FABRÍCIO LORENI DA SILVA CERUTTI
(ORGANIZADOR)

# IMPACTOS DAS TECNOLOGIAS NA ENGENHARIA BIOMÉDICA

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# IMPACTOS DAS TECNOLOGIAS NA ENGENHARIA BIOMÉDICA

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## APRESENTAÇÃO

O e-book: Impactos das Tecnologias na Engenharia Biomédica, é composto por 8 artigos científicos que abordam temas como a utilização de processamento de sinal para reconhecer padrões de cardiopatias em eletrocardiograma, engenharia de tecidos utilizando gelatina para regeneração de tecido cartilaginoso, engenharia química para liberação controlada de Ibuprofeno no sistema gastrointestinal e analise da bioatividade em superfícies de titânio tratada. Também apresenta um novo dispositivo eletrônico de segurança em coletores de perfurocortantes. Por fim, descreve o desenvolvimento de baixo custo de um *phantom* antropomórfico de crânio com impressora 3D para controle de qualidade em equipamentos de raios X.

Com certeza este *e-book* irá colaborar para expandir o conhecimento dos leitos nas diferentes áreas da Engenharia Biomédica.

*Desejo* a todos uma *excelente leitura!*

*Prof. MSc. Fabrício Loreni da Silva Cerutti*

## SUMÁRIO

# CAPÍTULO 4

## DIAGNÓSTICO DE ARRITMIAS CARDÍACAS APLICANDO TÉCNICAS DE APRENDIZADO DE MÁQUINA

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**RESUMO:** A arritmia cardíaca afeta milhões de pessoas em todo o mundo. Embora de ocorrência comum, sua identificação e o correto diagnóstico não são tarefas simples. Nesse contexto, esse trabalho apresenta um estudo sobre a aplicação de Aprendizado de Máquinas à identificação e ao diagnóstico de arritmias cardíacas. Classificadores foram obtidos utilizando os algoritmos *k*-NN e SVM, e os testes foram realizados com os dados do dataset Arrhythmia, que é constituído por informações obtidas a partir dos exames de ECGs dos pacientes, bem como informações relacionadas ao seus estilos de vida. Três testes foram executados, no primeiro foi verificado a capacidade dos classificadores para identificar se ocorreu ou não um episódio de arritmia. No segundo, foi verificado o desempenho dos classificadores na identificação do tipo de arritmia, e no terceiro, a investigação foi realizada considerando o sexo dos indivíduos. Os resultados indicam que a utilização de Aprendizado de Máquina pode, de fato, auxiliar os especialistas no diagnóstico de arritmias. Em todos os testes o *k*-NN apresentou melhor desempenho, quando comparado ao SVM. O melhor resultado entre todos os testes foi obtido na classificação por sexo, em que o *k*-NN apresentou uma taxa de acerto de 94.03% na identificação de ocorrências de arritmias em pacientes do sexo feminino.

**PALAVRAS-CHAVE:** Arritmia cardíaca, aprendizado de máquina, máquinas de vetor de suporte, vizinho mais próximo.

## CARDIAC ARRHYTHMIA DIAGNOSIS APPLYING MACHINE LEARNING TECHNIQUES

**ABSTRACT:** Cardiac arrhythmia affects millions of people worldwide. Although commonly occurring, identifying and correctly diagnosing is not a simple task. In this context, this paper presents a study on the application of Machine Learning to the identification and diagnosis of cardiac arrhythmias. Classifiers

were obtained using the *k*-NN and SVM algorithms, and tests were performed using data from the Arrhythmia dataset, which consists of information obtained from patients' ECG examinations, as well as information related to their lifestyles. Three tests were performed; in the first one, the ability of classifiers to identify whether or not an arrhythmia episode occurred. In the second one, the performance of the classifiers in the identification of the arrhythmia type was verified, and in the third one, the investigation was performed considering the gender of the individuals. The results indicate that the use of Machine Learning may, in fact, assist specialists in the diagnosis of arrhythmias. In all tests *k*-NN presented better performance when compared to SVM. The best result among all tests was obtained by gender classification, where *k*-NN presented a accuracy of 94.03% in identifying arrhythmia occurrences in female patients.
**KEYWORDS:** Cardiac arrhythmia, machine learning, support vector machine, nearest neighbour.

