Experimental Convolutional-Recurrent Network in ECG Rhythm for Atrial Fibrillation Classification

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***Abstract*— Atrial Fibrillation (AF) is a type of irregular heart beating problem which could lead to complications such as heart abnormalities events, including mortality and sudden cardiac death. The presence of AF can be diagnosed by electrocardiogram (ECG), including no clear P-wave and irregular pattern of RR-interval. Typically, the characteristics have been determined from the magnitude or duration of ECG. Unfortunately, it remains a difficult task due to its episodic nature. An automatic classification for AF from ECG signals is valuable for healthcare. This paper proposes a deep learning (DL) approach using a combination of convolutional neural network (CNN) as feature extraction and recurrent network as a classifier based on ECG short rhythm. Also, grid-search-based hyperparameter optimization is used to obtain optimal hyperparameters of the model. CNN learns to extract features used in the classification task, and a recurrent network is suitable for sequential prediction to model the flow of time directly. Among 60 models of hyperparameter tuning, the experimental results and analysis indicate that CNN-bidirectional long short-term memory (BiLSTM) outperformed the general model of recurrent neural network (RNN) and gated recurrent unit (GRU) with 96.49% accuracy. The proposed model by employing ECG short rhythm shows promising results and an important approach that can be applied to classify sequential data for AF signal classification.**

Keywords—atrial fibrillation, normal sinus rhythm, convolutional neural network, recurrent neural network, electrocardiogram signal

I. Introduction

Atrial Fibrillation (AF) is associated with hypertension and valvular heart disease, which requires both an initiating event and a permissive atrial substrate [1]. The wave of atrial depolarization is represented by P-wave on electrocardiogram (ECG). The P-wave indices are quantitative measurements of atrial electrical activity obtained from the ECG surface. The P-wave is accepted as the most reliable non-invasive marker of the atrial conduction time [2]. More recently, the prolonged duration of the P-wave was shown to be a marker of the AF incident in two independent cohort studies [3][4]. Both short and long P-wave durations, also an irregular RR-interval with no pattern to the irregularity are significantly associated with an increased risk of AF [5][6]. However, analyzing ECG signal to AF risk presence based on P-wave and irregular RR-interval is time consuming and requires an extensive years of study to acquire specialized expertise [7]. Also, human errors can be caused by fatigue and affect precision AF signal classification.

An automated ECG interpretation by computer-based is expanded to increase the performance of AF signal classification. The computer-based analysis interpretation can be done quicker and more cost-effective when compared to human interpretation [7][8]. Nowadays, the automated ECG interpretation is utilizing deep learning (DL) perspective as a part of artificial intelligence (AI) based on human knowledge. DL may not require extensive human interaction and knowledge for feature design [11]. Previous literatures have proposed various DL algorithms for AF signal classification [7–11]. Yuan et al. [8] proposed the stack sparse autoencoder neural network. Xia et al. [9] have explored deep convolutional neural networks (CNN). They used the short-term Fourier transform (STFT) and stationary wavelet transform (SWT) to analyze ECG segments to obtain two-dimensional (2-D) matrix input, which is suitable for CNN. Andersen et al. [10] combined an end-to-end model using CNN and recurrent neural network (RNN) for automatic detection of AF. Sun et al. [11] developed an RNN composed of stacked long short-term memory (LSTM) for AF prediction. All performance results of mentioned literatures obtained the accuracy or sensitivity of the proposed algorithm above 90%. Under such conditions, it can be concluded that the DL approach is of great significance in the monitoring of AF.

Due to the superiority of DL algorithms in AF detection, DL approach for AF and normal sinus rhythm (NSR) signal classification is proposed. Among the mentioned DL algorithms, this study developed the DL model using the combination of CNN as feature extraction and recurrent network architecture as the classifier. The convolutional layer, as a part of CNN architecture, can automatically produce local features of the ECG signal series to recognize regional patterns in the convolution window [13]. The process can extract deep features from ECG signal data points [14]. A recurrent network, or RNN, is a neural network with a recurrent connection that employs a recursive approach. It is applied for ECG classification tasks with time correlations [15]. RNN can be implemented for sequential prediction to model the flow of time directly. RNN and its variants (LSTM and gated recurrent unit (GRU)) can be implemented for AF signal classification.

