Classification of atrial fibrillation and normal sinus rhythm based on convolutional neural network

Mei-Ling Huang¹ · Yan-Sheng Wu¹

Received: 25 June 2019 / Revised: 5 December 2019 / Accepted: 6 January 2020 / Published online: 16 January 2020
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Abstract

Electrocardiogram (ECG) technology plays a vital role in detecting arrhythmia. Numerous achievements have been marked in ECG-related research. Most methods first pre-process ECG signals, then extract features, and finally classify them. Most of the ECG signals used in the related studies were analyzed in specific time intervals or using a fixed number of samples. However, it is not always possible to see significant changes in a short term, and the symptoms of some patients are relatively short-lived. Misjudgments are possible because the ECG signal was not accurately extracted. This study proposes a computer-aided diagnosis (CAD) system for classification of Atrial Fibrillation and Normal Sinus Rhythm based on ECG signals through convolutional neural network. The proposed system considers a single heartbeat, rather than a specific number of seconds. This study eschews the one-dimensional digital ECG signal used in previous studies and uses convolutional neural networks to analyze two-dimensional ECG image. This study explores whether two-dimensional image ECG requires signal filtering. The final classification results in filtered ECG signals is accuracy of 99.23%, sensitivity of 99.71%, and specificity of 98.66%. The best result in non-filtered ECG signals achieves accuracy of 99.18%, sensitivity of 99.31%, and specificity of 99.03%. With no cumbersome artificial settings, the results of this study are comparable to the related studies. The proposed CAD system has high generalizability; it can help doctors to diagnose diseases effectively and reduce misdiagnosis.

Keywords Atrial fibrillation · Electrocardiogram · Convolutional neural network

1 Introduction

In recent years, the World Health Organization's data on noninfectious chronic disease (NCD) have indicated that NCD is the leading cause of global death to date. In 2016, NCD accounted for 71% (41 million) of the world's 57 million deaths. The main cause of these deaths is cardiovascular disease (17.9 million deaths, accounting for 44% of all NCD deaths and 31% of global deaths) [1]. Another statistic is that the number of deaths from cardiovascular disease (CVD) increased from 17 million in 2008 (29% of global deaths) to 17.9 million in 2016 (31% of global deaths) [2, 3]. As early as 2010, the World Health Organization has already proposed countermeasures for cardiovascular diseases. However, from the data, cardiovascular disease has not improved

but has increased. This proves the danger to public health posed by cardiovascular disease. Common cardiovascular diseases include, stroke, hypertensive heart disease, rheumatic heart disease, and atrial fibrillation (AF). Some cardiovascular diseases may seem to be difficult to predict, but in fact, known signs and symptoms can be recognized; caregivers who know the signs can seize the opportunity of treatment before dangerous episodes occur [3].

Atrial fibrillation is the most common type of arrhythmia in clinical disease [4]. Unlike other arrhythmia, the main symptom is that the heart rate could be normal, slow, or fast, presenting an irregular pattern. Therefore, the blood output of the heart will decrease, and the blood pressure of the patient may decrease [5]. ECG is the primary diagnostic tool for understanding arrhythmias; ECG signals contain information about different types of arrhythmias, but manual analysis of ECG signals is difficult. Arrhythmia signals are not always present, and may require long-term records and observations; these signals are complex and nonlinear [6].

The ECG related literature has shown that using machine learning and electrocardiogram diagnosis through computer

✉ Mei-Ling Huang
huangml@ncut.edu.tw

¹ Department of Industrial Engineering and Management,
National Chin-Yi University of Technology, Taichung,
Taiwan

