REVIEW ARTICLE

Heartbeat Pattern and Arrhythmia Classification: A Review

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Abstract

In today's era, the lifestyle of people has become much more sophisticated due to the involvement of stress, anxiety, and depression in the daily routine of human beings. In such a scenario, cardiac diseases are growing rapidly in youngsters and senior citizens. It is also observed that cardiac diseases are crucial and sensitive, including life-threatening chances. So, it is essential to detect and prevent such cardiac disorders within the required time for recovery. Since there has been a lot of research in the prediction and prevention of cardiac disorders, cardiac arrhythmia is also one of the majorly occurring diseases in the bulk of the population. The electrocardiogram is the cheap and best way to diagnose the problem of cardiac arrhythmia, and a huge amount of data is collected daily in hospitals and pathological centers. Previously, various automated models were developed for detecting cardiac arrhythmia using deep learning approaches and machine learning. In this work, we have reviewed recently developed automated models and evaluated their performance based on specific parameters like deployed datasets, variation of input data, applied application, methodology, and results obtained by the developed model. The limitations of reviewed papers are also mentioned in addition to their future scope for improvement.

Keywords: Electrocardiogram; Arrhythmia Classification; Disease Detection; Heartbeat Classification.

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1. Introduction

Arrhythmia is generally considered a problem of irregular heartbeat in humans, which is crucial for life threats and miss happenings. The various kinds of arrhythmia have specific recognition and features, so it becomes very helpful to classify and distinguish the various arrhythmia categories. Generally, arrhythmia is detected by classifying it into two classes [1]. In contrast, the first one is diagnosed with a single irregularity in a heartbeat and is so-called morphological arrhythmia. The second phase of the arrhythmia is diagnosed with multiple irregular heartbeats and is hence considered a problem of rhythmic arrhythmia.

Changes and alterations in the heartbeat waveform are observed if an individual has morphological or rhythmic arrhythmia. The detection and diagnosis of the issue are made by Electrocardiography (ECG) as well as the Echocardiogram (ECHO) [2]. The arrhythmia problem is directly associated with an issue in the heart's valve, which results in irregular heart rates.

The ECG is a well-established tool in cardiology for assessing a patient's heart status. ECG stands for electrocardiogram, an electrical representation of the heart's contractile activity that may be conveniently recorded using surface electrodes on the patient's limbs or chest. The ECG is one of the most well-known and widely used biological signals in medicine. Counting the R peaks of the ECG wave throughout one minute of recording is a simple way to calculate the heart's rhythm in beats per minute (bpm) [3]. More importantly, cardiovascular illnesses and disorders impact the rhythm and morphology of the ECG waveform.

Finding and classifying arrhythmias can be extremely difficult for a human being because it is often necessary to assess each heartbeat of ECG readings obtained by a Holter monitor over hours or even days. Furthermore, due to fatigue, there is a risk of human error while processing ECG records. The use of computational tools for automatic classification is an option.

A complete automatic approach for detecting arrhythmias from ECG signals may be broken down into four parts: preprocessing of ECG signals, heartbeat segmentation, feature extraction, and learning/classification. A step is taken in each of the four processes, with the eventual goal of determining the type of heartbeat. The first two steps of such a classification system (ECG signal preprocessing and heartbeat segmentation) have been extensively studied [4]. Preprocessing procedures have a direct impact on the outcomes. In the case of QRS detection, the findings from the heartbeat segmentation stage are almost perfect. However, there is still room for exploration and improvements in the steps related to classification (feature extraction and learning algorithms). Even though the problem of ECG delineation is still open, it is not so useful for the methods in the literature surveyed here.

Given its history as the leading cause of death in women and men worldwide [5], heart disease receives much attention. Several risk factors have been discovered like Hyperlipidemia, hypertension, and obesity, all linked to heart disease, including smoking. Heart disease can be predicted and prevented by identifying such risk factors. In the beginning, risk variables hidden in unstructured clinical information must be identified. Many types of research have been published in the previous years, which have focused on identifying these risk variables, and that resulted in the formation of publicly available tools like the Examination of Clinical Observations and The Knowledge Extraction System, which is an open-source tool that can extract information from a variety of sources.

Other disorders, such as diabetes, are frequently linked to heart disease with several obvious qualities in common, such as obesity and smoking statuses, as well as some drugs, such as metoprolol, are all factors to consider. Each of these was considered a risk factor for heart disease for this investigation.

The greatest difficulty in recognizing all heart disease risk factors is that they appear in clinical texts in various categories. In 2014, the National Center of Informatics for Integrating Biology and besides (i2b2) announced a risk factor identification track in the clinical Natural Language Processing (NLP) challenge to examine the identification of all heart disease risk factors in depth [6]. The goal was to find medically relevant information about heart disease risk and follow its evolution across longitudinal patient medical records. After getting inspired by the revolution, a hybrid pipeline system was created that included machine learning and rule-based techniques.

There are several arrhythmias, each of which is associated with a pattern that can be used to identify and classify it. Arrhythmias are divided into two types. The first category includes morphological arrhythmias caused by a single irregular heartbeat. This survey focuses on the classification of normal heartbeats and the individuals who make up that category. The morphology or wave frequency of these heartbeats changes and the ECG exam can detect all these changes. Identification and classification of arrhythmias can be a time-consuming task for a human because it sometimes requires analyzing each heartbeat in ECG recordings.

Two broad groups can be used to categorize conventional arrhythmia categorization schemes. Considering the paradigms of the inter-patient and intra-patient in terms of their evaluating process, the training in the intra-patient paradigm heartbeats from the same subject can be included in evaluation datasets. For patients, however, a more realistic evaluation method is used in the inter-patient paradigm, where the heartbeat sets used for the test and training come from different people. These methods were categorized by Pan *et al.* [8] as shape-based and structure-based, respectively. The two primary paradigms of training plan inter-patient vs. intra-patient [9] classification are followed in the next level. The data set for the current patient is divided into training and testing subsets using intra-patient supervised classification. In comparison, the interpatient supervised classification technique evaluates the strong prediction generalization potential for anonymous patient data using separate training and testing sets from various patients. Additionally, some studies used a two-part Mixture Of Experts (MOE) [12] training strategy to take advantage of patient adaptation: an available training set collected from benchmark datasets and a particular patient training set taken from the patient who was being tested. Instead of using the interpatient scheme, a more realistic scenario, most previously published works in the literature have been reviewed using the intra-patient paradigm [3]. Avoid using patient samples from the same patients' training and testing the model. As a result, some systems used the intra-patient scheme to attain good accuracy, considering their evaluation process's unreliable, their results were partial [7].

We have chosen a few research articles for review based on deep learning and machine learning for arrhythmia detection in this paper. The articles chosen from PubMed, Embase, and Google Scholar are just a few available databases. Methods including deep learning, machine learning, and automated classifiers-based publications for arrhythmia detection were chosen by screening titles, keywords, and abstracts after removing duplicate records and non-English papers.

2. Background

Four steps can be used to create a fully autonomous system for identifying arrhythmias from signals obtained by ECG equipment. ECG signal preprocessing, heartbeat segmentation, feature extraction, learning/classification, and feature extraction are the first four steps. Each of the four processes involves doing something, and determining the type of heartbeat is the ultimate goal. The preprocessing of ECG signal and segmentation of heartbeat segmentation, the primary two steps of such a classification system, have received many studies in the literature [2–6]. Precaution should be taken when selecting the preprocessing approaches because they directly affect the outcomes. In QRS detection, the results of the heartbeat segmentation stage are extremely near to ideal. However, the classification-related phases (feature extraction and learning algorithms) still have the potential for investigation and advancement. Even though the issue of ECG demarcation is still up for debate, the methods in the literature reviewed here do not benefit from it. The literature on ECG-based arrhythmia classification algorithms has been reviewed in this study. It also examines the key methodologies for building these automatic systems and the two primary paradigms for evaluating them: intra-patient and inter-patient [7]. The most well-known databases and issues evaluating contemporary techniques mentioned in the literature are also reviewed. A workflow is suggested as a result of this debate to direct the assessment of future works.

Please note that this survey work's major contribution is the workflow for the evaluation procedure. We can find in the literature an overview of 20th-century strategies for knowledge-based ECG interpretation [29]. Deng, J. *et al.* [1] investigated the ECG signal processing techniques. Their research concentrated on the signal's physiology and processing methods particularly feature extraction and classification. Deng, J. *et al.* [1], in particular, should have concentrated on evaluating methodologies unique to our work and a more recent literature analysis on the subject. Additionally, our feature extraction survey includes a special feature selection analysis.

