Artificial intelligence classification methods of atrial fibrillation with implementation technology

Huey Woan Lim, Yuan Wen Hau, Chiao Wen Lim & Mohd Afzan Othman

Taylor & Francis
Taylor & Francis Group

RESEARCH ARTICLE

Artificial intelligence classification methods of atrial fibrillation with implementation technology

Huey Woan Lim[a], Yuan Wen Hau[a], Chiao Wen Lim[b] and Mohd Afzan Othman[c]

[a]IJN-UTM Cardiovascular Engineering Centre, Faculty of Biosciences and Medical Engineering, Universiti Teknologi Malaysia, Skudai, Johor, Malaysia; [b]Faculty of Medicine, Universiti Teknologi MARA, Sungai Buloh, Selangor, Malaysia; [c]Department of Electronics and Computer Engineering, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Skudai, Johor, Malaysia

ABSTRACT

Background: Atrial fibrillation (AFIB) is one of the most common types of arrhythmia, which leads to heart failure and stroke to public. As AFIB has the high potential to cause permanent disability in patients, its early detection is extremely important. There are different types of AFIB classification algorithm that have been proposed by researchers in recent years.

Methods: This paper reviews the features of AFIB in terms of ECG morphological features and heart rate variability (HRV) analysis on different methods. The existing classification method, particularly focusing on Artificial Intelligence technique, is also comprehensively described. Other than that, the existing implementation technology of arrhythmia detection platforms such as smart phone and System-on-Chip-based embedded device are also elaborated in terms of their design trade-offs.

Conclusion: Current existing AFIB detection algorithm cannot compromise for high accuracy and low complexity. Due to the limitation of embedded system, design trade off should be considered to strike the balance between the performance of algorithm and the limitation.

Introduction

About 17 millions of people worldwide are suffering from stroke according to World Stroke Organization.[1] According to the finding of Savino,[2] atrial fibrillation (AFIB) patients have higher risk of stroke and more likely to occur in elderly people who are above the age of 60 [3] or even earlier.[4] AFIB is one of the most common types of arrhythmia, where it refers to a condition in the heart having irregular rhythm or abnormal heart beats. AFIB is a common condition of heart failure where the heart fails to provide sufficient blood to the body and leads to other complications.[5,6] As a consequence, it increases the mortality, progression of pump-failure, and arrhythmic death of population.[7] Due to the mentioned severity of heart failure and stroke, the best prevention is the management of AFIB.[8]

In AFIB, atria chamber is randomly firing and eventually override the electrical impulse originated from the natural pacemaker, sinoatrial (SA) node. This action disturbs the normal rhythm of the heart and creates chaos. For some people, AFIB can be occurring continuously, although others may recover back to normal rhythm after a certain time. There are three categories used to differentiate the severity of AFIB, which are (i) paroxysmal, (ii) persistent, and (iii) permanent. Paroxysmal AFIB will begin or terminate the abnormal signal spontaneously. It might last for seconds or sometimes even days. If the AFIB does not stop completely by itself, but last until the treatment is given, it is called as persistent AFIB. When the usual treatment works no longer, a permanent AFIB is developed. The frequently occurring of the paroxysmal and persistent AFIB might grow over prolonged time to become permanent AFIB if the prevention or precaution steps are not taken.[9]

AFIB is normally first diagnosed using electrocardiogram (ECG), a non-invasive measurement method of heart signal or electrical activity of heart. It can be recorded by different modalities, such as resting ECG device, stress test ECG device, event recorder, and Holter monitor. The ECG morphology of AFIB is different from the normal ECG waveform, such as missing of P wave or irregular ventricular response.[10]

CONTACT Yuan Wen Hau ✉ hauyuanwen@biomedical.utm.my ▣ IJN-UTM Cardiovascular Engineering Centre, Faculty of Biosciences and Medical Engineering, Universiti Teknologi Malaysia, 81310 Skudai, Johor, Malaysia

With this characteristic based on the ECG signal, AFIB detection algorithm is being developed and used for screening purposes.

In this paper, the authors review the features of AFIB in both ECG morphology and heart rate variability (HRV) analysis at different domains. The existing technique of AFIB classification technique is also discussed, as well as the implementation technology of AFIB classifier. The paper is organized as below. Section 'Features of AFIB' describes the AFIB features, follow by a discussion of AFIB classification focusing on artificial intelligence (AI) in the Section 'Classification Method for AFIB'. The current common AFIB implementation technology is presented in the Section 'Arrhythmia detection platform'. Sections 'Discussion' and 'Conclusions' present the discussion and conclusion, respectively.

