The Sensitivity of The Heart Rate Detection for Atrial Electrograms Signal

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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].

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.

| 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 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.

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
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 χ(t) is defined as:

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

where \(a\) is dilatation parameter of the wavelet, \(b\) is location parameter of the wavelet, and \(\psi^* = \overline{\psi}\) 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 reduce 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.

![Flowchart of Modified Pan-Tompkins Algorithm](image_url)

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.

\[ \text{Load Data} \rightarrow \text{DWT} \]
\[ \text{Choose D3 and D4 coefficients} \rightarrow \text{IDWT} \]
\[ \text{Squaring Function} \rightarrow \text{R peak Detection} \rightarrow \text{R-R Interval/Heartrate} \]

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 Algorithm using MIT/BIH Arrhythmia Database. The duration ECG signal used is 10s and the sampling rate, Fs is 360Hz. The equation of Sensitivity, \( \text{Se} = \frac{\text{TP}}{\text{TP}+\text{FN}} \times 100\% \) 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, TI, 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.
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 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              |

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

| ECG Signal | Mean RR Interval (Seconds) | Heart Rate (bpm) | TP | FN | Sensitivity, % |
|------------|---------------------------|------------------|----|----|----------------|
| 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, % |
|------------|---------------------------|------------------|----|----|----------------|
| 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 isoprorenaline is used to lower heart rate. However, the datasets about pre and post atropine infusion and isoprorenaline 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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