Analysis of Noise Perturbation on Neural Network Based ECG Classification

Abdoul-Dalibou Abdou[1,3(✉)], Ndeye Fatou Ngom[2,3], Oumar Niang[2,3], and Mohamed Cheikh Ould Guera[4]

[1] Université de Thies, Thiès, Senegal
abdould.abdou@univ-thies.sn
[2] Ecole Polytechnique de Thies, Thiès, Senegal
{fngom,oniang}@ept.sn
[3] Laboratoire Traitement de l'Information et Systémes Intelligents, Thiès, Senegal
[4] Université Gaston berger, Saint-Louis, Senegal
gueramed@gmail.com

Abstract. The heart diseases are diagnosed by analysing the ECG signals. However, during the acquisition process, the ECG signals are affected by different noises. Therefore, it is crucial to realize a pretreatment of the ECG signals before extracting the features. This article aims to study the effects of the Empirical Mode Decomposition filtering and Butterworth filtering on arrhythmia classification based on the convolutional neural network. Five classes of arrhythmia are concerned, including the sino-auricular node dysfunction, the supra-ventricular tachycardia, the ventricular tachycardia, the auricular flutter and the auricular Fibrillation. The proposed approach is evaluated with the MIT-BIH Arrhythmia database.

Keywords: ECG denoising · Arrhythmia classification · Convolutional Neural Networks · Empirical Mode Decomposition · Butterworth filter

1 Introduction

The arrhythmia diagnosis depends on the analysis of electrocardiogram (ECG) signal properties. Usually real ECG signal faces various types of noises [19]. These noises influence the ECG signals components and lead to false diagnosis. Therefore, all operations of electrocardiograms signals processing must begin with a pretreatment in order to suppress or attenuate noise. The preprocessing allows to filter out signal interference [23] and to remove different types of noise [10]. This paper studies the effects of the four filtering methods on the classification of ECG signals with the convolutional neural network, the Empirical Mode Decomposition filtering, Butterworth filtering and their combination. The proposed CNN consists of the five convolutions, corresponding to five classes of

© Springer Nature Switzerland AG 2019
S. Misra et al. (Eds.): ICCSA 2019, LNCS 11623, pp. 349–358, 2019.
https://doi.org/10.1007/978-3-030-24308-1_29

cardiac arrhythmias: sino-auricular node dysfunction; supra-ventricular tachycardia; ventricular tachycardia; auricular flutter and auricular Fibrillation. The schematic diagram of the processing steps is illustrated by Fig. 1.

The rest of the paper is organized as follows: The ECG signal denoising methods at the Sect. 2; the comparison of the EMD and the Butterworth based on filtering methods at the Sect. 3.1; the classification of cardiac arrhythmias based on CNN at the Sect. 3.2, the data description and the performance indices at the Sect. 3.3; Finally the Sect. 4 presents the results of the approach.

2 Literature Review

Various types of noises [19] such as muscular noise, motion artifacts, baseline drifts changes, are present in an ECG signal. The ECG signals denoising aims to remove different noises of the ECG signals. The noises are originated from various sources:

- Power frequency from 5 Hz to 2 KHz;
- Frequency Interference around 50 Hz;
- Baseline drift from 0.05 to 2 Hz;
- Power line interference around 50 Hz or 60 Hz;
- Baseline wandering with a frequency bellow 0.5 Hz;
- Electrodes motion artifacts from 1 Hz to 10 Hz;
- Electromyographic noise from 25 Hz to 100 Hz.
- Etc.

Many techniques have been implemented to suppress or attenuate noise. Several methods are proposed for noise elimination. The signal are denoised with the empirical mode decomposition [6,16,20]. The lower order IMFs represent the high frequency and the upper order IMFs correspond to low frequency. If the ECG is corrupted by baseline wander, it should appear in some higher order IMF. The power frequency noises must be represented in some lower order IMF. Rodriguez [19] has used a 6th order band-pass Butterworth filter for removing high frequencies and baseline wander. Abdou et al. [3] have combined the advantages of EMD filtering and 6th order band-pass Butterworth filter for ECG signal denoising. The high frequency noise is treated by subtracting the first IMF and the signal is smoothed by the Butterworth filter [1,2]. Many others methods of ECG denoising exist such as:

- Digital filter for the baseline wander;
- Low pass filter for removing power frequency interference;
- PCA-ANN-WT for high frequency noise elimination;
- Butterworth filter for the ECG signal noise smoothing;
- EMD filtering for low and high frequency noise;
- Wavelet threshold shrinkage (WTS);
- Empirical Denoising Algorithm;
- Etc.

