Determining The Optimal Time Interval For AF Classification From ECG Signal By Machine Learning

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Abstract **- Atrial Fibrillation (AF) is the most common cardiac arrhythmia. AF patients should receive urgent treatment to reduce risk of death. A classification model is needed for helping doctors to diagnose. Then, they can make an effective plan for the treatment of a patient. Electrocardiogram (ECG) signals display biological signals that are influenced by the autonomic of the heart; it is one of the effective methods that show abnormality of a patient's heart. Current classification models from ECG signals activity are mostly developed by existing databases that may not be suitable for local patients. Therefore, ECG signals of local patients were used in this research for training and constructing the AF classification model by machine learning, the popular technique for classification. However, the appropriate time interval for AF classification by machine learning has not been deeply investigated. In this research, both non-AF and AF signals were divided into segments of 2.5, 2.0, and 1.5 minutes. R peak, RR intervals, F-wave, HRV, heart rate, and SampEn are significant features that were extracted from lead II-ECG. Then, the machine learning method was used to find the most suitable time interval and classification model. Finally, the time interval at 2.5 minutes was the most appropriate length, showing the highest performance by an ensemble (bagged tree) and a tree (fine tree) models at 100% ACC, SE, SP, TRP, and 0% FPR respectively. The proposed time interval and classification models can be deployed as a decision tool to assist cardiac physicians in diagnosis of AF patients.**

Keywords - Time interval, ECG, Classification, AF, machine learning

I. INTRODUCTION

Atrial Fibrillation (AF) is an arrhythmia of the heart, which is often an abnormally fast and irregular heart rate [1, 2]. AF patients are often not detected due to insufficient data for diagnosis or unclear symptoms. Generally, they go to see a doctor with related symptoms which include hypertension, diabetes, dyslipidemia, heart disease, and stroke. In Thailand, AF patients were found to have a population ratio of 1: 100,000 [3]. If AF patients do not receive urgent treatment or do not know their condition, their risk of death will be increased.

Electrocardiogram (ECG) is the most important physiological device used to display biological signals. ECG signals influenced by the autonomic activity of the heart can show normal and abnormal symptoms [4]. A 24-hour ECG monitoring is clinically accepted for the diagnosis of AF conditions [5-9]. The normal sinus rhythm (NSR) signals from ECG are composed of 3 components, which are P wave, QRS complex wave, and T wave [10] as shown in Figure 1. These 3 components exist once with a similar size in each cycle. If one cycle of ECG signal contains more than one of each component or one does not exist, it indicates an abnormality.

Normally, diagnosis of AF can be done by measuring lead II and V1 of ECG signals because these signals can clearly show abnormal waves of AF patients as shown in Figure 2 [7, 8] where ECG of AF signal fluctuates and is unpredictable [11]. Although many AF classification models have been proposed, there are several practical conditions that make it is difficult to use the existing AF classification models [12, 13].

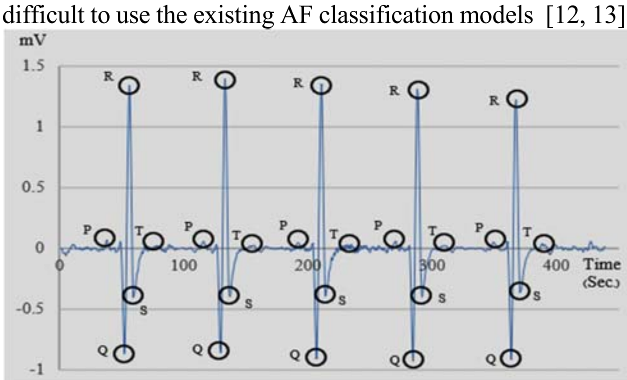


Figure 1. Example of ECG decomposition.

Figure 2.

Examples of ECG segments for two types of signals:

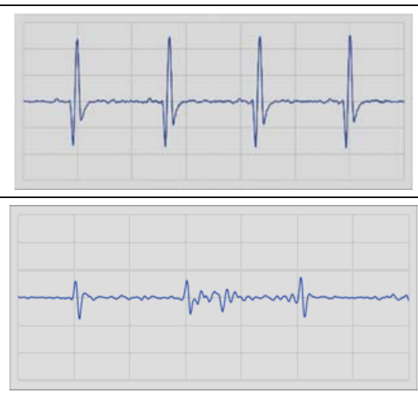
(a) non-AF

and

(b) AF with lead II.

a

b



The study and development of an AF classification model have attracted high attention from many researchers [14]. Most of the classification models use available ECG databases to develop and test their models. There are a few research works that use clinical data because datasets are difficult to obtain. The models from the database showed high accuracy, but clinical practice rejected them because the signals from the database were selected and adjusted before use [15]. Using clinical data is more practical and realistic for local patients. However, the appropriate collecting time interval of the signal is still a question; some research works used 24 hrs signals, while others used a few seconds [16]. Using long time intervals to predict is more accurate than short time intervals, but, it is difficult to acquire sufficient data for testing. The short time interval is easier to obtain and is more practical. The best time interval for predicting AF and non-AF classification for clinical data should be investigated seriously.

