ORIGINAL ARTICLE

A Deep Learning Approach for Detecting Atrial Fibrillation using RR Intervals of ECG

Shrikanth Rao S.K [1*] ,**MaheshKumar H Kolekar** [2], **Roshan Joy Martis** [3]

[1] *Department of Electronics & Communication Engineering, Vivekananda College of Engineering & Technology, Puttur, Dakshina Kannada, India*

[2] *Department of Electrical Engineering, Indian Institute of Technology, Patna, India*

[3] *Department of Computer Science and Engineering, Global Academy of Technology, Bangalore, India*

*Corresponding Author: Shrikanth Rao S.K
Email: skanthrao@gmail.com

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Abstract

Purpose: Atrial Fibrillation (AF) is one of the most common types of heart arrhythmias observed in clinical practice. AF can be detected using an Electrocardiogram (ECG). ECG signals are time-varying and nonlinear in nature. Hence, it is very difficult for a physician to manually perform accurate and rapid classification of different heart rhythms.

Materials and Methods: In this paper, we propose a method using Discrete Wavelet Transform (DWT) with db6 as the basis function for denoising ECG signal.

Results: The denoised ECG is smoothened using the Savitzky- Golay filter. Deep learning methods, such as a combination of Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) (CNN-LSTM) and ResNet18 are used for the accurate classification of ECG signals using Physionet Challenge 2017 database.

Conclusion: With a 10-fold cross-validation method the model provided overall accuracy of 98.25% with the CNN-LSTM classifier.

Keywords: Atrial Fibrillation; Electrocardiogram; Discrete Wavelet Transform; Savitzky-Golay Filter; Convolutional Neural Network; Long Short Term Memory; ResNet18.

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1. Introduction

One of the major causes of a reduced lifespan and health span is Cardiovascular Disease (CVD). CVD can lead to strokes, heart attacks, and heart failures, and can damage many organs in the body. The incidence and prevalence rate of CVD is increasing globally. 50 million people in the world are affected by CVD [1]. In 2020, nearly 19 million deaths were attributed to CVD globally which amounted to an increase of 18.7% from 2010 [2]. The annual healthcare budget of America for CVD is estimated to be $555 billion and in Europe, it is estimated to be $210 billion [3]. Arrhythmia is a CVD. Atrial Fibrillation (AF) is one of the common arrhythmias characterized by irregular heartbeat. AF is associated with serious potential health complications, such as stroke, heart failure, morbidity, etc. 3.046 million new cases of AF were registered globally in 2017 and the prevalence rate of AF has increased by 33% in the last 20 years [4]. AF has been associated with an increased risk of mortality in patients with COVID-19 [2]. In order to accurately detect AF, using an Electrocardiogram (ECG), lot of analysis and medical expertise is required. This problem increases especially in developing countries where there is an acute shortage of clinical equipment and medical expertise. Hence a computer-assisted system can help medical expertise in accurately diagnosing AF.

1.1. Previous Studies

Previously Machine Learning (ML) methods have been widely used for the accurate classification of ECG signals into various rhythms.ML methods such as Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), K- Nearest Neighbor (K-NN), etc. were implemented using handcrafted features extracted from ECG signal [5-10]. Ahmed *et al.* [11] developed low-cost AF detecting machine using a microcontroller and Bitalino ECG sensor. The method adopted RR intervals to detect AF. Mohit *et al.* [12] suggested a flexible analytic wavelet transform approach to detect AF using entropy features. The developed algorithm demonstrated an accuracy of 96.84 % with a random forest classifier. Liu *et al.* [13] proposed a statical, f wave presence, and entropy features-based approach to detect AF. The method used an SVM classifier and demonstrated an F1 score of 84%. Zhao *et al.* [14] proposed a new entropy method that included a ranged function, fuzzy function, density estimation, and flexible distance threshold to diagnose AF, and demonstrated an accuracy of 87.10%. Shao *et al.* [15] suggested a method that used RR interval and multi-level features to detect AF. The method used a decision tree ensemble classifier and recorded an F1 score of 82%.

