Improving ECG signals classification by using deep learning techniques: A review

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Abstract. Heart diseases are serious global health concerns that could result in many deaths. Detecting and classifying the heart diseases early is crucial for initiating treatment and improving patient outcomes. ECG signals contain valuable information to analyze cardiac functions. It can be argued that techniques of Deep learning (DL) are effective aid to classify ECG signals accurately through learning from large amount of ECG data, ability to extract hidden information, and achieving superior performance in detection heart abnormalities. ECG signals processing involves three phases, preprocessing, extraction features and classification. This paper intends to review several studies published from 2019 to 2024 in this field. It follows a method of comparative analysis, considering specific performance metrics, preprocessing techniques, and the DL model used. The aim is to determine the most accurate DL technique for classifying ECG signals. Eventually, the paper indicated that the debate on the most accurate technique for classification remains ongoing. However , the reviewed studies demonstrated that models based on CNN and RNN can achieve significant level of accuracy in classifying ECG signals. On other hand, according to the conducted comparative analysis, it is recommended to use VGG16 as a classifier for ECG signals. As a suggestion, the complexity of VGG16 can be reduced, allowing for the implementation of a real-time application.

1 Introduction

The heart performs an essential function in the human body, pumping blood throughout the circulatory system to supply oxygen and nutrients. When the heart is not functioning properly, it can have deadly consequences [1]. The number of people suffering from heart diseases is increasing dramatically. These diseases are responsible for the majority of global deaths. According to WHO (World Health Organization) in 2019, a total about 17.9 million individuals died of heart diseases, which stands for 32% of the worldwide fatalities. Heart attacks accounted for 85% of these fatalities. So, it is very important to detect heart diseases

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in its preliminary stages in order to initiate treatment and increase the possibilities of patient's survival [2].

Electrocardiogram (ECG) is a form of biomedical signals that gives vital information about the heart's electrical activity and can be used to understand heart function [3]. It represents by wave forms P, T, Q, R, and S. Where QRS complex (depolarization of ventral) indicates high-frequency components, while P (repolarization) and T (depolarization) indicate low-frequency components. ECG signal contains frequency domain of 0.5 Hz to 100 Hz. Additionally, its signal's amplitude is relatively low, falling between 0.4 and 3 mV. Therefore, before beginning the analysis, the signal must be appropriately filtered [4]. Certain types of noise, including muscle noise, baseline drift, electromagnetic interference, and power line noise, can effect on ECG data [5]. The observed changes in ECG waveforms such as amplitude increase or decrease and inconsistency, enable doctors to identify abnormalities in the heart such as arrhythmia. Furthermore, the data of ECG contain valuable information that can be utilized to analyse heart rate [6]. Figure 1 displays the diagram of main ECG features.

Since different doctors may interpret the same ECG signal differently, therefore there is continuous progress in implementing and designing automated intelligent systems that can aid doctors in analysing and classifying signal patterns more accurately. This is achieved by employing various methods, including Deep Learning (DL), which is the leading technique used in this field. Although a considerable progress has been made in ECG signals classification using DL methods, there many challenges, such as the availability of datasets that trained and validated, the feature extraction technique and the choice of a DL structure that satisfies the requirements. Tackling these challenges and continuing progress are essential to improving treatment plans and reducing the death of heart diseases.

However, the classification process of ECG signals using DL techniques passes through various stages, starting from acquisition the data form ECG, then go through preprocessing stage, after that features extraction and finally ECG classification. In the preprocessing stage the model employs different techniques to reduce noise and improve quality of ECG signals through filtering procedures. Then, relevant features are extracted and selected and finally the model classify these features as normal or abnormal ECG [9, 10].

Based on the all examined studies in this paper, the DL techniques can be argued as effective and accurate in identifying and classifying different heart diseases, because they can learn a large amount of data, can deal and adapt with missing data, have the ability to uncover the hidden information from ECG signals, and identify long-term relationships of temporal patterns. The existing studies in this field do not provide the most accurate classifier that can be implemented in real-time applications and the best classifier is still for debate. This review article sheds light on promising DL models for effective and accurate heart diseases detection and classification in ECG signals through a comprehensive review for different studies related to classifying ECG signals by DL in order to identify the most accurate DL model that can automatically select the most relevant and informative features from the ECG signal and classify them effectively. Comparing these studies is based on the preprocessing method, the ECG datasets employed, the features extraction method, DL architectures and performance metrics such as accuracy, and precision that are using for evaluating the effectiveness and efficiency of proposed DL model, so we can fill the existing gap in current studies.

The aim of this paper is to explore the most effective and efficient DL model to detect Heart diseases in ECG signals accurately through conducting a comparative analysis among different studies related to this field based on some parameters.

This study reveals that VGG16 outperforms the other techniques for the classification of ECG signals. For further study we propose to simplify the complexity of the VGG16 architecture, thus it can be implemented using an FPGA or Raspberry pi boards. Among the different datasets studied in this paper, the MIT-BIH Arrhythmia dataset is recommended for training and testing, because it contains forty-eight half-hours of ECG recordings from substantial number of patients with different heart disorders.

The structure of paper is divided into several sections, which include research methodology in section 2 and study contribution in section 3. In section 4, there is an overview of Deep Learning concept. Section 5 explains the process of classifying ECG signals and presents the common techniques used in the examined studies. Section 6 discusses the performance parameters used to evaluate the classification process. Section 7 showcases the ECG databases utilized for testing and training purposes. In section 8, a comparison between different DL methods is provided based on certain parameters. Section 9 presents a literature review in tabular form. Lastly, sections 10 and 11 compose of the discussion and conclusion, respectively.

