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The Sensitivity of The Heart Rate Detection for Atrial Electrograms Signal

Kong Pang Seng[1], **Nasarudin Ahmad**[1], **Fazilah Hassan**[1] and **Anita Ahmad**[1*]

[1]School of Electrical Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia.

[*]Corresponding author: anita@utm.my, Tel: 607-5557179, Fax: 607-5566262

Abstract: Atrial Fibrillation (AF) is the most familiar example of arrhythmia that will occur health problems such as stroke, heart failure and other complications. Globally, the number of AF patients will more than triple by 2050 worldwide. Current methods involve performing large-area ablation without knowing the exact location of key parts. The reliability of the technology can be used as a target for atrial fibrillation's catheter ablation. The factors that leading to the onset of atrial fibrillation include the triggering factors that induce arrhythmia and the substrate that maintains the arrhythmia. The project's aim is to create a method for identifying AF that can be used as screening tool in medical practice. The primary goals for the detection method's design are to develop a MATLAB software program that can compare the complexity of a normal ECG signal and an AF ECG signal. Currently, this can be achieved by the ECG Signal's R peaks and RR Interval. For AF detection, there are more R peaks and RR Intervals and it is irregular. In this research, the detection of AF is based on the heart rate (RR Intervals). For the ECG preprocessing, Pan-Tompkins Algorithm and Discrete Wavelet Transform is used to detect the sensitivity on the R peaks and RR Intervals. As a result, Discrete Wavelet Transform algorithm gives 100% sensitivity for the dataset obtained from MIT-BIH Atrial Fibrillation and MIT-BIH Arrhythmia Database.

Keywords: Atrial Fibrillation, Classification, Detection ECG, Preprocessing.

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1. INTRODUCTION

Humans are affected by a variety of heart illnesses, one of which is Atrial Fibrillation (AF). The most frequent type of arrhythmia is AF, which is caused by a malfunction of one of the heart's atria. In 2013, 33.5 million people worldwide suffered from AF [1]. Its prevalence ranges from 1% to 2% of the overall population. Moreover, by 2050, it is expected to triple, facing a serious health threat [2]. Its prevalence rises with age, from less than 0.5% in people aged 40 to 50 to 5% – 15% in people aged 80 [3]. Atrial areas responsible for maintaining the arrhythmia can cause AF [4]. Figure 1 shows the normal heart rhythm and atrial fibrillation rhythm. A small group of cells in the sinus node send an electrical signal during a regular heartbeat. The signal is then transmitted through the atria to the atrioventricular (AV) node. It enters the ventricles and induces them to contract, causing the blood to be pumped out. During AF, electrical signals are emitted from multiple locations in the atria, causing them to beat violently [5]. The natural pacemaker of the heart (AV node) is unable to prevent all of these inconsistent signals from entering the ventricles. Therefore, the ventricles respond by beating more quickly than usual [6]. High blood pressure, heart attack, coronary artery diseases, heart valve abnormalities, heart defects, lung disease, previous heart surgery, hypertension, diabetes, viral infection and stress are all risk factors of AF [7].

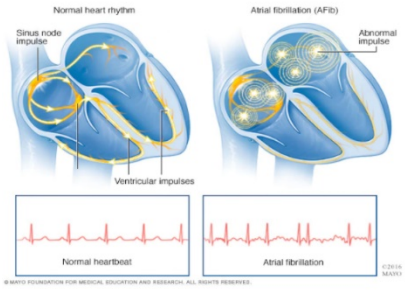

Figure 1. Normal Heart and Atrial Fibrillation

AF is the most prevalent persistent arrhythmia, which affects 3% of adults and 8% of the elderly [8]. It is still the leading cause of stroke, cardiac arrest, premature death and heart disease in the world. As a result, the risk of stroke is five times higher in individuals with AF than in the general population [9]. The lifetime risk of AF is approximately 25%, according to Framingham's cardiac study [10]. Moreover, AF is the leading cause of hospitalization and death [11]. Therefore, the commercial and medical burden of AF is significant and is expected to continue to go up [12]. In addition, fast and irregular ventricular contractions

are common in AF [13].