In recent years, many Deep Learning (DL) models have been extensively used for rhythm identification. DL models include CNN, LSTM, GoogleNet, AlexNet, ResNet, etc. which use either extracted features or extracting deep features from the given signal [16-20]. Zhang *et al.* [21] proposed a method that extracts multi-scale features to improve the performance of classification. The method used CNN and demonstrated an accuracy of 99.84%. Dagher *et al.* [22] proposed deep a neural network approach to detect AF using a smart phone. The model demonstrated an accuracy of 94%. Xie *et al.* [23] proposed a combination of ResNet34 and 3-layer LSTM for the classification of heart rhythm and observed an F1 score of 86.1%. Feng *et al.* [24] suggested an improved bidirectional LSTM approach to automatically detect AF. The method demonstrated an accuracy of 98.2%. Manisha *et al.* [25] made a review of ML and DL methods available for the classification of ECG beats. The paper concluded that data augmentation and model optimization are important areas to focus on improving the performance of the system. Murat *et al.* [26] made a comparative study on the various DL approaches available for arrhythmia detection. The paper highlighted some of the techniques that make DL more effective for ECG classification. Rezaee *et al.* [27] proposed a graph CNN method extracting features using heart sound signals and obtained an accuracy of 99.44%. Moradi *et al.* [28] designed a sleep stage classification method using time-frequency features extracted from ECG combined with deep features of CNN and recorded an accuracy of 98.92%.

1.2. Challenges and Problems

Among the existing literature on AF detection, various authors have proposed feature-based methods for pattern classification of ECG using either traditional machine learning algorithms or deep learning algorithms where features are automatically mapped into respective output classes. A few pieces of literature are available where RR interval features are used for classification, yet systematic and exhaustive experimental evidence to prove which combination of methods provides a superior performance is lacking in this domain.

1.3. Proposed Method

In this study, CNN-LSTM and ResNet18 network are independently used to classify three rhythms of ECG i.e. normal, AF, and other rhythms. ECG data is taken from Physionet Challenge 2017. ECG signal is denoised using DWT with db6 as the basis function. The denoised ECG signal is smoothened using the Savitz-Golay filter. RR intervals are computed and are given to the CNN-LSTM and ResNet18 classifier independently. The class-specific accuracy corresponding to normal, AF, and other rhythms is computed.

2. Materials and Methods

The proposed approach is shown in Figure 1. It involves the removal of baseline wander and other noise components by using DWT, and smoothening of ECG signal using the Savitz-Golay filter, R peak detection using Pan Tompkins algorithm, RR interval extraction, and finally classification into normal, AF, and other rhythms.

2.1. Data Set Used

In this study open source dataset, Physionet Challenge 2017 is used. The dataset used in this study comprises 5,154 signals with normal rhythm (N), 771 signals with AF, and 2557 signals with other rhythms. Each of the ECG signals has varied length between 9 seconds and slightly more than one minute [29].

