Integration of Results From Convolutional Neural Network in a Support Vector Machine for the Detection of Atrial Fibrillation

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***Abstract*— Atrial fibrillation (AF) can cause a variety of heart diseases and its detection is insufficient in outside hospital. We proposed three methods for AF diagnosis in ambulatory settings. The first method is a convolutional neural network (CNN) trained on modified frequency slice wavelet transform (MFSWT) data. The second is a support vector machine (SVM) classifier trained on multiple AF features data. The third method is an SVM trained on the same feature set but extended by the predictive probability of the CNN. The proposed method (the third one) achieved the highest detection accuracy. MIT-BIH AF database was used as a training set with an accuracy of 97.87% for 30-s ECG episodes and 96.09% for 10-s ECG episodes from fivefold cross-validation. The trained model was tested on the PhysioNet/Computing in Cardiology (CinC) Challenge 2017 database, achieving an accuracy of 93.21% for 30-s episodes and 93.03% for 10-s ECG episodes. When tested on the China Physiological Signal Challenge (CPSC) 2018 database, the corresponding accuracies were 98.48% and 98.61%. The results on the wearable ECGs from a clinical AF patient were 99.21% and 97.04%. We retrained the model on the PhysioNet/CinC Challenge 2017 data set and tested on the other database to explore the generalization ability of the proposed method. Corresponding test results on the MIT-BIH AF database showed accuracies of 96.84% and 95.13%, on the CPSC 2018 database were 96.21% and 98.45%, on the wearable ECGs were 99.08% and 96.43%. The results proved that the proposed method could provide high accuracy and reliable recognition for AF events.**

***Index Terms*— Atrial fibrillation (AF), convolutional neural network (CNN), electrocardiogram (ECG), support vector machine (SVM), wearable ECGs.**

I. Introduction

ATRIAL fibrillation (AF) is a tachyarrhythmia disease, and its prevalence accounts for 1%–2% of the total population. It is expected to increase threefold by 2050, which is a serious health problem [1], [2]. AF can cause many cardiovascular diseases, which can greatly affect the health of patients and even endangers the lives of patients [3], [4]. AF is independently related to age, and a survey found that the lifetime risk of AF is 25% by the age of 40 [5]. Therefore, the auxiliary diagnosis of AF can help doctors to improve treatment strategies for patients and achieve higher treatment quality, thereby reducing the morbidity and mortality of AF and critical illness caused by AF.

Many researchers have proposed AF detection algorithms based on the analysis of atrial activity [6], including wavelet sample entropy [7], wavelet entropy [8], relative wavelet energy [9], detection algorithms based on P-wave absence [10], and F-waves-based detector [11]. However, P- and F-waves are extremely sensitive to noise. Especially in the wearable monitoring situations, daily activities will produce complicated interferences, and the analysis of atrial activity will not be applicable. Thus, the AF detection algorithms based on the analysis of ventricular response have been developed [12]. Typical methods include variability analysis, statistical methods, complexity estimation, and entropy estimation, such as Lorenz plot analysis [13], Poincare plot analysis [14], density histogram of delta RR intervals [15], median absolute deviation of RR intervals [16], coefficient of sample entropy [17], normalized fuzzy entropy [18], and entropy of AF [19].

AF detection algorithms based on several of the above features and machine learning algorithms could achieve better performance. Babaeizadeh *et al.* [20] trained a decision-tree classifier using P-wave and RR interval features, resulting in the performance: sensitivity of 92% and positive predictivity of 97%. Mohebbi *et al.* [21] proposed an AF detector using a support vector machine (SVM) and spectrum features and nonlinear features, reporting a sensitivity of 96.30%, a specificity of 93.10%, and positive predictivity of 92.86%. On the

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PhysioNet/Computing in Cardiology (CinC) Challenge 2017, the tied first Datta *et al.* [22] trained a multilayer cascaded binary-based classifier using multiple AF features, including statistical features, frequency features, morphological features, heart rate variability features, and other abnormality features. Although modest successes were achieved, the generalization capabilities of the developed machine learning-based models have not been comprehensively verified and were not tested on multiple data sets with different data properties. Due to the significant individual differences, the poor generalization capability can be inevitable when tested on wearable ECGs [23], which limits the developed AF detectors that can be robustly used in the wearable monitoring situations.

Convolutional neural network (CNN) has good performance for feature extraction and has been widely used in signal classification [24]. Some researchers directly trained CNN on I-D ECG and obtained good performance. However, as a nonstationary signal, the variation on ECG waveforms may bring negative impacts upon classifying tasks with CNN. When the ECG waveform changes greatly, the model may not be able to classify accurately. Time–frequency (T-F) analysis is a common signal processing method by spectrum transform on short time windows and weakens the negative impact of long-term nonstationary. The modified frequency slice wavelet transform (MFSWT) [25] as new T-F technology can convert the 1-D ECG segment to 2-D T-F image, with an accurate expression for the relationship between time and frequency domains. Thus, in this study, MFSWT was used to transform 1-D ECG into 2-D T-F images and CNN was used to extract features from T-F images, and then an AF/non-AF classifier was trained by the CNN model.

