Computer Aided Methods for Multiple Heart Disease Detection using ECG Signal: A Review

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ABSTRACT
Cardiology is a group of disease that affect the heart and its vessels. All heart conditions characterized by blockage of blood vessels, myocardial problems, valve malfunctions and varied heart rhythms are called heart abnormalities. The heart disease is one of the proven causes of death worldwide. Mortality resulting from heart disease can be reduced if the ailments are detected in an initial stage which helps in treating the patients on time. Cardiac abnormalities are reflected in the morphological features of the 12-lead clinical ECG signal. A lesser degree of detection time for doctors to analyze long-term electrocardiogram data and detect slight deviations in the electrocardiogram morphology. Automated computational diagnostic methods using deep learning techniques need to be developed to improve the performance of conventional machine learning based methods used for cardiac disease detection. The review article is therefore intended to present a detailed overview of the work on different computer aided automated methods used by many researchers from many years to automatically detect various heart ailments by characterizing and classifying ECG signal. This work includes a brief introduction on major heart ailments including CAD, MI, CHF, Cardiomyopathy, their typical ECG patterns and characteristics. The credibility of traditional computer aided methods used to detect multiple heart ailments is explored and further the deep learning techniques required to improve the performance of existing methods is discussed. From the results obtained by many researchers it is also revealed that the classification performance is to be improved by using deep learning techniques.

Keywords
Electrocardiogram (ECG), coronary artery disease (CAD), myocardial infarction (MI), congestive heart failure (CHF), cardiomyopathy, deep learning (DL), machine learning(ML)

1. INTRODUCTION
The focus of the article is on the review of automated methods for diagnosing and detecting cardiovascular disease. Heart disease is the leading cause of cardiac death worldwide and is a range of illnesses that affect the structure and function of the heart. Coronary artery disease, heart attacks, heart failure, and cardiomyopathy are some of the harmful heart diseases. According to World Health Organization reports from 2012, 31% of all deaths worldwide—or 17.5 million deaths—were attributed to cardiovascular disease [1]. Nearly half (45%) of deaths from heart disease in the United Kingdom (UK) are attributable to CAD [2]. Heart attacks cause 175000 hospital admissions overall [3]. The most prevalent kind of cardiovascular disease is coronary artery disease (CAD). In CAD, the inner lining of the coronary artery wall's extracellular matrix combines with lipoproteins, exposing them to inflammation and leading to the development of atherosclerotic plaques [4]. Thus the narrowed coronary artery prevents oxygen-rich blood from reaching the heart muscles, resulting in ischemia. Most of the time, CAD symptoms appear much later. If this condition is not treated early, it can cause irregular heartbeats, strokes, heart attacks, and heart failure [4].

The gradual increase in plaque volume that encroaches the diameter of the coronary lumen in atherosclerotic lesions with thick fibrous caps can slowly cause ischemia. As opposed to this, some atherosclerotic lesions with larger lipid cores and thinner fibrous caps are more prone to rupture, in which case the contents are abruptly spilled into the coronary lumen, causing thrombus formation that can obstruct the lumen and completely impair myocardial blood flow [5]

Congestive heart failure (CHF) can be brought on by a variety of factors, with CAD or myocardial infarction (MI) being the most frequent. Chronic repeated episodes of heart attacks can cause heart chamber remodeling that is harmful and reduce the heart's ability to contract which in turn can lead to heart failure. An early diagnosis of CAD and MI is necessary for effective therapy and to prevent the potential onset of CHF. Cardiomyopathies are observed due to enlargement of heart muscle cells.

Invasive diagnostic procedures including cardiac catheterization and blood testing are being used to diagnose heart related diseases in any health centres. The inability to predict which cardiac imaging tests to run when, in what order, and how frequently in various medical circumstances is another drawback of existing noninvasive cardiac diagnostic approaches. Generally, physicians in the hospital use Electrocardiogram (ECG) as a most preferred tool in diagnosing any heart abnormality. The heart's electrical activity simply referred as ECG, can change as a result of any heart ailments [5]. Figure. 1 depicts the ECG sample.