Features of AFIB

Every arrhythmia has identical features in ECG. The features for AFIB are seen in Figure 1, in which the ECG shows the missing of the P wave with fluctuation baseline due to the activation of atrial being fired spontaneously without rhythm. Other than that, the duration between R peaks, the so-called RR intervals, are inconsistent because atrioventricular (AV) node receives a bunch of electrical impulses from the atria without rhythm, causing the ventricular to contract rapidly.

However, there are other types of arrhythmia which might also share the same features as AFIB such as premature ventricular contraction (PVC). PVC is another common type of arrhythmia where the ventricular contracted twice as much faster than normal. Based on the ECG signal, PVC also shows the missing of P wave and variance in RR intervals. Although the morphological features in time domain between PVC and AFIB have high similarity, but both arrhythmia still able to be differentiated in other domains such as frequency or time–frequency domain. One of the most famous methods is HRV analysis which has been introduced to differentiate the arrhythmia in more detail and accuracy. In HRV analysis, the RR intervals are converting into different domains, such as the time domain and the frequency domain. With the view from different perspectives of the ECG signal, the underlying information can be revealed and it is very useful for the AFIB detection.

P wave morphology

P wave is generated by the depolarization of the atrial chamber, hence the missing of P wave in the ECG signal could indicate the risk of AFIB. There are few parameters based on P wave morphology which are important to detect AFIB as listed in below [12]:

1. Amplitude of the P-wave.
2. Area under the P-wave.
3. Width of the P-wave.
4. Time distance of the onset of the P-wave till its peak.
5. Time distance between the P peak and the R peak.

The detection of the P wave could be a challenge because the amplitude of P wave is relatively smaller than R wave and is easy to be covered up by the noise in poor quality ECG recording.

QRS complexes morphology

In ECG, QRS complexes have the highest peak amplitude and could be easily detected. The most famous QRS detection algorithm is Pan and Tompkins algorithm,[13] which is able to detect the QRS up to 99.30% of accuracy. Other than that, it is simple and easy to implement because only four filters are needed for the detection, that are (i) band pass filter, (ii) derivative, (iii) smoothing function, and (iv) moving window integration. Similar to P wave, there are three parameters which can be extracted from the morphology of QRS complexes, which are the following: amplitude of the R peak, area under the QRS complex, and width of the QRS complex.

Usually, QRS complexes are significant for identifying arrhythmia by calculating RR intervals where it is the total time duration between the R peak and the
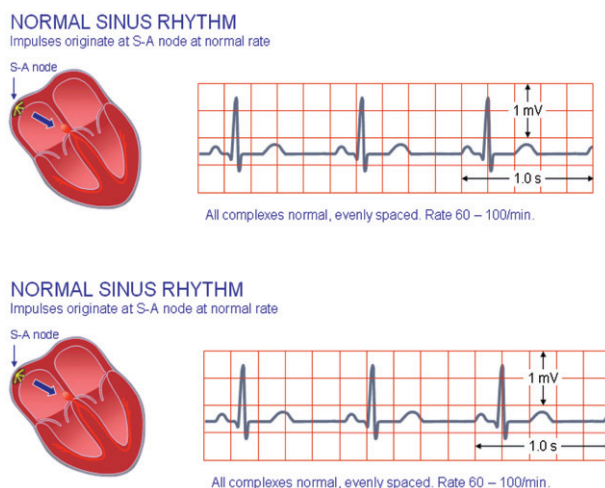

Figure 1. ECG for normal heart condition and AFIB [11].

adjacent R peak. Other than that, RR intervals act as the main features for HRV analysis.

HRV

HRV analysis provides hidden meaning of cardiac condition which cannot be done through manual visual inspection in ECG morphology. In arrhythmia detection, HRV analysis is one of the significant features for cardiac disease indication such as AFIB. Basically, HRV analysis has several methods, including time domain analysis, frequency domain analysis, and non-linear method of analysis.[14]

Time domain analysis used RR intervals to obtain the parameters (Table 1) for the features of arrhythmia detection such as PVC and AFIB. The NN intervals in the table refer to time duration between one beat and another beat which also represent the RR intervals.

