Electrocardiogram Classification Based on Deep Convolutional Neural Networks: A Review

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Abstract

Due to many new medical uses, the value of ECG classification is very demanding. There are some Machine Learning (ML) algorithms currently available that can be used for ECG data processing and classification. The key limitations of these ML studies, however, are the use of heuristic hand-crafted or engineered characteristics of shallow learning architectures. The difficulty lies in the probability of not having the most suitable functionality that will provide this ECG problem with good classification accuracy. One choice suggested is to use deep learning algorithms in which the first layer of CNN acts as a feature. This paper summarizes some of the key approaches of ECG classification in machine learning, assessing them in terms of the characteristics they use, the precision of classification important physiological keys ECG biomarkers derived from machine learning techniques, and statistical modelling and supported simulation.

Keywords: ECG classification, deep learning, machine learning, convolutional neural networks.

1.Introduction

One of the best and quickest measures used to measure the heart is an electrocardiogram (ECG). As electrodes, they are connected to the stomach, arms, and legs (small, plastic patches that adhere to the skin). The electrodes are attached by lead wires to an ECG system. The heart's electrical activity is calculated to determine its function, purpose, and motivation [1]. There is no energy being sent into the body. To maintain blood flowing the way it should, natural electrical impulses control contractions of the different sections of the heart, those preferences reflect how fast the heart strikes, the rhythm of the heartbeats constant or erratic, and the frequency and pacing of the electrical impulses as they pass around the separate heart regions. ECG variations can be a symptom of many heart-related conditions. The leading causes of morbidity and mortality worldwide have been cardiac arrhythmias, manifested as irregular heart rates or disrupted rhythms [2]. Efficacy, reliability and economy, the electrocardiogram (ECG) is now the most popular diagnostic method for arrhythmias. Wearable ECG tracking services are becoming more prevalent as technologies continue to advance and miniaturization becomes widespread. The manual processing of ECG recordings, however, is tedious and vulnerable to errors, making it a costly and time-consuming operation. Therefore, to face this challenge, automated ECG analysis technology is in demand [3].

Electrocardiography is the most basic and accessible means of diagnosing cardiac arrhythmia and other heart rhythm problems since it is non-invasive and simple to use [4]. an important index showing the incidence and occurrence of cardiac arrhythmia is the high prevalence, however, both the prevalence and frequency are serious social problems, a high prevalence of heart arrhythmias is fine, but the prevalence and incidence of the problems can be huge problems in society, accounting for 37% of completely losses globally [5], [6], [7]), and 3) present high costs of treatment (the normal chronic path of the condition requires substantial long-term and costly treatments [8], [9] [10], [11], [12], [13]).

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The CNN technique is becoming more common, especially in image processing, text analysis, audio analysis, and video. CNNs combine input and output layers, but like most neural networks, they also have hidden layers. These pretrained features concentrate on the characteristics of learning data, the convolutional, prediction, and gating layers being the most often used [14]. The layers include a set of convolutional filters that can trigger and learn certain input data characteristics. Each layer learns the numerous features by repetitive extraction from hundreds of convolutional layers. CNN will automatically extract rich features which will create sharper features of the image. In order to process time-series signals, recurrent neural networks (RNNs) are a modern deep learning technique that is effective [15]. A RNN differs in that it retains a weight relation between neurons in its hidden layers, which are similar to neurons in other kinds of neural nets. The sequence of layers is passed on from one to the next. This type of learning algorithm is efficient because of the tremendous efficiency. However, even though the secret RNN introduces a weighting relationship between neurons, there is a short-term transfer of weight [16]. By including a gate, the LSTM networks may provide short- and long-term memories, preventing the gradient from vanishing. The cell states that handle input, forget, and have a memory are the main components of LSTM. An LSTM network can better understand long-term historical information and change its projections as long-term memory is improved, thus offering a superior model as compared to the conventional RNN system [17].

A Convolution Neural Network (CNN) is a neural network with a convolutional layer and is used for image detection, tagging, segmentation and other related data [18]. A convolution is essentially sliding a filter over the input. A modified artificial neural network is an advanced form of neural network (NN). It varies from traditional neural networks with respect to the speed at which the signal progresses through neurons [19]. It is distinguished from classical neural networks in terms of how rapidly signals pass across neural networks. CNN has a few hidden layers that complete the element extraction. There are four different types of layers in a neural network (NN). The convolutional layer, SoftMax layer, pooling layer and linked layer layers. CNN highly parallels artificial neural networks (ANNs) built up of a layer of convolution, a subsampling layer, and an associated layer which is somewhat similar to a multilayer perceptron (MLP). In the ECG study, we describe emerging advances in the diagnosis and validation of heart diseases and disorders, the advantages and disadvantages of different ML approaches, and their synergies with computer simulation.

