

# Wavelet Transform Based Feature Extraction and Classification of Atrial Fibrillation Arrhythmia

SHIPRA SARASWAT<sup>1</sup>, GEETIKA SRIVASTAVA<sup>2</sup>, SACHIDANAND SHUKLA<sup>3</sup>

<sup>1</sup>Department of Computer Science, Amity University Uttar Pradesh India.

<sup>2</sup>Department of Electronics and Communication, Amity University Uttar Pradesh India.

<sup>3</sup>Department of Physics and Electronics, Dr. RML Avadh University Faizabad India.

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## ABSTRACT

A new approach of automatic classification of atrial fibrillation (AF) arrhythmia is proposed in this paper. Our approach is based on discrete wavelet transform method followed by cross recurrence quantification analysis (CRQA) for extracting the features of experimental ECG signals. The features like laminarity, determinism, entropy, trapping time and transitivity are used for measuring the RQA measures. After that, the classification process has been performed using the concept of probabilistic neural network (PNN) approach. This method is applied to make a differentiation between normal persons and the persons having atrial fibrillation arrhythmia. For testing our approach PHYSIOBANK database of ECG signals have been used. The significance of this classification method has been shown in our Matlab generated results. The outcome of this paper will be very beneficial in treating AF patients. We achieved 100% accuracy by using this method.


**Keywords:** Atrial fibrillation; Discrete wavelet transform; Cross recurrence quantification analysis; Probabilistic neural network.

## INTRODUCTION

Electrocardiogram (ECG) is a very popularly performed cardiology test for recording the electrical activity of the heart over a specified period of time by using the electrodes placed on the human body. Health care professionals are using this tool for identifying the various heart disorders. Cardiac arrhythmias are the type of heart disorder in which the heart beats are either too slow (bradycardia), too fast (tachycardia) or may be irregular. Atrial fibrillation arrhythmia is a condition of irregular heart rhythms in the upper chambers of the heart. It is one of the

most common type of arrhythmia that can lead to heart attack, blood clots in the heart and sometimes heart failure also<sup>1</sup>. Approximately 2.7 million persons in United States are living with this disorder. In this mechanized world, AF may occur in minority of the Shipra patients, presenting with this rhythm disorder. The treatment goals of atrial fibrillation should start with a detailed examination from a cardiologist. Healthcare professionals can use several treatments helping to control the heart rate during AF. The untreated atrial fibrillation can lead to sudden death also. Accurate detection of AF arrhythmia are extremely important for treating arrhythmic



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patients as well as in other biomedical applications. For carried out this work the MIT-BIH Long Term AF Database (lafdb) and MIT-BIH Fantasia Database (fantasia) have been used (<https://physionet.org/cgi-bin/atm/ATM>). Although many methods have been proposed during the last many years for correct and reliable detection of AF arrhythmia<sup>2-5</sup>, but the objective of this paper is to propose an easy method to classify atrial arrhythmia based on the combined approaches of DWT and CRQA with PNN. This can contribute to timely detection and management of AF patients.

### Related Work

ECG monitoring was performed on a group of 22 arrhythmic patients having paroxysmal atrial fibrillation shown the more occurrence of asymptomatic atrial fibrillation than symptomatic atrial fibrillation. It increases the risk of stroke also<sup>6</sup>. The study showed the risks of postoperative atrial fibrillation<sup>7</sup> based on specific subgroups of patients in order to decrease the after side effects of treatment. The report made on the basis of C- reactive protein elevation in patients with atrial arrhythmias due to the occurrence of sudden changes in the atria<sup>8</sup>. It has been observed that atrial fibrillation is more common in adults in the United States. For estimating the prevalence of atrial fibrillation, the adults between 60 to 70 years have observed. The calculated prevalence of AF was 0.95% calculated by<sup>9</sup>. A new approach was proposed for catheter ablation of atrial fibrillation for representing a mapping of electro physiologic substrate. It was an ideal target sites for ablations to eliminate atrial arrhythmias. Complex hypothesis testing was used to perform this work<sup>10</sup>. A focal source mechanism of AF was treated by using discrete radiofrequency ablation on the basis of 9 patients. A condition of AF called sole cardiovascular for pulling an independent stroke incidence. The findings based on the impact of each cardiovascular condition was associated with the risk of stroke<sup>11</sup>. For detecting the ECG signals accurately, a comparison has been made between four popular QRS detection algorithms i.e. Window pair, KNN, Slope vector and Dynamic Plosion index algorithms<sup>12</sup>. Beat detection and pressure signal algorithms for ECG are also very important for clinical applications. Using the empirical mode decomposition method, a new beat detection algorithm has been proposed by<sup>13</sup>.

