Biosignal Classification Based on Multi-Feature Multi-Dimensional WaveNet-LSTM Models

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Abstract—Electrocardiogram (ECG) effectively records the difference between body potentials generated during the physiological function of the heart. Both ECG and heartbeat sounds are viewed as powerful tools to diagnose abnormal arrhythmias. In the past, the accuracy of such diagnoses has been significantly improved due to the development of machine-learning algorithms. However, current models still do not provide acceptable performance due to similarities of signal waveforms as well as ambient noises and interferences. In this paper, we propose a novel deep-learning model that incorporates a WaveNet model based on dilated convolutions as the backbone followed by multiple bi-directional long-short-term memory (Bi-LSTM) layers to further enhance the discriminant capabilities of temporal relations. A typical clinical dataset, i.e., the MIT-BIH arrhythmia database, which considers intra-patient and inter-patient paradigms based on the American Association of Medical Instrumentation (AAMI) EC57 standard, is used to demonstrate the performance of the proposed approach. Numerical results show that our model has achieved the state-of-the-art classification accuracies.

Index Terms—ECG analysis; deep learning; WaveNet model; confusion matrix

I. Introduction

Smart medical care seeks to make use of advanced Internet of Things (IoT) technologies and artificial intelligence (AI) algorithms to connect patients to physicians via multiple sensors to ensure that patients have a convenient and timely access to medical services. Hence, intelligent medical treatment is generally viewed as the integration of the life science and the information technology, which benefits from significant advances in system integrations and infrastructure upgrades. With the continuous development of the AI technology, it has been gradually applied to practical systems and achieved remarkable results. In particular, the vast amount of medical data enables the adoption of AI algorithms in the areas of early diagnoses and medical treatments.

With the development of economy and society, social rhythm has significantly accelerated. This causes the incidence and mortality rate of cardiovascular and cerebrovascular diseases to increase at an astounding speed. According to the statistics of the World Health Organization (WHO), cardiovascular disease (CVD) is the largest cause of death in the world, with more people dying each year from CVD than from the other causes and accounts for more than one third of the total number of global deaths. Of these deaths, more than 60 percent died of coronary-related heart diseases. As a result, the development of an automatic approach that detects coronary diseases quickly and accurately has a significant impact on the social well-being. Specifically, it is of interest to fully streamline and automate the first level of cardiac pathology screening by physicians in a hospital environment and by patients using mobile devices at home.

Recently, deep learning has made breakthroughs in the fields of image and natural language processing. It has been widely applied to various fields for its powerful capability to analyze complex data [1]. With respect to health monitoring, ECG is one of the most commonly used tests for clinical heart diseases, and records the differences in terms of the electrical potentials of the body surface produced in the process of the cardiac physiological function, based on which a diagnosis can be made to effectively reduce the mortality rate. The conventional ECG diagnosis requires that a patient wear sensors and a physician manually interprets the sampled data, which is time-consuming and laborious especially when an overwhelming number of patients are present. Due to unavoidable factors such as fatigue and impossibility to interpret the recorded data instantly, the accuracy of the diagnosis will inevitably decline. Therefore, it is particularly useful to develop a technique to perform an efficient, accurate, and low-cost automatic analysis of ECG signals.

Over the past years, various AI algorithms have been applied to analyze ECG signals, such as the Support Vector Machine (SVM), Multilayer Perceptron (MLP), Logistic Regression (LR) and Decision Trees (DT), to perform the classification of ECG signals [2]-[5]. These algorithms perform the pre-processing of raw signals, e.g., wavelet packet decomposition (WPD) [3], short-time Fourier Transform (STFT) [6], sampled entropy [7], and subsequently conduct the extraction of handcrafted features from the denoised signals. The design of manually extracted signal features, however, requires a substantial amount of domain-specific expert knowledge.

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Automatic feature representation has proved to be more scalable and empowers the model to deliver discriminant capabilities in a timely manner. Recently, deep learning methods have made notable achievements in various fields ranging from computer visions to natural language processing (NLP) [6], [7]. It manifests an overwhelming amount of potentials as well when applied to biomedical signal analysis by performing exhaustive data mining and feature extraction to build an end-to-end deep neural network model. In particular, deep supervised learning techniques include convolutional neural networks (CNNs) and recurrent neural networks (RNNs). In [8], Acharya proposed a 9-layer CNN model for the recognition of five types of ECG signals. Kiranyaz [9] designed an adaptive one-dimensional (1-D) network model to extract the features of the patient. In [10] and [11], the authors constructed a model to classify normal and abnormal ECG signals by combining inference results with expertise rules. In [12], a hybrid architecture was proposed to perform ECG signal classification based on blockwise components and particle swarm optimization. In [13], a model composed of the stacks of Bi-LSTM layers was presented for the classification of ECG signals.

