Cardiology Predictor: An aid to diagnosis of heart disease

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Abstract

Diagnosis of a heart disease is complex. Aspects such as clinical details, blood pressure, pulse rate, cholesterol level and blood test reports, and even patient's history, gender and age all are important when diagnosing cardiovascular disease. Interpretation of an Elector Cardiogram (ECG) is one of a key skill developed by cardiologists. Difficulties in analysing complicated ECG may lead to inaccurate diagnosis thus affecting the accuracy and quality with the diagnosis of cardiovascular disease especially among novice.

"Cardiology Predictor" is a software system which is capable of assisting medical practitioners to diagnose cardiovascular diseases accurately. The inputs to the system would be ECG and other cardiac factors which would be processed to provide an output of the possible cardiovascular disease. To ensure accuracy and efficiency, ECG signals are used with digital signal processing for decrypting and feature extracting. Furthermore, artificial intelligence is used to diagnose cardiovascular diseases due to the complexity embedded into it. Therefore, an Artificial Neural Network was used to predict cardiovascular disease. The average success rate of the system was 85.6% based on the user evaluation. Domain experts such as cardiologists suggested that the system is most suitable for the emergency room where expert knowledge was not readily available.

Keywords - Cardiology predictor; Electrocardiogram; Signal processing; Artificial Neural Network; ECG

Introduction

Medical treatment has always been an area of utmost importance. Modern medical practitioners use technology to support their decisions in order to ensure accuracy and treat patients in an effectively. However, sometimes human error is a decisive factor in patient care decisions. This is one of the main reasons for inaccurate diagnosis.

Within the complex medical subject matter, cardiology is one of the main areas that face difficulties. Inaccurate and inefficient cardiology diagnosis could lead to dire consequences. Therefore, cardiology is a delicate area that needs high accuracy levels in comparison to some of the other medical areas. At present, medical practitioners who use ECGs to diagnose cardiovascular diseases are specially trained to interpret ECGs. However, in reality, ECG patterns could be comparatively different to the pre-defined patterns that are available in theoretical situations. Therefore, specialised skills, training and knowledge are required to analyse and diagnose cardiovascular diseases, using ECGs. The lack of specialised cardiologists in rural areas has been a problem and in such situations computerised analysis of ECG reports can assists non cardiovascular medical practitioners to make quick and correct decisions. However, more research is required to generate ICT based cardiology assistance.

This paper proposes the Cardiology Predictor as an aid to non-specialised medical practitioners. Figure 1 gives a schematic representation of the system. This is facilitated by feeding in a given ECG, the patient's history and other factors such as blood pressure and pulse rate to an Artificial Intelligence System, which enables the Cardiology Predictor to generate a diagnosis as an output.