In frequency domain analysis, the parameters in Table 2 can be used to observe RR variation. Other than that, there are feature extraction techniques in frequency domain such as power spectral density (PSD), Burg method, higher order spectra (HOS), short time Fourier transform (STFT), and continuous wavelet transform (CWT).[14]

Non-linear method is able to describe the processes from biological system in an effective way. It includes the following methods: Recurrence plots, Sample entropy (SampEn), Hurst Exponant (H), Fractal dimension, Approximate Entropy, Largest Lyapunov Exponent, Detrended Fluctuation analysis, and Correlation Dimension analysis.[14]

Classification method for AFIB

With the advancement of technology, AI is being invented and developed. The basic concept of AI is to exhibit intelligence from machine or software, which are capable of thinking and making decisions depending on the past experiences. AI technology can be applied in different fields such as neuroscience, psychology, linguistics, mathematics, and computer science.

Machine learning is the sub-field of the computer science which evolved from the pattern recognition and computation learning theory in AI. The aims of machine learning are to develop an algorithm which can discover the features and make predictions based on the data. Due to it is evolvable and dynamic, it changes the previous classification method which relies on static behaviors like rule-based classification or decision-based classification. Machine learning can be further divided into supervised learning and unsupervised learning. Supervised learning provides a set of training data to the classifier, so that it could learn and generalize the data according to the desired result. During unsupervised learning, training is given without a correct result so that this model will keep classifying the data based on their statistical properties with the continuous self-learning process.

Based on the literature findings, the model of supervised learning is mostly used for AFIB detection algorithm, such as Bayes Bayesian classification, linear discrimination analysis (LDA), k nearest neighbor (kNN), artificial neural network (ANN), support vector machine (SVM), and knowledge-based classification (KBC).

Naive Bayesian classifier (NBC)

NBC is based on Bayes theorem as shown in Equation (1) with the assumption that all the features are mutually exclusive or independent with each other.[15] In the training phase, a training set is given to the classifier and the probability of n classes $P(x_1|C_i), P(x_2|C_i), \ldots, P(x_n|C_i)$ are obtained. Since $P(X)$ is constant, only $P(X|C_i)P(C_i)$ needs to be maximized.[16] The classification result is given to the highest probability of $P(C_i|X)$. X is assigned to classes C_i if and only if

$$P(C_i|X) = \frac{P(X|C_i)P(C_i)}{P(X)} \qquad (1)$$

$$P(C_i|X) > P(C_j|X) \text{ for } 1 \leq j \leq n, \ j \neq i$$

Here are a couple of AFIB classification algorithms which are based on NBC are proposed to compare the performance with the other techniques. It can be found that the performance of the NBC is generally lower than other classifiers.[17,18] Pourbabaee and Lucas [17] have proposed three different classifiers to identify the AFIB that are kNN, ANN and Naive Bayesian by using the beat information and power

Table 1. Parameters of time domain analysis.

Index	Definition
AVNN	Average of NN intervals
SDNN	Standard deviation of the NN intervals
SDANN	Standard deviation of the average of NN intervals
RMSSD	Root Mean Square Standard Deviation
NN50	Number of pairs of successive NNs that differ by more than 50ms
pNN50	Proportion of NN50 divided by total number of NNs.
TINN	Triangular interpolation of NN interval histogram

Table 2. Parameters of frequency domain analysis.

Index	Frequency of power spectrum/definition
ULF	0 and 0.0033 Hz
VLF	0.0033 and 0.04 Hz
LF	0.04 and 0.15 Hz
HF	0.15 and 0.40 Hz
LF/HF ratio	Ratio of low- to high-frequency power

spectral density. This research shows that among the AFIB classifiers, kNN provides the highest AFIB detection accuracy of 93.75% compared with ANN and Naive Bayesian, which have 87.50% and 75.00% of accuracy, respectively. In the paper of Joy et al.,[18] he has proposed Naive Bayesian and Gaussian mixture model (GMM) to classify AFIB. It is discovered that GMM provides slightly higher performance in all sensitivity, specificity, and accuracy compared with Naive Bayesian, However, all of them still have the accuracy of 99.00% and above.