The Electrocardiogram (ECG) already contains significant data on how the heart is working. This signal gives a doctor vital detail about a patient's cardiac function and can be used to predict and identify heart disease. Due to its non-invasiveness and the useful information, it offers, it is one of the most often employed signals in diagnosis. You can assess the pathophysiological state of the heart using its analysis. Several systems have been created for ECG analysis and recording [8]. Early ECG systems merely printed the signal to record it. Modern systems offer automatic diagnostics using computer technology. The diagnosis of chronic myocardial illnesses, the detection and classification of arrhythmias, and the detection of ischemia are all areas of this broad study field that have seen the implementation of numerous methods and approaches. These techniques often involve processing the signal to remove noise and artifacts, extracting important disease-related features, and then examining the features to conclude. Signal processing, artificial neural networks, fuzzy logic, and clinical symptoms reported by medical professionals are typically used in the study. These systems' performance is assessed using conventional databases [9]. The Sino Atrial (SA) node, known as the heart's pacemaker, is where normal heart activity begins. From there, it travels via both atria to the Atrioventricular Node (AV), where it exits through the ventricle. Heart rhythm abnormalities, or arrhythmias, come in a variety of forms. The electrical activity in cardiac arrhythmias typically begins elsewhere than the sinus node or abnormally propagates quickly. Dangerous arrhythmias include ventricular fibrillation and tachycardia. Other cardiac arrhythmia examples include premature atrial beats.

The heart's electrical and mechanical activity occurs regularly. The heart's electrical activity causes potential recordable differences of 300 to 1000 milliseconds per cycle, with fast changes in voltage and direction. These electrical vectors can be captured on film by affixing the electrodes to the patient's skin. The heart generates electrical vectors that change and move in three dimensions, so an ECG recorded on the skin in one direction will not provide adequate information [10]. To capture signals in 12 dimensions of space, the ECG uses 12 vectors, collectively known as leads, of which 6 are in the horizontal plane, and 6 are in the frontal plane. These leads record signals by attaching electrodes to the patient's upper and lower limbs, chest, and abdomen [11]. A doctor examines the ECG by looking at the lead's plotted signal and having prior knowledge of the space angle of each lead.

3. Literature Review

An automated model for detecting heart disease risk factors was developed in 2015 based on the relationship among diseases like diabetes, hypertension, high blood pressure, etc., and their impact on heart risk [12]. This model had data set from I2V2 organizers of challenges and organized it into three different tags (Phrase-based, logic-based, and discourse based) associated with their indicators or features. In this research, the data was pre-processed using annotated guidelines, and their features were extracted based on the above-discussed three tags. Then, SSVM was applied using SVM hmm, bib short text 6 for the implementation of SVM, and CRF suite for the implementation of CRF [13]. Furthermore, upgraded parameters of all classifiers using 10-fold cross-validation on the training set were deployed and obtained 92.68, while I2B2 challenge organizers have already obtained an accuracy of 92.76 [14]. The developed model was not fit for the diseases like Coronary Artery Disease (CAD), obesity status, and smoking status.

The most common pattern recognition uses an ECG signal to detect arrhythmia, as it occurs with an irregular variation of the ECG signal. Krizhevsky *et al.* [5] applied a popular convolutional neural network to perform pattern recognition. Popular pattern recognition model and their challenges encourage many researchers to explore the pattern in medical signals and images using various processing techniques. Application of machine learning and deep learning are found to be very promising in solving complex pattern recognition in body signals. Isjn *et al.* [2] obtained a recognition task using a deep learning approach in which fluctuation of the ECG signal was measured. Highly representative features are extracted and categorized into various medical symptoms, including heart disease. The variation in the EGC signal makes the classification process time-consuming and consequently reduces the robustness of the model. Jun *et al.* [4] recognized the pre-mature ventricular contraction signals of the heartbeat from the EGC signal using a deep neural network. The network contains six hidden layers with different parameters to extract features from the ECG signal. The classification is conducted between normal and PVC beats. Pourbabaee *et al.* [9] applied a deep CNN model for the training with rich features disengaged from the ECG signal and recognized two classes, i.e., paroxysmal atrial fibrillation and normal heartbeats. The issue in this model is the requirement of the large-sized labeled dataset to obtain improved performance by applying a greater number of layers. The computation cost will be increased if there is an increase in the depth of the network during the application of complex CNN operations. Thus, system requirement has also been increased to handle such training tasks. Tajbakhsh *et al.* [10] introduced transfer learning to find solutions to these challenges by enabling deep learning methods. The model may perform well in the limited dataset and moderate computer resources. The transfer learning automatically performs the feature extraction task when the desired task is imported to the pre-trained CNN model. Pre-training CNN has been trained with the available dataset containing common and large medical imaging. It works in the classification of pathology symptoms and does automatic feature analysis. It is also used to tune the parameters of the learning model to receive desired results [14].

Figure 1 shows the basic building block of the ECG signal analysis to classify feature symptoms. In the current work, one of the techniques called intracoronary optical coherence tomography [15] performed efficient recognition of heartbeat disorder by using intracoronary diagnostic tools with lower resolution to reach detailed and specified feature analysis. The feature acquisition method has been proven safe and highly effective. The earlier study suggests that the OCT technique can also translate vulnerable features. Tsantis *et al.* [11] applied the Markov random field method to segment the vessel lumen automatically. Athanasius *et al.* [12] recognized plaque regions from OCT images to analyze the effect of calcified plaque in heartbeat disorder. The ECG signals are the bioelectric signals generated by the human heart. Heart diseases are the inculcation of potential abnormalities and malfunctions in the ECG signals and cause variations in blood flow. Predictive algorithms are evolved that use machine learning techniques to predict the chances of variation in heart rate using earlier data. Continuous observation is required to analyze ECG input in the clinical trial method. The diagnostic system relies on computer-aided technology to analyze the features automatically in less time. Some popular methods involved in analyzing features more accurately and in less time are existing models [16], such as statistical methods, wavelet transform, ANN, hidden Markov models, and heuristic-based approaches. These techniques are used to translate the signal into machine-level features to generate mathematical models to predict test signals. Chazal *et al.* [14] introduced a hybrid system for ECG Heartbeat Arrhythmia detection classes using a linear discriminant analysis classifier. The model's training happened first at the global level, where ECG signal fluctuation was measured. Then the specific local-level features are employed with the global-level features to tune the whole classifier. Park *et al.* [15] proposed a hierarchical model by applying a support vector machine to improve the effectiveness of the classification using AAMI classes and the data division method. This experiment has been performed using 95 samples, and the rate is 365 seconds per second for 255 million seconds. The features of 180 samples of time series were segmented for each beat. The scheme of the Hermite basis function has been used to extract the frequency coefficients of these 180 samples.

Table 1 shows the various existing literature work that contributes to the classification of arrhythmia from the heart ECG signals. Various techniques, features, models, and results are discussed in Table 1 showing the effectiveness of computer-aided recognition of medical events. Table 2 shows the analysis of Arrhythmia heart disorder.

Table 2 contains the various causes of arrhythmia and heart disorders and their respective symptoms. The study of ECG includes various P, Q, R, S, and T cycle waves that are generated through 20 electrodes with 12 signals [16]. A single lead includes the formation of rapid and slow assessment of a heartbeat. The P-wave stands for the deflection in the positive direction of the ECG signal. The other waves of the ECG cycle represent the activation of the left and right

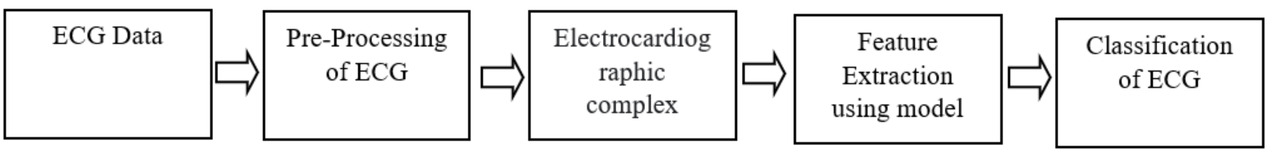

Figure 1. The basic building block of the ECG pattern recognition

ventricles. The PR interval is the distance from the starting of the P-wave to the first deflection to the QRS