Most of existing research works have studied about detection of ECG signal elements and significant of each element to AF. Supervised learning techniques have been used to create classification models for healthcare classification problems [17], which are machine learning (ML) [18] and deep learning [19]. ML is a practical simple tool for classification. However, there are a few works of ML for AF.

This research aims to find the best classification model by ML for non-AF and AF signals of local patients. The significant elements of ECG signals are inputs of the developed model. Moreover, the optimal time interval of ECG recording is also investigated.

II. LITERLATURE REVIEW

An AF ECG recording is intermittent, nonlinear, and unpredictable, so it is difficult to use the common medical device for diagnosing AF patients. The researchers studied the relationship between the number of abnormal ECG signals in the atrial chamber and the irregularity of signal recording. AF ECG signals show irregular RR intervals [20, 21], absence of P waves or P waves fluctuating (f-waves) [22], inconstant heart rate, inconsistent heart rate variability (HRV), and high sample entropy (SampEn) value [23]. However, each ECG patient is different. Features extracted from ECG signals are a good choice for supporting the doctor's diagnosis [7, 24, 25].

Machine learning (ML) is a decision-making process based on experience data, which can be widely applied in many applications [26]. The health care industry has applied ML for diagnosis of cancer, cardiovascular disease, risk assessment for hypertension disease, atherosclerosis level, and predicted symptoms of patients. ML requires significant variables and learning techniques to create a model. It is applied in this research by use of significant features from ECG signals.

The related literature reviews of AF classification are shown in Table I. Most AF classification models collected data from MIT-BIH Atrial Fibrillation Database. These models applied feature extraction to get significant features for training/test AF classification models for both time-domain [6, 9, 15, 27, 28] and frequency-domain [29, 30].

TABLE I. RELATED LITERATURE REVIEW OF AF CLASSIFICATION

Authors	Total data (segment of time)	Feature extraction (Time,T/ Frequency,F / Entropy,E)	Classification Method	Results
Faust, et al. (2018)	23 (24 hrs.) from database	(T): R peak and RR intervals	RNN + LSTM	98.51%ACC
Singh, et al. (2018)	48 (60 sec.) from database	(F): DWT	BPN, FFN, RBFNN	100%SE, 100%TPR, 100%SP, and 100%ACC.
Kumar et al., (2018)	515 (4 sec.) from database	(E): LEE and Pen	WEKA toolbox	96.84%ACC., 95.8%SE and 97.6%SP
Ladavich and Ghoraani, (2015)	25 (5 min.) from database	(T): P-wave and P-wave absence	PWA with majority voter	98.09%SE, 91.66%SP and 79.17%TRP.
Sannino & De Pietro, (2018)	47 (24 hrs.) from database	(T): RR intervals and QRS complex	7-layer DNN	99.68%ACC., 99.48%SE, 99.83%SP.
Babaeizadeh, et al. (2009)	23 (24 hrs.) from database	(T): RR intervals and PR intervals	Hidden Markov model	99.26%ACC.

Selected features from ECG signals were R peak, RR interval, PQRST wave, P wave, QRS complex, heart rate, HRV, and entropy. Most of them use 2-3 features to classify AF signal with complex classification methods. This research uses lead II ECG signals from Thai patients in clinical environments and unbiased early diagnosis [31]. ML is applied to classify non-AF and AF signal, which is more simple than existing algorithms. It can use with limited data and execution time with high performance [32]. Moreover, the optimal time interval of ECG recording is also investigated, which have not been deeply considered before.

II. EXPERIMENTAL METHODOLOGY

The flow diagram of the study is shown in Figure 3. After inputting the ECG signals, noise removal and decomposition were done by the constructed program using a bandpass filter and continuous wavelet transform (CWT), respectively. Then, the variables, which were R peak, RR intervals, F-wave, HRV, heart rate, and SampEn were extracted from signal recordings to fit ML. The classification models were trained and tested with 10-cross validations. Then, performances were checked and the best model could be found.

