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Exploring ECG Signal Analysis Techniques for Arrhythmia Detection: A Review

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Abstract

The heart holds paramount importance in the human body as it serves the crucial function of supplying blood and nutrients to various organs. Thus, maintaining its health is imperative. Arrhythmia, a heart disorder, arises when the heart's rhythm becomes irregular. Electrocardiogram (ECG) signals are commonly utilized for analyzing arrhythmia due to their simplicity and cost-effectiveness. The peaks observed in ECG graphs, particularly the R peak, are indicative of heart conditions, facilitating arrhythmia diagnosis. Arrhythmia is broadly categorized into Tachycardia and Bradycardia for identification purposes. This paper explores diverse techniques such as Deep Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Support Vector Machines (SVM), Neural Network (NN) classifiers, as well as Wavelet and Time–Frequency Transform (TQWT), which have been employed over the past decade for arrhythmia detection using various datasets. The study delves into the analysis of arrhythmia classification on ECG datasets, highlighting the effectiveness of data preprocessing, feature extraction, and classification techniques in achieving superior performance in classifying ECG signals for arrhythmia detection.

Keywords: Arrhythmia, Electrocardiogram, MIT-BIH ECG signal dataset, Tachycardia, and Bradycardia.

1. Introduction

The human heart plays a vital role in circulating blood, sending it to the lungs to receive oxygen before distributing it throughout the body. Cardiovascular diseases (CVDs) stand as the primary cause of mortality worldwide[1], as highlighted by research conducted by the World Health Organization (WHO). In 2019 alone, WHO reported a staggering 17.9 million deaths globally, accounting for nearly 32% of all deaths, attributable to CVDs. Of these deaths, 85% were due to heart attack and stroke. These diseases encompass a range of conditions, broadly classified into three main groups: electrical, structural, and circulatory[2]. Electrical disorders, such as arrhythmia, arise from irregular heartbeats due to abnormalities in the heart's electrical system. Structural issues, like cardiomyopathy, involve diseases affecting the heart muscle itself. Circulatory disorders, such as high blood pressure and coronary artery disease, affect the flow of blood within the body. Notably, coronary artery blockages are a leading cause of heart attacks which is shown in figure 1.

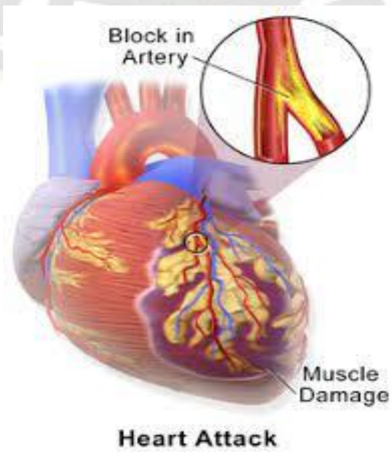

Figure 1 HEART ATTACK AND DAMAGED MUSCLE

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Electrocardiography (ECG) serves as the primary method for examining the myocardial electrical transmissions of the human heart through waveform analysis. An instrument known as the Electrocardiogram (ECG or EKG) is utilized for this purpose, depicting voltage against time to visualize the heart's electrical activity. By placing electrodes on the skin, ECG records the electric signals generated by each heartbeat[3]. This diagnostic tool is widely employed to detect various heart diseases such as coronary artery issues, arrhythmias, cardiomyopathy, and heart attacks. In this study, we explore the classification of arrhythmia using Long Short-Term Memory (LSTM), Deep Convolutional Neural Networks (DCNNs), and Machine Learning (ML) techniques.

ECG signals provide valuable insights into the human heart, including its position, chamber size, impulse source, and propagation[4]. It enables visualization of cardiovascular rhythm and conduction abnormalities, and aids in identifying medication effects on the heart. Arrhythmia, characterized by irregular heartbeats, is a prevalent condition among various heart diseases[5],[6]. Arrhythmias are categorized based on heartbeat speed into two main types:

Tachycardia: Characterized by rapid heartbeats, with a heart rate exceeding 100 beats per minute.

Bradycardia: Marked by irregular, slow heartbeats, with fewer than 60 beats per minute.

Arrhythmias can occur due to illness, injury, or genetic factors. ECG testing is commonly recommended by doctors to diagnose heart rhythm irregularities[7],[8]. Without appropriate treatment, arrhythmias can lead to insufficient blood pumping by the heart, potentially causing harm to vital organs such as the heart, brain, and other body parts. Hence, accurate identification of abnormal heart rhythms by cardiologists is crucial for effective management and treatment[9].

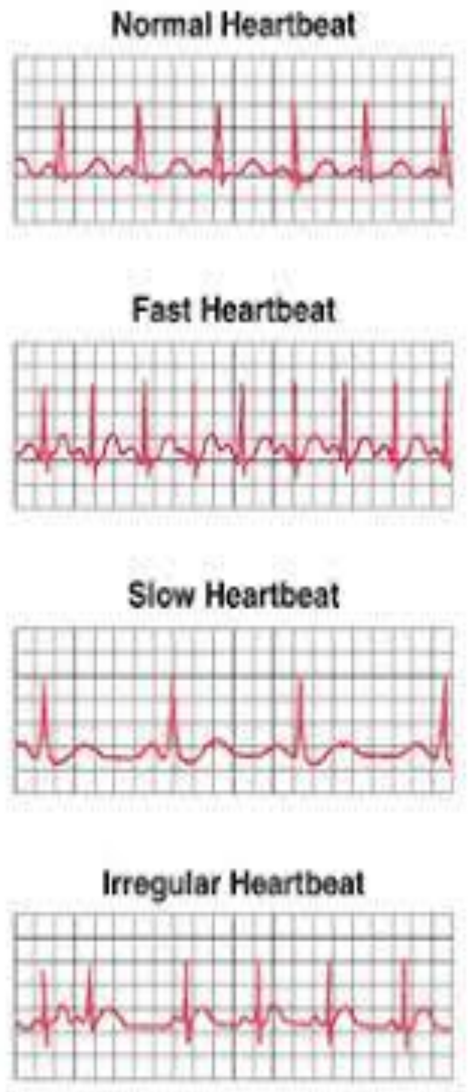

Figure 2 TYPES OF HEARTBEAT

To develop an artificial intelligence system, sophisticated deep learning methodologies are employed, with artificial neural networks (ANN) serving as the foundation for conducting intricate analyses. Among these methodologies, deep convolutional neural networks (DCNNs) have emerged as highly effective tools, demonstrating superior performance across diverse domains such as object detection[10], image classification, recommendation systems[11], and natural language processing[12]. This review study specifically concentrates on classifying arrhythmias using datasets derived from electrocardiograms (ECG), harnessing the prowess of DCNNs. The rationale behind this focus lies in the widespread success of DCNNs in tasks related to image classification. By applying DCNNs to ECG data, researchers aim to capitalize on their ability to discern patterns and features indicative of different arrhythmias. This approach represents a promising avenue for enhancing the accuracy and efficiency of arrhythmia detection, leveraging the expertise gained from DCNNs' proficiency in analyzing complex visual data. In summary, the utilization of DCNNs for arrhythmia classification using ECG datasets presents a novel and potent strategy, leveraging deep learning techniques to advance diagnostic capabilities in the field of cardiovascular medicine.