Compared with the traditional AF detectors, the CNN model is data-driven. If the training samples lack diversity, the model is prone to overfitting, and the generalization ability of the model will be correspondingly poor. But the use of CNN offers the advantage that extracts ECG features automatically without the need for QRS detection [26]. The problems faced by the traditional AF detectors are that it is challenging to locate QRS complexes on wearable ECGs, the AF detector based on multiple features is unable to achieve the expected performance. If the advantages of the two methods can be combined, an AF detector with better generalization ability and universality can be realized. Thus, we further integrate the CNN model output with the SVM classifier, and to see if the combination of methods can significantly increase the performance of AF detection.

In the current study, we trained three models for AF classification: a CNN model with the MFSWT method, an SVM model trained on RR interval features, and an augmented SVM model trained with the combination of RR interval features and CNN prediction probability for AF. In order to verify the generalization ability and universality of the proposed method, we tested models on four databases from rest and dynamic ECG recording environments, and added noise with different noise ratio (SNR) to verify the robustness of the proposed method.

TABLE I

DATA DETAILS FOR ECG EPISODES

Database	# 30-s ECG episode		# 10-s ECG episode	
	Non-AF	AF	Non-AF	AF
MIT-BIH AF database	11020	11020	33456	33456
PhysioNet/CinC Challenge 2017	619	619	2,066	2,066
CPSC 2018	66	66	902	902
Wearable ECG data	1,200	1,200	3,600	3,600

II. METHOD

A. Database

Four databases were used, including the MIT-BIH AF database [27], [28], the PhysioNet/CinC Challenge 2017 database [29], the first China Physiological Signal Challenge (CPSC) 2018 database [30], and the wearable long-term record collected directly from the clinic. We trained the models on the MIT-BIH AF database (rest ECG recording environment) and the PhysioNet/CinC Challenge 2017 database (dynamic ECG recording environment), respectively, and tested them on all the other databases except themselves.

1) MIT-BIH AF Database: The database is from an open-source data website PhysioNet (https://www.physionet.org/content/afdb/1.0.0/) [27], [28]. ECG signals were sampled at 250 Hz. The database has 23 publicly available ECG recordings from AF patients (mostly paroxysmal) with every 10 h 15 min in duration and two ECG channels. The database has four types of rhythm annotations: AF, AFL (atrial flutter), J (AV junction rhythm), and N (normal). In this study, AFL, J, and N were classified as non-AF category as suggested in [18]. All recordings have manually corrected annotations. In our study, lead I was selected. We divide the data into AF group and non-AF group according to the annotation. The 30- and 10-s time windows were used to segment ECG recordings into an episode. Table I shows the data details.

2) PhysioNet/CinC Challenge 2017 Database: This database is also from the website PhysioNet (https://www.physionet.org/content/challenge-2017/1.0.0/) [29], including four types of rhythms: normal sinus rhythm (NSR), AF, an alternative rhythm, and noisy ECGs. ECG signals were sampled at 300 Hz. The opened training set contains 771 AF recordings lasting from 9 to just over 60 s. We selected the recordings from AF group and non-AF group (containing normal and other arrhythmias). These AF recordings were segmented into 30- and 10-s episodes, respectively. Then, these episodes were re-labeled by the doctor. The data details were shown in Table I.

3) CPSC 2018 Database: The CPSC2018 was the first CPSC (http://2018.icbeb.org/Challenge.html). ECG signals were sampled at 500 Hz, lasting from a few seconds to tens of seconds [30]. We selected the first lead ECGs from AF group and normal group as the test data. The signal was segmented into 30- and 10-s episodes, and each episode was labeled by the doctor (see Table I).

4) Wearable Long-Term Record: To verify the practical usefulness, a 24-h ECG recording (12 h before and 12 h

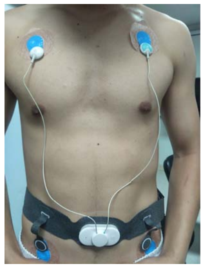

Fig. 1. Wearable ECG device. It can collect the Lead I, Lead II, and Lead III ECG signals simultaneously.

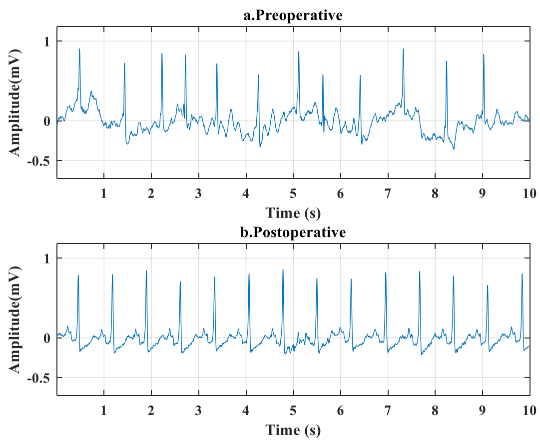

Fig. 2. Examples from a 10-s preoperative ECG and a 10-s postoperative ECG.

after the radio frequency ablation surgery) was collected from an AF patient by the wearable ECG device. The device was developed by Southeast University and Lenovo [31]. Fig. 1 shows the wearable ECG device. ECGs were sampled at 400 Hz. Fig. 2 shows a 10-s preoperative ECG episode and a 10-s postoperative ECG episode. Data were labeled by the doctor. We removed the episodes with pure noises, then selected 1200 30-s AF episodes before surgery and 1200 30-s non-AF episodes after surgery (see Table I). The AF patient was recruited from Qilu Hospital of Shandong University and has signed the informed consent form. The protocol was approved by the Ethics Committee of Qilu Hospital of Shandong University.