K nearest neighbor (kNN)

Dimension kNN is the most straightforward classification method among the machine-learning techniques.[19] Basically, it classify unknown data into a class where the class is closer to the data and having higher majority. As shown in Figure 2, q1 belonged to the group O and q2 is under group X. kNN classifies q2 into group X because the majority of neighbors are X. Number of neighbors can be defined in k, for example, the value of k in Figure 2 is 2. Whereas the boundary line between classes are labeled by calculating Euclidean distance between them. It can be only determined after training phase with a set of data.[20]

Some of the researchers found that the simplest classifier, kNN, is able to classify AFIB with a better accuracy compared with other classifiers with the same set of features. Padmavathi and Ramakrishna [21] show that the accuracy results of both SVM and kNN are 92.30% and 100%, respectively, with the features extracted by using the Burg method. Meanwhile, Pourbabaee and Lucas [17] also show the performance of kNN are approximately 6% and 20% higher than ANN and NBC classifiers, respectively. Also some researches have found that using kNN as a classifier can yield a good accuracy in detecting or predicting AFIB.[22,23]

Artificial neural network (ANN)

ANN is inspired by the biological nervous systems of human brain. It patterned the way of brain processing the incoming information and signal.[24] In ANN, it consists of few interconnected layers which are input layer, output layer, and hidden layer as shown in Figure 3. Each layer consists of a number of nodes, where the number of nodes in the input layer is depended on the number of features and the output layer is depended on the number of classes. The connections between the input and output layers are hidden layers, where the number of layers and nodes in
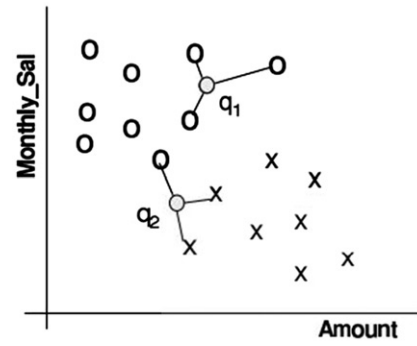

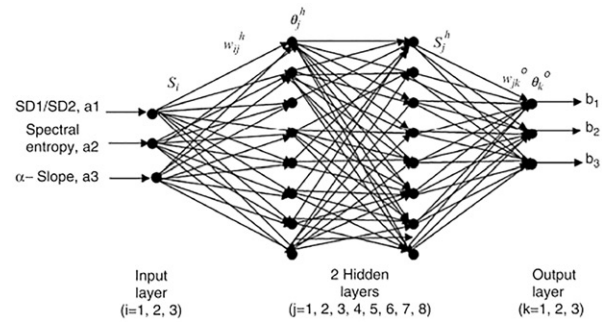Figure 2. Simple example for kNN classification [19].

Figure 3. ANN layers [24].

the hidden layers are defined by the user based on the performance at the training phase.[25]

Similar to other classifiers, ANN has both training phase and testing phase. In training phase, a feed forward neural network is trained by the back-propagation algorithm. As a result, the best set of weights for each of the nodes from each layers are calculated and obtained.[26] These weights are chosen based on the best performance and used for the classification at the testing phase.

Since 1994–2013, ANN was widely used for the AFIB detection algorithm. Yang et al. [27] used ANN to separate the sinus rhythm from AFIB with a sensitivity of 92% and a specificity of 92.3%. Moreover, Chesnokov et al. [28] and Kikillus et al. [29] were able to classify AFIB with a high sensitivity and specificity with HRV features. ANN classifier is comparing with other classifiers and showing a good classification result compare to others except kNN.[17,24,30,31]

Support vector machine (SVM)

SVM is used for the classifier or regression function to reduce the empirical risk and confidence interval.[16,32] It solves the problem by drawing either a linear or a quadratic decision rule so that high-dimensional data can also be classified correctly. The following two equations are the functions of the decision

rule, where Equation (2) is for linear and Equation (3) is for quadratic problem. Due to the high feasibility of SVM, it can classify a variety of data with high dimensional and high performances in practical applications and is popular in using it [16]:

$$f(x) = sign(w.x + b) \tag{2}$$

$$f(x) = sign\left[\left(\sum_{i=1}^{N} \alpha_i \mathcal{Y}_i(x_i.x)\right) + b\right] \tag{3}$$

