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Comparative Analysis of Electrocardiogram Signals Using Several Discrete Transforms Based on Deep Learning

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ABSTRACT

Physicians use ECG to evaluate the electrical activity of patients' hearts to know whether their hearts working effectively or not. In this paper, ECG is classified into normal and Atrial Fibrillation AF patients using new methods of extracting features from ECG signals. Extracted features from ECG signals are conducted as follows: in the first step ECG signals are normalized and detrended. Then, 24 algorithms are examined. The best performance algorithm is obtained using short time Fourier transform STFT. After that, power is calculated by squaring the signal. Then discrete cosine transform DCT is considered. First and second derivative are computed for the DCT signal. Finally statistical calculations are applied for DCT signal, 1st derivative and 2nd derivative. Many classifiers are compared as Artificial Neural Network, KNN, Support Vector Machine SVM, ANFIS, Deep Learning DL with bi-long short term memory BILSTM and long short term memory LSTM. The maximum obtained accuracy is achieved by using DL with BILSTM layer after extracting features from ECG signals using the best algorithm. The obtained training and testing accuracies are 99.5% and 99.1% respectively. Receiver operating characteristics (ROC) of the selected algorithm are approaching to 1. So, the novelty of this research is obtained by applying this algorithm for extracting ECG signals.

1. Introduction

The electrical activity of the heart versus time is illustrated by ECG. It is a very safe noninvasive method. It is used to diagnose many diseases such as Atrial Fibrillation, myocardial ischemia and infarction. The most important familiar three waves within each heart beat in the normal ECG are P-wave, QRS-complex and T-wave. Many heart diseases can be detected with ECG i.e Atrial Fibrillation AF. AF is a very dangerous disease because it can cause blood clots and heart failure. AF rhythms in ECG have no P-wave and irregular RR interval. Many researching papers have been investigated about classification of ECG signals. Li Gang and his colleagues made analysis of ECG signals using back propagation neural netwroks [1]. A. Khamene and S. Negahdaripour extracted fetal ECG from abdominal signals using wavelet transform[2]. P. de Chazal et al use wavelet coefficients for the classification of ECG signals [3].H. L. Lu, K. Ong and P. Chia classified ECG signals using neuro-fuzzy system [4]. S. M. Szilagyi and L. Szilagyi detected QRS signal using wavelet transform and neural networks[5].S. Osowski and T. H. Linh recognized ECG beat using fuzzy hybrid neural network [6].M. I. Owis et al. extracted features from ECG signal using nonlinear modeling for arrhythmia detection and classification [7]. T. H.

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Linh et al. made classification of heart rhythms based on ECG waveform using neuro fuzzy network[8]. L.Y. Shyu and his colleagues detected ventricular premature contraction using wavelet transform and fuzzy neural network [9]. J. Rodriguezet al. made real time classification of ECG on personal digital assistants (PDAs) [10]. R. Jafari et al. extracted features from ECG signals based on distributed embedded systems [11]. R. V. Andreao et al. made analysis of ECG signals using hidden markov models [12]. B. R. Greene et al. detected seizure in new born using ECG signals[13]. W. Jiang and S. G. Kong used block based neural networks for classification of ECG signals[14]. F. Melgani and Y. Bazi used support vector machine with particle swarm optimization to classify ECG signals [15]. A. H. Khandoker and his colleagues used support vector machine to recognize obstructive sleep apnea from recordings of ECG signals [16]. H. Kim et al. used quad level vector to compress and classify signals of ECG [17]. E. Pasolli and F. Melgani used active learning methods to classify ECG signals [18]. T. Mar et al. classified ECG signals by means of feature selection[19].F. Agrafioti et al. analysed ECG signals to detect emotion [20]. T. Chen et al. determined ECG signals if normal or abnormal using low power on body device to notice cardiovascular monitoring [21]. S. Banerjee and M. Mitra used cross vector transform for classification of ECG signals [22].S. Lee et al. used low power wireless ECG to classify ECG signals [23]. S. Kiranyaz et al. used one dimension convolutional neural networks for real time ECG classification[24]. S. Raj and K. C. Ray used discrete cosine transform based on discrete orthogonal stockwell transform for analysis of ECG signals [25].Y. Xia et al. detected AF by deep convolutional neural networks[26]. K. Li and his colleagues suggested a way to detect obstrsuctive sleep apnea based on deep neural network and Hidden Markov model (HMM) using single-lead ECG signal [27]. G. Swapna et al.detected cardiac arrhythmia automatically using deep learning[28]. R. S. Andersen and others made approach for real time detection of AF using deep neural networks [29]. B. Houet al. used deep learning neural networks for classification of ECG arrhythmias [30]. J. Yang and R. Yan made multidimensional feature extraction for classification of ECG arrhythmias [31]. In this paper, analysis techniques are discussed in section 2. In section 3, experiments and results are conducted. Finally conclusions about this paper are presented in section 4.

