Prediction of Ventricular Tachyarrhythmia in Electrocardiograph Signal using Neuro-Wavelet Approach

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Abstract: *Ventricular Tachyarrhythmias (VTs), especially ventricular fibrillation (VF), are the primary arrhythmias which are cause of sudden death. The object of this study is to characterize VF prior to its onset. Two prediction methods are being presented using neuro-wavelets approach. ECGs of patients are studied having three types of VTs i.e. Ventricular Tachycardia (VT), Ventricular Flutter (VFl) and Ventricular Fibrillation (VF). ECGs of subjects having normal sinus rhythm (NSR) are also studied. Three classes of signals are decomposed using Wavelets. For Classification of theses decomposed signals Generalized Regression Neural Network (GRNN) and Learning Vector Quantization (LVQ) are used. These methods can recognize VT class so onset of VF can be predicted before time. Promising results are found for prediction of VF.*

Keywords: *Neural Networks, Life threatening arrhythmia prediction. Wavelets*

1. INTRODUCTION

Electrocardiography signal is electric measure of heart activity. Atrial and ventricular of heart contract and expand to pump the blood from lungs to body and vise versa. An arrhythmia is a change in the regular rhythm of heartbeat. It has two main types. If the heart beat is too slow it is considered as bradycardia and if the heart beat is too fast it is called tachycardia. A missing heart beat is also considered as arrhythmia. The heart has four chambers. The heart contracts and pushes blood through chambers. The contraction of heart is controlled by an electric signal produced by "pacemaker" called sinoatrial node. The rate of contraction depends upon hormones in the blood and nerve impulses. Problems in any of these are results in arrhythmia [1]. All the arrhythmias are not dangerous. The ventricular arrhythmias are considered more dangerous than atrial arrhythmias. The ventricular tachyarrhythmias have heart rate higher than normal. They often arise from ventricles (lower part of heart). There are three main categories of ventricular tachyarrhythmias i.e. Ventricular Tachycardia (VT), Ventricular Flutter (VFl) and Ventricular Fibrillation (VF). Ventricular fibrillation (VF) is a severely abnormal heart rhythm (arrhythmia) that, unless treated immediately, causes death. VF is responsible for 75% to 85% of sudden deaths in persons with heart problems [2]. The immediate cure of VF is defibrillation. Defibrillation is a process in which electric shock is given to heart in attempt to terminate life threatening arrhythmia (i.e. VF). Defibrillation process depolarizes the entire heart due to which heart start normal rhythm. The cells of pacemaker also resume the normal behavior. For success of this process sufficient myocardial high-energy phosphate (HEP) stores must be available for contractions to resume. During global ischemia the HEP stores are depleted rapidly. Therefore it is necessary to defibrillate the heart well before HEP level reduces. If defibrillation is processed well in time then the probability of success is as 90%. The probability decreases as time elapsed. Before onset of VF there is almost always a series of VT. So if we can recognize those VT signals which are just before onset of VF, we can predict VF in nearby future.

Literature review shows that much work is going on prediction of VF and it is considered a challenge in present day cardiology. Minija et al. [3] presented neural network (NN) based ECG segment prediction for classification of Ventricular Fibrillation (VF). He used the classification of ST segment of ECG. Karen Liu [4] used wavelets decomposition of the ECG and Hidden Markov model was used to classify the Ventricular Tachycardia (VT) and Ventricular Fibrillation (VF). Kautzner et al. [5] presented the prediction of sudden death after acute myocardial infarction. They found that depressed Heart Rate Variability (HRV) computed from short-term pre discharge ECG recordings obtained under standardized conditions is associated with an increased risk of sudden cardiac death. Kapela et al. [6] studied the wavelet analysis of ECG signals with VT/VF. Jekova et al. [7] used modified K-nearest neighbors algorithm for prediction of VF/VT.

In current study fifty ECGs signals of healthy subjects and thirty five signals of patients before onset of VF and thirty five signals after the onset of VF are taken. Wavelets transform is used for ECG signals decomposition. Generalized Regression Neural Network and Learning Vector Quantization are used for classification of these decomposed signals. Section 2 & 3 describe ECG Signals and disease associated with them. Section 4 describes the wavelet transform of signals. Section 5 describes the two neural network architectures i.e. GRNN, and LVQ for prediction. Prediction Methodology is described in section 6. Results and comparisons of methods are described in section 7. Section 8 is conclusion followed by the References.

