IJCI V11-2(2024) 44–65
International Journal of Computers and Information (IJCI)
Available online at https://ijci.journals.ekb.eg/

Arrhythmia Classification: A Pipeline-based Comprehensive Survey

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Abstract

Recently, Artificial Intelligence (AI) has played an indispensable role in advancing healthcare data systems, particularly in intricate medical data analysis. Its efficacy in unveiling meaningful relationships has proven pivotal for diagnosis, treatment, and prediction across clinical scenarios. One such critical area is arrhythmia, a condition marked by deviations in the heart's electrical system, posing a substantial risk of sudden cardiac arrest and potential fatality. Electrocardiograph (ECG) signals serve as the primary medium for capturing and documenting the heart's electrical activity. This paper provides a comprehensive overview of the application of AI techniques at various stages of the arrhythmia classification process. A distinctive presentation approach was used as the survey was made in the form of a pipeline. Encompassing the preprocessing of ECG data, extraction and selection of pertinent features, classifier training, and performance evaluation, the swift and accurate analysis of ECG signals is imperative for monitoring and treating individuals with heart conditions. The key goal is deploying these AI-driven solutions in clinical scenarios, ensuring enhanced patient care and outcomes.

Keywords: *Classification, Arrhythmia Classification, Arrhythmia classification pipeline, Arrhythmia, ECG Signals.*

1. Introduction

The abundant data resources over social media, online shopping, smart devices, and healthcare systems are considered an exquisite challenge in various computer applications. This challenge demands artificial intelligence techniques for analysing and managing the exponential growth which raises non-trivial concerns regarding the efficiency of data gathering, processing, analytics, and security [1].

Nowadays, artificial intelligence contributes massively to advancement in dealing with healthcare data systems. The healthcare system is mainly associated with data sensitivity and severity in crucial

decisions about human life. Patient records, x-rays, magnetic resonance imaging (MRI), ultrasounds, biometric device data, and electrocardiography (ECG) signals are various types of healthcare data [2]. Healthcare workers use medical artificial intelligence techniques to aid them in their daily tasks, helping with duties that depend on manipulating and understanding data. Given AI's capability to analyse intricate medical data and leverage meaningful relationships for diagnosing, treating, and the physical examination of cardiovascular diseases (CVDs) due to its affordability and non-invasive characteristics. The heart's electrical activity is examined and documented through ECG electrical waves, generated by connecting ten electrodes to the human chest and limbs to produce a 12-lead image named lead I, II, III, aVF, aVR, aVL, V1, V2, V3, V4, V5, V6 [4-6].

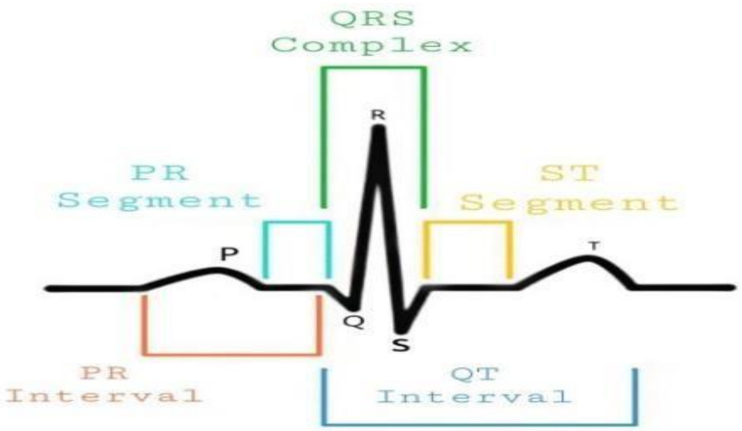


Fig. 1. *ECG Heartbeat Components.*

Each cycle of the ECG comprises five waves, namely P, Q, R, S, and T, as illustrated in Fig. 1, each corresponding to distinct phases of heart activities. The P wave signifies the standard depolarization of the atrium, the QRS complex indicates the depolarization of the right and left ventricles, and the T wave signifies the repolarization (or recovery) of the ventricles [7].

Arrhythmia refers to irregular heartbeats, characterized by an increase (tachycardia), decrease (bradycardia), or irregularity in the heartbeats [8]. Arrhythmia causes changes or distortions in the heart's electrical system. The severity of arrhythmias varies, ranging from mild cases to critical conditions, with some leading to sudden cardiac arrest. Consequently, the prompt analysis of ECG signals is crucial for monitoring and treating individuals with heart conditions. Although specialized experts traditionally analyse ECGs to assess heart health, the process is stressful and time-consuming, potentially resulting in inaccurate diagnoses. That underscores the need for AI techniques within healthcare systems [9,10].

This paper's principal contribution is a comprehensive survey of AI techniques employed across various stages of the arrhythmia classification pipeline, addressing one of the most prevalent heart diseases. A pipeline strategy of systematically presenting and organizing classification techniques was adopted, providing readers with a clearer understanding of each stage's workflow and contributions. Contrary to [40], which focuses on the broader ECG analysis pipeline, this paper specifically concentrates on the arrhythmia classification pipeline. Notably, focusing on recent post-2020 papers, ensuring exploration of the latest advancements in AI for arrhythmia classification is achieved, providing valuable insights through an in-depth examination of the arrhythmia classification process as a comprehensive pipeline.