2. REALTED WORKS

Acharya et al.[14] proposed a convolutional neural network architecture consisting of nine layers for classifying irregular heartbeats. Each layer comprises three convolutional layers, one fully connected layer, and one max-pooling layer. They categorized the heartbeats into five classes: Fusion (F), Non-ectopic (N), V, S, and unknown beats (Q), focusing on accurately identifying these patterns in ECG data. The ECG heartbeats were sourced from the MIT-BIH arrhythmia database and meticulously verified by two cardiologists before utilization.
To address imbalances in the underlying dataset's Z-score, the researchers generated synthetic heartbeat data by adjusting the mean and standard deviation. This augmentation technique resulted in an enhanced accuracy of 94% when incorporating the additional data. However, when trained solely on the original dataset, the model achieved an accuracy of 89.07 percent.
Another study[15] proposed two deep learning methods based on convolutional neural networks (CNNs): an end-to-end approach that directly analyzes heartbeats, and a hierarchical two-stage process. In the first method, heartbeats are analyzed directly to determine their type, while the second method involves a two-stage process where the type of heartbeat is first determined, followed by sorting into 15 distinct categories using the MIT-BIH arrhythmia dataset. To address class imbalances, the researchers utilized data augmentation techniques, including Generative Adversarial Networks (GANs), to generate synthetic heartbeat data.
The end-to-end approach achieved an accuracy of approximately 98.30% and a precision of 90%, while the two-stage hierarchical process attained an accuracy of 98% and a precision of 93.5%.
Abdalla et al., [16]in their study by eleven layers of CNN were utilized to identify ten distinct types of arrhythmias. This CNN architecture included four convolutional layers and three max-pooling layers. The researchers utilized the hospital database at Massachusetts Institute of Technology's Beth Israel Medical Center for compiling statistics. After training and testing, the dataset was augmented using the Z-score technique to achieve a balanced dataset with different means and standard deviations. The dataset was divided into 80% for training and 20% for testing, resulting in an impressive accuracy of 99.84%.
Yildirim et al.[17] utilized the MIT-BIH ECG signal dataset to develop a 16-layer one-dimensional convolutional neural network (1D CNN) model aimed at recognizing 17 different rhythm types. They randomly selected one thousand signal fragments from the dataset, each comprising 3600 samples, obtained from 45 patients. For training, 70% of the samples (700 samples) were utilized, while 15% (150 samples) each were allocated for testing and validation purposes, respectively. The researchers applied a rescaling technique to enhance their results, achieving a noteworthy accuracy of 91.33% in classifying the 17 rhythm classes.
Zheng et al.[18] employed a two-dimensional convolutional neural network (CNN) model augmented with Long Short-Term Memory (LSTM) to classify eight different types of ECG signals sourced from the MIT-BIH arrhythmia dataset. These signals include "Premature Ventricular Contraction (PVC)," Ventricular Flutter Waves, Ventricular Escape Beat, Right Bundle Branch Block (RBBB), Left Bundle Branch Block (LBBB), and Normal Sinus Rhythm (NOR).
The study focused on medical patients in a hospital laboratory setting, utilizing machine learning (ML) and deep learning (DL) approaches for prediction. The primary outcome measures included important attributes, accuracy, and classification of the ECG signals. By integrating LSTM and a fully connected layer into the CNN model, the researchers achieved an impressive prediction accuracy of 99.01% across the convolutional, LSTM, and fully connected layers.

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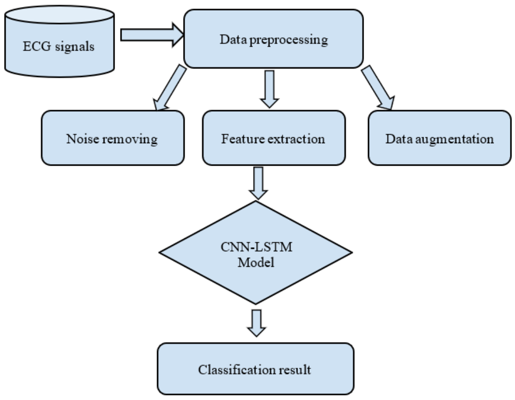

