified as defected, FP (false positive) denotes the number of cases that were incorrectly identified as defected, TN (true negative) denotes the number of cases that were correctly identified as non-detected, and FN (false negative) denotes the number of cases that were incorrectly identified as non-defected. (P) denotes the prediction as given by the method in Eq. 7. (PRE micro) stands for the micro-average, while (PREmacro) stands for the macro-average'.
- It is necessary to mention that the performance of each k-fold or train/test sets were separately due to firstly the possibility of the overfitting risk to the database of the training, and secondly the difficulty in comparison between the results that has the same goal and use the same dataset (S. Parvaneh, et al., 2019).
- Separating data to test sets that were used for the evaluation model and train that was for the training model.

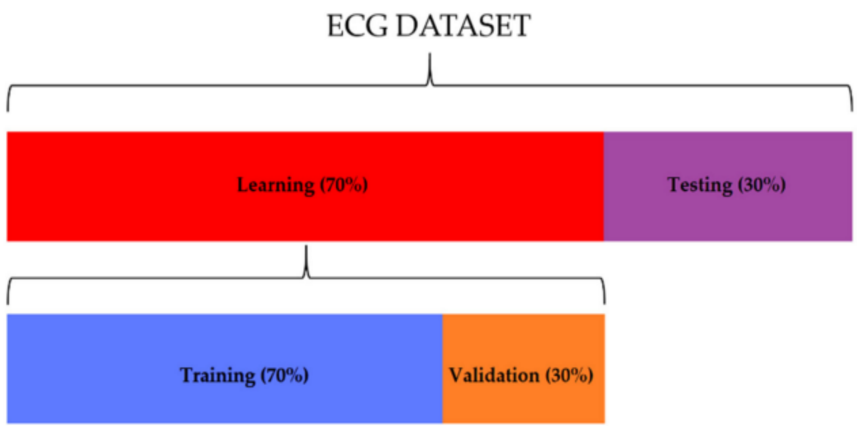

Figure 7 The distribution of ECG segments was used for learning (70%) and testing (30%). Thirty percent of the learning dataset was used for the validation of the network

Research Methodology

A survey was carried out to the previous studies from 2017 to 2021 that describe medical, interdisciplinary, and technical sides via Google Scholar and PubMed as well; eventually, the outcome of this search can be classified into the application (classified extraction of features), and technical (classified the various types of MI and arrhythmia). Sometimes the DLM was employed for the extraction of features to offer useful inputs to another classifier such as CNN, which is opposite to other DLM applications by which it is used as a great classifier.

The Distinction to the Other Survey Papers

In this section, the researcher discusses, compares, and analyzes the complexity of various DLM as well as its statistical sharing and distribution. Eventually, the limitation of current DL and its trends in the future was discussed in particular, the classification of MI, and arrhythmia based on DL. The papers that concentrate on the signals of ECG and its classification that comprised review the papers in DL that use the signal data and modality images from cardiology, and comparing these studies, it was found that Bizopoulos and Koutsouris 2018 (Bizopoulos, P., & Koutsouris, D., 2018) introduce the state-of-the-art to the techniques of the DL which gives an accurate result. Additionally, the topic that will be covered in this review includes; the limitation and the complexity of DLM that is used to classify arrhythmia of ECG, the database that was recorded by ECG, evaluation metrics of the performance, introduction on various DLM, medical background about arrhythmias. Recently, in 2019 Dinakarrao and his coworkers (Dinakarrao, S. M. P., et al., 2019) present a survey on the diagnosis of arrhythmia, they study a large number of detection and performance techniques and discuss its complexity considering a wide variety of arrhythmia like; MI, Ectopic Beat, PVC, PAC. In another study, in 2020 Roberta and Francesco B. (Roberta A., Francesco B., 2020) The proposed new neural architecture was a solution for the development of automated heart disease detection systems using electrocardiogram (ECG) signals, and it was based on the recent success of convolutional neural networks (CNN) ECG signals were sent directly to a CNN network that had been properly trained. More than 4000 ECG signal instances were collected from 47 subjects' outpatient ECG exams in the database: There are 25 males and 22 females in this category. The confusion matrix extracted from the research dataset suggested that the “normal” class had a 99 percent accuracy rate. ECG segments were correctly identified 100% of the time in the “atrial premature beat” category. Finally, ECG segments were correctly labeled 96 percent of the time in the “premature ventricular contraction” category. The average classification accuracy was 98.33 percent in total. The sensitivity (SNS) and specificity (SPC) were 98.33 percent and 98.35 percent, respectively.