Results generated by beat detection algorithm are betas of false positive and false negative are 22 and 33 respectively and total failure detection rate was 0.304% against 18,069 beats. The proposed method achieved sensitivity and positive predictivity for ABP signals are 99.58% and 99.85% respectively. Filter banks has been used for reducing the computational complexity of the algorithm. The feature detection in ECG signals can be improved with the help of denoising process. This process is useful in preserving the important locations and peaks of ECG signals<sup>14</sup>. An optimized wavelet filter bank approach is proposed for compressing the ECG signals for increasing the efficiency and performance in the bio medical signal processing field<sup>15</sup>. A comparative study of several existing and proposed filter banks is also shown in this work. This study is made on the basis of SNR, compression and various other values. The simulation results shown in this paper is clearly depicts the excellent impact of this work in biomedical signal processing field. In the wireless cardiology field, tamper detection of ECG signals can also be possible using watermarked bio hash code. The combination of several bio hashing and reversible watermarking techniques are used to invent an approach for knowing any kind of tampering in ECG signals<sup>16</sup>. This method will plays an important role in treating arrhythmic disorders. For detecting hemorrhage, the clinical classification schemes are presented based on the results obtained from the National Registry of Atrial Fibrillation<sup>17</sup>. Based on the aetiology, atrial arrhythmia can also be classified with respect to the features like hypertensive, valver etc. Classification has been performed on the basis of temporal patterns of the atrial fibrillation<sup>18</sup>. This paper presented the mechanisms of pathophysiology of arrhythmias and its drug treatment also. It is very important to recognize specific drug Pharmacological treatment discussed in this work which may be beneficial in controlling the rhythm and rate control.

The outline of this paper are as follows: Section 2 includes the techniques adopted in this work like DWT, RQA and PNN. Section 3 deals with the results and discussion. Section 4 shows the performance evaluation in terms of hit rate, false alarm, tn-ratio, missed hypothesis and accuracy and finally conclusion is mentioned in section 5.

## METHODOLOGY

### Discrete Wavelet Transform

A simple small wave which consists energy with respect to time involved in the analysis of non-stationary and transient signals is called a wave shown in figure 2.

A signal of a function called  $s(t)$  shown in above displayed figure 2 which can be better analyzed as the total sum of linear decompositions and the product obtained from the coefficients and functions. In the wavelet function, two parameter system is made that one side contains double sum value and the coefficients obtained with two indices. These set of coefficients are namely called the discrete wavelet transform of function  $s(t)$ . The function of the wavelet series maps the sequence of coefficients namely approximates and details. There are several unconditional properties also in wavelets for providing more and more information about the signal waves<sup>19</sup>. Following equation represents smooth function:

$$S = \sum_{m,n} (s, \varphi_{m,n}) \bar{\varphi}_{m,n}$$

In the wavelet transformation, the original experimental signal is transformed using predefined wavelets. The several forms of wavelets occurs are orthogonal, biorthogonal, multi wavelets or scalar. The decomposition process of discrete wavelet is performed on the basis of filter bank theory in which the experimental signals are under went to the down sampling process by 2 for obtaining the filter outputs. The whole process of decomposition is expressed only in two words known as approximation and details. These are the digital filters called as  $g(n)$  and  $h(n)$  representing the low and high phase values during decomposition process<sup>20</sup>.

$$\varphi_2^x = 2^{1/2} \sum_{\pi} g(\pi) \phi(x - \pi)$$

$$d_{j+1}(p) = \sum_{\pi} g(\pi - 2p) a_j(\pi)$$

$$a_{j+1}(p) = \sum_{\pi} h(\pi - 2p) a_j(\pi)$$

Where the number sets a (j) n represents the resolution of approximate signals  $2^j$  and number sets d (j) n producing the detailed lost signals at  $2^{-(j-1)}$  at the resolution  $2^j$ .