Figure 3 WORKFLOW OF CNN-LSTM MODEL

Gao et al.[19] introduced a LSTM model comprising four layers, including an input layer, two fully connected layers, and an LSTM layer, to classify eight different types of beats within the MIT-BIH arrhythmia dataset. Addressing data imbalance, they employed the focal loss technique. In the preprocessing stage, noise was eliminated from the ECG signal using the Daubechies 6 (db6) discrete wavelet transform. Subsequently, the sliding window search method was applied for heartbeat extraction, followed by the normalization of data using the Z-score technique. Through training the LSTM network with focal loss, they achieved an impressive overall accuracy of 99.26%.
Yildirim et al.[20] proposed a model combining Convolutional Auto Encoder (CAE) with LSTM to predict five distinct arrhythmia classes from the MIT-BIH database. The CAE model was employed to compress raw ECG signal beats, extracting coded features subsequently utilized in an LSTM network for arrhythmia classification. They attained a remarkable accuracy of 99.23% using raw data in the LSTM model and 99.11% accuracy utilizing coded features.
Alfaras et al. [26] introduced Echo State Networks, a machine learning method that classifies ECG heartbeats into two classes - SVEB+ and VEB+ based on morphology. They utilized two ECG datasets: MIT-BIH AR (with leads II and V1) and AHA (with leads A and B). After eliminating certain ECG records, they achieved 98.6% accuracy in lead II and 96.8% accuracy in lead V1 of MIT-BIH AR, while obtaining 98.6% accuracy in lead A and 97.8% accuracy in lead B of AHA.
An optimized block-based NN classifier is used to identify five several categories of heartbeats and achieve an accuracy of 97% [27].
Another study by Banerjee et al. [28] introduced a cross wavelet transform (XWT) based method for classifying normal and abnormal ECG patterns, achieving an accuracy of 97.6%. Using the MIT-BIH arrhythmia database,
Jha et al. [29] employed an SVM classifier and TQWT-based characteristics of ECG beats, achieving a remarkable accuracy rate of 99.27% in detecting eight different types of ECG beats.
In their study, Gupta et al. [30] explored various techniques, including Naïve Bayes, Random Forest, SVM, and Neural Networks, to identify 14 different arrhythmia classes. They utilized an arrhythmia dataset from the UCI Machine Learning Repository, initially containing 452 rows and 279 columns with missing values. After eliminating these missing values, the dataset was reduced to 252 columns. The dataset was labeled into 16 classes by cardiologists, where classes two to fifteen represented various arrhythmia types, class 1 indicated normal ECG, and class 16 represented unlabeled patients.
Two types of Naïve Bayes classifiers (binomial, multinomial) were applied without feature reduction, resulting in high train and test errors. SVM classifier with mRMR feature selection technique was employed, with bootstrapping utilized for improving model accuracy. However, the model struggled to classify class 16 and misclassified class 5 as class 1. To address this issue, an anomaly detector was integrated, achieving a 70% accuracy rate.
Random Forest classifier with bootstrapping yielded an overall accuracy of 72.3%, while a serial classifier composed of Random Forest and linear kernel SVM-poly degree 2 achieved 77.4% accuracy. Hierarchical two Random Forest classifiers were also applied, resulting in a 30% error rate. Additionally, Pattern Net Neural Network achieved a 69% accuracy rate.
Devdas et al. [31] employed three machine learning algorithms, namely SVM, Naïve Bayes, and KNN, to predict sixteen types of arrhythmias using a dataset sourced from the UCI Machine Learning Repository, containing 452 records with 280 attributes. They implemented a condition to remove missing values, resulting in the elimination of two features. The Mice method was then utilized for data imputation, filling in predicted values for the missing data points, while the Boruta method was applied for removing unnecessary features.
The dataset was divided into an 80% portion for training, with ten cross validations. Before employing feature selection techniques, SVM achieved an accuracy of 61.5%, Naïve Bayes reached 46.1%, and KNN attained 59.3%. However, after applying feature selection techniques, the accuracies of SVM, Naïve Bayes, and KNN improved significantly to 71.4%, 70.3%, and 62.6%, respectively. This

underscores the importance of feature selection techniques in enhancing model performance, as demonstrated by the researchers.

Andersen et al.[32]The model underwent training and validation on three distinct databases, encompassing a total of 89 subjects. Through a 5-fold cross-validation process, it demonstrated a sensitivity of 98.98% and a specificity of 96.95%. Moreover, the model exhibited computational efficiency, capable of analyzing 24 hours of ECG recordings in less than one second.

Furthermore, the proposed algorithm's robustness was evaluated by testing it on unseen datasets to assess its efficacy in detecting atrial fibrillation (AF) in new recordings. The results revealed a specificity of 98.96% and a sensitivity of 86.04%, underscoring the algorithm's effectiveness in identifying AF across different datasets.

Yi Gan et al.[33]To enhance the classification performance of the model for various arrhythmias, a parallel classification model based on DenseNet-BiLSTM is proposed. This model incorporates a parallel structure that allows for the simultaneous capture of waveform features from both small-scale and large-scale heartbeats, achieved through wavelet denoising and heartbeat segmentation of ECG signals. The model leverages deep learning techniques, including Densely connected convolutional network (DenseNet) for extracting local features and bidirectional long short-term memory network (BiLSTM) for capturing time series features of ECG signals.

Furthermore, to address class imbalance in arrhythmia data, a weighted cross entropy loss function is utilized. The model employs the Softmax function to achieve four classifications of arrhythmia. Experimental results conducted on the MIT-BIH arrhythmia database showcase promising outcomes. Under the intra-patient paradigm, the model demonstrates a training time of 42 seconds per epoch, with an overall accuracy and specificity of 99.44% and 95.89%, respectively. Under the inter-patient paradigm, the training time per epoch is reduced to 23 seconds, with an overall accuracy and specificity of 92.37% and 63.49%, respectively.

Ali Sellami et.al [34]We introduce a novel deep convolutional neural network (CNN) leveraging state-of-the-art deep learning techniques for precise heartbeat classification. To address class imbalance, we propose a batch-weighted loss function that dynamically adjusts loss weights based on class distribution within each batch. Additionally, we advocate for the utilization of multiple heartbeats to enhance classification effectiveness.

Despite employing ECG signals from a single lead without any preprocessing, our method consistently surpasses existing approaches for 5-class heartbeat classification. Under the intra-patient paradigm, our model achieves impressive metrics with an accuracy of 99.48%, positive productivity of 98.83%, sensitivity of 96.97%, and specificity of 99.87%. Similarly, under the inter-patient paradigm, our model maintains strong performance with an accuracy of 88.34%, positive productivity of 48.25%, sensitivity of 90.90%, and specificity of 88.51%.

Manisha Jangra et.al[35] The paper presents a novel convolutional neural network (CNN) model designed for arrhythmia classification, offering several enhancements over traditional CNN architectures. Firstly, the model incorporates a multi-channel design that allows for the concatenation of spectral and spatial feature maps, thereby improving the model's ability to capture diverse features. Additionally, the structural unit of the model comprises a depthwise separable convolution layer followed by activation and batch normalization layers, facilitating more efficient utilization of network parameters.

Furthermore, hyperparameter optimization is conducted using the Hyperopt library, employing the Sequential Model-Based Global Optimization (SMBO) algorithm. These optimizations enhance the efficiency and accuracy of the network for arrhythmia classification tasks. The proposed model is evaluated using tenfold cross-validation, following both subject-oriented inter-patient and class-oriented intra-patient evaluation protocols.

The evaluation results demonstrate the effectiveness of the proposed model, with accuracies of 99.48% and 99.46% achieved in classifying ventricular ectopic beats (VEB) and supraventricular ectopic beats (SVEB), respectively. These findings underscore the robustness and performance of the proposed CNN model for arrhythmia classification.