In contrast to over prevalent research i.e. [57] and [63], often emphasized single stages such as the learning stage, denoising, or feature extraction, all stages were covered by meticulous investigation from preprocessing to evaluation. This systematic approach aims to offer a nuanced understanding for both researchers and practitioners in the field of arrhythmia classification.

2. Dataset and Imbalance Treatment

In addition to, the widely recognized database extensively studied in arrhythmia classification research: the MIT-BIH database [11], it's noteworthy that some studies in arrhythmia classification have opted to utilize multiple datasets in their testing stage. The American Heart Association (AHA) database [58], and the St. Petersburg Institute of Cardiological Technics 12-lead Arrhythmia (INCART) database [59], For instance; [60] used both MIT-BIH and AHA datasets, while another investigation [61] integrated the MIT-BIH and INCART. The rationale behind such amalgamation lies in the aim of enhancing the robustness and generalizability of their findings by considering diverse sources and increasing the variability in the dataset.

The MIT-BIH database plays a crucial role as a benchmark dataset in ECG classification, significantly advancing the field of arrhythmia classification. This dataset enables the development of more accurate models for arrhythmia classification and detection. It consists of 48 half-hours of two-channel records from 47 subjects studied by the BIH Arrhythmia Laboratory. Each channel records 360 samples per second with 11-bit resolution over a 10-mV range, annotated by two or more cardiologists. However, studies [12-18] have emphasized that the MIT-BIH data is heavily imbalanced, with the number of regular beats exceeding other irregular ones. This imbalance negatively impacts the classification performance of models. As a solution, [14], [17,18] applied the Synthetic Minority Oversampling Technique (SMOTE) [19] to address this data imbalance by generating synthetic samples of the minority class. Conversely, [13], [15,16] employed the focal loss function, a modified version of the cross-entropy loss function, to counteract the imbalanced data by assigning greater weight to minority class samples.

The AHA dataset, on the other hand, comprises 154 ECG recordings, each lasting for 3 hours, with beat class information available only in the last 30 minutes. Each recording in the AHA dataset includes two leads (A, B) sampled at 250 Hz. Importantly, the documentation of the AHA database does not specify the names of these leads. Annotations within the AHA dataset indicate the class of each heartbeat and its position, and these annotations have been verified by independent experts. Adhering to the standards and recommendations outlined by the American National Standards Institute, as developed by the Association for the Advancement of Medical Instrumentation (AAMI) for the evaluation of ECG classifiers. All heartbeat annotation labels in the MIT-BIH and AHA datasets (ventricular ectopic beats), F (fusion beats), and Q (unclassifiable beats).

Furthermore, the INCART database includes 75 annotated recordings from 32 Holter records, each lasting 30 minutes. Each record has 12 standard leads, and the data was sampled at 257 Hz with gains varying from 250 to 1100 analog-to-digital converter units per millivolt. The original records were collected from 32 patients (17 men and 15 women, aged 18-80, with an average age of 58) undergoing tests for coronary artery disease. None of the patients had pacemakers, but most of them had ventricular ectopic beats. The records were chosen based on ECG patterns suggesting ischemia, coronary artery disease, conduction abnormalities, and arrhythmias.

3. Arrhythmia Classification Pipeline

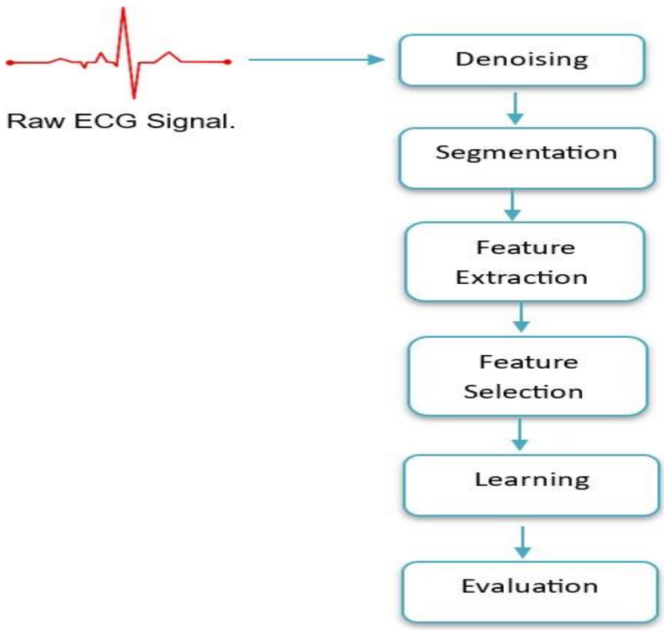


Fig. 2. *Arrhythmia Classification Pipeline.*

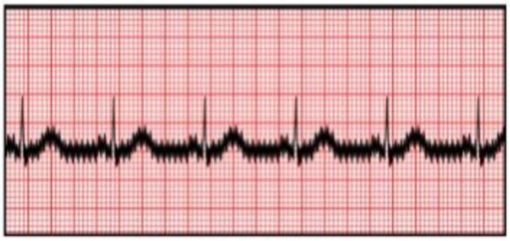
The arrhythmia classification process involves several key steps, starting with the preprocessing of ECG data, followed by the extraction and selection of relevant features, then training a classifier, and finally evaluating its performance before deploying it for clinical use (refer to Fig.2). This section explores the various AI techniques employed at each stage of the pipeline.

3.1 Denoising

It is worth noting that denoising techniques can deform the ECG signal and affect the accuracy of arrhythmia classification. Therefore, it is essential to carefully evaluate and validate the performance of any denoising filter before applying it to ECG signals.

