UNIVERSIDAD DE INVESTIGACIÓN DE TECNOLOGÍA EXPERIMENTAL YACHAY

Escuela de Ciencias Biológicas e Ingeniería

TÍTULO:

Bibliographic Review of methods of detection of Ventricular Fibrillation based on ECG signals

Trabajo de integración curricular presentado como requisito para la obtención del título de Ingeniero Biomédico

Autor:

Tacuri Pineda José Andrés

Tutor:

Ph.D. Salum Marisa Graciela

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DEDICATORIA

A mis queridos padres Pepe y Luisa, por estar siempre a mi lado, apoyarme y creer en mí siempre, ya que ellos han forjado la persona que soy en la actualidad, TODO LO HAGO POR ELLOS.

A mi tía Livia, tío Flavio, tía Charo y a toda mi familia en general, por acompañarme en cada paso que doy con su aliento.

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José Andrés Tacuri Pineda

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José Andrés Tacuri Pineda

RESUMEN

La fibrilación ventricular es una de las arritmias más peligrosas, porque causa un ritmo cardíaco caótico que puede provocar un paro cardíaco que conduce a la muerte súbita en las personas. Por ello, detectar esta enfermedad a tiempo le da al médico especialista la posibilidad de tratarla y aumenta la esperanza de vida del paciente. El objetivo de este trabajo de investigación es recopilar los diferentes métodos de detección de fibrilación ventricular que se pueden obtener a partir de la señal ECG de bases de datos como: IEEEexplore, ScienceDirect, Scopus, etc., destacando el trabajo de los últimos 10 años, en base a la relevancia del tema, las credenciales de los autores y la objetividad. Los métodos de detección de fibrilación ventricular se basan en características o patrones que se encuentran en las señales de ECG que permiten reconocerlas entre las señales de otras arritmias. Sin embargo, los métodos han evolucionado y se combinan con algoritmos de inteligencia artificial como redes neuronales y técnicas de aprendizaje automático para mejorar la detección de FV. Los resultados se evalúan utilizando bases de datos que cubren diferentes rangos de edad y pacientes hospitalarios y extra hospitalarios, como las bases de datos de arritmias y arritmias ventriculares del MIT-BIH y la base de datos de taquiarritmia ventricular de la Universidad de Creigton; y los parámetros que validan estos resultados son la sensibilidad, especificidad y precisión. Entre los métodos de mejor rendimiento para la detección de fibrilación ventricular se encuentran los algoritmos que presentan el pre procesamiento de la señal de ECG en el que se elimina gran parte del ruido. Esto facilita la fase de búsqueda de características o patrones dentro del ECG de señal y finalmente la detección de fibrilación ventricular basada en métodos de aprendizaje automático con una sensibilidad y especificidad promedio entre el 80% y el 90%.

Palabras clave: Fibrilación ventricular, detección, métodos, ECG, sensibilidad, precisión, inteligencia artificial, algoritmos.

ABSTRACT

Ventricular fibrillation is one of the most dangerous arrhythmias, because it causes a chaotic heart rhythm that can lead to cardiac arrest leading to sudden death in individuals. For this reason, detecting this disease on time gives the specialist doctor the possibility of treating it and increases the life expectancy of the patient. The objective of this research work is to compile the different ventricular fibrillation detection methods that can be obtained from the ECG signal from databases such as: IEEEexplore, ScienceDirect, Scopus, etc., emphasizing the work of the last 10 years, based on the relevance of the topic, the credentials of the authors and objectivity. Ventricular fibrillation detection methods are based on characteristics or patterns found in ECG signals that allow them to be recognized among the signals of other arrhythmia. However, the methods have evolved and are combined with artificial intelligence algorithms such as neural networks and machine learning techniques to improve the detection of VF. The results are evaluated using databases that cover different age ranges and hospital and extra-hospital patients, such as the MIT-BIH arrhythmia and ventricular arrhythmia databases and the Creigton University Ventricular Tachyarrhymia database; and the parameters that validate these results are the sensitivity, specificity and precision. Among the best performing methods for ventricular fibrillation detection are algorithms that feature preprocessing of the ECG signal in which much of the noise is removed. This facilitates the phase of searching for characteristics or patterns within the signal ECG and finally the detection of ventricular fibrillation based on machine learning methods with an average sensitivity and specificity between 80% and 90%.

Keywords: Ventricular Fibrillation, detection, methods, ECG, sensitivity, precision, artificial intelligence, algorithms.

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1. INTRODUCTION

The purpose of this research work is to make a bibliographic review on the different methods of detection of ventricular fibrillation from ECG signals. The main sources of information were databases such as: IEEEexplore, Scopus and ScienceDirect. The results of each author's research were evaluated based on the parameters of sensitivity, specificity and precision. For which it is necessary to explain the following basic concepts to facilitate the understanding of the document.

1.1. Heart Anatomy

The heart is an organ part of the cardiovascular system that is responsible for two main activities such as: collecting blood from all tissues to pump it to lungs and collect this blood of the lungs and pump it to all parts of the organism. Heart is located inside the chest, above the diaphragm in the mediastinum region, which is the middle part of the thoracic cavity between the two pleural cavities (1). Besides two thirds of the heart is located in the left hemitorax region (2).

Heart is covered by several membranes that carry out a distinct function. Pericardium is a membrane that surrounds and protect the heart to displace it from the mediastinum; and it is composed of two parts, fibrous and serous pericardium (3). The fibrous pericardium is located on the outside consisting of a sack of non-elastic hard fibrous connective tissue, which prevents excessive stretching of the heart during diastole, providing protection and fixing it to the mediastinum (4). On the other hand, the serous pericardium is located in the internal part, which is a thin membrane formed by a visceral layer, attached to the myocardium and a parietal layer which fuses with the fibrous pericardium(5).

Heart wall is formed by three layers: outer layer (epicardium) that is the visceral layer of the serous pericardium; a middle layer (myocardium) made up of heart muscle tissue; and an inner layer (endocardium) that covers inside the heart and the heart valves (6).

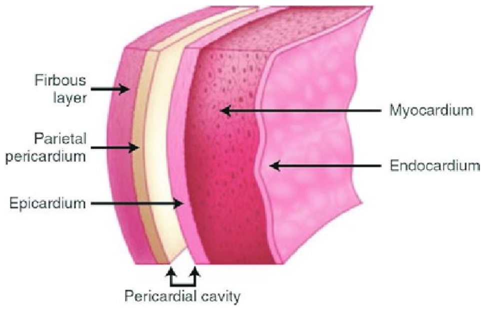

Figure 1. Heart wall anatomy. (7)

Heart is made up of four chambers: two auricles (superior) and two ventricles (inferior) that are delimited by the presence of furrows such as: the atrioventricular and anterior and posterior interventricular.

- Right auricle is formed of thin walls that constitute the right border of the heart and separated from the left atrium by the interatrial septum. It receives blood from the superior and inferior vena cava, and the coronary sinus. Blood flows from the right atrium to the right ventricle through the right atrioventricular orifice, where the tricuspid valve is located.
- Right ventricle is made up of thick walls that form the anterior face of the heart and is separated from the left ventricle by the interventricular septum. The interior presents muscular elevations (fleshy trabeculae). Blood flows from the right ventricle through the pulmonary semilunar valve to the pulmonary artery trunk.
- The left auricle is made up of thin walls that lie behind the right atrium and form most of the base of the heart. It receives blood from the lungs through the four pulmonary veins; blood passes from this cavity to the left ventricle through the left atrioventricular orifice, lined by a valve that has two mitral valve cusps.
- The left ventricle constitutes the apex of the heart, made up of a thick wall and has fleshy trabeculae and chordae tendineae, which attach the valve cusps to the papillary muscles. Blood flows from the left ventricle through the aortic semilunar valve into the aorta artery.

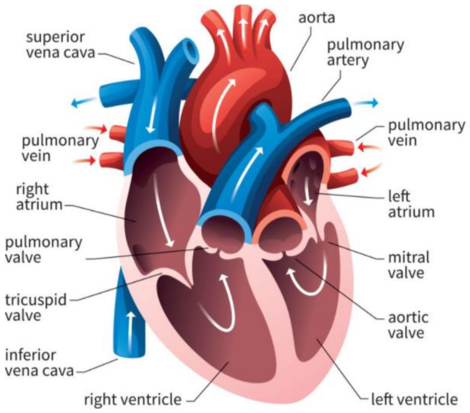

Figure 2. Heart anatomy. (8)

The heart is innervated by autonomic nerve fibers of the parasympathetic and sympathetic systems, which constitute the cardiac plexus. Branches of the cardiac plexus innervate the conduction tissue, the coronary blood vessels, and the atrial and ventricular myocardium. Sympathetic fibers originate from the cervical and thoracic spinal segments, and parasympathetic innervation derives from the vagus nerves.

In the initial part of the ascending aorta come the right and left coronary arteries, which branch to distribute the oxygenated blood throughout the myocardium. On the other hand, non-oxygenated blood is drained by veins that flow into the coronary sinus and flow into the right atrium. The coronary sinus is located in the posterior part of the atrio-ventricular sulcus (1).

1.2. Heart physiology

The cardiac cycle encompasses all events that happen in the heart from the beginning of one beat to the beginning of the next. The main components are systole, diastole, and filling, which include several stages. In systole, it begins with the isovolumetric contraction in which the heart wall is stressed and the pressure of the ventricle begins to increase causing the blood to seek a place to exit, therefore the atrioventricular valves (noise S1) are closed so that there is no blood return to the atrium. The volume remains constant, the pressure is increasing. Later, in the ejection phase, the atrioventricular valves remain closed and the ventricle slightly exceeds the pressure of the aorta and the aortic valve opens, which is why blood ejection begins. That is, as the volume decreases the pressure also decreases.

In diastole, isometric relaxation is characterized by the fact that the atrioventricular valves remain closed, which causes the semilunar valves (noise S2) to close and therefore there is no entry or exit of blood. Ventricular pressure is higher than atrial pressure, but lower than aortic pressure since blood does not flow to either side and the ventricular volume remains constant.

In the filling phase, rapid ventricular filling occurs in which the atrioventricular valves open and blood flows rapidly from the atrium into the ventricle (S3 noise). Then slow ventricular filling occurs, causing the ventricle to remain relaxed and is receiving flow from the atrium. Eventually atrial contraction occurs and the atrium contracts to finish filling the ventricle (noise S4) (4).

The cardiac membrane potential is divided into 5 phases:

- Phase 0 is the fast upswing of the action potential
- Phase 1 is the repolarization after a quick depolarization
- Phase 2 is the plateau of the action potential
- Phase 3 is the repolarization to the resting membrane potential
- Phase 4 is the resting membrane potential in atrial, ventricular, and Purkinje cells and the pacemaker potential in nodal cells.

In resting ventricular muscle cells, the potential inside the membrane is stable at approximately in -90 mV relative to the outside of the cell. When the cell is brought to threshold, an action potential occurs. Starting with a rapid depolarization from -90 mV to 20 mV (phase 0). Then a slight decrease in membrane potential (phase 1) to a plateau (phase 2), at which time the membrane potential is close to 0 mV. After that, rapid repolarization (phase 3) returns the membrane potential to its resting value (phase 4) (9).