### Recurrence Quantification Analysis

Recurrence quantification analysis (RQA) method was developed for computing different recurrence plots (RPs) on the basis of their small scale structures. This method involves the analysis using RP toolbox for calculating the recurrence behavior of dynamical systems. It involves in the quantification of limited scale structures of recurrence plots presenting the number and length of the recurrences of a system. RQA provides several parameters for measuring the complexity of a system<sup>21</sup>. It presents best results even in the case of non-stationary data, where other techniques fail to do so. This method can be applied to any kind of data even in the physiology also. But it is more popular in the field of engineering, chemistry, bio medical, signal processing and many more. In this paper, following RQA measures have been used for calculating the values of signals at specified level of decomposition<sup>22</sup>. They are as follows:

- **Laminarity:** It calculates the amount of laminar phases in the dynamical systems. As well as, it measures the length of diagonal and vertical lines.

$$L = \frac{\sum_{v=v_{\min}}^N v P(v)}{\sum_{v=1}^N v P(v)}$$

Where  $P(v)$  represents the frequency distribution of length  $V$ , having at least minimum length  $V(\min)$ .

- **Determinism:** It deals with the percentage value of recurrence points forming diagonal lines in the recurrence plots in minimum length called length<sub>min</sub>.

$$D = \frac{\sum_{l=l_{\min}}^N l P(l)}{\sum_{i,j=1}^N R(i,j)}$$

Where  $P(L)$  represents the frequency distribution of the length  $L$ , whereas  $N(l)$  is the absolute number of diagonal lines.

- **Entropy:** It can be estimated from a probability which depends on a diagonal line has

length  $L$ . The entropy of this probability is as follows:

$$E = - \sum_{l=l_{min}}^N p(l) \ln p(l)$$

Where  $p(l)$  represents the frequency distribution of length  $L$ .

- Trapping Time: It calculates the average length between the vertical lines.

$$TT = \frac{\sum_{v=v_{min}}^N v P(v)}{\sum_{v=v_{min}}^N P(v)}$$

It also analyzes the predictability time of the complex systems.

