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SURVEY ON COMPUTER PROGRAMS AND METHODS FOR HEART DISEASES PREDICTION AND CLASSIFICATION

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ABSTRACT

This paper presents several approaches carried out for the prediction, risk assessment of heart diseases such as Coronary Artery Disease (CAD), Congestive Heart Failure, Myocardial Infarction (MI). Researchers of applied soft computing, image processing, data mining has taken strenuous efforts in prediction, risk assessment and classification of cardiac diseases. The paper thoroughly reviewed their contribution and several cross functional research dimensions.

Keywords: congestive heart failure, coronary artery disease, heart rate variability.

1. INTRODUCTION

A number of different tests are used to diagnose heart-related problems, including:

- Electrocardiogram (ECG)
- X-rays
- Echocardiogram
- Blood tests
- Coronary angiography
- Radionuclide tests
- Magnetic resonance imaging (MRI) scans
- Computerized tomography (CT) scans

Electrocardiogram (ECG)

An ECG records the rhythm and electrical activity of your heart. A number of electrodes (small, sticky patches) are put on your arms, legs and chest. The electrodes are connected to a machine that records the electrical signals of each heartbeat.

Although an ECG can detect problems with your heart rhythm, an abnormal reading does not always mean there is anything wrong. Similarly, a normal reading does not always rule out heart problems.

In some cases, you may have an exercise ECG test, or "stress test". This is when an ECG recording is taken while you are exercising (usually on a treadmill or exercise bike). If you experience pain while exercising, the test can help identify whether your symptoms are caused by angina, which is usually due to CHD.

X-rays

An X-ray may be used to look at the heart, lungs and chest wall. This can help rule out any other conditions that may be causing your symptoms.

Echocardiogram (echo)

An echocardiogram is similar to the ultrasound scan used in pregnancy. It produces an image of your heart using sound waves. The test can identify the structure, thickness and movement of each heart valve and can be used to create a detailed picture of the heart.

During an echocardiogram, you will be asked to remove your top and a small handheld device called a transducer will be passed over your chest. Lubricating gel is put onto your skin to allow the transducer to move smoothly and make sure there is continuous contact between the sensor and the skin.

Blood tests

In addition to cholesterol testing, you may need to have a number of blood tests to monitor the activity of the heart. These may include cardiac enzyme tests, which can show whether there has been recent damage to the heart muscle.

Coronary angiography

Coronary angiography, also known as a cardiac catheter test, can identify whether the coronary arteries are narrowed and how severe any blockages are. It also provides information about the pressure inside your heart chambers and how well your heart is functioning.

In an angiogram, a catheter (flexible tube) is passed into an artery in your groin or arm and guided into the coronary arteries using X-rays. A dye is injected into the catheter to show up the arteries supplying your heart with blood. A number of X-ray pictures are taken, which will highlight any blockages. It is usually performed under local anaesthetic.

A coronary angiogram is relatively safe and serious complications are rare. The risk of having a heart attack, stroke or dying during the procedure is estimated at about one or two in every 1,000. However, after having a coronary angiogram you may experience some minor side effects, including:

- a slightly strange sensation when the dye is put down the catheter
- a small amount of bleeding when the catheter is removed
- a bruise in your groin or arm

Radionuclide tests

Radionuclide tests can indicate how strongly your heart pumps and show the flow of blood to the muscular walls of your heart. Radionuclide tests provide more detailed information than the exercise ECG test.

During a radionuclide test, a small amount of a radioactive substance called an isotope is injected into your blood (sometimes during exercise). If you have difficulty exercising, you may be given some medication to make your heart beat faster. A camera placed close to your chest picks up the radiation transmitted by the isotope as it passes through your heart.

Magnetic resonance testing (MRI)

An MRI scan can be used to produce detailed pictures of your heart. During an MRI scan, you lie inside a tunnel-like scanner that has a magnet around the outside. The scanner uses a magnetic field and radio waves to produce images.

Computerized tomography (CT) scan

A CT scan uses X-rays and a computer to create detailed images of the inside of your body. During a CT scan, you lie on a bed while a small tube that takes X-rays moves and rotates around your body.

2. RELATED WORKS

Coronary Artery Disease (CAD) is a condition wherein plaque deposits in the inner walls of the coronary arteries. When these arteries narrow down due to the deposit, the amount of blood flow and oxygen supply to vital organs becomes reduced, and eventually, angina and heart failure occur. It is a disease with a very high mortality rate. Unfortunately, in the early stages of this disease, there are generally no symptoms. Therefore, screening and monitoring of the progress of this condition is the best way to detect and treat it, and thereby, reduce the mortality rate.

