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CARDIAC ARRHYTHMIA CLASSIFICATION USING FUZZY CLASSIFIERS

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ABSTRACT

Electrocardiography deals with the electrical activity of the heart. The condition of cardiac health is given by ECG and heart rate. A study of the nonlinear dynamics of electrocardiogram (ECG) signals for arrhythmia characterization is considered. The statistical analysis of the calculated features indicate that they differ significantly between normal heart rhythm and the different arrhythmia types and hence, can be rather useful in ECG arrhythmia detection. The discrimination of ECG signals using non-linear dynamic parameters is of crucial importance in the cardiac disease therapy and chaos control for arrhythmia defibrillation in the cardiac system. The four non-linear parameters considered for cardiac arrhythmia classification of the ECG signals are Spectral entropy, Poincaré plot geometry, Largest Lyapunov exponent and Detrended fluctuation analysis which are extracted from heart rate signals. Linguistic variables (fuzzy sets) are used to describe ECG features, and fuzzy conditional statements to represent the reasoning knowledge and rules. Good results have been achieved with this method and an overall accuracy of 93.13%.

Key words: *Arrhythmia detection, ECG, statistical, Heart rate variability, Spectral entropy, Poincaré plot geometry, Lyapunov exponent, Detrended fluctuation analysis, Fuzzy*.

1. INTRODUCTION

The Electrical Activity of Heart

The electrical signal that stimulates the heart beat starts from the Sino Atrial node (SA) is known as the heart's "natural pacemaker" and is located at the top of the right chamber or Atrium (RA). This signal branches through atria, causing them to contract and pump blood to the lower chambers, the ventricles, where the signal continues via the Atrio Ventricular node (AV). If the pacemaker is disrupted, the heart may beat at an abnormal rate, impacting the circulation of blood throughout the body.

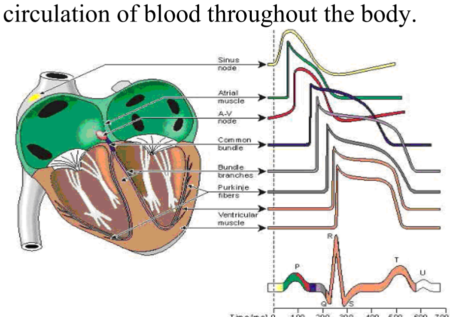

Figure1: ECG waveform characteristics and their corresponding positions in heart.

ECG Characteristics

The electrical signals described above are measured by the electrocardiogram or ECG where each heart beat is displayed as a series of electrical waves characterized by peaks and valleys. An ECG gives two major kinds of information. First, by measuring time intervals on the ECG the duration of the electrical wave crossing the heart can be determined and consequently we can determine whether the electrical activity is normal or slow, fast or irregular. Second, by measuring the amount of electrical activity passing through the heart muscle, a pediatric cardiologist may be able to find out if parts of the heart are too large or are overworked. The frequency range of an ECG signal is [0.05 – 100] Hz and its dynamic range is [1-10] mV. The ECG signal is characterized by five peaks and valleys labeled by successive letters of the alphabet P, Q, R, S and T. A good performance of an ECG analyzing system depends heavily upon the accurate and reliable detection of the QRS complex, as well as the T and P waves. The P wave represents the activation of the upper chambers of the heart, the atria while the QRS wave (or complex) and T wave represent the excitation of the ventricles or the lower chambers of the heart. The detection of the QRS complex is the most important task in automatic ECG signal analysis. Once the QRS complex has been identified, a more detailed examination of ECG signal, including the heart rate, the ST segment, etc., can be performed. Figure1 shows ECG waveform characteristics and their corresponding positions in heart and a typical normal ECG signal is as shown in figure 2 [1].

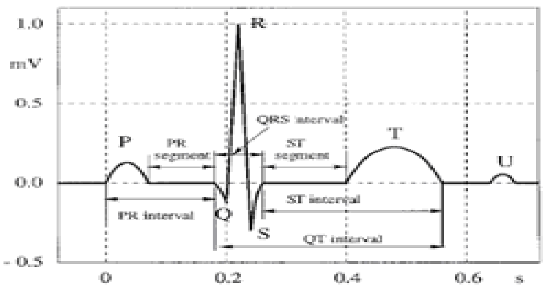

Figure 2: The ECG signal and its different components.