Table 1. Various existing works on the classification of arrhythmia

S.No.	Reference	Techniques	Features	Optimization technique	Modeling	Feature classes	Result
1.	Yazdani *et al.* [16]	Threshold method	electrocardiographic complex QRS wave	Empirical mode decomposition	ANN	3	Sensitivity is 97.18%, Prediction accuracy is 97.54% and error rate is 1.42%
2.	Huang *et al.* [17]	Wavelet transformation	Morphological features	Independent component analysis	CNN	4	Accuracy is 91.94% and average loss is 0.05
3.	Wang *et al.* [18]	Daubechies wavelet	Morphological features	Haar Wavelet	ResNet + LSTM	4	Specificity is 97.99%, Sensitivity is 98.43% and accuracy of classification is 98.91%.
4.	Re *et al.* [19]	Kalman filter	Q, R and S waves of ECG signal	EMD model	Deep neural network	4	Average accuracy is 98.78%
5.	Zhu *et al.* [20]	Morphological process, window integration	Peaks of RR, PP, ST, R, P, T waves of ECG signal	Discrete wavelet transforms	SVM	3	Average accuracy is 94.08%

Table 2. Analysis of Arrhythmia heart disorder

S.No.	Arrhythmia	Cause	Symptoms
1.	Sinus bradycardia	low sinus rate < 60 beats per minute (bpm)	Reduced heart rate
2.	Sinus tachycardia	high sinus rate > 100 bpm may be due to exercise or other conditions which increase the SA node firing rate	Increased Heart Rate
3.	Sick sinus syndrome	disturbance in the functionality of the SA node	
4.	Atrial tachycardia	More than 2 consecutive atrial premature beats occur at a frequency > 100/min	Alteration of P wave in different ECG leads
5.	Atrial flutter	Sinus rate of 250-350 bpm	-
6.	Atrial fibrillation	Clumsy atrial depolarization	-
7.	Junction escape rhythm	AV-node generates a rhythm of 40-60 bpm due to SA node suppression	-
8.	AV-node Blocks	A block of impulse conduction within the AV-node	-
9.	a) First-degree AV-block	Speed of impulse conduction slightly slowed down	Increased PR interval
10.	b) Second-degree AV-block	Conduction speed is slow that some impulses from the atria cannot move to the AV-node	Absence of QRS complexes after P wave in some beats
11.	c) Third-degree AV-block	Complete block of conduction through AV-node	Anomalous shape and duration of QRS complex
12.	Supraventricular tachycardia	Due to reentry currents flowing between ventricles and atria or within the atria	Increased heart rate to 140-250 bpm
13.	Ventricular premature beats/ premature ventricular complex (PVC)	Ecotopic ventricular foci	Widened QRS complex
14.	Ventricular tachycardia	Ventricular foci or intraventricular reentry	Increased heart rate to 100-280 bpm, widened QRS complex
15.	Ventricular flutter	Rapid depolarization of ventricles> 250/min	Sine wave appearance
16.	Ventricular fibrillation	Clumsy ventricles depolarization	-

complex. The QRS interval is the distance measured from the start of the QRS complex to the end of the T-wave. The AAMI stands for the association of advanced medical instrumentation and represents the standardization of various classes of heartbeat, including ventricular ectopic beat, normal beat, supra-ventricular ectopia beat, etc.

Risk factor extraction and time attribute identification were the two subtasks that made up the heart disease risk factor identification track of 2014 i2b2 clinical NLP challenge [17]. Identification of illness risk factors, despite several related research, has been put forward. A hybrid NLP pipeline system was developed in the Jun et al.'s [4] study that is most pertinent to extract Framingham. Computerized health criteria for heart failure with time attributes [4] are recorded in this extract. Extracting risk factors for heart disease is a common information process. Clinical concept recognition extraction task [5–9], the-Identification of genotyping [10], smoking status [11–15], obesity [10], and NER task extracts all disease and observable characteristics and problems in tests. Medicines are used in the treatment of tics. One of the best examples in 2010 i2b2 client-work focuses on clinical concept recognition. Clinical NLP challenge, in which different machine learning-based, rule-based, hybrid, and other approaches were suggested [18–20]. They include illnesses, and some recognizable traits have also received extensive research. Chaitanya *et al.* [5] briefly stated phenotyping methods [10]. The clinical NLP problems of i2b2 featured a track on smoking status identification in 2006 and 2008 that focused on identifying obesity [18]. The ideal setup of an approach based on support was employed to determine the smoking status of people. SVMs [21], though the most effective strategy for identification, utilize rule-based and dictionary-based approaches.

The muscle that pumps blood throughout the body, the heart, contracts rhythmically. The atrial sine node, which functions as a natural pacemaker, initiates this contraction, and then spreads it to the rest of the muscle. There is a pattern in how this electrical pulse spreads [19]. This action causes fluctuations in the skin's surface's electrical potential by producing electricity currents on the body's surface. Electrodes and the proper tools can be used to record or measure these signals. An instrumentation (operational) amplifier with ocular isolation is typically used to increase the electrical potential difference between the spots on the skin designated by the electrodes. The signal is then put via a high-pass filter and, in a subsequent step, an antialiasing low-pass filter. It then appears in a converter from analog to digital. The heart's electrical activity has been documented since Augustus Desiré Waller showed off the first human ECG in 1887 [20]. Nevertheless, it took until 1960 for detecting arrhythmias and the normal heart rhythm to become a standard part of physical examinations [21]. There are numerous methods available now for measuring and recording ECGs. Modern ECG measurement techniques are classified as in-the-person, on-the-person, and off-the-person by da Silva *et al.* [13]. The in-the-person category includes devices made to be used inside the human body, including those implanted surgically, applied subcutaneously, or even taken orally as tablets. When less invasive approaches are not appropriate, these technologies are used. The off-the-person category is in contrast to the in-the-person category. This group of devices includes those made to measure ECG with little or no skin contact. This category is in line with projected medical application developments where ubiquitous computer systems are a reality, claims [13]. Examples of such devices include those based on capacitive sensors, which track changes in the body's electric field to monitor the ECG at distances of 1 cm or more.

Researchers and engineers are using deep learning approaches in the field of biomedical image and signal processing as a result of these techniques' recent state-of-the-art triumphs in well-known pattern recognition problems. Recurrent Neural Networks (RNN), more precisely Long Short-Term Memory Networks (LSTM) and Convolutional Neural Networks (CNN) [22] have shown promising results in the ECG domain using deep learning techniques. One of the main advantages of using Deep Neural Networks (DNNs) is their capacity to automatically learn complex representative features straight from the data, which eliminates the requirement for human feature extraction [23]. By making use of this attribute, end-to-end learning algorithms that receive ECG data as input and forecast the different types of arrhythmias can be created, all while automatically extracting the "deep features." Deeper networks are better at classifying fine-grained ECG signals when given adequate data, which is another advantage of using a DNN.

In [24], it was demonstrated that a 34-layered deep convolutional neural network could detect anomalies and arrhythmias in ECG signals better than a board-certified cardiologist. In their research, the DNN was trained using a dataset of over 64000 ECG records from about 30.000 patients. But given that this dataset is roughly 500 times bigger than comparable datasets, it is clear that data volume was a key element in achieving such performance. Despite the advantages that DNNs in electrocardiography provide, the disadvantage of data volume is mostly preventing the mainstream implementation of these methods. DNNs require a lot more data to train than traditional classification techniques do. This problem leads to a gap between dataset size and deep features because there aren't enough publicly available datasets in this field [25]. According to this study [26], transfer learning from the 2-dimensional domain might be used to bridge the gap and solve the problem of low ECG data volume when compared to high-performing in-depth features. Contrary to the ECG signal domain, where datasets are extremely modest, the picture classification and object recognition domains are among the richest in terms of training data volume. There is a tonne of data available from these domains that may be used to train DNNs and find feature maps that can effectively capture intricate patterns in images. These learnt feature maps can be applied to the ECG domain by employing spectrograms to transform the 1-D ECG signal into a 2-D image. A Deep Neural Network, DenseNet, which has been pre-trained using ImageNet classes (ST), will be used to classify four different rhythms, including Normal Sinus Rhythm (Normal), Atrial Fibrillation and Flutter (AF), Ventricular Fibrillation (VF), and ST Segment Change [27].

The ability to create a system that would aid in heartbeat categorization for the identification of arrhythmias has been the subject of extensive research over the past ten years [28]. As a result, there have been many different approaches with unique strategies and goals. Based on the evaluation system utilized, L. S. Athanasiou *et al.* [12] conducted a thorough review and divided these works into intra-patient and inter-patient categories. These categories were referred to as class-oriented and subject-oriented assessment methods by B. Chen *et al.* [17].