The rest of this review paper is organized as follows. Section 2 theory and background. Section 3 presents a review of the literature for ML, CNN and ECG. Section 4 Dissection the result. Section 5 Conclusion.

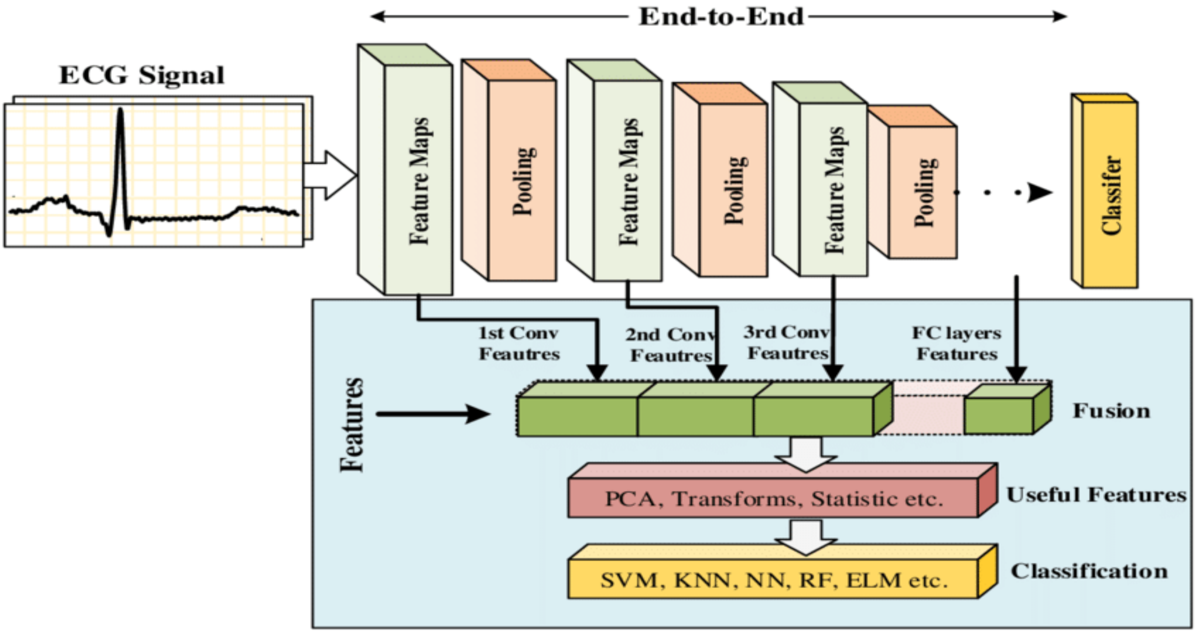

Figure 1. A basic convolutional configuration of the neural network that has convolution, pooling and completely linked layering: [20].

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2. Theory and Background

When the heart agreements and regularly relaxes, a heartbeat is a phenomenon that occurs. The heart's electrical system consists of two primary parts: the sinoatrial (SA) node in the right atrium of the heart and the atrioventricular (AV) node in the middle of the heart between the atrium and the ventricle. The electrical trigger proceeds to travel from the atrium to the AV node within the SA node. The pulse slows inside the AV node and then extends across the lower chambers. The ventricles contract, sending blood throughout the body, and a pulse occurs. The ECG is a method for measuring cardiac electrical function. Each heartbeat's P wave, QRS complex, and T wave reflect repolarization and depolarization of the heart's atria and ventricles. A stable human spectrum of heart rates from 60 to 100 beat/ min.

2.1 Machine learning (ML)

ML algorithms have been used to recognize image views, calculate measurements, and classify pathological trends in ECG for technical quality assurance, arrhythmia detection, and prognostic forecasts, and in echocardiography [21][22][23][24][25]. The ability to improve risk stratification and include new disease classifications has been seen using the synergistic use of Machine Learning in ECG and echocardiograms [26]. There is growing evidence that testing on a mixture of ML and ECG outperforms a test group on ECG and echocardiography.