aid diagnosis (CAD) system has good results. Maji et al. [7] proposed an empirical mode decomposition (EMD) to automatically detect AF. The study used 110 normal rhythms and 68 AF rhythms in the MIT-BIH AF dataset. The average sensitivity was 92.89% and the average specificity was 90.48%. Martis et al. [8] used the discrete wavelet transform (DWT) to interpret the MIT-BIH arrhythmia Dataset with an ECG signal length of 200 beats as an analysis. The experimental results proved that the combination of DWT, ICA, and PNN was better than other combinations, and the average accuracy was 99.28%. Pławiak [9] proposes an innovative research method based on the MIT-BIH arrhythmia dataset, using the Welch method and the discrete Fourier transform to extract features from a 10-s ECG signal. A genetic algorithm was used to test its parameters and features, and finally cross-validation and Their SVM results were optimal, with an accuracy rate of 98.85%. Jung and Lee [10] proposed a research method that integrated PCA and LDA to ECG signal features of 256 samples; they used kNN to classify, but not all of the data could be effectively classified. They used a weighted kNN (WkNN) for classification. Their main purpose was to classify all ECG signals efficiently and accurately, and their display accuracy was 94.41%. These studies focused on preprocessing, feature extraction, feature selection, and classification of ECG signals.

The related CAD systems for ECG signal classification can be divided into four steps as follows: (1) ECG signal preprocessing; (2) heartbeat segmentation; (3) feature extraction; and (4) classification [11]. These steps are developed to correctly classify/identify the type of heartbeat. However, these methods are complicated and cumbersome, many scholars have used convolutional neural network (CNN) on ECG in recent years. Acharya et al. [12] studied AF, atrial flutter, and ventricular fibrillation arrhythmia with a CAD system. In their system, a one-dimensional convolutional neural network (1D-CNN) automatically detected ECG signals within 2-s and 5-s intervals. The results showed an accuracy of 92.50% and 94.90%, respectively. Fausta et al. [13] used deep learning long short-term memory (LSTM) to detect AF heartbeats in the MIT-BIH AF dataset signal. The study used 20 subjects with an ECG signal length of 100 beats with tenfold cross-validation, and 98.51% accuracy. The study also showed that feature extraction is not required. Yıldırım et al. [14] applied convolution operations to ECG. They utilized 1000 10-s ECG signal segments from the MIT-BIH arrhythmia dataset and classified them using a 1D-CNN. The results of this study achieved an overall accuracy of 91.33%. Oh et al. [15] published an automated system that used a 1D-CNN and a LSTM to diagnose cases from the MIT-BIT arrhythmia Dataset with an ECG signal length of 260 beats for analysis. The accuracy rate under this architecture was 98.10%. An LSTM is a time recurrent neural network that does deep learning; LSTMs are widely

used to analyze time series. The present study added an LSTM to a CNN to achieve accurate classification results. Andersen et al. [16] proposed a model combining CNN and Recurrent Neural Networks with an ECG signal length of 30 beats for analysis. The model obtained 98.98% and 96.95% sensitivity and specificity in the MIT-BIH AF Dataset via fivefold cross-validation, respectively. Rahhal et al. [17] applied stacked denoising autoencoders (SDAEs) to ECGs and then classified them with deep neural network (DNN). In addition, the author used three different ECG Datasets to experiment. The overall accuracy of the final experiment was as high as 98%. Pourbabaee et al. [18] used a large number of paroxysmal AF (PAF) ECG signals for analysis. The method is divided into four types. Finally, the study used CNN as feature extraction, and KNN was the best result of classification. Kiranyaz et al. [19] used 256 samples of the MIT-BIH arrhythmia dataset in 1D-CNN to evaluate Abnormal Beat Synthesis (ABS). The final accuracy rate is 97.75%. Zubair et al. [20] used a simple 1D-CNN, including three convolution layers, three fully connected layers, a multi-layer perceptron layer, and a softmax layer on the MIT-BIH arrhythmia dataset. The ECG signal length was 128 samples for analysis and the final accuracy was 92.7%.

In summary, most of the literature on applied machine learning focuses on feature extraction, classification, etc. to improve accuracy. The main method applying deep learning used in the literature is one-dimensional CNN, and the performance is comparable to the machine learning literature. The advantage is that feature extraction and feature selection was not required to be set manually in CNN. Azad et al. [21] converted 1D signals to 2D images, extracted features, and applied support vector machine and empirical mode decomposition algorithm for classification. Adel et al. [22] presented an ECG data compression algorithm converting ECG signals to images and discussed the effect of additive white Gaussian noise on the quality of ECG signals. A transfer learning approach transferring ECG signals to images was proposed through the application of continuous wavelet transform for Arrhythmia detection, and a deep CNN trained on ImageNet was employed [23]. ECG signals were transformed into a binary image via one-hot encoding, and the 2D image captures the morphology of a single heartbeat and the relationship between adjacent beats [24].

