Arrhythmia Modern Classification Techniques: A Review

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Abstract

Artificial intelligence methods are utilized in biological signal processing to locate and extract interesting data. The examination of ECG signal characteristics is crucial for the diagnosis of cardiac disease. This heart condition, known as arrhythmia, is quite prevalent. To put it simply, an irregular heartbeat is known as cardiac arrhythmia. It manifests itself when the heart beats abnormally (too slowly, too quickly, or erratically) for no apparent reason. Specifically, the ECG features of the PR, QRS, T, PQ, QT, RR, and cardiac frequency and rhythm are analyzed to diagnose cardiac arrhythmias. The performance of several arrhythmia classification and detection models is analyzed in this work through extensive simulations, emphasizing the most recent developments in this field. Ultimately, the research provides new perspectives on arrhythmia classification methods to address the shortcomings of the current approaches.

Keywords: ECG ; Arrhythmia; classification; Neural Network; Optimization

1. Introduction

According to the latest statistical provided by World Health Organization (WHO), cardiovascular diseases (CVDs) are the leading cause of death globally and caused death of approximately 17.9 million people in 2019 [1]. Arrhythmias indicate irregular speed of heartbeats, considered as a type of CVD, and causing approximately 80% of sudden cardiac death [2]. A several heart diseases considered as arrhythmias such as; atrial fibrillation (AF), ventricular fibrillation (VF), premature ventricular contraction (PVC), tachycardia, and bradycardia. Detecting arrhythmia early will effectively safes the life of the patient [3]. CVD is detected using Electrocardiographs (ECG), which is a waveform indicates the electrical activity of the heart and picked up using electrodes connected to the chest of the patient. The normal ECG signal can be divided into three waves P, QRS, T as shown in Figure 1 [4].

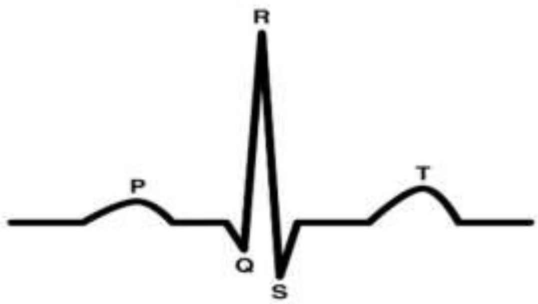

Figure 1: Normal ECG Waveform.

ECG tracings represent the conduction of electrical impulses from the atria to the ventricles. The P wave is the first event of a normal ECG waveform. It represents atrial contraction. The QRS marks the start of the contraction of the ventricles. That contraction ejects blood from the ventricles and

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pumps it through the arteries, creating a pulse. The T wave represents the relaxation of the ventricles [5]. Table 1 indicates the amplitude and duration of each wave in normal ECG.

Table 1: Amplitudes and duration in normal ECG.

Wave	Amplitude	Duration
P-wave	0.2 - 025 mV	0.06 - 0.12 S
QRS- wave	0.5 – 3 mV	0.06 – 0.1 S
T-wave	0.1 – 0.8 mV	0.05 – 0.25 S

Detecting CVDs from ECG by manual inspection is a very difficult process and takes more time. Therefore, an automatic diagnosis system using computers is needed to facilitate and accelerates the process of diagnosing.

2. Related Work

In recent years, detecting CVD from ECG attracted large number of researchers to present new algorithms aim to increase the accuracy of detecting. A proposed method depends on measuring and analyzing the ECG measurements which reflects the CVDs conditions is presented in [6-7]. Machine learning algorithms based on ECG signal also presented in [8-9]. A suggested three methods used convolutional neural networks (CNN) to classify atrial fibrillation, the first one achieves 89% accuracy [10], the second one achieves 86% accuracy [11], while the third one classifies ECG signal into three types and achieves 99% [12].