2.2 Supervised Versus Unsupervised Learning

Major types of activities within the ML framework: supervised and unsupervised [27][28][29][30]. There is growing evidence that checking for ML and ECG, but not echocardiography, better suggests myocardial injury. The key objective of supervised learning is the deduction of a score from labelled or annotated results. Classification and regression are the two main techniques of supervised machine learning, which differ on which data types are used as outputs in the model. This applies to regression methods, help vector machine, neural networks, and random forests technologies [30]. The use of Machine Learning in the classification of ECG is a rich and thriving area of study (see for example [31][32], [33], [34], and [35]). The key explanation of why the resources is readily accessible is that there are public databases such as MIT-BIH Arrhythmia [36][37] that offers massive datasets for training. Common machine learning algorithms are logistic regression, support vector machines, artificial neural networks, and random forests.

The object of unsupervised learning is to uncover secret knowledge while not paying attention to findings or current information. Unsupervised machine learning aims to discover information that cannot be discovered by simply paying attention. One of the most common tasks in the medical study is to minimize dimensionality; the most popular approach applied for this is PCA. One of the more popular approaches utilized in medical research is to eliminate dimensions, and one of the more common means of achieving this is PCA. The ECG phenotypes were based on the visible morphology of the QRS complex and the position of the T wave. Eventually, these data were linked to the arrhythmic injury.

2.3 Traditional Techniques Versus Deep Learning

We call standard ML techniques that require the original explanation of the beat of the ECG, based on the initial-beat models. When extracting features, the classifier is trained upon certain features. The key emphasis of most studies is inferred ECG characteristics dependent on EAG records or reports. Other considerations include such aspects as QRS length, QT interval, heart rate, blood pressure, and other morphological characteristics. Clinicians will also take into account QRS and QT waves, heart rate, anatomies such as wavelet or Hermite coefficients into their estimates. A typical problem in machine learning algorithm is overfitting, However, when the latest unseen dataset or test set is tested, it indicates low results. Additionally, traditional machine learning methods allow for the most reliable features to be measured and provide the machine learning system with clarity [38][39].

Artificial neural networks (ANNs) the best features for execution are programmed to automatically extract a given task with they are hard to comprehend, in opposition to ML templates utilizing hand-crafted features. The perceptron, is a type of artificial neural network, is a simplistic neural network [40]. It includes a transfer function followed by a non-linear transfer function sigmoid activation function (weighted input sum) or a linear rectifier unit leading to the output of neurons. Categorizing neurons into intertwined groups is feasible, the first layer is the input, and the last layer is the output. Once a neural network's architecture is developed, the training process consists of adjusting the way the artificial neuron connections operate to maximize the output so that the deep learning algorithm learns the best knowledge from combinations of patterns [41]. Deep neural networks are multi-layer neural networks (DNNs), the most well-recognized of which are the FNNs and the CNNs. The FNNs have neurons connected to the neurons in the previous layer and each relationship has its own weight. On the other hand, the hierarchical data pattern of CNNs takes advantage of and design more complex prototypes and develop techniques for improving on multiple large scales [42][43]. Through the implementation of the applicable filters, CNN can then effectively capture 1D ECG signal patterns. For defining the program's characteristics and implementing its activation, the model consists of a convolution layer followed by a pooling layer which sub-samples the output of the convolution layer. Convolutional layers take advantage of local information or characteristics that occur at low scales, while the last ones are taught the most global and higher-level feedback patterns related to particular tasks. The Electrocardiogram Time Series Design allows the use of recurrent neural networks capable of efficiently capturing the signal's temporal characteristics a stronger candidate. Therefore, several works, such as [44] based on ECG classification, long-short-term memory (LSTM) convolutional layers have been successfully fused for feature extraction, a recurrent neural network architecture that allows data to be aggregated temporally. Deep learning approaches take advantage of extensive data volumes and optimized methodologies for operating efficiently with those data in a short period of time. The number of connections/parameters, however, allows these prototypes vulnerable to data overfitting. Via early termination approaches, drop out and regularization of cost functionality, the most common techniques to minimize overfitting are [45][46].

ML strategies present benefits and disadvantages. The effectiveness of machine learning approaches such as random forests and linear techniques in the context of electrocardiography data depends on how well the features derived from ECG data are interpreted. However, as the contribution to classification by each derived attribute is comprehensive, the findings of conventional ML as checked are usually clinically interpretable. On the other hand, with the use of data, ANNs, like deep learning methods, know the right characteristics and features for a particular task. Usually, this ideal trait can be difficult to understand by biochemical factors from scientific information that has often focused on predefined biomarkers. This lack of interpretability gives the impression of operating with a "black box" which necessitates functional coupling between inputs and outputs cannot be inferred.