B. Feature Extraction

To locate QRS complex waves, we used the QRS detector presented by Paoletti and Marchesi [32]. For each ECG episode, if no QRS complexes were detected, we consider the signal as noise, and this signal was excluded in the followed analysis. If the number of detected QRS complexes waves was less than 5, the sample entropy (SampEn) [33] of the signal cannot be calculated. The specific calculation process can refer to [33] and [17]. We consider the signal as non-AF signal.

In [34], eight features for AF detection in dynamic ECG were introduced. We selected these features and four heart rate features, including mean RR intervals of episode (mRR), maximum heart rate of episode (maxHR), minimum heart rate of episode (minHR), and median heart rate of episode (medHR).

Fig. 3. MFSWT spectra of 10-s ECG episodes. (a) MFSWT spectrum of 10-s AF episode. (b) MFSWT spectrum of 10-s normal episode.

Then traversed all the feature combinations, and input SVM in turn, and finally selected the combination with the highest accuracy. The optimal feature set includes mRR, maxHR, minHR, and medHR, entropy of AF [19], SampEn [33], and coefficient of sample entropy (CosEn) [17]. The minimum (maximum or median) heart rate was calculated from the maximum (minimum or median) RR interval, respectively.

Entropy of AF was presented by Zhao *et al.* [19] to improve the performance of AF algorithms based on entropy. The detailed calculation process for entropy of AF can be found in [19]. SampEn was proposed in 2000 by Richman and Moorman [33], which was used in the analysis of ECG signals and other biological time series. Zhao *et al.* [19] presented CosEn which was improved based on SampEn. The specific calculation process can refer to [33] and [17].

C. MFSWT and CNN

MFSWT was used to transform 1-D ECG waveforms into 2-D T-F images. CNN was trained on 2-D T-F MFSWT images.

1) MFSWT: Luo *et al.* [25] proposed an MFSWT method for abnormal ECG beat identification. MFSWT was improved on the basis of the frequency wavelet transform, which used a T-F representation to accurately locate the time and frequency information in ECG (such as QRS complexes wave and P-wave). The detailed calculation process for MFSWT can be seen in [25].

All signals are resampled to 300 Hz. For 10-s ECG episodes, MFSWT produced T-F spectrograms with a resolution of 500×900 (corresponded time resolution of 500 and 0–90-Hz frequency range). Then we reduced the resolution to 100×45 by an average 5×20 template operator. For 30-s ECG episodes with a resolution of 1000×2700, we reduced the resolution to 200×45. Fig. 3 shows MFSWT spectrums with a resolution of 100×45 from 10-s ECG episodes.

2) CNN: CNN was implemented with the Neural Network Toolbox in MATLAB R2017b, by inputting 30 or 10-s MFSWT images. In order to reduce parameters, expand the perception field, and achieve more efficient learning, we used multiple small convolution layers. For 30-s images, the size of the input layer (layer 0) is $45 \times 200 \times 1$, followed by a 19-layer network, containing seven convolution layers, two max pooling layers, seven ReLU layers, one full-connection layer, and one softmax layer besides the output layer. For 10-s images, the size of the input layer (layer 0) is $45 \times 100 \times 1$, followed by an 18-layer network, containing seven convolution layers, one max pooling layer, seven ReLU layers, one full-connection layer, and one softmax layer besides the output layers. Fig. 4 shows the architecture of the CNN model.

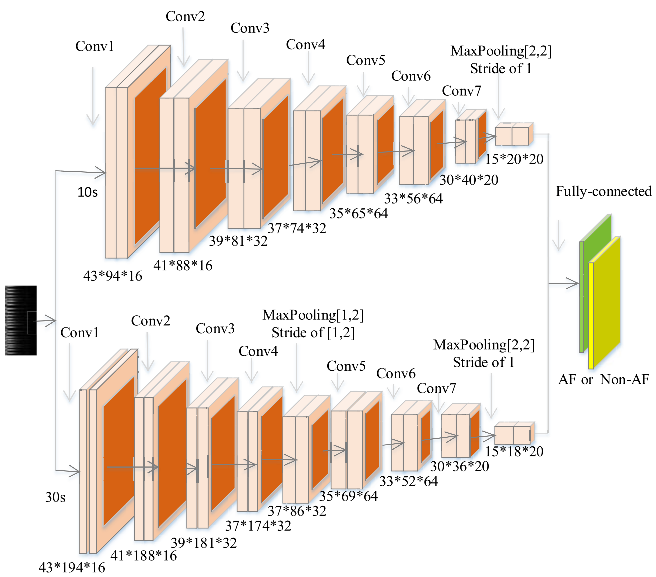

Fig. 4. Architecture of the CNN model.

