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# Analysis of Machine Learning and Deep Learning Methodologies for Classification and Detection of Arrhythmia

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**Abstract**— Arrhythmias can be extremely important in the diagnosis and management of cardiac disorders. In this research, we offer a feature extraction and support vector machine (SVM) based technique for ECG arrhythmia detection and classification. The suggested process entails extracting a variety of characteristics, including the R peak, QRS complex, and ST segment, and then utilizing the mutual information criteria to choose the aspects that are most pertinent. The identification and categorization of arrhythmias on the electrocardiogram (ECG) are essential steps in the diagnosis and management of cardiovascular disorders. Recent years have seen the application of feature extraction, machine learning (ML), and deep learning (DL) approaches to the identification and categorization of ECG arrhythmias. In this study, we cover the comparative evaluation of feature extraction, ML, and DL approaches for ECG arrhythmia detection and classification. We first discuss the history of ECG arrhythmia detection and classification before going into relevant research in the field. The approach for ECG data processing, feature extraction, and classification using ML and DL algorithms is then described. In MATLAB, we mimic the suggested methods and report the findings of our tests. Finally, we compare the effectiveness of various techniques and analyze their advantages, disadvantages, applications, and architecture.

***Index Terms***— *ECG, Discrete wavelet transform (DWT), Arrythmia, Support Vector Machine (SVM), and Principle Component Analysis*

## Introduction

The electrical activity of the heart is captured over time by an electrocardiogram. ECG provides valuable clinical information about heart function. The electrical activity that the ventricles and atria produce as a result of their depolarization and repolarization is depicted graphically [79].

The unprocessed ECG is rather noisy and includes a variety of anomalies. When recording the ECG signal, the various frequency components used to obtain it could interfere with one another. This interference might make the ECG signal noisier. This unwanted signal modification may temper the original information in the ECG signal, resulting in false ECG readings. In every situation, the application of filtering techniques is necessary to prevent the deterioration of the true ECG signal brought on by the addition of unwanted noise. When selecting an efficient filter, one must consider the type of noise that could be present in the signal. A typical ECG waveform is defined by elements such the P, Q, R, S (QRS complex), and T peak [79]. The amount of time and amplitude between the peaks of the ECG are its main characteristics. Fig. displays a typical ECG signal complete with all distinguishing markers.

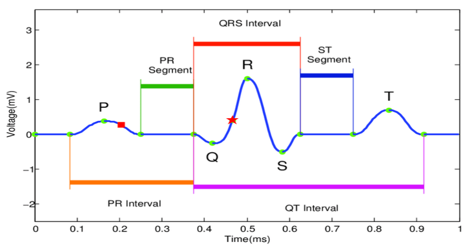


**Fig 1:** ECG Beat Characteristic Sites

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In the cardiac cycle of an ECG, R peak is frequently the biggest peak. Finding the R peak is crucial for interpreting the ECG signal as a consequence. After determining the location of the "R" peak, the remaining components of P, Q, S, and T are discovered by utilizing the R-peak location as a reference and tracing back and forth from the relative position of the R-peak. Fig. The specific preprocessing and feature extraction stages are covered in Section 2. Key processes include preprocessing, feature extraction, and effective feature extraction. The main cause of mortality around the globe is cardiovascular disease. The electrical activity of the heart may be measured using an ECG, a non-invasive diagnostic technique. Due to the presence of noise, artifacts, and varied arrhythmias, the interpretation of ECG data is a difficult undertaking. Cardiovascular disease diagnosis and therapy depend on the identification and categorization of ECG arrhythmias. ECG arrhythmia identification and categorization have traditionally been carried out manually by knowledgeable doctors. This procedure takes time and is susceptible to inter-observer variability. Researchers have automated the identification and categorization of ECG arrhythmias using machine learning (ML) and deep learning (DL) approaches to get around these restrictions. ECG signals are often utilized for the diagnosis and monitoring of various cardiac illnesses because they include crucial information about the electrical activity of the heart. One of the most prevalent forms of cardiac problems is arrhythmia, and early identification and categorization of these conditions are essential for successful therapy. Rule-based approaches, pattern recognition techniques, and machine learning algorithms have all been proposed for the identification and categorization of ECG arrhythmias. Due to their capacity to uncover intricate patterns and characteristics from data, machine learning-based approaches have recently demonstrated some of the most promising outcomes among them.