1. The Methodological Comparison

This part was focused on the comparison and classification for arrhythmia methods, as well as the percent of every arrhythmia from the total studies. Six methods of DL have been studied carefully and their application on the classification of ECG arrhythmias such as GRU, DBN, LSTM, RNN, MLP, and CNN, also the associated percentage of each type and model was studied. It was found that the most preferable method to extract features was CNN with a contribution of 52%. Figure 8 indicate the papers that considered the heart disease percentage in the studied cases, and they were classified as SVEB/VEB, and AF which represents 21 and 48% respectively.

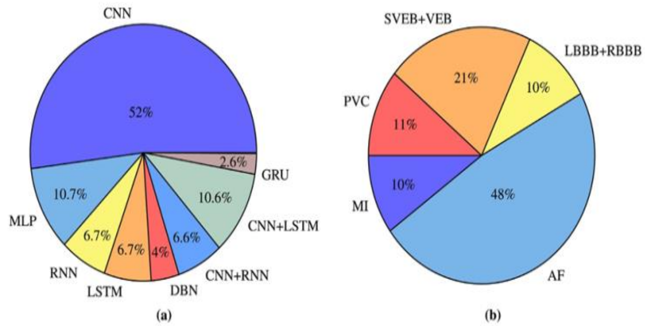

Figure 8 (a) Contribution percent of each DL model. (b) The percent of each heart disease

Figure 9 sums up and review previous myocardial infarction and arrhythmia studies that founded on performance according to their method of classification (Z. Ebrahimi, et al, 2020).

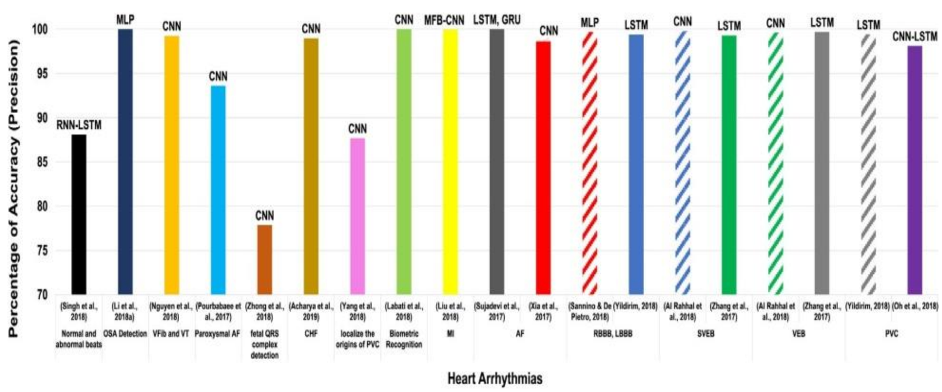

Figure 9 Previous studied reports for MI and arrhythmias according to the method of classification
(Z. Ebrahimi, et al, 2020)

2. Complexity of Computational of DLM (Methods)

Generally, the complexity of the processing to DL M usually relays on operation floating-points of the model, and the operation of the model of the CNN, consumption energy model ($R^2 = 0.9641$, p-value <0.0001), and the time of the inference ($R^2 = 0.8888$, p-value < 0.0015) (Loni, M., et al, 2019). The real-time inference of DLM relies on many factors such as; utilized APIs, compiler optimization, and hardware platform (like TensorFlow as described by Torch as described by (Paszke et al., 2019) Table 1 shows different DLM of the recent computational overhead which needs an enormous resource of computing to find the actual time of processing. Generally, the methods of DL are slow compared to other techniques such as SVM (Loni et al., 2020).