In ECGs, the presence of artifacts poses a challenge to accurate classification [20,21]. Therefore, a pressing objective is the timely removal of these artifacts to ensure data cleanliness and prevent interference with the classification task. Powerline interference arises from electrical disturbances in the power supply, while baseline wander entails a slow drift or fluctuation in the ECG signal baseline, influenced by factors such as respiration, body movement, or inadequate skin-electrode contact. Muscle noise results from the electrical activity of skeletal muscles, electrode artifact stems from issues with electrode-skin contact, and device interference encompasses artifacts introduced by electronic devices near ECG recordings [22,23]. Various ECG motion artifact examples are shown in Fig.3 [62]. Addressing these varied artifacts is essential to enhance the reliability of ECG data and optimize the accuracy of subsequent classification processes.

(a)



(b)

(c)

Fig. 3. *ECG Artifact examples: (a) Baseline Wander, (b) Powerline Interference, (c) Muscle Interference. [62]*

Discrete wavelets transform (DWT) [24], empirical mode decomposition (EMD) [25], and adaptive filtering [26] are examples of the frequent denoising techniques used to reduce different ECG artifacts [27].

A wavelet transform is an ideal tool for analyzing signals in the time and frequency domains used widely to remove noise from ECG signals. For example, [17] proposed an algorithm for ECG signal preprocessing based on wavelet transform for diagnosing arrhythmia types to reduce the noise in original ECG signals using the db6 wavelet basis function. While [18] conducted a wavelet threshold

denoising method to remove the artifacts in ECGs by decomposing it into nine levels using the Daubechies 9 (db9) wavelet and then applying soft thresholding filtering to reconstruct the signal. Other examples of DWT, [16] and [28] subjected the ECG signal to a threshold on wavelet transform using 'db5′ wavelet base to remove the high-frequency noise. In addition, applying 6-level daubechies-6 mother wavelet DWT, band-pass filtering, and EMD during the preprocessing stage to remove baseline drift artifacts from the signal [29]. Using dual-tree complex wavelet transform (DTCWT) after sampling the ECG signal to 360 Hz bandwidth, the noise is deleted and further divided into 10 s segments [30].

Additionally, [23] and [31] applied a median filter to obtain a smooth ECG. Also, the median and low-high band-pass filters eliminate the baseline in the ECGs. Likewise, [33] applied a first-order median filter to remove baseline wander and a low-pass filter to remove high frequencies. Furthermore, adaptive techniques for ECG denoising are also well-researched. The adaptive filter proposed with a low pass filter effectively removes power frequency interference noise and preserves the original characteristics of the ECG signal [34]. After denoising, identifying individual heartbeats and extracting relevant features is essential before the classification.

3.2 Segmentation

For heartbeat segmentation, it's required to accurately detect the R peak positions of the ECG signals as reference points. The MIT-BIH arrhythmia database annotated these R peaks to be segmented [35].

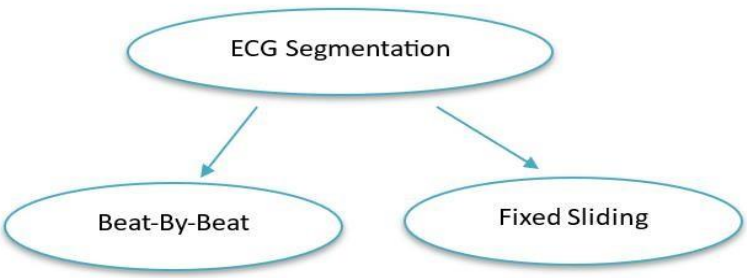


Fig. 4. *ECG Segmentation Methods.*

Significant studies in arrhythmia classification apply a fixed sliding window technique to segment ECG signals. Others classify arrhythmias using a beat-by-beat level, which means they look at each heartbeat separately, as presented in Fig. 4.

Complete patient's ECG data was cut into a single valid beat to improve the system recognition accuracy [16]. In [18], the ECG signals were segmented into separate heartbeats. Each cardiac cycle segment contains the QRS complex of interest in most instances within 0.6–0.8 s length. For a heartbeat sample, the QRS localization method based on the Physiobank WFDB toolbox was used [28]. The continuous ECG signal beats were divided into single beats with 300 samples for each Using the R-wave peak [34]. According to the position of the R peak, ECG beats were segmented with 300 sampling points and transformed into an ECG image by drawing it as a separate 128 × 128 grayscale image [13]. Furthermore, [36,37] split ECG signals into individual heartbeats using The PanTompkins algorithm [38] adopted for the R-peak point detection of ECG signals. With the same approach, [14], [21],[39], and [31] segmented ECG signals into a series of individual heartbeats.

The fixed sliding window technique is a trivial method used in many signal processing applications, including ECG signals [40]. It is a simple and easy-to-implement method involving dividing the ECG signal into equal-sized segments or windows, each of which is analyzed independently. An example thereof, [29] segmented the ECG signals with a window size of 0.4 s and with 50 % overlap. [32] constructed a 180-size window throughout the R-peak for each beat. After detecting the QRS complex using an adaptive thresholding technique, a window size of 700 MS around the R-peak is set for heartbeat segmentation [41]. The extraction window is set to 170 samples [42] to capture the most relevant waves that define a heartbeat, and a window of length 0.512 MS is taken across each R-peak to determine the size of each ECG signal consisting of 256 samples [23].

