Asymmetric Back Propagation Neural Network-Based Automatic Cardiac Disease Detection Using Electrocardiogram Signal

M. Mohamed Suhail[1], Dr. T. Abdul Razak[2]

[1]Research Scholar,Department of Computer Science, Jamal Mohamed CollegeAffiliated to the Bharathidasan University, Tiruchirappalli.
[2]Associate Professor,Department of Computer Science, Jamal Mohamed College, Tiruchirappalli.
[1]suhilnabi@hotmail.com, [2]abdul1964@gmail.com

Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 28 April 2021

Abstract : Early detection of unusual heart conditions is of vital importance to recognize heart disappointment and maintain a strategic distance from unexpected death. The humans with similar heart conditions have been practically identical using electrocardiogram (ECG) signals. By reviewing the ECG signal models, one can anticipate heart disease. Since the standard techniques for heart disease disclosure depend upon securing morphological features of the ECG signals, which are repetitious and tedious, the customized recognizable proof of cardiovascular disease is progressively perfect. Subsequently, in order to have the programmed identification of heart diseases, a satisfactory strategy is required. This could arrange the ECG signals with dark features as appeared by the similitudes among them and the ECG signals with known features. If this classifier can discover the similitudes, the likelihood of cardiovascular disease disclosure is broadened. This count can change into a significant procedure in research facilities during this examination work. Another classification technique is brought into the system. The Asymmetric Back Propagation Neural Network classification methodology, which all the more precisely orders ECG signals that rely upon a powerful model of the Electrocardiogram (ECG) signal classification. With this proposed method, a convolutional gated recurrent neural network is constructed, and its simulation results show that this classification can partition the ECG with 98.5% accuracy.

Key Words: Electrocardiogram, Asymmetric Back Propagation Neural Network, Multi-model feature extraction, stationary wavelet transformation

1. Introduction

Even though the Electrocardiogram (ECG) signal is generally utilized in the medical conclusion of heart maladies, there are numerous difficulties in extricating important and solid data from ECG signals, subsequent use of PC programs also prove to be beneficial in data extrication. In the cardiac cycle, every heartbeat comprises particular electrical depolarization and repolarization designs. This property could delineate the heart's electrical exercises. Notably, the morphological attributes of the heartbeat are not quite the same as person to person. For a similar subject, there are a few time-shifting qualities, such as the states of QRS complex and R-R interval. They would likewise change under various conditions [1]. For experienced specialists, any irregularity could be handily identified by heartbeat or change in the morphological example. It's anything but a simple undertaking for the programmed mechanized framework since there are outside clamor and imbalanced classes in the data set.

In the most recent decade, to diminish labor cost and the objectivity of recognition, some machine learning algorithms have been utilized here to identify and group cardiac sickness. The typical procedure of these methodologies depends on three principle steps: preprocessing, feature extraction, and classification. Right off the bat, preprocessing techniques are applied to de-clamor the ECG signals. After denoising, the ECG waveforms are separated by methods for segmentation [2]. The waveforms are then used to figure out and produce features. Meanwhile, dimension decrease algorithms could be applied to diminish moderately autonomous features.

Classification of heartbeats [3-5] is likely to be the most evolved use of machine learning to the ECG. It centers on the discovery of anomalous, sporadic beats that may happen at unpredicted occasions and assists with recognizing cardiac malady. Different examinations center on tolerant classification [6-8], in light of the ECG's general conduct, to analyze explicit illnesses. Likewise, with the advancement of wearable gadgets and the requirement for the continuous conclusion, different difficulties like speed or memory prerequisites have risen, requiring the variation of these techniques for snappy classification [9]. Analyzing the ECG with machine learning strategies is a promising methodology; however, managing medical data for clinical applications raises some extra difficulties, such as the absence of databases accessible for approval and the need to decipher ECG variations from the norm of the organ and cell level. Therefore in this research, a powerful classification strategy is introduced to address these issues.

2. Literature survey

The ECG signal classification is broadly ordered into four stages: data preprocessing, heartbeat peak segmentation [10], feature extraction, and classifiers [11, 12]. The preprocessing data stage underlines noise expulsion from signal obtaining like electrical cable obstruction and benchmark meander commotions [13–15].

Heartbeat peak segmentation stage (for example, the finding of R pinnacles and Q-R-S complex in the signal) has been utilized roughly throughout the previous three decades. Feature extraction assumes a significant job all through the classification procedure and various methods have been presented and approved.

For manual application based strategies, features are removed from frequency area, for example, wavelet transforms [16–18], cosine transforms [19], and Fourier transforms [20] just as time-space, are utilizing the morphological features of the signal that can be straightforwardly extricated from the ECG data. The generally utilized morphological features are R–R interval, P–R interval, P duration, Q–R–S duration, T duration, and Q–T intervals [21, 22]. Writing [23] has likewise investigated some higher-order factual features. In [24], creators have investigated an alternate sort of features, such as the point of view of visual level feature blends and view level feature mixes. The best outcome was gotten when all the visual features were consolidated.

Feature selection was applied to utilize a wrapper-based strategy to improve the accuracy of the classifier. An AI approach called repository processing was proposed to arrange the heartbeat [25]. A multi-class classifier has performed well on the proposed MIT-BIH Arrhythmia dataset [26]. A multitask learning approach was proposed for ECG based biometric acknowledgment [27]. Joint feature extraction and classifier structure strategy were successfully contrasted with other regular techniques. The nonlocal implies (NLM) approach was proposed to denoise the biomedical signal [28]. A calculation based on forwarding inquiry was proposed to recognize the ECG signal's boundaries for the conclusion of cardiovascular maladies [29]. The work has consolidated the incorporated circuit with the Android application to recognize the sickness. NLM-based denoising strategy has accomplished great signal-to-noise ratio, like wavelet-based techniques. An equal General Regression Neural Network (GRNN) to order the heartbeat was proposed in [30] and has accomplished 95% accuracy.

