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SUDDEN CARDIAC ARREST DETECTION WITH T-WAVE ALTERNANS USING ONE-CLASS CLASSIFICATION

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Abstract. *Cardiovascular diseases are the cause of sudden cardiac arrest, which is the leading cause of death in humans. T-Wave Alternans is one of the methods to analyze and find indicators of cardiovascular diseases. The imbalance of T-Wave Alternans found in the data for analysis is a common problem that generally occurs in classification. This study aims to further ease T-Wave Alternans data analysis by using one-class classification method. The model used to identify T-Wave Alternans was using time domain and frequency domain as its features. The model's result shows that ONESVM model has achieved an F1-Score of 95.12% with a classification time used of 324 microsecond. R-wave interval feature contributes the most out of all 5 features used to achieve the mentioned F1-Score. The result shows the ONESVM model has more advantages than two-class classification due to its accuracy and less classification time used in analyzing TWA.*
Keywords: T-Wave Alternans, Sudden cardiac arrest, One-class classification, Imbalanced data, Cardiovascular diseases

1. **Introduction.** The biggest cause of death in humans is cardiovascular disease. In 2016, it was estimated that 17.9 million people died with a percentage of 31% worldwide [1]. In Indonesia, it reaches 35% or 1.8 million people [2]. Cardiovascular can be caused by disruption of the structure and function [3-5], lack of oxygen the heart [6], and lack of blood pumped out at each heartbeat [7,8]. The incidence of the emergence of acute cardiovascular disease can be referred to as a sudden cardiac arrest. These incidents can lead to reduced blood in the heart and brain and loss of consciousness and refer to sudden cardiac death [9].

In diagnosing the incident, a series of Electrocardiograms (ECG) can be used. Indicators of sudden cardiac arrest on the ECG can use several methods such as heart rate variability or T-Wave Alternation (TWA). TWA is a beat-to-beat variation on the T wave that indicates a more accurate dynamic change in the heart's electrical system. The emergence of TWA is consistent before the occurrence of ventricular fibrillation [10].

Data obtained from ECG are divided into two classes: TWA positive class indicating the presense of TWA and TWA negative class indicating the absence of TWA. Several researchers have studied the correlation of sudden cardiac arrest and the presence of TWA. Some of the studies used rule-based concept [11-14] correlating between TWA positive class and TWA negative class data, that is then used to indicate the presense of TWA. Other study used machine learning with two-class classification methods [15], where balancing data is needed in two-class classification. One study also uses augmented data TWA to balance the data [16]. The results of studies using rule-based method are

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similar to studies using the machine learning method. However, in terms of flexibility, machine learning is more advantageous.

The indicators are used from the ECG; therefore, the ECG plays an important role in diagnosing indicators of sudden cardiac arrest. In practice, amount of ECG data are more inclined to show more negative sudden cardiac arrest indicators than positive indicators. This data imbalance causes misleading result in the classification stage [17] and can reduce evaluation results [18]. Whereas data that indicate TWA plays an important role in identifying sudden cardiac arrest [16]. From this data imbalance, one-class classification is a more suitable model to analyze indicators, because it focuses on outliers [17]. One-class classification is a classification model that has received considerable attention in the literature recently [19,20]. In a one-class classification, only TWA as a positive class is used during training. This will help the classifier to indicate positive or negative TWA classes. One thing that needs to be considered is that the difference with other classifiers is that one-class classification only uses one-class in training [21]. In previous research, to overcome data imbalance, new augmented TWA data from the ECG is formed [18]. However, the drawback is that it takes more step and time to establish new data. This is because the formation of new data uses calculations from existing ECG data.

In previous related works in identifying TWA, previous researchers used a rule-based or machine learning approach. Identifying TWA on ECG using the rule-based method is measured from the value of the T-wave that is present in the data [11], and R-wave interval can be used to reach an accuracy of 99.6% as a part presence of TWA [13]. Furthermore, the calculation between the odd and even value of the T wave gives an accuracy of 98% [14]. The rule-based concept determines the threshold for each data used. To minimize threshold use, other researchers use machine learning to identify TWA.

Machine learning has also been used in previous researchers. SVM method was used with the ECG derived risk marker [22] to be used as a parameter to identify TWA presence. Karnaukh et al. discovered the right combination of classifier and selection features to produce an optimal evaluation. The result combination of selected feature selection (SFFS) and classifier (Random Forest) from Karnaukh et al. obtained 89% accuracy in the identification of TWA [15]. In balancing the TWA data to improve evaluation results, Karnaukh and Karplyuk used the TWA augmentation method to increase accuracy up to 95.9% [18], but it takes a considerable amount of time to balance the data. The advantage of using machine learning is to minimize the use of thresholds. In previous researchers, only two-class classification was used. However, one-class classification needs to be researched because a suitable data structure and faster usage time classification is yet to be researched.

