Materials Today: Proceedings 45 (2021) 2293–2305

Contents lists available at ScienceDirect

Materials Today: Proceedings

journal homepage: www.elsevier.com/locate/matpr

Comparative study of ANN and fuzzy classifier for forecasting electrical activity of heart to diagnose Covid-19

T. Nivethitha [a], Satheesh Kumar Palanisamy [b,*], K. Mohana Prakash [c], K. Jeevitha [d]

[a] Department of ECE, Hindusthan College of Engg. and Technology , Coimbatore, India
[b] Department of ECE, Coimbatore Institute of Technology , Coimbatore 641014, India
[c] Department of ECE, V.S.B. Engineering College, Karur, India
[d] Department of EEE, Government College of Technology, Coimbatore 641004, India

ARTICLE INFO

Article history:
Received 18 September 2020
Received in revised form 12 October 2020
Accepted 15 October 2020
Available online 27 October 2020

Keywords:
Covid-19
First return maps
HRV signal
Spectral entropy
Lyapunov exponent

ABSTRACT

Covid-19 is a dangerous communicable virus which lets down the world economy. Severe respiratory syndrome SARS-COV-2 leads to Corona Virus Disease (COVID-19) and has the capability of transmission through human-to-human and surface-to-human transmission leads the world to catastrophic phase. Computational system based biological signal analysis helps medical officers in handling COVID-19 tasks like ECG monitoring at Intensive care, fatal ventricular fibrillation, etc., This paper is on diagnosing heart dysfunctions such as tachycardia, bradycardia, ventricular fibrillation, cardiac arrhythmia using fuzzy relations and artificial intelligence algorithm. In this study, the heart pulse base signal and features like spectral entropy, largest lyapunov exponent, Poincare plot and detrended fluctuation analysis are extracted and presented for classification purpose. The RR intervals of Poincare plot summarize RR time series obtained from an ECG in one picture, and a time interval quantities derives information duration of HRV. This analysis eases the prediction of heart rate fluctuation due to Covid or other heart disorders. The better accuracy level in diagnosing heart pulse irregularity using Artificial Neural network(ANN) is an integer value (0 to 4)but for Fuzzy Classifier, it is 0.8 to 0.9.The processing time for analyzing heart dysfunctionalties is 0.05 s using ANN which is far better than Fuzzy classifier.

Selection and peer-review under responsibility of the scientific committee of the International Conference on Advances in Materials Research – 2019.

1. Introduction

Nowadays, the world has been suffering from epidemic and pandemic issues periodically. The wake of epidemic destroyed millions of lives. This year has literally stopped the entire world with the outbreak of Covid-19 and the world is continuously fighting against the virus devastation. The covid targets the respiratory organs and the critical issues leads to malfunctioning of heart. The heart's "natural pacemaker" generates electrical pulse originating from Sino Atrial node(SA) situated at the top of the right Atrium (RA). This electric signal branches via atria, triggers to contracts and dilates to pump blood to the ventricles. If the pacemaker gets affected, the heart, beats at an abnormal rate, influences the irregular circulation of blood. Fig. 1 shows ECG waveform components [1]. The heart beat is a series of electrical waves characterized by positive and negative peaks which has two distinct information are measured by Eelectrocardiogram(ECG) where each. First, by measuring time intervals, the total time of electrical wave from the heart can be found and able to find whether the electrical activity is abnormal or normal. Second, by measuring the quantity of electrical pulse over the heart muscle. A pediatric cardiologist able to find, if the heart pumping is overworked or not. The normal rate of ECG signal ranged as [0.05 – 100] Hz and its pulse level is [1–10] mV [1]. The characterization of ECG is derived by positive and negative peaks by successive alphabetical letters as P, Q, R, S and T.

The duration and amplitude of the different segments in the electrocardiogram are given in the Table 1. The accuracy and reliability of the QRS complex, T and P waves determines the performance of ECG analyzing system. The P wave signifies the activating status of upper chambers of the heart, while the QRS wave (or complex) and T wave represents the excitation of the ventricles.

* Corresponding author.
E-mail address: satheeshkumar.p@cit.edu.in (S.K. Palanisamy).

https://doi.org/10.1016/j.matpr.2020.10.400
2214-7853/
Selection and peer-review under responsibility of the scientific committee of the International Conference on Advances in Materials Research – 2019.

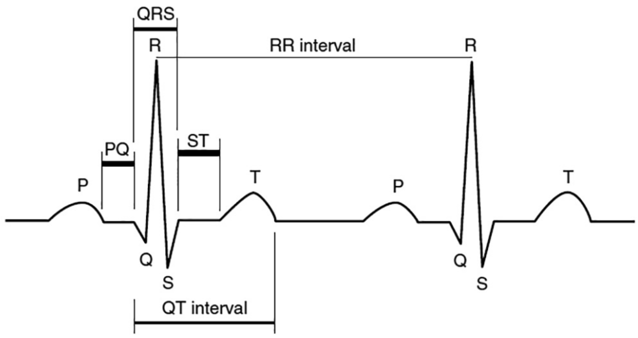

Fig. 1. ECG signal components.

Table 1
Values of ECG signal components.

	Amplitude (mV)	Duration (s)
P wave	0.25	0.12 to 0.22
R wave (QRS complex)	1.60	0.07 to 0.1
T wave	0.1 to 0.5	0.05 to 0.15
U wave	< 0.1	0.2

The need of QRS complex is essential in automatic signal analysis and detailed study of ECG.

2. Related work

Cuiwei Li et al. [11] comprehends the multiple scaling information in wavelets to analyse the ECG electric waves. The time interval between P and T waves, drift in baseline, noise and interference were identified [12]. Senhadi et al. [13] examined wavelet transforms for characterizing cardiac waves and discusses the usage of analyzing function and wavelet family in the Daubechies decompositions given by the complex wavelet (10 levels) and the spline wavelet (6 levels) and [14]. Amara Graps [15] symbolizes the analytical computation capability and complexity level is very high in D6 algorithm and analyses the importance of Harr wavelet algorithm, which is less complex and less mathematical computation. D6 of Debauchees and QRS complex are similar in the characteristics and its spectrum level of energy is more concentrated at lower frequencies of heart pulse [11]. Zong and Jiang [16] sophisticated for ECG, beat and rhythm extraction and classification using fuzzy reasoning approach. For single channel ECG beat and rhythm extraction and categorization, using fuzzy logic approach is discussed [13]. Sugiura et al. [17] shows the new innovative technique to detect cardiac arrhythmias based on fuzzy to separate NSR from VF [15]. Acharya et al. [18] emphasizes on fuzzy equivalence for extraction and categorization of four cardiac arrhythmias based on heart rate variability. The classification was accurate [16,19,9,10,20] . Kannathal et al. [21] uses three parameters as inputs in proposed Artificail Neural Network(ANN) classifier for classification of heart beat dysfunctionalities [17]. R.J.Adams [22] updated a report from American Heart Association to classify heart disease [18]. Abhishek Murthy, et. al [1] analysed the cardiac excitation of wavefront [2,3,4,23] .V.C.Veera, et. al., [5] classified the Cardiac arrhythmia based on fuzzy classifiers [1]. S.Z. Mohmoodabadi, et.,al [10] extracted the ECG feature using daubechies waveletets [8].Woo.M.A,et.al.,[7] classifies the Patterns of variations in time interval of heart rate in fatal heart dysfunctions [5,6] . Demir BE, Yorulmaz F, Guler .I. [9] simulated ECG in Microcontroller [7].

3. Cardiac arrhythmia

Normally, heartbeats originate as electrical impulse in the sino atrial node, and the sequence of heartbeats is called as sinus rhythm. Arrhythmia is nothing but an abnormality in the pulse. Electrical pulse instability and abnormal mechanical activity of the heart are associated with cardiac Arrythmia. Arrhythmias categorized based on origin of the abnormal electrical activity, usually, abnormal heart beats originates from the atria, the ventricles, or the atrio ventricular node [3].

The complexity nature of the HRV signal is defined by spectral entropy, H ($0 < H < 1$). The Poincare plot of RR intervals is used for detecting heart rate variability (HRV) which in turn summarizes an entire RR time interval derived from an ECG.

A Poincare plot of RR intervals is composed of $i + 1$ number of points (RR_i, $RR_i + 1$), in which each individual point corresponds to two successive RR intervals. The resulting clumpy of points is categorized by its length (SD_2) and its breadth across this line (SD_1) and its corresponding value as follows in equation (1) and (2).

$$SD1 = \sqrt{var(x1)} \tag{1}$$

$$SD2 = \sqrt{var(x2)} \tag{2}$$

where Var(x) is the variance of x.