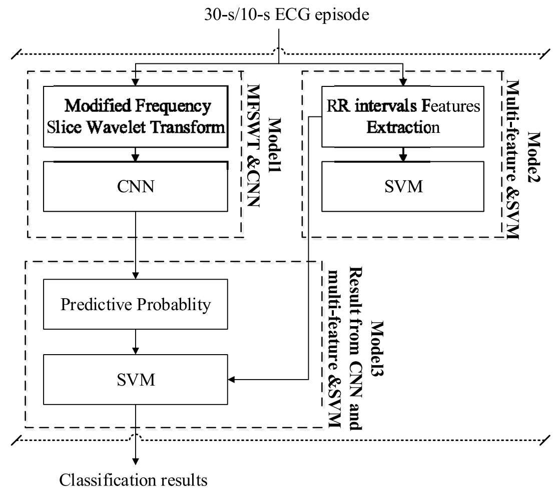

Fig. 5. Flowchart of our study.

TABLE II
CNN SPECIFICATIONS DESIGNED FOR THE 30- AND 10-S ECG CLASSIFICATION MODEL

CNN parameters	30-s images	10-s images
Learning rate	0.05	0.05
First convolutional layer kernel size	3*7	3*7
# corresponding feature maps and sub-sampling layer	16	16
Second convolutional layer kernel size	3*7	3*7
# corresponding feature maps and sub-sampling layer	16	16
Third convolutional layer kernel size	3*8	3*8
# corresponding feature maps and sub-sampling layer	32	32
Fourth convolutional layer kernel size	3*8	3*8
# corresponding feature maps and sub-sampling layer	32	32
Sub-sampling layer kernel size	1*2	-
Fifth convolutional layer kernel size	3*18	3*10
# corresponding feature maps and sub-sampling layer	64	64
Sixth convolutional layer kernel size	3*18	3*10
# corresponding feature maps and sub-sampling layer	64	64
Sixth convolutional layer kernel size	4*17	4*17
# corresponding feature maps and sub-sampling layer	20	20
Sub-sampling layer kernel size	2	2
# neurons in the fully connected layer	2	2
# minimal batch	256	256

Parameters were listed in Table II. When the MIT-BIH AF database was as a training set, epochs were 20 for 30-s images and 10 for 10-s images. When the PhysioNet/CinC Challenge was as a training set, the corresponding epochs were 165 and 55.

D. Classifiers and Evaluation Methods

SVM was adopted as the classifier. A Gaussian kernel function was selected with two important parameters: the kernel width Gamma and regularization parameter capacity. In this work, we used LibSVM Toolbox in MATLAB R2017b. To parameter optimization, we selected the grid search method [35] with Gamma range as $\{2^{(-15:F2:F3)}\}$ and capacity range as $\{2^{(-5:F2:F15)}\}$.

To evaluate the proposed algorithm, we adopted three widely evaluation indicators: accuracy (Acc), sensitivity (Se), and specificity (Sp). According to the positive or negative of the label, four indexes were generated: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). In this work, Acc is defined as

$$\mathrm{Acc} = (\mathrm{TP} + \mathrm{TN})/(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}).$$

Se is defined as

$$\mathrm{Se} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN}).$$

Sp is defined as

$$\mathrm{Sp} = \mathrm{TN}/(\mathrm{TN} + \mathrm{FP}).$$

Fig. 5 shows the flowchart of our study. To verify the generalization abilities of the proposed methods, they were trained with either MIT-BIH AF (using fivefold cross-validation) or PhysioNet/CinC Challenge 2017 database and evaluated on the three holdout databases.

III. RESULTS

A. Results From Training on the MIT-BIH AF Database

1) Results From Fivefold Cross-Validation on the MIT-BIH AF Database: We divided 23 recordings from the MIT-BIH AF database into fivefold, and each fold is three or four recordings for testing, leaving 18 or 19 recordings alone for training. We selected the average of the experimental result to be evaluated, the classification results as shown in Fig. 6.

When combining MFSWT and CNN, Acc, Se, and Sp were 92.49%, 92.17%, and 92.86%, respectively, from the 30-s episode analysis, and Acc was 91.30% for the 10-s episode (Se 90.91% and Sp 91.91%).

TABLE III
TEST RESULT FROM TRAINING ON THE MIT-BIH AF DATABASE

Method	Time window	PhysioNet/CinC Challenge 2017			CPSC2018			Wearable long-term record		
		Acc (%)	*Se* (%)	*Sp* (%)	*Acc* (%)	*Se* (%)	*Sp* (%)	*Acc* (%)	*Se* (%)	*Sp* (%)
Only CNN	30-s ECG episode	91.11	93.53	88.69	96.97	95.50	98.43	94.13	94.00	94.25
	10-s ECG episode	85.70	86.74	84.67	88.87	97.45	80.27	92.31	93.44	91.17
Multi-feature & SVM	30-s ECG episode	91.60	90.95	92.41	95.45	90.91	100.00	98.92	98.33	99.50
	10-s ECG episode	90.95	88.33	93.56	93.51	87.69	99.33	90.06	83.50	96.61
Augmented SVM	30-s ECG episode	93.21	93.70	92.73	98.48	98.48	98.48	99.21	98.58	99.83
	10-s ECG episode	93.03	89.25	96.80	98.61	97.67	99.55	97.04	94.58	99.50