However, from previous research, no one has used one-class classification in analyzing TWA. Whereas the use of one-class classification can be used to identify TWA which takes less time than using augmented TWA, this becomes the main motivation for executing this research. The aim of this study is to provide the different performance evaluation results of using one-class classification and two-class classification in analyzing TWA. In addition, the features that affect the evaluation of the selected model will be analyzed. By understanding and analyzing TWA using one-class classification, several future research objectives are also provided to enhance this research topic. Thus, the sufficient potential of one-class classification in analyzing TWA can be explored. Methods used in one-class classification are ONESVM and Isolation Forest. The method uses only positive TWA data to build the model.

The structure of this paper is arranged as follows. Section 2 explains the methodology of the research and the statistical narrative of the references. Process and classification results will be discussed and compared in Section 3. Section 4 concludes the research, adding several research objectives for the future.

2. **Methods.** The illustration of the experimental steps can be seen in Figure 1. The experiment begins with data acquisition, preprocessing, extraction to feature selection, split the selected features data, training and classification model formation, and evaluation of the one-class classification model against the two-class classification.

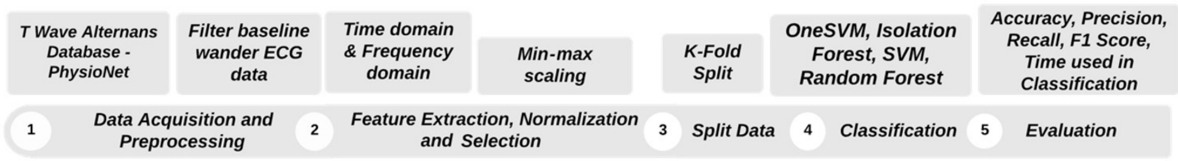

FIGURE 1. Steps of experiment

2.1. **Data acquisition and preprocessing.** The data set used comes from the PhysioNet T-Wave Alternans Challenge Database (TWADB) [23]. The database contains 100 multichannel ECGs with a sample rate of 500 mV and a resolution of 16 bits that can reach a range of 32 mv. The duration of each ECG data is approximately 2 minutes. ECG recordings that have TWA indicators with different levels are sorted by a ranking system [23]. The TWA indication level is ranked from 1 to 100 based on the presence of TWA on the ECG data. ECG data have TWA indications shown at level 80 to 100, while ECG data do not have TWA indications shown at level 1 to 30 [15]. The baseline wander is removed by the Butterworth high pass method. The low cutoff frequency was used at 0.5 Hz. Each cleaned ECG record is divided into 4. The total data to be used for the next process is 200 data.

2.2. **Feature extraction, normalization, and selection.** Previously there was a paper that used time and frequency in analyzing anomalies [24]. In identifying the TWA, the authors use extracted features from the ECG, that are divided into the time domain and frequency domain. The time domain includes R-wave interval (RR), T-wave duration (Tint), QT-wave duration (QT), T-wave maximum amplitude position (Tmax), standard deviation of RT-wave interval (sdRT), standard deviation of R-wave interval (sdRR), standard deviation of even and odd RT-wave intervals (sdRTc), root mean square of RT-wave interval (rmsRT), root mean square of R-wave interval (rmsRR), and root mean square of even and odd RT-wave intervals (rmsRTc). While the frequency domain includes the standard deviation of TWA (sdtDT) and the root mean square of TWA (rmsDT).

Data from extracted features were eliminated to 205 data. Other data cannot be used for the next process, because the data cannot be delineated. The extracted value is scaled using MinMaxScaler because of the vast difference in feature value. Feature values are scaled in the range of 0 to 1 in Equation (1). After the data is scaled, the features will be selected to find optimal features in the model using brute force method. This method applies feature selection alternately from all extracted feature options. The selected subset is based on the highest evaluation results. The selected subset is sdRT, sdRTc, QT, Tint, and RR. The selected features will be used to train the final model [25].

$$\mathit{scaled\ feature} = \frac{\mathit{feature} - \min \mathit{feature}}{\max \mathit{feature} - \min \mathit{feature}} \tag{1}$$

2.3. **Split data.** The data is divided into 70% training and 30% testing. The training data will be used for data validation using cross validation and training models. In cross validation, parameter tuning is executed to find the optimal parameters. The selected parameters will be explained in Section 2.4. The cross-validation used is the k-fold split using 5-fold cross-validation with a data percentage of 70%, while testing uses a data model from training with a percentage of 30%. The value of k represents the number of parts in the data division. The accuracy obtained in each data division is averaged to get the final accuracy [26].