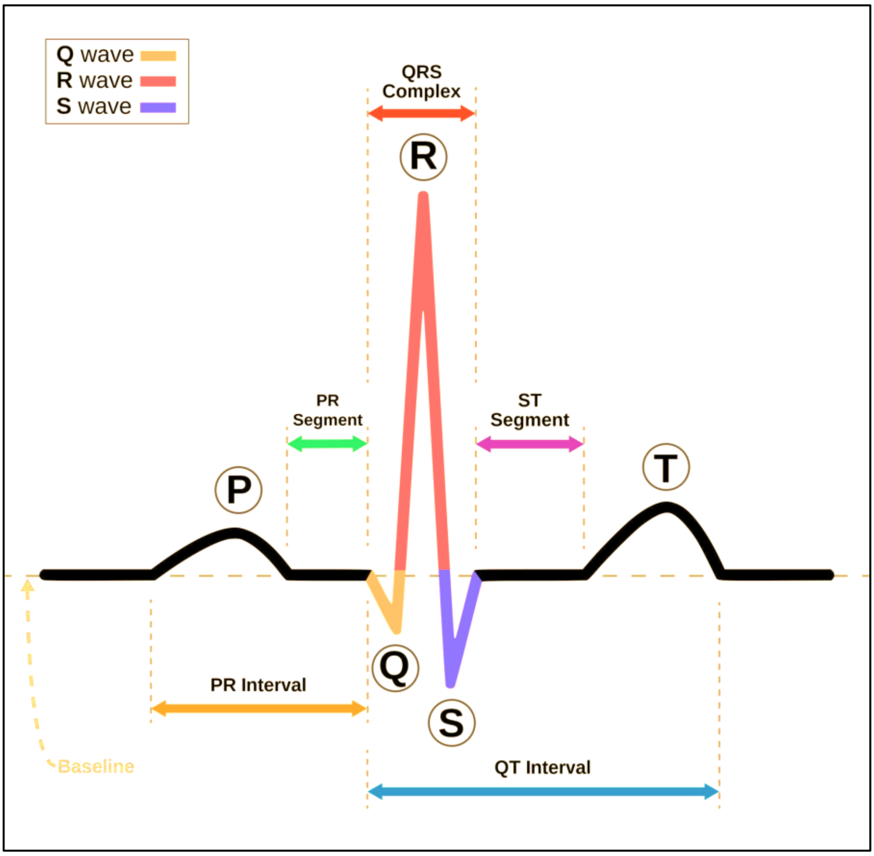

Fig. 1. Diagram of main features of ECG signal [1].

2 Research methodology

This review conducts a comparative analysis different studies published from 2019 to 2024 that related to employing Deep learning (DL) techniques for ECG signals classification to overcome the challenges exist in the classification of heart diseases. The analysing process of each single paper is based on four factors: the employed dataset, and feature extraction method, the proposed DL structure and performance parameters such as accuracy. In this regard, we used the measurement of sufficient, and effectiveness of models by measuring the accuracy with 100%.

Therefore, the main keywords are 'ECG,' 'Deep learning' and 'classification.' By using the search engines along with different well-known journals such as Google Scholar, Springer, IEEE, Elsevier, Electro cardiology, and PubMed. We found the relevant papers that describe the medical and technical sides.

3 Study's contribution

This study contributes to the field of employing DL techniques to improve the classifying of ECG signals in order to detect heart diseases accurately through several keyways:

- This review article sheds light on promising DL models for effective and accurate heart diseases detection and classification in ECG signals. Through analysing and comparing various architectures and their performance. It provides researchers with valuable insights to select the most suitable strategy for their specific needs. This can contribute to the development of clinically useful tools for doctors.
- Summarizes findings from numerous studies to create a comprehensive picture of DL process in this area.
- Advanced methodological approach by exploration of different metrics that consider accuracy and other factors including dataset, preprocessing method feature features extraction technique, and the proposed DL structure. This would provide a more complete evaluation framework for DL models this field.
- Highlights the need for further research on integrating DL models in heart diseases detection with real-time clinical applications, through suggesting mechanisms for effective developing models.

4 Deep Learning (DL) concept

Deep learning is considered an effective tool for ECG signals analysing and classifying through learning from large amount of data, and automatically extract information from signals with ability of uncover hidden patterns in ECG signals and discover patterns in sequential data. These features of DL led to revolutionizing the field of ECG signals classification and many studies relied on these methods instead of traditional methods and machine learning techniques in order to design an efficient and effective model that can achieve higher accuracy in classification process. Deep learning employs artificial neural networks combined with multiple layers for extracting features from the raw ECG signal directly, this eliminated the requirement of feature extraction manually [9].

The advantages of deep learning comprise improved accuracy, remarkably when dealing with huge and complex datasets. It also can reduce the burden of work for medical professionals in interpreting and analysis of the ECGs. However, there are some challenges when dealing with DL techniques such as data dependency, the imbalanced or limited datasets can result biased models, and the complexity of deep learning models [10]. Although of these challenges, DL provide a powerful approach for classification of ECG signals. However, as research progress continues and datasets are being grow, it can be expected more advancements in this field [11]. The most common DL approaches that have been employed in the examined papers and demonstrated an increase in the accuracy were based CNNs, RNNs, and LSTM.

4.1 ECG signals processing

ECG refers to electrocardiogram which shows the heart's electrical activity as a non-stationary physiological signal. This measurement is used to detect heartbeat patterns that are pathological, as well as to measure the regularity and stress of the heartbeats [12]. There are two types of information that cardiologists can obtain from an ECG. Firstly, they can analyse the electrical waves that pass through the heart's conduction system to measure time intervals. This enables them to identify both regular and irregular rhythms. Secondly, they can assess the condition of the heart by showing areas that are overworked or enlarged. This kind of data helps determine the heart's electrical activity's frequency and speed [13]. The DL steps applied to process ECG signals in the training phase is shown in Figure 2. The steps involved in ECG signal analysis include data collecting, preprocessing, extraction and selection of features, and classification [14].

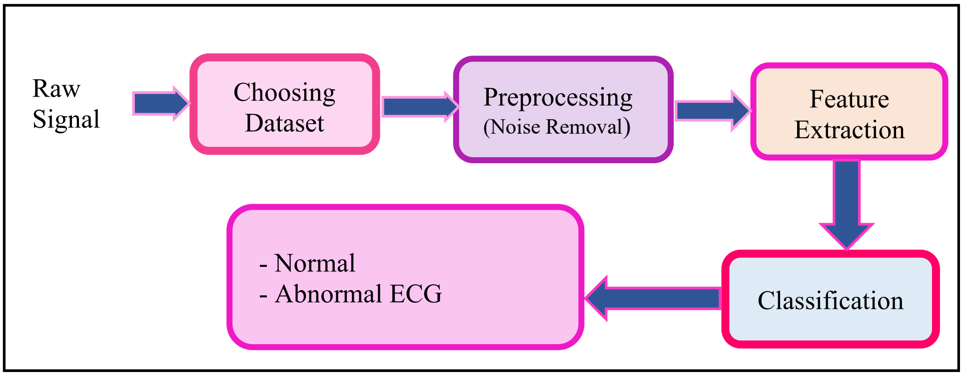

Fig. 2. ECG signal processing phases [14].