2. Analysis & Techniques

The DTT is related to the discrete tan transform. Discrete Sine transform (DST). DSNT is related to discrete sinc transform. DTT, DST, DSNT are deduced from DCTas shown in the next equations (1-6). DTT and DST can be used for applications of data reduction.

$$y(k) = w(k)\sum_{n=1}^{N} x(n)\tan\left(\frac{\pi}{2N(2n-1)(k-1)}\right) \qquad (1)$$

$$y(k) = w(k)\sum_{n=1}^{N} x(n)\sin\left(\frac{\pi}{2N(2n-1)(k-1)}\right) \qquad (2)$$

$$y(k) = w(k)\sum_{n=1}^{N} x(n)\cos\left(\frac{\pi}{2N(2n-1)(k-1)}\right) \qquad (3)$$

$$y(k) = w(k)\sum_{n=1}^{N} x(n)\mathrm{sinc}\left(\frac{\pi}{2N(2n-1)(k-1)}\right) \qquad (4)$$

$$\mathrm{sinc}(t) = \begin{cases} \dfrac{\sin(\pi t)}{\pi t}, t \neq 0 \\ 1, t = 0 \end{cases} \qquad (5)$$

$$w(k) = \begin{cases} \dfrac{1}{\sqrt{N}}, k = 1 \\ \sqrt{\dfrac{2}{N}}, 2 \leq k \leq N \end{cases} \qquad (6)$$

N is the length of x. The size of x and y are the same. All these discrete transforms are used as shown below in analysis and extracting features from ECG signals [32-34].

Fast Fourier transform FFT is calculated as discrete Fourier transform DFT but FFT is faster than DFT with ratio N/$\log_2$(N). DFT is calculated as shown in equation(7) [35].

$$X(k) = DFT(x(n)) = \sum_{n=1}^{N} x(n)\mathrm{e}^{-\mathrm{jkn}} \qquad (7)$$

$$STFT(\omega,\tau) = F\{x(t).w(t-\tau)\} = \int_{-\infty}^{\infty} x(t).w(t-\tau)e^{-j\omega t}dt \qquad (8)$$

$$w(m) = 0.54 - 0.46\cos\left(\frac{2\pi m}{N}\right) \qquad (9)$$

STFT is FFT which is windowed by hamming window as shown in equation (8,9). Where m=1,2…N. X is divided into 8 segments with 50% overlap. Each segment is windowed by hamming window[35].

$$W_{\Phi}(j_0,k)=\frac{1}{\sqrt{N}}\sum_{1}^{N} f(x).\Phi_{j_0,k}(x) \qquad (10)$$

$$W_{\Psi}(j,k)=\frac{1}{\sqrt{N}}\sum_{1}^{N} f(x).\Psi_{j,k}(x) \qquad (11)$$

Discrete wavelet transform W is calculated as shown in equations (10,11). Where $j \geq j_0$, $x=1,2,\dots N$.

$j=1,2,3,\dots J$. $N=2^J$.

The used mother wavelet transform ϕ, Ψ is Daubechies wavelet familydb2[36].