Lyapunov exponents quantifies close state-space trajectories using its exponential divergence and determines the chaos. This method is used for predicting the nearest neighbour of each individualpoint in and predicts the distance of separation Detecting the presence of chaos in a dynamical system is solved by measuring the LLE.

The detrended fluctuation analysis can be applied to non-stationary signals using modified root-mean-square analysis [24]. The fluctuation function is calculated using the equation (3),

$$F(n) = \sqrt{\frac{1}{n}\sum_{k=1}^{N}[y(k) - y_n(k)]^2} \tag{3}$$

This computation is repeated for all time scales to predict the relationship between the average fluctuation, F(n), and the box size, n.

4. Fuzzification

ECG signal quality is monitored for electrical noise and other irregularities before starting the analysis..After extracting the above mentioned features, the output (out) is compared with the known value and depending upon the range the several disease can be identified and is shown in flow chart Fig. 2.

If output of the fuzzy classifier lies in the range of

- 0.8 to 0.82-Tachycardia (TC)
- 0.82 to 0.83-Ventricular fibrillation (VF)
- 0.83 to 0.84-Bradycardia (BC)
- 0.84 to 0.85-Cardiac Arrythmia(CA)
- 0.85 to 0.9-Normal ECG

4.1. Maximal lyapunov exponent

The maximal Lyapunov exponent is described by the equation (4)

$$\lambda = \lim_{t\to\infty} \lim_{\delta Zo\to 0} \frac{1}{t} \ln \frac{\delta Z(t)}{\delta Zo} \tag{4}$$

The limit $\delta Zo \to 0$ evaluates the effectiveness of the linear approximation at all time.

For discrete time system, $X_{n+1} = F(x_n)$, the equation (5) defines the orbit starting with x_0.

$$\lambda(x_0) = \lim_{n\to\infty} \frac{1}{n} \sum_{i=0}^{n-1} \ln f'(x_i) \tag{5}$$

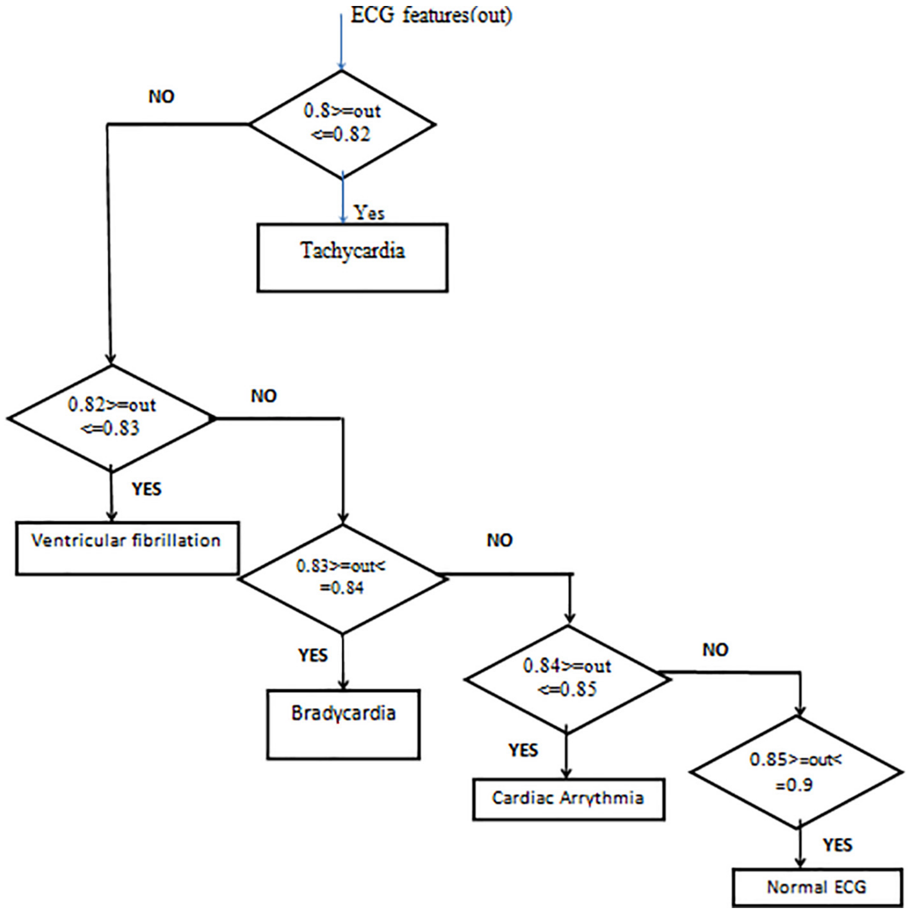

Fig. 2. Fuzzification steps.

4.2. Variability in heart rate

Heart beats are caused by relaxation and dilation of the heart muscle is nothing but electrical depolarization which can be observed on an electrocardiogram . The depolarization of the heart chambers are visualized by the P-wave. The Q, R and S waves generates the QRS complex, which represents the depolarization lower portion of heart chambers [6].

The analysis of Poincare plots of nonlinear dynamics is very much useful in HRV analysis. The Poincare plot [6] is defined for a vectors, x1, x2, … xN. The polars for heart beat represented by x^+ and x^-

In the medical perspective, the interval between the successive RR is RRin and RRin + 1 respectively. The Poincare plot for a normal ECG of a person shown in Fig. 3.

4.3. Numerical calculation of LLE

A conservative procedure is to do numerical calculation for each iteration is shown in the flowchart below Fig. 4:

Sample software calculating the Lyapunov exponent for normal ECG is shown in the Fig. 5. Lyapunov exponent for normal ECG system is an ordinary differential equations (a flow) inplace of difference equations (a map).

4.4. Iterative learning process

A neural network is an iterative learning process where data cases (rows) are distributed to the network, and the associated weights of inputs are adjusted. Iteration of artificial neural network is represented in Fig. 6. The algorithm used for training the data sets is back propagation which is more accurate and sigmoid function is used as activation function.

5. Results and discussion

This chapter presents the discussion on results obtained from the proposed algorithm. A sample ECG signal was obtained from the database.

The results are shown for the following cases:

i) Normal ECG
ii) Ventricular fibrillation
iii) Cardiac arrhythmia
iv) Bradycardia
v) Tachycardia

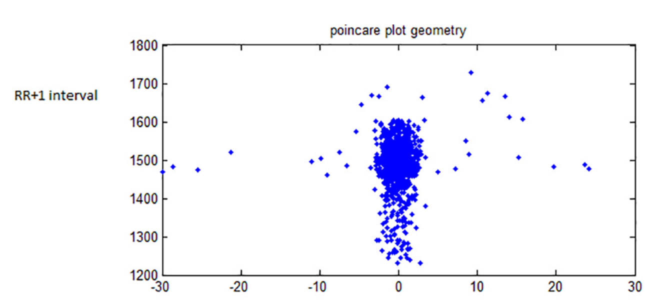

Fig. 3. The Poincare plot for normal ECG.

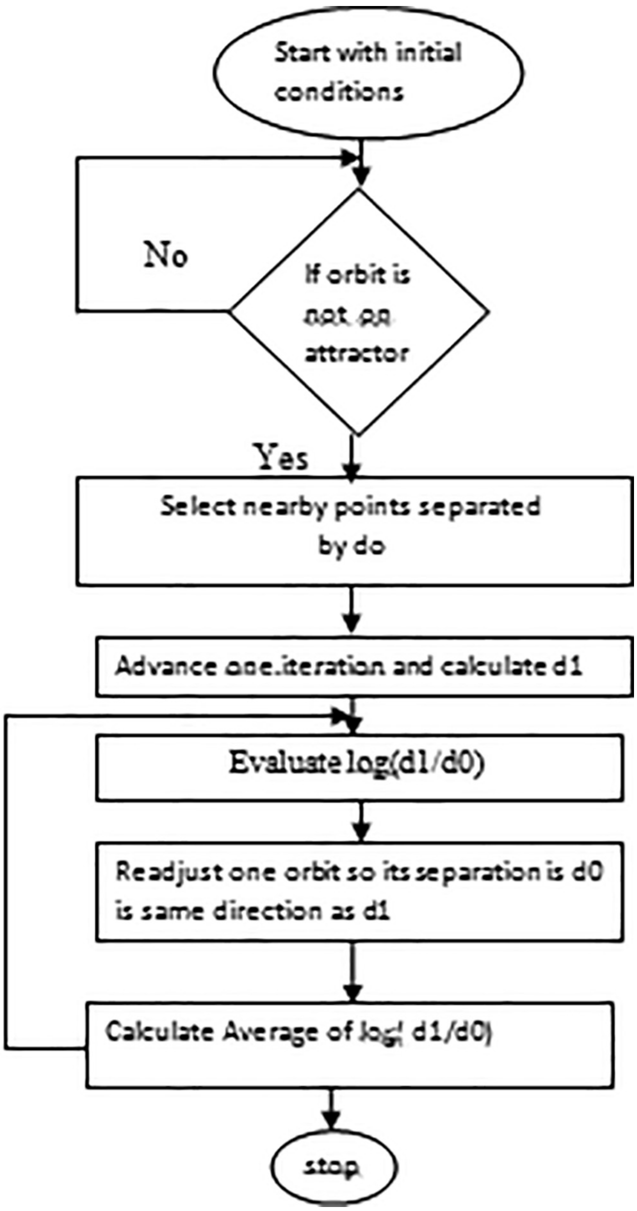

Fig. 4. Numerical calculation of LLE.