3. Proposed Cardiac Disease Detection

The block diagram of proposed cardiac disease detection is shown in Figure 1. The automatic cardiac disease detection method is proposed using Asymmetrical Back Propagation Neural Network (ABPN). The proposed cardiac disease detection systems involve the wavelet decomposition method for preprocessing of input ECG signals. The neural network used in current studies is an Asymmetrical Back Propagation Neural Network trained in extracting features that detect cardiac disease efficiently. Asymmetrical Back Propagation Neural Network includes four levels of repetition training, namely Initialization of weights, Feed forward, Back Propagation of errors, and updating weights and biases.

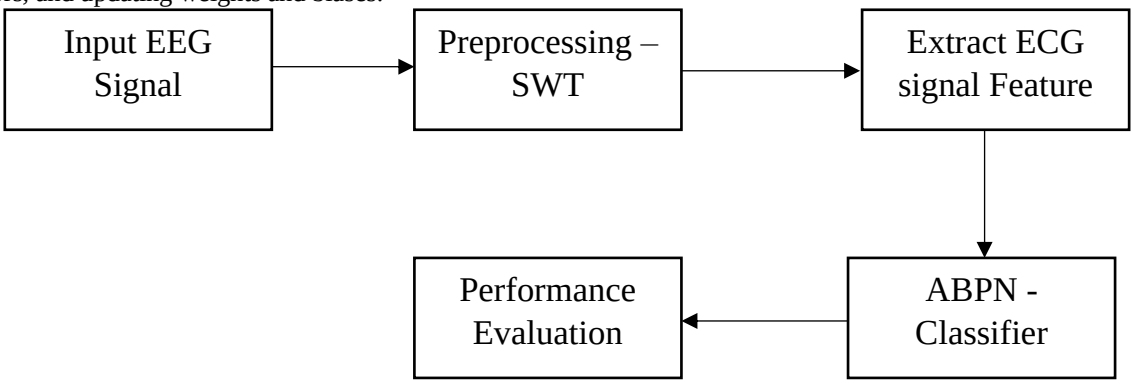

Figure 1. Block Diagram of the Proposed System

Figure.1 represents the functional block diagram of the Automatic cardiac disease detection system. The proposed ECG recognition system recommends the use of a method that includes various protocols and techniques to create a cardiac disease system, and these are categorized as

a. Pre-processing: There are various noises removed where for both internal as well as external noises are considered

b. Feature Extraction: It comprises the methods that extract the spectrum frequency bands which are effectively retrieved, and these channels are based on each spectrum effect density feature

c. Classification: To discriminate the seizure and non-seizure signals based on encompasses algorithms and procedures.

3.1 Preprocessing Stationary Wavelet Transformation

In Stationary Wavelet Transformation (SWT) at each level, when the high pass and low pass filters are applied to the data, the two new sequences have the same length as the original sequences. To do this, the original data is not decimated. However, the filters at each level are modified by padding them out with zeros.

Supposing a function f(x) is projected at each step j on the subset $V_j(\ldots \ldots \ldots \cap V_3 \cap V_2 \cap V_1 \cap V_0)$. This projection $c_{j,k}$of f(x) is defined by the scalar product of the scaling function φ(x), which is dilated and translated

$$\varphi_{j,k}(X) = 2^{-j}\varphi(2^{-j}X^{-k}) \ldots (1)$$

Where φ(x) is the scaling function, which is a low pass filter. $C_{j,k}$ is also called a discrete approximation at the resolution 2^j

If ϕ(x) is the wavelet function, the wavelet coefficients are obtained by

$$\omega_{j,k} = f(X), 2^{-j}(2^{-j}X^{-K}) \ldots (2)$$

$\omega_{j,k}$ is called the discrete detail signal at the resolution 2^j.

$c_{j+1,k}$ can be obtained by direct computation from $c_{j,k}$

$$C_{j+1,k} = \sum h(n-2k)C_{j,n} \ldots (3)$$

$$\frac{1}{2}\emptyset\left(\frac{X}{2}\right) = \sum g(n)\varphi(x-n) \ldots (4)$$

The scalar products are $(f(X), 2^{-(j+1)}\varphi\ (2^{-(j+1)}X - K))$computed with

$$\omega_{j+1,k} = \sum g(n-2K)C_{j,n} \ldots (5)$$

Equations (4) and (5) are the multi-resolution algorithm of the traditional DWT. In this transform, a down sampling algorithm is used to perform the transformation. That is, one point out of two is kept during transformation. Therefore, the whole length of the function f(x) will reduce by half after the transformation. This process continues until the length of the function becomes one. However, for stationary or redundant transform, instead of down sampling, the up sampling procedure is carried out before performing filter convolution at each scale. The distance between samples, increasing by a factor of two from scale to the next. $C_{j+1,k}$ is obtained by

$$C_{j+1,k} = \sum h(1)C_{j,K+2^{j_l}} \ldots (6)$$

And the discrete wavelet coefficients

$$\omega_{j+1,k} = \sum g(1)\, C_{j,K+2^{j_l}} \ldots (7)$$

The redundancy of this transform facilitates the identification of salient features in a signal, especially for recognizing the noises. This is the transform for a one-dimensional signal

3.2 Multi-Model Feature Extraction Strategy

The preprocessed ECG waveform will be used for further processing and it has many components, namely P, Q, R, S, T waves. Also, the combinations of the components represent the activity of the heart at different time frames. The electrocardiogram contains various time domains and space domain values; they are the amplitudes and intervals of various sectors. We extract P-wave interval, P-wave Amplitude-wave interval, T-wave amplitude, QRS-Wave interval values. Each feature extracted is constructed in the form of a pattern in the database for further manipulation.

