ECG image Analysis for Arrhythmia Classification Using Deep Learning

A
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Submitted by

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INTRODUCTION

Cardiovascular Disease (CVD) is the main cause of human death, responsible for 31% of the worldwide deaths. Electrocardiogram (ECG) test is used as a diagnostic tool in healthcare institutes. Electrodes attached to the patient's body surface can record the heart's electrical signal over time.

Deep Neural Network (DNN) has been widely used for classification and prediction purposes in different domains. However, an ECG-based automatic arrhythmia classification is typically faced with several important challenges.

PROBLEM STATEMENT

Arrhythmias is a condition where the heart beats too slowly, or too quickly or irregularly. Brings changes to the heart's anatomy, reduces blood flow to the heart or damage to the heart's electrical system and causes stiffening of the heart tissue, known as fibrosis, or scarring.

SOLUTION

The electrocardiogram (ECG) is one of the most extensively employed signals used in the diagnosis and prediction of cardiovascular diseases (CVDs). The ECG signals can capture the heart's rhythmic irregularities, commonly known as arrhythmias. A careful study of ECG signals is crucial for precise diagnoses of patients' acute and chronic heart conditions. We propose a two-dimensional (2-D) convolutional neural network (CNN) model for the classification of ECG signals into eight classes; namely, normal beat, premature ventricular contraction beat, paced beat, right bundle branch block beat, left bundle branch block beat, atrial premature contraction beat, ventricular flutter wave beat, and ventricular escape beat. So simply by using the image of the ECG scan we could predict these eight classes and future chances of arrythmia.

LITERATURE SURVEY

Based on the selection criteria, the fifty technical articles on arrhythmia classification are examined which are published between January 2010 to January 2020. Selected articles are critically examined, and if any selected articles are available on more than one scientific repository or database, it is considered only once. Different kinds of methodologies, classification algorithms with their accuracy results, and optimization methods used for arrhythmia classification are reviewed from the selected articles. It shows the literature survey on arrhythmia classification techniques that are used in this study. Authors present the recent trends for arrhythmia classification, the techniques used for features extraction, and the variation of deep neural networks. Study is beneficial for the scientific community to select the arrhythmia classification techniques as per their desires.

learning techniques used for Arrhythmia:-

I) Autoencoder:-

Autoencoder belongs to the family of artificial neural network- (ANN-) based architecture, which is used for training efficient data coding in an unsupervised manner. They are recognized as a tool to learn basic patterns for a similar set of data. Autoencoder also performs dimensionality reduction, and it tries to generate a class similar to its original input. In the cited research studies, the author proposed different variations in autoencoder-based architecture. Figure 6 shows the basic architecture of the autoencoder.

II) Convolutional Neural Network (CNN).

CNN is a deep learning-based algorithm. CNN is widely recognized as a tool in the field of computer vision and image processing. It consists of an input layer, hidden layers, and the last output layer. In the forward pass convolutional neural network, the middle layers are called hidden layers that are masked with activation function (ReLU), pooling layer, and convolution.

III). Deep Neural Network (DNN):-

A simple DNN contains multiple hidden layers that can process the input to output layers. The DNN can recognize different kinds of unstructured data. In arrhythmia classification, authors proposed different kinds of neural networks but the proposed network is composed of the same components: neuron, weight, bias, and function. All these components are capable and act just like the human brain.

