Classification of Heart Sounds using Neural Networks – A Survey

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Abstract : In the modern world, one of the most dangerous and crucial disease is the heart disease which leads the causes of more number of deaths. In order to diagnose, the great prerequisite for the detection of heart disease is heart sound. Now a days, extensive research has been carried out for different feature selection and classification technique. According to this survey paper we deal with the most important feature for the detection of heart disease that is feature evaluation or ranking and feature selection. They are the most important features to the classification problem. During classification section we compared many neural network techniques which give 90% and above accuracy as classifier for heart valve disease detection. Then, a comparative study is applied to determine the most effective techniques that are capable for the detection of heart valve disease with a high accuracy.

***IndexTerms* – Neural networks, Heart sound, Deep learning.**

I. INTRODUCTION

Cardiovascular diseases are one of the leading cause of death in worldwide. A number of people died due to some heart diseases are about 17.3 million and it will reach 23.3 million by 2030 across the world. Every year a number of heart diseases specifically a myocardial infarctions and other diseases occur in every countries. Regular check-up has a possibility to detect heart sounds abnormalities of a person and it helps to avoid many heart complications, and it can increase the chance of recovery of a person. Because of a fast life and improving technologies, it is possible to develop an automated, diagnosing and screening tool for identifying various heart diseases of an individual and it supports primary medication at home without doctor involvement.

Phonocardiography (PCG) is one of the most important method which is used for monitoring and analysing the human circulatory system. Using this system we can record the whole biomechanical activities of the heart. And this technique has two phases: such as development phase and self-analysis phase. Smart stethoscopes are used to capture heartbeats, heart rate of a person and it is unable to detect heart diseases. The efficient methods are needed to develop self-diagnosis tool to detect disease in the individual. These methods should provide an early detection of abnormal conditions of an individual and commencement of an appropriate actions to save their lives.

Recent research area is mainly focus on the development of algorithms to classify various diseases of a patients automatically, which may lead to the development of an smart kits to detect diseases in the future. Diagnosis process is divided into two steps by various PCG signals of a patients and some noise occurs during examination. The first step is to analyse the collected or observed signals to extract various features, which helps to differentiate all types of heart sound signals, and the second step is the signal classification. Many researchers have tried their best to develop such classification technique, where the majority of works are based on different types of Neural Networks (NN).

II. CLASSIFICATION OF HEART SOUNDS USING NEURAL NETWORKS

2.1 Synaptic delay-based artificial neural network

A synaptic delay-based artificial neural network method was developed to classify intra-cardiac electrograms. Using MATLAB, synaptic delay-based artificial neural network is implemented and it is used to detect abnormal conditions of the heart from the obtained recordings. Errors range in detection of atrial, and ventricular electro grams were 1-2 ms. It is used for effective detection of temporal patterns in the electrophysiological and biological signals. Some of the disadvantages are: It is not suitable for poorer quality signals, Time taken for the complete computations is high and more memory was required to store data for individual nodes. A positive match for this method was the probability of 80% or greater than that. [1]

2.2 Multilayer Perceptron -Backpropagation (MLP-BP) Neural Networks

The classification of heart sounds (HSs) which was obtained from single cardiac cycle (S1-Systole-S2-Diastole) a new method was proposed using homomorphic filtering and K-means clustering. Hence the classification has been done feature vectors were formed by Daubechies-2 wavelet detail coefficients. These feature vectors are given as an input to the neural networks. Multilayer perceptron -Backpropagation (MLP-BP) neural networks and Grow and Learn (GAL) are used for classification of three different Heart Sounds (HSs). The classification performance of MLP-BP was similar to GAL. Multilayer perceptron -Backpropagation (MLP-BP) neural networks and Grow and Learn (GAL) are compared by its training and testing time. The training and testing times of GAL are lower than MLP-BP. The data used to evaluate these methods were taken from Singapore General Hospital (SGH). The data obtained was divided into three datasets. The overall accuracies for both methods are around 97% [2].