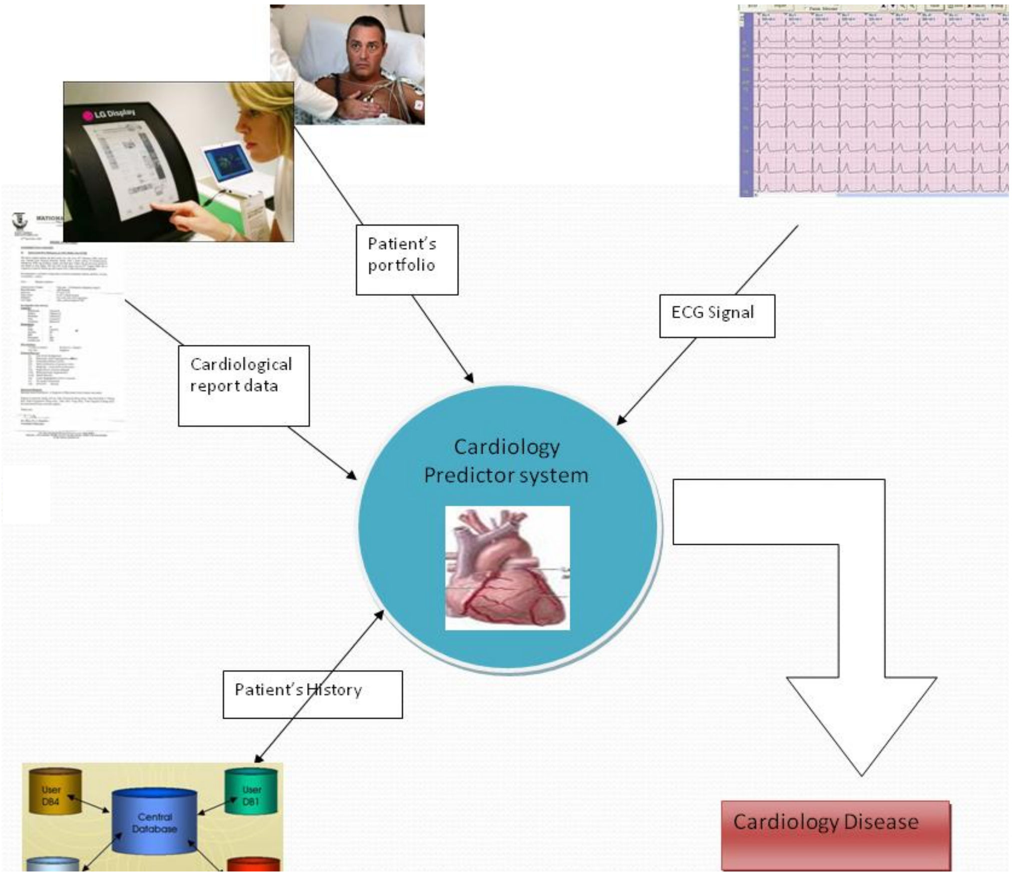

Figure 1. Schematic presentation of the System

The shortage of powerful systems for pattern recognition in the medical field has accelerated research and development. Confirming this, Cios(1) stated that experts argued about the appropriate methodology for accommodating medical data such as Electrocardiograms (ECGs). The discussions focused on artificial intelligence, hybrid systems, data mining systems and rule-based systems. Hudson and Cohen(2) argued that artificial intelligence was a better solution for many medical assessments with fuzzy data.

Literature review

Van Mieghem et al(4) stated that electrocardiograms were an important component in cardiology as it gives an accurate diagnosis of the heart. However, medical practitioners find it rather difficult to give a proper and accurate diagnosis using the ECG unless they have specialised themselves in the area, particularly because ECGs contain very complex and fuzzy data. Hudson and Cohen(2) carried out investigations and evaluations in order to discover a methodology to increase the efficiency and accuracy of the ECG diagnosis.

Sornmo and Laguna[5] point out image processing and signal processing as suitable processing methods to analyse ECG data. According to Sitar-Taut[6], the aim of image processing is to prepare the ECG image for transformation using the wavelet transform where wavelet features may contain richer and more discriminative information for expression classification. Confirming this, Hennings et al[7] state that the aim of ECG signal processing is to extract information not readily available from the signal. However, according to Sornmo and Laguna[5], ECG signals are frequently overwhelmed by impulsive noise due to muscle activities and power line interference. Therefore, noise filtering is typically the first step performed in processing ECG signals.

Electrocardiogram is the most common time series fuzzy data that is used for clinical and emergency diagnostics. According to Hudson and Cohen[2], analysing time series fuzzy data is extremely complex and needs a high level of intelligence and training. With the help of Figure 2 they elaborated that automatic analysis of ECGs that have built in patterns is largely dependent on variations from the normal QRS complex and that the maximum ST depression is a feature extracted from the QRS complex of the ECG.

Also, in addition to the ECG, the heart rate and R-R interval fluctuations are important features in the chaotic analysis of the ECG. After considering many approaches such as Bayesian, Heuristic, Expert systems, Markov, Self-organising map and Artificial Neural Networks (ANNs), to deal even with nonlinear discrimination between classes and to accept incomplete or ambiguous input patterns, Mitra and Liu[8] state that existing approaches generally tend to suffer from problems that result from high sensitivity to noise included in the data and unreliability in dealing with new or ambiguous patterns.