4.1.1 Preprocessing phase

The preprocessing in ECG analysis involves cutting noise and preparing raw data for further processing. Noise sources include power grid interference, movement artifacts, device noise, quantization noise, signal processing disturbances, and baseline diversion. Different methods like linear phase filters, adaptive filters, wavelet transform-based methods, and non-linear Bayesian filters are used for noise attenuation[7]. Automatic classification systems are affected by noise and require noise attenuation for exact results. Finite impulse response (FIR) filters and adaptive filters have shown promising results. The impact of signal pre-processing on later classifiers is an underexplored research area. The efficiency of noise reduction techniques is frequently expressed through the evaluation of the signal-to-noise ratio[15].

4.1.2 Features extraction phase

This stage involves the characteristics that can be derived from signal morphology in the time/frequency domain. For ECG signals is indicates to the process of extracting Q, R, T, and U waveforms [11]. There are common methods like wavelet transform which are frequently employed for this process. DL techniques like CNN can automatically extract these features. Heartbeat classification involves linear such as RR interval, frequency spectrum and nonlinear such as fractal characteristics methods. Optimization using particle swarm optimization enhances the efficiency of the wavelet transform. Achieving the highest accuracy in heartbeat classification involves using the wavelet function[16, 17].

4.1.3 Classification phase

The last step in ECG signals processing is classification. The Classification is a process of utilizing automatic algorithms to analyze and categorize ECG signals based on diverse cardiac conditions. For this task we use DL techniques with supervised learning, which uses data with known tags in training models [18]. The most methods commonly used in examined studies that proved high efficiency in ECG classification process are CNNs, RNNs, and LSTM Networks.

4.2 ECG classification methods

4.2.1 Convolutional neural networks (CNNs)

The CNNs are one of the networks which functions similarly to the neural network in the brain in that it transmits data from input to output. It has both complex and simple layers, like the brain's visual cortex, and usually includes convolutional and pooling layers[19]. CNN typically uses images as its data format. Images can be composed of one-color channel (like grayscale) or three separate color channels (red, green, and blue)[20]. Figure 3 depicts CNN's architectural layout. CNN involves numerous layers comprising input, convolutional, and pooling layers. Entirely connected layers are also included. Predictions are made by the last layer. These tiers could or might not have activation functions. For CNN classification, we can use one or more fully connected layers [21]. Each layer has a special function that decides how many numbers will go to the next part, which is called the activation function. Rectified linear unit (ReLU), a kind of activation function found in the intermediate layer, is frequently employed as:

$$f(a^l_i) = max(0,a^l_i) \quad (1)$$

Where a^l_i, belongs to R, which denotes the number of signals that the middle layer's i unit has received. The last layer employs the soft-max function [20]. To get potential results from the output, the equation (2) is used.

$$f_k(z) = \frac{exp\ (z_k)}{\sum_{k=1}^{K} exp\ (z_k)} \quad (2)$$

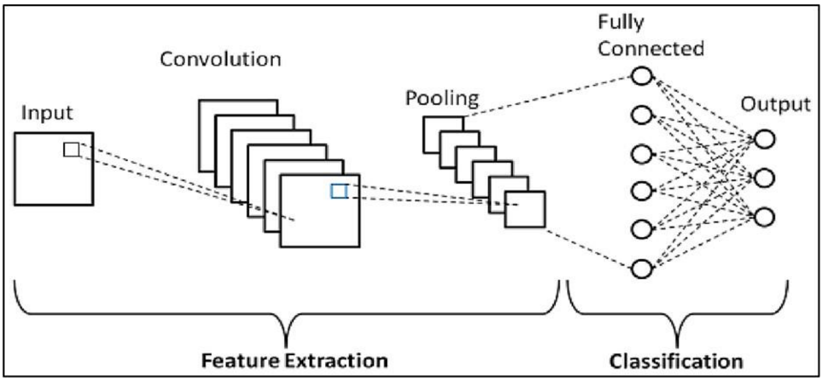

Fig. 3. Diagram of CNN's structure [26].

Many researchers utilize CNNs for classification purposes for the ECG signals, as they demonstrated superior accuracy. CNNs can serve as both classifiers and feature extractors, as seen in studies [8] and [22], or they can be combined with other methods, as confirmed in studies [23] and [24]. No additional feature extraction was needed since CNNs are capable of extracting features directly as proved in studies [8] and [25].

4.2.2 Artificial neural networks (ANNs)

The ANN emulates the data processing mechanism observed in natural nervous systems, like the human brain [11]. It consists of a sum of interdependent processing parts known as neurons, which collaborate to address various problems. Like humans, ANNs acquire knowledge through examples, and the accuracy of their understanding increases with larger datasets [22]. ANNs specialize in specific applications like pattern recognition or data classification, using the brain's computing powers to create algorithms. Reverse propagation neural networks use weight adjustment, backpropagation, and forward propagation, which depend on learning parameters like momentum and learning rate. ANNs offer self-teaching, flexibility, rapid training, high accuracy, noise resistance, and scalability. However, they may struggle to locate the global optimum in big issues. Probabilistic neural networks and Multilayers perceptron are commonly used for heartbeat classification.[27]. The ANN's structure is illustrated in figure 4.

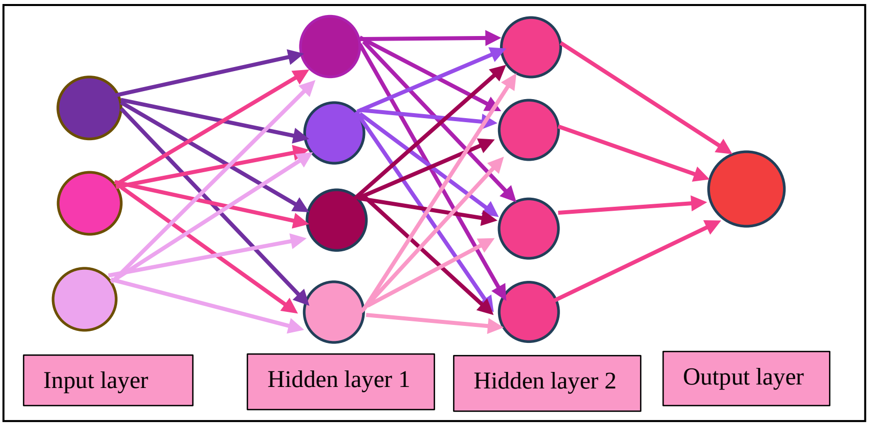

Fig. 4. ANN's structure (the figure is constructed by the author based on references[3 , 27]).