There are several clinically tried and tested techniques to detect the presence of CAD [Brubaker *et al.* 2001, San Roman *et al*. 1998, Zhonghua and Multislice., 2010, Moudi *et al.* 2011, Alizadehsani *et al.* 2013. Invasive coronary angiography is the gold standard technique for CAD diagnosis. However, in this technique, the catheter that is inserted as part of the examination might pierce an artery or may remove some plaque from the artery walls and result in embolism, and therefore, increase the risk of stroke. One of the most commonly practiced non-invasive techniques for CAD detection is the Exercise Stress Test (EST). However, EST has limited use as most patients will not be able to reach the heart rate required for this test (Brubaker *et al.* 2001) and also EST recorded less sensitivity of 66% for CAD detection (San Roman *et al.* 1998). Other techniques include Single-Photon Emission Computed Tomography (SPECT), Positron Emission Tomography (PET), and multi-slice Computed Tomography (CT) (Zhonghua and Multislice., 2010). Moudi *et al.* (2011) conducted a systematic review of published studies to investigate the diagnostic value of SPECT, PET, and PET/CT in CAD detection. The study reveals the following mean values of sensitivity, specificity and accuracy of these imaging modalities: 82%, 76%, and 83% for SPECT; 91%, 89%, and 89% for PET; and 85%, 83%, and 88% for PET/CT. However, most of these techniques use radioactive material which restricts repeated examinations. Other limitations include higher cost and time of examination. Therefore, efficient, inexpensive, radiation-free, fast and safe non-invasive techniques are needed to diagnose CAD.

The Heart Rate Variability (HRV) technique measures beat to beat intervals in the heart rate [Garcia-Gonzalez *et al.* 2013], and it has been used to diagnose several cardiovascular and non-cardiovascular diseases (Isler and Kuntalp, 2007; Acharya *et al.* 2004). Compared to healthy subjects, the time and frequency domain measures of HRV have been found to be lower in CAD patients (Bigger Jr *et al.* 1995). However, these measures may not always classify normal and CAD cases accurately as they are sensitive to noise. Studies that have developed techniques with the assumption that the cardiac system is nonlinear have demonstrated that nonlinear parameters derived from HRV help detect the presence of CAD (Kim *et al.* 2007; Lee, Kim and Noh *et al.* 2009; Lee, Noh and Ho *et al.* 2009).

Coronary arteries supply nutrients and oxygen to heart muscles. Coronary Artery Disease (CAD) is a pathological condition where the diameter of the arteries decreases either due to the formation of cholesterol plaque on its inner wall (Steinberg and Gotto., 1999) or due to the contraction of the whole wall for other reasons, such as tobacco smoking (Ockene *et al.* 1990) and environmental pollution (Brook *et al.* 2004). The condition is often ominously silent, but progressive in nature. If it is not treated appropriately, it will eventually lead to ischemia (i.e., interruptions of blood supply) and then infarctions (i.e., the complete loss of blood supply). Usually one of the reasons for Sudden Cardiac Death (SCD) is CAD (Thompson and Levine, 2006). Hence, early detection of CAD is essential to prevent SCD. One of the most commonly used techniques for CAD detection is the Exercise Stress Test (EST). EST increases the workload of the heart and records exaggerated electrophysiological information. For this test to be accurate, a target Heart Rate (HR) has to be attained. Not all CAD patients can reach this rate. Furthermore there is considerable risk for the patient, because such a stress test can trigger Ventricular Tachycardia (VT) or cardiac arrest (San Roman *et al.* 1998).

Electrocardiogram (ECG) could be a useful physiological measurement tool to detect the presence of CAD. However, visual interpretation of the ECG signals is not so effective as 50–70% of CAD patients do not show any notable difference in their ECGs (Silber and Katz., 1975). However, the minute variations in the ECG signals have to be identified in order to diagnose specific type of heart disease. Due to the presence of noise and baseline wander, it is tedious to detect the minute variations by evaluating the morphological features of ECG signals. Hence, in this study, we extracted the HR from the ECG signals and used them for analysis. The study of heart rate variability (HRV) is a better technique to diagnose CAD risk levels. HR is a nonlinear, non-stationary signal which indicates the subtle variations of the underlying ECG signal (Acharya *et al.* 2004). The HRV evaluates the changes in the consecutive heart rates and it assesses the health of the autonomic nervous system (ANS) non-invasively. The HRV analysis conveys information about homeostasis of the body (Lombardi, 2000). Standard methods to analyze the HRV were proposed in various domains (Members of Task Force, 1996).

