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

T. Nivethithaa, Satheesh Kumar Palanisamyb,⇑, K. Mohana Prakashc, K. Jeevithad

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

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 dysfunctions is 0.05 s using ANN which is far better than Fuzzy classifier.

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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.

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

2. Related work

Cuwei 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 stationary signals using modified root-mean-square analysis [24]. The fluctuation function is calculated using the equation (3),

\[ F_n = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (y(k) - y_0(k))^2} \]  

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 Arrhythmia (CA)
- 0.85 to 0.9-Normal ECG

4.1. Maximal lyapunov exponent

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

\[ \lambda = \lim_{t \to \infty} \lim_{\delta Z \to 0} \frac{1}{t} \ln \frac{\delta Z(t)}{\delta Z_0} \]  

The limit \( \delta Z \to 0 \) 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 \( x_0 \).

\[ \lambda(x_0) = \lim_{n \to \infty} \frac{1}{n} \sum_{i=0}^{n-1} \ln f(x_i) \]
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, \( x_1, x_2, \ldots, x_N \). 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. 2. Fuzzification steps.

Fig. 3. The Poincare plot for normal ECG.
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 to 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.

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.

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. Fig. 11 shows the input signal, approximation coefficient, detail coefficient for a 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. Fig. 13 shows the input signal, approximation coefficient, detail coefficient for a bradycardia.

d) 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. Fig. 15 shows 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.
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: the 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...
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 lyapunov exponent, Poincare plot and the message box which indicates that the selected signal is ventricular fibrillation.
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 interpreting the disease even for very larger input dimensional spaces and allows a rapid detection of functionalities 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 trials, the performance of the system can be further enhanced which increases the network ability to classify unknown signals.

CRediT authorship contribution statement

T. Nivethitha: Data curation, Writing - original draft. Satheesh Kumar Palanisamy: Conceptualization, Methodology, Software. K. Mohanaparakash: 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.

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Further Reading

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