IV) Deep Belief Network (DBN):-

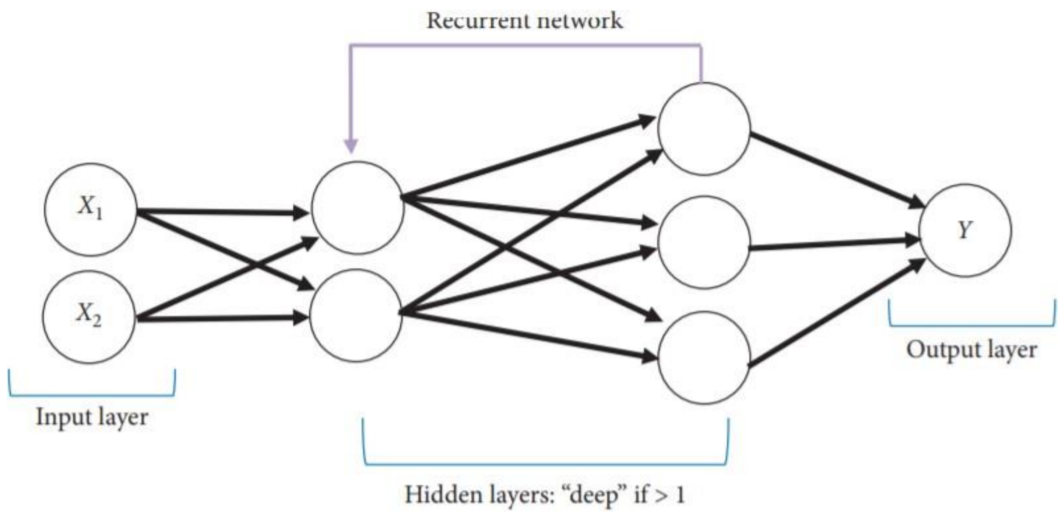
DBN is a class of deep neural networks; it consists of multiple layers that have a connection between all the layers in the network but not with units of each other layers. DBN can be trained by supervision to achieve better prediction.

V)ECG Databases:-

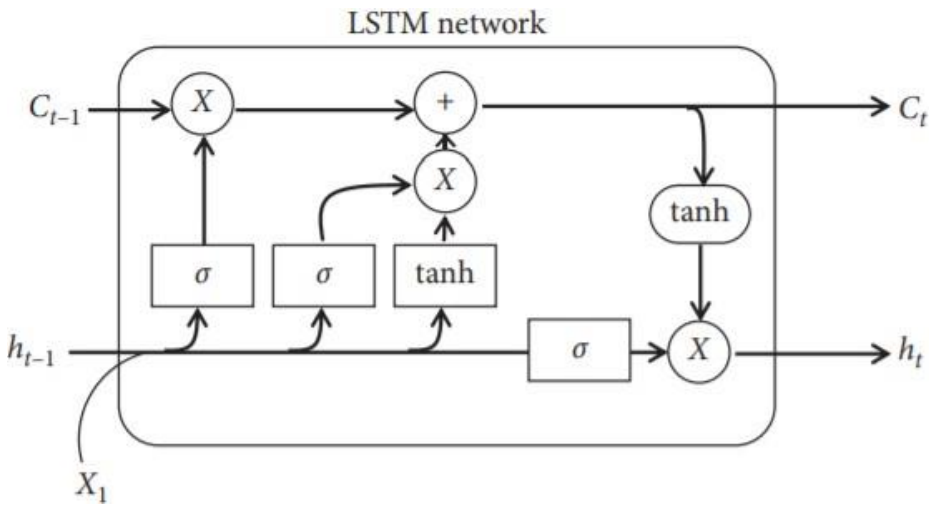
The expert systems for automatic detection of arrhythmia disease required training data to understand different patterns of each class. Authors of the selected research study critically analyze arrhythmia classification systems and enlist the most cited/publicly open access ECG databases.