3. Methodology

First, detrended Normalized ECG signals DNECG are obtained. The ECG signal (Volt) y is normalized to $y_{normalized}$ as shown in equation (12). Where y_{min} is minimum of y. y_{max} is maximum of y. Then the signal is detrended to $y_{detrended}$ as shown in equation(13,14). Where y_{mean} is mean of y.

$$y_{normalized}=\frac{y-y_{\min}}{y_{\max}-y_{\min}} \qquad (12)$$

$$y_{detrended}=y_{normalized}-y_{mean} \qquad (13)$$

$$y_{mean}=\frac{\sum y}{length(y)} \qquad (14)$$

there are 24 algorithms are applied to the normalized detrended ECG signals. In the 1st algorithm, STFT of NDECG is calculated then DST is applied as shown in Fig.1. In the second algorithm, FFT of NDECG is calculated then DST is applied as shown in Fig.2. In the 3rd algorithm, discrete wavelet transform of NDECG is calculated then DST is applied as shown in Fig.3. In the 4th algorithm, power (signal is squared) of STFT of DNECG is applied then power is calculated after that DST is applied a shown in Fig.4.In the 5th algorithm, FFT of DNECG is applied then power is calculated after that DST is applied as shown in Fig5. In the 6th algorithm, DWT of DNECG is applied then power is calculated after that DST is applied as shown in Fig.6. In the 7th algorithm, STFT of DNECG is calculated after that DSNT is applied as shown in Fig.7. In the 8th algorithm, FFT of DNECG is calculated after that DSNT is applied as shown in Fig.8. In the 9th algorithm, DWT of DNECG is calculated after that DSNT is applied as shown in Fig.9. In the 10th algorithm, STFT of DNECG is applied then power is calculated after that DSNT is applied as shown in Fig.10. In the 11th algorithm, FFT of DNECG is applied then power is calculated after that DSNT is applied as shown in Fig.11. In the 12th algorithm, DWT of DNECG is applied then power is calculated after that DSNT is applied as shown in Fig.12. In the 13th algorithm, STFT of DNECG is calculated after that DCT is applied as shown in Fig.13. In the 14th algorithm, FFT of DNECG is calculated after that DCT is applied as shown in Fig.14. In the 15th algorithm, DWT of DNECG is calculated after that DCT is applied as shown in Fig.15. In the 16th algorithm, STFT of DNECG is applied then power is calculated after that DCT is applied as shown in Fig.16. In the 17th algorithm, FFT of DNECG is applied then power is calculated after that DCT is applied as shown in Fig.17. In the 18th algorithm, DWT of DNECG is applied then power is calculated after that DCT is applied as shown in Fig.18. In the 19th algorithm, STFT of DNECG is calculated after that DTT is applied as shown in Fig.19. In the 20th algorithm, FFT of DNECG is calculated after that DTT is applied a shown in Fig.20. In the 21th algorithm, DWT of DNECG is calculated after that DTT is applied as shown in Fig.21. In the 22th algorithm, STFT of DNECG is applied then power is calculated after that DTT is applied as shown in Fig.22. In the 23th algorithm, FFT of DNECG is applied then power is calculated after that DTT is applied as shown in Fig.23. In the 24th algorithm, DWT of DNECG is applied then power is calculated after that DTT is applied as shown in Fig.24.

Tabel 1. Comparison between percent of accuracies of 24 algorithms using different classifiers

Algorithm	ANN	KNN	SVM	ANFIS	DL BILSTM	DL LSTM
1st algorithm	88.7%	78.89%	88.23%	87.37%	87.4%	87.2%
2nd algorithm	90.44%	78.72%	89.79%	90.38%	87.2%	87.2%
3rd algorithm	91.2%	84.6%	88.75%	92.62%	94.5%	97.2%
4th algorithm	84.8%	78.55%	85.47%	86.53%	90.5%	83.9%
5th algorithm	88.3%	82.35%	90.66%	87.02%	87.2%	87.2%
6th algorithm	91.6%	80.62%	93.08%	96.51%	98.4%	94.1%
7th algorithm	87.23%	81.35%	86.16%	92.85%	96.2%	84.63%
8th algorithm	91.24%	85.44%	75.95%	90.83%	87.2%	86.52%
9th algorithm	88.29%	83.76%	81.66%	92.04%	98.4%	89.46%
10th algorithm	87.71%	81.52%	68.68%	85.84%	99%	86.87%
11th algorithm	88.09%	81.27%	87.54%	89.64%	87.2%	88.42%
12th algorithm	90.46%	80.18%	86.16%	95.31%	98.6%	97.41%
13th algorithm	87.08%	82.25%	87.02%	86.98%	83.9%	87.91%
14th algorithm	89.87%	83.37%	87.02%	91.58%	93.4%	87.56%
15th algorithm	90.71%	83.59%	85.81%	86.81%	97.4%	90.33%
16th algorithm	89.32%	80.69%	71.97%	91.93%	**99.1%**	87.22%
17th algorithm	89.43%	81.29%	78.72%	93.1%	87.2%	86%
18th algorithm	91.29%	83.13%	85.98%	93.28%	96.5%	95.85%
19th algorithm	91%	79.69%	86.51%	94.74%	87.2%	88.77%
20th algorithm	88.15%	78.28%	81.48%	92.85%	97.8%	88.4%
21th algorithm	86.98%	80.58%	71.45%	87%	87.2%	86.2%
22th algorithm	88.26%	79.62%	72.49%	91.81%	95%	84.5%
23th algorithm	87.75%	82.68%	83.91%	92.6%	87.2%	87.74%
24thalgorithm	86.91%	80.41%	85.46%	90.9%	90.8%	87.7%