2. ECG SIGNAL

Whenever the heart starts systole, there is atrial contraction due to atrial depolarization, depicted by an upward deflection as P wave, which is relatively small amplitude equal to the mass of what is depolarized. P wave is followed by ventricular polarization that results in the form of Q, R, S waves. At the same time as ventricular polarization is in process, there is atrial repolarization masked within ventricular polarization and not normally seen. Ventricles start repolarizing after a plateau which results T wave upward deflection. A cycle of ECG signal has been shown in Figure 1.

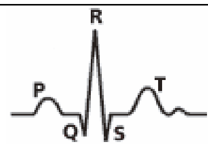

Figure 1: One Cycle of ECG

ECG signals are usually in the range of 1mV in magnitude and a bandwidth of about 0.05-100 Hz. Raw signal needs to be amplified and filtered. Electrical activity of the heart can be detected by placing small metal discs called electrodes on the skin. During electrocardiography, the electrodes are attached to the skin on the chest, arms, and legs. ECG monitoring machine records the ECG signal and prints it on the paper.

3. VENTRICULAR TACHYARRHYTHMIAS

Ventricular Tachyarrhythmias are fast heart beat arrhythmias produced in lower part of heart called Ventricular. There are three main types of VTs.

3.1 Ventricular Tachycardia

Ventricular tachycardia is defined as three or more consecutive beats of ventricular origin at a rate greater than 100 beats/min. There are widened QRS complexes. The rhythm is usually regular, but on occasion it may be modestly irregular. Ventricular tachycardia can be referred to as sustained or non-sustained. Sustained refers to an episode that lasts at least 30 seconds and generally requires termination by anti-tachycardia pacing techniques. Non-sustained ventricular tachycardia suggests that the episodes are short (three beats or longer) and terminate spontaneously. An ECG of patient having VT is shown in Figure 2.a.

3.2 Ventricular Flutter

Ventricular Flutters (VFl) are high frequency (250-350/min) beats. The ECG signal looks like sinusoidal as shown in Figure 2.b. Due to high rate of contraction of heart chambers the time of blood flow into the chamber becomes very small, so very little blood flows to body. The person who is experiencing VFl is close to unconsciousness [8].

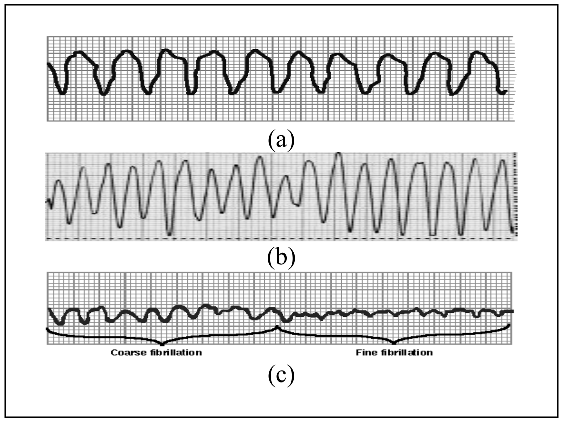

Figure 2: (a) ventricular Tachycardia (b) Ventricular Flutter (c) Ventricular Fibrillation

3.3 Ventricular Fibrillation

This is the most dangerous type of arrhythmia. The heart beat frequency in this case is 350-450 /min. In this case, rhythm is totally uncoordinated with no discriminate waves. Which such a high beat frequency, the blood does not flow to the body. Due to this brain does not receive blood and sudden death can occur. Immediate defibrillation is only care for VF. If a person is luck to survive after of VT he/she is at high risk of VF in near future [9]. ECG of VF patient is shown in figure 2.c.