2.4 Deep Learning for Patient Classification

Deep learning's applications to the electrocardiogram through vast amounts of data (over 90,000 ECG recordings for model training) as described in two recent journal papers, optimized methodologies to deal efficiently with such data are demonstrated. In an end-to-end way, they all offer DNNs. The first study described twelve different types of arrhythmias and identified such a wide range of rhythms, atrioventricular, ventricular or sinus tachycardia, noisy recordings or arrhythmias. A 34-layer DNN with more than 90,000 single lead ambulatory ECG was trained and checked findings against an objective dataset of study of 300 recordings annotated by a qualified cardiologist board. For each of the rhythm groups of the individual, the results reveal an area under the curve (AUC) above 0.91. AUC is an output indicator that results in 1.00 for an ideal classification and 0.50 for a random classification. Even if the vast majority of the previous studies of ECG classification mentioned in this article, the comparable accuracies over 90 percent are present, the smaller data sets used are the biggest downside in comparison to the latest [47]. This will restrict the ability to generalize outcomes from new datasets. The second study compared a method of screening using CNN to differentiate patients with left ventricular systolic dysfunction (EF b 35%) to 12 lead ECGs. This CNN was approved and checked for approximately 45,000 patients using simultaneously reported 12-lead electrocardiograms and echocardiography from approximately 45,000 patients. The AUC obtained for B-type natriuretic peptide was 0.93, improving the current blood tests with an AUC of 0.79 to 0.89.

2.5 Deep Learning Processing Tasks

The medical images are developed, and processing has undergone an absolute renovation due to machine learning as an example of important analysis in the basic field of cardiology, the best summary of recent image segmentation and analysis studies. The use of deep learning has allowed repetitive and complex tasks to be done automatically, particularly for the pre-processing level, such as cardiac magnetic resonance (MR) image segmentation of heart chambers [48]. Recent research has shown that the completely human-level CNN for MR image segmentation on a large database is a starting point for automated MR processing. In comparison, The ECG signal counterpart, which is the delineation of the waveforms of the ECG, remains a problem. In clinical practice, the study of ECG recordings usually requires computational norm biomarkers such as heart rate, QRS distance, QT interval, and ST-segment elevation. For doctors and automated protocols for decision-making, for the evaluation of complex cardiac disorders and monitoring events such as ventricular arrhythmias, these biomarkers are relevant. A first stage consisting of the delineation of the various ECG waveforms is involved in their calculation by taking account of fiducial points such as the onset and offset of the complex

QRS, R wave max, and T-wave onset, peak and offset. When tested on the accessible and sparse annotated datasets, the state-of-the-art ECG delineation systems demonstrate high efficiency, without variability in their findings, which is restricted. For the QT database, [49] (QTDB) recordings with low noise levels were only considered, since most of the recordings have tachycardia. By utilizing different datasets from those that were built in the original concept, many of the automated methods of delineation tend to create erroneous boundaries. Deep learning algorithms gain information about how to organize the data without the aid of any training data [50, 51].

Furthermore, ML methods autoencoders use unlabeled or unannotated ECG data for learning in the delineation system architecture to increase generalization through the use of improved flexibility of the training process. Recently, a multi-load-based approach to ECG visualization was presented, demonstrating progress in laying claim to the QRS complex on the QTDB.

2.6 Interpretability of ML Effects

Even though ML can deliver risk classification and stratification metrics, functional dependencies among inputs and outputs, as well as the relative significance of every particular model impact feature, it is therefore difficult to decide how these various traits are going to interact, and how. In ML models, in that way, this could be fatal to a few lives [52], using it in an ML classifier is challenging, and it is technically difficult to add it in the method, and more specifically, when using deep learning methods, in order to demonstrate a biologically sound biochemical basis. Effects of ML experiments can be best understood by linking systemic and electrophysiological changes to ECG anomaly, new simulation methods allow for the creation of human biophysically detailed computational models [53]. The research explored the underlying pathways illustrated in the ML-based R-R interval ECG phenotypes [54][55][56][57][58] in Cardiomyopathy hypertrophy as a promising illustration of its promise. The ECG pattern was defined and clarified as T wave inversion by the possible prolongation of action in the hypertrophied region; Purkinje-myocardial coupling plays a major role in understanding the normal QRS complexes.

