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QTc as Predictor of Cardiac Autonomy Function in Type-2 Diabetic Patient Using Neural Network

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Abstract
The Cardiac autonomic neuropathy is a major issue in patients diagnosed with diabetes. Prolonged QTc is inclined to ventricular arrhythmia and sudden cardiac arrest. QTc prolongation shows a positive relationship with a degree of cardiac autonomic neuropathy in diabetic patients. This study intends to make a prediction based on the consecutive QTc prolongation of diabetic patients based on their ECG report taken in 3-5 years. A good prediction of the model designed with the help of the input and output data has been obtained with the help of an artificial neural network. The least mean square error can give us the best prediction result of our targeted output data.

Keywords
QTc Prolongation, Cardiac Autonomy Neuropathy, Arrhythmia, Artificial Neural Network, Prediction

Introduction
Cardiac Autonomic Neuropathy (CAN) is known as “silent killer” because the patients suffering from it are unable to realize at preliminary stages. As discussed in the paper [1], cardiac autonomic neuropathy is a major issue in patients diagonized with diabetes. Diabetes is a metabolic disorder which is analyzed by raised hemoglobin sugar levels in the body that affects some of the body parts like eye, kidneys and also leads to heart break down. Early detection of cardiac autonomy neuropathy and intercession are the prime importance for risk delamination in averting sudden death due to silent myocardial infarction. QT_c interval prolongation is considered to predict sudden cardiac death in both type 1 and type 2 diabetic patients. QT_c interval is also found to be an independent risk factor for strokes in type 2 diabetic patients. As per the discussion in the paper [4], type 2 diabetics with NSTEMI have greater QTc max and may have a relationship with worse cardiac outcomes and poorer prognoses. Diabetic patients having both QT_c prolongation and cardiac autonomic neuropathy can be utilized for the risk stratification for cardiovascular mortality. QT interval corrected for heart rate is a significant predictor of cardiovascular mortality. One of the possible ways to avoid risk in a diabetic patient is to use QT interval analysis measured from the electrocardiogram [2].
When plotted the signal in MATLAB with the help of patient digital data that has been recorded for 10 seconds, a lot of noises founded in the signal. So, first of all, it is required to filter the signal to make it noise free. So many techniques are available for noise cancellation. Since our signal is non-linear, time-varying and non-stationary, so discrete wavelet transform technique are very much useful for noise cancellation in ECG signal [5]. Since wavelets are localized in both time and frequency, and it can separate the signal into multi-resolution components, for analyzing non-stationary signals such as ECG it has jumps and non-smooth features.
The application of artificial intelligence is increasing day by day which leads to the increased implementation of neural networks. Paper [9], clearly depicts that these neural networks are inspired by different biological neural networks which provided a platform for integrating intelligent systems. In recent years, profound implementation of neural network has been there to achieve different tasks, e.g., weather forecasting [3], stock market prediction [10], diagnosis of breast cancer [6].
As discussed by the authors of the paper [7], different models have been developed to analyze the data from several diabetic patients. Having the QTc data of all the patients help to make a model for the prediction analysis. The number of times QTc value of the patients creates the input set for the prediction model. Taking the mean value of the data gives the data set for the model output. Using standard scaled conjugate algorithm [6] the training process of the model with a definite number of neurons and hidden layer takes place. It is completely based on the number of experimentations that at which iteration the model gives the best output that nearly matches our target output.

Electrocardiogram
The electrodes placed on the skin of a body records the electrical activity of the body over a certain period of time is generally known as an electrocardiogram. During each heartbeat, the electrode detects the tiny electrical changes on the skin arise through the heart muscle in the process of depolarizing and re-polarizing.
The QT interval is measured from the beginning of the QRS complex to the termination of the T-wave and it is measured in milliseconds. The QT interval on the electrocardiogram defines the total duration of ventricular

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polarization and depolarization. If there is a presence of U wave in the signal, QT is measured to the zenith of the curve between the T and U waves. The QT interval corrected is calculated by the Bazett's formula [2, 8].

$$QT_c = \frac{QT}{\sqrt[2]{RR}}$$

The normal range of QT_c for the healthy person is < 440ms for male and < 470 for the female. Once the person exceeds the normal range, he or she comes under the prolonged QT_c value that increases the chances of sudden cardiac arrest.

Noises in ECG Signal

A large number of noises interfere while recording ECG signals. While some of the significant ones are discussed below:

a) POWER LINE INTERFERENCE: Occurrence of this type of interference is due to electromagnetic interference by a power line; grounding fault of ECG machine or patient, as well as electromagnetic field by nearby machines creates such noises.
b) BASELINE WANDER: It is a low-frequency noise component present in the ECG signal. It occurs due to the respiration or body movement. Baseline wander has a frequency greater than 1Hz.
c) CHANNEL NOISE: When ECG signal is transferred due to poor channel connection such noises occurs in the signal.
d) ELECTRODE CONTACT NOISE: Improper contact between electrode and skin generally disconnects the measurement system from subject produce such type of noises.