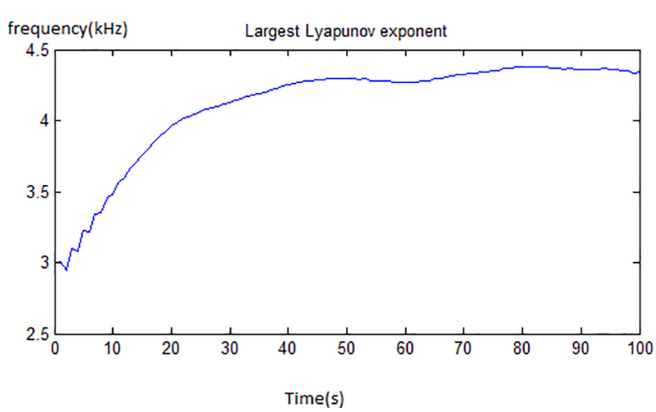

Fig. 5. Representation of LLE.

The user selects the input signal from the ECG database. The input signal is then filtered using discrete wavelet transform. The discrete wavelet transform used is daubechies wavelet(db4). The compression ratio of db4 is 1.1363. The discrete wavelet transform produces approximation coefficient and the detailed coefficient. The approximation coefficient is used for extraction of certain parameters like detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot and the fuzzy classifier classifies the disease according to the output range. In the Artificial neural network, training of the neural network is done prior classifying the disease.

5.1. Results from Fuzzy Classification

The simulation results of classification and analysis of cardiac waves using fuzzy classification have been obtained and shown below.

a) The normal ECG signal selected by the user from the database has the fuzzy classifier's combined parameter range of 0.85–0.9. The four parameters in this fuzzy classifier are detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot. The input signal after discrete wavelet transform produces the approximation coefficient and detailed coefficient. Fig. 7 shows the input signal, approximation coefficient, detail coefficient for a normal ECG signal. Fig. 8 shows the detrended fluctuation and analysis, Poincare plot and largest lyapunov exponent and the message box which indicates that the selected signal is a normal ECG.

a) The ventricular fibrillated ECG signal selected by the user from the database has the fuzzy classifier's combined parameter range of 0.82–0.83. The input signal after discrete wavelet transform produces the approximation coefficient and detailed coefficient Fig. 9 shows the input signal, approximation coefficient, detail coefficient for ventricular fibrillated signal. Fig. 10 shows the detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot and the message box which indicates that the selected signal is a ventricular fibrillation.

b) The cardiac arrhythmia ECG signal selected by the user from the database has the fuzzy classifier's combined parameter range of 0.84–0.85. The four parameters in this fuzzy classifier are detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot. The input signal after discrete wavelet transform produces the approximation coefficient and detailed coefficient. Fig. 11 shows the input signal, approximation coefficient, detail coefficient for a cardiac arrhythmia signal. Fig. 12 shows the detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot and the message box which indicates that the selected signal is cardiac arrhythmia.

c) The bradycardia ECG signal selected by the user from the database has the fuzzy classifier's combined parameter range of 0.83–0.84. The four parameters in this fuzzy classifier are detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot. The input signal after discrete wavelet transform produces the approximation coefficient and detailed coefficient. Fig. 13 shows the input signal, approximation coefficient, detail coefficient for a bradycardia signal. Fig. 14 shows the detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot. and the message box which indicates that the selected signal is bradycardia.

The tachycardia ECG signal selected by the user from the database has the fuzzy classifier's combined parameter range of 0.8–0.82. The four parameters in this fuzzy classifier are detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot. The input signal after discrete wavelet transform

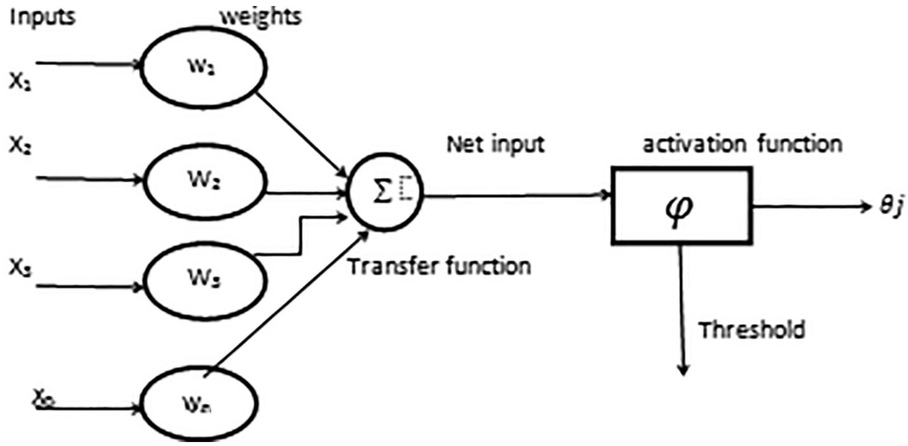

Fig. 6. Iteration of artificial neural network.

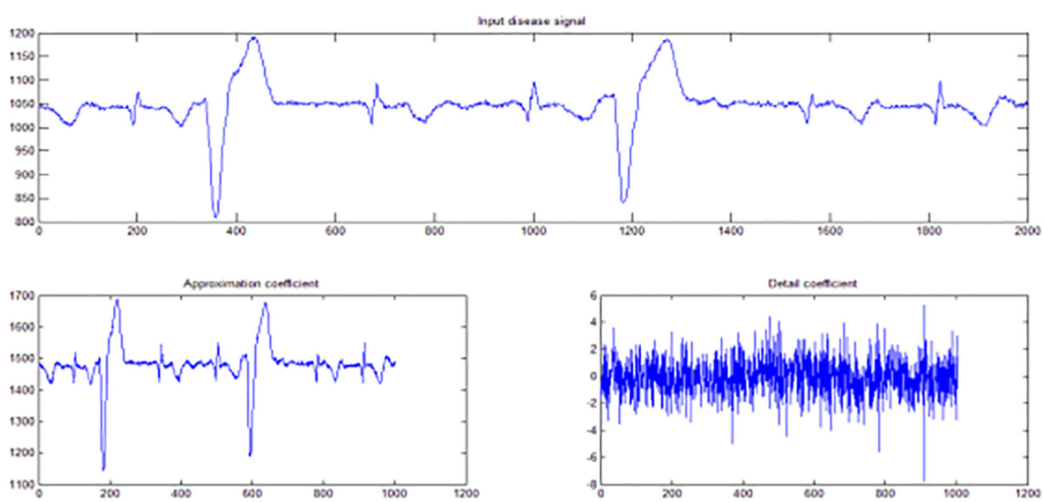

Fig. 7. Input signal, approximation and detail coefficient for normal ECG.

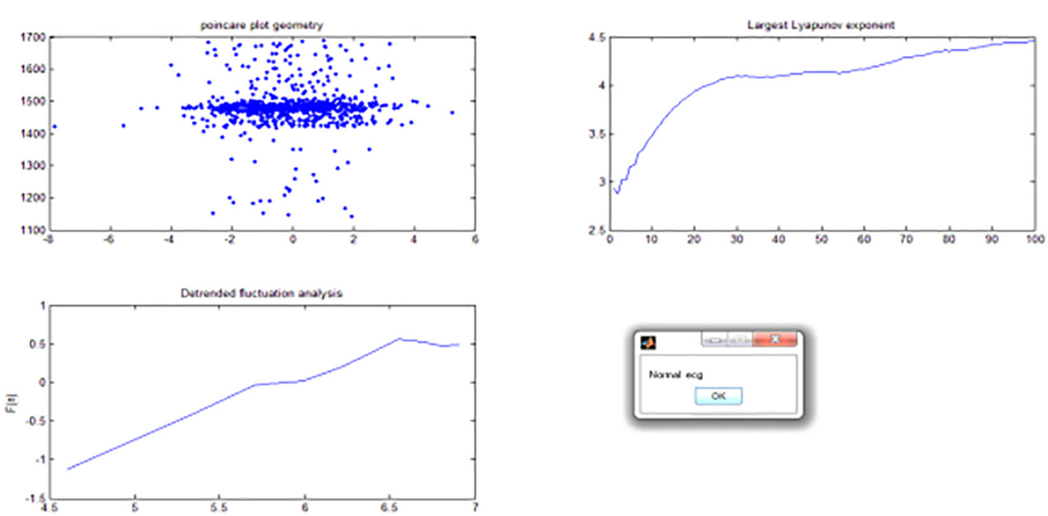

Fig. 8. Poincare plot, LLE and DFA of normal ECG.

