International Journal of Scientific Research & Engineering Trends
Volume 9, Issue 3, May-June-2023, ISSN (Online): 2395-566X

Review On Classification And Prediction Of Ecg Morphology And Intervals Features

Vedant Verma, Hemant Amhia
Department,of Electrical Engineering
Jabalpur Engineering College, Jabalpur (M.P.)

Abstract- The electrocardiogram (ECG) provides essential characteristics of the human heart's multiple cardiac conditions. The classification of arrhythmias provides a major part in the diagnosis of cardiac disease. Any deviation from the normal sequence of electrical impulses is considered an arrhythmia. Traditional methods of signal processing, machine learning and its sub-branches, such as deep learning, are popular techniques for ECG signal analysis and classification and, above all, for the development of early detection and treatment applications for cardiac conditions and arrhythmias. This article presents a detailed literature survey on ECG signal analysis. This paper aims to analyze the most recent studies on data utilized, features, and machine learning approaches that can address the time computational challenge and be implemented in wearable technology. The study methodology began with a search for relevant papers, followed by a study of the data provided. The second stage was to explore the evaluated ECG characteristics and the machine learning method used to identify arrhythmia. According to the analysis, a significant number of studies selected the MIT-BIH database, even though it needs a substantial ratio of pre-processing effort. We address a detailed existing research work review on the data of real-time signal collection, pre-recorded diagnostic ECG data, analysis and denoising of ECG signals, identification of ECG spectrographic states based upon function technologies, and classification of ECG signals, as well as comparative discussions between the studies analyzed.

Keywords- Arrhythmia, Electrocardiogram, MIT-BIH ECG signal dataset, Tachycardia, and Bradycardia.

I. INTRODUCTION

Cardiovascular disease is a disease with the highest incidence and mortality of human no communicable diseases [1]; they are threatening the lives of millions of people. Therefore, it is of great significance to diagnose ECG signals efficiently and accurately. The ECG signals can monitor the rhythm of the heart's activity, and it is useful to monitor heart diseases [2]; it contains a wealth of basic physiological signals of the heart, so it is often used to detect physical health disorders. At present, the processing methods of ECG signals are mostly manual analysis, which is very tedious and time-consuming. With the continuous progress of deep learning, the efficiency of ECG analysis and processing has been greatly improved.

There are various methods to automatically detect and classify abnormal ECG signals, such as wavelets analysis [3], deep belief network (DBN), and support vector machine (SVM) [4]. For the time-domain features, Mehrdad Javadi et al. [5] used the complementary features of Mixture of Experts (ME) and Negatively Correlated Learning (NCL) to classify ECG signals; they obtained a recognition rate of 96.02%. Rajpurkar et al. [6] constructed a CNN model, which diagnoses 14 types of arrhythmias, and it achieved a high accuracy rate. Li et al. [7] employed a 1-dimensional CNN, they introduced SMOTE algorithm to augmented data and achieved 98.12% accuracy. Alif et al. [8] have developed a 2D CNN for extracting shape-related features to detect arrhythmia. In their study, the classifier contains six convolutional layers, and the method shows an accuracy of 94.37%. Marinho et al. [9] introduced Structural Co-Occurrence Matrix (SCM) to extract features for the first time, and it was demonstrated to be promising for ECG classification.

Due to the limitations of the time-domain methods, these methods just analyse the ECG signal in time domain, and the results are not very well. For the frequency-domain features, Faziludeen et al. [10] used wavelets and SVM for classification, and they achieved 98% accuracy, but they only identified two types of abnormal ECG signals. Radovan et al. [11] utilized PQ intervals and QRS complexes to extract features and used genetic algorithm to select features and train SVM. They obtained a recognition rate of 84%. To reduce the segmentation step, Mondéjar-Guerra et al. [12]

The human heart sends blood to the lungs to acquire oxygen, then returns it to the blood and carries it throughout the body. The leading cause of death is cardiovascular disease (CVDs) worldwide [1]. By doing research, WHO (World Health organization) found closely 17.9 million, almost 32% of the global deaths caused by CVDs, in 2019. CVDs can be classified into three major groups – electrical (irregular heartbeats owing to malfunctions of the heart's electrical system or arrhythmia), structural (heart muscle disease or cardiomyopathy), circulatory (high blood pressure and coronary artery disease) [2].