Various cardiac and non-cardiac diseases have been diagnose during HR signals (Acharya *et al.* 2004, Isler and Kuntalp., 2007; Schumann *et al.* 2002; Gujjar *et al.* 2004; Carney *et al.* 2000). They have analyzed the HR signals using various linear and non-linear techniques (Acharya *et al.* 2004) also they have analyzed the CAD subjects using HRV signals and showed that, the circadian rhythm decreases in CAD subjects. Hayano *et al.* 1990 have shown a correlation between CAD severity and a reduction low-frequency power reduction decrease in high frequency power were shown in CAD subjects (Lavoie *et al.* 2004, Nikolopoulos *et al.* 2003) and features of time and frequency domain were found to be lower for CAD subjects (Bigger Jr *et al.* 2003). The statistical measures changes with time and hence time domain analysis is not effective and effectiveness of frequency domain analysis decreases with reduction in the signal to noise ratio (Acharya *et al.* 2006). Nonlinear techniques are more in tune with the nature of physiological signals and systems, therefore, they outperform time and frequency domain methods. Hence, they are widely used in many biological and medical applications (Acharya *et al.* 2003, Fell *et al.* 2000). Owis *et al.*, (2002) performed ECG-based arrhythmia detection and classification based on nonlinear modeling. Sun *et al.* (2000), Acharya *et al.* (2007) and Chua *et al.* (2008) used nonlinear techniques to analyze cardiac signals for the development of cardiac arrhythmia detection algorithms. Schumacher (2004) elaborated the effectiveness of linear and nonlinear techniques in analyzing HR signals. The onset of various cardiovascular diseases like, Ventricular Tachycardia (VT) and Congestive Cardiac Failure (CCF) can be predicted using non-linear analysis of HR signals (Cohen *et al.*1996). Chua *et al.*2006 introduced a method to extract features like bispectral entropy from HR signals by employing Higher Order Spectra (HOS) techniques. In their study, HOS features from HR signals were used to differentiate between a normal heart beat and seven arrhythmia classes. CAD results in reduced Baroreflex Sensitivity (BRS) and reduced vagal activity which can be understood by HRV analysis. BRS is an indicator of increased risk of SCD in myocardial infarction patients. Arica *et al.* (2010) used HR and systolic pressure signals to assess BRS.

Some heart diagnosis systems (Andreao., 2004, Anuradha., 2005, Li *et al.*2007, Taddei and Constantino., 1995, Izabel *et al.*2008, Afsar *et al.*2008) are based on computer algorithms that use signal processing techniques for the interpretation of the electrocardiogram characteristics, thus allowing preliminary diagnosis of a cardiopathy. Andreao (2004) proposed the multi-channel beat detection and segmentation, waveform models and unsupervised patient adaptation method used to detect ischemia. It demonstrates the use of segmentation for the data analysis in the signal processing. It uses the same ECG data bank and the same sensitivity and positive prediction as in our work. Heuristic rules provided by cardiologists are used as knowledge base. On the other hand, (Anuradha, 2005) introduces a cardiac arrhythmia classification system using fuzzy classifiers, that uses artificial intelligence algorithms and a knowledge base to classify arrhythmias. Li *et al.* (2007) detects specific points of the electroencephalogram (segment ST) using network-based fuzzy interferences and a MIT-BIH (Moody and Mark, 2001) knowledge base to classify the segment forms and thus provide the diagnosis of few cardiac illnesses. Those works provide detection mechanism by comparison of the signal with a databank.

The importance of filtering on the ECG signal was provided Li *et al.* 2010. It also uses two combined research methods; the fast Fourier transform (FFT) and the wavelet threshold de-noising (WTD) to demonstrate the importance of real time processing. That work was validated in a field programmable gate arrays (FPGAs). Yutana and Prabhas (2010) shows an ECG signal classification system using neural network that was implemented in hardware. It demonstrated the portable hardware implementation using FPGA.

Armato *et al.* (2009) presents a system that extracts and performs real time analysis of the QRS complex to indicate the presence of a cardiopathy that was also implemented in FPGA. ECG QRS complex detection using an adaptive lifting scheme (ALS) on a MIT-BIH database is also implemented in FPGA by Yan et al., 2010.

The filter is among the most relevant component in an ECG signal processing (Li *et al.* 2010), and it is used also to identify and to classify the signal. It is necessary the use of filters in the ECG input signal, so that the GK fuzzy cluster algorithm (Gustafson and Kessel, 1978) can be conducted later. The cluster algorithm consists basically of adapting the rule sets technique. In other words it is the process of grouping a set of rules, real or abstract objects into sets of rules or similar objects (Rich and Knight, 1993; Russell and Peter, 2004). The technique is adapted to identify points that describe the main features of an electrocardiogram signal. The signal processing becomes restricted to those points, thus reducing the number of data to be processed, which in turn simplifies the hardware implementation. Nevertheless, artificial intelligence techniques have been used to identify and to classify the ECG signal (Yutana and Prabhas, 2010; Phong and Thien 2009).