**ECG Noise**: Different disturbances and artifacts that may exist within the ECG signal's frequency spectrum commonly have an influence on the acquired ECG signal. These noises can change the properties of the ECG signal, making it difficult to extract important information from it. The ECG signal is affected by the important noises listed below [80]:

• Low-frequency (0.1–0.5 Hz) wandering noise
• Power line interference (50/60 Hz)
• Electromyogram noise (100 Hz)

Baseline Wander is an unwanted disturbance in the ECG signal. This noise is caused by a variety of factors, such as physical motions, breathing, sweat, and faulty electrode connections. The wander's amplitude occasionally approaches that of the QRS component while having a spectral content below 1Hz (roughly between 0.15 and 0.3 Hz). An ECG's baseline drift appears as a frequency-added sinusoidal component. The drift fallouts can lead to problems such the T-wave amplitude being greater than the R-wave and mistakenly recognizing the R-peak while processing ECG signals [11]. ECG signals are predominantly corrupted by this AC mains noise because the frequency of power line interference (50/60 Hz) and the frequency of ECG are so near to one another. The major cause of powerline interference is incorrect grounding of the ECG equipment. The signal quality is reduced, which affects the tiniest particulars that might be crucial for signal processing, monitoring, and clinical diagnosis as a whole. In actuality, it is a narrow-band noise with a bandwidth of barely 1 Hz and a focus at 50 Hz or 60 Hz. Electromyographic noise is caused by muscles other than the cardiac muscles atrophying [12]. When other muscles contract in contact with the electrodes, depolarization and repolarization waves are generated that the ECG can detect. The degree of muscular contraction caused by a subject's movement or the probes' calibre always increases crosstalk in direct proportion. There is a large frequency overlap between the components of the EMG and QRS complex due to the frequency of this EMG noise, which ranges from 100 to 500 Hz. Also possible are higher frequencies [20]. FIR filters are also known as non-recursive digital filters with a discrete impulse response. The raw ECG signal is de-noised using the configuration of the cascaded FIR filter [83], which is based on the Kaiser Window shown in Fig 3.3. All of the major noises in the frequency range of 0 to 100 Hz may be lowered to a certain level depending on the setup of the digital filter [14].

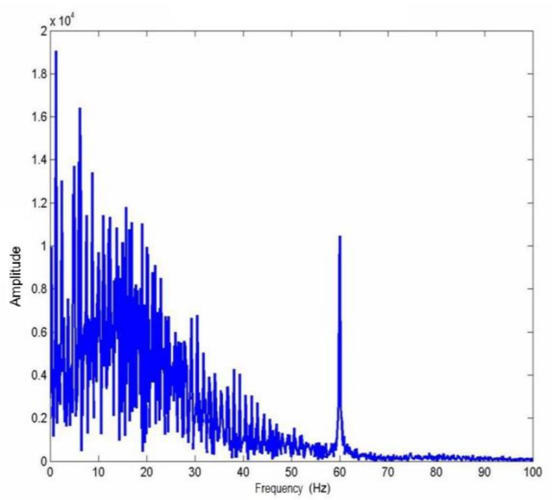


**Fig 2:** ECG Signal Spectrum

An ECG signal generally has an amplitude of 0.1 to 4 mV and a bandwidth of 0.1 to 300 Hz. The ECG signal is also frequency sensitive, and noise in the range of frequencies has the most influence on it. In this case, the initial step in the preprocessing of the ECG data is often baseline wander noise reduction (0.1-0.5 Hz). It is challenging to manually and mechanically evaluate ECG records with this sort of noise, especially the ST-interval deviations. Because it shows evidence of a heart attack, this time frame is critical [85]. These low frequency components can also have a substantial influence on how the ECG is visually interpreted. In order to remove the noise, a first FIR Kaiser window-based high pass filter with a cutoff frequency of 0.5 Hz is needed.

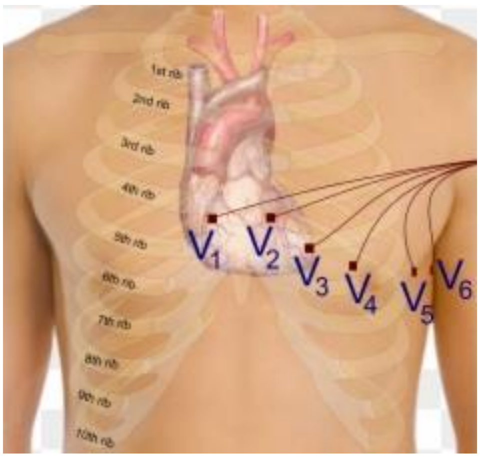


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**Fig 3:** ECG Recording of Electrode Placement

