This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

Cardiac Arrhythmia Classification Techniques: A Review

Ioana Cretu[1], Alexander Tindale[2], Maysam Abbod[1], Hongying Meng[1], Mark J. Mason[2], Ashraf W. Khir[1]

[1]College of Engineering, Design and Physical Sciences, Brunel University Uxbridge, Middlesex UB8 3PH, UK

[2] Royal Brompton and Harefield NHS Trust, Sydney Street, SW3 6NP, UK

Abstract:

Cardiac arrhythmia is a condition caused by an impaired electrical conduction of the heart, resulting in irregular rhythms that can increase the risk of stroke or even lead to sudden cardiac deaths. Luckily, bio-signals such as electrocardiogram (ECG) and arterial blood pressure (ABP) can be utilized to assess the health of the patient. This work presents a comprehensive review on the recent machine learning (ML) and deep learning methods applied for arrhythmia classification using both, ECG and ABP signals, including preliminary steps such as pre-processing, feature extraction and feature optimization. This review considers various ML techniques such as Artificial Neural Networks, Support Vector Machine, K Nearest Neighbour, Decision Tree, as well as DL methods such as Convolutional Neural Networks, Deep Neural Networks, Deep Belief Networks (DBN), and Recurrent neural networks.

1. Introduction

According to the World Health Organization, cardiovascular diseases (CVDs) are the leading cause of death globally. Approximatively 17.5 million deaths due to CVD were reported in 2012 [1], and 17.9 million were reported in 2016, which indicates an overall increase from 30% to 31% globally. Arrhythmia is a CVD, that refers to any irregular deviation from the normal heart rhythms. Various types of arrythmia exist, including supraventricular arrhythmias, ventricular arrhythmias, sinus node dysfunction, heart block, and premature contractions. Even though some arrhythmias do not have immediate effects, the long-term exposure to irregular heartbeats can lead to serious damage to the heart. Atrial fibrillation, for instance, is a common type of supraventricular arrhythmia that causes an increased heart rate. Patients with atrial fibrillation being associated with a risk of stroke five times higher than patients with a normal heart rhythm [2]. Premature atrial (PAC) or ventricular (PVC) contractions are premature beats that originate from the atria or ventricles, respectively. Frequent PVCs can lead to far more dangerous, ventricular arrhythmias such as ventricular fibrillation (VF) or ventricular tachycardia (VT), that can immediately lead to heart failure [3].

Arrhythmias can be prevented with early detection and treatment. In clinical settings, arrhythmia diagnosis is mostly based on individual patient's electrocardiogram (ECG) analysis. An ECG represents a signal that compresses important information regarding the electrical activity of the heart. Although ECG is the gold standard for arrhythmia detection [4], other bio-signals such as arterial blood pressure (ABP) can be used in addition to the ECG to detect the presence of arrhythmias. While extremely useful, analysing bio-signals can be very challenging for a person, as it is time consuming and requires a great amount of expertise [5]. Therefore, in the last decades researchers proposed a wide range of methods for automatic arrhythmia classification by means of machine learning and deep learning techniques.

Traditional machine learning (ML) techniques require steps such as feature extraction, selection and optimization that transform the bio-signals into a compressed set of features prior to the final classifier. The hand-crafted feature extraction process requires deep knowledge of the signals and pre-processing steps such as noise filtering or signal segmentation. The main problem when using hand-crafted methods is that patients can have different features for the same disease, or different diseases could have very similar features, making the classification a difficult process. However, ML techniques

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

have been made an incredible progress among the years due to the wide range of strategies proposed for feature extraction. Deep learning (DL) methods on the other hand, combine the feature extraction, selection and classification steps into the same learning body. Recently developed, these techniques are much deeper (multiple hidden layers) and more complex than the traditional ML methods and can take as inputs low filtered or even raw signals. Nevertheless, deep learning methods require large datasets to achieve good results and the training process is computationally expensive compared to ML networks. Thus, both ML and DL techniques have their pros and cons, and the choice of one approach must take into consideration the available datasets used to train the model, the application and the available resources.

In this work, a comprehensive review is conducted for arrhythmia classification methods using ECG and blood pressure signals. Although other papers that review ECG arrhythmia classification methods exist in literature [5]–[14], they either discuss classical feature extraction and machine learning techniques [6], [9], [13], [15], or focus just on deep learning methods [11], [12], [14]. To our knowledge, this is the first review paper on arrhythmia classification that covers a broad range of topic that incorporates all the major aspects of ECG analysis, including pre-processing, feature extraction, feature optimization, and classification with both machine learning and deep learning techniques. Furthermore, our paper covers a review of the arrhythmia detection methods that use blood pressure waveforms. Specifically, this paper reviews the existing studies on ECG, PPG and ABP analysis present in the literature mainly from the last decade.

This paper is organized as follows: Section 2 provides the medical background needed to understand the ECG and ABP characteristics that will be further discussed in this paper. Sections 3, 4, and 5 present a general overview of the pre-processing, feature extraction and feature optimization steps required before the machine learning classification. Section 6 describes the most frequently used machine learning techniques. Similarly, Section 7 provides short descriptions of the deep learning methods used for classification and reviews the outstanding methods present in literature. Some of the methods are describes in detail throughout the paper, while other are summarised in table 4. Section 8 presents deep learning methods that have been used for feature extraction. In addition, in Section 9 this paper reviews feature extraction and classification methods that use arterial blood pressure waveforms. Finally, Section 10 concludes the paper.

2. Medical background

This section provides an overview about the electrocardiogram (ECG), arterial blood pressure (ABP) signals and their morphologies. Both of these signals reflect the status of the heart. Specifically, the ECG reflects the electrical activity of the heart, while the ABP waveforms describe the effect of the volume of ejected blood by the left ventricle in the circulatory system. General knowledge about the normal morphologies of these signals is essential when developing arrhythmia detection algorithms. Thus, the following subsections will present the normal morphologies and meaningful segments of these signals.

2.1. Electrocardiogram signal analysis

The analysis of the Electrocardiogram (ECG) waveforms, intervals and segments reveals important information regarding the state of the patient and are widely used for diagnosis purposes. The ECG is a test that uses electrodes attached to the skin able to record the currents produced by the atrial and ventricular muscles during stimulation. The electrical stimulation of the heart is produced in different phases: atrial depolarization, ventricular depolarization, and the relaxation phase. Each of these phases are depicted on the ECG by a specific wave or segment. A typical ECG signal along with some meaningful segments and intervals can be seen in Figure 1. The P wave is visible on the ECG signal as the first positive deflection and is caused by the spread of the electrical stimulation through the atria

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

(atrial depolarization). The spreading of the stimulus from the atria to the ventricle causes the ventricular depolarization, represented by the QRS complex. As the name suggests, the QRS complex is composed of three individual waves: Q wave, R wave, and S wave. The Q wave is the initial negative deflection of the complex, the R wave is the positive deflection of the complex and normally the wave with the highest amplitude, and the S wave is the negative deflection following the R wave. The contraction of the ventricles is followed by a relaxation phase, knows as ventricular repolarization, that is represented on the ECG signal by the T wave. The T wave is an asymmetrical wave, followed sometimes by a small, rounded deflection called U wave. The time intervals and segments between these waves also provide a great deal of information that can be used for patient's health assessment. The first interval on the ECG signal is the PR interval, measured from the onset of the P wave to the beginning of the QRS complex. Also called the atrio-ventricular (AV) delay, the PR interval represents the time interval taken from the stimulus to travel from the sinoatrial node through the atria and pass through the atrio-ventricular node. A normal conduction of the stimulus from the sinoatrial node to the ventricles is known as normal sinus rhythm (NSR) and is usually indicated by a heart rate between 60-100 beats per minute. The next interval is the QRS width, representing the time interval required for the depolarization of the ventricles, whereas the QT interval represents both depolarization and repolarization of the ventricles. The isoelectric line between the depolarization and repolarization of the ventricles is known as ST segment.

Table 1. Normal values of the ECG parameters

ECG parameter	Normal values
P wave amplitude	0.05-0.25 mV
P wave duration	0.06-0.12 s
PQ interval	0.10-0.20 s
PR interval	0.12-0.20 s
QRS interval	0.06-0.10 s
Q wave amplitude	0.23-0.27 mV
Q wave duration	0.01-0.03 s
R wave amplitude	1-1.60 mV
R wave duration	0.02-0.06 s
S wave amplitude	0.25-0.45 mV
S wave duration	0.02-0.04 s
ST segment	0.08 s
Heart rate	60-100 bpm

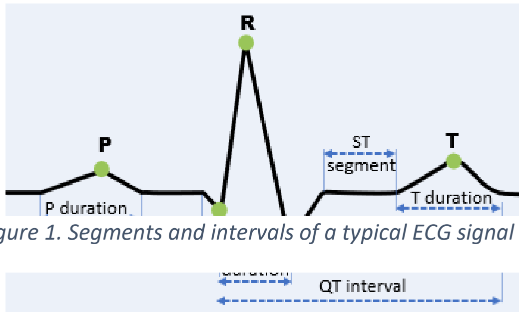

Figure 1. Segments and intervals of a typical ECG signal

The normal amplitudes and time intervals of the ECG waves and segments can be seen in Table 1. Any deviation from the normal values can indicate the presence of arrhythmias. For example, as shown in Figure 2, the presence of atrial fibrillation is suggested by the absence of P waves which are replaced by inconsistent fibrillatory waves [7], whereas distorted S and T waves indicate the occurrence of an atrial premature beat.

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

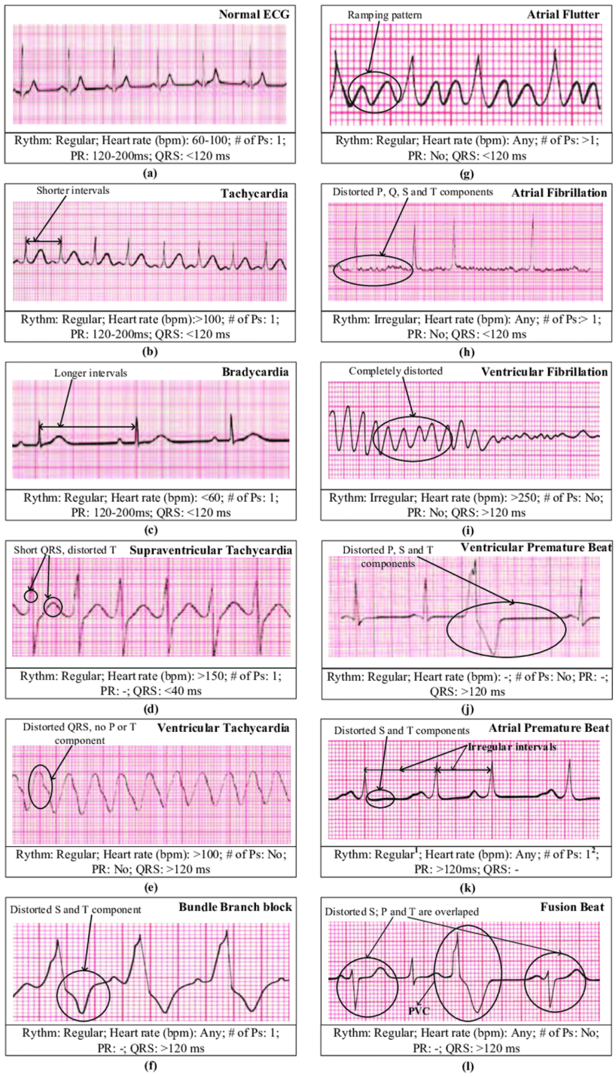

Figure 2. Examples of arrhythmias and their characteristics [8]

2.2. Arterial blood pressure (signal analysis

The behaviour of the arterial blood pressure (BP) waves, their timing and amplitudes provide valuable information about the function and compressibility of the arterial system. These waves are generated by the volume of the blood ejected throughout the arteries with every heartbeat. As illustrated in Figure 3, the blood pressure waveform is generally composed of a systolic phase, indicated by the rapid increase in pressure, followed by a diastolic phase, indicated by a quick drop related to the left ventricular ejection. The incisura between these two phases is known as the dicrotic notch and represents the closure of the aortic valve.

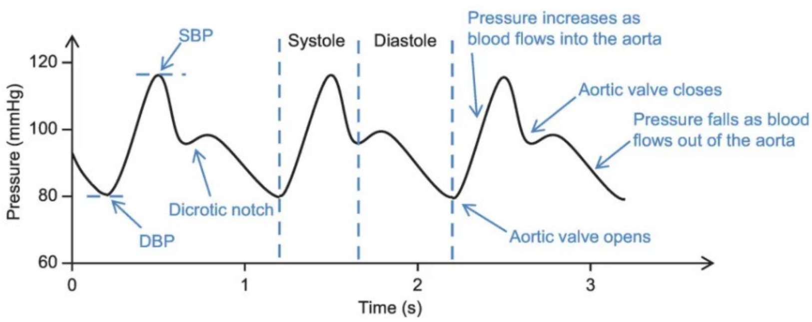

Figure 3. An illustration of the arterial blood pressure signal [16]

The relationship between ECG and ABP signals is usually described by the correlation between the R-peaks in the ECG followed by the systolic peaks in the ABP. Recent studies also demonstrated that arrhythmias produce imperfect oscillation of blood pressure [17]. The contraction of the heart, shown on the ECG by the QRS complex, causes the ejection of the blood to different parts of the body. The systolic peaks can be seen in the ABP signals after a delay, correlated to the time taken for the blood to reach the measurement site. Thus, any disturbances in the electrical activity of the heart should have an impact on the morphology and parameters of the ABP waveforms. Although less explored, this correlation could improve the ability to detect arrhythmias.

