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PROPOSAL OF A NEW AND BETTER METHOD, BASED ON ESTIMATORS OF INFORMATION MEASURE AND ARTIFICIAL NEURAL NETWORK, TO CLASSIFY DIFFERENT TYPES OF CARDIOPATHIES

MASTER DISSERTATION

CORNÉLIO PROCÓPIO

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Master Dissertation graduate program in Electrical Engineering of Federal Technological University of Paraná as a requirement for obtaining the master's degree in electrical engineering.

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ABSTRACT

SUTERIO, Vinícius. DETECTION OF CARDIOPATHIES BY ELETROCARDIOGRAM USING NEURAL NETWORK. 76 f. Master Dissertation – Programa de Pós-Graduação em Engenharia Elétrica, Universidade Tecnológica Federal do Paraná. Cornélio Procópio, 2018.

Among all the illness which affect the population, the cardiovascular diseases are the mainly causes of death in the world, they are related to several factors, as for example: the life quality, use of narcotics and mainly the aging. Thereby, this work proposes a system to aiding health's professional, aimed to facilitate the interpretation of patient's ECG for cardiopathies detection between the healthy and unhealthy ECG. The new proposed method ensure the obtaining of better results than those found in literature and with a low degree of uncertainty. Basically it consists of analyzing some given electrocardiogram signals in order to detection if there is or not some cardiopathy, and the scope of these cardiopathies was delimited to classification between healthy ECG and some most common types of diseases, that cause disorders of heart rhythm - arrhythmia, in population; such diseases are: atrial fibrillation, ventricular bigeminy, sinus bradycardia, supraventricular tachyarrhythmia, ventricular trigeminy, ventricular flutter and supraventricular arrhythmia. This automatic detection technique of cardiopathies uses as features the wavelet packet components, called *SuScAlhets*, which is the new proposed method in this work, and that which is found in literature and considered one of the best to treat ECG signals, the *Daubechies* 3 - *db*3. Jointly with these features it is also used some estimators of information measures which are: *Rényi entropy*, *correlation coefficients* and *Cauchy-Schwartz quadratic mutual information* and are responsible to extract the most valuable informations of the studied signals.

Keywords: wavelet packet, estimators of informations measures, neural networks, feature extraction, eletrocardiograms, cardiopathies.

RESUMO

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Dentre todas as doenças que acometem a população, as doenças cardiovasculares são as principais causas de morte no mundo, estão relacionadas a vários fatores, como por exemplo: a qualidade de vida, uso de entorpecentes e principalmente ao envelhecimento. Assim, este trabalho propõe um sistema para auxiliar o profissional de saúde, visando facilitar a interpretação do ECG do paciente para a detecção de cardiopatias entre o ECG saudável e o não saudável. O novo método proposto garante a obtenção de melhores resultados que os encontrados na literatura e com baixo grau de incerteza. Basicamente, consiste em analisar alguns sinais do eletrocardiograma para detectar se há ou não indícios de alguma cardiopatia, e o escopo dessas cardiopatias foi delimitado para classificação entre ECG saudável e alguns tipos mais comuns de doenças, que causam distúrbios do ritmo cardíaco - arritmia, na população; tais doenças são: fibrilação atrial, bigeminia ventricular, bradicardia sinusal, taquiarritmia supraventricular, trigeminismo ventricular, flutter ventricular e arritmia supraventricular. Esta técnica de detecção automática de cardiopatas utiliza como características os componentes do pacote wavelet, denominado *SuScAlhets*, que é o novo método proposto neste trabalho, e o que é encontrado na literatura e considerado um dos melhores para tratar sinais de ECG, o textit Daubechies 3 - *db*3. Juntamente com estas características também são utilizados alguns estimadores de medidas de informação que são: Rényi entropy, coeficientes de correlação e informação mútua quadrática de Cauchy-Schwartz, que são responsáveis por extrair as informações mais valiosas dos sinais estudados.

Palavras-chave: *wavelet packet*, estimadores de medidas de informação, redes neurais artificiais, extração de características, eletrocardiogramas, cardiopatias.

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1 CARDIOPATHIES: OVERVIEW

The cardiovascular diseases (CVDs) are the main causes of death in the world. There is a global estimate that the CVDs caused about 17.9 million of deaths corresponded 31% of total global deaths, in 2016. There are more death annually by CVDs than any other disease, and over three quarters of these deaths take place in low- and middle-income countries (WHO, 2017). According to (MCALOON et al., 2016), the cardiopathies cases have been growing over the years, there was an increase of 1.4 millions in only twelve years - 2000 until 2012, about 17.6 millions of death in the world by CVDs, being three out of ten deaths. Thereby, in 2012, 7.4 millions of death were by ischemic heart disease. In general, approximately 50% of all deaths are due to heart disease. More informations about cardiopathies in (BENJAMIN et al., 2018).

There are many more adults (>40 years old) with congenital heart disease than children, an estimated 2 million adults in the USA surviving with congenital heart disease (PAPADAKIS; MCPHEE, 2018). It is estimated that 50% of all patients will manifest some atrial arrhythmia by 55 years of age (BHATT et al., 2015). According to (UNITED NATIONS, 2015), it is estimated that the number of people with 60 years and older, will grow by 56%. Besides, it is expected that these population, to be double in 2050, about 2.1 billion of people (SINGH; TIWARI, 2006). Thereby, the forecasts show that the world is already facing an aging population.

The cardiovascular system becomes weaker over the years which makes it susceptible to diseases (BHATT et al., 2015). Moreover, the muscle wall of the left ventricle thickens with aging and the arteries stiffen, resulting in a decrease in the compliance of blood vessels of the arteries (CHOW et al., 2012). Consequently, this affects the heart and compromises the circulatory system, leading to the arrhythmia. Cardiac arrhythmia is a heath condition faced by the populationis and is defined as the frequency alteration, formation and/or conduction of electric impulse through of myocardium, it consists in the abnormal rhythm of the heart beat, which can be harmless or critical (PASTORE et al., 2016).

If the cardiopathy detection occurs in the early stages of the disease, it is possible to remedy its effects by simpler and safe procedures to the patient, on the other hand, late diagnoses can be problematic, requiring more invasive treatments. Beyond the improvements on cardiopathy treatment, it is indispensable that the diagnosis been performed faster and more efficiently.

With this cardiopathies overview, it can be confirmed that the cardiopathies prevention and diagnosis are essential to improving the current global situation (WHO, 2017; PAPADAKIS; MCPHEE, 2018; BENJAMIN et al., 2018). According to (SUTERIO et al., 2018), the increasing technological development have been benefiting several areas with direct application of technology. The medicine area is one of the most important which has benefiting with such development, some exams and even surgeries are done remotely and this is called tele-medicine (GONÇALVES et al., 2008; CHOI et al., 2006).

Even with de increasing technological development, the electrocardiogram (ECG), remains one of the most versatile, used and inexpensive of clinical tests. The ECG is considered the initial clinical test for diagnosing dangerous cardiac electrical disturbances related to conduction abnormalities in the AV junction and bundle branch system and to brady- and tachyarrhythmias. Its usually provides immediately available information about clinically important mechanical and metabolic problems, as myocardial ischemia/infarction, electrolyte disorders, as well as hypertrophy and other types of chamber overload. Finally, it may provide clues that allow to forecast preventable catastrophies (GOLDBERGER et al., 2012).

2 ECG PROCESSING

The ECG signal processing has been a strong line of research in last decades, as presented in (MONTEIRO; FARIAS, 1985; HUALLPA, 1992; ORESKO et al., 2010; SUTERIO et al., 2017), and one of the factors that enabled the strengthening of research, in this area, was the creation of the MIT database (Massachusetts Institute of Technology) in the year 2000, which is composed by ECGs collected in several situations and grouped into cathegories serving as the basis of study (GOLDBERGER et al., 2000).

This work consists in proposing of a system to aiding heath's professional, aimed to facilitate the interpretation of patient's ECG for cardiopathies detection between the healthy and unhealthy ECG. The work uses some estimators of information measures as *Rényi entropy*, *correlation coefficients* and *Cauchy-Schwartz quadratic mutual information* for feature extraction, and a machine learning technique, the *artificial neural networks - ANN*, as classifier of the features. This work provides the results obtation with a low degree of uncertainty and consists of analyzing some given electrocardiogram signals in order to detection if there is or not some cardiopathy. The scope was delimited to classification between healthy ECG, with atrial fibrillation, ventricular bigeminy, sinus bradycardia, supraventricular tachyarrhythmia, ventricular trigeminy, ventricular flutter and supraventricular arrhythmia.

The atrial fibrillation (AF) affects millions of people worldwide, and it is expected that the cases to increase. The AF has large impact on a person's life, because may cause: the increased risk of stroke, dementia, heart failure and even the death. Multiple comorbidities have been associated with incident AF (VERMOND et al., 2015). According to (KRIJTHE et al., 2013), the AF is the most common sustained arrhythmia in the general population, and it is expected that there will a substantially increase, to the coming decades, of the adults cases with AF in the European Union. Such cases may even double between 2010 to 2060

The ventricular bigeminy and trigeminy (ectopic beats), both are included to ventricular premature beat class (VPB). Such class are commonly encountered in patients with congestive heart failure (CHF). Frequent ventricular ectopy can be associated with deterioration of cardiac function and may lead to VPB induced cardiomyopathy. So, the VPBs, in the setting of

CHF, can not be regarded as a benign arrhythmia, thus needing a differentiated attention (CHEN et al., 2013).

The bradycardia consists in a heart rate lower than 60 beats per minute. The asymptomatic sinus bradycardia is usually harmless and can be regarded as a sign of good physical conditioning. On the other hand, the symptomatic sinus bradycardia, such as that associated with the sick-sinus syndrome, can be a life-threatening condition and deserves special medical attention (MILANESI et al., 2006).

The term supraventricular tachyarrhythmia is used to treat some different types of cardiopathies, one of them and used in this work, is the paroxysmal supraventricular tachycardia (PSVT) (GOLDBERGER et al., 2012). The PSVT is a clinical syndrome characterized by the presence of a regular and rapid tachycardia of abrupt onset and termination and if not treated correctly, can trigger other more serious heart diseases. In the U.S. there are approximately 89,000 new cases per year and 570,000 persons with PSVT (PAGE et al., 2015).

The ventricular flutter consists in fast and completely disordered beats, stimulated from the ventricular automaticity focus (ectopic). Due to its quickness, the ventricles does not have enough time to fill with blood, even partially, so this arrhythmia becomes into a deadly arrhythmia (DUBIN, 2000).

The supraventricular arrhythmia, by its name, consists in a kind of arrhythmia that occurs above the ventricles. The identification of the local where occurs the arrhythmia always its used, otherwise, its used the supraventricular generic term (PASTORE et al., 2016). Thus, the supraventricular arrhythmia can be composed by excerpts of others arrhythmias, but whatever the frequency alteration or heart rhythm disorder, it is important the follow-up by a professional

This work was divided in two steps. Firstly it was performed the feature extraction process of the ECG and its subsequent use for the classifier development - ANN. After, it was performed an analysis of the obtained results.

In other words, it was performed the implemetetion of pattern recognition in ECG signals, which was responsable to find a determined signal profile, followed of the analysis to identify if there is cardiopathies evidence.

In the following are presented the steps of this work:

- Download of healthy and unhealthy ECGs from MIT database;
- Pre-processing of the data;
- Feature extraction, with the selection of best features.
- Apply and trainning the artificial neural networks to classify the ECG, between healthy or one of the cardiopathies
- Analyze the obtained results

3 INTERPRETATION OF ELECTROCARDIOGRAM (ECG)

3.0.1 BASIC PRINCIPLES

The electrocardiogram (ECG) is a special graph that represents the recording of cardiac functioning, that is, the electrical activity of the heart from one instant to the next. Such graph provides valuable information of heart's function and structure. The data collected usually are obtained by means of conductive electrodes positioned on the surface of the body, and inscribed on a ruled paper striped, or depending on collection device, can be import by a software, allowed a computational analysis. For the standard ECG recording, electrodes are placed on the arms, legs, and chest wall (precordium - derivations V1 until V6). These data represents a permanent recording of cardiac activity (DUBIN, 2000; GOLDBERGER et al., 2012).

Basically the central function of the heart is to contract rhythmically and pump blood to the lungs for oxygenation and then to pump this oxygen-enriched blood into the general (systemic) circulation. The registered information on ECGs represents the electrical impulses of the heart and these impulses represents the various steps of cardiac stimulation (DUBIN, 2000; GOLDBERGER et al., 2012).

The ECG register the electrical impulses that stimulate the cardiac contraction. The signal for cardiac contraction is the spread of electrical currents through the heart muscle. These currents are produced both by pacemaker cells and specialized conduction tissue within the heart and the working heart muscle itself (DUBIN, 2000; GOLDBERGER et al., 2012).

Pacemaker cells are like tiny clocks (technically called oscillators) that repetitively generate electrical stimuli. The other heart cells, both specialized conduction tissue and working heart muscle, are like cables that transmit these electrical signals (DUBIN, 2000; GOLDBERGER et al., 2012).

When there is the cardiac muscle stimulation they contract, that is, the cardiac cells are polarized in the resting state, but when they are stimulate electrically depolarize itself and contract, as presented in Figure 1 (DUBIN, 2000).

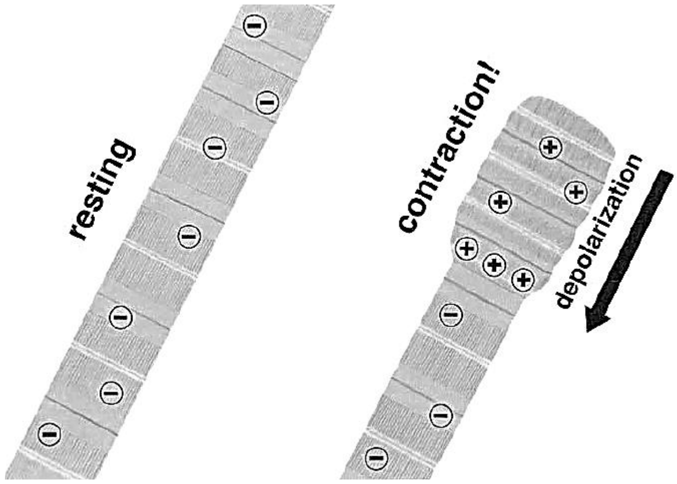


Figura 1: **The interiors of heart muscle cells.**
Fonte: (DUBIN, 2000)

A polarized cell, in rest, has negative internal load and surface with positive load. In order to simplify, it will be considered just the interior of the myocardial cell. So its interior, that usually is negatively loaded, becomes positively loaded when the cells are stimulate, then there is the contraction. Technically the electrical stimulation of these specialized muscle cells its called depolarization, contracting them. Thereby, a stimulation progressive wave (depolarization) cross the heart causing the myocardial contraction. The depolarization stimulate the myocardial cells contraction, and the interior load of each cell become positive (DUBIN, 2000).

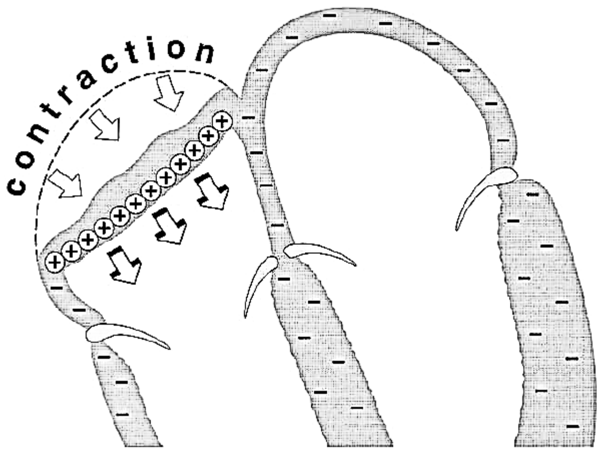


Figura 2: **Myocardial contraction due the wave of depolarization crossing the heart.**
Fonte: (DUBIN, 2000)

The graph representation performed by the ECG consists in the depolarization wave, when the cells interior become positive, and the repolarization, when the cells interior return to negative (DUBIN, 2000). These representation is presented in Figure 3.

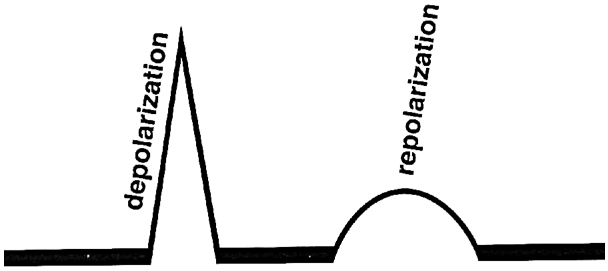


Figura 3: **Representation of the depolarization and repolarization in ECG.**
Fonte: (DUBIN, 2000)

When the electrical activity cross the heart, it can be detected by the conductive electrodes and then recorded. This consists on electrocardiogram (DUBIN, 2000).

Normally, the sinus or sinoatrial (SA) node its responsible to start the electrical impulse. It consists in a small collection of specialized cells capable of automatically generating an electrical stimulus (spark-like signal) and functions as the normal pacemaker of the heart. Its located in the right atrium near the opening of the superior vena cava and from the sinus node, the stimulus spreads first through the right atrium and then into the left atrium, contracting them and pump blood simultaneously through the tricuspid and mitral valves into the right and left ventricles, as presented in Figures 4 and 5. The electrical stimulus then reaches specialized conduction tissues in the atrioventricular (AV) junction (DUBIN, 2000; GOLDBERGER et al., 2012).