Algorithm for Feature Extraction:

The procedure of Feature Extraction is as follows:

Step 1: Read the preprocessed noise - removed signal Ds.

Step 2: Extract features Fi = $\int_{i=1}^{N}\int_{j=1}^{K} \forall(j \in Ds)$.

K- Number of features

Step 3: Construct pattern Ps = $\int_{j=1}^{k} Ps \cup Ds(j)$

Step 4: Stop

The snapshot of the Pattern generated using the proposed approach shows that the features of the ECG waveform have been extracted and represented in such a way to use it appropriately. Each row of the table is considered as ECG pattern, based on which the separation is performed.

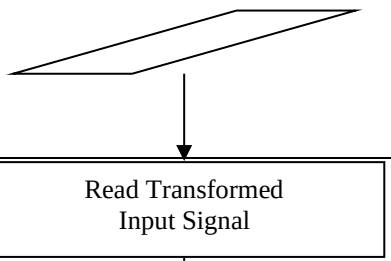

Figure 2. Flowchart of the feature extraction phase

The working flowchart of the feature extraction phase for P, Q, R, S, T extraction is shown in Figure 2. After extraction, the P, Q, R, S, T features are extracted for classification strategy.

Coefficient of variation

The coefficient of variation is also called Relative Standard Deviation (RSD). This is a standardized measure of the probability distribution or frequency distribution technique. This is usually expressed as a percentage and is defined as the ratio of the mean at the standard deviation.

$$C_v = \frac{\sigma}{\mu} \dots (8)$$

Standard Deviation

This is a measurable component that demonstrates the distribution of information for the mean. Low standard deviation indicates that the data points become very close to the meanwhile high standard deviation which indicates that the data points are spread over a large range of values. The standard deviation is evaluated using equation (9).

$$\mu = \frac{1}{N}\sum_{i=0}^{N-1} y_i \dots (9)$$

Where

μ= Mean value of Noise Removed EEG signal

y_i= Denoised Component of EEG signal

Energy

It signifies the strength of the EEG signal. High Energy implies a seizure activity. Let x(n) sequence be an input signal, then the instantaneous energy of the signal is given by x (n). The average energy (EG) of the signal is given by equation (10):

$$E(F_L) = \sum_{x=0}^{n} A_x^2 \dots (10)$$

Where

F_L = Frequency Level
n = Quantity of samples
A = Amplitude Range

Entropy

It measures the signal complexity and quantifies regularity and order in the signal. It is observed that the low entropy value of EEG signals represents fewer dominating processes and the EEG signals with high entropy represent a large number of dominating processes. The entropy is calculated using equation (11).

$$E_i(y) = \int f(y)\log(f(y)dy \ \ldots (11)$$

Where
y = Represent as Random Variable
f(y) = Represent as Probability of Density Function

3.3 Asymmetrical Back Propagation Neural Network classifier

Improved non-zero sampling of the calculation method is presented as a novelty for seizure detection systems and practical lessons. The design incorporates climate-variable parameters and time variation functions. Time sequencing operations are used to describe the computation rate and the temporal changes between tired detection responses. The time variance of each imagery is fully identified by the Asymmetrical Back Propagation Neural Network approach for variable parameters identified by a backward compound probability distribution. Experimental data determine the likelihood function. Markov chain Monte Carlo (MCMC) methods are used to get samples from the joint posterior distribution. Therefore, each subject, rather than a single-dimensional parameter, is represented by a sample parameter vector set from a rear distribution rather than a vector.

3.3.1 Asymmetrical Back Propagation Neural Network (ABPN) - Algorithm

Asymmetrical Back Propagation Neural Network is built into the back cover network or the five hidden layers of the rules. It is estimated that each node output has an adaptive setup control that ends with a fixed mapping from its entries. A node output only means that its current data depends on which node is the F for any dynamic or indoor positions. The topology of ABPN networks is shown in Figure 3.

