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CLASSIFICATION AND DETECTION OF DYSRHYTHMIA FOR LECTROCARDIOGRAPHY SIGNALS BY CONVOLUTIONAL NEURAL NETWORK

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Abstract: **Electrocardiography is the most useful method for diagnosing cardiovascular disease such as arrhythmia. Heartbeat classification of electrocardiography signals is a valuable and hopeful technology for early warning of dysrhythmia because it contains the cardiac electrical activities and reflects the abnormal cardiac activity. Therefore, a novel electrocardiogram-based arrhythmic beats classification was proposed to automatically detect the main types of dysrhythmia using electrocardiography signal in this work. A convolutional neural network model was used to automatically detect the normal and the types of dysrhythmia electrocardiography beats. The beat was transformed into a matrix as two-dimensional input to the model. The classification system was assessed to detect the normal, left bundle branch block, premature ventricular contraction and right bundle branch block beats using the MIT-BIH arrhythmia database. The results showed that an average accuracy of 99.30% and 98.85% was achieved by using ML2 lead of electrocardiography data with one-dimensional and 2-dimensional input, respectively. An average accuracy of 97.00% and 97.20% was achieved by using V1 lead of electrocardiography data with one-dimensional and 2-dimensional input, respectively. Moreover, no feature extraction of signals was carried out in this study. Consequently, the proposed model can accurately test the unknown electrocardiography signal and aid the clinician in the diagnosis of dysrhythmia.**

***Keywords*: Electrocardiography, Dysrhythmia, Convolutional neural network, Heartbeat classification**

I. INTRODUCTION

Dysrhythmia (also called heart arrhythmia or arrhythmia) is a set of conditions in which the heartbeat is abnormal. Arrhythmias are due to problems with the electrical conduction system of the heart [1]. Supraventricular tachycardias, bradyarrhythmias, extra beats, and ventricular arrhythmias are the four main types of dysrhythmia which usually have no symptoms. Ventricular arrhythmias result in about 80% of sudden cardiac death [2]. Electrocardiography (ECG) contains a lot of information about the function of heart's electrical conduction system and its structure. An experienced clinician can distinguish different types of cardiac of dysrhythmia by monitoring the patient's ECG signals. These conditions can indicate serious cardiovascular diseases. Heartbeat classification of ECG signals is a valuable and hopeful technology for early warning of dysrhythmia for the study of dysrhythmia detection in medical center. Electrocardiography has been widely used because of its low cost, convenience and noninvasive detection. Early diagnosis of dysrhythmia may help patients to get timely treatment, and hence decreasing the mortality [3]. Currently, there is a challenge for the computer to carry out automatic analysis because of the variety and complexity in ECG signals [1]. Accurate ECG beat classification is essential for automated detection of dysrhythmia and is one of the most challenges in heartbeat analysis. ECG signal amplitude is generally in millivolts and its duration is in seconds [4]. Analysis of ECG signals is a time-consuming and laborious work. Furthermore, the explanation of ECG signals is subjective and might change in the different clinicians. The disadvantaged manual examination of ECG signals can be defeated by using computer-aided diagnosis (CAD) system. Computer-aided diagnosis system is more and more paid attention because of its objective, speedy, and trustworthy analysis. Many studies have been performed on the development of CAD for dysrhythmia [5-10].

