Arrhythmia Classification on ECG by Deep Learning

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***Abstract*—Computer-assisted cardiac arrhythmia classification can play a significant role in the management of cardiac disorders. The prevailing approach for disease identification involves analyzing Electrocardiogram(ECG) data, a medical monitoring technology capturing cardiac activity. However, the scarcity of expert analysts to interpret vast amounts of ECG data poses a significant challenge, consuming substantial medical resources. Consequently, leveraging machine learning for identifying ECG characteristics has emerged as a promising alternative. Our study focuses on classifying five distinctive types of heartbeat features, employing a wavelet self-adaptive threshold denoising method in our experiments. To enhance our understanding, we conduct a comparative analysis of various models, including Custom-designed CNN model, VGG, ResNet, and leveraging commonly used wavelet waveforms. Our objective is to identify optimal features and models, providing reference material for researchers in this domain. Accurate classification through this approach effectively conserves medical resources, presenting a favorable impact on clinical practices.**

***Index Terms*—ECG, CNN, wavelet, feature extraction**

I. Introduction

A. *Define*

Arrhythmias are deviations from the regular heartbeat rhythm, leading to either an accelerated or decelerated heart rate, depending on the specific type of arrhythmia [1,2]. Precise classification of these conditions is vital for comprehending and addressing irregularities. Multiple approaches, such as machine learning, deep learning models, and signal processing techniques, have been utilized to categorize arrhythmias using Electrocardiogram (ECG) signals. The preprocessing of ECG signals involves the removal of noise and the extraction of essential features, facilitating effective information representation within the models.

Methods for accurately classifying these diseases include the utilization of machine learning, deep learning models, and signal processing techniques. Cardiovascular disease poses a significant threat to human health, particularly among middle-aged and older individuals, characterized by its high prevalence, disability, and mortality rates. In the current era, with a growing aging population, the exacerbation of cardiovascular disease has emerged as a major public health concern. ECG analysis serves as an effective means of assessing heart health. Therefore, the identification and classification of ECG signals are crucial for cardiovascular diseases, not only for early prevention but also for timely detection and appropriate treatment. Studying the classification of related ECG signals holds considerable significance [3].

B. *ECG signal*

Electrocardiography involves the creation of an electrocardiogram (ECG), a record detailing the heart's electrical activity across repeated cardiac cycles. The ECG comprises three key components:
- The P wave represents atrial depolarization.
- The QRS complex signifies ventricular depolarization.
- The T wave denotes ventricular repolarization.

This visual time series captures real-time electrical activity in each heart cycle and is widely utilized for heart rate detection. As a non-invasive method, ECG analysis is user-friendly and has become an indispensable tool for aiding doctors in pathology assessment. Presently, cardiovascular disease diagnosis relies largely on the expertise of medical professionals. However, the multitude of heart conditions, coupled with the potential for manual detection errors, underscores the need for a quicker and more accurate analysis approach. Furthermore, ECG signals possess traits such as randomness, low-frequency nature, and susceptibility, leading to unstable diagnostic outcomes. Intelligent automatic recognition and classification of ECG signals are now imperative for enhancing efficiency and accuracy in ECG interpretation.

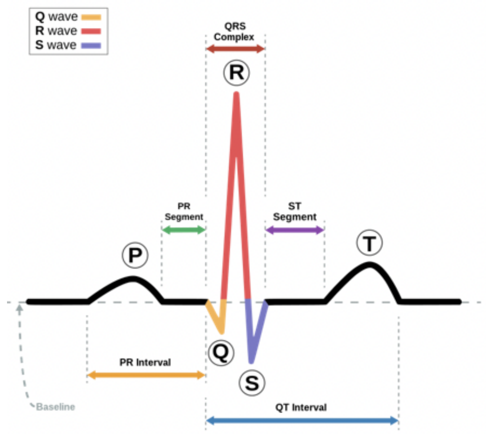

Fig. 1: Peaks of ECG signal.

C. R-R Interval Features

Features such as wavelet and Independent Component Analysis (ICA) are derived from a single heartbeat's waveform. The rationale behind incorporating these features lies in the recognition that irregular heart rhythms differ not only in structure but also in their dynamic behavior. To capture the rhythm in the vicinity of a heartbeat, four dynamic attributes are introduced, drawing inspiration from established research [4]. These attributes include the previous RR interval, subsequent RR interval, local RR interval, and average RR interval. The RR interval signifies the duration between the given heartbeat and the preceding one, offering insights into the temporal pattern. Conversely, the subsequent RR interval represents the time gap between the given beat and the subsequent one, providing information on the following heartbeat. The local RR interval is defined as the average of ten RR intervals surrounding the specific beat, contributing to a comprehensive understanding of the immediate context. Additionally, the average RR interval is calculated for each dataset, divided into six 5-minute intervals. This calculation involves averaging the RR intervals within the corresponding 5-minute interval, reflecting the overall rhythm dynamics during those periods.