1.3. Ventricular Fibrillation

Ventricular fibrillation is determined by a frenzied and disorderly electrical activity; represented by QRS complexes, ST segment and T waves of irregular amplitude. The voltage of the ECG waves detectable during ventricular fibrillation is close to 0.5 mV when the ventricular fibrillation phase begins, but it dissipates rapidly after 20 to 30 seconds values drop to 0.2 to 0.3 mV (10). This produce that heart stops pumping blood to the brain and the rest of the body and in approximately 6 to 8 seconds the individual loses consciousness (11). Therefore, immediate medical assistance is essential to prevent irreversible brain damage; the actions to be taken are cardiopulmonary resuscitation and unsynchronized defibrillation (12). Among the most frequent causes for an episode of ventricular fibrillation in individuals, we have the following:

- Heart Failure: it is the pathophysiological state in which the heart supplies an insufficient amount of blood for peripheral metabolic needs (13).
- Myocardiopathies: they are a group of diseases characterized by causing a myocardial malfunction with a diverse origin and a variable expressivity (14). Cardiomyopathies are classified into four main groups: dilated cardiomyopathy, hypertrophic cardiomyopathy, restrictive cardiomyopathy and arrhythmogenic right ventricular dysplasia.
- Cardiogenic Shock: can be defined as the perennial and gradual drop in blood pressure, with appropriate ventricular filling pressure, with general and severe decrease in tissue perfusion (15).
- Reentrant Phenomenon: under normal conditions in the individual, when the cardiac impulse travels the area of the ventricles in its entirety, this then has no place to go because the ventricular muscle is refractory (16). However, when this does not occur, reentry occurs, which causes circular movements in the heart that are the precursors of ventricular fibrillation (17).

1.4. Electrocardiogram

The electrocardiogram (ECG) is a graphical representation in which the different voltage variations that occur in a time interval are captured. This is the result of the electrical activity that occurs in the heart and that is commonly recorded on strips of graph paper by an electrocardiograph. ECG consists of five waves: P, Q, R, S and T. The P wave arises from atrial activation, followed by Q, R and S waves, which constitute the ventricular complex due to the propagation of the wave of excitation to the musculature of the right and left ventricle and the interventricular septum (18). Once the depolarization process of the atrial and ventricular muscle mass is finished, a small pause occurs, known as the S-T segment, and finally the T wave appears as a result of the repolarization process (19).

To perform an ECG it is needed an electrocardiograph, ECG patches (sensors that are placed on the skin and act as electrodes), and a system of cables that transmit the micro-currents collected by the patches to the electrocardiograph. The ideal position of the patient is completely horizontal, then the technician or doctor places a total of 10 electrodes; some are placed on each limb (limb leads) and the remaining six electrodes are placed at six specific points on the chest in the precordial region (precordial leads) (20). It should be noted that an electrocardiographic lead is made up of the union of two electrodes. Each of the leads allows a different electrocardiographic view of the different observation points to be obtained.

It is important to bear in mind that from the moment the operator starts the electrocardiographic recording, the patient must maintain his position, since a movement distorts the recording and the ECG must be repeated. In addition, it must be ensured that the contact between the patches and the skin is as close as possible since it causes a low sharpness of the register. On other occasions, it will be necessary to shave the patient's hair, since it can also exert a certain barrier effect on the capture of the electrical signal.

1.5. Databases

The database is an organized collection of structured data in order to make it easily accessible, manageable and update. In the following review investigation several databases were used for the authors in order to evaluate the performance of the algorithms proposed.

- The arrhythmia database of the MIT-BIH has 48 extracts of half an hour of records that were obtained by a two-channel electrocardiograph of 47 individuals analyzed. The first 23 records were the result of a mixed inpatient (60%) and outpatient (40%) population, and the remaining 25 recordings were chosen with the goal of including less common but clinically significant arrhythmias at Beth Israel Hospital in Boston (21).

- Creigton University Ventricular Tachyarrhythmia Database was obtained from an ECG holter and then the signals registered passed through an active second-order Bessel low-pass filter (22). Every record contains 127,232 samples, the minimum number of non-ventricular fibrillation beats before a ventricular fibrillation occurs is 61 with a mean time interval from the beginning of the record to the episode of VF is 5 minutes with 47 seconds (23).
- The American Heart Association Database for Evaluation of Ventricular Arrhythmia Detectors consisted of 80 two-channel excerpts of analog ambulatory ECG recordings. These 80 recordings contains several heart diseases but the most important are ventricular tachycardia, ventricular flutter and ventricular fibrillation, the register start after five minutes of unannotated ECG signals, then thirty-minute annotated segment of each recording is done (22).
- The MIT-BIH Malignant Ventricular Arrhythmia Database includes 22 half-hour of ECG recordings of subjects who suffered episodes of ventricular tachycardia, ventricular flutter, and ventricular fibrillation (22).

1.6. Description of the methods for ventricular fibrillation detection

The research project is based on the recompilation of diverse methods of ventricular fibrillation detection of different authors and showed the evolution of the techniques over the years. For the analysis of ECG signals, features are extracted from the signal with the objective to help the differentiation between healthy and non-healthy (ventricular fibrillation) patients. Thus, feature extraction methods can determine the presence of diverse segments, intervals, deflections and complexes that are present in a normal ECG signal.

Table 1. Methods for ventricular fibrillation detection

Method of detection	Description	Reference
Threshold crossing interval (TCI)	Threshold is the 20% of the peak value of ECG signal for every second of register, with the ability to adapt if any changes are present in amplitude. The pulses that exceed the threshold are counted in the register consecutively registers and an average is obtained.	(24)
Threshold crossing sample count (TCSC)	It analyses the ECG signals in intervals of three seconds and positive and negative thresholds are defined instead of only positive threshold. Samples above the thresholds are considered to count instead of the pulses and a moving average filter is applied to make decisions on ECG episode.	(25)

Complexity measure (CPLX)	It allows the analysis of spatiotemporal patterns that shows if a dynamical equilibrium state is reached and what its complexity is as compared to a random pattern. Besides, CPLX indicates the rate of new patterns arising and it is showed with the increase of the CPLX value.	(26)
Phase space reconstruction (PSR)	Signals are analyzed to find a dynamic law or random behavior. ECG signals are plotted in a two dimensional phase space diagram where the x axis is the signal and the y axis is the signal plus a time constant. Normal ECG signals, show a curve with a regular structure however VF signal produces a curve with an irregular structure.	(27)
Autocorrelation function (ACF)	It defines how data points in ECG signals are related to the preceding data points. This means that ACF measures the self-similarity of the signal over different delay times	(28)
Ventricular Fibrillation filter	This procedure applies a narrow band filter centered on the middle frequency of obtaining as a result a leakage of the VF filter. VF filter technique uses threshold crossing intervals to determine if a signal is classified as normal or arrhythmia when the VF filter leakage exceed the threshold value	(29)
Neural Networks (NN)	This are interconnected assembly of simple processing elements, with the capability to store information in each unit by the repetitive exposure to the information, in order to take decision in an autonomous way using the data stored when a similar condition happens	(30)
Fourier Transform	It decomposes a signal as the sum of sinusoidal functions, each sinusoid has an associated amplitude, phase, and frequency and transforms data from the time domain into the frequency domain.	(31)
Fast Fourier Transform	It multiplies sine periodicities to perform the calculation and takes the Fourier matrix and factors it into several sparse matrices. These sparse matrices have many inputs that are equal to zero and reduce the total number of calculations required.	(31)
Discrete Wavelet Transform	It returns a data vector of the same length of the input signal. The output vector contains data that are almost zero due to the decomposition of the signal into a group of wavelets that are orthogonal to its translations and scaling. Thus, the decomposition of a signal is done to a same or lower number of the wavelet coefficient spectrum as is the number of signal data points.	(32)
Hilbert Transform	It is a technique used to obtain the minimum-phase response from a spectral analysis. This relies on FFT, for this reason it will produce a frequency response with this linear-phase component removed (delay). In other words the algorithm signal processing in done in time and frequency domains.	(33)
Machine learning	It is a method that enables a system to learn from data rather than through a previous programming. It uses several algorithms that iteratively learn from the input data in order to describe data, and predict outcomes. A machine learning model is the result of the training with data of machine learning algorithm	(34)
Support Vector Machine (SVM)	It has the ability to learn in order to make a decision based on two different classes of entry points. When acting as a	(35)

	single class classifier, the data-given description of the support vectors is necessary to form a decision boundary around the domain of the learning data with little or no knowledge of the data outside of this boundary	
K-Nearest Neighbour (K-NN)	It is a supervised learning technique that assumes the similarity between the new data and available data and put the new case into the category that is most -similar to the available categories. Thus K-NN algorithm can be used for regression as well as for classification	(36)
Empirical Mode Decomposition (EMD)	It decomposes adaptively and locally any non-stationary time series in a sum of Intrinsic Mode Functions (IMF) that are zero-mean amplitude and frequency modulated components. The superimposing all extracted IMFs together with the residual slow trend reconstructs the original signal without information loss or distortion.	(37)
Bayesian Classifier	It generates a probabilistic model of the features and uses that model to predict the classification by establishing the relationships between features in a general way of information. Also it is useful to discriminate the feature of any social network dataset if these feature relationships are known before	(38)

1.6.1. Parameters to evaluate the performance of the methods

To determine the performance of the methods used for detection of ventricular fibrillation techniques, it is necessary to define parameters. These parameter are: accuracy, sensitivity and specificity. Next the definitions of the above mentioned parameters.

- Accuracy: is the agreement between a quantity obtained by measurement *a*nd the true value of the measurand. Besides, it is the rate of the number of correct predictions compared to the total number of input samples (39).

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions\ made} \quad (1)$$

- Sensitivity: it is the proportion of positive data points correctly considered as positive- with respect to all data points (40). In the formula true positive is defined as the result that detects the condition when the condition is present and false negative as the result that does not detect the condition when the condition is present.

$$Sensitivity = \frac{True\ positives}{True\ positives + False\ Negatives} \quad (2)$$

- Specificity: it is the proportion of negative data points that are mistakenly considered as positive, with respect to all negative data points (40).

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Negatives} \quad (3)$$

2. JUSTIFICATION AND PROBLEM STATEMENT

2.1. Justification

In 2017 the American Heart Association estimated the total number of patients of Out of Hospital Cardiac Arrest (OHCA) at 356,500. A 23% of OHCA attended by Emergency Medical Service have ventricular fibrillation or ventricular tachycardia as a first stage. Approximately a 60% of cardiovascular deaths are the result of a cardiac arrest and several investigations have identified VF as the most common underlying arrhythmia in patients with sudden cardiac death. Among patients hospitalized with acute MI, 5% to 10% have VF or VT, and another 5% will have VF or VT within 48 hours of admission (41). Cardiovascular diseases are a serious public health problem in our country that grows exponentially. According to data from the Ministry of Public Health, in 2016 of the 68,000 deaths registered the main causes were: heart attacks, diabetes and strokes, with the 10%, 7% and 6% respectively (42).