Table 2 Metrics of classification of the proposed algorithms

Algorithm	%Accuracy	Sensetivity%	Specificiy%	%Precision	Recall%	F_measure%	Gmean%
dct(fft)	93.44	98.42	99.46	94.31	98.42	96.32	96.5%
dct(p(fft))	87.22	100	0	87.22	100	93.17	0
dct(p(stft))	**99.14**	**100**	**93.24**	**99.02**	**100**	**99.51**	**96.56**
dct(stft)	83.94	81.58	100	100	81.58	89.86	90.32
dct(wav)	97.41	99.8	81.08	97.3	99.8	98.53	89.96
dsin(p(stft))	98.45	98.42	98.65	99.8	98.42	99.1	98.5
dsin(stft)	87.4	100	1.3	87.37	100	93.26	11.6
dsnct(fft)	87.22	100	0	87.22	100	93.17	0
dsnct(p(stft))	98.96	99.8	93.24	99.02	99.8	99.41	96.47
dsnct(p(wav))	98.62	98.42	100	100	98.42	99.2	99.2
dsnct(stft)	96.2	100	70.2	95.82	100	97.87	83.83
dsnct(wav)	98.45	100	87.8	98.25	100	99.11	93.72
dtt(fft)	97.75	97.43	100	100	97.43	98.69	98.7
dtt(p(fft))	89.22	100	0	87.22	100	93.17	0
dtt(p(stft))	94.99	100	60	94.57	100	97.21	77.98
dtt(p(wav))	87.7	100	0	87.73	100	93.47	0
dtt(wav)	87.22	99.6	2.7	87.48	99.6	93.15	16.41

Table 3 Metrics of classification of the selected algorithm using BILSTM

Accuracy%	AUC	Fmeasure	Sensetivity%	Specificiy%	%Precision	Recall%	Gmean%
99.13%	0.966	99.51%	100%	93.24%	99.02%	100%	96.56%