The QRS complex is the combination of three of the graphical deflections seen on a typical ECG. The QRS complex detection is the basis of automated ECG analysis algorithms. Many approaches to QRS detection have been proposed such as calculus of variation [3], swarm intelligence-based search method called salp swarm algorithm [11], wavelet transform [12], deep learning [13,14], adaptive filtering [15].Moreover, many researches have provided some techniques of ECG feature classification and delimited the parameter structure of different ECG features such as hidden Markov models, discrete wavelet transform, feature selection, and mixture of experts' method [16-18]. These approaches need to have basic knowledge of physiological signals analysis, which limit the method application. Greater and more complex changes may be appeared when processing a new subject's ECG signals. However, it is a difficult task to locate the P, Q, R, S and T waves of ECG for dysrhythmia and their extraction is uncertain. Many researchers focus on convolutional neural network (CNN) to avoid the limitation of these approaches that need manual feature selection. CNN has relatively little data pretreatment comparing to other classification algorithms and is independent of manual feature extraction knowledge. CNN has been used in drug discovery [19], image recognition systems [20], video classification [21], health risk assessment and biomarkers of aging discovery [22]. Recent researches have also displayed great potentialities of CNN in handling biomedical applications, such as people sleep behavior disorder classification [23], histopathological images diagnosis [24], relative location prediction in computed tomography (CT) scan images [25], and thyroid nodule classification in ultrasound images [26]. Recent researches have also exhibited encouraging application of CNN in electro-physiological signals such as ECG classification [27], electromyography (EMG) pattern recognition [28], and mental load classification based on electroencephalogram (EEG) [29].

CNN structure possesses apparent superiority in using large-scale training data for promoting classification performance. For example, an average accuracy, sensitivity, and specificity of 93.53%, 93.71%, and 92.83% are achieved using myocardial infarction ECG beats with noise by CNN [30]. Some recent researches have exhibited promoting performance of automatic detection with CNN for classification of normal sinus rhythm, atrial fibrillation, other rhythm [31-33]. These improvements of classification and recognition may result from the feature learning ability of CNN. Detection of ECG classification and recognition was performed with 1-dimensional CNN in most of the previous studies. CNN does not need for manual feature extraction or selection comparing to many conventional methods in detection of ECG classification, which may bring about loss of some information in the data at different stages. Based on the superiority of feature learning ability of CNN, we tried to explore the 2-dimensional method for ECG classification with CNN.

II. MATERIALS AND METHODS

2.1 Database

In this study, the ECG signals was gained from the MIT-BIH arrhythmia database (https:// www.physionet.org/ content/ mitdb/1.0.0/). The MIT-BIH arrhythmia database contains 48 thirty-minute excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH arrhythmia laboratory. In this study, we used the signals of modified lead II (ML2) and V1 lead. Seven records (#100, #102, #103, #104, #114, #123 and #124) were excluded because they do not contain ML2 and V1 lead signals. The record information of all patients is available at the website (https:// www.physionet.org/ physiobank/ database/html/ mitdbdir/records.htm#101). According to the annotations, every ECG beat is classified as N (normal beat), S (premature or ectopic supraventricular beat), A (atrial premature beat), L (left bundle branch block beat), R (right bundle branch block beat), V (premature ventricular contraction), F (fusion beat) or Q (unclassifiable beat).

2.2 Pre-processing

The R-peak detection of both datasets (ML2 and V1 lead) was carried out by Pan Tompkins algorithm [34]. After segmenting all the ECG signals, Z-score normalization was used to normalize every segment which can solve the problem of amplitude scale and remove the offsetting effect before taking the ECG segment into the one-dimension deep learning CNN. Every ECG beat contains 256 samples (100 samples before R-peak and 155 samples after R-peak) and was reconstructed matrix with image size 16×16 for ML2 and V1 lead datasets, respectively (Figure 1-2). Mapminmax function was used to adjust every ECG beat data between 0 and 1, and the data were rearranged into 16 rows and 16 columns by reshape function in the software program Matlab (version 2017b). The adjusted data were multiplied by 255 to show in the right of Figure 1-3 with 0-255 gray levels. After classifying the types of ECG beat, type A, type S, type F and type Q were excluded because they are too few. Each ECG beat consists of 484 samples (242 ML2 samples plus 242 V1 lead samples) and was reconstructed matrix with image size 22×22 for ML2 plus V1 lead datasets (Figure 3). The 242 samples were composed of 100 samples before R-peak and 142 samples after R-peak for ML2 and V1 lead datasets, respectively. Pre-processing of datasets was completed by the software program Matlab (version 2017b), and the number of beats was showed in Table 1.