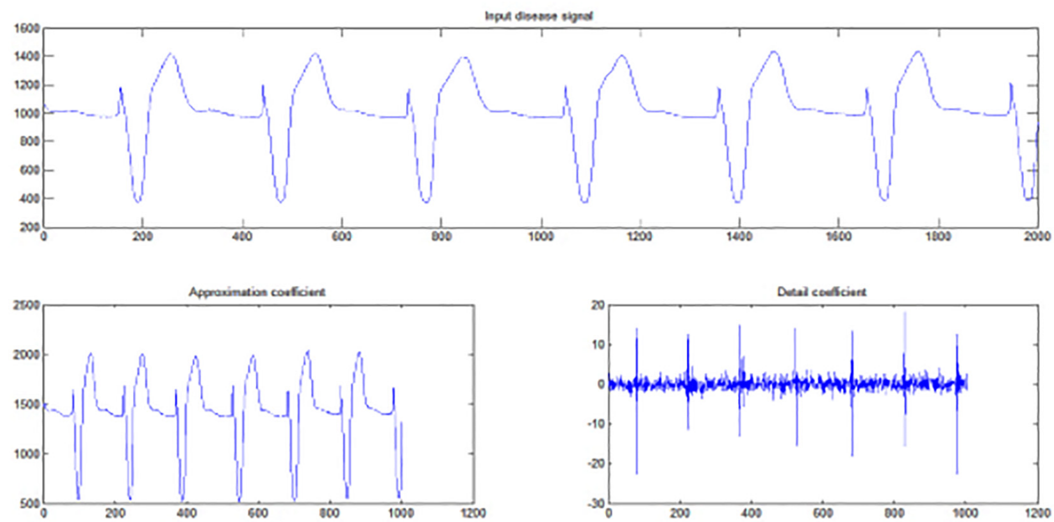

Fig. 9. Input signal, approximation and detail coefficient of ventricular fibrillation.

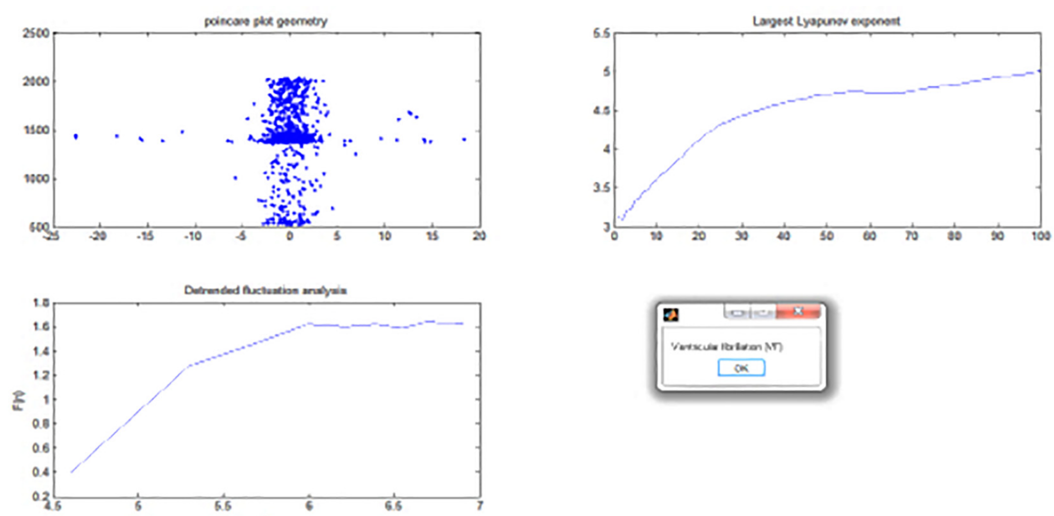

Fig. 10. Poincare plot, LLE and DFA of ventricular fibrillation.

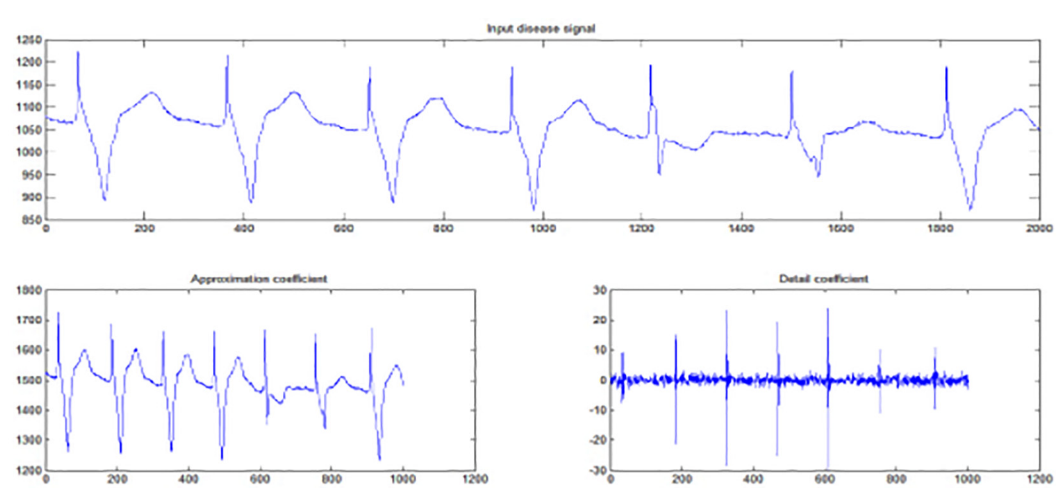

Fig. 11. Input signal, approximation and detail coefficient cardiac arrhythmia.

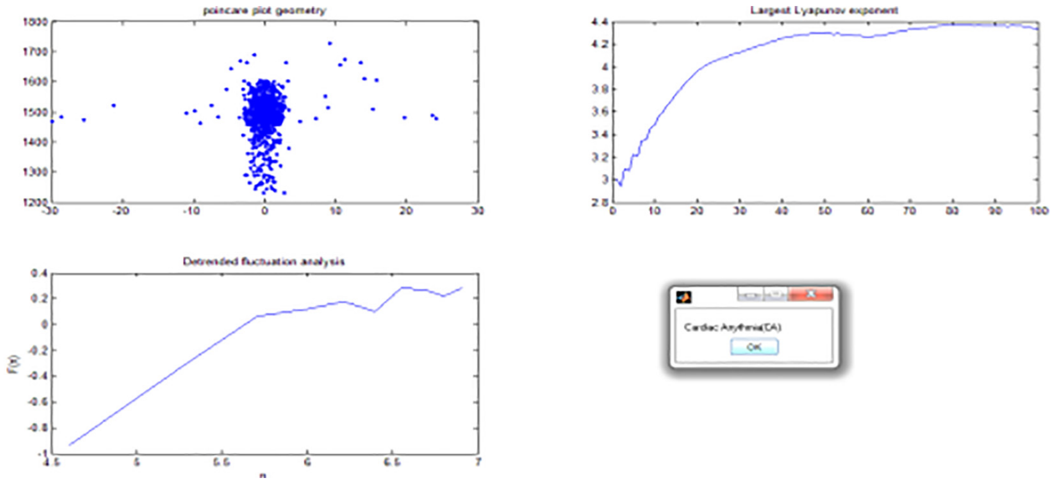

Fig. 12. Poincare plot, LLE and DFA of cardiac arrhythmia.

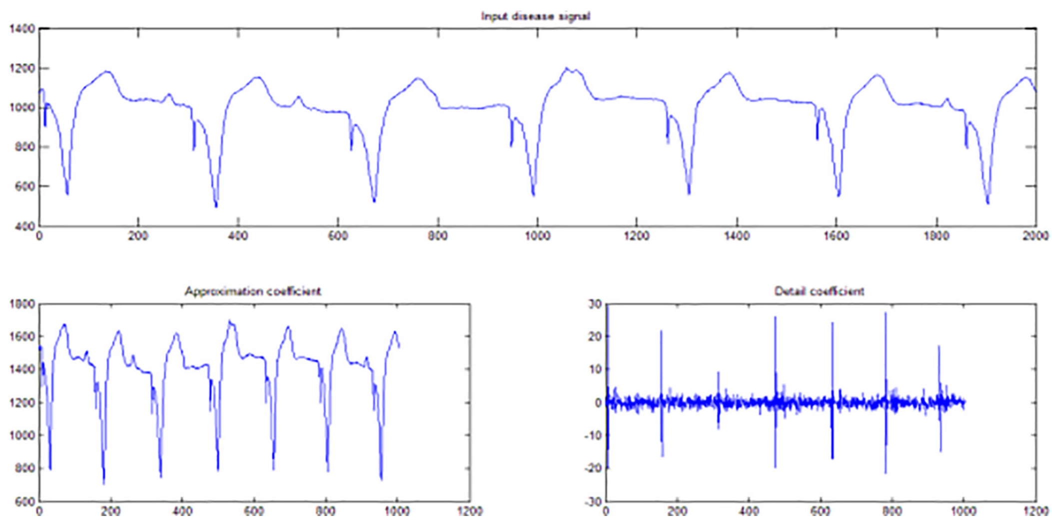

Fig. 13. Input signal, approximation and detail coefficient of bradycardia.