Since the inter-patient methodology does not introduce any bias into the classification, it is more realistic from a clinical or medical standpoint [28]. As a result, if an algorithm is trained and tested on the heartbeats of the same patient, it may only recognize the special traits of that patient and show promise during the test [29]. L. S. Athanasiou *et al.* [12], who compiled the results from studies that included both groups, provide support for this assertion. Although intra-patient tends to produce "greater" accuracy, low generalization is sacrificed.

4. Methodologies

Figure 2 shows the study of a general methodology for the classification of normal and cardiac disease that is followed by earlier research.

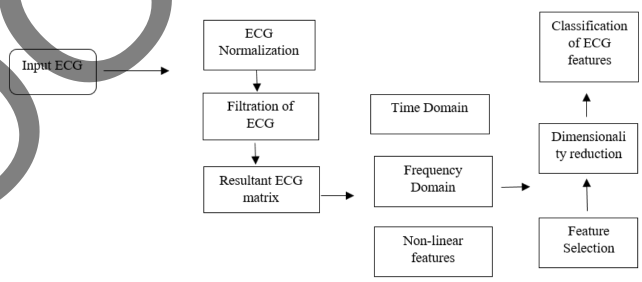

Figure 2. Study of existing methodology

4.1. Database

Datasets of ECG heartbeat from various sources have been collected and applied in the existing literature work. The dataset matters a lot in the recognition of heart diseases such as arrhythmia. Some common ECG datasets have been given below in which the classification of heart diseases has been performed in the existing work.

- *MIT-BIH database* [12]: - 48 recordings with two 30-min ECG lead signals each are stored in the database (denoted lead A and B). In 45 recordings, lead A is converted into lead II, and in the remaining three, lead V5 is used. Lead B is lead V1 for 40 recordings, and leads II, V2, V4, or V5 for the remaining recordings. A representative sample of 23 of the recordings—

which include 25 difficult ventricular, junctional, and supraventricular arrhythmias—is intended to mimic typical clinical recordings [15]. The data are filtered between 0.1 and 100 Hz and recorded at 360 Hz. 15 different heartbeat types totaling more than 109 000 ventricular beats. The number of examples of the many heartbeat kinds varies significantly. "Normal beat" (NOR) is the largest class, accounting for approximately 75 000 instances, and "Supraventricular Premature beat" (SP), accounting for only two cases, is the smallest.

- *EDB database* [13]: - The Cardiology Society of Europe collected the dataset, containing 90 records in which each record was taken for 2 hours. This database contains ECG records of a person suffering from myocardial Ischaemia and heart disease formed by the irregularity in the T wave.

The 90 records in the EDB database were obtained from 79 participants and captured at a rate of 250 Hz with a 12-bit resolution. Eight women and 70 men aged 30 to 84 provided these records (between 55 and 71 years old). The database was initially designed to enable ST-segment and T-wave analysis because each of these participants had a certain cardiac condition (namely, myocardial Ischaemia). Over two hours, the heartbeats were captured, and each one had two signals (i.e., two leads). The record's annotations were created by two cardiologists using the AAMI standard.

- *AHA database* [14]: -The database contains approximately 80 records of Arrhythmia ECG signals taken by the American heart association. Each record has been generated for 35 minutes. This database is collected for the recognition of ventricular arrhythmia.

- *Creighton University database* [15]: -It contains 35 Arrhythmia ECG records, in which each record has been collected for 35 minutes. This database is used to classify heart diseases such as ventricular tachycardia, ventricular flutter, and ventricular fibrillation.

- *Noise stress database* [16]: - A total of 12 ECG records are contained in this database. Each record was taken for 30 minutes. The datasets in this database have been artificially created by manually inserting noise in the ECG patterns.

4.2. ECG Data Collection

The wearable equipment used to gather ECG signals consists of three things, i.e., textile carrier, biosensor platform, and smart terminals are its three component pieces. The cloth carrier is made of elastic fabric to achieve sufficient adherence of textile electrodes to the pectoral muscles. The usage of the magnetic connector ensures the stability of the connection between the hardware platform and the textile electrodes. The ADI ECG analog front-end (ADAS1001) is utilized in the biosensor platform to obtain the ECG signals [30]. The Bluetooth 4.2 protocol is utilized to implement data processing, packaging, and retransmission to Smart Terminals using the Microcontroller (STM32). Introducing an LDO DC-DC regulator with a 95% conversion efficiency would help further reduce energy use. We build a digital filter group to limit the influence of significant disturbances for subsequent evaluation because the ECG signal is weak and easily distorted by many noise sources.

4.3. ECG Data Pre-Processing

The preprocessing of the ECG signal has been required to remove noise events and extract the fine-tuned features for further analysis. ECG signals translate biological heartbeat into an electrical variation concerning the voltage and time, which may contain noise that the filters can remove. Various filters have been used in the existing work to discard or improve the attenuation in ECG signals. Filters are also utilized to reject and accept the specific frequency bands of the ECG signal. The high pass filter, low pass filter, and mid pass filter are used to fetch and discard the specific range of frequency band from the ECG signal. Some of the noises found in ECG signals are low-frequency signals, power line interference, high-frequency signals, etc. Various distortions in the signal may also occur due to improper equipment supply. These noises are required to be removed using filters such as notch filter [17], Anisotropic Diffusion (DPAD) method [18], bilateral filter [19], deletion of a region of occlusion [20], etc., with a significant threshold value. The preprocessed data has undergone further feature extraction.

The installation of recursive digital filters of the Finite Impulse Response (FIR) [22], which was made computationally viable with the advancement in microcontrollers and microprocessors, is the simplest and most extensively used method for minimizing noise in ECG data. Since they enable the quick and simple application of the reject-band filter, these approaches are effective for attenuating the known frequency bands, such as the noise coming from the electrical network (50 Hz or 60 Hz). Applying filters for different frequency bands to the signal can fix the issue with this method, which is that the noise frequency is not always known. However, the signal's shape is distorted by the indiscriminate application of high-pass and low-pass filters, rendering them useless for detecting heart disorders. The noise in the ECG signals was also removed using adaptive architectures [23, 24]. A. Davari Dolatabadi [25] claims that this approach has limitations and does not significantly outperform FIR digital filters. Through the use of adaptive filters based on neural networks, P. de Chazal *et al.* [22] were able to significantly enhance noise reduction by overcoming some of these challenges. When compared to the same method utilizing linearly adaptive filters, this strategy proportionally increased the detection of the QRS complex. Since wavelet transforms preserve ECG signal features, preventing the loss of its crucial physiological details, and are straightforward from a computing standpoint, various approaches based on them have been used to eliminate noise over the past decade [24]. Işn *et al.*'s [2] multi-adaptive bionic wavelet transform modification of the wavelet transform was used to lessen noise and baseline volatility in the ECG signal. Results from this method were better than those from the conventional wavelet transform. Interesting results on noise attenuation have also been obtained using other methods. Nonlinear Bayesian filters have been suggested by w. zhu et al. [20] who have demonstrated promising results. A significant contribution was made by a new algorithm based on the Extended Kalman Filter [3], which combines the parameters of the ECG dynamic model for ECG noise reduction and signal compression. This technique demonstrated the highest level of efficiency to date. It should be noted that the works in [2, 3] publish their findings with regard to the signal-to-noise ratio. Although many methods for preprocessing the ECG signal have been developed, the choice of which method to apply depends on the study's ultimate goal. Methods concentrating on the automatic classification of arrhythmias tend to require a different preprocessing than methods focusing on the segmentation of the heartbeat from the ECG signal (i.e., detection of the QRS complex, other waves, or fiducial points aiming at heartbeat delimitation).

