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Electrocardiogram Signal Analysis Using Artificial Neural Network

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Abstract

The electrocardiogram (ECG) is the electrical manifestation of the contractile activity of the heart and can be recorded fairly easily with surface electrodes on the limbs and chest. It is the most commonly known, recognised and used biomedical signal. ECG wave shape is altered by cardiovascular diseases and abnormalities such as myocardial ischemia and infarction, ventricular hypertrophy, and conduction problems. For the ECG analysis, the method adopted involved extracting features that represent the ECG signals. Eight sets of ECG signals were used. This was achieved by extracting the QRS complexes within the ECG data first and finally using feature extraction scheme, to extract key features: Spectral Entropy, Pointcare plot geometry and Largest Lyapunov Exponent (LLE) that were used to train an Artificial Neural Network (ANN) model. The ANN model thereafter classified the ECG signals into eight key classes. The analysis showed a very good match from the extracted features after training the ANN model. The chosen features gave a 100% match when tested against known ECG data samples. Performance analysis was performed using a confusion matrix to describe how well the classification model performs in classifying the ECG data. The study was able to achieve the set objective in classifying the cardiac disorders correctly into their respective classes; showing 90.6% and 97.7% accuracies for two-thirds and 90% of data used, respectively.

Keywords: Electrocardiogram analysis, Artificial neural network, ECG signals, Classification

1. Introduction

Cardiovascular diseases constitute a class of diseases considered to be one of the main causes of mortality [1]. These diseases occur in the form of myocardial infarction (MI). Myocardial infarction, commonly referred to as heart attack, stands for the failure of heart muscle. The electrocardiogram (ECG) is the electrical manifestation of the contractile activity of the heart and can be recorded fairly easily with surface electrodes on the limbs and chest. It is the most commonly known, recognised and used biomedical signal. Classifications of these ECG signals play an important role in diagnoses of heart diseases.

Artificial Neural networks have previously been used for classification of ECGs both in a classical-feature-based setup [2]. An early and accurate detection of ECG arrhythmia types is important in detecting heart diseases and is essential in choosing appropriate treatment for a patient. The favourable characteristics to use the ECG or EEG signals as biometric include universality, measurability, uniqueness and robustness. Unlike conventional biometrics, the ECG or EEG is highly confidential and secure to an individual which is difficult to be forged [3].

ECG Feature Extraction plays a significant role in diagnosing most of the cardiac diseases. One cardiac cycle in an ECG signal consists of the P-QRS-T waves. This feature extraction scheme determines the amplitudes and intervals in the ECG signal for subsequent analysis. The amplitudes and intervals value of P-QRS-T segment determines the functioning of heart of every human.

ECG waveform pattern is usually altered by heart disease called arrhythmia and precise monitoring of arrhythmia can be achieved over a 24 hour period using a Holter ECG device. Most often physicians analysing the ECG data can overlook abnormal cycles and proffer incorrect diagnosis. Recent studies have provided several techniques

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to address this area and the most widely used are machine learning techniques. Most often these techniques show very good performance when used on offline ECG data and perform poorly when used online. This can be disastrous where results are required on the fly and in little time. Researchers are looking for efficient ways to develop models that can correctly classify an ECG signal based on known diagnosis without errors.

In this study, an ECG signal analyser that would proffer prognosis based on information extracted from the ECG signal was proposed with the following objectives:

1. To develop a Systematic feature extraction algorithm in the presence of noise and distortion
2. To develop an ANN model for classifying the ECG data
3. To do a performance analysis in order to validate the effectiveness of the model.

2. RELATED WORKS

ECG analysis usually involves reading ECG signals from a patient, which is analysed using pattern recognition. For the pattern recognition to work, a full understanding of the ECG signal itself is required. Clinical ECG signal is mainly collected from body surface, this design directly adds the potential of the two limbs to ECG input amplifier using standard wire in a connected way. The design of a high precision, high stability, high input impedance, high common mode rejection ratio, low noise and strong anti-interference ability ECG signal acquisition system is usually required in order to get back a Non-distorted ECG signal.

Various research and techniques have been developed for analysing the ECG signal [4]. Different classifiers are available for ECG classification that utilise the features extracted from the ECG data, but amongst all classifiers, the artificial neural network (ANN) has been very popular and the most widely used for ECG classification.

According to Tsipouras [5], a knowledge-based method for arrhythmic beat classification and arrhythmic episode detection and classification using only the RR-interval signal extracted from ECG recordings was proposed. In their method, a three RR-interval sliding window was used in arrhythmic beat classification algorithm. The classification was performed for four categories of beats: normal, premature ventricular contractions, ventricular flutter/fibrillation and 200 heart block. The beat classification was used as input of a knowledge-based deterministic automaton to achieve arrhythmic episode detection and classification.

Bonsai [6] asserted that the detection of cardiac pathologies from the electrocardiogram, i.e. recordings of the electrical activity of the heart muscle, required the use of more accurate tools for signal processing and decision making. In this context, the paper presented the design of a cardiac pathologies detection system with high precision of calculation and decision, which consists of the Mel Frequency Coefficient Cepstrum algorithms like fingerprint extractor (or features) of the cardiac signal.

Memić [7] implemented the classification algorithm of ECG signals based on segmentation of basic waveform using artificial neural networks. Inputs of the classification process were different types of features: time-domain, morphological and statistical features. Comparison of results using these types of features as well as their combination was performed. The algorithms was implemented in the MATLAB environment and its performance was evaluated on the MIT-BIH Arrhythmia Database fingerprints extracted into two classes: normal or abnormal.

