Survey on Cardiac Arrythmia Detection Techniques

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*Abstract*— A cardiac arrhythmia is defined by an irregular heartbeats, it is a common medical condition that affects millions of people worldwide, which can occur at any age like kids, teenagers, adults and old people and can be either excessively rapid more than 100 beats per minute or too slow 60 beats per minute. Accurate prediction and classification of these arrhythmias are crucial for early diagnosis and treatment of cardiovascular diseases. In recent years, advances in medical technology and treatments have made it possible to better understand, diagnose and manage these conditions. In order to identify and categorize cardiac arrhythmias, many techniques and methods are discussed in this survey paper. The aim of this paper is to provide a comprehensive understanding of the current progress and potential directions in the prediction and classifications of cardiac arrhythmias from ECG signals. In addition, framework for cardiac arrhythmia detection using Deep Learning is proposed.

Keywords—Cardiac Arrhythmia, Machine Learning, Deep Learning, Heartbeat, 2D-CNN, ECG

# Introduction

Any irregular heartbeat is referred to as a cardiac arrhythmia, a broad phrase. Arrhythmias come in a variety of forms, each with its own characteristics and possible health consequences. Electrocardiograms (ECGs), which are recordings of the heart's electrical activity, are frequently used in the categorization of cardiac arrhythmias. Due to its low cost, simplicity of use, great efficiency, and non-invasiveness, ECG has emerged as a promising tool for the research of the anatomy and function of the heart [1].

It shows the electrical pattern of the cardiac muscles' depolarization and repolarization throughout each heartbeat. Any deviations from the regular patterns of electrical impulses in the heart that result in aberrant cardiac rhythms are referred to as "arrhythmias." Arrhythmias can either be absolutely non-threatening or fatal. Tachycardia or even a sudden heart arrest might result from it. Heartbeat classification based on ECG data has emerged as a vital and promising approach in the study of arrhythmia identification for early warning of arrhythmias. However, there might be a large difference in ECG signals between patients[2].

## The Convolutional Neural Network (CNN) has achieved great success in the field of computer vision research and is currently widely used in image processing tasks. Due to its unique ability of capturing position and translation invariant patterns, CNN is applied to physiological signals for morphological analysis. The CNN is relativelyless sensitive to noise capable of extracting useful information even when the signals are noisy.This attribute is built within the hierarchical deep structure. As the layers in the network progresses, features are learnt and represented in a more abstract manner[3].

These techniques can be trained on ECG data to classify arrhythmias. The performance of these techniques can be improved by selecting appropriate features and fine-tuning their parameters. It is important to note that the performance of machine learning techniques depends on the quality and size of the data used for training and testing[4].

There are many types of cardiac arrhythmias, but some of the most common include- supraventricular ectopic beats , ventricular ectopic beats, fusion beats , unknown beats. These are just some of the many types of arrhythmias that can occur. It's important to seek medical attention if you experience symptoms such as palpitations, shortness of breath, chest pain, or fainting, as these can be indicative of a serious arrhythmia[5].

Several reviews and survey papers are available but this survey paper reviews most of the research done in the last decade and proposes several challenges and conceptual framework for cardiac arrhythmia.

This paper has also been broken into the following sections:

Section II provides a quick overview of research.Section III lists potential difficulties and potential research paths.Section IV presents the proposed research project, while Section V wraps up the study.

# Literature review

Based on the availability of the paper, this section is further divided into two sub sections namely Machine Learning and Deep Learning. Machine Learning is a subfield of Artificial Intelligence that focuses on the design and development of algorithms that can learn from and make predictions or take actions based on input data. Deep Learning is a sub field of Machine Learning that uses algorithms inspired by the structure and function of the brain, known as Artificial Neural Network, to analyze and model complex patterns in data. These deep neural networks can have multiple hidden layers, following them to learn and model highly abstract representation of data.

## A.Machine Learning Techniques

Support Vector Machine (SVM) for ECG arrhythmia classification methods. The biggest distance from the hyperplane to the closest training samples is what the SVM algorithm looks for when it locates a hyperplane. The best segmentation hyperplane, in other words, maximizes the boundary of the training sample. A decision function that is learnt from the training set to predict the class label in the ensuring tests serves as the optimal separating hyperplane's representation [6].

