

Development of STNN& its application to ECG Arrhythmia Classification &Diagnoses

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ABSTRACT: Neural network have impressively demonstrated the capability of modeling spatial information. On the other hand, the application of parallel distributed models to processing of temporal data has been restricted in several places . In space time neural network, the synaptic weights between two artificial neurons are replaced with an adaptable – adjustable filter. Instead of single synaptic weight, it provides a plurality of weights, which represents not only association but also temporal dependencies. Now the synaptic weights of the neural network are the coefficients of the adaptable digital filter, which gives a neural network that is defined both spatially and temporally. This network is a Time-Delayed neural network and also known as Elman network. In this paper, an attempt is made to design a Spatio-Temporal artificial neural network which is used to classify arrhythmias. In this Spatio Temporal Neural Network the spatial information is the output from the 12 leads of ECG, which is obtained from an electrocardiograph, and temporal information from a particular lead output. The output of this model is that particular arrhythmia from which patient is suffering. Spatio temporal neural network differs from standard neural network in terms of memory. In STNN the networks memory is distributed over the connections rather than being implemented as a special layer of nodes. STNN can deal with spatial as well as temporal data.

KEYWORDS: ECG, Arrhythmia classification , Spatio Temporal neural network

I. INTRODUCTION

Analysis of the electrocardiogram (ECG) for detecting different types of heartbeats is of major importance in the diagnosis of cardiac dysfunctions. Some arrhythmias appear infrequently, and very long ECG recordings are needed to capture them. Analysis of such large amount of data is very time consuming and, therefore, automatic processing systems can be of great assistance to the clinician. ECG data is the spatio temporal data, which varies with space as well as time. Spatio temporal neural network deals with the data which varies with space as well as time. As in this paper spatio temporal neural network is used cardiac arrhythmia classification. 12 lead ECG data has been taken. 5 branches of STNN are used and each branch is given 12 inputs. 12 inputs are given so the no. of delays given to the network are 12. Then the network is trained to classify different arrhythmias such as dextrocardia, posterior wall mi, tachycardia, bradycardia, ischemia, pericardial effusion, hyperkalemia etc.

II. PROBLEM FORMULATION

The electrocardiogram (ECG) is the most important bio signal used by cardiologists for diagnostics purposes. ECG signals provide the key information about the electrical activity of the heart. The objective of this thesis work is to design a spatio temporal neural network for detection and identification of cardiac arrhythmias using ECG data. Firstly calculate the ECG parameters then use these parameters to design the spatio temporal neural network for arrhythmia classification. This neural network is trained to classify 10 Arrhythmias which are dextrocardia, corpulmonale, atrial fibrillation, posterior wall mi, pericardial effusion, hyperkalemia, ischemia, pericardial, first degree heart block, tachycardia and bradycardia.

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III. METHODOLOGY

In this paper Spatio temporal neural network has been used to identify 10 different Cardiac arrhythmias using ECG data. Thesis work has been divided into three steps.

- Calculating ECG parameters from real ECG data: In the first step various ECG parameters are calculated and are normalized. These parameters are P, R, T, PR and HR.
- STNN: In the next step these parameters are used to train the neural network. Inputs to the neural network are these ECG parameters. in this step the STNN is used for arrhythmia classification.
- Feature extraction: In the third step Feature extraction is used for arrhythmia diagnosis.

In the first step ECG parameters P, R, T, PR and Heart Rate are calculated and normalized From the real ECG trace. Then in the second step Spatio temporal neural network is trained with parameters by considering following conditions.

- For $p > 2$ output is 20; for $p \leq 2$ output is 10; for $p \leq 0$ output is 0. Where p is the p wave amplitude.
- For $R \leq 13$ output is 1; for $R > 13$ output is 10
- For $1 < T \leq 2$ output is 10; for $T > 2$ output is 20, for $T < 0$ output is 0.
- For $PR \leq .16$ output is 10; for $PR > .16$ output is 15.
- For $60 \leq HR \leq 100$ output is 10; for $HR < 60$ output is 20.

After training STNN next step is Feature extraction. In feature extraction output of the neural network is used for arrhythmia diagnosis. MATLAB software is used to write the program.