At present, the application of 2D-CNN to the field of biomedical imaging is quite popular and has desirable results [7–10]. This study proposes a CAD system for classification of AF and NSR based on ECG signals through 2D-CNN. The proposed CAD system first extracts the heartbeat from datasets, performs heartbeat segmentation to form a single heartbeat signal, converts the digital electrocardiogram signal into 2D image data, and finally sends the image data to CNN for classification. The CAD system is divided into three parts: (1) Data pre-processing: signal filtering and

segmentation; (2) Create of image dataset; and (3) CNN classification. The major contribution of the proposed CAD system includes no feature extraction and no feature selection, heartbeat segmentation, image preparation and ECG classification through the application of a 2D-CNN. Unlike other 2D-CNN used in the related studies, the proposed heartbeat segmentation can be used for the rapid changeable and irregular heart rates. The proposed CAD system can be applied on the wide variety of arrhythmia.

2 Methods

2.1 Dataset

The ECG Dataset used in this article was downloaded from a publicly available source, PhysioBank [25]. This study used the MIT-BIH AF (AF) Dataset and the MIT-BIH NSR Dataset. The AF Dataset includes 25 long-term ECGs. Of these, records 00735 and 03665, represented only by the rhythm (.atr) and unaudited beat (.qrs) annotation files, are not included in this study. Therefore, this study used 23 cases of AF ECG. The NSR (NSR) Dataset includes 18 long-term

ECGs. Subjects in this Dataset were found to have no significant arrhythmias. A total of 41 patients signal files (.dat), annotated files (.atr), and QRS files (.qrs) files were collected from the PhysioBank ATM. Each ECG record of AF and NSR Datasets contains leads for ECG1 and ECG2. In this study, we selected ECG1 record for further analysis. Table 1 shows the number of patients in the collected Dataset.

In this study, the P-QRS-T wave of the heartbeat of the MIT-BIH AF Dataset and the NSR Dataset was compiled by the archives downloaded from the PhysioBank (dat, atr, qrs). Table 1 summarizes the total number of heartbeats, the number of AF, and the total number of heartbeats used in AF dataset. The ECG signals of the first 1000 AF heartbeats were segmented for each patient. The AF of patients with numbers 04015, 0448, 05091 and 06453 is less than 1000 (For example, 04015 patients all have only 525 AF heartbeats, so only 525 are used; 04043 patients all have 14,634 AF heartbeats, so only the first 1000 AF heartbeats are used, and so on.), so a total of 20,985 heartbeats are used in the AF Dataset. Table 1 also provides the total number of heartbeats and the number of heartbeats used in NSR dataset. Since the total number of heartbeats for each record with NSR is greater than 1000, the first 1000

Table 1 AF and NSR dataset

MIT-BIH AF dataset					MIT-BIH NSR dataset			
	Patient	Total heartbeat	Total AF	Use heartbeats		Patient	Total heartbeat	Use heartbeats
1.	04015	44,005	525	525	1.	16265	100,485	1000
2.	04043	61,915	14,634	1000	2.	16272	95,883	1000
3.	04048	40118	873	873	3.	16273	89,877	1000
4.	04126	43,752	3436	1000	4.	16420	102,094	1000
5.	04746	49,048	30,904	1000	5.	16483	104,342	1000
6.	04908	63,192	5811	1000	6.	16539	108,288	1000
7.	04936	54,919	39,587	1000	7.	16773	81,999	1000
8.	05091	36,778	141	141	8.	16786	101,636	1000
9.	05121	49,615	32,818	1000	9.	16795	86,904	1000
10.	05261	47,228	1023	1000	10.	17052	87,542	1000
11.	06426	57,497	55,441	1000	11.	17453	100,692	1000
12.	06453	34,975	446	446	12.	18177	116,202	1000
13.	06995	56,535	28,895	1000	13.	18184	102,633	1000
14.	07162	39,298	39,298	1000	14.	19088	99,641	1000
15.	07859	61,298	61,298	1000	15.	19090	81,619	1000
16.	07879	58,032	40,145	1000	16.	19093	75,241	1000
17.	07910	37,807	7878	1000	17.	19140	96,805	1000
18.	08215	44,170	33,993	1000	18.	19830	110,348	1000
19.	08219	60,827	14,297	1000				
20.	08378	46,336	11,492	1000				
21.	08405	61,592	47,881	1000				
22.	08434	40,762	2311	1000				
23.	08455	61,571	46,328	1000				
			Sum	20,985			Sum	18,000
			Total AF and NSR heartbeat					38,985