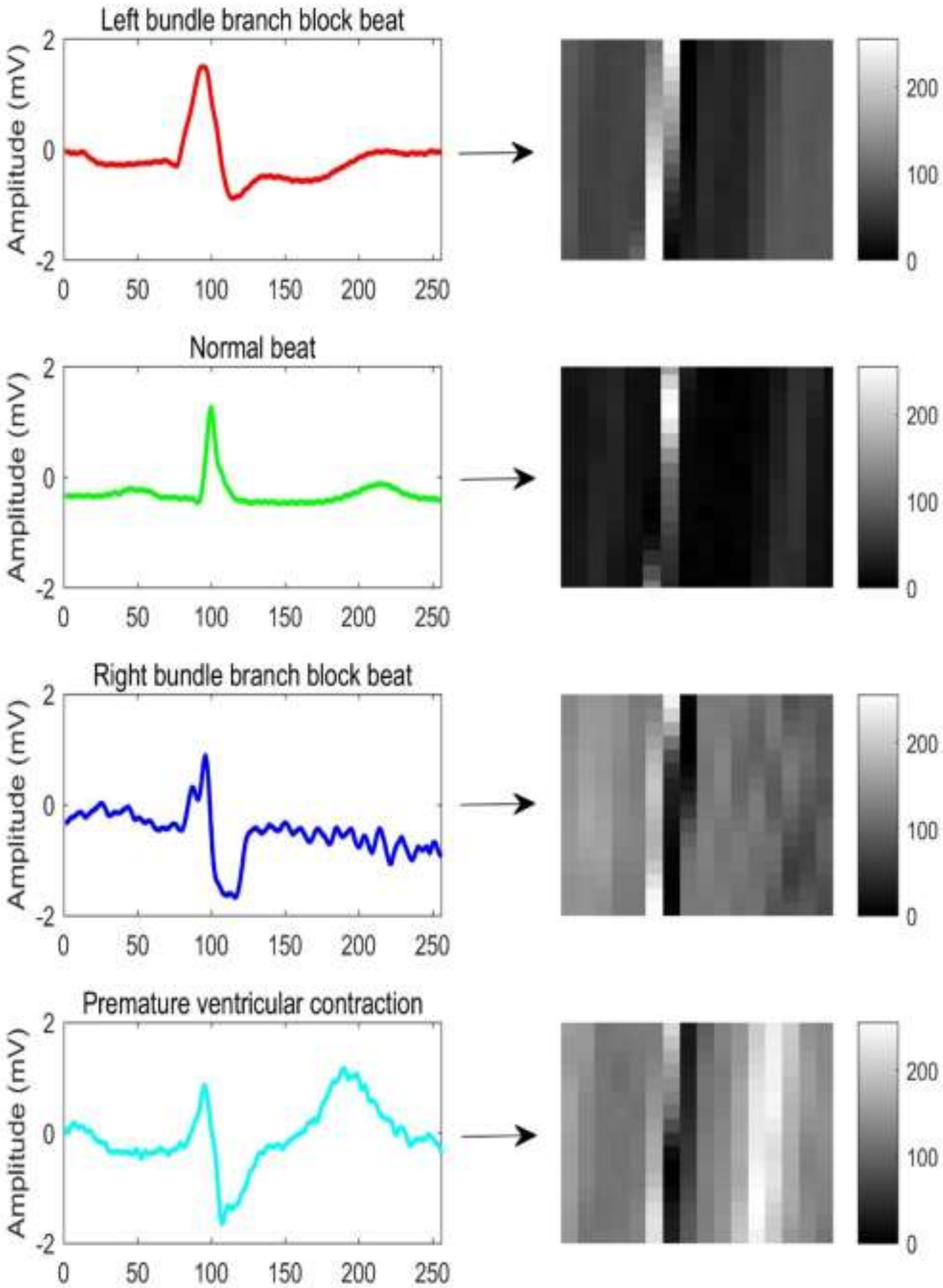

Figure 1. Sample normal and dysrhythmia electrocardiography beat with ML2 lead. Left: one-dimensional beat signals. Right: the beat was transformed into a matrix as 2-dimensional inputs