Aiyun Chen.et al[36] A novel Multi-information Fusion Convolutional Bidirectional Recurrent Neural Network (MF-CBRNN) is introduced for automatic detection of arrhythmias. The performance evaluation of the proposed model is conducted using ECG signals from the MIT-BIH databases, employing both intra-patient and inter-patient paradigms.

Under the intra-patient paradigm, the proposed MF-CBRNN model achieves an impressive accuracy of 99.56% and an F1-score of 96.40%. When evaluated under the inter-patient paradigm, the model demonstrates an overall accuracy of 96.77% and an F1-score of 77.83%. These results highlight the effectiveness of the MF-CBRNN model in accurately detecting arrhythmias from ECG signals, showcasing its potential for clinical applications.

Muhammad Zubair[37] The proposed method achieved remarkable results, with an overall accuracy of 99.81% for intra-patient classification and 96.36% for inter-patient classification of heartbeats. Experimental findings indicate that the proposed approach effectively addressed the challenge of imbalanced data, resulting in a balanced representation of ECG beats.

This paper proposes a deep learning-based multi-model system for the classification of electrocardiogram (ECG) signals, aiming to contribute significantly to the management and treatment of cardiovascular diseases. The system consists of two distinct deep learning bagging models designed to classify heartbeats into different types of arrhythmias.

The first model, CNN-LSTM, combines a convolutional neural network (CNN) with a long short-term memory (LSTM) network to effectively capture both local features and temporal dynamics present in the ECG data. Meanwhile, the second model, RRHOS-LSTM, integrates classical features such as RR intervals and higher-order statistics (HOS) with the LSTM model to highlight abnormal heartbeats more effectively.

To address the high imbalance distribution of arrhythmia classes in the ECG data, a bagging model is created from the CNN-LSTM and RRHOS-LSTM networks. Each model is trained on a different sub-sampling dataset, and a weighted loss function is employed during training to assign higher weights to classes that are not sufficiently represented.

These models are then combined using a meta-classifier, which is a feedforward fully connected neural network that takes the predictions of the bagging models as input and generates a final prediction. To mitigate false positives, the output of the meta-classifier is further verified by another CNN-LSTM model.

Essa E. et al.[38]Experimental evaluations are conducted on ECG data from the MIT-BIH arrhythmia database, resulting in an overall accuracy of 95.81% under the "subject-oriented" patient-independent evaluation scheme. Moreover, the averages of F1 score and positive predictive value exceed those of all other methods by more than 3% and 8%, respectively.

Yuanlu Li et al.[39] The proposed method achieves a sensitivity of 94.54%, a positive predictivity of 93.33%, and a specificity of 80.80% for normal segments. For the supraventricular ectopic segment, the method demonstrates a sensitivity of 35.22%, a positive predictivity of 65.88%, and a specificity of 98.83%. Regarding the ventricular ectopic segment, the proposed method achieves a sensitivity of 88.35%, a positive predictivity of 79.86%, and a specificity of 94.92%.

Mainul Islam Labib.et al [40] Electrocardiogram (ECG) analysis plays a crucial role in diagnosing cardiac arrhythmias, yet traditional deep learning methods often struggle due to the lack of diverse and representative training data across different demographics such as age, weight, and gender. This can lead to misclassification, as temporal features extracted from these datasets tend to be demographically biased. To address this limitation, this paper introduces the Optimum Recurrence Plot based Classifier (OptRPC), a dynamical systems-based approach that embeds ECG beats in higher dimensions and constructs an optimized recurrence plot. Subsequently, a Convolutional Neural Network (CNN) architecture is employed to classify these recurrence plots.

The proposed OptRPC scheme achieves an impressive overall accuracy of 98.67% and 98.48% on two benchmark databases, outperforming previous state-of-the-art methods. This highlights the effectiveness of the OptRPC method in addressing the demographic biases inherent in traditional deep learning approaches, thereby improving the accuracy and reliability of ECG arrhythmia classification.

Guijin Wang et all.[41] We propose a novel Domain-Adaptive ECG Arrhythmia Classification (DAEAC) model aimed at enhancing the inter-patient performance of deep neural networks without requiring additional expert annotation. Initially, we develop a robust model to address the inter-patient ECG heartbeat classification problem, achieving state-of-the-art performance on various public databases, including the MIT-BIH database, SVDB, and INCARTDB.

Subsequently, based on our observation of clustering characteristics within the data, we introduce two novel objective functions: the Cluster-Aligning loss and the Cluster-Maintaining loss. The Cluster-Aligning loss is designed to align the distributions of training and test data in the feature space, thereby enabling deep models to adapt more effectively to new data. On the other hand, the Cluster-Maintaining loss is utilized to preserve the structural information and enhance the discriminability of new data by leveraging a short period of unlabeled data from test records.

Saroj Kumar Pandey et al.[42]In this research, we propose a novel deep learning approach based on Restricted Boltzmann Machine (RBM) for arrhythmia classification using Electrocardiogram (ECG) signals. The study is structured into three phases:

Signal processing: This phase involves normalizing and segmenting the heartbeats from the ECG signals.

Stacked RBM model implementation: The essential features are extracted from the ECG signal using a stacked RBM model.

Classification using SoftMax activation: The ECG signals are classified into four types of heartbeat classes based on ANSI/AAMA standards.

The stacked RBM model is evaluated through three types of experiments: patient-independent data classification for multi-class, patient-independent data for binary classification, and patient-specific classification. The best result is achieved in patient-independent binary classification with an overall accuracy of 99.61%. For patient-independent multi-class classification, the accuracy obtained is 98.61%, and for patient-specific data, the accuracy is 95.13%.

The experimental results demonstrate that the proposed RBM model outperforms existing methods in terms of accuracy, sensitivity, and specificity.

Jing Zhang. Et.al[43] he proposed method demonstrates exceptional performance in detecting supraventricular ectopic beats (SVEBs), a particularly challenging task, while also achieving comparable performance in identifying ventricular ectopic beats (VEBs). Specifically, the sensitivities for detecting SVEBs and VEBs are 78.8% and 92.5%, respectively, highlighting the method's effectiveness in identifying these abnormal heart rhythms. Moreover, the precisions for SVEBs and VEBs are 90.8% and 94.3%, respectively, further underlining the robustness of the proposed approach.

Given its high performance in detecting pathological classes such as SVEBs and VEBs, this study presents a promising method for ECG classification tasks, especially in scenarios where the number of patients is limited.