Another two methods depend on heart rate variability features and support vector machine to classify heart failure and normal sinus rhythm are proposed the first achieves 93.33% accuracy [13], while the second depend also on multifractal fluctuation analysis [14]. Extracting features from the interval between two successive peaks in the ECG and using deep learning algorithm which is consists of CNN with neural network is presented and achieves 99% accuracy [15].

Another research depends on the morphological conditions of ECG signal to detect heart failure used ECG heartbeats as an input of the CNN and achieves 100 % accuracy [16]. Three classifier algorithms used k-mean clustering, k-nearest neighbor (K-NN), and multilayer perception achieve 88%, 99%, and 99% respectively presented in [17] Another approach used classifier with least square, maximum likelihood, and support vector machine and each approach achieve 84%, 88%, and 76% accuracy respectively [18].

Numerous researchers used entropy-primarily based features to extract data from ECG signals. An entropy based atrial fibrillation classifier and achieve area under the curve score of 0.981 proposed in [19]. Another approach used entropy as a feature in classifying atrial fibrillation and achieve area under the curve score 0.972 [20]. Area under score 0.97 is achieved also when using entropy feature with support vector machine classifier [21]. Calculating Shannon entropy and sample entropy feature and prove that it represents atrial fibrillation and normal sinus rhythm is done with accuracy 91% [22].

Feature extraction is the difficult step in the process of ECG classification, the following researches used a statistical method by applying Hjorth descriptor algorithm for ECG feature extraction [23-25]. However, this method suffers from noise that affects the value of variance. Therefore, the statistical method is limited and can't be used to extract ECG feature effectively.

Other approaches used Discrete wavelet transform (DWT) to extract ECG features in time or frequency domain, which provides decomposition of the signal into sub bands containing low frequency component and high frequency component which gives more information for the feature selection. A suggested algorithm to classify arrhythmia depend on DWT achieves 99% accuracy is presented in [26].

Fifty technical articles published on arrhythmia classification between 2010 and 2020 are reviewed based on the selection criteria. We thoroughly evaluate the three publications you've chosen, counting them once if they appear in more than one scientific archive or database. The classification methods for arrhythmias utilized in this investigation are listed in Table 2 of the following document. Recent developments in arrhythmia classification, feature extraction methods, and

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variations in deep neural networks are discussed. This research will help the medical community choose the best arrhythmia categorization methods. The most up-to-date tendencies from suggested investigations for arrhythmia classification are shown in Table 3.

Table 2: Modern Arrhythmia classification techniques

Method	Method	Optimizer	Accuracy (%)
D. Kumar et al. [27]	Convolutional-neural network	Bat ridder	93.189
J. Zheng et al. [28]	Extreme gradient boosting tree	Low pass filter	97.1
J. Ferretti et al. [29]	Convolutional neural network	-	95.2
W. Zhu et al. [30]	Deep neural network	Principal component analysis	97.88
R. He et al. [31]	Deep neural network	-	92.072
J. Huang et al. [32]	1D cognitive network - 2D Convolutional neural network	-	90.933
P. Wang et al. [33]	Residual networks	Data augmentation	99.83
E. Izci et al. [34]	Empirical mode decomposition	Latent Dirichlet Allocation	87.02
S. L. Oh et al. [35]	Convolutional neural network long short-term memory	Deep learning	98.105
M. S. Mathew [36]	Deep belief networks	-	95.575
Ali et al [37]	Deep neural network	-	92.05
S. Sahoo et al. [38]	Support vector machine	-	98.95
P. Li et al. [39]	General regression neural network	-	88.05
S. Shadmand et al. [40]	Neural network	-	97.05
L. Oliveira et al. [41]	Dynamic Bayesian	Principal component analysis	99.02
P. Sakhare et al. [42]	Adaptive network-based fuzzy inference system	-	96.06
Vijayavanan et al. [43]	Feed forward PNN	-	96.56
N.P. Joshi et al. [44]	Support vector machine	Principal component analysis	86.09
M. K. Das et al. [45]	Machine learning classifier	-	99.486
R. J. Martis et al. [46]	Support vector machine	Principal component analysis - Latent Dirichlet Allocation	99.288
R. J. Martis et al. [47]	Neural network	Principal component analysis	94.524
V. Kumari et al. [48]	A multilayer perceptron neural network	-	95.16
V.Srivastava et al. [49]	A multilayer perceptron neural network	-	856
A. Khazaee et al. [50]	A probabilistic neural network	Particle swarm	76.05
S. M. Jadhav et al. [51]	Generalized feed forward neural network	-	86.675
J. S. Wang et al. [52]	A probabilistic neural network	Principal component analysis	99.719
B. Kamath et al. [53]	Neural network	-	95.05
A. Dallali et al. [54]	Fuzzy clustering	-	99.056
E. Zeraatjar et al. [55]	A multilayer perceptron neural network	-	96.78
Z. Slimane et al. [56]	MDPSO	-	95.585