Also implementations of ANN-based ECG classification schemes have, in general, focused on problems within narrow clinical domains. Since ANNs are inherently nonlinear, further research has been done and various ANN classifications such as Transform Neural Networks, Recurrent Neural Networks, and Back Propagation Neural Networks have been used for ECG analysis[9]

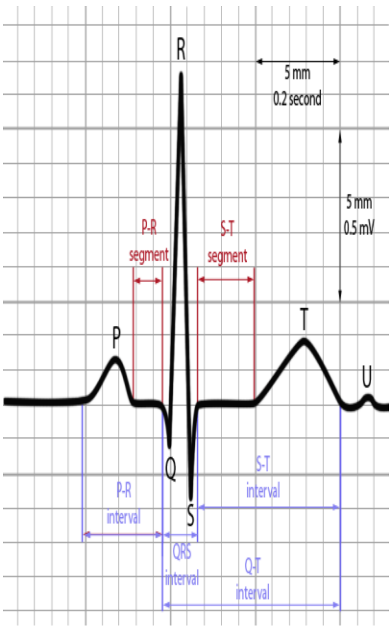

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Figure 2. ECG Waveform

With new knowledge available from the theory of ANNs combined with a proper data input process with signal processing where noise filtering removes unwanted waves, the stage was set for moving towards the development of a practically applicable ANN-based clinical ECG interpretation systems.

Method

A qualitative method was used to gather information by conducting in depth interviews with different stakeholder categories such as doctors (15), nurses (10), medical students (25), biomedical engineers (2) and other medical practitioners (6) to gather domain specific knowledge.

With the analysed and categorized data, functional and non-functional requirements were derived followed by a design which was mapped into architecture as shown in Figure 3 that defines the components, interface and their behaviours.