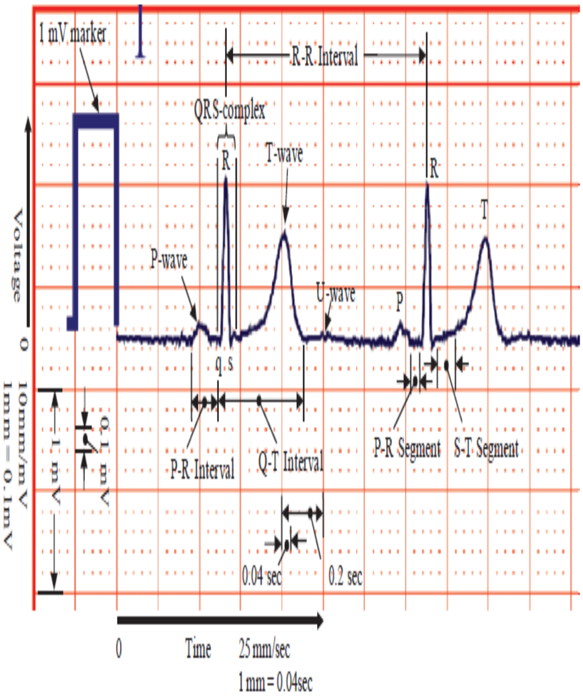

Figure. 1 ECG sample [5]

These ECG abnormalities are diagnostic and have tiny amplitudes. Consequently, visual interpretation by medical professionals are liable to inter- and/or intra-observer bias. Most individuals do not exhibit any fluctuations in their ECG rhythms, and the clinically recorded ECG signal is non-stationary, non-linear, and noisy. Manually interpreting the ECG to distinguish between various heart disorders takes time, is laborious, and is prone to error. This highlighted the requirement for the development of automated computer-aided diagnosis methods that employ various algorithms for detecting irregularities, accurately diagnosing, and categorizing cardiac disorders. Any computer-aided diagnostic procedure has four steps: 1. Preprocessing: Using several transformation methods to remove all noise components and to identify the cardiac cycle 2. Feature Extraction: This technique uses transform, methods to extract the most distinctive characteristics of diverse diseases. 3. Feature Selection- Different studies have employed various statistical, ANOVA-based techniques to choose the most pertinent characteristic traits. 4. Classification with suitable machine learning techniques.

This article reviews the currently available computer-aided methods for automatically detecting major heart diseases namely CAD, MI, CHF and cardiomyopathy and emphasizes the creation of an ECG-based diagnostic method for numerous heart illnesses. This research examines the validity of current machine learning methods first then discuss the deep learning-based classification approaches to enhance classification performance in detecting numerous heart diseases. Using real-time ECG signals, the deep learning methods based approach can be used for mass cardiac screenings to identify any heart illness at an early stage.

2. MACHINE LEARNING TECHNIQUE TO DETECT HEART DISEASE

Because of the improvements in algorithms that researchers are pursuing, the use of signal processing techniques to biological electrical signals began in earlier decades and has continued into the twenty-first century. Both ECG and Heart Rate Variability signals are subjected to these signal processing techniques using the machine learning classifiers in order to identify different cardiac abnormalities. The non-linear features, including multiple entropies and statistical features, showed meaningful variances across the numerous temporal domain features, frequency domain features, and wavelet coefficients retrieved that are necessary to accurately distinguish between healthy and diseased subjects [5]. To accurately extract features from Heart Rate or ECG signals for the classification of normal or abnormal signals, numerous signal processing algorithms have been developed, including linear (time and frequency domain) [6–9], nonlinear methods [10–14], Discrete Wavelet Transform [15–18], and Tunable Q Wavelet Transform [19].

2.1 Machine learning Techniques to detect Coronary Artery Disease (CAD)

In [20], the heart rate variability signal for continuous time wavelet analysis disease detection is reported. The fractal dimension is discovered from the input heart rate variability data, and it provided greater confidence intervals than wavelet analysis for all classes examined. In order to detect CAD using HRV signals, the feature extraction techniques of recurrence plots, poincare plots, and detrended function analysis are used in [21]. In [22], the heart rate signals are divided into three level sub-bands using a flexible analytical wavelet transform, and two features, K-NN entropy and Fuzzy entropy, are then extracted from these sub-band signals. and these features are then fed into the Least Squares-Support Vector Machine, In [23], the cross information potential parameters and flexible analytic wavelet transform are used to breakdown the ECG beats. The cross information potential parameters with least square support vector machine and morlet wavelet kernel are more effective in detecting CAD with an accuracy of 99.5%. The fuzzy entropy is extracted from the HRV signal using principal component analysis in [24], and a support vector machine is utilized as a classifier to distinguish between normal and CAD with an accuracy of 99.2%