PREPROCESSING STNN FEATURE EXTRACTION

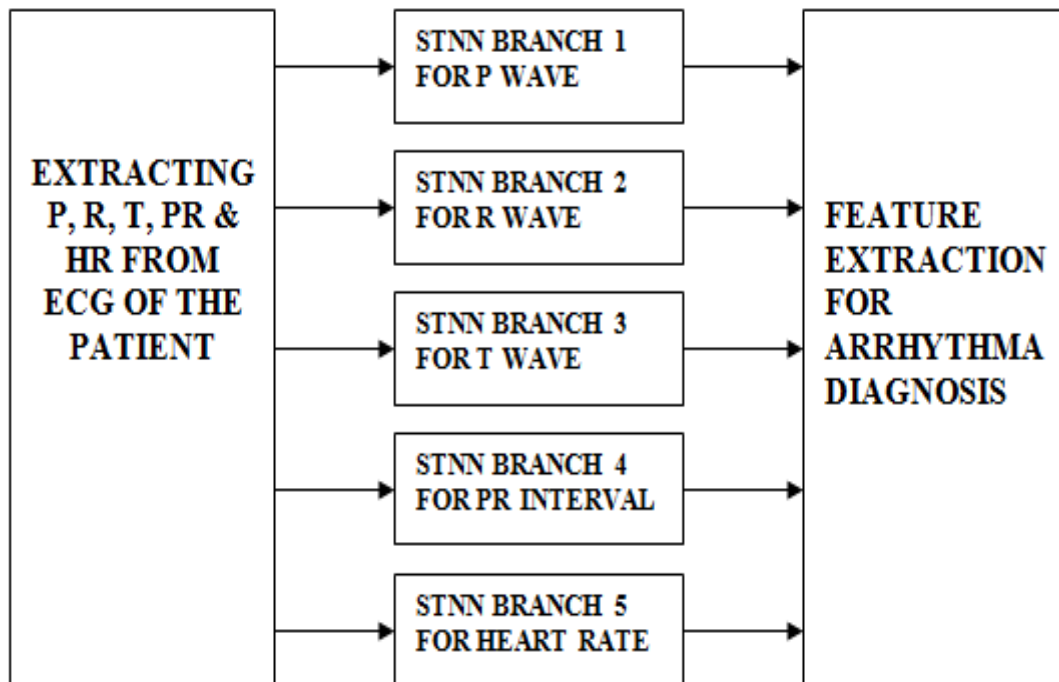


Fig 1. Block diagram for ECG arrhythmia classification & diagnosis

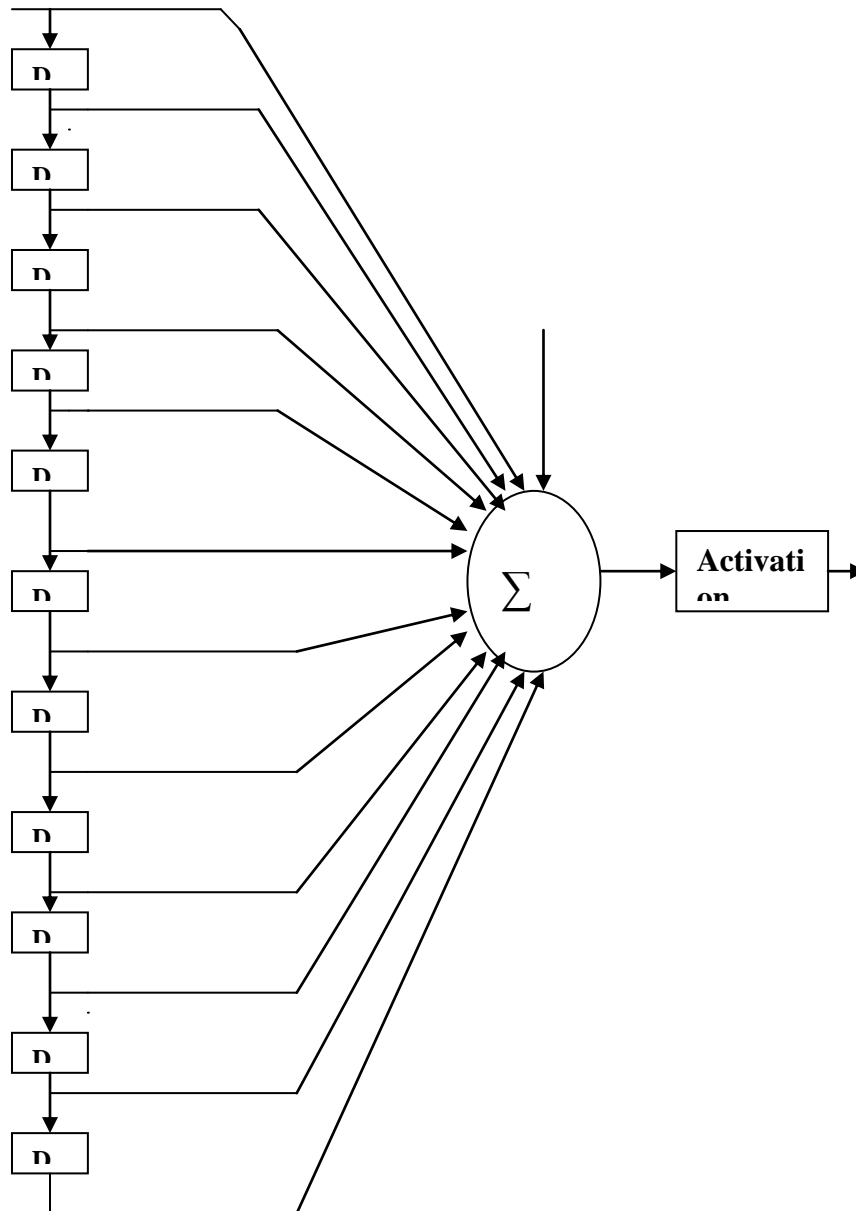


Fig.2 Architectural view of one branch of STNN

Fig.2 shows the architectural view of a branch of STNN. Here STNN consists of 5 branches each for P, R, T, PR & HR. 11 delays are used as there are 12 lead data of ECG is used for input. P, R, T, PR & HR has 12 inputs at the same time. Linear activation function is used at the out put.

IV. RESULTS