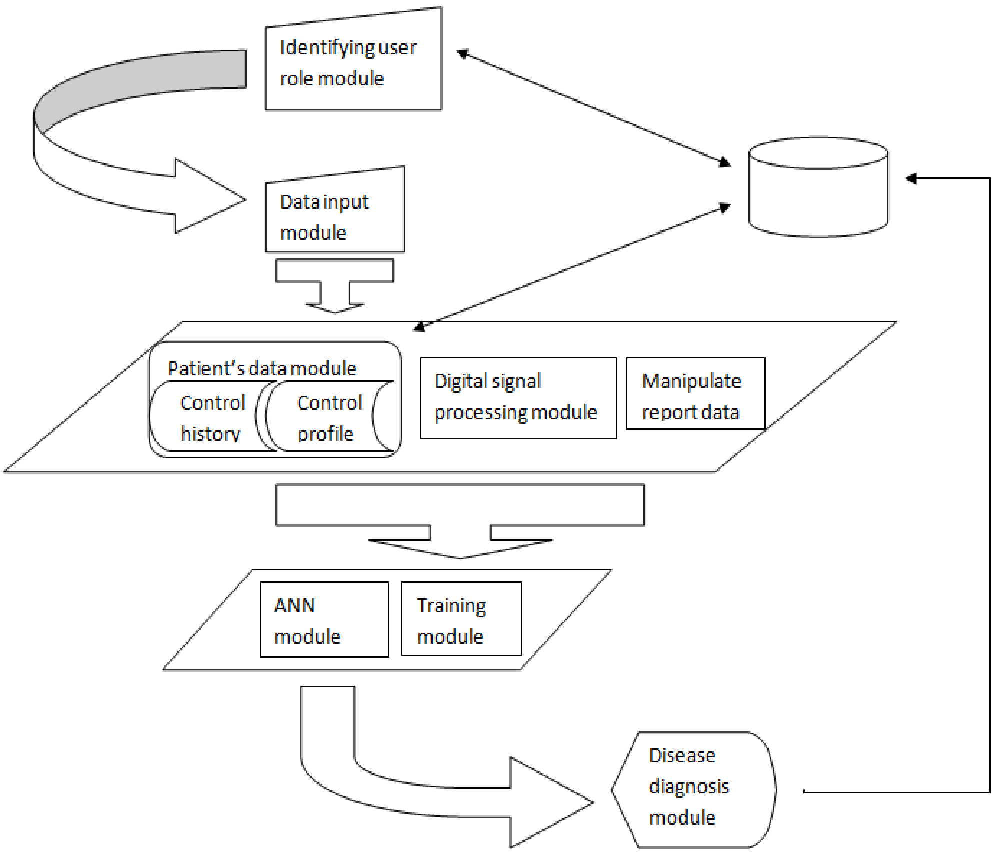

Figure 3. High Level Diagram

The high level architecture depicts the modules of the 'Cardiology Predictor' system and the relationship between each module. Identifying the user role module and data input modules are managing manual inputs to the system. Identifying the user role module takes place with the manual input of username and password provided by the administrator. Manual input is taken through the user interface and the inputs will be validated against the storage which has a corresponding user role such as a medical doctor, nurse and medical student. Similarly, the data input module contains ECG signal input which will be selected through a file chooser. Patient's profile details such as age and gender are taken as additional inputs to the system. Additionally, the user is facilitated to enter medical details such as blood pressure, pulse rate to enhance the cardiovascular disease prediction. Within the patient's details module, the system retrieves the patient's history from storage. This consists of the ECG report, medical diagnosis and the predicted cardiovascular disease in the previous diagnosis. Moreover, the diagnosis depends on the patient's age and gender as well. Therefore, the patient's age and gender is retrieved when entering data to the system which is then passed on to the trained neural network in order to obtain the interpreted cardiovascular disease.

To define a pattern recognition problem, it is necessary to arrange a set of Q input vectors as columns in a matrix. Then arrange another set of Q target vectors so that they indicate the classes to which the input vectors are assigned. Therefore, the most suitable type of defining a problem for the 'Cardiology Predictor' was selected to be 'Recognising a Pattern'.

Technical Implementation

Implementation of the digital signal processing module was the most critical component of the project. ECG signals (Figure 4) are decrypted according to the protocol extracting the real voltage values from the ECG signal.

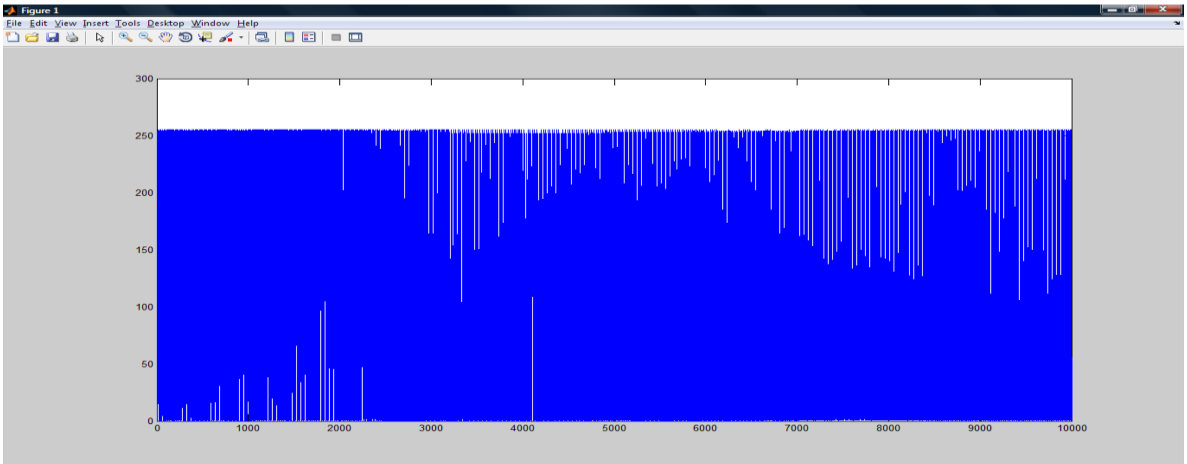

Figure 4. ECG Signal in Analogue Format

The decryption function rdsamp()[10] was used to read signal files for the specified record and write the samples as decimal numbers on the standard output. A legible ECG that was decrypted using the open source rdsamp() functionality is shown in (Figure 5).