4. WAVELET TRANSFORM OF ECG SIGNALS

Wavelets are mathematical functions that gives both time and frequency information of the signal. It provides more information as compare to Fourier transform which only gives the spectral information of the signal. Given a signal $\{x(t), -\infty < t < \infty\}$ the collection of coefficient $\{w(\lambda, \tau) : \lambda > 0, -\infty < \tau < \infty\}$ is known as the continuous wavelet transform of x(t) where $w(\lambda, \tau) = \int_{-\infty}^{\infty} \Psi_{\lambda,\tau}(u)\, x(u)\, du$ and $\Psi_{\lambda,\tau}(u) = \frac{1}{\sqrt{\lambda}} \Psi(\frac{u-\tau}{\lambda})$, where λ is the scale associated with the transformation and t is the translation factor. The function ψ satisfies the properties $\int_{-\infty}^{\infty} \Psi(u) du = 0$ and $\int_{-\infty}^{\infty} \Psi^2(u) du = 1$. Fourier transform $\Psi(\omega) = \int_{-\infty}^{\infty} \Psi(u) e^{-j\omega u} du$ of this function should be $0 < \int_{-\infty}^{\infty} \frac{|(\Psi(\omega)|^2}{\omega} d\omega < \infty$. The 2D and 3D wavelet transform of NSR, VT and VF is shown in Figure 3.

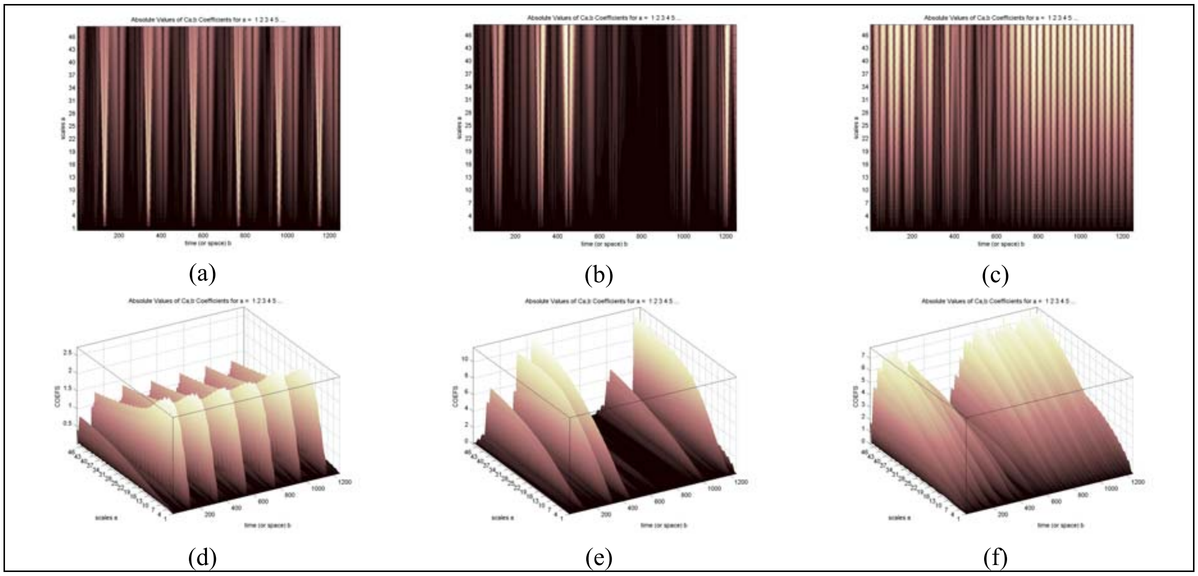

Figure 3: (a) 2D wavelet of NSR, (b) 2D wavelet of VT, (c) 2D wavelet of VF, (d) 3D wavelet of NSR, (e) 3D wavelet of VT, (f) 3D wavelet of VF

5. NEURAL NETWORK ARCHITECTURES FOR PREDICTION

For classification and prediction of NSR, VT and VF two neural network architectures are used.

5.1 Generalized Regression Neural Network

Generalized Regression Neural Network (GRNN) is memory-based feed forward network. It is based on the estimation of probability density functions. GRNN can model non-linear functions, and have been shown to perform well in noisy environments given enough data. A symbolic structure of GRNN is shown in Figure 4.

The GRNN topology consists of 2 layers. One is Radial Basis Layer and second is Linear Layer. The distance of Input P and weight of layer IW is calculated and multiplied with bias. According to this result (n1) Radial basis transfer function gives the output a1.

$$radbas(n) = e^{-n^2} \quad (1)$$

$$a1 = radbas(\|W - P\| b) \quad (2)$$

The normalized dot product of a1 and weight of this layer (LW) is calculated and gives output n2.

$$n2 = nprod(W, a1) \quad (3)$$

The output of the network is the result produced by linear transfer function.

$$a2 = purelin(n2) \quad (4)$$

At the heart of the GRNN is the radial basis function which is also consider as kernel function. The output of the kernel function is an estimation of how likely the unknown pattern or spectrum belongs to that distribution. The larger the output from the kernel function the more likely the concentration of the unknown input is close to that of the input in the hidden layer. Thus, the output layer is a weighted average of the target values close to the input [10].