2.4. **Classifier.** One-class classification is used as the main classifier according to the proposed research. However, two-class classification is executed to compare the evaluation results of one-class classification. One-class classification only accepts positive data for training. However, the two-class classification accepts positive and negative data. Each classification will be compared at the end of the research to find the best result. One-class classification uses ONESVM and Isolation Forest. Meanwhile, the two-class classification uses SVM and Random Forest. Because the data from the PhysioNet [23] is limited for two-class classification, new data is reproduced using Synthetic Minority Over-Sampling Technique (SMOTE). The core concept of SMOTE is to apply synthetic examples instead of applying a straightforward replication of the instances of the minority class. Interpolation between several instances of minority classes within a given neighborhood generates this new data [21].

2.4.1. *One-class classification.* This study uses one-class classification to identify TWA. The methods used are ONESVM and Isolation Forest.

a) **ONESVM**. The one-class classification with SVM concept was developed by Schölkopf et al., called ONESVM. The concept is trained with one data class and can predict different data from the trained class [27]. ONESVM uses the kernel to find the maximum hyperplane margin. The kernel is used to transform data into linear dimensions to separate data. The kernel function used is rbf. If the result of the margin of the hyperplane is less than 0, it is then considered as an anomaly, and vice versa [28]. The parameters used in ONESVM are kernel rbf, gamma 1, and nu 0.0591.

b) **Isolation Forest**. Isolation Forest was developed by Liu et al., which used the concept of feature selection or called a branching in all directions. The branch selection process is changed using the random slope at the intersection of branches and a random intercept for selected branch pieces from training value to isolated data [29]. The parameters used in Isolation Forest are random state 42 and verbose 0.

2.4.2. *Two-class classification.* The two-class classification model was also used to compare the evaluations with one-class classification.

a) **Support Vector Machine (SVM)**. In this particular classification, the term is called Support Vector Classification (SVC). In training, SVC will form a model by entering data into one of two classes. The SVC model represents the separation of class categories with the wide clear gap [25] using a linear method [30]. The parameters used in SVM are kernel parameters sigmoid and gamma auto.

b) **Random Forest**. Random Forest is an ensemble method that uses a combination of a decision tree for classification, regression, and others. Each sample in the decision tree is picked in random with equal distribution onto each decision tree. Random Forest will form a new random piece of data from the original data [31]. The parameters used in Random Forest are random state none and verbose 0.

2.5. **Evaluation.** The cross-validation of the feature selection results will be evaluated using the F1-Score in Equation (2) from the confusion matrix concept and the time used in the classification. The confusion matrix shown in Figure 2 represents the correct classification of the model. The precision value is inversely proportional to recall. If the precision value increases, the recall value will decrease. Therefore, to combine optimal precision and recall, the F1-Score can be used [26].

$$F1\text{-}Score = 2\,\frac{Precision \cdot Recall}{Precision + Recall}$$
$$\text{where } Precision = \frac{TP}{TP+FP} \text{ and } Recall = \frac{TP}{TP+FN} \tag{2}$$

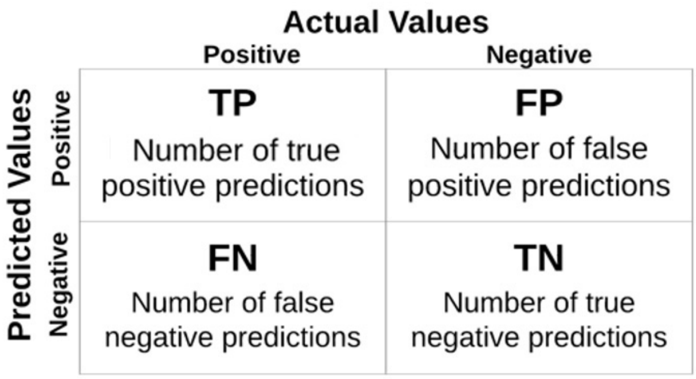

FIGURE 2. Confusion matrix

3. **Experiment Results and Discussion.** In this study, one-class classification is used as the proposed classification method for identifying TWA as an indicator of sudden cardiac arrest. For the purpose of comparison, two-class classification is also executed to obtain evaluation results. Each classification model built refers to Section 2 from data acquisition until evaluation. In this study, a comparison of the evaluation results obtained between the one-class classification and the two-class classification will be analyzed. Features in one-class classification will be analyzed further because the intent of this study is to see how one-class classification affects evaluation results.

3.1. **The evaluation testing comparison analysis.** ONESVM and Isolation Forest are one-class classification that are the focus of this study. The evaluation results are to be compared with two-class classification methods based on its F1-Score and time used on classification. The comparison of one-class classification and two-class classification results is shown in Table 1.