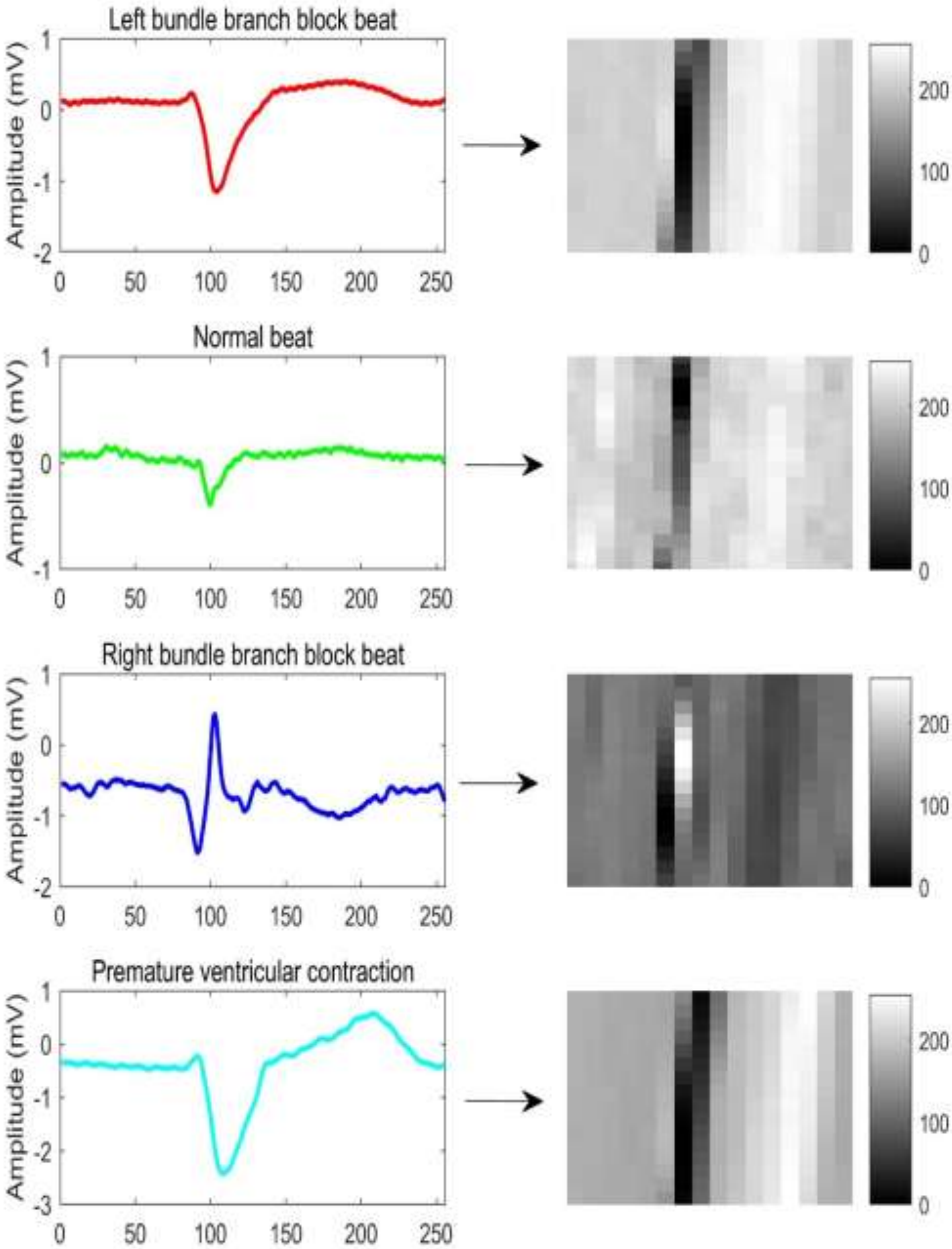

Figure 2. Sample normal and dysrhythmia electrocardiography beat with V1 lead. Left: one-dimensional beat signals. Right: the beat was transformed into a matrix as 2-dimensional inputs