2. LITERATURE REVIEW

Cuiwei Li *et al*. (1995) showed that with multi scale information in wavelets it is easy to characterize the ECG waves and the QRS complex. The difference from high P and T waves, noise, baseline drift and interference were recognized [2]. Senhadi *et al*. (1995) compared wavelet transforms for recognizing cardiac patterns. The choice of the wavelet family as well as the selection of the analyzing function into these families have been discussed to the Daubechies decompositions provided by the spline wavelet (6 levels) and the complex wavelet (10 levels) [3]. Amara Graps (1995) showed that though D6 algorithm is more complex and has a slightly higher computational overhead but it picks up detail that is missed by the Harr wavelet algorithm, which is simpler than the former. D6 of Debauchees is similar in shape to QRS complex and their energy spectrum is concentrated around low frequencies [4]. Zong and Jiang (1998) presented a fuzzy reasoning approach for ECG beat and rhythm detection and classification. Linguistic variables were used to represent beat features and fuzzy conditional statements perform reasoning. A fuzzy logic approach to single channel ECG beat and rhythm detection and classification was presented good results have been achieved [5].

Sugiura *et al*. (1998) has found a new technique based in fuzzy logic for detecting cardiac arrhythmias that can separate NSR from VF and proposed for discrimination of ventricular arrhythmias using fuzzy logic [6]. Acharya *et al.* (2003) used heart rate variability as the base signal from which certain parameters are extracted and used for fuzzy equivalence to classify four cardiac arrhythmias. The classification was accurate in over 90% of the cases [7]. Kannathal *et al*. (2005) used three non-linear parameters as inputs to the proposed ANF classifier for classification of heart abnormalities [8].

ECG Feature extraction

An electrocardiogram (ECG) feature extraction system is based on the multi-resolution wavelet transform. ECG signals from Modified Lead II (MLII) are chosen for processing as the peaks of the R waves in signals from the ML II lead have the largest amplitudes among other leads The result of applying two Daubechies wavelet filters (D4 and D6) of different length on the signal is compared. The wavelet filter with scaling function more closely similar to the shape of the ECG signal achieved better detection [9].DB wavelet family is similar in shape to QRS complex and their energy spectrums are concentrated around low frequencies the signal is approximated by omitting the signal's high frequency components. The ECG signal and the details for eight wavelet scales are used which are scaled for better illustration. The detection of R peaks is as shown in Figure 3.

ECG data used

All the ECG data required for this work is used from the MIT-BIH dataset has been used [10].

Non –Linear dynamics for ECG

Recent developments in chaos theory suggest that fluctuations could be nonrandom and play important role in the dynamics of the cardiovascular complex systems. Poor prognosis for cardiological patients with diminished heart rate variability (HRV) is clinically confirmed. Fluctuations in the frequency and time domain may reveal significant information on the dynamic characteristics lost with routine averaging or linear spectral methods. New computational techniques for the analysis of non-linear dynamics such as correlation dimension, recurrence plot analysis, non-stationary fluctuation analysis, detrended fluctuation analysis are useful in revealing the extent of long-range correlations in time series (x). We applied this approach to data analysis in classification work [11]. The four parameters considered for cardiac arrhythmia classification using ANN are

1. Spectral entropy
2. Poincaré plot geometry
3. Largest Lyapunov exponent
4. Detrended fluctuation analysis

Spectral entropy

Spectral entropy quantifies the spectral complexity of the time series. Application of Shannon's channel entropy gives an estimate of the spectral entropy of the process, where entropy is given by

$$H = \sum_f p_f \log(\frac{1}{p_f}) \qquad (1)$$

Where pf is the PDF value at frequency f. The spectral entropy H (0<H<1) describes the complexity of the HRV signal. This spectral entropy H was computed for the various types of cardiac signal [12].

Poincaré plot geometry

In this paper, a physiological oscillator model of which the output mimics the shape of the R-R interval Poincaré plots used. To validate the model, simulations of various nervous conditions are compared with heart rate variability (HRV) data obtained from subjects under each prescribed condition. By exploiting the oscillator basis, we detail the way that low- and high-frequency modulation of the sinus node translates into R-R interval Poincaré plot shape by way of simulations and analytic results [13]. With this, we establish that the length and width of a Poincaré plot are a weighted combination of low- and high-frequency power. This provides a theoretical link between frequency-domain spectral analysis techniques and time-domain Poincaré plot analysis. We ascertain the degree to which these principles apply to real R-R intervals by testing the mathematical relationships on a set of data and establish that the principles are clearly evident in actual HRV records [14 and 15].