The convolutional Neural Networks (CNN) have been used in many domains as computer vision tasks [5,8,9], ECG signals processing [4,17,18,22], time series prediction and completing [24], retinal disease diagnosis [5], ureteral stone identification [9], etc.

3 Methodology

The proposed approach is composed of a double denoising method and a CNN Classifier as depicted by the Fig. 1. After the pre-processing steps, the CNN assigns an ECG signal to one of the following arrhythmia classes:

- Class 0: normal, heart rate between 60 and 100 beats per minute.
- Class 1: sino-auricular node dysfunction, heart rate less than 50 beats per minute.
- Class 2: supra-ventricular tachycardia, heart rate between 160 and 200 beats per minute.
- Class 3: ventricular tachycardia, heart rate between 200 and 250 beats per minute.
- Class 4: auricular flutter, heart rate between 250 and 300 beats per minute.
- Class 5: Auricular Fibrillation, heart rate between 300 and 600 beats per minute.

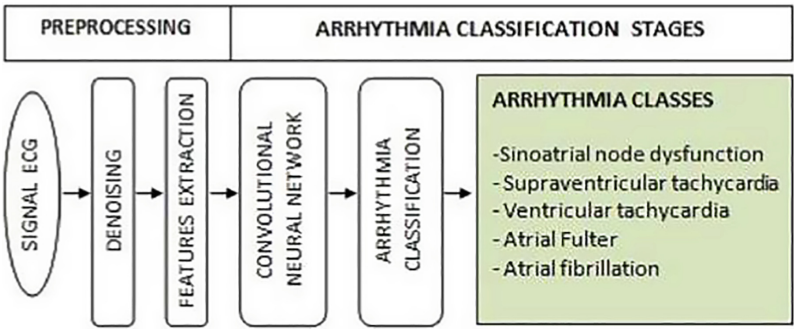

Fig. 1. Chart Flow of the proposed classification system. After, denoising and cardiac frequency computation steps, the CNN classified the ECG signal.

3.1 EMD and Butterworth Denoising

EMD is an auto-adaptive method for decomposing a signal. It decomposes a signal into Intrinsic Mode Functions [6,14,16,20]. The EMD principle is to identify locally the fastest oscillations. The EMD is formulated by Eq. 1. The Fig. 2 illustrated the EMD of the ECG 100 of the MIT-BIH database.

$$s(n) = r_k(n) + \sum_{k=1}^{K} imf_k(n) \tag{1}$$

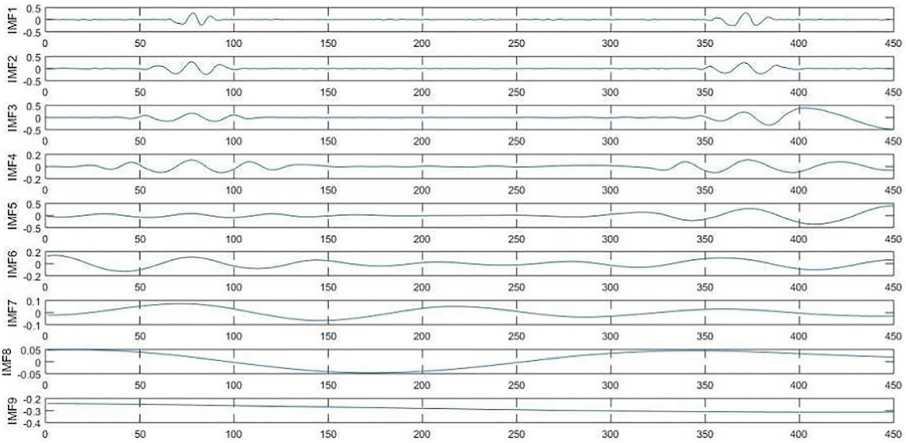

Fig. 2. Empirical mode decomposition of ECG 100

where imf_k is the kth Intrinsic Mode Functions and r_k is the trend residual. The Butterworth filter and empirical mode decomposition are implemented. The two filtering methods are tested and compared. The Fig. 3 shows the Butterworth filter effect and the Fig. 4 presents the EMD filtering effect. The Fig. 5 shows the double filtering based on Butterworth and EMD.