Most of the AFIB detection algorithms with SVM classifier are able to generate a good performance. In Asgari et al.,[33] it is able to detect AFIB with 97% of sensitivity and 97.1% of specificity. It is also found that an algorithm is able to produce approximately 100% of accuracy.[21] Whereas Jeon et al. [34] are able to produce 95.1% of sensitivity and 95.9% of specificity with the beat features. In Bruser et al. [35] and Padmavathi and Ramakrishna,[21] both used the Burg method for feature extraction and provided a good performance. The Pointcare plot is used for the feature extraction and SVM as classifier in this paper.[36] The features of the arrhythmia is important for the classifier to produce a good result. Although the SVM is a advance classifier, the features will highly affected the performance.[37,38]

Linear discrimination analysis (LDA)

LDA is a simple and linear classification method which is used to classify data into K classes based on K discrimination function. Each class has one discrimination function. Discrimination function draws a linear line between the data and classifies it into classes. It also allows the data to be multicut to classify it into more classes. There are two categories under LDA, which are supervised and unsupervised techniques. Supervised technique classifies data into known classes, while unsupervised classifies the data into unknown classes. There are a few assumptions that are made before the LDA is performed, such as variables are distributed normally within the classes and the correlation and the variance with each group should be similar.

In this paper,[39] AFIB was classified by LDA based on F wave and RR intervals with clinical evaluation.

While in,[32] LDA was used to classify the AFIB and implemented in smart phone.

Arrhythmia implementation platform

Embedded system is a system with microcontroller or microprocessor which equipped with peripheral I/O ports. It is portable and able to perform a specific task according to the design and requirement. The drawbacks of embedded system are limited power consumption and slow computation time. Normally, an algorithm with high performance consumes high power due to its complexity. So, the best design trade off should be considered before implementing on any embedded system.

It has been found that there are some researchers that implemented the AFIB detection algorithm into the embedded system successfully. The comparison between the AFIB detection devices in terms of their algorithms, performance, and implementation technology is shown in Table 3. Based on the observation, the most famous and popular features for the detection of AFIB are RR intervals. That is because R peak is the highest peak in ECG and it is easier to be detected compared to P wave. The favored classifiers in Table 3 are SVM and decision rule. The decision rule classifier provides a lowest complexity of algorithm, where SVM provides a high performance in detecting AFIB. Other than that, most of the implementation technologies are using smart phone because it is most commonly used embedded system for this current generation.

Discussion

Early detection of AFIB gives significance impact to the society because any precaution steps can be taken early to reduce the risk of having permanent disability and stroke. Different types of AFIB detection algorithms have achieved good classification results with higher sensitivity, specificity, and accuracy. However, the complexity of algorithm increased proportionally to its performance. Implementing a high complexity of algorithm in embedded system will cause high-power

Table 3. Related work of AFIB detection with implementation platform.

Years	Journals	Platforms	ECG sensor	Arrhythmia class	Features	Classification AFIB	Performance (%)		
							Sen	Spec	Acc
2014	Jeon et al. [34]	ARM processor	√	AFIB, MI	RR intervals	SVM	95.10	95.90	—
2013	Chong et al. [40]	Smart phone	Pulsatile	AFIB, PVC, PAC	RR intervals	Decision rule	96.84	97.83	—
2013	Kwon et al. [41]	Smart phone	√	AFIB	ECG morphological, FFT	SVM	—	—	87.50
2013	Oster et al. [42]	Smart phone	√	AFIB	RR intervals	Decision rule	92.70	94.20	—
2011	Bruser et al. [35]	Matlab	Ballistocardiogram	AFIB	PSD	SVM	96.20	91.90	95.10
2010	Kaiser et al. [43]	Smart phone	X	AFIB	RR intervals	Decision rule	99.10	88.30	—

consumption and slow computation time which is not desired for the public. Some of the AFIB detection algorithms tend to reduce the complexity of the algorithm and sacrificing its performance, while some of the AFIB detection algorithms tend to increase the complexity with high performance.

In Tables 4–8, different types of algorithms based on the AI classifier are presented. It also compares the feature extraction techniques and its performance based on the different algorithms. Other than that, there are also some journals that have proposed an algorithm which is able to classify the AFIB based on the non-AFIB episode. The prediction of the AFIB detection algorithm is beneficial to the people who have paroxysmal AFIB which only last for few seconds or minutes.

Different types of algorithms use different features. It can be observed that some of the classification performance are highly depended on the performance of the feature extraction such as HRV analysis. For instances, the miss detection of R wave or P wave will degrade the accuracy of AFIB detection. Some features are extracted in frequency domain such as power spectral density which does not require the beat detection. So, the performance of algorithm can be independent of the beat extraction.