In this paper, we propose a novel deep-learning architecture incorporating the serial concatenation of the WaveNet model and the Bi-LSTM model to perform a highly accurate detection of ECG anomalies. The WaveNet model, which was previously used in speech recognition and reconstruction, shows an impressive capability to learn discriminant features from deep convolution layers by efficiently using multi-resolution dilated convolutions and various receptive fields. Wavelet-based denoising algorithms [14] are applied in the signal pre-processing stage to remove low-frequency noises and facilitate feature extraction. Numerical results on the typical ECG dataset show that the proposed approach improves the classification accuracy up to 96.8% and performs noticeably better than the current state-of-the-art techniques. The performance gain is attributed to the capabilities of both the WaveNet and the LSTM model to effectively learn both global and local temporal dependencies inherent in ECG signals. Besides, the proposed method in this paper can be well generalized to analyze other categories of biological signals [15] such as electroencephalogram (EEG) and heartbeat sound signals.

The rest of this paper is organized as follows. In Section II, we introduce the WaveNet and the LSTM model. In Section III, we present the proposed WaveNet-LSTM architecture in detail. The experimental results are presented and discussed in Section IV. The conclusion is drawn in Section V.

II. Overview of WaveNet and LSTM

A. WaveNet

WaveNet is a recent speech generation and reconstruction model proposed by the Google DeepMind. The model directly inputs the speech data in the form of signal waveforms and obtains remarkable performance in speech-to-text (SST) and text-to-speech (TTS) tasks. WaveNet adopts a novel method to adjust adaptively the receptive field based on the depth of the network, which enables the model to effectively alleviate the information loss in the propagation through the network.

The model features an autoregressive (AR) mechanism that predicts the probability distribution of the current sample based on all previously generated samples. By using the so-called causal convolutions, the WaveNet ensures that the order of modeling the data is maintained. The prediction $p(x_{t+1}|x_1,...,x_t)$ delivered by the model at time step t does not depend on any future time steps x_{t+1}, x_{t+2},..., x_t. Hence, an equivalent form of the causal convolution is also known as the mask convolution. A residual short-circuit is incorporated in the WaveNet to assist in the information flow and avoid the gradient diminishing problem. The final result is obtained by superimposing multiple skip-connections based on the intermediate results of each layer.

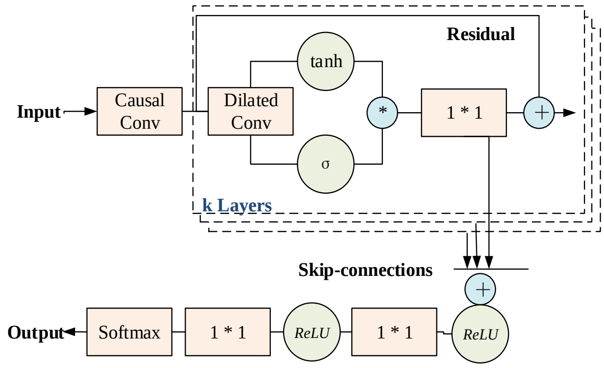

Fig. 1. Block diagram of the wavenet model

B. LSTM

The most well-known RNN is the LSTM network model, which consists of three multiplication gates to control the proportion of information that will be neglected or passed onto the next time step.

Essentially, LSTM successfully mitigates the problem of diminishing gradients and handles long-term dependencies embedded in sequential data more effectively. Fig. 2 gives the basic structure of an LSTM unit.

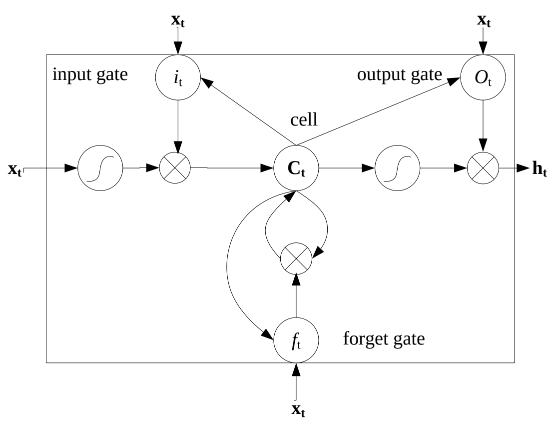

Fig. 2. A long-short-term-memory (LSTM) cell.