Denoising the Signal

The signal generated through the raw data in MATLAB contains noise in it. So, it is very important to remove the noise from the signal to get the actual value of QT from the signal analysis. Figure 1 shows the signal generated in MATLAB through the raw data of the patient report generated through the lead connection in the body. Figure 2 shows the denoised signal generated through discrete wavelet transform technique for noise cancellation from the signal.

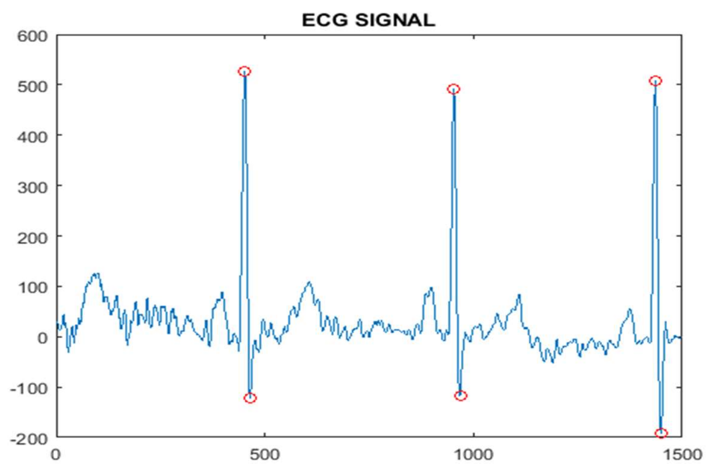

Fig 1: The Plot of Noisy ECG Signal of the Patient.

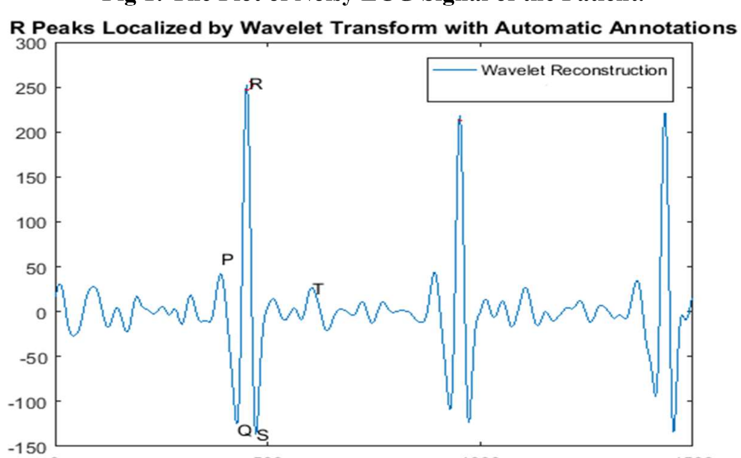

Fig 2: The Plot of Noise-free ECG Signal of the Patient.

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Neural Network for Prediction Analysis

The prediction of myocardial infarction in a type-2 diabetic patient with the help of their QTc prolongation that has been collected from their ECG report plays an important role in the risk stratification. Prediction through the neural network can be done through the model data of the patient's previous record of the ECG that shows the respective variation of their QTc value that has been changing from last few years since they are suffering from diabetes.

Methodology

To create the model for the neural network a dataset of at least 50 patients has been generated that contain the QTc value of the patients. For the better prediction analysis of myocardial infarction, 10 consecutive time QTc value of a single patient has been taken who has gone through frequently ECG test from last 3-5 years. An input, a hidden, and an output layer are the three main constituents of a typical feed-forward network having back propagation. The neurons present is the appropriately chosen hidden layers are properly trialed. To train the artificial neural network standard training algorithm such as scaled conjugate gradient algorithm has been applied. The termination of the algorithm is guided by the early stopping criteria which involve a validation set chosen randomly.

Mean Square error (or MSE) has been implemented to predict results of the training function. In one complete cycle of the training process, a set of input data of QTc value is presented to the input node. The target output is the mean value of the patient's QTc value. The mean of the input is fed to the output node to clarify the type of behavior required. The difference between the desired response and output signal is fed as a control signal to correct the weights and biases of the neuron. The iterating process of correction and updating of the weights and biases of the neuron proceeds until the difference between the desired and the output response is lower than 'ε' (a very small finite value). An abundance of training sets is utilized to train the neural network. The neural network is then tested at the end of the iteration for its performance and efficiency of the neural network to predict the output.