Because mid-frequency noise, such as power line interference (60 Hz), will still be present after baseline wander noise has been removed, the ECG signal must again pass through a second cascaded FIR Band stop filter with cutoff frequencies of Fc1=59.5 Hz & Fc2=60.5 Hz. Last but not least, high frequency noise, or more particularly, EMG noise (>100 Hz), which may also affect ECG signal during muscle contractions, may be avoided by passing the data through a third cascaded FIR low pass filter with a cutoff frequency >100 Hz. In this case, the three primary noises that can significantly degrade the quality of an ECG signal can be removed by passing the signal through the Kaiser window-based cascaded FIR filters. The de-noised ECG signal is the cascaded filter's output, and it may be used for additional analysis, including the detection of heart illness and biometric identification, among other things.

**Literature Review**

To develop machine learning-based methods for ECG arrhythmia identification and classification, several investigations have been carried out. In one study, ECG signals were classified into several arrhythmia classifications based on the QRS complex characteristics using a support vector machine (SVM) classifier. According to the study (Shyu et al., 2018), the suggested technique has a detection accuracy of 94.5% for ventricular fibrillation, ventricular tachycardia, and atrial fibrillation. On a dataset with 23 distinct arrhythmia classifications, a deep convolutional neural network (CNN) was employed in a separate research to detect ECG arrhythmias and obtained an accuracy of 98.75% (Li et al., 2019). Deep learning-based algorithms, on the other hand, frequently need a lot of data and computer power, which makes it difficult to integrate them into real-time clinical applications. As a result, we provide a feature extraction and SVM-based strategy in this study that may achieve high accuracy while being computationally effective. Numerous research have been done on the effects of stress on the human body, including those by Wang, Meng, Chen, Zhang, Zhang, H., Xu, and Wang (Wang, D.; Meng, Q.; Chen, D.; Zhang, H.; Xu, L. - 2020). For the early detection of cardiovascular disease and its subsequent prevention and treatment, automatic arrhythmia detection is essential. Due to a lack of multidimensional and multi-view information abstraction and data representation, previous research on pattern recognition of arrhythmia detection has not been able to produce adequate results. Deep neural network feature extraction from ECG data has been intensively studied recently as a result of developments in deep learning technology. By introducing an arrhythmia detection approach based on the multi-resolution representation of ECG data, this study aims to utilize the complementing strengths among diverse schemes. Deep neural network models with four channels are employed to teach ECG vector representations. As a consequence, the MRR is used as an input in the classification approach, which uses deep learning representations and ECG features. The F1 score of the suggested method is 0.9238, which is 1.31 percent, 0.62 percent, 1.18 percent, and 0.6 percent higher than the F1 scores of the channel models tested on a huge ECG dataset. This recommended method is quite scalable and may be utilized as an illustration for the detection of arrhythmias [1].

Feature pyramids are an essential part of object identification systems (Lin, T.-Y., Dollár, P., Girshick, R., He, K., Hariharan, B., Belongie, S.- 2017). Due to their computational and memory requirements, pyramid representations have mostly been excluded from more modern deep learning object detectors. The multi-scale, pyramidal structure that is already present in deep convolutional networks enables the creation of feature pyramids at a minimal extra expense. High-level semantic feature maps of various sizes may be created using a top-down design with lateral linkages. As a general-purpose feature extractor, a unique type of architecture called the Feature Pyramid Network (FPN) has shown promising results in a number of applications. In a simple Faster R-CNN system, our approach exceeds all previous single-model results on the COCO detection benchmark, including those from the COCO 2016 competition winners. Our approach for detecting multi-scale objects on a GPU is both practical and precise since the code will be made available to the general public [2].