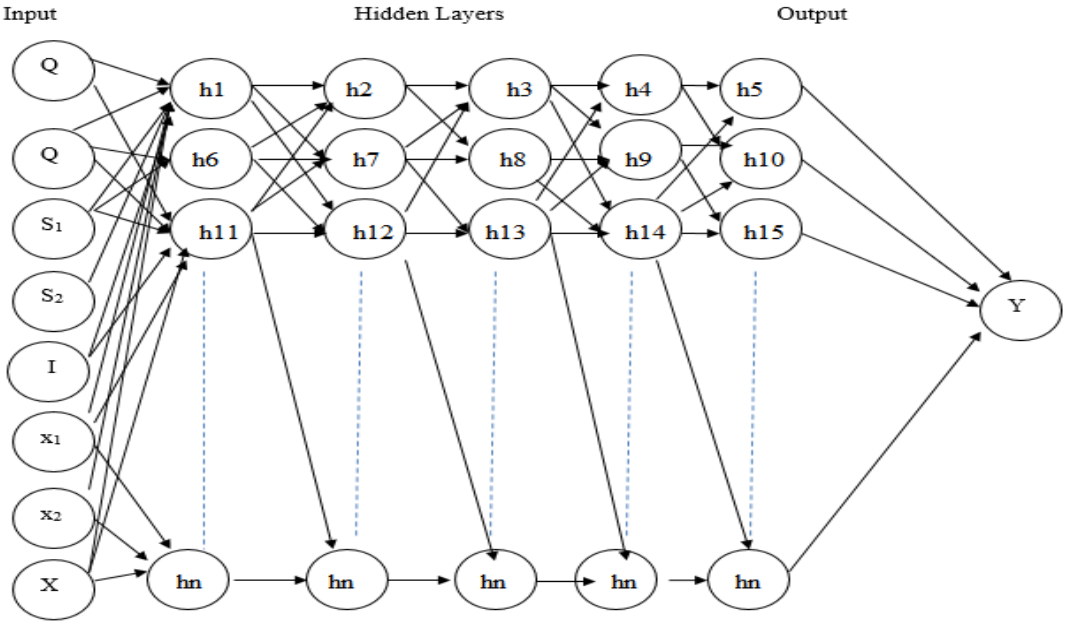

Figure 3 ABPNN network architectures

3.3.2 Asymmetrical Back Propagation Neural Network Training

Many characteristic attribute values are calculated based on values and unity. Each input diagram of the Practical Stats Package is available in the Practice, and Network Package, we calculate the unique unity of each terminal on the Unity list at NN. To calculate the overall similarity of the characteristic attributes, we set in training models based on the film's calculated computationally. Similarly, the same set of sets of the same class is calculated for each attribute. Finally it is considered to represent the sensory data pattern synchronization of the index aspect

of the entity aspect of a discharge of the value of the emotion. The algorithm steps of ABPN are discussed in the following subsection.

3.3.3 Algorithm steps of Asymmetrical Back Propagation Neural Network (ABPN)

Asymmetrical Back Propagation Neural Network Basic processing companies are a network that integrates to create a complex output system. The input layer of the processes is sorted into the middle layer and the output layer. The ABPN algorithm steps are discussed below and the main advantage of ABPN algorithm lies in its simplicity and speed

Step 1: Loading the Database

Step 2: Identification of the epileptic seizure detection elements using the Asymmetrical Back Propagation Neural Network.

Step 3: Generating the network. Sigmoid transfer function with a feed-forward network is used by the default network hidden layer and output layer.

Step 4: Random values are assigned to input weight and bias.

Step 5: Allocation for 80% of training data, 10% reservation of validation data, and 10% of test data.

Step 6: Training and testing of the entire network using the ABPN algorithm.

Step 7: Comparison of training methods using accuracy.

Step 8: Evaluation of the ABPN algorithm performance through Mean Squared Error and Confusion Matrix

The process of epileptic seizure detection approach is composed of the Asymmetrical Back Propagation Neural Network algorithm training. As a result, the comparative study program is taken by the training of neuro networking training programs which have been tested and verified with only EEG signals.

3.3.4 Cardiac Disease Detection - ABPN

Generated networks are used to seize the computation. Launching the signal and networks generated from the network are used as input and data retrieved from the predefined network set. Input Network, to calculate the multi-character similarity action in each class with networks available in the network package. Furthermore, setting up a network unity is identifiable. The value of each signal is based on the EEG signal's identification signal that the components of the input system are separated and built into a wave. The sequestration procedure is as follows:

Pseudo Code of ABPN-Multi-Attribute Closure:

Start: For each class Cl from C
For each Network G_i of C
For each Node N_iG_i
Compute Node Similarity NS = $\int_{i=1}^{N} \sum Dist\left(Ni - TG(Ni)\right) < Dth$
End
Add to Cumulative Node Similarity CNS = $\sum(Nsi(CNS) + NS)$
End
Compute Multi-Attribute Similarity Measure MASM.
MASM = $\int_{i1}^{C} \frac{CNS}{\emptyset(Cl)}$
$\emptyset - Number\ of\ networks\ of\ class\ Cl$
Add MASM to MS.
MS = $\sum(MASM(MS) + MASM)$
End
Stop

The ABPN is developed to classify the EEG signals has an input layer with 4 neurons corresponding, one hidden layer with 4 neurons and an output layer with 2 neurons. The following parameters are used to evaluate the performance of the proposed system.

Accuracy: The consistent true or accepted value measuring is determined by the degree of accuracy. It is usually expressed in terms of percentages. The equation (12) is used to calculate the value of accuracy.

$$\text{Accuracy} = \frac{\text{TPc+TNc}}{\text{TPc+FPc+TNc+FNc}} \ldots (12)$$

Sensitivity: The ratio between the numbers of seizures detected and total seizures, expressed in percentage and the equation (13) is used to calculate the value of sensitivity.

$$\text{Sensitivity} = \frac{\text{TPc}}{\text{TPc+FNc}} \ldots (13)$$

Specificity: Ratio between the number of a true negative decision and the total negative case, it is expressed in percentage and the equation (14) is used to calculate the value of specificity.

$$\text{Sensitivity} = \frac{\text{TNc}}{\text{TNc+FPc}} \ldots (14)$$

Where, TPc = True Positive, TNc = True Negative, FPc = False Positive and FNc = False Negative

False Negative Ratio (FNR): It is the number of positive numbers used to quantify positive occasions that are determined inaccurately with the end goal and the quantity of genuine positive occasions. The equation (15) is used to calculate FNR.

$$\text{FNR} = \frac{\text{FNc}}{\text{FNc+TPc}} \ldots (15)$$

False Discovery Rate (FDR)

The rate of false discovery is defined as the predicted level of inaccuracy between assumptions at all.

$$\text{FDR} = \frac{\text{FPc}}{\text{FPc+TPc}} \ldots (16)$$

Matthew Correlation Coefficient (MCC)

The TPc, TNc, FPc and FNc are the combination of MCC. This keeps the score even if the balance class is a very different size signal.

$$MCC = \frac{(TPc \times TNc) - (FPc \times FNc)}{\sqrt{(TPc+FPc)(TPc+FNc)(TNc+FPc)(TNc+FNc)}} \ldots (17)$$

4. RESULTS AND DISCUSSION

The proposed ABPN approach has been implemented using Matlab and has been evaluated using different ECG waveforms. The method has produced an efficient result in cardiac disease detection and separation. This section lists the results produced by the proposed method. The dataset used for this system is shown in Table 1.