As an ensemble learning technique for classification, regression, and other tasks, random forests or random decision forests create a large number of decision trees during the training phase and output the class that represents the mean of the classes (classification) or mean prediction (regression) of the individual trees [11].

Each tree in a random forest is built in a specific way:

Given a training set of N data, n random samples with repeats, or bootstrapping, are utilised as the training set.

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Ref** | **Dataset** | **Data Pre-processing** | **ECG Feature** | **Modeling technique** | **Feature Extraction** | **Tools** | **Accuracy** | **No. Of Beats** | **Sampling Frequency** |
| [7] | MIT-BIH  ARRYTHMIA | Morphological  processing | Peak R,P,T,  QRS duration | SVM Classifier | FE: DWT | Matlab | 97.80% | 04 | The normal PR  ranges from 0.12 to 0.20 sec |
| [[8](#_References)] | MIT-BIH  ARRYTHMIA | NLM-Based denoising  method | RR Interval | SVM Classifier | Raw ECG Signal, Pan Tompkins QRS detect | PhysioNet ATM Database | 92.20% | 04 | RR interval |
| [[9](#_Random_Forest)] | MIT-BIH  ARRYTHMIA | Spark Scala  Firmware | RR Interval,  QRS peak | Random forest  ,Gradient boost tree | FE: DWT | Matlab  Hidden Markov model and apache spark | RF=97.98,  GBT=96.75 | 04 | 360 samples per second per channel with 11-bit resolution over a 10 mV range |
| [10] | MIT-BIH  ARRYTHMIA | Feature selection | QRS duration | SVM,JRIP, Random Forest | chi-square, symmetrical uncertainty, and gain ratio | Weka, Datamining Tools | RF=85.585% ,SVM=79.30%, JRIP=81.86% | 30 | --- |

M input variables are chosen for each node of the tree by determining M variables for each node. The node is picked at random based on which variable is most significant. The value of m stays the same.

Each tree is developed to the point of maximal extension. K-Nearest Neighbor (KNN): KNN is used to classify ECG signals based on their similarity to other ECG signals in the training dataset.These machine learning techniques have shown promising results in detecting and classifying cardiac arrhythmias, and they have the potential to improve the diagnosis and management of these conditions. However, it is important to keep in mind that these techniques should be used in conjunction with other methods and clinical expertise for accurate and effective diagnosis and treatment[12]. The research work discussed in this subsection is summarised in Table I.

*B. Deep Learning Techniques*

The approach for classifying ECG arrhythmias proposed in this study uses a (CNN). The five different heartbeat types represented by the time domain signals of the ECG, including the normal beat (NOR), left bundle branch block beat (LBB), and right bundle branch block beat (RBB), premature ventricular contraction beat (PVC), and atrial premature contraction beat (APC) were initially converted by short-time Fourier transform into time-frequency spectrograms. Finally, the ECG arrhythmia types were recognized and categorized using the spectrograms of the five different arrhythmia kinds as input to the CNN[13].

The novelty of this work is that we used ECG segments of variable length from the MIT-BIT arrhythmia physio bank database. The proposed system demonstrated high classification performance in the handling of variable-length data, achieving an accuracy of 98.10%, sensitivity of 97.50% and specificity of 98.70% using ten-fold cross validation strategy[13].

In this research a deep learning-based methodology called LSTM is used to suggest a way of classifying arrhythmias. The MIT-BIH Arrhythmia Database is used for testing and assessment before the five kinds of arrhythmias proposed by the AAMI are analysed[14].

This study suggests using LSTM, a deep learning-based approach,to automatically detect heart arrhythmias. A key property of deep learning is its ability to learn feature representation from the data entry done automatically.

The suggested model has two LSTM layers and an output layer with five neurons, one for each of the arrhythmia classes N, S, V, F, and Q. By including a Softmax regression function on the resultant hidden layer, the technique may distinguish between the classes of normal and pathological input signals to find the most discriminant cardiac arrhythmias. Contrary to other approaches, the interaction phase does not comprise the denoising and feature extraction stages[15].

In this article we propose to classify electrocardiographic arrhythmias method based on two-dimensional convolution neural network on classification of five different rhythms that are supraventricular ectopic, ventricular ectopic, fusion, unknown beats [16].

