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A Review on The State of Art in Atrial Fibrillation Detection through Computerized Approach

Poonam Chhabra[1], Rosy Madaan[2]

[1]Research Scholar, Manav Rachna International Institute of Research and Studies, [2]Associate Professor, Manav Rachna International Institute of Research and Studies

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KEYWORDS

Atrial fibrillation, data mining, machine learning, ECG

ABSTRACT:

Introduction: In this era of electronic health, healthcare data has gained significant popularity due to its high influence on human survival information. Regular health monitoring plays a prominent role in the early detection and prevention of any illness. Electrocardiograms (ECGs) are pictorial healthcare data that can be utilized to define a variety of cardiac diseases. It can be used to monitor a lot of cardiac diseases. An example of a cardiac disease characterized by an ECG is atrial fibrillation, or shortly AF, which poses a challenge to healthcare systems around the world. The detection of AF as early as possible is equally important and challenging due to its asymptomatic and episodic nature, which may be capable of reducing mortality rates and alleviating the economic burden of this disease.

Objectives: This review paper presents a brief review of various aspects of analysis of AF through ECG signals and the relevant procedures and methodologies that can potentially influence the analysis.

Conclusions: The review paper has also explicated the applications of various computerized technologies and methodologies that can enhance the process of analysis of AF through ECG signals.

1. Introduction

Modern and rapid changing lifestyles of individuals have resulted in an inevitable rise in heart related problems, including chest pain, difficulty breathing, irregular blood pressure and irregular heartbeat. Heart related problems can come in any shape in a human body. One such shape includes irregular heartbeats or arrhythmias [1]. Electrical impulses that travel around and through your heart establish the rhythm of your heart. These impulses are initially generated by the sinoatrial node of the heart. Following this, they move through a network of fibres to reach each chamber of the heart. This electrical pattern allows the heart's chambers to pump out blood and then relax and fill with blood in a controlled sequence [2]. It keeps blood flowing steadily throughout the body. Arrhythmias are changes in the electrical activity of the heart, which result in unusual or unpredictable patterns of heartbeats. Atrial fibrillation (AF) is one of the most common arrhythmias, which poses challenges to healthcare systems worldwide [3]. AF occurs when the beats of the atrium of the heart are rapid and irregular [4]. It usually begins as short periods of abnormal beating, which becomes more frequent and continuous with time.

Heart disease has been the leading cause of mortality in the last ten years. According to the European Public Health Alliance, the majority of deaths in the globe are caused by circulatory diseases such as heart attacks and strokes, accounting for more than 41 percent of all deaths. Reports show that most of the diseases were non-communicable diseases like cancer, chronic respiratory disorders, cardiovascular diseases, and diabetes. According to the Economic and Social Commission of Asia, the reports have impacted one-fifth of Asian countries. According to the Australian Bureau of Statistics, around 33.7 percent of Australians die as a result of heart and circulatory system problems. According to South African data, heart and circulatory system problems are the underlining cause of death in Africa. Every year, the number of people who die from heart disease climbs. The average cost of treatment of heart disease is also very high [5]. That is one of the reasons why healthcare companies are under increasing

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pressure to improve the quality of the healthcare system and reduce costs. These issues led to the need of a computerized estimation system that can estimate the disease and its related risks on time. AF being a life-threatening disease has grasped the interest of the researchers. A lot of clinical study is proof of the same. The methodology of detection AF through computerized approach is summarized in figure 1 below [6].

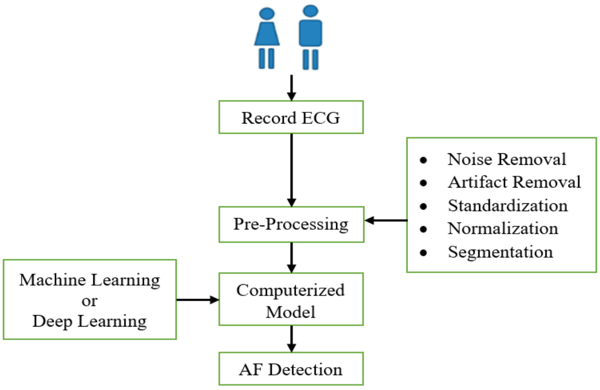

Figure 1: AF detection using computerized approach

Now the study of presence of atrial fibrillation rhythms in a patient is studied through Electrocardiogram (ECG) signals. ECG signals are basically the identification of electrical activity of the heart [7]. It is a pictorial healthcare data which is used to identify AF [8]. This data is read manually by the experts or doctors to detect the presence of AF in a patient identified with cardiac issues. A manual study of ECGs to diagnose AF is labour-intensive, time-consuming, and requires high levels of expertise [9]. It is important to detect, predict, and classify AF early and automatically in order to be able to treat it effectively. This has drawn the interest of researchers for a computerized design to detect AF. Data mining and machine learning methods are some of the presently utilized computerized techniques to identify AF using ECG signals.