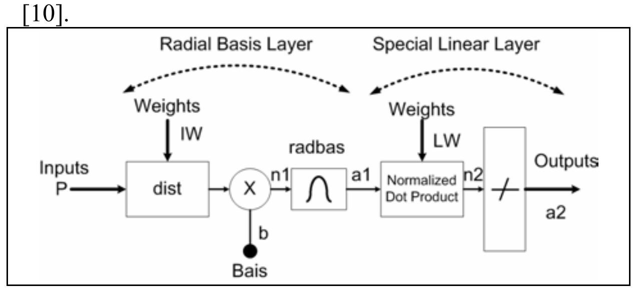

Figure 4: GRNN Symbolic Structure

The only adjustable parameter in a GRNN is the smoothing factor for the kernel function. The smoothing factor allows the GRNN to interpolate between the patterns or spectra in the training set. The optimization of the smoothing factor is critical to the performance of the GRNN and is usually found through iterative adjustments and the cross-validation procedure.

5.2 Learning Vector Quantization Networks

Learning Vector Quantization (LVQ) is used to approximate the distribution of a class using a reduced number of codebook vectors where the algorithm tries to minimize classification errors.

The learning vector quantization Network consists of two layers i.e. a) competitive layer b) linear layer. In competitive layer, negative distance of input vector (P) and weight vector (IW) is calculated [10].

$$n1 = -\|W - P\| \quad (5)$$

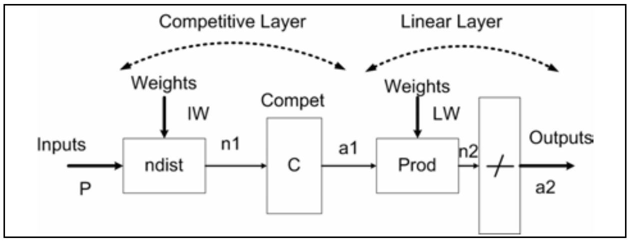

Figure 5: LVQ Symbolic Structure

The competitive transfer function gives the output value 0 except for the winner. Winner is the input whose distance with weight vector is minimum.

$$a1 = compet(n1) \quad (6)$$

The competitive layer forms the subclasses. The linear layer transforms the subclasses into user defined target classes.

$$a2 = purelin(W2, a1) \quad (7)$$

The symbolic Structure of LVQ is shown in Figure 5.

6. PREDICTION METHODOLOGY

ECG signals are decomposed using wavelets transform. Theses decomposed signals feed to GRNN and LVR to classify it into three classes, NSR VT, VF. If algorithm is able to classify these data sets then we can predict VF before time. The real time data of ECG of the patient can be analyzed and if it belongs to VT class it will predict the VF arrhythmia in future.

6.1. Data Sets

The data analyzed here is taken from Creighton University Ventricular Tachyarrhythmia Database and MIT-BIH Normal Sinus Rhythm Database. The VT data consist of thirty five ECG recordings of patients with Ventricular Tachycardia, Ventricular flutter and ventricular fibrillation.

The normal sinus rhythm data set consists of long-term ECG recordings of subjects having no significant arrhythmias. These data sets are available from PhysioBank [11].For training and testing five seconds segment of ECG signals are taken before and after onset of ventricular tachyarrhythmias. The signal segment before onset of ventricular tachyarrhythmias is considered as class VT and signal segment after onset of ventricular tachyarrhythmias is considered as class VF. The signals with normal sinus rhythm (NSR) are considered as class NSR.

6.2 Comparison Parameters

In medical statistics few parameters are important to evaluate the performance of an algorithm. To classifying VT and VF classes suppose we have a test set of VT and VF class signals. From test set of VT class, algorithm classifies A signals in VT class and B in VF class. For VF class it classifies C signals in VT class and D signal in VF class. Then the statistical parameters will be as follows [12]:

Sensitivity =A/(A+C)
Specificity = D/(D+B)
Positive Predictive Value = A/(A+B)
Negative Predictive Value = D/(C+D)
Efficiency=(A+D)/(A+B+C+D)

7. RESULTS AND DISCUSSIONS

Thirty three signal of VT, VF, and fifty signals from NSR are selected. Twenty five signals of all three classes are used for training. Eight signals of VF and VT and fifteen NSR signals are selected as test set.