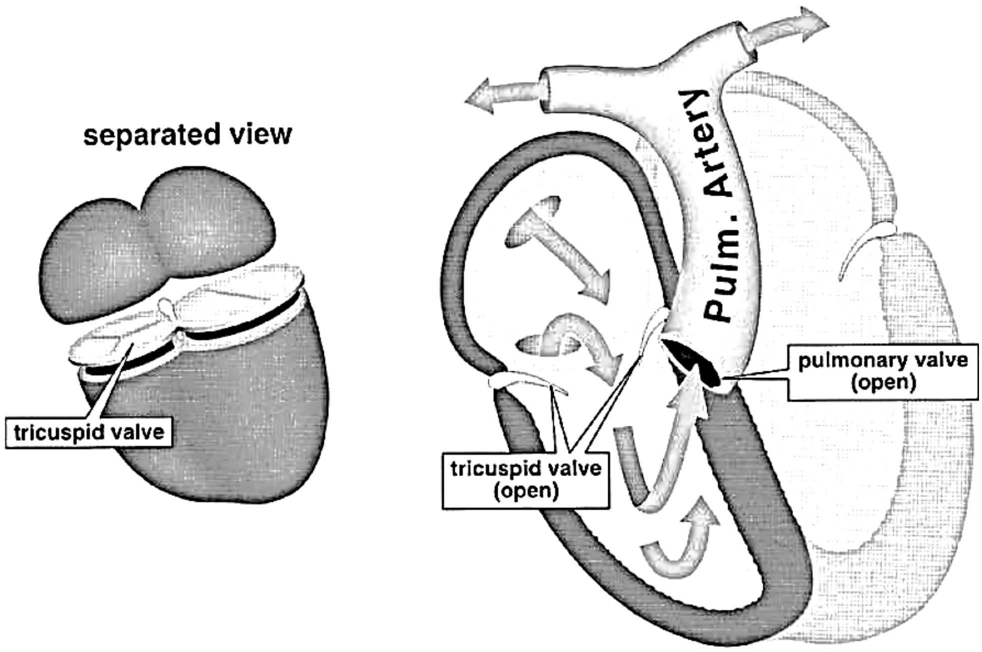


Figura 4: **The pumping blood through the heart tricuspid valve.**
Fonte: (DUBIN, 2000)

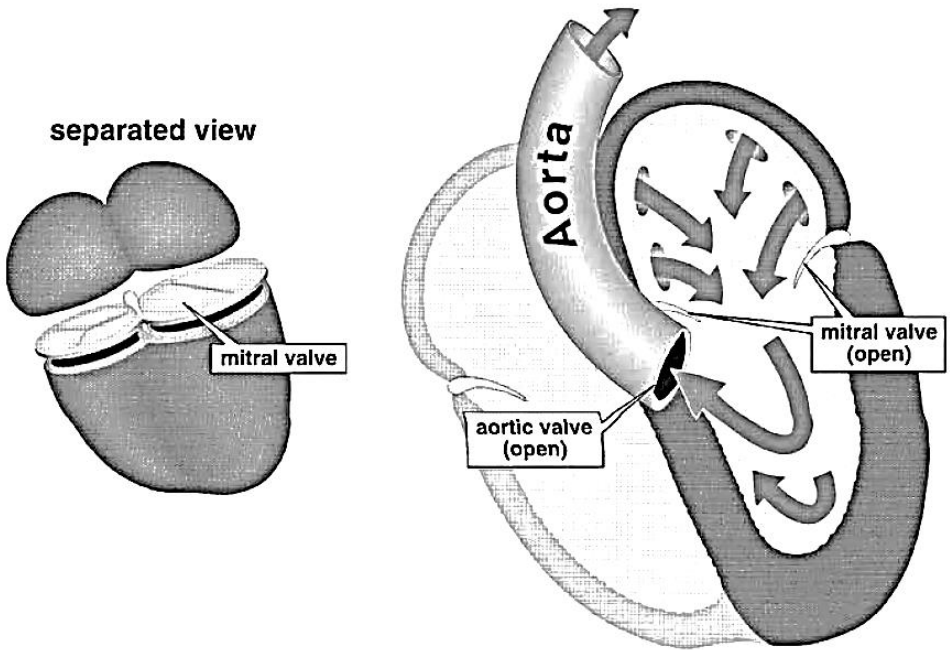


Figura 5: **The pumping blood through the heart mitral valve.**
Fonte: (DUBIN, 2000)

The AV junction, which acts as an electrical ”relay”connecting the atria and ventricles, is located at the base of the interatrial septum and extends into the interventricular septum (GOLDBERGER et al., 2012), as in Figure 6 .

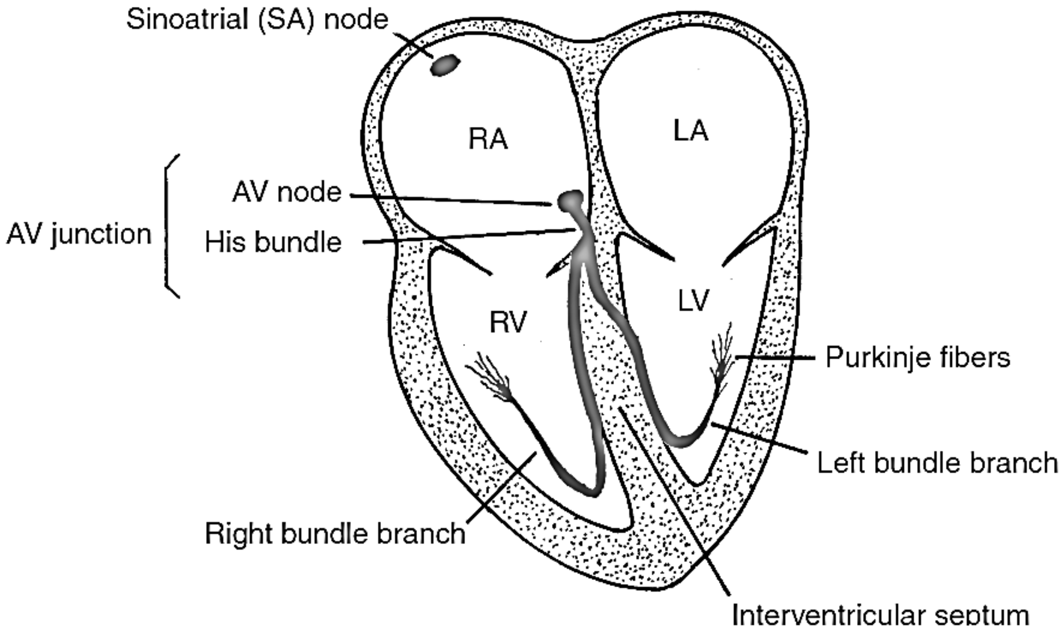


Figura 6: **Heart anatomy.**
Fonte: (GOLDBERGER et al., 2012)

The upper (proximal) part of the AV junction is the AV node and he lower (distal) part of the AV junction is called the bundle of His. The bundle of His then divides into two main branches: the right bundle branch, which distributes the stimulus to the right ventricle, and the left bundle branch, which distributes the stimulus to the left ventricle (GOLDBERGER et al., 2012), as in Figure 6.

The electrical signal then spreads simultaneously down the left and right bundle branches into the ventricular myocardium (ventricular muscle) by the specialized conducting cells, called Purkinje fibers and located in the subendocardial layer (inside rim) of the ventricles. From the final branches of the Purkinje fibers, the electrical signal spreads through myocardial muscle toward the epicardium (outer rim). The His bundle, its branches and their subdivisions, are referred to collectively as His-Purkinje system (DUBIN, 2000; GOLDBERGER et al., 2012).

Just as the spread of electrical stimuli through the atria leads to atrial contraction, so the spread of stimuli through the ventricles leads to ventricular contraction, with pumping of blood to the lungs and into the general circulation. The depolarizing electrical current is recorded by the ECG as a P wave (when the atria are stimulated and depolarizes - Figure 7) and with the QRS complex (when the ventricles are stimulated and depolarizes - Figure 8) (GOLDBERGER et al., 2012).

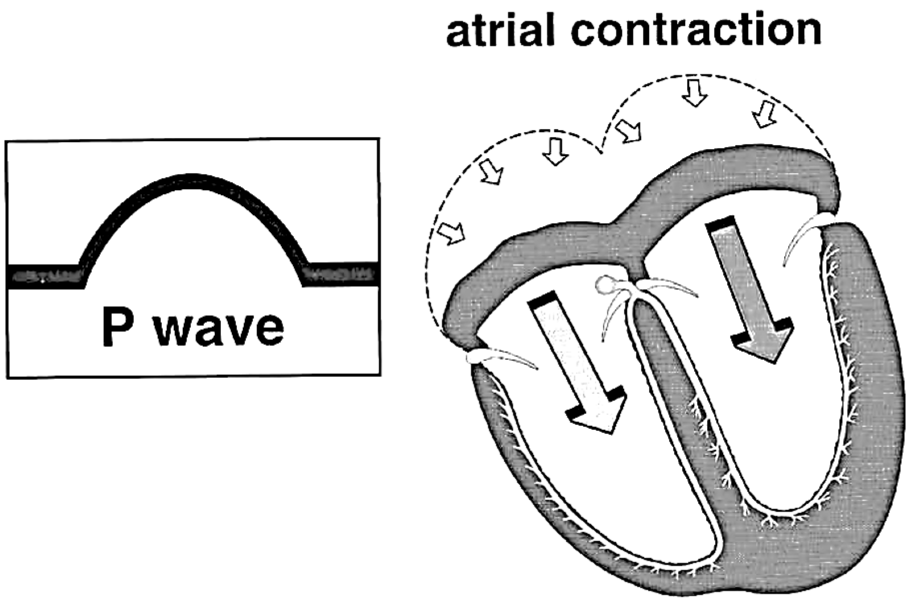


Figura 7: **Atrial contraction - P.**
Fonte: (DUBIN, 2000)

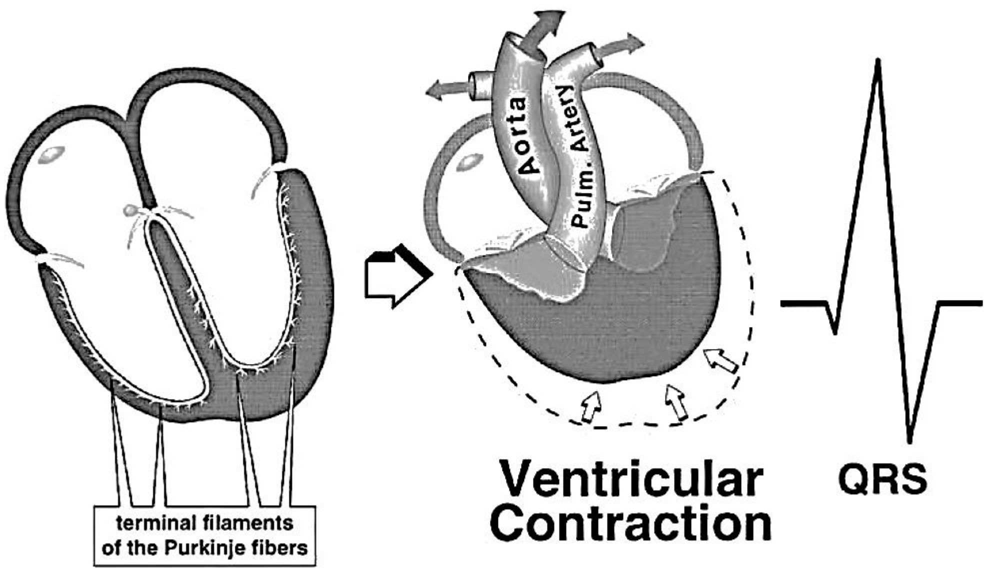


Figura 8: **Ventricular contraction - QRS.**
Fonte: (DUBIN, 2000)

After a time, the fully stimulated and depolarized cell begins to return to the resting state, it is called of repolarization. Ventricular repolarization is recorded by the ECG as the ST segment, T wave, and U wave, as presented in Figure 9 (DUBIN, 2000; GOLDBERGER et al., 2012; BAYÉS DE LUNA, 2007).

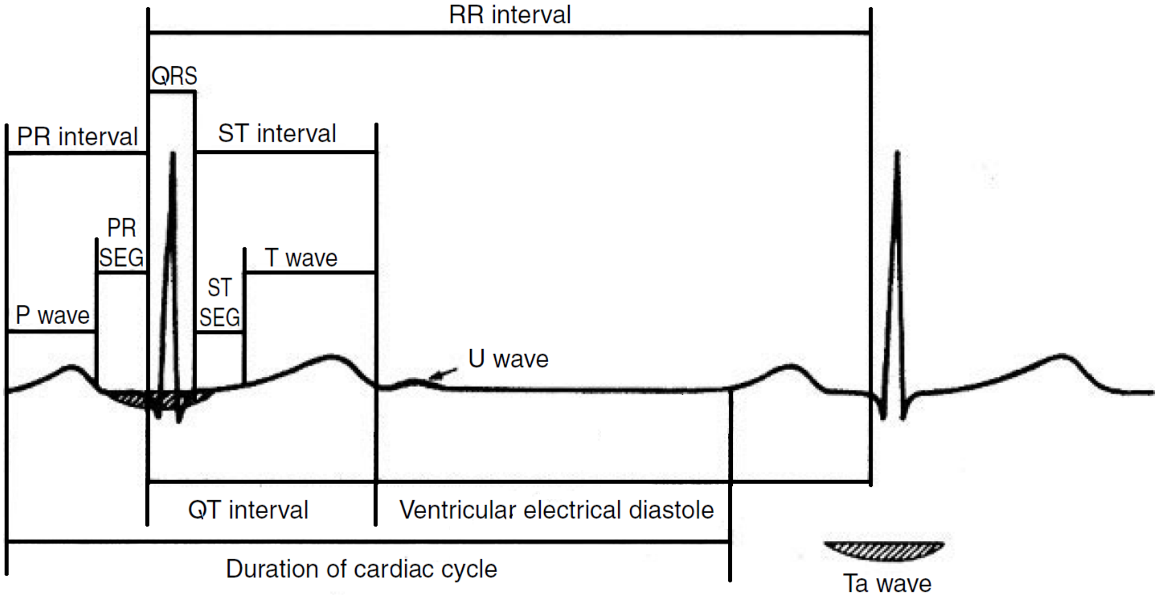


Figura 9: **ECG segments analysis.**
Fonte: (BAYÉS DE LUNA, 2007).

As mentioned earlier, the sinus node normally is the primary (dominant) pacemaker of the heart because of its inherent automaticity, however under special conditions, other cells outside the sinus node (in the atria, AV junction, and ventricles - Figure 10), can also act as independent (secondary) pacemakers. For example, if sinus node automaticity is depressed, the AV junction can act as a backup secondary (ectopic) pacemaker. Escape rhythms generated by secondary pacemakers provide important physiologic redundancy (safety mechanism) in the vital function of heartbeat generation (DUBIN, 2000; GOLDBERGER et al., 2012).

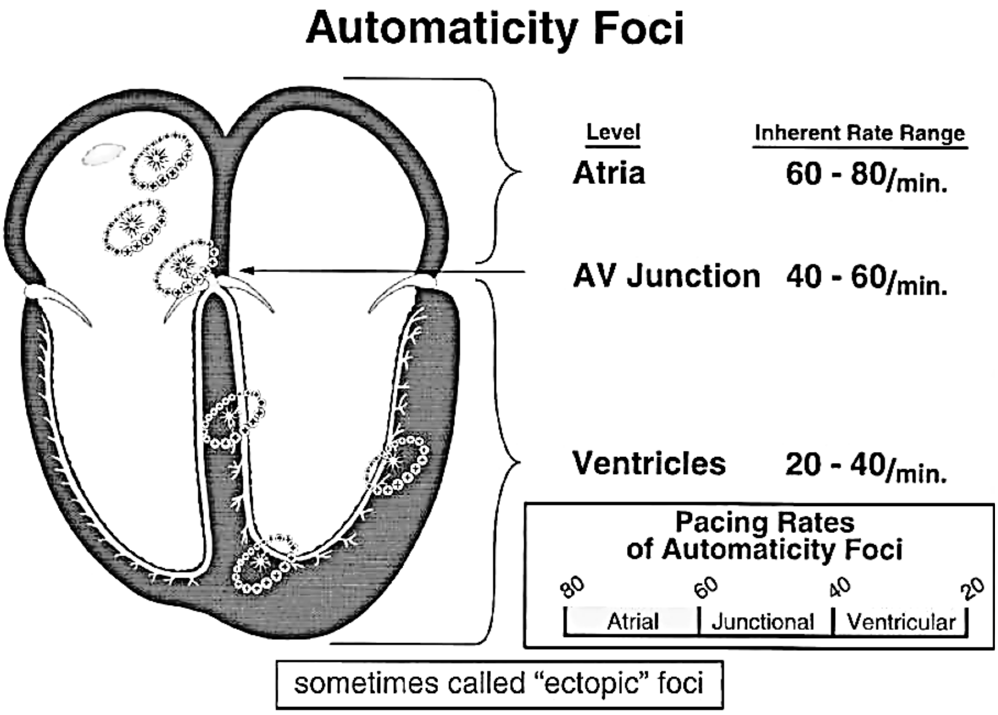


Figura 10: **Secondary pacemaker (ectopic) in atria, AV junction and ventricles.**
Fonte: (DUBIN, 2000)

For example, a rapid run of ectopic atrial beats results in atrial tachycardias, as presented on Chapter 14 of (GOLDBERGER et al., 2012). A rapid run of ectopic ventricular beats results in ventricular tachycardia, a potentially life-threatening arrhythmia, as presented on Chapter 16 of (GOLDBERGER et al., 2012).

The electrical conductivity can be considered the other important property of the heart, besides the automaticity. The speed with which electrical impulses are conducted through different parts of the heart varies, so the conduction is fastest by the Purkinje fibers and slowest by the AV node (DUBIN, 2000; GOLDBERGER et al., 2012).

The relatively slow conduction speed through the AV node, Figure 11, allows the ventricles to fill with blood before the signal for cardiac contraction arrives. By the other hand, the rapid conduction, through the His-Purkinje system, ensures synchronous contraction of both ventricles (DUBIN, 2000; GOLDBERGER et al., 2012).

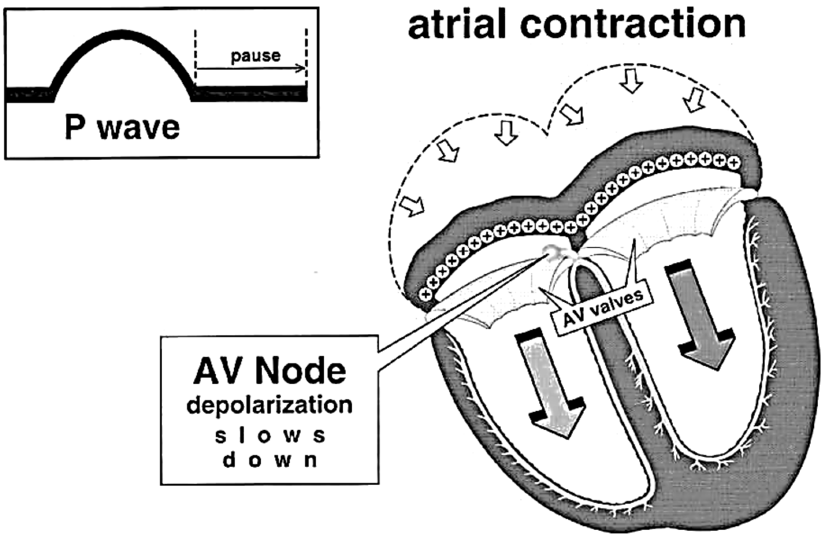


Figura 11: **The slow conduction speed through the AV node.**
Fonte: (DUBIN, 2000)

Briefly, the cardiac cycle can be represented by the P wave, the QRS complex, the T wave, and the baseline that follows until another P wave appears, as presented in Figure 12. These cycle is repeated continuously (DUBIN, 2000).