Paroxysmal AF, persistent AF, long-standing persistent AF, permanent AF, valvular AF, nonvalvular AF, acute onset AF and postoperative AF are the eight forms of AF [14]. Paroxysmal AF occurs for a few minutes or many days and is impulsively terminated within seven days, whereas persistent AF cannot be stopped by on its own but will stop if the DC cardioversion or medication helps to restore the sinus rhythm [4]. Moreover, long-standing persistent AF lasts for more than 12 months [4]. Permanent AF is a persistent AF and no medication can restore the sinus rhythm [4]. Meanwhile, valvular AF primarily affects people who have artificial heart valves or valve diseases, whereas nonvalvular AF is mostly caused by high blood pressure or an overactive thyroid gland [15]. On the other hand, acute onset AF is characterized by a rapid, abnormal heartbeat that appears and disappears quickly, whereas postoperative AF is the most common complication of cardiovascular surgery [15].

2. LITERATURE REVIEW

2.1 ECG Signal Preprocessing

An Electrocardiogram (ECG) signal is a signal that records and shows the heart's electrical activity through a signal wave [16]. ECG is also an important diagnostic tool to detect the abnormal activity of the heart [6]. Figure 2. shows a general ECG waveform [16]. This normal ECG signal consists of ten features, namely P wave, Q wave, R wave, S wave, T wave, U wave, QRS complex, PR Interval, RR Interval and QT Interval [16]. These features are described in Table 1.

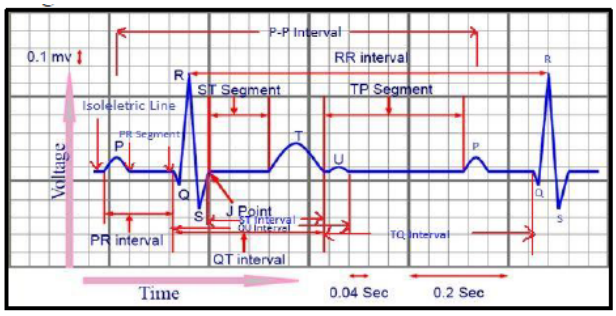

Figure 2. A General ECG Waveform [16]

The AF's characteristics on the ECG signal are irregular and rapid, facing a variety of hazards to the human body [18]. Figure 3. shows the AF signal of one second and three seconds. The irregular and rapid characteristics of AF on the ECG signal lead to a number of risks to the human body. The disappearance of the P wave and the formation of f wave are all AF attributes of the ECG signal, as is the complexity in determining the PR Interval, the irregular RR interval with increased ventricular rate, and a normal QRS complex if intraventricular conduction is not different [6]. The ECG preprocessing methods include P wave detection, R peak detection, RR interval detection and wavelet transform.

Table 1. ECG Features and Description [16], [17]

Features	Description
P Wave	P-waves represent atrial depolarization.
Q Wave	The normal Q wave represents septal depolarization and is any initial downward deflection after the P wave.
R Wave	The R wave represents early ventricular depolarization and is normally the easiest waveform to identify on the ECG.
S Wave	The first negative deflection after the R wave represents the S wave indicating the late ventricular depolarization.
T Wave	The T-wave represents ventricular repolarization.
U Wave	U waves represent re-polarization of the Purkinje fibers that indicates the last remnants of the ventricular repolarization. Generally, it is 0.05mV and has duration of 0.1s.
QRS Complex	The depolarization of the ventricles is represented by the QRS Complex
PR Interval	The time taken for electrical activity to move between the atria and ventricles is represented by this interval.
RR Interval	The RR interval begins at the peak of one R wave and ends at the peak of the next R wave and represents the time between two QRS complexes.
QT Interval	It represents the time taken for the ventricles to depolarize and then repolarize.