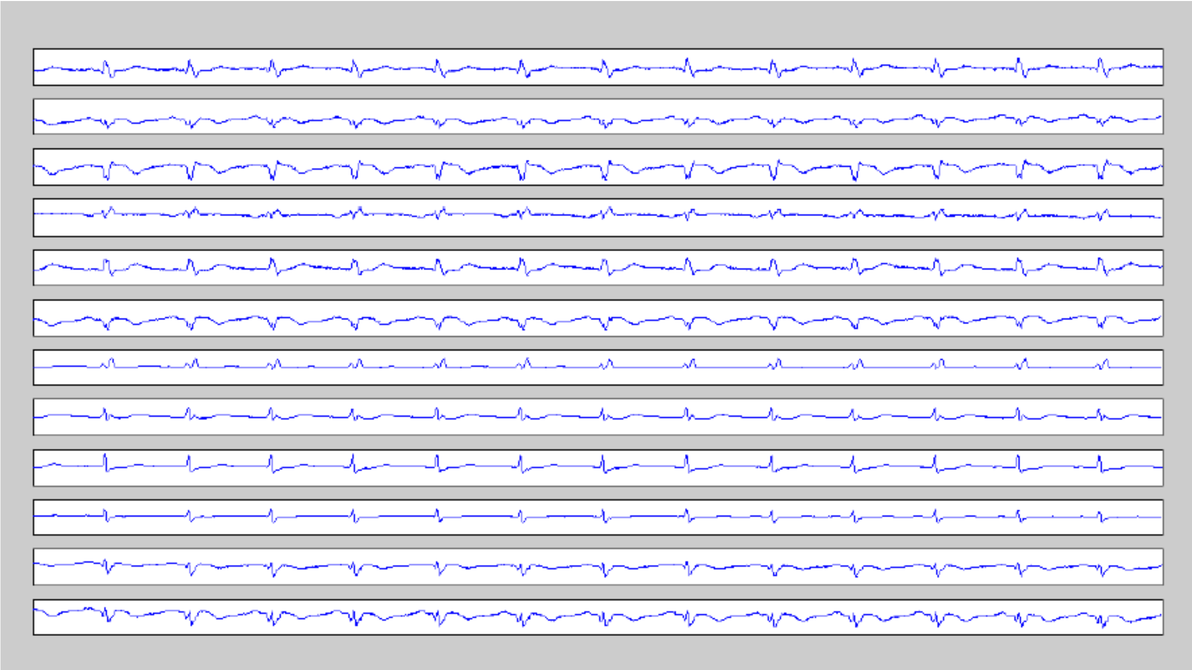

Figure 5. Decrypted ECG Signal

The decrypted ECG signal is used to extract several features from the ECG using the algorithms that depict the same theories as the medical practitioners use. Firstly, the average of the data set was calculated in order to decide on a threshold value that was to be used to track the peaks of the ECG. The threshold was set as a proportion (value of proportion variable) of the difference between the calculated average and the maximum value of the data set. To overcome the problem of detecting the local maxima within a peak, minimum difference variable was initialised with the minimum possible heart rate period. (Figure 6).

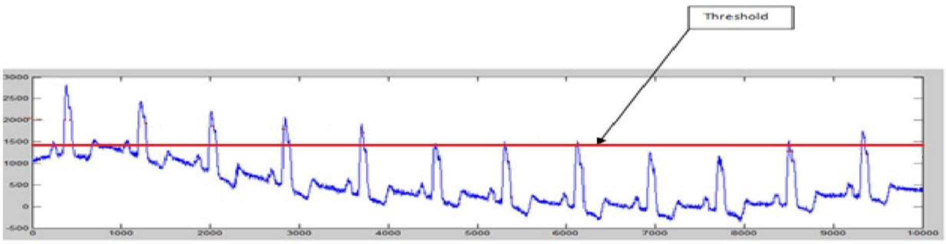

Figure 6. Threshold Value

To enhance the detection of the peaks and to be able to incorporate all peaks, the threshold was calculated for small intervals, resulting in a higher level of accuracy in heart rate extraction. Right ventricular hypertrophy could be checked because the S wave of the ECG is more visible than the P wave of the EGC in this condition. As a result, peak calculation was done using the S wave rather than the P wave which resulted in successful heart rate extraction.

Implementing axis extraction helped to determine whether Lead I (Figure 7) has a positive QRS with a similar method that was adopted in calculating RR-Interval. For the corresponding time value of QRS waves, a positive orientation or a negative orientation in Lead VF (Figure 6) was observed. The comparison of the difference between the local maximum and local average was calculated against the difference between local minimum and local average. The process was exercised on every QRS wave that was present in the signal and most of the time similar orientation was observed. This process was implemented on every QRS wave that was present in the signal and most of the time we observed similar orientation for all QRS waves within the same signal. In the rare case of having varying orientations within a signal, the result of this algorithm was based on the most common orientation.