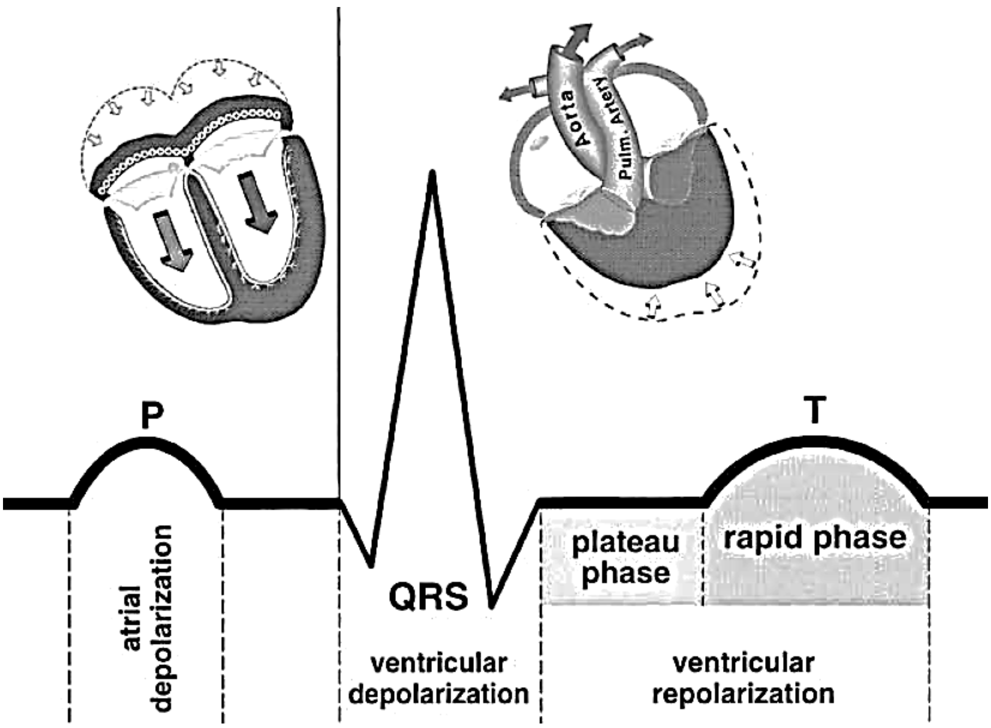


Figura 12: **Cardiac cycle composed by the P wave, the QRS complex, the T wave, and the baseline that follows until another P wave.**
Fonte: (DUBIN, 2000)

Thereby, the P wave represents the atrial depolarization, the QRS complex represents the ventricular depolarization, and finally the T wave represents the ventricular repolarization. Physiologically, the cardiac cycle represents the atrial systole (segment PR), the ventricular systole (segment QT) and the resting phase between the beats. The ECG segments are presented in Figure 13 (DUBIN, 2000).

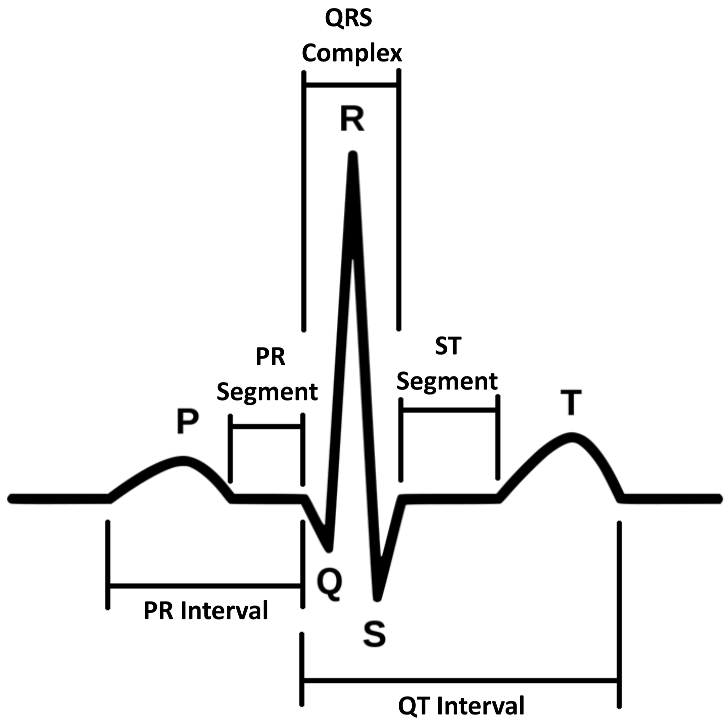


Figura 13: **ECG segments.**
Fonte: Dubin.

There are some abnormalities of heart rhythm and conduction that results in distinctive ECG patterns. For example, failure of the sinus node can occur because of a SA failure automaticity or because of local conduction block the sinus node, which can result in apparent sinus node dysfunction - marked bradycardia (slow heartbeat) (GOLDBERGER et al., 2012).

The reentry, in contrast of abnormal conduction, can be considered as a short-circuiting the normal activation pathways, its can lead to various types of tachycardia. The reentry plays an important role in the genesis of paroxysmal supraventricular tachycardias (PSVTs), as well as in many ventricular tachycardias (GOLDBERGER et al., 2012).

The stimuli spread blockage, through the AV node or infranodal pathways, can produce various degrees of AV heart block, sometimes with severe, symptomatic ventricular bradycardia, necessitating placement of a temporary or permanent placement pacemaker, as presented on Chapter 17 of (GOLDBERGER et al., 2012).

The disease of the bundle branches can produce right or left bundle branch block, resulting in electrical dyssynchrony, which is an important contributing mechanism in many cases of heart failure, as presented on Chapters 7 and 21 of (GOLDBERGER et al., 2012).

Other information about the signal morphology are also presented in Figure 9 and can be found in (BAYÉS DE LUNA, 2007). The abnormalities, that happen in the segments and intervals that compose the ECG signal, can be considered as indications of cardiopathies (DUBIN, 2000; GOLDBERGER et al., 2012; BAYÉS DE LUNA, 2007).

3.0.2 ECG EVALUATION

The ECG correct evaluation requires that a health professional performs the analysis of 5 general areas, taking into account its order of presentation (DUBIN, 2000).

1. Rate / Frequency;
2. Rhythm;
3. Axis;
4. Hypertrophy;
5. Infarction.

The focus of this work will be restricted only in the first and second area, because the data used are related with the disorders heart rhythm - arrhythmias.

The first aspect that should be analyzed is the rate/frequency. It must be read in cycles per minute and in a normal state, it is the SA node that determine the frequency of heart beats. There are some secondary pacemakers (ectopic), as previously mentioned, which go into action when there is a failure in the normal pacemaker mechanisms, in an emergency cases. These pacemaker has, each one, their own pacing rates, as presented in Figure 10 (DUBIN, 2000; GOLDBERGER et al., 2012).

The normal heart rate beat is between 60 and 100 cycles per minute. When is less than 60 it is characterized as sinus bradycardia and when is more than 100, is sinus tachycardia (DUBIN, 2000; GOLDBERGER et al., 2012).

The second aspect is the rhythm, and it subdivides into 2 parts. The first one has focus on arrhythmia, but to understand it, there is a need to better understand the normal electrophysiology of the heart, including the normal conduction pathways. Technically a normal rhythm is characterized as normal sinus rhythm (regular), and consists to equal distances between identical cardiac waves. Any signal with irregular heartbeat is considered arrhythmia signal, that means signal without rhythm (DUBIN, 2000; GOLDBERGER et al., 2012). The second part consists in the blocks, which are subdivided into: sinus block, AV block, bundle branch block and hemiblock. However such part will not be addressed in this work.

The definition of cardiac arrhythmia is the frequency alteration, formation and/or conduction of electric impulse through of myocardium. The identification of the origin local of arrhythmia, whenever possible, will be used; otherwise, it will be use the supraventricular generic term (PASTORE et al., 2016).

The arrhythmias subdivide into 4 groups and each one has their subdivisions as the following (DUBIN, 2000):

- Irregular rhythms:
  - Wandering pacemaker;
  - Multifocal atrial tachycardia;
  - Atrial fibrillation.
- Escape:
  - Escape rhythm;
  - Escape beat;
- Premature Beats:
  - Premature atrial beat;
  - Premature junctional beat;
  - Premature ventricular beat.
- Tachy-arrhythmias
  - Paroxysmal and Tachycardia;

- Flutter;
- Fibrillation.

According to the data used in this work there are some groups, among the previously presented, that will be addressed in this work, and they are:

- Atrial fibrillation;
- Premature ventricular beat: ventricular bigeminy and trigeminy;
- Tachycardia: supraventricular;
- Flutter: ventricular.

The atrial fibrillation (AF), presented in Figure 14, consists in the disorganized electrical activity, with atrial frequency between 400 and 600 cycles per minute and variable ventricular response. The base line may presents itself isoelectric, with fine irregularities, coarse irregularities or by a mixture of these changes (”f”waves). The occurrence of intervals RR indicates the dissociation AV (GOLDBERGER et al., 2012; PASTORE et al., 2016).

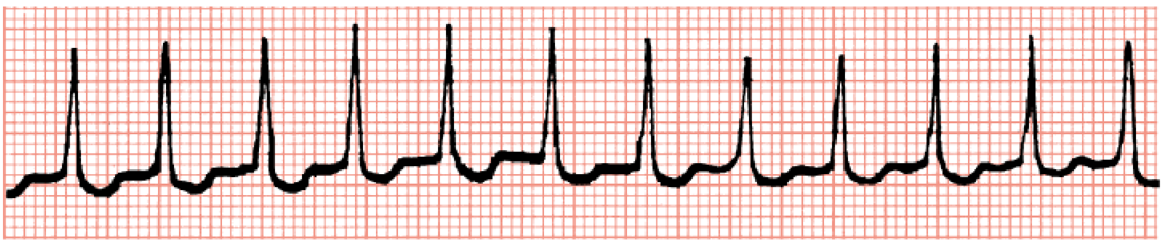


Figura 14: **Atrial fibrilation signal.**
Fonte: (GOLDBERGER et al., 2012)

Most cases of AF are thought to originate in the area of pulmonary vein-left atrial junctions. With time, more and more of the atrial tissue becomes involved in the active maintenance of the arrhythmia, associated with the simultaneous formation of multiple unstable reentrant circuits throughout the atria (GOLDBERGER et al., 2012), as presented in Figure 15.

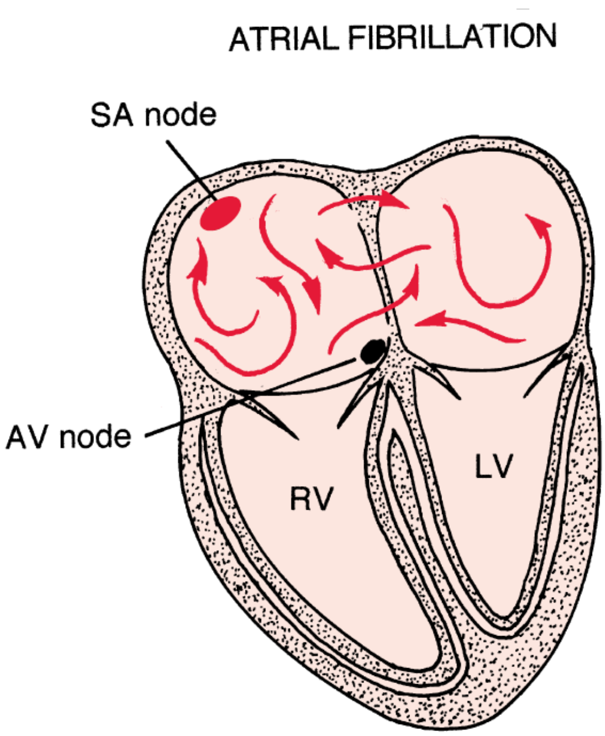
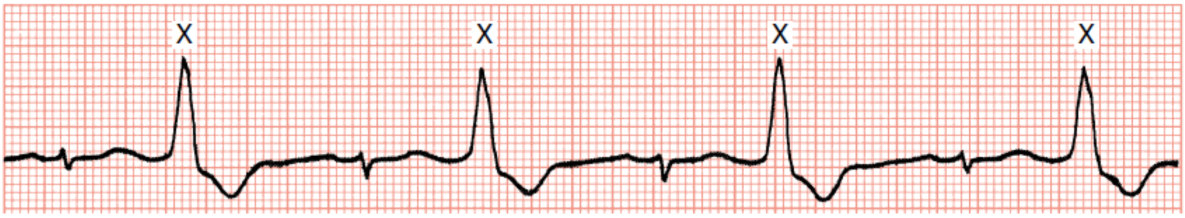


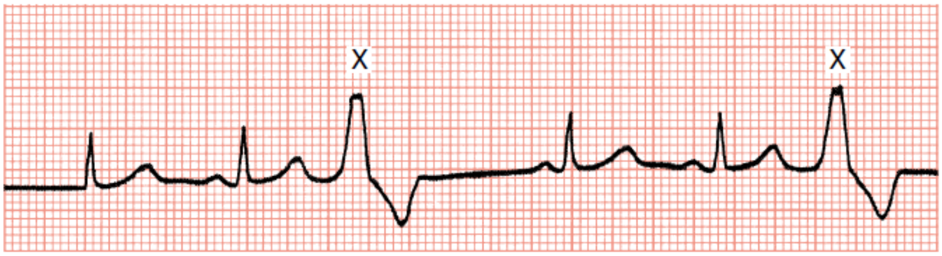
Figura 15: **The simultaneous formation of multiple unstable reentrant circuits throughout the atria.**
Fonte: (GOLDBERGER et al., 2012)

Usually, the single best lead to identify the diagnostic irregular atrial activity of AF is lead V1 (precordium), where irregular (”f”waves) are likely to be most clearly seen (GOLDBERGER et al., 2012).

The premature ventricular beat, called a premature ventricular contraction (PVC) or ventricular premature beats (VPB), are premature depolarizations and typically arise in either the right or left ventricle. Thus the ventricles are not stimulated simultaneously, and the stimulus spreads through the ventricles in an aberrant direction and asynchronous way. The focus of PVC in this work is the bigeminy and trigeminy ventricular, presented respectively in Figure 16 (GOLDBERGER et al., 2012).



(a) Ventricular bigeminy



(b) Ventricular trigeminy

Figura 16: Ventricular bigeminy (a), in which each normal sinus impulse is followed by a ventricular premature beat (marked X). Ventricular trigeminy (b), in which a ventricular premature beat occurs after every two sinus pulses
Fonte: (GOLDBERGER et al., 2012)

The term supraventricular tachyarrhythmia is used to treat four different types of cardiopathies: sinus tachycardia, paroxysmal supraventricular tachycardia (PSVT), atrial flutter, and AF. One measure often used to help separate these arrhythmias is carotid sinus massage (CSM). Pressure on the carotid sinus produces a reflex increase in vagal tone (GOLDBERGER et al., 2012).

Thereby, the supraventricular tachycardia are usually known as paroxysmal supraventricular tachycardia (PSVT), and presented in Figure 17, consists in a resulting from AV nodal reentry tachycardia (AVNRT) or AV reentry tachycardia (AVRT) involving a concealed or manifest bypass tract usually has an all-or-none response to (CSM). In successful cases the tachycardia breaks suddenly, and sinus rhythm resumes, as presented on Chapter 14 of (GOLDBERGER et al., 2012). At other times CSM has no effect, and the tachycardia continues at the same rate. In cases of PSVT caused by atrial tachycardia (AT), CSM may have no effect or may increase the degree of block, resulting in a rapid sequence of one or more nonconducted P waves (GOLDBERGER et al., 2012).

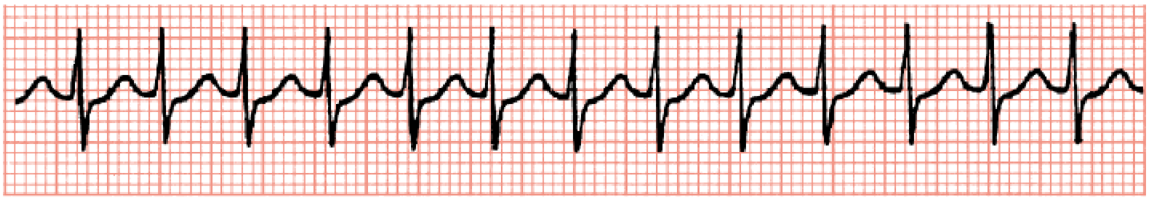


Figura 17: **Paroxysmal supraventricular tachycardia signal.**
Fonte: (GOLDBERGER et al., 2012)

The ventricular flutter, as presented in Figure 18, is produced by a single ventricular automaticity focus firing at an exceptionally rapid rate between 250 and 350 cycles per minute. It produces a rapid series of smooth sine-waves of similar amplitude. The ventricular rate is so rapid that the ventricles hardly have enough time to fill - even partially, so this arrhythmia rapidly deteriorates into a deadly arrhythmia (DUBIN, 2000).

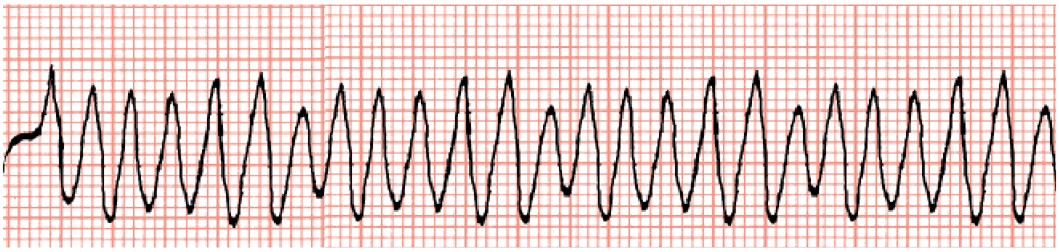


Figura 18: **Ventricular flutter signal.**
Fonte: (GOLDBERGER et al., 2012)

4 PATTERN RECOGNITION

The pattern recognition is the science that acts in the recognition, description, classification and grouping of patterns. These are important problems addressed in several areas of engineering and scientific disciplines as biology, medicine, computer vision, artificial intelligence among others. It is the objects classification and description which consists in feature extraction, select them and generate a classifier referring to the study object (JAIN et al., 2000). The feature extraction process can be called of compression, since the obtained object has less information than the original one, however the most relevant characteristics are preserved (CROVATO, 2004).

The fingerprint, the cursive handwriting, the human face or even the voice signal can be considered as examples of patterns. The recognition/classification test can be divided in two categories: supervised classification, when the pattern to be recognized is identified, by a specialist, as member of a predefined class, and consists in the data allocation in these class; and the unsupervised classification, when the pattern is attributed to a class hitherto unknown, that is, the data are grouped by the similarity. The pattern recognition system involves basically three aspect: data acquisition and preprocessing, data representation, and decision making (JAIN et al., 2000).