## 1 I INTRODUCTION

Cardiac arrhythmia is a health problem which affects a large number of people worldwide. Such problem consists of alterations in the normal sequence of electrical impulses that control the heartbeats, causing abnormal rhythms of functioning.

Under the arrhythmia condition, the heart may present very fast beats (tachycardia), very slow beats (bradycardia), or even completely irregular beats that can oscillate between fast and slow in short time intervals. The precise determination of the type of arrhythmia is an important condition in specifying the most appropriate treatment.

However, preparing the diagnosis may not be a simple task, even for the most experienced experts. In many cases, the disease does not present apparent symptoms. The diversity of types of arrhythmia is another factor that can make diagnosis difficult. To make an accurate diagnosis, experts analyze the outcomes of medical exams, such as, echocardiogram, stress test, holter and, mainly, the electrocardiogram. Such tests investigate problems related to the functioning and the heart anatomy. In addition, lifestyle related factors are considered to be associated with episodes of arrhythmias.

In view of the difficult in making good diagnosis as previously stated, this work investigates the cardiac arrhythmia diagnosis applying machine learning techniques. The approach is based on using artificial intelligence tools, and aims to assist experts in improving cardiac arrhythmia diagnosis.

## 2 I CARDIAC ARRHYTHMIA AND MACHINE LEARNING

Electrocardiogram (ECG) corresponds to the electrical activity of the heart throughout a cardiac cycle. Each cardiac cycle is initiated by the emergence of an electrical potential in the sinus node which starts depolarization. Such event corresponds to the P wave on the electrocardiogram, which represents atrial electrical activity.

As the potential crosses the myocardium, occurs the ventricle contraction, generating the QRS complex. Therefore, the QRS complex is a reflection of ventricular activity.

After depolarization, follows the repolarization of the cells. In ECG signals, the T wave represents ventricular repolarization, that happens when diastole occurs. The atrial repolarization occurs simultaneously to the QRS complex, so there is no waveform representing this step (HALL, 2015).

The cardiac cycle occurs at a rate that varies from 60 to 100 beats per minute, depending on the individual, (THALER, 2013). Arrhythmias are characterized by irregular heartbeats provoking changes in the normal heart rate. Such occurrences may be caused by malformation and/or abnormal conduction of the electrical pulse responsible for the beating through the myocardium (PASTORE, 2016). The extraction and the analysis of descriptors from EGG signals associated to Machine Learning algorithms may assist in identifying arrhythmia occurrences.

In this context, several studies have addressed the problem of cardiac arrhythmia classification by applying Machine Learning techniques. More recently, some researchers have been investigating the use of Deep Learning to solve the problem.

In the early, Kaur and Arora (2012) proposed a approach for feature reduction by using orthogonal rotations. Wavelet coefficients for beat segments were taken as features which were reduced by factor analysis method using orthogonal rotations. LDA (Linear Discriminant Analysis) and ANN (Artificial Neural Network) classifiers were used for classification. The MIT-BIH arrhythmia database were used to classify into Normal, PVC, Paced, LBBB and RBBB. The authors reported the accuracy of 96% and 99.2% with LDA and ANN classifiers, respectively.

Park and Kang (2014), proposed a method for automatic classification of an individual's ECG beats for Holter monitoring. The authors used the Pan-Tompkins algorithm to extract QRS complex and P wave features from the MIT-BIH Database, and employed a decision tree to classify the type of arrhythmias.

Ouelli *et. al.* (2015) presented a two phase method for cardiac arrhythmia detection and diagnosis. In the first phase, features were extracted using autoregressive (AR) and multivariate autoregressive (MVAR) modeling of one-lead and two-lead electrocardiogram signals. Obtained features were used as input to the second phase. In that stage, classification were carried out using a quadratic discriminant function (QDF) and a multilayer perceptron (MLP).