D. Related work

As Artificial Intelligence (AI) technology advances, various machine learning methods are increasingly applied to detect features in Electrocardiogram (ECG) signals, addressing challenges associated with extensive ECG data and the burdensome nature of manual detection. Commonly used methods include neural networks (NN), support vector machine (SVM), path forest, and the Independent Component Correlation Algorithm (ICA).

Recently, machine learning and deep learning networks has shown significant progress not only in image processing and audio recognition but also in the assisted diagnosis of heart diseases based on ECG signals.

In the work by Mengze Wu et al [1], the authors propose a distinctive convolutional neural network (CNN) structure comprising twelve layers, specifically designed to categorize five subclasses of cardiac arrhythmia. In contrast to traditional neural networks, CNNs employ convolution and pooling layers to extract and map features from input data, accelerating learning and mitigating overfitting. Unlike the prevalent two-dimensional CNNs used in image processing, this model is uniquely crafted to process one-dimensional time series data gathered through regular interval sampling. Notable adaptations include the utilization of an average-pooling layer, preserving fundamental input data features vital for heartbeat classification. Moreover, this modified CNN architecture integrates an additional alternating convolution and pooling layer compared to standard CNN networks. These structural enhancements aim to optimize the accurate classification of cardiac arrhythmia subclasses.

The findings from Masko and Hensman's study conducted in 2015 [2] indicate that imbalanced training data may significantly deteriorate the overall performance of CNN models, with balanced training data demonstrating superior outcomes. Subsequently, the application of oversampling techniques on imbalanced training sets is employed to enhance their performance, aiming to match that of the balanced dataset. This study concludes that employing oversampling techniques presents a viable strategy to mitigate the detrimental impact of imbalances present within training data.

R. Ganesh Kumar et al [3] introduce a method for classifying arrhythmic beats based on the RR interval. Their approach involves converting the RR interval using discrete cosine transform. Extracted RR intervals from the ECG signal serve as the fundamental feature for classification purposes. The MIT-BIH arrhythmia database was utilized to conduct diverse experiments in their study.

In the work by Sameer K. Salih et al [4] , a methodology aimed at detecting the QRS complexes within ECG signals, along with analyzing the RR intervals. The proposed technique is evaluated using the MIT-BIH Arrhythmia dataset. Additionally, a comparison is made with traditional techniques, positioning this method as one of the best comparable approaches in the field.

While most studies concentrate on extracting vital information from ECG data, challenges persist, including data processing and feature extraction. In comparison to traditional neural networks, deep learning networks excel in automatically extracting features, recognizing intricate data patterns, and eliminating the need for complex signal preprocessing. Convolutional neural networks (CNN) have been successfully applied to arrhythmia classification. In this study, our focus lies in adopting a combined approach, leveraging CNN along with the incorporation of wavelet characteristics. The aim is to compare feature structures suitable for each network type, thereby enhancing accuracy. Furthermore, we aim to compare these models with other prominent deep learning classifiers such as VGG and ResNet.

II. Method

A. Data Processing

1) Dataset: The MIT-BIH Arrhythmia Database comprises 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Among these, 23 recordings were randomly selected from a set of 4000 24-hour ambulatory ECG recordings, collected from a mixed population of inpatients (approximately 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital. The remaining 25 recordings were specifically chosen to include less common but clinically significant arrhythmias not well-represented in a small random sample.

The diagram below is our proposed method.

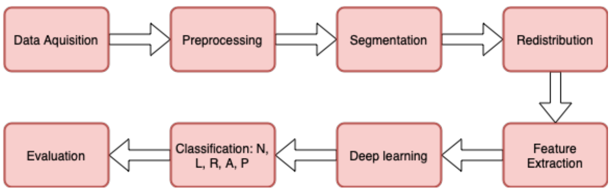

Fig. 2: Proposed method

2) Data Preprocessing: ECG signals collected in clinical settings often face interference such as power frequency disruptions, baseline drift, and electromyographic (EMG) interference. To enhance classification accuracy, raw data requires denoising procedures. Commonly used methods in ECG denoising include bandpass filters, low-pass filters, and wavelet transforms (Ahlstrom and Tompkins, 1985; Bazi et al., 2013; Wang et al., 2015; Yadav et al., 2015). This study employs the wavelet transform technique for preprocessing ECG signals, an algorithm proficient at decomposing non-stationary signals into distinct frequency bands. The following figures depict the filtered data obtained from an example file, where the blue line represents the raw signal, and the red line signifies the filtered signal.