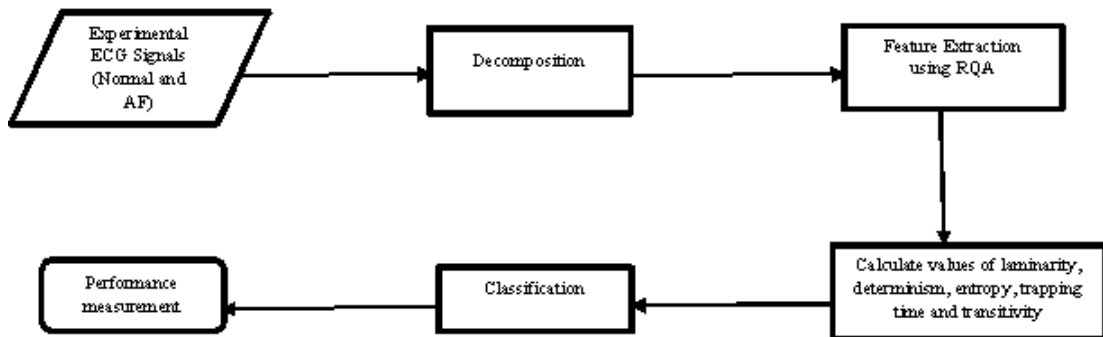


Fig. 1: Shows the steps involved in this work

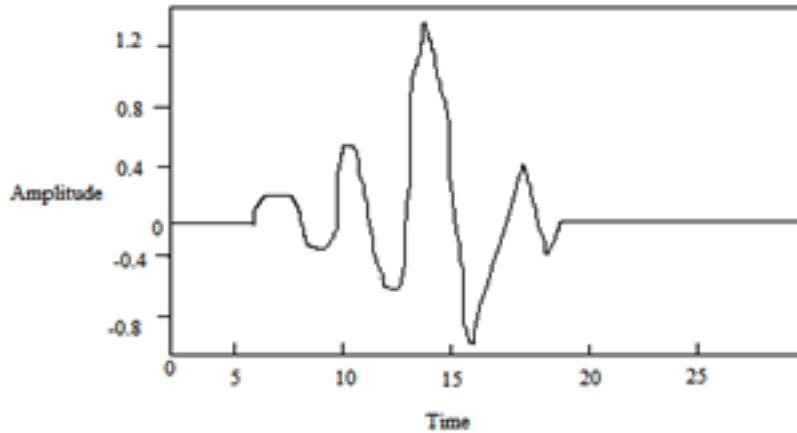


Fig. 2: Presents simple wavelet

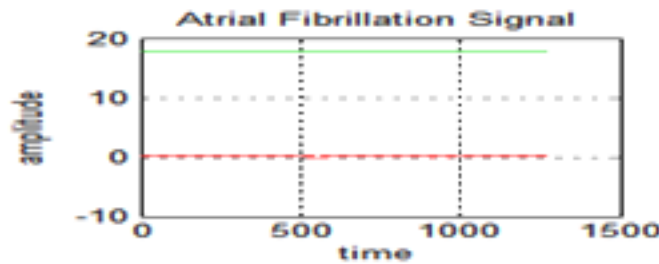


Fig. 3: Experimental AF Signal (abnormal)