2. Causes of Atrial Fibrillation

AF can occur for a variety of reasons. Sometimes it occurs due to purely cardiac factors, sometimes it occurs due to non-cardiac factors, and sometimes both cardiac and non-cardiac factors are involved [10-12]. Some of the cardiac issues responsible in occurrence of AF is High blood pressure, lack of flow of blood and oxygen in heart, inflammation to heart caused due to rhematic fever, enlarging of blood pumping chambers to the heart, shortening of heart muscles, improper pumping of blood in and out of the heart, stiffening of the heart's ventricles, heart failure and post heart surgery, hole in between the upper chambers of the heart and increased pulse pressure. Non cardiac factors responsible in occurrence of AF is age (With age there is chances of heart beats being irregular which can further result in occurrence of AF), consumption of excessive alcohol, smoking or Drugs, Diabetes, Obesity and Pneumonia and genetic disorder.

3. AF and its types

It is possible for atrial fibrillation to develop when there is swelling, redness, stress, anxiety, damage, or ischemia affecting the heart anatomy. A patient's atrial fibrillation can be iatrogenic in some cases [13]. AF is referred to as recurrent beats if there are two or more episodes. Various patterns of AF are discussed in the below sub-sections and is defined through figure 2 given below.

3.1 Paroxysmal AF (PAF)

AF that reverts spontaneously is known as paroxysmal AF. It usually takes seven days for episodes to resolve spontaneously. Young patients usually experience PAF because pulmonary veins contain electrically active foci. By eliminating these foci, this type of AF can be effectively treated since the trigger for it is eliminated.

By employing CNN, Mendez, Hsu, Yuan, and Lynn, 2022 [14] predicted Paroxysmal AF (PAF) based on input image matrices using three PhysioNet databases. With approximately 5 min long HRV sequences, the proposed PAF detection system achieved an accuracy of 87.2%. Castro, H., Garcia-Racines, J.D. and Bernal-Norena, A., 2021 [15] predicted PAF episodes in ECG signals through ML models. RF, conditional RF, KNN and SVM are the ML models explicated by the author. Based on ECG signals from PhysioNet's AF prediction database, 106 signals from 53 pairs of ECG recordings were analysed.

3.2 Persistent AF

Persistent AF is characterized by a periodic cycle of AF that requires electrical cardioversion. The occurrence of a cycle that lasts more than a week and is accompanied by an uncontrollable ventricular rate can result in cardiac

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myocyte remodeling. As a result, a dilated cardiomyopathy may develop. It is a type of AF that occurs as a result of the first episode of paroxysmal AF or as a result of repeated episodes that may result in this condition.

3.3 Long-standing persistent AF

Patients with persistent AF for over 12 months, either because pharmacological interventions or cardioversion were not initiated.

3.4 Permanent AF

Permanent AF is a repeating and periodic cycle of AF that persists despite the fact that all the treatments have been administered, and has stopped responding to any external treatment.

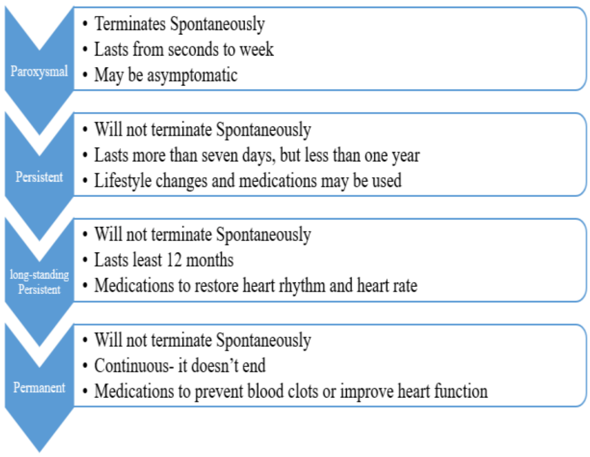

Figure 2: Summary of various types of AF

4. Symptoms of Atrial Fibrillation

AF can present with a variety of symptoms including those that range from no symptoms to severe disabling symptoms, depending on the patient and the severity of the disease. Some of the symptoms indicating AF are Pain in chest, Irregular breathing or shortening of breath, Weakness or dizziness, palpitation and fatigue.