In Li, *et. al.* [8], feature extraction and classification of electrocardiogram (ECG) signals are necessary for the automatic diagnosis of cardiac diseases. In this study, a novel method based on genetic algorithm-back propagation neural network (GA-BPNN) for classifying ECG signals with feature extraction using wavelet packet decomposition (WPD) was proposed. The WPD combined with the statistical method was utilized to extract the effective features of ECG signals. The statistical features of the wavelet packet coefficients were calculated as the feature sets. The GA was employed to decrease the dimensions of the feature sets and to optimize the weights and biases of the back propagation neural network (BPNN).

3.0 METHODOLOGY

Figure 1 shows the framework adopted for this study

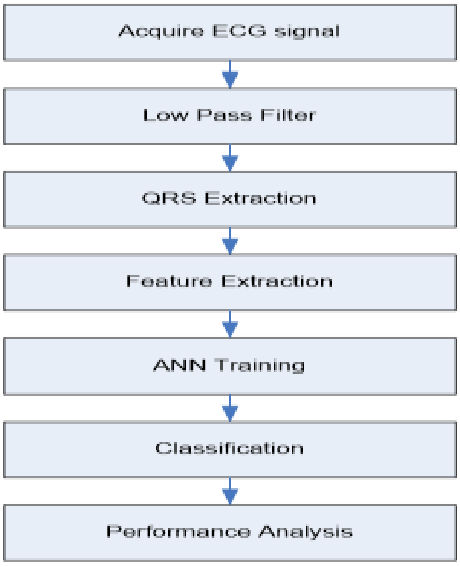


Figure 1: ECG Signal Analysis Framework

3.1 The ECG Dataset

The dataset used for this study was derived from the MIT-BIH database hosted by Physionet, described in Goldberger *et. al.* [9]. The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample.

The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Two or more cardiologists independently annotated each record; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110,000 annotations in all) included with the database attenuating this important signal.

A total of 48 ECG data samples representing the respective classes was utilised such that 70% of the data was used in training the ANN model and the remaining 30% used in testing and validating the ECG analysis model.

3.2 Detecting the QRS Complex

The detection of the major characteristic waves in ECG, namely the QRS complexes, P and T waves, is one of the essential tasks in ECG analysis. The performance of an automated ECG analysis system depends heavily on the reliable detection of these fiducial waves. The difficulties of characteristic waves detection lie in oscillations in the baseline, irregular morphology of the waveforms, and frequency overlapping among the wide-band distribution of the characteristic waves [10],

The QRS complex provides an insight into one of the features of interest, the heart rate and thus gives an accurate means to measure it. The QRS complex has the largest slope (rate of change of voltage) in a cardiac cycle by virtue of the rapid conduction and depolarization characteristics of the ventricles. As the rate of change is given by the derivative operator, the $\frac{d}{dt}$ operation would be the most logical starting point in an attempt to develop an algorithm to detect the QRS complex.

Pan and Tompkins [11, 12] proposed a real-time QRS detection algorithm based on analysis of the slope, amplitude, and width of QRS complexes. The algorithm includes a series of filters and methods that perform low-pass, high-pass, derivative, squaring, integration, adaptive thresholding, and search procedures.

The Pan–Tompkins algorithm maintains two averages of RR intervals: RR AVERAGE1 is the average of the eight most-recent beats, and RR AVERAGE2 is the average of the eight most-recent beats having RR intervals within the range specified by

$$RR\ LOW\ LIMI = 0.92 \times RR\ AVERAGE2 - (1)$$

and

$$RR\ HIGH\ LIMIT = 1.16\ \times RR\ AVERAGE2 - -(2)$$

Eq. 2 represents one of the most important features that are extracted from an ECG signal. This heart rate serves as an indication of the state of a patient’s health. The heart of all the features is the RR –interval, extracted from the QRS complex, using the Pan-Tompkins algorithm. Three other major features other than the heart rate are Spectral Entropy, Pointcare plot geometry and Largest Lyapunov Exponent

(LLE). These features serve to summaries the ECG data for further analysis and diagnosis.

3.3 Pointcaré Plot Geometry

It is a geometrical interpretation of the RR-interval. The Pointcaré plot of the RR intervals is one of the techniques used in heart rate variability (HRV) analysis. It is both a useful visual tool which is capable of summarizing an entire RR time series derived from an electrocardiogram in one picture, and a quantitative technique which gives information on the long- and short-term HRV. A Poincare plot of RR intervals is composed of points (〖RR〗 _i, 〖RR〗 _(i+1)), that is each point in the plot corresponds to two consecutive RR intervals. The resulting cloud of points is usually characterized by its length (SD2) along the line of identity and its breadth across this line (SD1). This is illustrated in Figure 2.

