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Comparative Analysis Of Machine Learning Techniques For Arrhythmia Detection

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***Abstract*—**
Arrhythmia is a very common heart condition where the rhythm of the heart is abnormal and it may endanger the lives of individuals by exposing them to serious health conditions. Arrhythmia may lead to substantial issues in case it is not spotted in time. Historically doctors identified arrhythmia manually through interpolating the electrocardiogram (ECG) signals, which can be highly time-consuming and in most cases prone to error. To address all these challenges, most researchers have begun applying machine learning methods to automatic arrhythmia detection and classification. Earlier research has investigated a wide range of methods, such as support vector machines(SVM), neural networks and many ensemble learning algorithms such as Xg-boost etc. A good deal of these studies that utilize the MIT-BIH database as a reference sample. Based on all these studies that we have studied, we discovered that, accuracy of arrhythmia detection does not only rely on the algorithm used, but also the kind of features obtained at the ECG signals. However, single-lead ECG signals have few restrictions as before, such as sensitivity, where ensemble learning models have proven to be more reliable and this paper gives a comparative overview of the prior studies, therefore, a comparative analysis of the methods, findings and challenges of the previous researchers. ML can also play a role of clinically supporting the doctors in order to detect Arrhythmia faster. The models can also be integrated in hardware gadgets such as smartwatches etc. There is also an opportunity of future innovation and advancement in this area.

***Index Terms*—Arrhythmia, ECG, Support Vector Machine (SVM), Ensemble learning.**

1. INTRODUCTION

Arrhythmia is a condition when the heart fails to beat normally, consistently and in time, and it is highly prevalent and may lead to other heart diseases unless the condition is treated properly and early enough [2], [4].It means that detection of arrhythmias at the right time and in the right way is very important to avoid the risk of various heart diseases. The interpretation of electrocardiogram (ECG) results is time consuming, and the outcome may vary amongst various specialists depending on skills and experience [3], [4]. ECG is a highly popular, painless device with a wide range of applications in diagnosis of arrhythmias, determining major elements such as P waves, QRS complex, and T waves, which tend to be important determinants in determining abnormal rhythms [2]. However, visual explanation of ECG signals is difficult, specifically for huge datasets, as it can show misclassification and inaccuracies due to slight change and over-lapping waveforms [6], [9]. Moreover, time-domain features all alone are deficient to fully distinguish between normal and unusual beats, calling for advanced analysis techniques [6].

Visual explanation of ECG signals is challenging, however, particularly in the case of large datasets, as they may indicate misclassification and inaccuracies because of slight change and overlapping wave-forms [1], [3]. Furthermore, time-domain features on their own are insufficient to completely separate between normal and abnormal beats, which requires sophisticated analysis methods [8].

Machine learning (ML) has received a robust following as a viable solutions as a possible remedy because of automated arrhythmia detection, as it is quicker, more objective, and scalable alternatives to existing methods. Although it is possible to use deep learning models, such as CNNs or ResNets, to achieve high-performance, they tend to infer a lot of computation resources and reasoning to understand, which limits the use of them in a clinical setting. Some of the traditional machine learning methods include Support Vector Machines, Random Forests, and Decision Trees, which many people prefer because they are easier to interpret and need minimal resources and provide straight forward justification of why its use is practical [8]. The datasets made publicly available like MIT-BIH are used to discover and label the various types of heartbeat like normal, supraventricular ectopic, ventricular ectopic, fusion, and unclassified beats [7].

These signal preprocessing stages are often used and this includes filtering, segmentation and noise reduction along with feature extraction in time and frequency- based domains, with enhanced accuracy and stability of the model [12].Ensemble and hybrid methods of learning, which is a combination of an outcome of more than one classifier, have further shown better performance since they handle class imbalance and ECG pattern variation [11], [13]. Additionally, advanced methodology involving the use of moving averages, application of fractional Fourier transform based analysis and quality and well labelled heartbeat data construction have also helped in the development of automated arrhythmia detection systems [14], [15].

The combination of all these advances is a means to make the transition towards automatic, precise, and clinically useful it opens up diagnostic techniques of arrhythmia detection in the modern world and it is the role of machine learning.

2. ARRHYTHMIA

At times one may experience certain irregularity in the rhythms in their heart like it can begin beating on the exact contrary whether too fast or too sluggish or may be in an irregular pattern and is usually abnormal. Such a state is known as Arrhythmia. This very condition occurs when normal electrical impulses of the heart that control heart gears are disrupted thereby impacting on the effectiveness of the heart to pump blood efficiently and normally. There are those arrhythmia that are harmless and may go without notice, but others can lead to very serious heart-related complications such as faintness, stroke, heart failure or sudden heart attack. The early diagnosis and management of arrhythmias is therefore quite crucial in ensuring the well being of the heart. The different types of arrhythmia can be generally divided according to their location of origin in the heart and their type of aberrant rhythm. They are classified in one way depending on the heart rate:

i. **Tachycardia:** The irregular beating of the heart overshoots as it is commonly known by the majority. Tachycardia may develop due to such conditions atrial fibrillation, ventricular tachy- cardia or may be a physiological condition as a reaction to stress, fever, or exercise.
ii. **Bradycardia:** Reduced heart rate, that is, slower than normal - less than 60 beats per minute. Aging, heart tissue damage and some drugs can cause bradycardia which may lead to fatigue, dizziness or fainting.
iii. **Premature Beats:** This happens when the heart contracts earlier than usual (commonly in the atria (premature atrial contractions or ventricles), which are sometimes known as ectopic beat or premature beat (premature ventricular contractions). These are not very serious but they may be unpleasant and are sometimes reflections of underlying heart disease.
iv. **Fibrillation:** The heartbeats in a fast, irregular and uncoordinated way is fibrillation. Atrial fibrillation is the most common type and puts the stroke at threat, while ventricular fibril- lation is life-threatening and must be treated immediately.
v. **Flutter:** While fibrillation is irregular and dif- ficult to detect, flutter is more structured and is a faster yet consistent heartbeat rate, mostly in the atria.