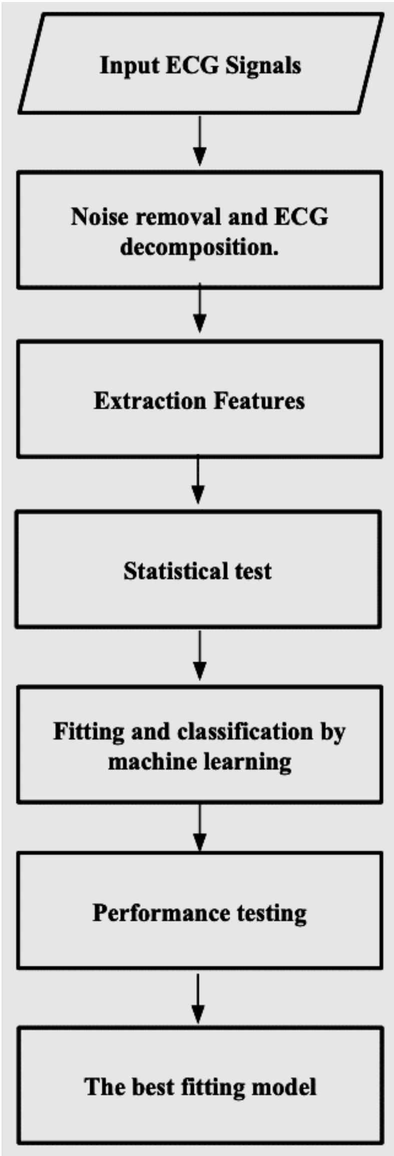


Figure 3. Research flow diagram

A. Population and ECG Measurements

This study measured lead II of 40 patients, which included 20 non-AF and 20 AF at 1000 Hz sampling rate. All patients had consented to participate in the study approved by the local ethics committee. Characteristics of patient data were female (non-AF: 25%, AF: 55%), heart failure (non-AF: 0%, AF: 10%), hypertension (non-AF: 15%, AF: 65%), diabetes (non-AF: 0%, AF: 25%), and vascular disease (non-AF: 0%, AF: 10%). All recordings were made in a state equivalent to rest and in a comfortable position, measured in 5 minutes by a cardiologist. ECG recording data were segmented according to studied time intervals.

B. Noise Removal and ECG Decomposition

This research aims to find the best classification model and the most suitable time interval for AF and non-AF classification by machine learning. Both AF and non-AF signals were divided into segments of time intervals, which were 2.5, 2.0, and 1.5 minutes. 80 recorded signals were used to compare the performance of classification. Each segment was adjusted for baseline wander. The noise was removed with a bandpass filter (high-pass and low-pass filter with 0.5 Hz and 50 Hz cut-off frequency, respectively). Each recording was uncertain and complex. The developed function was used to separate the ECG components, which were P, QRS, and T waves by the continuous wavelet transform (CWT) method. CWT formulation shows in (1) where *a* and *b* are signal magnitude values at positions *a* and *b* of the ECG signal, *t* is the duration, and *V* is the voltage of ECG signal.

$$C_{a,b}(V_{ECG}(t), \Psi(t)) = \int_{-\infty}^{\infty} V_{ECG}(t) \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right) dt \qquad (1)$$

C. Extraction of Features

After the noise removal and the decomposition process, significant variables were extracted. Previous researches have shown that R wave, RR interval [6, 15, 33], QRS complex [9], P wave [27], entropy [8, 34, 35], and HRV [36] correlated to AF symptoms. So, in this research 6 features from ECG recording were studied.

R Peak, RR Intervals, Heart Rate, and F Wave

After ECG signals were decomposed by the CWT method, the positions of the P, QRS, and T waves were found. The maximum amplitude of the wave is called the R wave and that shows the R peak value. Rhythm-to-beat or RR interval is the time elapsed between two consecutive R waves of an ECG cycle. RR interval can be used to determine the heart rate in beats per minute (BPM). P wave is normally shown once a cycle. If it happens more than once or is not found, it is a sign of abnormality of ECG signals, which is called F wave. This occurrence is difficult to detect because it only happens occasionally.

Sample Entropy

Autonomic activity of the heart needs a trigger for initiation and maintenance. AF ECG signal is a complex arrhythmia with multiple possible mechanisms [37]. ECG signals of AF patients have both repetitiveness and disorder of signals. Repeating wave indicates higher levels of risk for AF patients as well as a high value of SampEn [23]. The SampEn equation is the negative logarithm of conditional probability (c) that two sequences of similar-order range m and the tolerance window r match the next position. This study used m =2 and r = 0.25 for the classification between non-AF and AF signals. N is the length of data [8, 23].

$$SampEn\ (m, r, N) = -\ln \frac{c^{m+1}(r)}{c^{m}(r)} \tag{2}$$

Heart Rate Variability

Heart rate variability (HRV) is a characteristic of autonomic heart activity, and analysis of it provides useful information about autonomic nervous system disorders of many heart diseases including AF symptoms. The simple variables from HRV are the standard deviation of normal-to-normal intervals (SDNN), the root mean square of successive differences between normal-to-normal intervals (rMSSD), and the proportion of successive normal-to-normal intervals that are greater than 50 ms (pNN50). SDNN represents beat-to-beat changes during RR intervals and it reflects vagal outflow such as abnormality or fluctuations [36]. Most HRV studies use 24-hour ECG recording of signals (Holter), which is often not practical. This study uses rMSSD to classify the model because rMSSD is the non-linear metric that reflects short-term HRV. The formulation is shown in (3). N is the number of R to R interval.

$$rMSSD = \sqrt{\frac{1}{N-1}\left(\sum_{i-1}^{N-1}((R-R)_{i+1} - (R-R)_{i})^2\right)} \tag{3}$$

D. Discriminant Check by Z-Test

The Z-Test was used to check the difference between two sample means of selected features to ensure the discrimination of the features. Its formulation is shown in (4), where $\bar{X}$ is a sample average, s is a standard deviation, and n is a sample size.

$$Z = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{4}$$

E. Fitting and Classification by Machine Learning

Machine learning (ML) is the method of learning from previous sample data or user experience for predicting the new incoming data. It is used to construct the best fit model for predicting and classification from suitable rules or mathematic functions. The classification learner toolbox of Matlab was used to find the most suitable model for AF and non-AF signals. Decision trees, discriminant analysis, logistic regression, naive bayes, support vector machines (SVM), K nearest neighbor (KNN), and ensembles model were evaluated. The training and testing ratio of this study was 2:1.