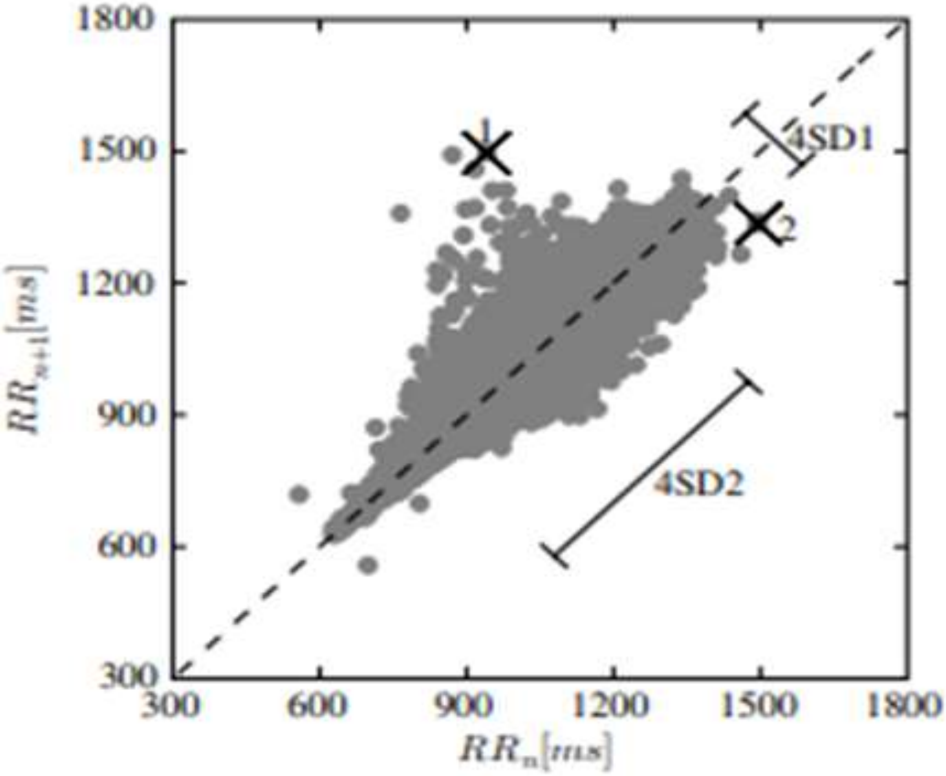


Figure 2: An example Poincare plot of RR intervals of sinus origin only, derived from a 4hr long recording taken from a 25 year old male during sleep, with the basic descriptors. The points marked with a cross correspond to an outlying (but still of sinus origin) point (1) and the consecutive point (2).

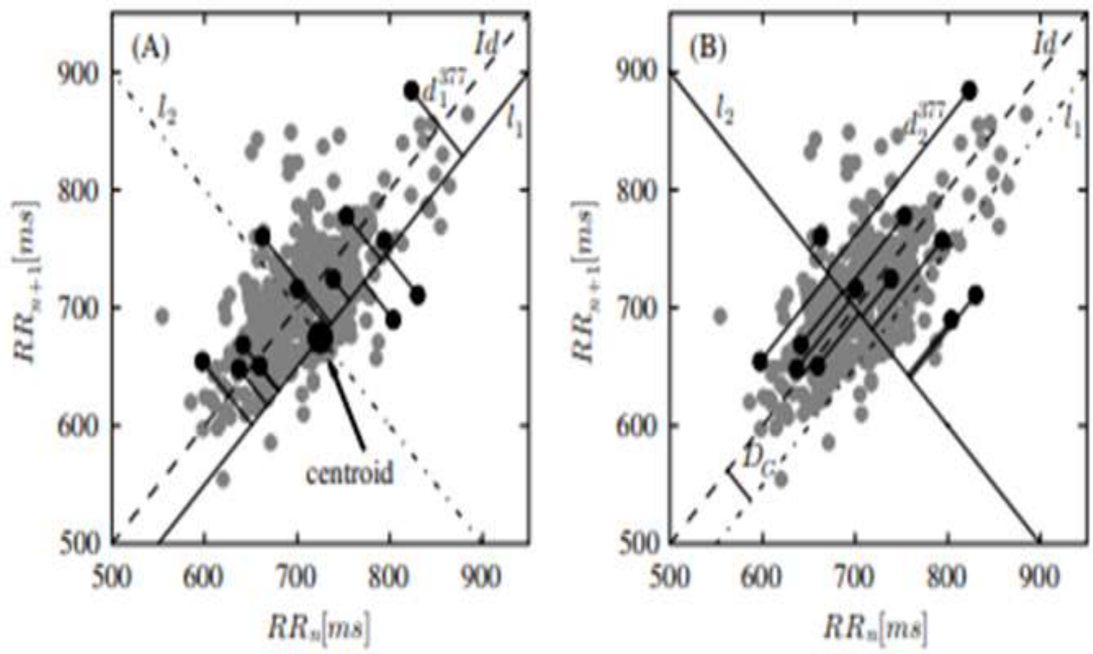


Figure 3: Calculation of the standard Poincare plot descriptors with the use of geometric language. The value of DC, which is the perpendicular distance from the identity line to the centroid (or l1), is exaggerated by a few orders of magnitude for better readability. Id stands for Identity line.

3.4 Applying Artificial Neural Network (ANN)

Having an ANN structure and the necessary training algorithm, a set of ECG signals representing the eight cardiac disorder were acquired. Their features (Spectral Entropy, Pointcare plot geometry and Largest Lyapunov exponent) extracted served as inputs to the ANN model. Their target class was a set of class ids from 1 – 8 mapped to those disorders, which were then used to train the ANN model on ECG diagnosis.

3.5 Performance Analysis

Many measures are used by practitioners for evaluation of classification accuracy of neural network. For beat classification, measures used are sensitivity, specificity, accuracy, MSE, Rate of Misclassification (RMC), and MCN etc. For signal classification, measures used were sensitivity, specificity, accuracy, ROC curve, MSE, training time etc. Moreover, confusion matrix is also used by researchers as a performance measure. Evaluation measures calculated from confusion matrix are Sensitivity, Specificity and Accuracy. Sensitivity is the ratio of true positive beats to total of true positive and false negative beats. Specificity is the ratio of true negative beats to total of true negative and false positive beats. The overall accuracy is the ratio of total number of true negative and true positive beats to total number of beats.

4.0 RESULTS

4.1 Feature Extraction Results

A typical example of feature extraction is taken from 100.dat ECG data whose waveform is shown in Figure 4. It is difficult to see the ECG pattern since the number of samples shown is large. Zooming into the ECG plot, between 0.7s to 10s, reveals a familiar ECG pattern as seen in Figure 5.

Though the ECG data shows a familiar pattern, it clearly doesn't look like the familiar ECG signal. This is due to inherent noise in the ECG raw data. Using QRS detection algorithm, the ECG signal was first scaled down to the specifications of the ECG sensor, then it was passed through a second-order Butterworth low-pass filter with centre frequency, $f_c = 20Hz$ as shown in Figure 6. The Pan-Tompkins algorithm was then applied to detect the QRS complex and the result is shown in Figure 7.