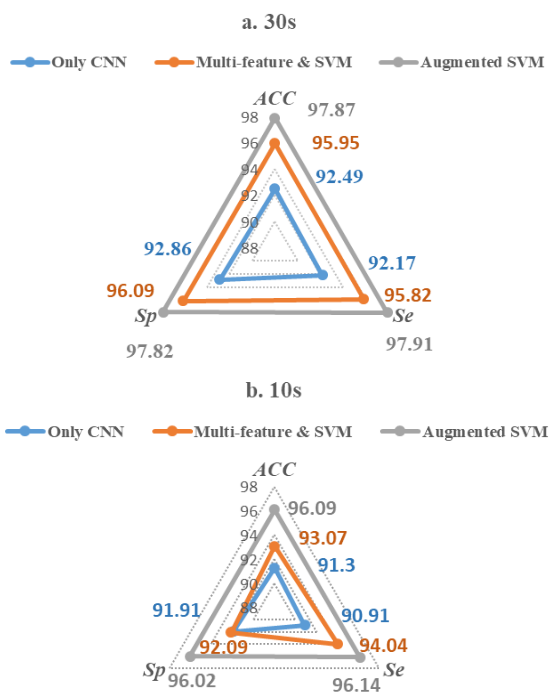

Fig. 6. Classification results from fivefold cross-validation on the MIT-BIH AF database.

When using multiple AF features and the SVM method, Acc, Se, Sp were 95.95%, 95.82%, and 96.09%, respectively, from the 30-s episode analysis, and Acc was 93.07% for the 10-s episode (Se 94.04% and Sp 92.09%).

Since CNN can output the predictive probability for each sample, we added it to the same SVM. This model is called Augmented SVM, which achieved the highest accuracy. Herein, Acc, Se, Sp were 97.87%, 97.91%, and 97.82%, respectively, from 30-s episode analysis, and were 96.09%, 96.14%, and 96.02%, respectively, from the 10-s episode analysis.

2) Test Results From Training on the MIT-BIH AF Database: Table III shows the test results from training on the MIT-BIH AF database. The model that additionally added CNN prediction to the same SVM achieved the highest accuracy.

The trained model was tested on the PhysioNet/CinC Challenge 2017 database, achieving Acc of 93.21%, Se of 93.70%, Sp of 92.73% for 30 s and Acc of 93.03%, Se of 89.25%, Sp of 96.80% for the 10 s ECG episodes.

When tested on the CPSC 2018 database, for 30-s ECG episodes, Acc, Se, and Sp were 98.48%, 98.48%, and 98.48%, respectively. For the 10-s ECG episodes, Acc, Se, and Sp were 98.61%, 97.67%, and 99.55%, respectively.

On the wearable ECGs from a clinical AF patient, for 30-s ECG episodes, Acc, Se, and Sp were 99.21%, 98.58%, and 99.83% respectively. For the 10-s episode, Acc, Se, and Sp were 97.04%, 94.58%, and 99.50% respectively.

B. Results From Training on the PhysioNet/CinC Challenge 2017 Database

The algorithms were trained on the PhysioNet/CinC Challenge 2017 database and tested on the last three databases. The test results were shown in Table IV. After adding CNN prediction, SVM achieved the highest Acc.

On the MIT-BIH AF database, for the 30-s ECG episodes, Acc, Se, and Sp were 96.84%, 94.98%, and 98.83%, respectively. For the 10-s ECG episodes, Acc, Se, and Sp were 95.13%, 92.69%, and 97.85%, respectively.

On the CPSC 2018 database, for the 30-s ECG episodes, Acc, Se, and Sp were 96.21%, 96.97%, and 95.45%, respectively. For the 10-s ECG episodes, Acc, Se, and Sp were 98.45%, 98.33%, and 98.55%, respectively.

On the wearable long-term record, for the 30-s ECG episodes, Acc, Se, and Sp were 99.08%, 98.67%, and 99.50%, respectively. For 10-s ECG episodes, Acc, Se, and Sp were 96.43%, 96.36%, and 96.50% respectively.

IV. DISCUSSION

There is no difference in the risk of complications caused by paroxysmal AF and persistent arrhythmia. Due to the short onset of the paroxysmal AF from some patients, it needs to be detected in the dynamic environments during daily life. This study focused on two types of short-time windows: 30- and 10-s ECG episodes.

A. Performance Comparison of Classification Models

1) CNN Compare to SVM: When used fivefold cross-validation on the MIT-BIH AF database the classification results of CNN are worse than SVM on independent recordings. The test set PhysioNet/CinC Challenge 2017

TABLE IV
TEST RESULTS FROM TRAINING ON THE PHYSIONET/CINC CHALLENGE 2017 DATABASE

Method	Time window	MIT-BIH AF database			CPSC2018			Wearable long-term record		
		Acc (%)	*Se* (%)	*Sp* (%)	*Acc* (%)	*Se* (%)	*Sp* (%)	*Acc* (%)	*Se* (%)	*Sp* (%)
Only CNN	30-s ECG episode	91.13	92.99	89.26	92.42	89.39	95.45	94.42	96.00	92.83
	10-s ECG episode	88.62	91.37	85.87	95.18	95.56	94.79	94.15	92.79	95.50
Multi-feature & SVM	30-s ECG episode	95.53	93.02	98.31	95.52	98.53	92.42	98.66	98.49	98.83
	10-s ECG episode	92.36	88.40	96.32	94.51	90.69	98.33	95.50	95.88	95.17
Augmented SVM	30-s ECG episode	96.84	94.98	98.83	96.21	96.97	95.45	99.08	98.67	99.50
	10-s ECG episode	95.13	92.69	97.85	98.45	98.33	98.55	96.43	96.36	96.50

database contains more than 600 AF patients. Test results on PhysioNet/CinC Challenge 2017 database showed CNN is worse than SVM. But the CPSC2018 database has 66 samples for 30-s ECG episodes, CNN test results are slightly better. It shows that the performance of the CNN model depends on the diversity of the database. When there are few types of data in the training set and many types of data in the test set, the performance of CNN is not as good as that of SVM.