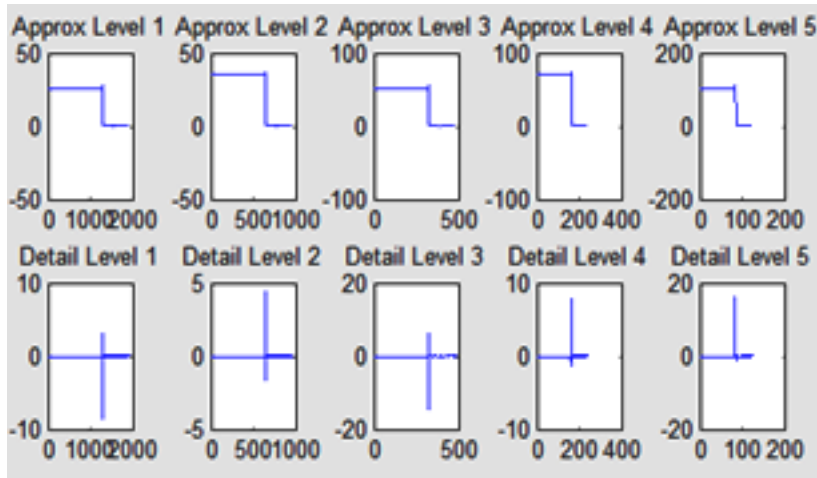


Fig. 4: Shows approximate and detail levels of AF Signal

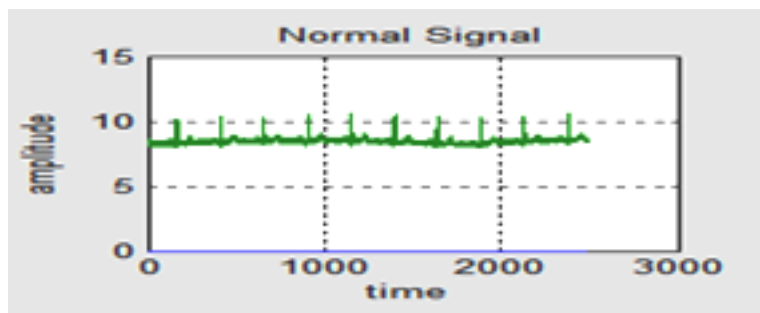


Fig. 5: Experimental Normal Signal

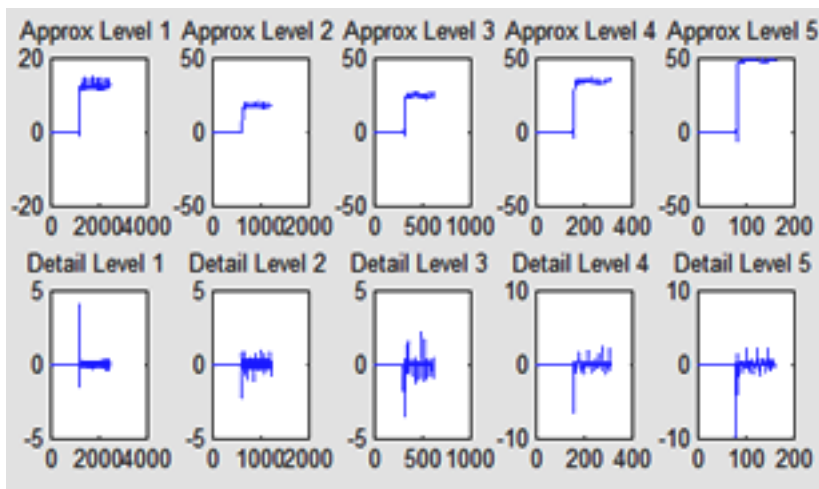


Fig. 6: Shows approximate and detail levels of normal Signal

**Table 1: Displays the computed RQA measure values based on abnormal (atrial fibrillation) signal**

<b>Records taken from MIT-BIH Long Term AF Database (Itafdb)</b>					
<b>Decomposition Levels</b>	<b>Laminarity</b>	<b>Determinism</b>	<b>Entropy</b>	<b>Trapping Time</b>	<b>Transitivity</b>
<b>Record Number 01</b>					
Approx Coeff.1	320.5021	1.0000	6.4603	320.5021	964.0907
Approx Coeff.2	161.1722	1.0000	5.7708	Nan	160.5000
Approx Coeff.3	81.1904	0.9999	5.0824	81.1914	80.2571
Approx Coeff.4	41.3682	0.9997	4.4008	Nan	40.5000
Approx Coeff.5	21.2542	0.9820	3.7255	21.3418	35.5042
Detail Coeff.1	99.4289	0.9994	4.6501	129.1205	135.9181
Detail Coeff.2	69.3094	0.9988	4.5024	110.9459	81.2321
Detail Coeff.3	80.5000	0.9999	5.0664	120.1858	108.0755
Detail Coeff.4	40.0014	0.9996	4.3517	59.5000	54.8761
Detail Coeff. 5	20.1696	0.9819	3.6376	29.6768	19.3228
<b>Record Number 03</b>					
Approx Coeff.1	321.0031	0.9990	6.4614	321.0031	825.4718
Approx Coeff.2	161.1722	1.000	5.7708	Nan	160.5000
Approx Coeff.3	81.5230	0.9958	5.0853	81.4380	134.7787
Approx Coeff.4	41.3682	0.9997	4.4008	Nan	40.5000
Approx Coeff.5	21.4454	0.9815	3.7311	21.6387	35.1345
Detail Coeff.1	145.8495	0.9998	5.3263	187.8839	205.5196
Detail Coeff.2	102.0135	0.9987	5.3536	155.1694	79.4201
Detail Coeff.3	80.5098	0.9999	5.0661	120.1343	107.4595
Detail Coeff.4	40.1162	0.9996	4.3547	59.6279	54.9200
Detail Coeff. 5	20.5029	0.9987	3.6544	30.2500	28.8412
<b>Record Number 05</b>					
Approx Coeff.1	534.3339	1.0000	7.0971	Nan	963.5882
Approx Coeff.2	268.8375	1.0000	6.4077	Nan	160.5000
Approx Coeff.3	135.1687	1.0000	5.7146	Nan	81.0000
Approx Coeff.4	69.2448	0.9999	5.0361	Nan	40.5000
Approx Coeff.5	101.8248	0.9992	4.1635	123.8635	129.1771
Detail Coeff.1	35.5333	0.9995	4.3485	Nan	20.5000
Detail Coeff.2	80.9950	0.9976	4.2467	121.4528	51.8646
Detail Coeff.3	121.1233	1.0000	5.0808	161.1070	136.3493
Detail Coeff.4	60.8758	0.9999	4.4806	80.8895	70.7521
Detail Coeff. 5	30.8766	0.9994	3.8747	40.8901	37.4492
<b>Record Number 06</b>					
Approx Coeff.1	320.5021	1.0000	6.4603	320.5021	964.0907
Approx Coeff.2	161.1722	1.0000	5.7708	Nan	160.5000
Approx Coeff.3	81.1904	0.9999	5.0824	81.1914	80.2571
Approx Coeff.4	41.3682	0.9997	4.4008	Nan	40.5000
Approx Coeff.5	21.2542	0.9820	3.7255	21.3418	35.5042
Detail Coeff.1	60.8635	0.9979	4.0707	75.6192	76.7107
Detail Coeff.2	46.5581	0.9942	4.0266	78.3743	43.9129
Detail Coeff.3	80.4993	0.9999	5.0663	120.1217	107.9780
Detail Coeff.4	40.0014	0.9996	4.3517	59.5000	54.8761
Detail Coeff. 5	20.1696	0.9820	3.6376	29.6725	19.3084