F. Performance testing

The classification models used 10-fold cross-validation. They were evaluated by accuracy (ACC), sensitivity (SE), specificity (SP), true positive rate (TPR), false-positive rate (FPR) for the time intervals of 2.5, 2.0, and 1.5 minutes as shown in (5)-(8). TP is a true positive, TN is a true negative, FP is a false positive, and FN is a false negative. TP is the result of the positive class that the model can correctly predict. On the other hand, TN is the result of the model that can predict the negative class correctly. FP is a result of incorrect prediction of the positive class. Conversely, FN is a result of incorrect prediction of the negative class.

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \tag{5}$$

$$SE = \frac{TP}{TP + FN} \tag{6}$$

$$SP = \frac{TN}{FP + TN} \tag{7}$$

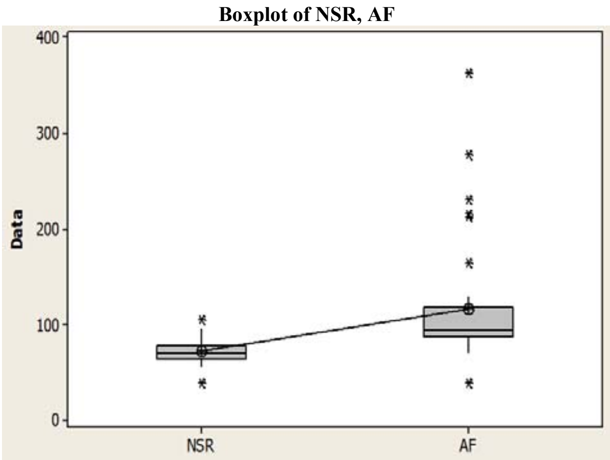
$$TPR = SE \quad \text{and} \quad FPR = 1 - SP \tag{8}$$

IV. RESULTS AND DISCUSSION

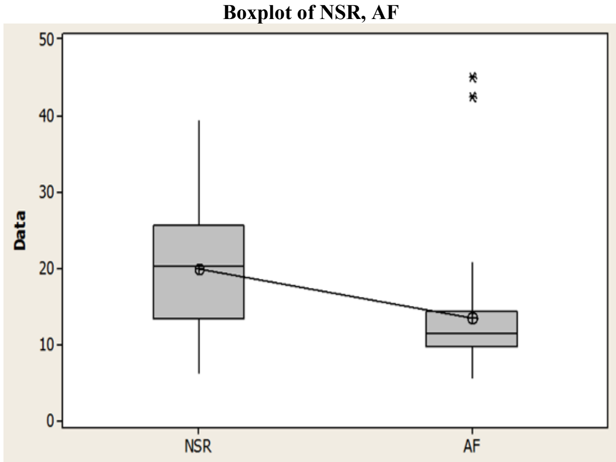
The ECG signals of non-AF and AF were divided into 3 types of time intervals, which were 2.5, 2.0, and 1.5 minutes. Each component signal of ECG was detected by CWT. After ECG decomposition, significant features were extracted and input variables for the classification model for each group of the time interval were collected. Then, the classification learner toolbox was used to find the most suitable model.

These six input variables studied are heart rate, R peak, RR intervals, F wave, SampEn, and HRV. Non-AF at time intervals of 2.5, 2.0 and 1.0 minutes had beat rates 182.36 ± 31.39, 74.92 ± 18.41, and 75.06 ± 18.55 times (beats), respectively, and the AF at the time intervals of 2.5, 2.0 and 1.0 minutes had beat rates 293.15 ± 154.45, 121.51 ± 58.28, 128.11 ± 69.76 beats, respectively.

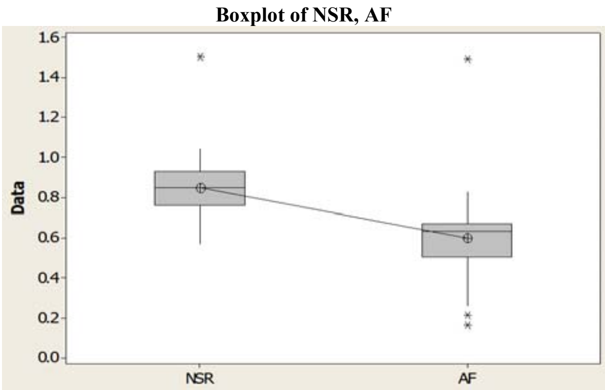
Figure 4 shows box plots of non-AF and AF signals for each variable. R peak, RR intervals, and HRV of non-AF were higher than those of AF, whereas heart rate, F wave, and SampEn of AF were higher than non-AF.