There are many applications in several different areas, including data mining (identifying a pattern, e.g., correlation, or an outlier in millions of multidimensional patterns), document classification, financial forecasting, organization and retrieval of multimedia databases, and biometrics (personal identification based on various physical attributes such as retinal, face and fingerprints) (JAIN et al., 2000).

According the object to be classified, there are four approach types to the pattern recognition (JAIN et al., 2000):

- Statistical approach: The decision limits are defined by probabilistic models, allowing only to discriminate of which group the studied object fits;
- Syntactic approach: Describes the patterns structure using the descriptives features inter-

relationships of studied object. Beyond the classification, these approach also provides a description of how the given model is constructed from the primitives.

- Neural networks: Ability to learn complex nonlinear input-output relationships, use sequential training procedures, and adapt themselves to the data. The main characteristic its the pattern recognition almost independently of the specific domain knowledge, since there is no need to know what are the data and studied groups.
- Template matching: Used to determinate the similarity between two entities (points, curves, or shapes) of the same type. The template matching it is a generic operation from pattern recognition class, which the object to be recognized is compared with an established model, taking into account all possible changes in which the pattern may suffer.

This work uses a neural approach, that is, we only want to perform the pattern detection so that the results can be studied/analyzed, which would be a ”black-box”approach. Therefore, classifiers based on artificial neural networks (ANNs), will be designed and implemented.

4.1 ARTIFICIAL NEURAL NETWORKS

The data processing, in this work, will happen using the artificial neural networks (ANNs). The ANN are computational models inspired process of learning the human brain emulating its functioning. They can be defined by a set processing units characterized by artificial neurons and interconnected with artificial synapses, that are represented by matrixs/vectors of synaptic weights (SILVA et al., 2016).

Increasingly, the ANNs have been applied to solve complex problems, especially when working with large masses of data that should be modeled and analyzed.

Following the same research line of this work can be cited (SUTERIO et al., 2018; ACHARYA et al., 2017). Both perform the detection of cardiopathies using the ANNs. The first one propose the detection of arrhythmias, between ECGs patients healthy and unhealthy, using the wavelet packet transform to feature extraction, and the multilayer perceptron to classification. The second one propose the detection of some arrhythmias using the convolutional neural network (CNN) technique.

Another research line, using voice signals, can be found in (XU et al., 2015). These work presents a supervised method to enhance speech by means of finding a mapping function between noisy and clean speech signals based on deep neural networks (DNNs). In this case, the DNN architecture is employed as a nonlinear regression function to ensure a powerful modeling capability

The process control area can be found in (WANG et al., 2016). In this work the author considers the dynamics of the closed-loop system, and proposes a non-linear model predictive, using artificial neural networks (ANN). These adaptive sampled-data ANN control scheme is proposed to solve the tracking problem for nonlinear systems at device layer, where the ANNs are used to approximate the unknown nonlinear functions.

Recognition of Power-Quality Disturbances is presented in (KUMAR et al., 2015). This work presents an algorithm based on Stockwell's transform and artificial neural network-based classifier. These algorithm extracts significant features of various PQ disturbances using S-transform, which are used as input to the hybrid classifier for the classification of PQ disturbances.

Among the several applications of ANNs, for this work, its implementation will be restricted in (SILVA et al., 2016):

- Universal function approximation: It consists to map the relationship between the system variables from a known set of their representative values;
- Pattern recognition/classification: It is the association of a input pattern to one of previously defined class. In this case, the problem to be treated has a discrete and known set of the desired outputs;
- Clustering: It is the identification and detection by similarity of the particularities between many input patterns, in order to enabling a grouping;
- Systems optimization: It is to minimize or maximize a function, also obeying eventual constraints.

There are many types of ANNs, and what stands out the most is the perceptron, due their ability to recognize patterns (SILVA et al., 2016). Among the types of ANN perceptron, it will use in this work the multilayer perceptron (MLP), as presented in Figure 19.

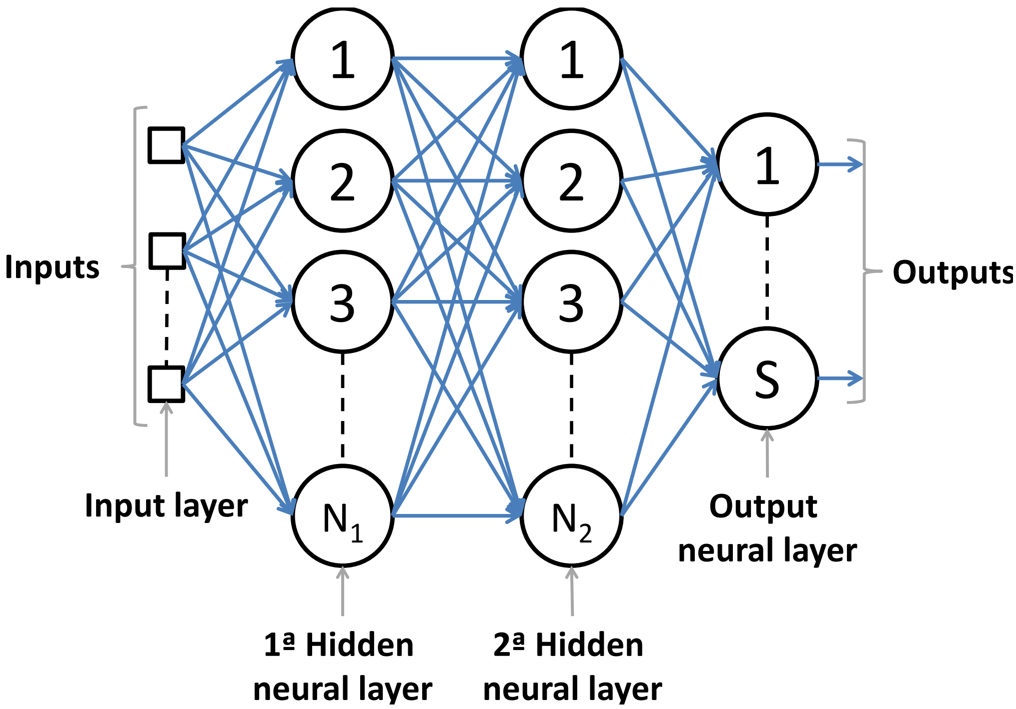


Figura 19: **Multilayer perceptron (MLP).**
Fonte: Dubin.

The MLP has multiple layers, that is, characterized by at least one intermediate layer of neurons, the hidden layer for feature extraction, located between the input layer and the output layer. These difference, when its compared to the others perceptrons, makes its configuration with higher processing capacity. The MLP are able to work with classes that are not linearly separable and one of its main advantages is that once ready, do not require processing time, just memory, which makes it a better implementation technique (SILVA et al., 2016). Other informations can be found in (HAYKIN, 2008)

4.2 WAVELET AND WAVELET PACKET

This work will use the wavelet tool and the coefficients will be obtained by its decomposition using the wavelet packet transform, which is a generalization of wavelet decomposition. The wavelet packet coefficients, are in fact, the projection of the signal, composed by wavelet and scale function, which the last one, are complementary functions of the wavelet functions (AGULHARI et al., 2013). These coefficients contains signals energy informations in each frequency band, and these informations aids on pattern detection (MALLAT, 2008).

It is worth mentioning that the wavelet function chosen must be adapted to the signal, thus the signal energy will be at some representation coefficients and the quality of compression improves (AGULHARI et al., 2013).

In the last decade, many methods based on wavelet transforms have been employed to remove noise or features that does not want to study, since they preserve ECG signal properties avoiding loss of its important physiological details and are simple from a computational point of view, as presented in (SINGH; TIWARI, 2006; ZADEH et al., 2010; WANG et al., 2016).

The wavelet packet decomposition and reconstruction occurs in levels. Thus if a decomposition takes place in 4 levels, as made in this work, according to (SUTERIO et al., 2017) and presented in Figure 20, the signal may be represented by some parts: the approximation *A* and details *D*.

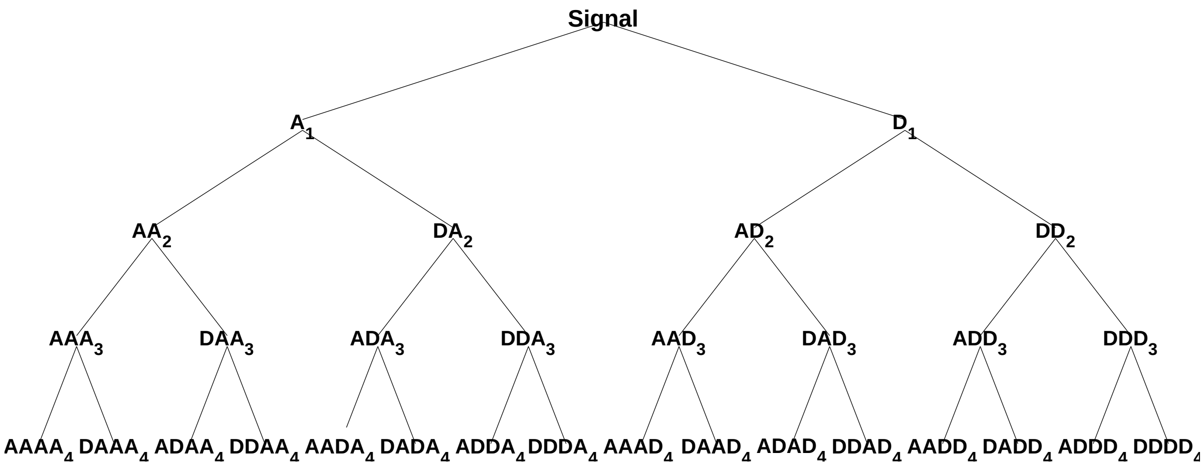


Figura 20: **Wavelet packet decomposition in fourth levels.**
Fonte: Dubin.

There are, in the literature, several wavelet functions (or wavelet families) computed to satisfy some studies in certain applications (MALLAT, 2008). According to (BESAR et al., 2000), the *Daubechies* family is considered one of the best to treat ECG signals. In (SUTERIO et al., 2017), the *Daubechies* 3 (db3) family is used to treat the health and arrhythmia ECG signal.

In (SUTERIO et al., 2018) it is propose a new wavelet, to treat ECG signals, better than those found in literature. The authors uses the GA algorithm to find new decomposition and reconstruction coefficients, to perform the filtering of the signal. It is woth to mentioning that these coefficients are low-pass and high-pass of decomposition and reconstruction:

- LO_D and HI_D - Low and high frequency coefficients, respectively of the decomposition filter;

- LO_R and HI_R - Low and high frequency coefficients, respectively of the reconstruction filter;

The filtering coefficients are obtained minimizing the Percent Root-Mean-Square Difference (PRD), wich is a kind of distortion measure between two signals, in this case the original and the reconstructed one. According to (AHMED et al., 2000) a PRD less than or equal to 10% corresponding a adequate reconstruction, without loss information, and the PRD using GA was 8.2984%, using 14 filtering coefficients of each type: low-pass and high-pass of decomposition and reconstruction, while the PRD with *db3* was 15.6745%, using 6 filtering coefficients, also of both types (SUTERIO et al., 2018).

4.3 ENTROPY AND RÉNYI ENTROPY

The entropy estimators has a wide application in several areas. They can be used for goodness-of-fit testing, parameter estimation in semi-parametric models, studying fractal random walks and texture classification (PÁL, D. et al., 2010). The entropy provide a natural notion to quantify the uncertainty of random variables (WACHOWIAK et al., 2005).

The entropy also can be used to biological signals, as presented in (PEREIRA. et al., 2018). In this work, the author makes the analysis of EEG complexity during the electrical stimulation, using the permutation entropy.

In this work it will be used the *Rényi entropy*, which is a generalization of Shannon entropy and has several applications in signal processing and statistical estimation (SRICHARAN; HERO, 2011). In the context of this work, (LEMIRE et al., 2000), presents the fast wavelet transform that was used along with Shannons entropy to distinguish between normal and ischemic beats.

The *Shannon entropy* is given by:

$$H_(\mathbf{y}) = -\int_{\mathbb{R}^d} f(\mathbf{u}) \log f(\mathbf{u}) d(\mathbf{u}). \quad (1)$$

The estimation of Shannon entropy can be carried out, e.g., by k-nearest neighbor techniques (SZABÓ et al., 2012; SZABÓ, 2014), as performed in this work.

The *Rényi entropy* can be defined as:

$$H_{R,\alpha}(\mathbf{y}) = \frac{1}{1-\alpha} log \int_{\mathbb{R}^d} f^{\alpha}(\mathbf{u}) d(\mathbf{u}), \quad (\alpha \neq 1), \tag{2}$$

where the random variable $\mathbf{y} \in \mathbb{R}^d$ have density function f. The *Shannon entropy* Eq. 1 is a special case of the *Rényi entropy* family, in limit:

$$\lim_{\alpha \to 1} H_{R,\alpha} = H. \tag{3}$$

4.4 CORRELATION COEFFICIENTS

One of the more frequently reported statistical methods, representing the degree of linear association between two variables, is the correlation coefficients analysis, Eq. 4, due to the need of understanding the statistical analysis on professional medical literature (TAYLOR, 1990).

$$r = \frac{\overline{(y-\overline{y})(d-\overline{d})}}{\sigma_y \sigma_d} \tag{4}$$

Where y and d are different variables (vectors), $\overline{y}$ and $\overline{d}$ are the mean of y and d, respectively, σ_y and σ_d are the standard deviation of y and d and finally $\overline{(y-\overline{y})(d-\overline{d})}$ is the mean of $(y-\overline{y})(d-\overline{d})$.

The correlation coefficients can also be considered as important a feature to classify ECG signals. In (HONG, 2001) the author apply the Spearman rank correlation coefficient to evaluate the correlation between heart rate and cardiac imaging quality.

In (CHIU, 2001), an arrhythmia classifier its performed based on correlation coefficients, to identify normal beats, abnormal premature ventricular contraction (PVC) beats and atrial premature contraction, on ECG signals.

4.5 MUTUAL INFORMATION

The mutual information estimators has also wide application, and some examples where they have been used are: in feature selection, clustering, causality detection, optimal experimental design, fMRI data processing, prediction of protein structures, and boosting and facial expression recognition (PÁL, D. et al., 2010).

The mutual information can also be used, as a feature, in ECG signals. In (TAGHAVI; HERO, 2015), the author uses some techniques to perform the ECG denoising. These techniques are the combination of two Empirical Mode Decomposition based on the interval thresholding, the mutual information and the correlation coefficient.

In (SOUFAN; ARAFAT, 2015), is presented the propose an application of mutual information based ensemble methods to the analysis and classification of heart beats associated with different types of Arrhythmia.

The Shannon mutual information tool is also known in the literature as the special case of total correlation or multi-information when two variables are considered (SZABÓ, 2014).

The mutual information can be defined by making use of existing entropy estimators, as presented in Eq. 5.

$$I(\mathbf{y}^1,...,\mathbf{y}^M) = \sum_{m=1}^{M} H(\mathbf{y}^m) - H([\mathbf{y}^1;...;\mathbf{y}^M]). \tag{5}$$

The estimation of the mutual information, used in this work, is the *Cauchy-Schwartz quadratic mutual information*. These measures are defined for the $y^m \in \mathbb{R}^{d_m} \quad (m = 1,2)$, and its can be defined by Eq. 6

$$I_{QMI-CS}(\mathbf{y}^1,\mathbf{y}^2) = \log\left[\frac{(\int_{\mathbb{R}^{d_1}}\int_{\mathbb{R}^{d_2}}[f(\mathbf{u}^1,\mathbf{u}^2)]^2 d\mathbf{u}^1 d\mathbf{u}^2)(\int_{\mathbb{R}^{d_1}}\int_{\mathbb{R}^{d_2}}[f_1(\mathbf{u}^1)]^2[f_2(\mathbf{u}^2)]^2 d\mathbf{u}^1 d\mathbf{u}^2)}{[\int_{\mathbb{R}^{d_1}}\int_{\mathbb{R}^{d_2}} f(\mathbf{u}^1,\mathbf{u}^2) f_1(\mathbf{u}^1) f_2(\mathbf{u}^2) d\mathbf{u}^1 d\mathbf{u}^2]^2}\right] \tag{6}$$

The measure can be approximated using the technique presented in (SZABÓ et al., 2012; SZABÓ, 2014), as Eq. 7.

$$\hat{f}_m(\mathbf{u}) = \frac{1}{T}\sum_{t=1}^{T} k(\mathbf{u} - \mathbf{y}_t^m) \tag{7}$$

The KDE (kernel density estimation; also termed the Parzen or the Parzen-Rosenblatt window method) (SZABÓ et al., 2012; SZABÓ, 2014).

Other information about the estimators of information measures, used in this work can be found in (PRINCIPE, 2010).

5 MATERIALS AND METHODS

This section will present the materials and methods used in this work.

5.1 DATA USED FOR THE DEVELOPMENT

The data used for this work was obtained by database MIT (Massachusetts Institute of Technology). It can be found healthy people data and others composed by cardiopathies, as arrhythmia, ischemia, myocardial infarction, among others. Thereby, it is possible to provide healthy people signals and with some cardiopathies allowing the neural network to classify healthy and unhealthy data. It is worth to emphasize that each signal comes with information as sampling frequency and total collection time. Such informations are very important for data processing. (GOLDBERGER et al., 2000).

In order to the dataset was processed it was necessary to perform a pre-processing. Such processing is called data normalization, and it consists to keep data within the domain of dynamic region of activation functions, with the aim of improving training performance by avoiding saturation at the output of ANN and data processing problems. Some cases there is even the need for post-processing, called data denormalization. (SILVA et al., 2016; HAYKIN, 2008).

5.2 MATLAB®

The main computational tool used for import the data, processing and obtaining results is the MATLAB (matrix laboratory), which is a software with great capacity of processing applied directly to the numerical calculation. The MATLAB is able to integrate numerical analysis, matrix calculation, data processing and graphic construction easily, treating problems which solutions can be expressed mathematically. For this work, the MATLAB becomes a effective tool, since it can work with a data vast mass, processing in fractions of time. Furthermore, the problems are solved with elementary mathematical operations and presents almost identical form if written mathematically.

5.3 DEVELOPMENT

The flowchart of Figure 21 presents the steps development of this work, and each one of them will be explained in the following.