5. ECG data for AF diagnosis

The primary tool for diagnosing AF is through an ECG test. An ECG test signal as shown in figure 3 includes an ECG signal that are defined by P-waves, QRS complexes, and T-waves, which show depolarization of the atrium, depolarization of the ventricular chambers, and repolarization. The highest point of an ECG signal is known as the R-peak of an ECG signal, and the time interval between two consecutive R-peaks is known as RR interval. It is possible to measure the state of cardiovascular well-being of the heart by measuring the amplitude, shape, and duration of the waves that make up these waves.

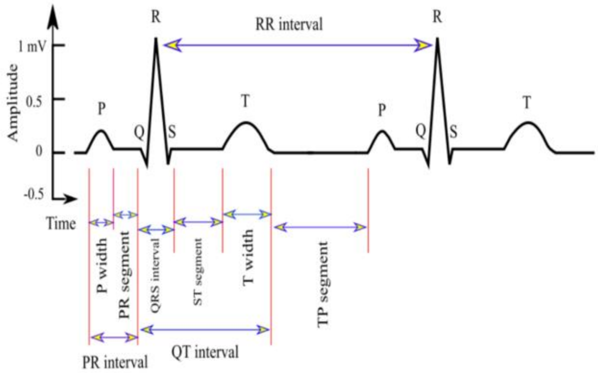

Figure 3: ECG Signal

Now the presence of AF rhythms in a patient is studied through ECG signals. ECG signals are basically the identification of electrical activity of the heart (Vos, T., Lim, S.S., *et al.* 2020). It is a pictorial healthcare data which is used to identify AF (Morillo, C.A., Banerjee, A., *et al.* 2017). This data is read manually by the experts or doctors to predict the presence of AF in a patient identified with cardiac issues. A manual study of ECG to diagnose AF is labor-intensive, time-consuming, and requires high levels of expertise (Forouzanfar, M.H., Afshin, A., *et al.* 2016). It is important to predict and classify AF early and automatically in order to be able to treat it effectively. It has been found to be profitable to predict arrhythmias using ECG when it comes to atrial fibrillation in the early stages. Data mining and machine learning methods are some of the presently utilized computerized techniques to identify AF using ECG signals.

6. Pre-processing of ECG Signal

Analysis of a continuous signal or ECG signal is made simple by pre-processing. Pre-processing involves the cleaning of the ECG signal with any distortion or disturbance. This cleaned signal is than further normalized and segmented to make it simpler for understanding of the computer. The process involved in

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pre-processing is further explicated in below sub-section. These processes are summarized in figure 4.

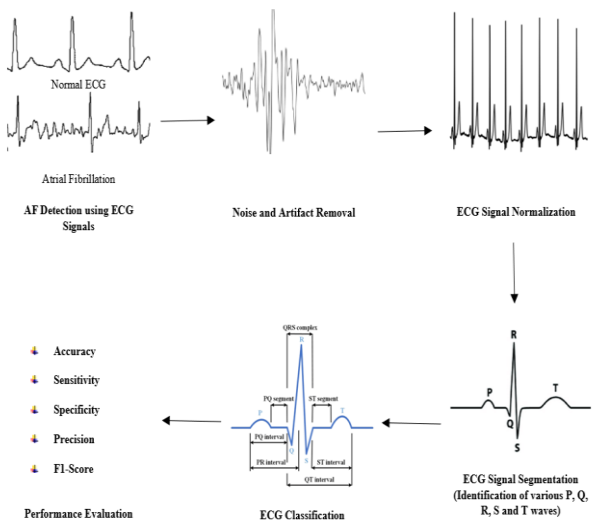

Figure 4: Pre-processing of ECG Signal

6.1 Noise and Artefacts Removal

In order to attenuate the noises in ECG signals as well as to emphasize the typical waves in the ECG signals, it is necessary to remove artefacts and noise from the signal as a major pre-processing step. In addition to the inherent characteristics of the ECG as well as any diseases-specific characteristics, noises and artefacts of the ECG belong to the spectral range of interest as well.