3.2 Convolutional Neural Network

A CNN consists of several convolutional layers alternated with pooling layers and then followed by fully connected layers and finally a classification/regression layer. A CNN has four basics layers:

1. Convolution: The prime objective of convolution is to extract features from the input.
2. Rectified linear activation function: The ReLU layer serves to map nonlinearity into the data.
3. Pooling: This layer reduces the number of parameters and calculations in the network.
4. Fully connected: It returns a vector of size N, where N is the number of classes. Each element of the vector indicates the probability for the image to belong to a class.

The proposed approach is based on the CNN [7,21] and the instantaneous heart rate [12] for arrhythmia classification. The Fig. 6 presents the CNN used for the arrhythmia classification. The convolutions ($conv_{1..5}$) use respectively the reverse of 50, 160, 200, 250 and 300. Then the pooling step reduces the vector size by taking only the frequency corresponding to the arrhythmia class. Finally, the fully connected step compute the probability of the ECG to belong to each

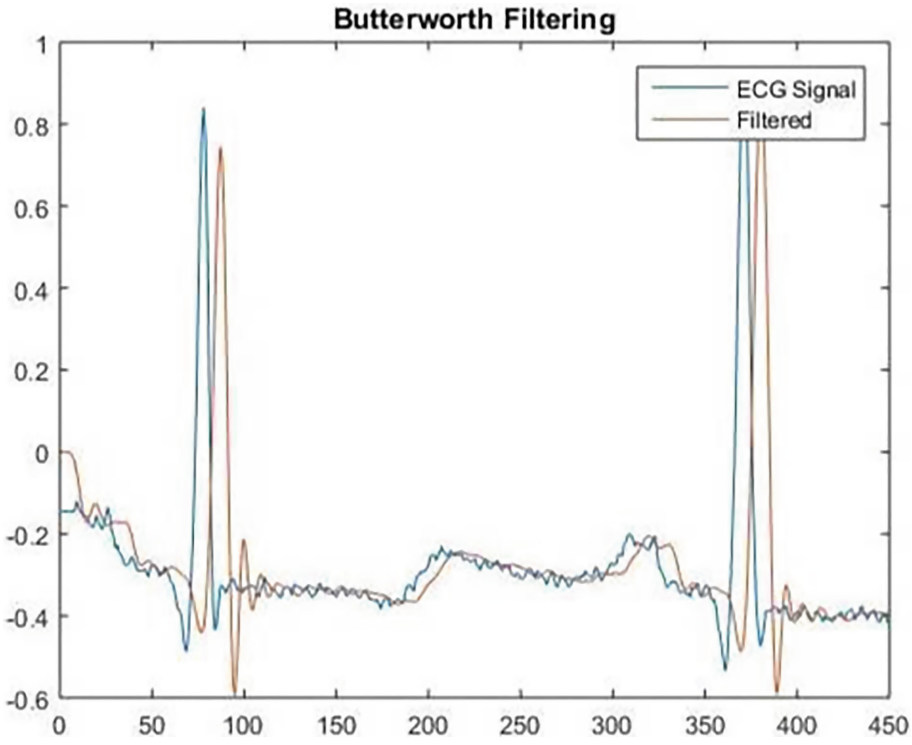

Fig. 3. The Butterworth filter denoises and smooths the ECG Signal 100 of the MIT-BIH Database.

arrhythmia class. That probability is computed with the Eq. 2. The output layer determines the arrhythmia class with the high probability.

$$P = \frac{size(PFV)}{size(CFV)} \tag{2}$$

Where PFV is the frequency vector after the pooling step and CFV is the input vector.