SYSTEM ARCHITECTURE

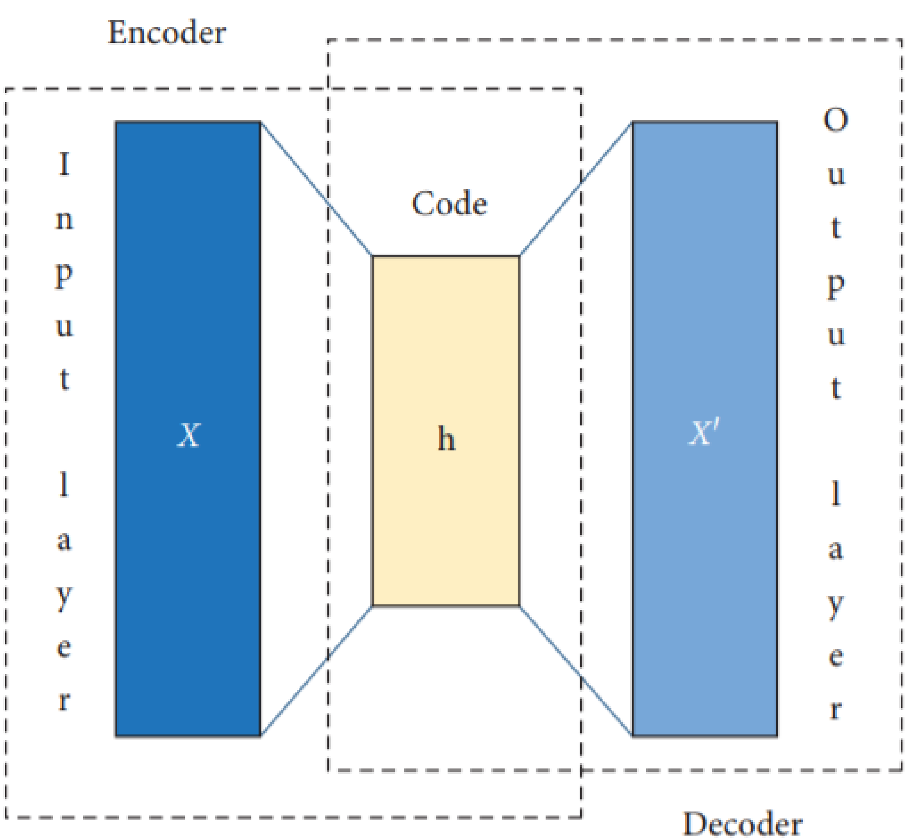
I)RNN architecture:



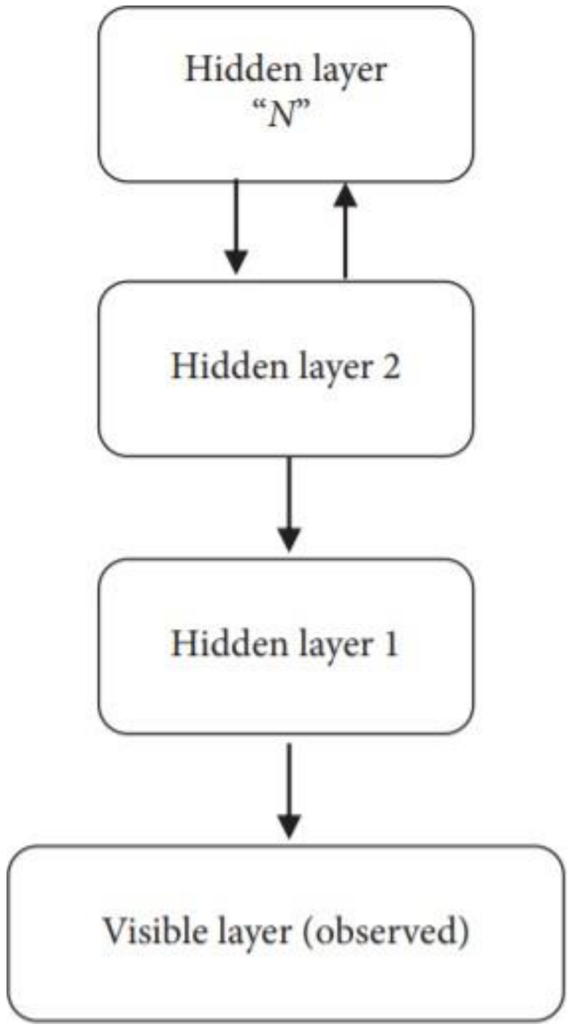
II) LSTM-based architecture.



III) AE-based architecture:-



IV) Structure of basic DBN architecture.