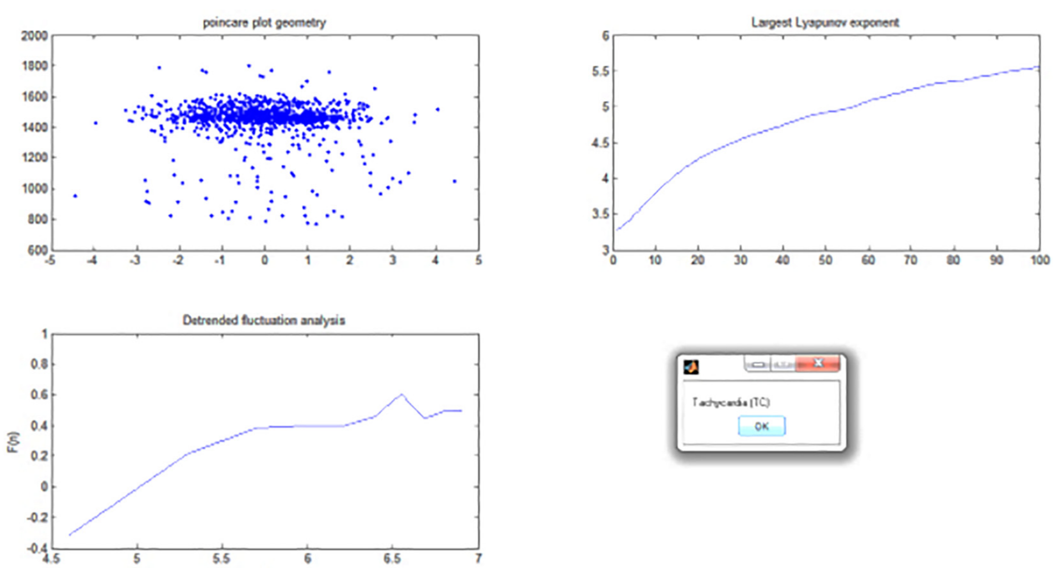

Fig. 14. Poincare plot,LLE and DFA of bradycardia.

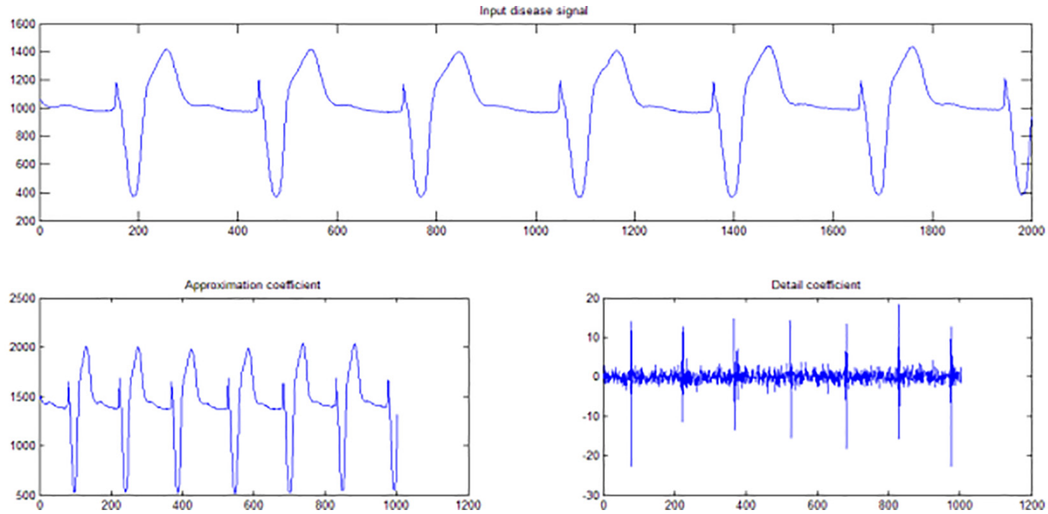

Fig. 15. Input signal, approximation coefficient, detail coefficient of normal ECG.

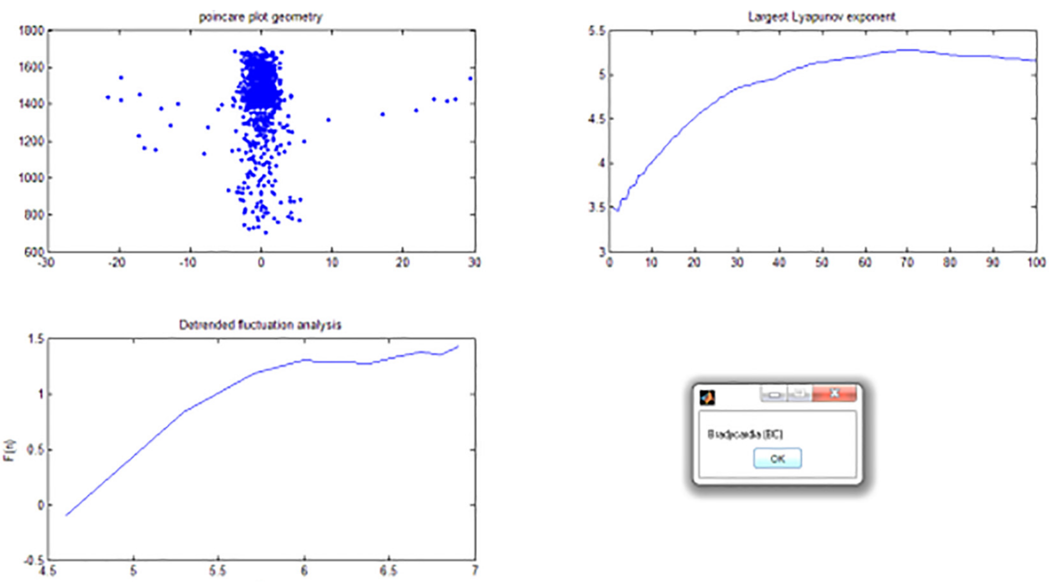

Fig 16. Poincare plot, LLE and DFA of tachycardia.

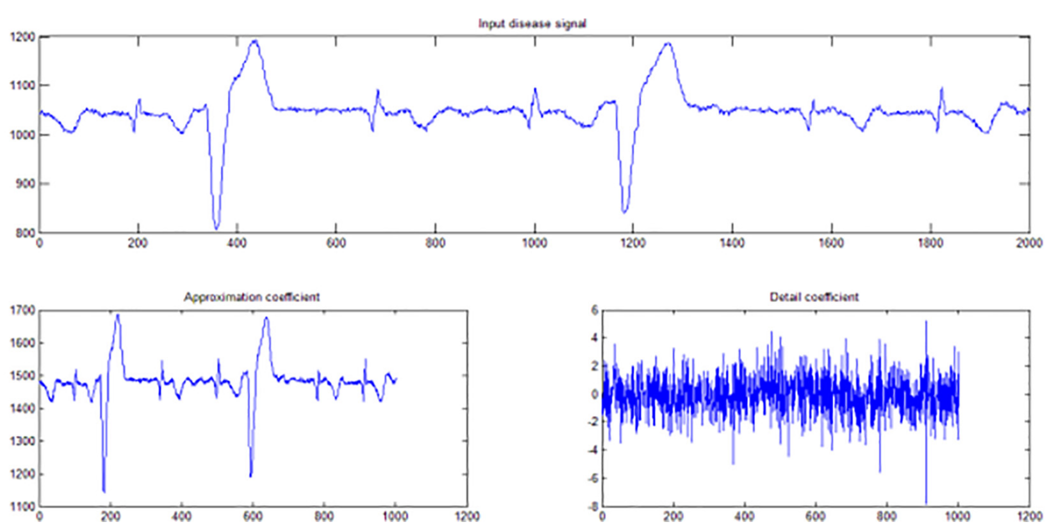

Fig. 17. Input signal, approximation coefficient, detail coefficient of normal ECG.