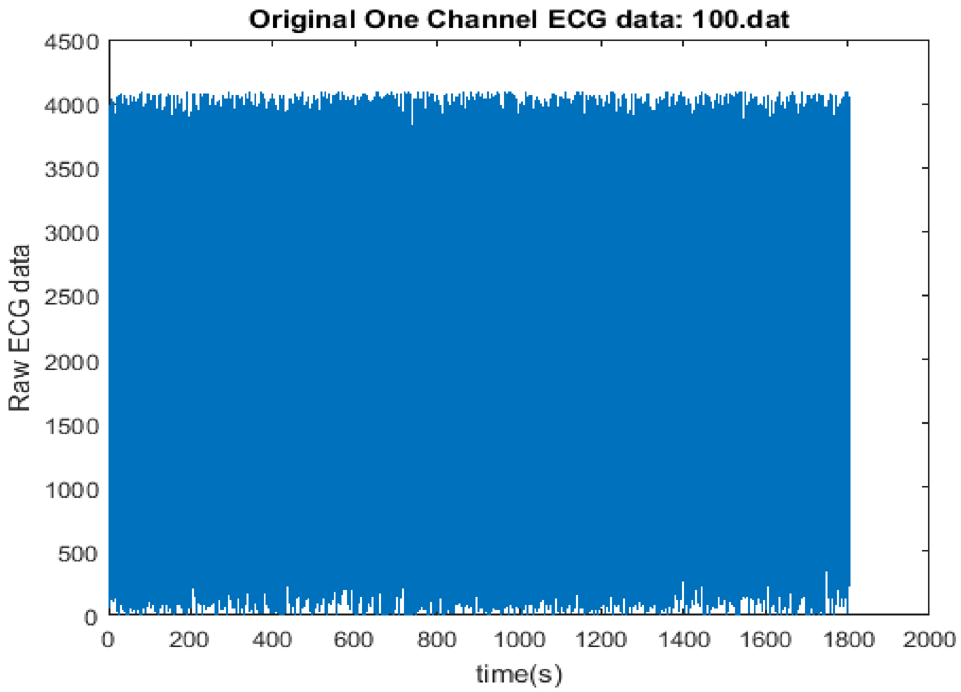


Figure 4: ECG Data 100.dat

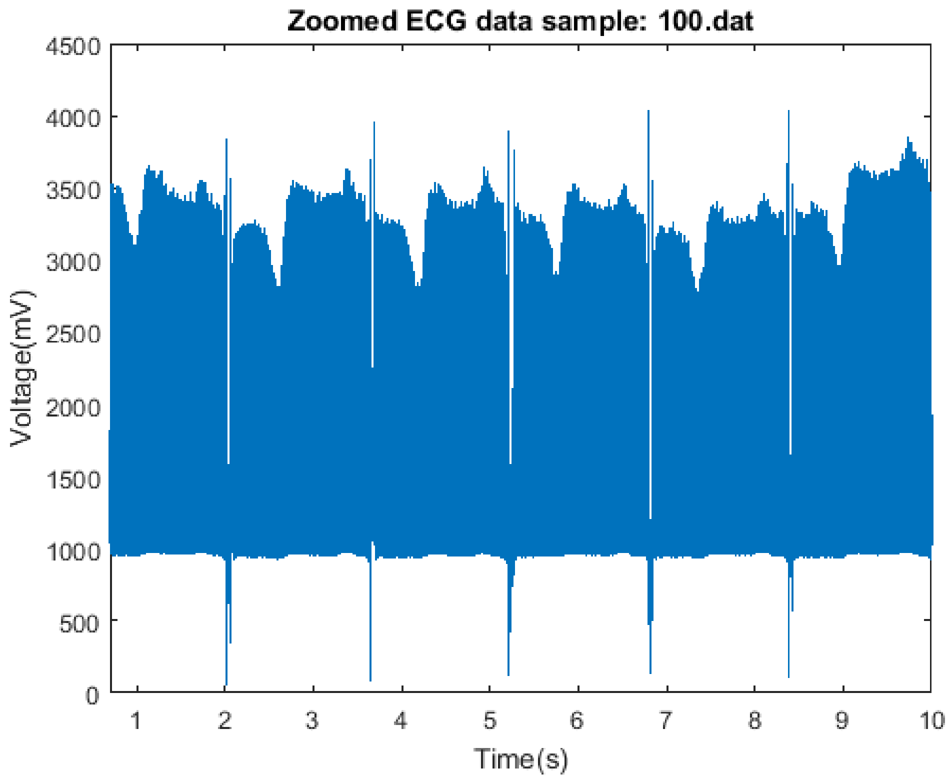


Figure 5: Zoomed ECG Data

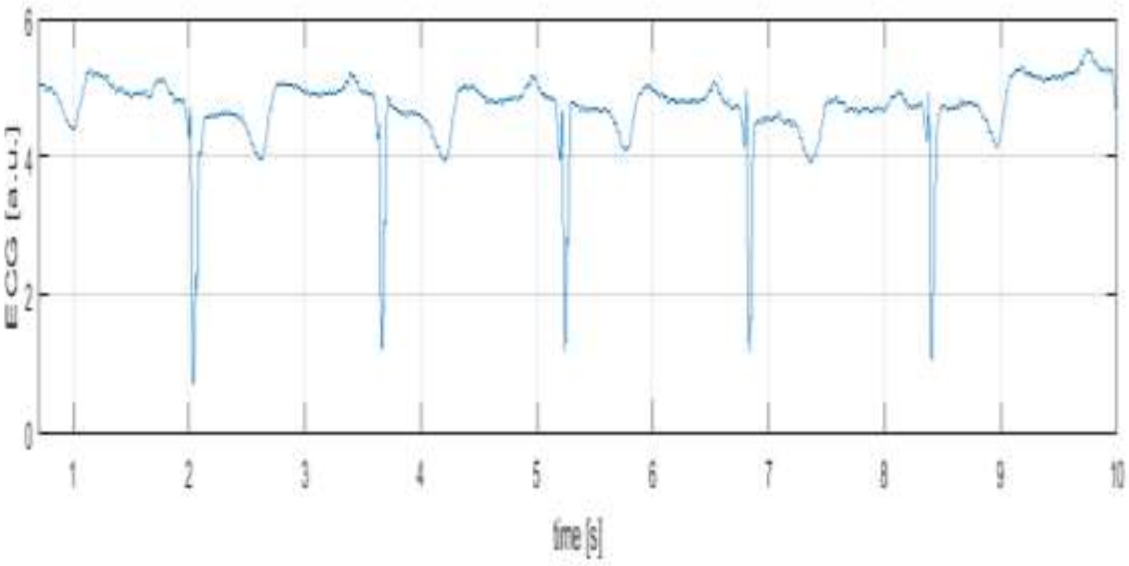


Figure 6: Second-order Butterworth low-pass filtered ECG Signal

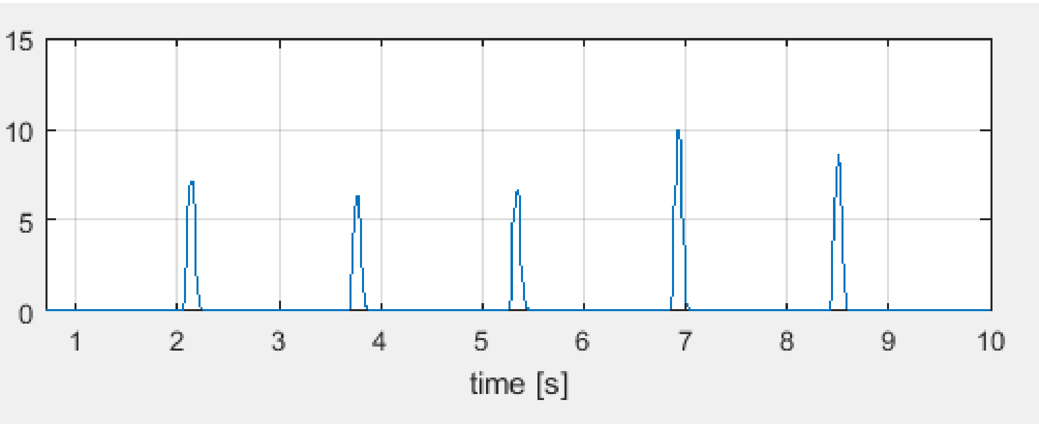


Figure 7: Detected QRS complex

Three features are extracted for the detected QRS complex; Spectral Entropy, Pointcare plot geometry and Largest Lyapunov Exponent (LLE). The result of these features are tabulated in Table 1:

Table 1: Extracted features for 100.dat

ECG Feature	**Value**
Spectral Entropy	2649.5
Pointcare	5.3226
Largest Lyapunov Exponent (LLE)	2.3553

4.2 Classification of the ECG Signals

The algorithm was applied to all 48 ECG data samples and classified into the eight chosen ECG cardiac disorders. An ANN feedforward network was modelled with 100 neurons in the hidden layer and 8 neurons in the output layer as shown in Figure 8.

The ECG signal was divided in training and testing data, with 70% of the data used for training the ANN model. The ANN model was set for 1000 training epochs, with the best performance achieved after 6 epochs, with a cross-entropy value of 0.4157 as shown in Figure 9.

A summary of the classification was provided using a confusion matrix, for the eight classes of ECG cardiac disorders as shown in Figure 10.