For decomposition of ECG signal different wavelets are studied e.g. Haar, Daubechies, Morlet. Various levels of decomposition are explored. It is found that prediction results were same as in case of Daubechies and Haar. The decomposition levels did not play important role for better classification.

In stead of training neural network for small set of wavelet coefficients we train the neural network for whole coefficient of decomposed signal. The ECG signal sample was of 1250 data points because it was of five seconds and sampling frequency was 250/sec. The wavelets coefficient for third level of decomposition was 1256. So the feature vector for NN was of length 1256.

Classification results of training data sets using GRNN are shown in Table 1. It is found that GRNN 100% classifies three classes of training set. Classification parameters of Table 3 show that sensitivity and specificity of the algorithm for classification are 100%. For test set the sensitivity in case of classification of normal to arrhythmic class is 84% but specificity is again 100%. The efficiency of the algorithms is 94% in this. Sensitivity and specificity of classification of VT and VF classes for test set is 64% and 80% respectively. This shows that algorithms has tendency towards VT class. Positive predictive value (PPV) for test set shows that algorithm can classify VT class well. Negative predictive value (NPV) shows that VF class is not well classified by algorithm. The efficiency of algorithm for classification of VT and VF is 69% which is fair.

There are two VT class signal in test set which are classified by GRNN network into NSR class. One of the signals which are misclassified is shown in Figure 8c. NSR class signal is shown in Figure 8.a and VT class signal is shown in Figure 8.b. From these figures it can be seen that the misclassified signal is more resembling with NSR signal than VT class signal because in VT class signal there are missing R peak, and the misclassified signal have R peaks.

To evaluate the classification performance of GRNN and LVQ for fifteen seconds data before VF, five seconds overlapped windows are used. Thirty three ECGs of the patients of VF are evaluated the mean value of the simulation parameter is plotted with error bars of standard deviation. Figures 6 & 7 show the classification of these data windows.

Table 1: Classification of Training Set using GRNN

Class	Samples	NSR	VT	VF
NSR	25	25	0	0
VT	25	0	25	0
VF	25	0	0	25

Table 2: Classification of Test Set using GRNN

Class	Samples	NSR	VT	VF
NSR	15	15	0	0
VT	8	2	5	1
VF	8	0	4	4

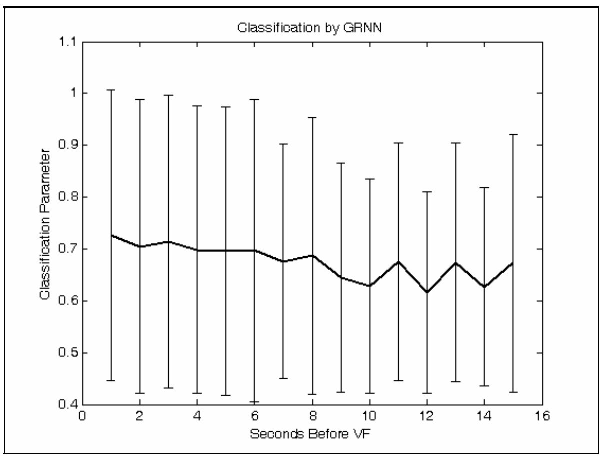

Figure 6: Classification of data Fifteen Seconds before VF using GRNN

X-axis of the Figure 6 & 7 is overlapped windows i.e. 1st windows is 0-5 seconds data, 2nd window is 2-6 second data before onset of VF so on. Y-axis is the classification parameter simulated by network. If the classification parameter is between 0-0.5 it corresponds to normal sinus rhythms (NSR) and if it is between 0.5-1 then it is corresponds to VT class. Figure 6 shows that the classification parameter is close to 0.7 till 8th window which is for data 7-11 seconds before VF. Which shows that using this algorithm prediction of VF is possible 7 second before its onset with 82% confidence.