3. Pre-processing

The aim of the pre-processing stage is to reduce the unnecessary parts of the signal that can potentially cause misdiagnosis. The recorded signals, whether we are talking about ECG, ABP or other bio-signals, are usually contaminated with noise or artefacts. The most common types of noise are the powerline interference, instrumentation noise, muscle artefacts and baseline wander [18]. Although a variety of methods are available for the elimination or reduction of these noises, there is no universal method that can be effective for all of them. Thus, researchers choose one or more denoising methods depending on their application and the state of the signals that they are working with.

The ECG signals are usually filtered using high pass, low pass, band pass or median filters (Table 2). High pass filters are used to remove low frequency noises such as baseline wander, a noise caused by respiration with a frequency between 0.5- 0.6 Hz [19], or baseline drift, a variation of the signal from the baseline found in frequency components less than 3 Hz [20] On the other hand, lowpass filters are applied to remove high frequency noises such as powerline interference, a sinusoidal interference of 50 ~ 60 Hz [21], or EMG noise, with a variable frequency between 1-10000 Hz. Bandpass filter is also extensively used for ECG signal filtering, as it can be applied to eliminate both low- and high-frequency noises including artefacts, power line interference and muscle noise (table 2).

Table 2. Examples of filters used to denoise the ECG signals in the pre-processing step.

Ref	Filter	Frequency/ Time
Chen et al. [22]	Band pass	1-30 Hz
Zhang et al. [23]	Band pass	1-45 Hz
Xu et al. [24]	Band pass	5-45 Hz
Prakash et al. [25]	Band pass	0.1-40 Hz
Wang et al.[1]	Median	200 and 600 ms
Mondejar-Guerraa et al. [26]	Median	200 and 600 ms
Shi et al. [20]	High pass, Low pass	0-0.28125 Hz, 45-90 Hz
Ashtiyani et al. [27]	Notch	60 Hz
Bhoi et al. [28]	Band pass	5-15 Hz
Essa et al. [29]	Median Low pass	200 and 600 ms 35 Hz
Sayantan et al [30]	Median Low pass	200 and 600 ms 35 Hz
Cai et al. [31]	Band pass	0.5-35 z

4. Features extraction

Signals can be divided into a sequence of phases that describe their patterns and ideally suppress all the important information. The identification of those patterns is known as feature extraction. Classical machine learning approaches use hand-crafted feature extraction methods, transforming the input data (ECG signals) into a set of features that can be further utilized for

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

classification. These methods depend heavily upon the mathematical approaches used for feature extraction. Among the years, researchers used different mathematical measurements and transformations to extract, optimize, and store a wide range of patterns into feature vectors [32], [33]. According to the methods used for extraction, the obtained patterns can be classified in categories such as: wavelet, statistical, and heartbeat or morphological features. Researchers use them either individually [34]–[38] or coupled with other features [1], [32], [39], [40].

4.1.QRS complex, P and T waves detection

A wide range of features can be extracted from the ECG signals based on location, amplitude, duration and morphology of the P, Q, R, S, T waves. An accurate localization of those deflections is crucial for calculating the signals features and predicting a correct diagnosis. Although all the waves provide essential information, the QRS complex features provide the most meaningful information for ECG analysis, as it characterizes the electrical activity of the heart during ventricular contraction. Therefore, QRS complex detection plays a vital role in ECG analysis and can either compromise or enhance the accuracies of the final classification.

In the last decades, a significant number of QRS complex detection methods have been published in literature (Table 3). Still among the most extensively applied methods in state-of-the art papers ([41]–[44]), Pan-Tompkins is an efficient algorithm used for noise removal and QRS complex detection, that provides an excellent accuracy. This algorithm includes a bandpass filter, a five-point derivative, moving window integrator and automatically adjustable thresholds which discriminate the locations of the QRS complexes [45]. Although efficient, Pan-Tompkins algorithm necessitates a relatively large complexity due to all the above-mentioned steps that are required [46]. To address this problem **Hamilton and Tompkins** [47] proposed a QRS detection method based on optimized decision rule threshold process and upgraded the denoising stage by using linear and nonlinear digital filters, obtaining a higher precision. Later, **Benitez et al.** [48] introduced a detection method that applies Hilbert transform on the first differential of the ECG signal and detects the QRS peaks using an adaptive threshold. More recently, **Zhang et al.** [23] achieved a 99.83% detection sensitivity by applying an optimal bandwidth-bandpass filter and thresholding method to denoise, amplify and detect the QRS complexes. The P and T waves are further detected by removing the QRS complexes from the signals, cross correlating the main signal with a triangular filter and applying the threshold processing. Other QRS detection methods use wavelet techniques, which are well known due to their ability to filter the noise, and to their capacity to emphasise and delimitate the ORS peaks. The decomposition coefficients obtained by applying wavelet transforms on the signals can be used to divide the low and high frequency components. Thus, the signals can be reconstructed using just the useful coefficients, obtaining a filtered signal with well-preserved R peaks. **Pal et al.** [49] detected the QRS complex, P and T waves using multiresolution wavelet analysis. DWT wavelet was applied to decompose the signals on 8 decomposition levels, and different levels were used to detect QRS complex, Q and S waves, and P and T waves, respectively. Similarly, **Banerjee et al.** [50] used multiresolution wavelet analysis and adaptive thresholding, achieving a sensitivity (Se) of 99.8% and a positive predictive value (PPV) of 99.6%. More recently, **Bouny et al.** [51] used stationary wavelet transform (SWT) along with Teager energy operator (TEO) and adaptive thresholding to localize the frequency content of QRS complexes. Their method yielded a 99.84% Se, with 0.3% detection error rate (DER). **Beyramienanlou and Lotfivand** [52] achieved a DER of just 0.155% using a method based on signal energy. For each sample, the energy of the local spectrum is calculated using Shannon energy (SE) and further used to make an envelope and remove the small spikes around the R peaks. Finally, the QRS peaks are detected using a threshold. Methods that combined wavelet transform and entropic criterion also yielded good results due to the elimination of the unnecessary signals using entropy [53]–[56].

Despite their good detection accuracies, peak detection techniques and their extracted features can sometimes fail to accurately describe specific arrhythmias, especially when dealing with unusual

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

morphologies. Luckily, methods such as waveform analysis can also be used by themselves to extract wavelet coefficients, which can be used as frequency-based features. Various wavelet transform methods have been used to extract the frequency-based features such as continuous wavelet transform (CWT) [1], [57], [58], dual tree complex wavelet (DTCWT) [59], discrete wavelet transform (DWT), or Meyer Wavelet Transform (MWT) [60].

Table 3. Comparison between QRS, P and T wave detection algorithms

Ref.	Year	Method	Se (%)	Ppv (%)	Acc (%)	Der (%)
Pan-Tompkins [45]	1985	bandpass filter, differentiation, squaring, and moving-window integration	99.75	99.54	-	0.71
Hamilton and Tompkins [47]	1986	linear and nonlinear digital filtering, optimized threshold decision rule process	99.69	99.77	-	-
Benitez et al. [48]	2000	Hilbert transform	99.81	99.83	-	0.36
Chen et al. [61]	2006	Moving average	99.55	99.49	99.50	-
Banerjee et al. [62]	2012	Multiresolution DWT and adaptive thresholding	99.80	99.60	-	-
Zeng et al. [63]	2013	Wavelet transform (combination of Mexican hat and Morlet wavelet)	99.71	99.53	-	0.77
Merah et al. [64]	2015	Stationary Wavelet Transform (SWT)	99.84	99.88	-	0.28
Rekik et al. [53]	2017	Entropy Criterion (EC) of the Wave l e t Transform (WT)	99.94	99.99	-	-
Beyramienanlou and Lotfivand [52]	2017	Shannon energy and threshold	99.92	99.92	99.84	0.16
Abdul et al. [65]	2019	differentiation, Hilbert transform, adaptive threshold	99.62	99.88	-	0.50
Bouny et al. [66]	2020	SWT and Teager energy operator (TEO)	99.84	99.87	99.70	0.30
Alhussainy [67]	2020	DWT and two adaptive thresholds	99.682	99.36	99.36	0.32
Chen et al. [22]	2020	hierarchical clustering and DWT	99.89	99.97	99.83	-
Anuhya et al. [68]	2020	adaptive Stockwell transform (AST)	99.93	99.94	-	0.15
Fotoohinasab et al. [69]	2021	graph-constrained changepoint detection (GCCD)	99.76	99.68	-	0.55

5. Feature optimization techniques

Large number of features are often extracted from the ECG signals and, although useful, these features increase the training time and can hamper an optimized training to be performed [70]. Thus, when the feature set has a high dimension, optimization is required in order to reduce the complexity of the models and obtain relevant and accurate classification. As a result, a reduced number of meaningful and most representative features are identified.

Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Linear Discriminant Analysis (LDA) are the most used techniques applied to dimensionally reduce and optimize the features. PCA is a linear method that transforms the input vectors into principal components which contain uncorrelated variables in decreasing order of the total variability. The components with the highest variability suppress the most meaningful information. Unlike PCA, which is maximizing variance, the ICA is a statistical method that allows the separation of mixed signals into their components by maximizing the independence between them, thus obtaining statistically independent components. LDA, on the other hand, discriminates the features by maximizing the separability between classes. To compare the accuracy of these methods, **Martis et al.** [71] used Pan-Tompkins algorithm and discrete wavelet transform to detect the QRS complexes and extract the wavelet coefficients. The wavelet coefficients were then separately fed into three different dimensionality reduction methods (PCA, ICA, LDA) and each one of the resulted features were tested on support vector machines, probabilistic and backpropagation neural networks for the final

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

classification. IDA on wavelet coefficients provided the highest accuracy when used with the probabilistic neural network classifier. PCA and LDA on wavelet coefficients provided 99% and 98.59% accuracy using probabilistic neural network and backpropagation neural network, respectively.

6. Machine learning techniques for ECG arrhythmia classification

In the last decades, significant number of techniques have been proposed for ECG arrhythmia classification using machine learning approaches. In the next subsections, widely used machine learning methods such as Artificial Neural Networks (NN), Support Vector Machine (SVM), K Nearest Neighbour (KNN) and Decision Tree (DT) will be discussed.

6.1.Artificial Neural Networks

Artificial Neural Networks are brain-inspired networks composed of three types of layers known as input layers, hidden layers, and output layers, that mimic the functionality of the human neurons. These layers are composed of several interconnected units called nodes or artificial neurons that are associated with adaptable weights. According to the reviewed studies, in this paper we classify the ANNs in four categories: Feed-forward Neural Networks (FNN), Back Propagation Neural Networks (BPNN), Probabilistic Neural Networks (PNN) and other.

- **Feed-forward Neural Networks**

In Feed Forward Neural Networks (FNNs), as the name suggests, the information travels in just one direction from input to output, the final decision being based on a specified threshold. Although outdated by other modern methods, in [72] FNN provided a better classification accuracy compared to SVM and multi-layer perceptron. **In** [73], FNN combined with Particle Swarm Optimization, which optimised the weights and biases of the network, achieved a surprisingly good accuracy of 99.41% using a set of seven features.

- **Back Propagation Neural Networks**

Back Propagation Neural Networks (BPNN) were introduced to overcome the simplicity of FNN by comparing the achieved output with the expected output using a loss function. According to this loss function the weights are adjusted from the output layer to the input layer (back propagated) and the process continues until the minimum error is reached. Although more precise than FNN, the random weights that are initially assigned lead to fluctuations in BPNN response, as different initial weights can result in different classification results [74]. BPNN are employed in some recent studies for ECG arrhythmia classification [33], [36], [71], [75]–[79]. In other papers [80]–[83], fuzzy clustering algorithms are combined with BPNNs and employed for arrhythmia classification, increasing the accuracy of the results.

- **Probabilistic Neural Networks**

Introduced by Specht in 1990, Probabilistic Neural Networks **(**PNNs) are composed of input, pattern, summation, and decision layers. Similarly organised as a BPNNs, PNNs use a statistically derived activation function capable to compute non-linear decision boundaries, which under certain conditions approach the Bayes optimal decision surface [84]. The PNN was used to classify arrhythmia in ECG signals using ICA and RR-interval features [74], PCA and LDA features [85], heartbeat features [86], as well as statistical and wavelet features [87]. PNN was also used in studies such as [36], [71], [88], [89]. Although PNNs are much faster and precise than BPNNs, this comes at the cost of computational memory.

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

- **Other**

In addition to the above-mentioned methods, ANN techniques such as radial basis function neural network (RBF-NN) ([88]–[90]), generalized regression neural network (GRNN) ([91]), and neural network with adaptive activation function (NNAAF) [92], [93] are also applied in literature.

6.2.Support Vector Machine

Support Vector Machine (SVM) is a supervised learning algorithm, that can be used for both classification and regression problems. Roughly speaking, SVM returns the hyperplane that has maximum margin between the training data and the decision boundary [5]. SVM was first designed to solve binary classification problems, but methods such as “one vs one” and “one vs all” have been proposed and extensively used for multi-class classification. When dealing with nonlinear datasets, kernel functions such as polynomial, Gaussian, Radial Basis Function (RBF) and sigmoid are used to project the features into a higher dimensional space where they are linearly separable.