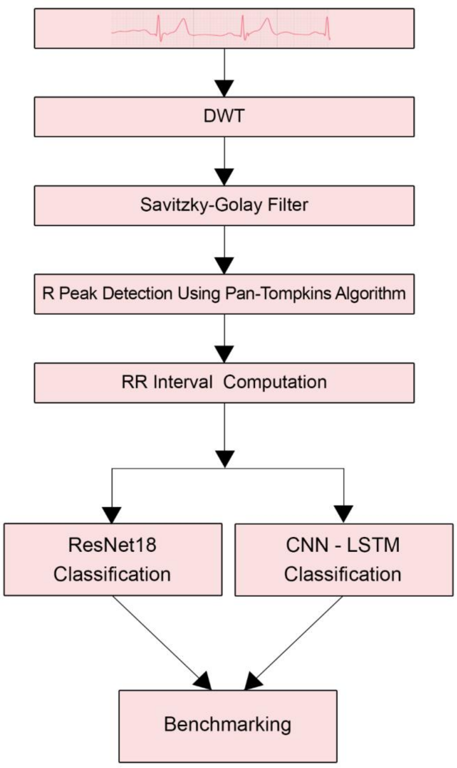


Figure 1. Proposed methodology

2.2. Pre-Processing

ECG signals include distinct noises such as baseline wander, muscle and movement artifacts, interference of power line, electrode pop noise, etc. DWT is used to remove the noises present in the ECG signal. Daubechies6 (db6) is used as the basis function in the time-frequency decomposition of ECG signal using DWT [30, 31]. The ECG signal is sampled at 300Hz and is decomposed into 8 levels. The frequency band of 75Hz -150Hz does not include the required components of the ECG signal. This sub-band represents Ist level detail. Hence, this sub-band is not considered during the reconstruction step. The frequency component of 0-0.5Hz represents baseline wander and is the eighth-level approximation sub-band which is also not required. The necessary bands are IInd, IIIrd, IVth, Vth, VIth, and VIIth levels detail sub-bands. Hence first-level detail coefficients and VIIIth-level approximation coefficients are replaced with zeros during the reconstruction process of inverse wavelet transformation to obtain the denoised ECG signal. The denoised ECG signal is further subjected to the Savitzky-Golay filter for smoothening. In this study, we have used 5th order polynomial for ECG smoothening. The smoothened ECG is subjected to QRS complex detection with the help of the Pan Tompkins algorithm to detect RR intervals [32].

2.3. Classification

In order to discriminate the ECG signal into 3 rhythms viz: normal, AF, and other rhythms, DL classifiers such as ResNet18 and CNN-LSTM are used.

2.3.1. ResNet18

Very deep neural network suffers from the problem of vanishing gradient. To address this problem, a new learning method based on a residual learning framework was introduced by Kaiminh He *et al.* [33]. They proposed ResNet architecture. ResNet18 has 18 deep layers. Formulation of residual network in the ResNet architecture is similar to feedforward network with shortcut connections as shown in Figure 2.

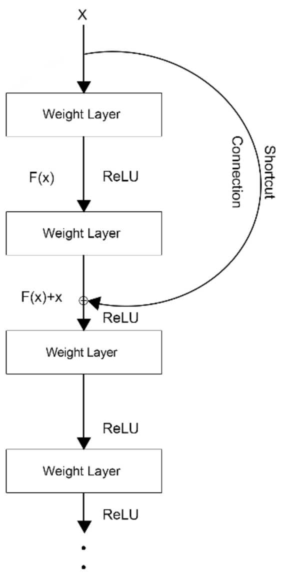


Figure 2. ResNet architecture [33]

The steps that built up in ResNet network are listed below:

```
Load 1D ECG signal
Set training label
Set training data
Compute the size of training data
Reshape training data (m, n);
Set testing label
Set testing data
Compute the size of testing data
Reshape testing data (m, n);
Load pretrained convolutional Network
net = ResNet18

layers = [
imageInputLayer([m n 1])
net(2 : end - 3)
convolution2dLayer(m - 1, n)
reluLayer()
maxPooling2dLayer(2, 'Stride', 1)
fullyConnectedLayer(3)
softmaxLayer()
classificationLayer()];

options = trainingOptions('adam');
net = trainNetwork(training data, training label, layers, options);
netCNN = net;
inputSize = net.Layers(1).InputSize(1 : 2);
layerName = "maxpool";
activations(netCNN,XTrain,layerName,'OutputAs','columns');
end
```

2.3.2. CNN-LSTM

CNN works on the principle of convolution. If x and y are the two functions, then the convolution integral expresses how these two functions are correlated. CNN is extensively used for time series classification because of dilated convolution. Dilated convolution allows CNN to understand the relationship between the different observations in the time series in a better manner. LSTM is a recurrent neural network. LSTM accounts for sequential dependencies in time series [34]. Often CNN-LSTM combinations are used for time series classification because of the dilated convolution nature of CNN and the sequential time dependency nature of LSTM architecture [35].

In our study, CNN architecture extracts the dimensionally reduced deep features and these extracted features are given to LSTM layer. The architecture of CNN-LSTM network used for our study is shown in Figure 3.