Table 3: Classification Parameters GRNN

Sets	Com Pari son	Sensi-tivity	Speci-ficity	Pos Pred Val	Neg Pred Val	Eff iciency
Train	A[1]	100%	100%	1	1	100%
	B[2]	100%	100%	1	1	100%
Test	A	89%	100%	1	0.88	94%
	B	64%	80%	0.88	0.50	69%

[1] A is NSR vs. Arrhythmia, [2] B is VT vs. VF

Classification results for training set using LVQ are shown in Table 4. They show that NSR class is well recognized by LVQ algorithm but classification of VT and VF class is poor.

Table 4: Classification of Training Set using LVQ

Class	Samples	NSR	VT	VF
NSR	25	25	0	0
VT	25	3	22	0
VF	25	8	7	10

Table 5: Classification of Test Set using LVQ

Class	Samples	NSR	VT	VF
NSR	15	15	0	0
VT	8	2	6	0
VF	8	2	6	0

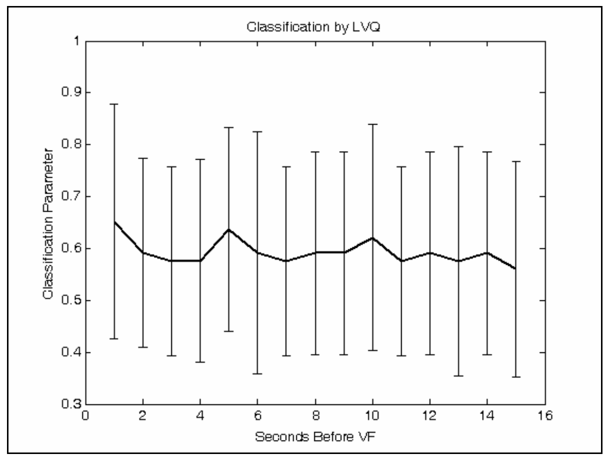

Figure 7: Classification of data Fifteen Seconds before VF using LVQ

Table 6: Classification Parameters LVQ

Sets	Comp-arison	Sens-itivity	Spec-ificity	Pos Pred Val	Neg Pred Val	Effi-ciency
Train Set	A	82%	100%	1	0.78	89%
	B	71%	100%	1	0.59	79%
Test set	A	80%	100%	1	0.75	88%
	B	50%	-	1	0.00	50%

Sensitivity and specificity parameters show that this algorithm have tendency towards VT class. Training set classification shows that the algorithm can again recognized NSR class well but the distinction between VT and VF classes is much poor. Algorithm did not classify any data sample of VF class in VF i.e. NPV is zero in this case. The efficiency of algorithm is fair in training class but for test class efficiency is poor. Fifteen seconds before VF data also evaluated by LVQ algorithm the performance of LVQ found poor again (Figure 7). With this algorithm prediction of VF is possible 5 seconds before its onset with confidence of 74% and for data before 5 seconds prediction efficiency of LVQ algorithm drops abruptly.

Both algorithms can well classify normal and arrhythmic ECGs. The distinction between VT and VF class is much better in case of GRNN as compare to LVQ. Both algorithms classify VF class signals into VT class but LVQ based algorithm did not classify and of Signal fro, VF class into VF class.

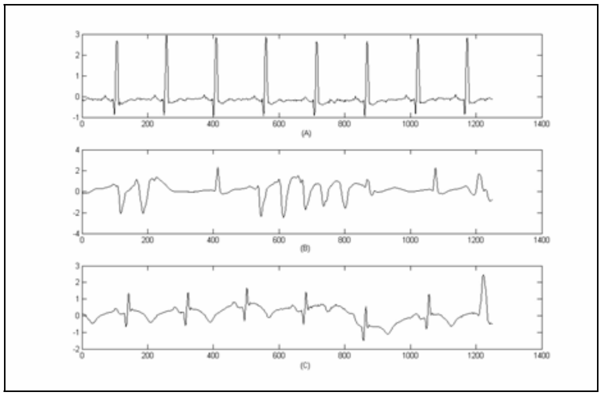

Figure 8: (a) NSR (b) VT (c) Misclassified

8. CONCLUSION

Life threatening Arrhythmia prediction especially VF prediction is challenging problem of cardiology and biomedical. In this paper two methods for classification based prediction using neuro-wavelet technique have been presented for prediction of Ventricular Tachyarrhythmia. It has been found that GRNN based prediction for life threatening arrhythmias gave promising results. In future algorithm can be made more robust with larger data set.

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