<b>Record Number 07</b>					
Approx Coeff.1	534.3339	1.0000	7.0971	Nan	963.5882
Approx Coeff.2	268.8375	1.0000	6.4077	Nan	160.5000
Approx Coeff.3	135.1687	1.0000	5.7146	Nan	81.0000
Approx Coeff.4	69.2448	0.9999	5.0361	Nan	40.5000
Approx Coeff.5	35.5333	0.9995	4.3485	Nan	20.5000
Detail Coeff.1	30.2951	0.9966	3.2261	43.9909	44.2653
Detail Coeff.2	27.7056	0.9801	3.2273	46.9751	16.1485
Detail Coeff.3	121.1202	1.0000	5.0805	160.8799	136.0913
Detail Coeff.4	60.8758	0.9999	4.4806	80.8895	70.7521
Detail Coeff.5	30.8766	0.9994	3.8747	40.8901	37.4492

**Table 2: Displays the computed RQA values based on normal signals**

<b>Records taken from MIT-BIH Fantasia Database (fantasia)</b>					
<b>Decomposition Levels</b>	<b>Laminarity</b>	<b>Determinism</b>	<b>Entropy</b>	<b>Trapping Time</b>	<b>Transitivity</b>
<b>Record Number f1o01</b>					
Approx Coeff.1	54.4233	0.9744	4.3725	87.7381	60.0970
Approx Coeff.2	43.1872	0.9981	4.2318	69.4442	135.4717
Approx Coeff.3	23.3262	0.9970	3.5876	35.7448	20.6590
Approx Coeff.4	16.9733	0.9970	3.3260	23.0465	13.1252
Approx Coeff.5	28.9493	0.9957	3.9848	31.8097	19.5407
Detail Coeff.1	35.7754	0.9276	1.4229	149.5712	34.7364
Detail Coeff.2	62.4054	0.9040	2.3688	66.8769	45.4709
Detail Coeff.3	6.3722	0.9183	1.8570	10.7470	6.8914
Detail Coeff.4	7.8690	0.9156	1.9355	13.3745	9.3871
Detail Coeff.5	7.9464	0.8366	1.6179	13.2489	9.2848
<b>Record Number f1o02</b>					
Approx Coeff.1	47.0208	0.9938	4.1890	73.7454	122.3060
Approx Coeff.2	30.7063	0.9942	3.7526	47.7739	88.1426
Approx Coeff.3	17.8096	0.9947	3.1349	26.8109	15.1467
Approx Coeff.4	15.2155	0.9861	3.1212	20.5616	9.5704
Approx Coeff.5	26.9009	0.9966	3.7251	28.2330	15.2672
Detail Coeff.1	9.6844	0.7738	1.0767	17.8468	11.9371
Detail Coeff.2	12.5900	0.7729	0.9396	22.9116	14.6339
Detail Coeff.3	6.1235	0.8546	1.4148	10.5835	6.6712
Detail Coeff.4	8.0222	0.8868	1.8774	13.6344	8.6213
Detail Coeff.5	8.2525	0.9006	1.8470	13.5306	13.0847
<b>Record Number f1o05</b>					
Approx Coeff.1	57.4967	0.9822	4.3975	95.3652	83.6983
Approx Coeff.2	40.0167	0.9980	4.0383	62.9804	124.2381
Approx Coeff.3	22.5560	0.9968	3.4152	34.7983	19.0963
Approx Coeff.4	18.3096	0.9959	3.3681	23.1870	12.4777
Approx Coeff.5	39.2209	0.9997	4.3243	39.5851	36.1954
Detail Coeff.1	24.8525	0.9310	1.0758	62.3524	37.2883
Detail Coeff.2	29.9685	0.9155	1.2224	40.4707	44.7393
Detail Coeff.3	10.0381	0.9492	2.5795	16.6192	9.4686
Detail Coeff.4	7.4613	0.9383	1.8468	12.6900	9.6126
Detail Coeff.5	10.7684	0.7598	2.0586	17.3821	8.1278