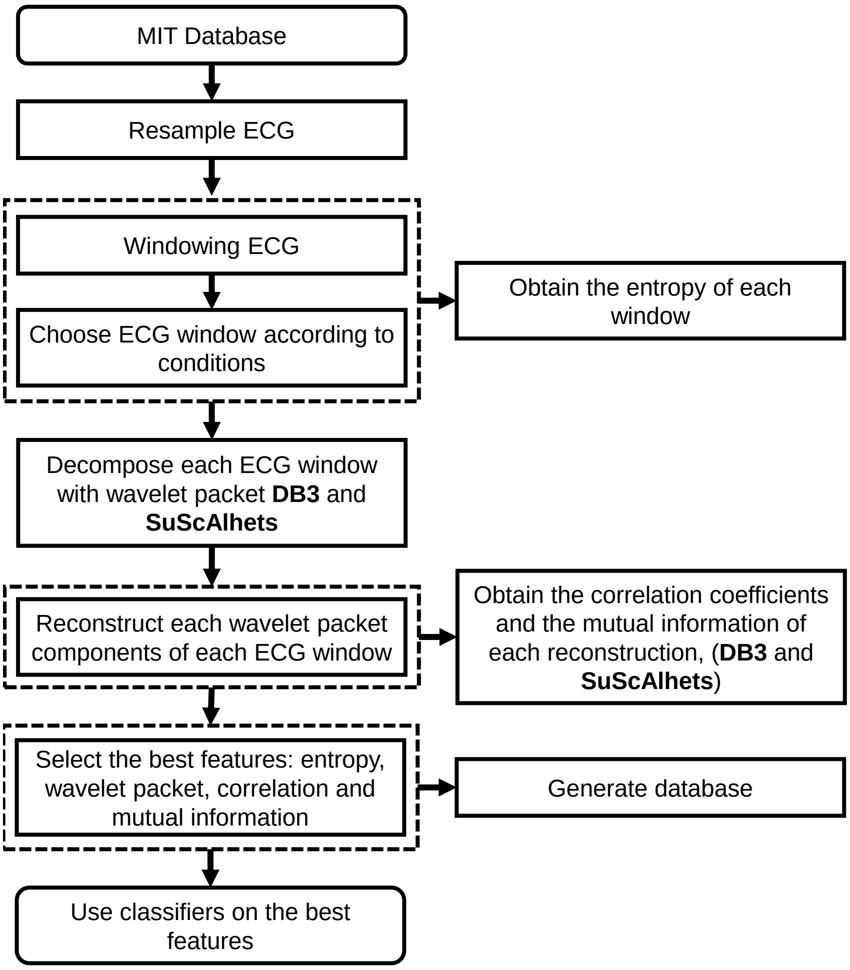


Figura 21: **Development flowchart of this work.**
Fonte: Autoria própria.

5.3.1 MIT - DATABASE

The data used in this work was electrocardiograms data, obtained from MIT (GOLDBERGER et al., 2000). It was chosen some databases at PhysioBank, in order to get signals ECGs of healthy and unhealthy patients. The databases chosen were:

- MIT-BIH Atrial Fibrillation Database:
  - 23 long-term ECG recordings of human subjects with atrial fibrillation (mostly pa-

roxysmal), with sampling frequency of 250 samples per second and samples size between 8,325.000 e 9,205.760.

- MIT-BIH Arrhythmia Database:
  - 48 half-hour excerpts with sampling frequency of 360 samples per second and 650,000 samples for each ECG. Some recordings includes less common but clinically significant arrhythmias.
- MIT-BIH Normal Sinus Rhythm Database:
  - 18 long-term ECG recordings of subjects that were found to have no significant arrhythmias, with sampling frequency of 128 samples per second and samples size between 8,861.966 and 10,837.767.
- MIT-BIH Malignant Ventricular Arrhythmia Database:
  - 22 half-hour ECG recordings with a sampling frequency of 250 samples per second and 525,000 samples for each ECG. Individuals that presented episodes of sustained ventricular tachycardia, ventricular flutter, and ventricular fibrillation.
- MIT-BIH Supraventricular Arrhythmia Database:
  - 78 half-hour ECG recordings with supraventricular arrhythmia. The sampling frequency of these excerpts is 128 samples per second, with 230,400 samples for each ECG.

The Table 1 presents all database and their informations.

Tabela 1: The databases and their information.

Database	**Amount**	**Sampling frequency**	**Size**
Atrial Fibrillation	23	250	8,325.000 $\sim$ 9,206.760
Arrhythmia	48	360	650,000
Normal Sinus Rhythm	18	128	8,861.966 $\sim$ 10,837.767
Malignant Ventricular Arrhythmia	22	250	525,000
Supraventricular Arrhythmia	78	128	230,400

Technical information about the conditions under which patients were submitted, at the time of ECG collection, can be found in (GOLDBERGER et al., 2000).

The intention of choosing these databases is to address some most common types of diseases, that cause disorders of heart rhythm - arrhythmia, in population (BENJAMIN et al., 2018; CHOW et al., 2012). Such disease are: atrial fibrillation, ventricular bigeminy, sinus bradycardia, supraventricular tachyarrhythmia, ventricular trigeminy, ventricular flutter and supraventricular arrhythmia, and they are presented by groups in Table 2.

Tabela 2: Diseases that involve disorder of heart rhythm - Arrhythmia.

Disorders of heart rhythm/Conduction - Arrhythmia	
Bradycardia	Sinus bradycardia
Tachyarrhythmia	Supraventricular: Atrial (multifocal), Junctional
	Ventricular: Idioventricular rhythm
Ventricular premature beats	Bigeminy and trigeminy
Flutter/Fibrillation	Flutter (atrial and ventricular), Fibrillation (atrial and ventricular)

When the download is performed, besides the information of sampling frequency, total collection time and the data itself, comes the informations of ECG excerpts with diagnosis. This is the audited annotations, about healthy and unhealthy ECG excerpts, performed from a health professional. These audited annotations consist of acronyms that refers to diseases and healthy excerpts, addressed in this work (GOLDBERGER et al., 2000):

- **(AFIB** - Atrial fibrillation;

The Figure 22 presents an example of signal with atrial fibrillation and 8 seconds of duration. The morphological informations of these kinds of signals can be found in (GOLDBERGER et al., 2012).

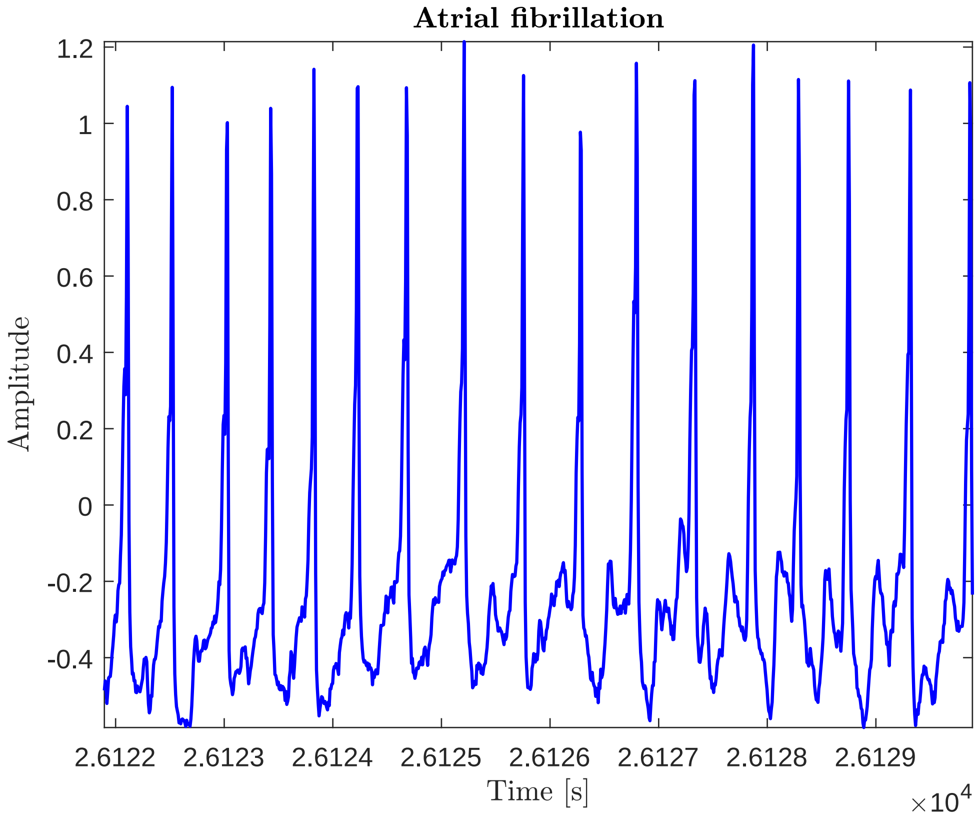


Figura 22: **Example of signal with atrial fibrillation.**
Fonte: Autoria própria.

- (**B** - Ventricular bigeminy;

The Figure 23 presents an example of signal with ventricular bigeminy and 8 seconds of duration. The morphological informations of these kinds of signals can be found in (GOLDBERGER et al., 2012).

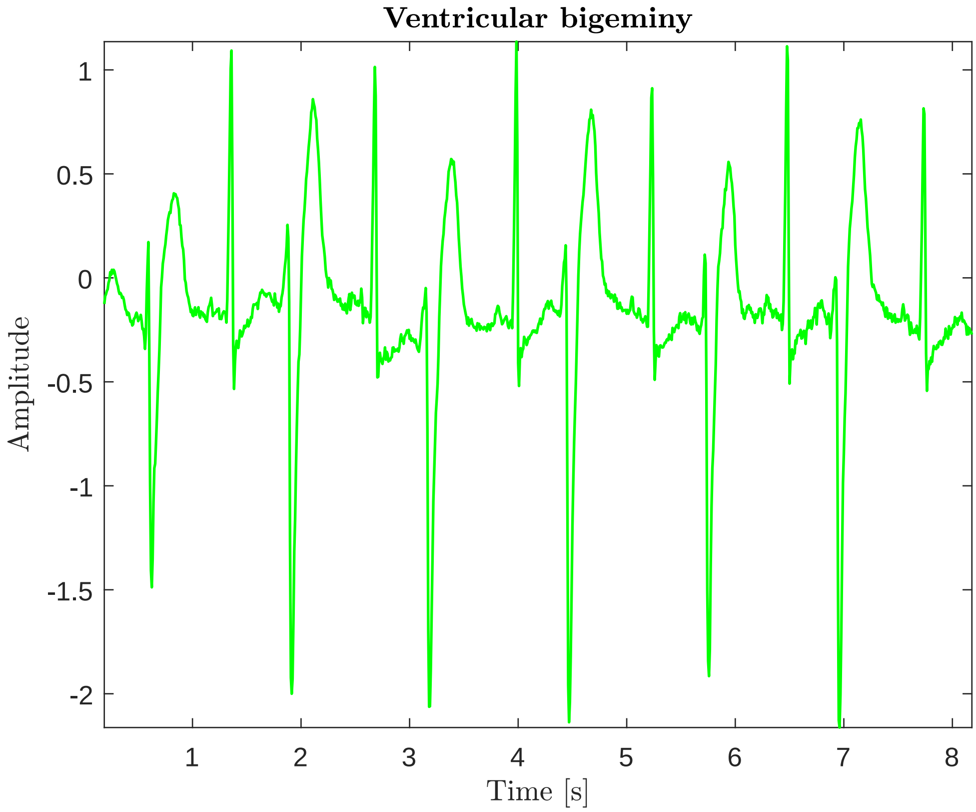


Figura 23: **Example of signal with ventricular bigeminy.**
Fonte: Autoria própria.

- (**N** - Normal sinus rhythm;

The Figure 24 presents an example of signal with normal sinus rhythm and 8 seconds of duration. The morphological informations of these kinds of signals can be found in (GOLDBERGER et al., 2012).

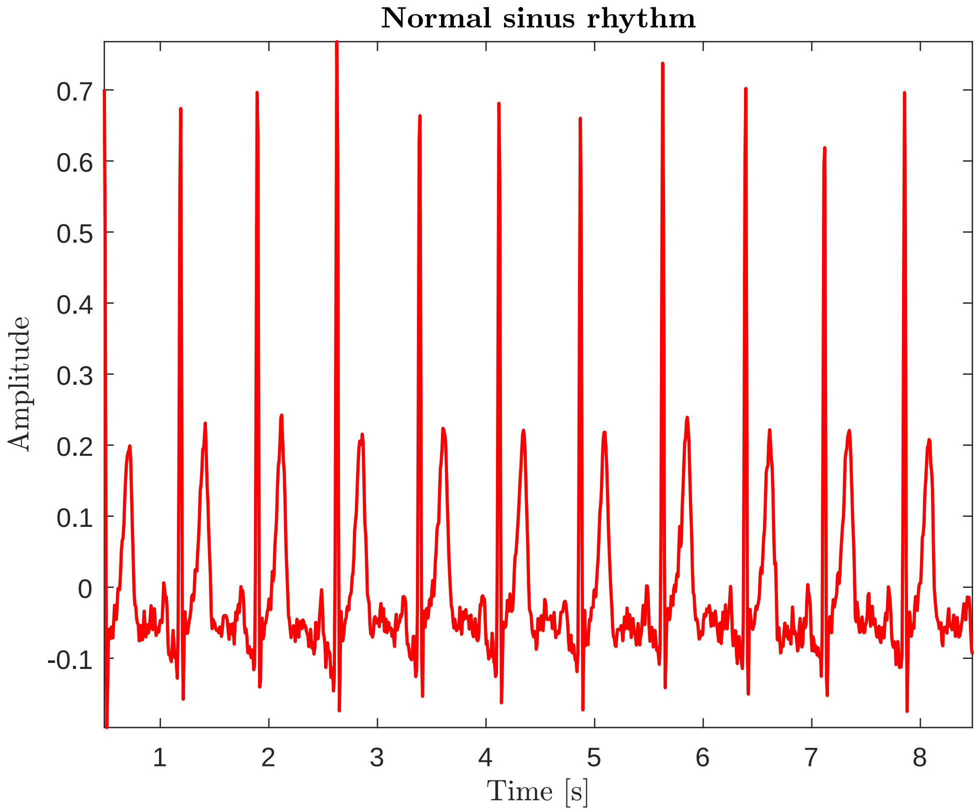


Figura 24: **Example of signal with normal sinus rhythm.**
Fonte: Autoria própria.

- **(SBR** - Sinus bradycardia;

The Figure 25 presents an example of signal with sinus bradycardia and 8 seconds of duration. The morphological informations of these kinds of signals can be found in (GOLDBERGER et al., 2012).

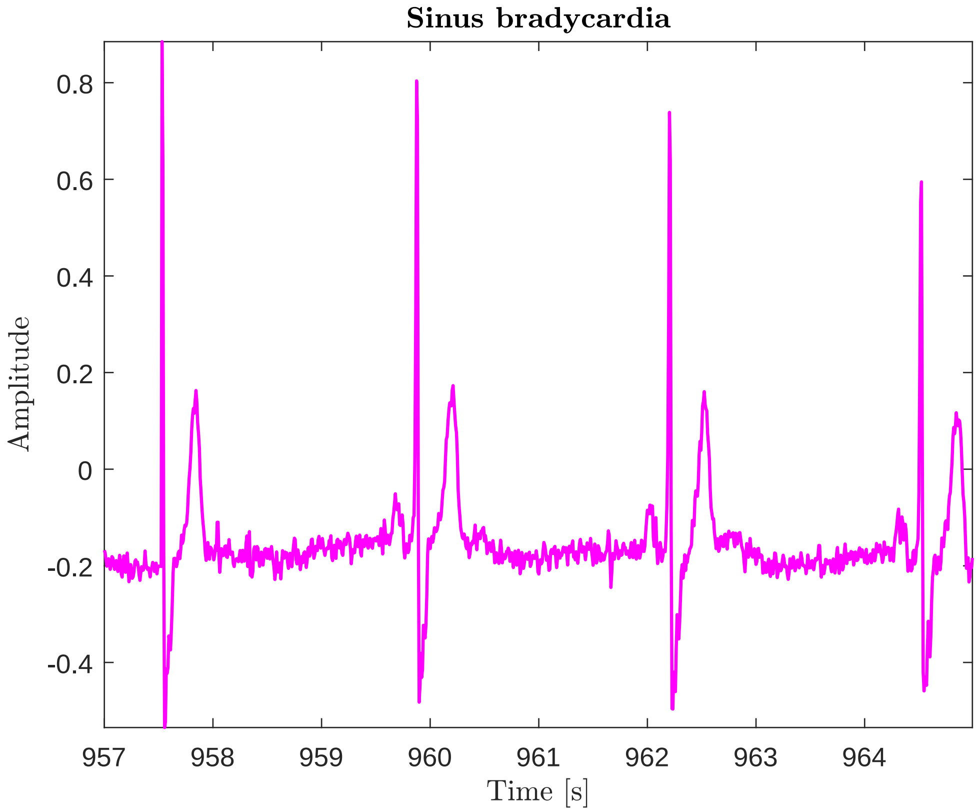


Figura 25: **Example of signal with sinus bradycardia.**
Fonte: Autoria própria.

- **(SVTA** - Supraventricular tachyarrhythmia;

The Figure 26 presents an example of signal with supraventricular tachyarrhythmia and 8 seconds of duration. The morphological informations of these kinds of signals can be found in (GOLDBERGER et al., 2012).

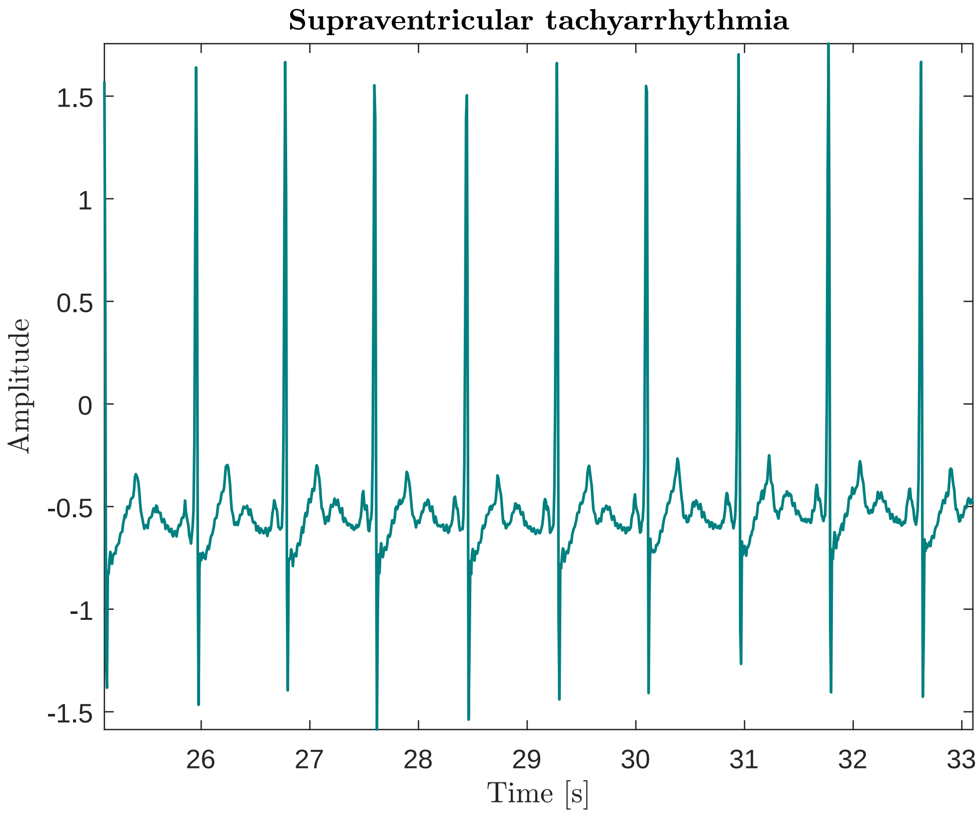


Figura 26: **Example of signal with supraventricular tachyarrhythmia.**
Fonte: Autoria própria.