Yazdanian et al. [94] detected five classes of arrhythmia using SVM classifier on a set of wavelets, apparent and time-domain features, achieving a precision of 96.97% using Radial Basis Function kernel and 92.72% using sigmoid kernel. **Sahoo et al.** [77] classified temporal, morphological and heartbeat features with an accuracy of 96.67% using an SVM model. Heart rate variability (HRV) features are also frequently used for arrhythmia detection using SVM classifiers **(** [27], [39], [95]–[98]), being advantageous as they can also be calculated from other bio-signals such as PPG [99]. Other papers that employed SVM for the final classification are illustrated and summarized in table 4 [27], [39], [100]**.**

6.3.K Nearest Neighbour

K Nearest Neighbour (KNN) is a supervised classifier which assumes that each type of arrhythmia has a group of similar features that exists in the near neighbourhood. A new feature vector is classified by calculating the distances from this vector to all the learning vectors from the training dataset. The new vector is then assigned to the class in which the majority of the closest vectors belong to. The most frequently used distance calculated in KNN is the Euclidean distance. Although with a higher computational cost, Manhattan, Chebyshev or Mahalonobis distances can also be used. Recent developed methods used KNN for ECG arrhythmia classification [35], [88]–[90], [101].

6.4.Decision Tree

Decision trees (DT) networks are machine learning algorithms that can be categorised in classification or regression trees. DTs map the dataset from a set of observations about an item to conclusions represented by target values or target classes. In classification trees the observations (branches) are groups of features, whereas the conclusions (leaves), are target class labels. In regression trees, on the other hand, the targets are represented by real values. Random forest (RF) classifiers are a collection of many decision trees that produce a response by aggregating the results from all the individual trees. RFs are often used in recent papers for ECG arrhythmia classification [25], [102]–[104].

7. Deep learning techniques for ECG arrhythmia classification

Deep learning methods are a subset of machine learning techniques, able to perform intelligent decision making using a neural network with multiple hidden layers. Compared to classical machine learning techniques, deep neural networks are providing a better performance due to their ability to

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

deal with unstructured data and thus, the ability to process a substantially larger number of features. Deep Neural Networks are essentially feed-forward neural networks with many layers that can be trained end-to-end. In other words, the deep hidden layers of DNNs can learn the features that best describe the dataset without any prior processing. In the last decades, various deep learning methods have been proposed including Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), Deep Belief Networks (DBN), and Recurrent neural networks (RNN). These methods, as well their variants are all summarized in Table 5. The most frequently used will be presented and explained in this section.

7.1.Convolutional Neural Networks

Convolutional Neural Networks (CNN) are a special type of artificial neural networks that consist of multiple connected layers assembled in a feed forward manner. CNNs have three main types of layers: convolutional layers, pooling layers and fully connected layers. The first layers are responsible for pattern extraction, whereas the fully connected layers are responsible for the final classification.

A wide range of methods that use CNN for ECG arrhythmia classification exists in literature. As CNNs were first introduced for image recognition tasks, these methods can be classified in two categories such as one-dimensional CNNs, able to analyse raw time series signals, and two-dimensional CNNs, that require the conversion of time series signals to images. The transformation of the ECG signals into images is considered advantageous as noise filtering and feature extraction steps can be avoided and steps like data augmentation can be used to expand the training data, reduce overfitting and balance the class distribution when dealing with an imbalanced dataset. For 2D CNNs, researchers applied different conversions of the signals using grayscale images of the segmented ECG beats [3], recurrence plot images of 2-second ECG signals [105]**,** or time-frequency images obtained by applying wavelet transforms on the ECG signals [106], [1].

More recently, 1D CNN models, firstly introduced by **Kiranyaz et al. in 2015** [107], were applied for signal classification. In 2017, **Andrew Ng** [108] proposed a 34-layers deep 1D CNN for heartbeat classification. This method takes as input raw ECG signals from 30,000 unique patients and can classify 12 different arrhythmias with a sensitivity and productivity superior to that of cardiologists. Likewise, **Sarvan and Nalan** [109] used raw ECG signals and fed them into a 9-leyer deep CNN. Although their method obtained high accuracy and specificity, the sensitivity was just 26.85%. The poor results of deep networks are most probably caused by the relatively small size of data used to train the models, as deep networks are closely linked with the amount of data used. Thus, Wan et al. [110] proposed a method that uses denoised ECG signals and a 4-layer CNN model to classify five types of arrhythmia, reaching a 99.10% accuracy. **Cai et al.** [31] proposed a one-dimensional densely connected neural network (DDNN) for atrial fibrillation detection using 12-lead ECG signals. The DDNN was composed of four dense blocks with a total of 36 layers, and each block consisted of 2, 4, 6, and 4 convolutional layers. Before each dense block and transition layer, squeeze-and-excitation module was applied for feature recalibration. Pooling layers were used between dense blocks to improve the efficiency, and global average pooling and softmax activation function was employed before and after the fully connected layer. Accuracy, sensitivity, and specificity of the results on the test dataset were 99.35%, 99.19%, and 99.44%, respectively. **Yildirim et al.** [111] proposed a DNN composed of 6 one-dimensional convolutional layers and 4 sub-sampling (max-pooling) layers in the representation learning phase (feature extraction), and a 128 LSTM block in the sequence learning phase. Two batch normalization and two dropout layers were used to normalize the data and avoid overfitting. Leaky-ReLU activation function was used in the first part of the algorithm. The average accuracy of the result

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

was 96.13% when model was tested on 12-lead ECG signals, with the best performance obtained on Lead-II (95.43% sensitivity, 98.71% specificity, 95.78% precision). Other recent methods that use CNN for arrhythmia detection are summarized in table 5.

7.2.Deep Belief Networks

Deep Belief Networks (DBN) are probabilistic generative deep learning algorithms introduced to provide a better alternative to the traditional neural networks that can get stuck in local minima and become slow when training in deep layered networks. DBNs consist of multiple Restricted Boltzmann Machines (RBMs), that are composed of two unidirectional connected layers: a layer of visible units and a layer of hidden units with no connections between the units. The visible layer of an RBM represents the input data, while the hidden layer has the ability to perform unsupervised learning.

Recent papers such as [112]–[114] applied DBN classification networks. Tripathy et al [112] proposed a two-stage variational mode decomposition (VMD) method for the extraction of sample entropy and VMD estimated center frequency features, and a DBN for the detection of atrial fibrillation. Both Bernouli–Bernouli and Gaussian–Bernouli were used for the probability distribution of visible and hidden units of the DBN, but Gaussian–Bernouli yielded a better detection accuracy of 98.27% when tested on MIT-BIH arrhythmia and MIT-BIH AF databases. Similarly, Mathews et al. [113] used two sets of extracted features and a DBN to detect supraventricular ectopic beats and ventricular ectopic beats, achieving an accuracy of 93.78%, and 96.94%, respectively.

7.3.Recurrent Neural Networks (RNN)

Recurrent neural networks are networks with feedback connections specially designed to learn sequential or time-series patterns. RNNs make predictions according to both the present input value and the prior input values (feedback) using backpropagation through time with gradient descent. Compared to feed-forward neural networks, in RNN the weights are shared across layers and thus the errors are summed at each time step, allowing them to memorize previous sequences. Although RNN gives a better performance than FNN, both algorithms deal with vanishing gradients. This problem is related to the size of the gradients, which decrease exponentially during backpropagation and thus, these networks cannot learn long time-series data. To reduce the vanishing gradient problem, **Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU)** Networks were proposed. LSTMs can make predictions based on both short and long-term sequences, using memory cells composed of input, forget and output gates that use sigmoid functions to decide which information needs to be retained or withdrawn in order to make the next predictions. Similar to LSTM, GRU are another generation of RNNs composed of just two types of gates: reset gate and update gate, being considered faster and less computationally expensive than LSTM networks. Moreover, LSTM and GRU can be extended to **bidirectional LSTM and GRU networks**. Introduced by Schuster et al. [115], these networks can be trained in both past and future directions by connecting two hidden layers from opposite directions to the same output, increasing the accuracy of the model. A few of these methods are explained below.

Zhang et al. [116] proposed a patient specific classification method, that uses clustering to extract both common features from the dataset and patient-specific features. Morphology information is fed into an LSTM model that learns time correlation among signal points and detects the VEB and SVEB with an overall accuracy of 99.7% and 99.3%, respectively. Wang et al. [91] proposed a four-layer global and updatable heartbeat classification model, called Global Recurrent Neural Network (GRNN), composed of two parts: a morphological and a temporal part. In the morphological part, LSTM blocks were used to memorize longer history, and their output was fed into a fully connected layer. In the temporal part, a fully connected layer was designed and used to learn temporal information. In the end, GRNN learns the differences among various classes, detecting VEB and SVEB with an accuracy,

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

sensitivity and precision over 99%. The main advantage of this system is that a single model can classify samples from multiple patients, and, when different databases are used for training and test samples, the generalization performance of the GRNN improves.

More recently, Zhang et al. [117] developed a heartbeat detection model using CNN and GRU. The algorithm extracts spatial and temporal CNN features and feds them in a GRU network capable to detect nine arrhythmia classes, with an overall F1 score of 83.5%. Similarly, Pandey et al. [29] detected five types of arrhythmia with a 99.52% accuracy using CNN encoded features and a bidirectional LSTM. Essa and Xie [29] proposed an ensemble model for arrhythmia classification. Both hand-crafted features and CNN-based features were extracted, and LSTM is used for the final classification. Although it seems an interesting approach and the overall accuracy is 95.81%, this model fails to detect SVEB (supraventricular arrhythmia) and F (fusion) heartbeats. Other recent methods that used RRNs for ECG arrhythmia classification methods are summarized in table 4.

8. Deep learning-based feature extraction

Recently, researchers proposed deep learning techniques for automatic feature extraction, which overcome the time-consuming hand-crafted feature extraction process required in machine learning techniques. These methods are known as end-to-end learning, where feature extraction, feature optimization, and classification are integrated in one body [118].

The strong ability of the convolutional layers to extract complex features that describe the analysed signals or images, makes the convolutional neural networks among the most extensively used methods for automatic feature extraction. Oh et al. [119] proposed an automated hybrid system that uses CNN to extract the spatial feature maps and LSTM to extract the temporal dynamics of these feature maps. The advantage of this method is that it has the ability to classify ECG segments of variable lengths with a high accuracy of 98.10%. However, an imbalanced dataset was used to develop the model and assumed that each ECG segment contains just one type of arrhythmia, which may decrease the classification accuracy if tested on other signals. Zhang et al. [117] developed a multi-class arrhythmia detection model based on CNN and GRU. The features are extracted by embedding spatial and temporal attention mechanism in each convolutional block. The attention mechanisms are used to assign specific weights for a feature map, helping them to focus on the representative features. Other recent papers that use CNN for automatic feature extraction are [29], [120]–[123].

Intentionally designed for analysing time-series datasets, the long short-term memory networks can be used for both classification and future extraction. Hou et al. [124] proposed an arrhythmia detection model that applies LSTM-based auto-encoder (AE) model for feature extraction and SVM for the final classification. The LSTM-based AE consists of two layers: one that works like an encoder and extracts the ECG features, and the other one that decodes the features and transforms them back into signals. The features obtained after the LSTM encoder layer are fed into an SVM which detects five types of heartbeats with a 99.74% accuracy. Yildirim [125] developed a deep bidirectional LSTM network that used wavelet sequences to extract ECG features. Another deep LSTM is then used for classification, obtaining an outstanding performance that yielded a 99.39% accuracy.

9. Arrhythmia classification using Arterial Blood Pressure signals

In the last decades various techniques have been reported for the analysis and classification of arrhythmia. Although most of the methods have been focused on the ECG analysis, signals such as arterial blood pressure waveforms (ABP) or photoplethysmogram (PPG) can be employed as an alternative or in addition to the ECG to increase the accuracy of the model or to provide supplementary information that can help in assessing the cardiovascular function. The APB and PPG

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

waveforms are both pressure waveforms, but the difference between them is the recording technique. The ABP waveforms are invasively acquired using a catheter placed in an artery (e.g., femoral, brachial, radial), while the PPG is an optical signal acquired using a pulse oximeter placed on the fingertip of the patient.

Blood pressure waveform analysis is well known for its potential to assess the haemodynamic and cardiovascular function [126]. Traditional methods analyse the ABP waveforms through single parameter analysis such as pulse wave velocity (PWV) and augmentation index (Alx) [127]. Even though these methods made possible the estimation of arterial stiffness using non-invasive measurements, the ABP understanding would be highly improved using multi-parametric techniques. Thus, feature extraction techniques have been proposed for studying the morphology, temporal, and frequency proprieties of the blood pressure waveforms. **Melis et al.** [127] proposed an ABP waveform feature extraction method using wavelet analysis of carotid artery pressure waveforms. Daubechies 4 was used to decompose the ABP signals in seven decomposition levels and clear differences in the morphology of different ABP waveforms could be seen in the fifth detail. Although the choice of the wavelet function is closely associated with the utilized dataset, this study demonstrated that wavelet analysis can be employed to extract features from ABP waveforms. In 2011, **Almeida et al.** [128] proposed the prominent point's identifier algorithm (PPIA) to extract hemodynamic features from ABP waveforms. The signals are first segmented pulse by pulse and lowpass filtered to remove the high frequency components. The systolic peak (SP), dicrotic peak, and reflection point were detected using a combined analysis between the ABP waveform and its first order derivative. Moreover, according to the location of the mentioned points, the augmentation index is calculated, and the ABP waveforms are classified into one of four classes: A, B, C and D; where type A indicates large arterial stiffness and type C and D indicate elastic arteries, specific to young patients [126]. This method achieved 99.09% sensitivity for localizing the peaks in time measurements and 99.08% sensitivity for localizing the peaks in amplitude measurements. Later, **Almeida et al.** [126] improved their initial method and used a multi-parametric approach to compute morphological attributes of the ABP waveforms. Ratios, indices and root mean square of successive differences were computed for the initial parameters for both time and amplitude measurements. The extracted features were optimized using Weka package, which uses a discretization method to measure the information gain for each feature and used to classify two types of groups: hypotensive and healthy patients. Several machine learning models such as decision tree and BayesNet have been tested, but Random Forest yielded the best accuracy (96.95%).