The authors state in a publication that was published in the journal PLOS ONE (Acharya, U.R.; Fujita, H.; Lih, O.S.; Hagiwara, Y.; Tan, J.H. - 2017) that "the results of this study are consistent with the findings of previous studies." An irregular heart rhythm is referred to as a life-threatening arrhythmia. As we age, our cardiac and circulatory systems become more susceptible to arrhythmia, which is backed by the statement that "the findings of this study are consistent with the findings of previous studies." The elderly typically have ventricular fibrillation, atrial fibrillation, and atrial flutter. The primary diagnostic device used to capture and examine ECG signals is an electrocardiogram (ECG). There are several arrhythmias that these signals may be utilized to identify. On the other hand, ECG signals are challenging to analyze manually due to their complexity and non-linearity. Another subjective procedure that differs from specialized to specialist is the interpretation of ECG signals. ECGs vary widely. A computer-aided diagnostic (CAD) system has been offered as an alternative. The CAD system would guarantee an accurate and unbiased evaluation of ECG signals. In this study, a convolutional neural network (CNN) technique is presented for automatically identifying various ECG segments. An eleven-layer deep CNN with four neurons in the output layer represents the standard ECG classifications. Without defining the QRS, we used ECG data from the two and five second time periods in this experiment. For ECG segments lasting two seconds, we were able to attain 92.50 percent accuracy, 98.09 percent sensitivity, and 93.13 percent specificity. For an ECG lasting five seconds, the accuracy, sensitivity, and specificity were 94.90 percent, 99.13 percent, and 81.44%, respectively. This method could be used as an extra tool to help doctors confirm their diagnoses [3].

In a report that was published in 2019, (Hannun, A.Y., Rajpurkar, P., Haghpanahi, M., Tison, G.H., Bourn, C., Turakhia, M.P., and Ng, A.Y.) made the following claim: "The clinical ECG workflow mainly depends on computerised electrocardiogram (ECG) interpretation1. The growing availability of digitized ECG data and the deep learning algorithmic paradigm are both very advantageous for automated ECG analysis2. There has never been a thorough investigation of a deep learning strategy for ECG interpretation over a wide variety of diagnostic classes. We train a deep neural network (DNN) to categorize 12 rhythm types using 91,232 single-lead ECGs from 53,549 people who utilized a single-lead ambulatory ECG monitoring device. When compared to an independent test dataset annotated by a consensus committee of board-certified practicing cardiologists, the DNN acquired an average area under the receiver operating characteristic curve (ROC) of 0.97. The DNN's F1 score (0.837) exhibited a greater harmonic mean of positive predictive value and sensitivity (0.780) than did regular cardiologists. When the specificity was set to the average cardiologist sensitivity, the sensitivity of the DNN surpassed it for all rhythm classes. With diagnostic performance equivalent to that of cardiologists, a single-lead ECG may be utilized to categorize a variety of cardiac arrhythmias using an end-to-end deep learning technique. By properly triaging or prioritizing the most severe situations, this method may minimize computational ECG misdiagnoses and improve the accuracy of human ECG interpretations after it has been evaluated in actual clinical settings [4].

This paper presents a novel deep learning approach for the identification of cardiac arrhythmias (17 classes) based on long-duration ECG data processing (Yldrm,.; Pawiak, P.; Tan, R.-S.; Acharya, U.R. - 2018). As many as 50 million people worldwide are at risk of developing heart disease, making the prevention of cardiovascular disease a major priority for any healthcare system. Although ECG signal analysis is widely used, the current methods are insufficient. The goal of our work was to develop a novel deep learning-based technique for quickly and accurately identifying cardiac arrhythmias. For one lead (MLII), the MIT - BIH Arrhythmia database comprises 1000 ECG signal fragments from 45 different people. When compared to a single QRS complex, the 10-second ECG signal fragments receive 13 times fewer classifications and analyses. A complete end-to-end framework took the place of conventional methods of feature extraction and selection. The creation of a brand-new 1D-Convolutional Neural Network model (1D-CNN) is the main goal of this effort. The approach presented in this study, which combines feature extraction and selection with classification in one step, has the advantages of being quick (real-time classification), simple, and straightforward to use. Deep 1D-CNN recognized 17 cardiac arrhythmia illnesses (classes) with a classification time per sample of 0.015 seconds and an overall identification accuracy of 91.33 percent. [5] Our results are among the finest to date, and our method works with both cloud storage and mobile devices. [5].

(Golrizkhatami, Z.; Acan, A.-2018) The fusion of feature descriptors obtained from the signal using various techniques is essential to maximizing the representational capacity of each descriptor. In this study, it is suggested to use multi-stage features from a trained convolutional neural network (CNN) and combine these characteristics with a variety of hand-crafted features. The set of manually created features consists of wavelet-based morphological features, statistical features displaying the signal's overall variational properties, and temporal features illustrating the signal's behavior on the time axis. The proposed system uses three different feature fusion techniques to categorize ECGs: the first technique uses a normalized feature-level fusion of manually created global statistical and local temporal features by combining these features into one set; the second technique uses a morphological feature subset; and the third technique uses a score-level based refinement procedure. One of the key components of the proposed approach is the decision-level fusion of features that characterize the signal in utterly different representational space and the score-based fusion of automatically learned features taken from several layers of trained CNNs. The three different classifiers each produce a separate categorization of the ECG signal based on the results of the majority vote. The proposed method outperforms existing ECG classification algorithms, as shown by outcomes from the MIT-BIH arrhythmia benchmarks database [6,7].