II. RESEARCH MOTIVATION

The electrocardiogram (ECG) is an electrophysiological signal that contains a large amount of valuable information about the electrical activity of the heart. ECG waveforms are seen in clinical assessments of heartbeats and include P-waves, QRS complexes, and T-waves [1,2]. The amplitudes and time intervals of ECG waveforms provide insight on heart rhythm abnormalities and heart diseases such as ischemia, QT syndrome (long and short), and myocardial infarction [[2], [3], [4]]. ECG waveform delineation is utilized for determining characteristics such as amplitudes and time intervals. Performing an accurate delineation, however, is quite a difficult task for many reasons:
(i) P-waves have low amplitudes and can be obscured by electrode motion or muscle noise [2];
(ii) P- and T-waves can be biphasic, which increases the difficulty of accurately determining the starting points or endpoints of the waves [2];
(iii) P-waves can be absent, although they can also partially overlap with the T-waves from the previous beat in rapid heart rate patterns [3]; and
(iv) some arrhythmia entities cannot contain all the standard ECG waves [5]. The start of the wave is the initial onset of the signal, while the end of the wave is the offset of the signal. Therefore, designing an automated and accurate ECG delineation would be useful for making good decisions about heart rhythm abnormalities.

The importance of an automatic delineation algorithm is that it recognizes the individual waveform components of P-waves, QRS complexes, and T-waves. These signal recognition processes include the ECG positions (onset, peak, and offset) and the magnitudes from all waveform components [5]. In previous studies, the automated delineation of ECG signals was widely performed in a way that aimed to measure the width or duration of the waves [6,7]. However, the starting and ending points of the durations were very complicated and difficult to measure. Due to this, it always appears in well-known and distinguishable frequency bands.

Several automated methods for making such measurements have been proposed, such as linear regression, logistic regression, and classification [3,4,8,9]. Regression was the most prominent method, as it was utilizable when all the attributes were numeric, while classification was used when all the attributes were categories. However, the ability of the two methods to draw boundaries between the two classes was restricted at some points. An essential challenge is to find more than one boundary to partition the set. Several algorithms have been proposed in the literature to accomplish this, including threshold-based algorithms [10], hidden Markov models [11], curve fitting [12], wavelet transforms [13], and machine learning techniques [3,14,15]. For most current algorithms, the typical strategy is to extract the P-waves, QRS complexes, and T-waves. The accuracy of the overall device, therefore, depends greatly on the accuracy of the segmentation of the ECG and the measurement of its features. However, due to the subjective nature of the measurements in the segmentation and measurement phases, there is always a high degree of uncertainty and variability. Thus, designing and developing an automated delineation algorithm for ECG signals in a robust condition is a crucial process [6].

Several studies have been undertaken to evaluate the performance of these algorithms. Unfortunately, there is a lack of standardized databases containing a reasonably large number of carefully annotated heartbeats with manually performed waveform boundary measurements. This situation reflects the enormous effort a clinician must undertake to manually annotate a statistically relevant collection of QRS complexes. Deep learning (DL) with automated feature learning allows multi-layered computational models based on traditional neural networks to learn from multi-level abstraction representations of data [1]. DL is a relatively new approach, but in many healthcare applications, it has shown a promising capacity for data synthesis [[8], [9], [2]]. Neural networks are used for complex cardiological tasks—in particular, detection of heartbeats in arrhythmia [8], discrimination between hypertrophic functional and pathological remodeling patterns [1], risk stratification and heart failure prognosis [2], and various implementations of ECG analysis [5].

III. BACKGROUND

Cardiovascular disease is one of the leading causes of death worldwide. An important class of cardiovascular disease is cardiac arrhythmia and is an abnormal heart rhythm that is too fast, too slow or erratic. Atrial fibrillation (AF) is the most common form of cardiac arrhythmia, it affects millions of people around the world and is also associated with substantial morbidity and mortality (Narayan et al., 2017; Zhao et al., 2017). Currently, 1 in 5 strokes in people aged over 60 years is caused by AF, and the prevalence of AF is ~2% of the general population (Lip et al., 2016).