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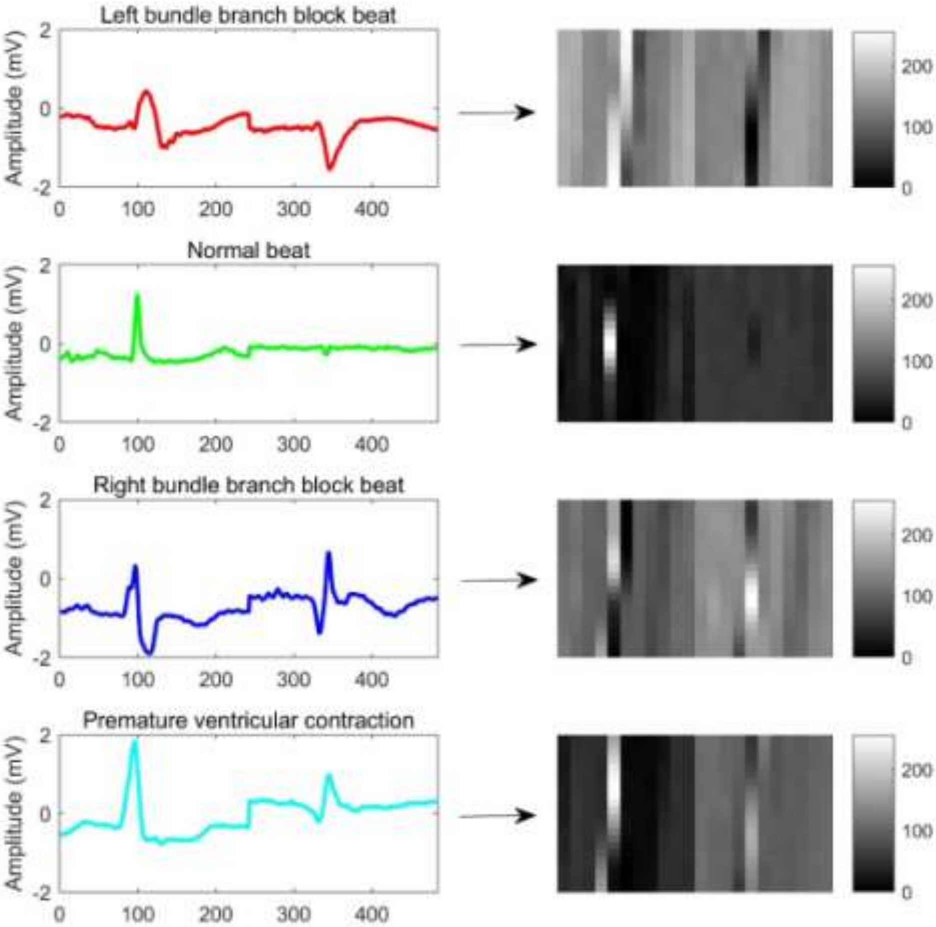

Figure 3. Sample normal and dysrhythmia electrocardiography beat with ML2 plus V1 lead. Left: one-dimensional beat signals. Right: the beat was transformed into a matrix as 2-dimensional inputs

2.3 CNN framework

The CNN structure is composed of four-stage process: convolution layer, rectified linear activation layer, pooling layer and fully-connected layer. Table 2 shows the detailed information of the CNN framework employed in this study. The CNN structure includes three convolutional layers, three pooling layers, one fully-connected layer and a softmax layer. Activation function uses rectified linear units (ReLU).