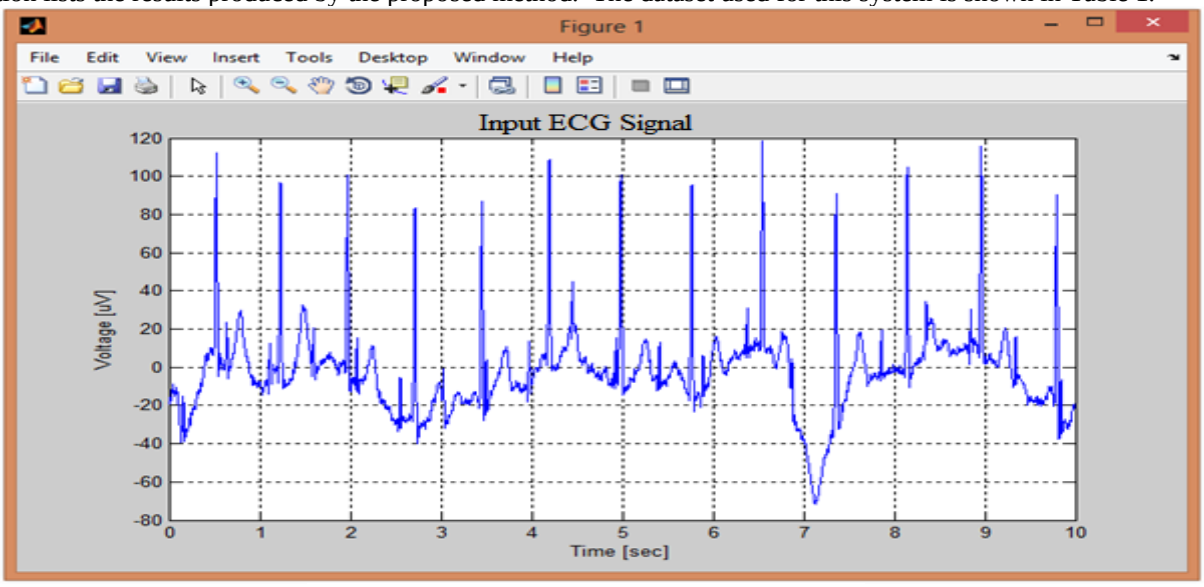

Figure 4: shows the Abdominal signal as input ECG

Figure 4 shows the snapshot of the input electrocardiogram signal from a single-channel electrode. This data is taken from the physionet dataset.

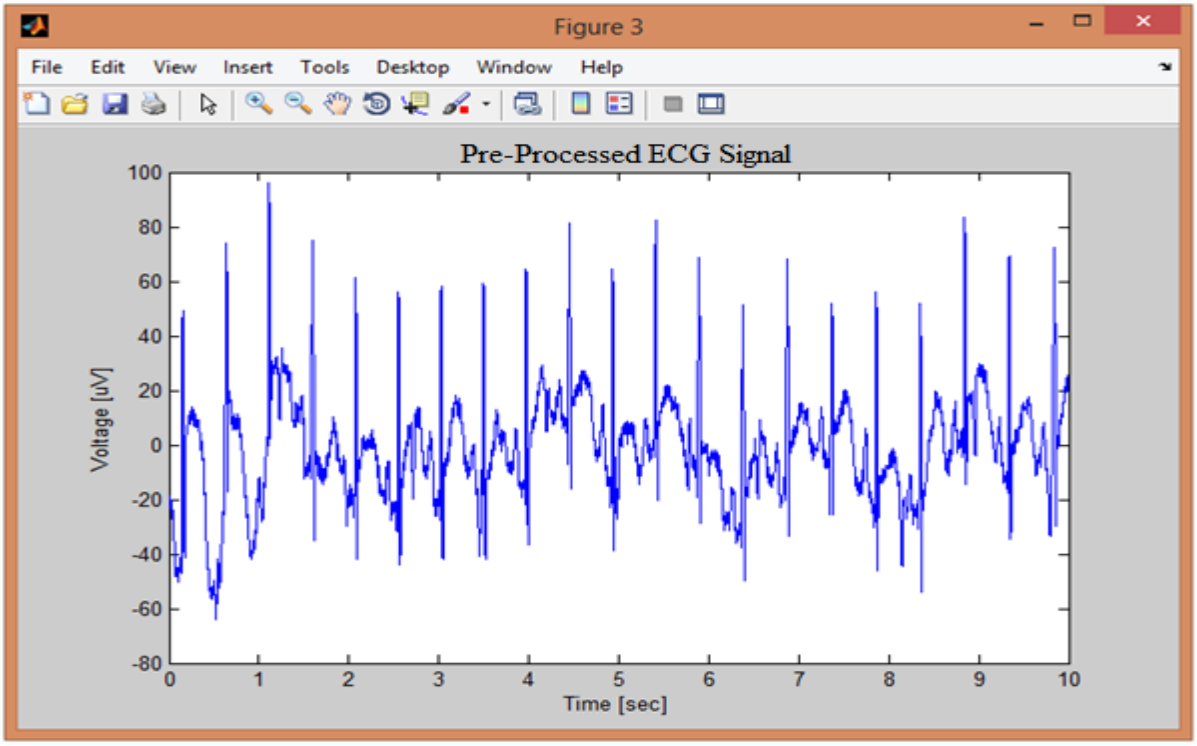

Figure 5: Separated Noise removed ECG

The simulation result of Separated Noise removed ECG is shown in Figure 5. When global templates failed to yield satisfactory results for a particular week of data and resulted in large numbers of missed QRS complexes, a self-template was generated based on the current ECG data.