Jing Cai et.al[44] This paper presents a real-time arrhythmia classification algorithm based on deep learning, aiming for low latency, high practicality, and reliability suitable for real-time arrhythmia classification systems. The algorithm

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begins by detecting the QRS complex position in real-time for heartbeat segmentation, followed by the construction of the ECG_RRR feature based on the segmentation results. Subsequently, another classifier is employed to classify arrhythmias in real-time using the ECG_RRR feature.

The study utilizes the MIT-BIH arrhythmia database, dividing the 44 qualified records into two groups (DS1 and DS2) for training and evaluation, respectively. Results indicate that the recall rate, precision rate, and overall accuracy of the algorithm's interpatient QRS complex position prediction are 98.0%, 99.5%, and 97.6%, respectively. Furthermore, the overall accuracy for 5-class and 13-class interpatient arrhythmia classification reaches 91.5% and 75.6%, respectively.

Additionally, the proposed real-time arrhythmia classification algorithm boasts practicality and low latency. Deployment of the algorithm is straightforward since it requires no feature processing of the original ECG signal. Moreover, the latency of arrhythmia classification is only the duration of one heartbeat cycle.

Tao Wang et.al[45] In our paper, we propose an automated ECG classification approach leveraging Continuous Wavelet Transform (CWT) in conjunction with Convolutional Neural Network (CNN). The CWT is utilized to decompose ECG signals, thereby obtaining various time-frequency components, while the CNN is employed to extract features from the resulting 2D-scalogram composed of these time-frequency components. Additionally, considering the importance of the surrounding R peak interval (RR interval) in arrhythmia diagnosis, four RR interval features are extracted and combined with the CNN features. These combined features are then inputted into a fully connected layer for ECG classification.

Through testing on the MIT-BIH arrhythmia database, our method achieves an overall performance of 70.75% for positive predictive value, 67.47% for sensitivity, 68.76% for F1-score, and 98.74% for accuracy. Compared to existing methods, our approach yields an improvement in the overall F1-score ranging from 4.75% to 16.85%.

Saandeep Chandra et.al[46]This study examines a dataset comprising 953 independent life-threatening arrhythmia alarms from ICU bedside monitors, originating from 410 patients. The research aims to accurately detect the onset and offset of various arrhythmias using ECG signals (4 channels), arterial blood pressure, and photoplethysmograph signals, without prior knowledge of the alarm type.

A hybrid convolutional neural network (CNN)-based classifier is proposed, which integrates traditional handcrafted features with features automatically learned using CNNs. This architecture remains adaptable to different arrhythmic conditions and multiple physiological signals. Notably, the hybrid CNN approach demonstrates superior performance compared to methods solely relying on CNNs.

The algorithm is evaluated using 5-fold cross-validation repeated 5 times, resulting in an accuracy of 87.5% ± 0.5% and a score of 81% ± 0.9%. Independent assessment on the PhysioNet 2015 Challenge database yields an overall classification accuracy of 93.9% and a score of 84.3%, underscoring the algorithm's effectiveness and generalizability.

Fatma Murat[47]et al. In this study, a dataset comprising over 10,000 subject records of electrocardiogram (ECG) signals was utilized for training and diagnosing arrhythmia. A deep neural network (DNN) model was employed to extract features from the ECG inputs. Feature maps obtained from different layers of the DNN were then inputted into various shallow classifiers after reducing the dimensionality using Principal Component Analysis (PCA).

Additionally, morphological features extracted using DNN were supplemented with various ECG features derived from lead-II to enhance performance. Through the fusion of these ECG features, an accuracy of 90.30% was achieved. Furthermore, utilizing only deep features resulted in an accuracy increase to 97.26%. Remarkably, by combining both deep and ECG-based features, the accuracy was further enhanced to 98.00%.

3. ANALYTICAL EVALUATION

The ECG device interprets signals captured by electrodes attached to the skin and generates a visual depiction of the patient's heart's electrical activity. The fundamental pattern of the ECG can be understood as follows:

When electrical activity moves towards a lead, it results in an upward deflection.

Conversely, when electrical activity moves away from a lead, it leads to a downward deflection.

Depolarization and repolarization deflections occur in opposite directions.

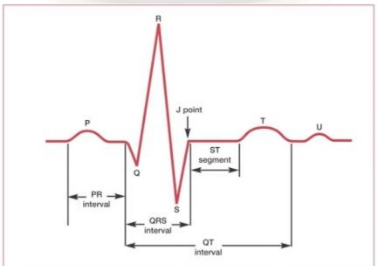

Figure 4 ECG SIGNAL PEAKS

The basic pattern of electrical activity across the heart

The P wave signifies atrial depolarization, while the PR interval measures the time from the onset of the P wave to

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the beginning of the QRS complex, indicating the duration of atrial depolarization and the transmission of electrical impulses through the atrioventricular node.

The QRS complex consists of three waves: Q, R, and S. If the wave following the P wave is an upward deflection, it is labeled as an R wave, whereas a downward deflection is labeled as a Q wave. Small Q waves indicate depolarization of the interventricular septum, while the R wave represents depolarization of the main mass of the ventricles and is typically the largest wave. The S wave indicates the final depolarization of the ventricles at the base of the heart.

The ST segment, or interval, follows the QRS complex and precedes the T wave, representing the period of zero potential between ventricular depolarization and repolarization.

Lastly, the T wave represents ventricular repolarization, as atrial repolarization is obscured by the large QRS complex.

Deep learning models require a significant amount of ECG signals for training to understand the relationship between ECG characteristics and various types of arrhythmias. However, collecting such data is challenging due to privacy concerns surrounding sensitive health information. Table 1 show publicaly available databases of ECG. To address this issue and facilitate fair comparisons among different DL methods, the majority of studies (89%, 326 out of 368) have utilized publicly available datasets like the MIT-BIH Arrhythmia Database (MITDB)[51] and MIT-BIH Atrial Fibrillation Database (AFDB)[52]. MITDB is particularly popular, with approximately 61% (223 out of 368) of studies using it for arrhythmia classification. Other commonly used databases include PTB[53], PTB-XL[54], NSRDB, and INCART.