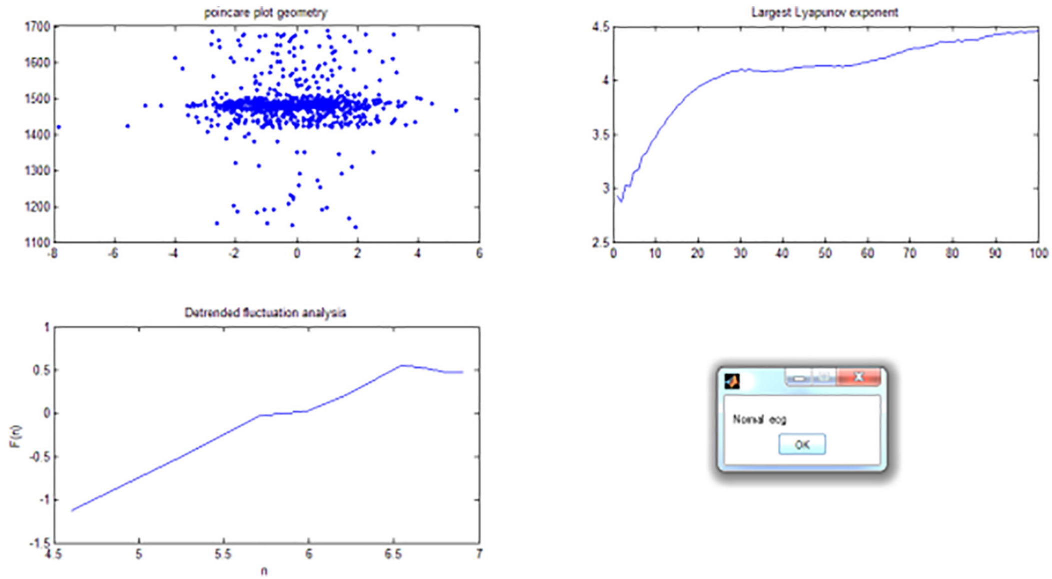

Fig. 18. Poincare plot, LLE, DFA of normal ECG.

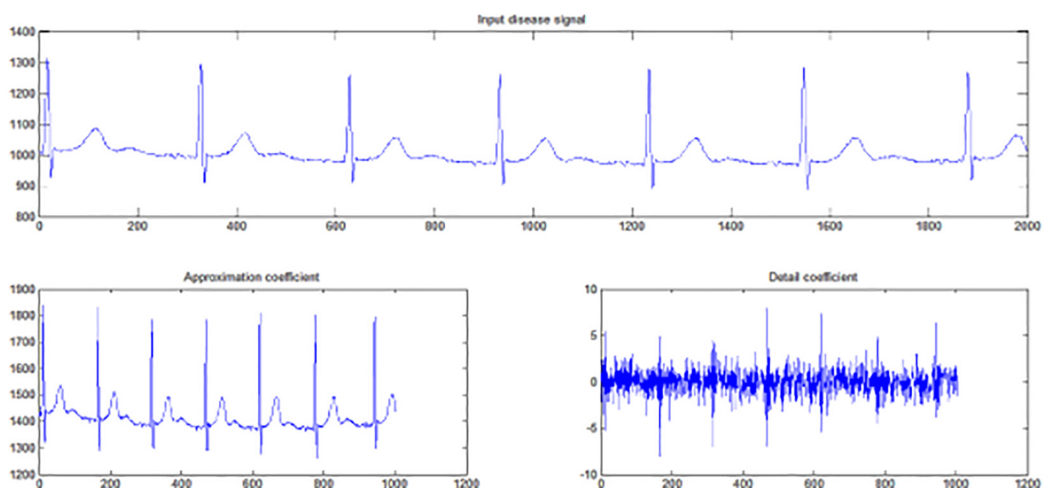

Fig. 19. Input signal, approximation and detail coefficient of bradycardia.

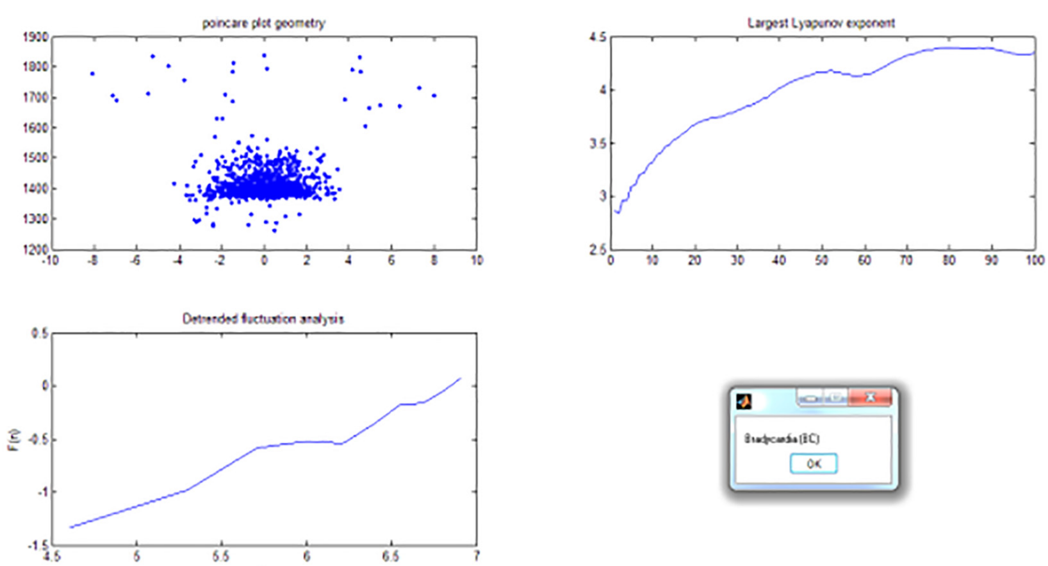

Fig. 20. Poincare plot, LLE, DFA of bradycardia.

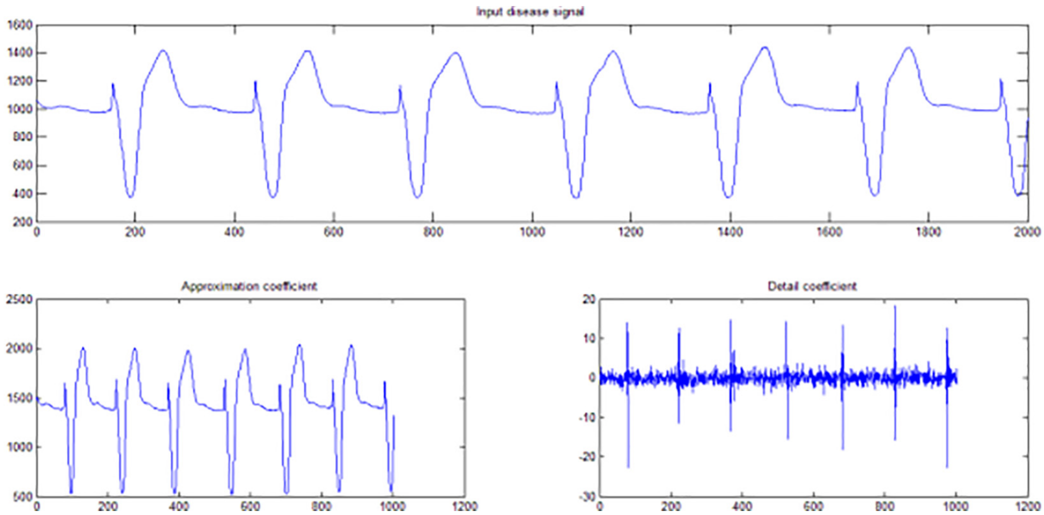

Fig. 21. Input signal, approximation and detail coefficient of ventricular fibrillation.

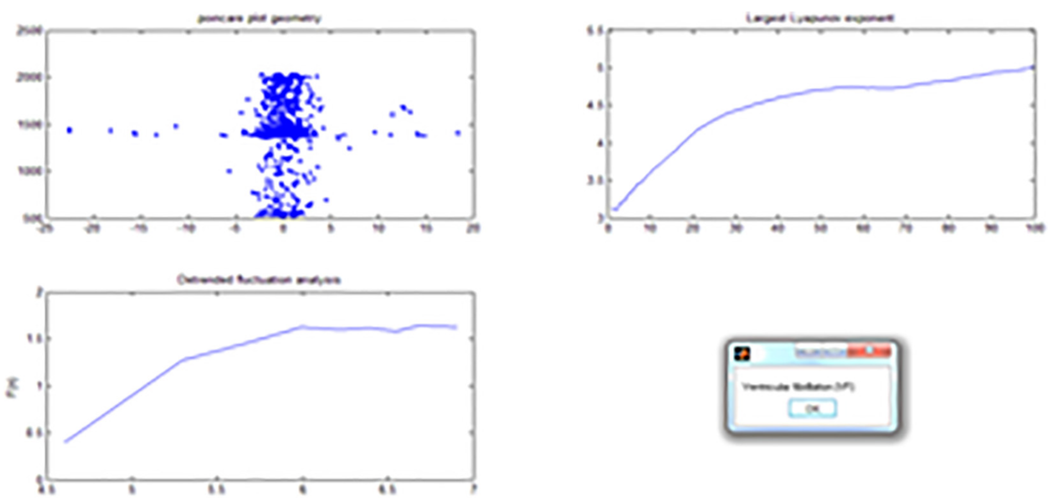

Fig. 22. Poincare Plot, LLE and DFA of ventricular fibrillation.

produces the approximation coefficient and detailed coefficient. Fig. 15 shows the input signal, approximation coefficient, detail coefficient for a tachycardia signal. Fig. 16 shows the detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot and the message box which indicates that the selected signal is tachycardia.