4.4. Heartbeat Segmentation

Techniques for segmenting heartbeats, such as locating the R peak or the QRS complex, have been studied for more than 30 years [24]; the evolution of these algorithms and more recent, cutting-edge techniques reflects the growth in computing power. Due to the opportunity to employ faster processors, authors started concentrating on heartbeat segmentation accuracy rather than computational cost. When assessing the accuracy of heartbeat segmentation, sensitivity and positive predictivity, measured as Sensitivity and Positive predictivity, respectively, are frequently taken into account. The letters TP (True Positive), FP (False Positive), and FN (False Negative), respectively, denote the quantity of heartbeats. To accurately compare the heartbeat segmentation-focused techniques, a common database must be employed. However, additional databases are also used, including those of the AHA [20] and CSE [21]. However, many of the methods discussed in the literature, according to G. de Lannoy *et al.* [23], only use a small percentage of a standardized database, making it difficult to properly compare alternatives. A segmentation technique that is often employed relies on digital filters to reduce noise and get rid of baseline fluctuations. Nonlinear translations that increase the R peak and a flexible detection threshold were created by Pan and Tompkins [26]. More sophisticated methods have also been used, such as those based on neural networks [27], evolutionary algorithms [28], wavelet transformations, filter banks [28], and quad-level vectors [29]. Table 1 uses evaluation data from the MIT-BIH database to demonstrate the efficacy of a few heartbeat segmentation strategies. Based on the Sensitivity (Se) and Positive predictivity (+P) scores, it should be noted that there are some discrepancies amongst the methodologies tested. It is important to note that the approaches mentioned in this table took into account a wide spectrum of complexity, from straightforward processes to sophisticated ones. Some methods are also proposed to identify other heartbeat-related waves, such as the P wave and the T wave [30], which can be useful for arrhythmia classification approaches since more information about the heartbeats can be gathered. Although identifying heartbeats of arrhythmias is not the main focus of this survey, it should be noted that errors committed at this level can extend to following stages and have a substantial impact on the final classification of the arrhythmia system. However, the majority of the studies we looked at used databases that had already been used to identify and label heartbeat-related events, such as the finding of the R peak or the QRS complex. As a result, segmentation was reduced to a simple database search for a labelled event. In this way, the conclusions presented in these publications neglect the effects of the segmentation stage, despite the fact that database labelling is susceptible to human error. So comparing how various segmentation algorithms impact methods for categorizing arrhythmias automatically may be a relevant research field. [28] proposed evaluating the resistance of their feature extraction method to the R-peak mislocate error. A Gaussian-distributed artificial jitter was applied to R-peak annotations in order to boost error. We suggest other authors to incorporate such a test in subsequent efforts that attempt to automatically classify heartbeats.

4.5. Feature Extraction

4.5.1. RR-Interval Features of ECG Signal

RR interval points differ between two successive fiducial points of the heartbeat intervals generated in a single time stamp. The RR waves are interpreted into points of their passage concerning the X (voltage) and Y (time) axis. The irregularity in the RR wave can easily be analyzed through the previous RR interval points generated from earlier successive fiducial points in different time intervals. And so, the post-RR interval points can be easily predicted based on commutative feature points of various fiducial points. The R wave in QRS waves is the function of the basic property of autonomic influences and the sinus node [18].

4.5.2. Heartbeat Interval Features

Three general features of heartbeat ECG from 12 leads have been mostly used in the research to detect irregularities of the heartbeat. These intervals are calculated using segmentation between the required intervals. These three waves are the P wave, QRS complex, and T wave. All these waves contain features of ventricles in terms of fiducial points. The QRS complex occurs by depolarization of ventricle points. The P wave of ECG features is generated through the depolarization of atria [19]. The T wave feature points are generated through the repolarization of ventricle points. The irregularity in any of these feature points is the missing of uneven fluctuation that occurs concerning time. Table 3 shows the normal values of the respective features relating to the ECG of a healthy human.

Table 3. Normal values of ECG with a cardiac rate of 60 beats per minute of a healthy human

S. No	Features	Values
1.	T wave amplitude	0.2mV
2.	P wave amplitude	0.114mV
3.	P signal	110ms
4.	PQ interval	160ms
5.	QRS amplitude	1.6mV
6.	QT interval	400ms
7.	Width of QRS	100ms

4.5.3. ECG Morphology Features (Frequency)

The ECG feature points are first segregated into eight groups. These groups are contained amplitude and frequency information. The digital information of ECG can be collected using various computerized ECG measuring tools. The signals are sampled with a fixed interval sampling rate in which similar frequency components are grouped. The frequency and amplitude components are analyzed by applying morphological operations to find information content from the digital ECG imaging. The feature contains power spectrum density that can be calculated using a fast Fourier transform [20]. The high range frequency includes 0.15 hz to 0.5 hz of power density. The low range frequency includes 0.04 hz to 0.15 hz of power density. The very low-frequency range includes 0.0033 hz to 0.04 hz of power density.

4.5.4. Nonlinear Features

The features are biological signals that must be extracted using some nonlinear dynamics. Biological signals are analyzed using approximate entropy, correlation dimension, recurrence quantification, sample entropy, analysis of detrended fluctuation, and

Poincare plots, etc. [16] The Poincare plot is used to find the correlation between consecutive intervals on ECG signal per unit of time. The recurrent quantification measures the phase space of ECG along with its time duration and counts. Approximate entropy measures the disorder that occurs in the ECG signal. It measures the various irregularities that occur in the signal. In the correlation dimension, the self-similarity of the signal at various intervals has been analyzed.

4.5.5. Time Domain Features

Time domain features are the mathematical features derived from RR intervals [17]. Some of the time domain features are given below:

- Calculation of standard deviation of two normal RR intervals
- Calculation of standard deviation of differences of successive RR interval
- The square root of the mean of NN intervals
- The square root of the mean of RR intervals
- The square root of the mean of differences of successive NN interval
- The width of NN and RR histogram

The above mathematical computation over various intervals of ECG complexes provides crucial information about the ECG signal that is worth finding irregularities in the signal.

4.5.6. Phase-Based Feature Extraction

The system saw the goal of extracting proof from phrase-based tags as a NER task. Every piece of evidence was identified by a BIOES tag, where S denotes that the token is a piece of evidence and B, I, O, and E denote that the token is positioned at the piece of evidence's beginning, middle, outside, or end, respectively. As "medication" is a type of tag and "beta blockers" and "calcium-channel blockers" are two indications, the sentence "Continue beta blocker, CCB" was tagged as "Continue/O; beta/B-medication beta + blockers; blocker/E- medication beta + blockers;/O; CCB/S-medication calcium-channel + blockers." It needs to be stressed that there are two symptoms of medications. This study has focused on an ensemble system for phrase-based tag extraction [12]. The system first used Conditional Random Fields (CRFs) [22] and Structured SVMs (SSVMs) [24] to extract evidence from each clinical note. It then returned the union of those findings without taking into account any redundant information. All other properties, except for the dictionary features and negation information, were identical to those in our de-identification system. Bag-of-words, Part-Of-Speech (POS) tags, token and POS tag combinations, sentence information, affixes, orthographical features, word shapes, section information, general NER information, word representation features, and negation information were among the features used in these two base classifiers.

4.5.7. Logic-Based Tag Extraction

Two criteria are filtered polarity and phrase type to extract evidence of logic-based tags.

The system was judged on the following standards:

Numeric restrictions: -Find all numerical evidence, such as "LDL measurement of over 100 mg/dL," which indicates hyperlipidemia with high LDL as shown by "LDL > 100 mg/dL." Numerical limitations: Such numerical evidence is included in each category of logic-based tags.

Co-occurrence restrictions:-Find all evidence based on a combination of terms, such as "Early-onset CAD in mother," which is evidence of a family history based on "early CAD, mother." Using this criterion, the system only extracted data related to family history tags. Any evidence has been eliminated with a pejorative or subjunctive mood. The subjunctive mood was found using manually defined procedures, and the negation information of the evidence was determined using NegEx [21].

4.5.8. Discourse-Based Tag Extraction

Contrary to the other two tag categories discussed above, discourse-based tags need to explicitly state the evidence they include, making it challenging to extract it directly. In this feature extraction, first evidence candidate sentences have been created with discourse-based tags under indicator-related words or phrases, such as symptom-related phrases like "unstable angina." Then SVMs or any machine learning model has been used to assess whether or not those sentences were indicators-related. The Term Frequency-Inverse Document Frequency (TF-IDF) of words, unigrams, bigrams, negation information of sentences stated in the phrase-based tag extraction module, and negation information of indicator-related words/phrases determined by NegEx were among the features employed in the classifier. It should be emphasized that although the phrase-based subsystem used the negation information of sentences, the logic- and discourse-based tag extraction subsystems employed the negation information of words/phrases. This is because target words/phrases have already been extracted in the discourse-based and logic-based tag extraction subsystems but have yet to be in the phrase-based subsystem.

4.5.9. Time-Based Attribute Extraction

Time attribute identification is the extraction of temporal relationships for evidence and DCT pairs, a classification problem akin to the one addressed in the prior study for the 2012 i2b2 challenge [22]. The time attribute identification problem is a multi-label classification problem because any combination of "before," "during," or "after" might describe the temporal relationship between a piece of data and DCT in this task. This study reduced the multi-label classification problem to a single-label classification problem using the label-powerset technique [22], which was then solved using SVMs. TF-IDF of words, unigrams of words, bigrams of words, evidence tag type, evidence indicator, and the temporal link between the evidence-related time and DCT were among the characteristics of a piece of evidence employed for time attribute identification. Using customized NorMA [23], a rule-based temporal-expression normalizer for clinical texts—the evidence-related timings and DCT were recovered.