- **(T** - Ventricular trigeminy;

The Figure 27 presents an example of signal with ventricular trigeminy and 8 seconds of duration. The morphological informations of these kinds of signals can be found in (GOLDBERGER et al., 2012).

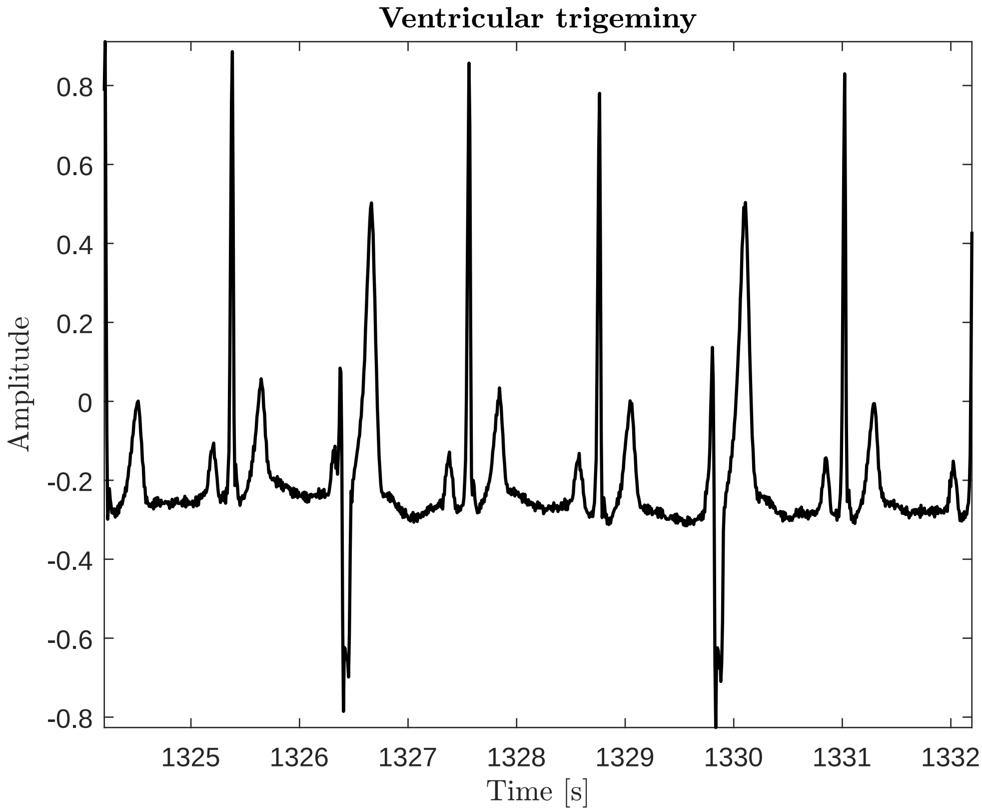


Figura 27: **Example of signal with ventricular trigeminy.**
Fonte: Autoria própria.

- **(VFL** - Ventricular flutter;

The Figure 28 presents an example of signal with ventricular flutter and 8 seconds of duration. The morphological informations of these kinds of signals can be found in (GOLDBERGER et al., 2012).

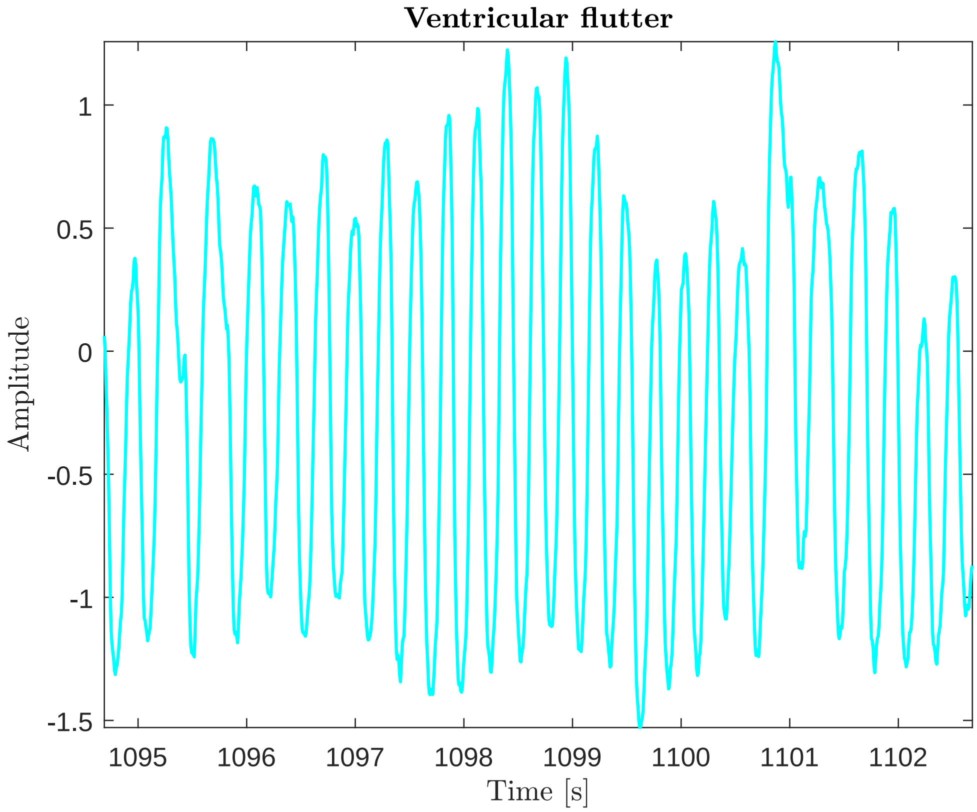


Figura 28: **Example of signal with ventricular flutter.**
Fonte: Autoria própria.

- **(ASV** - Supraventricular arrhythmia.

The Figure 29 presents an example of signal with supraventricular arrhythmia and 8 seconds of duration. The morphological informations of these kinds of signals can be found in (GOLDBERGER et al., 2012).

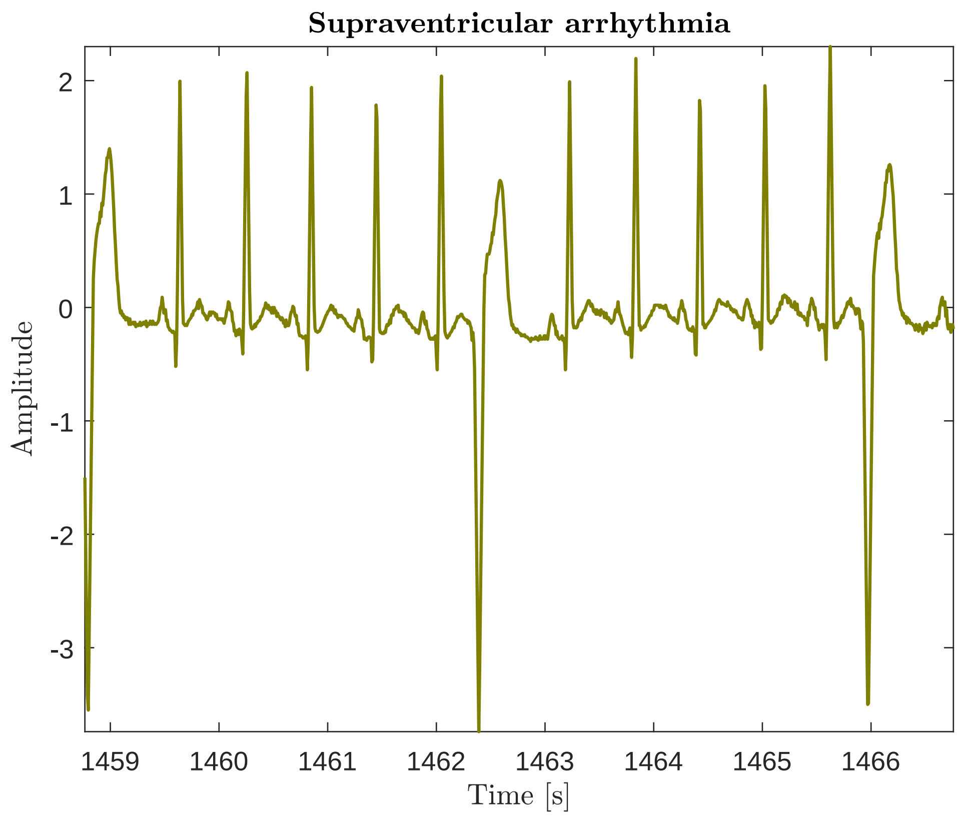


Figura 29: **Example of signal with supraventricular arrhythmia.**
Fonte: Autoria própria.

5.3.2 RESAMPLE ECG

Analysing all databases it can be seen different sampling rates. Thus, in order to avoid divergence of data processing, it was performed the downsampling for those ECGs with sampling frequency bigger then 128 samples per second, to 128.

After ECG downsampling, the samples size was as follows in Table 3:

Tabela 3: Samples size after ECG downsampling.

Database	Amount	Sampling frequency	Size
Atrial Fibrillation	23	128	4,262.400 ∼ 4,713.350
Arrhythmia	48		231,112
Normal Sinus Rhythm	18		8,861.966 ∼ 10,837.767
Malignant Ventricular Arrhythmia	22		268,800
Supraventricular Arrhythmia	78		230,400

5.3.3 WINDOWING ECG, CHOOSE OF THE WINDOW AND RÉNYI ENTROPY

A signal windowing was performed with the purpose of obtain more judicious analysis of time and frequency of each signal slice. According to (SUTERIO et al., 2017), it was chosen 1024 samples with annotations of healthy and unhealthy ECG excerpts, and each one refers to the conditions of the excerpts that are certain ECG cardiopathies or normal rhythm.

After signal windowing and the choice of windows, it was applied the information theoretical estimator: *Rényi entropy*, in each chosen window, and these measure is one of the features that will compose the group of the features to be classified. The *Rényi entropy* estimator, using k-nearest neighbor (K-NN) (PÁL, D. et al., 2010), its one of the informations measure tools which can be found on Information Theoretical Estimators (ITE) Toolbox (SZABÓ et al., 2012; SZABÓ, 2014).

5.3.4 DECOMPOSE WITH WAVELET PACKET (DB3 AND SUSCALHETS)

This work propose the creation of a wavelet packet using the filtering coefficients of (SUTERIO et al., 2018), since the wavelet packet components contains signals energy informations in each frequency band that aids the pattern recognition. The created wavelet packet its called *SuScAlhets* and the purpose of his creation is a more judicious analysis of the signal and the attempt of obtaining more satisfactory result than those using *db3*. The Figure 30 presents the comparison between scale and wavelet function, of *SuScAlhets* and *db3*.

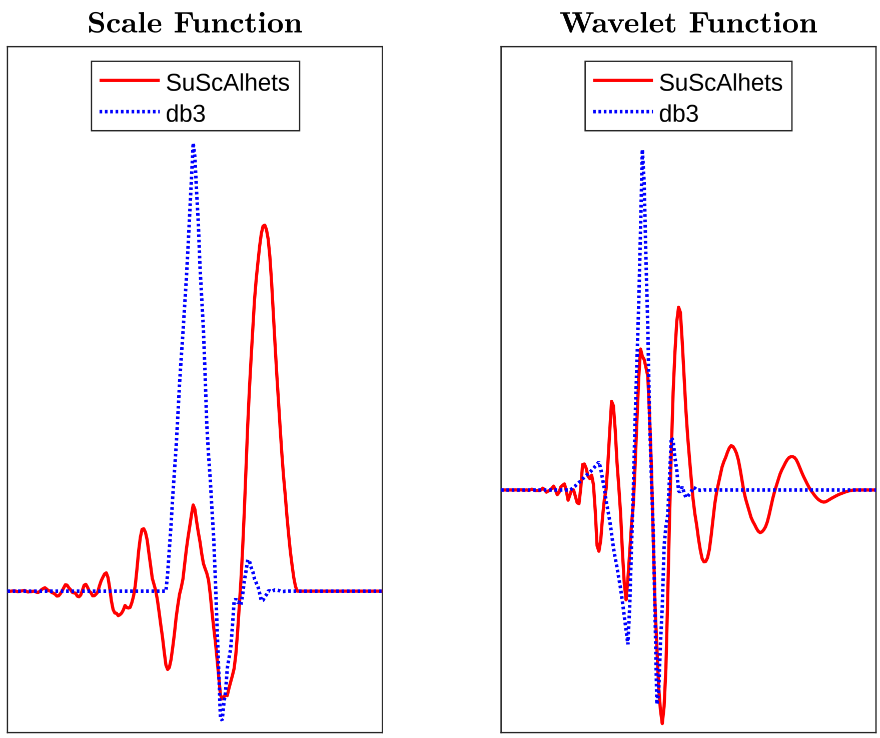


Figura 30: **Comparison between scale and wavelet function, of *SuScAlhets* and *db3*.**
Fonte: Autoria própria.

As previously presented, *Daubechies* family is considered one of the best to treat ECG signals. So, the wavelet packet components db3 and those of *SuScAlhets*, with fourth level of decomposition, also will compose the features group to be classified.

5.3.5 RECONSTRUCT EACH WAVELET PACKET COMPONENTS OBTAINING THE CORRELATION COEFFICIENTS AND THE MUTUAL INFORMATION

After obtaining the wavelet packet components of each window, using *db3* and *SuScAlhets*, each one of them was reconstruct returning to the original signal, these reconstruction allows that the reconstructed signal to priorize just the most relevant informations, discarding some characteristics that one does not want to study. Thus, with each signal reconstructed, it was obtained the *correlation coefficients* and the *mutual information*. These coefficients will also be considered as other features that makes up the group of the features, to be classified.

The mutual information estimator, used in this work is the *Cauchy-Schwartz quadratic mutual information*, and these estimator is one of the informations measure tools which can also be found on Information Theoretical Estimators (ITE) Toolbox (SZABÓ et al., 2012; SZABÓ, 2014).

5.3.6 SELECT THE BEST FEATURES, GENERATE THE DATABASE AND USE IT ON THE CLASSIFIER

Once obtained the window entropy, the wavelet packet components (*db3* and *SuScAlhets*), the *correlation coefficients* and *mutual information*, it was generated the features group. These group consists in the union of all features for each signal window, that is: the entropy of the window, plus 32 wavelet packet components of *db3* and *SuScAlhets* (16 of each one), plus 32 correlation coefficients of *db3* and *SuScAlhets* (16 of each one), and plus the 32 mutual information of *db3* and *SuScAlhets* (also 16 of each one).

Thereby, there are 97 different features types, in the generated group, for each signal window, what is a lot of informations. Thus, it was decided to selected the best features to treat each health and unhealthy signal and create a database with them. The purpose to select just the bests of them is to facilitate the classification. This is, discarding some features that would hinder the classification process. These selection was performed using the error bar of each disease, grouped two to two, and the parameters used by it were the variance and standard deviation. The error bar is the distance of each index in a vector, above and below, analyzing two different variables, as presented in Figure 31.

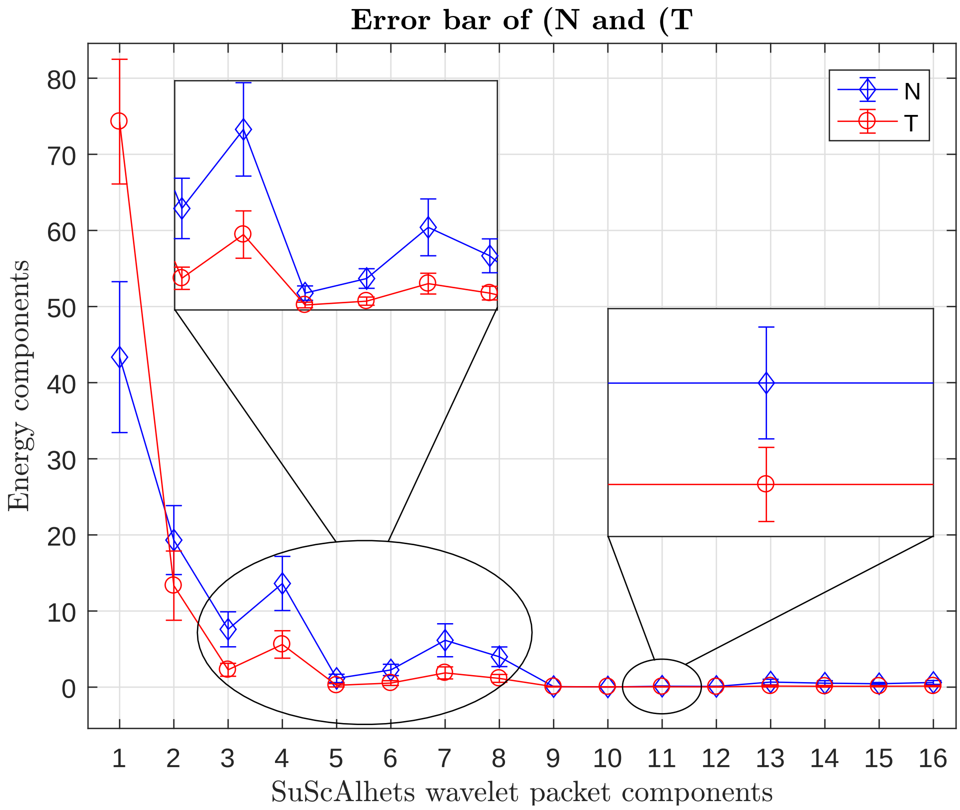


Figura 31: **Example of the error bar analysis, using the *SuScAlhets* wavelet packet components, between** $(N$ **and** $(T$.
Fonte: Autoria própria.

The Figure 31 presents an example of error bar, using the SuScAlhets wavelet packet components, evaluating the $(N$ class with the $(T$ class. It can be seen that among the 16 components, some of them can be separated (vertical bars do not invade each other), and another components can not be separated. Some components can not separated visually, as the 5 and 11 components, but performing an evaluation by software they are separable.