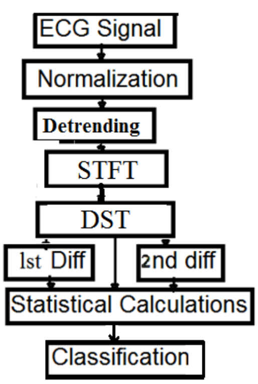

Fig. 1. The 1st algorithm

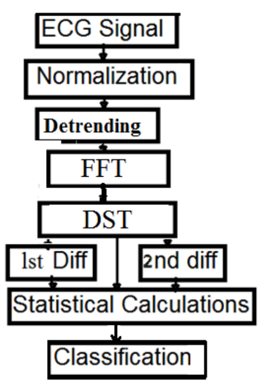

Fig. 2. The 2nd algorithm

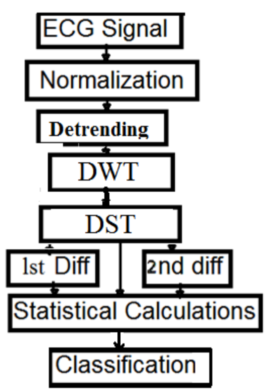

Fig. 3. the 3rd algorithm

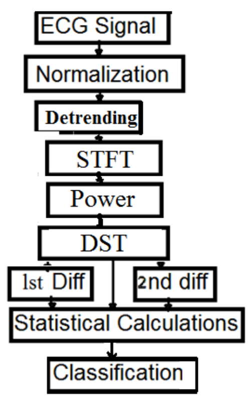

Fig. 4. The 4th algorithm

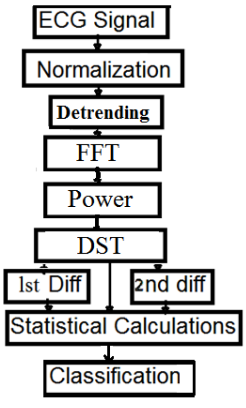

Fig. 5. The 5th algorithm

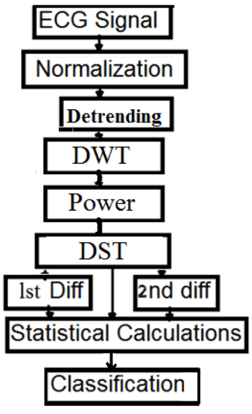

Fig. 6. The 6th algorithm

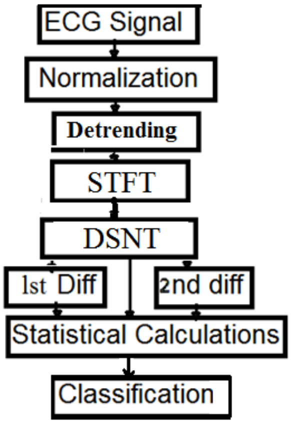

Fig. 7. The 7th algorithm

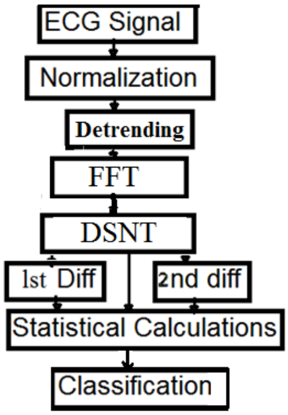

Fig. 8. The 8th algorithm

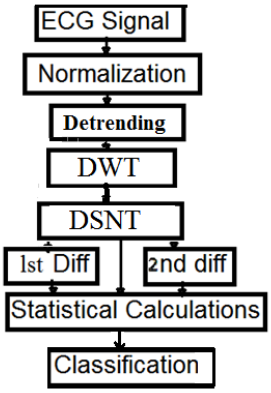

Fig. 9. The 9th algorithm

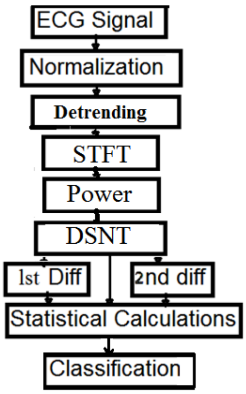

Fig. 10. The 10th algorithm

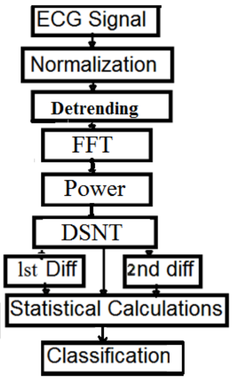

Fig. 11. The 11th algorithm

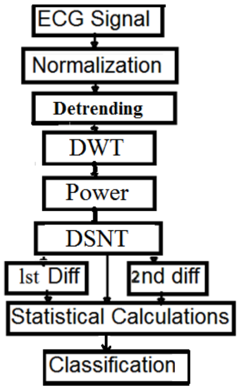

Fig. 12. The 12th algorithm

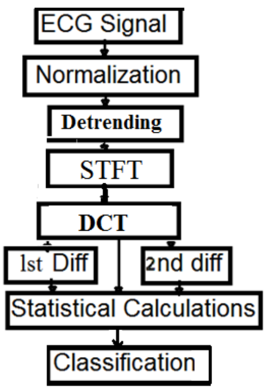

Fig. 13. The 13th algorithm

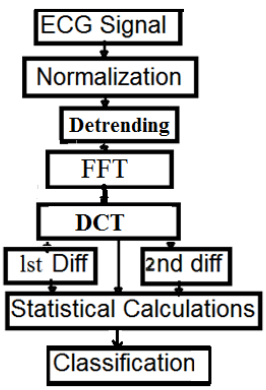

Fig. 14. The 14th algorithm

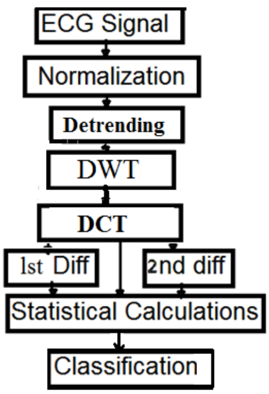

Fig. 15. The 15th algorithm

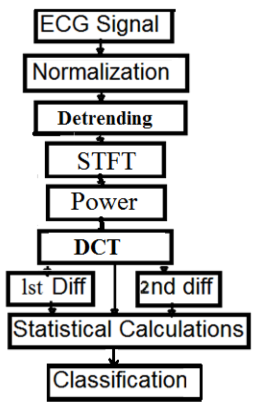

Fig. 16. The 16th algorithm

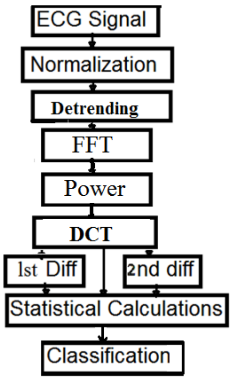

Fig. 17. The 17th algorithm

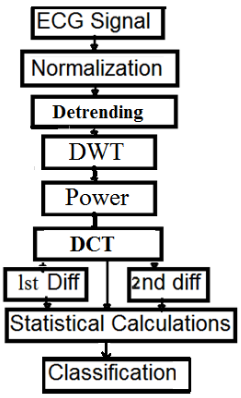

Fig. 18. The 18th algorithm

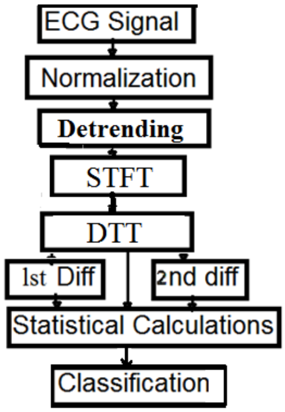

Fig. 19. The 19th algorithm

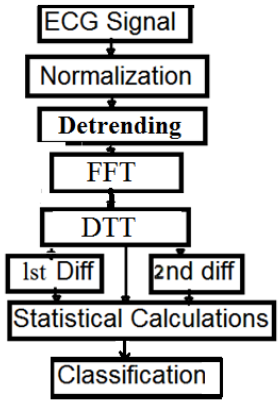

Fig. 20. The 20th algorithm

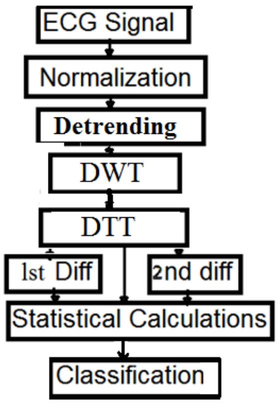

Fig. 21. The 21th algorithm

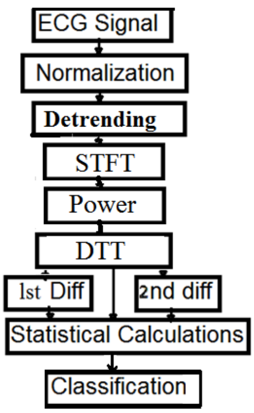

Fig. 22. The 22th algorithm

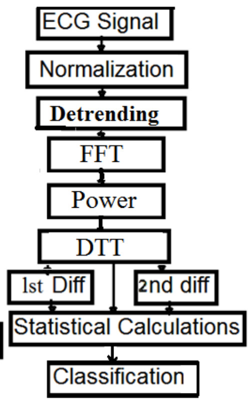

Fig. 23. The 23th algorithm

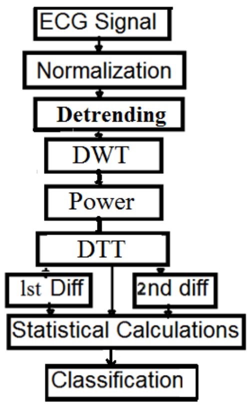

Fig. 24. The 24th algorithm

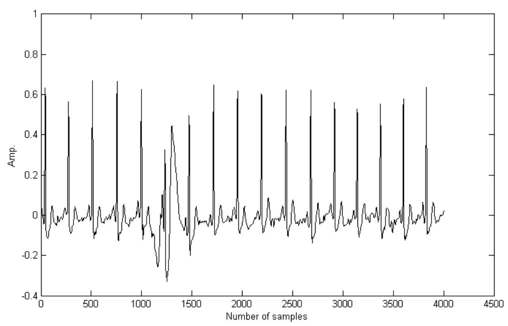