3.3 Feature Extraction

The extraction of informative and pertinent features from ECG signals is a pivotal stage in arrhythmia classification. Feature extraction is a critical step of the pipeline, aiming to generate a set of features that faithfully represent the signals. These features are then processed and input into machine learning models to make precise predictions while retaining the information from the original dataset. This section provides a concise overview of various techniques employed in feature extraction for arrhythmia classification from 2018 onwards.

Initially, [36] utilized a principal component analysis network (PCANet) algorithm with a two-level convolution layer to extract heartbeat features, while [23] applied the Discrete Orthogonal Stockwell Transform (DOST) Algorithm. The latter involves computing the Fourier spectrum of the ECG signal using an N-point FFT, multiplying it with a rectangular window function, and then applying a β-point inverse FFT to compute the DST coefficients for each central frequency.

Subsequently, [43] utilized an ECG-derived respiratory (EDR) function from the PhysioNet MATLAB toolbox to compute QRS complex features and a set of eleven heart rate variability (HRV) features. For increased accuracy, [44] extracted a combination of temporal, morphological, and spectral features from ECG recordings. The Short-Time Fourier Transform (STFT) Algorithm with a window function was applied to extract frequency features of the heartbeat signals for classification [31]. In [12], the power spectral density (PSD) of the ECG signal was estimated using the Welsh method and discrete Fourier transform (DFT), with four Hamming window widths: (a) 128, (b) 256, (c) 512, and (d) 1024 samples; the transformed signal was logarithmized to normalize the frequency components of the PSD.

More recently, [32] employed the Wavelet Transform Descriptor (WTD) and Local Binary Pattern Descriptor (LBP) for feature extraction from ECG signals. Similarly, [21] extracted essential features such as RR intervals, morphological characteristics, and high-order statistics from each segmented heartbeat for the classification system. Pre-processed ECGs were fed into an autoencoder to extract features, with the interval between two adjacent R peaks (RR interval) extracted as an auxiliary feature and input to the model to enhance classification accuracy [30]. Convolutional Neural Networks (CNNs) were employed by [16], [29], and [45] due to their capability to automatically learn and

extract relevant features from ECG signals, thereby improving the accuracy and efficiency of arrhythmia diagnosis and treatment.

3.4 Feature Selection

Following feature extraction, identifying the most informative aspects of ECG signals becomes imperative. The feature selection stage seeks to reduce the feature space dimensionality and the computational complexity of classification algorithms [46].

One widely employed technique is Principal Component Analysis (PCA), which transforms the original feature space into a lower-dimensional one while retaining crucial information by pinpointing principal components capturing the most variance in the data [47]. For instance, [44] utilized PCA to enhance classification performance, reducing the dimensionality of the original 22-dimensional space to an 8-dimensional feature space. Similarly, [36] applied a Principal Component Analysis Network (PCANet) to perform feature extraction and selection, which is particularly beneficial for dealing with noisy ECG signals.

Given the often high dimensionality of ECG signals, certain studies have devised methods for feature selection. [48], for example, introduced an enhanced wrapper feature selection method integrated with a random forest classifier, effectively choosing the most relevant features. Additionally, [49] developed a Multi-Label Feature Selection Algorithm based on ECG signals (MSECG) to address high-dimensional challenges in the intelligent annotation of ECG. That algorithm efficiently selects the optimal ECG feature subset by assessing feature importance.

Another avenue for selecting relevant ECG features involves the use of metaheuristic algorithms and powerful optimization techniques employed in arrhythmia classification. [50], for instance, proposed an ensemble feature selection method leveraging the strengths of whale optimization, grasshopper optimization, and Grey Wolf Optimization (GWO) methods to identify pertinent features effectively.

3.5 Learning Techniques for Arrhythmia Classification

Arrhythmia classification involves discerning irregular heart rhythms that may pose significant health risks [51]. As a result, the development of dependable and highly accurate models is essential for making critical medical decisions affecting patients' lives [52]. In recent years, investigations have employed a spectrum of learning algorithms, ranging from straightforward approaches to intricate deep neural networks, to address the challenges posed by arrhythmia classification.

Deep neural networks, particularly convolutional neural networks (CNNs), have demonstrated significant success in the task of arrhythmia classification, yielding promising outcomes. For instance, [37] devised a 9-layer deep CNN capable of automatically identifying five categories of ECG signals, achieving accuracies of 94.03% and 93.47% for heartbeat classification in original and noise-free ECGs, respectively. [42] introduced a novel deep CNN using state-of-the-art techniques, achieving an accuracy of 99.48% and 88.34% under intra-patient and inter-patient paradigms, respectively, for accurate heartbeat classification of five categories in a single lead without data preprocessing. In a unique approach, [12] developed a three-layer (48 + 4 + 1) deep genetic ensemble of classifiers (DGEC), combining ensemble learning, deep learning, and evolutionary computation to detect 17 categories of arrhythmias with an accuracy of 99.37%. Leveraging a depthwise separable CNN with focal loss (DSC-FL-CNN) method, [13] achieved an accuracy of 98.55% for automatically classifying 17 categories of arrhythmias in an imbalanced dataset. Employing transfer learning for rapid and robust arrhythmia classification, [41] introduced the 'CardioNet' system, a deep learning-based automated system that classified 29 arrhythmias with a higher accuracy of 98.92%. Additionally, [53] proposed a hybrid model named 2D-CNN-LSTM, combining 2D CNN and the Long Short-Term Memory (LSTM) Network, achieving accuracy rates of 98.7%, 99%, and 99% for Cardiac Arrhythmias (ARR), Congestive Heart Failure (CHF), and Normal Sinus Rhythm (NSR), respectively. In another innovation, [15] presented an improved deep residual CNN for automatically classifying five arrhythmias in imbalanced ECGs with an accuracy of 88.99%. [14] introduced an ECG classification model combining a new capsule network with sequence-to-sequence (Seq2Seq) modeling, achieving an accuracy of 99.85% for the classification of five types of arrhythmias. Furthermore, [10] proposed a novel classification method, the three-heartbeat multi-lead (THML) ECG data, utilizing 1D-CNN combined with a priority model integrated voting method to optimize classification effectiveness. That approach achieved average accuracies of 94.82%, 98.10%, 97.28%, 98.70%, and 99.97% for the N, V, S, F, and Q classes, respectively.