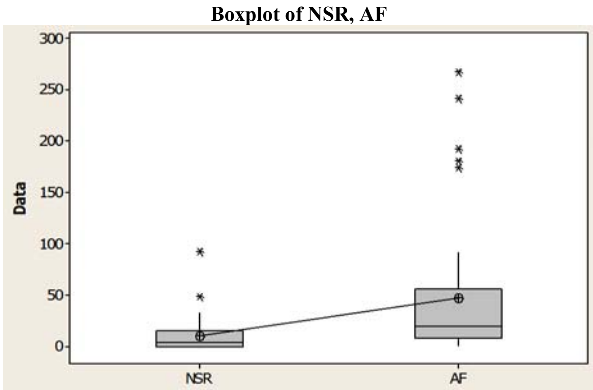
(a) Heart rate



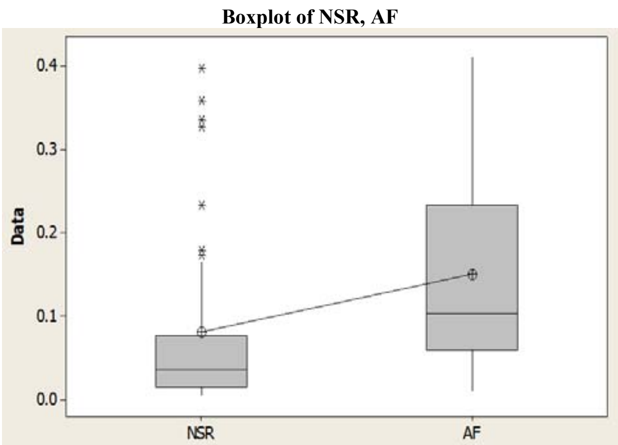
(b) R-Peak



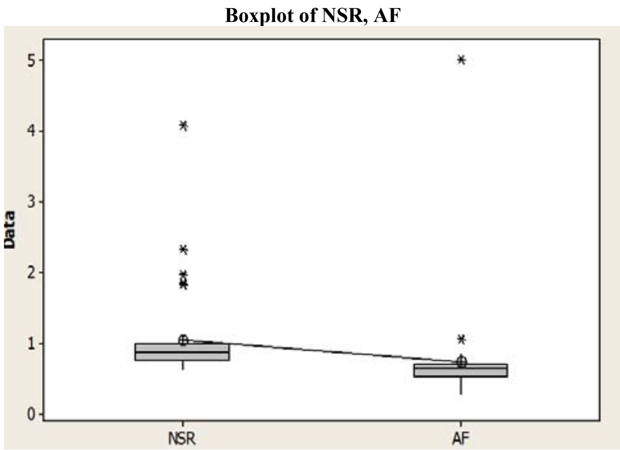
(c) RR intervals



(d) F-wave



(e) SampEn



(f) HRV

Figure 4. Box plot of variables

Table II shows mean ± standard deviation (SD) of both groups, having heart rate (non-AF:AF = 72.94±12.56 : 117.26±61.78 BPM), R peak (non-AF:AF = 20.08±2.08 : 13.69±3.20 μV), RR intervals (non-AF:AF = 1.54 ±0.28 : 1.09±0.39 second), F wave (non-AF:AF = 10.63±17.34 : 48.08±67.82 times), SampEn (non-AF:AF = 0.08±0.03 : 0.15±0.03), and HRV (non-AF:AF = 1.04±0.62 : 0.77±0.71). Then, the data subjected to Z-tests at a significance level of 0.05. P-values of all variables showed that all of the studied variables of non-AF and AF signals were different as illustrated in Table II.

TABLE II. SUMMARY OF THE Z-TEST AT 2.5 MINUTES

Type	Heart rate (BPM)	R peak (μV)	RR intervals (Second)	F wave (Times)	SampEn	HRV
Non-AF (n=40)	72.94± 12.56	20.08 ± 2.08	1.54 ± 0.28	10.63± 17.34	0.08± 0.03	1.04± 0.62
AF (n=40)	117.26± 61.78	13.69 ± 3.20	1.09± 0.39	48.08± 67.82	0.15± 0.03	0.77± 0.71
Z-test (P-value)	0.00	0.00	0.00	0.00	0.01	0.04

Table III illustrates the performance comparison of the classification models for several time intervals by ML. The performances of an ensemble (bagged tree) and a tree (fine tree) with 2.5 minutes time intervals have 100% accuracy (ACC), sensitivity (SE), specificity (SP), true positive rate (TPR), and 0% false-positive rate (FPR). So, 2.5 minutes is the most appropriate time interval for classification by ML, by indicating the highest performance.

ACC of the best classification models for AF and non-AF for time intervals: 2.5, 2.0, and 1.5 minutes were at 100%, 74.36%, and 71.79%, respectively.

TABLE III. PERFORMANCE TEST OF THE CLASSIFICATION MODELS

Model	Training (10 cross-validation)	Testing				
		ACC	SE	SP	TPR	FPR
A. 2.5 min (non-AF = 182.36 ± 31.39 Beats, AF = 293.15 ± 154.45 Beats)						
Ensemble (Bagged Tree)	87.50%	100.00	100.00	100.00	100.00	0.00
Tree (Fine Tree)	87.20%	100.00	100.00	100.00	100.00	0.00
SVM (Cubic SVM)	85.90%	84.62	76.92	88.46	76.92	11.54
B. 2.0 min (non-AF = 74.92 ± 18.41 Beats, AF = 121.51 ± 58.28 Beats)						
Ensemble (Subspace KNN)	100.00%	69.23	52.94	81.82	52.94	18.18
KNN (Fine KNN)	94.40%	74.36	57.89	90.00	57.89	10.00
KNN (Weighted KNN)	94.40%	74.36	57.89	90.00	57.89	10.00
C. 1.5 min (non-AF = 75.06 ± 18.55 Beats, AF = 128.11 ± 69.76 Beats)						
Ensemble (Subspace KNN)	100.00%	69.23	52.63	85.00	52.63	15.00
KNN (Fine KNN)	96.30%	71.79	56.25	82.61	56.25	17.39
SVM (Quadratic SVM)	94.40%	71.79	56.25	82.61	56.25	17.39

Tree models present a high flexibility to classify AF patients. Ensemble (bagged tree) is the best model, which constructed many trees and combine the predictions. Due to the complex of the classification problem, fine tree also performs very well in classification AF patients.