For the purpose of CAD detection, [25] extracts sixteen various entropies, including Shannon, Tsallis, Renyi, bi-spectrum, phase, wavelet, Stein's unbiased risk estimate, recurrence, permutation, normalized, log energy, Kolmogorov-Sinai, approximation, sample, modified multi-scale, and fuzzy. It has been demonstrated that this entropy-based feature extraction works well. The bi- spectrum entropy with support vector machine showed to be more effective with a classification accuracy of 99.27%. For the first time, [26] implements the ideally time-frequency concentrated even length biorthogonal wavelet filter bank for CAD detection utilizing ECG segments with 2s and 5s durations with accuracy of 99.53%. Ten machine learning algorithms, were applied in [27] to detect CAD.

2.2 Machine learning Techniques to detect Myocardial Infarction (MI)

The artificial neural network classifier and phase space fractal dimension characteristics are investigated to detect the MI [28]. In [29], authors used a multi-lead ECG signal and a neuro-fuzzy technique to diagnose MI patients. To differentiate between the MI and regular ECG, a hybrid strategy based on hidden Markov models and Gaussian mixture models is adopted. Using a discrete wavelet transform, [30] characterizes the QRS complex of normal and MI individuals. It has been discovered that the QRS complex can be used to identify MI subjects [31]. The method described in [32] evaluated multiscale energy and Eigen space characteristics. The proposed method, which employed a support vector machine classifier with a radial basis function kernel, produced a classification accuracy of 96.15% [32]. The dual tree complex wavelet transform of the 12-lead ECG signal's wavelet coefficients is used in [33] to determine the wavelet coefficients' phase. The detection and localization of MI using a multilead ECG signal is described in [34]. A discrete wavelet transform is used, and 12 nonlinear features are extracted from these wavelet coefficients, and fed to KNN classifier which resulted in an accuracy of 98%. In order to detect MI using lead II ECG signals, a Flexible Analytic Wavelet Transform method is used in [35]. Sample entropy is extracted from each sub band signal and fed to various classifiers, including Random Forest, J48 decision tree, back propagation neural network, and least-square support vector machine. A two-band optimal biorthogonal filter bank is suggested for ECG analysis in [36], which also discusses a MI diagnostic system for both noisy and clean ECG data.

2.3. Machine Learning Techniques to detect Congestive Heart Failure (CHF)

The examination of HRV's nonlinear characteristics in [37] provides independent information for patients with CHF who are being risk-stratified. Both linear and non-linear characteristics are employed in [38] to identify CHF. It is discovered that Detrended Fluctuation Analysis, Approximate Entropy, and Sample Entropy are useful in analyzing CHF HRV signals. The sequential trend analysis and multiscale entropy features from the RR-time series were calculated by the author in [40-42] and they reported a higher classification result for normal and CHF. Power spectral densities from the sub-band signals of the RR-time series were used by the author in [43] as characteristics for the detection of CHF. The same authors' wavelet filters and soft decision technique for CHF identification from the RR-time series are proposed in [44]. [45] uses a flexible analytic wavelet transform to decompose the HRV signal and finds accumulated entropy and accumulated permutation entropy features. In order to distinguish between the normal and CHF classes, the study [46] found that wavelet-based feature extraction employing frequency localized wavelet filter banks was effective.

The procedure for analyzing the time-frequency sub band matrices produced from ECG signals and detecting CHF is described in [47]. It is based on the Stock well transform and frequency division. In [48–49], automated characterization and classification of multiple classes simultaneously—normal, CAD, MI, and CHF—using ECG signals is taken into consideration. To extract the non-linear entropy and statistical features, wavelet transformation techniques are used.