Different studies, done by the World Health Organization, make approaches that by 2020, the mortality rate due to cardiovascular diseases will increase to 20% and by 2030, 23.6 million people will be the cause of death around the world (43). There are several risk factors that increase the probability that an individual presents this type of diseases such as: genetic factors, sedentary lifestyle, obesity, diabetes, smoking, among others (44). Faced with this reality, it is justified to carry out that it will allow to deepen the knowledge about the various existing methods for the detection of ventricular fibrillation based on ECG signals.

2.2. Problem Statement

Ventricular fibrillation is one of the most dangerous cardiovascular disease because it is characterized by a disorganized and rapid ventricular activity, which is a synonym for clinical cardiac arrest (45). In a phase of ventricular fibrillation, many parts of the ventricular muscle contract simultaneously while others relax, causing the pumping of blood levels to be imperceptible (46). Due to the asymptomatic nature of ventricular fibrillation, individuals suffering from this arrhythmia have a short time of action to apply a treatment (ventricular defibrillation, medications, implantable cardioverter defibrillator, etc.) with a low success rate, which drastically reduces the hope of survival of the individual. For this reason, by studying the patient's ECG signals, it allows us the early detection of ventricular fibrillation. This is achieved through different methods in which algorithms based on pattern recognition, feature extraction, time-frequency analysis of ECG signals are used, as well as electronic prototypes, neural networks and machine learning. The results produced by the different methods must be evaluated in terms of sensitivity, specificity and precision, in order to determine the optimal detection methods. Therefore, it is proposed to make a bibliographic review of the available detection methods from valid information sources of the last 10 years.

3. OBJECTIVES

3.1. General Objective

To analyze the different available methods for the detection of ventricular fibrillation from the ECG signal.

3.2. Specific Objectives

- To describe the methods analyzed in the bibliographic investigation.
- To classify the existing methods according to the algorithms used by the authors.
- To determine the performance of each of the established methods in terms of sensitivity, specificity and accuracy.

4. METHODOLOGY

The bibliographic review is a synopsis that summarizes different investigations and articles that gives us an idea about the current state of the question to be investigated. The review makes a critical appraisal of other research on a given topic; it is a process that helps us to put the topic in context [50]. The present bibliographic review is descriptive, since it presents a systematic and rigorous perspective that focuses on profiling the knowledge about the methodology, theoretical knowledge to draw conclusions on the issue raised. A fundamental characteristic of this type of review is that a series of criteria are established in a transparent manner that ensure the quality of the results of the review.

In the development of this research work, a detailed, selective and critical study was carried out in order to examine the existing bibliography on ventricular fibrillation detection methods published in various sources of information. The research process has been divided into four stages:

1. To identify the relevant known and unknown aspects of the topic.
2. To delimit the research topic, establishing the objective that our work seeks to satisfy, which is the collection of information on the different methods of ventricular fibrillation detection from the ECG signal.
3. To select the most appropriate analysis methods.
4. To compare the information available from different authors in order to generate updated conclusions based on the proposed topic.

At the time of choosing the documents to be analyzed, it has been done prioritizing only those that contribute decisive information to the investigation and avoiding the use of irrelevant references. The chosen criteria to evaluate the documents to be considerate in this bibliographic review were:

• The credentials of the author/s: they will allow to know what is the type of activity or qualification of the authors responsible for the content.

• Primary information sources: They contain original information that has been published for the first time and that are the product of research or an eminently creative activity [51].

• Objectivity: the information is not biased, nor loaded with the author´s feelings or judgments to persuade the reader.

The sources that have been consulted to obtain the information are: IEEExplore, Google Scholar, PubMed, SciELO, Elsevier, Science Direct, ResearchGate and Scopus. The bibliographic review was developed empathizing the articles from the year 2010 using the descriptors: ventricular fibrillation, detection, ECG, identification and prediction, obtaining 10 possible search combinations applying statistics. More than 70 articles by different authors were analyzed to show the progress in ventricular fibrillation detection methods, in order to give the reader a global spectrum on the proposed topic.

The analyzed information was classified based on the ventricular fibrillation detection technique into 5 fundamental groups:

1. feature extraction,
2. use of time-to-frequency domain change methods.
3. neural networks,
4. machine learning,
5. empirical mode decomposition, and
6. use of electronic devices

From the set of studies analyzed, it was summarized the technique used for detection. Also, the results were validated based on sensitivity, specificity and precision. Besides, the database of ECG signals that the authors used for their work was identified.

5. RESULTS

In this bibliographic review, information was collected from various scientific articles, of which 75% (48) are from sources from 2010 to 2020 and the remaining 25% (19) comprise sources from 2000 to 2010, as can be seen in fig 3.

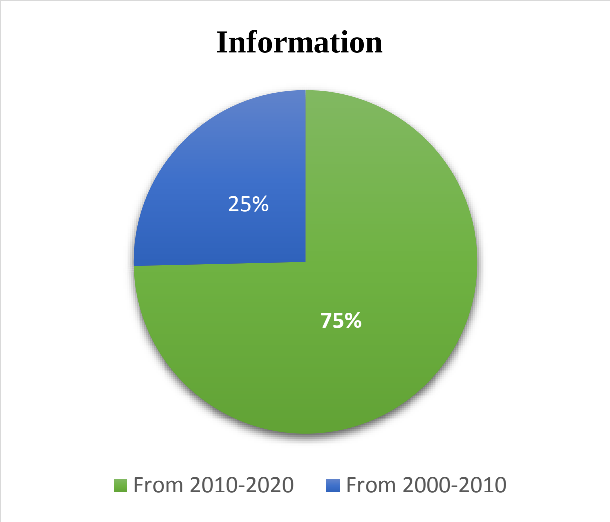

Figure 3. Distribution of information used in the investigation

The detection methods were classified into 7 categories, the method with the highest number of articles analyzed being feature extraction with 27% (18), followed by machine learning with 25% (17), neural networks with 13% (9), use of time to frequency domain change with 12% (8), other with 9% (6), electronic devices with 7% (5) and empirical mode decomposition with 6% (4), as you can see in fig 4. On the other hand in fig 5, it is showed the number of publications used in the review classified per year from 2010 to 2020.

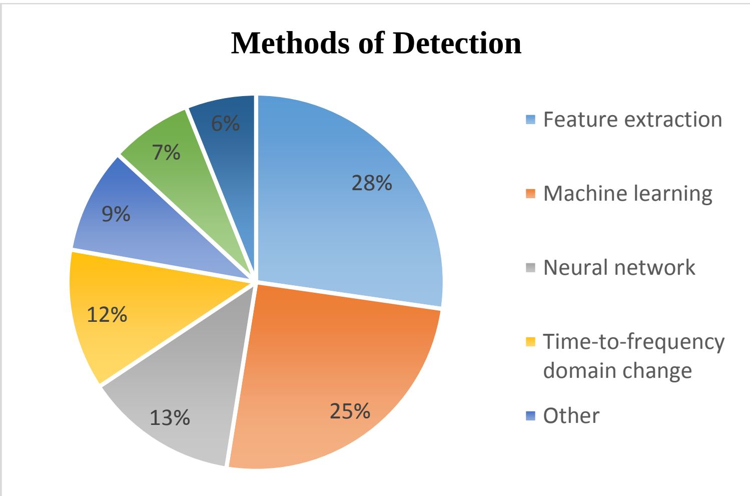

Figure 4. Percentage of information found for each method of detection

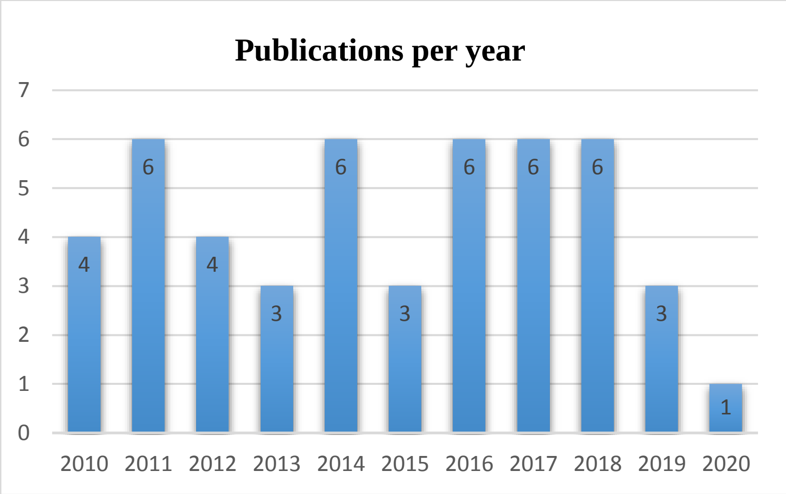

Figure 5. Publications per year used in the investigation

5.1. Feature extraction

Ventricular fibrillation detection methods are based on feature extraction techniques that are the precursors of current methods and that have evolved to be considered a current identification method. These techniques are characterized by the search for features in ECG signals and the categorization of a signal as a normal rhythm or an arrhythmia.

According to Thakor et al. (24) a TCI-based algorithm (as mentioned before, TCI is Threshold crossing interval) is presented that begins with the use of various digital filters (low pass and notch filter) to eliminate muscle noise and baseline interference. This results in a binary sequence where the values above and below the threshold (20% of the peak value every second of register) are registered over successive records of the ECG signal until 200 samples per second in order to get the probability distribution of VF between the number of sample.0s that exceed the threshold value. The authors uses 85 records of VF and 85 records of monomorphic and polymorphic VT and showed a detection of VF with an accuracy of 97.64%, specificity and sensitivity values are not specified.

In the work of Arafat et al. (25), a method based on TCSC (Threshold crossing sample count) is presented. TCSC method begins with the preprocessing of the ECG signal in which a low-pass Butterworth filter is used to eliminate the high frequencies. Then, each ECG segment is normalized using the absolute maximum value and is transformed in a binary sequence comparing each of the data with a previously described threshold value. After that the percentage of samples (N) that are greater than the threshold value divided by the total number of samples per hundred is calculated. Finally, the decision is made by analyzing each second of the ECGs by averaging 2 consecutive N values obtained in 3-second ECG segments (Na).

Therefore, if Na is greater than the threshold value, VF is detected. Authors based their investigation on MIT-BIH arrhythmia and the Creighton University ventricular tachyarrhythmia database and with 80.97% of sensitivity and a 98.51% of specificity, and 98.54% of accuracy perform the detection of VF.

According to Amann et al. (27), with the help of PSR an algorithm has been developed that begins with a treatment of the ECG signal with a Butterworth filter to eliminate information above a frequency of 50 Hz, then a phase space plot is performed, taking in consideration the positions of the discrete ECG data points to calculate d value that is going to be compared with the threshold value so if d is higher than the threshold we assign the ECG signal as VF. Authors in the article used a window length of 8 seconds and the databases used are the same as of Arafat et al. [23] and showed a sensitivity of 83.8%, a specificity of 97.8% of detection of VF.