Input a one-way ECG signal in the time domain signals are converted into two-way time frequency spectrum. However, in this step, the noise filtering and Manual feature extraction is no longer required. Moreover, training data obtained by increasing the derived data ECG image, may lead to higher classification accuracy.

Segmented 2D time-frequency spectra input to the convolutional neural network. The CNN model can automatically delete the measurement noise and extract relevant feature maps throughout convolution layer and smart synthesis.

The approach in Spectroscopy (2-D images) was used, generated from 1-D ECG signals using STFT. In addition, data enhancement was used to represent 2D images of the ECG signal. State-of-the-art performance was achieved in the classification of ECG arrhythmias using the proposed CNN-based method with 2D spectra as input[16].

An ANN called a deep neural network (DNN) has additional hidden layers in between the input and output layers. DNNs may simulate intricate non-linear interactions in a manner similar to shallow ANNs.

Our proposed Architecture the combination of DAEs and DNNs structure, gives a better performance compared to the other selected DL approach[16].

In contrast, DL makes it possible to directly use raw data for embedded feature extraction and feature selection in the pre-training and fine-tuning stages of DAE and DNN. As a result, DAEs is capable of extracting high-level features from both training data and unknown data.

Probabilistic neural networks (PNNs) are used for classification. The electrocardiogram is beating. It is a feed forward network with an input, hidden, summarizing, and output layer. When an input is given, the hidden layer computes the distance between the inputs and the training input vectors to produce a vector with elements indicating how close the input isfor training input. The summation layer adds these contributions to each input type to produce a probability vector as the net output. The output layer selects the maximum of these probabilities and produces 1 for this class and 0 for the others. The radial basis function (RBF) is used as the transfer function. PNN trained with 88101 ECG rhythm patterns including training examples from all five categories. The training and test matrix is ​​calculated so that each row represents the ECG heart rate and the features occupy the columns.

In this paper, they used PNN as a classifier and the MIT-BIH dataset to classify cardiac arrhythmias. They used discrete wavelet transform for pre-processing, for classification they used ECG function like R peak interval and they measured efficiency of 99.83% and 5 beats used for classification at a sample rate of 360Hz.

Recurrent neural networks come into being due to their very dynamic behaviour while multilayer feedback networks have static mapping. RNNs have been used in

many fields and have interesting applications in the areas of associative memory, optimization, and generalization. Time series data is best classified by RNN where the response and current values ​​are fed back to the network and so the output also contains traces of the existing values ​​in memory growing classification performance and provides better results than conventional feedforward networks.In this paper three RNN layers were used with the number of neurons in each layer being 128, 256 and 100 respectively with 9 iterations. A reduction ratio of 0.2 has been added after each layer. The activation used is linear with MSE as a loss function[20]. ]. The research work discussed in this subsection is summarised in Table II.

# CHALLENGES AND FUTURE RESEARCH DIRECTIONS

The following are challenges and future directions discussed below:

Complexity of arrhythmia patterns and difficulty in accurate classification. This is due to variability in the morphologies of heartbeats, the presence of noise in ECG signal, and the co-occurrence of multiple arrhythmias in a single recording. Difficulty in generalizing algorithms to diverse populations. Integration with existing clinical systems and regulatory approval for use in clinical settings. Balancing sensitivity and specificity of prediction algorithms. Difficulty in detecting rare arrhythmia events, this is due to difficulty in capturing

and recording them, also due to lack of sufficient training data and the limited ability of these methods to generalize to new, unseen cases. Ensuring robustness of deep learning models against ECG artifact and noise. Improving accuracy of prediction algorithms through