The most crucial problem to be solved among the many shortcomings of machine learning approaches is: The majority of machine learning algorithms can be used to solve specific problems, making it difficult to choose the best algorithm for a given dataset. Deciding on the best feature selection approach or classification is also very difficult. These algorithms require enough time to train and test in order to produce results. The dataset used in the majority of research had a small number of features and samples, which constrained the results because the quantity of features and samples might influence how well machine learning methods perform [50].

The machine learning field has been revolutionized in recent years by the introduction of deep learning algorithms. These deep learning algorithms has proven its performance in various fields of science and engineering including gaming, automobile, robotics, disease diagnosis, and computer vision [50]. These deep learning methods can be applied for the automated diagnosis of multiple heart diseases with improved classification accuracy.

3. DEEP LEARNING ECHNIQUES TO DETECT HEART DISEASE

MIT-BIH Arrhythmia, St. Petersburg Institute of Cardiological Technics 12-lead Arrhythmia Database, and MIT-BIH Supraventricular Arrhythmia Database are three major ECG databases where Deep Learning approach is used for the first time for active classification of ECG signals [51]. In this approach, features are learned from raw ECG using stacked denoising auto encoders, and once the feature is learned, a deep neural network is used to detect the diseased subjects. The Z score normalization technique is utilized to normalize the ECG segments in [52], which uses a one-dimensional, 11-layered convolutional neural network (CNN) composed of four convolution layers, four max pooling layers, and three fully connected layers to detect cardiac artery blockage. According to the findings of [52], deep CNN can identify blocked cardiac arteries with 94.95% accuracy for 2s signal length.

Implemented in [53] for the purpose of detecting heart attacks utilizing lead II ECG rhythms with and without noise, the 11-layer deep CNN acquired accuracy of 93.53% with noise and accuracy, 95.22% without noise, respectively. For the automatic detection of artery blockage using ECG signals, an 8-layer hybrid CNN-LSTM network structure is proposed in [54]. It attained an average accuracy of 99.85% with both subject-specific and non-subject-specific data. As more ECG segments with minor differences are produced by the suggested method, the data augmentation is used in [54] to increase the robustness of the system. To detect and pinpoint heart attacks using 12-lead ECG signals, a multiple feature branch CNN with seven layers is used. The method includes feature extraction using feature branches and classification using softmax layer. To evaluate the algorithm, both class-based and patient-specific subjects have been used. The accuracy of the technique was up to 99.95% and 99.81% for class-based heart attack identification and localization, and up to 98.79% and 94.82% for patient-specific heart attacks [55]. 11 layers thick Four separate data sets were utilized to train and test the CNN model for identifying CHF [56], which does not involve R peak detection or feature extraction.

On Lead-I ECG beat segments, the 16-layer multichannel CNN and LSTM algorithm is presented for the automated identification of heart attacks [57] and achieved classification accuracy of 95.4%. On a 12-lead ECG signal, the trained CNN model detected 10 different MI types with 99% accuracy [58]. From the multi resolution analysis, 108 statistical features, including kurtosis, skewness, and entropy, are extracted and fed to a deep layer least square support vector machine, which has the highest accuracy of 99.74% [59]. Additionally, [60] implements the Fourier Bessel Series Expansion based Empirical Wavelet Transform in conjunction with convolutional neural network to detect and locate heart attack. The LSTM-CNN based network is constructed to extract deep learning features, and an ensemble classifier is then utilized to identify normal and congestive heart failure with accuracy of 99.85% [61].

It is clear from the literature review that computer-aided cardiac diagnostic techniques in conjunction with deep learning techniques are required. Deep learning approach is suggested to find the best feature to detect cardiac illnesses in order to overcome the limitations of machine learning classifiers. The deep learning techniques can automatically identify the distinguishing factors from the raw ECG data required for predicting multiple heart diseases. This eliminates the need for feature reduction, ranking, and selection frameworks because they are all fused within the model. Deep learning techniques can also self-learn the critical distinctive features from the large dataset.