Table 1. A summary table with the breakdown of the 4 classes of beat subtypes

Lead	Type	Number of beats (every beat contains 256 samples)	Number of beats (every beat contains 242 samples)
V1	R	5724	5724
	L	8058	8058
	N	63644	63645
	V	6426	6426
ML2	R	5724	5724
	L	8068	8068
	N	67048	67049
	V	6939	6939

N=normal beat, L=left bundle branch block beat, R=right bundle branch block beat, V=premature ventricular contraction, ML2= modified lead II.

Table 2. The convolutional neural network model structure for electrocardiography data

Layers	Type	Output maps	Kernel size	Stride
1	convolution	6	5	-
2	pooling	-	-	2
3	convolution	12	3	-
4	pooling	-	-	1
5	convolution	24	3	-
6	pooling	-	-	1
7	fully-connected	2	-	-

2.4 Training and testing

Four types of beats were extracted from 41 patients. 5000 heart beats were selected in each arrhythmia type according to the result of beats segmentation, and the total number of heart beats was 20000. After randomly sorting these beats samples,90% ECG beat was randomly selected as CNN training data, and 10% ECG beat was selected as CNN testing data for each ECG lead type. Batch size, learning rate and epoch parameter in the backpropagation were set to10, 0.999and 30, respectively. We adjusted these parameters accordingly for optimal performance. Data training and testing were completed bythe software program Matlab (version 2017b).

2.5 Evaluation indicators

Four statistical indicators were used to access the performance of the proposed classifier in this work, which are classification sensitivity (Sen), positive predictive value (PPV), accuracy (Acc) and specificity (Spe). The classification accuracy reflects the total performance of the suggested way on all valid beats. Sen, PPV and Spe can objectively evaluate the classifier performance for different types of beat vary. The calculation method of four indicators is as follows:

$$Acc=\frac{TP+TN}{TP+TN+FN+FP} \quad (1)$$

$$Sen=\frac{TP}{TP+FN} \quad (2)$$

$$PPV=\frac{TP}{TP+FP} \quad (3)$$

$$Spe=\frac{TN}{TN+FP} \quad (4)$$

Where TN is true negative, TP is true positive, FN is false negative and FP is false positive.False positive is an error in data reporting in which a test result improperly indicates presence of a condition (the result is positive), when in reality it is not present, while a false negative is an error in which a test result improperly indicates no presence of a condition (the result is negative), when in reality it is present. True positive is a correctness in data reporting in which a test result properly indicates presence of a condition (the result is positive), when in reality it is present, while a true negative is a correctness in which a test result properly indicates no presence of a condition (the result is negative), when in reality it is not present. For example, the Table 3 shows the result of four category of a classification model. For the first category, the number of TP, TN, FP and FN is respectively obtained as follows: TP=a, TN=f+k+p, FP=e+i+m, FN=b+c+d.

Table 3. Confusion matrix of a classification model

		Predict category			
		1	2	3	4
True category	1	a	b	c	d
	2	e	f	g	h
	3	i	j	k	l
	4	m	n	o	p

Note: Lowercase letters represent the number of samples

III. RESULTS

Our algorithm was trained on a workstation with quad-core Intel i7-7700HQ 2.80 GHz processor and an 8GB RAM in this work. It took about 1996.2371 s to finish the training and testing for ECG beat data with modified lead II and 2068.6156 s for ECG beat data with V1 lead. It took about 10 s per epoch to train the input data with 1D or 2D.

The confusion matrix for ECG beats with modified lead II inputs in 1D level was presented in Table 4. It can be observed from Table 4 that, out of 504 left bundle branch block beats, approximately 0.40% of the ECG beat was wrongly identified as normal beats and only one beat was wrongly classified as premature ventricular contraction beat. Similarly, few normal beats, right bundle branch block beats and premature ventricular contractionbeats were wrongly classified as the others, respectively. The model's average accuracy and specificity value exceeded 99.00%. The sensitivity and positive predictive value also exceeded 98.30%. The overall accuracy of ML2 inputs in 2D level was increased by 0.45% comparing to ML2 inputs in 1D level.