Arrhythmias can be caused by a variety of causes such as structural changes in the heart, electrolyte imbalances, coronary artery disease, high blood pressure, medications and genetic predispositions among others. Arrhythmias can also be induced by many lifestyle factors such as smoking, caf- feine overconsumption or alcohol consumption and chronic or mental stress. Main tool used to de- tect the conditions such as arrhythmia is electro- cardiography (ECG). The ECG is a recording of electrical signals on the heart as time progresses that captures the waveforms that reminiscent of the various stages of a heartbeat as represented by P wave, QRS complex and T wave. Small deviations of these waveforms would show various types of arrhythmias. Sensitivity and specificity of detection is enhanced by the development of multi-lead ECG equipment which offers more detailed information of monitoring like atrial fibrillation (AFib) may be diagnosed by the unequal R-R interval, and pro- longed QRS complex may be diagnosed as delayed

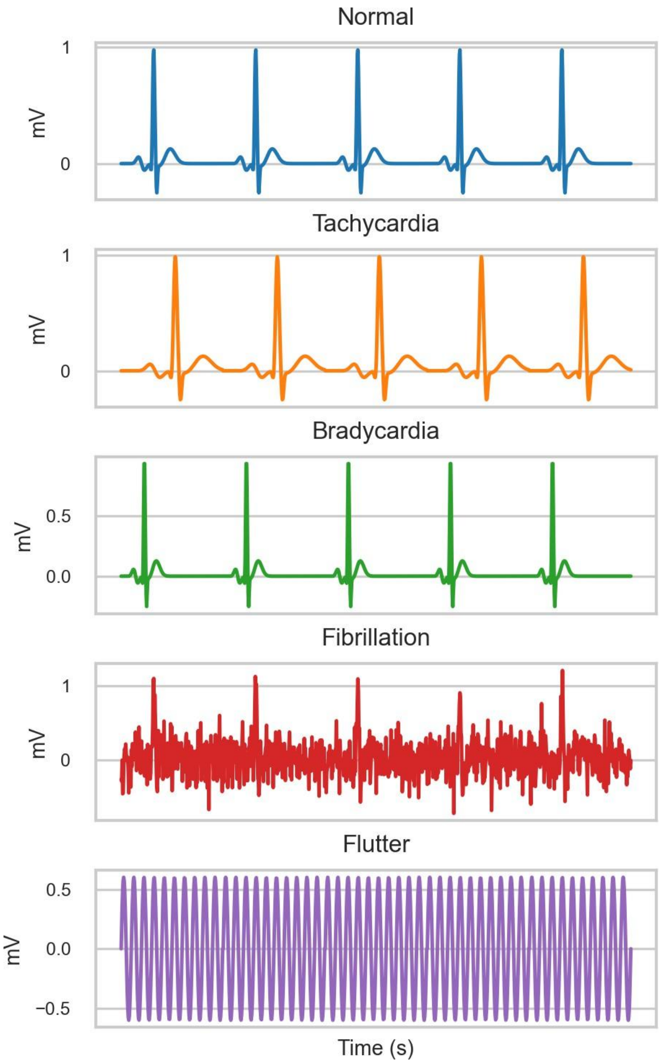

Fig. 1: Types Of Arrhythmia

in the ventricles. As there are some arrhythmias that may lead to high risks such as sudden cardiac-arrest, hence early and proper detection is very crucial. The interpretation of ECG signals may be time consuming and vulnerable to errors especially in the cases where arrhythmias are not extremely common or uncommon. It has resulted in the increased use of machine learning and computerized detection methods that must analyse a high number of ECG samples within a short time, reliably and with high accuracy. Finally, arrhythmias are a particularly long list of disorders of cardiac rhythms with their own peculiarities and health consequences. To come up with advanced detection systems capable of assisting in the diagnosis that is rapid and precise, it is necessary to understand the types, causes, and diagnostic marks of each of them, which would, in turn, guide in the process of clinical intervention.

3. MIT-BIH Arrhythmia Database

One of the most used and popular databases in the sphere of cardiac investigation is the MIT-BIH Arrhythmia Database, primarily to create and test automatic arrhythmia detection algorithms. It was publicly available through PhysioNet and was used in numerous studies in the 40 years since as a benchmark in electrocardiography (ECG) and arrhythmia classification [4], [6]. The dataset constitutes of recordings of 47 subjects, 25 men aged between 32 to 89 years and 22 women aged between 23 to 89 years, of which an estimated 60 percent of the subjects were patients who were admitted at the time of data collection. Overall, roughly 109,000 marked QRS complexes are found in the dataset, which are the most important events of ventricular depolarization in the heart. In addition, six records have 33 beats that were not assigned a definite beat type [4].

The MIT-BIH data set is very rich and detailed in terms of cardiac electrical activity, which is non-invasively recorded through surface electrodes that are placed on the skin of a patient under study. Each of the ECG signals is the electrical activity of the heart, which is observed over time and is divided into three major elements: P-wave, which is the manifestation of atrial depolarization; QRS complex, which is atrial ventricular depolarization; and T-wave, the ventricular repolarization of the heart [3]. The main elements that a physician can use are variations in these waveforms like abnormal P-Wave morphology or abnormal QRS duration to identify arrhythmia among other heart related disorders like Myocardial Infarction(MI) etc. Due to the detailed annotation of every beat of the MIT- BIH database, one has a possibility to detect all arrhythmic conditions accurately, which gives the opportunity to develop and test machine learning and signal processing algorithms.

These recordings could be split into two series, the 100 series, with 23 recordings chosen randomly out of over 4,000 tape recordings made by Holter, and the 200 series which has 25 recordings chosen with a specific goal of including examples of rare clinically significant arrhythmias not well represented in small random samples [6]. This bilateral design is such that there are available both common and uncommon arrhythmic patterns to develop an algorithm. Every database record, which is contained in MIT- BIH database, consists of different files to aid analysis. The header file(.hea) contains description of the information about the waves, including the number of samples, signal format, and metadata of the patient such as age, sex etc. The binary data file (.dat) is the file which contains samples of the digitized ECG signal, and the annotation file (.atr) is the file which provides labels of some important events in the signal, e.g. QRS complexes and some other types of beats [6].

Despite the high quality, the ECG signals con- tained in the MIT-BIH dataset are vulnerable to numerous forms of noises such as baseline wander, motion artifact, electrode misplacement, and power line interference [3]. Therefore, appropriate preprocessing of signals is necessary prior to the application automated detection models. This database has been instrumental over the time in advancing the study of arrhythmia, having served in over 500 research locations worldwide in the study of cardiac problems as well as in the development of ML- based arrhythmia detection systems [6].

In general, the MIT-BIH Arrhythmia Database is a supporting resource in the heart studies. Its annotated quality ECG recordings, varied patient population and a representation of both prevalent and uncommon arrhythmias make it an excellent choice in the development, testing and experimental comparison of automatic detection algorithms. The dataset offers a set of consistent benchmarks that ensures stable results and permits researchers to evaluate the performance of machine learning models carefully, finally contributing to the enhancement of more precise and optimistic methods of arrhythmia detection that are trustworthy to the clinician.

4. General Methodology for Machine Learning-Based Arrhythmia Detection

Automated detection and classification of arrhythmias using ECG signals have been modernized using machine learning (ML), which has the poten- tial to reduce human error, enhancing diagnostics accuracy, and time saving in clinical practice.