3.3 Performance Measurement

The proposed approach is evaluated with the ECG signals of the MIT-BIH database. The MIT-BIH database is described in many works such as [1–3,13]. It is a set of 48 data files, 48 annotations files and 48 head files.

The Table 1 presents the 48 ECG signals of the MIT-BIH arrhythmia database. Each data has 21600 samples (time), 21600 MLII signals and 21600 V5 signals. The recordings were digitized at 360 samples per second per channel with 11 bit resolution over a 10 mV range.

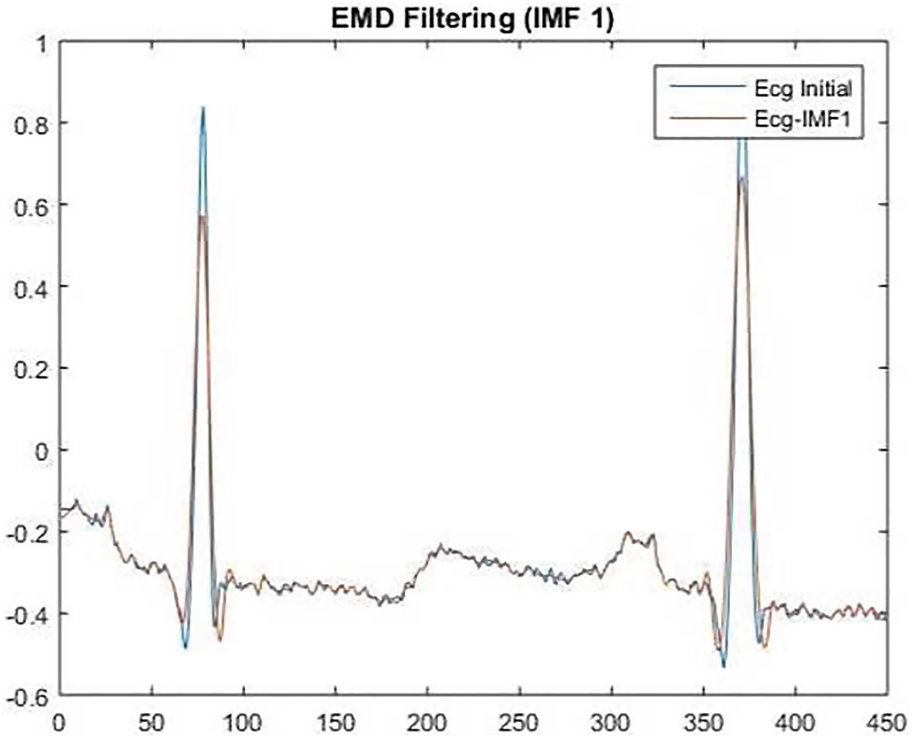

Fig. 4. The EMD Filtering subtracts the upper IMF to denoise the ECG Signal 100 of the MITBIH Database.

Table 1. The ECG signals of the MIT-BIH Arrhythmia database

100	101	102	103	104	105	106	107	108	109	111	112	113	114	115	116
117	118	119	121	122	123	124	200	201	202	203	205	207	208	209	210
212	213	214	215	217	219	220	221	222	223	228	230	231	232	233	234

The CNN is trained with 70% and tested with 30% of the MIT-BIH database ECG signals. After the test, the performance criteria are computed [11,15]:

1. Accuracy $Ac.(\%) = \frac{TP+TN}{TP+TN+FP+FN}$ x 100,
2. Sensitivity $Se.(\%) = \frac{TP}{TP+FN}$ x 100,
3. Specificity $Sp.(\%) = \frac{TN}{TN+FP}$ x 100,
4. Positive Predictivity $Pp.(\%) = \frac{TP}{TP+FP}$ x 100.

Where TP, TN, FP and FN mean:

- TP (True Positive): Abnormal class classifies as abnormal.
- TN (True Negative): Normal class classifies as abnormal.
- FP (False Positive): Normal class classifies as normal.
- FN (False Negative): Abnormal classifies as normal.