Various methods of ECG denoising have been classified. The first of these is ECG denoising via the EMD algorithm, which is a local and adaptive method of frequency–time analysis. As a computerized defined mechanism for nonlinear and nonstationary signals, empirical mode decomposition (EMD) is proposed to be applied. Statistical analysis is used in the second and third categories to obtain a statistical model from the noisy signal. These techniques are statistical in nature and are used to analyse the noisy signal statistically. As a second category, there are deep-learning based auto-encoder models, which are capable of generating an uncorrupted ECG signal from a distorted ECG signal by optimising the objective function in order to achieve this. By decomposing the signals, deciding what threshold to use, and reconstructing them afterwards, wavelet-based methods de-noise ECG signals using the wavelet transform (WT). Fourthly, sparse optimization is used to de-noise ECG signals. As a result of adaptive filtering, a key de-noising approach is derived from the extended Kalman filter (EKF), extended Kalman smoother (EKS), and unscented KF, all of which are Bayesian-derived Bayesian filters. Using Bayesian filters, the fifth category uses changes to the usual dynamic ECG model of KF in order to de-noise ECG signals utilizing Bayesian filters. Lastly, there is the hybrid method, which combines various methods that are defined in the literature in a single approach.

In ECG signals, signal levels are very compact and small (around 0.001V), so filtering is necessary in order to eliminate noise from a wide range of sources of noise. It has been observed that noise can be caused by unstable DC offsets at the electrode and body interface, muscle noise, and electrical noise generated by equipment in the environment or the ECG equipment itself, including power converters.

6.2 Normalization

Normalization of the signal defines a denoised and filtered signal between zero and 1. This creates uniformity among all the signals to be studied.

6.3 Segmentation

Segmenting an ECG signal is the process by which waves, segments, and intervals are located and their characteristics are analysed in terms of time and morphology in order to compare them with known patterns. As a result of this, a variety of downstream tasks can be simplified by reducing the need for labelled data. Segments in an ECG are the regions between two waves.

Summary of past two years' research work on pre-processing of ECG Signals is discussed in table 1. Most utilized methodologies in ECG Signal cleaning and preprocessing are explicated in the table.

Table 1: Summary of past two years' research work on pre-processing of ECG Signals

Author and Year	Determinant	Diligence
Faiz, M. M. U., Kale, I. (2022)	ECG signal cleaning	Proposed a cascaded 4 stage adaptive noise canceller
Prashar, N., Sood, M., Jain, S. (2021)	ECG signal cleaning	Dual tree complex WT

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Dhas, D. E., Suchetha, M. (2022)	Baseline interference during ECG signal acquisition	Proposed a dual phase dependent-recursive least square (DPD-RLS) adaptive filter
Tomas, B., Grabovac, M., Tomas, K. (2022)	ECG denoising by locating false R-peaks which can indicate the noise-contaminated segments	R-peak detection algorithm
Eltrass, A. S. (2022)	Denoising and surpassing artifacts	Improved Sparse Low-Rank algorithm and Kernel Recursive Least Squares with Approximate Linear Dependency algorithm
Malghan, P. G., Hota, M. K. (2022)	Muscle artefact removal in ECG	Grasshopper optimization algorithm based improved variation mode decomposition technique
Boda, S., Mahadevappa, M., Dutta, P. K. (2021)	ECG Signal cleaning	Hybrid approach of empirical mode decomposition and empirical WT
Tulyakova, N., Trofymchuk, O. (2022)	Filtering of non-stationary noises	Lightweight adaptive method
Yao, L., Pan, Z. (2020)	ECG Signal cleaning	Author developed a hybrid model of empirical mode decomposition with adaptive noise algorithm
Madan, P., Singh, V., Singh, D. P., et al. (2022)	ECG Signal cleaning	Stationary Wavelet Total Variation
Upadhyay, P., Upadhyay, S. K., et al. (2022)	ECG Signal cleaning	Gaussian type WT to the Schrödinger equation is obtained
Huo, R., Zhang, L., Liu, F., et al. (2022)	Prediction of ST segment, T wave, and TP segment. Detection of P wave and PQ segments.	Bidirectional hidden semi-Markov model (BI-HSMM) based on the probability distributions of ECG waveform duration was proposed.

7. Conclusion

This review paper outlines a comprehensive review on Atrial fibrillation detection through a computerized approach with ongoing detection methodology which involves manual study of ECG signals. The state of art in research is carried out by a literature driven methodology that is conducted to find out an appropriate analogy. The main issues that are highlighted in this review paper includes demerits of manual study of ECG, appropriate method, and determinants for computerized based analysis of AF. It is observed that being a mature methodology, a lot of issues are prompted with the detection of AF with ECG signal due to the noise and disturbance prompted by them, but with sequential development and up-gradation in these fields' Computerized approach in detection of AF has a capability to govern the healthcare system.

DECLARATIONS

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