4. SUMMARY OF SURVEY ON DEEP LEARNING TECHNIQUES TO DETECT HEART DISEASE

The literature survey on automated detection methods of heart diseases using deep learning techniques are summarized as in Table 1

Table 1. Survey on automated detection methods of various heart diseases – Coronary Artery Disease (CAD), Myocardial Infarction(MI), Congestive Heart Failure (CHF) using Deep Learning Techniques

Author	Dataset/Disease	Techniques	Outcome
Allah Verdi et al., 2016 [51]	**CAD using ECG signal** Subjects: 85 Source: Physio Net	Deep belief network (DBN)	Accuracy= 98.05% Sensitivity =96.02% Specificity =98.88%
Acharya et al., 2017 [52]	**CAD using ECG signal** Subjects: 47 2s and 5 s ECG segments, Source: Physio Net	11-layer deep Convolutional Neural Network	Accuracy= 95.11% Sensitivity = 91.13% Specificity = 95.88%
Acharya et al., 2017 [53]	**CAD using ECG signal** Subjects: 200 Source: Physio Net	11- layer deep Convolutional Neural Network	Accuracy = 95.22% Sensitivity = 95 .49% Specificity = 94 .19%
Tan et al.,2018 [54]	**CAD using ECG signal** Subjects: 47 Physio Net	Long short term memory networks 8-layer deep Convolutional Neural Network,	Accuracy= 99.85% Sensitivity =99.85% Specificity =99.84%
Wenhan Liu et al., 2018 [55]	**MI using ECG signal** Subjects: 52 normal, 148 MI ECG Lead: 12 lead, Source: Physio Net	Multiple-Feature-Branch Convolutional Neural Network	Class-based: MI detection-Accuracy-99.95%,
Acharya et al., 2019 [56]	**CHF using ECG signal** Source: Physio Bank Dataset: NSRDB, BIDMC& Set B (Fantasia, BIDMC), (UD)-CHF-30000 Normal – 70308.	11 layer deep CNN	Set A- Acc – 95.98% Set B- Acc – 98.97%
Kai Feng et al., 2019 [57]	**MI using ECG signal** ECG Lead: Lead I Source: Physio Net	16 layer Convolutional Neural Network and Long Short Term Memory, Spatial and temporal features-Deep structural features	Accuracy= 95.4%, sensitivity= 98.2%, specificity = 86.5%, F1 score of 96.8%
Ulas Baran Baloglu., 2019 [58]	**MI using ECG signal** Subjects: 52 normal, 148 MI ECG Lead: 12 Lead Source: Physio Net Beats: 125,652 normal, 485,752 MI	R-peak detection, Wavelet transform-for denoising 10 layer deep Convolutional Neural Network end to end structure	Lead IV: Accuracy= 98.73% All lead Accuracy= 99%
Ludi Wang et al.,2019 [61]	**CHF using ECG signal** Subjects: 3 CHF, 3 normal Source: BIDMC CHF database	Expert features from RRI LSTM-CNN Conv Pool-CNN-C to extract DL features Blind fold validation	3 CHF, 3 normal Accuracy= 99.85%, 99.41%, and 99.17% for N = 500, 1000, and 2000 length

5. CONCLUSION

Cardiovascular disease is the leading cause of cardiac death worldwide and is a category of circulatory system illnesses that affect the anatomy and operation of the heart. Cardiomyopathy, congestive heart failure, myocardial infarction, and coronary artery disease are only a few of the dangerous cardiovascular conditions. For the purpose of monitoring cardiac health, prompt and precise diagnosis of various cardiac disorders is essential. Only highly skilled professionals with in-depth knowledge are able to give patients the essential direction and care, lowering their risk of cardiovascular death. ECGs must be carefully examined by skilled doctors as part of the standard medical procedure for any cardiovascular disease screening. Reading and analyzing these ECG records is a mental challenge to the professionals, as minor alterations in the ECG cannot be seen with the unaided eye. The adoption of the computer-aided cardiac diagnostic system can help to solve the issues with observer variability mentioned above and shorten the time needed for ECG diagnosis. In this paper, a thorough examination of traditional computer-aided methods for heart disease detection using ECG signals is provided. It is found that these methods do not scale well for larger applications and do not perform well when multiple diseases or a larger number of subjects are taken into account. It is laborious to increase the precision of current machine learning techniques to identify many diseases for larger databases. Due to this, automated approaches that integrate deep learning techniques with ECG signals have been developed. These methods are expected to increase the classification accuracy, and the paper also presented an analysis of deep learning techniques used to diagnose cardiac disorders.

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