Table 3: Best arrhythmia classifiers.

Method	Classifier	Optimization	Accuracy

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			(%)
M. Li et al. [57]	Fuzzy clustering	Cognitive neural network	99.955
R. Labati et al. [58]	Convolutional-neural network	Cognitive neural network	100.00
J. Takato et al. [59]	Convolutional-neural network	-	84.02
M. chen at al. [60]	Convolutional-neural network	-	84.03
J. Rubin et al. [61]	Fuzzy clustering	Fourier transform	81.05
Y. Xia et al. [62]	Deep neural network	Fourier transform	98.345
Z. Zhao et al. [63]	Convolutional-neural network	-	96.367
R. Kamal et al. [64]	Multilayer perceptron neural network	-	76.798
X.Xhsi et sl. [65]	Convolutional-neural network	-	98.65
Robby et al. [66]	AlexNet VGGNet	Transformation	99.050
F. Andreotti et al. [67]	ResNet	-	72.19
O. Yildrim et al. [68]	Fuzzy clustering	-	91.335
U. Acharya et al. [69]	Convolutional-neural network	-	95.988
C. Zhang et al. [70]	Fuzzy clustering	Cognitive neural network	97.56
Chandra et al. [71]	Recurrent neural networks	Cognitive neural network	94.034
Pourbabaee et al. [72]	Convolutional-neural network	-	93.68
L. Wang et al. [73]	Recurrent neural networks	-	99.266
G. Sayantan et al. [74]	Support vector machine	GD-DBM	99.54
B. Zhang et al. [75]	Recurrent neural networks	Long short-term memory	99.45
V. Sujadevi et al. [76]	Recurrent neural networks	-	95.09

3. Modern Trends in Arrhythmia Classification

The purpose of present paper is to present the methodologies utilized in arrhythmia classification utilizing an ECG database used in deep/machine learning algorithms. The degree to which a computer could be trained to identify the ground truth automatically is reflected in the accuracy outcomes, which are the product of the learning algorithm. The primary aim of this study is to aid researchers by providing a consolidated list of arrhythmia categorization methods alongside their respective prediction outcomes. Statistics of commonly used arrhythmia classification methods from relevant studies are displayed in Figure 3.