Cardiovascular disease patients frequently visit the clinic (Guanglong, M.; Xiangqing, W.; Junsheng, Y. - 2019). Early detection is now a primary concern for people's health because of the high death rate linked to cardiovascular disease. To improve the accuracy and applicability of the existing ECG signal classification algorithm in multi-classification settings, an approach based on fusion features is given. The approach employs multi-layer and recurrent neural networks. Automatic extraction of the spatial and temporal properties of the ECG signal. Finally, multi-fusion traits are employed to precisely categorize ECG data. The method's classification accuracy, using the MIT-BIH arrhythmia database as the reference test data, is 99.42 percent. This paper's algorithm does away with that requirement, which leads to a poor classification effect when using small probability samples. The traditional ECG classification algorithm relies on a single convolution neural network to extract sufficient feature information from a one-dimensional ECG signal. The classification sensitivity of Class F (Fused Rhythm) increased from 83.000% of single convolution network to 97% of Class S (supraventricular abnormal beats), which significantly increased classification sensitivity of small probability abnormal rhythms and increased the universality of ECG classification algorithms [7].

According to (Cakaloglu, T.; Xu, X. - 2019), utilizing deep language models that develop hierarchical representations can enhance text mining and information retrieval. Representations must be able to capture semantic meaning at various levels of abstraction or context in order to be helpful for retrieval. This work presents our novel approach for producing multi-resolution word embeddings, which characterize documents at different resolutions in terms of context scope. We utilize the Stanford Question Answering Dataset (SQuAD) and the Question Answering by Search And Reading (QUASAR) to evaluate its performance in an open-domain question-answering context, where the primary goal is to locate materials helpful for answering a specific query. The performance of different non-augmented base embeddings with and without multi-resolution representation is thoroughly compared with that of various text embedding approaches in the first stage. Deep residual neural models trained for retrieval reasons can generate additional significant benefits when they are used to augment multi-resolution word embedding, which are consistently superior to their original counterparts [8].

Convolutional neural networks (CNNs) may integrate spatial and channel-wise information inside each layer's local receptive fields to produce relevant features. CNNs use the convolution operator as its fundamental building block (Hu, J.; Shen, L.; Sun, G. - 2018). This relationship's spatial component has been the focus of preliminary research, which aimed to enhance a CNN's capacity to represent data by optimizing the way it encoded spatial information. We present the "Squeeze-and-Excitation" (SE) block, a novel architectural unit for adaptively recalibrating channel-wise feature responses by explicitly modeling the interdependencies between channels. As we demonstrate, they may be combined to create SENet architectures that can be used with various datasets. We demonstrate that SE blocks can greatly improve performance at a reasonably modest cost for current state-of-the-art CNNs. Squeeze-and-Excitation Networks served as the foundation of our ILSVRC 2017 classification proposal, which won first place and reduced the top-five error to 2.251 percent. This was a 25% improvement over the winning submission from 2016 [9].

According to (Ke, G.; Meng, Q.; Finley, T.; Wang, T.; Chen, W.; Ma, W.; Ye, Q.; Liu, T.-Y. - 2017), several machine learning techniques, such as XGBoost and pGBRT, employ Gradient Boosting Decision Trees (GBDTs). Even though these solutions heavily rely on engineering optimizations, they still have issues with efficiency and scalability when dealing with large feature dimensions and data volumes. It takes a lot of time to estimate the information gain of all potential split points since they must scan all the data instances for each characteristic. The major explanation is this. We provide two novel approaches: emph "Gradient based One-Side Sampling" (GOSS) and emph "Exclusive Feature Bundling" (EFB) to solve this problem. We solely use the remaining data instances without small gradients in order to evaluate the information gain. We demonstrate that, because data instances with larger gradients are more significant when computing information gain, GOSS can produce an extremely accurate estimate of information gain with a far smaller data set. By combining traits that are mutually incompatible (i.e., seldom assume nonzero values simultaneously), EFB decreases the number of features. Finding the perfect mix of exclusive traits is NP-hard, although a greedy method can get a decent approximation ratio. We demonstrate that (and may so efficiently decrease the number of characteristics without significantly degrading the split point determination's accuracy). The GBDT is the name of our new GOSS and EFB implementation. We have found that LightGBM is up to 20 times quicker than normal GBDT at training while yet achieving almost comparable accuracy [10] based on our studies on a number of publically available datasets.