DATABASE	PUBLICLY AVAILABLE	RELEASE YEAR	NO. CHANNELS	SAMPLING RATE(Hz)	SUBJECTS	NO.OF RCEORDS	DEMOGRAPHIC INFORMATION
MIT-BIH Arrhythmia (MITDB)	Yes	2005	2	360	47	48	M-25 F-22
MIT-BIH AtrialFibrillation (AFDB)	Yes	2000	2	250	25	23	Subjects are suffering from atrial fibrillation
PTB Diagnostic ECG Database (PTB)	Yes	2004	15	1000	290	549	M-370 F-139
PTB-XL ECG DATA SET(PTBX)	Yes	2020	12	500	18885	21837	M-9820 F-9065
MIT-BIH Normal Sinus (NSRDB)	Yes	1999	2		18	18	M-5 F-13
St Petersburg INCART 12-lead Arrhythmia(INCART)	Yes	2008	12	257	32	75	M-17 F-15

Table 1 POPUULAR ECG DATABASES

The MIT-BIH Arrhythmia Database contains several classes of arrhythmias, including:
Normal Sinus Rhythm (NSR)
Atrial Premature Contraction (APC)
Premature Ventricular Contraction (PVC)
Ventricular Flutter Wave (VFW)
Atrial Fibrillation (AF)
Ventricular Tachycardia (VT)
Fusion of Venticular and Normal Beat (FUS)
Supraventricular Tachycardia (SVTA)
Left Bundle Branch Block (LBBB)
Right Bundle Branch Block (RBBB)
Nodal (Junctional) Premature Contraction (NPJC)
Ventricular Escape Beat (VEB)
Atrial Tachycardia (AT)
Supraventricular Premature Beat (SVPB)
Unclassifiable Beat (UN)
Noisy Data (N)
These classes represent different types of arrhythmias and signal abnormalities that are observed in the MIT-BIH Arrhythmia Database.

4. METHODOLGY

Basics steps for ECG analysis for arrhythmia classification are

a. Preprocessing of data

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b. Feature Extraction
c. Feature Dimension reduction and optimization
d. Classification

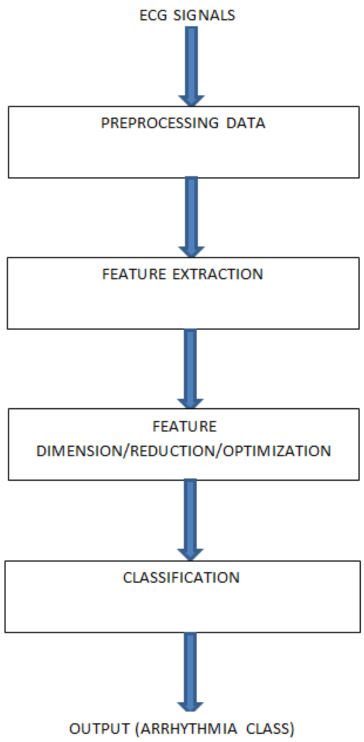

Figure 5 STEPS FOR ECG CLASSIFICATION

a. Preprocessing data

Each entry in the database corresponds to a 30-minute duration of two-channel ECG signals sampled at a frequency of 360 Hz. Due to the lengthy duration of these signals, direct analysis of the entire duration is impractical. Therefore, the signals are sampled at a rate of 360 samples per second and filtered using a bandpass filter within the frequency range of 0.1–100 Hz[51]. However, this filtering process introduces various types of noise into the ECG signal[55], including power line interference, baseline drifts, motion artifacts, and electromyography (EMG) noise.

To mitigate these sources of noise, researchers have employed various preprocessing methods are used like recursive filters [51],[56],[57],[58]and wavelets[51] are the most commonly used. Wavelet-based denoising, although effective, requires advanced levels of decomposition and is more time-consuming and complex compared to other techniques[61]. Therefore, alternative algorithms are often preferred for preprocessing tasks. For instance, discrete wavelet transform (DWT)[59][61] is commonly used to remove baseline wander, while notch filters [7]are applied to eliminate power line interference. Butterworth filters [57]and median filters[56][60] are employed to mitigate the effects of EMG noise and baseline shift, respectively.
Researchers typically focus on addressing specific types of noise and utilize corresponding denoising techniques. However, when multiple types of noise are present in the ECG signal, individual removal methods may be inadequate. Therefore, there is a need for novel denoising techniques capable of effectively addressing various types of noise simultaneously, thereby reducing processing time. Evaluation of the effectiveness of such techniques often involves performance measures such as signal-to-noise ratio (SNR)[51].

While various preprocessing techniques have been explored for ECG signals, the selection of a specific technique depends on the researcher's ultimate objectives. However, detailed analysis of ECG signals may be limited due to the computational complexity associated with certain preprocessing methods. Additionally, the discretization inherent in wavelet transforms may lead to less natural and efficient signal representations, posing another limitation in preprocessing.

b. Feature Extraction

Following the preprocessing stage, the next step involves feature extraction from the ECG signal. ECG signal features primarily depend on characteristics such as time intervals, amplitudes, and segment durations, which are standard attributes of ECG signals. These features play a crucial role in identifying various cardiac abnormalities and arrhythmias.

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S.No	Features	Amplitude(milliVolts)	Duration(milliSeconds)
1	P wave	0.1mV-0.2mV	60ms-80ms
2	QRS complex	1mV	80ms-120ms
3	T wave	0.1mV-0.3mV	120ms-160ms
4	PR-interval		120ms-200ms
5	ST-interval		320ms
6	QT-interval		0.4s-0.43s
7	RR-interval		0.6s-1.2s
8	PR-segment		50ms-120ms
9	ST-segment		100ms-120ms
10	TP segment		0.38s-0.4s

Table 2 ECG WAVE FEATURES

The ECG signal, depicted in Figure 4, exhibits various morphological features, as outlined in Table 2 [51]. Additionally, temporal and statistical features [62], such as slopes and pre-intervals, can be leveraged for effective classifications. The identification of peaks, including P, R, T, and QRS complexes, is a prerequisite for determining amplitudes and intervals. Several algorithms, including peak detection algorithms [57, 60], QRS complex detection methods [57, 63], wavelet transforms [64, 65, 66, 67, 68], empirical mode decomposition [74, 58], Pan-Tompkins algorithm [56, 70], fixed threshold algorithms [69], Symlet4 [71], and Re-En algorithm [72], have been explored by various researchers, as summarized in Table 2.

Feature extraction algorithms are often tailored based on the specific features utilized for classification. For instance, if only R amplitude and RR interval are considered, fixed level thresholding [69] or peak detection algorithms [60] may suffice. Researchers have proposed feature extraction algorithms encompassing a range from 1 to 13 features. However, extracting a larger number of features can increase algorithmic complexity. Therefore, there is a need for novel algorithms capable of extracting a maximal set of features.