ABP waveforms provide a great deal of information regarding the function and compressibility of the arterial system which could be studied as additional information regarding the impact of arrhythmias on patient's health. However, up to date, a limited number of methods have been proposed for ABP arrhythmia detection (Table 4). **Schack et al.** [129] proposed an algorithm for atrial fibrillation based on photoplethysmogram (PPG) signals generated based on the red channel of 50x50 pixels images acquired using smartphone's cameras. The peaks are detected using 20s windows and selected as the samples that are larger than their two adjacent data samples. Time-domain and frequency-domain features are extracted and dimensionally reduced using a sequential forward selection (SFS) which found the best feature combination as being the Shannon entropy of peak differences and the median of peak rise height. Their method has low computational costs and achieved 100% accuracy. However, the classification is exclusively based on pairs of two features and a simple linear SVM model was employed. Thus, this method does not seem reliable when multiple classes of arrythmia must be distinguished. In 2017, **Arvanaghi et al.** [17] classified for the first time five types of arrhythmias based just on ABP waveforms and achieved a 95.75% accuracy. However, ECG signals were synchronically recorded and used to analyse the ABP signals based on a window with the length of the RR intervals which were detected with DWT. Frequency-domain features such as min and max FFT values, mean and median frequency and the median normalized frequency are extracted together with other features based on power and entropy of the signals. The feature vector is fed into the Least Square Support Vector Machine (LS-SVM) model where the final classification is performed.

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

Hussin et al. [130] proposed an arrhythmia detection model based on Acceleration Plethysmogram (APG) signals and Multi-Layer Perceptron (MLP). The APG signals are obtained by calculating the second derivative of the denoised PPG signals. Here, Weka software is used as a feature extraction tool and MLP classifies the signals into normal and abnormal classes with 96% accuracy.

Table 4. Arrhythmia classification methods based on arterial blood pressure signals.

Ref	Signal	Denoising filter	Feature extraction	Features	No of features	Feature optimization	Classification	No of classes	Results
Schack et al. [129]	PPG	Bandpass filter	R-peak detection algorithm; Fourier transform	Time-domain; Frequency-domain	85	Sequential Forward Selection (SFS)	SVM	2	Accuracy: 100, Sensitivity 100 Specificity 100
Arvanaghi et al. [17]	ABP	DWT	DWT	Frequency based features, power and entropy	10	-	LS-SVM	6	Accuracy: 95.75 Sensitivity: 96.77 Specificity: 96.32
Hussin et al. [130]	APG	Bandpass	Weka software	-	-	-	MLP	2	Accuracy 96
Besleaga et al. [131]	ABP PPG ECG	Lowpass	first derivative and Fourier transform	PPG features before and after the onset of ventricular tachycardia; Heart rate from ECG signals	-	Least absolute shrinkage and selection operator (LASSO)	logistic regression	2	Accuracy 86
Kalidas and Tamil [132]	ABP PPG ECG	Bandpass Lowpass	Pan-Tompkins for ECG and threshold based peak detection for PPG and ABP	Specific features for each arrhythmia type	-	-	SVM and logical analysis techniques	5	Sensitivity: 94 Specificity 82

Other studies used blood pressure waveforms together with ECG for a better accuracy. **Besleaga et al.** [131] used invasive ABP waveforms, PPG and ECG signals to distinguish between stable and unstable ventricular tachycardia events. Most of the used features consisted of PPG parameters, while ECG signals were used to extract the heart rate and the ABP signals were used to extract mean ABP and the drop in mean ABP. The best pair of features were selected using Least absolute shrinkage and selection operator (LASSO) models. As a result, an 86% accuracy was obtained using PPG markers in combination with the heart rate, indicating the link between PPG and ECG. **Kalidas and Tamil** [132] classified five types of cardiac arrhythmias using ECG, PPG, and ABP signals. After the signals were filtered by noise, ECG R-peaks were detected using Pan-Tompkins algorithm, whereas PPG and ABP systolic peaks were detected as the peaks whose amplitude was higher than 40% of the maximum value of the first-order derivative of the signals. For each arrhythmia, 2 feature vectors were extracted, one of them from the ECG signal and the other from the PPG signal, and fed into the SVM classifier. If both features have met the criteria for a specific arrythmia, then that specific record was labelled with that arrythmia. Otherwise, the record was labelled as normal. The records that were detected with arrhythmias underwent further threshold-based logical analysis to reduce false positives. ABP was used when PPG information lacked. The method achieved an overall sensitivity of 94%, but the main drawback is that individual features and algorithms have been created for each arrythmia types, making this technique time consuming and computationally expensive.

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

10. Conclusions

This study presents a comprehensive review on different machine learning and deep learning methods employed for cardiac arrhythmia detection. Although other arrhythmia detection review articles exist in the literature, they are restricted to only specific subjects. In this work, all the major aspects of arrhythmia detection have been discussed, including both deep learning and hand-crafted machine learning techniques with steps such as pre-processing, feature extraction, and feature optimization. Moreover, techniques that use ABP signals either by themselves or in addition to ECG signals have also been reviewed and explained in this paper.

Appendix

Table 5. Recent cardiac detection techniques using ECG signals

Reference	Pre-processing	Feature extraction method	Features	No of features	Optimization	Classification	Database	Classes	Results (%):
Jambukia et al. [73]	-	Pan-Tompkins	Morphological (R peak, QRS duration) and timing features (RR interval)	7	-	PSO and FNN	MIT-BIH arrhythmia	3 4 6	Accuracy 99.41%, 98.68% 98.69%
Deriche et al. [41]	-	DWT and Pan-Tompkins	Heartbeat features	13	-	Bayesian	MIT-BIH Arrhythmia	5	Accuracy 92%
Moreira et al. [43]	Bandpass and DC filter	Pan-Tompkins Dynamic segmentation	RR intervals; amplitude; Hjorth parameters	21	-	**SVM**	MIT-BIH Arrhythmia	2	Sensitivity 72.46%
Sueaseenak et al. [42]	-	Pan-Tompkins	mean and SD of RR interval	2	-	SVM	-	4	Accuracy 96.43%
Bhoi et al. [28]	Low pass, high pass and passband	Pan-Tompkins improvised with difference operation method (DOM)	Mean QRS complexes, mean ST segments, Ratio of power spectrum and power spectral density, area under the curve of QRS and ST segment	4	-	ANN	FANTASIA, MIT-BIH Arrhythmia, and long-term ST	3	Accuracy 91.7%
Martis et al. [71]	DWT	Pan-Tompkins and DWT	DWT coefficients	12	PCA LDA ICA	BPNN SVM, PNN	MIT-BIH arrhythmia	5	Accuracy: PCA-PNN: 99% LDA-BPNN: 98.59% ICA-PNN 99.28%
Sahoo et al. [100]	Wavelet transform	Hilbert transform	wavelet, temporal and morphological features	-	PCA	SVM	MIT-BIH arrhythmia	5	Accuracy: 98.50% Sensitivity: 95.68% Specificity: 99.18%
Thilagavathy et al. [37]	DWT (Daubechies D6)	Pan-Tompkins and DWT	wavelet coefficients	-	-	**SVM**	MIT-BIH arrhythmia	6	Accuracy 98.67%

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

Prakash et al. [25]	Bandpass filter (band-pass frequency of 0.1-40 Hz)	Pan-Tompkins and dual tree complex wavelet transform (DTCWT)	Temporal (AC power, kurtosis, skewness, and timing information), and frequency domain	-	-	Random forest	MIT-BIH arrhythmia	5	Accuracy: 99.52 Sensitivity: 99.24 Specificity: 99.12 Precision: 99.26
Abdalla et al. [133]	-	annotations from mit; DWT with Multiresolution Analysis (MRA)	Average Power (AP), Dispersion Coefficient (CD), Sample Entropy (SE) and Singular Values (SV)	36 and 15 after PCA	PCA	**SVM**	MIT-BIH arrhythmia	10	Accuracy: 99.84
Chashmi et al. [134]	DWT (Daubechies D6)	R-peak annotations from mit database DWT and HOS	linear statistical parameters (minimum, maximum, mean, standard deviation and power of the wavelet coefficient)	22	Shannon's Entropy	BPNN, SVM-RBF	MIT-BIH arrhythmia	5	Accuracy 99.03 99.83
Kumari et al. [135]	-	Auto-Regressive, Shannon entropy, Multi-fractal wavelet variance	-	190	-	**SVM**	MIT-BIH arrhythmia; MITBIH NSR; BIDMC database	3	Accuracy: 95.92
Harkat et al. [57]	-	Pan-Tompkins; Continuous Wavelet Transform (CWT)	Wavelet coefficients	-	-	RBF-NN (radial basis function)	MIT-BIH arrhythmia	2	Accuracy: 98.32% Sensitivity: 98.92%
Ye et al. [136]	WT for baseline wander and bandpass (5-12 Hz)	MIT database R-peak annotations, WT and ICA	RR interval, morphological features (wavelet features and ICA features)	22	PCA	**SVM**	MIT-BIH arrhythmia	16	Accuracy: 99.3% Sensitivity: 53.46% Precision: 62.79
Gupta et al. [101]	ICA for noise filtering	Auto Regressive Burg Method and Hilbert transform	-	-	PCA	KNN	Massachusetts Institute of Technology	-	Accuracy: 99.84% Sensitivity 99.90%, Precision: 99.93%,
Mathunjwa et al. [137]	Conversion of 2s ECG signals into recurrence plot images	-	-	-	-	2D CNN	MIT-BIH arrhythmia	6	Acc. First stage: 95.3 % ± 1.27 % and second stage 98.41 % ± 0.11 %
Jun et al. [3]	Conversion of ECG beats into grayscale images	-	-	-	-	2D CNN	MIT-BIH arrhythmia	8	Accuracy 99.05% Sensitivity: 97.85%
Wang et al. [1]	Two median filters (200 ms and 600 ms)	R-peak annotations and CWT (mexh)	RR intervals (previous, post, ratio, local-RR) CWT Scalogram	-	-	2D CNN	MIT-BIH arrhythmia	4	Accuracy: 98.74% Sensitivity: 67.47% Precision: 70.75%

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

Sarvan et al. [109]	-	-	-	-	-	1D CNN	MIT-BIH arrhythmia	5	Accuracy: 93.72% Sensitivity: 26.85% Specificity: 99.6% Precision: 85.43%
Wan et al. [138]	Bandpass filter (5-15 Hz)	-	-	-	-	1D CNN	MIT-BIH arrhythmia	5	Accuracy: 99.10%
Shaker et al. [139]	Butterworth filter with a gange [0.5-40] Hz	-	-	-	-	1D CNN	MIT-BIH arrhythmia	16	Accuracy: 97.30
Ferretti et al. [140]	-	-	-	-	-	Deep 1D CNN	MIT-BIH arrhythmia	16	Accuracy: 98
Li et al. [141]	Wavelet decomposition for signal filtering	-	-	-	-	1D CNN	MIT-BIH arrhythmia	5	Accuracy: 97.5
Rajpurka et al. [108]	-	-	-	-	-	1D CNN	ECG signals from 30,000 unique patients	12	Sensitivity: 82.7 Precision 80.9
Li et al. [142]	Conversion of time-frequency signals to images using Morlet, Paul wavelets, and Gaussian derivative	-	-	-	-	2D CNN	MIT-BIH arrhythmia	3	Accuracy 97.96
Afadar et al. [104]	Low pass; High pass	-	RR interval, QRS duration, Heart rate	3	-	SVM Naïve Bayers, RF	MIT-BIH arrhythmia, NSR, LBBB	4	Accuracy: SVM 92.3 NB: 91.0 RF: 98.9
Sahoo et al. [77]	DWT	multiresolution DWT	RR intervals, heartbeat features (Q, R, S, T amplitudes, QRS duration), Morphology (Q-T interval, S-T interval)	-	-	BPNN SVM	MIT-BIH arrhythmia	4	Accuracy 96.67 98.39
Yazdanian et al. [94]	DWT	Shanon Energy and Hilbert Transform	Morphology, time-domain, wavelet features	189	-	SVM	MIT-BIH arrhythmia	5	Precision: 96.97
Martis et al. [76]	DWT for denoising and Pan-Tompkins for segmentation	PCA	Principal components	-	PCA	SVM	MIT-BIH arrhythmia	5	Accuracy: 98.11 Sensitivity: 99.90 Specificity: 99.10%
Ge et al. [143]	CWT for denoising and signal segmentation	wavelet transform, higher order statistics (HOS)	R-R interval, wavelet and HOS features	-	-	SVM	MIT-BIH arrhythmia	4	Accuracy: 98.40