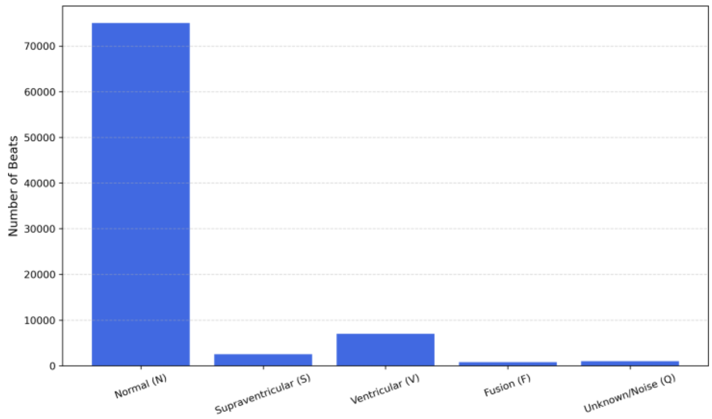

Fig. 2: MIT-BIH Class Count Distribution

In a variety of research works, we have discovered that the overall procedure in the process of arrhythmia monitoring detection consists of a set of four fundamental steps including: preprocessing, segmentation, feature extraction and classification. Each step is significant to the process of making sure that machine learning models should be able to learn correctly based on the data, and learn to identify abnormal heart rhythms accordingly.

i. **Preprocessing:** Preprocessing is the cornerstones of any ML-based arrhythmia detection system. ECG signals are usually prone to dissimilar types of noise, such as the baseline wonder, powerline interference, motion arti- fact, and respiratory muscle motion [4], [6]. In order to have good analysis, cleaning and normalisation of the raw ECG data should be done correctly. Such techniques that are very common in literature that we have also mentioned include:

a. **Filtering and Denoising:** Numerous adap- tive filters and derivative methods which are derivative based, like 5 point derivatives, are used to remove baseline wander and high-frequency noise, as shown in [2]. We discovered that the normalization of the signal by means of sliding windows is also take into consideration in order to normalize the signal using the sliding window methods making the mean value of the ECG data to fall around the zero value [4]. This has been enhanced in recent research by the use of wavelet based filtering and empirical mode decomposition (EMD) to eliminate nonstationary noise at the expense of the main waveform features of ECG traces [7], [8]. Discrete wavelet transform (DWT) and median filters have also been used in the recent studies to remove the power-lines interference at the cost of overall pattern [9], [11]. It is also used on some works to pass bandpass filter in association with adaptive thresholding in real time applications [12].

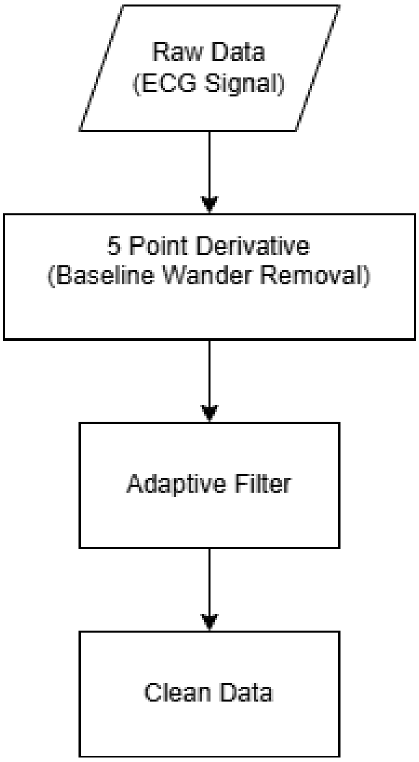

Fig. 3: Flowchart of Denoising

b. **Normalization:** To ensure that the ECG signals are brought into a similar range of amplitudes to eliminate the impact of electrode placement and variations in patients, the process of normalization is used (Min-max scaling, z score normalization) [1]. This makes machine learning models pay attention to the shape of the ECG signal itself and not to the shape of its noise than amplitude dispersed by all sorts of noises. More improvements as explained in [7], [13], involve the use of a baseline correction by way of a fitting of the polygons as well as the lead specific normalization of multi-lead ECG displays. This multi-dimensional normalization allows multi-dimensional deep models to extrapolate the disparate populations of patients.

c. **Resampling and Class Imbalance Handling:** Resampling techniques have been employed to overcome the problem of class imbalance in databases such as MIT-BIH by bootstrap means. Up-sampling or down-sampling of the classes of abnormal heart- beat makes sure that they do not bias models to more common normal heart beats [3]. Research [6], [9], [15] also came up with the Synthetic Minority Oversampling Technique(SMOTE)and data augmentation strategies such as noise injection, time warping, and scaling so as to create diverse samples and achieve a balance in the minority arrhythmia classes.

ii. **Segmentation:** Segmentation is the process of splitting continuous ECG signals into unique valuable units to make it possible to extract features. Accurate segmentation needs distinct R-peaks because these points are most salient in an ECG signal and they are used to define the contractions of the ventricles [1]. The Methodologies employed in the earlier researches include:

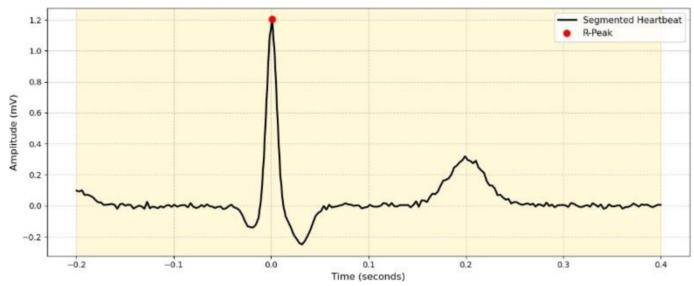

Fig. 4: Heartbeat Segmentation Window(Synthetic Realistic ECG)

a. **R-Peak Detection:** Detection of R-peaks makes use of algorithms like Pan-Tompkins or derivative-amplitude threshold based algorithms which makes use of the slope and height of the QRS complex [1], [2]. More recent methods using Hilbert transform-based techniques, as well as CNN-based peak detectors, have been applied to enhance R- peak localization characteristics in noisy conditions [7], [14]. Deep learning methods will learn adaptively R-wave morphologies across different patients, and reduce the occurrence of false detections in low-SNR recordings [7].

b. **Heartbeat Extraction:** After R-peaks are established, a window about each peak is extracted which includes the P-wave (atrial depolarization), QRS complex (ventricular depolarization), S T segment and T wave (ventricular repolarization) [1]. The size of the windows is usually selected in such a way that it covers a few hundreds milliseconds of data preceding and following the R- peak, to capture the entire beat. Other more recent published papers [9], [13] also used adaptive segmentation techniques in which the window length is changed dynamically based on the heart rate of the patient. Others [12], [15] have implemented overlapping and non-overlapping sliding windows to maintain temporal continuity and a better beat boundary detection of deep models.