Nowadays, CNNs continue to be extensively utilized. For instance, [16] introduced two-way multiplex CNNs, comprising a 12-layer one-dimensional CNN model and an 11-layer auxiliary two-dimensional CNN architecture. These models address both time-domain and frequency-domain features for arrhythmia classification across 8 categories, achieving an average accuracy of 99.10% for the time-domain model and 96.30% for the frequency-domain model. [45] proposed a precise end-to-end arrhythmia classification model named WavelNet, utilizing a novel CNN architecture based on wavelet transform-based spectral analysis of raw time-domain waveforms. That approach achieved a 90% overall accuracy in automatically classifying five classes of arrhythmias. In a unique approach, [54] determined a subset of 12 ECG data via a forward stepwise selection procedure, transforming the selected 1D ECG data into 2D recurrence plot (RP) images. These images served as input to train a shallow ParNet-adv Network with 12 layers, resulting in an accuracy of 97.60%. Additionally, [33] proposed an ECG signal stitching scheme for detecting arrhythmias in drivers during driving. That research involved extracting stable ECG signals and transforming them into full 10-second ECG signals, subsequently classifying three types of arrhythmias using CNN. The accuracy achieved was 82.39% for the stitched ECG data and 88.99% for the original ECG data. [61] contributed to the field of arrhythmia classification by presenting an automatic end-to-end 2D CNN with an efficient DenseNet model. That model is specifically designed for the classification of four classes of arrhythmias. The research demonstrated impressive results, achieving high accuracies of 99.80% and 99.63% on the MIT-BIH arrhythmia and INCART datasets, respectively. The utilization of a DenseNet model enhances the effectiveness of the proposed CNN architecture, showcasing its potential for accurate and reliable arrhythmia classification across different datasets. That study aligns with the broader trend of employing deep neural networks, particularly CNNs, to address the complexities of arrhythmia classification, contributing to advancements in automated diagnostic systems.

Another instance of widely employed deep neural networks in arrhythmia classification involves recurrent neural networks (RNNs), with a specific focus on Long Short-Term Memory (LSTM), designed to capture long-term dependencies in sequential data, making them well-suited for time-series analysis such as ECG signal classification. For example, [30] introduced a model combining Auto-Encoder and Bidirectional Long Short-Term Memory (AE-biLSTM) to automatically classify six types of ECG signals with an accuracy of 97.15%. In a similar vein, [34] devised a novel network layer based on LSTM to enhance the autoencoder structure for improved classification effectiveness across five different categories of arrhythmias. Another application of LSTM, as presented by [29],

involved a comparison of four different approaches for detecting and classifying atrial fibrillation (AF), a heart rhythm disorder. That included a Convolutional LSTM (CLSTM) model with convolution and LSTM layers, and a deep learning architecture with a Bidirectional Long Short-Term Memory (BiLSTM) network, achieving the best training accuracy of 97.88% for spectral features and the best test accuracy of 87.65% based on P wave detection.

Support Vector Machine (SVM) stands out as a suitable machine learning algorithm for classification tasks, demonstrating widespread use in arrhythmia classification with notable success in accurately identifying various types of arrhythmias, thereby contributing to the enhancement of healthcare systems. For instance, [36] utilized a linear support vector machine in conjunction with features extracted by a principal component analysis network (PCANet) to classify five types of imbalanced original and noise-free ECGs, achieving accuracies of 97.77% and 97.08%, respectively. Similarly, [23] employed an artificial bee colony (ABC) optimized least-square support vector machine (LS-SVM) for classifying 16 categories of ECG signals, achieving accuracies of 96.29% overall and 96.08% for five specific classes. Another application of SVM by [31] involved a state-of-the-art method utilizing a multi-class support vector machine to classify five types of heart disease. Furthermore, [32] introduced a hybrid approach named MRFO-SVM, which combines the metaheuristic algorithm Manta ray foraging optimization (MRFO) to optimize SVM parameters and select significant feature subsets, resulting in the best classification performance for five categories of arrhythmias with an accuracy of 98.26%.

Active learning, a machine learning technique facilitating the selection of samples from an unlabelled dataset for expert labeling, has been employed to enhance classifier accuracy and reduce training time and expert labor costs. [39] introduced an active and incremental learning system called Active Broad Learning System (ABLS) to classify five types of arrhythmias with an accuracy of 98.89%.

An attention mechanism, a technique allowing models to selectively focus on relevant parts of input data, has recently found application in various machine learning tasks, including arrhythmia classification. For instance, [17] proposed an algorithm based on the multi-head self-attention mechanism (ACA-MA) for the classification of five categories of arrhythmias, achieving an accuracy of 99.4%.