heartbeat ECG signals were extracted for each record. The total number of heartbeats used in patients with AF and NSR was 38,985 (20,985 AF and 18,000 NSR).

2.2 Pre-processing

2.2.1 Signal filtering

In fact, the noise signal is superimposed when the ECG signal is collected and transmitted. The most effective method to eliminate the noise signal is signal filtering. It mainly eliminates noise in continuous ECG signals, but signal filtering also has the potential to attenuate the characteristic peaks of ECG signals. The output does not retain the original information of the ECG signal. Singh and Tiwari [26] proposed a selection method based on a wavelet basis function in 2006 for the removal of noise in ECG signals in the wavelet domain. This method can retain the signal peak and a large proportion of the full amplitude. The ECG signal after the final removal of the noise preserves the necessary diagnostic information contained in the original ECG signal. Singh and Tiwari's signal filtering method was used in this study. To explore whether it is effective to use signal filtering in CNN for ECG signals, this study established one filtered signal dataset and one non-filtered signal dataset to compare the classification performance in Sect. 3.

2.2.2 Heartbeat segmentation

Heartbeat segmentation is to ensure that each heartbeat segmentation contain a single heartbeat P-QRS-T wave. Since the heart rate of patients with AF is not the same, this study does not divide the fixed sample with the R peak as the center. Instead, the R peak position of each heartbeat is divided into front and rear. Equations (1) and (2) were developed for the segmentation, where N_{Left} is the total number of samples between the $(n-1)$ th R peak and the n th R peak divided by 2, N_{Right} is the total number of samples between the n th R peak and the $(n+1)$ th R peak divided by 2, R_N is the position of the R peak, and N denotes the samples of a single heartbeat (Fig. 1).

$$N_{\text{Left}} = (R_N - R_{N-1})/2 \quad (1)$$

$$N_{\text{Right}} = (R_{N+1} - R_N)/2 \quad (2)$$

$$N = N_{\text{Left}} + N_{\text{Right}} \quad (3)$$

Fig. 1 Heartbeat segmentation

2.3 Create an image dataset

Two image datasets were created to be prepared using a CNN. The first one-dimensional digital ECG dataset was formed after signal filtering and segmentation for the filtered signal experiment, and the second one-dimensional digital ECG dataset was formed after signal segmentation for the non-filtered signal experiment. As shown in Fig. 2, each patient's ECG digital signal was used and converted to draw a 2D image type ECG via MATLAB, in order to obtain a 2D heartbeat ECG image for CNN. Figure 2a was part of the original ECG signals download from the dataset. In the X–Y domain, the Y-axis represents the ECG signals and X-axis represents the time sequence to convert ECG signals into 2D ECG images as plotted in Fig. 2b. The 2D image indicates the ECG value of ECG signal at the corresponding time space by representing the amplitudes of the EEG signals as a function of time.

2.4 Convolutional neural network

Before deciding on the optimal architecture and configuration of CNN, one must consider the particularities for ECG classification. A black-and-white ECG image is a meaningful waveform and differs from a color image relating to a structure with a specific direction and complexity. Although humans can define waveforms intuitively and simply, it is not an easy task to process numerous and complicated ECG waveforms. That is the reason why many articles using deep learning discuss ECG in the literature.

2.4.1 Convolutional neural network—import dataset

The CNN software used in this study was MATLAB R2018a. First, AF and NSR ECG images were loaded into

Fig. 2 Process of converting ECG signals into ECG images

MATLAB, and then all images were divided into training and test sets. This study used 80% of the data as a training set and 20% of the data as a test set.