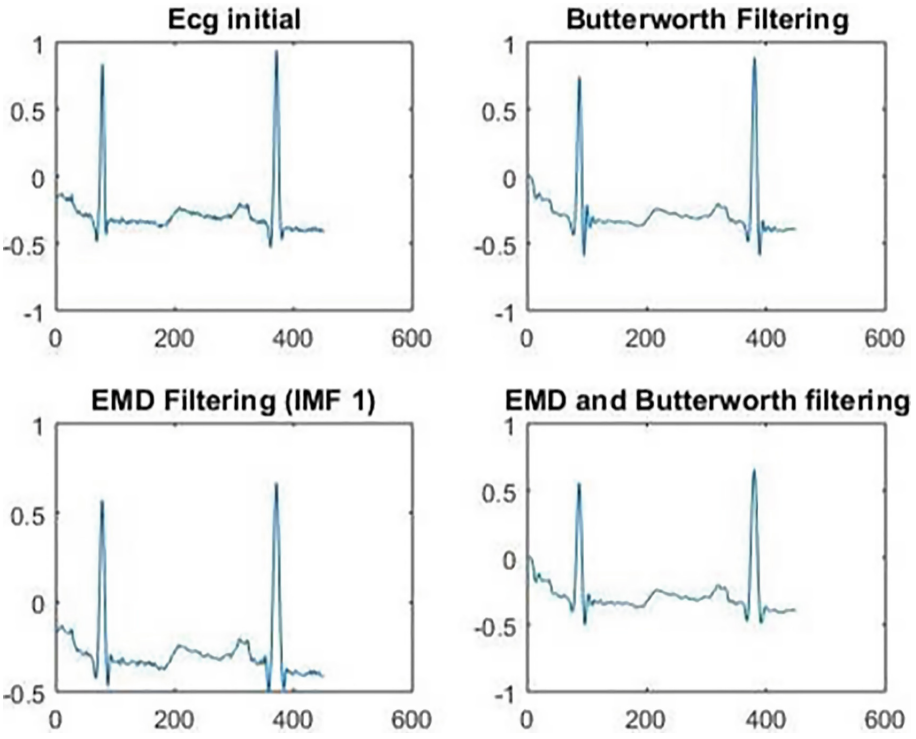

Fig. 5. The two filtering methods are combined to denoise the ECG Signal 100 of the MITBIH Database.

4 Results

The Table 2 shows the performance indices following different denoising method. The first denoising method is the Butterworth filtering. The second is the EMD filtering with the subtracting of the first IMF. The third and the fourth method are the doubles filtering based on the combination of EMD and butterworth filtering. The analysis of the Table 2 contents shows that EMD filtering and Butterworth filtering have the same accuracy of 47%. Butterworth filtering and EMD + Butterworth filtering has more sensitivity (22%) than EMD and Butterworth + EMD filtering, which has 11% sensitivity. In terms of specificity and

Table 2. Performance indices

Performance indices	TP	FP	TN	FN	Ac	Se	Sp	Pp
Butterworth	2	1	5	7	47%	22%	42%	67%
EMD	1	0	6	8	47%	11%	43%	100%
EMD + Butterworth	2	1	5	7	47%	22%	42%	67%
Butterworth + EMD	1	0	6	8	47%	11%	43%	100%

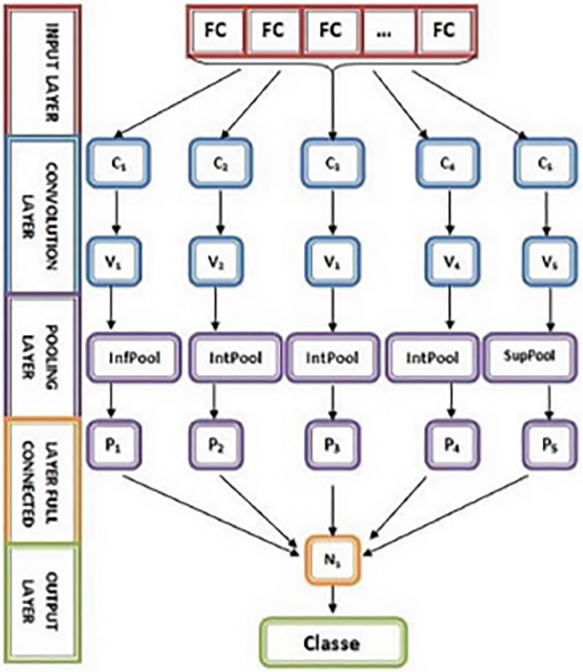

Fig. 6. Convolutional Neural Network for Arrhythmia classification takes input a vector of cardiac frequencies.