Various approaches beyond SVM and attention mechanisms have been investigated for arrhythmia classification. [43] trained two artificial neural network (ANN) classifiers to predict Ventricular fibrillation (VF), achieving prediction accuracies of 72% using eleven HRV features and 98.6% using four QRS complex shape features. Another approach [44] introduced a two-staged classification structure employing a global k-nearest neighbors (kNN) algorithm and a personalized classifier, yielding an accuracy of 96.6% for the early prediction of heart problems. In a different study [21], an automated system was presented using the linear discriminant (LD) algorithm to classify five types of arrhythmias based on single-lead ECG signals. Furthermore, a few-shot ECG diagnosis framework called Meta Siamese Network (MSN) was proposed [26], utilizing metric learning and the N-way K-shot meta-testing strategy for automatic ECG arrhythmias classification of five categories. That approach achieved a high accuracy of 99.34% for five shots versus 96.96% for only one shot.

Additionally, the study [60] proposed an innovative approach for automatic and efficient ECG arrhythmia classification using Echo State Networks (ESN), a brain-inspired machine learning technique. The classifier has been trained and validated through an inter-patient procedure; the ESN model exhibited noteworthy results in classifying ventricular ectopic beats (VEB) on both the MIT-BIH AR and AHA databases. With a high sensitivity of 92.7% and positive predictive value of 86.1%for the ventricular ectopic beats, using the single lead II, and a sensitivity of 95.7% and positive predictive value of 75.1% when using the lead V1.

3.6 Performance Evaluation

The last step in the pipeline involves assessing the model's performance, and commonly used evaluation metrics include Accuracy, Specificity, Sensitivity, F1-score, and Precision, as widely observed in state-of-the-art methods found in the literature [55]. The definitions of these metrics are as follows:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{TP + TN + FP + FN} \tag{1}$$

$$Specificity = \frac{TN}{TN + FP} \tag{2}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$F1 - Score = \frac{2 * Precision * Sensitivity}{Precision + Sensitivity} \tag{5}$$

Here, TP represents true positives, TN is true negatives, FN denotes false negatives, and FP indicates false positives. Typically, researchers employ multiple metrics during the evaluation process to comprehensively gauge the model's performance and identify potential areas for enhancement. In the context of arrhythmia classification, the evaluation entails assessing how well a model accurately classifies various types of heart rhythms.

Tables 1,2, & 3 below present a comprehensive summary of the various research studies discussed in this paper. The tables outline the models proposed in each study, along with details on the experimental approach, the number of classes considered, and the diverse set of evaluation metrics employed. The 'experience' column in the tables reflects the authors' efforts to refine their work, encompassing aspects such as applied data, techniques, or classified categories.

The results presented in Tables 1,2, & 3 showcase a diverse range of approaches and models employed in arrhythmia classification studies. Various models, including CNN, SVM, LSTM, and hybrid architectures, have been utilized across different studies shown in Fig.5. The bar chart vividly illustrates the varying trends in the utilization of these models over the specified years. Notably, the plot reveals a consistent increase in studies utilizing CNN, reaching its peak in 2023. The achieved accuracy levels demonstrate the effectiveness of these models, with several studies surpassing 95% and some even exceeding 99%. For instance, studies [42] and [56] utilized CNN, achieving accuracy levels of 99.48% and 99.4%, respectively. These high accuracy values underscore the effectiveness of CNNs in detecting arrhythmias.

Table 1. Exploration of Arrhythmia Classification Models with Diverse Evaluation Metrics via 2017 - 2020.

Study	Year	No. of classes	Model	Experiences	Accuracy	Sensitivity	Specificity	Precision	F1-Score
[37]	2017	5	CNN	Original Data. Noise-Free Data.	93.47% 94.03%	96.01% 96.71%	91.64% 91.54%	-	-
[36]	2018	5	PCANet - Linear SVM	Original Data. Noise-Free Data.	97.77% 97.08%	86.35% 82.44%	97.75% 97.16%	95.34% 93.56%	-
[23]	2018	16 5	(LSTSVM - ABC)	Class scheme. Personalize scheme.	96.29% 96.08%	96.29% 94.04%	-	96.29% 94.04%	76.06% 94.04%
[42]	2018	5	CNN	Intra-patient paradigm. Inter-patient paradigm.	99.48% 88.34%	96.97% 90.90%	99.87% 88.51%	-	-
[60]	2019	4	Echo State Networks (ESN)	(MIT-BIH) Lead II Lead V1 (AHA) Lead A Lead B	98.6% 96.8% 98.6% 97.8%	84.4% 81.5% 90.4% 87.9%	99.7% 98.0% 99.5% 98.9	-	-
[31]	2020	5	Multi-class SVM	-	90.24%	90.35%	90.18%	-	-
[12]	2020	17	Deep genetic ensemble of classifiers (DGEC).	-	99.37%	94.62%	99.66%	-	-
[32]	2020	5	MRFO-SVM	SVM MRFO-SVM	94.47% 98.26%	70.29% 97.43%	95.55% 99.31%	66.35% 97.65%	67.09% 97.54%
[30]	2020	6	AEbiLSTM	-	97.15%	99.43%	96.22%	-	-

Table 2. Exploration of Arrhythmia Classification Models with Diverse Evaluation Metrics via 2021- 2022.