3. Related Work

Amrani et al. [59] proposed a deep Convolutional Neural Network to detect four general topics (normal heartbeats, atrial fibrillation, atrial flutter, and paroxysmal supraventricular tachycardia). The MIT-BIH arrhythmia databases were used to add the ECG signals in the proposed classifier (MIT-BIH), Ventricular fibrillation database where 80% of the data are used for planning and the other 20% for further analysis. To increase the training task rate and increase the accuracy from 94.74% to 99%, the authors have used a non-standard mathematical analysis without noise filtering and protocols in pre-testing.

Sannino et al. [60] proposed a system for classifying ECG heartbeats based on the deep neural network (DNN) method. They preprocessed the data by eliminating noise, segmenting expressions, resampling and extracting facial features. Based on seven completely intertwined secret layers, DNN was ranked, each with 5, 10, 30, 50, 30, 10, and 5 neurons. On the well-known MIT-BIH arrhythmia database, the scientists undertook experiments. They reported that 99% accuracy was attained, but knowledge on how their DNN was educated or what parameters they used was not included.

Kachuee et al. [61] built an approach for transferring organized information from one ECG dataset to another. In keeping with the AAMI norm, the system will distinguish five distinct arrhythmias. The authors taught the proposed CNN model of the MIT-BIH file in five seminars to resolve the two-class issue of diagnostic datasets of PTB and then passed on the information gained by CNN.

Ramirez et al. [62] a paradigm was developed that merged two neural network models for two separate ECG leads. Using two forms of fuzzy logic strategies, at the judgment stage, the two models were mixed. For the two simple modules using principal 1 and principal 2, respectively, the final classification precision was increased to 93.80 percent from 92.90 percent and 92.70 percent.

Yildirim et al. [63] Left bundle branch (LBB) block of the atrial premature pulse, block of the right branch of natural sinus rhythm, a convolutional auto-encoder (CAE) model, and premature ventricular contraction, in order to diagnose five arrhythmia classes, a Long-Short-Term Memory (LSTM) classifier is used It's been created. The 16-layer deep CAE suggestion resulted from a linear compression structure that compressed from 260 to 32 samples per minimal loss segment. LSTM, a special kind of recurrent neural network (RNN) with thick layers of five units, was then developed to use coded ECG features to distinguish the compressed signals the authors used 70%, 15% and 15% of MIT-BIH ECG

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signals to plan, test and analyze their model, and respectively. They reached an average of 99 percent accuracy, precision, recall, and F1-score. The disadvantages of the suggested solution were the lengthy time required to achieve the coded ECG functions and the sophistication of the compression model.

Marinho et al. [64] mentioned the simple Fourier conversion method, Goertzel created order data, and structural cooccurrence matrix was introduced as feature extraction techniques. Naive Bayes (NB), SVM, MLP, and optimum path forest (OPF) were then added to classify heartbeats into five groups that conform to the AAMI norm (N, S, V, F, and Q). With the HOS extractor system and NB classifier, the best results were obtained using a variety of the listed linear classifiers and classifier feature extraction techniques. This mix reached 94.3 percent precision.

Mousavi et al. [65] the chance of a steady heartbeat is also calculated using a sequence model list and a deep CNN. The sequence-to-sequence model was composed of a recurrent neural network (RNN) encoder and decoder with Long Short-Term Memory (LSTM) to map input sequences to out-of-vocabulary sequences. The authors adopted their method and achieved a 96.18 percent accuracy on the MIT-BIH database.

Li et al. [66] exploited the bottomless remaining network in order to classify cardiac arrhythmias the CNN has 4 residual blocks and consists of 3 1D convolutional layers, 3 layers of batch normalization, and 3 convolutional layers, three layers of ReLU, and a structure of identity shortcut relation. To achieve an average of 99.06 percent, 93.21 percent and 96.76 percent in accuracy, sensitivity and positive predictivity, respectively, the writers used their CNN from the MIT-BIH data package.

Pandey et al. [67] to automatically diagnose anomalies in heart rhythms an LSTM-based expert system was developed. In their research, doctors looked at 45 cardiac characteristics from EKG signals and how they used wavelets, morphological descriptors, and RR intervals. To identify five different arrhythmic rhythms, we used derived features from the LSTM model to identify five different arrhythmic rhythms. Again, this indicates that the technique has not harnessed the full capacity for deep learning. 99.37 percent precision, 96.73 percent accuracy, 99.14 percent specificity, 94.89 percent sensitivity, and 95.77 percent F1-score were obtained by the model's success measurement.