Based on Artificial Neural Network, a new method was proposed to classify collected heart sounds (HSs). The classification of S1–S2 sounds was done by Discrete wavelet transform and it will detect various features. In classification procedure, Kohonen's SOM network and an incremental self-organizing map (ISOM) are effectively compared to evaluate its performance with the same data. Computerized techniques gives good results and reliable method. An incremental neural network was proposed to increase the performance of heart sound classification. The disadvantages of the method are: it requires excessive number of nodes in the network, and the problem lies in determining optimum number of nodes and network topology. The overall accuracy of this method was 95% [3]

A multiresolution wavelet-based algorithm is utilized to carve the important characteristics of the heart sounds. To choose proper exclusive features, an artificial neural network (ANN) along with the classifier with statistical measures were alternatively deployed. These two classification techniques were using Daubechies wavelet filter to remove noise from the heart sounds and to establish the occurrence of diseases. The features are transferred to the wavelet domain and linear regeneration is carried out. The data used was taken from Androscope IS28A00. This method was feasible but it simulates the ambient noise. ANN gives the percentage classification accuracy of 94.42% [4].

2.3 Multi-Layer Perceptron (MLP) neural network

A new method was proposed which is based on MLP neural network. It classifies paediatric heart sounds of a children. The segmentation of the heart sounds was carried out in three steps. Autoregressive (AR) parameters are used to extract some features Multi-Layer Perceptron (MLP) neural network classifier for classification of number of heart sounds. The data was taken from 60 normal and abnormal samples of their own databank. This method was efficient and used as an effective screening tool for a complete segmentation of heart sounds but it was inconvenience in some cases. The overall accuracy was 93.6% [5].

To epitomise different types of heart sound (HS) of a person, there are two methods were comparatively used for feature extraction. Before doing the pre-processing that is processing the collected data, first, a rectangular window was formed for the collected heart sounds then the equivalent windowed time samples are normalized. For the windowed one period of HS, Discrete wavelet transform is applied to extract features. In this survey, performances of above mentioned both the feature extraction methods were moderately examined based on the divergence analysis. Some advantages are compared to other two methods and it gives high accuracy and also better performance. The overall accuracy was 98%. [6]

2.4 Time-delayed neural networks (TDNN)

In order to classify five different heartbeat types, phase space reconstruction approach was used. Three methods were compared to classify five types of heartbeats. The features were extracted by Re-constructed phase space (RPS) and Gaussian mixture model (GMM). Many methods were applied and reported in previous work for automatic heartbeat classification but only few methods are compared here. The three proposed methods are compared with the results reported on previous work, for patient self-determining heartbeat classification. And the three methods are superior to previously proposed methods. The data was obtained from MIT-BIH arrhythmia database. The best result was achieved using GMM–Bayes method with 92.5% classification accuracy. [7]. The Time-delayed neural networks (TDNN) method deals with analysis and detection various heart diseases. The features are extracted by using discrete wavelet transform and principal component analysis and classification was done by using Time-delayed neural network. The proposed method was tested on the collected set of heart sounds obtained from publicly available databases and they are also recorded by electronic stethoscope. An average classification performance obtained was 0.92 for noise free heart sounds. The TDNN method shows good results and high noise robustness for most of the heart sounds. To enhance the bias of heart sounds, more tests are conducted. Some disadvantages are: it only classifies given heart sounds are normal or abnormal, and the training set are having some inclination due to oversampling of the normal set and different frequency response. [8]

2.5 Wavelet neural network (WNN)

To know the cardiac status of each and every patient, ECG signal was one of the greatest significant tool in clinical practice. The classification of ECG was categorized into different pathologic disease which was one of the complex pattern recognition task. A method was proposed for ECG heartbeat pattern recognition process using wavelet neural network (WNN. First, an algorithm for QRS detection in ECG signals was implemented, then WNN Classifier was used for classifying various heart sounds. The experimental results are obtained by using MIT-BIH arrhythmia database and it more efficient approach when compared with other methods on the previous work. The overall accuracy obtained was 98.78%. [9]