Table 4. Related work of AFIB detection algorithm using SVM classifier.

Years	Journals	Features extraction	Performance (%)		
			Sensitivity	Specificity	Accuracy
2015	Asgari et al. [33]	Peak to average power ratio log energy entropy	97.00	97.10	—
2015	Ortigos et al. [38]	Modulus and phase	—	—	81.00
2015	Padmavathi and Ramakrishna [21]	Burg method	—	—	100.00
2014	Jeon et al. [34]	RR intervals with Pointcare plot	95.10	95.90	—
2013	Colloca et al. [37]	R peak	100.00	82.00	85.45
2009	Park et al. [36]	RR intervals with Pointcare plot	91.40	92.90	—

Table 5. Related work of AFIB detection algorithm using ANN classifier.

Years	Journals	Features extraction	Performance (%)		
			Sensitivity	Specificity	Accuracy
2013	Prasad et al. [23]	Higher order spectra	99.60	99.22	98.87
2009	Kikilus et al. [29]	HRV analysis	92.31	98.36	—
2008	Pourbabaee and Lucas [17]	PQRST wave Power spectral density	—	—	87.50
2007	Chesnokov et al. [28]	FFT HRV analysis	94.50	96.50	—
2007	Kostka and Tkacz [30]	P wave Energy and entropy	88.00	85.00	—
1994	Yang et al. [27]	P wave PR wave	92.00	92.30	—

Table 6. Related work of AFIB detection algorithm using kNN classifier.

Years	Journals	Features extraction	Performance (%)		
			Sensitivity	Specificity	Accuracy
2015	Padmavathi and Ramakrishna [21]	Burg method	—	—	100.00
2013	Prasad et al. [23]	Higher order spectra	100.00	99.22	99.50
2008	Pourbabaee and Lucas [17]	PQRST wave	—	—	93.75
2004	Ros et al. [22]	P wave	84.00	76.00	—

Table 7. Related work of AFIB detection algorithm using LDA classifier.

Years	Journals	Features extraction	Performance (%)		
			Sensitivity	Specificity	Accuracy
2007	Sovilj et al. [44]	P wave RR intervals	42.00	90.00	—
2002	Blanc [45]	Hidden Markov Model	70.00	65.00	—
2001	Lepage et al. [46]	Hidden Markov Model	70.00	65.00	—

Table 8. Related work of AFIB detection algorithm using NBC classifier.

Years	Journals	Features extraction	Performance (%)		
			Sensitivity	Specificity	Accuracy
2013	Joy et al. [18]	QRS complexes	99.32	99.33	99.33
2008	Pourbabaee and Lucas [17]	PQRST wave Power spectral density	—	—	75.00

Conclusions

In conclusion, there is no one prefect AFIB detection algorithm which is suitable for implementing in embedded system. This is due to the algorithm complexity and detection accuracy as well as the targeted execution timing performance. In short, ANN and SVM can provide high accuracy but involves complex algorithm which is not suitable for implementing in the embedded system. Naive Bayesian offers lower accuracy compared with SVM and ANN or other classifiers, it still provides considerable and acceptable accuracy with lower algorithm complexity which is suitable for implementing in the embedded system. Other than that, some of the characteristics of the AFIB are still under discovery. AI classifiers have proposed an intelligence classification method to classify the AFIB from normal episodes. Besides, it is also found that the features that feed into the system will highly affect the results. A complicated classifier may not necessarily give a good result if the feature is not clear.

Disclosure statement

Funding

References

[1] Capitec Bank Holdings Ltd. Annual report. 2014. World Stroke Organization [Internet]. 2014; Available from: https://www.capitecbank.co.za/investor-relations.

[2] Savino JA, Halperin JL. Age, ethnicity, and stroke risk in patients with atrial fibrillation: another stitch in the patchwork. J Am Coll Cardiol. 2015;66:1348–1349.

[3] Go AS, Hylek EM, Phillips KA, et al. Prevalence of diagnosed atrial fibrillation in adults: national implications for rhythm management and stroke prevention: the anticoagulation and risk factors in atrial fibrillation (ATRIA) study. J Am Med Assoc. 2001;285:2370–2375.