Lui et al. [15] found that the addition of a recurrent layer of RNN improved the ECG signal classification sensitivity by 28% compared to the CNN alone. Hence, it is imperative to investigate the convolutional layer of CNN and the recurrent network model improvement to increase the AF signal classification result. To achieve an optimal model, this study also proposes a set of optimal hyperparameter optimization (tuning) by using grid search for a learning algorithm. Its aim is to discover a tuple of hyperparameters that yields in an optimum model that minimizes a predefined loss function on independent data. Grid search-based hyperparameter tuning is simply an exhaustive search across a manually selected subset of the learning algorithm's hyperparameter space [16][17]. In this study, we give the contributions as follows:

- Stacking the CNN as feature extraction and recurrent network model as the classifier for AF and NSR signal classification;
- Experimenting with recurrent network architectures (RNN, LSTM, and GRU) based on ECG short rhythm segmentation to simplify the process with a highly accurate result;
- Implementing a grid search-based hyperparameter optimization to get optimized average values after several trial-and-error processes

The rest of this paper is organized as follows: Section II describes the material and method which consisted of ECG raw data, pre-processing, and the proposed CNN and recurrent network architecture. Section III presents the theory and background of the proposed method. Section IV analyzes results and discussion. Finally, the conclusion is presented in Section IV.

II. CONVOLUTIONAL-RECURRENT NETWORK CLASSIFIER

A. Convolution and pooling layer

Convolutional and pooling layers are the most common layers of CNN. A convolutional layer is made up of a number of filters, each of which has its own set of parameters that must be learned. The height and weight of filters are less than that of the input volume. Each filter is convolved with the input volume to produce a neuron-based activation map. The convolutional layers extract features from the input, which can be expressed as follows:

$$a_{ij}^{m} = \varphi(b_i + \sum_{k=1}^{M} w_{ik} x_{j+k-1}) = \varphi(b_i + w_i^T x_j) \qquad (1)$$

where a_{ij}^{m} is the activation of the jth neuron of the ith filter for the m th convolutional layer, M is the kernel size, φ is the neural activation function, b_i is the shared bias of the ith filter, $w_i = [w_{i1} \quad w_{i2} \quad ... w_{iM}]^T$ are the shared weights of the i th filter, and $x_j = [x_j \quad x_{j+1} \quad ... x_{j+M-1}]^T$ are the corresponding M inputs.

A pooling layer is composed of two convolutional layers. By down-sampling the representation, it reduces the number of parameters and processing.

B. Recurrent network classifier

RNN is commonly applied for ECG classification tasks with time correlations, which input $x = (x_1, x_2, x_3, ..., x_T)$ represents a sequence of length T, and h_t represents memory of RNN at time step t. RNN, is also known as vanilla RNN, has similar forward and backward pass processes as another common neural network (refer to Fig. 1) [15][22]. However, the process of RNN in the backward pass often happens gradient problems; i.e., vanishing or exploding gradient. The gradient problems caused by an iterative nature, which the gradient is essentially equal to the recurrent weight matrix raised to high power. The iterated matrix powers cause the gradient to grow or to shrink at a rate that is exponential in the number of timesteps [23].