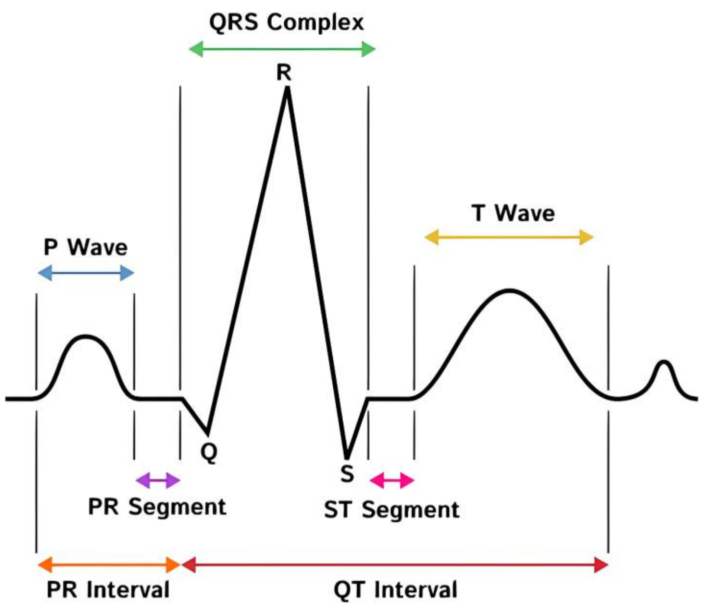

Fig. 5: ECG waves

iii. **Feature Extraction:** The segmented ECG signals can be converted into numbers through feature extraction, revealing the characteristics of each beat of the heartbeats that is more informative and discriminative to be able to be used more and more efficiently in ML models for the classification. Ordinary methods of extracting features are:

a. **Time-Domain Features:** Features like amplitude, QRS in duration, The establishment of the base of arrhythmia detection may be completed with the help of RR intervals and slopes of the waveforms [2]. These are measures of autocorrelation and beat to beat differences to find the irregularities in rhythm have also been improved on using temporal features [9].

b. **Frequency-Domain and Area-Based Features:** When the beat is obtained below the curve of QRS complex by means of numerical integration, e.g., Simpson rule, then it becomes possible to tell the different types of the beats [4]. This has been done with overlapping and non-overlapping sliding windows [7], [8], wavelet coefficients and Hilbert Huang transform features of the ECG that are more applicable in the determination of smaller scale transitions.

c. **Morphological and Statistical Features:** P, QRS and T-waves morphological parameters, the slope, and shape of the waves help in outlining structural changes in the heart- beats [2]. In addition, newer models [11], [14] extract higher-order statistical features such as skew, kurtosis and entropy in lieu of signal complexity. Multi-lead features, especially that of the MLII and V5 lead, have been fused with feature concatenation to enhance its performance and interpretability [9].

d. **Deep Feature Extraction:** Recent advances integrate Convolutional Neural Networks (CNNs) and autoencoders for automated feature extraction directly from raw or denoised ECG signals [13], [15]. These models capture multi-scale temporal and morphological representations. Some studies [12] also employed hybrid feature sets, combining handcrafted features with learned embeddings for improved robustness.

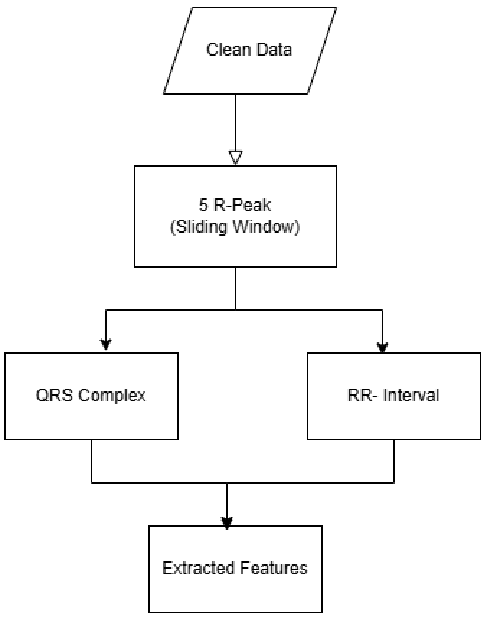

Fig. 6: Flowchart of feature extraction

iv. **Classification and Model Training:** The classifications step entails application of machine learning algorithms to either label medical heartbeats as normal or abnormal, depending on the extracted features. Various reports have investigated various classifiers, including classic algorithms as well as advanced deep learning models:

a. **Traditional ML Models:** Includes Support Vector Machines (SVMs) with vary- ing kernel types, Decision Trees, Random Forests (RF), and Naive Bayes classifiers [1], [4]. RFs make use of several decision trees to increase the prediction stability. It has also been studied that k-Nearest Neighbors(KNN) and Linear Discriminant Analysis (LDA) could compete with each other on low dimensional features. [7], [9]

b. **Ensemble and Boosting Methods:** All the strengths of multiple learners are combined into the ensemble methods such as Gradient Boosting, AdaBoost, and Voting Classifiers to enhance generalization [3], [12]. A hybrid ensemble of both traditional and deep features proves to be especially helpful on imbalanced ECG datasets [11], [14].

c. **Deep Learning Methods:** : Like Convolutional Neural Networks (CNNs), Artificial Neural networks (ANNs), and Long Short- Term Memory (LSTM) networks have become leading methods of temporal and morphological dependence modeling in ECG data [3], [7], [13]. CNN-LSTM hybrids [15] also enhance the ability to comprehend the context with the help of spatial convolution and sequential memory, which helps to improve classification even of noisy segments of ECG signals.

d. **Training and Evaluation:** Databases are primarily split into 70:30 divisions of training and testing by optimization of databases (k-fold cross-validation to estimate model stability), and the training is done again after the analysis. Accuracy, sensitivity, specificity, and precision are used to measure the performance [3], [4], [6]. A grid search, random search, and Bayesian optimization are hyperparameter tuning methods that are used to discover optimal tunings of classifiers [5], [9]. Recent attention mechanisms and transfer learning were also proposed [14], [15] to enhance generalization in small samples of the situation.

e. **Hyperparameter Optimization:** Hyperparameter optimization can be used to more models, including Random Forests, which are more fine-tuned with grid search or randomized search to identify the optimal parameters, including the number of trees to use, maximum depth and minimum samples per split [1].