The PhysioNet/CinC Challenge 2017 database as a training set has many types of data, but the amount is relatively small. There are 23 recordings on the MIT-BIH AF, and 66 AF samples for 30-s ECG episodes on the CPSC2018. Test results show the SVM model is better than CNN. But the CPSC2018 database contains more data types for 10-s ECG episodes, and the accuracy of the CNN model is better than the SVM. When the training set contains many types of data, but the amount is relatively small, the type of test set will affect the performance of the CNN model.

2) SVM Compare to Augmented SVM: In this study, when we integrate the CNN model output with the SVM classifier, the combination of methods can significantly increase AF recognition accuracy.

When the MIT-BIH database was as the training set, cross-validation results demonstrated that the Acc of 30-s episode increased by 1.92% by adding the CNN feature into SVM. Similarly, the Acc of 10-s episode increased by 3.02%. The test Acc of 30- and 10-s episode increased by 1.61% and 2.08%, respectively, on PhysioNet/CinC Challenge 2017 database. The corresponding test Acc increased by 3.03% and 5.1% on the CPSC 2018 database. When the wearable long-term record was tested, achieving an Acc of 99.21% for 30 s and 97.04% for 10-s ECG episodes.

When the PhysioNet/CinC Challenge 2017 database was as the training set, the test Acc of 30-s episode increased by 1.31% and the test Acc of 10-s episode increased by 2.77% on the MIT-BIH AF database. Similarly, the test Acc increased by 0.69% and 3.94% on the CPSC 2018 database. When tested on the wearable long-term record, achieving an Acc of 99.08% for 30 s and 96.43% for 10-s ECG episodes. This indicates that the algorithm is believed to have some potential for clinical use.

3) Comparison of the ROC: The ROC curve is called "receiver operating characteristic curve (ROC)." Its ordinate true positive rate (TPR) represents the probability that AF samples are predicted to be AF, TPR = 1 − Sensitivity. Its abscissa false positive rate (FPR) indicates the probability that non-AF is predicted to be AF. FPR = 1 − Specificity = FP/(FP + TN). When the TPR is higher, the FPR is lower, and the area under the ROC curve is larger, the better the generalization abilities of the model.

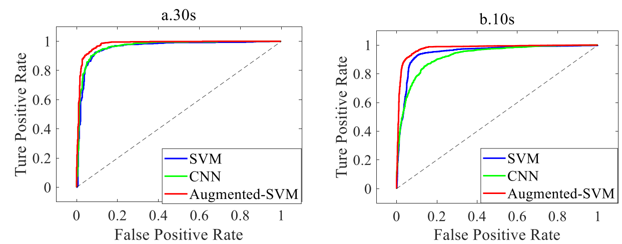

Fig. 7. ROC from testing on the PhysioNet/CinC Challenge 2017 database.

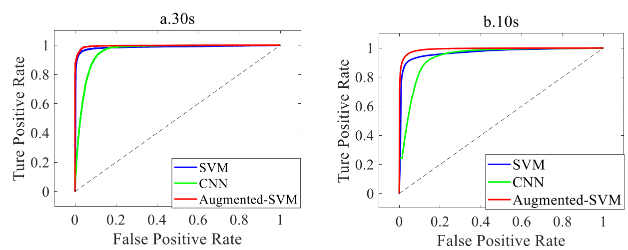

Fig. 8. ROC from testing on the MIT-BIH AF database.

Fig. 7 showed when the MIT-BIH AF database was as the training set, the ROC on the PhysioNet/CinC Challenge 2017 database. Fig. 8 showed when the PhysioNet/CinC Challenge 2017 database was as the training set the ROC on the MIT-BIH AF database. It can be seen that the SVM model has better generalization ability than the CNN model on the independent database, and the generalization ability of the augmented SVM model is the best.

The classification results of the SVM are better than the CNN in the independent recordings, which showed the CNN is data-driven. Although the AF detector based on RR interval features and SVM has a certain generalization ability, it is easy to misjudge other arrhythmia diseases with irregular RR intervals as AF. Using the predicted probability of CNN as a new feature can correct the SVM detection algorithm based on the RR interval, which not only improves the detection Acc of the model but also improves the generalization ability of the model. That is because the prediction probability of CNN is extracted by CNN integrated with the T-F image of the ECG.

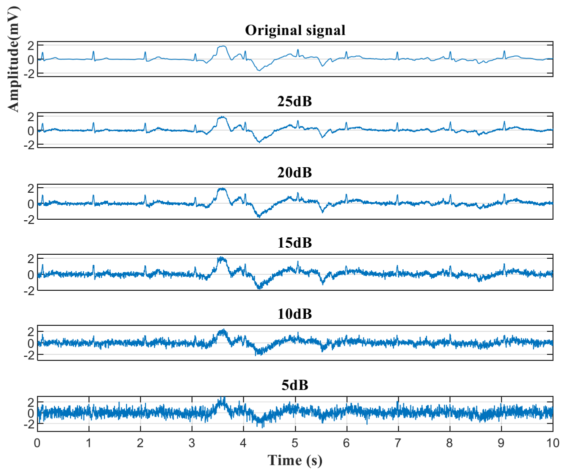

Fig. 9. 10-s original signal and signals under different SNR.