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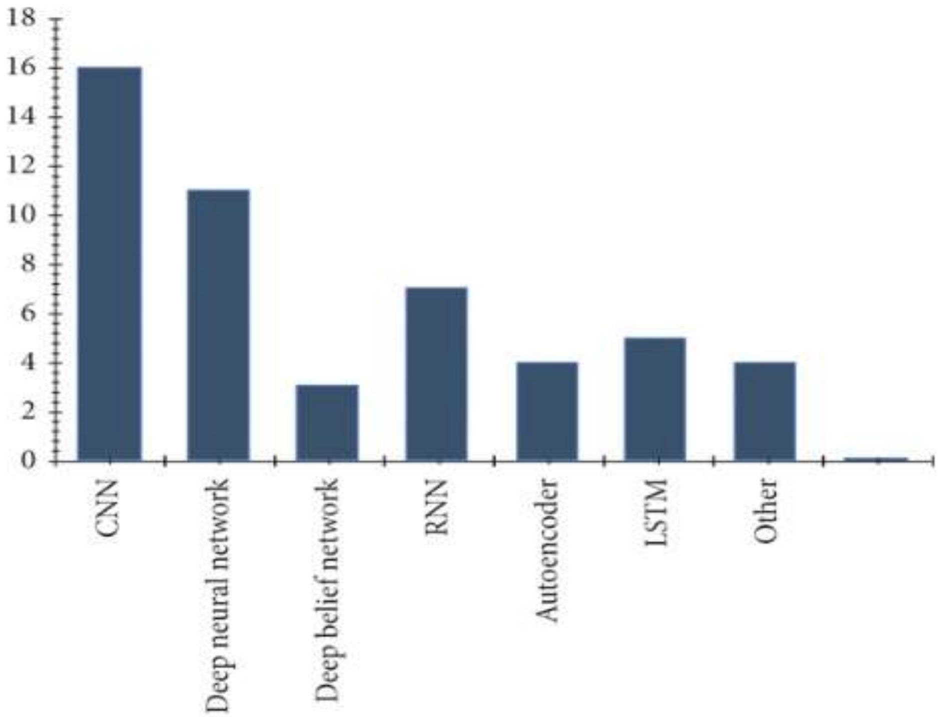

Figure 3: Different classification methods.

A. Deep learning architectures

Medical image analysis frequently employs deep learning methods. A deep neural network (DNN) architecture is designed to mimic that of the human brain. One neuron may decode the logic at work among several parts and detect the pattern. The building block of a deep neural network is a neuron, which, like a human neuron, can learn from experience and improve with practice. Learning and practice are geared toward making that input-output link. Once trained, the system can accurately identify the targets it has been taught to look for. The most widely-used DNN approaches for arrhythmia classification are as follows, as determined by a survey of published research on the topic: (1) Recurrent neural network (RNN)

(2) Long short-term memory (LSTM)

(3) Autoencoder

(4) Convolutional neural network (CNN)

(5) Deep neural network (DNN)

(6) Deep belief network (DBN)

A.1 Recurrent Neural Network (RNN)

To the family of neural networks, of which RNN architecture is a part, we now add the RNN family. With RNN, data can be stored iteratively across layers. Recurrent neural networks (RNNs) are standard because of their ability to employ inference from previous data to teach the network about potential future outcomes. Many arrhythmia classification algorithms use RNN-based deep architecture to train the sequence vectors. The inner workings of an RNN architecture are depicted in Figure 4.

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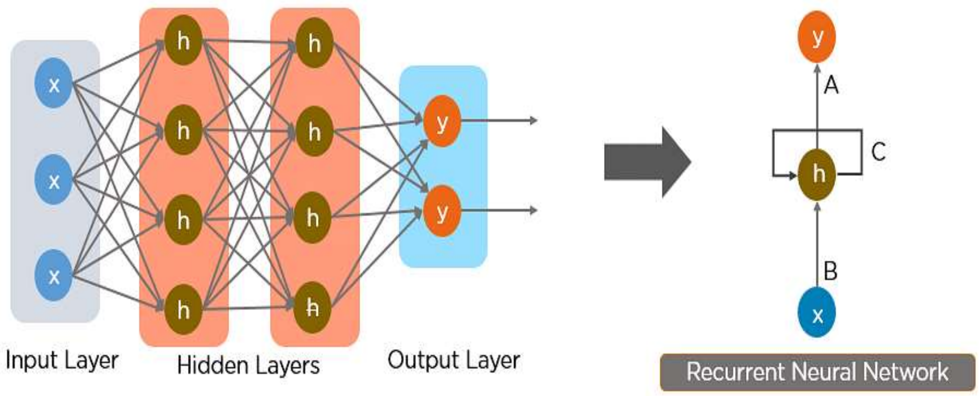

Figure 4: RNN architecture.