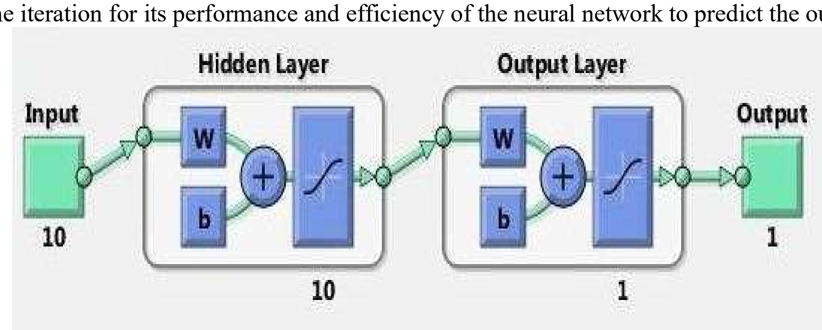

Fig 3: A Neural Network Model

The above model generated by the neural network with nonlinear auto-regressive with external input problem as per the data mentioned. Here it shows that it has three layers as an input layer, an output as well as a hidden layer with delay. For this model, a 10×50 matrix has been taken as input and a 1×50 matrix as an output for better prediction.

In this artificial neural network model, the total datasets have been divided into three different set as a training set, testing set, and validation set. For my input and output data this ANN model has divided the data into 70% of the training set, 15% of testing and 15% of validation datasets with 10 number of neurons, one hidden layer, and two delays. However, we can distribute our data into a different ratio with a different number of hidden layers and a greater number of neurons. Normally more numbers of hidden layers with a different number of neurons per layers need experimentation whether it gives the better result or not. With created network training of the model with the standard defined algorithm for the output takes place. If it does not give the better result, retrain the model number of times to get the least mean square error that describes the best output of the model. Sometimes too much low MSE (mean square error) may create the problem of over-fitting. So over-fitting has to be taken into consideration.

Results

As shown in figure 4 there is a large difference between the test data and validation data that creates a large difference in MSE (Mean Square Error) which does not represent the best model for our target output.

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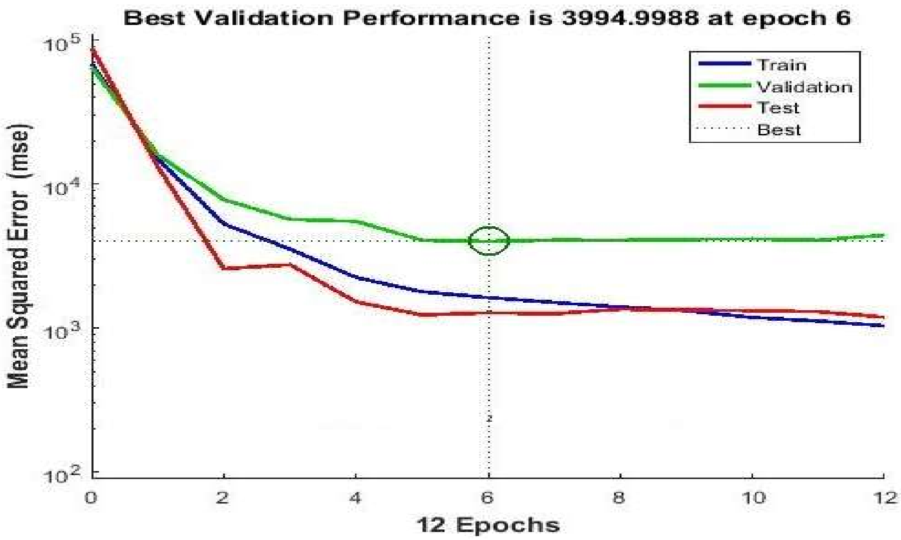