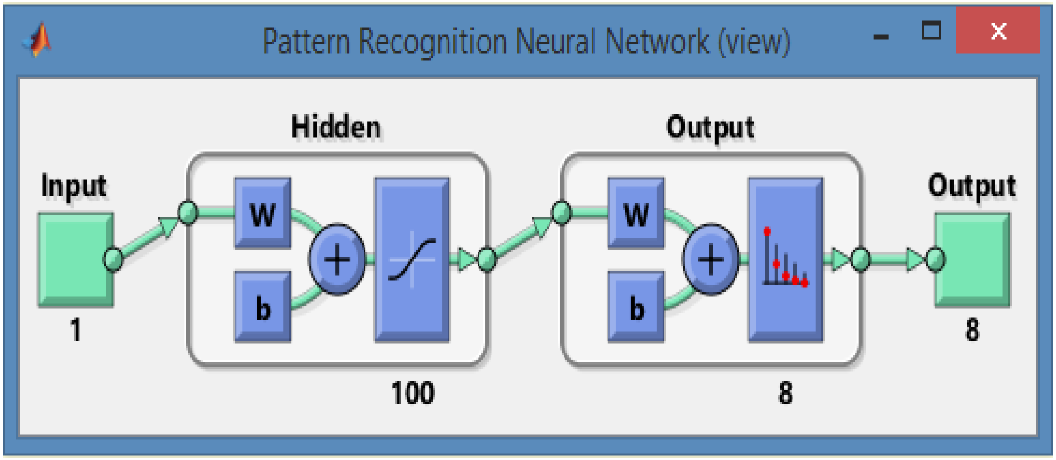


Figure 8: Feedforward ANN pattern recognition model

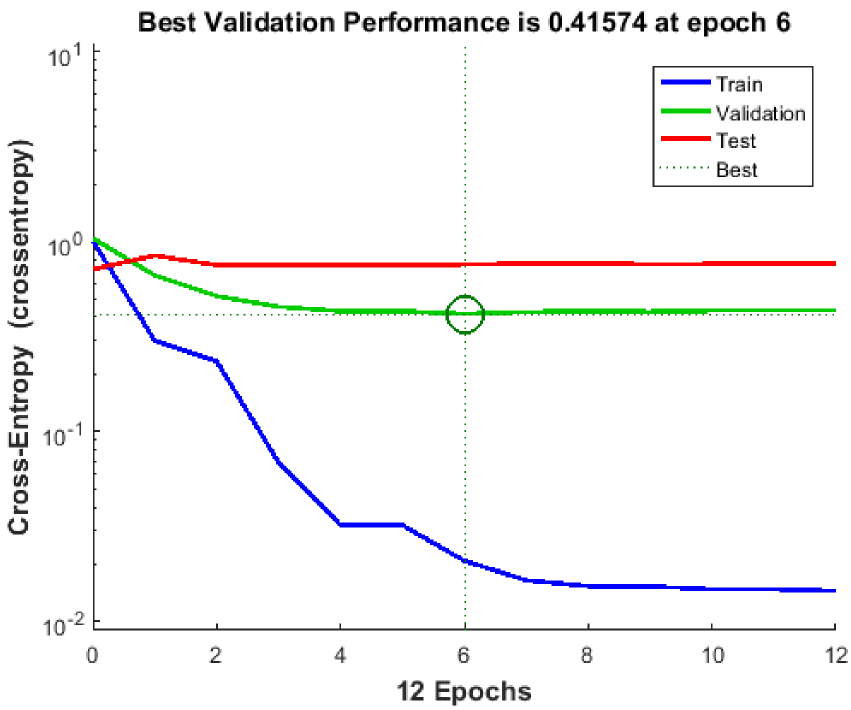


Figure 9: ANN Cross-Entropy Performance evaluation

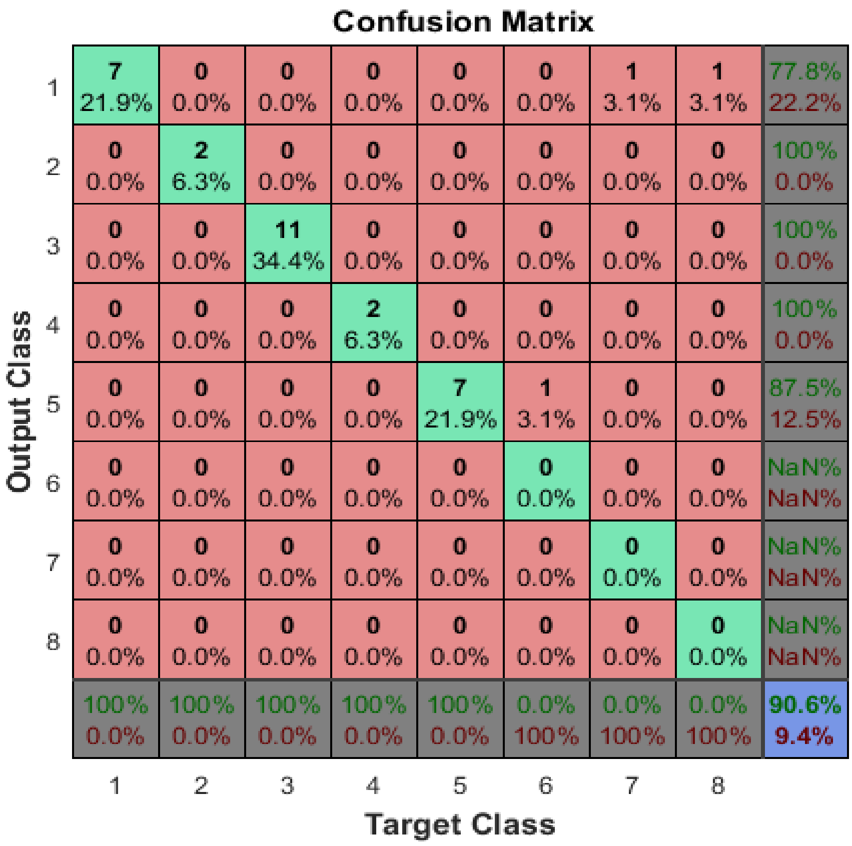


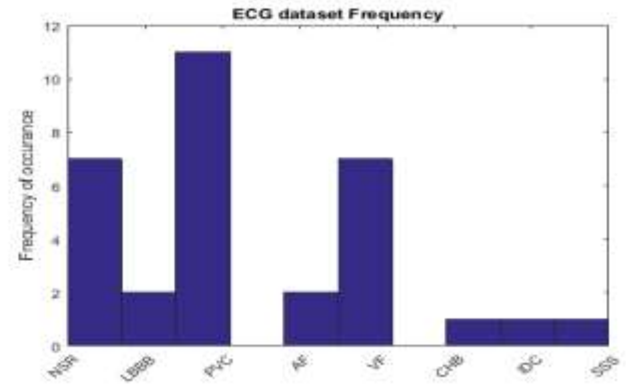
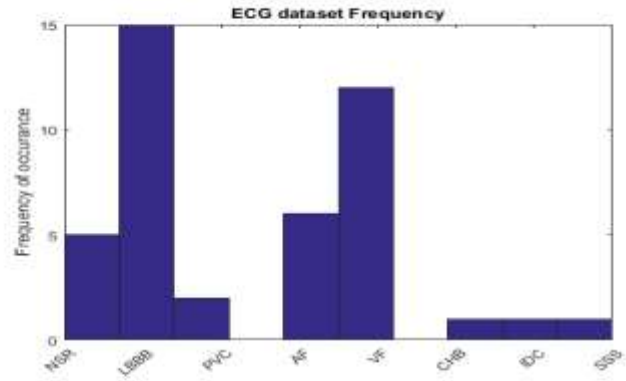
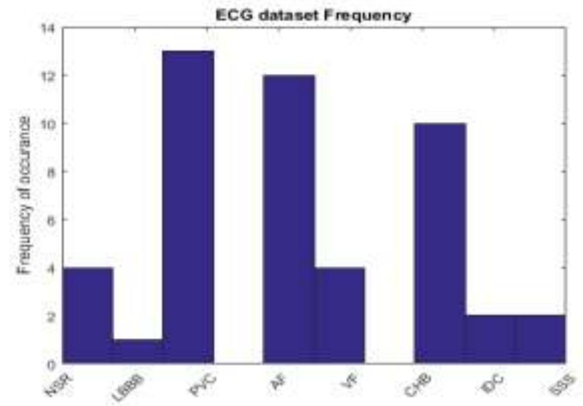
Figure 10: ECG Classification Confusion Matrix