The confusion matrix for ECG beats with V1 lead inputs in 1D level was presented in Table 4. It can be observed from Table 4 that, out of 506 left bundle branch block beats, approximately 1.19% of the ECG beat was wrongly identified as premature ventricular contraction beats and only one beat is wrongly classified as the others. Out of 488 normal beats, approximately 4.10% of the ECG beat was wrongly identified as premature ventricular contraction beats and approximately 1.64% of the ECG beat was wrongly identified as left bundle branch block beats. Few right bundle branch block beats were wrongly classified as the others. Out of 514 premature ventricular contraction beats, approximately 1.36% of the ECG beat was wrongly identified as normal and left bundle branch block beats respectively. The model's average accuracy was 97.00% and the specificity value exceeded 98.00%. The sensitivity and positive predictive value also exceeded 94.00%. The overall accuracy of V1 inputs in 2D level was decreased by 0.20% comparing to V1 inputs in 1D level. Overall, classification recognition results of the ML2 lead were superior to the V1 lead for the four heartbeat types in this study.

As Table 4 shows, there were differences among the three datasets in the levels of accuracy, sensitivity and positive predictive value. No significant differences were found in the level of specificity for the three datasets. Accuracy of ML2 plus V1 lead group was increased by 1.25% comparing to V1 lead group. However, its accuracy was decreased by 1.05% comparing to ML2 lead group. It is noteworthy that the sensitivity of ML2 plus V1 lead group is 100.00% for the right bundle branch block beat type. Overall, classification recognition results of the ML2 plus V1 lead was superior to the V1 lead for the four heartbeat types in this study.

Table 4. Confusion matrix of the electrocardiography beat classification result for different leads

Original/Predicted		L	N	R	V	Acc (%)	PPV（%）	Sen (%)	Spe (%)
ML2(1D)	L	496	1	0	1	98.85	98.22	99.60	99.40
	N	8	496	1	9	98.85	99.40	96.50	99.80
	R	0	2	493	0	98.85	99.80	99.60	99.93
	V	1	0	0	492	98.85	98.01	99.80	99.33
ML2(2D)	L	501	2	0	1	99.30	99.60	99.40	99.87
	N	0	486	1	1	99.30	98.78	99.59	99.60
	R	0	1	509	0	99.30	99.22	99.80	99.73
	V	2	3	3	490	99.30	99.59	98.39	99.87
V1 lead(1D)	L	459	9	1	1	97.20	96.84	97.66	99.00
	N	13	463	8	12	97.20	96.26	93.35	98.80
	R	0	3	512	1	97.20	98.27	99.22	99.38
	V	2	6	0	510	97.20	97.33	98.46	99.03
V1 lead(2D)	L	498	1	1	6	97.00	97.08	98.42	98.97
	N	8	459	1	20	97.00	97.87	94.06	99.33
	R	0	2	487	3	97.00	98.78	98.98	99.59
	V	7	7	4	496	97.00	94.48	96.50	98.03
ML2+V1(1D)	L	492	7	0	0	98.95	98.99	98.60	99.66
	N	4	506	0	1	98.95	97.50	99.02	98.99
	R	0	2	497	0	98.95	100.00	99.60	100.00
	V	1	6	0	484	98.95	99.7	98.57	99.93
ML2+V1(2D)	L	485	2	0	6	98.25	98.58	98.38	99.53
	N	3	503	2	4	98.25	98.05	98.24	99.32
	R	0	0	514	0	98.25	98.47	100.00	99.45
	V	4	8	6	463	98.25	97.89	96.26	99.34