2.4.2 Convolutional neural network—architecture

The image of this study and the MNIST data set belong to a simpler image. Therefore, this study is set up with reference to Wan's [27] CNN architecture (2-layer convolutional layer and 2-layer fully-connected layer), as shown in Fig. 3.

The CNN architecture of this study has two layers of convolutional layers and two layers of pooling layers. Before the image is convoluted, four parameters must be set, namely kernel size, L kernel size, Padding number, and stride number. After the convolution layer operation, the pooling layer is calculated. Before the pooling layer operation, two parameters must be set, namely the kernel size and the stride number. These settings must be established both in the first layer and in the second layer. Therefore, 12 parameters are relevant after the operation, and the parameters are listed in Table 4. Besides, the Dropout was used for checking over-fitting. After the CNN

architecture has been determined, the system must define the photo size of the input CNN. The input size of the photo of this study was 250×250 . The convolutional layer is the main building block of CNN and it's the representative structure of deep models. The convolutional applied in CNN can expressed as [28]:

$$x_j^l = f \left(\sum_{i \in M_j} x_j^{l-1} * k_{ij}^l + b_j^l \right)$$

where x_j^l is the output of the current layer, x_j^{l-1} is the previous layer output, k_{ij}^l is the kernel for the present layer, and b_j^l are the biases for the current layer. M_j represents a selection of input maps. For each output map, an additive bias b is given. The symbol $*$ indicates the convolutional operation. The max pooling applied in CNN can expressed as [29]:

$$x_{r,c}^l = \max_{0 \leq m, n < s} \{ x_{r*s+m, c*s+n}^i \}$$

Fig. 3 CNN architecture diagram

where $x_{r,c}^i$ is the neuron located at (r, c) in the i th output map of a max-pooling layer, and it is assigned with the maximum value over a local region of size $s \times s$ in the i th input map x^i .

2.4.3 Convolutional neural network—activation function

The activation function [30] converts the input neurons into a neuron output through an activation function. Activation functions are divided into linear functions and nonlinear functions. The outputs of linear functions change uniformly with the inputs; no matter how many layers are added, the hidden layer network will have the same content, thus a linear function becomes meaningless; therefore nonlinear functions are commonly used.

The sigmoid function Eq. (4) [30], is the most common activation function, defining the domain from positive infinity to negative infinity, with some value from 0 to 1, and a slope symmetric to the y -axis.

$$h(x) = \frac{1}{1 + \exp(-x)} \quad (4)$$

The commonly used rectified linear unit (ReLU) function [30] is Eq. (5). If the input x exceeds 0, the input x is directly output, and if the input x is less than or equal to 0, the output is 0.

$$h(x) = \begin{cases} x & (x > 0) \\ 0 & (x \leq 0) \end{cases} \quad (5)$$

In today's deep neural networks, the learning effect of the Sigmoid function is relatively poor, and the ReLU function is often used as the activation function of the neural network. In this study, the activation function was arranged in the CNN architecture of this study after the convolutional layer and the fully-connected hierarchy, and finally the softmax layer was output as depicted in Fig. 3.

2.4.4 Convolutional neural network—update parameters

The main purpose of the CNN is to discover the parameters that can minimize the loss function, which is the decision variable. This minimization problem is a specific type of optimization. The loss function is mainly used as an indicator of the advantages or disadvantages of the neural network. It is used to indicate that the training data set is not suitable for the current neural network. Two common loss functions are Mean Squared Error and Cross Entropy Error.

Optimization methods include Stochastic Gradient descent (SGD), Root Mean Square Propagation (RMSProp), Adaptive Gradient Algorithm (AdaGrad) [30], and Adaptive Moment Estimation (Adam). The common point of the aforementioned method formula is the learning rate (η), and in the learning of the neural network, the quality of the

learning rate (η) is crucial. If the learning rate is too large, it will spread out and make it impossible to learn accurately. If the learning rate is too small, the system will require excessive time for learning.

Since each optimization method has its own advantages, each method is effective for some set of problems and ineffective for a different set of problems. Until now, no optimization method has been able to solve all problems perfectly. The updated parameter used in this study is SGD.