The network details are shown in Table 1.

Table 1. CNN-LSTM network hyper parameters

Layer	Parameter Name	Parameter Value
2D CNN	Filer size Filers	6 36
LSTM	Hidden units	300
Other parameters **Optimizer**	Adam Epochs Dropout rate Batch size	300 20% 25

3. Results

In this study, a three-class pattern classification problem of detection of normal, AF, and other rhythms using the ECG-derived RR interval is proposed. The methodology is implemented in MATLAB using the Physionet Challenge 2017 dataset. Baseline wander and high-frequency noise present in the ECG are removed

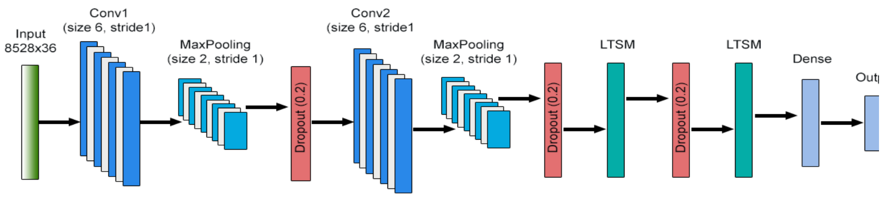
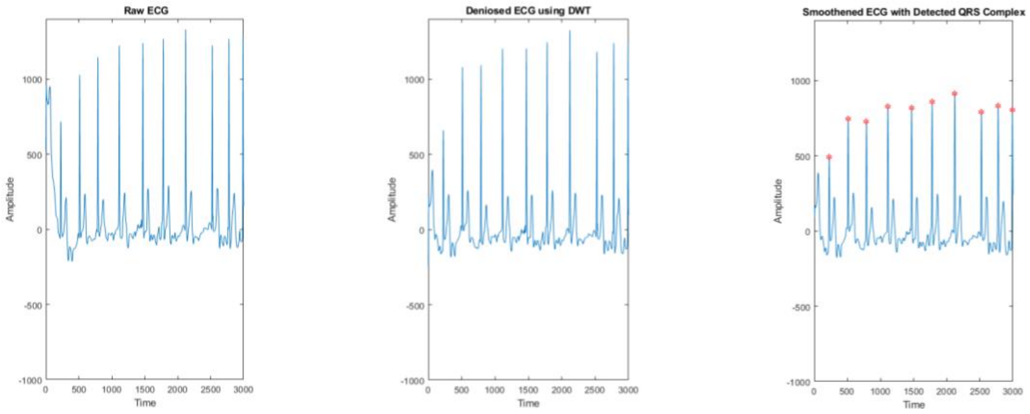


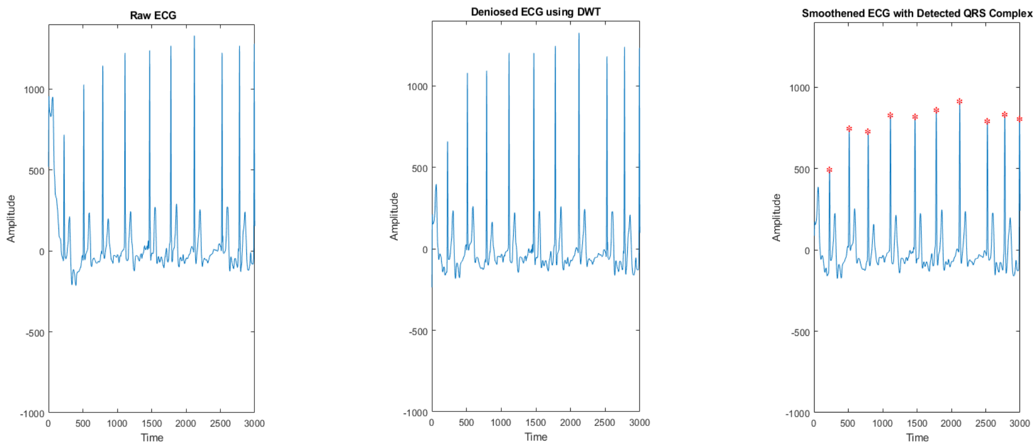
Figure 3. Proposed CNN-LSTM architecture