Zhang *et. al.* (2015) developed an automatic classification system to distinguish five geometric patterns of Poincaré plots from four types of cardiac arrhythmias. For that, the authors applied an ensemble of three types of neural networks. In the tests the authors used a 24 h ECG monitoring recordings from 674 patients, containing four types of cardiac arrhythmias. For comparison, Support Vector Machine (SVM) classifiers with linear and Gaussian kernels are also applied.

Gnecchi *et. al.* (2017) proposed an arrhythmia classification method implemented on a Digital Signal Processing (DSP) platform intended for on-line, real-time ambulatory operation to classify eight heartbeat conditions (N, AF, PAC, LBBB, RBBB, PVC, SHB SVT). The algorithm uses wavelet transform for identifying individual ECG waves, and classification is conducted by means of a Probabilistic Neural Network. Tests were performed using 17 ECG records obtained from the PhysioNet repository. The results yielded on-line classification accuracy of 92.69% (AF), 97.15% (N), 76.82% (PAC), 91.06% (LBBB), 87.5% (RBBB), 71.04% (PVC), 91.94% (SHB) and 95.45% (SVT), and overall classification rate of 92.746%.

Some papers on arrhythmia diagnosis used the data of Cardiac Arrhythmia ECG Database from the University of California at Irvine (UCI). The same dataset applied in the present study.

In Polat and Gunes (2007) the authors used Principal Component Analysis (PCA) and Least Square Support Vector Machine (LS-SVM) to diagnose arrhythmias. The proposed method consisted of two steps. In the first one the authors applied PCA to dimensionality reduction, and reduced the number of descriptors from 279 to 15. In the second one, the LS-SVM algorithm was used to classify various types of arrhythmias. In that step, the dataset was partitioned between train and test set, considering three different proportions, 50% - 50%, 70% - 30% and 80% - 20%. The classification accuracy values obtained for each partition were 96.86%, 100% and 100%, respectively.

In Kohli and Verma (2011), the authors tested four different Support Vector Machine approaches: One Against One (OAO), One Against All (OAA), Fuzzy Decision Function (FDF) and Decision Directed Acyclic Graph (DDAG), to verify the occurrence and classify episodes of arrhythmia. Performance of the four methods were investigated considering the accuracy rate in two different tests. In the first one all features were used for classifying. In the second one, features selection was carried out using principal Component Analysis (PCA). In both tests the OAA method performed better, in addition tests using features selection gives better results than classification without feature selection.

Mustaqueen *et. al.* (2018) conducted a study to classify patients into one of the sixteen subclasses, among which one class represents absence of disease and the other fifteen classes represent electrocardiogram records of various subtypes of arrhythmias. For multiclass classification, support vector machine (SVM) based approaches including one-against-one (OAO), one-against-all (OAA), and error-correction code (ECC) were employed to detect the presence and absence of arrhythmias. The SVM method were compared with other standard machine learning classifiers, and the results show that OAO method outperforms all other classifiers by achieving an accuracy rate of 81.11% when used with 80/20 data split and 92.07% using 90/10 data split option.

In Wosiak (2019), a new PCA-based method named igPCA (in-group Principal Component Analysis) for feature reduction was proposed. The authors assumed that the set of attributes could be split into subgroups of similar characteristic and then subjected to principal component analysis. The proposed method transforms the feature space into a lower dimension and gives the insight into intrinsic structure of data. The authors claimed which experiment results showed the advantage of the presented method compared to base PCA approach.

## 3 I PATTERN RECOGNITION AND MACHINE LEARNING

According to Bishop, the Pattern Recognition purpose is to enable automatic discoveries of regularities in data through the use of computer algorithms (BISHOP, 2015). Regularities in data enables the extraction of information, decision making and data classification, among other applications.

Machine Learning is related to algorithms development to enable computers to learn, modify or adapt their actions to make them more precise (MARSLAND, 2014). In this context, precision is the measure of similarity between the expected actions and those taken by the computer.

The Machine Learning area can be seen as an evolution of Pattern Recognition field, since learning is based on modifying actions by analyzing regularities in data. In this way, it can be stated that classification belongs to the interception of these two areas of knowledge. Several Machine Learning algorithms have been proposed to perform classification tasks. In this work will be used the *k*-Nearest Neighbour (*k*-NN) and Support Vector Machines (SVM).