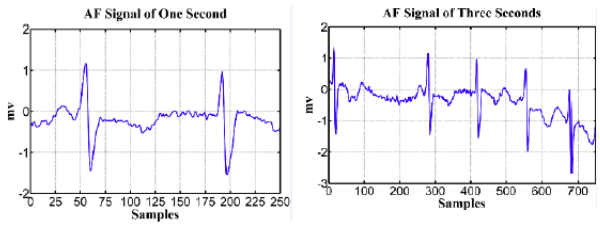

Figure 3. AF Signal of One Second and Three Seconds

2.1.1 P Wave Detection

P waves are replaced by f wave in AF and the peaks of P waves disappear. Therefore, an algorithm is used to search for points that could be the P wave's peak [19]. If no such point is found, the p wave is assumed to be non-existent, it is considered that the P wave does not exist, which is one of the characteristics of AF [20]. At the same time, if such a point can be found, it is considered that there is a P wave, indicating that the ECG signal is non-AF. However, since motion and noise artefacts affect P waves, an AF detection

algorithm that is based solely on the nonappearance of P waves will execute poorly in the presence of disturbances [21].

2.1.2 R Peak Detection

Since R waves pass through the main part of the ventricular walls in ECG signal, thus it represents the electrical stimulus [16]. Then, R peak is checked as an important reference point in the ECG signal due to its larger amplitude [16]. R peak is also an important feature because it is noise resistant [22]. Furthermore, the number of R peaks in a given time interval determines the heart rate (measured in beats per minute) [17]. When compared to a normal ECG signal, AF has a high number of R peaks at the same time interval. The Pan-Tompkins algorithm [23] is then used to complete the R Peak detection. The Pan-Tompkins algorithm consists of four stages: the ECG signal must pass through a low pass filter [24] and a high pass filter (bandpass filter [25] to filter out the noise such as 50Hz power line noise), a differentiator is applied to the signal to provide QRS slope information, a squaring function is applied to make the points positive and amplify the higher frequency output, and a moving window integrator is introduced to detect the QRS complex by averaging the samples [23]. The R peaks are clearly being noticed after the QRS complex have formed.

2.1.3 RR Interval Detection

The RR Interval is the time between two QRS complexes represented by the interval between the peaks of R wave and the peak of the next R wave [17]. This interval is a crucial part of diagnosing abnormal heart rhythms, which can help learners understand a variety of heart facts [17]. Heart rate variability can be estimated because this interval is one of the most critical significant durations [26]. In AF, ventricular rate increases and is frequently rapid, resulting in an irregular RR Interval [5]. The RR Interval that divides AF and normal ECG signals can be indicated by heart rhythms. The signal is considered normal if there is a gap between the peak and the regular rhythm [27]. If there is no gap between them, the signal is regarded as AF. The irregularity of the RR Interval is the key feature of those systems designed for real-time AF detection. In addition, the entropy of RR Interval irregularity is a popular feature [28].

2.1.4 Wavelet Transform

The wavelet transform represents a signal on a time and space scale, with each scale representing the signal's focus level [29]. Furthermore, the wavelet transform is one of several time-frequency signal analysis technology capable of providing high resolution in time-frequency space [30]. As a result, it has been demonstrated that the wavelet transform is a useful tool for signal echo cancellation, contouring and contraction [29]. The main advantage of wavelet analysis is that it can provide a wide range of wavelets [31]. Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) are the two types of wavelet transform [30].

The Continuous Wavelet Transform (CWT) is a time-frequency analysis method that can reflect the data frequency band over time [30]. Moreover, CWT can handle with regional, temporary and unpredictable trends in non-stationary signals such as ECG signal [32]. Classical time domain or frequency domain analysis cannot provide as much information as CWT. The CWT's sequence $x(t)$ is defined as:

$$CWT(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\psi * \left(\frac{t-b}{a}\right) dt \qquad (1)$$

where a is dilation parameter of the wavelet, b is location parameter of the wavelet, and $(\psi) * t$ is the complex conjugate of the analyzing wavelet function $\psi\ (t)$ [30].

The Discrete Wavelet Transform (DWT) is a wavelet transform that performs discrete sampling on it. DWT represents the necessary characteristics of the ECG signal. As different graphs were obtained, the ability of DWT in ECG signal feature extraction was proved [31]. Moreover, DWT is used to remove redundant parts in the ECG signal such as baseline drift and other high-frequency noise [23].

A Stationary Wavelet Transform (SWT) is introduced to address the interpretation variance issues that arose with DWT. Because of each decomposition level is time-invariant, SWT is a subset of DWT [30]. Then, the wavelet coefficients of SWT have the identical sample count as the initial signal. SWT outperforms DWT in terms of repeatability and robustness of analysis [33].