Fig 4: Output of the First Iteration

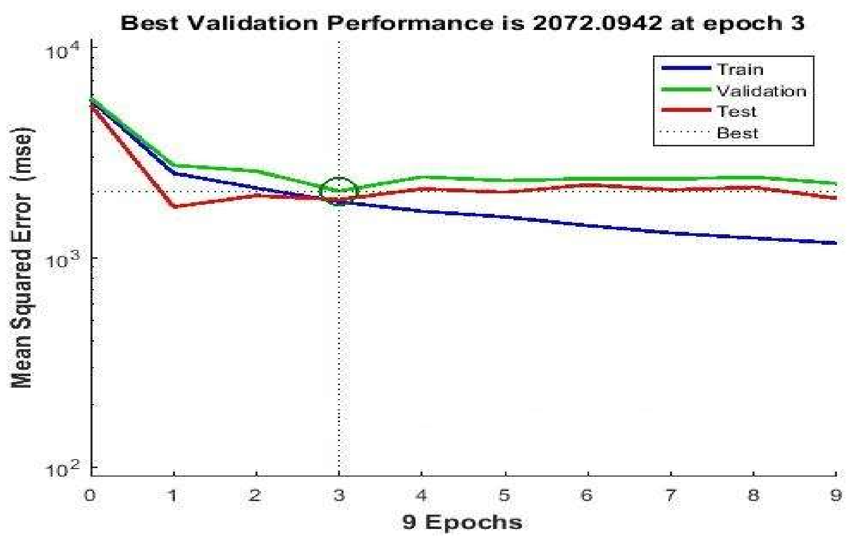

Fig 5: Output of the Second Iteration

So, while going for the next iteration it was found that this iteration gives the result somewhat better than the previous iteration, as there is a least minimum square error that shows the better accuracy of the model shown in figure 5 than the previous one as it has least mean square error and it gives more accurate output.

Figure 6 shows the regression plot of the first iteration where we find that the output tracks the target for training testing and validation properly. The overall value of R is 0.86. while comparing it with figure 7 regression plot it is found that figure 7 regression plot output tracks the target for training testing and validation more accurately compared to the previous one with overall R-value 0.99, that shows a better result of our model.

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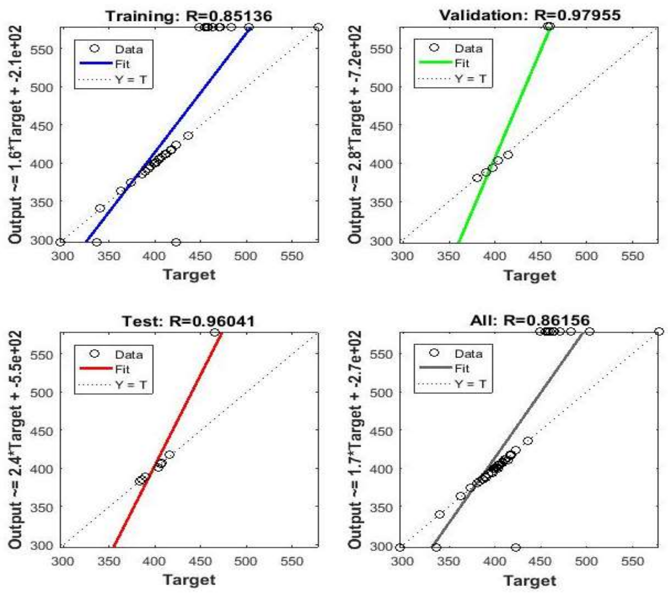

Fig 6: Regression Plot of Figure 4

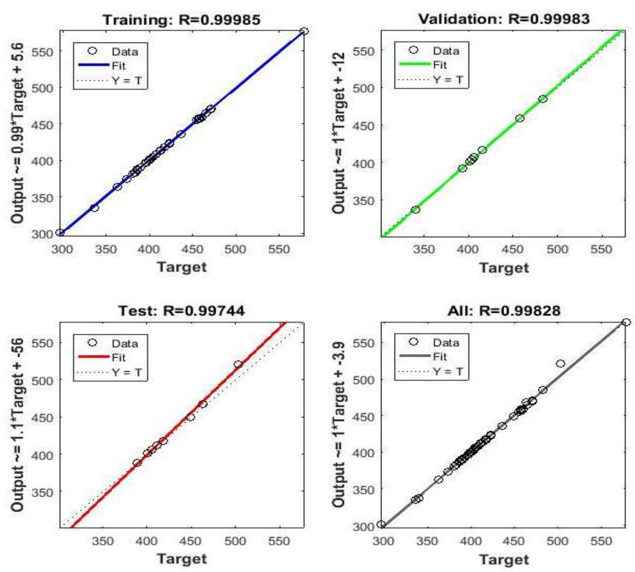

Fig 7: Regression Plot of Figure 5

While getting the best network model for the prediction analysis, A sample of data set is created with a smaller number of patients QTc value to check whether the model provides the best prediction result. A sample of 10×5 matrices is created and fed to the network. The predicted result given by the model network provides valuable information through which patients who are under the influence of myocardial infarction can be differentiated with others. The more strong the datasets, the better predicted result is found through the neural network model. Number of iterations is taken into consideration with different number of neurons to validate a network which gives best result with minimum mean square error and the value of R nearly equal to one, so that network can perform well in real time datasets of diabetic patients.

Conclusion

In this paper, the described model is trained with a large number of training sets to achieve the desired output. The abundance of training sets for the described model provides better output results given the input and output parameters. The output result may vary every time depending on different factors such as input and output

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parameters, number of training sets, initial gain or weights chosen. However, resetting the initial network weights values and biases with new values and retraining the model with an abundance of training sets would yield a more accurate result. This can be achieved by increasing the number of hidden layers or by increasing the number of training vector. Increasing the number of input values will be more applicable if relevant data is available or else training the model with a different algorithm is desired.

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