Following feature extraction from denoised ECG signals, a feature set is formed. However, not all features within this set are necessary for classification, necessitating optimization. The accuracy of classification hinges on the detected features post-optimization. Moreover, misclassification in large datasets can occur due to minor fluctuations in ECG feature values. Given that a person's heart rate can vary over time due to factors such as stress, activity, or exercise, it is imperative to consider multiple beats from the same patient and compare them to mitigate unwanted feature changes. These features must be carefully transformed to account for unstable heart rates.

c. Feature Dimension reduction and optimization

When dealing with a large feature set, optimization becomes essential. Independent Component Analysis (ICA) [75] and Principal Component Analysis (PCA) [76, 61, 74] are commonly employed for feature dimension reduction and optimization. ICA statistically separates components from mixed signals, effectively extracting features but often failing to reduce noise adequately. On the other hand, PCA utilizes orthogonal transformation to convert correlated variables into uncorrelated ones. It is an unsupervised technique used for optimization. The best fit is determined through regression and general factor analysis.

In the classification process, not all extracted features are equally important. Different classes of arrhythmia may require specific features for accurate classification. Therefore, it is crucial to select the most relevant features for each class. However, there is no standard optimization rule for feature selection. The optimization process varies depending on the features required for classification. Establishing a standardized optimization rule is necessary to ensure that important features, such as peaks, are not overlooked.

d. Classification

After defining the set of features, various learning algorithms can be employed to develop models based on these features. Commonly found algorithms in surveys include Support Vector Machine [60, 61, 77], Logistic Regression, Modular Neural Networks [5, 6], Machine Learning algorithms [64, 70, 74], Linear Classifiers [70], and Deep Neural Networks [78, 79, 76].

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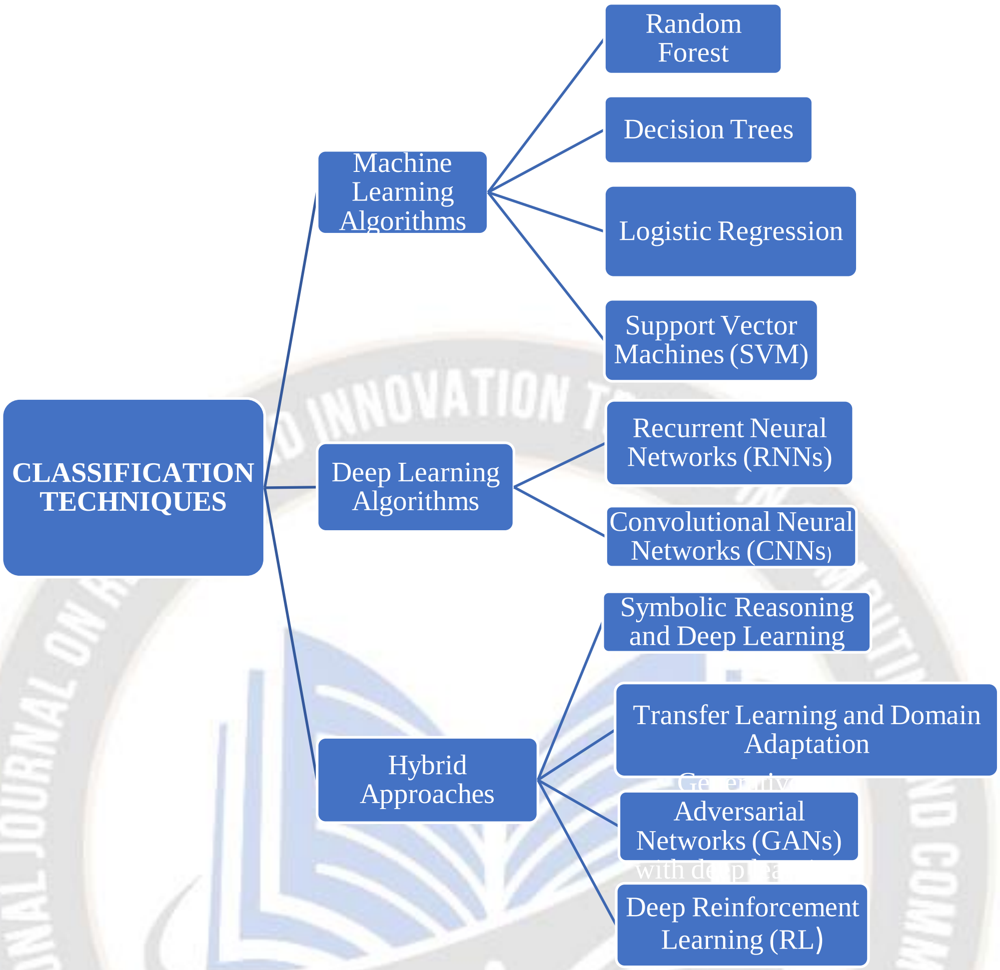

Figure 6 Classification Techniques

Machine Learning Algorithms

There are several classification techniques or algorithms used in machine learning and deep learning. Here are some commonly used ones:

1. Decision Trees: Decision trees are a popular classification method that uses a tree-like model of decisions and their possible consequences. Each internal node represents a feature or attribute, and each branch represents a possible value or outcome. Decision trees are easy to interpret and can handle both numerical and categorical data.
2. Random Forest: Random Forest is an ensemble learning method that combines multiple decision trees. It creates a "forest" of decision trees and makes predictions by averaging the predictions of individual trees. Random Forest improves prediction accuracy and handles high-dimensional data well.
3. Support Vector Machines (SVM): SVM is a powerful classification algorithm that finds the best hyperplane to separate different classes in a feature space. It aims to maximize the margin between the classes while minimizing the classification error. SVM can handle linear and non-linear classification problems and works well with small to medium-sized datasets.
4. Logistic Regression: Logistic Regression is a commonly used algorithm for binary classification. It models the relationship between the input variables and the probability of belonging to a particular class using a logistic function. Logistic Regression is simple, interpretable, and can handle large datasets.

These are just a few examples of classification techniques in machine learning. The choice of algorithm depends on factors such as the nature of the data, the size of the dataset, interpretability requirements, and the specific problem at hand. It is often beneficial to experiment with multiple algorithms and select the one that performs best for a given task.