4.2.3 Recurrent neural networks (RNNs)

RNNs is one of deep learning methods designed to process serial data [9]. RNNs works frequently and implement the same account for each element in a sequence, with outputs that depend on previous accounts. It excels in dealing with sequences such as time chains data or natural language processing tasks [8]. RNNs have rings in architecture, allowing information to continue (self-looping). However, they suffer from the problem of explosion, which limits their ability to capture long -term dependencies effectively. RNN's basic structure can be seen in Figure 5. At each time step (t), the RNN updates its hidden vector(h), in accordance with the following equations [28].

$$h_t = \tanh\,(Wh_{t-1} + Ix_t) \tag{3}$$

Where I, refers to projection matrix, tanh is the function of the hyperbolic tangent, and W stands for the recurrent weight matrix. We utilize the hidden state h to make predictions.

$$y_t = \mathrm{softmax}(Wh_{t-1}) \tag{4}$$

$$h^l{}_t = \sigma(Wh^l{}_{t-1} + Ih^{l-1}{}_t) \tag{5}$$

The soft-max in equation(4) offers a normalization of probability distribution across the potential classes. While the σ in equation (5) indicates the logistic sigmoid function, and W is a weight matrix. Higher-order RNNs may be created by stacking RNNs and utilizing h as the input to another RNN[29].

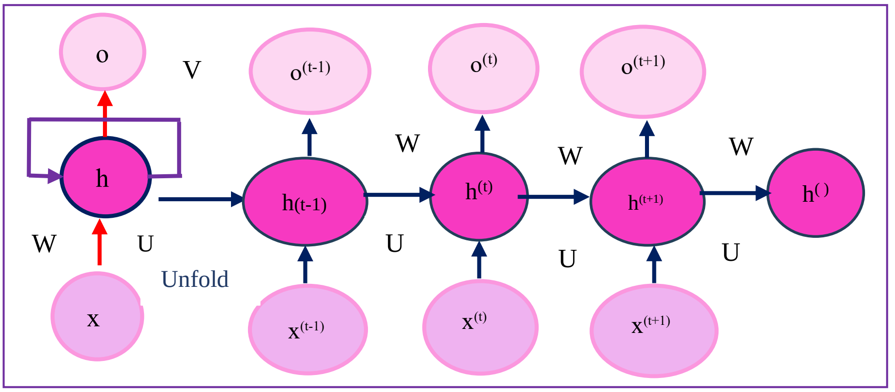

Fig. 5. RNN structure(the figure is constructed by the author based on reference[27]).

4.2.4 Long short-term memory (LSTM) networks

LSTM networks are extended from the general RNNs which have ability of learning the long-term dependencies [30]. The LSTM networks contain three distinct categories of gates, Sequential data is fed into the network through the input layer, which is the first layer. The bidirectional layer is the next, where determining the persistent relationship between signal time steps and sequence data in both forward and feedback directions [28]. The last layer is completely connected, includes a vector of biases, and manages the weight matrix multiplication of the numerical input values. The LSTM's fundamental structure is seen in Figure 6 [29].

$$W= \begin{bmatrix} W_i \\ W_f \\ W_g \\ W_o \end{bmatrix}, R = \begin{bmatrix} R_i \\ R_f \\ R_g \\ R_o \end{bmatrix}, b= \begin{bmatrix} b_i \\ b_f \\ b_g \\ b_o \end{bmatrix} \tag{6}$$

Equation (6) describes the relation between Weight (W), Recurrent weight (R), and bias (b) letters i, f, g and o are representing inputs, forgets, output gates, and cell candidates, respectively [30].

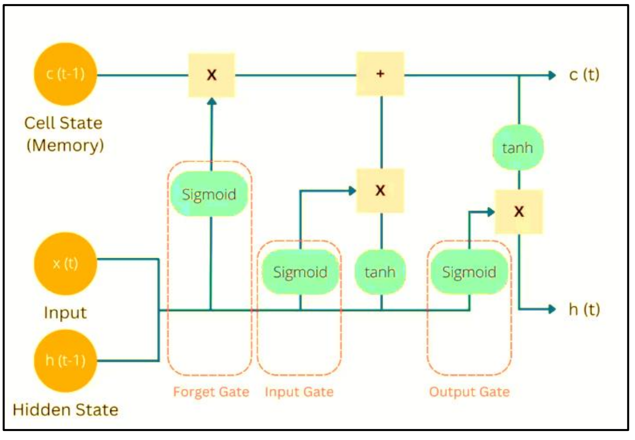

Fig. 6. Diagram of LSTM architecture [26].

5 Performance evaluation metrics

The classification model performance effectiveness is measured by using different metrics to get precise classification results. Throughout the classification process accuracy, precision and sensitivity are the most valuable parameters to assess the model performance. Following classification, the confusion matrix ,explained in table 1, is used for validation, which is a data mining approach for evaluating the effectiveness of an algorithm. The percentage of ECGs that were correctly classified overall is shown in equation 7:

$$\text{Acc.} = \frac{T_P+T_N}{T_P+F_P+F_N+T_N} \tag{7}$$

The precision measures the percentage of actual abnormal ECGs among the expected abnormal ones as shown in equation 8:

$$\text{Precision} = \frac{T_P}{T_P+F_P} \tag{8}$$

Sensitivity or Recall This is the percentage of actually abnormal ECGs that the model accurately classified as normal as shown in equation 9:

$$\text{Sensitivity} = \frac{T_P}{T_P+F_N} \tag{9}$$

Following classification, the confusion matrix ,explained in table 1, is used for validation, which is a data mining approach for evaluating the effectiveness of a model by showing a number of correct and incorrect predictions. Here, the size of matrix is 2x2, meaning binary classification.

Table 1. The description of confusion matrix.