Fig. 5 below shows the area under ROC curves (AUC) for ensemble (bagged tree) and tree (fine tree) models, which have the highest AUC values among the other models. A high AUC value indicates high sensitivity and specificity.

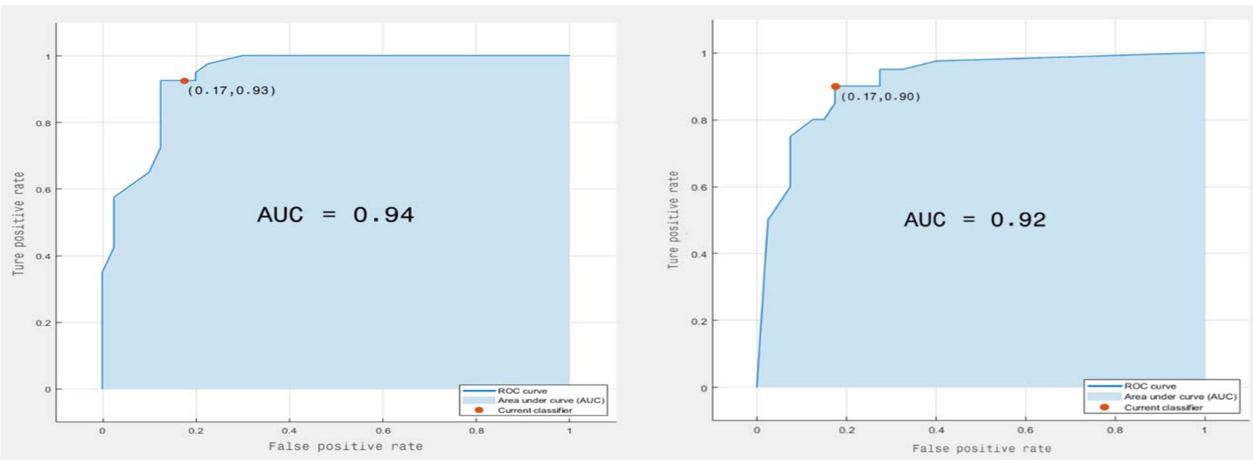
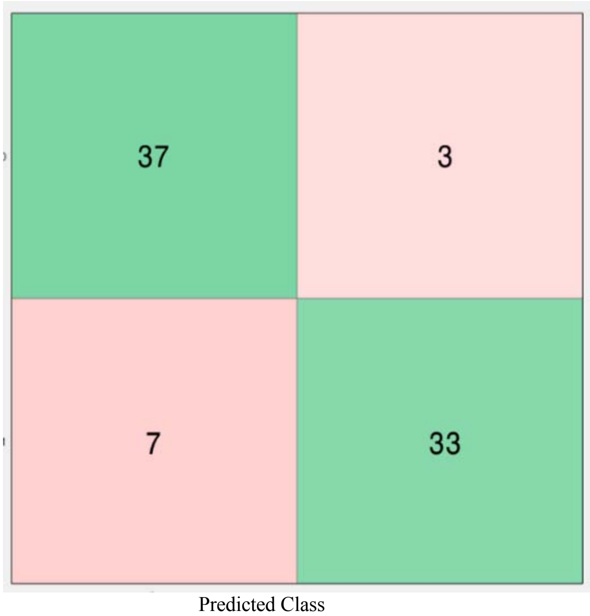


Figure 5. AUC of the ensemble (Bagged Tree) (left) and the tree (Fine Tree) (right) models for all variables.

Confusion matrixes of these two models are shown in Fig.6 below, True Class (vertical axis) against Predicted Class (horizontal axis). The number of FP and FN are small, which means high performance in AF classification.



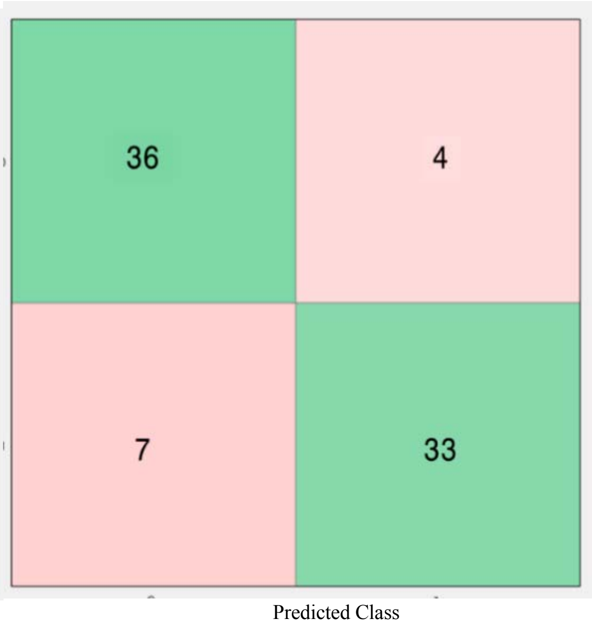


Figure 6. The confusion matrix of the ensemble (Bagged Tree) (left) and the tree (Fine Tree) (right) models for all variables.