Record Number f1o06					
Approx Coeff.1	67.3195	0.9924	4.4870	106.1820	141.1609
Approx Coeff.2	36.0982	0.9975	3.8273	57.3611	120.4051
Approx Coeff.3	19.4992	0.9929	3.1262	29.7439	17.5737
Approx Coeff.4	11.7776	0.9832	2.6798	15.9088	9.2292
Approx Coeff.5	10.5602	0.9780	2.7346	14.2121	6.9768
Detail Coeff.1	19.2648	0.9152	1.0413	49.3608	28.3598
Detail Coeff.2	35.2666	0.8994	1.3604	44.2580	40.9979
Detail Coeff.3	8.9501	0.9695	2.4529	14.7455	9.4769
Detail Coeff.4	10.1702	0.9165	2.3756	16.8683	10.1299
Detail Coeff. 5	6.0972	0.9118	1.3843	10.1030	9.9109
Record Number f1o08					
Approx Coeff.1	37.8829	0.9750	3.7594	63.3349	56.9933
Approx Coeff.2	26.2136	0.9945	3.5007	41.5826	81.2785
Approx Coeff.3	18.6109	0.9967	3.2126	28.3381	15.6717
Approx Coeff.4	20.4481	0.9977	3.3044	29.3646	15.7543
Approx Coeff.5	29.0734	0.9997	3.9709	30.8951	19.8033
Detail Coeff.1	29.6064	0.9272	1.1573	94.2026	34.7165
Detail Coeff.2	83.6513	0.9175	2.9130	78.1592	52.9170
Detail Coeff.3	6.3448	0.8905	1.7145	10.6174	7.0085
Detail Coeff.4	7.3697	0.8888	1.4711	12.7517	9.3412
Detail Coeff.5	17.5211	0.7667	2.5893	26.1139	9.6333

- Transitivity: It estimates the behavior of the scale dependent dimensions.

$$T = \frac{\sum_{i,j,k=1}^N R_{i,j}^{m,\epsilon} R_{j,k}^{m,\epsilon} R_{k,i}^{m,\epsilon}}{\sum_{i,j,k=1}^N R_{i,j}^{m,\epsilon} R_{k,i}^{m,\epsilon}}$$

Based on above mentioned formulas of RQA measures, RP toolbox has been used for calculating the values of ECG signals.