Sivanantham et al. [39]	Bandpass (0.1-35 Hz)	Hamilton and Tomkins	time-domain, frequency-domain and Heart rate variability features	16	-	SVM	MIT-BIH arrhythmia	5	Accuracy: 90.26
Ashtiyani et al. [27]	Notch (60 Hz)	Pan-Tompkins, wavelet transform	Heart rate variability features	-	Genetic Algorithm (GA)	SVM	MIT-BIH arrhythmia	3	Accuracy: 97.14 Sensitivity: 97.54, Specificity: 96.9 Precision: 97.64
Zhu et al. [144]	Morphological filter	Pan-Tompkins; PCA; Dynamic time warping (DTW)	Morphological features; PCA features;	19	-	SVM	MIT-BIH arrhythmia	4	Accuracy: 97.8
Nahak et al. [98]	moving average filter	Pan-Tompkins; DWT	Heart rate variability, wavelet features and auto-regressive model coefficients	-	-	SVM	MIT-BIH arrhythmia, BIDMC Congestive Heart Failure, MIT-BIH Normal Sinus Rhythm	3	Accuracy 93.33
Thomas et al. [75]	Bandpass (4-22 Hz)	dual tree complex wavelet transform (DTCWT)	wavelet coefficients, QRS features (AC power, kurtosis, skewness and timing information)	28	-	BPNN	MIT-BIH arrhythmia	5	Accuracy: 94.64
Alqudah et al. [87]	Bandpass (0.1-100 Hz) and moving average filter+ heartbeat segmentation	Gaussian mixture modeling, DWT	**statistical** (mean, standard deviation, energy, entropy, skewness, variance) and **wavelets** (energy, variance, standard deviation, waveform length)	38	PCA	PNN	MIT-BIH arrhythmia	6	Accuracy: 99.99
Yu et al. [74]	-	Independent component analysis (ICA)	ICA-based, and RR-interval features	33 ICA components	-	PNN	MIT-BIH arrhythmia	4	Accuracy 98.71
Wang et al. [85]	signal normalization and segmentation	PCA, LDA	RR time intervals, PCA and LDA features	22	LDA and PCA	PNN	MIT-BIH arrhythmia	8	Accuracy: 99.71
Gutiérrez et al. [86]	Wavelet transform for noise reduction	Wavelet transform	heartbeat features (number of P waves, QRS duration, RR interval, position of R, heart rate, PR interval, global rhythm, P wave polarity)	8	-	PNN	MIT-BIH arrhythmia	8	Accuracy: 92.75

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

Pławiak et al. [89]	Rescaling	Welsh method for power spectral density estimation of the signals, and the discrete Fourier transform	frequency components	4001	Genetic algorithms	SVM	MIT-BIH arrhythmia	13 15 17	Accuracy: 95 91 90
Raj et al. [88]	DWT	Pan-Tompkins; Sparse signal decomposition (Gabor Dictionary)	time delay, frequency, width parameter, and square of expansion coefficient	-	Particle Swarm optimization	SVM	MIT-BIH arrhythmia	5	Accuracy: 99.11
Rai et al. [36]	multiresolution DWT moving average filter	DWT for QRS detection; multiresolution DWT	Wavelet features	21	-	PNN BPNN SVM MLP	MIT-BIH arrhythmia	5	Accuracy: 99.53 97.94 99 98.53
Wang et al. [91]	Combined wavelet-based denosing and median filtering algorithm	Morphological and Premature-or-Escape-Flag (PEF)	Morphological and temporal features	-	-	GRNN	MITDB, INCA-TDB, SVDB	4	Over 99% accuracy, sensitivity and precision for VEB and SVEB classes
Li et al. [34]	Butterworth filter	difference operation method (DOM) for QRS detection;	heartbeat features	8	-	parallel GRNN	MIT-BIH arrhythmia; 300 real patients' holter data from the Navy General Hospital in Beijing	5	Accuracy: 95%
Karboub et al. [35]	DWT (Daubechies-db4)	CWT, DWT, maximum overlap discrete transform (MODWT) and autoregressive modelling (AM)	wavelet features	-	PCA	SVM, CNN, quadratic discriminant, KNN and Naïve Bayes	MIT-BIH arrhythmia, normal sinus rhythm and BIDMC congestive heart failure	3	Quadratic discriminant and KNN classifiers obtained the highest accuracies of 99.92 and 98.63
Mazaheri et al. [90]	Normalization	DWT, ECG wave detection algorithm	morphological features, frequency domain features, and nonlinear indices (entropy, fractal dimension, Lyapunov exponent)	-	non-dominated sorting genetic algorithm (NSGA II)	KNN FNN RBFNN Fit NN Pat NN	MIT-BIH arrhythmia	7	**Accuracy:** 93.26 98.75 83.78 98.65 97.97
Alickovic et al.[145]	multiscale principal component analysis (MSPCA)	DWT	statistical features (2 indices for frequency distribution and 2 indices for the amount of change in the frequency distribution)	4	-	CART C4.5 RF	MIT-BIH and St. -Petersburg Institute of Cardiologic al Technics 12-	5	Accuracy: 98.7 98.4 99.3

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

							lead Arrhyt hmia		
Lu et al. [123]	transform the heartbeats into grayscale images	2D-CNN, Early fusion algorithm	convolutional features (200), PQRST features (25)	225	-	RF	MIT-BIH arrhythmia	5	Accuracy: 99.90
Singh et al. [146]	Normalizatio n, Segmentation in 3 beats	-	-	-	-	RNN GRU LSTM	MIT-BIH arrhythmia	2	Accuracy: 85.4, 82.5 88.1
Zhang et al. [116]	Dual-Tree Complex Wavelet Transform (DTCWT) and median filtering	Clustering algorithm	-	-	-	LSTM	MIT-BIH arrhythmia	3	Accuracy 99.7 for VEB detection and 99.3 for SVEB detection
Pandey et al. [122]	ECG signal segmentation	CNN	convolutional encoded features	-	-	Bidirec tional LSTM	MIT-BIH arrhyth mia	5	Accuracy: 99.52
Zhang et al. [117]	The signals are down-sampled to 60s	CNN with spatial and temporal attention mechanism s	Spatial and temporal features	-	-	GRU	China Physiologic al Signal Challenge 2018	9	F1 score 83.5
Lynn et al. [118]	low order polynomial and bandpass filter for noise filtering; segmentation with Pan-Tompkins algorithm	-	-	-	-	Bidirec tional LSTM Bidirec tional GRU	MIT-BIH arrhythmia	-	Accuracy: 96.4 98.55;
Kim and Pyun [147]	derivative filter, moving average filter, normalization , and signal segmentation	-	-	-	-	Bidirec tional LSTM	MIT-BIH Normal Sinus Rhythm (NSRDB) and MIT-BIH Arrhythmia (MITDB)	-	MITDB: Accuracy: 99.8 Sensitivity 99.8 Precision: 99.8
Khan and Kim [148]	PCA	-	-	-	PCA	LSTM	University of California, Irvine (UCI) repository	16	Accuracy 93.5, Sensitivity 90.7 Precision 92.8
Essa and Xie [29]	2 median filters (200 and 600 ms) and low-pass filter	CNN and R peak detection	RR intervals and HOS (68), convolutional features	-	-	LSTM	MIT-BIH arrhythmia	5	Accuracy 95.81 Sensitivity 69.20 Specificity 94.56 Precision 74.97

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

Yildirim et al. [111]	Lowpass filter, local polynomial regression smoother (LOESS), and Non-Local Means (NLM)	1D CNN	Convolutional features	-	-	LSTM	Chapman University and Shaoxing People's Hospital	4 7	Accuracy: 96.13 92.24
Cai et al. [31]	Bandpass filter (0.5-35Hz) and segmentation in 10s segments	-	-	-	-	DNN (36 layers)	Chinese PLA General Hospital; CardioCloud Medical Technology (Beijing) Co. Ltd; The China Physiological Signal Challenge 2018	3	Accuracy: 99.35 Sensitivity 99.19 Specificity 99.44
Xu et al. [149]	-	i-vector	-	-	-	DNN	MIT-BIH arrhythmia	2	Accuracy 99.1 for SVEB detection 99.7 for VEB detection
Xu et al. [150]	heartbeat segmentation using Pan-Tompkins algorithm and heartbeat alignment along the time axis	DNN	-	-	-	DNN	MIT-BIH arrhythmia	2	Accuracy: 93.1
Sannino and De Pietro [151]	Denoising (2 median filters and lowpass filter);	Pan and Tompkins	RR interval features (pre RR; post-RR; local average RR; global average RR)	4	-	DNN	MIT-BIH arrhythmia	5	Accuracy: 99.68
Hannun et al. [152]	-	CNN	-	-	-	DNN	MIT-BIH arrhythmia	12	F1 score 83.7
Tripathy et al. [112]	High pass filter	Hilbert transform and frequency heterodyning	sample entropy (SE) and the Variational mode decomposition estimated centre frequency features	18	-	DBN	MIT-BIH arrhythmia and MIT-BIH AF	2	Accuracy: 98.27 Sensitivity 97.77 Specificity 98.67
Mathews et al. [113]	Bandpass, 2 median filters and adaptive filters;	Detection of R-peak using filter bank based approach and T-wave using search windows with adaptive thresholds	RR intervals; heartbeat intervals; segmented morphology intervals; fixed interval morphology	48	-	DBN	MIT-BIH arrhythmia	2	Accuracy 93.78 for VEB detection 96.94 for SVEB detection

This article has been accepted for publication in a future issue of this conference proceedings, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/EMBC.2022.XXXXXXX, 2022 44th Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBC)

Altan et al. [114]	2 median filters	Wavelet packet decomposition, higher order statistics, morphology and Discrete Fourier transform	High Order Statistic; Morphological features; Higher order statistic of Wavelet Packet decomposition; Discrete Fourier transform features	150	-	DBN	MIT-BIH arrhythmia	5	Accuracy 94.15 Sensitivity 92.64 Specificity 93.38
Sayantan et al. [30]	noise removal (2 median filters and a lowpass filter)	unsupervised feature learning using GB-DBN	-	-	-	SVM	MIT-BIH arrhythmia; SVDB database	2	Accuracy 99.5 for SVEB and 99.4 for VEB on MITdb; Accuracy 97.5 for SVEB and 98.6 for VEB on SVDB database
Oh et al. [119]	Different lengths signal segmentation	CNN and LSTM	-	-	-	Fully connected layer	MIT-BIH arrhythmia; SVDB database	5	Accuracy: 98.1%, Sensitivity: 97.5% Specificity: 98.7%

References

[1] T. Wang, C. Lu, Y. Sun, M. Yang, C. Liu, and C. Ou, “Automatic ECG classification using continuous wavelet transform and convolutional neural network,” *Entropy*, vol. 23, no. 1, pp. 1–13, 2021, doi: 10.3390/e23010119.

[2] C. Gustafsson, M. Blombäck, M. Britton, A. Hamsten, and J. Svensson, “Coagulation factors and the increased risk of stroke in nonvalvular atrial fibrillation.,” *Stroke*, vol. 21, no. 1, pp. 47–51, Jan. 1990, doi: 10.1161/01.STR.21.1.47.

[3] T. Jun, H. Nguyen, D. Kang, D. Kim, D. Kim, and Y.-H. Kim, “ECG arrhythmia classification using a 2-D convolutional neural network,” *ArXiv*, vol. abs/1804.0, 2018.

[4] T. Pereira *et al.*, “Photoplethysmography based atrial fibrillation detection: a review,” *npj Digital Medicine*, vol. 3, no. 1, p. 3, 2020, doi: 10.1038/s41746-019-0207-9.

[5] S. Kaplan Berkaya, A. K. Uysal, E. Sora Gunal, S. Ergin, S. Gunal, and M. B. Gulmezoglu, “A survey on ECG analysis,” *Biomedical Signal Processing and Control*, vol. 43, pp. 216–235, 2018, doi: https://doi.org/10.1016/j.bspc.2018.03.003.

[6] S. Sahoo, M. Dash, S. Behera, and S. Sabut, “Machine Learning Approach to Detect Cardiac Arrhythmias in ECG Signals: A Survey,” *IRBM*, vol. 41, no. 4, pp. 185–194, 2020, doi: https://doi.org/10.1016/j.irbm.2019.12.001.

[7] Y. Hagiwara *et al.*, “Computer-aided diagnosis of atrial fibrillation based on ECG Signals: A review,” *Information Sciences*, vol. 467, pp. 99–114, 2018, doi: https://doi.org/10.1016/j.ins.2018.07.063.

[8] S. M. P D, A. Jantsch, and M. Shafique, “Computer-Aided Arrhythmia Diagnosis with Bio-signal Processing: A Survey of Trends and Techniques,” *ACM Computing Surveys*, vol. 52, Mar. 2019, doi: 10.1145/3297711.

[9] A. Chang, L. M. Cadaret, and K. Liu, “Machine Learning in Electrocardiography and Echocardiography: Technological Advances in Clinical Cardiology,” *Current Cardiology Reports*, vol. 22, no. 12, p. 161, 2020, doi: 10.1007/s11886-020-01416-9.

[10] J. R. Annam, S. Kalyanapu, S. Ch., J. Somala, and S. B. Raju, “Classification of ECG Heartbeat Arrhythmia: A Review,” *Procedia Computer Science*, vol. 171, pp. 679–688, 2020, doi: https://doi.org/10.1016/j.procs.2020.04.074.

[11] F. Murat, O. Yildirim, M. Talo, U. B. Baloglu, Y. Demir, and U. R. Acharya, “Application of deep learning techniques for heartbeats detection using ECG signals-analysis and review,” *Computers in Biology and Medicine*, vol. 120, p. 103726, 2020, doi: https://doi.org/10.1016/j.compbiomed.2020.103726.

[12] Z. Ebrahimi, M. Loni, M. Daneshtalab, and A. Gharehbaghi, “A review on deep learning methods for ECG arrhythmia classification,” *Expert Systems with Applications: X*, vol. 7, p. 100033, 2020, doi: https://doi.org/10.1016/j.eswax.2020.100033.

[13] Mohebbanaaz, Y. P. Sai, and L. V. R. kumari, “A Review on Arrhythmia Classification Using ECG Signals,” in *2020 IEEE International Students’ Conference on Electrical,Electronics and Computer Science (SCEECS)*, 2020, pp. 1–6, doi: 10.1109/SCEECS48394.2020.9.