Table 1 Computational complexity of diverse methods of DLs (Z. Ebrahimi, et al,2020)

Computational Complexity of DL Method	
GRU	(Low__complexity)
LSTM	(Medium__complexity)
RNN	(Medium__complexity)
DBN	(Low__complexity)
CNN	(High__complexity)
MLP	(Medium__complexity)

Deep Learning for Arrhythmia and Myocardial Detection: Advantages and Limits

Deep learning reduces pre-processing and features engineering efforts while also allowing for the discovery of novel features by learning hidden patterns that aren't visible using conventional machine learning techniques (Parvaneh S, et al; 2018). However, deep learning model interpretation is difficult (Parvaneh S, et al; 2018), and reaping the benefits of deep learning models necessitates access to large datasets. As a result, future research on improving performance will be necessary and Future research should focus on improving the interpretability of developed deep learning models and determining the appropriate size of training and test datasets for developing the best arrhythmia detection using deep learning (S. Parvaneh and J. Rubin, et al; 2019).

Results of the Review

This section presents a technical overview of the outstanding studies regarding the highest reported accuracy on ECG- based arrhythmia and MI diagnosis. Besides, a summary of other studied articles is presented. Table 2 'shows the list of the main techniques comparing the learning models used, the parameters of CNN implemented, and the obtained performance'.According to a detailed investigation of the use of DNN in biomedical signals, the majority of papers and researches were published after 2017, as shown in table 2. For biomedical diagnosis, the majority of papers have used convolutional neural networks (CNN). There are two major approaches to deep learning and its use for biomedical signal diagnosis.The first method is function extraction, which entails building optimal CNN features. The second method is to use CNN for classification. The following last parts will include a brief overview of deep learning applications.

Table 2 The Summary of the Results of Several Studies for CNN-based ECG arrhythmia and MI classification

Number of papers	Writer/Year	Framework	Dataset	Specifications	Sensitivity	Accuracy
1.	Acharya et al; 2017	1-D CNN, 11-laye	Physiobank (PTB)	94.19%	95.49%	95.22%
2.	Wenhan Liu 2018	MFB-CNN	Physiobank (PTB)	99.90%	99.97%,	99.95%
3.	Savalia et al., 2018	1-D CNN, 5-layer	MIT-BIH arrhythmia	-	-	88.7%
4.	Baloglu et al., 2019	1-D CNN, 10-layer	MIT-BIH arrhythmia	-	-	99.8%
5.	Kai Feng 2019	CNN-LSTM	Physiobank (PTB)	86.5%	98.2%	95.4%
6.	C. Han 2019	ML–ResNet	Physiobank (PTB)	97.37%	94.85%	95.49%
7.	Roberta et al., 2020	1-D CNN, 5-layer	MIT-BIH arrhythmia	98.35%	98.33%	98.33%
8.	L.A. Abdullah et al.,.(2020)	CNN-LSTM	PTB and MIT- BIH arrhythmia	96.80%	98.00%	99.45%
9.	Lidan Fu et al., 2020	MLA-CNN-BiGRU	Physiobank (PTB)	99.63%	99.99%	99.93%
10.	Fakheraldin Y. et. al ;2020	CNN	MIT-BIH Arrhythmia	99.9%	99.9%	99.84%
11.	Mohammad M. et al ;2020	CNN	MIT-BIH Arrhythmia	-	-	95.2%
12.	Zhenyu Zheng et al; 2020	CNN-LSTM	MIT-BIH Arrhythmia	99.57%	97.67%	99.01%
13.	J. Liu et al;2020	‘Dual-Q TQWT + DWPT + MPCA + Treebagger,	Physiobank (PTB)	90.76%	99.09%	97.46%
14.	P. Gopika et al ;2020	CNN	MIT-BIH & PTB	-	-	98% &99%
15.	Hao Tung et al ;2020	Attention CNN	MIT-BIH Arrhythmia	98.9%	94.5%	98.6%
16.	Muhammad A. Haroon 2020	CNN	MIT-BIH Arrhythmia	-	-	83 %
17.	Roberta et al., 2020	1-D CNN, 5-layer	MIT-BIH arrhythmia	98.35%.	98.33%	98.33%
18.	Amin Ullah et al; 2021	CNN	MIT-BIH Arrhythmia	-	-	97.38%
19.	Mengze Wu et al ;2021	CNN	MIT-BIH Arrhythmia	99.35%	97.05%	97.41%