Largest Lyapunov exponent

Detecting the presence of chaos in a dynamical system is an important problem that is solved by measuring the largest Lyapunov exponent. Lyapunov exponents quantify the exponential divergence of initially close state-space trajectories and estimate the amount of chaos in a system. . In this work the method proposed by Rosensetien *et al.,* (1993) which is robust with data length is used. This method looks for nearest neighbour of each point in phase space and tracks their separation over certain time evolution. Detecting the presence of chaos in a dynamical system is an important problem that is solved by measuring the LLE. For two points in a space X0 and X0+ΔX0, that are function of time and each of which will generate an orbit in that space using some equations or system of equations, then the separation between the two orbits Δx will also be a function of time. This separation is also a function of the location of the initial value and has the form Δx (X0, t). For a chaotic data set, the function Δx (X0, t) will behave erratically. The mean exponential rate of divergence of two initially close orbits is characterized by

$$\lambda = \lim_{t \to \alpha} \frac{1}{t} \ln \frac{|\Delta x(X_0, t)|}{|\Delta X_0|} \qquad (2)$$

The LLE is estimated using a least squares fit to an average line defined by

$$y(n) = \frac{1}{\Delta t}\left\{ \ln\left(d_i(n)\right)\right\} \qquad (3)$$

Where d_i (n) is the distance between the ith phase-space point and its nearest neighbour at the nth time step, and <,>denotes the average overall phase-space points. This last averaging step is the main feature that allows an accurate evaluation of the LLE, even when we have short and noisy data [16].

Detrended fluctuation analysis

The detrended fluctuation analysis (DFA) is used to quantify the fractal scaling properties of short interval R–R interval signals. This technique is a modification of the root-mean-square analysis of random walks applied to non stationary signals (17). The root-mean-square fluctuation of an integrated and detrended time series is measured at different observation windows and plotted against the size of the observation window on a log–log scale. The root-mean-square fluctuation of this integrated and detrended series is calculated using the equation

$$F(n) = \sqrt{1/N \sum_{k=1}^{N} [y(k) - y_n(k)]^2}. \qquad (4)$$

All the four non-linear parameters are computed for the entire database.

Arrhythmia classification

Arrthymia considered for the purpose of this study were classified into eight categories, namely

(i) Left bundle branch block (LBBB)
(ii) Normal sinus rhythm (NSR)
(iii) Pre-ventricular contraction (PVC)
(iv) Atrial fibrillation (AF)
(v) Ventricular fibrillation (VF)
(vi) Complete heart block (CHB)
(vii) Ischemic dilated Cardiomyopathy
(viii) Sick sinus syndrome (SSS) [18].

For the classification of cardiac arrhythmias using ANN we have taken the analysis of spectral entropy, Poincaré plot geometry, detrended fluctuation analysis and largest Lyapunov exponent as the input variables which are derived from heart rate signals. The specific values [19] for the different arrhythmias chosen are as shown in Table 1.

3. FUZZY CLASSIFIER

Medical diagnosis specifies the features, content and degree of the sickness. When a medical situation is very complicated, that is, there are many variables and diagnostic rules; the fuzzy method is especially useful. It is also easy to check, modify, and add delete every fuzzy variable for the better automated analysis. The method's feature of parallel reasoning assures that every possible conclusion regarding beat/rhythm labeling is considered before the final decision is made. This is a significant advantage over more deterministic algorithms, and permits multi conclusions to exist which are common in clinical practice [5]. If the problem is very complicated and the input dimension very high then the rule frame consist of very high number of fuzzy rules on a very high dimensional support. An important part of interpretation lies on quantification of the influence of the input features on the decision process. The proposed fuzzy Cardiac arrthymia classifier is comprised of two major function blocks, ECG Parameterizer and Fuzzy classifier as shown in Figure 3. In the ECG Parameterizer, the following work is carried out. ECG features of the database are detected using Daubechies wavelets. These features are used to calculate the non-linear parameters of ECG signals based on the methods discussed above. The non-linear parameters are utilized as inputs for the classification using Fuzzy classifier. The derived parameters will be exported to the latter for the classification. The Mamdani fuzzy method is used. Fuzzy logic if-then rules are formed by applying fuzzy operations to these membership functions for given inputs. The Gaussian membership function is used for the input parameters. The range of the input parameters are normalized from 0 to 1. The resulting output membership functions are added together using desired weights yielding a sort of probability function. The Trapezoidal membership function is used for output of the fuzzy classifier. This function can then be used to estimate the expected value of the output variable. Then, a set of characteristic vectors will be selected from those features for classification. In general, any fuzzy ECG classifier has to undergo iterative adjustment in terms of fuzzy variables, including the choice of membership functions, and the definition of rules in knowledge base.