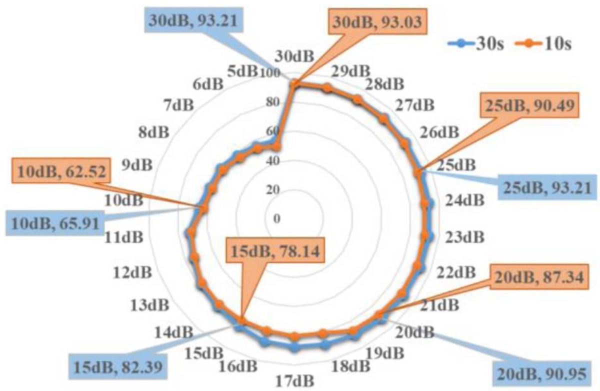

Fig. 10. Test Acc of different SNR on the PhysioNet/CinC Challenge 2017 database.

The T-F image can provide time and frequency information, RR interval, and P wave information. The information contained is comprehensive, which helped the SVM classifier to obtain a better classification performance.

B. Model Analysis

1) Robustness Analysis of the Augmented SVM: To check the robustness of the augmented SVM, we added noise with different noise ratio (SNR) to the PhysioNet/CinC Challenge 2017 database. The PhysioNet/CinC Challenge 2017 database comes from dynamic ECG recording environments and there is some noise in itself. Fig. 9 showed the 10-s original signal and signals under different SNR. Fig. 10 showed the test Acc of different SNR on the PhysioNet/CinC Challenge 2017 database. When the SRN is 20 dB, the test Acc is 90.95% for the 30-s ECG episode, which showed our model is relatively stable. When the SNR is 15 dB, the ECG waveform between the RR intervals is basically submerged, and the test Acc is 82.39% for the 30-s ECG episode, which showed our method has certain antinoise performance and robustness. When the SRN is 10 dB, the ECG is basically submerged by noise. At this time, the ECG can basically not be analyzed.

2) Complexity Analysis: In this study, the CNN model includes a total of 359 176 trainable parameters. The 1-D CNN model proposed by Andersen *et al.* [36] includes a total of 159 841 trainable parameters, and hence the computational complexity of this model exceeds 1-D CNN. But the augmented SVM can analyze and classify a 30-s ECG in 0.67s, and a 10-s ECG in 0.24 s on a GeForce GTX 1660 Ti GPU. Fig. 11 shows the framework for collecting and analyzing ECGs. Once the ECGs are collected, they are transformed into the mobile terminal via Bluetooth and displayed in real-time. After transmitting to the cloud via WIFI or 4G, our proposed algorithm analyzes the 10-/30-s ECG in the cloud, then feedbacks the results back to the mobile app for display.

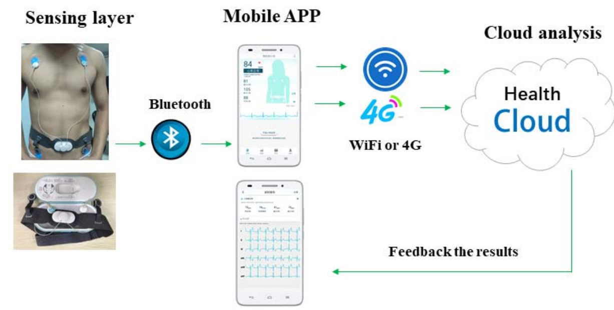

Fig. 11. Framework for collecting and analyzing ECGs.

C. Advantages Over Other Algorithm Models

1) Comparison With Traditional Machine Learning Algorithms: Compared with traditional machine learning algorithms, our proposed algorithm improves the classification Acc and is verified on independent databases. Ladavich and Ghoraani [10] achieved the detection of AF using P-waves features, resulting in the performance: Se of 89.37%, Sp of 89.54% on one beat time window. Andersen *et al.* [37] presented an automatic AF detection algorithm based on inter beat intervals and SVM. Test performed on 30-s ECG episodes reported the Acc of 96.98%, *Se* of 94.27%, and Sp of 98.84% using fivefold stratified cross-validation. Bruun *et al.* [38] combined discrete wavelet transform and HRV, and reported better classification results on 180-s time window data, the Acc of 98.22%, Se of 96.51%, and Sp of 99.19% using fivefold cross-validation. Xu *et al.* [26] used the combination of MFSWT and CNN to identify 1-s AF with the Acc of 84.85%, Se of 79.05%, and Sp of 89.99% using fivefold cross-validation. Solikhah *et al.* [39] made an automatic detection of AF adopting statistic features. But its performance is not good, with an Acc of 84.28% on the 30-s time window. The above detection algorithms are all trained and tested with different time windows on the MIT-BIH AF database. Our algorithm model has improved Acc on the MIT-BIH AF database. Mohebbi and Ghassemian [40] trained an SVM-based classifier using linear discriminant analysis. The performance was evaluated only using 769 episodes as training sets and 388 episodes as test sets from the MIT-BIH arrhythmia database, reporting the Se of 99.07%, Sp of 100%, and positive predictivity of 100%. Martis *et al.* [41] proposed automated detection of AF using Naive Bayes and Gaussian Mixture model classifiers. 1200 normal episodes (from MIT-