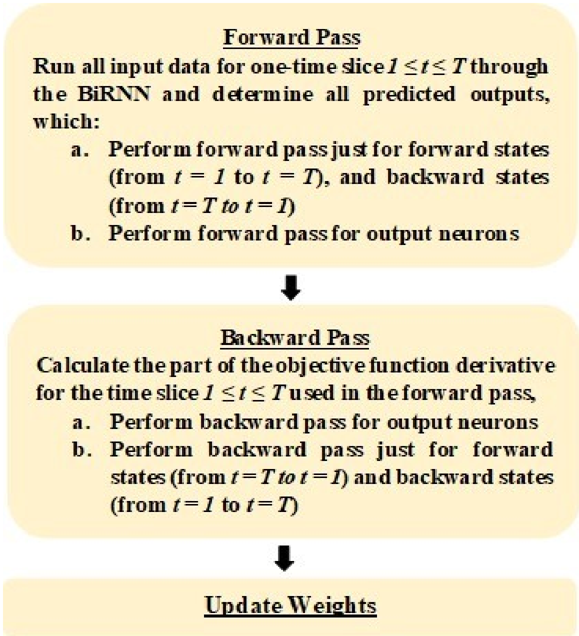


Fig. 1. The process of forward and backward of recurrent network

LSTM tends to overcome this problem by multiplicative gates that enforce constant error flow through the internal states of memory cells (c_t). LSTM learns long term correlations in a sequence and obviate the need for a pre-specified time window [24][25]. In LSTM architecture, there are three gates; input (i_t), output (o_t), and forget gates (f_t) [7][15]. The LSTM equations in the forward and backward passes are given below [31]:

$$\overrightarrow{LSTM}^1_{ft} = \tanh(W^1_{i\bar{h}} x_t + W^1_{\bar{h}\bar{h}} \overrightarrow{LSTM}^1_{t-1} + b^1_{\bar{h}} \qquad (2)$$

$$\overleftarrow{LSTM}^1_{bt} = \tanh(W^1_{i\bar{h}} x_t + W^1_{\bar{h}\bar{h}} \overleftarrow{LSTM}^1_{t+1} + b^1_{\bar{h}} \qquad (3)$$

where h_0 is initialized as a zero vector, b is the bias of network.

A recent variation on the LSTM architecture is the GRU, which introduces a single update gate in place of input and forget gates [26]. GRU has a simpler structure because only consist of two gates (reset (r_t)), and update gates (z_t))[27]. GRU contains a forward $\overline{GRU}$ which reads the signal from

w_{i1} to w_{iT_i}, and a backward $\overleftarrow{GRU}$ from w_{iT_i} to w_{i1}, which can be seen below;

$$\vec{w}'_{it} = \overrightarrow{GRU}(w_{it}), t \in [1, T_i] \tag{4}$$

$$\overleftarrow{w}'_{it} = \overleftarrow{GRU}(w_{it}), t \in [T_i, 1] \tag{5}$$

where w is the additional parameter.

III. Material and Methods

In this study, we developed the combination of CNN and recurrent network model for AF and NSR classification by using ECG short rhythm. We initially compared recurrent network architecture which consisted of RNN, LSTM and GRU. The workflow of AF and NSR classification can be presented in Fig. 2, which is consisted of; (i) ECG signals are enhanced by eliminating various kinds of noise and artifacts using discrete wavelet transforms (DWT); (ii) the segmentation by rhythm to 2700 nodes; and (iii) the CNN and recurrent network learns the characteristic of rhythm for AF and NSR classification.

As detailed in Fig. 2, it consisted of the following four main steps as follow;