V. CONCLUSIONS AND FURTHER RESEARCH

Classification models for ECG data from non-AF and AF patients by machine learning were developed in this research. Moreover, appropriate time intervals of input signals were also investigated. Three types of time intervals (2.5, 2.0, and 1.5 minutes) were studied. ECG signals were preprocessed by baseline wander, then noises were removed and significant variables extracted by a bandpass filter and CWT. Six features consist of heart rate, R peak, RR intervals, F wave, SampEn, and HRV were the input variables for machine learning. Then, the appropriate classification models were extracted. The results showed that the ensemble (bagged tree) and the tree (fine tree) were the most suitable classification models for non-AF and AF. The suitable time interval was 2.5 minutes, which gained the highest performance. These models can be used as decision-making tools in a hospital to help doctors in screening and diagnosis of AF patients.

In future research, AF alarm equipment for high-risk patients will be developed for use at home or in the hospital. However, the classification of the model needs to be improved for other cardiac arrhythmias.

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REFERENCES

[1] G. Stergiou, N. Karpettas, A. Protogerou, E. Nasothimiou, and M. Kyriakidis, " Diagnostic accuracy of a home blood pressure monitor to detect atrial fibrillation " J. Hum. Hypertens, vol. 23, p. 654, 2009.

[2] V. Fuster, L. Ryden, and L. Cannom, "ACC/AHA/ESC 2006 Guidelines for the management of patients with atrial fibrillation: A report of the American College of Cardiology/American Heart Association Task Force on Practice Guidelines and the European Society of Cardiology Commit," Journal of the American College of Cardiology, vol. 48, pp. 149-246, 2006.

[3] S. Kiatchoosakun, O. Pachirat, A. Chirawatkul, C. Choprapawan, and P. Tatsanavivat, "Prevalence of cardiac arrhythmias in Thai community," Journal of the medical association of thailand, vol. 82, pp. 727-33, 1999.

[4] P. Lanfranchi and V. Somers, Cardiovascular Physiology: Autonomic Control in Health and in Sleep Disorders. Principles and Practice of Sleep Medicine, 2010, p. 11.

[5] E. Jauch, J. Saver, H. J. Adams, and A. Bruno, "Guidelines for the early management of patients with acute ischemic stroke: A guideline for healthcare professionals from the american heart association/american stroke association," Stroke, vol. 44, no. 3, pp. 870-947, 2013.

[6] O. Faust, A. Shenfield, M. Kareem, T. R. San, and H. Fujita, "Automated detection of atrial fibrillation using long short-term memory network with RR interval signals," Computers in Biology and Medicine, vol. 102, pp. 327-335, 2018.

[7] R. Alcaraz, J. J. Rieta, and F. Hornero, "Non-invasive atrial fibrillation organization follow-up under successive attempts of electrical cardioversion," Medical & Biological Engineering & Computing, vol. 47, pp. 1247–1255 2009.

[8] R. Sungnoon, K. Suwanprasert, and S. Muengtaweepongsa, "Atrial electrophysiological property analysis by sample entropy and atrial fibrillatory rate with cardiac autonomic derangements in acute ischemic stroke with atrial fibrillation," Neurology Asia, vol. 19, no. 1, pp. 11-18, 2014.