2.5 Assess performance indicators

The CAD system proposed by the Institute is evaluated for sensitivity, specificity, and accuracy. Sensitivity refers to the proportion of samples that are actually positive (patients with arrhythmia), and that are judged to be positive (for example, in patients with arrhythmia, the proportion of arrhythmia judged by the doctor). The calculation method is the ratio of true positive divided by true positive + false negative (actually positive, but judged negative). Specificity refers to the proportion of samples that are actually negative (patients with normal heart rhythm), and that are judged to be negative (for example, the proportion of patients without true arrhythmia who are judged to have arrhythmia by the doctor). The calculation method is the ratio of true negative divided by true negative + false positive (actually negative, but judged positive). Accuracy refers to the ratio of positive and negative in a sample that is actually positive (a patient with arrhythmia) and negative (a patient with a normal heart rhythm). The calculation method is true positive and true negative divided by true positive + true negative + false positive + false negative.

$$\text{Sensitivity (Sen.)} = \frac{TP}{TP + FN}$$

$$\text{Specificity (Spe.)} = \frac{TN}{TN + FP}$$

$$\text{Accuracy (Acc.)} = \frac{TP + TN}{TP + FN + TN + FP}$$

2.6 Experiment setup

Step 1 The 23 cases of MIT-BIH AF (AF) Dataset and the 18 cases of MIT-BIH NSR Dataset were included. The total number of heartbeats used in patients with AF and NSR was 38,985 (20,985 AF and 18,000 NSR).

Step 2 Daubechies wavelet (db8) was applied to eliminate the signal noises.

Fig. 4 ECG segments for MIT-BIH AF and NSR Datasets

- Step 3** The number of samples of ECG signal length was calculated by using proposed Eqs. (1) and (2).
- Step 4** Experiment 1 contains a total of 38,985 filtered ECG signals, and the same number of non-filtered ECG signals was used in Experiment 2.
- Step 5** The above one-dimensional ECG digital signals of Experiment 1 and Experiment 2 were converted into 2D images. Y-axis represents the ECG signals and X-axis represents the time sequence, and each ECG image size was 250×250 .
- Step 6** Input the converted 2D ECG image to CNN, which is 2-layer convolutional layer and 2-layer fully-connected layer. Set the parameters including kernel size, padding number, and stride number. The updated parameter used in this study is SGD.
- Step 7** Record accuracy, sensitivity, specificity and training time for each experiemnt.

Table 2 Heartbeat segmentation information of AF 04015 patients

QRS wave	R peak position	Symptom	N _{Left}	N _{Right}	N
613th	102,658	AF	57	41	98
614th	102,796	AF	41	43	84
615th	102,919	AF	43	50	93
616th	103,023	AF	50	67	117
617th	103,122	AF	67	63	130

Table 3 Heartbeat segmentation information of NSR 16,265 patients

QRS wave	R peak position	Symptom	N _{Left}	N _{Right}	N
13th	995	NSR	40.5	39.5	80
14th	1074	NSR	39.5	40.0	80
15th	1154	NSR	40.0	41.0	81
16th	1236	NSR	41.0	41.5	83
17th	1319	NSR	41.5	41.0	83

3 Results

3.1 Pre-processing

3.1.1 Signal filtering

In this study, the method proposed by Singh et al. was used in the MATLAB environment to denoise all ECG signals using a Daubechies wavelet (db8). Figure 4 illustrates the signal filtering results of patients with AF 04015 and NSR 16,265. It can be clearly seen from the figure that the noise in the ECG signal is significantly reduced and the signal peak value is maintained close to the full amplitude.

3.1.2 Heartbeat segmentation

After pre-treatment, the five R peak positions of 04015 patients with AF in Table 2 were obtained, and the number of samples of ECG signal length was calculated by using Eqs. (1) and (2). Table 3 shows the five R peak positions of patients with NSR 16,265. In Tables 2 and 3, it can be seen that the samples of a single heartbeat for AF are quite different. This is because the heart rate of patients with AF could be fast or slow, presenting an irregular pattern. It is therefore inappropriate to use fixed samples of a single heartbeat as an analysis. In NSR patients, the samples of

Fig. 5 Schematic diagram of heartbeat segmentation in 04015 patients with AF

Fig. 6 Schematic diagram of heartbeat segmentation in 16,265 patients with NSR

a single heartbeat are similar for each heartbeat. Figures 5 and 6 are plots of heartbeat segmentation. The samples of a single heartbeat, N , was used as the input to create the image dataset.