2.2 AF Signal Classification

The samples will be classified into AF and non-AF category after the preprocessing methods are completed. Convolutional Neural Network (CNN), Decision Tree (DT), K-Nearest Neighbour (KNN) and Support Vector Machine (SVM) are the four types of classification methods.

2.2.1 Convolutional Neural Network

Convolutional Neural Network (CNN) is a deep neural networks that is used to investigate the graphical pictures [34]. The standard architecture of CNN consists of four components [22]:

- Convolution layer
  CNN's primary building block is the convolutional layer. The convolution is employed in the extraction of features from an ECG signal. The layers are organized using an attribute map.
- Activation function
  Generally, activation functions are used to map non-linearities to data. For the layer's activation function, the exponential linear unit is used and its odd number starts from one of the ten ranges. The Layer 11 also includes the softmax function.
- Pooling layer
  The pooling operation can reduce the network's function and its supercomputing difficulty.
- Fully connected layer
  The softmax layer is the last interface of the completely linked network and it generates the X-

dimensional vector, where X is the set of classes selected by the user.

Yong Xia et al. showed the sensitivity of the deep CNN using the SWT-based input form is 98.79%, the specificity is 97.87% and the accuracy is 98.63% [35]. Then, an AF detection algorithm based on CWT with CNN classifier is proposed by Ziqian Qu et al., with a 98% overall accuracy and the same specificity [36]. The RR Intervals detection method in the paper proposed by Shadi Ghaisi et al. then followed by the CNN classifier used for AF detection which has a test score of 0.80 [37]. In addition, Dakun Lai et al. presented RR Interval detection and f wave detection methods using CNN classifier that achieved 97.5% accuracy, 97.8% sensitivity and 97.2% specificity [38].

2.2.2 Decision Tree

Decision Tree (DT) is a nonparametric and supervised classifier [23]. The goal of using DT is to learn basic rules from the training set in order to develop a model capable of classifying the specific group or validity [23]. A tree structure caters to the classifier. The judgements are followed in the root of the tree (beginning) node down to a leaf node to estimate the reaction. Furthermore, the DT is built on if-else declarations. A method for detecting AF is proposed by Shrikanth et al. by using QRS detection, principal component analysis, energy computation and DT-based classifier for classification with a total average rate of 85.1% [23]. Guanyu Bin et al. presented a study in which they used the RR Intervals method with a DT classifier to detect AF and managed to achieve a test score of 0.86 [39].

2.2.3 K-Nearest Neighbour

K-Nearest Neighbour (KNN) has been used in a variety of applications including data analysis, empirical pattern classification and image recognition [27], [31]. The KNN classifier determines the subspace principle that is closest to the training dataset. In KNN, the data is divided into two sets which are training and testing. Furthermore, the KNN method ranks the instances by locating one third of the training set that are nearest to the example and then averaging the outcomes to calculate the score. Adiwijaya et al. had proposed a work in using RR interval methods with a KNN classifier to recognize AF ECG signal and normal ECG signal. This paper said the K parameter with value one had an accuracy rate of 91.75% opposed to other K values [27]. Furthermore, P.Kora et al. suggested a KNN classifier based input of DWT algorithm that achieved 99.5% accuracy, 96.97% sensitivity and 96.97% specificity [31].

2.2.4 Support Vector Machine

Based on mathematical studying principle, the Support Vector Machine (SVM) is a supervised studying machine that is an example of a binary linear classifier [5]. Support Vectors perform the object detection between two categories [40]. The kernel function in SVM can be used by converting data to a relatively high feature space [41]. Because of ECG signal is nonlinear, the Kernel function can be used in SVM.

Andersen et al. proposed that the R peak detection method using the SVM classifier had achieved an accuracy of around 96% same with sensitivity and specificity [42]. In the paper proposed by Thripuna Thatipelli et al., feature extraction used the DWT method which then followed by the SVM classifier which had 97.02% accuracy, 94.8% sensitivity and 95,7% specificity [43]. Moreover, S. Asgari et al. presented a paper that used the SWT method for AF detection and SVM as a classifier with a sensitivity of 97% and a specificity of 97.10% [33].