Table 2 shows the classification of ECG according to the available studies, and the used dataset was open-access Physiobank (PTB), and the arrhythmia dataset of MIT-BIH as explained by (L.A. Abdullah et al., (2020). In addition to the information that was demonstrated from the previous database, it can be transferred and used for inference models training. In all experiments, the used input frequency rate was 125 Hz for lead II ECG resample, however, the frequency rate was 360 Hz to record the dataset of MIT-BIH (with ECG) from 47 diverse subjects and every beat was explained by not less than 2 cardiologists. In this review, the explanation of this dataset was classified to create 5 diverse types according to the standard (EC57) in AAMI (Association for the Advancement of Medical Instrumentation).The dataset that was used in the diagnosis of PTB was collected from the records of ECG that belong to 290 matters, which were; 7 various diseases, 52 related control, and the 148 subjects were MI diagnosis. Every ECG record has 12 signal leads at 1000 Hz. In the current study, only ECG lead II has used the categories that were used in the analysis were control (healthy), and MI (Muhammad A. Haroon., 2020).

1. Application of CNN for ECG Analysis

Several studies have been published in the literature to find automated diagnostic tools for ECG signals for example in 2018, (Wenhan Liu et al; 2018) proposed the CNN (Convolutional Neural Network) that has multiple feature branches to detect MI with the uses of ECG. Every independent branch of the feature of MFB-CNN is related to a certain lead. 'SoftMax's fully connected global layer could have taken advantage of the integration, summarizing all the branches of the feature', and upon the framework of DL, no manually designed features were applied for the analysis. Moreover, and to manage the variances in inter-patient, and to automate the diagnosis, the adopted model was PSM (patient-specific model). For localization and detection of MI, the accuracy average was around 99.81% and 99.95% correspondingly, while it was 94.82% and 98.79 respectively for the experiment that related to patient-specific. However, to detect MI, a few researchers use CNN with 11-layer as depicted by (Acharya et al., 2017) by which the authors verified and focus on the inferior myocardial infarction with the help of S-CNN (Shallow-CNN) that has privilege from using different sizes of filters in the same layer of convolution that allows them to find out the features from regions of the signals of different lengths. In (Savalia and Emamian, 2018) proposed a system to classify the diseases that are related to cardiovascular by using CNN and Multi-Layer Perceptron (MLP-Network). Particularly, they evaluate the obtained results and compared them for each model using the similar set data but various classes. In MLP-Network, 2 classes were used “Normal”, and “Arrhythmia”, while for CNN with 4-Layers, nine classes were used.

The ECG data that were used for validation and training as well as the dataset of the test were uploaded from Kaggle.com and PhysioBank.com.Also, in the current review, it was noticed the low performance in using both CNN and MLP networks such as 93.5% and 88.7% respectively. Recently, (Fakheraldin et al; 2020) introduced a new tactic to classify automatically various types of arrhythmias (10 types) and were adopted and developed based on the theory of DL. Therefore, the famous and well-known CNN was developed to classify the various arrhythmia types. The projected model structure has 11 layers that dispersed according to the following: 3 layers were connected successfully, 4 of them were max-pooling while the last 4 layers were for convolution interchange. The dataset was uploaded from Physionet and the experiment was carried out using a dataset from the Massachusetts Institute of Technology-Beth Israel Hospital. To estimate the performance and evaluate the technique, a comparison with the earlier data was carried out and among them are; PRE, SEN, confusion matrix, SPE, and to calculate this, receiver operating characteristic, using the area under the operating curve. The outcome indicates that the suggested method enhances the performance of CNN and gives an accuracy of around 99.84%. Also, (Mohammad M. et al.; (2020) conducted a study to classify the signals of arrhythmia ECG (5 classes) and distinguished them from the arrhythmia dataset of Physionet's MIT-BIH. It was noticed that demonstrating ANN (the Artificial Neural Network) will lead to an important success and improvement in the classification of ECG signals. In the current article, it was proposed a certain model of CNN that based on customized CNN to classify the signals of ECG. The outcome of the tests shows that the suggested model can classify with accuracy recall and average precision can reach up to 95.4% and 95.2% respectively, and the proposed model can be used effectively in detecting the early stages of heart rhythm irregularities. The main goals of this paper were to automatically identify irregular or abnormal heartbeats from a large amount of ECG data, (Zhenyu Zheng et al; 2020). This paper provided an effective arrhythmia classification method that integrates 2-D CNN and LSTM and uses ECG images as input data. Thinking in a single dimension. The signals from the MIT-BIH arrhythmia database were converted into 192 *128 grayscale images. photographs A total of 107,620 ECG images were collected by processing data from the database. This method's accuracy was 99.01 percent, specificity was 99.57 percent, and sensitivity was 97.67 percent as a result. The results of the ECG arrhythmia classification showed that the method of arrhythmia detection using a combination of ECG image data and CNN-LSTM would aid doctors in better diagnosing cardiovascular disease while also reducing their workload'. Another study has used CNN in (Mengze et al; 2021) study and focus on certain micro-classes (as well as this study), and in particular the Ventricular Beats, Premature, Atrial Premature Beats, Right Bundle Branch Block. Left Bundle Branch Block, and the