Study	Year	No. of classes	Model	Experiences	Accuracy	Sensitivity	Specificity	Precision	F1-Score
[41]	2021	29	CardioNet - deep learning system.	-	98.92%	-	-	-	-
[13]	2021	17	CNN	-	98.55%	-	-	-	79.0%
[21]	2021	5	The linear discriminant (LD) classifier	Heartbeat N Heartbeat S Heartbeat V Heartbeat F	-	79.2% 92.2% 87.2% 81.4%	-	-	88.2% 55.0% 89.9% 8.6
[39]	2021	5	Active broad learning system (ABLS)	SVEB VEB	99.43% 99.59%	82.37% 96.56%	99.91% 99.82%	-	-
[34]	2021	5	LSTM	-	98.57%	97.98%	-	-	-
[53]	2022	3	2DCNN-LSTM	Without dropout regularization. With dropout regularization.	99.8% 99%	99.77% 98.33%	99.78% 98.35%	-	-
[14]	2022	5	Weight capsule network combined with Seq2Seq model	Heartbeat N Heartbeat S Heartbeat V Heartbeat F	99.85%	99.66% 99.56% 99.97% 93.81%	99.72% 99.68% 99.96% 100%	-	-
[15]	2022	15	CNN	N SVEB VEB	-	94.54% 35.22% 88.35%	80.80% 98.83% 94.92%	-	-
[56]	2022	2	Hybrid of CNN with LSTM	-	99.4%	99.3%	99.2%	-	-
[29]	2022	3	BiLSTM CLSTM	Spectral features. P wave detection.	97.88% 87.65%	-	-	-	-
[28]	2022	5	Meta Siamese Network (MSN)	5 shots. 1 shot.	99.34% 96.96%	-	-	-	-
[61]	2022	4	2D CNN with an effective DenseNet model	MIT-BIH INCART	99.80% 99.63%	-	-	98.34% 98.94%	98.91% 98.91%

Table 3. Exploration of Arrhythmia Classification Models with Diverse Evaluation Metrics via 2023.

Study	Year	No. of classes	Model	Experiences	Accuracy	Sensitivity	Specificity	Precision	F1-Score
[33]	2023	3	CNN	Stitched ECG data. Original ECG data.	82.39% 88.99%	-	-	-	0.5950 0.7163
[54]	2023	AF Prediction	CNN ParNetadv	-	97.60%	-	96.46%	96.54%	97.63%
[45]	2023	5	CNN	Heartbeat N Heartbeat S Heartbeat V	90%	91.4% 49.3% 91.4%	-	-	-
[16]	2023	8	CNN	Time domain model. Frequency domain model.	99.1% 99.3%	-	-	-	-

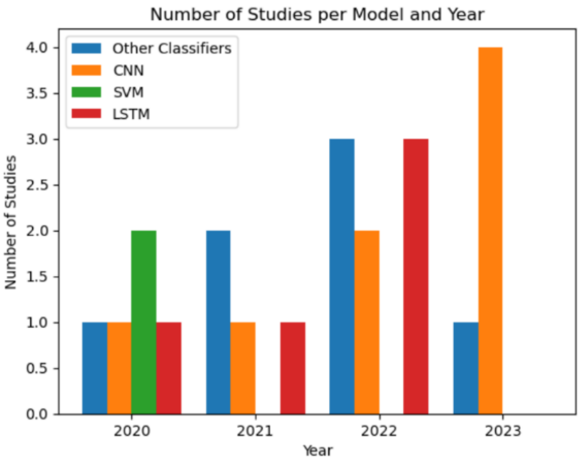


Fig.5. *Model-wise Distribution of Research Papers Over the Years.*

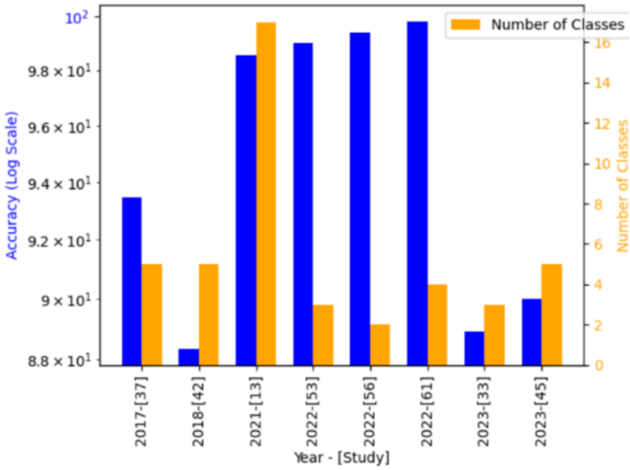


Fig.6. *CNN Model Evaluation Across Various Years: Accuracy and Class Count in Each Paper*

The grouped bar chart in **Fig. 6.** visually captures the performance metrics of CNN models in arrhythmia classification studies conducted over different years. The blue bars represent accuracy levels, showcasing variations across studies, with notable high accuracies in 2018, 2022, and 2023. Simultaneously, the orange bars depict the number of classes, revealing the diversity in classification tasks, ranging from 5 to 17 classes. The chart highlights intriguing relationships between accuracy and the number of classes. Some studies achieve high accuracy with a limited set of classes, while others maintain accuracy even with a larger number of arrhythmia categories. This suggests the influence of model architecture, training strategies, and dataset characteristics on the model's ability to handle diverse classification tasks.