Deep Learning Algorithms

Deep learning is a subset of machine learning that focuses on using neural networks with multiple layers to learn and represent complex patterns and relationships in data. Deep learning has achieved remarkable success in various classification tasks. Here are some popular deep learning classification methods:

1. Convolutional Neural Networks (CNNs): CNNs are widely used for image classification tasks. They consist of multiple convolutional layers that extract spatial hierarchies of features from the input image. CNNs utilize filters, pooling layers, and activation functions to capture patterns and local structures. They have achieved state-of-the-art performance in image recognition, object detection, and image segmentation.
2. Recurrent Neural Networks (RNNs): RNNs are designed to handle sequential or time-series data, making them suitable for tasks like natural language processing and speech recognition. RNNs maintain a hidden state that captures information from previous inputs, allowing them to model dependencies over time. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are popular RNN variants that address the vanishing gradient problem and improve long-term memory.

These are just a few examples of deep learning classification methods. Deep learning offers great flexibility and has been successfully applied in various domains, including computer vision, natural language processing, speech recognition, and more. The choice of deep learning method depends on the specific task, available data, and computational resources.

Hybrid Approaches

Hybrid approaches in deep learning refer to the combination of multiple techniques or models from different domains to solve complex problems or improve the performance of deep learning systems. These approaches leverage the strengths of different methodologies and integrate them into a unified framework. Here are a few examples of hybrid approaches in deep learning:

1. Deep Reinforcement Learning (RL): Deep RL combines deep learning with reinforcement learning, which is a branch of machine learning concerned with decision-making in sequential environments. Deep RL algorithms use deep neural networks as function approximators to learn policies or value functions that guide the agent's actions in an environment. By combining deep learning's ability to handle high-dimensional inputs and RL's ability to learn from trial-and-error interactions, deep RL has achieved impressive results in domains such as game playing, robotics, and autonomous driving.
2. Generative Adversarial Networks (GANs) with deep learning: GANs are a type of generative model that consists of two neural networks: a generator and a discriminator. The generator aims to generate realistic samples, such as images or text, while the discriminator tries to distinguish between real and fake samples. By training these networks in an adversarial manner, GANs can produce high-quality synthetic samples. The combination of deep learning and GANs has led to breakthroughs in image synthesis, style transfer, and data augmentation.
3. Transfer Learning and Domain Adaptation: Transfer learning and domain adaptation techniques aim to transfer knowledge from one task or domain to another. In deep learning, pre-trained models, such as convolutional neural networks (CNNs) trained on large image datasets like ImageNet, are often used as a starting point for related tasks. By leveraging the learned representations from pre-trained models, deep learning models can benefit from the generalization and feature extraction capabilities of the pre-trained networks. This approach helps in cases where labeled data is limited or when the target domain differs from the source domain.
4. Symbolic Reasoning and Deep Learning: Symbolic reasoning involves manipulating and reasoning about explicit symbols and rules. Deep learning, on the other hand, is primarily focused on learning from data without explicit rule representation. Hybrid approaches aim to combine deep learning's ability to learn from raw data with symbolic reasoning techniques for tasks that require structured knowledge representation and reasoning. This integration can be used to tackle problems like question answering, natural language understanding, and logical reasoning.

These are just a few examples of hybrid approaches in deep learning. The field of deep learning is continuously evolving, and researchers are exploring various combinations of methodologies and models to push the boundaries of AI capabilities. Hybrid approaches can provide new insights and solutions to complex problems by leveraging the strengths of different techniques and domains.

5. RESULT

This review clearly shows that CNNs are the most popular DL models for ECG classification thanks to their excellent capability for feature extraction [80]. As ECG signals are time series in nature, RNNs are another popular type of DL model that has been widely adopted. The transformer is a type of relatively new DL model with the emergence of the attention mechanism and has been used in some recent works. In addition, it clearly shows that more studies leverage hybrid DL models for the arrhythmia classification. Specifically, the CNNs often served as feature extractors right after the input layer of the hybrid model [81]. Other DL structures, such as RNNs and transformers, are exploited to further extract refined features. Their results show that in most cases, the hybrid model could achieve better classification performance but induce higher computational complexity [82,83,84–87]. However, as most selected studies consider traditional DL models such as CNNs and RNNs, the investigation into incorporating novel DL models or structures for arrhythmia classification with ECG signals is still limited. With the emergence of novel DL models such as ViT [88] and MLPMixer [89], the adaption of those novel DL models is expected to be introduced for ECG classification to pursue better performance improvement. In addition, most selected works focus on the improvement in classification performance as much as possible, while the

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interpretability of DL models is generally not discussed. The interpretable DL models [90] are highly desired to make the ECG classification results trusted in real clinical scenarios and could potentially further help cardiologists relate the heart abnormalities to possible hidden features of ECG signals, such as ECG phenotyping discussed in [91].

In most of the reviewed studies, the DL models are exploited under the supervised learning framework. However, how to leverage DL models in other artificial intelligence frameworks, such as active learning [92] and reinforcement learning [93], to improve the accuracy of ECG diagnosis could be one future research direction. In addition, how to systematically optimize the DL model structures, such as the size of convolutional kernels and hyperparameters, such as the minibatch size and learning rate, could be another crucial control knob for ECG classification.

CONCLUSION

The extensive exploration of deep learning techniques for ECG-based arrhythmia diagnosis highlights their promising potential for clinical applications. However, this survey underscores the need for further research efforts in several crucial aspects of the deep learning pipeline to ensure reliable implementation in clinical ECG arrhythmia classification.

Specifically, future research directions and opportunities include:

Utilizing diverse ECG databases: There is a need to incorporate a wide range of ECG databases for training and testing deep learning models, ensuring robustness and generalizability across different patient populations and data sources.

Advanced denoising and data augmentation techniques: Developing sophisticated methods for denoising ECG signals and augmenting the dataset to enhance model performance and resilience to noise and variability.

Innovative integrated DL models: Designing novel architectures that integrate multiple deep learning techniques or modalities to improve the accuracy and efficiency of arrhythmia classification.

Deeper investigation in the inter-patient paradigm: Exploring the inter-patient variability in ECG signals and developing models that can effectively handle variations among individuals, thus enhancing the reliability and applicability of DL-based arrhythmia classification in real clinical scenarios.

By addressing these research areas, the field can advance towards more trusted deep learning-based arrhythmia classification, ultimately facilitating its widespread adoption and impact in clinical practice.

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