using DWT and smoothened using the Savitzky-Golay filter. Pan-Tompkins algorithm is used to detect QRS complex from smoothened ECG. Figure 4a shows raw ECG consisting of baseline wander. Figure 4b shows denoised ECG using DWT where the baseline wanders are removed. Figure 4c provides the visualization of the detected QRS complex of smoothened ECG which is marked in red asterisk from the denoised ECG for normal rhythm. Similarly, Figures 5 and 6 depict the same for AF and other rhythm signals. In total, the extracted 36



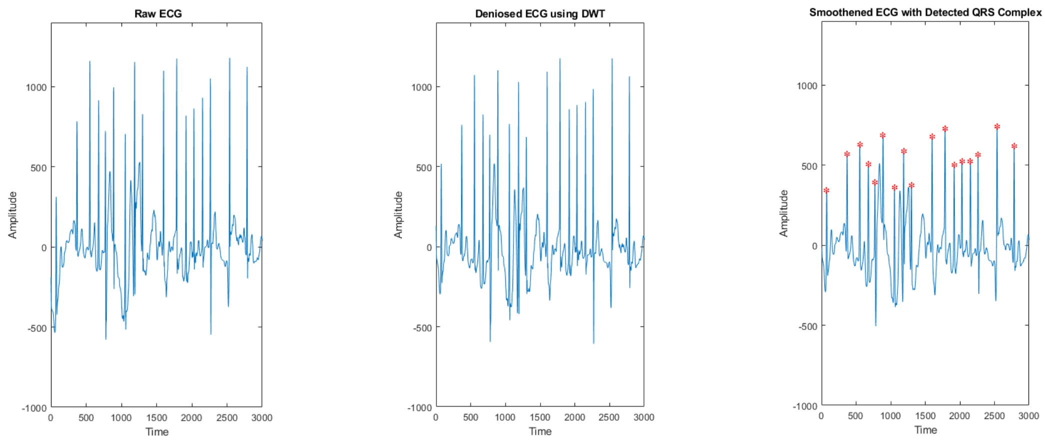
a b c

Figure 4. a: Raw ECG; b: Denoised ECG using DWT; c: Smoothened ECG QRS complex detection for normal ECG signal



a b c

Figure 5. a: Raw ECG; b: Denoised ECG using DWT; c: Smoothened ECG QRS complex detection for AF ECG signal



a b c

Figure 6. a: Raw ECG; b: Denoised ECG using DWT; c: Smoothened ECG QRS complex detection for another rhythm ECG signal

RR intervals are subjected to classification using DL algorithms. The average 10-fold cross-validation results of CNN-LSTM and ResNet18 classifier are shown in Table 2. It can be seen that the CNN-LSTM classifier achieved an overall accuracy of 98.25%. Figure 7 depicts the plot of overall accuracy and the class-specific accuracies of classifiers used.

Table 2. Average classification performance of CNN-LSTM and ResNet18 classifier

Classifier	NCSA	AFCSA	OCSA	OA
CNN-LSTM	98.98	93.77	98.49	98.25
ResNet18	98.51	92.34	97.81	97.53

NCSA: Normal Class Specific Accuracy;
AFCSA: AF Class Specific Accuracy;
OCSA: Other Rhythm Class Specific Accuracy;
OA: Overall Accuracy.

It can be seen from Figure 7 that the CNN-LSTM classifier provides higher performance metrics (NCSA of 98.98%, AFCSA of 93.77%, OCSA of 98.49%, and OA of 98.25%) in comparison with the ResNet18 classifier. During the training and the testing of the classifier 10-fold cross-validation is used. The variations in the overall accuracy with respect to different folds and different classifiers are plotted in Figure 8. It can be seen that the CNN-LSTM classifier provides the highest overall accuracy. Figure 9 shows the box plot of the OA of CNN-LSTM and ResNet18 classifier.