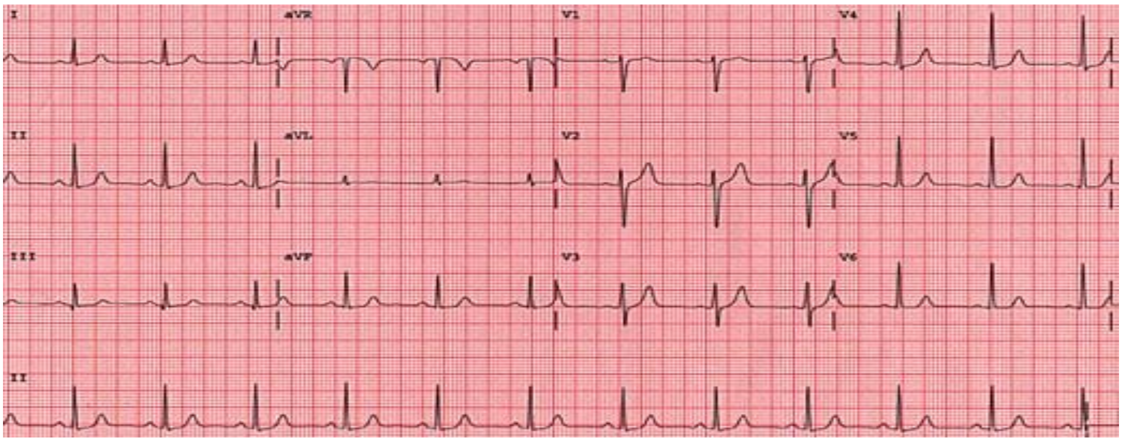

Figure 7. ECG Leads

In order to implement the hypertrophy feature extraction, the average values for S wave of V1 (Figure 7) and V2 were calculated. Similarly, average values for R wave of V5 and V6 leads were calculated. The calculated average values were considered as S wave/R wave of the corresponding leads. The larger S wave of V1 or V2 was added to the larger R wave of V5 or V6. If the sum is > 35mm, it meets "voltage criteria" for LVH (Left Ventricular Hypertrophy). Likewise, the average of R wave and S wave of V1 lead and the average of R wave of lead V6 were calculated. For R wave > S wave in V1 and R wave decreases from V1 to V6 it is taken as RVH (Right Ventricular Hypertrophy).

Extracted ECG data and other report data such as blood pressure, pulse rate were passed to the ANN where recognising a pattern algorithm was used to implement the ANN module. Training of the ANN was done using the ‘recognising a pattern’ algorithm of MATLAB. The data set consists of 320 samples while input, ‘ANN_input’ being a 7*320 matrix, constancy rows that are heart rate, axis, hypertrophy, age, blood pressure1, blood pressure2, pulse rate. The data set for target, ‘ANN_Target’ being a 4*320 matrix that’s rows are; Myocardioal Infarction, Artrial Hypertension, Healthy Control and Other Cardiac Disease and where each column indicates the correct category with one in one element and a 0 in the others. Implementation according to the design was accurate with 79.7% success rate (Figure 8).

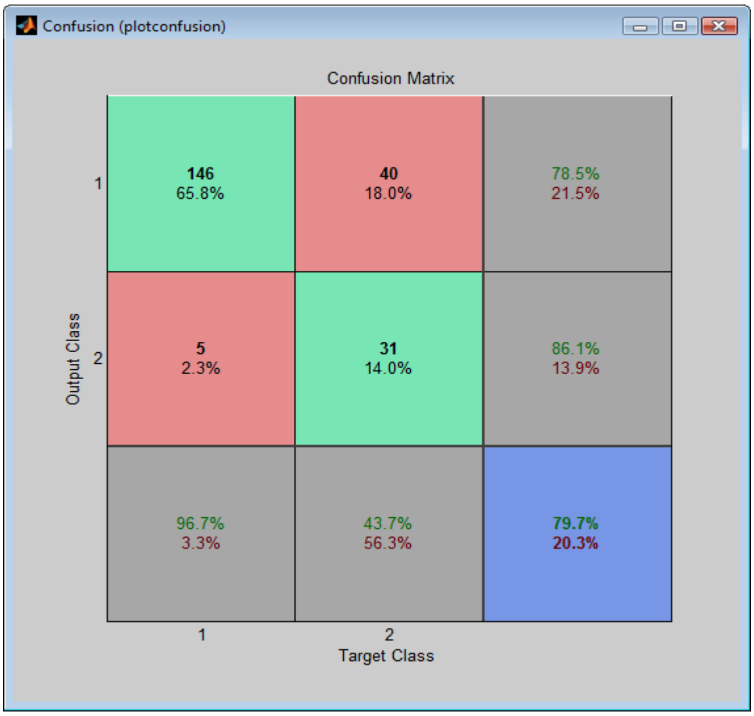

Figure 8. ANN Accuracy

The Graphical User Interface (GUI) was created using C# (Figure 9) providing a user friendly interface. The GUI is capable of taking the user inputs and processing the ECG signal input with signal processing. Subsequently, extracted features together with other user inputs are fed into the artificial neural network to obtain the predicted cardiovascular disease and display the output.