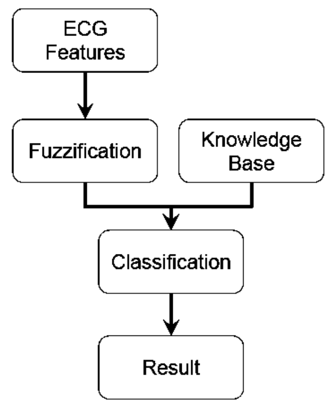

Figure3: The structure of Fuzzy ECG classifier

The algorithm for the proposed fuzzy classifier can be summed as given below.

- Initialization- Read ECG data from the database.
- Preprocessing-Find the ECG features required for the computation of non-linear parameters. Normalize these values to the range of 0 to 1.
- Fuzzification-Compute the fuzzy equivalence relation. Design the MFs to match the four inputs and eight outputs.
- Defuzzification-The data from the preprocessing is matched with the training data and the output is tabulated.

Table.1: Range of input parameters to Fuzzy classification model.

Class	**SE**	**Sd1/sd 2**	**LLE**	**α- slope**
LBB B	1.24 ±0.0 47	0.7±0. 20	0.47±0 .044	0.43±0.1 1
NSR	1.63 ±0.0 25	0.8±0. 16	0.50±0 .058	0.77±0.0 76
PVC	1.14 ±0.0 57	1.42±0 .54	0.62±0 .003	0.27±0.0 14
AF	1.20 ±0.0	2.98±1 .56	0.56±0 .112	0.13±0.0 43

	37			
VF	1.06 ±0.003	1.13±0.47	0.42±0.036	0.34±0.022
CHB	0.86 ±0.054	0.64±0.02	0.078±0.114	0.54±0.034
ISCH	1.12 ±0.11	0.59±0.37	0.193±0.066	0.97±0.11
SSS	1.27 ±0.135	0.96±0.32	0.82±0.102	0.55±0.013

4. RESULT AND CONCLUSIONS:

This proposed method represents a fast and easy tool for the interpretation of the fuzzy decision process even for very high dimensional input spaces and allows a fast detection of errors. The impact of the input features plays an important role on the final decision process. The algorithm supports the implementation of the expert's knowledge and optimized the system easily. The FIS editor of the classifier is shown in Figure5. The four input features were evaluated by fuzzy logic by assigning a value of 0-1 MFs and rule table used in the fuzzy inference and MFs of SE, SD1/SD2 and MF of Arrhythmia are given in the figures 6 to 8. The rule editor of the MFs are used to map fuzzy inputs into a fuzzy output. These linguistic variables allow a straightforward implementation of rules. These rules are obtained by investigating the four input features of the ECG data. The product and sum composition rules are used for inference. A total of 228 rules are used in this work for eight cardiac arrhythmia classifications. If the numbers of fuzzy rules are very large, real time implementation will be difficult. The cardiac arrhythmia classification using fuzzy logic approach has given better performance results when compared to analytical method and using artificial neural networks for classification. More over problems associated with conventional neural network arch such as learning rate limitation and difficulty in selecting the optimal number of hidden units are eliminated. Fuzzy-logic-based cardiac arrhythmia detection is promising for the realization of custom-made cardiac implants like cardiac pacemakers or implantable cardiac defibrillator (ICD). It is possible to increase the performance further by adding more related input variables and with more data to train the mode. The proposed method gives a framework to detect more arrhythmia. The main advantage of the presented method consists of the low-computational expenses inherited from the characteristics of fuzzy systems. This method can be used to analyze input feature merit in fuzzy systems. A fuzzy model is available for a given training set and its input features are analyzed as per the set conditions for the output and is implemented by the fuzzy mode. The reduction of the dimension of the data set does not worsen the fuzzy system's performance, if such reduction is performed on the basis of an appropriate fuzzy feature merit measure. The fuzzy classifier is applied to all ECG databases [10] and the classification was performed. Finally the accuracy of the classifier is as shown in Table 2. A few outputs of the classifier are as shown in Figures 9 and 11. The method's feature of parallel reasoning assures that every possible conclusion regarding beat/rhythm labeling is considered before the final decision is made. This is a significant advantage over more deterministic algorithms, and permits multi conclusions (common in clinical practice) to exist. Good results have been achieved with this method and an overall accuracy of 93.13%.