METHODOLOGY

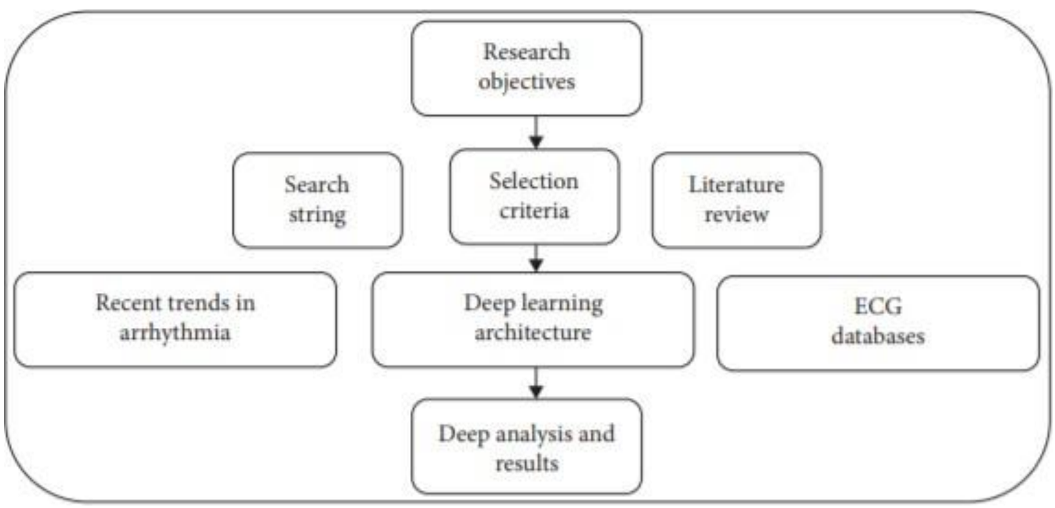
In arrhythmia classification techniques using a deep neural network. It demonstrates the systematic methodology in a four-step process.

The primary objective of this study is to critically review the existing methods based on arrhythmia classification

(1) To examine the arrhythmia classification techniques as practically implementable.

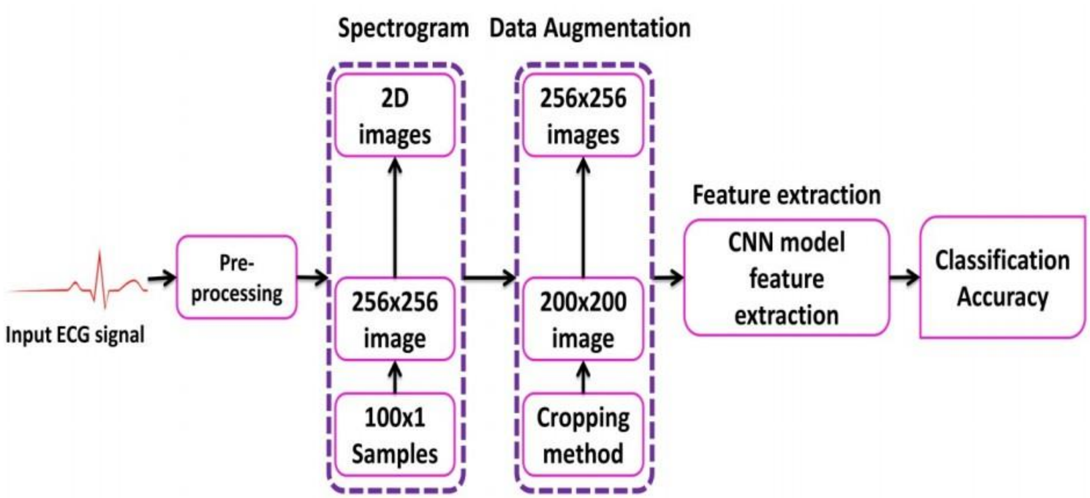
(2) To overview the existing research studies based on arrhythmia classification benefits and future research direction.

(3) Identify the latest research trends and publication interests based on arrhythmia classification.



Proposed Scheme:

The method consists of five steps, i.e., signal pre-processing, generation of 2-D images (spectrograms), augmentation of data, extraction of features from the data (using the CNN model), and its classification based on the extracted features. The details of these steps are presented in the following subsections.



I)Pre-Processing: -

The three primary forms of noise in the ECG signal are power line interference, baseline drift, and electromyographic noise. The noise from the original ECG signal must be removed to ensure that a denoised ECG signal is obtained for further processing. We combined wavelet based thresholding and the reconstruction algorithm of wavelet decomposition to remove noise from the original ECG signal.