TABLE V
PERFORMANCE OF METHODS TESTED ON THE INDEPENDENT DATABASES

Author	Method	Training set	Validation Performance			Test set	Test performance		
			Se (%)	*Sp* (%)	*Acc* (%)		*Se* (%)	*Sp* (%)	*Acc* (%)
Aderson [36]	30 RR +LSTM+CNN	MIT-BIH AF database	98.98	96.95	97.80	MIT-BIH arrhythmia database MIT-BIH NRS database	98.96	86.04	87.40
Chang [49]	12-s ECG +STFT+LSTM	Six databases	97.80	99.20	98.50	Separate data PhysioNet/CinC Challenge 2017	86.88 70.17	79.55 -	83.21 75.60
Proposed	10s-ECG +Augmented SVM	MIT-BIH AF database	96.14	96.02	96.09	PhysioNet/CinC Challenge 2017 CPSC2018 database Wearable long-term record	89.25 97.67 94.58	96.80 99.55 99.50	93.03 98.61 97.04

BIH arrhythmia database) and 887 AF episodes (from both MIT-BIH arrhythmia database and MIT-BIH AF database) were chosen. This method reported an average Acc of 99.42% using tenfold cross-validation. This method can only classify 30-min normal beats and 30-min AF beats.

Besides, AF features based on AF detection algorithms were developed by contestants on the PhysioNet/CinC Challenge 2017. Athif *et al.* [42] trained an AF/non-AF classifier using morphological features, statistical features, and SVM, achieving the Se of 77.5%, Sp of 97.9%, and Acc of 96.1%. Liu *et al.* [43] extracted 33 features including time-domain features, entropy features, and frequency features, achieving an Acc of 87.71% on the validation set. Shao *et al.* [44] adopted 26 AF features and four features of similarity index between beats and the decision tree ensemble on the training data set, ranking equal fifth in the 2017 PhysioNet/CinC Challenge. Sadr *et al.* [45] extracted a set of RR intervals features and processed by a single hidden layer neural network. This algorithm can provide reference and guidance for dynamic AF signal recognition algorithms.

2) Comparison With Deep Learning Algorithms: In recent years, many scholars have used deep learning algorithms to classify AF. Wang [46] proposed a deep learning approach based on convolutional and modified Elman neural network to classify 4-s AF or N, reporting an Acc of 97.4 from tenfold cross-validation on the MIT-BIH AF database. Zhou *et al.* [47] used 1-D CNN to detect 30-s AF and selected 20 056 training samples and 3122 testing samples on the MIT-BIH AF database, getting an Acc of 99%. Xia *et al.* [48] used short-term Fourier transform and stationary wavelet transform to analyze ECG, and 2-D CNN to detect 5-s AF, achieving the Acc of 98.29% from tenfold cross-validation on the MIT-BIH AF database. These models have high classification Acc, but they have not been tested on independent recordings, and the generalization ability of the model cannot be proved. In this article, we divided the MIT-BIH AF database into fivefold according to the recordings. Each fold is three or four recordings for testing, leaving 18 or 19 recordings alone for training. Although the classification is not so high, it shows a certain generalization ability.

3) Comparison of the Generalization Ability: Table V shows the performance of methods tested on the independent database or separate data. The test performance on the independent database can reflect the generalization ability of the model. Aderson *et al.* [36] tested their methods on two independent databases, including MIT-BIH arrhythmia database and MIT-BIH NSR database, and test Acc is 87.40%, dropping by about 10%. The AF detector proposed by Chang *et al.* [49] reported an Acc of 83.21% on separate data and 75.60% on the PhysioNet/CinC Challenge 2017 database. Contrasting with the current literature, the proposed method achieved an Acc of 93.03% on the PhysioNet/CinC Challenge 2017 database, 98.61% on CPSC2018, and 97.04% on the wearable long-term record, which implies that the generalization ability of our proposed algorithm is better than other algorithms.

V. CONCLUSION

In this study, we proposed three different methods for the detection of AF. The first method is a CNN trained on MFSWT data. The second is an SVM classifier trained on multiple AF features data. The third method is an SVM trained on the same feature set but extended by the predictive probability of the CNN, which outperforms previously proposed methods. For algorithm evaluation, we selected four databases, including the MIT-BIH AF database, the PhysioNet/CinC Challenge 2017 database, the CPSC 2018 database, and the wearable long-term record collected directly from the clinic. We trained the models on the MIT-BIH AF database (rest ECG recording environment) and the PhysioNet/CinC Challenge 2017 database (dynamic ECG recording environment), respectively, and tested them on all the other databases except themselves. The proposed method reported better performance on independent test data sets, indicating the proposed method has the potential for clinical application. However, the proposed algorithm combines traditional machine learning algorithms and CNN algorithms, increasing the computational complexity and time complexity, so it only processes ECG signals in the cloud. In the next work, we will continue to improve the algorithm.

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