**Probabilistic Neural Network Classifier**

Probabilistic Neural Network (PNN) classifier is based on an artificial intelligence method for mapping  $f: R^m \rightarrow Z^n$ . These mappings are implemented by artificial neural network (ANN) based on a group of numerous interconnected artificial neurons govern by human brain<sup>23</sup> For achieving specific classification results ANN can be trained with respect to I/P and O/P information database. PNN is basically a distance based ANNs, using some activation function. PNN classifier is more suitable to medical field because it uses Bayesian strategy which makes it more superior

in comparison to other AI techniques. PNN has basically four layers: the Input Layer, pattern layer, summation layer and output layer. I/P layer is used for giving input to the hidden layer, pattern layer uses the input for estimating the Euclidean distance between different neurons then summation layer starts training the classifier for obtaining the weighted values of neurons and then output layer produces the output after matching the weighted values of neurons with the help of pattern layer. PNN is very popular because of its fast learning process. In this work, for training and testing the data sets, PNN classifier has been used.

**RESULTS AND DISCUSSION**

For realizing this work, authors have taken the total ten records from MIT-BIH physio bank. The AF signals are taken from long term AF database and normal signals are taken from fantasia database. Firstly the records are decomposed by using the discrete wavelet transformation approach. According to the need of problem, level 5 decomposition is performed based on daubechies wavelet of order 4. Decomposition process is producing output in two



words called approximates and details. Every record of ECG signal gone through ten decomposed levels like AC1 to AC5 and DC1 to DC5. In this paper, we have calculated the values of experimental ECG signals based on hundred levels. These values are using for training and testing the classifier for producing output. Figure 3 and 5 shows the experimental AF (abnormal) and normal signal respectively, whereas figure 4 and 6 illustrates the approximate and detail features of abnormal and normal signal respectively.

Once the decomposition is complete, authors are calculating the values of RQA measures based on parameters like laminarity, determinism, entropy, trapping time and transitivity. Table 1 and 2 are producing the RQA values against the respective decomposition levels.

### Performance evaluation

For evaluating the performance of the classifier, following statistical measures were used<sup>24</sup>. They are stated as:

$$\text{Hit Rate (HR)} = \frac{TP}{TP+FN} * 100\%$$

$$\text{False Alarm Rate (FAR)} = \frac{FP}{TN+FP} * 100\%$$

$$\text{TN-Ratio (TNR)} = \frac{TN}{TN+FP} * 100\%$$

$$\text{Missed hypo (MH)} = \frac{FN}{TP+FN} * 100\%$$

$$\text{Accuracy (Ac)} = \frac{TP+TN}{TP+TN+FP+FN} * 100\%$$

Where TP, TN, FP, FN stands for: true positive, true negative, false positive and false negatives respectively. In this work, positive refers to AF patients and negative refers to normal patients. Hit rate is defined as correctly diagnosed AF cases, false alarm rate presents the normal

cases recognized as AF patients, TN ratio detects the normal persons correctly, missed hypothesis trace the number of AF cases as normal and overall accuracy means the number of sum of TP and TN to the total cases. Table 3 illustrates the comparison between other atrial fibrillation arrhythmia detection attempts by other researchers.

### CONCLUSION

This work focused on automatic feature extraction and classification of atrial fibrillation arrhythmic patients based on combined approach of wavelet transformation and recurrence quantification analysis. In this paper, till fifth level of decomposition process is preferred according to the need of problem. The feature extraction work is completed by evaluating the RQA measures like laminarity, determinism, entropy, trapping time and transitivity. The values obtained from RQA measures are calculated against the decomposition levels of DWT. PNN classifier is used for training and testing the ECG signals. This research work were carried out on atrial arrhythmic and normal signals. The RQA values are gathered on corresponding hundred levels of decomposition including both the signals. So, for training purpose 70 levels (seven records) of RQA values has been chosen and rest 30 (three records) are used in testing process. Experimental ECG signals were taken from Long term AF database and fantasia database from physio net.org. The results were verified on the basis of statistical parameters like hit rate, false alarm rate, TN ratio, missed hypothesis and accuracy used for evaluating the performance of proposed classifier. The results obtained using PNN classifier were strongly capable to differentiate between AF and normal ECG signals. The proposed method in this paper can be used for correct and reliable detection and classification of AF patients.

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