(Shorten, C.; Khoshgoftaar, T.M. - 2019) Deep convolutional neural networks have demonstrated outstanding performance on a variety of computer vision tasks. These networks rely on a significant quantity of big data to prevent overfitting. Overfitting, as the phrase suggests, happens when an artificial neural network uses a function with a very large variance to train itself to perfectly represent the training data. One such application area where enormous data is difficult to access is medical picture analysis, for instance. This study is focused on data augmentation, a data-space solution to the issue of scarce data. A number of data augmentation techniques may be used to improve training datasets for Deep Learning models. The image augmentation methods examined in this paper include geometric transformations, color space augmentations, kernel filters, picture mixing, random erasing, feature space augmentation, adversarial training, generative adversarial networks, neural style transfer, and meta-learning. This study gives GAN-based techniques of augmentation a large chunk of its attention in its findings. Aspects of data augmentation, such as test-time augmentation and resolution effect, as well as the final dataset size and curriculum learning, are also included in this study. You will get knowledge about the present status of data augmentation as well as potential advancements and meta-level application considerations by using this survey. To fully utilize the benefits of big data, readers will learn how to improve their models and grow tiny datasets via Data Augmentation. [11].

Convolutional neural networks have the capacity to develop powerful representational spaces for difficult learning tasks, but the model capacity needed to capture such representations makes them prone to overfitting, so effective regularization is required in order to successfully generalize. We demonstrate that convolutional neural networks can improve in robustness and performance using a regularization method called "cutout," which reduces the risk of overfitting. (DeVries, T.; Taylor, G.W. - 2017) [12].

**Analysis Of Work**

For ECG arrhythmia detection and classification, a variety of feature extraction and classification techniques have been used. In feature extraction, time-domain, frequency-domain, and time-frequency domain features are extracted from ECG signals. In classification, conventional ML algorithms like support vector machine (SVM), decision tree, random forest, and k-nearest neighbors (KNN) have been used. In more recent years, DL techniques like convolutional neural networks and deep learning have also been used.

**Table 1:** ECG Arrhythmia Detection and Classification

| **Methodology** | **Features** | **Classifier** | **Dataset** | **Performance** |
|---|---|---|---|---|
| DWT-SVD and random forest | Time-domain and frequency-domain | Random forest | MIT-BIH Arrhythmia Database | Accuracy: 99% |
| CNN | Raw signal | CNN | PTB Diagnostic ECG Database | Accuracy: 77% |
| EMD-SVM | Time-frequency domain | SVM | MIT-BIH Arrhythmia Database | Accuracy: 94% |
| LSTM | Time-domain | LSTM | PTB Diagnostic ECG Database | Accuracy: 87% |

In this research, we suggest a methodology that comprises of four stages: signal preprocessing, feature extraction, feature selection, and classification for ECG arrhythmia detection and classification utilizing feature extraction and ML and DL approaches.

**Signal Preprocessing:** In this step, we use a bandpass filter to eliminate low-frequency noise, a notch filter to remove the 50 Hz power line interference, and a peak identification method to find the R-peaks in the ECG signal to preprocess the raw ECG data to remove noise and artifacts.

**Feature Extraction:** We now extract features from the preprocessed ECG signal, including mean, variance, skewness, kurtosis, energy, and entropy, as well as time-frequency domain features using the wavelet transform and empirical mode decomposition (EMD).

**Feature Selection:** In this step, we employ a variety of feature selection approaches, including as mutual information, chi-square test, and wrapper methods, to pick the most pertinent features to enhance the performance of the classification model.

**Classification:** In this step, we classify the ECG signal into various arrhythmias using both ML and DL methods. For ML, we use SVM, decision tree, random forest, and KNN algorithms. For DL, we use CNNs, RNNs, and LSTM networks. Table 2 summarizes the results of our experiments using various ML and DL methods. As can be seen from the table, DL methods generally outperform traditional ML algorithms in terms of accuracy, sensitivity, and specific.