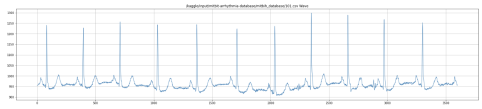

Fig. 3: Raw data from 101.csv

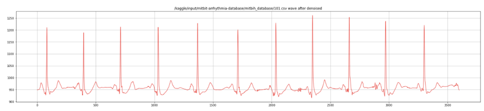

Fig. 4: Filtered data from 101.csv

3) Data Extraction: We performed a signal processing operation to extract beats from the signal. The beats were cut using a window size of 360 samples, with 180 samples preceding the annotation and 180 samples succeeding the annotation. We obtained a total of 100,012 beats from the dataset, and subsequently stored the beat data in a matrix with dimensions 100,012 x 360, where each row represents an individual beat, and the 360 columns capture the samples within each beat.

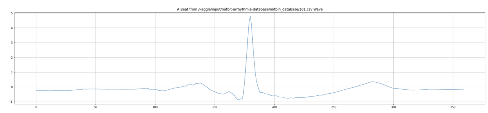

Fig. 5: An extracted beat wave from 101.csv

4) Data Segmemtation: With the input shape of 100,012 x 360, the data is then divided into 5 classes: normal (NOR), left bundle branch block (LBBB), and right bundle branch block (RBBB), Atrial premature beats (AP), premature ventricular beats (PVC). [1]

Class	Beats
NOR	75011
LBBB	8071
RBBB	7255
AP	7129
PVC	2546

TABLE I: Classes Distribution

Due to the initial imbalance in the dataset, we addressed this issue by adjusting the distribution of each class to achieve a more equitable representation. After the rebalancing process, each class comprises approximately 5000 beats. Consequently, the total number of beats in the dataset is now 25000. For model training purposes, we partitioned 20000 beats for the training set and reserved the remaining 5000 beats for the test set.

B. Feature Extraction

1) Wavelet transforms: In signal processing, various mathematical models can be used to analyze data, such as Fourier transforms, but they suffer from time leakage. Wavelet transform addresses this issue, providing both time and frequency parameters, as well as the signal spectrum. Popular wavelet families chosen for this research include db3, sym3, bior6.8, dmey, coif3, rbio2.2, bior1.3, and coif2.

a) Daubechies Wavelets:
The parameter N represents the number of vanishing moments present in these wavelets. Alternatively, in the literature, these filters are characterized by the number of filter taps, precisely 2N [5]. We opted for the Daubechies wavelet with 3 vanishing moments, commonly denoted as db3. This particular wavelet function is widely utilized in wavelet analysis and signal processing due to its ability to strike a balance between time and frequency localization.

b) Symlet Wavelets:
The symN wavelets are Daubechies' least-asymmetric wavelets. Compared to the extremal phase wavelets, symlets exhibit greater symmetry. In the symN wavelet, N denotes the number of vanishing moments. In literature, these filters are also identified by the number of filter taps, precisely 2N [5].

c) Biorthogonal Wavelet:
Biorthogonal wavelets are characterized by a pair of scaling functions and their corresponding scaling filters, encompassing one set for analysis and another for synthesis. Additionally, there exists a pair of wavelets accompanied by their respective wavelet filters, with one set dedicated to analysis and the other for synthesis [5].

d) Reverse Biorthogonal Wavelet:
Reverse Biorthogonal wavelet and scaling function are defined in the frequency domain. [5].

e) Coiflet Wavelets
Coiflet scaling functions also have vanishing moments. In coifN, N signifies the number of vanishing moments for both the wavelet and scaling functions. In literature, these filters are alternatively denoted by the number of filter coefficients, precisely 3N [5].

f) Meyer Wavelet:
The Meyer wavelet and scaling function are defined in the frequency domain. [5]

C. Model Selection

In the field of neurological research, the precise classification of disease labels within electroencephalogram (EEG) signals is crucial for diagnosing various neurological conditions. Machine learning techniques, particularly deep learning models, have shown promising potential in this domain. This study focuses on the exploration and comparison of three prominent deep learning architectures: Custom-designed Convolutional Neural Networks (CNN), VGG19, and ResNet18, with the aim of classifying disease labels within EEG signals.