4.5.10. Frequency Domain Feature

A Power Spectrum Density (PSD) estimate is computed using the frequency domain approach for the RR interval series. The RR interval series are interpolated into equidistantly sampled series before PSD estimation because the regular PSD estimators implicitly require equidistant sampling. The PSD estimate in HRV analysis is often done using either FFT-based or parametric AR modeling-based approaches. These approaches' specifics are covered in Reference [31]. The simplicity of FFT-based approaches' implementation is a benefit. However, the AR spectrum produces improved resolution, particularly for short-length samples. The capacity of the AR spectrum to be factorized into distinct spectral components is another characteristic that has made it useful in HRV analysis. The complexity of model order selection and the possibility of harmful components in the spectral factorization are the drawbacks of the AR spectrum, though. As a result, it might be useful to compute the spectrum using both techniques for comparable results [32].

The heart rate signal consists of three primary frequency regions:

- A High Frequency (HF) power band is defined as the power in the frequency range of 0.15 Hz to 0.5 Hz,
- Low Frequency (LF) power band is defined as the power in the frequency range of 0.0.4 Hz to 0.15 Hz.
- A Very-Low-Frequency (VLF) power band is the power in the frequency range of 0.0033 Hz–0.04 Hz.

The HF region indicates vagal activity and Respiratory Sinus Arrhythmia (RSA). In contrast, the LF region indicates the baroreceptor control mechanisms and the combined influence of the sympathetic and vagal systems. The renin-angiogenesis and vascular processes are both indicated by the VLF power spectrum. This study assessed overall power, HF, LF, and the ratio of LF power to HF power [13].

4.6. Feature Selection

Many authors have employed methods to condense the feature space. Still, according to M. Karimi *et al.* [7], only some have looked at feature selection methods in classifying arrhythmias. For the first time in the literature, the model used a floating sequential search technique to choose features for their classification of arrhythmias. This method switches between algorithms that do forward and backward searches to find a set of features with the most resilient features and avoid local optimum in the feature space. Using just eight chosen features, the suggested strategy outperformed the state-of-the-art method in terms of results.

Recent feature selection work was done by Jun *et al.* [4] utilizing the floating sequential search [28]. In that study, the authors looked at various feature selection options to find a balance between accuracy and feature count. The research aimed to improve a specially devised method suitable for ambulatory monitoring, making it particularly helpful in practical applications. For this purpose, a feature selection method-optimized objective function that verifies the accuracy of arrhythmia classifications from an ECG signal was created. Jun et al. [4] used a multi-layer perception system in addition to the Linear Discriminant (LD) classifier employed in earlier investigations. However, both of these findings were more accurate than the theories put forth by de M. Karimi *et al.* [7]. However, the emphasis of Jun *et al.*'s [4] work was on maintaining accuracy using fewer characteristics. Because they require fewer features to build the final model, feature selection techniques can provide several advantages for classification methods, including increasing the generalization power of the algorithms and decreasing computing costs [4]. However, these techniques received minimal attention in the works examined in this review.

More than 200 features (dimensions) are considered for the task in B. Chen *et al.*'s [17] comparing wrapper and filter feature selection techniques. A forward-backward search method is utilized to pick the wrapper features for the weighted LD model. The mutual information filtering method used a ranking methodology and weighted SVMs (Support Vector Machines). The authors claim that when a relatively limited number of features are chosen, higher figures can be attained. They emphasized that the R-R intervals, the size and duration of the T wave, and the second-order statistics are the aspects that stand out the most. Additionally, they asserted that the mutual information criterion is an effective technique for feature selection in this situation. Many traits are connected to mathematical interpretation, according to W. Zhu *et al.* [20], and are unclear to doctors. Typically, writers combine numerous features, and it is only sometimes evident from the literature which trait is responsible for detecting which class of heartbeat. To investigate the feature contribution for each type of arrhythmia/heartbeat, W. Zhu *et al.* [20] suggested a feature selection scheme specific to heartbeat classes. We advise including this approach in efforts attempting to classify heartbeats. It might significantly contribute to the body of literature by enabling a better understanding of the relationship between heart illnesses and features taken from ECGs. Modern attribute selection methods like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) [11, 12] can also yield promising results and ought to be further explored in upcoming research.

4.7. ECG Arrhythmia Classification

Various algorithms in the existing works have been applied to perform analysis of features and classification of features into various symptoms, including diseased and normal symptoms. The disease's features may be of various types, including Arrhythmia, Plaques, Coronary artery diseases, etc. A very common disease called Arrhythmia occurs due to an irregular heartbeat. Below are some of the latest algorithms based on machine learning, deep learning, and artificial intelligence. These have shown the effectiveness in recognizing Arrhythmia in the existing literature.

4.7.1. Support Vector Machine

Support vector machine (SVM) is found to be most suitable and recommended in existing literature for recognizing arrhythmia classification. Park *et al.* [21] applied SVM over AAMI standardized database to split the datasets into testing and training divisions. Chazal *et al.* [22] also performed a mock hierarchy configuration to form clusters of MIT BIH datasets. There exists weighted SVM applied by de Lannoy *et al.* [23] for the better classification of heartbeat ECG signals. The SVM uses statistical analysis of the ECG signal in terms of binary or decimal values. Every points of ECG amplitude in the X-Y axis have been translated into numeric values at each time stamp to apply statistical analysis [22]. The classification of features is segregated using a non-linear hyperplane. The method is used to generalize the statistical analysis of the numerical feature values by forming a mathematical model to minimize empirical risk. Sigma and cost are the two parameters that are classified using SVM to avoid overfitting the nonlinearity of the model, as introduced by Davari *et al.* [12]. A Gaussian radial based kernel has been used in SVM to detect arrhythmia disease from ECG has been employed by Banerjee *et al.* [13].

4.7.2. Artificial Neural Network

The ANN (artificial neural network is based on a deep learning technique in which multilayered Perceptrons are employed to process the statistical features of the ECG record. Each perceptron has an activation function that triggers the information received by the combination of the input ECG feature and its weight. The works are based on the probabilistic approach in which the optimum solution for the classification has been generated once and again, and its cost gets minimized. The cost of a classified feature is its distance from the actual class. And so a feedback network is also employed in this network to receive the noise from the classified features so that the improvement can be made by tuning weights of the network to receive a very optimum solution of the classified features. Guler et al. [11] applied a hybrid neural network to obtain a generalization of feature classification from ECG signals. The artificial neural network performs feature extraction and classification similar to the human brain with the information. Kim *et al.* [9] suggested a neural network technique for predicting coronary artery disease from AAMI standardized dataset. The technique is supervised in which the training data has been provided to the model. An artificial neural network can expand by increasing the number of hidden layers to perform deep feature analysis for accurate classification.

Multilayer Perceptrons (MLP) and Probabilistic Neural Networks are the ANN architectures most frequently employed for identifying heart rhythms (PNN). Tajbakhsh *et al.* [10] claim that PNN models are computationally more reliable and effective than conventional MLP. However, a hybrid neuro-fuzzy network strategy was presented in [12, 13] to reduce the issues with MLP while boosting its generalization and speeding up its training. There have been other different ANN-based strategies put forth. Multilayer Perceptrons (MLP) and Probabilistic Neural Networks are the ANN architectures most frequently employed for identifying heart rhythms (PNN). S. Tsantis *et al.* [11] claim that PNN models are computationally more reliable and effective than conventional MLP. However, a hybrid neuro-fuzzy network strategy was presented in [12, 13] to reduce the issues with MLP while boosting its generalization and speeding up its training. There have been other different ANN-based strategies put forth. To convert a more sophisticated type of cross-validation into a more general technique, Jun *et al.* [4] used coupled neural networks. However, only the paper by B. Chen *et al.* [17] employed MLP with a more equitable evaluation technique by implementing the patient division scheme suggested by de M. Karimi *et al.* [7]. This is out of all the articles listed in this study. It is, therefore, hard to do a fair comparison using the published findings from methods that use ANN as a classifier. Last but not least, S. Yazdani *et al.*'s [16] comparison of MLP with Linear Discriminants revealed that MLP was noticeably superior.