2.6 Artificial Neural Networks (ANN)

An automated classification of heartbeats was vital as some heartbeat irregularities are time consuming to detect. The methods proposed in the previous work was depend on the structure of a heartbeat cycle. The interval and amplitude based features together with a few samples from the ECG signal as a feature vector for these methods. A variety of classification algorithms are focused especially on a type of arrhythmia known as the ventricular ectopic fibrillation (VEB). The performance of the classifiers against algorithms proposed in the previous work and make recommendations regarding features, sampling rate, and choice of the classifier to apply in a real-time clinical setting. This study was based on the MIT-BIH arrhythmia database. The main contribution was the evaluation of existing classifiers over a range sampling rates, recommendation of a detection methodology to employ in a practical setting, and extend the notion of a mixture of experts to a larger class of algorithms. It gives high detection accuracy. [10] The proposed Artificial Neural Network (ANN) was combined with Modified Neighbour Annealing (MNA) to classify heartbeats into two categories such as normal and murmur classes. Wavelet transformer was used to separate heart beats from heart sounds. The features extracted from individual heart sounds are used as an inputs to the neural network and two classification techniques are used to produce outputs. The classification accuracy of the proposed model was compared with previously developed classification algorithms and also compared with Self-Organizing Map (SOM). The proposed ANN used the real heart sounds available in the Pascal database for evaluation. MNA method also produces better results. [11] An evolutionary ANN classification method was used to classify heart beats. To develop an efficient algorithm by using ANN and it provides useful feedback in processing of 12-lead Electrocardiography (ECG) recordings. And a developed algorithm uses PhysioNet 2011 database to evaluate its performance. The method was designed to overcome some problems and a very powerful analysis tool was designed based on evolutionary neural networks, and it has network topology and its corresponding connection weights. Discrete Fourier Transform was used to extract the various features to perform pre-processing algorithm. At the end of the process, a series number of evaluation was made to estimate the performance and the accuracy of the developed classifier system based on artificial neural network. The accuracy obtained was 0.9. [12]

2.7 Levenberg–Marquardt neural network (LMNN)

The abnormal heart sounds of the person were identified by the changes in the collected ECG signals. The first step of the proposed method was the detection of MI in the heart sounds and pre-processing of ECG signal was done by using some filters to remove noises. Feature extraction process was mainly carried out to detect changes in the ECG signals. By using Improved Bat algorithm, the key features are extracted from each cardiac beat. Using this algorithm best features were extracted from the heart sound, and then these best (reduced) features were applied as an input to the neural network classifier. The performance of the classifier was improved by using the optimized features. The time required to train the neural network was less, robust, and very simple method. The data used was taken from MIT-BIH PTB database. The overall accuracy obtained was 98.9%. [13]

2.8 Radial wavelet neural network (RWNN)

Radial wavelet neural network (RWNN) method was to detect various heart diseases. Automatic heart disease diagnosing devices are more reliable and efficient to find different heart murmurs; but they are only present in urban modern hospitals. The Extended Kalman Filter (EKF) was used to eliminate noises from the collected heart sounds. Dimensional features, extracted from real heart sounds are used as an inputs and it gives three classification outputs. The proposed model's classification accuracy was compared with other three algorithms. The proposed model was evaluated by using real heart sounds obtained from online databases to show its applicability. The overall accuracy obtained was 97.8%. [14].

2.9 Deep neural network (DNN)

Under some situations, the duration and interval information are unable to access, so the main objective of this approach was to evaluate the S1 and S2 heart sounds of a patients. A deep neural network (DNN) method was mainly proposed for analysing S1 and S2 heart sounds. In this proposed method, a series of Mel-frequency cepstral coefficients (MFCCs) features were selected for classification and these MFCC features are divided into two groups. The experiments results are evaluated by using real heart sound signals recorded using smart stethoscope. The proposed DNN-based method achieves more than 91% of accuracy. [15]

2.10 General Regression neural network (GRNN)

The acquiring of medical data of a person for personalized heartbeat classification was possible but the development of an automatic heartbeat classification method was difficult. Holter is the long-term data acquiring method, which was very difficult to process. Using its original method, it takes long time to process the classification. To solve above issues, a general regression neural network (GRNN) was proposed to classify the collected heartbeats, and it achieved a 95% accuracy. The data used was taken from MIT-BIH arrhythmia database. The efficiency of the parallel GRNN with GTX780Ti was improved by 450 times. [16]

2.11 Radial Basis Function Neural Network (RBFNN)

A method was proposed specifically to eliminate ectopics in heartbeats by classification and it shows that collected heartbeats are normal or abnormal beats. The proposed classification system was based on Radial Basis Function Neural Network (RBFNN). This proposed approach was compared with previous techniques for the ectopic classification. Here, 8 publicly available databases are used to evaluate its proposed methods. The obtained results shows that the improved ECG signals classification accuracy are compared with other methods. This method represents a very accurate representation of ECG, and providing high quality detection of various diseases. The overall accuracy obtained was 99.79%. [17]