[14] S. Parvaneh, J. Rubin, S. Babaeizadeh, and M. Xu-Wilson, “Cardiac arrhythmia detection using deep learning: A review,” *Journal of Electrocardiology*, vol. 57, pp. S70–S74, 2019, doi: https://doi.org/10.1016/j.jelectrocard.2019.08.004.

[15] S. Kaplan Berkaya, A. K. Uysal, E. Sora Gunal, S. Ergin, S. Gunal, and M. B. Gulmezoglu, “A survey on ECG analysis,” *Biomedical Signal Processing and Control*, vol. 43, pp. 216–235, 2018, doi: https://doi.org/10.1016/j.bspc.2018.03.003.

[16] Drzezo, “Chapter 35 – Arterial Pressure Waveforms,” *ANESTHESIA*, Sep. 27, 2020.

[17] R. Arvanaghi, S. Danishvar, H. Seyedarabi, and A. Goshvarpour, “Classification of cardiac arrhythmias using arterial blood pressure based on discrete wavelet transform,” *Biomedical Engineering: Applications, Basis and Communications*, vol. 29, p. 1750034, Oct. 2017, doi: 10.4015/S101623721750034X.

[18] A. Velayudhan and S. Peter, “Noise Analysis and Different Denoising Techniques of ECG Signal - A Survey,” 2016.

[19] R. Kher, “Signal Processing Techniques for Removing Noise from ECG Signals,” *Jber*, vol. 3, pp. 1–9, 2019, doi: 10.17303/jber.2019.3.101.

[20] H. Shi, H. Wang, Y. Huang, L. Zhao, C. Qin, and C. Liu, “A hierarchical method based on weighted extreme gradient boosting in ECG heartbeat classification,” *Computer Methods and Programs in Biomedicine*, vol. 171, pp. 1–10, 2019, doi: https://doi.org/10.1016/j.cmpb.2019.02.005.

[21] J. P. do Vale Madeiro, P. C. Cortez, J. M. da Silva Monteiro Filho, and P. R. F. Rodrigues, “Chapter 3 - Techniques for Noise Suppression for ECG Signal Processing,” in *Developments and Applications for ECG Signal Processing*, J. P. do Vale Madeiro, P. C. Cortez, J. M. da Silva Monteiro Filho, and A. R. A. Brayner, Eds. Academic Press, 2019, pp. 53–87.

[22] H. Chen and K. Maharatna, “An Automatic R and T Peak Detection Method Based on the Combination of Hierarchical Clustering and Discrete Wavelet Transform,” *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 10, pp. 2825–2832, 2020, doi: 10.1109/JBHI.2020.2973982.

[23] S. Zhang, T. Zhao, X. Wang, C. Peng, Q. Li, and X. Zhang, “Design and Implementation of A Novel Real Time P-QRS-T Waves Detection Algorithm,” in *2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)*, 2020, vol. 1, pp. 1109–1112, doi: 10.1109/ITNEC48623.2020.9084924.

[24] J. Xu, T. Gao, Y. Wang, and S. Zhou, *A Robust QRS Detection Method based on Adaptive Thresholding and Particle Swarm Optimization*. 2020.

[25] A. J. Prakash and S. Ari, "AAMI standard cardiac arrhythmia detection with random forest using mixed features," 2019, doi: 10.1109/INDICON47234.2019.9030317.

[26] V. Mondéjar-Guerra, J. Novo, J. Rouco, M. G. Penedo, and M. Ortega, "Heartbeat classification fusing temporal and morphological information of ECGs via ensemble of classifiers," *Biomedical Signal Processing and Control*, vol. 47, pp. 41–48, 2019, doi: https://doi.org/10.1016/j.bspc.2018.08.007.

[27] M. Ashtiyani, S. Navaei Lavasani, A. Asgharzadeh Alvar, and M. R. Deevband, "Heart rate variability classification using support vector machine and genetic algorithm," *Journal of Biomedical Physics and Engineering*, vol. 8, no. 4, pp. 423–434, 2018, doi: 10.31661/jbpe.v0i0.614.

[28] A. K. Bhoi, K. S. Sherpa, and B. Khandelwal, *Multimodal Classification of Arrhythmia and Ischemia Using QRS-ST Analysis*, vol. 442. 2018.

[29] E. Essa and X. Xie, "Multi-model Deep Learning Ensemble for ECG Heartbeat Arrhythmia Classification," in *European Signal Processing Conference (EUSIPCO)*, 2021, pp. 1085–1089, doi: 10.23919/Eusipco47968.2020.9287520.

[30] S. G., K. P. T., and K. K. V., "Classification of ECG beats using deep belief network and active learning," *Medical & Biological Engineering & Computing*, vol. 56, no. 10, pp. 1887–1898, 2018, doi: 10.1007/s11517-018-1815-2.

[31] W. Cai *et al.*, "Accurate detection of atrial fibrillation from 12-lead ECG using deep neural network," *Computers in Biology and Medicine*, vol. 116, p. 103378, 2020, doi: https://doi.org/10.1016/j.compbiomed.2019.103378.

[32] S. Sahoo, M. Mohanty, and S. Sabut, "Automated ECG beat classification using DWT and Hilbert transform-based PCA-SVM classifier," *International Journal of Biomedical Engineering and Technology*, vol. 32, no. 3, pp. 287–303, 2020, doi: 10.1504/IJBET.2020.106038.

[33] A. J. Chashmi and M. C. Amirani, "An Efficient and Automatic ECG Arrhythmia Diagnosis System using DWT and HOS Features and Entropy- Based Feature Selection Procedure," *Journal of electrical bioimpedance*, vol. 10, no. 1. Faculty of Electrical and Computer Engineering, Urmia University, Urmia, Iran., pp. 47–54, 2019, doi: 10.2478/joeb-2019-0007.

[34] P. Li *et al.*, "High-performance personalized heartbeat classification model for long-term ECG signal," *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 1, pp. 78–86, 2017, doi: 10.1109/TBME.2016.2539421.

[35] K. Karboub, M. Tabaa, F. Monteiro, S. Dellagi, F. Moutaouakkil, and A. Dandache, "Automated Diagnosis System for Outpatients and Inpatients with Cardiovascular Diseases," *IEEE Sensors Journal*, vol. 21, no. 2, pp. 1935–1946, 2021, doi: 10.1109/JSEN.2020.3019668.

[36] H. M. Rai and K. Chatterjee, "A unique feature extraction using MRDWT for automatic classification of abnormal heartbeat from ECG big data with Multilayered Probabilistic Neural Network classifier," *Applied Soft Computing*, vol. 72, pp. 596–608, 2018, doi: https://doi.org/10.1016/j.asoc.2018.04.005.

[37] R. Thilagavathy, R. Srivatsan, S. Sreekarun, D. Sudeshna, P. Lakshmi Priya, and B. Venkataramani, "Real-Time ECG Signal Feature Extraction and Classification using Support Vector Machine," in *2020 International Conference on Contemporary Computing and Applications, IC3A 2020*, Feb. 2020, pp. 44–48, doi: 10.1109/IC3A48958.2020.233266.

[38] R. J. Martis, U. R. Acharya, and L. C. Min, "ECG beat classification using PCA, LDA, ICA and Discrete Wavelet Transform," *Biomedical Signal Processing and Control*, vol. 8, no. 5, pp. 437–448, 2013, doi: https://doi.org/10.1016/j.bspc.2013.01.005.

[39] A. Sivanantham and S. S. Devi, “Cardiac arrhythmia detection using linear and non-linear features of HRV signal,” in *2014 IEEE International Conference on Advanced Communications, Control and Computing Technologies*, 2014, pp. 795–799, doi: 10.1109/ICACCCT.2014.7019200.

[40] M. Thomas, M. K. Das, and S. Ari, “Automatic ECG arrhythmia classification using dual tree complex wavelet based features,” *AEU - International Journal of Electronics and Communications*, vol. 69, no. 4, pp. 715–721, 2015, doi: https://doi.org/10.1016/j.aeue.2014.12.013.

[41] M. Deriche, S. Aljabri, M. Al-Akhras, M. Siddiqui, and N. Deriche, “An Optimal Set of Features for Multi-Class Heart Beat Abnormality Classification,” in *2019 16th International Multi-Conference on Systems, Signals & Devices (SSD)*, 2019, pp. 418–422, doi: 10.1109/SSD.2019.8893151.

[42] D. Sueaseenak, M. Thongpraiwan, N. Dangjaipong, and N. Roopkaew, “Development of Arrhythmia Classification System for Personal Cardiac Monitor in Thailand,” in *2019 IEEE 2nd International Conference on Electronics Technology (ICET)*, 2019, pp. 595–598, doi: 10.1109/ELTECH.2019.8839615.

[43] R. Moreira, J. Leite, T. C. Pimenta, and R. Moreno, “Online Heartbeat Classification Using Low Cost Algorithms,” in *2019 31st International Conference on Microelectronics (ICM)*, 2019, pp. 150–153, doi: 10.1109/ICM48031.2019.9021277.

[44] B. Mishra, N. Arora, and Y. Vora, “Wearable ECG for Real Time Complex P-QRS-T Detection and Classification of Various Arrhythmias,” in *2019 11th International Conference on Communication Systems & Networks (COMSNETS)*, 2019, pp. 870–875, doi: 10.1109/COMSNETS.2019.8711218.

[45] J. Pan and W. J. Tompkins, “A Real-Time QRS Detection Algorithm,” *IEEE Transactions on Biomedical Engineering*, vol. BME-32, no. 3, pp. 230–236, 1985, doi: 10.1109/TBME.1985.325532.

[46] W. Reklewski, K. Heryan, M. Miśkowicz, and P. Augustyniak, “Real time ECG R-peak detection by extremum sampling,” in *2020 6th International Conference on Event-Based Control, Communication, and Signal Processing (EBCCSP)*, 2020, pp. 1–7, doi: 10.1109/EBCCSP51266.2020.9291358.

[47] P. S. Hamilton and W. J. Tompkins, “Quantitative Investigation of QRS Detection Rules Using the MIT/BIH Arrhythmia Database,” *IEEE Transactions on Biomedical Engineering*, vol. BME-33, no. 12, pp. 1157–1165, 1986, doi: 10.1109/TBME.1986.325695.

[48] D. S. Benitez, P. A. Gaydecki, A. Zaidi, and A. P. Fitzpatrick, “A new QRS detection algorithm based on the Hilbert transform,” in *Computers in Cardiology 2000. Vol.27 (Cat. 00CH37163)*, 2000, pp. 379–382, doi: 10.1109/CIC.2000.898536.

[49] S. Pal and M. Mitra, “Detection of ECG characteristic points using Multiresolution Wavelet Analysis based Selective Coefficient Method,” *Measurement*, vol. 43, no. 2, pp. 255–261, 2010, doi: https://doi.org/10.1016/j.measurement.2009.10.004.

[50] S. Banerjee, R. Gupta, and M. Mitra, “Delineation of ECG characteristic features using multiresolution wavelet analysis method,” *Measurement*, vol. 45, no. 3, pp. 474–487, 2012, doi: https://doi.org/10.1016/j.measurement.2011.10.025.

[51] L. El Bouny, M. Khalil, and A. Adib, “A Wavelet Denoising and Teager Energy Operator-Based Method for Automatic QRS Complex Detection in ECG Signal,” *Circuits, Systems, and Signal Processing*, vol. 39, no. 10, pp. 4943–4979, 2020, doi: 10.1007/s00034-020-01397-8.

[52] H. Beyramienanlou and N. Lotfivand, “Shannon’s Energy Based Algorithm in ECG Signal Processing,” *Computational and Mathematical Methods in Medicine*, vol. 2017, p. 8081361, 2017, doi: 10.1155/2017/8081361.

[53] S. Rekik and N. Ellouze, “Enhanced and Optimal Algorithm for QRS Detection,” *IRBM*, vol. 38, no. 1, pp. 56–61, 2017, doi: https://doi.org/10.1016/j.irbm.2016.11.004.

[54] S. Rekik and N. Ellouze, “QRS detection combining entropic criterion and wavelet transform,” *International Journal of Signal and Imaging Systems Engineering*, vol. 9, no. 4–5, pp. 299–304, 2016, doi: 10.1504/IJSISE.2016.078264.

[55] S. Farashi, “A multiresolution time-dependent entropy method for QRS complex detection,” *Biomedical Signal Processing and Control*, vol. 24, pp. 63–71, 2016, doi: https://doi.org/10.1016/j.bspc.2015.09.008.

[56] C. Li, C. Zheng, and C. Tai, “Detection of ECG characteristic points using wavelet transforms,” *IEEE Transactions on Biomedical Engineering*, vol. 42, no. 1, pp. 21–28, 1995, doi: 10.1109/10.362922.

[57] A. Harkat, R. Benzid, and L. Saidi, “Features extraction and classification of ECG beats using CWT combined to RBF neural network optimized by cuckoo search via levy flight,” in *2015 4th International Conference on Electrical Engineering (ICEE)*, 2015, pp. 1–4, doi: 10.1109/INTEE.2015.7416767.

[58] H. Khorrami and M. Moavenian, “A comparative study of DWT, CWT and DCT transformations in ECG arrhythmias classification,” *Expert Systems with Applications*, vol. 37, no. 8, pp. 5751–5757, 2010, doi: https://doi.org/10.1016/j.eswa.2010.02.033.

[59] A. J. Prakash and S. Ari, “AAMI standard cardiac arrhythmia detection with random forest using mixed features,” 2019, doi: 10.1109/INDICON47234.2019.9030317.