The selection of these models is based on their diverse architectural complexities and their respective capabilities in learning intricate features from data. CNN serves as a foundational model for image processing, VGG19 offers a deeper architecture, and ResNet18 incorporates residual connections to address gradient vanishing issues. Each model brings distinct advantages to the task of disease classification within EEG signals.

The motivation for exploring these models lies in the effort to comprehensively evaluate and compare their performance in discerning disease labels within EEG data. This comparative analysis aims to highlight the strengths and weaknesses of each model, providing valuable insights to enhance diagnosis accuracy and contribute to more effective identification and treatment of neurological diseases.

The detailed structure of the CNN, VGG19, and ResNet18 models implemented in this study will be clearly outlined later in the paper.

1) Custom-designed CNN model Architecture:
The architecture of the Convolutional Neural Network (CNN) used in this study consists of a series of convolutional layers and average pooling layers. The model initiates with a 1D convolutional layer featuring 16 filters of size 13x1 and applies the ReLU activation function to input data of size (input_shape, 1). Following this, an average pooling layer with a window size of 3 and a stride of 2 is introduced. Subsequently, another 1D convolutional layer, utilizing 32 filters of size 15x1 with ReLU activation, is followed by another average pooling layer. The architecture further includes a 1D convolutional layer with 64 filters of size 17x1 and ReLU activation, succeeded by an average pooling layer. Additionally, a 1D convolutional layer with 128 filters of size 19x1 and ReLU activation is incorporated, followed by a final average pooling layer. The network concludes with a flattening layer, dropout regularization with a rate of 0.5, and two dense layers. The first dense layer comprises 35 units, and the second dense layer comprises 5 units, both employing softmax activation for final classification.

2) VGG19 Architecture: Adopting the VGG19 architecture as a template, a modified 1D Convolutional Neural Network (CNN) model is created. The architecture includes several convolutional layers and average pooling layers. The model starts with a 1D convolutional layer featuring 16 filters of size 13 with ReLU activation applied to an input shape of 380x1. The average pooling layers have window sizes of 3 and strides of 2. The 1D convolutional layers utilize 32, 64, and 128 filters, with kernel sizes of 15, 17, and 19, respectively. Each of these convolutional layers is followed by the application of the Rectified Linear Unit (ReLU) activation function. A flattening layer reshapes the output before a dropout layer with a rate of 0.5 is applied. The model concludes with two dense layers: the first with 35 units utilizing ReLU activation, and the second with 5 units using softmax activation for classification. Both dense layers incorporate L2 regularization with a rate of 0.0001.

3) ResNet18 Architecture: This architecture employs 1D convolutional layers within a Sequential model. The model starts with a single convolutional layer featuring 64 filters, each with a kernel size of 3, 'same' padding, and ReLU activation applied to an input shape of 380x1. Residual blocks are then constructed, comprising a total of four blocks, each consisting of two convolutional layers with a kernel size of 3x3, batch normalization, and ReLU activation. The stride parameter controls down-sampling in residual blocks, progressively increasing the output channel size from 64 to 512. GlobalAveragePooling1D is used for dimension reduction before the fully connected layers. The network concludes with two dense layers: the first containing 35 units with L2 regularization (rate of 0.0001), and the final layer producing output across the specified number of classes. Both dense layers incorporate bias and kernel regularizers along with a Softmax activation function for classification.

III. RESULTS AND DISCUSSIONS

We applied three models—CNN, VGG19, and ResNet18—incorporating 8 wavelet features. Each model exhibited varying levels of accuracy, all of which were notably high. This outcome holds promise for an effective solution in the classification of ECG signals based on deep learning.

	CNN		VGG19		ResNet18	
	T.A	T.L	T.A	T.L	T.A	T.L
db3	0.9924	0.0430	0.9924	0.0469	0.9838	0.0700
sym3	0.9930	0.0352	0.9924	0.0458	0.9782	0.1107
bior6.8	0.9910	0.0543	0.9924	0.0515	0.9858	0.0797
dmey	0.9936	0.0330	0.9934	0.0533	0.9844	0.0649
coif3	0.9970	0.0243	0.9900	0.0611	0.9836	0.0836
rbio2.2	0.9936	0.0386	0.9888	0.0655	0.9732	0.1036
bior1.3	0.9910	0.0509	0.9932	0.0587	0.9858	0.0660
coif2	0.9966	0.0253	0.9912	0.0628	0.9828	0.0792