The created database is composed by 900 ECG excerpts, and each of them, is a window of 1024 samples, as mentioned previously. These excerpts was chosen according to the audited annotations, which is a kind of ”flag”that indicates what means the excerpt. For example, the excerpts from 1 to 140 has the ”flag”(AFIB, what means that all of them are atrial fibrillation.

Thereby, the database was applied on the multilayer perceptron in order to classify each feature in his source cluster. There are 8 different classes, as previously mentioning, they are: (AFIB, (B, (N, (SBR, (SVTA, (T, (VFL and (ASV and the usable quantity, according to the audited annotations of each one, is presented in Table 4:

Tabela 4: The amount of each class.

Classes	Amount
(AFIB Atrial Fibrillation	140
(B Ventricular Bigeminy	80
(N Normal Sinus Rhythm	150
(SBR Sinus Bradycardia	150
(SVTA Supraventricular Tachyarrhythmia	40
(T Ventricular Trigeminy	60
(VFL Ventricular Flutter	80
(ASV Supraventricular Arrhythmia	200
TOTAL	**900**

The best features selected and applied in the ANN are presented in the Tables 5, 6 and 7, for the *wavelet packet components*, the *correlation coefficients* and the *Cauchy-Schwartz quadratic mutual information*, respectively.

The presentation, with these tables, allows a comparison between the features of each information measure for *db*3 and *SuScAlhets*. There are 16 coefficients for each information measure, being that those marked with 'x', were considered as features, and the others marked with '-' were disregarded.

Tabela 5: Comparison between *db*3 and *SuScAlhets* of the wavelet packet components.

	Wavelet packet components															
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
db3	x	x	x	x	x	x	x	x	x	-	x	-	x	x	x	x
SuScAlhets	x	x	x	x	x	x	x	x	x	-	x	x	x	x	x	x

Analysing the Table 5 it can be seen that the coefficients considered as features by *SuScAlhets* are all considered by *db*3 plus the coefficient 12, which is not considered by *db*3.

Tabela 6: Comparison between *db*3 and *SuScAlhets* of the correlation coefficients.

	Correlation coefficients															
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
db3	x	x	x	x	x	x	x	x	x	-	x	x	x	x	x	x
SuScAlhets	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

Analysing the Table 6 it can be seen that all the coefficients are considered as features by *SuScAlhets*, while for *db*3 the 10 coefficient is not considered.

Tabela 7: Comparison between *db*3 and *SuScAlhets* of the Cauchy-Schwartz quadratic mutual information.

	Cauchy-Schwartz quadratic mutual information															
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
db3	x	x	x	x	x	x	x	x	-	-	-	-	x	-	-	-
SuScAlhets	x	x	x	x	x	x	x	x	x	x	-	-	x	-	-	-

Analysing the Table 7 it can be seen that the coefficients considered as features by *SuScAlhets* are all considered by *db*3 plus the coefficients 9 and 10, which are not considered by *db*3.

Thereby, after the tables evaluation previously performed, it can be considered that the feature extraction, by proposed method using the *SuScAlhets*, is more judicious for ECG signals analysis than the *db*3, which is considered as one of the best to treat ECG signals in literature.

There were performed three types of classifications using the *Rényi entropy* coefficients, *wavelet packet components*, *correlation coefficients* and *mutual information coefficients*. The first one only with those obtained by *db*3, the second one only with those obtained by *SuScAlhets* and finally the third one with both together. Thus, making it possible a comparison between the *db*3 and *SuScAlhets* methods.

For the first classification, the amount of each feature used are presented in Table 8, according to Tables 5, 6 and 7.

Tabela 8: Amount of features using only *db*3.

<table>
<tr><th colspan="5">Daubechies 3 - db3</th></tr>
<tr><th>Wavelet Packet Components</th><th>Correlation Coefficients</th><th>Mutual Information Cauchy-Schwartz</th><th>Entropy</th><th>Total</th></tr>
<tr><td>14</td><td>15</td><td>9</td><td>1</td><td>39</td></tr>
</table>

For the second classification, the amount of each feature used are presented in Table 9, according to Tables 5, 6 and 7.

Tabela 9: Amount of features using only *SuScAlhets*.

<table>
<tr><th colspan="5">SuScAlhets</th></tr>
<tr><th>Wavelet Packet Components</th><th>Correlation Coefficients</th><th>Mutual Information Cauchy-Schwartz</th><th>Entropy</th><th>Total</th></tr>
<tr><td>15</td><td>16</td><td>11</td><td>1</td><td>43</td></tr>
</table>

For the third classification, the amount of each feature used are presented in Table 10, according to Tables 5, 6 and 7.

Tabela 10: Amount of features *db*3 and *SuScAlhets* together.

<table>
<tr><th></th><th colspan="5">db3 and SuScAlhets</th></tr>
<tr><th></th><th>Wavelet Packet Components</th><th>Correlation Coefficients</th><th>Mutual Information Cauchy-Schwartz</th><th>Entropy</th><th>Total</th></tr>
<tr><td>db3</td><td>14</td><td>15</td><td>9</td><td rowspan="2">1</td><td rowspan="2">81</td></tr>
<tr><td>SuScAlhets</td><td>15</td><td>16</td><td>11</td></tr>
</table>

6 RESULTS

There were performed a several tests with different parameters of the classifier. Such parameters are ANN topology, accuracy rate and learning rate. The best of them are presented in Tables 11, 12 and 13.

The data were normalized between 0 and 1 because it was used the activation function *tansig* (Hyperbolic tangent function), in the hidden layers, and the *purelin* (Linear function) in the output layer.

According to the amount data, it was used 90% (810) to training and 10% (90) for validation. It is worth to mentioning that all training convergences occurred by the performance, ensuring a complete training.

The results presented in the following Tables go beyond of just the accuracy. It is also important to evaluate the computational time, which is the processing time, and these evaluation will be performed when it is presented the training mean.

Tabela 11: Classification using *db*3.

Classification using *db*3						
Training	**Accuracy (%)**	**ANN topology**	**Accuracy rate**	**Learning rate**	**Epoch**	**Time (s)**
T1_1	**88.89**	**[25 8]**	$\mathbf{1.10^{-5}}$	**0.05**	**163**	**105.19**
T2_1	86.67	[20 8]	1.10^{-5}	0.05	92	33.25
T3_1	85.56	[20 8]	1.10^{-7}	0.01	600	237.96
T4_1	84.44	[20 8]	1.10^{-5}	0.05	61	25.24
T5_1	83.33	[20 8]	1.10^{-5}	0.05	90	38.79
Mean	**85.78**	**[20 8]**	-	-	**201.20**	**88.09**
σ	**2.1395**	-	-	-	-	-
T1_2	**93.33**	**[10 15 8]**	$\mathbf{1.10^{-5}}$	**0.05**	**126**	**28.96**
T2_2	92.22	[10 15 8]	1.10^{-5}	0.05	209	38.54
T3_2	91.11	[10 15 8]	1.10^{-7}	0.01	214	34.67
T4_2	88.89	[10 15 8]	1.10^{-5}	0.05	177	36.81
T5_2	86.67	[10 15 8]	1.10^{-5}	0.05	49	9.40
Mean	**90.44**	**[10 15 8]**	-	-	**155**	**29.68**
σ	**2.6732**	-	-	-	-	-
T1_3	**96.67**	**[10 15 20 8]**	$\mathbf{1.10^{-5}}$	**0.05**	**71**	**49.70**
T2_3	95.56	[10 15 20 8]	1.10^{-5}	0.05	37	20.70
T3_3	94.44	[10 15 20 8]	1.10^{-5}	0.05	46	26.00
T4_3	92.22	[10 15 20 8]	1.10^{-5}	0.05	42	22.75
T5_3	90.00	[10 15 20 8]	1.10^{-7}	0.01	75	35.22
Mean	**93.78**	**[10 15 20 8]**	-	-	**54.20**	**30.87**
σ	**2.6776**	-	-	-	-	-

Tabela 12: Classification using *SuScAlhets*.

Classification using *SuScAlhets*						
Training	**Accuracy (%)**	**ANN topology**	**Accuracy rate**	**Learning rate**	**Epoch**	**Time (s)**
T1_1	**96.67**	**[20 8]**	$\mathbf{1.10^{-5}}$	**0.05**	**30**	**14.49**
T2_1	95.56	[20 8]	1.10^{-7}	0.01	191	83.01
T3_1	94.44	[25 8]	1.10^{-5}	0.05	38	27.03
T4_1	93.33	[20 8]	1.10^{-5}	0.05	88	43.77
T5_1	92.22	[20 8]	1.10^{-5}	0.05	56	26.75
Mean	**94.44**	**[20 8]**	-	-	**80.6**	**39.01**
σ	**1.7598**	-	-	-	-	-
T1_2	**97.78**	**[10 15 8]**	$\mathbf{1.10^{-5}}$	**0.05**	**30**	**5.77**
T2_2	96.67	[10 15 8]	1.10^{-5}	0.05	44	9.92
T3_2	95.56	[10 15 8]	1.10^{-5}	0.05	47	8.70
T4_2	94.44	[10 15 8]	1.10^{-7}	0.01	132	26.00
T5_2	93.33	[10 15 8]	1.10^{-5}	0.05	85	20.06
Mean	**95.56**	**[10 15 8]**	-	-	**67.60**	**14.09**
σ	**1.7598**	-	-	-	-	-
T1_3	**98.89**	**[10 15 20 8]**	$\mathbf{1.10^{-7}}$	**0.01**	**75**	**35.64**
T2_3	97.78	[10 15 20 8]	1.10^{-5}	0.05	31	18.38
T3_3	96.67	[10 15 20 8]	1.10^{-7}	0.01	83	40.10
T4_3	95.56	[10 15 20 8]	1.10^{-5}	0.05	52	33.50
T5_3	94.44	[10 15 20 8]	1.10^{-5}	0.05	54	28.81
Mean	**96.67**	**[10 15 20 8]**	-	-	**59**	**31.29**
σ	**1.7582**	-	-	-	-	-

Tabela 13: Classification using *db*3 e *SuScAlhets*.

Classification using *db*3 and *SuScAlhets*						
Training	**Accuracy (%)**	**ANN topology**	**Accuracy rate**	**Learning rate**	**Epoch**	**Time (s)**
T1_1	**95.56**	**[25 8]**	**1.10^{-5}**	**0.05**	**30**	**74.32**
T2_1	92.22	[20 8]	1.10^{-7}	0.01	31	44.45
T3_1	91.11	[25 8]	1.10^{-5}	0.05	49	123.92
T4_1	90.00	[20 8]	1.10^{-5}	0.05	81	117.01
T5_1	88.89	[25 8]	1.10^{-5}	0.05	17	42.92
Mean	**91.56**	**[25 8]**	-	-	**41.60**	**80.52**
σ	**2.5593**	-	-	-	-	-
T1_2	**98.89**	**[10 15 8]**	**1.10^{-5}**	**0.05**	**41**	**22.56**
T2_2	97.78	[10 15 8]	1.10^{-7}	0.01	32	17.03
T3_2	94.44	[10 15 8]	1.10^{-5}	0.05	27	15.23
T4_2	93.33	[10 15 8]	1.10^{-5}	0.05	62	32.24
T5_2	90.00	[10 15 8]	1.10^{-7}	0.01	34	18.26
Mean	**94.89**	**[10 15 8]**	-	-	**39.20**	**21.06**
σ	**3.5672**	-	-	-	-	-
T1_3	**95.56**	**[10 15 20 8]**	**1.10^{-5}**	**0.05**	**38**	**34.82**
T2_3	94.44	[10 15 20 8]	1.10^{-5}	0.05	35	32.13
T3_3	93.33	[10 15 20 8]	1.10^{-5}	0.05	35	38.84
T4_3	91.11	[10 15 20 8]	1.10^{-5}	0.05	36	33.07
T5_3	90.00	[10 15 20 8]	1.10^{-7}	0.01	115	125.74
Mean	**92.89**	**[10 15 20 8]**	-	-	**51.80**	**52.92**
σ	**2.3046**	-	-	-	-	-

The best classification are presented in Table 14.

Tabela 14: Best classification.

Best training						
Classification using *db*3						
Training	**Accuracy (%)**	**ANN topology**	**Accuracy rate**	**Learning rate**	**Epoch**	**Time (s)**
T1_3	96.67	[10 15 20 8]	1.10^{-5}	0.05	71	49.70
Classification using *SuScAlhets*						
Training	**Accuracy (%)**	**ANN topology**	**Accuracy rate**	**Learning rate**	**Epoch**	**Time (s)**
T1_3	**98.89**	**[10 15 20 8]**	$\mathbf{1.10^{-7}}$	**0.01**	**75**	**35.64**
Classification using *db*3 **and** *SuScAlhets*						
Training	**Accuracy (%)**	**ANN topology**	**Accuracy rate**	**Learning rate**	**Epoch**	**Time (s)**
T1_2	**98.89**	**[10 15 8]**	$\mathbf{1.10^{-5}}$	**0.05**	**41**	**22.56**

For the best classification, using *db*3, it was obtained an accuracy of 96.67%, as presented in Figure 32. It means that within the 90 data, for validation, 3 samples were classified wrongly. A better explanation of the classification are presented in Figure 33, where is presented the confusion matrix, highlighting each one of the classification.

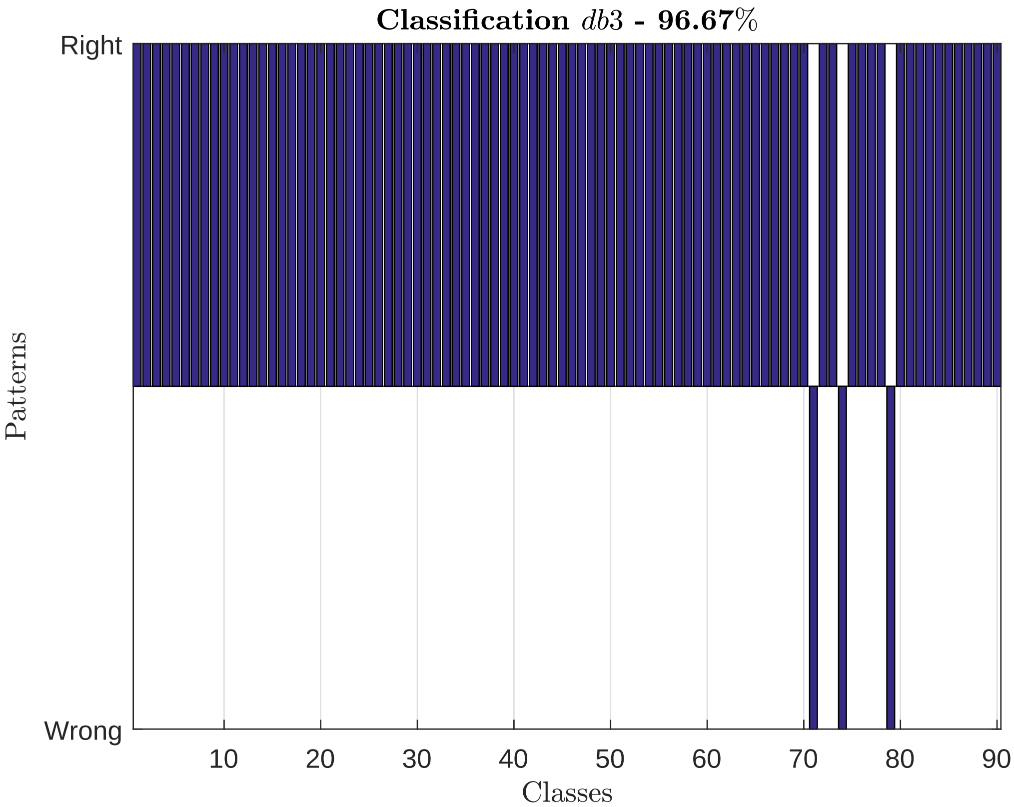


Figura 32: **Best classification using** $db3$ **with 96.67% of accuracy.**
Fonte: Autoria própria.

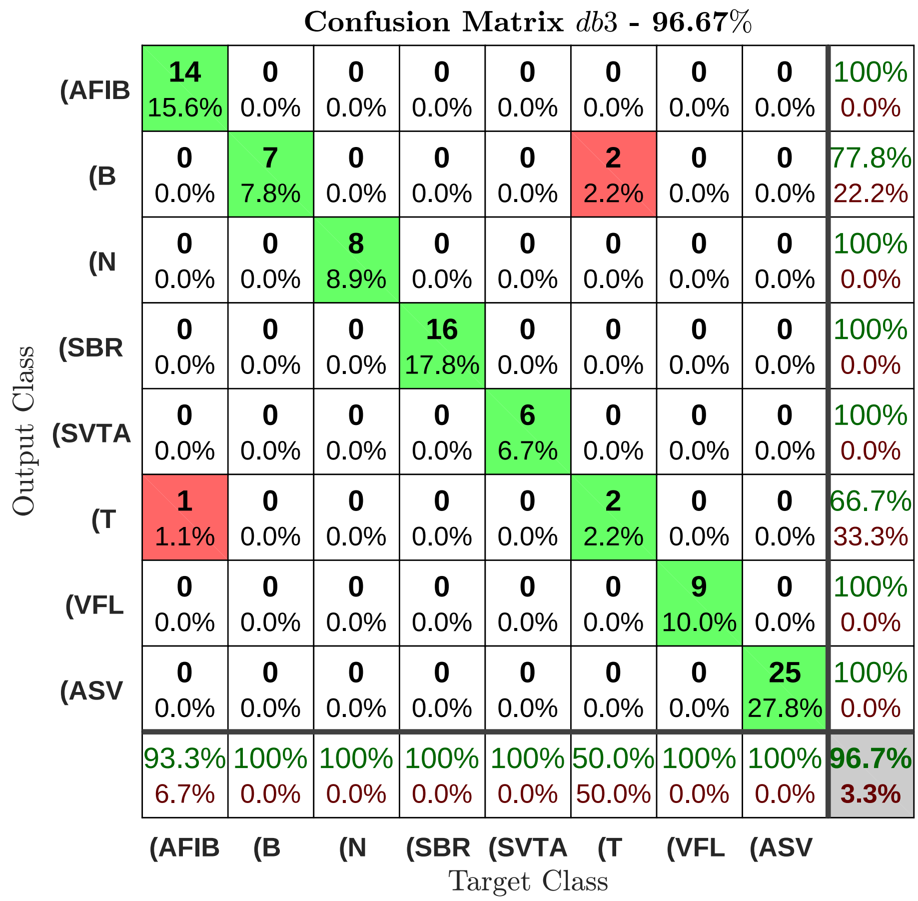


Figura 33: **Confucion matrix of** $db3$**.**
Fonte: Autoria própria.