### 3.1 k-Nearest Neighbour

The *k*-Nearest Neighbour (*k*-NN) algorithm is considered to be the simplest methods in Pattern Recognition (CUNNINGHAM; DELANY, 2007). Since it makes no initial assumptions about the rules applied to classify the unknown samples it is said to be a nonparametric method.

Because it is an instance-based method, *k*-NN stores all training data for classification or regression. When used for classification, examples are categorized as belonging to the same class as their *k* nearest neighbours, and this proximity can be calculated using different types of similarity metrics.

In the example pictured in Figure 1 and O and X are two classes. For sample , it can be assumed that it will be classified as O, since its three closest neighbours belong to that class. The example is not so straightforward, as it has two neighbours which belong to class X and one of class O.

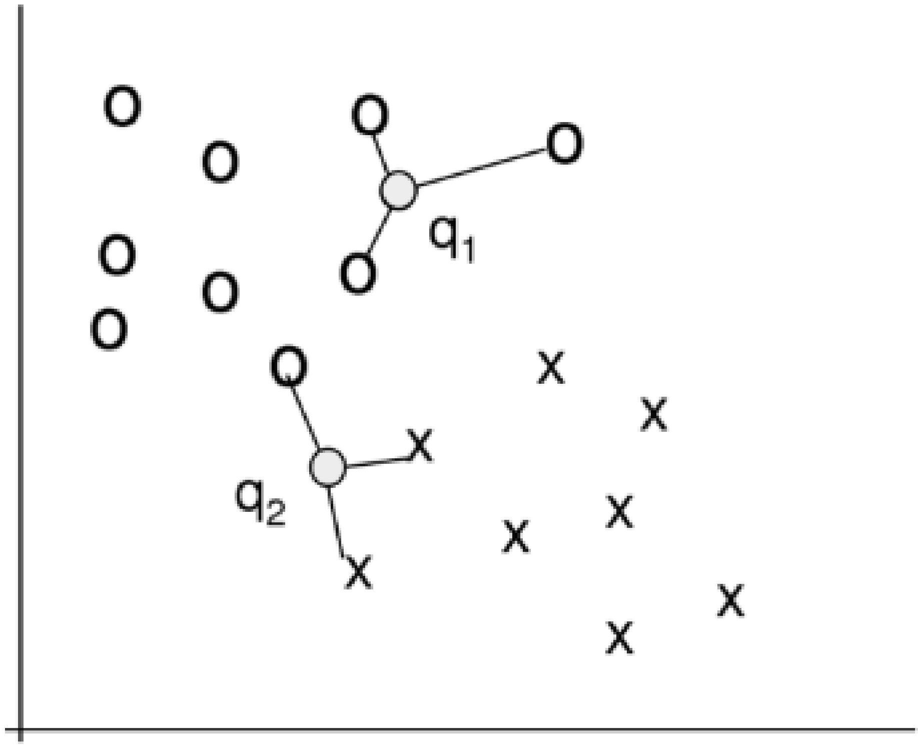


Figure 1 - k-NN with $k = 3$.

Fonte: (CUNNINGHAM; DELANY, 2007).

In order to assign its class, the majority voting method can be used, or a voting assigning a weight to the distance from each neighbour. In this step, several similarity metrics can be explored. This work adopted the one referred to as the euclidean distance, as can be seen in Equation 1, where  and  are n-dimensional points.

Equation 1 - Euclidean distance formula.

$$d = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \dots + (p_n - q_n)^2}$$

Given a value of  (number of neighbours), let  be a new observation and *d* the chosen similarity metric. The classification algorithm used by *k*-NN can be summarized in two steps: first, it is calculated  between  and the other training samples. Then,  is assigned to the most common class among these samples, according to the similarity metric adopted (ZAKKA, 2016).

### 3.2 Support Vector Machines

Support vector machines (SVM) are another machine learning algorithm widely used in the cardiovascular domain. SVM is based on two ideas: margin maximization and nonlinear classification using kernels. Physicians may find SVM useful because, while relatively simple, they can capture complex nonlinear relationships.