The equations to update an LSTM unit at time t are given by (1),

$$\begin{cases} \boldsymbol{i}_t = \sigma(\mathbf{W}_{\mathrm{i}}\boldsymbol{h}_{t-1} + \mathbf{U}_{\mathrm{i}}\boldsymbol{x}_t + \boldsymbol{b}_{\mathrm{i}}) \\ \boldsymbol{f}_t = \sigma(\mathbf{W}_{\mathrm{f}}\boldsymbol{h}_{t-1} + \mathbf{U}_{\mathrm{f}}\boldsymbol{x}_t + \boldsymbol{b}_{\mathrm{f}}) \\ \boldsymbol{c}_t = \boldsymbol{f}_t\boldsymbol{c}_{t-1} + \boldsymbol{i}_t \tanh(\mathbf{W}_{\mathrm{c}}\boldsymbol{h}_{t-1} + \mathbf{U}_{\mathrm{c}}\boldsymbol{x}_t + \boldsymbol{b}_{\mathrm{c}}) \\ \boldsymbol{o}_t = \sigma(\mathbf{W}_{\mathrm{o}}\boldsymbol{h}_{t-1} + \mathbf{U}_{\mathrm{o}}\boldsymbol{x}_t + \boldsymbol{b}_{\mathrm{o}}) \\ \boldsymbol{h}_t = \boldsymbol{o}_t \tanh(\boldsymbol{c}_t) \end{cases} \quad (1)$$

where σ is the logistic sigmoid function, $\boldsymbol{x}_t$ is the input vector (e.g. word embedding) at time t, $\boldsymbol{h}_t$ is the hidden state vector storing all the useful information at (and before) time t; $\mathbf{U}_{\mathrm{i}}$, $\mathbf{U}_{\mathrm{f}}$, $\mathbf{U}_{\mathrm{c}}$, and $\mathbf{U}_{\mathrm{o}}$ denote the weight matrices of different gates for input $\boldsymbol{x}$; $\mathbf{W}_{\mathrm{i}}$, $\mathbf{W}_{\mathrm{f}}$, $\mathbf{W}_{\mathrm{c}}$, and $\mathbf{W}_{\mathrm{o}}$ are the weight matrices for hidden state $\boldsymbol{h}_t$; and $\boldsymbol{b}_{\mathrm{i}}$, $\boldsymbol{b}_{\mathrm{f}}$, $\boldsymbol{b}_{\mathrm{c}}$, and $\boldsymbol{b}_{\mathrm{o}}$ denote the bias vectors. From (1), it is shown that the hidden state $\boldsymbol{h}_t$ only stores the past information and lacks the access to contextual knowledge. The Bi-LSTM model, which is an elegant variant of the LSTM, produces two sets of hidden states by presenting the sequence to the model in both the forward and the backward manner, the results of which are further concatenated to form the output to the subsequent layers.

III. WAVENET-LSTM MODEL

A. Signal Processing

Fig. 3 shows the waveforms of various classes of ECG signals in the MIT-BIH dataset. In this paper, a discrete waveform transformation (DWT) filtering technique is used to denoise ECG signals. In addition, to overcome the potential problem of overfitting resulting from unbalanced datasets, we use the boundary oversampling method [16] to oversample the under-represented classes with significantly less amount of data points.

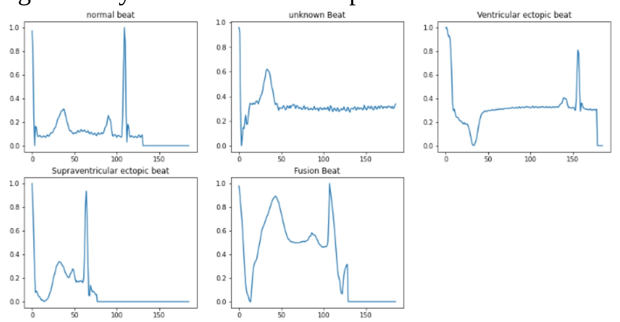

Fig. 3. Waveform of various categories of ECG signals in the MIT-BIH database.

B. ECG Classification Based on WaveNet-LSTM

As most signals in the MIT-BIH dataset are typically of short durations with a few hundred samples per signal, it is reasonable to employ multiple layers of 1-D convolutions to derive time-domain features of the denoised signals. To enable the model to learn temporal features more effectively, a combination of an attention-based mechanism and the LSTM layer are incorporated in the architecture. In Fig. 4, we show the block diagram of the proposed WaveNet-LSTM model.