Electrocardiograms (ECG), discovered by Muirhead in 1872 to record heartbeats in a patient using wires attached to the patient's wrists, is a widely used, non-invasive approach for clinical diagnosis in patients with cardiac arrhythmia, including AF. It has been suggested that early AF diagnosis from ECG recordings may enhance the effectiveness of clinical treatment and prevent serious complications (Artis et al., 1991). However, such diagnoses require specially trained health professionals to manually read and identify irregular ECGs, which is often a time consuming and a rather subjective process in some instances (Osowski et al., 2004). As a result, there is high interest in developing an automatic approach for AF detection from ECGs.

During AF, the electrical impulses that originate from the intrinsic cardiac pacemaker no longer pace the heart effectively, and are instead overrun by additional electrical sources (Haissaguerre et al., 1998). As a result, the P-waves in the surface ECG recordings devolve into a series of fibrillatory(f)waves with small magnitudes (Huang et al., 2011), and a fast and irregular heart rhythm is reflected in the short and variable R-peak-to-R-peak (RR) intervals (Tateno & Glass, 2001). Currently, two main approaches exist for AF detection from ECGs: atrial activity-based analyses detect AF by identifying the absence of P-waves and the presence of f-waves (Alcaraz et al., 2006; Du et al., 2014; García et al., 2016; Ladavich & Ghoraani, 2015; Pürerfellner et al., 2014; Ródenas et al., 2015), whereas ventricular activity-based analyses look for irregularity in the RR intervals of QRS complexes (Alcaraz et al., 2010;

Carrara et al., 2015; DeMazumder et al., 2013; Huang et al., 2011; Lake & Moorman, 2010; Linker, 2016; Park et al., 2009; Sarkar et al., 2008; Tateno & Glass, 2001). However, atrial activitybased analyses are often error-prone when performed on noise contaminated ECGs. This is due to the small signal-to-noise ratio caused by the low amplitude f-waves (COLLOCA, 2013). On the other hand, ventricular activity-based analyses alleviate this problem due to the well-defined, large amplitude QRS complexes in the ECGs (Zhao et al., 2015b). However, ventricular activity based analyses require relatively long ECG recordings (>30s) of AF episodes for reliable detection (Petrėnas et al., 2015). Recent studies have combined both atrial and ventricular activity-based analyses for more accurate AF detection (Babaeizadeh et al., 2009; Colloca et al., 2013; Oster & Clifford, 2015), and have obtained promising results on diverse datasets.

Non-linear classifiers such as support vector machines (SVM) (Cortes & Vapnik, 1995) have been used to enhance the performance (Colloca et al., 2013; Couceiro et al., 2017; Li et al., 2014a; Li et al., 2014b). These methods involve the extraction of features from ECGs, such as those described in (Lake & Moorman, 2010; Linker, 2009; Sarkar et al., 2008) to learn which features are specific to AF and non-AF. This generally requires domain expertise in the field of ECG analysis, as a rigorous feature generation and selection procedure is required to find the optimal feature combination for learning, which can be extremely time-consuming.

Neural networks have been applied in many different fields, including medicine and bioengineering, to overcome the issues above by automating the feature extraction step (Krizhevsky et al., 2012; LeCun & Bengio, 1995; LeCun et al., 2015; LeCun et al., 2010). This allows the algorithms to not only learn "end-to-end" to make predictions directly from raw data but to also increase the effectiveness of the learning process when large datasets are available, as well as to enable an ease of adaptability to a wider range of tasks. Convolutional neural networks (CNNs) (LeCun & Bengio, 1995) have been widely applied in recent years for imaging tasks (He et al., 2016a; Krizhevsky et al., 2012; Szegedy et al., 2015). By applying a series of independent nested filters through multiple layers, CNNs have also been successful in setting state-of-the-art performance in tasks such as acoustic scene classification (Valenti et al., 2016). But a major disadvantage of CNNs is that they cannot be used on inputs with varying lengths. On the other hand, recurrent neural networks (RNNs) can model data of arbitrary lengths and have been widely used for modeling sequential data such as in speech recognition (Graves et al., 2013). However, an RNN usually requires the input to be encoded into a set of features, as they do not learn effectively from raw data, and are often more difficult to train (Pascanu et al., 2013).