In the work of Zhang et al. (47), CPLX was used which for a precise window length, the algorithm makes a 0-1 string by comparing the raw ECG data in order to choose a convenient threshold. The obtaining of the complexity measure from 0-1 string can be done by two elementary operations, comparison and storage. When the window length is 7 s, the detection accuracy for discrimination of VF from VT and sinus rhythm is 100%, sensitivity and specificity is not specified, using the same database as Thakor et al. [24].

The study carried out by Chen et al. (48) focuses on ACF evaluate VF signals that are no periodic and with a random amplitude distribution. On the other hand, VT signals are periodic with uniform amplitude distribution. After that, a regression test is done to graph peak values of ACF versus the lag values. The authors registered 31 records of ECG signals that present VT, VF, and other monomorphic and polymorphic ventricular arrhythmias. The results obtained from the investigation said that after studying the signals in three consecutive periods of time of 1.5 s: in the first period the method showed a sensibility of 100% and 64% of specificity, in the second 100% of sensibility and 72% of specificity and in the third a 100% of sensitivity and specificity.

Thakor et al. (49) found that a VF detection method based on multiway sequential hypothesis testing algorithm (M-SHT) that calculates the probability operate from atrio-ventricular delay measurements, and compares this operate with thresholds derived from specified error possibilities for the arrhythmias to be separated. The execution of this algorithm was tested on 102 dual channel electrocardiograph records of 30 patients in the laboratory. M-SHT properly classified 31 out of 31 cases of supraventricular tachycardia and 41 out of 43 VF with an average time of 5.0 s and 1.6 s respectively; however, the results of the investigation are not tested with the parameters of specificity, sensitivity and accuracy.

Also, Chen et al. (50) analyzed an algorithm based on SPRT that works with TCI establishing a threshold of the 20% of the peak amplitude ECG signal for each 1 s record and calculating the places of successive threshold crossings was implemented. In order to prevent several counts for a depolarization, authors set a blanking interval when the heart is on a refractory period. Thus blanking interval variability (BV) have to be estimated for discrimination of VF from VT. Authors used the Malignant Ventricular Arrhythmia of MIT-BIH database and detection of VF have a specificity of 93% with a BV of 0.0118.

Amann et al. (51) adopt the standard exponential algorithm (STE) that sum the number of crossing points of the ECG signal with an exponential curve decreasing on both sides. ECG signal studied in time domain is investigated in the time domain. Thus, it is essential to get the absolute maximum value of the investigated ECG signal. After this step, they establish the length of the ECG register and if the number of crossings per minute is higher the signal is categorized as VF signal. The information of the ECG signal was taken from (25) and got the following results: an accuracy of 79% with a length of 8s of the ECG signal of detection of VF signals.

According to Ismail et al. (52), present a Modified Exponential algorithm which relies the decision of classification an ECG signal as VF signal on the number of crossings between a decreased exponential curve and the ECG signal. The process begins with the localization of the first relative maximum value of the studied signal. Then, the first decreased exponential curve is created with a time constant. Thus the crossing point between the ECG signal and the exponential curve is counted and the method elevate the curve to the next maximum value, so if the times that the algorithm elevates the curve is higher than 225 crossings per minute, the signal is assigned as VF. Creighton University ventricular tachyarrhythmia database was used and show that have a sensitivity of 56.49% and a specificity of 83.75% of detection VF.

In Romero (53), it is mentioned an algorithm of VF detection based on the mean absolute value (MAV) of the ECG signal. This technique relies on the sum of the absolute value of the force of the signal, normal signals have a low MAV value due to the low amplitude of the QRS complexes while VF have a high value of MAV. The Ventricular Fibrillation Data Base signals were used and for an accurate processing they have to be normalized in order to make the comparisons without generating inconsistencies in the results. Finally with the help pf SVM classifies the signals as VF obtaining results of discrimination with a sensitivity of 92.31% and a specificity of 84.23%.

In the work of Park and Yoon (54), it was presented a developed algorithm for detecting VF based on the clinical considerations on ECG signals for patient monitoring system. The procedure begins with a band pass filter application to the signal for the recognition of the peaks and valleys of the signal. Thus, time-difference and amplitude variation on peaks and valleys are calculated in order that the device classify if the signal is a VF pathology. The information used to probe the algorithm was taken from AHA ECG and MIT-BIH Arrhythmia Databases and present a detection of VF with a sensitivity of 98.1% in AHA database and a sensitivity of 88.5% in MIT-BIH database.

According to Li et al. (55), a morphology consistency evaluation algorithm for the detection of VF without interrupting the ongoing chest compression. For the quantification of the morphological consistency of the chosen waveforms, the autocorrelation of the template waveform and the cross correlation of the template waveform with the four selected candidate waveforms are computed. The difference between autocorrelation and cross correlations is compared, and if the difference in area surpass a defined threshold the signal is recognized as VF. Authors used Creighton University Ventricular Tachyarrhythmia Database and the detection of VF have a sensitivity of 92%, a specificity of 93% and an accuracy of 93%.

In an analysis of Irusta et al. (56), it was proposed a core algorithm of a high-temporal resolution rhythm analysis for VF detection in adults and children. The core relies on the presence of conducted or narrowed QRS complexes in the ECG signal in the time, slope and frequency domain. For this reason, rhythms with well-defined QRS complexes are normal broadband signals and narrow band signals are for VF. In addition, the use of a binary classifier based on a multiple logistic regression model assigned a 1 to normal ECG signals and 0 to VF. Records used for the study were collected in-hospital from digital acquisition systems EP-tracerTM and Prucka Cardiolab 400TM, and obtain results for VF detection with a sensitivity of 90 % and a specificity of 90 %.

Jekova and Krasteva (57) described an algorithm for VF detection based on a digital filter band-pass with integer coefficients, with the objective of an easy application in real time operations. The process starts with noise detection, after that VF detection uses a band-pass digital filter to pass the supraventricular complexes and ventricular complexes with frequencies up to 20 Hz and 14 Hz respectively. Finally rhythm classification by means of the absolute values of the digital integer-coefficients filter are used for the categorization of ECG signal as VF from other cardiac rhythms. The method used American Heart Association Ventricular Fibrillation and the Massachusetts Institute of Technology database files and the detection of VF from other ventricular tachyarrhythmias with a sensitivity of 95.93% and a specificity of 94.38%.

According to Monte et al. (58), an algorithm for real time detection of VF based on QRS detection can be implemented. The procedure begins with the segmentation that consists of the interpolation between two samples and then the error is calculated as the difference between the real sample and the interpolated sample. After that labeling description occurs where the difference is computed in the interpolation process and the sign of the error is stored. Finally, VF detection is done by the recognition of QRS pattern in the ECG signals. MIT-BIH Malignant Ventricular Arrhythmia database was used and the results obtained for VF detection are based on the change of pattern showing increment an irregular shape in ECG signals.

An algorithm for VF detection based on an adaptive threshold was presented and developed in the work of Lee and Yoon (59). This is based on a first phase of band-pass filtering of ECG signal from 2 to 40 Hz, then the adaptive threshold divides the signal in 2 parts and a 4 point moving average filter is applied. Finally the VF detection is done by ventricular activity segmentation based on the presence of QRS complexes in the signal. MIT- BIH and Creighton University Ventricular Tachyarrhythmia databases were used to extract the ECG signals for the VF discrimination with a sensitivity of 95.77 %.

Mohammad-Taheri (60) presented a method for VF detection based on slope analysis. The slope count is needed for this study that begins by the calculations of all the slopes of the ECG signal during 1 second. Then, the calculation of the slopes in the next second is required. After that, the results are concatenated for having a 2 second vector and the peak absolute value. Finally, a threshold value is established and all the signal that exceed it are considered as VF. MIT-BIH arrhythmia, CU ventricular tachyarrhythmia databases were used and detect VF with a sensitivity of 97.99% compared with normal signals.

According to Pardey (61), the detection of VF can be achieved by sequential hypothesis testing of binary sequences. The first stage is to convert ECG signals to binary sequences by the division of the signals in segments and the DC offset is subtracted from each segment. Then, the amplitude threshold is defined for each segment of the signal and threshold crossing interval (TCI) and the complexity (Cn) features are used for discrimination of the signal. Finally, sequential hypothesis testing of TCI and Cn values are used for VF discrimination from normal cardiac rhythms. MIT arrhythmia, AHA and the Creighton University ventricular tachyarrhythmia databases were used for the investigation and VF detection with a sensitivity of 75%.

Table 2. Comparison of methods based on feature extraction

Method	Sensitivity	Specificity	Accuracy	Reference
TCI-based algorithm	-	-	97.64%	(24)
TCSC	80.97%	98.51%	98.54%	(25)
PSR	83.8%	97.8%	-	(27)
CPLX	-	-	-	(47)
ACF	100%	64%-72%-100%	-	(48)
Multiway sequential hypothesis	-	-	-	(49)
SPRT	93%	-	-	(50)
Standard exponential algorithm	-	-	79%	(51)
Modified Exponential algorithm	56.49%	83.75%	-	(52)
Mean absolute value	92.31%	84.23%	-	(53)
Clinical considerations on ECG signals for patient monitoring system	98.1%	88.5%	-	(54)
Morphology consistency evaluation	92%	93%	93%	(55)
High-temporal resolution rhythm analysis	90%	90%	-	(56)
Digital filter band-pass with integer coefficients	95.93%	94.38%	-	(57)
QRS detection	-	-	-	(58)
adaptive threshold	95.77%	-	-	(59)
slope analysis	97.99%	-	-	(60)
sequential hypothesis testing	75%	-	-	(61)

5.2. Methods of transformation of time to frequency domain of signals.

Time-frequency processing and analysis is applied to signals with time-varying frequency content. These signals can be adequately represented by a time-frequency distribution, which can show the way in which the signal energy is distributed in the two-dimensional time-frequency space.

In Clayton et al. (62), it is defined a frequency domain algorithm where Fast Fourier Transform (FFT) is used for VF signal approximation to a sinusoidal waveform. The average interval of a fixed length of ECG signal are estimated by FFT so in the case that the data is close to a periodic signal, it will be canceled acting like a narrow band filter. The values that are not affected are considered as VF filter leakage. For this reason, it is necessary to find a suitable filter leakage value to detect VF in Malignant Ventricular Arrhythmia of MIT-BIH database, giving as a result of a sensitivity of 77% of VF detection with 0.515 leakage value, specificity and accuracy parameters are not used.

According to Sun et al. (63) wavelet transform is essential for a nonlinear descriptor (Hurst – index) algorithm that execute a wavelet transform and calculation of its coefficients at different scales, then Hurst index (H) which is a parameter that describes the fractal Brownian motion model useful for nonstationary stochastic self-similar processes with long term dependencies over wide ranges of frequencies. H is determined and finally the detection of the ventricular arrhythmia in the feature space of H is done. Authors used the MIT-BIH malignant ventricular arrhythmia database and obtain the following results: 83% of sensitivity and 84% of specificity when the length of ECG episode is of 1s of detection of VF between other ventricular arrhythmias.