As Spatio temporal neural network is trained to classify the arrhythmias. ECG data of a patient is used to train the network. In this work ECG data is taken & used to train the network for identifying particular arrhythmia.

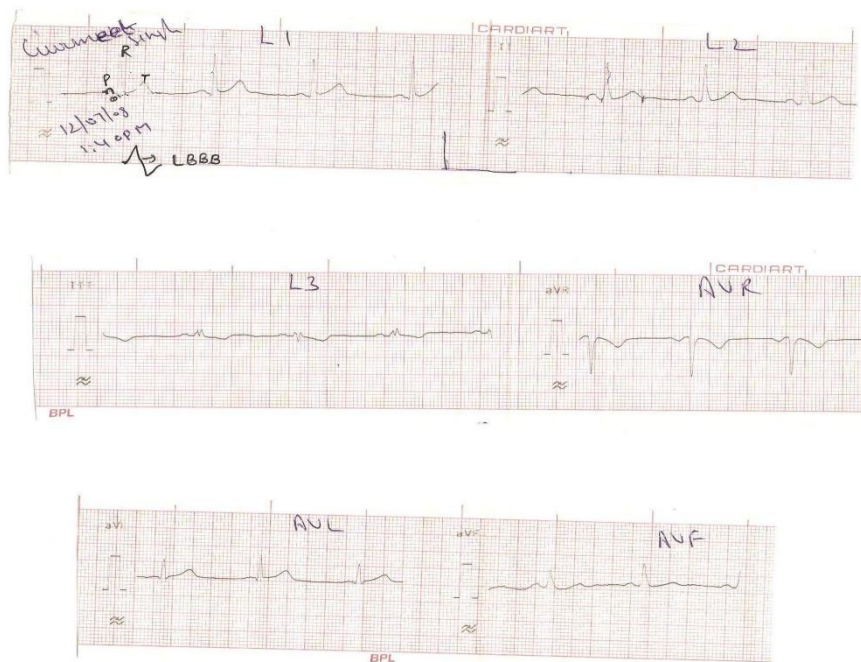


Fig.3 ECG Trace for lead I,II,III,AVR,AVL,AVF.ECG of 52 years old patient



Fig.4 ECG Trace for lead V1-V6. ECG of 52 years old patient

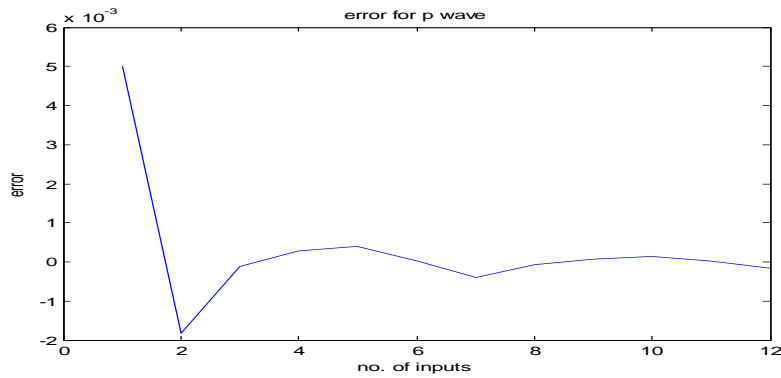


Fig.5 Error for P wave

Fig.5 shows error for the P wave for 1300 passes. This error is calculated by the program between the desired output and the network output Arrhythmia diagnosis for P wave is given in Table no.1.