2.12 Block-based Neural Network (BBNN)

A Block-based Neural Network (BBNN) was used as a classifier to classify different types of heart sounds. The BBNN was consists of 2-D array of blocks where all the layers are connected with each other. Particle Swarm Optimization (PSO) algorithm was used to estimate the internal structure of the network with its corresponding weights and also to determine the Network Optimization. Hermit function coefficient and temporal features are considered as extracted features to process the ECG signals. The BBNN parameters are optimized by PSO algorithm. PSO algorithm can work better in all variations of ECG signals. The performance evaluation was made on MIT-BIH arrhythmia database and it shows a high classification accuracy of 97%. [18]. A BBNN was defined as 2-D array of modular component with flexible structures and field-programmable gate arrays (FPGAs) are designed by using digital hardware for internal configurations of the network. The internal configuration of a block and the overall structure of the BBNN was determined by signal flow between the blocks in the network. A BBNN method was optimized with an evolutionary algorithm (EA) to make a best heartbeat classifier system specifically to cope with changing environments of the individuals and time-varying characteristics of ECG signals. Massachusetts Institute of Technology/Beth Israel Hospital (MIT-BIH) arrhythmia database was used to evaluate the performance of the proposed method and it gives high average detection accuracies of, 95.91%. And this method was more effective, high optimization speed and tackle changes in operating environments. It provides great improvement over existing reported electrocardiogram (ECG) classification results. [19]

2.13 1D-Convolutional neural network (1D-CNN)

The proposed 1D-Convolutional neural network (1D-CNN) mainly focuses to solve two major problems. First is the signal processing technique and second is the feature engineering. Both techniques were complicated, data-dependent, time consuming process and it cannot be suitable for specific datasets. To overcome these issues, a multiresolution convolutional neural network was used. A multiresolution 1D-convolutional neural network (1D-CNN) was designed for automatic extraction of various features to perform the user identification action. The performance evaluation was carried out on eight electrocardiogram (ECG) datasets. The evaluation was more extensive and gives an average classification accuracy of 93.5%. The proposed multiresolution 1D-CNN algorithm classifies collected heart sounds and identify heart diseases effectively. [20]

2.14 Probabilistic Neural Network

To classify different types of heartbeats, an arrhythmia Probabilistic Neural Network classification method was implemented on Digital Signal Processing (DSP) to perform real time operation. Here, eight heartbeat conditions are used for evaluation. The proposed algorithm uses a wavelet transform for identifying individual ECG signals to obtain a fiducial marker array was its extracted features. The algorithm was tested on PhysioNet databases which takes only 17 ECG records. The proposed classification technique was implemented on MATLAB and its results were compared with the previous work. The experimental results obtained shows its classification accuracy of 92.746% on the MATLAB and 100% for online DSP implementations. [21]

2.15 9-layer Deep Convolutional neural network (CNN)

The main determination of 9-layer DCNN is to recognise and categorize different kinds of heartbeats in ECG signals automatically. The mentioned categories of collected heartbeats are ventricular ectopic, non-ectopic, fusion, supraventricular ectopic and unknown heartbeats. And these collected signals were corrupted by noise, so it was difficult to classify these heartbeats on ECG and it takes long time for processing. The evaluation was made on both the original and noisy sets of ECG signals collected from an openly accessible database. The CNN method was trained using both noisy and noise free ECGs which gives an accuracy of 94.03% and 93.47%. When the proposed CNN method uses the original datasets, then the accuracy for noisy and noise free ECGs was reduced to 89.07%% and 89.3%. The proposed CNN model was a best screening tool to identify different types and frequencies of arrhythmic heartbeats quickly. [22]

2.16 Deep recurrent neural network (DRNN)

To perceive superfluous heart sounds like murmuring of the heart sound, third, fourth heart sounds and also other variations which includes cardiac arrhythmia are detected by DRNN.