[4] Chao TF, Wang KL, Liu CJ, et al. Age threshold for increased stroke risk among patients with atrial fibrillation: a nationwide cohort study from Taiwan. J Am Coll Cardiol. 2015;66:1339–1347.

[5] Dries D, Exner D, Gersh B, et al. Atrial fibrillation is associated with an increased risk for mortality and heart failure progression in patients with asymptomatic and symptomatic left ventricular systolic dysfunction: a retrospective analysis of the SOLVD trials. J Am Coll Cardiol. 1998;32:695–703.

[6] Ducharme A, Swedberg K, Pfeffer MA, et al. Prevention of atrial fibrillation in patients with symptomatic chronic heart failure by candesartan in the Candesartan in Heart failure: assessment of Reduction in Mortality and morbidity (CHARM) program. Am Heart J. 2006;152:86–92.

[7] Olsson LG, Swedberg K, Ducharme A, et al. Atrial fibrillation and risk of clinical events in chronic heart failure with and without left ventricular systolic dysfunction: results from the Candesartan in Heart failure-Assessment of Reduction in Mortality and morbidity (CHARM) program. J Am Coll Cardiol. 2006;47:1997–2004.

[8] Olsson S, Halperin J. Prevention of stroke in patients with atrial fibrillation. Semin Vasc Med 2014;5:285–292

[9] Harris K, Edwards D, Mant J. How can we best detect atrial fibrillation? J R Coll Physicians (Edinburgh). 2012;42:5–22.

[10] Wilkins LW. ECG Interpretation Made Incredibly Easy. Wolters Kluwer; 2005.

[11] Malmivuo J. The basis of ECG diagnosis. Bioelectromagnetism. 1995;91;1–23.

[12] Sahoo SK, Lu W, Teddy SD, et al. Detection of atrial fibrillation from non-episodic ECG data: a review of methods. Conference proceedings: … Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society Annual Conference, Vol. 2011; 2011. p. 4992–4995.

[13] Pan J, Tompkins WJ. A real-time QRS detection algorithm. IEEE Trans Bio-Med Eng. 1985;32:230–236.

[14] Rajendra Acharya U, Paul Joseph K, Kannathal N, et al. Heart rate variability: a review. Med Biol Eng Comput. 2006;44:1031–1051.

[15] Rish I. An empirical study of the naive Bayes classifier. Int Joint Conference on Artificial Intelligence. 2001;3: 41–46.

[16] An A. Classification methods. Encyclopedia of Data Warehousing and Mining; 2009. p. 196–201.

[17] Pourbabaee B, Lucas C. Automatic detection and prediction of paroxysmal atrial fibrillation based on analyzing ECG signal feature. IEEE Eng Med Biol. 2008;8:3–6.

[18] Joy R, Acharya UR, Prasad H, et al. Automated detection of atrial fibrillation using Bayesian paradigm. Knowledge-Based Syst [Internet] 2013;54:269–275. Available from: http://dx.doi.org/10.1016/j.knosys.2013.09.016.

[19] Cunningham P, Delany SJ. k-Nearest neighbour classifiers. Multiple Classifier Syst. 2007;34:1–17.

[20] Shi Y, Comparing K-Nearest Neighbors and Potential Energy Method in classification problem. A case study using KNN applet by E.M. Mirkes and real life benchmark data sets. 2012;23.

[21] Padmavathi K, Ramakrishna KS, Classification of ECG signal during Atrial Fibrillation using Autoregressive modeling. International Conference on Information and Communication Technologies, Vol. 46; 2015. p. 53–59.

[22] Ros E, Mota S, Fernández FJ, et al. ECG characterization of paroxysmal atrial fibrillation: parameter extraction and automatic diagnosis algorithm. Comput Biol Med. 2004;34:679–696.

[23] Prasad H, Martis RJ, Acharya UR, et al. Application of higher order spectra for accurate delineation of atrial arrhythmia. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS. 2013. p. 57–60.

[24] Acharya R, Kumar A, Bhat PS, et al. Classification of cardiac abnormalities using heart rate signals: a comparative study. Med Biol Eng Comput. 2004;42:288–293.

[25] Kannathal N, Acharya UR, Lim CM, et al. Classification of cardiac patient states using artificial neural networks. Exp Clin Cardiol. 2003;8:206–211.

[26] Rumelhart DE, Hinton GE, Williams RJ. Learning representations by back-propagating errors. Nature 1986;323:533–536.