The fuzzy sampling algorithm extracts the most relevant aspects of the ECG signal (Baraldi and Blonda, 1999), thus significantly reducing the amount of date to be analyzed, without loss of important information. It is a great advantage on an embedded system since it requires less computational effort. By using the correlation technique (Bendat and Piersol, 1993; Cintra *et al.* 2006), the ECG signal is compared with other previously sampled signals located in the system memory. The comparison provides the similarity factor between the ECG signal and the previously diagnosed data bank signals (Goldberger *et al.* 2000). The comparison offering the largest factor is recognized as a possible patient diagnosis. Other metrics such as conventional Euclidean distance or Kullback–Leibler could also be used, but the results are similar.

Heart rate variability (HRV) is a widely used tool for studying the role of cardiovascular diseases and affliction influences. Recently, numerous studies have focused on using HRV measurements for diagnosis purpose, especially in recognizing congestive heart failure (CHF) from normal sinus rhythms (NSR) (Asyali., 2003; Isler and Kuntalp, 2007; Melillo *et al.* 2011). CHF is an omen of cardiac morbidity, which is a dysfunction of the cardiovascular system that the heart is unable to drain the blood away. CHF usually accompanies with chest tightness, abdominal swelling, and hard breathing. However, the patients usually do not suffer from pain in daily life such that the symptoms may be ignored. The optimal subset of features is usually unknown and it is common to have irrelevant or redundant features at the beginning of the pattern classification tasks. To tackle this problem, two main dimension-reduction approaches, namely feature extraction and feature selection, are usually applied (Jain *et al.* 2000).

Feature extraction creates new features based on transformation or weight combination of the original feature set. On the contrary, feature selection refers to methods that select the best subset of features from the original feature set. Feature selection can be further categorized into filters and wrappers (Kohavi and Pfleger., 1994). A filter involves a predefined performance measure which is independent of the subsequent classifier. Alternatively, a wrapper requires a specific learning machine and refers its classification accuracy as a performance measure to search for an optimal feature subset. Although wrappers usually produce better accuracy than filters, they are criticized as being computational extensive and over-fitted only for specific classifiers. Consequently, filters are usually preferred to wrappers.

A number of measures, such as distance (Dash and Liu, 1997; Bins and Draper, 2001), correlation (Hall, 1999), and mutual information (MI) (Battiti, 1994), have been applied in filters for evaluating the efficacy of a feature. Techniques, such as linear discriminant analysis between features and classes (Schuman *et al.* 2002), fast correlation-base filter using approximate Markov blanket method for feature relevance calculation (Malarvili *et al.* 2007), and filters using entropy and other information concepts for feature selection (Malarvili *et al.* 2007), are some examples that have successfully applied feature selection in clinical practice. Among them, mutual information (MI) has been reported to be effective in selecting features for a global category of pattern classification problems (Battiti, 1994; Malarvili *et al.* 2007). The main advantages of using MI as a criterion for feature selection are two folds. Firstly, MI is capable of measuring the relationship among attributes and between attributes and classes which may not be easily characterized by other measures. Secondly, MI is invariant under space transformations. These advantages distinguish MI from other measures. In this study, we tackle the problem about how to improve the approximation of MI in a high-dimensional feature space and how to effectively use MIs as criteria for selecting the most representative features for CHF recognition. Battiti is one of the major pioneers who applied a greedy algorithm based on MI to select relevant features form the original feature set (Battiti, 1994). The greedy algorithm sequentially selects optimal features from the remaining feature set.

The criterion of selecting the next feature is based on maximizing the conditional mutual information between the candidate feature and the class attribute. It is apparent that this process is complicated and computational extensive as the number of features increases. To cope with these problems, Battiti's algorithm, termed mutual information feature selection (MIFS), approximates the conditional MI with the summation of paired MI between the candidate feature and each of the features inside the already-selected feature subset. However, a great deal of information was lost with this approximation. In view of MIFS's potential in feature selection, several attempts have been made to improve the performance of MIFS. Kwak and Choi (2002) assumed uniform distributions in the information of input features and proposed the MIFS-U algorithm that amends the ignorance of the joint probability term in the MIFS.

Cheng *et al.* (2008) proposed a conditional mutual information feature selector (CMIFS), which conditioned the calculation of mutual information with the first selected feature. Also included into consideration is the last feature selected just prior to the candidate feature. In this manner, the conditional MI required in the MIFS is more reasonably approximated. Other techniques, including min-redundancy max-relevance (mRMR) (Peng *et al.* 2005) and normalized mutual information feature selection (NMIFS), were also proposed to improve the performance of MIFS.

3. CONCLUSIONS

This paper presented a thorough study on various approaches made towards prediction of heart diseases. Several image processing, data mining and soft computing approaches are studied. This study concludes that the future scope of research can be done in risk assessment among diabetic patients those who are developing heart diseases.

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