The used data which has heart sounds were taken from the 2016 PhysioNet/CinC Challenge. Some spectral and envelope features are extracted from the recordings and the concert of different deep recurrent neural network (DRNN) architectures are assessed. The obtained results are compared with other existing methods and (DRNN) gives good results. By using spectral or envelope features, an event detection approach with DRNNs was suggested to propose a new method for the classification of heart sounds. The overall accuracy obtained was 95.6%. [23]

2.17 Convolutional neural network (CNN)

By using convolutional neural network (CNN), some features were selected. The set of these extracted features consists of three subsets namely, the behaviour of the signal was represented by wavelet transform based morphological features, the overall variation characteristics of the signal was represented by statistical features and the behaviour of the collected signals on the time axis was represented by its temporal features. The above mentioned various kinds of classifiers are united together constructed on the classification performance and the best one is taken for ECG classification. The results are evaluated by using MIT-BIH arrhythmia database shows that it has superior classification accuracy compared to other previous ECG classification methods. The overall accuracy obtained was 98%. [24]

Based on convolutional neural network (CNN), the classifier system was designed to classify different types of heart sounds. According to the changing heartbeat rate of a person, a single channel ECG signal was classified into different types of heartbeats. Then these heartbeats were converted into dual beat coupling matrix as 2-D inputs to the CNN classifier. To improve the classification performance, a systematic training heartbeat selection process was developed to automatically include heartbeats into the training phase. The classification technique was evaluated to detect abnormal heartbeats and variations in heartbeats of a person using the MIT-BIH arrhythmia database. The proposed method gives better concert than many existing methods. The proposed CNN classifier was designed for automatic training beats selection process. For long-term monitoring of cardiac arrhythmia it is to be implemented on portable device. The overall accuracy obtained was 98.6%. [25] To analyse different types of heart diseases of a person, ECG is used as a diagnostic tool to detect abnormalities of the heart. But it absences in diagnostic sensitivity of the heart. Due to its very low amplitude, it is very difficult to visually evaluate the ECG signals. The identification of abnormalities in the ECG signals sometimes went wrong by manually done by clinicians. The long short-term memory (LSTM) network with convolutional neural network (CNN) is designed to detect different types of heart diseases using ECG signals to evaluate its accuracy. The proposed convolutional neural network (CNN) model was able to detect different types of heart diseases with classification accuracy of 99.85%. [26] Here, paediatric heart disease screening applications are used to automatically detect the heart abnormalities from digital phonocardiogram (PCG) signals. The various systems are developed to classify PCG signals which are based on convolutional neural networks. Then these PCG signals were trained based on its time-frequency representations. The proposed work focuses on the classification and time-frequency representations of the CNN. The features like (MFCC and Mel-Spectrogram) are most commonly used in previous work and a time-frequency representation was essential for CNN, sub-band envelopes are also used as an alternative feature. The performance evaluation was carried on two public databases. The most commonly used features are sub-band envelopes and period synchronous windowing was preferred one over asynchronous windowing. The overall accuracy obtained was 0.815. [27] A convolutional neural network based tool was proposed to classify the healthy and pathological patients and that was able to decompose the ECG signals into frequency bands. Different networks was trained with the heart murmurs in heart sounds which was obtained from nine different databases. Sonogram images are generated with the same size in order to decompose ECG signals into frequency bands. By using the neuromorphic auditory sensor, these obtained samples are segmented and pre-processed. Then these sonogram images are used to train and test different types of convolutional neural network architectures. The modified version of developed AlexNet model gives best results of 97% accuracy. [28]

2.18 Probabilistic neural networks (PNN)

Based on probabilistic neural networks (PNN) and Gram polynomials, a new approach was proposed to diagnosis the activity of heart. On analysing the phonocardiogram (PCG) digital sequences, we can recognize different types of heart diseases. The PNN is a best screening tool for appropriate grouping for the composed data set. The powerful features were extracted by using Gram polynomials and Fourier transform. The suggested system shows respectable performance which gives an accuracy of 94%, using a publicly available database to classify collected heart sounds as normal or abnormal heart sounds. Gram polynomials and PNN was very efficient technique for characterizing different heart diseases. [29]

2.19 General regression neural network (GRNN)

Automated heartbeat classification technique to detect various diseases was a big challenge in past few years. The personalized heartbeat classification of a patient was become possible by using their medical data. The holter model was not able to get the analysis results within a short time by using the long-term data accumulation method. Recent research area is concerned with the development of automatic classification method. To solve above challenges, a general regression neural network (GRNN) was developed to classify the collected heartbeats, and gives 95% accuracy. An online program was designed to create a classification technique to detect diseases of patients. The data used to assess the performance of the proposed model was engaged from MIT-BIH arrhythmia database. The efficiency of the parallel GRNN with GTX780Ti was improved by 450 times. [30]