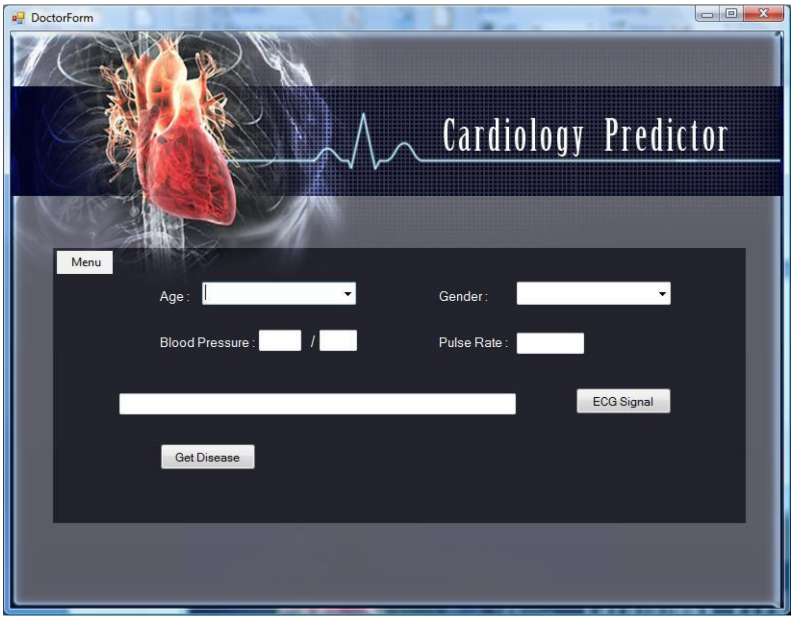

Figure 9. The Graphical User Interface

Performance

The design signal processing module of the ‘Cardiology Predictor’ was extensively tested as the module represents the crucial component that leads to the output. Testing was carried out in order to verify that the decryption of the ECG signal showed 100% accuracy. Moreover, each feature extraction algorithm was tested in order to confirm that the algorithm suits any ECG signal and gives a reliable output. As a result, features such as heart rate and axis were tested critically and the results were mathematically obtained. Several test cases were written to test the accuracy of the signal processing module.

Heart rate extraction was tested with 10 random ECG signals where each output of the system was compared against a doctor’s interpretation. The heart rate is a numerical value where the accuracy can be checked with the help of variation. Simultaneously, a graph was drawn (Figure 10) which shows the expected output and observed output for each ECG signal. The standard deviation of the tests was calculated to check the level of variation from the expected output.

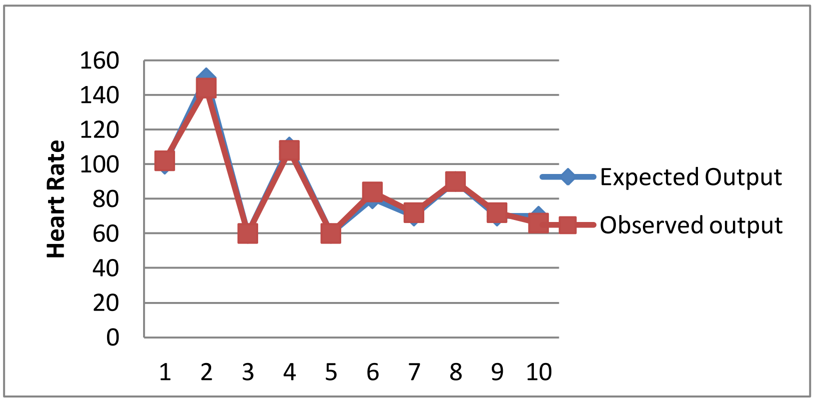

Figure 10. Heart Rate Extraction Testing

To check the accuracy of heart rate, standard deviation for variance was calculated in order to provide evidence on accuracy. The t-distribution for the above graph was 0.11375 suggesting that the level of accuracy in heart rate extraction from the ECG was at an acceptable level. Doctor’s interpretation of the heart rate always resulted in the value rounded to 10 as mentioned in the medical theory of six-second method[3]. Meanwhile, the system interpretation was more accurate as the calculation was done for 10 seconds rather than six seconds.