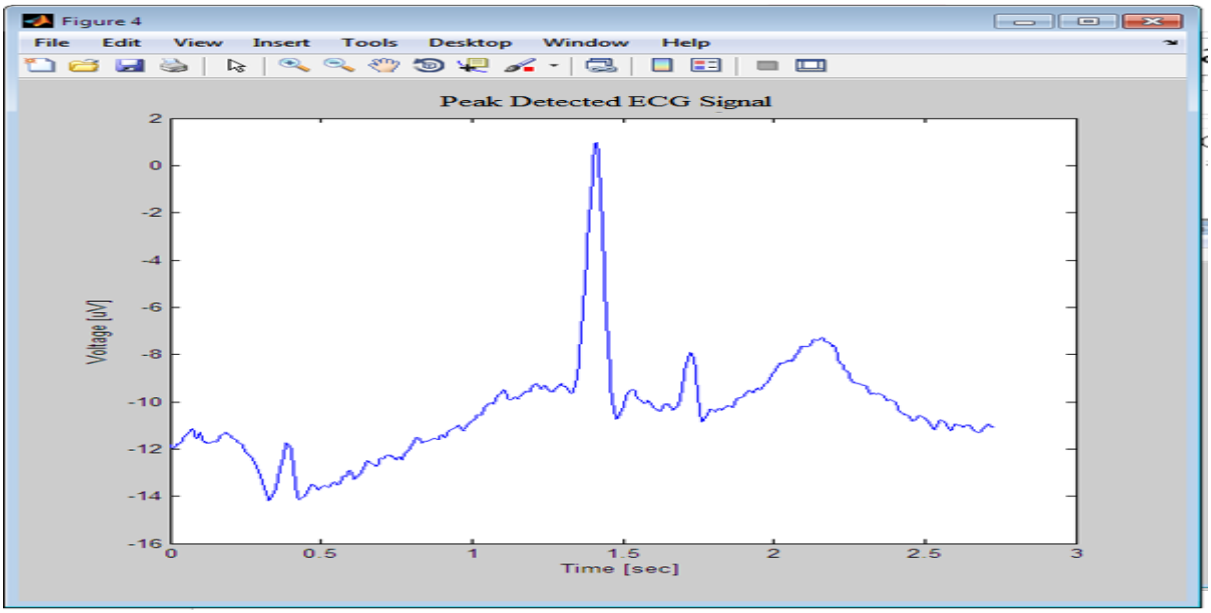

Figure 6 – Peaks detection Plots of ECG

Figure 6 shows the simulation of Peaks detection Plots of ECG. A sliding window was passed across the ECG signal, and a correlation coefficient was computed between the template and the ECG contained within each window of equal length. This process has produced a new data series containing correlation coefficients peaks interval. If the correlation peak interval between template and ECG segment has exceeded a defined threshold value, a detection flag was set to high.

Table 1: Performance Analysis of cardiac disease detection

Measures	LDA	PCA	NVDN	CG-RNN	ABPN
Precision	83	90	94	96	97.3
Recall	53	56	63	71	73.67
F-measure	0.63	0.67	0.73	0.87	0.95
Accuracy	52	57	67	93	98.5
Sensitivity	51	56	60	91	94.6
Specificity	59	61	78	92	95.1
FDR	0.16	0.10	0.06	0.02	0.02
FNR	0.48	0.43	0.27	0.21	0.17
FPR	0.39	0.26	0.21	0.18	0.14
FAR	5.10	3.06	2.16	1.95	1.67
FRR	21.03	20.25	15.01	12.03	8.01
MCC	0.07	0.20	0.29	0.21	0.16

Table 2 discusses the cardiac disease detection system's performance analysis for the proposed ABPN method with some other existing cardiac disease detection methods. This discussion clearly states that the proposed ABPN method delivers the best results.