IV. LITERATURE REVIEW

The Compressed sensing (CS) model proposed by David L. Donoho in 2007 has greatly improved the signal processing technique by breaking the original Nyquist-Shannon sampling law and eliminating the need to guarantee that the sampling frequency must be greater than twice the maximum frequency [9]. Once the method was proposed, it was soon applied substantially in the fields of magnetic resonance imaging and image processing. The application of CS on ECG signals is also very effective. Due to the large amount of ECG signal data, the ECG signal can also be reconstructed after using CS compression, which speeds up the data transmission time while ensuring the basic characteristics of the ECG signal and does not affect the medical staff's judgment of the pathology [4].

With the continuous development of deep learning, Bora et al. have combined CS with generators in neural networks to eliminate the limitation of signal sparsity and speed up the signal reconstruction to some extent, but the overall reconstruction still takes a relatively long time [1]. Wu et al. proposed a framework that combines generators and meta-learning to optimize the reconstruction process, which significantly speeds up the reconstruction of signals [2]. After the next, more and more studies are combining deep learning with CS, using neural networks to compress as well as reconstruct the process.

In wearable devices, the compression and classification of ECG signals is processed in two main modes. The first one is compressed on the wearable device, then the compressed data is transmitted to the remote end for reconstruction and classification, and finally the detection results are transmitted to the device user. Hua et al. used a binary measurement matrix for compression, which can greatly reduce the energy consumption of sensor nodes, the BSBL algorithm with better recovery performance was used in the reconstruction process, and Deep Neural Networks (DNN) was used in the classification process, which had 94% accuracy when the data was less compressed. However, the classification accuracy is not ideal at high compression ratios and only classifies the ECG signals into abnormal and normal categories [7]. Zheng et al. used Singular Value Decomposition (SVD) to compress and reconstruct the ECG signal and compared it on SVM as well as CNN classifiers, with an average accuracy of 96% when the number of singular values was 3 in the case of classification into N, PVC, R, and L. However, the method cannot specify the compression ratio, and the There is still room to improve the accuracy at high compression ratios [3].

Fira et al. investigated the classification performance of several different dimensionality reduction techniques on ECG signals and Electroencephalogram (EEG) signals, incorporating Laplacian Eigenmaps (LE), Locality Preserving Projections (LPP), and CS. Meanwhile, the classification accuracy of SVM, KNN, decision tree and other classifiers is compared. Experiments show that CS is computationally cheaper and more effective compared to LE and LPP, while using SVM as well as KNN as classifier classifies the best results [4]. Another work by Fira builds on this by comparing in more detail the effects of different projection matrices and dictionaries in CS on classification results and by proposing two CS methods specifically for ECG signals, patient-specific classical compression perception without pre-processing before projection (PSCCS) and cardiac pattern compression perception involving ECG signal pre-processing and segmentation of the cardiac cycle (CPCS).

Experiments have shown that if the ECG signal of the same patient for 24 hours needs to be detected in the ambulatory ECG. Then the PSCCS method can be chosen, and if the purpose is to identify and classify abnormalities in the ECG signal, the CPCS method with the presence of pre-processing as well as segmentation is more effective [5].
The second method is to classify compressed data directly on the wearable device. This processing method can significantly reduce the amount of data to be processed, reducing energy consumption and extending battery life while also speeding up recognition. Braun et al. skipped the costly reconstruction process in compression perception and compressed the MNIST database using a random orthogonal observation matrix and classified the compressed data. The error rate of the measured data at a compression rate of 0.4 differs from the error rate of the uncompressed data by only 0.22%, demonstrating the feasibility of compressed domain classification [6]. Hua et al. applied this feasibility to ECG signals, which were compressed using principal component analysis (PCA) after pre-processing and finally classified using SVM, yielding an average accuracy of 98.05% at a perceptual rate of 0.7 and an average accuracy of 98.58% for uncompressed data [8]. Another study improved on this by developing a new QRS detection algorithm capable of finding the location of QRS waves directly on the compressed ECG measurements and then classifying them using a Deep Boltzmann Machines (DBM). The experimental results show that at a compression rate of 0.4, the accuracy tested on the MIT-BIH database is 90.00% and 89.38% on its own database [7].
In addition to the above two common models, Yildirim et al. proposed a nonlinear compression structure based on a self-encoder (CAE), which can perform compression as well as decompression operations on ECG signals, and designed a Long short-term memory (LSTM) model to identify the compressed ECG signals, which can not only increase the classification efficiency, but also recover the compressed data when necessary [8].