Acc=accuracy, PPV=positive predictive value, Sen=sensitivity, Spe=specificity, N=normal beat, L=left bundle branch block beat, R=right bundle branch block beat, V=premature ventricular contraction, ECG= electrocardiogram, ML2= modified lead II

IV. DISCUSSION

The different techniques were employed by some researchers to detect dysrhythmia using ECG signals gained from the MIT-BIH public database. However, most studies mainly focused on one-dimensional sequential signals of one lead (ML2) ECG signals. For example, a principal component analysis network was applied for feature extraction of noisy

ECG signals in the MIT-BIH database and a linear support vector machine (SVM) was applied for classification, which identified five types of noise-free ECGs and obtained 97.08% accuracy [35]. Similarly, the features of ECG samples (RR series) were computed by different scales of the wavelet transform and the results achieved global accuracy of 93.00% [36]. In order to improve recognition performance, ECG signals in time-frequency space were represented by discrete cosine transform and the time-frequency features were decreased in smaller dimensional space through principal component analysis. Additionally, these morphological characteristics combined with dynamic features (RR-interval information) to represent the feature vectors as the input of SVM [37]. In recent years, some researchers turned attention to CNN and used it for identifying category of heartbeats in ECG signals. A nine-layer deep CNN was used to automatically pick out five different categories of heartbeats in ECG signals. The CNN was trained with original dataset and obtained an accuracy of 89.07%% and 89.3% in noisy and noise free ECG, respectively. When the CNN was trained using the augmented data, the accuracy of the CNN increased to 94.03% and 93.47% in original and noise free ECG [5]. Ten seconds ECG signals fragments were analyzed by deep one-dimensional-CNN and achieved the overall accuracy of 91.33% in seventeen cardiac arrhythmia disorders [32]. In this study, the overall accuracy was over 97.00% in classification of the four types of rhythm with two-dimensional-CNN. On the basic of MIT-BIH arrhythmia database, a classification method achieved sensitivity of 93.40% and positive predictivity of 94.90% in ventricular ectopic beat detection by two-level one-dimensional-CNN [38].

We have used ML2 and V1 lead in this study because they were a usually employed lead for cardiac rhythm monitoring. Moreover, ML2 can achieve good ECG morphological information. After the beat was transformed into matrix as two-dimensional input to the CNN classifier, Table 2 showed that the proposed system has perfect classification capability for the ECG beats. It suggested that more morphological information is contained in the ML2 comparing to the V1 lead for ECG signals with 2D-reconstruction. In general, the ECG beats noise weakened the overall performance of the presented system because noise was redundant information in the signals. In our study, the unidentified noisy ECG beats were accurately classified by CNN deep learning method. It suggested that our presented method is robust to unwanted noise and can distinguish the intrinsic structural characteristics of ECG with noise interference. Besides, it saved time for removing the noise in this method. CNN deep learning method does not need different types of feature selection or extraction technologies in ECG signals analysis which is the superiority of deep learning over the traditional machine learning methods. Moreover, the proposed system performance will be enhanced with the growing number of ECG data. The major high points of our presented method were as follows: (1) 7-layer CNN was carried out; (2) Denoising was not needed; (3) Feature selection and extraction technologies were not required. Meanwhile, the disadvantages of our presented method were computationally expensive and required a diversified and massive data. Actually, the long training time is less important when our presented method can accurately categorize the normal and the arrhythmia types. Our presented method can promptly classify an unknown ECG beat after it is trained. Additionally, it can contribute to lessen computational complexity and power dissipation if the CNN is trained with graphics processing unit (GPU).

In future studies, we plan to get more ECG data from different sources to improve the system overall performance. On the other hand, we also plan to popularize the method to other cardio-diseases such as myocardial infarction and heart-failure.

V. CONCLUSIONS

This study proposed a new method to automatically classify dysrhythmia types by seven-layer CNN which gains high performance result in the ECG signals and can help doctor in the course of diagnosis.

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