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Performance Evaluation of SVM Classifiers for Atrial Fibrillation Detection

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Abstract

Atrial fibrillation (AtrF) is described as uncoordinated atrial activity and inefficient atrial contraction, a supraventricular tachyarrhythmia. 1-2% of the general population suffers from AtrF, which is more common with older people but may go undiagnosed for a long time. Effective methods of identifying AtrF are required due to the increasing occurrence and rising hospitalization expenses and treatment associated with AtrF. In this study, 6000 ECG signals were used to evaluate AtrF classification using different types of Support Vector Machine (SVM) classifiers (Linear, Quadratic, Cubic, Fine Gaussian, Medium Gaussian, and Coarse Gaussian). Parameters used for feature extraction related to RR interval are (RR Interval) the interval between two consecutive R-waves of the ECG's QRS signal, Standard Deviation (SDRR) of normal RR intervals throughout the 24-hr of all normal RR intervals, Standard Deviation of the Average (SDANN) of all 5-min RR interval segments during the 24-hour recording period, (pNN50) the percentage of the discrepancy between adjacent normal RR intervals, Root Mean Successive Square Difference (R-MSSD) between adjacent normal RR intervals. In this work, the quadric SVM classifier was the most proficient with 89.9% accuracy, 0.93 AUC, 97% sensitivity, and 61% specificity. While the least proficient classifier was the cubic SVM, with 61% accuracy, 0.84 AUC, 96% sensitivity, and 54% specificity).

Keywords: Atrial Fibrillation, Artificial Neural Network, Classification, Standard Deviation, Support Vector Machine.

تقييم أداء مصنفات SVM للكشف عن الرجفان الأذيني

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الخلاصة

الرجفان الأذيني (AtrF) يوصف بنشاط أذيني غير منسق وانقباض أذيني غير فعال، وهو تسرع القلب فوق البطيني. يعاني 1–2% من عموم السكان من الرجفان الأذيني، وهو أكثر شيوعًا مع تقدم العمر وقد يبقى دون تشخيص لفترة طويلة. هناك حاجة إلى طرق فعّالة لتحديد الرجفان الأذيني بسبب تزايد حدوثه وارتفاع تكاليف العلاج والاستشفاء المرتبطة به. في هذه الدراسة، تم استخدام 6000 إشارة تخطيط كهربية القلب (ECG) لتقييم تصنيف الرجفان الأذيني باستخدام أنواع مختلفة من مصنفات الآلة الداعمة) (SVM) خطية، تربيعية، مكعبة، Gaussianدقيقة، Gaussianمتوسطة، و Gaussianخشنة .(تم استخدام عدة معايير لاستخلاص الميزات المرتبطة بفترة RR وهي) :فترة (RR الفترة بين موجتين متتاليتين R في إشارة QRS لتخطيط القلب، الانحراف المعياري (SDRR) للفترات الطبيعية لـ RR على مدار 24 ساعة لجميع الفترات الطبيعية لـRR ، الانحراف المعياري لمتوسط (SDANN) جميع مقاطع فترات RR لمدة 5 دقائق خلال فترة التسجيل البالغة 24 ساعة، (pNN50)نسبة التباين بين الفترات الطبيعية المتجاورة لـRR ، فرق الجذر التربيعي المتتالي (R–MSSD) بين الفترات الطبيعية المتجاورة لـ .RR في هذه الدراسة، كان المصنف التربيعي SVM هو الأكثر كفاءة بنسبة دقة بلغت 89.9%، ومنطقة تحت المنحنى (AUC) بلغت 0.93، وحساسية 97%، ونوعية 61%. بينما كان المصنف الأقل كفاءة هو المصنف المكعبSVM ، بنسبة دقة 61%، ومنطقة تحت المنحنى (AUC) بلغت 0.84، وحساسية 96%، ونوعية 54.%الكلمات المفتاحية: الرجفان الأذيني، التصنيف، آلة ناقل الدعم ، الشبكة العصبية الاصطناعية ، الانحراف المعياري.