In Figure 10 the first two diagonal cells show the number and percentage of correct classifications by the trained network. For example, 7 ECG signals were correctly classified as NSR out of the 48 ECG samples. This corresponds to 21.9% of all 32 ECG training data. Similarly, 2 cases are correctly classified as LBBB. This corresponds to 6.3% of all ECG analysis.

One (1) of the ECG data analysis was incorrectly classified as IDC and this corresponds to 3.1% of all 32 ECG training data. Similarly, one of the ECG analysis was incorrectly classified as VF and this corresponds to 6.3% of all ECG training data. Overall, 90.6% of the predictions were correct and 9.4% were wrong classifications.

It was observed that the Classification was seen to be 90.6% accuracy. This was due to the fact of using just 32 ECG data samples out of the provided 48 for training the ANN model. The histogram distribution further reveals this distribution and how it affects the result on the long run as seen in Table 2, when the dataset was increased up to 100% of the dataset.

Table 2: Result of increasing training data set

70% Data used	
90% Data used	
100% Data used	

It was obvious that this dataset was trivial and the minimum required to effectively train the ANN model for 100% classification accuracy. It is obvious that with just 32 ECG dataset used, the ANN model was able to achieve a 90.6% accuracy. This showed the ability of the ANN model to learn feature patterns provided to it. Improving on the accuracy entailed increasing the size of the dataset used and the accuracy increased further as evident in the confusion matrices of Figures. 11 and 12 respectively, with Figure 12 showing 100% accuracy when all the ECG data used. The accuracy of 100% should be expected if all the data was used, but with the percentage of the total data used showed how well the ANN model was able to perform the necessary classification.