TABLE 1. The evaluation testing result comparison

Classifier	Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Time used on classification (μs)
One-class classification	**ONESVM**	**95.1**	**95**	**95.7**	**95.12**	**324**
	Isolation Forest	88.7	89.7	90	88.7	160,000
Two-class classification	SVM	95.1	95	95.7	95.12	505
	Random Forest	95.1	95	95.7	95.12	123,400

From the evaluation results in Table 1, SVM and ONESVM methods have less time used on classification compared to Isolation Forest and Random Forest. ONESVM used less time than SVM because it is only trained with positive class on training model. This causes ONESVM to detect positive classes and classify other case tested as negative class. However, SVM method is trained with positive class and negative class on its training model. This causes the higher amount of time used on classification on testing model.

The time used on classification depends on the method used. Isolation Forest is a part of one-class classification, and it is taking a significant amount of time used on classification. Isolation Forest takes features randomly from all the features used. In addition, the Isolation Forest has anomaly value calculation phase, taking more time to classify. Random Forest takes features from a subset of features randomly. Random Forest naturally uses less time on classification because subset of features has already been formed. Apart from the high amount of time used on classification, the F1-Score of the Isolation Forest is lower than the method used. This is likely to happen because Isolation Forest is an unsupervised machine learning which is difficult to adapt to categorical data [32].

The result of the comparison evaluation between the one-class classification and the two-class classification shows that ONESVM provides an F1-Score result that is equivalent to the two-class classification method. In the F1-Score evaluation, OVESVM has the same performance in identifying TWA compared to two-class classification. In terms of time used on classification, ONESVM is superior with less time needed compared to two-class classification. This shows that ONESVM model is more advantageous with its high accuracy and faster classification time in identifying TWA as an indicator of cardiovascular disease, leading to sudden cardiac arrest.

3.2. **Feature analysis on ONESVM.** In the research process, we realized that the results of the F1-Score evaluation on ONESVM often changes compared to other method. Therefore, we conducted research on the selected classifier model that had been formed by replacing one feature (in the top row of Figure 3) with other features that were not previously selected (in the bottom row of Figure 3). The illustration of the feature analysis experiment is shown in Figure 3.

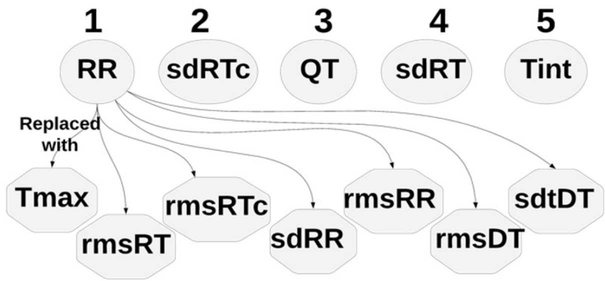

Figure 3. Illustration of feature analysis experiment

Table 2. The replaced feature results

Replaced feature	**RR**	sdRTc	QT	sdRT	Tint
F1-Score (%)	**55.70**	85.47	81.68	91.91	81.68

The feature analysis method in ONESVM uses a brute force system using the scheme in Figure 3. A summary of the feature analysis experiment results is shown in Table 2. From the experimental results, the RR feature contributes a significant F1-Score result for ONESVM. This is shown in the results of the F1-Score when RR feature with another feature, causing a significantly decreased F1-Score of 55.70%. RR is an R-wave interval that provides more predictive performance and higher accuracy than other features. The result of the performance evaluation and analysis of features in this study is hoped to be used as a new source of information for other studies in the future on TWA identification as indicators of sudden cardiac arrest.

4. **Conclusion.** This research illustrates ONESVM model as part of one-class classification can be used as a better method to identify TWA accurately with a faster time compared to the two-class classification. We proposed an ONESVM model consisting of

extraction formula feature, selection feature, and parameter of classification that is already explained in Section 2. The model result shows that ONESVM model has achieved an F1-Score of 95.12% with classification time used of 324 microsecond, the least amount of time compared to two-class classification. This model uses features from the time domain and frequency domain analysis for identifying TWA. R-wave interval (RR) feature contributes the most of all 5 features used to achieve the F1-Score. RR gives more predictive performance and high accuracy on ONESVM, which could be proven by the decreasing percentage of F1-Score to 55.70% when removing the RR from the classification model. The time used to accurately identify TWA classifications in ONESVM became an improvement in the area of this study. With the conclusion of this study, it is anticipated there will be other research in this area that can be explored. Some other one-class classification method has not been implemented to identify TWA and would need further research. Furthermore, this research can be developed with a larger dataset, which is the limitation of this research.

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