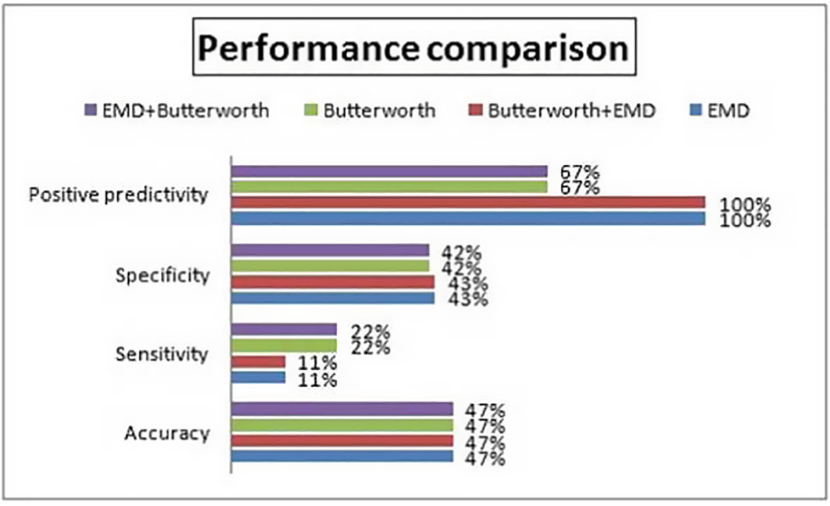

Fig. 7. Performance comparison between EMD and Butterworth based filtering methods.

positive predictivity, EMD filtering and Butterworth + EMD filtering are better than Butterworth filtering and EMD + Butterworth filtering, with respectively 43%, 43%, 42%, 42% for specificity and 100%, 100%, 67%, 67% for the positive predictivity. The Fig. 7 illustrates clearly the performance comparison of the EMD and the Butterworth based filtering methods.

5 Conclusion

This paper investigated the effects of four filtering methods on arrhythmia classification based on the convolutional neural network. It concerns the Butterworth filter, the EMD filtering and their combination. The CNN takes an input a heart rate vector and determines an arrhythmia class. The four pretreatment methods are tested and evaluated with the ECG signals of the MIT-BIH database. The performance comparison shows that the Empirical Mode Decomposition based on filtering methods are better than the Butterworth based on filtering methods. The future work will study the impact of each method on the different types of ECG signal noises.

References

1. Abdou, A.D., Ngom, N.F., Niang, O.: Electrocardiograms patterns analysis using artificial neural network and non-linear regression. In: Nabi, L.G., Eric, B., Watson, B. (eds.) CARI 2018 - Colloque africain sur la recherche en informatique et mathématiques appliquées, Stellenbosch, South Africa, pp. 25–36, October 2018
2. Abdou, A.-D., Ngom, N.F., Niang, O.: Classification and prediction of arrhythmias from electrocardiograms patterns based on empirical mode decomposition and neural network. In: Mendy, G., Ouya, S., Dioum, I., Thiaré, O. (eds.) AFRICOMM 2018. LNICST, vol. 275, pp. 174–184. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-16042-5_17
3. Abdou, A.D., Ngom, N.F., Sidibé, S., Niang, O., Thioune, A., Ndiaye, C.H.T.C.: Neural networks for biomedical signals classification based on empirical mode decomposition and principal component analysis. In: M. F. Kebe, C., Gueye, A., Ndiaye, A. (eds.) InterSol/CNRIA -2017. LNICST, vol. 204, pp. 267–278. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-72965-7_25
4. Pourbabaee, B., Howe-Patterson, M., Reiher, E., Frederic, B.: Deep convolutional neural network for ECG-based human identification. Can. Med. Biol. Eng. Soc. **41** (2018)
5. Al-Bander, B., Al-Nuaimy, W., Williams, B.M., Zheng, Y.: Multiscale sequential convolutional neural networks for simultaneous detection of fovea and optic disc. Biomed. Signal Process. Control **40**, 91–101 (2018)
6. Jin, F., Sugavaneswaran, L., Krishnan, S., Chauhan, V.S.: Quantification of fragmented QRS complex using intrinsic time-scale decomposition. Biomed. Signal Process. Control **31**, 513–523 (2017)
7. Karhe, R.R., Bhagyashri, B.: Arrhythmia detection using one dimensional convolutional neural network. Int. J. Eng. Technol. **5**(8) (2018)
8. Kim, Y.: Convolutional neural networks for sentence classification. In: Conference on Empirical Methods in Natural Language Processing (EMNLP), pp. 1746–1751 (2014)