- ECG raw data information is available from the 2017 PhysioNet/CinC Challenge database. It is comprised of a single short ECG lead recording that shows NSR, AF, noisy signal, and other rhythms (from 9 to 61 seconds) [18]. A total of 5,925 ECGs were only used in this study; 5,154 for NSR and 771 for AF records. ECG recordings were generously donated by the AliveCor device, which sampled as 300 Hz, 16-bit files with a bandwidth of 0.5–40 Hz and a ± 5 mV dynamic range.
- The changes of ECG waveforms indicate an illness of the cardiac that may occur for any reason. In the first step of preprocessing, ECG signals are enhanced by eliminating various kinds of noise and artifacts. This study proposed discrete wavelet transform (DWT), which is a frequently used denoising technique that offers a useful option for denoising ECG signals [19][20]. Some wavelet families for ECG signal, such as *symlets* (sym), *daubechies* (db), and *bior* are implemented to analyze which type of wavelet will obtain the best signal denoising result. Among them, based on the highest SNR results (refer to Table 1), *daubechies* wavelet, or db2, was the best wavelet function and chosen for ECG signal denoising. The SNR value obtained 11.205 decibel (dB).
- After denoising, ECG signals have segmented to short rhythm. i.e., 2700 nodes for each episode. The proposed nodes of AF signal segmentation have been published in detail in our previous works [12][21]. As in previous works, if the total nodes are less than 2700, a zero-padding technique is added, which consists of extending a signal with zero value (0). ECG segmentation divides a signal into numerous segments or episodes with similar statistical characteristics like amplitude, nodes, and frequency.
- First, a total of 21,382 NSR and 3178 AF episodes after being segmented by 2700 nodes were trained and validated using the recurrent network classifiers (RNN, LSTM, and GRU) alone. Second, the best model of recurrent networks is combined with CNN. In this stage, we analyze the impact of performance results between the recurrent network model alone, and with convolutional and pooling layers of CNN. To feature extraction, we generalized the CNN architecture that was published in our previous work [21]. The architecture consisted of 13 convolutional and five pooling layers. Rectified Linear Unit (ReLU) activation function has been adopted with 64, 128, 256, and 512 filter sizes. The ReLU removes redundancy by setting the negative value of the neuron to zero to increase the training speed.

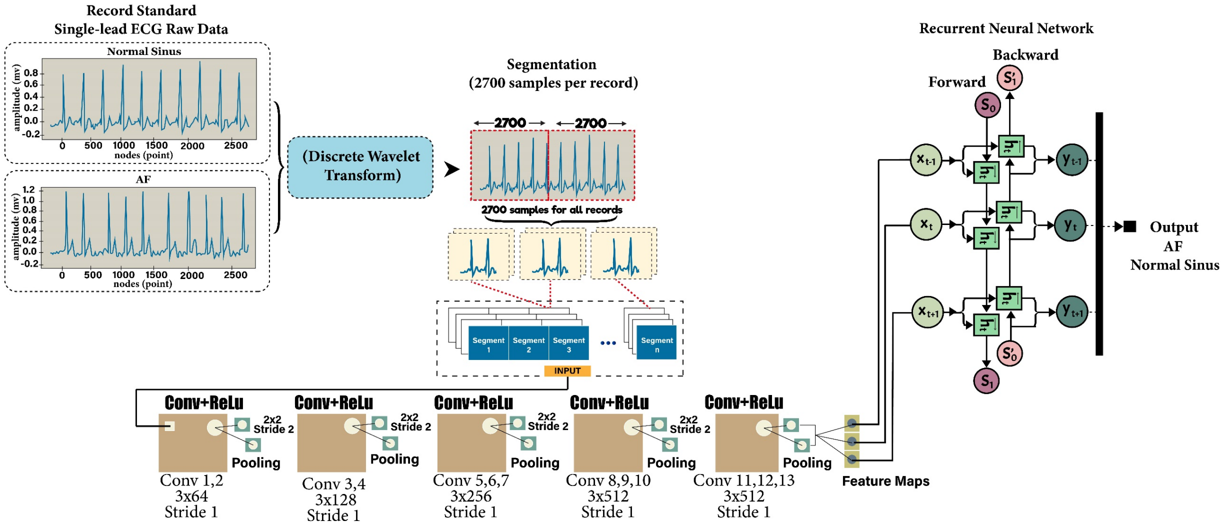


Fig. 2. The workflow of AF and normal sinus classification process based on CNN and recurrent network architecture

TABLE I. SNR VALUES OF VARYING MOTHER WAVELET

Mother Wavelet	SNR Value (dB)
sym5	11.139
sym6	10.747
sym7	10.838
sym8	10.704
db2	11.205
db4	10.768
db5	11.012
db6	10.852
db7	10.637
bior6.8	10.644