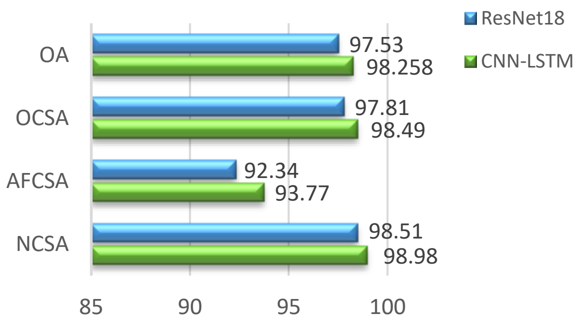


Figure 7. Overall accuracy, class-specific accuracies of ResNet18 and CNN-LSTM classifier

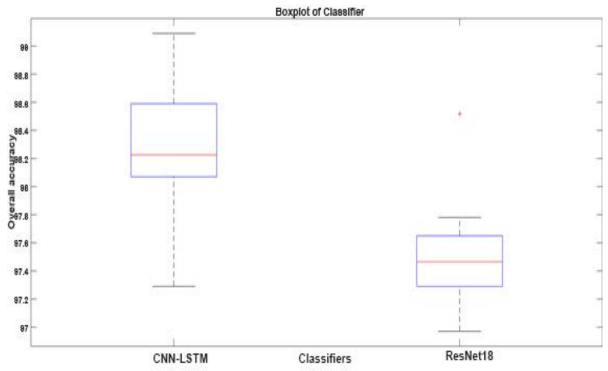


Figure 9. Box plot of OA

4. Discussion

In the present study, the CNN-LSTM classifier provided higher performance in comparison with ResNet18 classifiers. It is interesting to compare the performance obtained in the present study with the existing state-of-the-art methods available in the literature. Table 3 highlights some of the work carried out by authors on detecting AF using the Physionet challenge 2017 dataset. Wu *et al.* [17] proposed a hybrid CNN-LSTM architecture to detect AF. The method used 169 features of time, frequency domain, and nonlinear features and recorded an accuracy of 97.42%. Dagher *et al.* [22] proposed a deep neural network approach to detect AF using a smart phone. The model demonstrated an accuracy of 94%. Xie *et al.* [23] proposed a combination of ResNet34 and 3-layer LSTM for the classification of heart rhythm and observed an F1 score of 86.1%. Rubin *et al.* [36] proposed a spectrogram-based method to detect AF. The signal quality index technique was combined with DenseNet and the model achieved an F1 score of 82%. Sanchez *et al.* [37] suggested a gramian angular summation field method to detect AF. The author