Fig. 25. Detrended normalized normal ECG signal

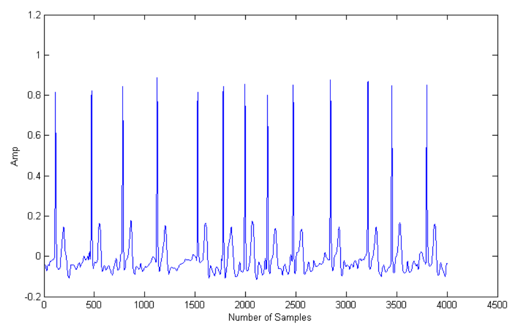

Fig. 26. Detrended normalized Afib ECG signal

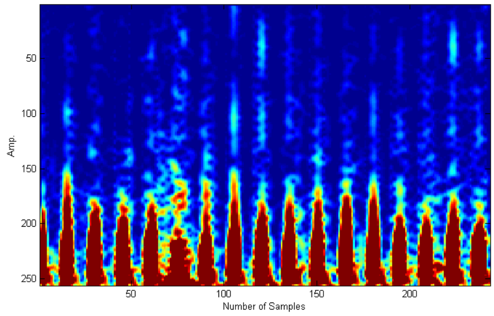

Fig. 27: STFT of DNECG of normal signal

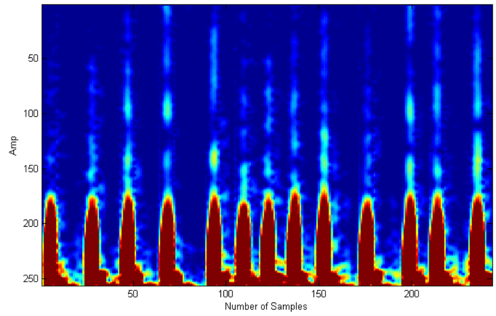

Fig. 29: STFT of DNECG of AFib signal

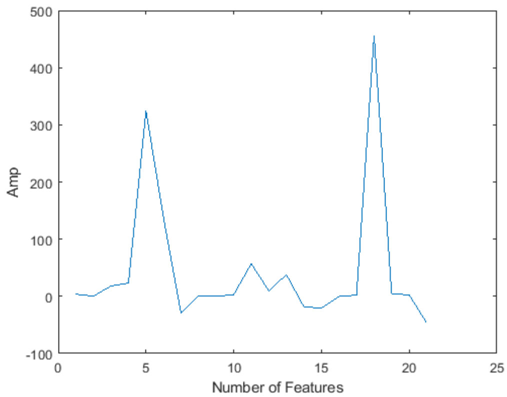

Fig. 28. Features of normal ECG

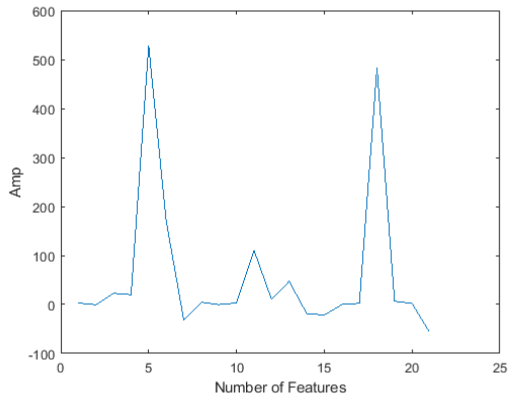

Fig. 30. Feature of Afib ECG

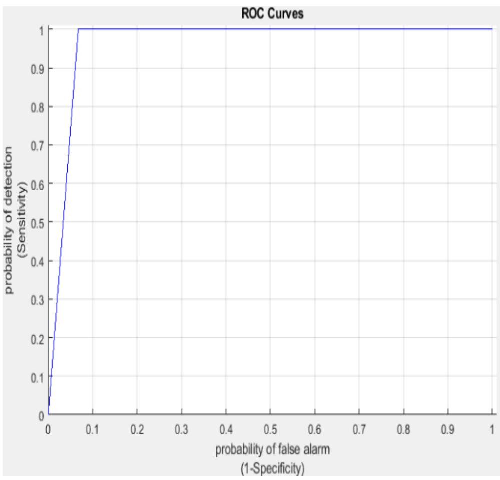

Fig. 31. AUC of the selected algorithm

4. Results & Discussion

Signals of ECG are selected from the PhysioNet 2017 Challenge [37]. These signals are sampled at 300 Hz. ECG signals are divided into 4 classes: Normal (N), AFib (A), Other Rhythm (O), and Noisy Recording. These dataset is collected from the training set. 90% of the database is used for training. 10% of the database is used for testing. In this paper, different classifiers differentiate between Normal ECG signals and AFib signals only. Other signals are discarded. 24 algorithms are applied. The best performance algorithm is selected when STFT of DNECG is applied then power is calculated after that DCT is applied which has the maximum accuracy rate and maximum F_measure rate. As shown in Fig.25, deterended normalized of normal ECG signal is presented. As shown in Fig.26, detrended normalized Afib signal is introduced. As shown in Fig27, absolute value of STFT of detrended normalized of normal ECG signal is presented. As shown in Fig. 28, features of normal ECG is presented. As shown in Fig 29, absolute value of STFT of detrended normalized Afib signal is introduced. As shown in Fig 30, feature of Afib ECG signal is presented. The number of extracted features from each