2.20 Fuzzy neural network

A basic method was developed which is based on Fuzzy neural network to analyse abnormal heart sounds of publicly available databases. A system was designed for automatic analysis and classification of collected heart sounds. The features are extracted using Normalized Shannon Energy for heart sound classification. A fuzzy neural network method was used with machine learning concepts for better classification. With their designed equipment, only one normal heart sound and two abnormal heart sounds with some heart diseases are recorded, to evaluate the performance of proposed method. The experiments was carried out with real data for appropriate classification. [31]

2.21 Incremental supervised neural network (ISNN)

In ISNN method, two processes are carried out, first, a rectangular window was generated for collected respiratory sound (RS). Then, normalization was done for the windowed time samples. Then these normalized RS signal is divided into 64 samples to extract various features. By using the averaged power spectrum components, feature vectors were formed which yields 32-dimensional vectors. The different classes are distributed successfully even in noisy environments and it gives high performance. In this proposed method, grow and learn (GAL) network, multi-layer perceptron (MLP) and incremental supervised neural network (ISNN) methods are compared to evaluate its classification performance. The overall accuracy of this method was 92%. [32]

III. RESULTS AND DISCUSSION

Table 4.1: Comparative analysis on classification of heart sounds using neural networks.

Author's Name	Merits	Demerits	Database	Accuracy
S. M. Chetham et al [1]	Effective detection of temporal patterns, More accurate and reliable method	The evaluation was carried out only on a single channel intra-cardiac heart sound, Not suitable for poorer quality signals, Low robustness, High computational, Requires large memory	1. Prucka Research Centre, Texas, USA 2. St Andrew's War Memorial Hospital	
Cota Navin Gupta et al [2]	Potentially useful in automatic analysis of HSs	_	Singapore General Hospital (SGH), 41 different heart sounds	DS1 DS2 DS3 1.97.01,98.50, 95.55 2. 97.01,97.01, 95.55
Zümray Dokur et al [3]	High performance, computational time required to process one cycle of heartbeat is less	It requires more number of nodes in the network, Difficult in determining optimum number of nodes in the network and its topology	Publicly available database from Internet	95%
Sepideh Babaei et al [4]	Feasible, It gives better diagnostic results	Simulating the ambient noise	Androscop IS28A00	94.42%

Amir A. Sepehri et al [5]	Efficient method to segment heart sounds and it is used as an effective tool	Inconvenience in some cases, Heart cycles are collected only with their corresponding ECGs	60 normal and pathological samples of their own databank	93.6%
Zumray Dokur et al [6]	1.High performance 2.Good performance 3.compared to other two methods it gives high accuracy and also better performance	1. Takes long time to execute Require excessive number of nodes 2. generates excessive number of nodes	The database contains 36 patients' records	98%
Isar Nejadgholi et al [7]	Rapid, Accurate, High performance	High computational cost	MIT-BIH arrhythmia database	92.5%
Sumeth Yuenyong et al [8]	It gives good results, robust, less noise	The proposed method shows only that the given heart sounds are normal or not, The training set has some inclination in collected heart sounds due to oversampling and different frequency response	Thinklabs Rhythm ds32a electronic stethoscope	0.9
Radhwane Benali et al [9]	Efficiency, Relatively better than some other neural network, Effective tool	_	MIT-BIH arrhythmia Database	98.78%
Tony Basil et al [10]	High detection accuracy	_	MIT-BIH arrhythmia database	1.94.2% 2.83.6% 3.95.2% 4.97.1%
Gholamhossein Eslamizadeh et al [11]	More reliable	Computational complexity	Pascal database	99%
Antonia Azzini et al [12]	Tremendous improvement in performance, Potentially best performance	Standard deviation results obtained from this method is very low	PhysioNet/Computing in Cardiology Challenge 2011	0.9
Padmavathi Kora et al [13]	Performance of the classifier is improved, Less time to train the dataset, Robust and Very simple method	Tuning of parameters for feature extraction has to be improved	MIT-BIH PTB database	98.9%
Juan E. Guillermo et al [14]	RWNN has uniform and stable accuracy, Low cost	Low successful rates	_	97.8%
Tien-En Chen et al [15]	High precision, effectiveness	Due to less training dataset, parameters represented by ($\boldsymbol{\theta}$) was unable to estimate the accuracy of DNN	Three sets of audio data are used for both training and testing	91.12%
Pengfei Li et al [16]	Shortens the data processing time, Efficient, Generic way to analyze large datasets, High performance computing	_	MIT-BIH arrhythmia database	95%
J. Mateo et al [17]	Very accurate representation of ECG signals and it provides high quality ectopic beat reduction	_	PhysioNet Database, MIT-BIH Arrhythmia Database and six other publicly available databases	99.79% for RBFNN