		Predicted Values		
		Yes (Positive)	No (Negative)	Total
Actual Values	Yes (Positive)	TP	FN	TP+FN
	No (Negative)	FP	TN	FP+TN
	Total	TP+FP	FN+TN	

* The table is constructed by the author based on references [16, 21].

The explanation of each symbol has been used in the Equations from (7) - (9) and the confusion matrix’s rows is indicating to actual ECG class, while the columns is indicating to predicted ECG class as described below:

- True Positive (TP): These are ECGs that are truly abnormal, and the model correctly classified them as abnormal.
- True Negative (TN): These are ECGs that are truly normal, and the model correctly classified them as normal.
- False Positive (FP): This includes all ECGs that the model classified as abnormal, regardless of their actual class.
- False Negative (FN): This includes all ECGs that the model classified as normal, regardless of their actual class.

By examining these metrics, it can be determined how well the model distinguishes between normal and abnormal ECGs. This emphasizes how crucial the consideration of various metrics to identify the effectiveness of the model.

6 Datasets

A dataset refers to a structured collection of ECG data which is essential tools to classify ECG signals. There are various forms of datasets depending on the study's purpose. A short-term ECG dataset which able to capture a brief period of ECG signal, while long term ECG datasets can capture recordings with a longer duration, such as 24 hours or more. Also, Lead configurations play a role in ECG datasets, as single-lead ECGs providing limited information while the multi-lead ECGs may provide a more comprehensive view. Another feature which is Diagnosis focus is considered crucial as well, with normal ECG datasets containing recordings from healthy individuals without known heart conditions, arrhythmia datasets containing recordings with various arrhythmias, and myocardial infarction datasets containing recordings during or after a heart attack [31].

The common type is the publicly available ECG datasets, MIT-BIH Arrhythmia, PTB Diagnostic, ECG-ID, INCART, and AF. The MIT-BIH Arrhythmia includes 48 half-hours of ECG recordings from 47 subjects, while PTB Diagnostic contains 549 10-second ECG recordings. The ECG-ID covers a wide range of arrhythmias, while the INCART evaluates algorithms for ischemic heart disease. The AF Database contains 100 long-term ECG recordings from patients with atrial fibrillation[32].

7 Comparison of Deep Learning methods

The computational complexity of DL techniques is affected by different parameters, such as the number of epochs used in training data, dataset size and desired accuracy level. Table 2 provides a comparison of different DL methods based on their computational complexity, and design factors [20, 33].

Table 2. Comparison of various Deep Learning models.

	Complexity level	Complexity factors	Advantages	Disadvantages
ANNs	Medium	Data size, neurons, layers, and connections	General-use, resistive to noise and processed in parallel.	Data-driven, black box, and sensitive to overfitting.
CNNs	High	Data size, filters, number of layers, and input size.	efficient for data that resemble images, lessen pre-processing, Managing various ECG shapes.	Expensive to compute, sensitive to data volume, and incapable of capturing temporal dynamics.
RNNs	Medium	Hidden units, number of layers, and Sequence length.	Detect variations, manage variable-length sequences, and record temporal relationships.	More complicated design, prone to disappearing or ballooning gradients, and inefficient for short sequences.
LSTM	Medium	Sequence length, hidden units, number of layers, gating mechanisms.	Superior performance, enhanced temporal memory, and a multitude of uses.	Hyperparameter tweaking, computationally demanding, and possible black box problems.

* The table above is constructed by the author based on references [16, 18, 20,35].

8 Literature review

Many studies published from 2019 to 2024 have been examined that related to ECG signals classification using deep learning techniques. Figure 7 display the distribution of reviewed papers across years. Investigators used different methods like RNN and CNN to classify ECG beats. This section's goal is to examine and contrast numerous studies proposed models. The outcomes of this comparative study are displayed in table (3).

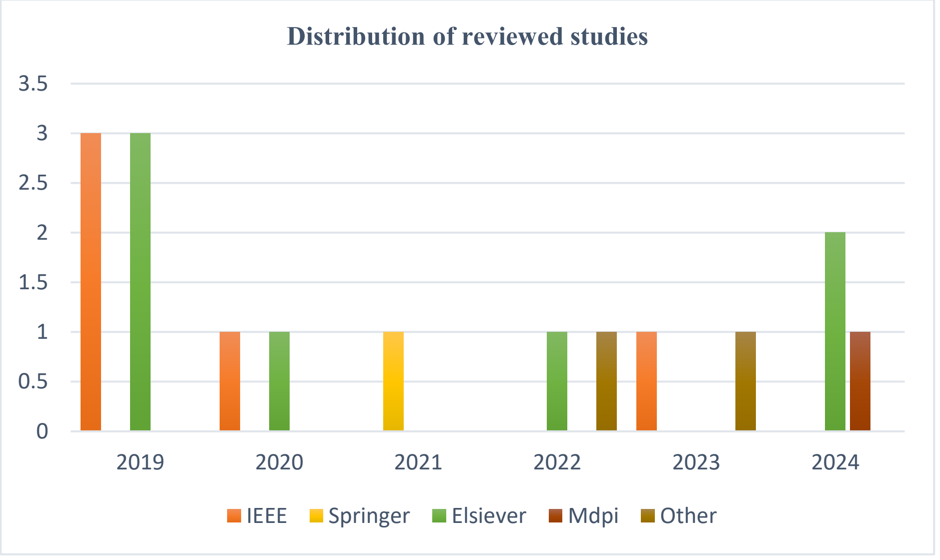

Fig. 7. Distribution of reviewed studies.

Table 3. A comparation study of literature review.

Study	Purpose of study	Dataset used for training and testing	Pre-processing method	Method used for Feature Extraction & Classification	Results
Rajkumar, et al. (2019) [8]	The paper aims to develop a model that effectively screens and differentiates patients with cardiac vascular arrhythmias.	MIT-BIH	Raw Signal in time domain.	CNN method used for both classification and feature extraction.	The system achieved an accuracy of 93.6% and a loss of 0.2 using the ELU activation function by adjusting the number of epochs.
Baloglu et al. (2019) [22]	To provide a model that may be used in wearable devices in healthcare and intensive care units, with the potential to identify myocardial infarction with exceptional accuracy.	PTB Database	Wavelet transform and sample entropy values.	CNN model for both classification and feature extraction.	The suggested architecture showed 99.00% accuracy and sensitivity on all ECG lead signals.
Amirshahi et al. (2019) [34]	To introduce a new ECG classification advanced DL method that can be used in extremely low-power wearable devices' real-time cardiac monitoring systems.	MIT-BIH arrhythmia	Segmentation.	- (STDP) Spike timing dependent plasticity for feature extraction. - (R-STDP) reward-modulated STDP classification.	The proposed method achieved accuracy of 97%.
Rana et al; (2019) [35]	The paper proposes utilizing a single-layer TensorFlow DL model to classify a series of heartbeats as normal or abnormal.	MIT-BIH arrhythmia	-	Single-layer LSTM for classification.	The proposed method obtained 95% accuracy.