The confusion matrix point the right classification and the false-positives/negatives. The trace of such matrix presents the right classification, that is, every samples classified correctly in its source group, what means that the more features on matrix trace, better is the classification. About the other samples, classified out of the trace, correspond to the false-positives/negatives. For example, in Figure 33, the number 1 in (6,1) means that one sample was classified as (T, while should be (AFIB and the same is for the number 2 in (2,6), there were two samples classified as (B and they should be (T.

For the best classification, using $SuScAlhets$, it was obtained an accuracy of 98.89%, as presented in Figure 34. It means that within the 90 data, for validation, 1 sample was classified wrongly.

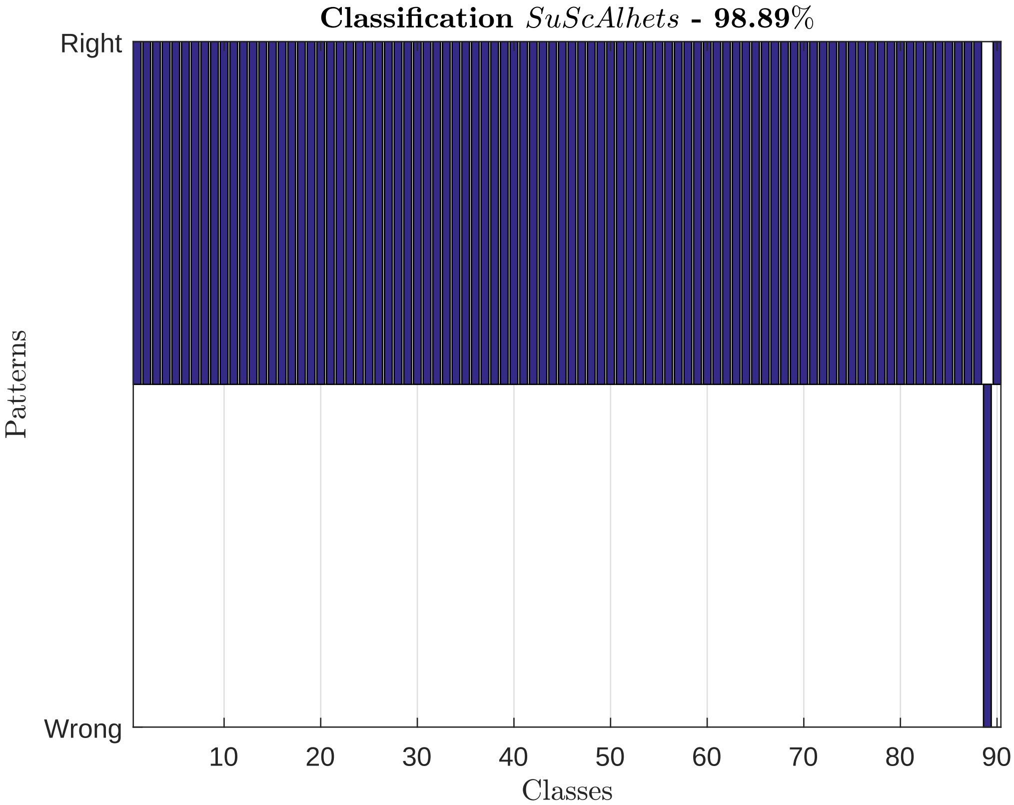


Figura 34: **Best classification using** *SuScAlhets* **with 98.89% of accuracy.**
Fonte: Autoria própria.

It also was obtained the classification confusion matrix, and it is presented in Figure35. There was only one wrong classification, in (1,5), and this one sample was classified as (AFIB while should be (SVTA.

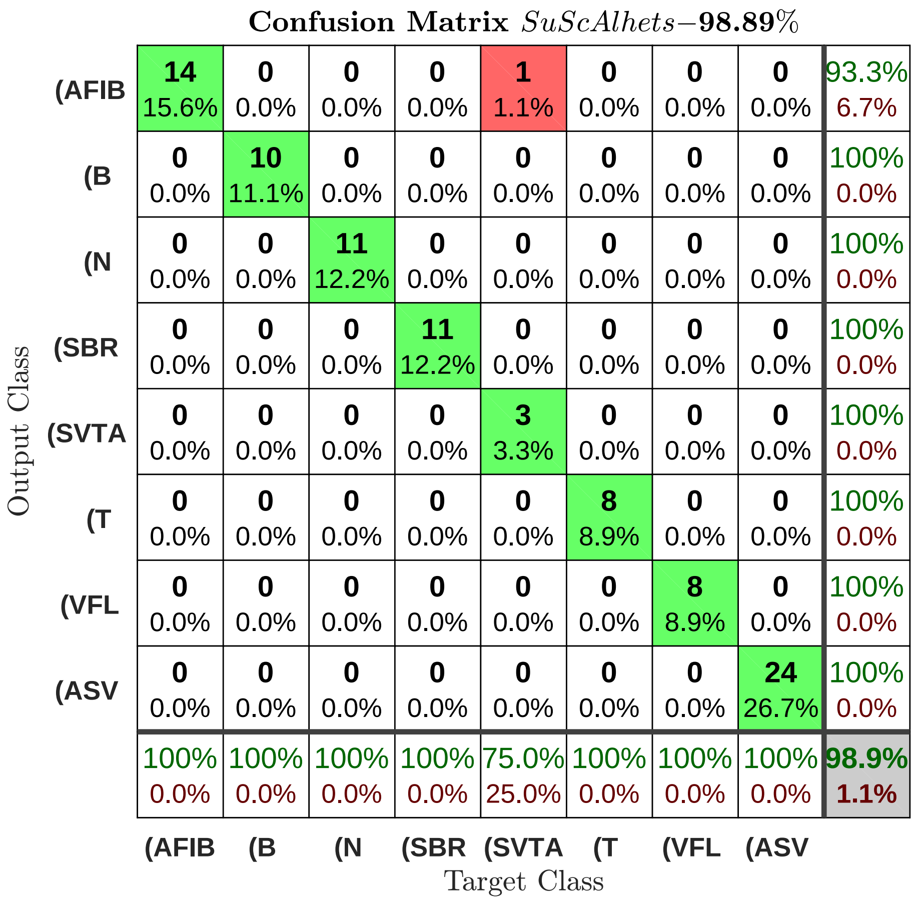


Figura 35: **Confucion matrix of** ***SuScAlhets*****.**
Fonte: Autoria própria.

For the best classification, using $db3$ and *SuScAlhets* together, it was obtained also an accuracy of 98.89%, as presented in Figure 36, what means that within the 90 data, for validation, also one sample was classified wrongly.

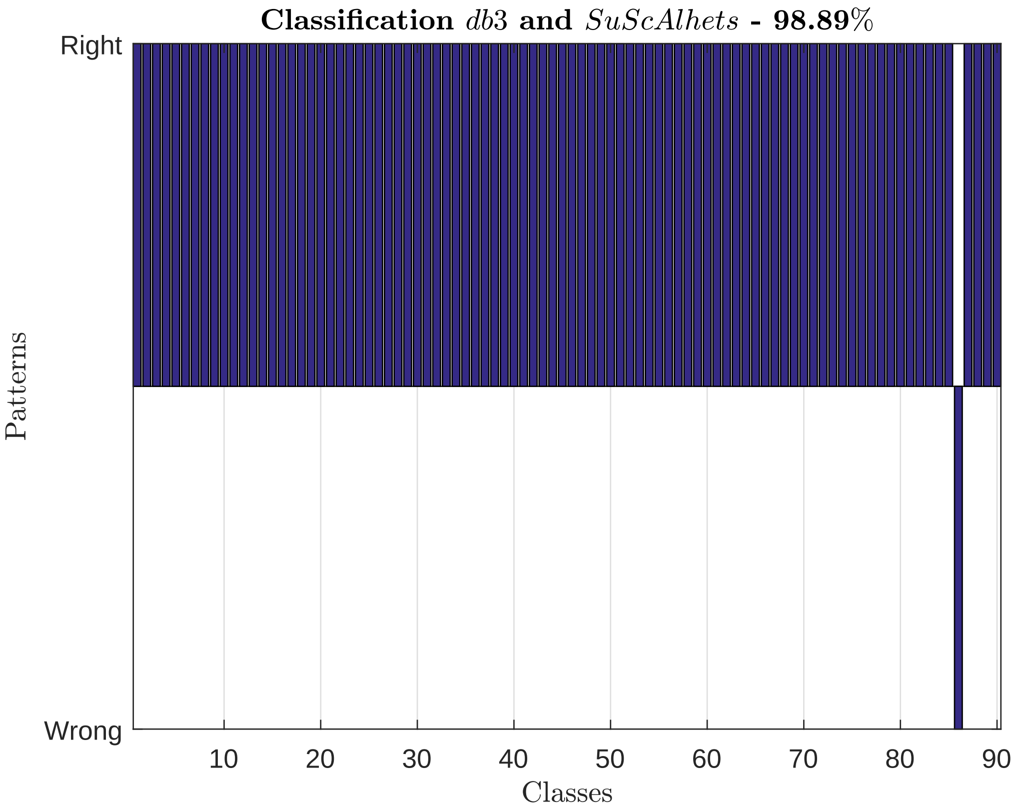


Figura 36: **Best classification using** $db3$ **and** $SuScAlhets$ **with 98.89% of accuracy.**
Fonte: Autoria própria.

For this last case the confusion matrix is presented in Figure 37, and the wrong sample of the classification, in (7,6), should have been (T, but it was classified as (VFL.

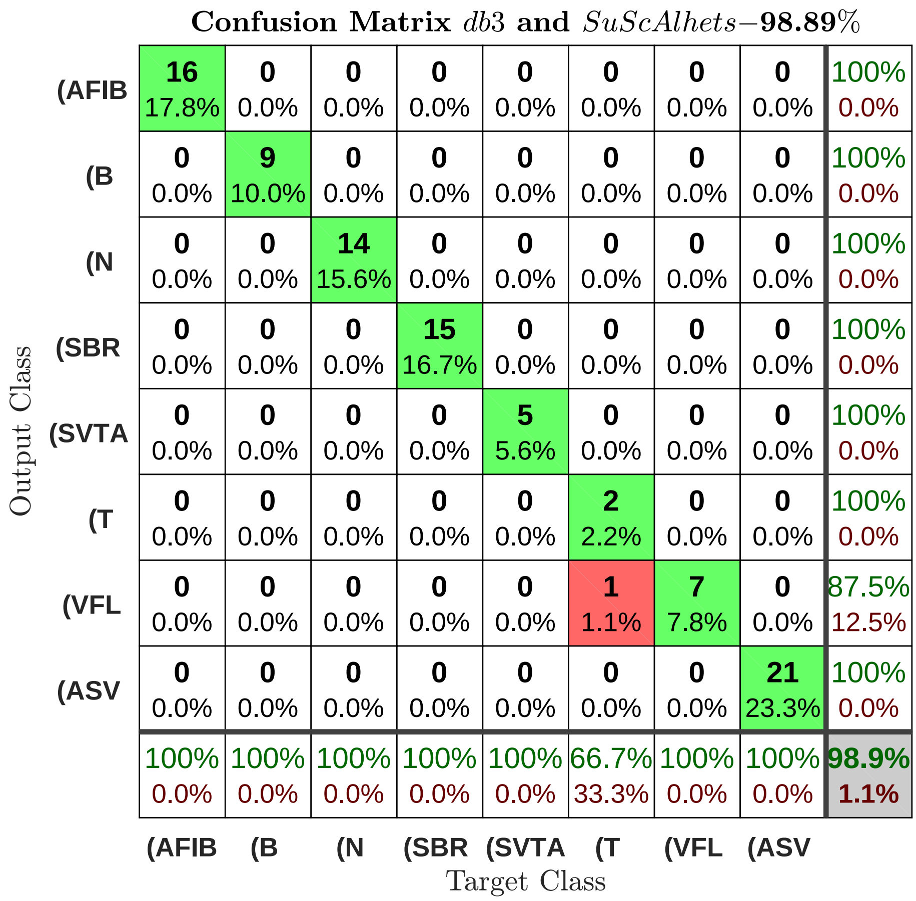


Figura 37: **Confucion matrix of** $db3$ **and** $SuScAlhets$**.**
Fonte: Autoria própria.

The Table 15 presents the training mean, according to Tables 11, 12 and 13. This Table provides the averages of accuracy, epoch and processing time. It is worth to mentioning that the epoch is an integer value, and in this Table is presented as a non-integer because it is the average, but its integer values was already presented in the previous Tables.

Tabela 15: Training mean.

Training mean			
Classification using *db*3			
Accuracy (%)	**ANN topology**	**Epoch**	**Time (s)**
85.78	[20 8]	201.20	88.09
90.44	[10 15 8]	155	29.68
93.78	[10 15 20 8]	54.20	30.87
Classification using *SuScAlhets*			
Accuracy (%)	**ANN topology**	**Epoch**	**Time (s)**
94.44	[20 8]	80.6	39.01
95.56	[10 15 8]	67.60	14.09
96.67	**[10 15 20 8]**	**59**	**31.29**
Classification using *db*3 and *SuScAlhets*			
Accuracy (%)	**ANN topology**	**Epoch**	**Time (s)**
91.56	[20 8]	41.60	80.52
94.89	[10 15 8]	39.20	21.06
92.89	[10 15 20 8]	51.80	52.92

For the first classification - *db*3, the best result was using three hidden layers. Such result provided 93.78% of mean accuracy in 54.20 convergence epochs and 30.87 processing seconds. The best result, for the second classification - *SuScAlhets*, was using also three hidden layers, which provides 96.67% of mean accuracy in 59 convergence epochs with 31.29 processing seconds. For the last classification - *db*3 and *SuScAlhets*, the best result was using two hidden layers, providing 94.89% mean accuracy in 39.20 epochs and 21.06 processing seconds.

The proposed method provides better results than the literature method, and this can be seen by the 96.67% of the mean accuracy, while the other one was about 93.78%. It was decided to use both methods together, to evaluate if the proposed method would work as a complement to the other one, but in this case the best result was 94.89% of accuracy, which is worse than using the proposed method alone.

Evaluating the computational time for the best cases, it can be seen that the *db*3 had 30.87 processing seconds, the *SuScAlhets*, in its turn, had 31.29 seconds, and finally, both methods together have 21.06 processing seconds. There was a small difference between the proposed method with the $db3$, but comparing with both method together, the *SuScAlhets* alone, showed about 40% faster than the other one.

Due the fact of this work uses medical data, the accuracy is extremely important to ensure only correct diagnoses, so always is chosen the results with the best accuracy, disregarding the computational time.

The best classification, using the proposed method - *SuScAlhets*, was with the following parameters:

- ANN topology: [10 15 20 8];
- Accuracy rate: 1.10^{-7};
- Learning rate: 0.01.

Thereby, it was performed some new tests with these parameters in order to prove the efficiency of the new proposed method. The results are presented in Table 16.

Tabela 16: Training with the best parameters.

Training with the best parameters						
Classification using *db*3						
Training	**Accuracy (%)**	**ANN topology**	**Accuracy rate**	**Learning rate**	**Epoch**	**Time (s)**
T1	95.56	[10 15 20 8]	1.10^{-7}	0.01	78	40.43
T2	94.44				124	65.69
T3	93.33				132	73.77
T4	92.22				80	43.00
T5	91.11				87	41.69
Mean	**93.33**				**100.20**	**52.92**
σ	**1.7582**				-	-
Classification using *SuScAlhets*						
Training	**Accuracy (%)**	**ANN topology**	**Accuracy rate**	**Learning rate**	**Epoch**	**Time (s)**
T1	98.89	[10 15 20 8]	1.10^{-7}	0.01	75	35.64
T2	98.89				77	38.15
T3	96.67				91	50.61
T4	96.67				60	30.68
T5	94.44				123	60.61
Mean	**97.11**				**85.20**	**43.14**
σ	**1.8610**				-	-
Classification using *db*3 **and** *SuScAlhets*						
Training	**Accuracy (%)**	**ANN topology**	**Accuracy rate**	**Learning rate**	**Epoch**	**Time (s)**
T1	96.67	[10 15 20 8]	1.10^{-7}	0.01	98	105.12
T2	95.56				64	59.77
T3	93.33				103	108.56
T4	92.22				131	120.88
T5	91.11				31	37.80
Mean	**93.78**				**85.4**	**86.43**
σ	**2.3068**				-	-

Analyzing the Table 16 it can be seen that, using only the proposed method, it was obtained better results comparing to the literature method. While the new method provides 97.11% of mean accuracy, the literature method provides 93.33%.

This Table shows the three classification, previously mentioned, and in this case the proposed method showed up better than the $db3$ method and even using both methods together. The classification using $db3$ provides 93.33% of mean accuracy, using *SuScAlhets* it was obtained 97.11% and using both methods together provides 93.78%.

7 CONCLUSION

Among all the illness which affect the population, the cardiovascular diseases are the mainly causes of death in the world, they are related to several factors, as for example: the life quality, use of narcotics and mainly the aging. Thereby, this work proposes a system to aiding health's professional, aimed to facilitate the interpretation of patient's ECG for cardiopathies detection between the healthy and unhealthy ECG. Such system ensure the obtaining of greats results with a low degree of uncertainty and basically consists of analyzing some given electrocardiogram signals in order to detection if there is or not some cardiopathy.

The scope was delimited to classification between healthy ECG and some most common types of diseases, that cause disorders of heart rhythm - arrhythmia, in population. Such diseases are: atrial fibrillation, ventricular bigeminy, sinus bradycardia, supraventricular tachyarrhythmia, ventricular trigeminy, ventricular flutter and supraventricular arrhythmia.

This automatic detection technique of cardiopathies used some estimators of information measures for feature extraction, as *Rényi entropy*, *correlation coefficients* and *Cauchy-Schwartz quadratic mutual information*. Such estimators are responsible to extract the most valuable informations of the studied signals, which were used on the classifier.

However, the most important features used were the *wavelet packet components*, they served as the basis for the estimators application. Specifically the wavelet packet *Daubechies* 3 - *db*3, which is listed as one of the best to treat ECG signals in literature. The mainly contribution of this work is the proposed of a new *wavelet packet*, called *SuScAlhets*, in order to provides better results than the *db*3.

After obtain all features, it was generate the database and applied on the classifier, which is a multilayer perceptron. Such classifier is a widely used machine learning technique.

This work provided satisfactory results which can be seen by the accuracy of proposed method. The new method, called *SuScAlhets*, provides 98.89% of accuracy, while the literature method *db*3 provides 96.67%. It was decided to evaluate both methods together, in order to analyze if the proposed method would work as a complement to the other one however, the results obtained in this case were worse than when is only used the *SuScAlhets*.

With the results obtained by the new proposed method, it is possible to develop something of practical utility, as to implement easily in a software or even hardware in order to generate a new tool able help the health professional to provide more effective diagnoses.

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