5.2. Results from artificial neural network

The simulation results of classification and analysis of cardiac waves using artificial neural network have been obtained as follows: he network is trained first and then the classification of cardiac diseases is done. The performance, epoch, time and gradient of the training network can be calculated using ANN. The normal ECG signal selected by the user from the database after training the neural network has the ANN's combined parameter value of 4. The input signal after discrete wavelet transform produces the approximation coefficient and detailed coefficient. Fig. 17 shows the input signal, approximation coefficient, detail coefficient for a normal ECG. Fig. 18 shows detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot and the message box which indicates that the selected signal is normal ECG.

a) The bradycardia ECG signal selected by the user from the database after training the neural network has the ANN's combined parameter value of 2. The four parameters in this ANN are spectral entropy, Poincare plot, largest lyapunov exponent, detrended fluctuation analysis. The input signal after discrete wavelet transform produces the approximation coefficient and detailed coefficient. Fig. 19 shows the input signal, approximation coefficient & detail coefficient for bradycardia signal. Fig. 20 shows the Poincare plot, largest lyapunov exponent and detrended fluctuation analysis and the message box which indicates that the selected signal is bradycardia.
b) The ventricular fibrillation ECG signal selected by the user from the database after training the neural network has the ANN's combined parameter value of 1. The input signal after discrete wavelet transform produces the approximation coefficient and detailed coefficient. Fig. 21 shows the input signal, approximation coefficient, detail coefficient

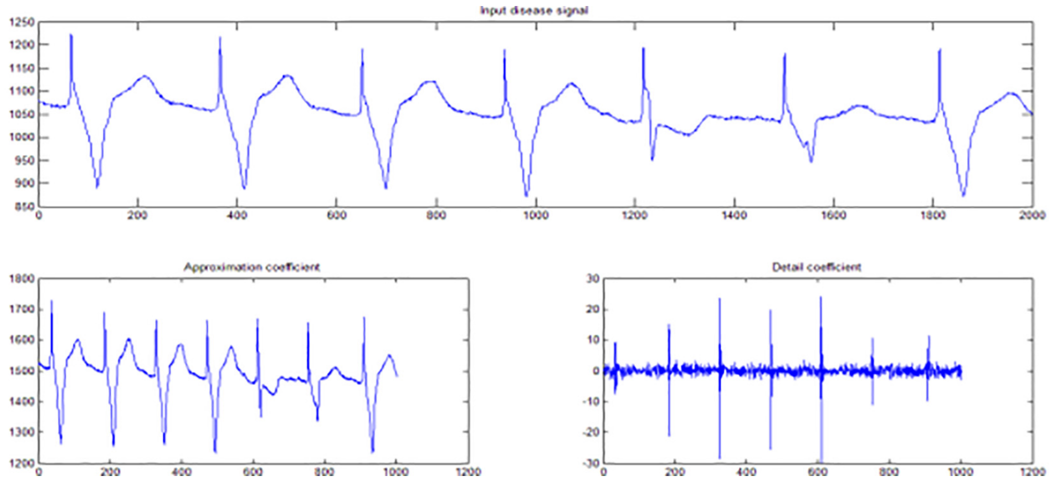

Fig. 23. Input signal, approximation and detail coefficient of cardiac arrhythmia.

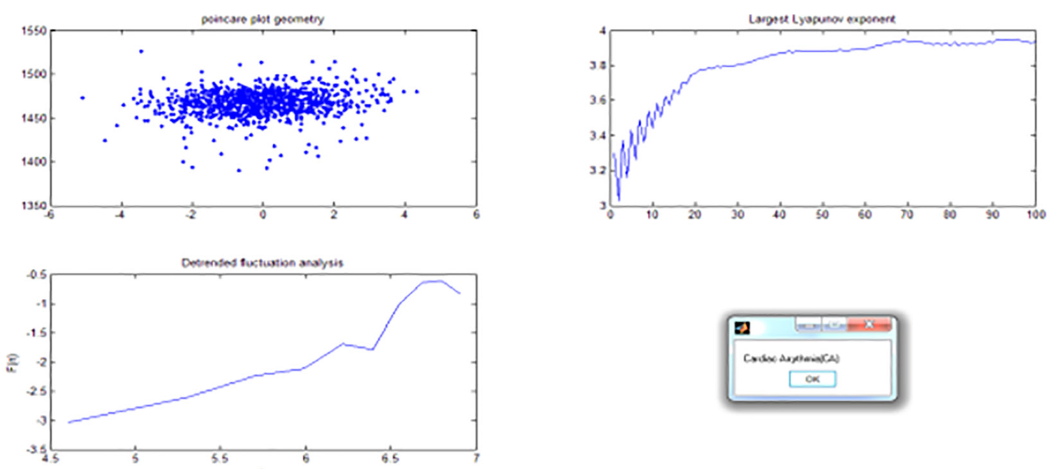

Fig. 24. Poincare plot, LLE and DFA of cardiac arrhythmia.

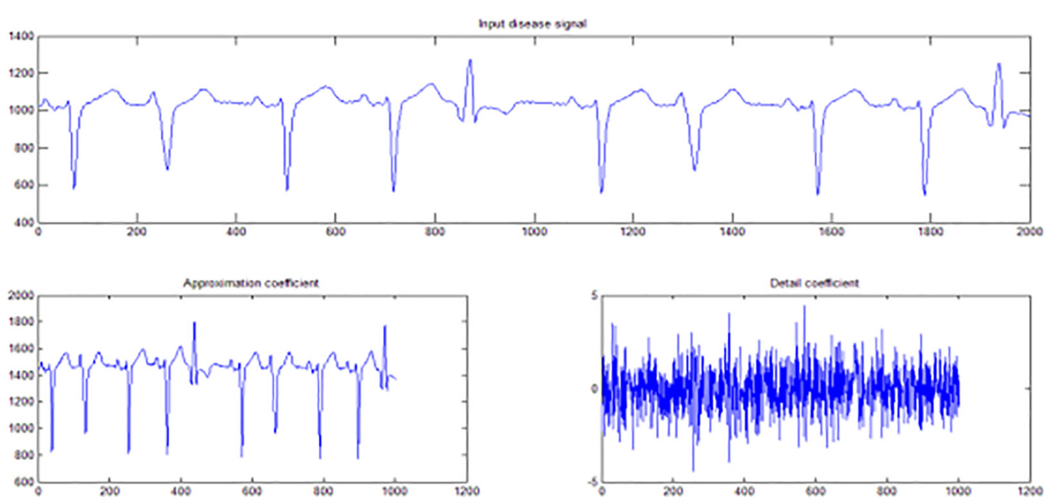

Fig. 25. Input signal, approximation and detail coefficient of tachycardia.

for a diseased signal. Fig. 22 shows detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot and the message box which indicates that the selected signal is ventricular fibrillation.

c) The cardiac arrhythmia ECG signal selected by the user from the database has the fuzzy classifier's combined parameter value is 3. The four parameters in this fuzzy classifier are detrended fluctuation analysis, spectral entropy, largest lya-