Bidias et al. [68] to separate heartbeats, the conditional information and permutation entropy of ordinal patterns are used; the ST-T and MIT-BIH IA and AF arrhythmia datasets have been used in the European Society of Cardiology. Their experiments showed that these parameter settings were not quite scalable to the system, and the effects of both approaches (PE and CEOP) were identical. For the MIT-BIH database, the writers obtained a classification rate of 93.62 percent.

Chen et al. [69] a new framework was proposed in order to look at beat-based information in heartbeats and segment-based information in adjacent segments of these beats. Morphological information was provided by each heartbeat and temporal information was increased by the neighboring intervals of the rhythm. Besides, CNN and bidirectional LSTM (BLSTM) were used by the authors of the paper in each branch to obtain temporal and morphological detail. Then, before going into the classification layers, the accumulated characteristics from each branch were merged. In the inter-patient model, the recommended method yielded a precision of 99.56% and an F1 score of 96.40%.

Table 1: Comparison of Classification ECG Based Deep Convolutional Neural Network

Ref.	Year	Methods	Problems	Classification	Result and Accuracy
[80]	2020	Heartbeat classification using deep residual convolutional neural network from 2-lead electrocardiogram	classify MIT-BIH arrhythmia	CNN	98.14%
[79]	2020	Precision Medicine and Artificial Intelligence: A Pilot Study on Deep Learning for Hypoglycemic Events Detection based on ECG	Hypoglycemic Events Detection	CRNN	88.91%
[78]	2020	popularization of CNN classification of ECG signal using a Generative Adversarial Network (GAN).	ECG generation	CNN + GAN	98.3%
[77]	2020	a convolutional neural network trained with end-to-end supervision, for fetal electrocardiogram signal denoising.	denoising	CNN (encoder decoder)	87%
[76]	2020	To improve ECG biometric recognition utilizing cascaded CNN	identification	CNN	94.3%
[75]	2019	Cardiologist-level arrhythmia detection and classification in ambulatory	classify 12 rhythm classes	resnet	78.4%

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		electrocardiograms using a deep neural network			
[74]	2019	Automated Heartbeat Classification Exploiting Convolutional Neural Network with Channel-Wise Attention	classify MIT-BIH arrhythmia	CNN+Attention	98.7%
[73]	2019	Early and remote detection of possible heartbeat problems with convolutional neural networks and multipart interactive training	beat classification	resnet	86.02%
[72]	2019	Inter- and Intra- Patient ECG Heartbeat Classification for Arrhythmia Detection: A Sequence-to-Sequence Deep Learning Approach	classify MIT-BIH arrhythmia	CRNN	80.2%
[71]	2018	A convolutional neural network for ECG annotation as the basis for classification of cardiac rhythms	arrhythmia	CNN	98.5%
[70]	2018	Abductive reasoning as a basis to reproduce expert criteria in ECG atrial fibrillation identification	AF	LSTM+expert	85.9%

4. Discussion

This paper proposes an advanced reason for programmed cardiology acknowledgement innovation CNN Inventive Organizations. The proposed method was of high goal and low intricacy of execution. This methodology saddled the capability of profound learning for model catch Attributes of a particular cardiovascular illness in the scope of ECG signal. Utilizing the "approval set", the Comparison strategy yielded the accompanying outcomes:

- 78.4% normal precision.
- 88.91% affectability.
- 98.7% protection.

By looking at and contrasting the various techniques in the "Conversation" segment, we can affirm the strategy applied in this paper brought about much preferable execution over that of the exceptional Cutting edge.

5. Conclusion

In general, machine learning techniques depend on data and the limitations in model output are enforced by how much data is present, and how reliable the data is. In the dataset, the model will be as strong as the relevant details. The electrocardiogram-applied ML algorithms are effective tools to assist with patient screening activities and have the ability to use population-based expertise to develop Clinical examination. The new DNN procedures have helped doctors detect abnormal heartbeats and develop mechanical control. DNNs handle a vast volume of data effectively, being suitable for real-time and portable applications in need of accurate and efficient ECG signal processing. Even though the convolutional neuronal network can be used to characterize electrocardiogram (ECG) beats in the detection of cardiovascular disease, ECG signals are usually treated as a dimensional marker while CNNs are more qualified for multi-dimensional examples or image recognition applications.

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