1. Introduction

The electrical impulse typically travels from the Sino Atrial (SA) Node and passes from the atria to the ventricles, which can generate the chambers' regular rhythmic contractions. The heart is a muscular organ that functions as a pump. The contraction and relaxation of its chambers are orchestrated by the SA node, which acts as an internal pacemaker that coordinates the heartbeat [1, 2].

An abnormal precocious heartbeat commencing from the atrium of the heart is known as Atrial Fibrillation (AtrF), which alters the heart's regular rhythm. AtrF may contribute to heart failure and stroke that could be fatal in subjects with cardiac conditions.

Although an ECG signal differs from one subject to another since it is affected by age, physical build, and location on the body at which it is recorded. There are distinguished electro-cardiac properties that are appropriate for analysis and case assessment [3]. The P, QRS, and T waves make up a typical ECG heartbeat wave. P, QRS, T, and U wave sequences are repeated with each rhythm, characterizing the ECG. The most notable waveform is the QRS complex, which is caused by human ventricular depolarization. The detailed model of a standard ECG heartbeat signal is shown in Figure 1, including the features of P, Q, R, S, T, and U, and various intervals including the QT, ST, and RR intervals.

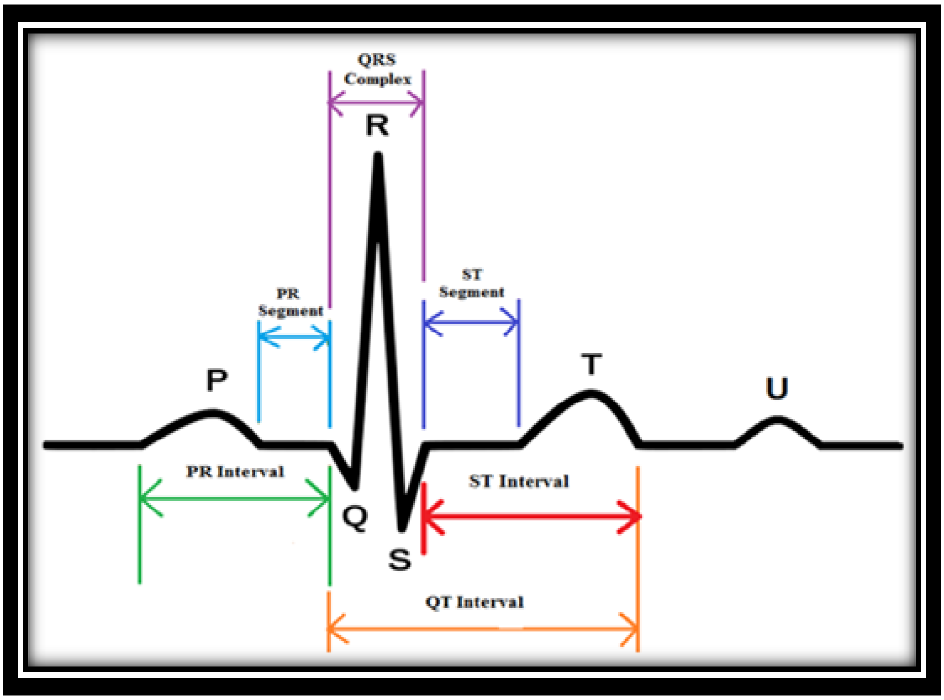

Figure 1: Schematic representation of typical ECG waveform [4].

Based on traces of AtrF in electrocardiograms, there are two primary groups of algorithms: algorithms for detecting the absence of the P-wave and those focusing on RR interval irregularities [1] [5]. In the context of analysing ECG recordings, techniques that rely on detecting irregularities in RR intervals are preferred due to the high level of noise and low amplitude of P waves commonly encountered [1]. For our study, we have employed features extracted from RR intervals.