3. RESEARCH METHODOLOGY

3.1 ECG Preprocessing Phase

Modified Pan Tompkins Algorithm and Discrete Wavelet Transform are discussed in this part.

3.1.1 Pan-Tompkins Algorithm

Figure 4 shows the flowchart of the Pan-Tompkins Algorithm. The previous researches mostly use five stages of the Pan-Tompkins Algorithm for preprocessing the ECG Signal. However, this Pan-Tompkins algorithm includes an additional stage of Cancellation DC Drift and Normalization, which is followed by the stages of Low Pass Filter, High Pass Filter, Derivative, Squaring Function and Moving Window Integration. The R Peak Detection, RR Interval and Calculation of Heartrate are discussed in the next session.

Cancellation DC Drift's purpose is to reduce the disturbance in the ECG signal by aligning the range of the mean QRS complex. Additionally, this can reduce noise caused by muscle noise, power line interference, baseline wander and T wave interference. Normalization is a process that is used to reduce any large range amplitude to a smaller range that is between negative one to one.

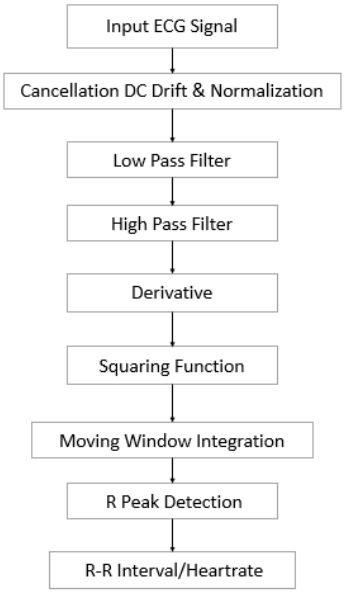

Figure 4. The Flowchart of Modified Pan-Tompkins Algorithm [44]

3.1.2 Discrete Wavelet Transform

Figure 5 shows the flowchart of the Discrete Wavelet Transform. Firstly, the ECG signal passed the stage of discrete wavelet transform (DWT). Frequencies related to R peaks must be preserved while other frequencies must be suppressed. Then, a bandpass action is needed. The discrete wavelet transform divides the signal into separate bandwidths. The bandpass filtering can be achieved by eliminating wavelet coefficients of some lower scales (high frequency) and higher scales (low frequency) of ECG signal. To achieve the purpose of bandpass filtering, an undecimated wavelet transform is used to get wavelet coefficients. So, a 4-level decomposition with sym4 wavelet of an ECG signal is used in this algorithm.

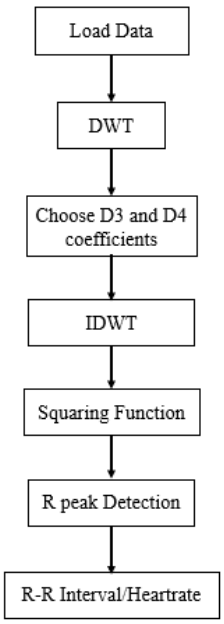

Figure 5. The Flowchart of Discrete Wavelet Transform

To achieve bandpass filter, Coefficients a4 is removed because it is approximate coefficients and carry all the low-frequency details of the signal. d1 and d2 also not be considered. Only d3 and d4 will be considered for getting bandpass filter effect. Only signals with d3 and d4 coefficients are considered and pass through inverse discrete wavelet transform (IDWT). After that, the signal passes through squaring function for R Peak detection and calculation of RR Interval.

4. PRELIMINARY RESULTS AND DISCUSSION

4.1 Outcome Modified Pan-Tompkins Algorithm

Table 2 shows the results of modified Pan-Tompkins Algorithms Using MIT/BIH Arrhythmia Database. The duration ECG signal used is 10s and the sampling rate, Fs is 360Hz. The equation of Sensitivity, Se = TP/(TP+FN) *100% where TP = True Peak Detection and FN = Failure to detect. Most of the Signal achieved above 80% of sensitivity while only ECG signal of 107 and 108 has lower sensitivity. However, this modified Pan-Tompkins Algorithm using with MIT/BIH Atrial Fibrillation Database cannot exactly detect the R peaks of the signals.