A.2 Long Short-Term Memory (LSTM).

The Long Short-Term Memory (LSTM) model replicates the well-known RNN architecture [77] in deep learning. While neurons in a feedforward network all have forward connections, an LSTM can also receive feedback in the opposite direction. LSTM may handle single data points, like photos, or data sequences, such as continuous images, videos, or audio signals. Unsegmented voice recognition and pattern detection are both within the capabilities of LSTM architecture. The electrical signals of the heart, or an electrocardiogram, can also be recognized by LSTM. Cells, input, output, and forget gates make up LSTM's core architecture. The gates control data exchange between the cells, and the cell is responsible for remembering the values throughout predetermined periods. The inner workings of an LSTM architecture are depicted in Figure 5.

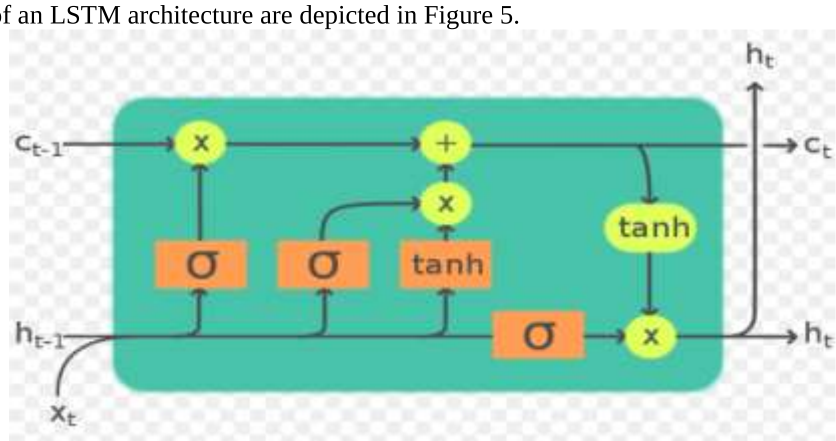

Figure 5: LSTM-based architecture.

A.3. Autoencoder.

The autoencoder is a type of artificial neural network (ANN)-based architecture that can be used to teach itself efficient data encoding without any human oversight. As such, they are widely used to discover commonalities within related datasets. In addition to reducing the number of dimensions, autoencoders attempt to produce an output class analogous to the one provided as input. The author of the referenced papers proposed different variants of autoencoder-based architecture. Schematic representation of the autoencoder's fundamental structure.

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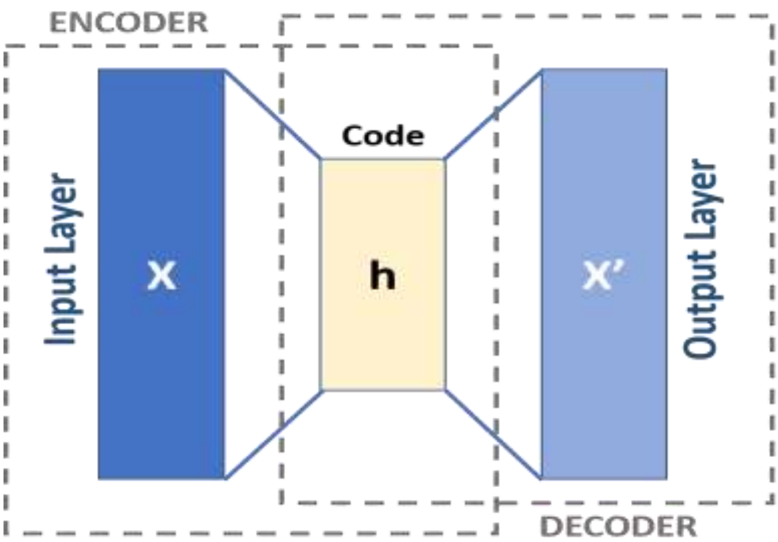

Figure 6: Autoencoder-based architecture.