2. Literature Review

Machine learning (ML) methods have been used to evaluate AtrF detection of ECG signals. In 2013, Martis et al. [6] proposed an approach for AtrF classification involving the use of Naive Bayes (NB) and Gaussian Mixture Model (GMM) classifiers. To reduce the data, independent component analysis (ICA) was utilized to diagnose and register ECG beats, with the resulting weights of the ICA serving as classification features. The GMM classifier was found to outperform the NB classifier, achieving an accuracy of 99.42% and lower error.
In 2015, the authors in [3]applied a Support Vector Machine (SVM) to detect AtrF. SVM and electrocardiographic heart rate variability variations were used to identify AtrF. SVM makes use of radial basis functions (RBF). The optimal SVM construction was chosen after testing many ones. In terms of sensitivity, specificity, and accuracy, the proposed method exhibited performance rates of 95.81%, 98.44%, and 97.50%, respectively. In 2017, [7] illustrated AtrF Detection and ECG classification based on Convolutional Recurrent Neural Network (CRNN). In their method, important patterns were retrieved from the ECG and heart rate using two distinct Convolution Neural Networks (CNNs), which were then combined into a Recurrent Neural Network (RNN) that accounted for the sequencing of the extracted patterns. The final choice is then assessed using an SVM.

In 2018, [8] used K-Nearest Neighbor (KNN) for AtrF disease diagnosis. In their research, three processes were suggested: feature extraction, pre-processing, and K-NN classification, which is a method of uniformizing data dimensions. Feature extraction can be performed by comparing the RR intervals of the AtrF signal and the control signal. Based on the overall scheme's accuracy, the most effective AtrF detection result was achieved with K = 1, yielding an average accuracy of 91.75%.

In 2019, [9] suggested Decision Tree (DT), SVM, and Artificial Neural Networks (ANN) for AtrF detection. The study evaluated the following 8 RR interval-related parameters: mean RR, SDNN, RMSSD, PLF, PHF, LF/HF, SD1, and SD2. Based on their analysis of the results, the optimal AtrF classifier was found to be a Decision Tree (DT) with 100 divisions .
In 2020 [10] used an SVM classifier for AtrF detecting and attended sensitivity of 100% and specificity of 97.6%. Also inn 2020 [11] proposed three methods for AtrF diagnosis: Convolutional Neural Network (CNN) trained on modified frequency slice wavelet transform data, SVM classifier trained on multiple AtrF features data, also SVM trained on the same features group but extended by the predictive probability of the CNN network, which gave the highest detection accuracy.

In 2022, [12] demonstrated that the probability density of RRIs from the ECG conserves comprehensive statistical data, making it a natural and effective input feature for AF detection rather than employing any specific numerical characteristic. Results on the MIT-BIH database show that Several SVM classifiers were tested before the best one is selected. In terms of sensitivity, specificity, and accuracy, the proposed method exhibited performance rates of 0.9524, 0.9994, and 0.9697, respectively.

In 2023, [13] suggested Traditional Machine Learning (TML) algorithms and Ensemble Machine Learning (EML) algorithms to detect AF. The authors compared the performances of both these methods, and suggested a mechanism for detecting AF based on RR interval characteristics. The proposed method was evaluated using the PhysioNet Challenge 2017. It was observed that the Random Forest (RF) classifier provided a good classification accuracy of 99.10% with an area under the curve of 0.998. With Normal Class Specific Accuracy (NCSA) of 99.65%, AF Class Specific Accuracy (AFCSA) of 99.50%, Other rhythm Class Specific Accuracy (OCSA) of 97.98%, and Overall Accuracy (OA) of 99.10%, it can yield that the RF classifier provided greater discrimination.

This study aims to evaluate the performances of SVM-based AtrF classifiers. AtrF Classification from a Short Single Lead (between 30 s and 60 s in duration) was performed on 6000 signals from the PhysioNet Database [14]. ECG recording: 2017 PhysioNet/Computing in Cardiology Challenge.