In Amann (64) the use of Hilbert transform is the basis for the detection algorithm, that starts with the elimination of 50 Hz component of the ECG signals in order to remove noise. Then the convolution of the signal is done, after this the Fourier transform is applied to get a phase-space plot of the signal. VF signal have to have a d value (visited boxes/number of all boxes) higher than threshold. Creighton University ventricular tachyarrhythmia database was used to get the following results: 83.1% of sensitivity and 96.2% of specificity with a window length of 8 seconds detection of VF from other ventricular arrhythmias.

According to Lee and Lim (65) a Hilbert transform and phase space reconstruction algorithm is applied for VF detection, Hilbert transform extract the peaks from ECG signals, then with the help of statistical methods obtain four characteritics of the peaks (mean, median, average power and standard deviation. After that using Euclidean distance are extracted 4 characteristics more (mean, median, average power and standard deviation). Finally with the 8 characteristics a neural network with weighted fuzzy membership functions is trained and classify the signals from Creighton university ventricular tachyarrhythmia database and obtain a sensitivity of 76.37%, a specificity of 89.18% and an accuracy of 86.63% of detection VF signals.

A method of detection of VF is introduced by Balasundaram et al. (66) based of recognition of patterns in ECG signal and classification with help of wavelet transform of VF. The patterns were grouped into either local or global pattern. A local pattern is a variation that occurs as a result of a local depolarization and a global pattern occurs as a result over multiple depolarizations. Wavelet analysis is used to detect the occurrence of signal patterns during an arrhythmia segment in order to classify the signal as VF or VT. The proposed method achieved a detection accuracies of 73.3% of VF using MIT-BIH ventricular arrhythmia database.

In Prabhakararao and Manikandan (67) it is developed an algorithm using discrete cosine transform (DCT) based on noise suppression to distinguish VF from VT. The DCT filter the signal in order to remove the power line interference and with the help of an adaptive threshold the signal is smoothed of high frequencies components. After that the DCT coefficients are obtained and the reconstructed signal without noise remains. MIT-BIH arrhythmia, Creighton University VT, MIT-BIH malignant VT, the normal sinus rhythm, noise stress test and the ST change databases are used for the investigation and obtain results of VF detection with a sensitivity of 99.61% and specificity of 99.96%.

In Zheng et al. (68) an algorithm based on symbol entropy and wavelet analysis is an efficient way to detect VF. Wavelet transform decomposes a time series (ECG signal) into -segments of diverse frequency sub bands with different resolutions and symbol entropy have the ability to operate with essential features of the signal in different frequencies and VF and VT have components in low frequencies. MIT-BIH Malignant Ventricular Ectopy and Creighton University Ventricular Tachyarrhythmia databases were used with help of SVM to detect VF obtaining the following results: a sensitivity of 95.38% and specificity of 91.62% of detecting VF from other ECG signals.

According to Ebrahimzadeh and Pooyan (69), an algorithm of VF detection based on processing heart rate variability signal through the classical and time methods. The method starts with the analyzation of one minute of ECG signals prior the arrhythmias happens and the information is extracted for the hearth rate variability calculation. There are five features in time domain extracted from the HRV signal defined as classical linear features. After that Wigner Ville transform is applied to the HRV signal and causes that 11 new features in time-frequency domain are obtained. For this reason principal component analysis is used to facilitate the categorization of the signals and neural network classifies VF or normal cardiac rhythms. MIT-BIH Sudden Cardiac Death Holter and Normal Sinus Rhythm databases are used by the authors and VF detection occurs with an accuracy of 99.16%.

Table 3. Comparison of methods based on analysis of time-frequency

Method	Sensitivity	Specificity	Accuracy	Reference
Fast Fourier Transform	77%	-	-	(62)
Wavelet transform	83%	84%	-	(63)
Hilbert transform	83.1%	96.2%	-	(64)
Hilbert transform and phase space reconstruction	76.37%	89.18%	86.63%	(65)
Recognition of patterns in ECG signal and classification with help of wavelet transform	-	-	73.3%	(66)
Discrete cosine transform	99.61%	99.96%	-	(67)
Symbol entropy and wavelet analysis	95.38%	91.62%	-	(68)
processing heart rate variability signal through the classical and time methods	-	-	99.16%	(69)

5.3. Neural Networks

The scope of the functions of neural networks is wide, due to their operation, they can approximate any existing function with sufficient training. Neural networks are mainly used for prediction and classification tasks.

According to Cortina et al. (70), with the help of an Artificial Neural Network (ANN) Perceptron with 20 neurons for the hidden layer have a low differentiation rate between VF and VT. The procedure begins with noise removal of the ECG signal by filters (FIR, median), then an extraction of characteristics and information from the signal is executed. Finally, ANN in Malignant Ventricular Arrhythmia and AHA databases that contains ECG records from normal, VF, VT and other arrhythmias detect VF with a sensibility of 67.33% and a specificity of 76.55%.

In Mjahad et al. (71) claims that an algorithm based on an Adaptive Neural Network (ANNC) with two -hidden layers with 20 neurons on each layer. The process consist of three phases, starting with ECG filtering to eliminate the baseline noise, after that extraction of information with the help of the Hilbert transform and finally the classification is performed by ANNC. Authors used Malignant Ventricular Arrhythmia and AHA databases for the investigation obtaining results of VF detection between VT with a sensitivity of 95.56%, specificity of 98.80% and an accuracy of 98.19%

According to Rosado-Muñoz (72) said that a supervised Self-Organizing Maps (SOM) a neural network with two layers used to identify and visualize patterns in N-dimensional data sets. In the case of two patterns have similitudes with other in the original space, they will also be close in the output space. For this reason, VT and VF were overlapped in the hit map because VT is an early stage of VF. The registers studied were taken from AHA arrhythmia and Malignant Ventricular Arrhythmia databases, however the results were not expressed in percentage and evaluated in terms of sensitivity, specificity and accuracy.

In Castillo et al. (73) it is proposed the utilization of Convolutional Neural Network (CNN) with three layers where convolution layer extracts features of the data, pooling layer decrease the number of connections and fully connected layer make the classification procedure of the ECG signals. The authors took the ECG signals from Malignant Ventricular Arrhythmia database and determine that with a batch of 100 and learning rate of 0.1 CNN have the best validation accuracy.

According to Ibaida and Khalil (74) a Correlation Based Feature Selection on algorithm used to filter the unwanted attributes and select the most relevant attributes. After this step the selected attributes are used to train and classify VT and VF using Radial Basis Function (RBF) Neural Network and k-nearest neighbor (KNN) technique. RBF have neurons in the hidden layer calculate the Euclidean distance between the input and the weights vector to produce the output, and KNN is based It is based on choosing the training sample nearest to the testing point. MIT-BIH Malignant Ventricular Ectopy Database were used and get the following results: RBF have a sensitivity of 90.6% and a specificity of 80% and KNN have a sensitivity of 81.54% and a specificity of 86.84% of detection VF from VT signals.

In Picon et al. (75) is described an algorithm for VF detection based on convolutional neural network (CNN) and SVM. In the initial step CNN extract the high-level descriptors of the ECG signal, then this values are integrated in a Long Short-Term Memory that allows a temporal representation. Finally the classification step is done by SVM in order to detect VF of the LSTM based on features found in previous works such as: VF filter leakage and sample entropy. The information was taken from MIT-BIH Malignant Ventricular Arrhythmia and Creighton University Ventricular Tachyarrhythmia Databases and obtain results for VF detection with a sensitivity of 98.5%, a specificity of 99.4% and an accuracy of 99.2% for a window length of 4s; and a sensitivity of 99.7%, a specificity of 98.9% and an accuracy of 99.1% for a window length of 8s.

In Acharya et al. (76) presented a method for VF classification based on convolutional neural network. The information of ECG signals goes to CNN as input and then it is divided and transformed for the propagation through the network with the objective to achieve the last layer responsible of classification of VF or other arrhythmias signals. The performance of the algorithm is guaranteed by a 10 fold cross validation where the first nine parts of the signals are designed for training and the remain part for testing the CNN. The authors used MIT-BIH arrhythmia, MIT-BIH malignant ventricular arrhythmia and Creighton University tachyarrhythmia databases for VF detection with a sensitivity of 95.32%, a specificity of 91.04% and an accuracy of 93.18%.

In Mjahad et al. (77) a ECG signal classification using a Boltzmann network is described, that is useful for pattern identification and tries to restore non available information filling the missing parts of the signal. Thus the algorithm have the capability to classify two different pathology groups, and signal preprocessing with filtering and R wave detection is needed. The author used AHA and MITBIH Arryhtmia databases have the following results: have a sensitivity of 86.66% and a specificity of 98.44% of detection VF from VT.

According to Noruzi et al. (78), an algorithm based on correlation dimension discrimination of VF from VT can be achieved in a database of ECG signals. This technique consider ECG signals as chaotic systems where the trajectory of the signal is the state variable in which normal rhythms can be captured in plain of one or two dimensions, however VF occupies a cylindrical volume. After estimating the state variables, the correlation dimension feature is computed considering an optimal time for the study. Finally surrogate data that contains all the important features of the signals is created and an artificial neural network classifies the signals as VF or VT. MIT-BIH arrhythmia and Coronary Care Unit of Royal Infirmary of Edinburgh databases were used and detect the VF from VT with an accuracy of 91.10%, sensitivity and specificity values were not used in the investigation.

Table 4. Comparison of methods based on neural networks

Method	Sensitivity	Specificity	Accuracy	Reference
Artificial Neural Network	67.33%	76.55%	-	(70)
Adaptive Neural Network	95.56%	98.80%	98.19%	(71)
Supervised Self-Organizing Maps	-	-	-	(72)
Convolutional Neural Network	-	-	-	(73)
Correlation Based Feature Selection	90.6%-81.54%	80%-86.84%	-	(74)
Convolutional neural network (CNN) and SVM	98.5%-99.7%	99.4%-98.9%	99.2%-99.1%	(75)
Convolutional neural network	95.32%	91.04%	93.18%	(76)
Boltzmann network	86.66%	98.44%	-	(77)
Correlation dimension	-	-	91.10%	(78)

5.4. Empirical mode decomposition

According to Kaur and Singh (79) is described an algorithm using empirical mode decomposition and approximate entropy for discrimination of VF from VT. The process starts with the classification between VF and VT with the decomposition of the ECG signal into intrinsic mode functions using Empirical mode decomposition, then these are filtered by Butterworth band pass filter to remove the noise and finally approximate entropy parameter is used to classify VF and VT signals. MIT/BIH Creighton University Ventricular Tachyarrhythmia, MIT/BIH Malignant Ventricular Ecotype databases were used to obtain a 90.47% of sensitivity, 91.66% of specificity and an accuracy of 91.17% of detection VF from other ventricular arrhythmias

In Xia et al. (80) is described a method for classification of VF and VT based on the Lempel–Ziv complexity and empirical mode decomposition. Empirical mode decomposition first decomposed the ECG signals into a group of intrinsic mode functions (IMF) and after that Lempel-Ziv complexity of each IMF was used to select the VF from VT. MIT-BIH Malignant Ventricular Ectopy and Creighton University Ventricular Tachyarrhythmia Databases were used and get a sensitivity of 98.15%, a specificity of 96.01% and an accuracy of 97.08% of detection of VF from VT ECG signals.