A.4. Convolutional Neural Network (CNN).

CNN is an algorithm that uses deep learning. In the realm of computer vision and image processing, CNN is well-known as a useful tool. To put it simply, it has an input layer, several levels of concealment, and an output layer as its final component. Hidden layers, which are concealed by an activation function (ReLU), a pooling layer, and a convolution, make up the bulk of a forward-pass convolutional neural network. Forward-pass convolutional neural networks are depicted in Figure 7. CNN is generally acknowledged as a method for the detection of ECG heartbeat signals in state-of-the-art research projects.

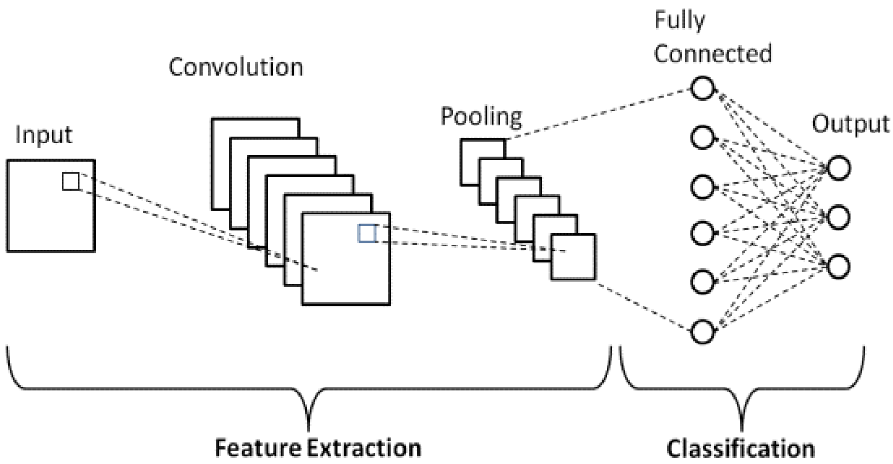

Figure 7: Forward pass convolution neural network structure.

A.5. Deep Neural Network (DNN).

Multiple hidden layers in a simple DNN allow it to handle data from an input layer to an output layer [78]. Different types of unstructured data are easily identifiable by the DNN. Different neural networks have been proposed for arrhythmia classification, but all have the same neuron, weight, bias, and function components. As a whole, these parts have the same capabilities and behavior as the human brain. When classifying electrocardiogram (ECG) images, the deep neural network is the gold standard. Figure 8 is a schematic depicting the fundamental framework of a DNN-based architecture [79-82].

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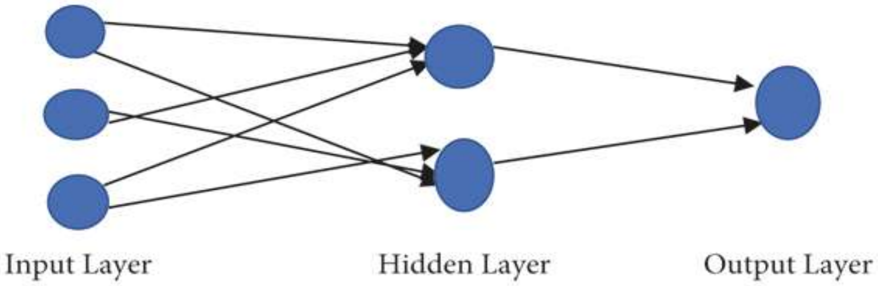

Figure 8: Structure of basic DNN architecture.

A.6. Deep Belief Network (DBN).

DBNs are a type of deep neural network with multiple interconnected layers that do not share units, as has been the trend in the classification of arrhythmias in recent years. DBN can be trained by supervision to achieve better prediction. Figure 9 is a schematic depicting the fundamental architecture of a DBN.