[60] S. P. Preethika and R. Gobinath, “Feature extraction of ECG signal using meyer wavelet transform,” *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 10 Special Issue, pp. 175–179, 2019, doi: 10.35940/ijitee.J1032.08810S19.

[61] S.-W. Chen, H.-C. Chen, and H.-L. Chan, “A real-time QRS detection method based on moving-averaging incorporating with wavelet denoising,” *Computer Methods and Programs in Biomedicine*, vol. 82, no. 3, pp. 187–195, 2006, doi: https://doi.org/10.1016/j.cmpb.2005.11.012.

[62] S. Banerjee, R. Gupta, and M. Mitra, “Delineation of ECG characteristic features using multiresolution wavelet analysis method,” *Measurement*, vol. 45, no. 3, pp. 474–487, 2012, doi: https://doi.org/10.1016/j.measurement.2011.10.025.

[63] C. Zeng, H. Lin, Q. Jiang, and M. Xu, “QRS Complex Detection Using Combination of Mexican-hat Wavelet and Complex Morlet Wavelet,” *J. Comput.*, vol. 8, pp. 2951–2958, 2013.

[64] M. Merah, T. A. Abdelmalik, and B. H. Larbi, “R-peaks detection based on stationary wavelet transform,” *Computer Methods and Programs in Biomedicine*, vol. 121, no. 3, pp. 149–160, 2015, doi: https://doi.org/10.1016/j.cmpb.2015.06.003.

[65] E. Abdul, A. Hassooni, and H. Al-Libawy, “Detection of electrocardiogram QRS complex based on modified adaptive threshold,” *International Journal of Electrical and Computer Engineering*, vol. 9, pp. 3512–3521, Oct. 2019, doi: 10.11591/ijece.v9i5.pp3512-3521.

[66] L. El Bouny, M. Khalil, and A. Adib, “A Wavelet Denoising and Teager Energy Operator-Based Method for Automatic QRS Complex Detection in ECG Signal,” *Circuits, Systems, and Signal Processing*, vol. 39, no. 10, pp. 4943–4979, 2020, doi: 10.1007/s00034-020-01397-8.

[67] A. Alhussainy, “QRS complex detection and R–R interval computation based on discrete wavelet transform,” *International Journal on Smart Sensing and Intelligent Systems*, vol. 13, pp. 1–11, Jan. 2020, doi: 10.21307/ijssis-2020-010.

[68] A. v Anuhya, V. R. Kolluru, and R. K. Patjoshi, “A novel adaptive S-transform based electrocardiogram signal analysis of QRS-peak detection,” *Journal of Green Engineering*, vol. 10, no. 9, pp. 5530–5547, 2020, [Online]. Available:

https://www.scopus.com/inward/record.uri?eid=2-s2.0-85094107298&partnerID=40&md5=ad3a1231a405801c446a4351b4e54181.

[69] A. Fotoohinasab, T. Hocking, and F. Afghah, "A greedy graph search algorithm based on changepoint analysis for automatic QRS complex detection," *Computers in Biology and Medicine*, vol. 130, p. 104208, 2021, doi: https://doi.org/10.1016/j.compbiomed.2021.104208.

[70] B.-J. Yi, D.-G. Lee, and H.-C. Rim, "The Effects of Feature Optimization on High-Dimensional Essay Data," *Mathematical Problems in Engineering*, vol. 2015, p. 421642, 2015, doi: 10.1155/2015/421642.

[71] R. J. Martis, U. R. Acharya, and L. C. Min, "ECG beat classification using PCA, LDA, ICA and Discrete Wavelet Transform," *Biomedical Signal Processing and Control*, vol. 8, no. 5, pp. 437–448, 2013, doi: https://doi.org/10.1016/j.bspc.2013.01.005.

[72] M. Hammad, A. Maher, K. Wang, F. Jiang, and M. Amrani, "Detection of abnormal heart conditions based on characteristics of ECG signals," *Measurement*, vol. 125, pp. 634–644, 2018, doi: https://doi.org/10.1016/j.measurement.2018.05.033.

[73] S. H. Jambukia, V. K. Dabhi, and H. B. Prajapati, "ECG beat classification using machine learning techniques," *International Journal of Biomedical Engineering and Technology*, vol. 26, no. 1, pp. 32–53, 2018, doi: 10.1504/IJBET.2018.089255.

[74] S.-N. Yu and K.-T. Chou, "Integration of independent component analysis and neural networks for ECG beat classification," *Expert Systems with Applications*, vol. 34, no. 4, pp. 2841–2846, 2008, doi: https://doi.org/10.1016/j.eswa.2007.05.006.

[75] M. Thomas, M. K. Das, and S. Ari, "Automatic ECG arrhythmia classification using dual tree complex wavelet based features," *AEU - International Journal of Electronics and Communications*, vol. 69, no. 4, pp. 715–721, 2015, doi: https://doi.org/10.1016/j.aeue.2014.12.013.

[76] R. J. Martis, U. R. Acharya, K. M. Mandana, A. K. Ray, and C. Chakraborty, "Application of principal component analysis to ECG signals for automated diagnosis of cardiac health," *Expert Systems with Applications*, vol. 39, no. 14, pp. 11792–11800, 2012, doi: https://doi.org/10.1016/j.eswa.2012.04.072.

[77] S. Sahoo, B. Kanungo, S. Behera, and S. Sabut, "Multiresolution wavelet transform based feature extraction and ECG classification to detect cardiac abnormalities," *Measurement*, vol. 108, pp. 55–66, 2017, doi: https://doi.org/10.1016/j.measurement.2017.05.022.

[78] C. Babu, M. Senapathi, R. Sahini, and R. Sudha, "Neural network based arrhythmia classification," *Journal of Advanced Research in Dynamical and Control Systems*, vol. 12, no. 6 Special Issue, pp. 154–159, 2020, doi: 10.5373/JARDCS/V12SP6/SP20201019.

[79] S. Mondal and P. Choudhary, "Detection of normal and abnormal ECG signal using ANN," *Advances in Intelligent Systems and Computing*, vol. 807. pp. 25–37, 2019, doi: 10.1007/978-3-319-94703-7_3.

[80] H. H. Haseena, A. T. Mathew, and J. K. Paul, "Fuzzy Clustered Probabilistic and Multi Layered Feed Forward Neural Networks for Electrocardiogram Arrhythmia Classification," *Journal of Medical Systems*, vol. 35, no. 2, pp. 179–188, 2011, doi: 10.1007/s10916-009-9355-9.

[81] A. Dallali, A. Kachouri, and M. Samet, "Fuzzy C-means clustering, neural network, WT, and HRV for classification of cardiac arrhythmia," *Journal of Engineering and Applied Sciences*, vol. 6, no. 10, pp. 112–118, 2011.

[82] C. K. Roopa, B. S. Harish, and S. v Aruna Kumar, "Classification of ECG Arrhythmia using symbolic dynamics through fuzzy clustering neural network," in *Proceedings of SPIE - The International Society for Optical Engineering*, 2018, vol. 10828, doi: 10.1117/12.2501850.

[83] H. H. Haseena, P. K. Joseph, and A. T. Mathew, “Classification of arrhythmia using hybrid networks,” *Journal of Medical Systems*, vol. 35, no. 6, pp. 1617–1630, 2011, doi: 10.1007/s10916-010-9439-6.

[84] D. F. Specht, “Probabilistic neural networks,” *Neural Networks*, vol. 3, no. 1, pp. 109–118, 1990, doi: https://doi.org/10.1016/0893-6080(90)90049-Q.

[85] J.-S. Wang, W.-C. Chiang, Y.-L. Hsu, and Y.-T. C. Yang, “ECG arrhythmia classification using a probabilistic neural network with a feature reduction method,” *Neurocomputing*, vol. 116, pp. 38–45, 2013, doi: https://doi.org/10.1016/j.neucom.2011.10.045.

[86] J. A. Gutiérrez-Gnecchi *et al.*, “DSP-based arrhythmia classification using wavelet transform and probabilistic neural network,” *Biomedical Signal Processing and Control*, vol. 32, pp. 44–56, 2017, doi: https://doi.org/10.1016/j.bspc.2016.10.005.

[87] A. M. Alqudah, A. Albadarneh, I. Abu-Qasmieh, and H. Alquran, “Developing of robust and high accurate ECG beat classification by combining Gaussian mixtures and wavelets features,” *Australasian Physical and Engineering Sciences in Medicine*, vol. 42, no. 1, pp. 149–157, 2019, doi: 10.1007/s13246-019-00722-z.

[88] S. Raj and K. C. Ray, “Sparse representation of ECG signals for automated recognition of cardiac arrhythmias,” *Expert Systems with Applications*, vol. 105, pp. 49–64, 2018, doi: 10.1016/j.eswa.2018.03.038.

[89] P. Pławiak, “Novel methodology of cardiac health recognition based on ECG signals and evolutionary-neural system,” *Expert Systems with Applications*, vol. 92, pp. 334–349, 2018, doi: 10.1016/j.eswa.2017.09.022.

[90] V. Mazaheri and H. Khodadadi, “Heart arrhythmia diagnosis based on the combination of morphological, frequency and nonlinear features of ECG signals and metaheuristic feature selection algorithm,” *Expert Systems with Applications*, vol. 161, p. 113697, 2020, doi: https://doi.org/10.1016/j.eswa.2020.113697.

[91] G. Wang *et al.*, “A global and updatable ECG beat classification system based on recurrent neural networks and active learning,” *Information Sciences*, vol. 501, pp. 523–542, 2019, doi: https://doi.org/10.1016/j.ins.2018.06.062.

[92] Y. Özbay and G. Tezel, “A new method for classification of ECG arrhythmias using neural network with adaptive activation function,” *Digital Signal Processing*, vol. 20, no. 4, pp. 1040–1049, 2010, doi: https://doi.org/10.1016/j.dsp.2009.10.016.

[93] G. Tezel and Y. Özbay, “A new neural network with adaptive activation function for classification of ECG arrhythmias,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 4692 LNAI, no. PART 1. pp. 1–8, 2007, doi: 10.1007/978-3-540-74819-9_1.

[94] H. Yazdanian, A. Nomani, and M. R. Yazdchi, “Autonomous detection of heartbeats and categorizing them by using Support Vector Machines,” in *2013 20th Iranian Conference on Biomedical Engineering (ICBME)*, 2013, pp. 223–227, doi: 10.1109/ICBME.2013.6782223.

[95] C. L. Herry, M. Frasch, A. J. E. Seely, and H.-T. Wu, “Heart beat classification from single-lead ECG using the synchrosqueezing transform,” *Physiological Measurement*, vol. 38, no. 2, pp. 171–187, 2017, doi: 10.1088/1361-6579/aa5070.

[96] K. Tripathi, H. Sohal, and S. Jain, “Statistical Analysis of HRV Parameters for the Detection of Arrhythmia,” *International Journal of Image and Graphics*, vol. 20, no. 4, 2020, doi: 10.1142/S0219467820500369.

[97] R. L. Devi and V. Kalaivani, “Machine learning and IoT-based cardiac arrhythmia diagnosis using statistical and dynamic features of ECG,” *Journal of Supercomputing*, vol. 76, no. 9, pp. 6533–6544, 2020, doi: 10.1007/s11227-019-02873-y.

[98] S. Nahak and G. Saha, “A fusion based classification of normal, arrhythmia and congestive heart failure in ECG,” 2020, doi: 10.1109/NCC48643.2020.9056095.

[99] Y. J. Kim, J. Heo, K. S. Park, and S. Kim, “Proposition of novel classification approach and features for improved real-time arrhythmia monitoring,” *Computers in Biology and Medicine*, vol. 75, pp. 190–202, 2016, doi: https://doi.org/10.1016/j.compbiomed.2016.06.009.

[100] S. Sahoo, M. Mohanty, and S. Sabut, “Automated ECG beat classification using DWT and Hilbert transform-based PCA-SVM classifier,” *International Journal of Biomedical Engineering and Technology*, vol. 32, no. 3, pp. 287–303, 2020, doi: 10.1504/IJBET.2020.106038.

[101] V. Gupta and M. Mittal, “Efficient R-peak Detection in Electrocardiogram Signal Based on Features Extracted Using Hilbert Transform and Burg Method,” *Journal of The Institution of Engineers (India): Series B*, vol. 101, no. 1, pp. 23–34, 2020, doi: 10.1007/s40031-020-00423-2.

[102] W. Lu, H. Hou, and J. Chu, “Feature fusion for imbalanced ECG data analysis,” *Biomedical Signal Processing and Control*, vol. 41, pp. 152–160, 2018, doi: 10.1016/j.bspc.2017.11.010.

[103] E. Alickovic and A. Subasi, “Medical Decision Support System for Diagnosis of Heart Arrhythmia using DWT and Random Forests Classifier,” *Journal of Medical Systems*, vol. 40, no. 4, pp. 1–12, 2016, doi: 10.1007/s10916-016-0467-8.

[104] Y. Afadar, A. B. Nassif, M. A. Eddin, M. AbuTalib, and Q. Nasir, “Heart Arrhythmia Abnormality Classification Using Machine Learning,” in *2020 International Conference on Communications, Computing, Cybersecurity, and Informatics (CCCI)*, 2020, pp. 1–5, doi: 10.1109/CCCI49893.2020.9256763.

[105] B. M. Mathunjwa, Y.-T. Lin, C.-H. Lin, M. F. Abbod, and J.-S. Shieh, “ECG arrhythmia classification by using a recurrence plot and convolutional neural network,” *Biomedical Signal Processing and Control*, vol. 64, p. 102262, 2021, doi: https://doi.org/10.1016/j.bspc.2020.102262.