The investigation proposed by Anas et al. (81) a sequential detection method to classify VF from other arrhythmias based on the mean absolute value of the ECG signal and specific low-order intrinsic mode functions (IMF) of the Empirical Mode Decomposition. The algorithm starts with a direct waveform quantification in order to discriminate VF from other ventricular arrhythmias. This quantification can be possible by the calculation of the mean absolute value of the signal, then we the IMF have the task to separate VF from VT due to the similitudes in the signal. Authors used MIT-BIH Arrhythmia, Creighton University Ventricular Tachyarrhythmia and MIT-BIH Malignant Ventricular Arrhythmia Databases to detect VF with a sensitivity of 86.49%, a specificity of 99.32% and an accuracy of 98.90%.

In Arafat et al. (82) was developed an algorithm using empirical mode decomposition and Bayes decision theory for VF detection. The empirical mode decomposition emphasize on the degree of orthogonality of the intrinsic mode functions (IMF) obtained from the decomposition of normal sinus rhythm and VF due to VF IMFs are closely orthogonal. For the classification the information taken from Boston's Beth Israel Hospital and MIT arrhythmia database is divided in two group (training and testing) using the Bayesian classifier in order to minimize the classification error probability. The results for VF detection with a window length of 3s have a sensitivity of 99.50%, a specificity of 99.90% and an accuracy of 99.70%.

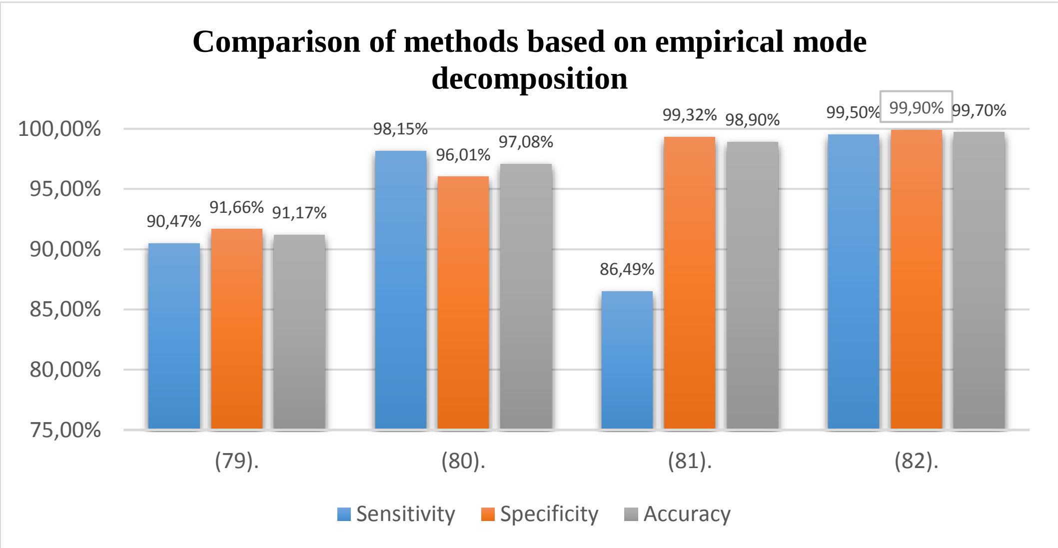

Figure 6. Comparison of methods based on empirical mode decompositions

5.5. Machine Learning

Machine Learning is a branch of Artificial Intelligence that creates systems that learn automatically, which gives them the ability to identify complex patterns in millions of data. The machine learns an algorithm that reviews the data and predicts future behavior, which implies systems that autonomously improve over time, without human intervention.

In Li et al. (83) was introduced a support vector machine (SVM) algorithm that works with two groups of information. A training group that it is used to evaluate the discrimination ability of the method and a second group of information that is used as inputs of the algorithm. The ECG signals were tested in a window of length of 3 seconds and then SVM 7classify if the signal is VF or VT. The authors used MIT-BIH arrhythmia and the Creighton University ventricular tachyarrhythmia databases for detection of VF with a sensitivity of 55.5% and a specificity of 99.5%.

According to Alonso-Atienza et al. (84), support vector machine (SVM) algorithm that classifies the ECG signals by the construction of N-dimensional hyperplane that optimally separates the data into two categories VF and non VF signals. The authors used MIT-BIH Arrhythmia, Creighton University Ventricular Tachycardia and MIT-BIH Malignant Ventricular Arrhythmia databases and get a sensitivity of 81% and specificity of 85% of detection VF from non VF signals.

In Li et al. (85) was used a support vector machine (SVM) algorithm in order to test the classification performance of several algorithm such as complexity measure, VF filter leakage, spectral analysis, time delay, and bandpass filter and auxiliary counts. SVM evaluate each technique with fivefold cross validation on the study database of ECG signals, this process was repeated 50 times in order to get an average of performance. The results showed that complexity measure have a 66% of sensitivity and 75 % of specify; VF filter leakage have 94% of sensitivity and 91% of specificity; spectral analysis have 79% of sensitivity and 93% of specificity; time delay method have 79% of sensitivity and 97.8% of specificity and bandpass filter have 94.4% of sensitivity and 95.9% of specificity in the detection of VF using MIT-BIH arrhythmia database.

A high-performance ventricular arrhythmias detection algorithm by combining different ECG detection methods described previously with the help of SVM was presented in Alonso-Atienza et al. (86). Thus SVM used the bootstrap resampling approach that makes a nonparametric estimation of the distribution of statistical magnitudes. Creighton University

Ventricular Tachycardia and MIT-BIH Malignant Ventricular Arrhythmia Databases were used to assess the algorithm proposed by the authors, and obtain the following results: TCI have a sensitivity of 49% and a specificity of 68%; PSR have a sensitivity of 74% and a specificity of 85%; CPLX have a sensitivity of 23% and a specificity of 47%; TSC have a sensitivity of 75% and a specificity of 92%; SE have a sensitivity 77% and a specificity of 90%; Hilbert transform have a sensitivity of 75% and a specificity of 80% and VF filter leakage have a sensitivity of 73% and a specificity of 89% in the detection of VF versus non VF ECG signals.

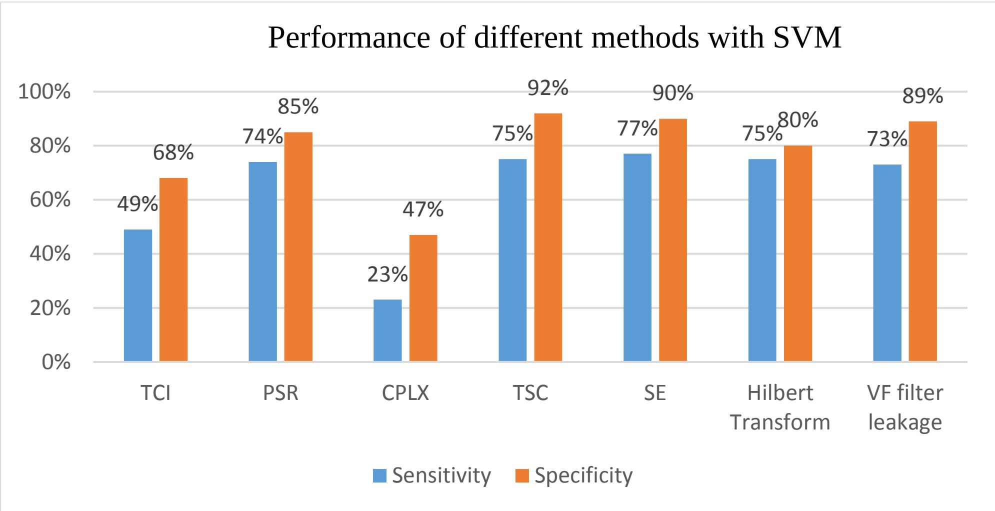

Figure 7. Summary of the detection performance of different methods with SVM

A multiclass classification was introduced by Alwan et al. (87), with SVM of VF from Heur8 and spectra parameters of database. Heur8 features consist in the sum of eight parameters such as: VF filter leakage, Count2, threshold crossing sample count, sample entropy, spectral parameter, spectral parameter A2, PST and PSH, that make up a 8-D representation space and spectra features are the absolute value of the discrete Fourier transform of ECG signals. European STT, Creighton University Ventricular Tachyarrhythmia Database, the MIT-BIH Arrhythmia and Malignant Ventricular Arrhythmia databases were used in order to get the following results: Heur8 parameters have a sensitivity of 73.4 % with a window length of 8s, spectra parameters have a sensitivity of 73.4% with a window length of 1 s and the combination of Heur8 and spectra parameters have a sensitivity of 79.8% of detection VF from other ECG signals.

According to Alwan et al. (88), an algorithm based on ensemble methods for SVM classification of arrhythmias which the local context information play an important role in cardiac rhythm classification and it is boosted by forming ensembles of classifiers temporally.

The main advantage that offers is that five cross-validation can be reduced to the minimum of three cross-validation. The methods tested in the article were Heur8 and spectra using the same databases as Alwan et al. (2015), and obtain the following results: Heur8 have a sensitivity of 73.6% with a window length of 8s; spectra have a sensitivity of 79.6% with a window length of 1s and the sum of Heur8 and spectra have a sensitivity of 80.7% of detection VF from other ventricular arrhythmias.

An algorithm based on the sum of signal processing and machine learning techniques was introduced by Ibtehaz et al. (89) with the objective to detect VF. The process if the signal was done with discrete Fourier Transform to study the impact of individual frequency bands that constitute the ECG signal and after the analysis it can be concluded if the signal is classified as VF based on the intrinsic mode function similarities present on the signal. After that support vector machines with the tool of random forest feature selection classify signals as VF or other arrhythmias. The MIT-BIH Malignant Ventricular Arrhythmia and Creighton University Ventricular Tachyarrhythmia Databases were used to work and detect VF with a sensitivity of 99.98%, a specificity of 98.40% and an accuracy of 99.19%.

In Hou and Zhang (90) was introduced an improved time domain algorithm combined with SVM. This algorithm is based on threshold crossing sample count and uses the information from Creighton University Ventricular Tachyarrhythmia and the MIT-BIH Malignant Ventricular Arrhythmia databases. The process starts with the division of information, in training ECG signals helpful for the construction of classifier model parameters; and the testing signals that evaluates the performance of the classifiers. Then the test signals are introduced to SVM and finally occurs the VF detection from VT. The results obtained for detection of VF have a sensitivity of 70.4%, a specificity of 99.5% and an accuracy of 98.4%.