The wavelet thresholding was performed using,

$$\overline{\omega_{x,y}} = \begin{cases} \operatorname{sgn}(\omega_{x,y}) \left\{ |\omega_{x,y}| - \frac{\lambda}{\exp^3\left[\alpha\left(|\omega_{x,y}|-\lambda\right)/\lambda\right]} \right\}, & |\omega_{x,y}| \geq \lambda \\ 0, & |\omega_{x,y}| < \lambda \end{cases}$$

II) Generation of 2-D Images:-

While 1-D CNN can be used for time series signals, the flexibility of such models is limited due to the use of 1-D kernels. On the other hand, 3-D CNNs require a large amount of training data and computational resources. In comparison, 2-D CNNs are more versatile since they use 2-D kernels and, hence, could provide representative features for time series data. Hence, for certain applications where sufficient data is available and for 1-D signals that can be represented in a 2-D format, using a 2-D CNN could be beneficial. Herein, for generating 2-D images to be used with the 2-D CNN model, the ECG signal was transformed into a 2-D representation.

III) Data Augmentation: -

Another significant advantage of using 2-D CNN models is the flexibility it provides in terms of data augmentation. For 1-D ECG signals, data augmentation could change the meaning of the data and hence is not beneficial. However, with 2-D spectrograms, the CNN model can learn the data variations, and augmentation helps in increasing the amount of data available for training. The ECG data is highly imbalanced, where most of the instances represent the normal class. In this scenario, data augmentation can help when those classes that are underrepresented are augmented. For arrhythmia classification using ECG signals, augmenting training data manually could degrade the performance. Moreover, classification algorithms such as SVM, fast Fourier neural network, and tree-based algorithms, assume that the classification of a single image based representation of an ECG signal is always the same.

IV) Deep Neural Network:-

A CNN-based model is proposed for an automatic classification of arrhythmia using the ECG signal in a supervised manner. The ECG data used in the study have corresponding labels (ground truth) identifying the type of arrhythmia present. These labels were assigned by expert cardiologists and are used for supervised training. For each heartbeat segment, the arrhythmia class label was transferred to the corresponding spectrogram image representation.

The existing neural networks with the feed-forward process for the automatic classification of the 2-D image was not feasible since these methods do not take into account the local spatial information. However, with the development of CNN architectures and using nonlinear filters, spatially adjacent pixels can be correlated to extract local features from the 2-D image. In the 2-D convolution algorithm, the downsampling layer is highly desirable for extracting and filtering the spatial vicinity of the 2-D ECG images.

Experimental Setup:-

I)Cost Function:-

The cost function is used to measure the error of the CNN model between the

estimated worth and the actual worth or the desired quality. An optimizer function was used to minimize the error function. Different cost functions have been used in neural network theory. In our

$$C = \frac{-1}{n}\sum_{c=1}^{N}([y_c * ln(a_c) + (1 - y_c)ln(1 - a_c)])$$

experiments, we used the cross-entropy function which is given as

II). Evaluation Parameters:-

Four evaluation metrics were used in this study, including accuracy, precision, sensitivity, and specificity. The accuracy for the multi-class problem was evaluated as,

$$A = \frac{1}{N}\sum_{c=1}^{N}\frac{(T_p^c + T_N^c)}{(T_P^c + T_N^c + F_P^c + F_N^c)},$$

CONCLUSION

Cardiac disorder or arrhythmia is the most dangerous disease that leads to human death. 'e researcher proposed lots of arrhythmia classification systems to assist the doctors every year. 'e automated systems predict the high accuracy results used for arrhythmia detection but still not adoptable by healthcare professionals because in the recent studies, authors used time-series data, which is not adaptable in different application environments. Moreover, ECG's time series data with signal leads are not appropriate for stable baseline wanders, muscle contraction, and power line interface.

The major concerns that affect the success of the developed arrhythmia detection systems are

(i) manual features selection,

(ii) techniques used for feature extraction, and

(iii)algorithms used for classification and the most important is the use of imbalanced data for classification. The automated arrhythmia detection required the feature extraction of ECG images that required domain knowledge. Further, the balanced dataset used for classification methods is required to avoid overfitting.

FUTURE SCOPE

The effect of multiple lead ECG data to further improve experimental cases will be studied in future work. CNN-based have proven to be effective for arrhythmia classification. This scope shows that dynamic classification methods that are capable of learning both short- and long-term contents of the signal in an efficient way, would be employed for such applications. CNN has shown excellent performance in classifying different types of arrhythmias. This powerful method would be one of the most efficient learning tools for this application.