[27] Yang TF, Devine B, Macfarlane P. Artificial neural networks for the diagnosis of atrial fibrillation. Med Biol Eng Comput [Internet]. 1994;32:615–619. Available from: http://www.springerlink.com/index/9V37872MR4J68T22.pdf.

[28] Chesnokov YV, Holden AV, Zhang H, Screening patients with paroxysmal atrial fibrillation (PAF) from non-PAF heart rhythm using HRV data analysis. Comput Cardiol. 2007;34:459–462.

[29] Kikillus N, Schweikert M, Bolz A. Identifying patients suffering from atrial fibrillation during atrial fibrillation and non-atrial fibrillation episodes. Int Fed Med Biol Eng. 2008;22:1349–1352.

[30] Kostka P, Tkacz E. Hybrid feature vector creation for atrial fibrillation detection improvement. Energy. 2007;14:922–925.

[31] Joy Martis R, Rajendra Acharya U, Prasad H, et al. Application of higher order spectra for accurate delineation of atrial arrhythmia. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, Vol. 8 [Internet]. 2013. p. 57–60. Available from: http://dx.doi.org/10.1016/j.bspc.2013.08.008.

[32] Drucker H, Wu D, Vapnik VN. Support vector machines for spam categorization. IEEE Trans Neural Netw. 1999;10:1048–1054.

[33] Asgari S, Mehrnia A, Moussavi M. Automatic detection of atrial fibrillation using stationary wavelet transform and support vector machine. Comput Biol Med [Internet]. 2015;60:132–142. Available from: http://www.sciencedirect.com/science/article/pii/S0010482515000839.

[34] Jeon T, Kim B, Jeon M, et al. Implementation of a portable device for real-time ECG signal analysis. Biomed Eng Online [Internet]. 2014;13:160. Available from: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=4273439&tool=pmcentrez&rendertype=abstract.

[35] Bruser C, Zink MDH, Winter S, et al. A feasibility study on the automatic detection of atrial fibrillation using an unobtrusive bed-mounted sensor. Comput Cardiol (CinC). 2011;18:13–16.

[36] Park J, Lee S, Jeon M. Atrial fibrillation detection by heart rate variability in Poincare plot. Biomed Eng Online. 2009;8:38.

[37] Colloca R, Johnson AEW, Mainardi L, et al. A support vector machine approach for reliable detection of atrial fibrillation events. Comput Cardiol. 2013;40:1047–1050.

[38] Ortigosa N, Fernández C, Galbis A, et al. Phase information of time–frequency transforms as a key feature for classification of atrial fibrillation episodes. Physiol Meas. 2015;36:409–424.

[39] Lee HO, Lee SJ, Jeong SH, et al. A development and clinical evaluation of automated diagnostic algorithm for atrial fibrillation using 12-lead EKG. IFMBE Proceedings; World Congress on Medical Physics and Biomedical Engineering 2006, Vol. 14; 2007. p. 1195–1198.

[40] Chong JW, McManus DD, Chon KH. Arrhythmia discrimination using a smart phone. 2013 IEEE International Conference on Body Sensor Networks, Vol. 19; 2013. p. 1–4.

[41] Kwon K, Hwang H, Kang H, et al. A remote cardiac monitoring system for preventive care. 2013 IEEE International Conference on Consumer Electronics (ICCE); 2013. p. 197–200.

[42] Oster J, Behar J, Colloca R, et al. Open source Java-based ECG analysis software and Android app for atrial fibrillation screening. Comput Cardiol. 2013;40:731–734.

[43] Kaiser S, Kirst M, Kunze C. Automatic detection of atrial fibrillation for mobile devices. International Joint Conference on Biomedical Engineering Systems and Technologies; 2009. p. 258–270.

[44] Sovilj S, Magjarevi R, Rajsman G. Classification methods for atrial fibrillation prediction after CABG. 11th Mediterranean Conference on Medical and Biomedical Engineering and Computing 2007, Vol. 16; 2007. p. 46–49.

[45] Blanc J. Automatic P-wave analysis of patients prone to atrial fibrillation. Med Biol Eng. 2002;40:63–71.

[46] Lepage R, Boucher J-M, Blanc J-J, et al. ECG segmentation and P-wave feature extraction: application to patients prone to atrial fibrillation. 2001 Conference Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vol. 1; 2001. p. 298–301.