algorithm is 21 features which are calculated from statistical calculations (mean ,maximum, minimum, standard deviation, variance, skewness and kurtosis) of 1st derivative , 2nd derivative of each output from each discrete transform (DST , DSNT, DCT or DTT) and themselves. The only selected algorithm which achieves the highest accuracy percent which is the 16th algorithm. Several classifiers are compared such as ANN, KNN, SVM, ANFIS and deep learning (BILSTM and LSTM) as shown in Table 1. The highest selected algorithm is deep learning with BILSTM. It is a kind of RNN. BILSTM layer is used to look at the time series of ECG data in the forward and backward direction. ECG data is divided into small batches during learning process. The size of input signals of BILSTM is 21 features. Numbers of neurons of BILSTM are 100 neurons. The final output is two, which is specified by fully connected layer. Then next layers are followed by softmax layer and classification layer. Then, the options of the classifier are determined. The number of maximum epochs is chosen to be 100 to permit the network to compose 100 passes during the training process. Minimum batch size is selected to be 150 to allow the network to deal with 150 training signals at a time. The initial learning rate is 0.01 to accelerate the process of training. The gradient threshold is set to be 1 to make the training process stable by stopping gradients from increasing too high. Adaptive moment estimation solver is applied which improve the performance of RNN. From data of ECG signals (AFib and Normal) 90% are chosen for training data and 10% are chosen as testing data. The accuracy is calculated by confusion matrix. The time required for training process