Table 2: Classification of cardiac arrhythmia using
Fuzzy classifier.

Cardiac signal	**No. of data sets used for testing**	**No. of data sets correctly classified**	**No of data sets mis-classified**	**Accuracy (%)**
LBBB	14	13	1	92.85
NSR	31	30	1	96.77
PVC	65	61	4	93.85
AF	20	18	2	90
VF	47	44	3	93.62
CHB	20	18	2	90
ISCH	18	17	1	94.44
SSS	18	16	2	88.9
Total	233	217	16	93.13

REFERENCES:

1. Joseph J. Carr and John M. Brown, Introduction to Biomedical Equipment Technology, Pearson Education Inc., 2001.

2. Cuiwei Li, Chongxum Zheng and Changfeng Tai, "Detection of ECG characteristic points using wavelets transforms", *IEEE Transactions on Biomedical Engineering*, vol. 42, no.1, pp. 21-28, 1995.

3. 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.

4. Amara Graps, "An Introduction to Wavelet", *IEEE Comp.Sc. And Eng*., vol.2, no. 2, 1995.

5. Zong W, and Jiang D., "Automated ECG rhythm analysis using fuzzy reasoning", *Computers in cardiology*, vol. 25, pp. 69-72, 1998.

6. 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.

7. Acharya U R, Subbanna Bhat P, Iyengar S S, Rao A and Dua S, "Classification of heart rate using artificial neural network and fuzzy equivalence relation", *Pattern Recognit*., vol. 36, pp. 61–68, 2003.

8. 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.

9. Walid El-Atabany, "Nonlinear dynamical modeling of ECG signals based on phase density matrix representation", 2004.

10. MIT-BIH arrhythmia database, 3rd ed, 1997, Harvard-MIT Division of Health Science Technology, Biomedical Health Centre, Cambridge, MA, USA.

11. Mietanowski M, Szelenberger, A.Trzebsk, "Non Linear Dynamics of the cardiovascular parameters in sleep and sleep apnea," Journal of Physiology and Pharmacology, 57, Suppl 11, 55.68. 2006.

12. Rezek, I. A., and Roberts, S. J. "Stochastic complexity measures for physiological signal analysis", IEEE Trans. Biomed. Eng., pp. 1186–1190. 1993.

13. Woo. M.A, Stevenson, W.G, Moser, D. K., Trelease.R.B, and Harper. R. H.: "Patterns of beat-to-beat heart rate variability in advanced heart failure," Am. Heart J., 123, pp. 704– 710. 1992.

14. Kaman. P.W., Krum.H, and Tonkin.A. M., "Poincare plot of heart rate variability allows quantitative display of parasympathetic nervous activity," Clin. Sci., 91, pp. 201–208. 1996.

15. Tulppo, M., Makikallio.T.H, Takala.T.E. S. and Seppanen, K.H., "Quantitative beat-to beat analysis of heart rate dynamics during exercise," Am. J. Physiol., 71, pp. H244–252. 1996.

16. Rosensetien. M., Colins, J. J., and DE Luca, C. J. "A practical method for calculating largest Lyapunov exponents from small data sets," Physica D, 65, pp. 117–134. 1993.

17. Huikuri H V, Makikallio T H, Peng C K, Goldberger A L, Hintze U and Moller M Fractal correlation properties of R-R interval dynamics and mortality in patients with depressed left ventricular function after an acute myocardial infarction Circulation, 101, 47–53. 2000.