V. PROBLEM STATEMENT

In the existing literature, the compression and classification of ECG signals are usually carried out in two steps.
In the compression stage, the method based on compressed sensing is to use measurement matrix to compress signals. However, for long-term ECG signals, the design of measurement matrix is very difficult. It is difficult to find an appropriate measurement matrix to compress a series of ECG signals, and the compression time is long, which is not suitable for wearable devices requiring rapid recognition. Many studies have proposed using SVD, PCA, LEE and other methods to compress signals. These compression methods have good applicability, but SVD cannot accurately control the compression ratio of ECG signals, and PCA and LEE cannot retain the features of original signals well under the extremely low compression ratio.

In the classification stage, although simple classifiers such as SVM, KNN and MLP can quickly recognize ECG signals, the accuracy of classification results is low, and they are not suitable for wearable devices that need to accurately identify heart rate abnormalities. With the development of deep learning, many classification networks based on CNN and LSTM have shown good results in the recognition of ECG signals. However, due to the small volume of compressed ECG signals, many classification networks of larger magnitude will consume a lot of time in the work, which is not good for rapid recognition.

To sum up, a lightweight network capable of fast compression and accurate recognition should be equipped with the actual application environment of heart rate monitoring combined with wearable devices.

VI. DISCUSSION AND CONCLUSION

This paper discusses some of the classification methods that are most frequently used to classify ECG signals. In general, there are two stages of ECG classification, namely, the feature extraction stage and the classification stage.

Before extracting features, the raw ECG signal data was processed first in the preprocessing stage since ECG signals were not necessarily free of noise. Noise will cause a decrease in accuracy during the classification process. After going through the pre-processing stage, feature extraction could be performed using various extraction methods, such as the Hadamard Transform feature Extraction in [7] or DWT in [9]. Deep learning methods such as CNN and RNN do not need to extract features manually because a deep neural network can extract its own features. The extracted features were then processed using the learning method to obtain accurate classification results. After getting the classification results, the validation of these results was performed; the most commonly used validation is the confusion matrix. For further research, the machine learning method needs to be improved to get high accuracy and high precision to give an accurate diagnosis; this can be achieved with better precision to differentiate each beat without going through complicated preprocessing stages.

REFERENCE

[1] 41, Issue 5, October 2020, Pages 252-260, https://doi.org/10.1016/j.irbm.2019.12.002.
[2] WeijieWang, Revisiting signal processing with spectrogram analysis on EEG, ECG and speech signals, Future Generation Computer Systems, Volume 98, September 2019, Pages 227-232, https://doi.org/10.1016/j.future.2018.12.060.
[3] MaheshChandra, Design and analysis of improved high-speed adaptive filter architectures for ECG signal denoising, Biomedical Signal Processing and Control Volume 63, January 2021, 102221, https://doi.org/10.1016/j.bspc.2020.102221.
[4] PéterKovác, Diagnostic quality assessment for low-dimensional ECG representations, Computers in Biology and Medicine Volume 150, November 2022, 106086, https://doi.org/10.1016/j.compbiomed.2022.106086.
[5] AmulyaAgrawal, ECG-iCOVIDNet: Interpretable AI model to identify changes in the ECG signals of post-COVID subjects, Computers in Biology and Medicine Volume 146, July 2022, 105540, https://doi.org/10.1016/j.compbiomed.2022.105540.
[6] A.S.A.Huque, HMM-based Supervised Machine Learning Framework for the Detection of fECG R-R Peak Locations, IRB Volume 40, Issue 3, June 2019, Pages 157-166, https://doi.org/10.1016/j.irbm.2019.04.004.
[7] Abel JD, Krupa D, Samiappan R, Kumar, Pravin Kumar S (2019) Multiple sub-filter adaptive noise canceller for fetal ECG extraction. Procedia Comput Sci 165:182–188. https://doi.org/10.1016/j.procs.2020.01.093.