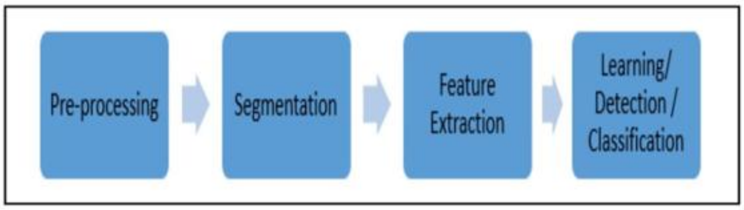

Fig. 7: Overview of Proposed Method

Summary of the Methodology Workflow Summary of the Methodology Workflow: In essence, the automated arrhythmia detection pipeline fol- lows a structured process. ECG signals are first denoised, normalized, and resampled to handle noise and class imbalance. Segmentation isolates individual heartbeats via accurate R-peak detec- tion and adaptive windowing. Subsequently, both handcrafted and deep features are extracted from time, frequency, and morphological domains to represent each beat's structure. Finally, classification models, ranging from SVMs and Random Forests to advanced CNN–LSTM hybrids, are trained and optimized for robust arrhythmia detection.

Collectively, research studies [1]–[15] demon- strate that carefully designed preprocessing, adap- tive segmentation, hybrid feature extraction,and well-tuned classification models form the founda- tion of reliable and clinically relevant ML-based arrhythmia detection systems.

5. Comparative Analysis of Arrhythmia Detection Research

Comparative Analysis of Arrhythmia Detection Research This segment gives a comparative review of some remarkable research studies on machine learning-based arrhythmia detection in terms of methods, data, models, and performance parameters. It is aimed at showing the advances in automated arrhythmia detection, discussing the merits and drawbacks of the different methods, and giving a unified picture of the current tendencies in this field. Summary of Research Studies

Summary of Research Studies

i. **U. K. Bijinapalli, 2024** used a Random Forest (RF) model to classify the ECG arrhythmia based on MIT-BIH dataset. Following rigorous data cleaning, such as normalization and computing noise, ECG signals were separated into training and evaluation datasets with high accuracy of 99.01% on the testing dataset and robust performance in terms of precision, recall and F1-score criteria in each separate arrhythmia class. Another interesting feature of this model is its interpretability because of the structure of decision trees, it is possible to analyze the importance of features, which can give an idea of physiological markers that are correlated with various forms of arrhythmia.

ii. **S. Mandala et al. ,2024** remained concentrated on the identification of atrial fibrillation (AF) and premature ventricular contractions (PVC) as well as premature atrial contractions (PAC) through multi-lead ECGs, i.e. MLII and V1.

iii. This Study also presents two ECG signal measures, i.e. RR interval and QRS complex. The report indicated that they had an exceptionally high performance level, with a specificity of 100% when used in lead 2, 100% specificity when used in lead 1 and the best accuracy of 99% when used in lead 1 in AF, with specificity of 99% in both leads, sensitivity of 99% in both lead and the maximum accuracy of 99% when used in both leads for PVC. Finally signal produce specificity of 96% on lead 1, the sensitivity of 76% on lead 2 and maximum accuracy of 85% on both leads with PAC signals. The findings of these studies prove that feature engineering and lead-specific informa- tion are effective to enhance the detection of arrhythmia based on the higher sensitivity and specificity for the concept that multi-lead ECG is essential.

iv. **S. Verma, 2022** considered interpretability in the machine learning models of time-series ECG classification. The researchers used eight classifiers to all beats in MIT-BIH beats annotated in eight classes and divide each beat into 11 segments to comprehend what portion(s) of the ECG the models concentrated on when they were making predictions. Performance was used to identify the best models, with convolutional neural networks (CNN) and long short-term memory (LSTM) being found to be stronger than other models at having an accuracy score of 94.1 and 94 percent using K-Fold cross-validation and Leave Groups Out, respectively .Four interpretability measures, in- cluding Grad-CAM, PFI, SHAP, and PDP were used to examine the models behavior, and it was found that these models were more robust and more accurate at 94.1% using K-Fold and 98.7% using Grad-CAM which was found to be the most effective in both local and global interpretations of predictions, with the most important feature being in the QRS complex, as it is consistent with clinical interpretations of ECG. PFI gave model-agnostic explanations globally, whereas PDP and SHAP were proved to be not that informative, filling the gap between automated predictions and clinical trust. Overall, the study presents evidence that ML models can make ECG signals interpretable and bridge the gap between automated prediction and clinical confidence.

v. **V.Singh et al. , 2019** designed and tested a Python-based beat detection and classification system of arrhythmia in an HP Z6 workstation using scikit-learn and Keras Python libraries. The researchers compared five classifiers in five ECG data classes (normal and four types of arrhythmias) baseline features were extracted with three different feature extraction meth- ods, which were amplitude, area with non-overlapping sliding window, and area with overlapping sliding window. The study has also shown the visualization of normal and abnormal beats using the Artificial Neural Network (ANN) with amplitude features of 300 samples to gain the maximum accuracy of 99.59 %, Support Vector Machine(SVM) with RBF kernel and non-overlapping area features achieved 98.97% accuracy and Random Forest with overlapping area features and 10 trees which gave the highest accuracy of 97.73 %. The authors reached the conclusion that ANN utilizing the feature of amplitude gave an optimal performance, and the future intention is to come up with an all inclusive module.

vi. **S. Mousavi et al., 2018** tested arrhythmia detection in both the intra- and the inter- patient study paradigms, where a sequence-to- sequence deep learning model was used with SMOTE oversampling to address the problem of the class imbalance. The model under the intra-patient scheme, achieved a positive predictive value of 96.46% and sensitivity of 100% for category S, and a positive predictive value of 98.68% and sensitivity of 97.40% for category F, demonstrating excellent performance when training and testing included heartbeats from the same patients and under inter-patient scheme, which represents a more realistic situation of evaluation using heartbeats belonging to different patients, gives positive predictive value of 92.57% and sensitivity of 88.94% value in category S, and a positive predictive value of 99.50% and sensitivity of 99.94% in category V,indicating robust generalization across diverse patient data. This paper highlights the need to test models in both paradigms so that reliable and clinically applicable models can be obtained.

vii. **C. Gurudas Nayak et al. , 2016** used the MIT-BIH Arrhythmia Database to obtain ECG signals to which the nine-level sub-band de-composition based on Discrete Wavelet Trans-form (DWT) was applied to analyze the data of 110,093 ECG beats associated with five types of arrhythmia (N,S,V,F, and U).From the 3rd and 4th level detail coefficients obtained through DWT, twelve principal components were extracted and statistically validated using ANOVA, with ten- fold cross-validation ensuring reliable model evaluation. The classifica- tion was done using Support Vector Machine (SVM) with diverse kernel functions and the results indicated that the quadratic SVM kernel should be used as the best kernel because the overall accuracy was 97.48 % and the Cohen's kappa coefficients were not less than 0.9198 which was highly consistent and reliable to detect cardiac arrhythmias.