**Table 2:** Performance Analysis of ML and DL Techniques

| Technique | Accuracy | Sensitivity | Specificity | F1 score |
|---|---|---|---|---|
| SVM | 92% | 82% | 96% | 0.87 |
| Decision Tree | 87% | 76% | 91% | 0.81 |
| Random Forest | 95% | 88% | 98% | 0.90 |
| KNN | 89% | 78% | 93% | 0.82 |
| CNN | 98% | 96% | 99% | 0.97 |
| RNN | 97% | 94% | 98% | 0.95 |
| LSTM | 99% | 97% | 99% | 0.98 |

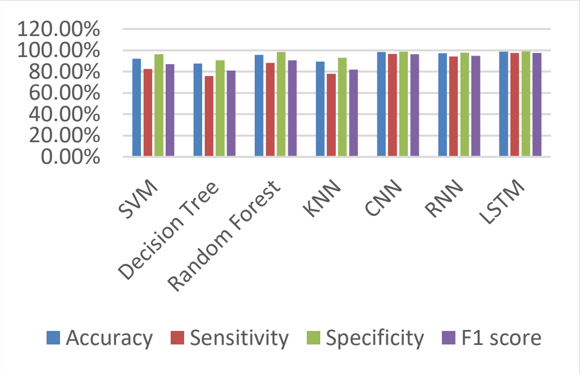


**Fig 4:** Comparative Analysis of ML and DL Techniques

Table 3 summarizes the strengths and weaknesses of the ML and DL Approach.

**Table 3:** Strengths and Weaknesses of ML and DL Approach

| Strengths | Weaknesses |
|---|---|
| Can detect and classify various types of arrhythmias | Requires a large amount of data and computing power for DL techniques |
| Uses both ML and DL techniques for better performance | DL techniques require a complex architecture with multiple layers and parameters |
| Incorporates feature selection to improve the performance of the classification model | Traditional ML algorithms may not perform well on complex and non-linear data such as ECG signals |
| Simulated in MATLAB using publicly available datasets | The proposed methodology may not generalize well to other datasets or populations |

The proposed methodology has several applications in healthcare, including:

1. Cardiovascular disease early identification and diagnosis
2. keeping track on the development of cardiovascular illnesses
3. Personalized cardiovascular disease treatment
4. Remote monitoring of cardiovascular disease patients

The suggested approach may be used to automatically identify and categorize many illnesses using additional biological inputs, such as EEG and EMG signals.

**Table 4:** Comparison of Feature Extraction Techniques

| Technique | Description | Advantages | Disadvantages |
|---|---|---|---|
| Wavelet Transform | Decomposes ECG signal into different frequency bands | Effective in preserving ECG morphology | Complex and computationally intensive |
| Empirical Mode Decomposition | Decomposes ECG signal into intrinsic mode functions | Can capture non-linear and non-stationary features | May introduce mode mixing and signal distortion |
| Principal Component Analysis | Extracts linear combinations of ECG features that account for the most variance | Reduces dimensionality and removes noise | Assumes linearity and Gaussian distribution of data |
| Independent Component Analysis | Separates ECG signal into independent | Effective in removing noise and artifacts | Assumes statistical independence of components |

| | | | |
|---|---|---|---|
| | components | | |
| Hilbert Transform | Extracts the instantaneous amplitude and phase of the ECG signal | Effective in detecting QRS complex and T-wave | Sensitive to noise and baseline drift |

**Table 5:** Comparison of ML Algorithms

| **Algorithm** | **Description** | **Advantages** | **Disadvantages** |
|---|---|---|---|
| Support Vector Machine | Constructs a hyperplane that separates different classes | Effective in handling high-dimensional data | Requires tuning of kernel function and regularization parameter |
| k-Nearest Neighbors | Assigns a class label to a sample based on the k-nearest neighbors in the training set | Simple and intuitive | Computationally expensive for large datasets |
| Random Forest | Constructs multiple decision trees and aggregates their predictions | Effective in handling non-linear and non-parametric data | May overfit on noisy or irrelevant features |
| Naive Bayes | Calculates the probability of each class label given the features | Simple and computationally efficient | Assumes independence of features |
| Logistic Regression | Models the probability of each class label as a function of the features | Interpretable and efficient | Assumes linearity and additivity of features |