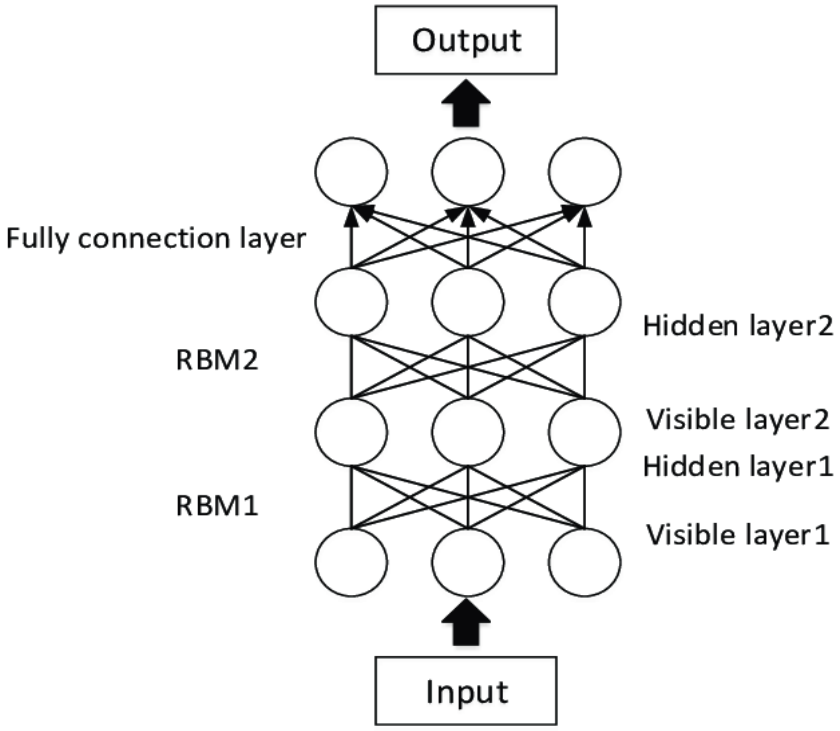

Figure 9: Structure of basic DBN architecture.

B. ECG Databases.

Expert systems for automatic arrhythmia illness identification require training data to comprehend the unique characteristics of each diagnostic category. Authors of the selected research study critically analyses arrhythmia classification systems and enlist the most cited/publicly open-access ECG databases. As was previously indicated, the database stores several ECG beat variations, each of which is classified as a unique arrhythmia. These data sources are particularly useful due to their domain-specific qualities. The context in which these ECG beats were collected, as described by the patient population, is crucial for understanding the technique and clinical utility.

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4. Conclusion

Arrhythmias are one of the causes of death, the researcher proposed multiple arrhythmia classification schemes to aid physicians each year. Recent studies have shown that automated systems can predict high-accuracy results for arrhythmia detection. However, they are still not widely adopted by healthcare professionals because the data used in these studies is time-series, which cannot be easily adapted to different application environments. In addition, steady baseline drifts, muscle contraction, and power line interface are not suitable for the time-series data acquired by an electrocardiogram because of the signal leads. The use of imbalanced data in classification algorithms is a major issue that has a significant impact on the performance of existing arrhythmia detection systems I due to the need for human intervention in selecting features, (ii) due to the complexity of feature extraction, and (iii) due to the lack of a universally accepted feature selection method. It was necessary to have domain expertise to automate the detection of arrhythmias by analysing ECG images for feature extraction. Overfitting can be prevented, however, by using a balanced dataset with classification techniques. For some time now, deep learning-based systems have been acknowledged as a helpful tool in healthcare institutes thanks to their ability to extract high-level abstract features automatically. This helps institutions save time and effort by eliminating the need for onerous manual feature creation. Ultimately, this research can aid the researcher in gaining a more thorough comprehension of arrhythmia classification and the deep learning techniques employed in creating automated systems.

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