SVM uses a hypothesis space of linear functions in a characteristic high-dimensional space, trained with an optimization theory learning algorithm. This learning strategy, introduced by Vladimir Vapnik and Alexey Chervonenkis (VAPNIK; CHERVONENKIS, 1963), is a very powerful method that in the few years since its introduction has surpassed most other systems in a wide variety of applications.

In binaries classification problems, as illustrated in Figure 2, SVM maps input observations (C1 and C2) into a larger dimensional space by constructing a hyperplane (Best Margin) that linearly separates the two classes. For a multiclass problem, SVM attempts to find multiple hyperplanes  able to separate the classes.

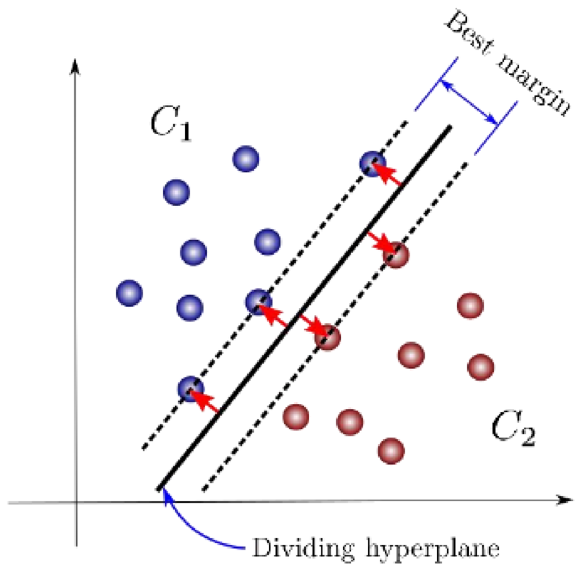


Figure 2 - SVM for binary classification.

Fonte: (https://towardsdatascience.com/support-vector-machines-for-classification)

In the training phase, the problem faced by SVM is to find the support vectors that create the largest margin between the classes. Cui *et. al.* (2017) demonstrated the utility of SVM by predicting intra-stent restenosis with 90% accuracy of plasma metabolite levels.

Despite your vast application in classification tasks, SVM have some problems. First, they perform non-probabilistic classification (BRIDGELALL, 2017). Second, similar to linear regression, calculating input observations in a very large space (ie when there are many variables) can be difficult or impossible.

## 4 I METHODOLOGY

The methodology that oriented the research consisted of the following steps:

dataset acquisition, pre-processing, modelling, classification.

### 4.1 Dataset Acquisition

The experimental phase was accomplished using the dataset Arrhythmia (DUA; GRAFF, 2019), which can be freely obtained on the UCI-Machine Learning Repository website. The dataset consists of a fusion between outcomes of medical exams and information related to the patient's lifestyle. In its original form it consists of 452 samples and 279 attributes (206 numerical and 73 nominal), distributed in 16 classes. Class 1 consists of data from healthy patients, classes 02 to 15 refers to different classes of arrhythmia and class 16 refers to the rest of unclassified ones. Even though the arrhythmia dataset has been a reference in the study of cardiac arrhythmias, it presents some problems in its structure. There is no samples in classes 11, 12, and 13. Some classes (7, 8, 14 and 15) has an insufficient number of samples, which could be a problem in the modeling phase. The attributes values in some descriptors are unknown. The worst case is referred to descriptor 14, with 84% unknown attributes. In addition, the dataset is very unbalanced. Among the 452 samples of the original set, 245 are related to the control patient class, that is, not having any type of arrhythmia.

### 4.2 Pre-processing

To fix problems in the dataset structure, in all tests the classes 11, 12 and 13 were removed because they lacked samples. In the same way, column 14 was removed because it had 84% of unknown values among the 452 attributes. Because the insufficient amount of samples in classes 7, 8, 14, and 15, such classes were also removed in some tests.

### 4.3 Modelling

In the experimental stage three different tests were performed considering different organizations of the dataset.