[9] G. Sannino and G. D. Pietro, "A Deep Learning Approach for ECG-based Heartbeat Classification for Arrhythmia Detection," Journal of Future Generation Computer Systems, vol. 86, pp. 446-455, 2018.
[10] B. Koeppen and B. Stanton, Berne & Levy Physiology. Philadelphia: Mosby/Elsevier, 2010.
[11] M. Yochum, C. Renaud, and S. Jacquir, "Automatic detection of P, QRS and T patterns in 12 leads ECG signal based on CWT," Biomedical Signal Processing and Control, vol. 25, pp. 46–52, 2016.
[12] F. Censi, G. Calcagnini, E. Mattei, A. Gargaro, G. Biancalana, and A. Capucci, "Simulation of monitoring strategies for atrial arrhythmia detection.," Annali dell'Istituto Superiore di Sanita vol. 49, pp. 176–182, 2013.
[13] A. Capucci et al., "Daily distribution of atrial arrhythmic episodes in sick sinus syndrome patients: Implications for atrial arrhythmia monitoring," Europace, vol. 14, pp. 1117–1124, 2012.
[14] F. Guo, D. He, W. Zhang, and R. G. Walton, "Trends in prevalence, awareness, management, and control of hypertension among United States adults 1999 to 2010," J. Am. Coll. Cardiol, vol. 60, pp. 599–606, 2012.
[15] S. Babaeizadeh, R. Gregg, E. Helfenbein, J. Lindauer, and S. Zhou, "Improvements in atrial fibrillation detection for real-time monitoring," Journal of Electrocardiology, vol. 42, no. 6, pp. 522-526, 2009.
[16] M. A. Lee et al., "The effect of atrial pacing therapies on atrial tachyarrhythmia burden and frequency," Journal of the American College of Cardiology, vol. 41, no. 11, pp. 1926-1932, 2003, doi: doi:10.1016/S0735-1097(03)00426-1.
[17] O. Faust, E. J. Ciaccio, and U. R. Acharya, "A Review of Atrial Fibrillation Detection Methods as a Service," Int. J. Environ. Res. Public Health, vol. 17, 2020.
[18] J. Waring, C. Lindvall, and R. Umeton, "Automated machine learning: Review of the state-of-the-art and opportunities for healthcare," Artificial Intelligence in Medicine, vol. 104, p. 101822, 2020/04/01/ 2020, doi: https://doi.org/10.1016/j.artmed.2020.101822.
[19] X. Liu, H. Wang, Z. Li, and L. Qin, "Deep learning in ECG diagnosis: A review," Knowledge-Based Systems, vol. 227, p. 107187, 2021/09/05/ 2021, doi: https://doi.org/10.1016/j.knosys.2021.107187.
[20] J. Lee, Y. Nam, D. D. McManus, and K. H. Chon, "Time-varying coherence function for atrial fibrillation detection," IEEE Transactions on Biomedical Engineering, vol. 60, no. 10, pp. 2783-2793, 2013.
[21] W. Cai et al., "Accurate detection of atrial fibrillation from 12-lead ECG using deep neural network," Computers in Biology and Medicine, vol. 116, 2020.
[22] S. Dash, K. Chon, S. Lu, and E. Raeder, "Automatic real time detection of atrial fibrillation," Annals of Biomedical Engineering, vol. 37, no. 9, pp. 1701–1709, 2009.
[23] R. Alcaraz and J. J. Rieta, "A review on sample entropy applications for the non-invasive analysis of atrial fibrillation electrocardiograms," Biomed Signal Processing and Control, vol. 5, no. 1, pp. 1-14, 2010.
[24] V. Corino, R. Sassi, L. Mainardi, and S. Cerutti, "Signal processing methods for information enhancement in atrial fibrillation: Spectral analysis and non-linear parameters.," Biomed Signal Process and Control, vol. 1, pp. 271-281, 2006.
[25] L. Clavier, J.-M. Boucher, and R. Lepage, "Automatic P-wave analysis of patients prone to atrial fibrillation," Medical & Biological Engineering & Computing, vol. 40, pp. 63-71, 2002.
[26] J. Mateo, A. M. Torres, A. Aparicio, and J. L. Santos, "An efficient method for ECG beat classification and correction of ectopic beat," Computers and Electrical Engineering, vol. 53, pp. 219–229, 2016.
[27] S. Ladavich and B. Ghoraani, "Rate-independent detection of atrial fibrillation by statistical modeling of atrial activity," Biomedical Signal Processing and Control vol. 18, pp. 274–281, 2015.
[28] R. Singh, R. Mehta, and N. Rajpal, "Efficient wavelet families for ECG classification using neural classifiers," Procedia Computer Science, vol. 132, pp. 11-21, 2018.
[29] S. Kara and M. Okandan, "Atrial fibrillation classification with artificial neural networks," Pattern Recognition, vol. 40, pp. 2967–2973, 2007.
[30] K. G. Reddy, P. A. Vijaya, and S. Suhasini, "ECG Signal Characterization and Correlation To Heart Abnormalities," International Research Journal of Engineering and Technology, vol. 4, no. 5, pp. 1212-1216, 2017.
[31] R. Tao et al., "Magnetocardiography-Based Ischemic Heart Disease Detection and Localization Using Machine Learning Methods," IEEE Transactions on Biomedical Engineering, vol. 66, no. 6, pp. 1658-1667, 2019, doi: 10.1109/TBME.2018.2877649.
[32] S. Liaqat, K. Dashtipour, K. Arshad, K. Assaleh, and N. Ramzan, "A Hybrid Posture Detection Framework: Integrating Machine Learning and Deep Neural Networks," IEEE Sensors Journal, vol. 21, no. 7, pp. 9515-9522, 2021, doi: 10.1109/JSEN.2021.3055898.
[33] R. Ceylan, Y. Özbay, and B. Karlik, "A novel approach for classification of ECG arrhythmias: Type-2 fuzzy clustering neural network," Expert Systems with Applications, vol. 36, pp. 6721-6726, 2009.
[34] M. Kumar, R. B. Pachori, and U. R. Acharya, "Automated diagnosis of atrial fibrillation ECG signals using entropy features extracted from flexible analytic wavelet transform," Biocybernetics and Biomedical Engineering, vol. 38, pp. 564-573, 2018.
[35] J. Lee, B. A. Reyes, D. D. McManus, O. Maitas, and K. H. Chon, "Atrial fibrillation detection using an iPhone 4S," IEEE Transactions on Biomedical Engineering, vol. 60, pp. 203–206, 2013.
[36] D. Nunan, G. R. Sandercock, and D. A. Brodie, "A quantitative systematic review of normal values for short-term heart rate variability in healthy adults," Pacing Clin Electrophysiol, pp. 1407-17, 2010.
[37] R. Bauernschmitt, H. Malberg, N. Wessel, G. Brockman, S. M. Wildhirt, and B. Kopp, "Autonomic control in patients experiencing atrial fibrillation after cardiac surgery.," Pacing and Clinical Electrophysiology, vol. 30, no. 1, pp. 77-84, 2007.