18. Maurice Sokolow, Malcolm B.Mcllroy, Melvin D.Cheitlin. Clinical Cardiology, Prentice Hall Int., 5th edition. 1990.

19. Acarya R, A. Kumar , P. S. Bhat , C. M. Lim, S. S. Iyengar, N. Kannathal and S. M. Krishnan, "Classification of cardiac abnormalities using heart rate signals," Med. Biol. Eng. Comput. 42, 288–293. 2004.

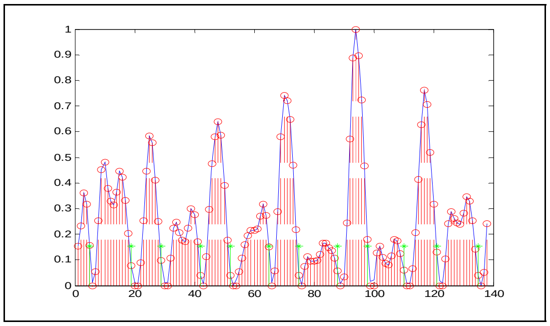

Figure 4: R peak detection.

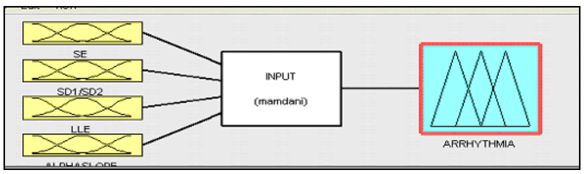

Figure 5: The FIS editor of the classifier.

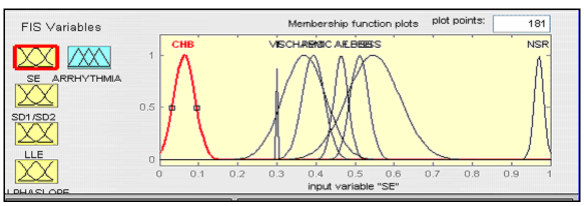

Figure 6: The MF of Spectral Entropy.

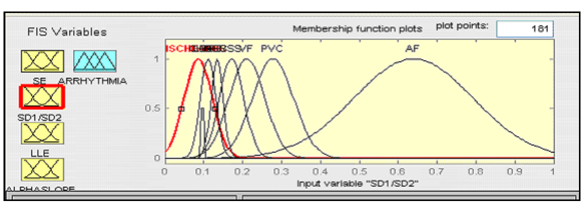

Figure 7: The MF of SD1/SD2.

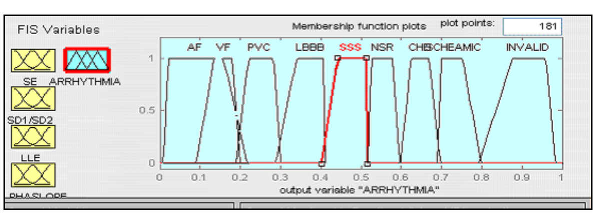

Figure 8: The MF of Arrhythmia

```
x =

          name: 'INPUT'
          type: 'mamdani'
     andMethod: 'min'
      orMethod: 'max'
  defuzzMethod: 'centroid'
     impMethod: 'min'
     aggMethod: 'max'
         input: [1x4 struct]
        output: [1x1 struct]
          rule: [1x228 struct]


y =

    0.7331
    0.8917

Type of signal detected: LBBB
>>
```

Figure 9: The output for cardiac signal condition-LBBB.

```
x =

          name: 'INPUT'
          type: 'mamdani'
     andMethod: 'min'
      orMethod: 'max'
  defuzzMethod: 'centroid'
     impMethod: 'min'
     aggMethod: 'max'
         input: [1x4 struct]
        output: [1x1 struct]
          rule: [1x228 struct]


y =

    0.7907
    0.8888

Type of signal detected: NSR
>> |
```

Figure 10: The output for cardiac signal condition-NSR.

```
x =

          name: 'INPUT'
          type: 'mamdani'
     andMethod: 'min'
      orMethod: 'max'
  defuzzMethod: 'centroid'
     impMethod: 'min'
     aggMethod: 'max'
         input: [1x4 struct]
        output: [1x1 struct]
          rule: [1x228 struct]


y =

    0.8900
    0.5194

Type of signal detected: pvc
Type of signal detected: AF
>>
```

Figure 11: Fuzzy Classifier indicating misclassification condition-1.