According to Elhaj et al. (91), a VF recognition and classification using combined linear and nonlinear features of ECG signals. The article used 5 kinds of beat categories of heart disease such as: non-ectopic, supraventricular posture, bodily cavity posture, fusion and unidentiable and paced beats. The selection capability of nonlinear characteristics such as high order statistics and cumulates are combined with linear features. Finally SVM and neural network strategies with multiple cross-validation in MIT-BIH arrhythmia database detect VF with a sensitivity of 98.91%, a specificity of 97.85% and an accuracy of 98.91%.

In Kalidas and Tamil (92) was defined a method of VF detection based on power spectrum density and SVM. The procedure begins with a preprocessing of the ECG signal to remove the noise, then a feature vector is created with a window length of 4s where the features were derived from normalized power spectrum density analysis and autocorrelation plots. After that these features were used an input to SVM for the training and posterior discrimination of VF. Physionet Challenge training and test datasets were used for the ECG signals and obtain results of VF detection with a sensitivity of 94%.

In Zhang et al. (93)was developed a real-time detection of VF signals with SVM. First the ECG signal have to be processed to eliminate noise, then for every 4s sliding window, we distribute the signal in a 20x20 grid and reconstruct phase space for the feature extraction of the signal. Finally the features have to be introduced to SVM for the classification and is assigned 1 it is a normal signal and O for VF. BIH-MIT arrhythmia and Creighton University Ventricular Tachyarrhythmia databases were used for VF detection and obtain results with a sensitivity of 70.7% and a specificity of 85.3% in BIH-MIT database; and a sensitivity of 68.6% and a specificity of 85.1% in CU database.

In Jovanovic and Milenkovic (94) was presented an algorithm for VF detection based on a method for recognition of QRS complexes and identification of the segments executed by a finite state machine. QRS identification and peak localization is the first stage of the process for this reason the calculation of RR interval in the ECG signal is essential. Then the noise level estimation is necessary thus threshold values are defined in order to reject signals when they have a high level of noise. Finally VF detection is achieved by finite state machine that considers three conditions such as: irregular heart rhythm, small amplitudes and three successive RR intervals. Creighton University Ventricular Tachyarrhythmia database was used to detect VF with a sensitivity of 90.86%, a specificity of 91.50% and an accuracy of 91.34%.

In Figuera et al. (95) was described machine learning technique for VF detection. This method begins with ECG signals preprocessing, identification and division in successive segments, then for every segment thirty features (temporal, spectral, time-frequency and complexity features) were calculated. Then the information was divided in training and test groups approximately the 80% and 20% respectively. After that the parameters for the training stage suffer different steps such as: the tuning of the parameters of the distribution algorithms, feature election using bootstrap resampling and training the algorithms. Finally with the help of boosting that sum weak classifiers to improve the efficiency of the algorithm make the detection of VF signals. MIT-BIH Arrhythmia, MIT-BIH Malignant Ventricular Arrhythmia, Creighton University Ventricular Tachycardia and AHA databases were used in the investigation and showed a VF detection with a sensitivity of 96.6% and specificity of 98.8%.

An algorithm based on L2-Regularized Logistic Regression to detect VF was described by Mjahad et al. (96), that consists in the creation of model that let the prediction of values taken by a categorical variable with a binary nature. This method is useful for dependent variables or with binomial distribution. MIT BIH Malignant Ventricular Fibrillation and AHA standard databases were used in order to detect VF with a sensitivity of 91.54%, specificity of 98.45% and an accuracy of 97.15%.

An algorithm based on decision tree classifier was developed by Mohanty et al. (97) to detect VF. The method classifies ECG signals based on the peak of the signal and then goes to a leaf node based on discrete valued target function where learning is based on a decision tree. Then the algorithm create a decision tree where the value at that leaf node gives the predicted output for the instance with the prediction based on learning of inductive inference algorithms. These trees can be implemented as a set of if-then rules to improve the decision taking capability. The authors used CU ventricular tachyarrhythmia and MIT-BIH malignant ventricular ectopy databases and obtain the following results: a decision tree with a confidence factor of 0.5 have the capability of detection a VF signal with a sensitivity of 98%, a specificity of 99.32% and an accuracy of 99.23%.

In Mjahad et al. (98) was implemented an algorithm based on K nearest neighbors without parameter extraction for VF detection. KNN classifies a new vector applying a set of training then KNN looks for the K neighbors to the vector, then a valuation is made to the classes that this vectors belongs based on the distance between the different classes. The algorithms used in this assessment can be various: mahalanobis distance, distances using the delta function, distance cosine and Euclidean distance. Authors used MIT-BIH Malignant Ventricular Arrhythmia and AHA 2000 series databases to obtain VF detection with a sensitivity of 94.97%, a specificity of 99.27% and an accuracy of 98.47%.

According to Tripathy et al. (99), an algorithm for VF detection based on random forest classifier. The procedure begins with a variation mode decomposition to decompose the ECG signal into segments for an easy investigation of the ventricular arrhythmia. The feature extraction step relies in three different characteristics such as: energy, renyi entropy and the permutation entropy, these features are used to evaluate the signals for the VF discrimination. Finally these features are discriminated by a random forest classifier that relies on a set of trees of decision that have a training and testing phase in order to detect VF using the 5-fold cross-validation techniques. Creighton University ventricular tachyarrhythmia, MIT-BIH arrhythmia and MIT-BIH malignant ventricular arrhythmia databases are used and produce a detection of VF with a sensitivity of 96.54%, a specificity of 97.97% and an accuracy of 97.23%.

Table 5. Comparison of methods based on machine learning techniques

Method	Sensitivity	Specificity	Accuracy	Reference
Support vector machine	55.5%	99.5%	-	(83)
Support vector machine	81%	85%	-	(84)
Support vector machine	66%-94%-79%-79%-94.44%	75%-91%-93%-97.8%-95.9%	-	(85)
Support vector machine	49%-74%-23%-75%-77%-75%-73%	68%-85%-47%-92%-90%-80%-89%	-	(86)
SVM of VF from Heur8 and spectra parameters	79.8%-73.4%	-	-	(87)
Ensemble methods for SVM classification	73.6%-79.6%-80.7%	-	-	(88)
Sum of signal processing and machine learning techniques	99.98%	98.40%	99.19%	(89)
Improved time domain algorithm combined with SVM	70.4%	99.5%	98.4%	(90)
Combined linear and nonlinear features of ECG signals	98.91%	97.85%	98.91%	(91)
Power spectrum density and SVM	84%	-	-	(92)
Real-time detection of VF signals with SVM	68.6%	85.1%	-	(93)
Recognition of QRS complexes and executed by finite state machine	90.86%	91.50%	91.34%	(94)
Machine learning technique	96.6%	98.8%	-	(95)
L2-Regularized Logistic Regression	91.54%	98.45%	97.15%	(96)
Decision tree classifier	98%	99.32%	99.23%	(97)
K nearest neighbors without parameter extraction	94.97%	99.27%	98.47%	(98)
Random forest classifier	96.54%	97.97%	97.23%	(99)

5.6. Electronic devices of detection

Healthcare devices are designed to collect the data of users and notify in the case of an abnormal situation is registered.

A detection algorithm Implemented in a Cell-Phone Platform was proposed by Rospierski et al. (100) that finds QRS complexes in the ECG signals using a band-pass filter to eliminate the low frequency components and recognize VF episodes by the measurement of a cardiac rate. If a VF case is found, cell phone will send a message for immediate help to a registered phone number. The algorithm was probed with MIT-BIH Malignant Ventricular Arrhythmia Database and with an average time of 79.65 milliseconds VF was recognized from other heart diseases.

In Krasteva et al. (101) was described an algorithm for VF detection based on the use of a module sensitive to shockable arrhythmia that continuously scan in intervals of four seconds. The process starts with ventricular rate (VR) calculation calculated from the location of periodic peaks of the signal and the phase space number estimation of the area of the ECG curve in a 2D phase space map of time shifted signals. VF detection is achieved when a signal have a VR value higher than 180 beats per minute and phase space number higher than 200. Authors used MIT-BIH Supraventricular Arrhythmia and MIT-BIH Arrhythmia databases to obtain a VF detection with a sensitivity of 78%.

According to Kwon et al. (102), a real-time VF detection using an embedded microcontroller. The procedure begins with the adoption of an interrupt service routine (ISR) to decrease the power consumption, then the microcontroller where is embedded ECG module to filter, process and detect VF patterns on the signals. Finally a step of adaptation of detection techniques (TCI, TCSC, VF filter leakage) for the microcontroller discrimination of VF. MIT-BIH and Creighton University Ventricular Tachyarrhythmia databases were used and detect VF with a sensitivity of 64.45% and a specificity of 78.05%.

An algorithm was proposed for VF detection by Brian et al. (103) which a computationally efficient way using a set of ECG features. The process stars with noise elimination of the ECG signal with a bandpass filter, then the feature extraction have to be as simple as possible in order to maintain a low complexity and high accuracy, these features are QRS, T and P width; TP, RR and PR intervals of the ECG signals. After that the classification is executed by a single bit classifier with the feature set as input based on the heart rate in order to detect VF or other arrhythmias. The databases used were obtained from MIT Physionet ATM and detection of VF were based on a heart rate between 60-80 beats per minute; QRS, T and P width of 90, 160, 80 milliseconds respectively; and RR and PR interval of 1.2 s and 75 milliseconds respectively.

In Fokkenrood et al. (104) was claimed that VF can be detected by an algorithm that relies on a 24/7 personal wireless heart monitoring system. The monitoring system uses a Bluetooth biosensors and with help of smart phones to supervise continuously cardiac patients vital signs. The main advantage is to minimize false alarms based on QRS complex identification and efficient processing for ECG signals to avoid waste of battery power of the smartphone. MIT-BIH arrhythmia and MIT-BIH malignant ventricular arrhythmia databases are used to extract the signals and obtain a VF detection with a sensitivity of 97%, a specificity of 98% and an accuracy of 98%.

Table 6. Comparison of methods based on electronic devices

Method	Sensitivity	Specificity	Accuracy	Reference
Implemented in a Cell-Phone Platform	-	-	-	(100)
Module sensitive to shockable arrhythmia	78%	-	-	(101)
Using an embedded microcontroller	64.45%	78.05%	-	(102)
Computationally efficient way using a set of ECG features	-	-	-	(103)
24/7 personal wireless heart monitoring system	97%	98%	98%	(104)

5.7. Other methods

In Xie et al. (105) was mentioned that approximate entropy based on fuzzy membership function algorithm has the ability to detect VF. Fuzzy sets define that means of characterizing input–output relations in an environment of imprecision. The addition of membership degree with a fuzzy function makes that each point x is relater with a real number in the classification of zero or one, providing a method for measuring the degree to which a pattern belongs to a given class: VF or VT. The results show that this method have a sensitivity of 91.84% and a specificity of 90.2% of detection VF using MIT-BIH databases.

An algorithm based on knowledge discovery in databases (KDD) for VF detection was described by Calderon et al. (106), that relies on the storing, transforming and analyzing the information of ECG signals. Thus it is a process that involves the participation of the end-user in each phase, the first step is a proper data selection, followed by a preprocess data and finally a model building is achieved that are able to distinguish VF from other ventricular arrhythmias with the help of SVM. The authors used Sudden Cardiac Death Holter and Fantasia databases and obtain results of detection VF with a sensitivity of 93%, a specificity of 84% and an accuracy of 89% of detection VF from other ventricular arrhythmias.