As described in Section II. A, the WaveNet is composed of several blocks of dilated convolution layers. The raw ECG signal is taken as the input to the model following wavelet denoising operations. On contrary to applications such as speech recognition that typically processes the frequency-domain characteristics of long data sequences, the 1-D convolution is a suitable approach to directly tackle short sequences in the time domain. Each convolution layer is followed by a LeakyRelu function to speed up the convergence of the training process, a batch normalization module to perform the scaling of each layer's output based on the specified batch size, and a pooling operation to obtain position invariance over local regions, as well as a dropout operation to reduce dependencies between adjacent layers. For the first convolution layer, the number of kernels is set to 8 and the kernel size is 5. The output is passed into a series of convolutions with the same configurations with the number of filters given by 16, 32, and 64, respectively. The pooling layer uses the max-pooling operation with size 5 and stride 2. The output of the last convolution layer is fed into a Bi-LSTM layer to further learn discriminant temporal features based on the 1-D features derived from the WaveNet. Finally, a soft-max operation is invoked to deliver the predicted class of the input signal.

In the training, the parameters of each layer are adjusted based on the backward-propagation (BP) algorithm targeted at minimizing a cross-entropy (CE)-based loss function. The learning rate for the Adam optimization [17] is set to 0.001 with decaying factors set to 0.9 and 0.999, respectively. A total of 50 epochs is adopted to train the model with the size of each data batch given by 512.

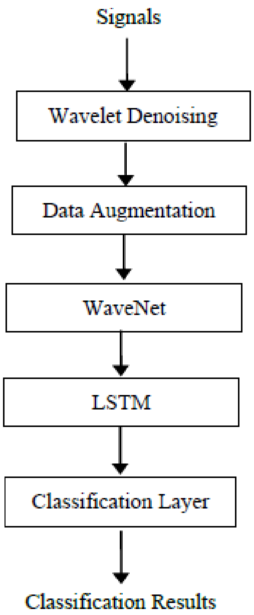

Fig. 4. Block diagram of the proposed WaveNet-LSTM model for ECG signal classification.

IV. NUMERICAL RESULTS

To demonstrate the effectiveness of the proposed scheme, we conduct the evaluation over the PhysioNet

MIT-BIH Arrhythmia database, which is typically used to benchmark the performance of various algorithms.

A. Dataset Introduction

The MIT-BIH dataset includes the ECG records of different subjects sampled at the rate of 360 Hz. The groundtruth label of each signal is verified by at least two cardiologists, and the database is endorsed by the American Association of Medical Instrumentation (AAMI) [15]. Table I shows the five categories of ECG signals, which consists of a nomal category and four categories resulting from mal-functioning hearts. The subject identifications of the database is divided into two sets of records by the AAMI, i.e., DS1 = {101, 101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, 230}, and DS2 = {100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, 234}, where DS1 is used to train the model and DS2 is applied to perform the evaluation. Note that there is strictly no overlap between the train dataset and the validation dataset. Hence we are able to ensure a fair performance comparison by avoding the data-leaking risks of the same patient being included in both datasets. Our task is to predict the most likely class (N/S/V/F/Q) to which an ECG signal belongs.

TABLE I. CATEGORIES OF HEARTBEATS IN THE MIT-BIH DATABASE BASED ON AAMI EC57 STANDARD

CATEGORY	DEFINITIONS
N	Normal beat (N) Left and right bundle branch block beats (L, R) Atrial escape beat (e) NODAL (JUNCTIONAL) ESCAPE BEAT (J)
S	Atrial premature beat (A) Aberrated atrial premature beat (a) Nodal (junctional) premature beat (J) SUPRAVENTRICULAR PREMATURE BEAT (S)
V	Premature ventricular contraction (V) VENTRICULAR ESCAPE BEAT (E)
F	FUSION OF VENTRICULAR AND NORMAL BEAT (F)
Q	Paced beat (/) Fusion of paced and normal beat (f) UNCLASSIFIABLE BEAT (U)

B. Evaluation Metric

The most commonly used metric to evaluate the performance of classification models is the confusion matrix, which is typically illustrated in Table II for a binary classification task. In Table II, TP, FP, TN, and TN denotes true positive, false positive, false negative, true negative rates, respectively. Based on the confusion matrix, other metrics can be derived, e.g., accuracy that is defined as the percentage of the total number of samples that correct results are predicted, i.e.,

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

Precision denotes the probability of all positive samples that are correctly predicted to be positive as follows,

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

Recall, which is also named sensitivity, denotes the ratio of the number of positive predictions that are correctly predicted to the total number of positive examples.