3. Materials and Methods

3.1 Suggested Method

In the suggested method, features need to be extracted, the essential characteristics are selected and then classified by SVM based on the training set of data. Classification performances are then assessed using the test data sets. Figure 2 illustrates the block diagram of suggested ECG signal classification:

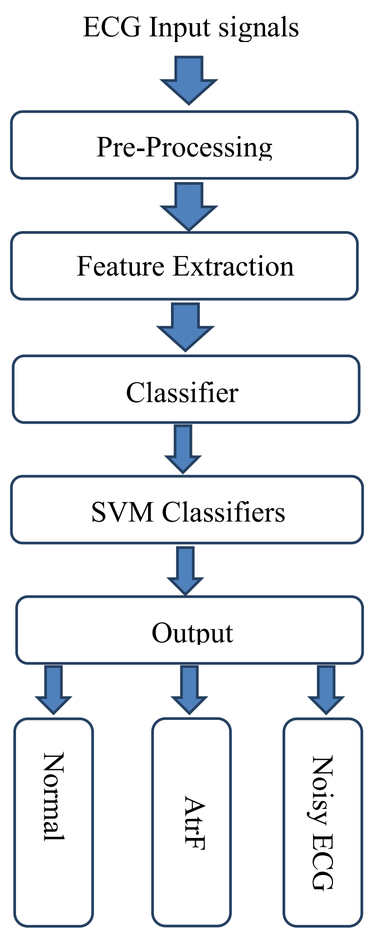

Figure 2: Suggested block diagram of ECG signal classification

3.2 Feature Extraction

ECG signal classification is conducted depending on the following parameters of time-domain heart period variability measurements:

RR Interval: refers to the time interval between two consecutive R-waves on an ECG's QRS signal (and it is the reciprocal of the Heart Rate), calculated by Eq. 1 [9, 15].

$$\underline{RR} = \frac{1}{N}\sum_{n=1}^{N} RR_n \tag{1}$$

where RR_n denotes the value of n'th RR interval and N is the successive beat intervals.

SDRR: refers to the Standard Deviation (SD) of all normal RR intervals throughout the 24-hr ECG recording which is calculated by Eq. 2 [16].

$$SDRR = \sqrt{E[RR_n^2] - \underline{RR}^2} \tag{2}$$

where E is the mean of RR interval denoted by $\underline{RR} = E[RR_n]$.

- SDANN: refers to the standard deviation of the average of all 5-min RR interval segments during the 24-hour recording period.
- pNN50: refers to the percentage of a discrepancy between normal RR intervals for longer than 50 msec computed throughout a 24-hour ECG recording, which is calculated by Eq. 3 [15].

$$pNN50 = \frac{NN50}{N-1} \times 100 \tag{3}$$

Where *NN50* is subsequent periods that differ by more than 50ms in number or the corresponding relative amount.

- RMSSD: refers to the root mean successive square difference between adjacent normal RR intervals throughout the 24-hour ECG recording, calculated by Eq. 4 [17].

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N-1}(RR_{n+1} - RR_n)^2} \tag{4}$$

3.3 SVM

A computer algorithm known as the SVM learns to label items. SVM is a useful classification method founded on two concepts: The first idea is to translate the measurements of vector features into a space of high dimensions using a non-linear approach. The second concept uses a margin hyperplane to divide the mapped values. The mapped values may be classified by a plane. Because of its excellent performance and low computing requirements, the SVM is highly favored. Typically, it can resolve both linear and non-linear issues. Once that is done, it represents unique points in a space of high dimensions, with each point represented by a vector of characteristics, see (5).

$$y \in \mathbf{R}d \tag{5}$$

where $\mathbf{R}d$ is the d-dimensional vector space. Norms are another name for a vector's length. The vector's length y is calculated by Eq. 6 [18, 19].