Table 2. Results of Modified Pan-Tompkins Algorithm Using MIT/BIH Arrhythmia Database

ECG Signal	Mean RR Interval (Seconds)	Heart Rate (bpm)	TP	FN	Sensitivity, Se (%)
100	0.7442	81	13	0	100
101	0.8126	74	11	0	100
103	0.7783	77	11	0	100
105	0.7194	83	13	1	93
106	0.8917	67	10	0	100
107	0.9718	62	7	5	58
108	1.0924	55	8	3	73
111	0.8540	70	11	1	92
112	0.7530	80	12	2	86
113	0.9509	63	9	0	100

Table 3 shows the types of drug infusion received by patients. There are 10 patients who received atropine infusion and five patients received isoprenaline infusion. Isoprenaline is a beta-receptor drug that can induce sympathetic response. Then, isoprenaline and atropine are given to stimulate the sympathetic and parasympathetic nervous systems, respectively [45]. During research, the isoprenaline is being used to raise heart rate and promote the occurrence of AF. So, the frequency of atrial stimulation rises [45]. Moreover, the function of atropine is to block the vagal activity and reduce the frequency of atrial activation thus decreases the heart rate [45].

Table 3. Types of Drug Infusion Received by Patients

Drug Infusion	Patients
Atropine	CC, CL, DC, DK, HL, KS, MW, TJ, VB, WE
Isoprenaline	DC, DK, HL, KS, MW
Atropine and Isoprenaline	DC, DK, HL, KS, MW

Table 4 shows the results of Modified Pan-Tompkins Algorithm between pre atropine and post atropine of 10 patients. The heart rate for patients of CL, KS, MW, TJ and WE increase after they consume the atropine infusion. Although after atropine infusion, the heart rate will decrease but these patients' heart rate increases.

Table 5 shows the results of Results of Modified Pan-Tompkins Algorithm between pre isoprenaline and post isoprenaline of 5 patients. The heart rate for patients of DC, HL and KS decrease after they consume isoprenaline infusion. Although after isoprenaline infusion, the heartrate will increase but these patients' heart rate increases.

Table 4. Results of Modified Pan-Tompkins Algorithm between Pre atropine and Post Atropine of 10 Patients

AF Data	Mean RR Interval (Seconds)	Heart Rate (bpm)
CC pre	0.5933	101
CC post	0.6032	99
CL pre	1.5848	38
CL post	1.0531	57
DC pre	1.1720	51
DC post	1.4683	41
DK pre	0.7923	76
DK post	0.7986	75
HL pre	0.5761	104
HL post	0.8753	69
KS pre	1.6462	36
KS post	1.1904	50
MW pre	0.6089	99
MW post	0.5009	120
TJ pre	0.9490	63
TJ post	0.9007	67
VB pre	0.4946	121
VB post	10.0395	6
WE pre	0.7404	81
WE post	0.5647	106

Table 5. Results of Modified Pan-Tompkins Algorithm between Pre atropine and Post Atropine of 5 Patients

AF Data	Mean RR Interval (Seconds)	Heart Rate (bpm)
DC pre	0.4457	135
DC post	1.4868	40
DK pre	0.6894	87
DK post	0.6922	87
HL pre	0.9866	61
HL post	1.0897	55
KS pre	1.1493	52
KS post	1.6064	37
MW pre	0.5189	116
MW post	0.4967	121

4.2 Outcome Discrete Wavelet Transform

Table 6 shows the results of the Discrete Wavelet Transform using the MIT/BIH Arrhythmia Database while Table 7 shows the results of the Discrete Wavelet Transform using the MIT/BIH Atrial Fibrillation Database. Both datasets of ECG signal are using the duration of 10s but the sampling rate is different. The sampling rate of the Arrhythmia Database is 360 Hz while the sampling rate of Atrial Fibrillation Database is 250Hz. The algorithm of Discrete Wavelet Transform that tested for both datasets achieved 100% sensitivity.