According to the results from Sect. 3.1, a total of 38,985 filtered ECG signals were obtained in Experiment 1, and the same number of non-filtered ECG signals was used in Experiment 2. The above one-dimensional ECG digital signals of Experiment 1 and Experiment 2 were converted into 2D images, and each ECG image size was (250×250) .

3.2 ECG classification

The converted 2D image ECG is input to the proposed CNNs. Table 4 shows the parameter combinations of 10 CNNs. Each parameter combination was replicated 5 times and the results were averaged in Table 5.

Table 5 shows the average results of 5 experiments of accuracy, sensitivity, specificity and training time of filtered

ECG signals and non-filtered ECG signals. The best recommended parameter setting in Experiment 1 (filtered ECG signals) was the fifth, with accuracy of 99.23%, sensitivity of 99.71%, and specificity of 98.66%. In addition, the best recommended parameter setting in Experiment 2 (non-filtered ECG signals) is the eighth with accuracy of 99.18%, sensitivity of 99.31%, and specificity of 99.03%.

4 Discussion

In the heartbeat segmentation results, it can be clearly seen from Figs. 5 and 6 that the heart rate of patients with AF is flickering and irregular. Therefore, it is not feasible to use a fixed number of samples to divide the AF heartbeat. According to the formulas (1) to (3) proposed in this study, it is more reasonable to perform heartbeat segmentation on the number of samples required for each AF heartbeat calculation. These formulas were also applied to patients with

Table 4 CNN parameter setting

No.	A Conv1 Kernel size	B Conv1 Number of kernel	C Conv1 Stride	D Conv1 Padding	E Pooling1 Kernel size	F Pooling1 Stride	G Conv2 Kernel size	H Conv2 Number of kernel	I Conv2 Stride	J Conv2 Padding	K Pooling2 Kernel size	L Pooling2 Stride
1	15	48	6	1	3	3	7	256	2	3	2	2
2	20	48	8	1	3	3	7	256	2	4	2	2
3	11	48	4	2	5	2	5	128	2	3	3	2
4	15	48	6	2	5	2	5	128	2	4	3	2
5	11	96	4	2	5	2	7	256	1	4	2	2
6	11	96	6	1	5	3	5	256	1	4	3	2
7	15	96	8	1	5	3	5	256	1	2	3	2
8	20	96	4	1	5	3	5	256	1	3	3	2
9	11	96	6	2	3	3	7	128	2	4	3	2
10	15	96	8	2	3	3	7	128	2	2	3	2

Table 5 Average results of five experiments in Experiment 1 and Experiment 2

No.	Experiment 1				Experiment 2			
	Accuracy (%)	Sensitivity (%)	Specificity (%)	Time	Accuracy (%)	Sensitivity (%)	Specificity (%)	Time
1	99.04	99.23	98.82	433	98.87	98.99	98.73	401
2	98.72	98.81	98.61	414	98.73	99.30	98.06	397
3	99.13	99.28	98.96	438	99.13	99.33	98.90	434
4	98.95	99.06	98.82	402	98.92	98.90	98.95	398
5	99.23	99.71	98.66	818	99.13	99.45	98.75	806
6	99.09	99.56	98.55	461	98.94	98.95	98.93	456
7	98.87	98.85	98.90	410	98.61	98.96	98.21	407
8	99.11	99.31	98.87	599	99.18	99.31	99.03	720
9	98.29	97.81	98.86	417	98.66	99.02	98.25	685
10	98.28	99.09	97.33	395	98.20	98.60	97.74	661

Bold values indicates the highest accuracies with corresponding Sensitivity, Specificity and Time for Experiments 1 and 2

NSR. Each patient's own heart rate may not change like the heart rate of patients with AF, but the heart rate varies from patient to patient. The studied formulas (1) to (3) provide a more accurate heartbeat segmentation standard.