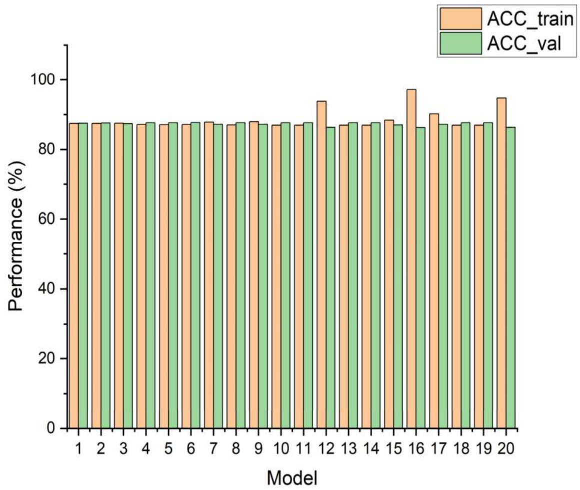
IV. RESULTS AND DISCUSSION

The recurrent network classifiers have been trained and validated by the general hyperparameters, 90% for the training and the rest for the validation set. All structure models have one hidden gate, 512 input nodes, Adam optimizer, and binary cross-entropy as loss function. Grid search-based hyperparameter optimization is deployed to select the best recurrent network structure in terms of its learning and structure parameter in the training data. Batch size (8, 16, 32, 64), learning rate (from 10^{-1} to 10^{-5}) and number of epoch (100, 200, 300) are hyperparameters-tuned that proposed in this study.

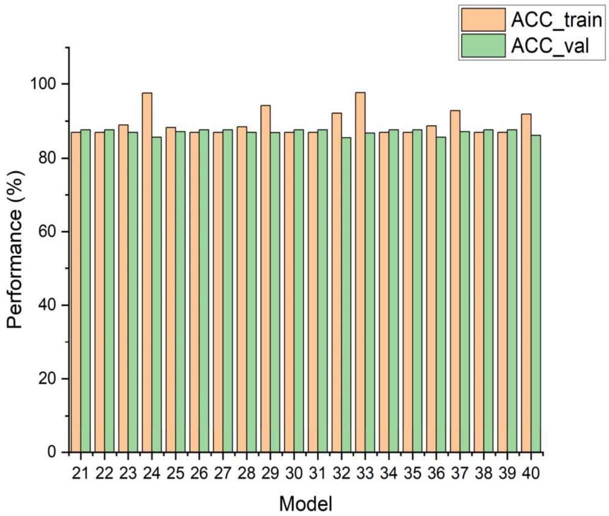
First, we conducted the RNN architecture to generate the initial model. From the proposed hyperparameters combination, 60 models of RNN architecture were obtained (refer to Fig. 3). Fig. 3 shows the accuracy results of training (ACC_train) and validation (ACC_val) performance to determine the generalization model, neither underfit nor overfit. In a good model, as the algorithm learns, the error on the training data goes downs and so does the error on the validation set. As seen in Fig. 3, almost the model can generalize well (good fitting). There is no significant gap between the accuracy of the training and the validation set (around 87% on average).

Among 60 recurrent network models, the best model of RNN has trained also in unidirectional-bidirectional LSTM and GRU. The performance results of recurrent network classifiers can be presented in Table 2. As listed in Table 2, overall, the bidirectional LSTM (Bi-LSTM) achieved good performance results. A sequence of bidirectional use both past and future (forward and backward phase) inputs for prediction with two separate LSTM hidden layers. The model is trained not only from input to output but also from output to input. A BiLSTM model feeds input data to an LSTM model, or feedback layer, first, and then repeats the training via another LSTM model, but in the reverse order of the input data sequence. The bidirectional phase of LSTM has been proved and provided much better performance in some cases. Although the performance of BiLSTM obtained a good performance, the accuracy is still achieved at around 87%.