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| [20] | MIT-BIH  ARRYTHMIA | Short Time Fourier Transform | ECG Signal of 10 sec | CNN | 2D time-frequency  Spectograms | --- | 99.00% | 05 Beats | Sampling rate 360Hz |
| [21] | MIT-BIH  ARRYTHMIA | --- | R peak | CNN AND LSTM | FE: DWT | --- | 98.1% | 05 Beats | 360 Hz |
| [22] | MIT-BIH  ARRYTHMIA | Noise removal  Wavelet transforming | PR interval  RR interval | CNN AND LSTM | PCA, DWT | --- | 99.35% | 05 Beats | Raw ECG  Signal |
| [23] | MIT-BIH  ARRYTHMIA | wavelet based thresholding to remove noise | ECG Signal | 2D-CNN | Cropping method | 97.91% | 99.11%  97.91% 99.61% 98.58% | 08  Beats | --- |
| [24] | MIT-BIH  ARRYTHMIA | Wavelet Threshold for denoise signal | Q wave Peak time | CNN | CWT | --- | 97.38% | 08 Beats | --- |

incorporation of more data sources for example genetic, lifestyle. Development of AI-powered wearable for real time arrhythmia detection. Integration of machine learning models with electronic health records for personalized prediction and treatment. Exploration of using deep learning methods for better arrhythmia classification. Can be used in real time for different types of diseases and can notify the user and alert them about it. A simplified manner to be deployed on embedded systems.

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Ref** | **Dataset** | **Data Pre-processing** | **ECG Feature** | **Modeling technique** | **Feature Extraction** | **Sensitivity** | **Accuracy** | **No. Of Beats** | **Sampling Frequency** |
| [17] | MIT-BIH  ARRYTHMIA | Discrete Wavelet Transform | R peak interval | PNN | DWT, PCA | 99.54% | 99.83%  99.54% | 05 Beats | sampled at 360 Hz |
| [18] | MIT-BIH  ARRYTHMIA | --- | R-Peak | RNN-LSTM | --- | 92.40% | 92.40%  83.35%  88.10% | 05 Beats | sampling rate 360Hz |
| [19] | MIT-BIH  ARRYTHMIA | DAEs  Beat segmentation | R peak | DNN | Auto Encoder | 91.20% | 99.73%  91.20%  99.80%  93.60% | 10 Beats | --- |

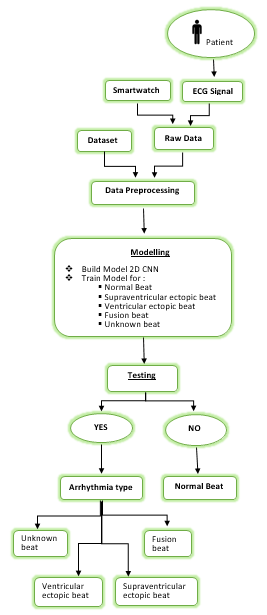
# IV PROPOSED APPROACH

For our model the input is taken from MIT-BIH Arrhythmia Dataset for classification from Kaggle and the input can be directly taken from the patients, each patients ECG signals can be recorded, also the ECG from selected smartwatches can be taken as input for the model. These ECG signals of patients with and without arrhythmia are collected and considered as raw data which will be pre-processed. Clean and preprocess the data collected to remove any irrelevant

information and noise, this involves filtering, smoothing,

resampling the signals.Meaningful features are extracted from the preprocessed signals that can be used for classification. Appropriate Machine Learning Model is used for classification based on the extracted features. The model is built using 2D CNN.

The selected model is trained using pre-processed signals and features. Its used to train for the Supraventricular ectopic, Ventricular, fusion and unknown beats of Arrhythmia and also the Normal heartbeats. Validate the model’s performance using cross-validation techniques to ensure its generalizability to new data. Test the data to check the predictions made for the raw ECG signals and the dataset taken from MIT-BIH. The types of arrhythmia are predicted in case it exists, otherwise Normal beats are displayed if arrhythmia isn’t detected. The output predicted is displayed on the users screen of the web application.



V.CONCLUSION

This article provides a thorough overview and compares several methods used in Cardiac arrhythmia detection.A combination of various machine learning and deep learning techniques such as SVM, Random Forest , RNN, PNN, DNN and LSTM have been used for this purpose with varying level of success. It has been found further that deep learning approaches are more accurate than conventional methods. In addition, other keys, difficulties, and research directions are laid out for further investigation needed to develop more robust and efficient algorithms to enhance the accuracy and reliability of arrhythmia prediction and classification systems.

In this paper, we have proposed conceptual framework for Cardiac Arrhythmia detection and its types using Deep Learning which will be implemented using CNN, TensorFlow, Keras and Python.

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