Study	Purpose of study	Dataset used for training and testing	Pre-processing method	Method used for Feature Extraction & Classification	Results
Appathurai. et al. (2019) [4]	The purpose is to analyse filtering methods, extraction of signal components, signal classification, and compression algorithms for the ECG signal.	MIT/BIH arrhythmia	IIR notch filters + Hybrid wavelet filters. For removing power line interference, and baseline wander respectively.	- For feature extraction 1) FFT algorithm to detect R peak. 2) Hybrid filtering method to detect T, QRS and P. -For classification: LSTM + CNN	The proposed method has shown a total accuracy of 99.85%
Saadatnejad. et al. (2020) [36]	To build a novel ECG classifier on wearable devices with limited processing capacity.	MIT-BIH arrhythmia	Segmentation + Pan-Tompkin's algorithm.	- Wavelet transforms For Feature extraction -RNN for classification.	The proposed method obtained 99% accuracy, 95% sensitivity, and 99.8% specificity.
Yao, et al. (2020) [37]	The study showcases the effectiveness of spatial and temporal fusion in ECG signal analysis for automatic arrhythmia detection, highlighting the improved accuracy of ATI-CNN, its benefits, and real-time processing efficiency.	6677ECG recordings. range in duration of 6-60 sec from the "First China Physical Signal Challenge"	Utilizes fully convolutional layers to preprocess the 12-lead ECG signals and generate a pre-processed time series.	- CNN for features extraction - Attention-based time-incremental ATI- CNN for classification.	The suggest model show an accuracy improvement of 81.2% in detecting 9 arrhythmias The obtained precision =82.6%, Recall=80.1%, F1=81.2%.

Study	Purpose of study	Dataset used for training and testing	Pre-processing method	Method used for Feature Extraction & Classification	Results
Rashed-Al, et al; (2021) [33]	To design a novel ECG classifier using CWT with scalogram, making it a powerful tool for assisting medical practitioners in diagnosing ECG arrhythmia.	MIT-BIH arrhythmia dataset with the LUDB and AHA database.	Segmentation.	- CWT + Hilber - Huang transform spectrum for feature extraction. - VGG16-based CNN for classification.	The model achieved accuracy: - using MIT-BIH Dataset a 100% after 21 epochs for 2-4 classes and 99.90% for five classes. - using premature ventricular contraction beats from AHA and LUDB database get a 99.91% for the 5-classes case.
Kumar, et al; (2022) [38]	The study analyses the techniques of ECG classification by DL to reduce the size of ECG signals for long-term storage and remote transmission.	MIT-BIH Arrhythmia	Raw signal with noise removal.	- Fast Fourier Transform (FFT) for feature extraction. - Improved AlexNet-CNN for classification.	99.7% accuracy, 98.3% sensitivity, 99.2% specificity, and 96.1% precision.
Mohonta, S.C, et al; (2022) [9]	The project aims to develop a deep learning method for automatic arrhythmia detection using short ECG data segments, thereby enabling personalized and digital healthcare.	MIT-BIH arrhythmia	Segmentation	- continuous wavelets transform (CWT) for Features extraction. - 2D-CNN with scalogram model has been proposed.	The model achieved an average sensitivity, specificity, and accuracy to be 98.87%, 99.85%, and 99.65%, respectively.

Study	Purpose of study	Dataset used for training and testing	Pre-processing method	Method used for Feature Extraction & Classification	Results
Shobanadevi et al; (2023) [11]	To categorize diverse types of Arrhythmias by developing a model that can analyse ECG signals, aligns with the AAMI standard.	MIT-BIH Arrhythmia	Raw Signal	Using CNN, RNN, oversampling and under sampling methods.	Accuracy is 99.03%, precision is 99.01%, recall 99.03% and f1-score 99.02%.
Espin-Ramos, D., et al. (2023) [39]	To advance medicine and aid doctors in diagnosing arrhythmia, by employing two deep learning models to automatically classify five types of arrhythmias in ECG.	PhysioNet MIT-BIH Arrhythmia	Raw Signal with segmentation.	- For feature extraction employed 1D convolutional deep residual neural network (ResNet) - For classification used CNN.	Achieved accuracy of 98.63%, precision of 92.86%, sensitivity of 92.41%, and specificity of 99.06%. The average F1-score 92.63%.
Sharma, P. et al. (2024) [29]	They aim to develop automated ECG classifier that increases search space, decreases biases, removes noise, and improves accuracy.	MIT-BIH Arrhythmia	Discrete Wavelet Transformation and OB-L-EO.	- Optimized feature vector for feature extraction. - For classification OBLEO based DNN.	They achieved accuracy of 98.779%, sensitivity of 98.67%, and specificity of 98.87%.
Allabun, Sarah (2024) [17]	The study develops a deep learning models for improving speed and accuracy. Assist cardiologists with faster and more objective ECG evaluation	- Public datasets from Germany, USA, and China with 12-lead ECG recordings with labels for different heart diseases and healthy rhythm.	-	- CNN for features extraction. - For classification two models based on pre-trained CNN: ResNet-50 Xception.	Accuracy, precision, and recall exceeding 99.87% for both models. Loss function reaching 3.38 x 10^-4 by the end of training and validation.