[106] Q. Li *et al.*, “Ventricular ectopic beat detection using a wavelet transform and a convolutional neural network,” *Physiological Measurement*, vol. 40, no. 5, 2019, doi: 10.1088/1361-6579/ab17f0.

[107] S. Kiranyaz, T. Ince, and M. Gabbouj, “Real-Time Patient-Specific ECG Classification by 1D Convolutional Neural Networks,” *IEEE transactions on bio-medical engineering*, vol. 63, Aug. 2015, doi: 10.1109/TBME.2015.2468589.

[108] A. Y. N. Pranav Rajpurka, Awni Y. Hannun, Masoumeh Haghpanahi, Codie Bourn, “Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks | Enhanced Reader,” 2017, Accessed: Jan. 20, 2021. [Online]. Available: chrome-extension://dagcmkpagjlhakfdhnbomgmjdpkdklff/enhanced-reader.html?openApp&pdf=https%3A%2F%2Farxiv.org%2Fpdf%2F1707.01836.pdf.

[109] Ç. Sarvan and N. Özkurt, “ECG Beat Arrhythmia Classification by using 1-D CNN in case of Class Imbalance,” in *2019 Medical Technologies Congress (TIPTEKNO)*, 2019, pp. 1–4, doi: 10.1109/TIPTEKNO.2019.8895014.

[110] B. Z. and H. X. Xiangkui Wan, Zhiyao Jin, Haibo Wu, Junjie Liu, “Heartbeat classification algorithm based on one-dimensional convolution neural network,” *Journal of Mechanics in Medicine and Biology*, vol. 20, no. 07, p. 2050046, Sep. 2020, doi: 10.1142/S0219519420500463.

[111] O. Yildirim, M. Talo, E. J. Ciaccio, R. S. Tan, and U. R. Acharya, “Accurate deep neural network model to detect cardiac arrhythmia on more than 10,000 individual subject ECG records,” *Computer Methods and Programs in Biomedicine*, vol. 197, p. 105740, 2020, doi: https://doi.org/10.1016/j.cmpb.2020.105740.

[112] R. K. TRIPATHY, M. R. A. PATERNINA, J. G. ARRIETA, and P. PATTANAIK, “AUTOMATED DETECTION OF ATRIAL FIBRILLATION ECG SIGNALS USING TWO STAGE VMD AND ATRIAL

FIBRILLATION DIAGNOSIS INDEX," *Journal of Mechanics in Medicine and Biology*, vol. 17, no. 07, p. 1740044, Oct. 2017, doi: 10.1142/S0219519417400449.

[113] S. M. Mathews, C. Kambhamettu, and K. E. Barner, "A novel application of deep learning for single-lead ECG classification," *Computers in Biology and Medicine*, vol. 99, pp. 53–62, 2018, doi: https://doi.org/10.1016/j.compbiomed.2018.05.013.

[114] G. Altan, N. Allahverdi, and Y. Kutlu, "A Multistage Deep Learning Algorithm for Detecting Arrhythmia," in *2018 1st International Conference on Computer Applications & Information Security (ICCAIS)*, 2018, pp. 1–5, doi: 10.1109/CAIS.2018.8441942.

[115] M. Schuster and K. K. Paliwal, "Bidirectional recurrent neural networks," *IEEE Transactions on Signal Processing*, vol. 45, no. 11, pp. 2673–2681, 1997, doi: 10.1109/78.650093.

[116] C. Zhang, G. Wang, J. Zhao, P. Gao, J. Lin, and H. Yang, "Patient-specific ECG classification based on recurrent neural networks and clustering technique," in *2017 13th IASTED International Conference on Biomedical Engineering (BioMed)*, 2017, pp. 63–67, doi: 10.2316/P.2017.852-029.

[117] J. Zhang, A. Liu, M. Gao, X. Chen, X. Zhang, and X. Chen, "ECG-based multi-class arrhythmia detection using spatio-temporal attention-based convolutional recurrent neural network," *Artificial Intelligence in Medicine*, vol. 106, 2020, doi: 10.1016/j.artmed.2020.101856.

[118] H. M. Lynn, S. B. Pan, and P. Kim, "A Deep Bidirectional GRU Network Model for Biometric Electrocardiogram Classification Based on Recurrent Neural Networks," *IEEE Access*, vol. 7, pp. 145395–145405, 2019, doi: 10.1109/ACCESS.2019.2939947.

[119] S. L. Oh, E. Y. K. Ng, R. S. Tan, and U. R. Acharya, "Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats," *Computers in Biology and Medicine*, vol. 102, pp. 278–287, 2018, doi: https://doi.org/10.1016/j.compbiomed.2018.06.002.

[120] S. Kiranyaz, T. Ince, and M. Gabbouj, "Real-Time Patient-Specific ECG Classification by 1-D Convolutional Neural Networks.," *IEEE transactions on bio-medical engineering*, vol. 63, no. 3, pp. 664–675, Mar. 2016, doi: 10.1109/TBME.2015.2468589.

[121] U. R. Acharya *et al.*, "A deep convolutional neural network model to classify heartbeats," *Computers in Biology and Medicine*, vol. 89, pp. 389–396, 2017, doi: https://doi.org/10.1016/j.compbiomed.2017.08.022.

[122] S. K. Pandey and R. R. Janghel, "Automated detection of arrhythmia from electrocardiogram signal based on new convolutional encoded features with bidirectional long short-term memory network classifier," *Physical and Engineering Sciences in Medicine*, vol. 44, no. 1, pp. 173–182, 2021, doi: 10.1007/s13246-020-00965-1.

[123] W. Lu, H. Hou, and J. Chu, "Feature fusion for imbalanced ECG data analysis," *Biomedical Signal Processing and Control*, vol. 41, pp. 152–160, 2018, doi: 10.1016/j.bspc.2017.11.010.

[124] B. Hou, J. Yang, P. Wang, and R. Yan, "LSTM-Based Auto-Encoder Model for ECG Arrhythmias Classification," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 4, pp. 1232–1240, 2020, doi: 10.1109/TIM.2019.2910342.

[125] Ö. Yildirim, "A novel wavelet sequence based on deep bidirectional LSTM network model for ECG signal classification.," *Computers in biology and medicine*, vol. 96, pp. 189–202, May 2018, doi: 10.1016/j.compbiomed.2018.03.016.

[126] V. G. Almeida *et al.*, "Machine learning techniques for arterial pressure waveform analysis," *Journal of personalized medicine*, vol. 3, no. 2, pp. 82–101, May 2013, doi: 10.3390/jpm3020082.

[127] M. de Melis *et al.*, "Blood pressure waveform analysis by means of wavelet transform.," *Medical & biological engineering & computing*, vol. 47, no. 2, pp. 165–173, Feb. 2009, doi: 10.1007/s11517-008-0397-9.

[128] V. Almeida *et al.*, "Hemodynamic Features Extraction from a New Arterial Pressure Waveform Probe," 2011.

[129] T. Schäck, Y. S. Harb, M. Muma, and A. M. Zoubir, "Computationally efficient algorithm for photoplethysmography-based atrial fibrillation detection using smartphones," in *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2017, pp. 104–108, doi: 10.1109/EMBC.2017.8036773.

[130] K. Hussin, K. A. Sidek, and A. F. Ismail, "Heart abnormality detection using acceleration plethysmogram signal," *Journal of Telecommunication, Electronic and Computer Engineering*, vol. 10, no. 1–6, pp. 21–24, 2018, [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85045213311&partnerID=40&md5=ac363b4f9a15572d216f49068d571d95.

[131] T. Besleaga, P. D. Lambiase, A. J. Graham, A. Demosthenous, and M. Orini, "Real Time Non-Invasive Hemodynamic Assessment of Ventricular Tachycardia," *IEEE Access*, vol. 8, pp. 138652–138660, 2020, doi: 10.1109/ACCESS.2020.3012494.

[132] V. Kalidas and L. Tamil, "Cardiac arrhythmia classification using multi-modal signal analysis," *Physiological Measurement*, vol. 37, pp. 1253–1272, Aug. 2016, doi: 10.1088/0967-3334/37/8/1253.

[133] F. Y. O. Abdalla, L. Wu, H. Ullah, H. Mkindu, Y. Nie, and Y. Zhao, "ECG arrhythmia Discrimination using SVM and Nonlinear and Non-stationary Decomposition," 2019, doi: 10.1109/ISSPIT47144.2019.9001889.

[134] A. J. Chashmi and M. C. Amirani, "An Efficient and Automatic ECG Arrhythmia Diagnosis System using DWT and HOS Features and Entropy- Based Feature Selection Procedure," *Journal of electrical bioimpedance*, vol. 10, no. 1. Faculty of Electrical and Computer Engineering, Urmia University, Urmia, Iran., pp. 47–54, 2019, doi: 10.2478/joeb-2019-0007.

[135] C. U. Kumari *et al.*, "Heart Rhythm Abnormality Detection and Classification using Machine Learning Technique," in *2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184)*, 2020, pp. 580–584, doi: 10.1109/ICOEI48184.2020.9142914.

[136] C. Ye, B. V. K. V. Kumar, and M. T. Coimbra, "Heartbeat Classification Using Morphological and Dynamic Features of ECG Signals," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 10, pp. 2930–2941, 2012, doi: 10.1109/TBME.2012.2213253.

[137] B. M. Mathunjwa, Y.-T. Lin, C.-H. Lin, M. F. Abbod, and J.-S. Shieh, "ECG arrhythmia classification by using a recurrence plot and convolutional neural network," *Biomedical Signal Processing and Control*, vol. 64, p. 102262, 2021, doi: https://doi.org/10.1016/j.bspc.2020.102262.

[138] B. Z. and H. X. Xiangkui Wan, Zhiyao Jin, Haibo Wu, Junjie Liu, "Heartbeat classification algorithm based on one-dimensional convolution neural network," *Journal of Mechanics in Medicine and Biology*, vol. 20, no. 07, p. 2050046, Sep. 2020, doi: 10.1142/S0219519420500463.

[139] A. Shaker, M. Tantawi, H. Shedeed, and M. Tolba, "Deep Convolutional Neural Networks for ECG Heartbeat Classification Using Two-Stage Hierarchical Method," 2020, pp. 137–147.

[140] J. Ferretti, V. Randazzo, G. Cirrincione, and E. Pasero, "1-D Convolutional Neural Network for ECG Arrhythmia Classification," in *Progresses in Artificial Intelligence and Neural Systems*, A. Esposito, M. Faundez-Zanuy, F. C. Morabito, and E. Pasero, Eds. Singapore: Springer Singapore, 2021, pp. 269–279.

[141] D. Li, J. Zhang, Q. Zhang, and X. Wei, "Classification of ECG signals based on 1D convolution neural network," in *2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom)*, 2017, pp. 1–6, doi: 10.1109/HealthCom.2017.8210784.

[142] Q. Li *et al.*, "Ventricular ectopic beat detection using a wavelet transform and a convolutional neural network," *Physiological Measurement*, vol. 40, no. 5, 2019, doi: 10.1088/1361-6579/ab17f0.

[143] Z. Ge, Z. Zhu, P. Feng, S. Zhang, J. Wang, and B. Zhou, "ECG-Signal Classification Using SVM with Multi-feature," in *2019 8th International Symposium on Next Generation Electronics (ISNE)*, 2019, pp. 1–3, doi: 10.1109/ISNE.2019.8896430.

[144] w. zhu, X. Chen, Y. Wang, and L. Wang, "Arrhythmia Recognition and Classification Using ECG Morphology and Segment Feature Analysis," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 16, no. 1, pp. 131–138, 2019, doi: 10.1109/TCBB.2018.2846611.

[145] E. Alickovic and A. Subasi, "Medical Decision Support System for Diagnosis of Heart Arrhythmia using DWT and Random Forests Classifier," *Journal of Medical Systems*, vol. 40, no. 4, pp. 1–12, 2016, doi: 10.1007/s10916-016-0467-8.

[146] S. Singh, S. K. Pandey, U. Pawar, and R. R. Janghel, "Classification of ECG Arrhythmia using Recurrent Neural Networks," in *Procedia Computer Science*, 2018, vol. 132, pp. 1290–1297, doi: 10.1016/j.procs.2018.05.045.

[147] B.-H. Kim and J.-Y. Pyun, "ECG identification for personal authentication using LSTM-based deep recurrent neural networks," *Sensors (Switzerland)*, vol. 20, no. 11, pp. 1–17, 2020, doi: 10.3390/s20113069.

[148] M. Ashfaq Khan and Y. Kim, "Cardiac Arrhythmia Disease Classification Using LSTM Deep Learning Approach," *Computers, Materials and Continua*, vol. 67, pp. 427–443, Jan. 2021, doi: 10.32604/cmc.2021.014682.

[149] S. S. Xu, M. Mak, and C. Cheung, "Patient-Specific Heartbeat Classification Based on I-Vector Adapted Deep Neural Networks," in *2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2018, pp. 784–787, doi: 10.1109/BIBM.2018.8621475.

[150] S. S. Xu, M.-W. Mak, and C.-C. Cheung, "Towards End-to-End ECG Classification with Raw Signal Extraction and Deep Neural Networks," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 4, pp. 1574–1584, 2019, doi: 10.1109/JBHI.2018.2871510.

[151] G. Sannino and G. de Pietro, "A deep learning approach for ECG-based heartbeat classification for arrhythmia detection," *Future Generation Computer Systems*, vol. 86, pp. 446–455, 2018, doi: https://doi.org/10.1016/j.future.2018.03.057.

[152] A. Y. Hannun *et al.*, "Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network," *Nature Medicine*, vol. 25, no. 1, pp. 65–69, 2019, doi: 10.1038/s41591-018-0268-3.