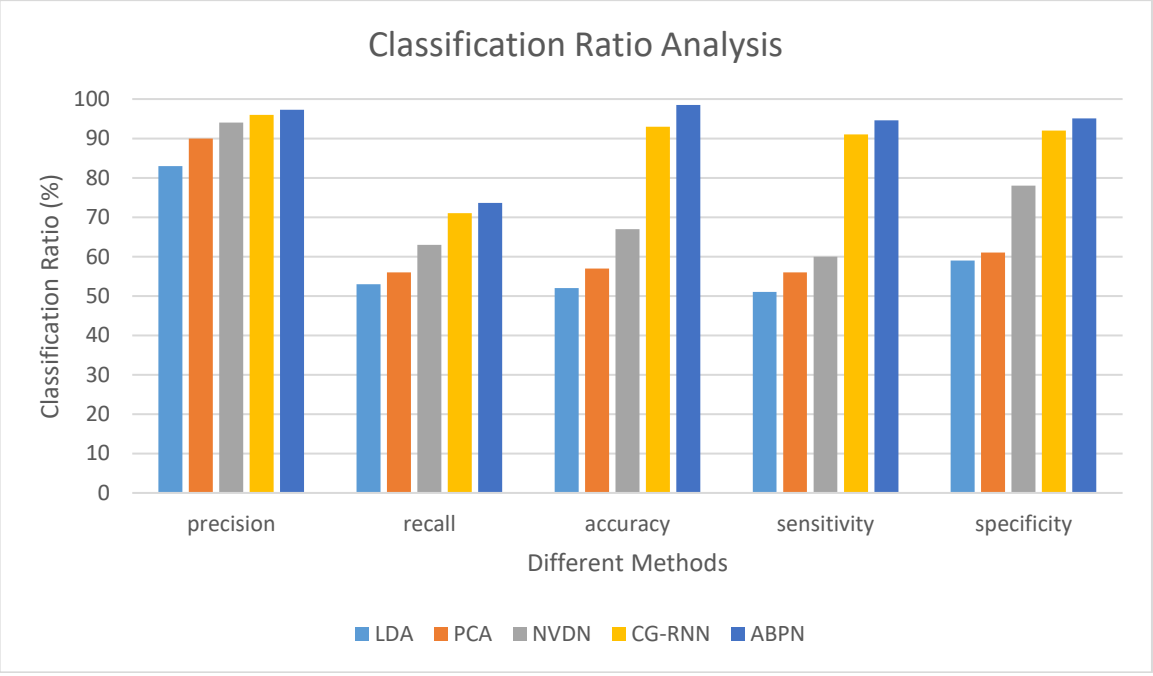

Figure 7. Performance Evaluation Metrics

Figure 7 discusses the cardiac disease detection system's performance analysis for the proposed ABPN method with some other existing cardiac disease detection methods. This discussion clearly states that the proposed ABPN method delivers the best results. For example, the sensitivity, specificity, accuracy, precision and recall of the proposed method are 94.6%, 95.10% ,98.5% ,97.3% and 73.67% respectively.

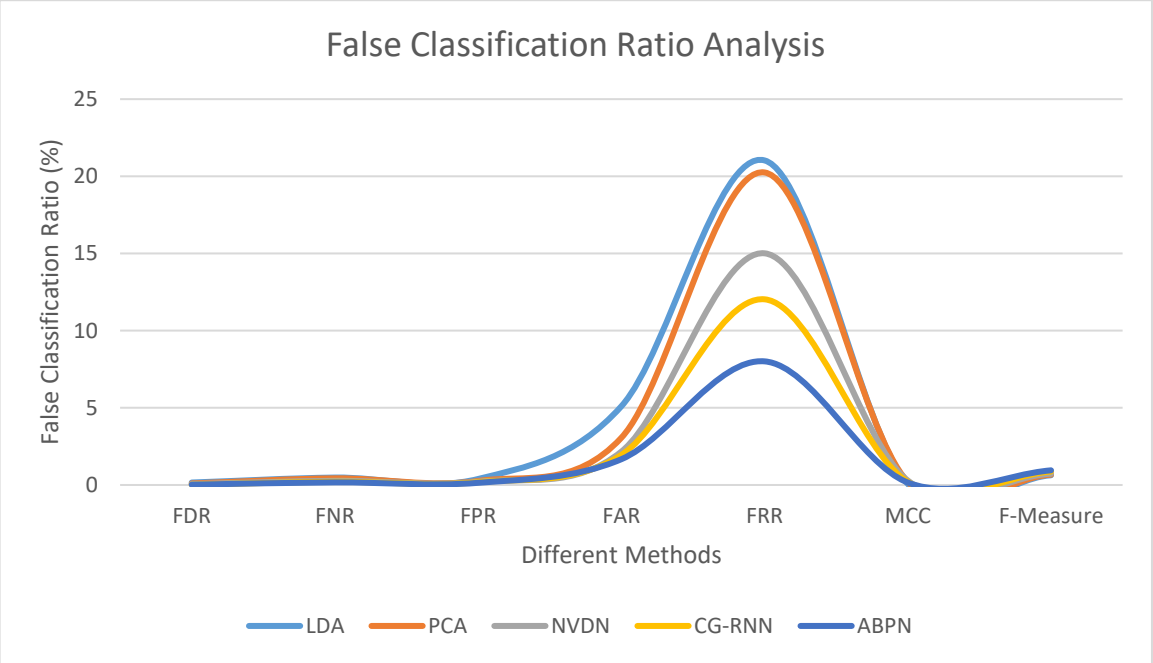

Figure 8. Performance Analysis of classification ration

Figure 8 discusses the performance analysis of the false classification ratio for the proposed ABPN method based cardiac disease detection system with some other existing cardiac disease detection methods. This discussion clearly states that the proposed ABPN method delivers the best results; for example, the F1-score of the proposed system is 0.95.

5. Conclusion

This research has proposed an automated heart disease recognition technique based on recent and innovative asymmetric back propagation neural networks. The proposed technique has high accuracy and had low complexity of implementation. This approach has harnessed machine learning's potential to capture the typical characteristics of given heart disease in the ECG signal domain. The method proposed here was developed by asymmetric back propagation neural network, and its simulation results show that the classification can isolate the electrocardiogram with high productivity. This proposed technique expands the accuracy of ECG classification regarding increasingly accurate arrhythmia findings. This proposed method increases the accuracy of the ECG classification regarding more precise arrhythmia detection. For example, sensitivity, specificity, accuracy, precision, and recall of the proposed method are 94.6%, 95.10%, 98.5%, 97.3% and 73.67% respectively