This study explores the effect of signal filtering on CNN classification using 2D ECG image. Table 5 shows the average classification result of the CNNs for Experiment 1 (filtered ECG signals) and Experiment 2 (non-filtered ECG signals). From the results in Table 5, both accuracies from Experiment 1 and Experiment 2 are higher than 98% regardless of parameter settings. Obviously, in this case, the signal filtering has no significant effect on the ECG classification results of CNNs. The 2D ECG image is not complicated and the selected CNN architecture in this study is quite simple which corresponds to the finding from Wan et al. [27] that

a multi-layered network architecture does not necessarily increase the accuracy for simple images.

The applications of CNN on ECG signals using MIT-BIH AF dataset were summarized in Table 6. Most of the ECG signal lengths used in the related literature in Table 6 are defined by a certain number of samples or for a fixed period of time. This study analyzes the ECG signals based on a single heartbeat. The automated CAD system implemented in this study does not require common feature extraction, feature selection, and signal filtering. The variable sample sizes of ECG signals for a single heartbeat was used in this study. The proposed CAD system converts ECG signals into a 2D ECG image and performs classification using a CNN. Finally, the results of this study are compared with the literature (Table 6). Most of the studies achieved high accuracies. It is clear that the results of this study outperform the related literature on sensitivity, specificity, and accuracy. Although

Table 6 Comparison of ECG CAD system

Author	Dataset	ECG signal length	ECG rhythms	Classifier	Result
Acharya et al. [12]	afdb	2 s	A_{fib}	1D-CNN	2 s
	mitdb cudb	5 s	A_{fl} V_{fib} N_{sr}		Acc = 92.50% Sen = 98.09% Spec = 93.13% 5 s Acc = 94.90% Sen = 99.13% Spec = 81.44%
Xia et al. [31]	afdb	5 s	A_{fib} non- A_{fib}	STFT	STFT
				SWT 2D-CNN	Acc = 98.29% Sen = 98.34% Spec = 98.24% SWT Acc = 98.63% Sen = 98.79% Spec = 97.87%
Faust et al. [13]	afdb	100 beats	A_{fib} N_{sr}	LSTM	Acc = 98.51% Sen = 98.32% Spec = 98.67%
Andersen et al. [16]	mitdb afdb nsrdb	30 beats	A_{fib} N_{sr}	Combine CNN and LSTM	Acc = 97.80% Sen = 98.98% Spec = 96.95%
This study	afdb nsrdb		A_{fib} N_{sr}	CNN	Experiment one Acc = 99.23% Sen = 99.71% Spec = 98.66%
					Experiment two Acc = 99.18% Sen = 99.31% Spec = 99.03%

Acc accuracy, Sen sensitivity, Spec specificity, A_{fib} AF, A_{fl} atrial flutter, V_{fib} ventricular flutter, N_{sr} NSR, mitdb MIT-BIH arrhythmia dataset, afdb MIT-BIH AF dataset, nsrdb MIT-BIH NSR dataset, cudb Creighton University Ventricular Tachyarrhythmia, STFT short-term Fourier transform, SWT stationary wavelet transform

the architecture of the proposed ECG CAD system of this study is simple, the classification performance is effective.

5 Conclusion

In general, detecting atrial fibrillation involves the use of changes in the waveform of the ECG, notably the length and number of times. The proposed ECG CAD system preprocesses, builds images, and predicts whether the waveform has pattern of AF. The system can easily process a heartbeat data series into a single heartbeat, and converts the series of single heartbeats into an image without feature selection. The results delivered 99.18% accuracy, 99.31% sensitivity and 99.03% specificity for non-filtered ECG signals. With no cumbersome artificial settings, the results of this study are comparable to the related studies. The proposed CAD system has high generalizability; it can help doctors to diagnose diseases effectively and reduce

misdiagnosis. This can save considerable time, and finally the doctors can easily deliver the diagnosis for the patient.

Acknowledgements The authors gratefully acknowledge the financial support of the Ministry of Science and Technology of Taiwan, R.O.C. through its grants MOST 108-2221-E-167-001.

Compliance with ethical standards

Conflict of interest All authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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