Study	Purpose of study	Dataset used for training and testing	Pre-processing method	Method used for Feature Extraction & Classification	Results
Eleyan, Alaa, and Ebrahim Alboghbaish (2024) [5]	This research develops a deep-learning-based system to predict arrhythmias and heart failure based on abnormalities in ECG signals.	- MIT-BIH Arrhythmia - BIDMC	Segmentation	- FFT for features extraction. - LSTM+CNN for classification.	Accuracy is 97.4%, precision is 97.3%, recall 97.4% and f1-score 97.3%.
Sharma, P. and S.K. Dinkar (2024) [6]	The study proposes an automated method for predicting arrhythmias based on ECG signal categorization, aiming to improve ECG interpretation accuracy and reduce biases caused by manual interpretation.	MIT-BIH Arrhythmia	Noise removal	- Discrete Wavelet Transformation (DWT) for feature extraction. - DNN (Deep Neural Network with optimized feature vector and the OBLEO method for classification.	98.779% accuracy, 98.67% sensitivity, 98.87% specificity

Based on the above table that we constructed from different reviewed papers, it can be seen that all of the examined studies focused on using DL techniques in order to provide an effective and accurate ECG signals classification to identify abnormalities in heart.

However, they differ in the proposed DL models such as employing different structures of CNN and RNN . In addition, the proposed models have been tested on various datasets and preprocessed using different methods for improving signal quality and removing noise, also they used various techniques in order to extract features from the ECG preprocessed signal. However, they depended on several parameters to evaluate the performance of their proposed models such as accuracy, sensitivity, and precision. Accordingly, it can be seen the following:

- The suggested method in paper [22] achieved accuracy and sensitivity above 99.00% on all ECG lead signals. Using CNN model for both classification and feature extraction based on PTB Database. The proposed method in this study shows good results.
- On other hand in this paper [37] the offered method obtained 99% accuracy, 95% sensitivity, and 99.8% specificity using MIT-BIH arrhythmia database and for preprocessing they used segmentation with Pan-Tompkin's algorithm . For Feature extraction it used Wavelet transforms and RNN for classification. The obtained results using RNN are good compared with other types.
- The method in paper [39] obtained 99.7% accuracy, 98.3% sensitivity, 99.2% specificity, and 96.1% precision on MIT-BIH Arrhythmia dataset with pre noise removal and applying an improved AlexNet- CNN technique for classification, and Fast Fourier Transform (FFT) for feature extraction to reduce the size of ECG signals for long-term storage and remote transmission. Which indicates a good result in comparing with same applying methods in other papers.
- The maximum accuracy and sensitivity are achieved in the proposed model in paper [33] achieved accuracy a 100% after 21 epochs for 2-4 classes and 99.90% for 5 classes using MIT-BIH Dataset, and get a 99.91% for the 5-classes case using premature ventricular contraction beats from AHA and LUDB database ,by applying CWT and Hilber -Huang transform spectrum for feature extraction, and sixteen layers of Visual Geometry Group labelled as VGG16-based CNN for classification. This method has the best obtained results, and it outperforms other papers, indicating that the CNN method used in this paper is the best.

9 Discussion

The key goal of this paper is to examine various studies that employed DL models for classifying the ECG signals. According to the examined papers CNNs are the most often used deep learning structures. They trained and learned using different ECG datasets. Each study showed that CNN is highly successful at evaluating various medical signals, including ECG, and can automatically extract the best characteristics and discriminate among distinctive groups. This improves productivity and the quality of healthcare.

However, it can be argued that the highest accuracy achieved among all examined studies is in the proposed model in paper [33] with accuracy a 100% after 21 epochs for 2-4 classes and 99.90% for 5 classes using MIT-BIH Dataset, and get a 99.91% for the 5-classes case using from AHA and LUDB database, they employed CWT and Hilber -Huang transform spectrum for feature extraction, and sixteen layers of Visual Geometry Group labelled as VGG16-based CNN for classification of ECG signals. This method has the best obtained results, and it outperforms other papers. So, this classifier is considered as a promising model that detects and classifies heart diseases using ECG signals.

It means that this model is sufficient and accurate, and effective for ECG signals classification which leads to better diagnosis. It is important to say that this model is the close measure to the highest accuracy of DL model targets which is 100%.

Although of the promising advantages in VGG16 model, it faces a challenge which is the computational complexity cost makes the implementation of model in real-time clinical applications difficult.

It can be suggested that this classifier can be implemented in real-time clinical applications if the computational complexity cost of VGG16 can be reduced. So, as a recommendation the architecture of this proposed model can be optimized using fewer layers or neurons in the CNN components using techniques like pruning which can help achieve this while maintaining the model's accuracy, or using specialized hardware such as GPUs which can significantly accelerate computations compared to traditional CPUs.

For future work the researchers can combine these techniques to improve the efficiency of VGG16-CNN models so it can be implemented in real-world clinical applications. This would enable a faster and accurate diagnosis of heart diseases using ECG signals.

10 Conclusion

This study examines the earlier papers that have been published from 2019 to 2024, with an emphasis on the best documented accuracy for identifying arrhythmia from ECG data. After evaluating the reviewed literature, we discovered that every research examined different techniques in which deep learning (DL) may be applied to analyze the ECG signals to improve early identification of cardiac issues and get correct classification. A trained CNN can automatically obtain the best characteristics from several groups, as each of this research has confirmed and shown. Consequently, CNN and RNN have demonstrated remarkable efficacy in examining medical signals, including ECG, which enhances the efficiency and caliber of healthcare delivery. Finally, applying the highly accurate technique VGG16-based CNN would enhance the early diagnosis of serious illnesses and reduce the likelihood of misclassification. The most commonly used dataset was MIT-BIH Arrhythmia, so it can be recommended as a dataset for training and testing.

References

1. Surantha, N., T.F. Lesmana, and S.M. Isa, Sleep stage classification using extreme learning machine and particle swarm optimization for healthcare big data. Journal of Big Data, **8**(1): p. 14 (2021).
2. World Health Organization "WHO" [Online] https://www.who.int ,a.d., Jan (2024).
3. Zhang, W., et al. ECG signal classification with deep learning for heart disease identification. in 2018 International Conference on Big Data and Artificial Intelligence (BDAI), IEEE (2018).
4. Appathurai, A., et al., A study on ECG signal characterization and practical implementation of some ECG characterization techniques. Measurement, **147**: p. 106384(2019).
5. Eleyan, Alaa, and Ebrahim Alboghbaish. "Electrocardiogram Signals Classification Using Deep-Learning-Based Incorporated Convolutional Neural Network and Long Short-Term Memory Framework." Computers **13**, no. 2 (2024).
6. Sharma, P. and S.K. Dinkar, an intelligent deep neural network with Opposition based Laplacian Equilibrium Optimizer to improve feature extraction using ECG signals. Biomedical Signal Processing and Control, 87: p. 105415 (2024).
7. Tayel, M.B., A.S. Eltrass, and A.I. Ammar, A new multi-stage combined kernel filtering approach for ECG noise removal. Journal of electro cardiology, **51**(2): p. 265-275(2018).