References

1. Das MK, Ari S. ECG beats classification using a mixture of features. Int Scholar Res Not. 2014;2014:12.
2. Dong Wang Si XCW. ECG beat classification via deterministic learning. Neurocomputing. 2017;240:1–12.
3. Wang G, Zhang C, Liu Y, Yang H, Fu D, Wang H, Zhang P. A global and updatable ECG beat classification system based on recurrent neural networks and active learning. Inf Sci. 2019;501:523–42.
4. Kaya Y, Pehlivan H, Tenekeci ME. Effective ECG beat classification using higher-order statistic features and genetic feature selection. Biomed Res. 2017;28(17):7594–603.
5. Arif M. Robust electrocardiogram (ECG) beat classification using discrete wavelet transform. Physiol Meas. 2008;29(5):555.
6. Sahoo S, Mohanty M, Behera S, Sabut SK. ECG beat classification using empirical mode decomposition and mixture of features. J Med Eng Technol. 2017;41(8):652–61.
7. Nurmaini S, UmiPartan R, Caesarendra W, Dewi T, NaufalRahmatullah M, Darmawahyuni A, Firdaus F. An automated ECG beat classification system using deep neural networks with an unsupervised feature extraction technique. Appl Sci. 2019;9(14):2921.
8. Alqudah AM, Albadarneh A, Abu-Qasmieh I, Alquran H. Developing of robust and high accurate ECG beat classification by combining Gaussian mixtures and wavelets features. AustralasPhysEngSci Med. 2019;42(1):149–57.

9. Alfaras M, Soriano MC, Ortín S. A fast machine learning model for ECGbased heartbeat classification and arrhythmia detection. Front Phys. 2019;7:103.
10. Zhao Q, Zhan L (2005) ECG feature extraction and classification using wavelet transform and support vector machines. In: International conference on neural networks and brain, ICNN&B, vol 2, pp 1089–1092
11. El-Khafif SH, El-Brawany MA (2013) Artificial neural networkbased automated ECG signal classifier. ISRN Biomed Eng 2013:1–6
12. Jiang W, Kong SG, Peterson GD (2005) ECG signal classification using block-based neural networks. In: Proceedings of international joint conference on neural networks, pp 326–331
13. Jiang W, Member S, Kong SG (2007) Block-based neural networks for personalized ECG signal classification. IEEE Trans Neural Netw 18(6):1750–1761
14. Subbiah S, Patro R, and Subbuthai (2015) Feature extraction and classification for ECG signal processing based on artificial neural network and machine learning approach. In: International conference on interdisciplinary research in engineering and technology, pp 50–57
15. Djahida M, Talha K, Slimane S (2012) Neural networks and SVM for heartbeat classification. In: 11th international conference on information sciences, signal processing and their applications, pp 830–835
16. Gu¨ler I, U¨ beyli ED (2005) ECG beat classifier designed by combined neural network model. Pattern Recognit 38(2):199–208
17. Tayel MB, Eltrass AS, Ammar AI (2018) A new multi-stage combined kernel filtering approach for ECG clamour removal. J Electrocardiol 51:265–275
18. Mahapatra S, Mohanta D, Mohanty P, Nayak S, Behari P (2016) A neuro-fuzzy based model for analysis of an ECG signal using wavelet packet tree. In: International conference on intelligent computing, communication & convergence, vol 92, pp 175–180
19. Lekhal, R., Zidelmal, Z. &Ould-Abdesslam, D. Optimized time–frequency features and semi-supervised SVM to heartbeat classification. *SIViP* (2020). https://doi.org/10.1007/s11760-020-01681-9
20. Zidelmal, Z., Amirou, A., Ould-Abdeslam, D., Merckle, J.: ECG beat classification using a cost sensitive classifier. Comput. Methods Programs Biomed. 111(3), 570–577 (2013)
21. Manab, K., Samit, A.: ECG beat classification using mixture of features. International Scholarly Research Notices (2014)
22. Raj, S., Ray, K.C., Shankar, O.: Cardiac arrhythmia beat classification using DOST and PSO tuned SVM. Comput. Methods Programs Biomed. 136, 163–177 (2016)
23. Oh, S.L., Ng, E.Y., Tan, R.S., Acharya, U.R.: Automated beat-wise arrhythmia diagnosis using modified U-net on extended electrocardiographic recordings with heterogeneous arrhythmia types. Comput. Biol. Med. (2018). https://doi.org/10.1016/j.compbiomed. 2018.12.012
24. Ramirez, E., Melin, P., Prado-Arechiga, G.: Hybrid model based on neural networks, type-1 and type-2 fuzzy systems for 2-lead cardiac arrhythmia classification. Expert Syst. Appl. (2019). https://doi. org/10.1016/j.eswa.2019.02.035
25. Rad AB, Eftestøl T, Engan K, Irusta U, Kvaly JT, Kramer-Johansen J, Wik L, Katsaggelos AK (2017) ECG-based classification of resuscitation cardiac rhythms for retrospective data analysis. IEEE Trans Biomed Eng 64(10):2411–2418
26. Escalona-Moran MA, Soriano MC, Ingo F, Mirasso CR (2015) Electrocardiogram classification using reservoir computing with logistic regression. IEEE J Biomed Health Inform 19(3):892–898
27. Gutta S, Cheng Q (2016) Joint feature extraction and classifier design for ECG-based biometric recognition. IEEE J Biomed Health Information 20(2):460–468
28. Trace BH, Miller EL (2012) Nonlocal means denoising of ECG signals. IEEE Trans Biomed Eng 59(9):2383–2386
29. Jain SK, Bhaumik B (2017) an energy efficient ECG signal processor detecting cardiovascular diseases on smartphone. IEEE Trans Biomed Circuits Syst 11(2):314–323
30. Li P, Wang Y, He J, Wang L, Tian Y, Zhou T, Li T, Li J (2017) High-performance personalized heartbeat classification model for long-term ECG signal. IEEE Trans Biomed Eng 64(1):78–86