$$||y|| = \sqrt{y_1\text{^}2 + y_2\text{^}2 + y_3\text{^}2} \tag{6}$$

where y_1, y_2 and y_3 are various y values. Eq. 7 [18, 19] for determining the vector y 's direction is:

$$\{\frac{y_1}{||y||}, \frac{y_2}{||y||}, \frac{y_3}{||y||}\} \tag{7}$$

A set of parameters typically affects the accuracy and SVM classifier. The kernel function is one of the critical parameters. The fantastic thing about the kernel is that it enables us to navigate through higher dimensions and conduct accurate calculations. To change the problem using a specific algebra, the kernel plays a crucial part in learning with the hyperplane. The kernel functions used by various SVM algorithms can be linear, Radial Basis Function (RBF), or Gaussian. The formula for predicting a new input (4) using the dot product of the input y and each support vector yi for a linear kernel is:

$$f_{liner}(\mathrm{y}, \mathrm{y}i) = \sum(\mathrm{y}.\ \mathrm{y}i) \tag{8}$$

The most popular and widely utilized kernel function in the SVM is RBF. It is frequently used for non-linear classification. It is determined as Eq. 9 [18]

$$f_{RBF}(\mathrm{y}, \mathrm{y}i) = \mathrm{e}(-\mathrm{gamma} \times ||\mathrm{y} - \mathrm{y}i||\text{^}2) \tag{9}$$

Where gamma can be any number between 0 and 1, with 0.1 being the most desired. Cross terms in mathematical equations are eliminated using the Gaussian kernel.

Several SVM classes were used in this work, including the linear, quadratic, fine Gaussian, medium, and coarse Gaussian SVM.

3.4 Classification

AtrF episode detection was performed using SVM classifiers. Comparing categorized classes from the testing set with reference annotations divided into 3 classes allowed us to measure the performance of each classifier.

Utilizing 5-fold cross-validation, the AtrF by SVM classification performance was evaluated. Three distinct scale classes (medium, coarse, and fine) were considered while comparing linear, quadratic, cubic, and Gaussian SVM kernels.

4. Result and Discussion

The dataset used was acquired from the PhysioNet/ Computing in Cardiology Challenge for 2017: classifying 6000 ECG signals into three categories: normal sinus rhythm, AtrF, or too noisy to be classified [14].

A total of 6000 subjects participated in this work, with five predictors for each. A computer with the following specifications was used for testing and training: A Lenovo-branded laptop with 8 GB of Random-Access Memory (RAM), an Intel Core (TM) i7 CPU, an 8th Gen processor running at 2 GHz, and a 1TB solid state hard drive.

For utilized SVM classifiers, Table 1 lists the Training Time (TT), and the number of observations for the three classes, where class 0 are normal recordings, class 1 AtrF cases, and class 3 are noisy recordings. For class (0): True Positives (TP) are normal subjects that were classified as class 0, False Positive (FP) for normal subjects classified as AtrF cases present as class 1, False Positive (FP) for normal subjects classified as noisy recordings present as class 2. For class 1: False Negative (FN) AtrF subjects classified as normal, True Negatives (TN) are AtrF subjects correctly classified as class 1, False Negatives (FN) AtrF subjects classified as too noisy signals. Class 2: False Negatives (FN) are noisy recordings that are classified as normal, False Negatives (FN) are noisy recordings that are classified as AtrF, and True Negatives (TN) are noisy recordings that are correctly classified as class 3.

Further calculations were made to better assess the classification performance concerning the accuracy (Acc), sensitivity, area under the curve (AUC), and specificity in Figure 3.