8. Rajkumar, A., M. Ganesan, and R. Lavanya. Arrhythmia classification on ECG using Deep Learning. in 2019 5th international conference on advanced computing & communication systems (ICACCS), IEEE (2019).
9. Mohonta, S.C., M.A. Motin, and D.K. Kumar, Electrocardiogram based arrhythmia classification using wavelet transform with deep learning model. Sensing and Bio-Sensing Research, 37: p. 100502. (2022).
10. Subbiah, S., Patro, R., and Subbuthai, Feature extraction and classification for ECG signal processing based on artificial neural network and machine learning approach. International Conference on Inter Disciplinary Research in Engineering and Technology, pp. 50–57, (2015).
11. Shobanadevi, A. and T. Veeramakali, Classification and Interpretation of ECG Arrhythmia through Deep Learning Techniques, (2023).
12. Ullah, A., et al., A hybrid deep CNN model for abnormal arrhythmia detection based on cardiac ECG signal. Sensors, **21**(3): p. 951(2021).
13. Loni, M., et al., Deep Maker: A multi-objective optimization framework for deep neural networks in embedded systems. Microprocessors and Microsystems, **73**: p. 102989(2020).
14. Wijaya, C., et al., Abnormalities State Detection from P-Wave, QRS Complex, and T-Wave in Noisy ECG. Journal of Physics: Conference Series,1230: p. 012015(2019).
15. Wasimuddin, M., et al., Stages-Based ECG Signal Analysis from Traditional Signal Processing to Machine Learning Approaches: A Survey. IEEE Access,**8**: p. 177782-177803(2020).
16. Acharya, U.R., et al., A deep convolutional neural network model to classify heartbeats. Computers in biology and medicine, **89**: p. 389-396(2017).
17. Allabun, Sarah. "An Intelligent Learning Approach for Improving ECG Signal Classification and Arrhythmia Analysis." International Journal of Advanced Computer Science & Applications **15**, no. 4 (2024).
18. Kłosowski, G., et al., The Use of Time-Frequency Moments as Inputs of LSTM Network for ECG Signal Classification. Electronics, **9**: p. 1452(2020).
19. Peimankar, A. and S. Puthusserypady, DENS-ECG: A deep learning approach for ECG signal delineation. Expert systems with applications, **165**: p. 113911(2021).
20. Ebrahimi, Z., et al., A review on deep learning methods for ECG arrhythmia classification. Expert Systems with Applications: X, **7**: p. 100033(2020).
21. Arsene, C.T., R. Hankins, and H. Yin. Deep learning models for denoising ECG signals. in 2019 27th European Signal Processing Conference (EUSIPCO), IEEE (2019).
22. Baloglu, U.B., et al., Classification of myocardial infarction with multi-lead ECG signals and deep CNN. Pattern recognition letters, **122**: p. 23-30 (2019).
23. Liu, F., et al. A LSTM and CNN based assemble neural network framework for arrhythmias classification. in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), IEEE (2019).
24. Kiranyaz, S., T. Ince, and M. Gabbouj, Real-time patient-specific ECG classification by 1-D convolutional neural networks. IEEE Transactions on Biomedical Engineering, **63**(3): p. 664-675(2015).
25. Savalia, S., and V. Emamian, Cardiac arrhythmia classification by multi-layer perceptron and convolution neural networks. Bioengineering, **5**(2): p. 35(2018).
26. Murat, F., et al., Application of deep learning techniques for heartbeats detection using ECG signals-analysis and review. Computers in biology and medicine, 120: p. 103726(2020).
27. Śmigiel, S., K. Pałczyński, and D. Ledziński, ECG signal classification using deep learning techniques based on the PTB-XL dataset. Entropy, **23**(9): p. 1121(2021).

28. Karim, F., et al., LSTM fully convolutional networks for time series classification. IEEE access, **6**: p. 1662-1669 (2017).
29. Sharma, P. and S.K. Dinkar, an intelligent deep neural network with Opposition based Laplacian Equilibrium Optimizer to improve feature extraction using ECG signals. Biomedical Signal Processing and Control, **87**: p. 105415 (2024).
30. Kłosowski, G., et al., The use of time-frequency moments as inputs of LSTM network for ECG signal classification. Electronics, **9**(9): p. 1452 (2020).
31. Xie, J. and B. Yao, Physics-constrained deep learning for robust inverse ECG modeling. IEEE Transactions on Automation Science and Engineering, **20**(1): p. 151-166 (2022).
32. Wu, M.-H. and E.Y. Chang. Deep arrhythmia database: a large-scale dataset for arrhythmia detector evaluation. in Proceedings of the 2nd International Workshop on Multimedia for Personal Health and Health Care, (2017).
33. Rashed-Al-Mahfuz, M., et al., Deep convolutional neural networks-based ECG beats classification to diagnose cardiovascular conditions. Biomedical engineering letters, **11**: p. 147-162 (2021).
34. Amirshahi, A. and M. Hashemi, ECG classification algorithm based on STDP and R-STDP neural networks for real-time monitoring on ultra-low-power personal wearable devices. IEEE transactions on biomedical circuits and systems,**13**(6): p. 1483-1493 (2019).
35. Rana, A., and K.K. Kim. ECG heartbeat classification using a single layer LSTM model. in 2019 International SoC Design Conference (ISOCC), IEEE (2019).
36. Saadatnejad, S., M. Oveisi, and M. Hashemi, LSTM-based ECG classification for continuous monitoring on personal wearable devices. IEEE journal of biomedical and health informatics, **24**(2): p. 515-523 (2019).
37. Yao, Q., et al., multi-class arrhythmia detection from 12-lead varied-length ECG using attention-based time-incremental convolutional neural network. Information Fusion, 53: p. 174-182 (2020).
38. Kumar M, A. and A. Chakrapani, Classification of ECG signal using FFT based improved Alexnet classifier. PLOS one,17(9): p. e0274225(2022).
39. Espin-Ramos, D., et al. A Deep Learning-Based Algorithm for ECG Arrhythmia Classification. in 2023 IEEE 13th International Conference on Pattern Recognition Systems (ICPRS), IEEE. (2023).