4.7.3. Linear Discriminant Analysis

The linear discriminant model also performs statistical analysis of the ECG features for the classification of heart diseases. The technique separates feature vectors linearly and applies weight adjustment to tune the classification efficiency. In the earlier works [5], the segregation of the feature vectors has been set by calculating the maximum likelihood from the training data. The classifier is recommended for its simplicity and efficiency. The model divides the problem into small parts to analyze them linearly.

4.7.4. CNN/Transfer Learning

Applying knowledge gained from patterns in one area or job to patterns in another is possible. This knowledge can be transferred between two domains and employed in the third domain to enable categorization by applying the Transfer Learning (TL) technique. Utilizing a pre-trained deep CNN for automatic feature extraction is one application of this method. This network's convolutional layers hold feature maps learned during training on the original dataset and contain information about the patterns found there. These feature maps are capable of extracting features from other datasets. These "off-the-shelf" recovered features from a deep neural network's intermediate layers are powerful enough to defeat manually produced features and are a prime candidate for feature extraction [4]. Applying a deep neural network (DenseNet) to the ECG domain to categorize a small dataset of thousands of examples utilizing this network as a feature extractor, this network was trained on millions of photos in the ImageNet dataset. Depicting ECG spectrograms using the patterns discovered from the ImageNet dataset, which contains numerous classes of images, such as those of objects and animals. A deep CNN with connections between each layer and every other layer using a feed-forward method is known as a densely connected CNN (DenseNet) [5]. This kind of link makes it easier to mitigate the vanishing-gradient issue, which improves feature propagation and training. In benchmark tasks for object identification, DenseNet displayed encouraging results. DenseNet's design consists of four Dense Blocks with configurable lengths. Using a pre-trained DenseNet with 161 convolutional layers distributed across its structure, we look at the outputs of these layers in this study [4] to extract features.

4.7.5. Other Classification Algorithms

Other arrhythmia classification algorithms are also applied in the current work to identify heart-related diseases from the ECG records. These classification algorithms are named Principal component analysis [4], K-nearest neighbor [5], Logistic regression [6], Hidden Markov models [7], Conditional random fields [8], Decision tree [9], etc. All these algorithms have various computational costs and efficiency. The principal component analysis is used to divide the whole feature vector into small components and analyze the features' eigenvalues. K-nearest neighbor applies the distance formula to find the nearest features in a class. All the similar features are combined in one class, and all the other similar features are stored in different classes. This way, the arrhythmia ECG segments are distinguished from the normal ECG records. Logistic regression is also applied for the continuous prediction of the ECG records. The decision tree method is used to translate the training ECG features into a tree having nodes (for solution) and branches (for condition. Each non-leaf node in the tree is the sub-class of the final normal and arrhythmia classes.

5. Results & Discussion

The state of art comparison of some existing models and various classifiers for classifying arrhythmia disease has been given in Table 4.

From the Table 4, it is clear that the major part of the Arrhythmia detection work has been accomplished with the help of machine learning and deep learning methods. The earlier study focuses on obtaining robustness with higher accuracy from ECG datasets. The standardization of the ECG dataset has been ensured by AAMI (Association for the Advancement of Medical Instrumentation) [15], which is a standardized committee containing a set of protocols defined to acknowledge the standard of datasets. The most popular and advised by ANSI/AAMI for the certification of medical equipment [10] is the MIT-BIH database for arrhythmia analysis [25], in this case, employed for heartbeat segmentation. The effectiveness of neural networks is found to be more as compared to other classifiers. S. Savalia *et al.* [24] re-implemented a neural network model with an overall accuracy of more than 95% to obtain Cardiac Arrhythmia classification using RR intervals. Then, to present trials in line with the procedure advised by AAMI and utilize the division scheme suggested in [7], they re-evaluated the results generated by the methodologies. Be aware that the approaches used for this experiment are very new, and consider the usage of different classifiers and feature extraction techniques. It can be seen that the results obtained by the same classification method using a scheme of random selection (in which heartbeats were randomly selected to compose the training and testing sets) are significantly better. The findings are not a realistic scenario. Heartbeats from the same patient should be absent from the training and testing sets to conduct a fair evaluation of ECG-based heartbeat classification algorithms. The evaluation of a method on the testing set using the heartbeats of a patient whose heartbeats are present in the training set is also biased, even if the heartbeats of the same patient are different because otherwise, the classifiers will learn the subtleties of the patients in the training set. Although certain literary works [28, 29] strongly highlight this bias problem, only some authors have adhered to the AAMI-proposed methodology to present the results and evaluate the methodologies, making it challenging to compare the works published in the literature fairly.

6. Conclusion and Future Work

The proposed paper provides a survey of the detection of arrhythmia and heart disease caused by the irregular action of a heartbeat. The paper reviews various recent publications on the classification of heart diseases. Various heart diseases are studied and discussed in the paper. A review has been discussed on some recently developed automated models and evaluated their performance based on specific parameters like deployed

Table 4. State of art comparison of recent existing work

S.No.	References	Features of ECG	Methods	AAMI standardized Dataset	Results of arrhythmia classification	Limitations
1.	S. Savalia *et al.* [24] (2018)	Cardiac Arrhythmia classification using RR intervals	Neural network	Yes	95% accuracy	Limiting to single variant feature
2.	A. Davari *et al.* [25] (2017)	Automated diagnosis of coronary artery disease using ECG intervals	SVM	No	90% accuracy	Model fails to deal with diversity in features
3.	Kim *et al.* [5]	Linear discriminant analysis	SVM	No	80% accuracy	Very slow learning rate
4.	Giri *et al.* [6]	Features of RR intervals	Gaussian matrix model	Yes	95% accuracy	Robustness is low
5.	Karimi *et al.* [7]	Frequency component analysis	ANN	Yes	97% accuracy	The method does not show results for other time domain features
6.	De chalaz *et al.* [22]	Morphological frequency features	Weighted linear discriminant	No	84% accuracy with 87% specificity	May fail to handle non-linear features
7.	Park *et al.* [21]	ECG intervals	SVM	Yes	86.4% accuracy with 88% specificity	Only applicable in a few ECG intervals.

datasets, variation of input data, applied application, methodology, and results obtained by the developed model. The review of the dataset, pre-processing techniques, features of ECG, and classification algorithm has been done in the proposed paper. The Artificial neural network with deep learning technology is the most recommended model for classifying arrhythmia diseases as it shows the most accurate result.

The next paragraphs examine several issues that researchers have brought up about the automatic classification of cardiac arrhythmias [24, 25, 26]. The notoriously uneven MIT-BIH database, also known as MIT-BIH ARR DB, is typically used to show results in the literature. However, authors who employ the intra-patient system need to pay more attention to this feature. For the heartbeat arrhythmia classes SVEB and VEB, authors who took a more practical approach and decided against mixing heartbeats for training and testing (inter-patient scheme) reported needing help generating positive findings. As a result, numerous proposed approaches that do not adhere to a more impartial review process may be found in the literature.

Several authors [3,4,5] use semi-automatic methods to enhance the results. [6] claims that semi-automatic methods can enhance the outcomes by more than 40%, even when only a small subset of heartbeats are chosen for adaptation. Such methods have the problem of necessitating expert assistance. However, professional intervention is typical in a therapeutic setting, making this strategy a viable research area. We emphasize that when it comes to fully automated approaches, even the protocol put out by de M. Karimi *et al.* [7], which is regarded as the fairest one offered in the literature, has certain issues that have previously been mentioned by Pourbabaee [9] and Park *et al.* [15]. Due to the class imbalance, the authors added two records for the same patient in the two previously mentioned sets. Because records 201 and 202 are from the same patient and are part of sets DS1 and DS2, respectively, findings that are slightly better than anticipated may be obtained. Records 201 and 202 focus heavily on a sizable portion of heartbeats class SVEB. Using the imbalanced record 232 in DS2 is a critical flaw in the protocol suggested in [7], which is another key vulnerability. More than 75% of heartbeats in the SVEB class are included in that record. As a result, techniques that correctly classify the heartbeats in this record may be mistakenly thought to be state-of-the-art. In reality, they may only be tailored to classify the heartbeat of a single patient. Machine learning researchers have demonstrated that the size and diversity of the datasets used to build methods have a greater impact than the selection of the learning algorithm and the methodologies used [24]. In numerous research fields involving pattern recognition, efforts have been undertaken to build new databases or even expand the size of current ones and provide standardized evaluation methodologies, particularly to prevent unfair comparisons between techniques [33].