Normal, and the comparison was carried out with other CNN networks, random forests, and BP Neural Network and the findings was very promising and shows higher robustness and accuracy, and in overall, the outcomes show 97.21% in prediction, 99.35%of specificity, 97.05% of sensitivity, and 97.41 of accuracy, these results were found on classifying the arrhythmia dataset that was in the type of micro-classes. Finally, (Amin Ullah et al; 2021) suggested a new model (1D-CNN) and applied it on the signal of ECG, using and learns from useful features of the presented data, and based on features that were extracted, the ECG signals were classified with the uses of 1D-CNN model and the output accuracy was up to 97.38% which indicates a better algorithm that reached by earlier studies.

Discussion

The main goal of this paper was to study several studies and articles in the field of deep learning in biomedical ECG signals. After reading more than 25 papers, 19 were selected for further study, with the findings of each article discussed. This survey aimed to implement the various applications of deep learning in the field of biomedical ECG signals. The majority of papers have been written in the last three years, according to the number of findings performed. Furthermore, convolutional neural networks CNN, especially the pre-trained CNNs, are the most widely used deep learning network. The types of signals used to train and apply deep neural networks can be seen to be very diverse.ECG. All of the research looked at how deep learning could be used to diagnose medical signals and compared it to current methods. Each of these studies has verified and demonstrated that a CNN trained with deep learning can automatically extract the best features and learn to differentiate between different groups. CNN has proved to be extremely effective at analyzing a variety of medical signals, including ECG. As a result, convolutional neural networks, or more broadly, deep learning, can improve healthcare productivity and quality. It would lower the chances of misclassification and improve the early detection of severe diseases. It can also be used to help CAD (computer-assisted diagnosis).

Conclusions

The content of the paper is structured to provide background information on how deep learning was developed, evolved, and revolutionized the field of biomedical signal analysis. The results of previous studies were presented that related to the MI, and arrhythmia classification to the signals of ECG. The most powerful methods of Deep Learning in detecting different types of arrhythmias were investigated. Deep Learning method was used to classify ECG Beats such as: 'N – Normal Beat, SVP – Supra – Ventricular Premature Beat, PVC – Premature Ventricular Contraction Beat, FVN – Fusion of Ventricular and Normal Beat, FPN – Fusion of Paced and Normal Beat, MI – Myocardial infarction and AF–Atrial Fibrillation', etc. Using the appropriate type of Deep Learning will enhance and improve the performance of the classification for the related application. The CNN-Based method shows the best technique to classify MI and arrhythmia. The efficient method to classify long and short-term signals is the dynamic classification which can be engaged in such application. CNN is the best performance to classify various types of MI and arrhythmia and can be considered as a capable learning tactic to be applied. There were numerous studies discussed. in this review that has an association with heart disease classification through the signal of ECG and with the use of DL data based on CNN. The research success to reach a DL-CNN technique and developed it in many versions to classify the performance of ECG. The findings of the ECG Classification studies could be used by cardiologists in the diagnosis and interpretation of arrhythmias, as well as in the development of systems that automatically connect remote doctors with their patients. Deep learning especially CNN has been verified as a possible technique for biomedical signal analysis based on the findings of these literature reviews. As a result, the survey's brief nature will moderately add to the existing body of literature while also shedding light on research problems and potential opportunities in the field of biomedical signal analysis. Finally, many studies have indicated that (The suggested ECG arrhythmia classifiers can be used in a variety of biomedical applications; including sleep staging; and a medical robot that monitors the ECG signal and assists medical experts in detecting cardiac arrhythmia more accurately).

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