Similarly, the axis extraction of the ECG was tested against the doctor’s interpretation for a random set of data. According to the tests carried out, the error rate was calculated which gave a value of 4%. This was considered to be a very low error rate. As the error rate of 4% was relatively low, we could conclude that the extraction of the axis is effective and is ready for use.

As the main modules of the system were tested and passed, testing of the output can begin. The output of the system was tested for its accuracy and efficiency. Accuracy of the system output was very important as described in the project aim. Likewise, the efficiency of the system was also important as the system will be used in the emergency unit of a hospital and detecting a severe cardiovascular disease fast is a core requirement. The testing of the output took place using 120 ECG data. Furthermore, the system was evaluated by 16 domain experts who consist of cardiologists working at national hospitals and private hospitals. Also, the system was evaluated by 55 possible users such as doctors, medical students and nurses under the evaluation criteria such as concept, usability, performance and approach. The average success rate of the system was 85.6% based on the evaluations (Table 1).

Therefore, it is concluded that the system output is accurate and reliable. Also, it was observed that the time taken for the interpretation is, in fact, efficient which took less than 1 minute for the interpretation. Efficiency of the system should be further checked with the help of a doctor and this will be done during evaluation.

Table 1. Results of user evaluation.

Targeted Group	**Concept**	**Usability**	**Performance**	**Approach**
Cardiologists	80%	85%	75%	-
Bio-medical Engineers	-	75%	85%	90%
Doctors	95%	90%	95%	-
Medical Students	95%	90%	80%	-
Academics	95%	-	80%	80%
Personnel	95%	80%	80%	85%

Conclusion and future work

The Cardiology Predictor extracts several features such as heart rate, axis, and hypertrophy, from the decrypted ECG signal. The feature extraction is 100% accurate as it is done with implemented algorithms based on medical theories. These features were fed into ANN with other data, in order to predict cardiovascular diseases. Current trained ANN system has an 80% accuracy level where it is closer to expert's diagnosis. Also, the accuracy could be improved with increasing the number of training data. The system can be enhanced by detecting sudden cardiac diseases. The ECG signal which holds sudden death has different features as shown in Figure 11. ECG signal shows some differences when a patient is experiencing a close death. Therefore, it is possible to identify sudden death cardiovascular disease. In order to read and identify this particular ECG, the system requires a different algorithm. When an algorithm is implemented, the system will be able to identify sudden deaths.

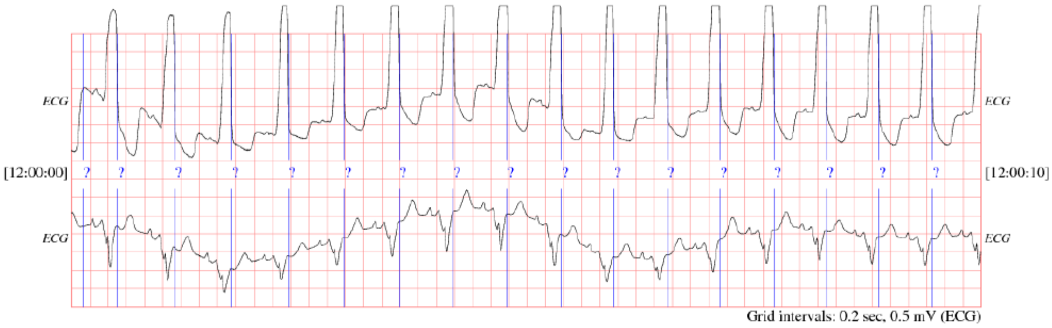

Figure 11. Sample ECG featuring Sudden death

Cardiology Predictor is a successful project which is aimed at a wide research community and provides a solution to assist medical practitioners, in order to interpret cardiovascular diseases accurately and efficiently. With the intention of meeting the target, research and computation methodologies were used. Implementation of the 'Cardiology Predictor' system was done with the help of reliable technologies such as digital signal processing and artificial neural networks.

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