The lack of readily accessible databases, in our opinion, is a significant barrier to progress in the field of fully computerized classification of heartbeats (arrhythmias) in ECG. We advise the scientific community studying the heartbeat classification challenge to support or stimulate the expansion of databases intended for this purpose. We also recommend the development of new databases using cutting-edge methods for capturing the ECG signal, such as off-the-person ways. However, developing such databases would be very difficult because, in addition to the associated expenditures, they would need to be integrated into standards like AAMI standards to reach the target audience. It is challenging to fairly compare the methods because only some writers utilize the same assessment approach for tests. Due to the intra-patient scheme's favoring of the reported figures, it is also challenging to determine the true contribution of the approaches. Studying and re-implementing intra-patient approaches published in the literature while adhering to a heartbeat selection scheme without bias (inter-patient approach) would be another difficulty; a beginning piece of work in this area can be found in [26]. Furthermore, the literacy of this subject must examine their impact from a non-biased perspective.

References

1- Deng, J. *et al.*, 2009. ImageNet: A Large-Scale Hierarchical Image Database. CVPR 09.

2- Işin, A., Direkoğlu, C., Şah, M., “Review of MRI-based Brain Tumor Image Segmentation Using Deep Learning Methods”. *Procedia Computer Science* 102, pp. 317-324, (2016).

3- Işin, A. *et al.*, “Monte Carlo simulation of PET/MR scanner and assessment of motion correction strategies”, *JINST 12*, C03089, (2017).

4- Jun, T. J. *et al.*, “Premature ventricular contraction beat detection with deep neural networks”. *15th IEEE International Conference on Machine Learning and Applications*, pp. 859-864, (2016).

5- W.S. Kim, S.H. Jin, Y.K. Park, H.M. Choi, “A study on development of multi-parametric measure of heart rate variability diagnosing cardiovascular disease”, *World Congress on Medical Physics and Biomedical Engineering 2006, Volume 14 of the series IFMBE Proceedings* pp. 3480–3483, (2006).

6- D. Giri, U.R. Acharya, R.J. Martis, S.V. Sree, T.-C. Lim, T. Ahmed VI, *et al.*, “Automated diagnosis of coronary artery disease affected patients using LDA, PCA, ICA and discrete wavelet transform”, *Knowl. Based Syst*, 37 (2013), pp. 274–282, (2013).

7- M. Karimi, R. Amirfattahi, S. Sadri, S.A. Marvasti, “Noninvasive detection and classification of coronary artery occlusions using wavelet analysis of heart sounds with neural networks”. *In The 3rd IEE International Seminar on Medical Applications of Signal Processing*, pp. 117–120, (2005).

8- Pan, J., Tompkins, W. J., “A Real Time QRS Detection Algorithm”. *IEEE Transactions on Biomedical Engineering*, 32, pp. 230-236, (1985).

9- Pourbabaee, B., Roshtkhari, M. J., Khorasani, K., “Feature Learning with Deep Convolutional Neural Networks for Screening Patients with Paraoxysmal Atrial Fibrillation”. *IEEE International Joint Conference on Neural Networks*, pp. 5057-5064, (2016).

10- Tajbakhsh, N. *et al.*, “Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning?”. *IEEE Trans. Med. Imaging*, 35, pp. 1299-1312, (2016).

11- S. Tsantis, G. C. Kagadis, K. Katsanos, D. Karnabatidis, G. Bourantas, and G. C. Nikiforidis, “Automatic vessel lumen segmentation and stent strut detection in intravascular optical coherence tomography,” *Medical physics*, vol. 39, no. 1, pp. 503–513, (2011).

12- L. S. Athanasiou, C. V. Bourantas, G. A. Rigas, T. P. Exarchos, A. I. Sakellarios, P. K. Siogkas, M. I. Papafaklis, K. K. Naka, L. K. Michalis, F. Prati, *et al.*, “Fully automated calcium detection using optical coherence tomography,” *in Engineering in Medicine and Biology Society (EMBC)*, pp. 1430–1433, IEEE, (2013).

13- Huang, H., Liu, J., Zhu, Q., Wang, R., Hu, G., “A new hierarchical method for inter-patient heartbeat classification using random projections and rr intervals”. *Biomedical engineering online* 13, 90, (2014).

14- De Chazal, P., Reilly, R.B., "A patient-adapting heartbeat classifier using ecg morphology and heartbeat interval features". *IEEE transactions on biomedical engineering* 53, pp. 2535–2543, (2006).

15- Park, K., Cho, B., Lee, D., Song, S., Lee, J., Chee, Y., Kim, I., Kim, S., "Hierarchical support vector machine-based heartbeat classification using higher order statistics and hermite basis function", *in: 2008 Computers in Cardiology, IEEE.* pp. 229–232, (2008).

16- S Yazdani, S Fallet, J. Vesin, "A novel short-term event extraction algorithm for biomedical signals", *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 4, pp. 754-762, (April 2018).

17- J. Huang, B. Chen, B. Yao and W. He, "ECG Arrhythmia Classification Using STFT-Based Spectrogram and Convolutional Neural Network", *IEEE Access*, vol. 7, pp. 92871-92880, (2019).

18- P. Wang, B. Hou, S. Shao and R. Yan, "ECG Arrhythmias Detection Using Auxiliary Classifier Generative Adversarial Network and Residual Network", *IEEE Access*, vol. 7, pp. 100910-100922, (2019).

19- R. He *et al.*, "Automatic Cardiac Arrhythmia Classification Using Combination of Deep Residual Network and Bidirectional LSTM", *IEEE Access*, vol. 7, pp. 102119-102135, (2019).

20- 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).

21- K.S. Park, B.H. Cho, D.H. Lee, S.H. Song, J.S. Lee, Y.J. Chee, I.Y. Kim, S.I. Kim, "Hierarchical support vector machine-based heartbeat classification using higher order statistics and hermite basis function", *in: Comput. Cardiol.*, pp. 229-232, (2008).

22- P. de Chazal, M. O'Dwyer, R.B. Reilly, "Automatic classification of heartbeats using ECG morphology and heartbeat interval features", *IEEE Trans. Biomed. Eng*., 51 (7) (2004), pp. 1196–1206, (2004).

23- G. de Lannoy, D. Franc¸ois, J. Delbeke, M. Verleysen, "Weighted SVMs and feature relevance assessment in supervised heart beat classification", *in: Biomedical Engineering Systems and Technologies (BIOSTEC)*, pp. 212–223, (2010).

24- S. Savalia, V. Emamian, "Cardiac Arrhythmia Classification by Multi-Layer Perceptron and Convolution Neural Networks" *Bioengineering MDPI journal*, 5 (2), p. 35, (2018).

25- A. Davari Dolatabadi, S. E. Z. Khadem, and B. M. Asl, "Automated diagnosis of coronary artery disease (CAD) patients using optimized SVM", *Computer Methods and Programs in Biomedicine*, vol. 138, pp. 117–126, (2017).

26- Arabasadi, Zeinab, *et al., "*Computer aided decision making for heart disease detection using hybrid neural network-Genetic algorithm". *Computer methods and programs in biomedicine* 141 (2017), pp. 19-26, (2017).

27- Ketu, Shwet, and Pramod Kumar Mishra. "Empirical analysis of machine learning algorithms on imbalance electrocardiogram-based arrhythmia dataset for heart disease detection". *Arabian Journal for Science and Engineering* 47.2, pp. 1447-1469, (2022).

28- Saikumar, Kayam, Vullanki Rajesh, and Bulepe Sankara Babu. "Heart Disease Detection Based on Feature Fusion Technique with Augmented Classification Using Deep Learning Technology". *Traitement du Signal* 39.1, (2022).

29- Chitra, R., *et al.*, "Performance Evaluation of Machine Learning Algorithms in Design and Development of Heart Disease Detection". *2022 International Conference on Computing, Communication, Security and Intelligent Systems (IC3SIS). IEEE*, (2022).

30- Saleh, Basma, *et al.*, "Analysis of weka data mining techniques for heart disease prediction system". *International journal of medical reviews* 7.1, pp. 15-24, (2020).

31- Khan, Younas, *et al.*, "Machine learning techniques for heart disease datasets: a survey". *Proceedings of the 2019 11th International Conference on Machine Learning and Computing*. (2019).

32- Benhar, Houda, Ali Idri, and J. L. Fernández-Alemán. "Data preprocessing for heart disease classification: A systematic literature review". *Computer Methods and Programs in Biomedicine*, 195 (2020), pp.105635, (2020).

33- Yahaya, Lamido, N. David Oye, and Etemi Joshua Garba. "A comprehensive review on heart disease prediction using data mining and machine learning techniques". *American Journal of Artificial Intelligence*, 4.1, pp. 20-29, (2020).