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

TABLE II. CONFUSION MATRIX FOR A BINARY CLASSIFICATION TASK

Actual/Predicted	0	1
0	TN	FP
1	FN	TP

C. Performance Results

Fig. 5 shows the confusion matrix of the proposed model for the MIT-BIH dataset. The numerical results are evaluated based on the validation dataset, which consists of 4,000 samples. The probabilities of correctly classified results are recorded on the diagonal, while those of incorrect predictions are scattered through the matrix. It is shown that the proposed WaveNet-LSTM model classifies five classes of ECG signals very well and achieves impressive performance, though the accuracies of class S and class F are slightly lower as compared with the other three classes of N, V, and Q.

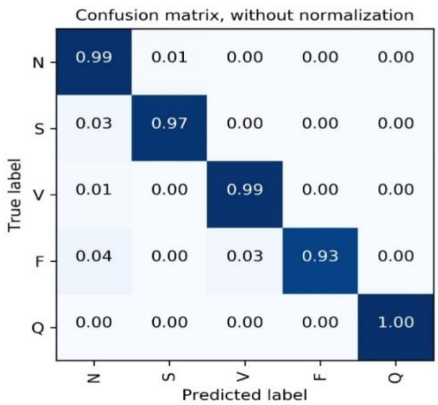

Fig. 5. Confusion matrix for ECG signal classification on the validation set, which shows the ratio of the number of samples classified in each category normalized by the total number of samples.

In Table III, we present the average accuracy of the proposed method as compared with several state-of-the-art approaches in the literature. It is shown that the proposed method achieves significant performance gains over other methods. Compared with the machine learning models [14], [18], the proposed WaveNet-LSTM model achieves a noticeable increase in terms of the classification accuracy by nearly 3%. The performance is also benchmarked against deep-learning CNN models including the deep residual network model [14] and the data-augmented CNN model [19], [20]. The proposed model obtains much better performance and increases the accuracy up to 96.8% on the evaluation set, which is the best result to our knowledge.

The performance gain is accredited to the design of dilated convolutions and attention mechanisms in the WaveNet structure, which was originally developed to reconstruct human speeches. With respect to ECG signal classifications, the WaveNet backbone empowers the model with a large and self-adaptive receptive field to grasp the global structure of the input data sequence. Moreover, the subsequent LSTM layers refine local temporal relations based on the deep features learned by casual convolutions of the WaveNet backbone. Hence, the proposed model manifests an excellent capability to extract multi-scaled temporal dependencies embedded in the input time sequences.

TABLE III. ACCURACY OF DIFFERENT METHODS

Source	Compare	
	Methods	***Average Accuracy (%)***
This Paper	Deep Wavenet-LSTM	96.8
Kachuee [13]	Deep residual CNN	93.4
Acharya [19]	Augmentation + CNN	93.5
Martis [20]	DWT + SVM	93.8
Li [18]	DWT + Random Forest	94.6

V. CONCLUSION

In this paper, we proposed a novel deep-learning model for ECG signal classifications. The serial concatenation of the WaveNet and the LSTM layer enables the proposed model to learn both global and local discriminant features inherent in the wavelet-denoised ECG signals. Performance results over the typical benchmark dataset, i.e., the MIT-BIH dataset, shows that the proposed model achieves a noticeable gain over several advanced methods in the literature and obtains the state-of-the-art accuracy on the evaluation dataset.

We believe that the seamless integration of AI algorithms into medical diagnoses and pre-emptive treatments will bring unprecedented opportunities to the whole industry. The proposed method can be fully generalized to analyze various categories of biological signals, such as heartbeat sound signals, EEG, and EMG (Electromyography) signals. When processing signals of long durations, we will experiment with frequency-domain features combined with self-attention mechanisms.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Yue Meng, Linghao Lin, and Zhiliang Qin conducted the research and prepared the paper; Yuanyuan Qu, Yu Qin, and Yingying Li analyzed the experimental data and contributed to the numerical studies. All authors had approved the final version.

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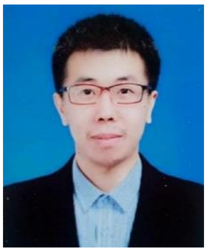

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