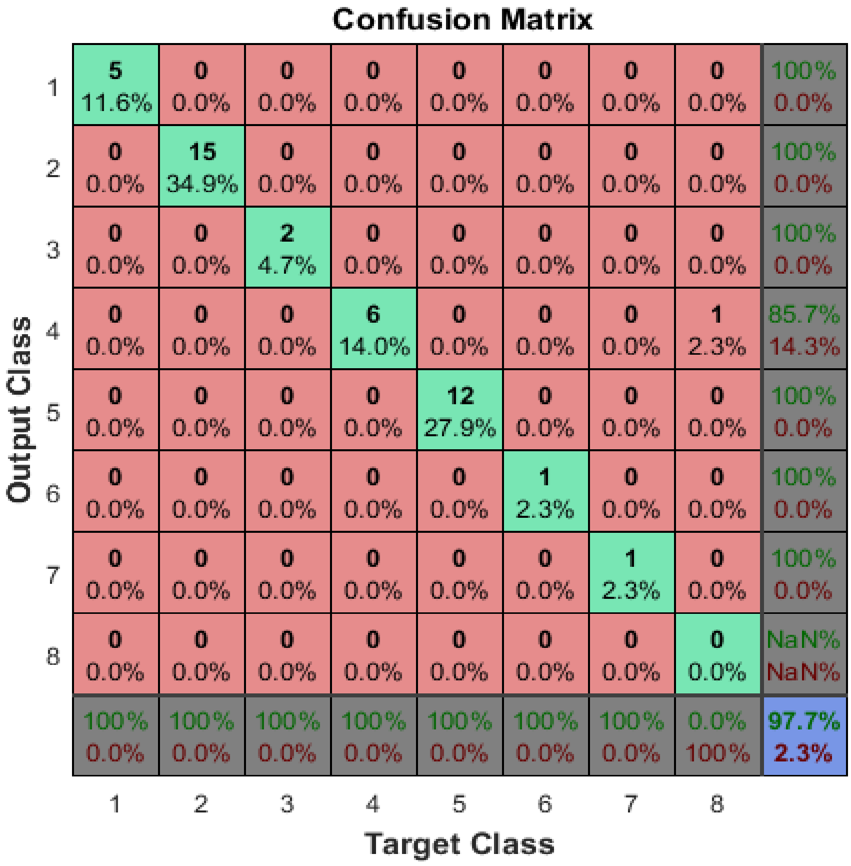


Figure 11: ECG Classification Confusion Matrix for 90% ECG Data

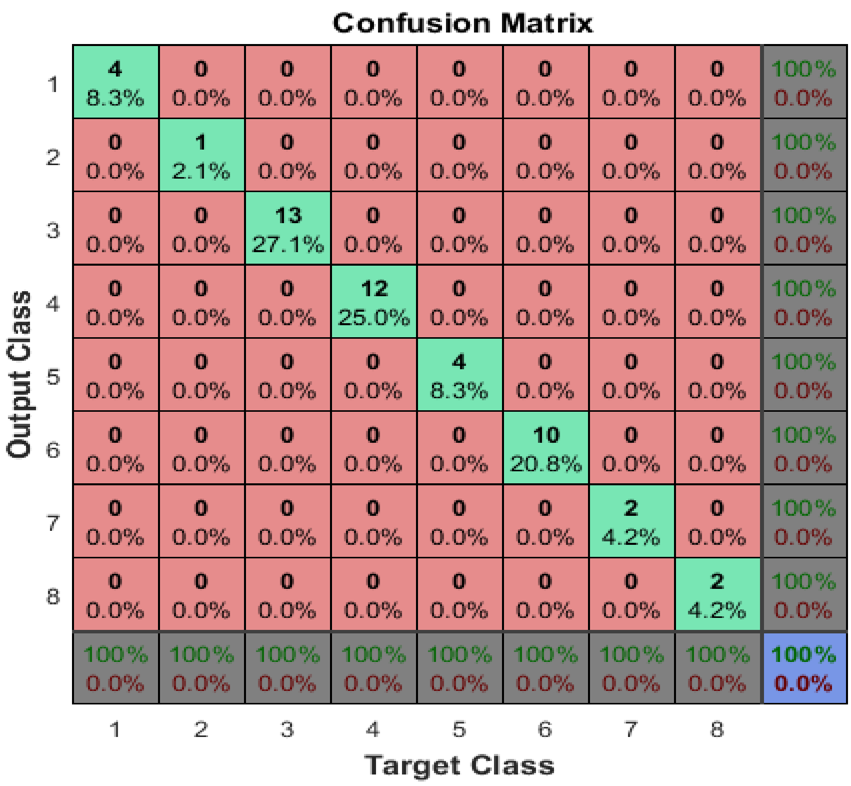


Figure 12: ECG Classification Confusion Matrix for 100% ECG Data

Figure 11 shows classification accuracy as a result of using the ECG data, ranging from 70% to 100% of the data for training and testing. It shows the PVC has the highest, followed by AF, etc. This was the actual amount of ECG data samples for each class group, but utilising less than the 48 samples provided introduced mis-classification, with the ANN model under-generalising. The MIT-BIH provided the exact amount necessary to provide the necessary model accuracy.

The analysis showed how the ECG signals was analysed utilising Pan-Tompkins Algorithm for QRS extraction and the subsequent extraction of the RR-intervals used for feature extraction. The features extracted each provided useful information about the ECG signal with the ECG spectral information extracted using the spectral Entropy feature, the RR-interval interpreted using the Pointcare plot geometry and the presence of chaos within the ECG data measured by the Largest Lyapunov Exponent. These features representing the large ECG dataset helped to enable the ECG ANN model identify and group the various cardiac disorders. The classification accuracy using these data samples and the developed ANN model was verified using confusion matrix which showed very good pattern matching.

5. CONCLUSION

The proposed ECG algorithm has shown notabe good performance in classifying ECG signals into the chosen ECG cardiac disorders. This is due to the fact that features were extracted such that the spectra of the ECG signal provided the necessary spectral entropy for varying degree of ECG variations. Also the heart rate variability geometry was observed using the pointcare plot summary and finally the stochastic and chaos inherent in the ECG signal was fully addressed utilising the Largest Lyapunov exponent. These there combined as features was able to map ECG signal to their appropriate more efficiently.

References

[1] Roth, G. A. *et al.* (2018). Global, regional and national age-sex-specific mortality for 282 causes of death in 195 countries and territories, 1980-2017: a systematic analysis for the Global Burden of Disease Study 2017. *Lancet* 392, 1736–1788.

[2] Tripathy, R. K., Bhattacharyya, A. & Pachori, R. B. (2019). A novel approach for detection of myocardial infarction from ECG signals of multiple electrodes. *IEEE Sens. J.* 19, 4509–4517.

[3] Singh, Y. N. and Singh S. K.(2015). “Bioelectrical Signals as Emerging Biometrics: Issues and Challenges”, *International Conference on Advances in Computer Engineering and Applications* (ICACEA), IMS Engineering College, Ghaziabad, India..

[4] Karpagachelvi S., Arthanari M. and Sivakumar M. (2010). “ECG Feature Extraction Techniques - A Survey Approach”, *International Journal of Computer Science and Information Security*, Vol. 8, No. 1.

[5] Tsipouras M. G., Fotiadis D. I. and Sideris D., “An arrhythmia classification system based on the RR-interval signal”, *Artificial Intelligence in Medicine*, Volume 33, Issue 3, 237-250, 2005.

[6] Bonsai M., Atouf I., Atibi M. and Bennis A. (2016). “ECG Signals Classification Using MFCC Coefficients and ANN Classifier”, *2nd International Conference on Electrical and Information Technologies* ICEIT.

[7] Memić J. (2017). “ECG Signal Classification Using Artificial Neural Networks: Comparison of Different Feature Types”, Part of the *IFMBE Proceedings book series*, Vol. 62, pp 467-474.

[8] Li H., Yuan D., Ma X., Cui D. and Cao L (2017). “Genetic algorithm for the optimization of features and neural networks in ECG signals classification”, *Sci. Rep*. 7, 41011.

[9] Goldberger A. L., Amaral L. A. N., Glass L., Hausdorff J. M., Ivanov P.Ch., Mark R. G., Mietus J. E., Moody G. B, Peng C-K., Stanley H. E. (2000) “PhysioBank, PhysioToolkit, and PhysioNet: of a New Research Resource for Complex Physiologic Signals”, *Circulation* 101(23):e215-e220.

[10] Emilio E. S., and Sober M. M. (1998). "Application of adaptive signal processing for determining the limits of P and T waves in an ECG", *IEEE Transactions on Biomedical Engineering*, 45:1077–1080.

[11] Tompkins W.J. and Pan J. (1985). "A real-time QRS detection algorithm", *IEEE Transactions on Biomedical Engineering*, 32:230–236.

[12] Tompkins W. J. (1995). "Biomedical Digital Signal Processing", *Prentice-Hall*, Upper Saddle River, NJ.