In Rohani Sarvestani et al. (107) was described a method for VF discrimination from VT using trajectory analysis in the state space. The procedure start with signals diagramed in the state space using the delay time method. After that, the state space is treated as a picture and trajectories of VT and VF signals are considered as two distinct images. The aim of the algorithm is to create various filter in order to use them on the images to discriminate the filtered images by a box counting method. These filters are produced to eliminate the irrelevant information between the two pictures and just distinct pixels are stored, then the stored pixels are counted and a threshold is established for the classification of VT and VF trajectory images. The ECG signals were taken from MIT/BIH and Coronary Care Unit of the Royal Infirmary of Edinburgh databases and provide a VF detection with an accuracy of 100% from VT. This work does not report results based on sensitivity and specificity.

According to Zhang et al. (108), a method based on fuzzy network to detect VF from VT. The procedure begins with the extraction of the ECG signal from the Creighton University Ventricular Tachyarrhythmia database, then the signals are divided in segments of 8 seconds and a preprocessing is done in order to select the signals with the help of a threshold value where the values greater than threshold are directly determined as VF or VT. The signals with lower value than the threshold, a wavelet transform is applied to remove noise and then feature extraction is done by phase space reconstruction and peak number method. Finally these features are used as input for training and testing of the neural fuzzy network for the discrimination of VF from VT. The results of detection of VF have a sensitivity of 93%, a specificity of 93% and an accuracy of 92%.

An algorithm for VF detection using interval type-2 TSK fuzzy system classifier was proposed by Phong et al. (109) which is applied to distinguish normal cardiac signals, VF and VT. The procedure starts with a fuzzyfier stage where the QRS complex and the average period of ECG signal are the inputs and categorize the signals in groups such as small, medium and large. Then the rule base of type-2 TSK fuzzy system is made of training data, and using fuzzy C-mean clustering and back-propagation the parameters are determined for the investigation.

Finally generalized bell primary membership function is allow to evaluate the classification of the signals. MIT-BIH Malignant Ventricular Arrhythmia database was used and the detection of VF signals from normal signals and VT have a 93.3% of accuracy.

In Othman et al. (110) was developed a semantic mining approach algorithm for detecting VF from VT signals. The method starts with the information extracted from Creighton University Ventricular Tachyarrhythmia database and a filtration of the ECG signal is applied to remove noise and a binary decomposition as preprocessing stage. Then parameters extraction happens based on natural frequency, damping coefficient and input parameter as features for VF detection. Finally semantic miming monitors the behavior of the three parameters defined in order to obtain the mean amplitude to discriminate VF from VT with a sensitivity of 95.2% and a specificity of 97.4%.

Table 7. Comparison of methods based on other methods

Method	Sensitivity	Specificity	Accuracy	Reference
Fuzzy membership function	91.8%	90.2%	-	(105)
Knowledge discovery in databases	93%	84%	89%	(106)
Trajectory analysis	-	-	100%	(107)
Fuzzy network	93%	93%	92%	(108)
Type-2 TSK fuzzy system classifier	-	-	93.3%	(109)
Semantic mining approach	95.2%	97.4%	-	(110)

6. DISCUSSION

The bibliographic review of the several existing methods for the detection of ventricular fibrillation have undergone an important evolution, starting with algorithms based on the recognition of characteristics or patterns of ECG signals (feature extraction) until methods based on electronic devices. Feature extraction detection methods have been widely used due to the practicality of their operation, although they give uneven results and give rise to many errors. This is caused due to the disorganized nature of the heart rhythm of ventricular fibrillation that can be confused with signal noise.

The morphology consistency evaluation algorithm is the method of detection based on feature extraction with the best results in terms of sensitivity, specificity and accuracy with a 92%, 93% and 93% respectively (55). The reason of this values is that VF classification method is not sensitive to chest compression artifacts and detect VF from sinus rhythm when cardiopulmonary resuscitation is performed. The second detection method is ACF that shows a high percentage of identification of VF among VT evaluating three consecutive periods of 1.5 seconds of ECG recordings, showing 100% sensitivity but an initial specificity of 64% increasing to 72% and 100% at the third ECG recording (48). Modified Exponential algorithm based on TCI has the lowest sensitivity of 56.49%, since the number of crosses between the ECG signal and a decreasing exponential curve is similar in several arrhythmias (52).

In the case of methods that are based on the analysis of signals in time-frequency, they are used in order to convert the signal to the frequency plane. Then, the noise can be eliminated and the signal can be studied in detail by frequency band and thus obtain a greater amount of information, which will help us to determine if a signal is ventricular fibrillation or not based on the approximation to sinusoidal signals.

The algorithm developed using discrete cosine transform, between the methods of conversion in time and frequency, shows the best results in sensitivity and specificity due the ability to compress the signal has a high degree of spectral compaction. This means that tends to have more of its energy concentrated in a small number of coefficients when compared to other transforms with a sensitivity of 99.61% and specificity of 99.96% (67). VF detection methods that use the Wavelet transform show better results in sensitivity compared to the Fourier transform with 83% (63) and 77% (62) respectively, because the wavelet analysis performs better in non-periodic signals and Fourier gives us little information as there is a significant loss of temporary information.

Detection methods based on feature extraction and time-frequency analysis can improve their performance by verifying the results they present either when going through a stage of classification by neural networks or machine learning techniques. Both neural networks and machine learning techniques are characterized by self-learning based on training information, which consists of data from ECG signals that will allow the algorithm to identify the parameters that ventricular fibrillation signals must have and then enter our data to the study algorithm that is able to classify ventricular fibrillation signals without problem.

In the case of neural networks, adaptive neural networks present better performance since they have the ability to process large amounts of information and parameters at the same time, which facilitates the detection of ventricular fibrillation signals with a sensitivity and specificity of 95.56% and 98.80% respectively (71), due to the fact that they have the ability to adapt to changes that occur in the input information and it significantly reduces errors and processing time for large data sets and results in faster results. On the other hand, detection method based on a convolutional neural network and a support vector machine presents better results than an adaptive neural network with a sensitivity of 99.7% and a sensitivity of 98.7% (75). This is because to the fact that the information that the neural network processes and classifies as fibrillation ventricular then goes through the support vector machine which confirms that a good detection has been made and the existing errors are eliminated.

In Machine learning detection techniques, the most recurrent by researchers are the support vector machines due to it is efficient handling large data sets based on the generation of subset of data for training or learning that guarantees a proper classification of information.

Ventricular fibrillation detection methods that are based on the use of SVM perform better depending on the pre-processing phase of the algorithm. Such is the case of algorithms that use feature extraction such as TCI, CPLX, which are methods that present a high number of errors in the detection of ventricular fibrillation, which is reflected in the results in terms of sensitivity with 49% and 23% respectively and with a specificity of 68% and 47% (86). However, in the case of more robust methods, such as the algorithm based on the sum of signal processing techniques and machine learning, there will be adequate detection of ventricular fibrillation with values of a sensitivity of 99.98%, a specificity of 98.40 % and an accuracy of 99.19% (89). This occurs because the signal is pre-processed by the Fourier transform for a detailed study of the frequency bands of the ECG signal and then SVM with the help of the forest features random selection tool recognizes the most important variables that provide information, to finally average the prediction results of each of these variables.

Methods of detection based on Empirical Mode Decomposition shows the best results because it removes noise from ECG signals, decomposing the noise in oscillatory components (Intrinsic mode functions) that is filtered by a threshold filter and gives the signal with a minimum amount of noise. The average sensitivity of this method is 93.65%, the best method is based on EMD with Bayes decision theory with a 99.50% (82) and mean absolute value of the ECG signal and specific low-order intrinsic mode functions with an 86.49% (81) shows the lowest performance. In the case of specificity EMD with Bayes decision theory with 99.90% (82) have the best yield and EMD and approximate entropy with 91.66% (79) have the lowest values.

A little-explored branch is the detection methods that are based on electronic devices such as microcontrollers, cell phones, wearable devices, biosensors and applications, which present approximations of ECG signals with ventricular fibrillation based on the presence of RR intervals, QRS complexes, heart rhythms, for which in the greatest number of investigations they cannot be evaluated in terms of sensitivity, specificity and precision such as (100) and (103). The algorithm that relies on a 24/7 personal wireless heart monitoring system uses a Bluetooth biosensors and with help of smart phones to supervise continuously cardiac patients vital signs with a sensitivity of 97%, a specificity of 98% and an accuracy of 98% (104).

Among the methods that could not be classified in a category due to the limited amount of information available, the method with the best performance is the one based on fuzzy network to detect VF from with results of detection of VF have a sensitivity of 93 %, a specificity of 93 % and an accuracy of 92 % (108).

7. CONCLUSIONS

The main conclusions of the present work are:

Ventricular fibrillation is a cardiac arrhythmia that if it is detected at an early phase can decrease the risk of a sudden death giving the opportunity to doctors to control the patient in an efficient way; however, in most cases the nature of this disorder is asymptomatic and it is final stage of prevalent heart diseases.

A pre-processing stage of the signals is required, which consists of filtering the ECG signals to remove the noise that can be caused by movements of the individual during the recording of the signal or a bad positioning of the electrodes in order to use the essential part of the signal and avoid wasting time in additional calculations.

Most ventricular fibrillation detection methods use the following databases: MIT-BIH Malignant Ventricular Arrhythmia and Arrhythmia databases and the Creigton University Ventricular Tachyarrhythmia database to check the operation of the algorithms proposed because they contain records of hospital patients and that include both men and women of different age groups.

Threshold crossing interval is the ventricular fibrillation detection method that has served as the basis for other methods such as: threshold crossing sample count, phase space reconstruction, VF filter leakage, and modified exponential algorithm. This occurs because a threshold value is established based on the amplitude of the peaks of the ECG recordings every second at which it is compared with the information we have to classify a signal as normal or arrhythmia.

Neural networks are a method used to classify ECG signals in the different types of arrhythmias, for which it is necessary that a considerable amount of information be allocated in the training phase so that detection is as reliable as possible. Also, if the neural network has a greater number of layers, it will allow the handling of large amounts of information.

About the ventricular fibrillation detection methods that are based on the use of prototypes and electronic devices, they have few advances in research. Also, the vast majority of results that they present are not evaluated in terms of sensitivity, specificity and precision, since the detection of ventricular fibrillation is related to the number of beats per minute, the presence or absence of QRS complexes in the ECG signal and heart rhythm values.

8. RECOMMENDATIONS

When carrying out the scientific search, it is recommended that it be done in valid bibliographic databases and relevant journals, since recent and verified information can be found, which gives us the certainty of avoiding the publication of erroneous information.

Continuing research is recommended, since a guide may be written in the future detailing the existing methods for ventricular fibrillation, which can be updated each year by Biomedical Engineering students.

It is recommended that the results presented by researched articles be evaluated based on sensitivity, specificity and precision, which will facilitate the contrast between the various methods studied.

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