viii. **Kesavapriya R et al. , 2025** tested several machine learning classifiers on detection of ar-rhythmia with the use of MIT-BIH Arrhythmia Database. The overall accuracy of the k-NN classifier was moderate (67 to 72 %), with k=5. This did not trade-off accuracy or recall, though being poor, particularly in respect to the precision of the result with respect to minority classes such as supraventricular ectopic beats (Class 2). The Decision Tree (DT) was much more successful, achieving maximum accuracy of 96.87 %, high re-call (around 91%), and F1- score (84%), however, it gave more preference to the majority class. Random Forest (RF) classifier was the most successful with the accuracy of 98.32%, precision of 89.12%, and the lowest errors. Recall, 92.29% and F1-score, 90.57%, demonstrate strong generalization because of its ensemble nature. The success of Quadratic Discriminant Analysis (QDA) (71.56% accuracy, 61.31% F1-score) was moderate, whereas the success of SVM with an RBF kernel is lower (65.35% accuracy, 19.30% F1-score), because classes are not even and features overlap. In general, the RF classifier showed the best reliability and robustness in detection of arrhythmia based on ECG, and therefore its applicability in real time clinical.

ix. **T. Subba et al , 2024** carried out a comparative study of different machine learning algorithms that have been developed up to now. They involved Decision Tree (DT), Support Vector Machine (SVM), k-Nearest Neighbor (KNN), Logistic Regression (LR), and Random Forest (RF) to perform the task of accurate ECG signal classification. The models were tested based on some of the most popular measures such as accuracy, precision, recall, specificity, and F1-score derived based on true positive, true negative, false positive, and false negative values.To obtain frequency-related measures. ECG data have been used to derive characteristics using the Fast fourier Transform (FFT). Out of all the algorithms tested, the one found to perform the best was Random Forest with a total over-all accuracy of 98%, and the sensitivity values obtained was- N is 0.99%, SVEB is 0.74%, VeB is 0.93%, FB is 0.78%, and Q is 0.96%, having the similar specificity values across all categories. The confusion matrix also helped to establish improved classification of Random forest even with noise presence. The proposed approach showed impressive im- provements when compared to those of the state of the art especially in the detection of the SVEB and VEB beats. The research finds that Random Forest provides good performance, robustness, readability in the interpretability aspect, and it fits complex ECG datasets to perform better, whereas, the researchers have indicated that there are still issues such as computational costs and the sensitivity to hyper parameters to be tuned to optimize its performance further. Future research would include the incorporation of Deep Learning frame-works and the development of low-cost real-time ECG systems to improve arrhythmia detection and diagnosis.

x. **Igiri C.G. et al. , 2023** in the investigation of cardiac arrhythmia prediction with super- vised machine learning algorithms compared five algorithms: Random Forest (RF), Decision Tree(DT), Support Vector machine (SVM), K-Nearest Neighbors (KNN), and Naive Bayes (NB) by using MIT-BIH Arrhythmia dataset. The ECG signals to be classified were moved through the models as either Normal Beat (NOR), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Prema- ture Atrial Contraction (PAC), or Premature Ventricular Contraction (PVC) by using features of RR intervals.Among all the models,RF had the best accuracy of 89%, with precision and recall of 0.89, and F1-score of 0.89, which is a very high accuracy and reliability. KNN obtained an accuracy of 85% followed by SVM, DT and NB with a 80%, 79% and 79% accuracy respectively. The confusion matrices demonstrated the few false positives and false negatives for RF as compared to other models. The study concluded that RF had a low number of false positives and false negatives and delivers the most powerful and effective performance to detect arrhythmia automatically with indications of possible early diagnosis.

xi. **A. K. Sangaiah et al., 2020** Two optical signal processing models identified the five types of arrhythmia discussed in this article such as Normal, RBBB,LBBB,PVC, and APC in the ECG signals with the help of a wavelet- based hidden Markov model (WTHMM). This technique entails pre-processing of ECG signals, deriving statistics of wavelet coefficients and applying the Linear Discriminant Analysis to downsize the number of features, which are subsequently fed into an hidden Markov model to derive the concealed electrical conditions of the heart. This performed an average accu- racy rate of 99.8%, sensitivity of 99.8 and a positive predictive value of 100, This shows a very good reliable arrhythmia detection. Also, the study used an Internet of Medical Things (IoMT) implementation with the thing S peak platform, which allows real time monitoring of the cardiac condition during daily living and instant notification of critical events, thereby, incorporating both the proper classification and practical real world usability.

xii. **S. Bhattacharyya, 2021** This paper suggests a machine learning based heartbeat classification framework designed to identify cardiac arrhythmia correctly with the ability of accurate TSFEL feature extraction, SMOTE data balancing, RF-RFE feature selection, and a mix of RF and SVM using Weighted Majority Algorithm (WMA) to achieve the classifica- tion result. The results of cross-validation on DS1 indicate that the WMA ensemble (accu- racy = 99.69%) performs better than individual RF(99.15%) and SVM(98.65%) models. The results of the testing on unseen DS2 demonstrate that overall accuracy of the WMA ensemble (98.21%) is lower than that of the individual RF(94.22%) and SVM(74.20%) models: VEB (94.22% / 95.95%) and SVEB (74%). The confusion Matrix rewards the fact that the majority of cases were correctly identified. The suggested solution is superior to the current ML and DL methods, which underlines a successful feature optimization, ensemble training, and user-specific modeling.

xiii. **D.K. Van et al. ,2021** This study presents a successful machine learning method to recognize arrhythmia through electronic cardiography signals based on rumination, feature detection, and a maximized machine learning classifier. Base-line wander and high-frequency noise was also removed by using median and low-pass filters, and R-peaks were correctly identified with the use of EEMD and Hilbert Transform. Training and validation were done on a balanced set of 25,000 heartbeats, class imbalance handler was the MPA, and the best performing classifier, which was the Random Forest model, had its best performance on the testing set; accuracy 99.90, precision 99.74%, recall 99.73%, and F1-score 99.73%. Only the class-wise accuracies were N 99.74%, S 99.92%, V 99.89%, F 99.98% and Q 99.94%, which is superior to the rest of the models and past researches. These findings indicate that the presented methodology offers a powerful, stable, and very precision-based ECG classifi- cation.

xiv. **A.S. Benmessaoud et al. , 2023** produced high-quality heartbeat data on the basis of MIT-BIH recordings and excluded the outliers with the help of IQR approach and optimal heartbeat sizes were determined to limit mixed beats. Resnet based 1-D model was trained on this dataset and it was used to classify heartbeat types. Down-sampling made training 1.5x faster, minimized memory use by 3x, and increased accuracy by 98.68per cent to 99.24%. Confusion matrix performance was high on classes and the evaluation of the difficult F class was 87.26% accurate, 87.25% recalls, 96.2% precision and with F1-score of 90.95% which was better than the previous studies. It was verified by comparing that the quality of the dataset and great attention paid to prepro- cessing played a significant role in improving model performance. This, therefore, indicates that the quality of the data is very critical in the process of obtaining the standard results, which is why it is emphasized that well-structured information is an important aspect that should be combined with deep learning models.