Two-class problem - The initial tests investigated the ability of the models to identify the occurrence of episodes of cardiac arrhythmias. For this stage, classes 7, 8, 14 and 15 were also removed because they had a reduced number of samples, generally less than 9, which would make it impossible to model these classes. With the samples removed, the dataset samples were reorganized into two classes, the Class 1 corresponding to healthy individuals and the Class 2 corresponding to individuals with arrhythmia. Since some samples had unknown attribute, it was decided to investigate the use of Principal Component Analysis (PCA) to estimate such values.

Multiclass problem - The multiclass problem consists in identifying the occurrence and the type of arrhythmia. In the first test, Principal Component Analysis was used to estimate unknown attributes values, as well as to eliminate variables that are poorly correlated with the sources of variability associated with the phenomena to be modelled. For this case, the dataset consisted of 452 samples and 59 attributes, distributed in

13 classes. In the second test, unknown values and classes with reduced number of samples (7, 8, 14 and 15) were eliminated and Principal Component Analysis was applied to reduce the size of the dataset. The dataset used in the modelling step had 412 samples and 53 attributes, distributed in 9 classes.

Classification by sex - The third phase investigate the occurrence of arrhythmias considering the gender of the patient. Samples of female and male patients were organized in separate *datasets*, which corresponded to a total of 234 and 178 samples, respectively. For these tests the attributes with unknown values and classes with reduced amounts of samples were eliminated.

### 4.4 Classification

Models were constructed using *k*-NN and SVM algorithms. In each case 70% of the samples were used to train the models and 30% in the test phase. The performance of the models was measured using the correct classification rate. All tests were accomplished applying Matlab functions.

## 5 I RESULTS

Two-class problem - In these tests, samples from classes 7, 8, 14 and 15 were removed, and the unknown attributes values were kept, instead, PCA was used to estimate the unknown attribute values. The best results obtained with the *k*-NN and SVM classifiers were 84.88% and 76.69%, respectively. When attributes with unknown values were removed, the correct classification rate for *k*-NN and SVM were, respectively, 84.47% and 73.38%. In both cases, the *k*-NN classifier settings were (3 neighbours), euclidean distance and the exhaustive search method. The SVM models used kernel linear.

Multiclass problem - Keeping the samples of classes 7, 8, 14 and 15 and using PCA to estimate unknown attributes values, the best result with the *k*-NN and SVM classifiers were, respectively, 74.12 of 67.4%. When the samples of classes 7, 8, 14 and 15 and the attributes with unknown values were removed, the correct classification rate obtained with the classifiers *k*-NN and SVM were, respectively, 82.52% and 66.40%. In both cases the *k*-NN classifier settings were , euclidean distance and the exhaustive search method. The SVM models used kernel linear.

Classification by sex - When the analysis considered the gender of the patient, the best result for the *k*-NN classifier was, for males 78.65% and for female 94.03%. In turn, the results with SVM were, 60.34% and 70.0% for the male and female sex, respectively.

## 6 I DISCUSSION AND CONCLUSIONS

This work investigated the use of Machine Learning techniques to assist specialists in identifying the type of arrhythmia in cardiac patients. The classification models were implemented using the *k*-NN and SVM algorithms. Tests were carried out using the dataset Arrhythmia. The referred dataset gathers information from male and female patients obtained from medical examinations, as well as information related to the patients lifestyle.

As can be seen from the results, in all test scenarios the best performance was obtained with *k*-NN classifier, and that among the scenarios tested, the best result was obtained with the two-class problem.

We can justify such a result by arguing that, as the used dataset presents a high level of imbalance some classes have reduced quantities of samples. Such conditions are not favourable for good SVM classifier performance, since it works based on a decision border, which, in consequence cannot be well adjusted in case of few samples.

On the other hand, the performance of the *k*-NN classifier, whose decision is based on the distance between samples, is less influenced by the imbalance between classes. As expected, the average performance of the classification improves slightly when the analysis is done by sex, which confirms the theoretical knowledge that cardiac diseases affect men and women differently.

It is not possible to compare the results of this work with those obtained in the papers that used the same dataset, reported in section 2, because the respective authors did not mentioned the dataset configurations used.

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