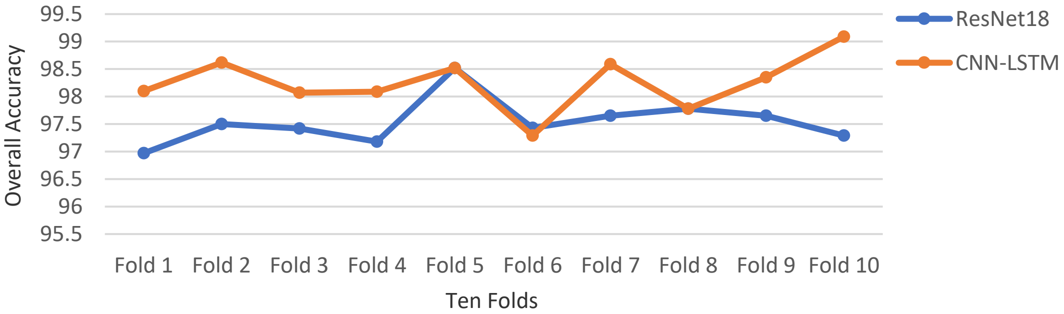


Figure 8. Plot of overall accuracy against different folds

used a CNN classifier and achieved an accuracy of 97.6%. Hsieh *et al.* [38] suggested a grid search method to detect AF. The algorithm used 1D CNN and recorded an F1 score of 78.2%. Rao *et al.* [39] proposed the DWT method combined with Principal Component Analysis to diagnose AF. The method used CNN and recorded an accuracy of 91.71%. Rao *et al.* [40] proposed a spectrogram method using RR intervals to detect AF. The method used CNN and observed an accuracy of 94.67%. Shi *et al.* [41] proposed a multiple feature fusion method to screen out AF. The model used 1D CNN architecture and recorded an accuracy of 91.7%. Nguyen *et al.* [42] suggested a method based on statistical features of segments to detect AF. The model used CNN architecture and recorded an F1 score of 84.19%. Najmeh *et al.* [43] suggested a neural architecture search method to diagnose AF using a CNN classifier and observed an F1 score of 84.15%. Wesselius *et al.* [44] proposed a methodology using the transfer learning method to detect AF. The model used the XGBoost classifier and observed an F1 score of 97.9%. Disha *et al.* [45] proposed a VGG16-based method to detect AF and observed an accuracy of 97.60%.

The current study focuses on extracting RR intervals and their classification using traditional DL classifiers. The 36 RR intervals are extracted from denoised and smoothened ECG signals are subjected to classification using the CNN-LSTM and ResNet18 classifier. During the study, it is found that CNN-LSTM classifier performed better compared to ResNet18 achieving an overall accuracy of 98.25%.

5. Conclusion

The prevalence rate of AF has increased in the last few years and is expected to increase in the near future. The public healthcare development system is an important area of focus especially in countries with a middle socio-demographic index. In this direction design of computer-assisted system that will classify ECG signals into different rhythms is very much required. This paper presents computer assisted system using DWT combined with a Savitzky-Golay filter-based method to detect AF using CNN-LSTM and ResNet18 classifier. ECG signal is denoised using the DWT method and smoothened using the Savitz-Golay filter. Pan-Tompkins algorithm is used to detect RR intervals. 36 RR intervals are extracted and are fed to CNN-LSTM and ResNet18 classifier, independently, for the detection of AF. A 10-fold cross-validation method is used to calculate the accuracy of the model. It is observed that the CNN-LSTM method provided an overall accuracy of 98.25% in comparison with other DL methods such as ResNet18. The improved performance of 98.25% with CNN-LSTM can be useful

Table 3. Overview of studies on the classification of ECG signal using the Physionet challenge 2017 database.

Literature	Techniques	Classifier	Overall accuracy
Wu *et al.* [17] 2021	Hybrid features	CNN-LSTM	97.42%
Dagher *et al.* [22] 2021	Time and frequency domain	CNN	94%
Xie *et al.* [22] 2021	Deep features	ResNet34 and LSTM	F1 score of 86.1%
Rubin *et al.* [36] 2018	Spectrogram	DenseNet	F1 score of 82%
Sanchez *et al.* [37] 2019	Gramian angular summation fields	CNN	97.6%
Hsieh *et al.* [38] 2020	Grid search	1D CNN	F1 score of 78.2%
Rao *et al.* [39] 2021	PCA and ICA	CNN	91.71%
Rao *et al.* [40] 2021	Power Spectrum	CNN	94.67%
Shi *et al.* [41] 2021	Multiple feature fusion	CNN	91.7%
Nguyen *et al.* [42] 2021	Stacking method	SVM and CNN	F1 score of 84.19%
Najmeh *et al.* [43] 2021	Neural architecture search	CNN	F1 score of 84.15%
Wesselinus *et al.* 2022 [44]	Transfer learning method	XGBoost	F1 score of 97.9%
Disha *et al.* [45]	RR intervals	VGG16	97.60%
Current Study	RR intervals	ResNet18	97.53%
Current Study	RR intervals	CNN-LSTM	98.25%

in applications such as defibrillators, pacemakers, and smartwatch applications which require higher performance. The proposed methodology has overcome some of the disadvantages of traditional approach like selection features and opting best features for better discrimination of signals. Further, the same methodology can be implemented using ResNet101 and CNN-BiLSTM classifier and a comparative study can be made.

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