reaches 11 minutes. The total training accuracy is 99.5% but the accuracy of AFib signals is 100% and the accuracy of normal signals is 99.5%. During testing process, the overall accuracy is 99.1%, the accuracy of AFib signals is 100% and the accuracy of normal signals is 99%. As shown in Table2, several algorithms are compared by calculating accuracy, sensitivity rate, specificity rate, precision rate, recall rate, F_measure rate and gmean rate. As shown in Table 2, the selected algorithm which achieve maximum accuracy rate and F_measure rate of DCT of power of STFT of the signal dct(p(stft))). As shown in Table 3, AUC Area under curve of the selected algorithm equals 0.966. %F-measure equals 99.51%. Sensitivity rate and precision rate equal 99.02%. Recall rate equals 100%. Gmean rate equals 96.56%. As shown in Fig.31, Receiver operating characteristics (ROC) of the selected algorithm is approaching to 1. From all these values, the performance of the selected algorithm satisfies high classification stability.

5. Conclusion

In this paper, several classifiers are used for analyzing ECG signals. Features of ECG signals are compared between 24 algorithms. The classification phase is conducted by ANN, KNN, SVM,ANFIS, Deep Learning with LSTM and BILSTM. The simulation results demonstrated that classification using DL with BILSTM has the most recognition rate of 99.1% using the selected algorithm which is calculated by DCT of powered STFT of DNECG signals. So this is the selected algorithm for analyzing ECG signals. In the future, it is suggested to find a new classification method more rapid than DL method for extracting features from the biomedical signals.

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