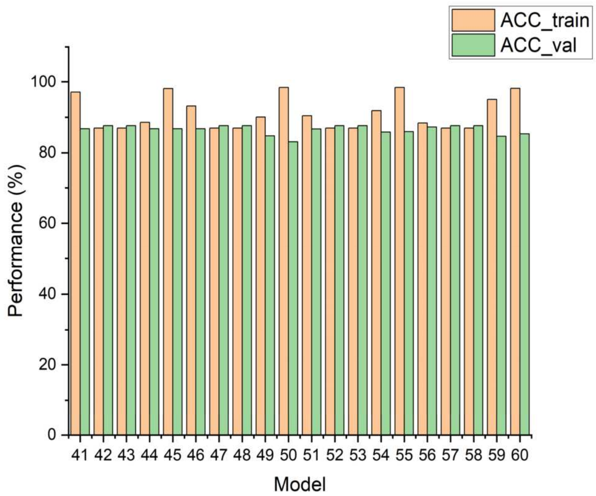
Second, we have combined the recurrent network model with the convolutional layers of CNN as feature extraction to increase the performance. In our previous work [28], we proposed and successfully generated the combination of convolutional layers and the BiLSTM (ConvBiLSTM) model for the ECG delineation process. The convolutional layer of CNN aids in the extraction and learning of low-level hierarchical and invariant features from raw data through weight-sharing.



a. Models 1 – 20



b. Models 21 – 40



c. Models 41 – 60

Fig. 3. The training and validation accuracy performance in 60 recurrent network models

TABLE II. THE PERFORMANCE RESULTS OF RECURRENT NETWORK CLASSIFIERS COMPARISON

Recurrent Network Classifiers	Performance Results (%)				
	ACC	*SEN*	*SPE*	*PRE*	*F1*
RNN	87.62	99.90	33	87.69	93.39
LSTM	87.66	99.90	66	87.72	93.42
BiLSTM	87.54	99.72	99	87.74	93.34
GRU	87.74	100	66	87.73	93.46
BiGRU	87.54	99.76	66	87.70	93.35

a. ACC = Accuracy; SEN = Sensitivity; SPE = Specificity, PRE = Precision; F1 = F1-score

TABLE III. THE PERFORMANCE RESULTS OF COMBINATION CONVOLUTIONAL LAYERS OF CNN WITH RECURRENT NETWORK CLASSIFIER

Recurrent Network Classifiers	Performance Results (%)				
	ACC	*SEN*	*SPE*	*PRE*	*F1*
BiLSTM	87.54	99.72	99	87.74	93.34
CNN-BiLSTM	96.49	99.07	78.21	96.99	98.02

a. ACC = Accuracy; SEN = Sensitivity; SPE = Specificity, PRE = Precision; F1 = F1-score

As the result, the accuracy significantly increased from 87.54% to 96.49% (refer to Table 3). Overall, the other performances increased to above 96%, though the specificity only achieved 78.21%. In this case of study, the AF class belongs to the negative class. Specificity measures how the model got predicted as the negative of true negative. The imbalanced ratio between NSR and AF episodes with 6.72 imbalanced ratios can affect the AF performance, as a minority class. The AF distribution can vary from a slight bias.

V. CONCLUSION

AF is a public health issue of epidemic proportion, which is associated with a wide range of heart abnormalities events. ECG signals provide data to clinicians and individuals at home using a range of devices that collect information with different degrees of accuracy. Nowadays, an automated algorithm that analyzes ECG signal data is a popular research topic using DL. A convolutional layer of CNN succeeds at extracting features from ECG data points. Also, recurrent networks, including LSTM and GRU are designed to classify, process, and predict data points, which are listed in the temporal order. The networks are known to be powerful, clinical, and medical time series data classifiers. Hence, this study experimented with and combined both powerful DL architectures for AF signal classification. In addition, the comparison of the recurrent network classifiers to determine which one of the classifiers can be proposed. In this experimental study, among the recurrent network classifier, the CNN-BiLSTM combination has outperformed RNN, LSTM, and GRU alone with 96.49% accuracy. By offering a more objective and faster interpretation of ECG data, the proposed model may be implemented into practice and serve as diagnostic assistance for clinicians in the future.

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