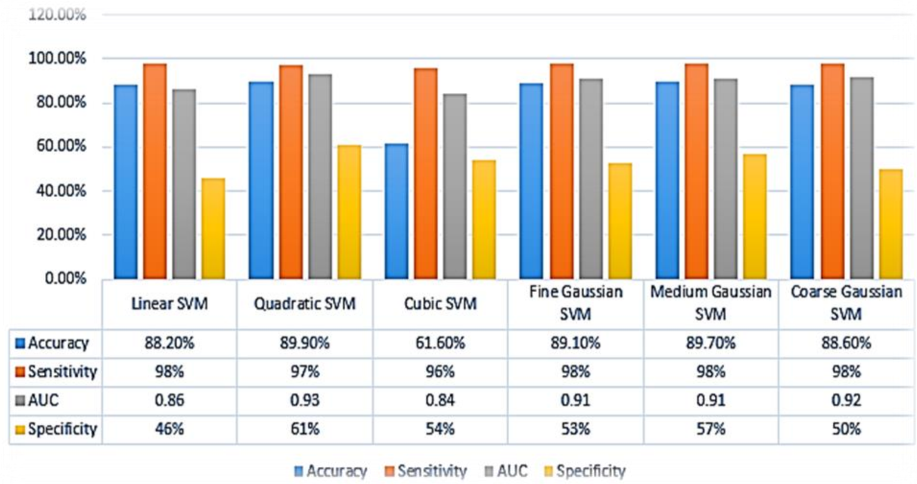

Figure 3: Performances illustration by comparing Acc, sensitivity, AUC, and specificity for the utilized SVM classifiers

Table 1: Classification performance for different SVM classifiers illustrated by TT and the number of observations.

Classifier	TT (sec)	Class 0			Class1			Class2		
		TP	FP	FP	FN	TN	FN	FN	FN	TN
Linear SVM	44.607	4898	336	204	92	393	67	6	2	2
Quadratic SVM	579.01	4863	240	147	96	474	75	37	17	51
Cubic SVM	1145.1	3252	296	138	682	347	40	1062	88	95
Fine Gaussian SVM	20.815	4879	288	182	95	420	45	22	23	46
Medium Gaussian SVM	24.22	4884	257	173	87	459	60	25	15	40
Coarse Gaussian SVM	27.717	4905	332	178	79	396	81	12	3	14

AUC, the area under the receiver operating characteristic (ROC) curve, measures how well a classifier can distinguish between different classes [20-24].

Specificity shows how much of the negative class was correctly determined, whereas sensitivity shows how much of the positive class was correctly categorized. Eq. 10 and Eq. 11 are used to compute them, respectively [25].

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \tag{10}$$

$$\text{Specificity} = \frac{TN}{(TN+FP)} \tag{11}$$

The classification results reveal slight variations among the SVM classifiers. Considering the main parameters differentiating the performance, the highest Acc value of 89.9%, was obtained for the quadric SVM classifier. At the same time, the lowest was for cubic SVM, with an Acc value of 61.1%. As for AUC best result it was for the quadric SVM, which is 0.93, and the lowest for cubic SVM, with 0.84. Specificity is highest when using quadric SVM at 61% and lowest when using cubic SVM with a specificity of 46%. On the other hand, regarding sensitivity, the difference is hardly noticeable since most SVM classifiers had an equal sensitivity of 98% except for quadric SVM with 97% and cubic SVM with 96%.

With the above in mind, it can be deduced that the difference is relatively small in most cases. Overall, the quadric SVM classifier was the most proficient with 89.9% Acc, 0.93 AUC, 97% sensitivity, and 61% specificity. The least proficient classifier was the cubic SVM, with 61% Acc, 0.84 AUC, 96% sensitivity, and 54% specificity.

Conclusion

This study presents a performance comparison among SVM classifiers for detecting AtrF on 6000 ECG signals from the PhysioNet database. The classification was based on the following features: RR interval, SDRR, SDANN, pNN50, and RMSSD. The performance of SVM was tested by using 5-fold cross-validation.

Among the SVM classifiers used in this work, Quadratic SVM gave the best performance with the following criteria: Acc 89.90%, AUC 0.93, and specificity 61%, while the sensitivity was 97%.

For future work, a recent dataset with our suggested method can be utilized in training and testing.

Authors' Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.

Authors' Contribution Statement

All authors provided collaborative effort for the execution of this research. M.A., M.M.,R.A and G.H. contributed to the writing and editing of the manuscript, construction of deep learning models and analyzed the obtained results. D.M. and M.A. conducted case analyses, collected samples, and performed various tests. Moreover, D.M, R.R. and M.S. contributed to feedback and revision suggestions. The final version of the manuscript was thoroughly reviewed and approved by all authors.

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