TABLE II: Test Accuracy and Test Loss of our proposed method

T.A: Test Accuracy T.L: Test Loss

In the comparative analysis of three models—CNN, VGG19, and ResNet18—utilizing various wavelet features, the CNN consistently outperforms with higher test accuracy and lower test loss. Specifically, the coif2 and coif3 wavelet features exhibit remarkable performance across all models, showcasing superior accuracy and minimal loss. VGG19 demonstrates competitive results but generally lags slightly behind CNN. ResNet18 exhibits comparable accuracy but tends to have higher test loss, emphasizing sensitivity to the choice of wavelet features. Notably, the selection of wavelet features significantly influences the models' performance, with features like "dmey" and "coif3" also yielding promising results. This analysis underscores the importance of both model architecture and the choice of wavelet features in optimizing the classification of the given data. Conversely, 'rbio2.2', 'bior1.3', and 'sym3' demonstrated lower accuracy and stability across CNN, VGG19, and ResNet18, indicating a consistent pattern of performance decline with these families.Especially, Tte two highest accuracy belongs to CNN model with coif3 and coif2 Wavelet which is 99.70 % and 99.66%, respectively. The two lowest accuracy belongs to ResNet18 with rbio2.2 and sym3 Wavelet which is 97.32% and 97.82%, respectively.

These findings highlight the pivotal role of wavelet family selection in influencing the stability and accuracy of the models. The observed discrepancies emphasize the need for tailored optimization strategies and meticulous hyperparameter tuning for individual wavelet families to achieve optimal synergy with each model, thereby enhancing performance and stability.

The provided references present a comprehensive overview of different approaches to ECG signal classification, highlighting diverse feature sets, classifiers, and associated accuracies. In our proposed method, the use of Wavelet and Coif3 features with a CNN classifier results in an outstanding accuracy of 99.70%. Additionally, the proposed method employs Wavelet and dmey features with a VGG19 classifier, achieving a commendable accuracy of 99.34%. For ResNet18 in the proposed method, using Wavelet features such as bior6.8 or bior1.3 leads to a notable accuracy of 98.58%. This collective evidence underscores the effectiveness of diverse feature sets and classifiers in ECG signal classification, with the proposed method showcasing particularly promising results across different configurations.

IV. CONCLUSIONS

Cardiovascular disease remains a significant global health concern today. Early detection of cardiac arrhythmia heavily relies on electrocardiogram (ECG) analysis. However, the scarcity of expert-level medical resources makes visually identifying ECG signals challenging and time-intensive. We particularly highlight Normal, Left Bundle Branch Block, Right Bundle Branch Block, Atrial Premature Beats, and Premature Ventricular Beats in MIT-BIH Arrhythmia database.

Our study demonstrates the effectiveness of our proposed method in accurately distinguishing between these 5 categories of heartbeats, leveraging wavelet and RR interval features. The method has been rigorously validated across the entire MIT-BIH Arrhythmias

Database, achieving an average accuracy of 99.70% and 99.67% with Coiflet Wavelets in the CNN model presented in this paper. This accuracy notably surpasses other parameters and outperforms VGG and ResNet models.

Moreover, our research delves into an in-depth analysis of the classification of ECG signal micro-classes, comparing techniques in deep learning, including VGG and ResNet. We contribute valuable insights by discussing the results of less commonly explored micro-classifications of Arrhythmia and Wavelet wave types. These findings serve as a robust benchmark for researchers in this field, paving the way for further advancements and investigations.

The table below is a survey of some previous studies and were all conducted on the MIT-BIH arrhythmia Database. The comparison table shows that the wavelet methods we tested and gave the best results outperformed previous studies.

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References	No.Cl	Feature set	Classifier	Acc (%)
Li et al. (2014) [6]	5	WPE+RR	RF	94.61
Osowski et al. (2004) [7]	13	HOS+Herminte	SVM	98.18
Martis et al. (2013) [8]	5	Cumulant+PCA	NN	94.52
Zubair et al. (2016) [9]	5	Frequency components	CNN	92.70
Plawiak and Acharya (2020) [10]	17	Gagor Filter+Wavelet	DGEC	94.60
Atal and Singh (2020) [11]	5	Wavelet	BaRQA - DCNN	93.19
Mengze Wu et al. (2021) [1]	5	Wavelet, Sym4	CNN	97.20
Our method	5	Wavelet, coif2 or coif3	CNN	99.70
Our method	5	Wavelet, dmey	VGG19	99.34
Our method	5	Wavelet,bior6.8 or bior1.3	ResNet18	98.58

TABLE III: Evaluation of our method with previous research.

No.Cl: Number of classes, Acc: Accuracy

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