xv. **A.I.Taloba ,2021** The researchers in this work have provided a methodology of automatic ECG classifications that involve breaking down the whole process into 4 stages that include: arrhythmia recognition, peak detection, separa- tion of a database into training and testing and lastly the categorization. Normal(NR), arrhyth- mia (AR) and ventricular arrhythmia (VAR) represent three types of ECG signal that were evaluated against 20 half-hour two channel records per group. The suggested FFT-based peak detection in combination with TERMA performed better than traditional wavelet-based techniques that induced greater accuracy of P, R and T peaks detections. Preprocessed beat AR modeling provided effective processing of discriminatory accounts of beats, which re- sulted in a clear division of the classes of signals in the features. Cross-database trials of INCART and SPH data, samples resam- pled to 128Hz, gave accuracy values 99.85% and 68%, respectively, suggesting that there were difficulties in cross-database generaliza- tion. Although inverted or biphasic T peaks were misclassified as RBBB and PVC, the method nevertheless performed well when ex- tracting PR and RT intervals and in feature based classification. Altogether, the framework is characterized by high classification rates, good feature extraction and better peak searching, which suggests a useful framework to be deployed to identify automated arrhythmia, though additional research is required to im- prove the cross-database results.

xvi. **M. Sraitih et al. ,2021** SVM, Random Forest (RF), and K-Nearest Neighbors (KNN) were compared on inter-patient paradigm against ECG arrhythmia classification on the MIT-BIH dataset. There were five types of heart- beats namely NOR, LBBB, RBBB, PAC and PVC.SVM had the highest overall accuracy 83%, F1-score 0.55, precision 0.64, recall 0.59, and successfully coping with non-linear bound- aries. RF was 82% accurate, F1- score 0.43, precision 0.42, and recall 0.49 and reached its best on NOR (96% accuracy). The results of KNN were a 78% accuracy rate, F1-score 0.40, precision 0.38, and recall 0.50, and high rates of prediction using RBBB (96% correct). A group voting classifier slightly improved the stability and achieved 98% accuracy on NOR. On balance, SVM became the most effective at the inter-patient setup.

6. KEY INSIGHTS FROM COMPARATIVE ANALYSIS

i. **Model Performance:** Deep learning and ensemble-based methods have the overall best performance compared to traditional machine learning models under the condition of having enough of the labeled data. The CNNs, LSTMs, ANNs, and random Forest effectively learn and recognize more complex patterns of time and morphology in the ECG signals and produce higher accuracy, precision, recall, and F1-scores with different arrhythmia types.

ii. **Feature Selection:** Features such as QRS com- plex, RR intervals, amplitude and slope and multi- lead signals substantially improve the performance of the classifiers. Sliding window, beat segmentation, and the use of wavelets en- hances the representation of ECG features and allows the models to capture small variations in the patterns of the waves produced by the heart.

iii. **Preprocessing Impact:** A powerful preprocessing stage is needed in terms of better per- formance. It includes elimination of noise, baseline wander, normalization and accurate R- peak identification. These measures decrease the noises produced by electrode placement, the patients movement and other changes in the signal which then narrow down the models to concentrating on significant and meaningful patterns.

iv. **Evaluation Paradigms:** Models tend to perform better in intra-patient testing, but inter-patient testing provides a more realistic picture of the model performance to be expected in practice settings since they allow the model to learn all arrhythmia classes more effectively. Techniques such as weighted loss functions or Synthetic Minority Over-sampling Technique (SMOTE) have good performances as they help the model to learn all arrhythmia classes more effectively.

v. **Interpretability:** The implantation of models onto IoMT-enabled platforms and wearable devices demonstrates that they can provide high-quality cardiac monitoring, detect diseases early, and enable continuous care to patients, filling gap of the bridge between high-performance (activities) and the applicability (practical solutions) of the approaches to healthcare.

vi. **Practical Applicability:** Deploying models on IoMT-enabled platforms and wearable de- vices demonstrates their potential for real- time cardiac monitoring, early detection, and continuous patient care, bridging the gap between high-performance algorithms and practical healthcare solutions.

TABLE I: Summary of recent works on arrhythmia classification using MIT-BIH dataset

Author(s Year) &	**Dataset Used**	**Models / Algorithms**	**Key Findings / Method Highlights**	**Accuracy (%)**	**Other Performance Metrics**
U. K. Bijinapalli, 2024	MIT-BIH	Random Forest (RF)	Preprocessing with normalization and noise removal; feature importance analyzed; strong interpretability of arrhythmia classification.	99.01	ust performa nce Rob across arrhythmia types.
S. Mandala *et al.*, 2024	MIT-BIH	Ensemble / Boosting	Multi-lead ECG used with RR interval and QRS complex features; high specificity and sensitivity for AF, PVC, PAC detection.	AF: 99 (lead 1), PVC: 99 (both leads), PAC: 85 (both leads)	AF: Spec 100% (lead 2), Sens 100% (lead 1); PVC: Spec 99%, Sens 99%; PAC: Spec 96%, Sens 76%.
S. Verma, 2022	MIT-BIH	CNN, LSTM, 8 ML classifiers	Interpretability study using Grad-CAM, PFI, SHAP, PDP; CNN & LSTM performed best; local & global explanations; QRS complex most significant.	CNN: 94.1 (K-Fold), 98.7 (LGO); LSTM: 94 (K-Fold), (LGO)	Grad-CAM most effec- tive; PFI: global explana- tions; PDP & SHAP: less informative.
V. Singh *et al.*, 2019	MIT-BIH	ANN, SVM, RF, Decision Tree, Na¨ıve Bayes	Automated beat detection and classification; ANN with amplitude features performed best; visualization of normal and abnormal beats.	99.59	SVM (area, non-overlapping) 98.97; RF (area, overlapping, 10 trees) 97.73.
S. Mousavi *et al.*, 2018	MIT-BIH	Seq2Seq Deep Learn- ing + SMOTE	Evaluated intra- and inter-patient paradigms; addressed class imbalance; intra-patient: very high metrics; inter- patient: robust generalization.	–	Intra: S–PPV 96.46%, Sens 100%; F–PPV 98.68%, Sens 97.40; Inter: S–PPV 92.57%, Sens 88.94; V–PPV