Table 6. Results of Discrete Wavelet Transform Using MIT/BIH Arrhythmia Database

ECG Signal	Mean RR Interval (Seconds)	Heart Rate (bpm)	TP	FN	Sensitivity, Se (%)
100	0.7442	81	13	0	100
101	0.8129	74	11	0	100
103	0.7783	77	11	0	100
105	0.6681	90	14	0	100
106	0.8944	67	10	0	100
107	0.7656	78	13	0	100
108	0.8319	72	12	0	100
111	0.7826	77	12	0	100
112	0.6454	93	14	0	100
113	0.9506	63	9	0	100

Table 7. Results of Discrete Wavelet Transform Using MIT/BIH Atrial Fibrillation Database

ECG Signal	Mean RR Interval (Seconds)	Heart Rate (bpm)	TP	FN	Sensitivity, Se (%)
04015	0.7471	80	14	0	100
04048	0.8560	70	12	0	100
04126	0.7947	76	13	0	100
04746	0.9268	65	11	0	100
04908	0.6165	97	16	0	100
05121	0.7703	78	13	0	100
05261	0.8260	73	11	0	100
06426	0.6230	96	16	0	100
05121	0.7703	78	13	0	100
05261	0.8260	73	11	0	100
06426	0.6230	96	16	0	100
06995	0.6565	91	11	0	100
07162	0.9156	66	11	0	100
07859	0.6037	99	15	0	100
07879	0.9084	66	11	0	100
07910	1.0385	58	9	0	100

Table 8 shows the results of Discrete Wavelet Transform between pre atropine and post atropine of 10 patients. Table 9 shows the results of Discrete Wavelet Transform between pre isoprenaline and post isoprenaline of 5 patients. In Table 8, the heart rate for patients of CC, HL, KS, MW, TJ and WE increase after they consume the atropine infusion. Although after atropine infusion, the heart rate will decrease but these patients' heartrate increases. In Table 9, the heart rate for patients of DC and KS decrease after they consume isoprenaline infusion. Although after isoprenaline infusion, the heartrate will increase but these patients' heartrate increases.

Table 8. Results of Discrete Wavelet Transform between Pre atropine and Post Atropine of 10 Patients

AF Data	Mean RR Interval (Seconds)	Heart Rate (bpm)
CC pre	0.2865	209
CC post	0.2833	212
CL pre	0.2694	223
CL post	0.2807	214
DC pre	0.2889	208
DC post	0.3083	195
DK pre	0.3926	153
DK post	0.4020	149
HL pre	0.4833	124
HL post	0.2966	202
KS pre	0.5291	113
KS post	0.4275	140
MW pre	0.3684	163
MW post	0.3044	197
TJ pre	0.3082	195
TJ post	0.2828	212
VB pre	0.2275	264
VB post	1.0595	57
WE pre	0.3081	195
WE post	0.2253	266

Table 9. Results of Discrete Wavelet Transform between Pre atropine and Post Atropine of 5 Patients

AF Data	Mean RR Interval (Seconds)	Heart Rate (bpm)
DC pre	0.3261	184
DC post	0.3371	178
DK pre	0.6894	87
DK post	0.3668	164
HL pre	0.3546	169
HL post	0.2860	210
KS pre	0.4693	128
KS post	0.5049	119
MW pre	0.3897	154
MW post	0.3490	172

5. CONCLUSION

In this research, the detection of AF is based on the heart rate (RR Intervals). Pan-Tompkins Algorithm and Discrete Wavelet Transform are used for ECG preprocessing to detect sensitivity on R peaks and RR Intervals. As a result, Discrete Wavelet Transform algorithm gives 100% sensitivity for the dataset obtained from MIT-BIH Atrial Fibrillation and MIT-BIH Arrhythmia Database. Based studies, atropine is used to raise heart rate while isoprenaline is used to lower heart rate. However, the datasets about pre and post atropine infusion and isoprenaline infusion that tested on both algorithms give some of the opposite results.

R peak, RR interval and heart rate are important features that can be detected well in the Discrete Wavelet Transform algorithm for comparing the normal signal and AF Signal. Then, the next step will proceed with the AF Signal Classification which classifies AF Signal and non-AF signal by comparing the accuracy between methods of CNN, Decision Tree, KNN and SVM.

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