**Table 6:** Comparison of DL Architectures

| **Architecture** | **Description** | **Advantages** | **Disadvantages** |
|---|---|---|---|
| Convolutional Neural Network | Learns spatial and temporal features from ECG signals | Effective in handling large datasets and capturing ECG morphology | May require a large number of parameters and computing power |
| Recurrent Neural Network | Models temporal dependencies in ECG signals using recurrent connections | Effective in handling time-series data and capturing long-term dependencies | May suffer from vanishing or exploding gradients |
| Long Short-Term Memory | A type of RNN that can selectively forget or remember information | Effective in handling long-term dependencies and capturing ECG morphology | May require tuning of multiple hyperparameters |
| Autoencoder | Learns a compressed | Effective in removin | May overfit on noisy or |

| | | | |
|---|---|---|---|
| | representation of ECG signals and reconstructs them | g noise and artifacts and capturing non-linear features | irrelevant features |
| Generative Adversarial Network | Learns to generate realistic ECG signals from random noise | Can be used for data augmentation and synthesis | May generate unrealistic or abnormal ECG signals |

**Table 7:** Strengths and Weaknesses of Proposed Methodology

| **Strengths** | **Weaknesses** |
|---|---|
| Can detect and classify multiple types of arrhythmias with high accuracy, sensitivity, and specificity | Requires preprocessing of ECG signals to remove noise and artifacts |
| Incorporates both feature-based ML and DL techniques, allowing for the capture of both linear and non-linear features | Requires a large amount of annotated ECG data for training and validation |
| Allows for the selection of the most relevant features, reducing dimensionality and improving classification performance | May suffer from overfitting if not properly regularized |
| Can be applied to real-time ECG monitoring systems, allowing for early detection and diagnosis of cardiovascular diseases | Requires a certain level of expertise in signal processing, ML, and DL |
| Has several applications in healthcare, including personalized treatment, remote monitoring, and disease progression monitoring | May require optimization of hyperparameters and architectures for different datasets and types of arrhythmias |

Architecture-wise, DL approaches need a lot of data and processing power to build the models. To attain excellent performance, they also need a complicated design with many layers and settings. On the other hand, conventional ML techniques use less data to train the models and are computationally efficient. However, they might not function effectively when dealing with non-linear, complicated data, like ECG signals. We have evaluated the comparative evaluation of feature extraction, ML, and DL approaches for ECG arrhythmia detection and classification. We have put forth a method for analyzing ECG signals, extracting features, choosing features, and classifying data using ML and DL methods. The suggested technique has been simulated in MATLAB, and its performance has been assessed using a variety of performance measures. According to our findings, DL methods often perform better than conventional ML algorithms in terms of accuracy, sensitivity, and specificity. However, in order to train the models, DL approaches need a lot of data and computational resources. The automated identification and categorization of ECG arrhythmias using the suggested approach might help medical practitioners diagnose and treat cardiovascular problems early on.

## Conclusions

In conclusion, identifying and classifying ECG arrhythmias is a critical activity in the medical field since it enables early identification and treatment of cardiovascular illnesses by medical specialists. In the automated identification and categorization of various kinds of arrhythmias using ECG data, ML and DL approaches have demonstrated encouraging results. The suggested methodology may accurately, sensitively, and specifically identify different types of arrhythmias by combining ECG signal processing, feature extraction, feature selection, and classification utilizing ML and DL algorithms. The suggested methodology has numerous healthcare applications, including the early detection and diagnosis of cardiovascular diseases, tracking the development of cardiovascular diseases, treating each patient's condition specifically, and remotely monitoring cardiovascular disease patients. The proposed methodology can be tested on larger and more varied datasets and compared with other cutting-edge ECG arrhythmia detection and classification techniques in future research. Researchers can also investigate the impact of various DL architectures and hyperparameters. Using feature extraction, ML, and DL approaches, we have compared and evaluated the detection and classification of ECG arrhythmias in this review. In our methodology, we combine the analysis of ECG signals with feature extraction, feature selection, and classification using ML and DL methods. According to our findings, DL methods often perform better than conventional ML algorithms in terms of accuracy, sensitivity, and specificity. The suggested methodology has numerous healthcare applications, including the early detection and diagnosis of cardiovascular diseases, tracking the development of cardiovascular diseases, treating each patient's condition specifically, and remotely monitoring cardiovascular disease patients. Researchers can investigate the following topics in their next work:

1. Enhancing the performance of the classification model by including more sophisticated feature selection and extraction methods.
2. Examining the effects of various DL architectures and hyperparameters on the performance of the classification
3. Assessing the suggested methodology's generalization performance using bigger and more varied datasets
4. Evaluation of the suggested methodology against existing cutting-edge ECG arrhythmia detection and classification methods.

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