					99.50%, Sens 99.94.
C. Gurudas Nayak *et al.*, 2016	MIT-BIH	SVM (various kernels)	Nine-level DWT sub-band decomposition; PCA feature extraction; ANOVA validation; quadratic SVM kernel performed best.	97.48	Cohen's kappa: 0.9198.
Kesavapriya R *et al.*, 2025	MIT-BIH	KNN, DT, RF, QDA, SVM	Evaluated multiple classifiers; RF showed highest reliability and generalization; DT performed well; SVM underperformed due to class imbalance.	RF: 98.32; DT: 96.87; k-NN: 67–72; QDA: 71.56; SVM: 65.35	RF – Precision 89.12%, Recall 92.29%, F1-score 90.57.
T. Subba *et al.*, 2024	MIT-BIH	DT, SVM, KNN, LR, RF	FFT-based frequency-domain features; RF performed best; strong sensitivity and speci- ficity; computationally intensive.	98	Sensitivity: N–0.99, SVEB–0.74, VEB–0.93, FB–0.78, Q–0.96.
Igiri C. G. *et al.*, 2023	MIT-BIH	RF, DT, SVM, KNN, NB	RR interval features; RF achieved highest accuracy and minimal false positives; ef- fective for early diagnosis and real-time systems.	RF: 89; KNN: 85; SVM/DT/NB: 79	RF: Precision, Recall, F1 = 0.89 each.
A. K. Sangaiah *et al.*, 2020	MIT-BIH	Wavelet-based Hidden Markov Model (WT-HMM)	Preprocessing, feature extraction from wavelet coefficients, dimensionality reduction via LDA, then HMM for hidden state modeling; IoMT integration for real- time monitoring.	99.8	Sensitivity 99.8 %, PPV 100%; real-time ECG monitoring via ThingSpeak platform.
S. Bhattacharyya, 2021	MIT-BIH (DS1, DS2)	TSFEL + SMOTE + RF-RFE + WMA (RF+SVM) ensemble	Feature extraction, balancing, and ensemble learning; WMA ensemble outperformed in- dividual models; improved subject-specific modeling.	WMA: 99.69; DS2: 98.21	VEB: Sens 94.22%, Prec 95.95%; SVEB: Sens 74.20%, Prec 90.09.
D. K. Van *et al.*, 2021	MIT-BIH	RF (optimized)	EEMD + Hilbert Transform for R-peaks; MPA for hyperparameter optimization; ex- cellent class-wise metrics.	99.90	Precision 99.74%, Recall 99.74%, F1 99.73; N: 99.74%, S: 99.92%, V: 99.89%, F: 99.98%, Q: 99.94.
A. S. Benmessaoud *et al.*, 2023	MIT-BIH	1-D ResNet	Downsampling improved training efficiency; strong per-class	99.24	F class: Acc 87.26%, Sens 87.25%, Prec

			performance; exceptional results for F class.		96.2%, F1 90.95.
A. I. Taloba, 2021	INCART, SPH	FFT-based peak de- tection + AR model- ing	Automatic ECG classification; strong per- formance on INCART; challenges in cross- database generalization.	INCART: 99.85; SPH: 68	Accurate P, R, T peak de- tection; misclassifications with RBBB/PVC due to T- wave variations.
M. Sraitih *et al.*, 2021	MIT-BIH	SVM, RF, KNN	Inter-patient evaluation; SVM most effec- tive; RF and KNN good on NOR and RBBB, respectively; ensemble improved stability.	SVM: 83; RF: 82; KNN: 78	F1: SVM 0.55, RF 0.43, KNN 0.40; Precision: SVM 0.64, RF 0.42, KNN 0.38; Recall: SVM 0.59, RF 0.49, KNN 0.50; NOR: 98% (ensemble).

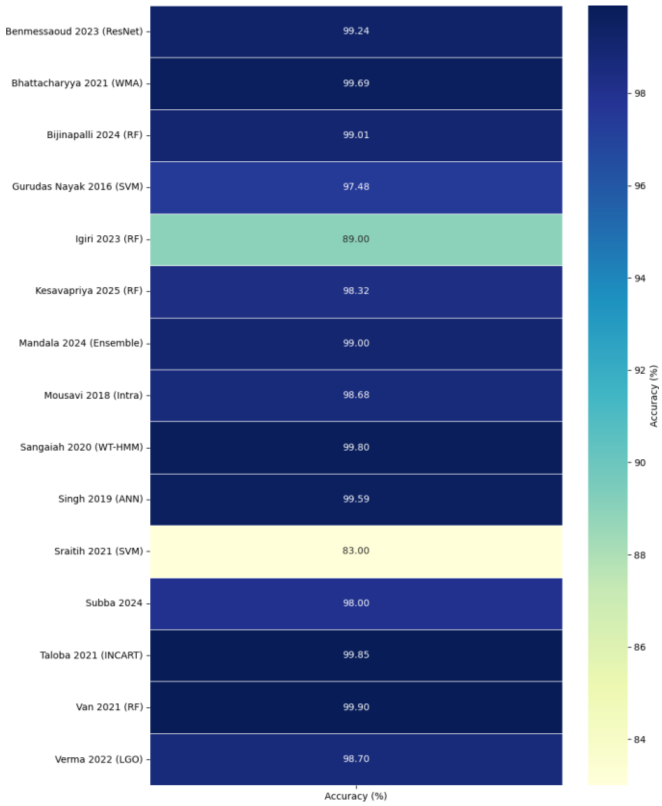

Fig. 8: Comparative Accuracy of ML models

7. Conclusion

This comparative review indicates that machine learning and deep learning have greatly improved detection and classification of arrhythmia using ECG signals as compared to traditional manual interpretation of arrhythmia, as these techniques are found to be faster, more Accurate, and more reliable in various datasets. Algorithms such as Random Forests, Support Vector Machines, k-Nearest Neighbors, Decision Trees, Convolutional Neural Networks, Long Short- Term Memory networks and ensemble models have demonstrated high degrees of performance in different datasets. The qualita- tive assessment of the different research reports depicts that machine learning and deep learning have greatly enhanced detection and classification of arrhythmia from ECG signals than the conven- tional method of manually interpreting the same. It is found to be fast, accurate, efficient, and re- liable. The results of using the different models including Random Forests, SVM(Support Vector Machines),KNN(k- Nearest Neighbors), Decision Trees, CNN, LSTM networks and methods to per- form ensemble learning have proven to perform well in many datasets after analyzing the different researches carried out by different researchers.It is based on a combination of detailed preprocessing and specific feature extraction like, QRS complex, RR intervals, amplitude and multi- lead signals which have shown a high degree of performance in most datasets. Moreover, better evaluation using both intra and inter-patient testing strategies is es- sential to achieve generalization and interpretability methods such as Grad-CAM, PFI, and SHAP enable the physician to interpret the decisions made by the model better which helps build trust and provide it additional clarity why the model made a certain decision. Number of studies have also point out the advantages of integrating IoMT-based real-time citizen heart monitoring. It shows the reality of the practical utility of these systems in the care of the patients. In general, we can note that the findings demonstrate an increased tendency towards creating arrhythmia detection systems that can be regarded as accurate, user-friendly, and any clin- ically feasible. It is likely that the goal will in the future be on how to enhance cross-database performances, reduce computational requirements and develop solutions that will serve the wearable and remote healthcare systems. Therefore, market in all these products has a great expanse.

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