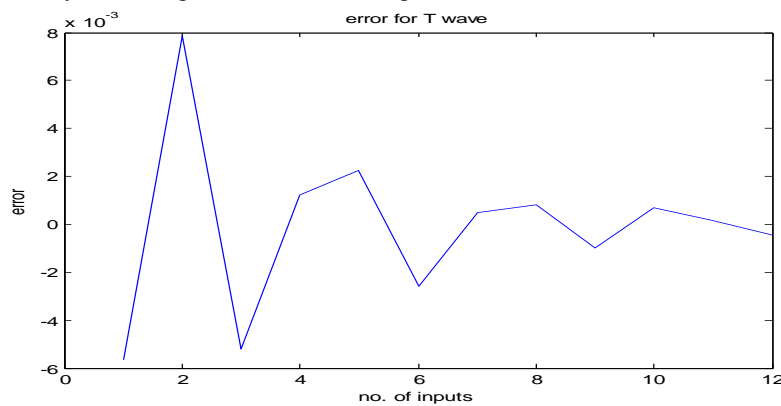


Fig.6 Error for T wave

Fig 6 shows the error for T wave for 7000 passes. Error for T wave is calculated by the program as a difference between desired out put and network output is given in Table no.2

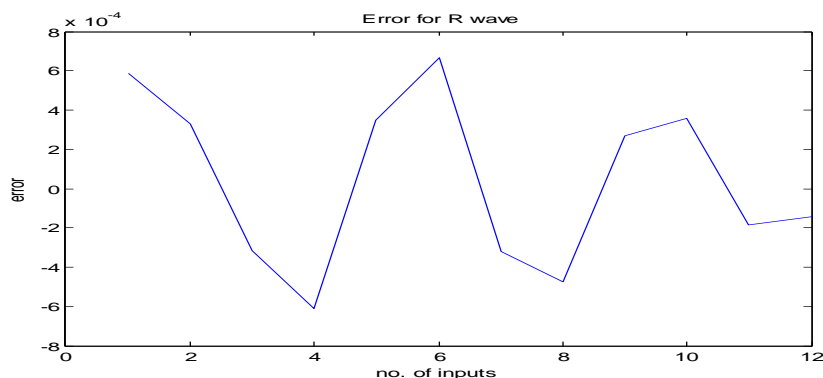


Fig.7Error for R wave

Fig. 7 shows the error for R wave with 300 passes.error for R wave is calculated by the program as a difference between desired output and network output is given in Table no 3

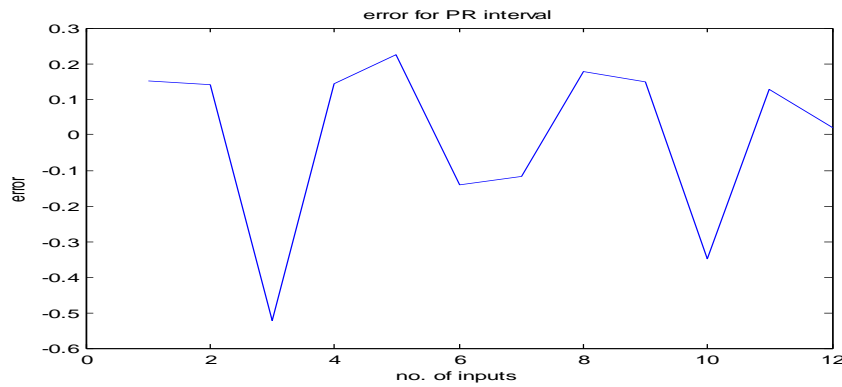


Fig.8 Error for PR interval

Fig.8 shows error for PR interval for 4500 passes. This error is between the network output and desired network output is given in Table no. 4