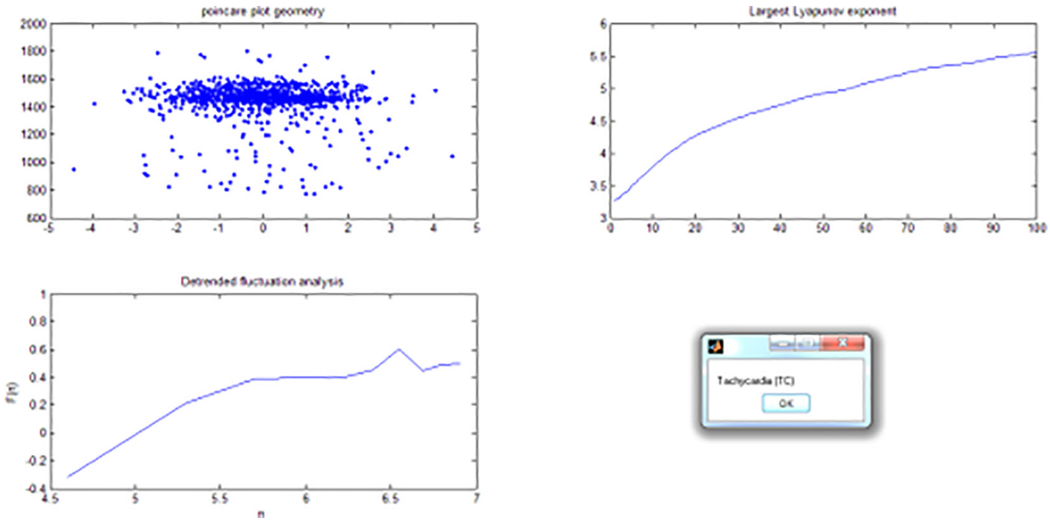

Fig. 26. Poincare plot, LLE and DFA of tachycardia.

punov exponent, Poincare plot. The input signal after discrete wavelet transform produces the approximation coefficient and detailed coefficient. Fig. 23 shows the input signal, approximation coefficient, detail coefficient for a diseased signal. Fig. 24 shows the detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot and the message box which indicates that the selected signal is cardiac arrhythmia.

d) The tachycardia ECG signal selected by the user from the database has the fuzzy classifier's combined parameter range of 0. The four parameters in this fuzzy classifier are detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot. The input signal after discrete wavelet transform produces the approximation coefficient and detailed coefficient. Fig. 25 shows the input signal, approximation coefficient, detail coefficient for a diseased signal. Fig. 26 shows detrended fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot and the message box which indicates that the selected signal is tachycardia.

5.3. Comparison of ANN and fuzzy logic

Thus from the above results are concluded and compared the following characteristics.

6. Conclusion

The proposed method gives a framework to classify and analyze cardiac waves to predict COVID-19. The detection of COVID-19 disease by using fuzzy classifier is easier and accurate when compared to artificial neural network which is better for the interpretating the disease even for very larger input dimensional spaces and allows a rapid detection of malfunctionalities in heart Table 2. ANN model is useful for less input variables to analyse. The advantage of the ANN classifier is its ease and simplicity to implement in medical care The final decision process if fully influenced by input features. The fuzzy logic and artificial neural network evaluates the following four input features such as fluctuation analysis, spectral entropy, largest lyapunov exponent, Poincare plot. By training with a larger number of training input triats, the performance of the system can be further enhanced which increases the network ability to classify unknown signals.

Table 2
Comparative Analysis Chart.

	ANN	FUZZY CLASSIFIER
TIME	Processing time is much fast i.e. t = 0.05 s	Slow when compared to ANN (>0.05 s)
ACCURACY	Output is rounded off to nearest integer value (0 to 4)	Output is accurate (0.8 to 0.9)
PERFORMANCE	Better performance characteristics	Performance criteria is low when compared to ANN.

CRediT authorship contribution statement

T. Nivethitha: Data curation, Writing - original draft. **Satheesh Kumar Palanisamy:** Conceptualization, Methodology, Software. **K. Mohanaprakash:** Visualization, Investigation. **K. Jeevitha:** Software, Validation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Abhishek Murthy, Ezio Bartocci, Flavio.H,Fenton,James , Glimm, Richard A. Gray, Elizabeth M.Cherry,Scott A.Smolka and Radu Grosu, "Curvature analysis of cardiac excitation wavefront", IEEE transactions on Computational Biology and Bioinformatics, vol. 10,No.2, 2013.
[2] "Sourabh Shastri Kuljeet Singh, et. Al., "Time series forecasting of COVID-19 using deep learning models: India-USA compaitive case study" Chaos, Solitons, and Fractals,140, 2020.
[3] G.R. Shinde, A.B. Kalamkar, P.N. Mahalle, et al., "Forecasting models for coronavirus disease(COVID-19): a survey of the state-of-the art, SN Comp Sci. 1 (2020) 197.
[4] Carro,J., Rodriguez,J.F., Laguna.P, Peuyo,E. "Analysis and improvement of a human ventricular cell model for investigation of cardiac arrhythmias", Computing in Cardiology,vol.2,no.2, 2010.
[5] Mrs. B.Anuradha, V.C.Veera Reddy "Cardiac arrhythmia classification using fuzzy classifiers", Journal of Theoretical and Applied Information Technology, vol.20,no.1, 2008.
[6] E.M. Cherry, F.H. Fenton, Visualisation of spiral and scroll waves in simulated and experimental cardiac tissue, New Journal of Physics (2008).
[7] M.A. Woo, W.G. Stevenson, D.K. Moser, R.B. Trelease, R.M. Harper, Patterns of beat-to-beat heart rate variability in advanced heart failure, American Heart Journal 123 (3) (1992) 704–710, https://doi.org/10.1016/0002-8703(92)90510-3.

[8] Kaman. P.W., Krum.H, and Tonkin.A.M., "Poincare plot of heart rate variability allows quantitative display of parasympathetic nervous activity," Clinical Science, 91, pp. 201–208. 1996
[9] Demir BE, Yorulmaz F, Guler .I. "Microcontroller controlled ECG simulator" National Biomedical Engineering Conference (BIYOMUT'10), Antalya, Turkey; 2010.
[10] S.Z. Mohmoodabadi, A. Ahmadian, M.D. Abolhasani, "ECG feature extraction using daubechies wavelets", Proc, of the fifth IASTED International Conference, 2005.
[11] Cuiwei Li, Chongxum Zheng andChangfeng Tai, "Detection of ECG characteristic points using wavelets transforms", IEEE Transactions on Biomedical Engineering 42 (1) (1995) 21–28.
[12] U. Rajendra Acharya, P. Subbanna Bhat, S.S. Iyengar, Ashok Rao, Sumeet Dua, Classification of heart rate data using artificial neural network and fuzzy equivalence relation, Pattern Recognition 36 (1) (2003) 61–68, https://doi.org/10.1016/S0031-3203(02)00063-8.
[13] Senhadi L, Carrault G, Bellanger J.J, and Passariello G, "Comparing Wavelet Transforms for Recognizing Cardiac Patterns", IEEE Engineering in Medicine and Biology Magazine, Publication, vol.14, no. 2, pp. 167-173. Mar/Apr 1995
[14] www.ecgteacher.com.
[15] Amara Graps, "An Introduction to Wavelet", IEEE Comp.Sc. And Eng.,vol.2, no. 2, 1995.
[16] W. Ziong, D. Jiang, Automated ECG rhythm analysis using fuzzy reasoning, Computers in cardiology 25 (1998) 69–72.
[17] Sugiura, T. Hirata, H.Harada, Y.and Kazui, T., "Automatic discrimination of arrhythmia waveforms using fuzzy logic", Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, vol. 20, no. 1, 1998.
[18] U.R. Acharya, P. Subbanna Bhat, S.S. Iyengar, A. Rao, S. Dua, Classification of heart rate using artificial neural network and fuzzy equivalence relation, Pattern Recognit. 36 (2003) 61–68.
[19] MATLAB,"SymbolicMathToolbox,"http://www.mathworks. com/help/toolbox/symbolic, 2012.
[20] Margarita Sordo, Introduction to Neural Networks in Healthcare-A review, ARPN Journal of Engineering and Applied Sciences 3 (3) (June 2002).
[21] Kannathal N, Puthusserypady S.K, Lim Choo Min, Acharya, U.R. and Laxminarayan, S. "Cardiac State Diagnosis using Adaptive Neuro-Fuzzy Technique", Proceedings of the IEEE Engineering in Medicine and Biology 27th Annual Conference Shanghai, China, September 1-4, 2005.
[22] R.J. Adams, Heart Disease and Stroke Statistics 2010 update: A report from American Heart Association, Circulation 121 (2009.) e46–e215.
[23] B. Yegnanarayana, Artificial Neural Networks, Prentice Hall, India, 2007.
[24] MATLAB,"AlgorithmIsocontour,"http://www.mathworks.com/matlabcentral/fileexchange/30525-isocontour, 2012.

Further Reading

[1] H. Gholam Hosseini, D. Luo, K.J. Reynolds, The comparison of different feed forward neural network architectures for ECG signal diagnosis, Medical Engineering & Physics 28 (4) (2006) 372–378, https://doi.org/10.1016/j.medengphy.2005.06.006.
[2] www.physionet.com.
[3] Mietanowski.M, Szelenberrger.A, Trzebsk, " Non Linerar Dynamics of the cardiovascular parameters in sleep and sleep apnea", Journel of Physiology and Pharmacology,2006