Analyzing the prementioned models' performance reveals intriguing variations. That study [36] employed a PCANet-Linear SVM combination, achieving an accuracy of 97.77% for classifying five arrhythmias. In contrast, the study by [30], implementing an Auto Encoder and Bidirectional LSTM (AE-biLSTM), reported a commendable accuracy of 97.15%. The comparison between these models will help to understand the implications of model choices on accuracy levels and sensitivity. The "Experiences" column in Tables 1, 2, &3 provides valuable insights into the methodological considerations of the studies. For instance, another study [39] utilized the Active Broad Learning System (ABLS) with supraventricular (SVEB) and ventricular ectopic beat (VEB) classes, achieving an impressive accuracy of 99.43%. Understanding the experiences and challenges encountered in implementing such systems will contribute to a more comprehensive evaluation of their practical feasibility. This discussion explores how the restricted number of channels and focus on specific arrhythmias in publicly available datasets, such as MIT-BIH, might influence the generalizability of these models to a broader arrhythmia spectrum encountered in clinical practice. Through this focused analysis, we aim to provide a nuanced interpretation of the reported results, offering insights into the performance variations across studies and the practical considerations in arrhythmia classification methodologies.

4. Arrhythmia Classification Challenges

Rising stress and depression in society levels underscore the need for timely AI-based Arrhythmia classification. After investigating each stage in its pipeline, challenges arise from the signal acquisition through all stages to model evaluation. Firstly, publicly available ECG databases pose limitations; uneven dataset distribution in MIT-BIH and class imbalance hinder consistent assessment. Furthermore, the available datasets lack diverse diagnoses from clinical practice, needed to aid physicians in reducing cardiac-related fatalities. Most datasets address only five diagnoses while clinical experts refer to more than 25 different diagnoses. Secondly, the non-stationary nature of the raw signal susceptibility introduces unwanted noise, achieving acceptable accuracy requires the complex process of noise elimination while preserving essential information. Thirdly, the lack of feature standardization and variability influenced by the lifestyle of the person whose ECG is studied whether he is an athlete, under stress, or doing exercise adds complexity, requiring careful consideration of heart rate-related features.

Addressing these challenges imperatively improves the accuracy and efficiency of ECG arrhythmia classification. Consequently, it is essential to consider the real-world implications and strive for advancements that align with the practical needs of healthcare professionals. Future research directions should focus on solutions that fill the gaps in dataset diversity, feature standardization, and algorithmic robustness. Innovative approaches are needed to enhance classification accuracy and efficiency.

5. Conclusion

In conclusion, this extensive survey offers a thorough insight into the pivotal role of AI in advancing arrhythmia classification. Researchers have made substantial progress, employing diverse approaches at each stage of the classification process. The wavelet transform has emerged as a key tool for enhancing signal fidelity by removing artifacts in ECG signals. Accurate ECG segmentation, achieved through fixed sliding window techniques or beat-by-beat analysis, contributes significantly to precise classification. Various advanced techniques such as CNNs, RNNs, SVMs, active learning, and attention mechanisms have demonstrated remarkable performance in accurately classifying arrhythmias. Notably, CNNs consistently achieve results surpassing 99%, solidifying their widespread adoption and continued utilization in the field. This underscores their efficacy in arrhythmia classification tasks and their enduring significance in the evolving landscape of medical research and healthcare applications. Despite these successful research outcomes, the translation of these models into clinical practice faces challenges. Integrating advanced AI techniques holds great promise for enhancing the accuracy and efficiency of arrhythmia detection, ultimately benefiting healthcare professionals and patients. Moving forward, a concerted effort is required to fill the gap between research outcomes and practical clinical applications, ensuring that the full potential of AI in arrhythmia classification is realized.

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تصنيف اضطراب نظم القلب: دراسة شاملة قائمة على التتابع

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ملخص البحث

لقد لعب الذكاء الاصطناعي **(AI)** مؤخرًا دورًا جوهريًا في الارتقاء بأنظمة بيانات الرعاية الصحية، لا سيما فيما يتعلق بتحليل البيانات الطبية المعقدة. وأثبتت فعاليته في الكشف عن علاقات جوهرية، لتثبت محوريتها في التشخيص والعلاج والتنبؤ عبر مختلف الحالات السريرية. ومن بين هذه المجالات المهمة، عدم انتظام ضربات القلب، وهي حالة تتميز بانحرافات في النظام الكهربائي للقلب، ما يُشكل خطرًا كبيرًا لحدوث سكتة قلبية مفاجئة ووفاة محتملة. وتُعتبر إشارات تخطيط كهرباء القلب **(ECG)** الوسيلة الأساسية لالتقاط وتوثيق النشاط الكهربائي للقلب. تقدم هذه الورقة مراجعة شاملة لتطبيق تقنيات الذكاء الاصطناعي في مراحل مختلفة من عملية تصنيف عدم انتظام ضربات القلب. وقد تم استخدام نهج عرض متميز؛ حيث أُجريَ المسح على شكل خط عمليات متتابع يشمل معالجة أولية لبيانات تخطيط كهرباء القلب واستخراج واختيار الخصائص ذات الصلة وتدريب المصنف وتقييم الأداء. يعتبر التحليل السريع والدقيق لإشارات تخطيط كهرباء القلب أمرًا بالغ الأهمية لمراقبة وعلاج الأفراد المصابين بأمراض القلب. والهدف الرئيسي هو نشر هذه الحلول القائمة على الذكاء الاصطناعي في السيناريوهات السريرية، ما يضمن تحسين رعاية المرضى ونتائج العلاج.