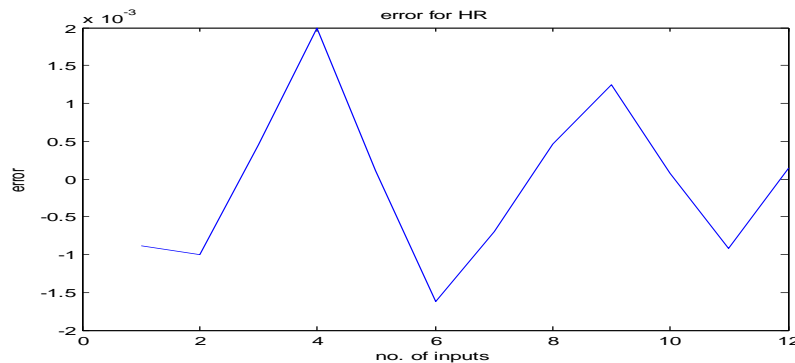


Fig.9 Error for Heart Rate

Fig.9 shows the error for Heart Rate for 1200 passes. Given in Table no. 5

Table no.1 Arrhythmia Diagnosis For P wave

Lead No.	Value	Diagnosis
I	p = 9.985	patient normal
II	p =20.0052	corpulmonale
III	p =10.0004	patient normal
AVR	p =19.9992	corpulmonale
AVL	p = 9.9989	patient normal
AVF	p =9.9999	patient normal
V1	p =0.0012	dextrocardia
V2	p =10.0002	patient normal
V3	p = -1.8535e-004	dextrocardia
V4	p =19.9996	corpulmonale
V5	p =9.9999	patient normal
V6	p =10.0005	patient normal

Table no.2 Arrhythmia Diagnosis for T wave

Lead No.	Value	Diagnosis
I	Tn=10.0056	patient normal
II	Tn =19.9922	hyperkalcemia
III	Tn =10.0052	patient normal
AVR	Tn = 9.9988	patient normal
AVL	Tn = 9.9979	patient normal
AVF	Tn = 20.0026	hyperkalcemia
V1	Tn = -4.8129e-004	ischemia
V2	Tn = -8.2908e-004	ischemia
V3	Tn=10.0056	patient normal
V4	Tn =19.9922	hyperkalcemia
V5	Tn =10.0052	patient normal
V6	Tn = 9.9988	patient normal

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Table no.3 Arrhythmia Diagnosis for Heart Rate

Lead No.	Value	Diagnosis
I	hr = 1.0009	patient normal
II	hr =1.0010	patient normal
III	hr =0.9996	patient normal
AVR	hr = 0.9980	patient normal
AVL	hr = -1.1544e-004	tachycardia
AVF	hr = 1.0016	hyperkalcemia
V1	hr =1.0007	patient normal
V2	hr =0.9995	patient normal
V3	hr = 0.9998	patient normal
V4	hr = 0.999	patient normal
V5	hr = 1.0009	patient normal
V6	hr = 0.9999	patient normal

Table no.4 Arrhythmia Diagnosis for R wave

Lead No.	Value	Diagnosis
I	r =1.0057	patient normal
II	r = 0.9975	patient normal
III	r = 9.9933	patient normal
AVR	r = 0.9939	patient normal
AVL	r =10.0141	patient normal
AVF	r =1.0076	patient normal
V1	r = 9.9866	patient normal
V2	r =0.9987	patient normal
V3	r =1.0124	patient normal
V4	r =1.0009	patient normal
V5	r = 19.9911	posterior wall mi
V6	r = 0.9999	patient normal

Table no.5 Arrhythmia Dignosis For PR interval

Lead No.	Value	Diagnosis
I	ps = 0.8488	patient normal
II	ps = 0.8599	patient normal
III	ps = 0.5216	I degree heart block
AVR	ps = 0.8554	patient normal
AVL	ps = 0.7755	patient normal
AVF	ps =1.1411	patient normal
V1	ps =1.1184	patient normal
V2	ps =0.8222	patient normal
V3	ps =0.8501	patient normal
V4	ps = 0.3477	I degree heart block
V5	ps =0.8738	posterior wall mi
V6	ps =0.9804	patient normal

V. CONCLUSION AND FUTURE SCOPE

A spatio temporal neural network is used for the classification & diagnosis of different arrhythmias such as dextrocardia, corpulmonale, atrial fibrillation, posterior wall mi, percardiac effusion, hyperkalemia, ischemia, posterior wall mi, first degree heart block, tachycardia and bradycardia. For this ECG parameters P, R, T, PR, and HR are calculated manually. These parameters are used to train the neural network to determine the cardiac arrhythmia. Spatio temporal neural network is used here which has 5 branches and each branch has 12 input variables. Delays used in this network are 11. and 5 neurons are used one neuron for each branch. This approach make the work simpler as it can deal with spatial as well as temporal data. STNN is better than normal back propagation neural network as lesser no. of neurons are required in STNN and it can deal with Spatio as well as temporal data at the same time. This approach has its scope in the field of medical i.e. where Doctors can use this program to classify the arrhythmia. This will improve the performance of heart treatment .EEG data can be applied to Spatio temporal neural network to detect abnormalities in the electrical activity of the brain which may help diagnose the presence and type of various brain disorders, to evaluate head injuries, tumors, infections, degenerative diseases, and other disturbances that affect the brain.

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