Shirin Shadmand et al [18]	High quality system, Speed of convergence is very high	_	MIT-BIH arrhythmia database	97%
Wei Jiang et al [19]	Effectiveness, Optimization speed, Tackle changes in operating environments	_	MIT-BIH arrhythmia database	95.91%
Qingxue Zhang et al [20]	Algorithm engineering effort was low, Provides a good generalization ability	High computational power	CEBSDB, WECG, FANTASIA, NSRDB, STDB, MITDB, AFDB, VFDB	CEBSDB -99.0, WECG-94.5, FANTASIA-97.2, NSRDB-95.1, STDB-90.3, MITDB- 91.1, AFDB- 93.9, VFDB-86.6
Jose Antonio Gutiérrez-Gnecchi et al [21]	High classification accuracy	_	PhysioNet repository	92.746%
U. Rajendra Acharya et al [22]	Quick, Reliable, Fully automatic, Robustness	More time is required to train dataset, Specialized hardware is required, Training the dataset is expensive, To train the model, very large number of images are required	PhysioBank, MIT-BIH Arrhythmia database	89.07% acquired in noisy ECGs and 89.3% acquired in noise free ECGs
Elmar Messner et al [23]	Suitable method even in the absence of noise, signal, and cardiac arrhythmia disease, Easily detect extra heart sounds	Requires appropriate training data	2016 PhysioNet/CinC Challenge dataset	95.6%
Zahra Golrizkhatami et al [24]	Fully automatic, Non-invasive, Higher accuracy	Balanced datasets to be used	The MIT-BIH (Mark & Moody, 2001) arrhythmia database	98%
Xiaolong Zhai et al [25]	Superior performance, Reliable, Fully automatic tool, Flexible platform	No robustness	MIT-BIH arrhythmia database	98.6%
Jen Hong Tan et al[26]	The system is fully automatic, Highest diagnostic performance, Installed in a portable device, Less expensive	For subject specific data, this method is difficult to achieve optimum diagnostic performance	PhysioNet database	95.76%
Baris Bozkurt et al [27]	Low cost, Fast screening of diseases and Non-invasive	The feed-forward CNN Models evaluation was limited to use, Requires in-depth analysis of the method	University of Crete, PhysioNet-2016 database	0.815
Juan P. Dominguez-Morales et al [28]	The system is very useful	Un reasonable amount of time	PhysioNet/CinC Challenge database	97.05%
Francesco Beritelli et al [29]	Very efficient technique, Very robust, Rapid, easy to operate, non-invasive and low cost	_	Physionet Challenge database-2016	94%
Pengfei Li et al [30]	Efficiency reduces the computing cost	High computational complexity	MIT-BIH arrhythmia database	95%
Lijuan Jia et al [31]	Computational efficiency is enhanced	Limited dataset is used	One normal heart sound and Two	100%

			abnormal heart Sounds are recorded with their designed equipment	
Zumray Dokur [32]	1. Classes are distributed successfully even in noisy environments, High performance 3. During the training section, the histogram controls the number of nodes in the ISNN	1.Takes too long time to process 2.GAL network creates more number of nodes in the network	–	92%

Table 1 displayed the authors name, method used, merits, demerits and accuracy providing a comparative analysis on classification of heart sounds using neural networks.

IV. CONCLUSION

Recent research area is mainly focusing on the development of algorithms to classify various diseases of a patients automatically, which may lead to the development of an smart kits to detect diseases in the future. Diagnosis process is divided into two steps by various PCG signals of a patients and some noise occurs during examination. The first step is to analyze the collected or observed signals to extract various features, which helps to differentiate all types of heart sound signals, and the second step is the signal classification. Many researchers have tried their best to develop such classification technique, where the majority of works are based on different types of Neural Networks (NN). This paper provides a comprehensive study and analysis on the classification of heart sounds using neural networks.

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