9. Martin, L., Johan, J., Per, T., Amy, L., Mats, L.: Computer aided detection of ureteral stones in thin slice computed tomography volumes using convolutional neural networks. Comput. Biol. Med. **97**, 153–160 (2018)
10. Hadjem, M., Salem, O., Naït-Abdesselam, F.: An ECG monitoring system for prediction of cardiac anomalies using WBAN. In: IEEE 16th International Conference on e-Health Networking, Applications and Services (Healthcom), pp. 441–446 (2014)
11. Nazarahari, M., Namin, S.G., Markazi, A.H.D., Anaraki, A.K.: A multi-wavelet optimization approach using similarity measures for electrocardiogram signal classification. Biomed. Signal Process. Control **20**, 142–151 (2015)
12. Mitra, M., Chakrabarty, S., Mia, Md.S., Rahman, A.: Identification of arrhythmia in electrocardiogram (ECG) using statistical tools and non-linear analysis. Int. J. Bioinform. Biomed. Eng. **4**(2) (2018)
13. Moody, G.B., Mark, R.G.: The impact of the MIT-BIH arrhythmia database. IEEE Eng. Med. Biol. **20**, 45–50 (2001)
14. Niang, O., Thioune, A., Delechelle, E., Lemoine, J.: Spectral intrinsic decomposition method for adaptative signal representation. ISRN Signal Process. **9**, 3 (2012)
15. Padmavathi, S., Ramanujam, E.: Naïve Bayes classifier for ECG abnormalities using multivariate maximal time series Motif. Procedia Comput. Sci. **47**, 222–228 (2015)
16. Pal, S., Mitra, M.: Empirical mode decomposition based on ECG enhencement and QRS detection. Comput. Biol. Med. **42**, 83–92 (2012)
17. Acharya, U.R., Fujita, H., Oh, S.L., Hagiwara, Y., Tan, J.H., Adam, M.: Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals. Inf. Sci. **415–416**, 190–198 (2017)
18. Acharya, U.R., Fujita, H., Lih, O.S., Hagiwara, Y., Tan, J.H., Adam, M.: Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network. Inf. Sci. **405**, 81–90 (2017)
19. Rodriguez, R., Mexicano, A., Bila, J., Cervantes, S., Ponce, R.: Feature extraction of electrocardiogram signals by aplying adaptative threshold and principal component analysis. J. Appl. Res. Technol. **13**, 261–269 (2015)
20. Slimane, Z.H., Nait Ali, A.: QRS complex detection using empirical mode decomposition. Digital Signal Process. **20**, 1221–1228 (2010)
21. Subbiah, S., Suresh, S.: Biomedical arrhythmia heart diseases classification based on artificial neural network and machine learning approach. Int. J. Eng. Technol. **7**, 10–14 (2018)
22. Xiang, Y., Lin, Z., Meng, J.: Automatic QRS complex detection using two level convolutional neural network. BioMed. Eng. OnLine **17**, 13 (2018)
23. Zhang, H.: An improved QRS wave group detection algorithm and matlab implementation. Phys. Procedia **25**, 1010–1016 (2012)
24. Ziat, A.Y.: Apprentissage de représentation pour la prédiction et la classification de séries temporelles. Réseau de neurones. PhD thesis, Université Pierre et Marie Curie - Paris VI (2017)