CAB: Classifying Arrhythmias based on Imbalanced Sensor Data

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Abstract

Intelligently detecting anomalies in health sensor data streams (e.g., Electrocardiogram, ECG) can improve the development of E-health industry. The physiological signals of patients are collected through sensors. Timely diagnosis and treatment save medical resources, promote physical health, and reduce complications. However, it is difficult to automatically classify the ECG data, as the features of ECGs are difficult to extract. And the volume of labeled ECG data is limited, which affects the classification performance. In this paper, we propose a Generative Adversarial Network (GAN)-based deep learning framework (called CAB) for heart arrhythmia classification. CAB focuses on improving the detection accuracy based on a small number of labeled samples. It is trained based on the class-imbalance ECG data. Augmenting ECG data by a GAN model eliminates the impact of data scarcity. After data augmentation, CAB classifies the ECG data by using a Bidirectional Long Short Term Memory Recurrent Neural Network (Bi-LSTM). Experiment results show a better performance of CAB compared with state-of-the-art methods. The overall classification accuracy of CAB is 99.71%. The F1-scores of classifying Normal beats (N), Supraventricular ectopic beats (S), Ventricular ectopic beats (V), Fusion beats (F) and Unclassifiable beats (Q) heartbeats are 99.86%, 97.66%, 99.05%, 98.57% and 99.88%, respectively.
Unclassifiable beats (Q) heartbeats are 99.86%, 97.66%, 99.05%, 98.57% and 99.88%, respectively.

1. Introduction

Heart arrhythmia is a common disease in elderly people [1]. It can lead to serious health problems and even sudden death [2]. Therefore, it is important to have immediate diagnosis and treatment for heart arrhythmias [3]. Electrocardiogram (ECG) is a popular sensor signal for diagnosing heart diseases [4]. However, manually analyzing the complex ECG signals is difficult [5] [6]. Therefore, it is necessary to develop efficient methods to assist experts in detecting heart arrhythmias automatically [7].

The Association for Advancement of Medical Instrumentation (AAMI) groups the heartbeats of arrhythmia patients into five categories: Normal beat (N), Ventricular ectopic beat (V), Supraventricular ectopic beat (S), Unclassifiable beat (Q) and Fusion beat (F) [8]. Heartbeats in class N are normal or bundle branch block heartbeats. Class S includes abnormal supraventricular heartbeats and premature heartbeats. Class V refers to ventricular ectopic beats, which are not paced by the sinus node of the ventricle. Class F refers to the fusion heartbeat, and Q refers to the unclassified heartbeat. **Fig. 1** shows the heartbeat types contained in each category.

Class	Annotation	Heartbeat type
N	N	Normal beat
	L	Left bundle branch block beat
	R	Right bundle branch block beat
S	A	Atrial premature beat
	J	Nodal (junctional) premature beat
	S	Supraventricular premature beat
	a	Aberrated atrial premature beat
	e	Atrial escape beat
	j	Nodal (junctional) escape beat
V	E	Ventricular escape beat
	V	Premature ventricular contraction
F	F	Fusion of ventricular and normal beat
Q	P	Paced beat
	Q	Unclassifiable beat
	f	Fusion of paced and normal beat

Fig. 1. Five categories of heartbeat types defined by AAMI.

In ECG data, some classes of data are rare, such as F and Q classes. Therefore, data imbalance is a significant problem in ECG classification. The lack of data can make the classification model not adequately trained. Insufficient model training can affect the accuracy of heartbeat classification, especially the classification accuracy of rare heartbeats. To solve the data imbalance problem, some data augmentation methods have been proposed. A commonly used algorithm for time series data augmentation is Synthetic Minority Oversampling Technique (SMOTE) [9]. However, SMOTE has the following limitations: (1) it has blindness in the selection of neighbors; (2) the problem of data distribution cannot be overcome, and it is easy to cause distribution marginalization [9]. So we propose a data augmentation method based on Generative Adversarial Network (GAN). It can generate high-quality ECG data to prevent data imbalance from affecting classification.

GAN is a generative model [10] for data generation. It is composed of a generator and a discriminator. When the generator is fixed, the discriminator is optimized to maximize discriminant accuracy. When the discriminator model is fixed, the generator is optimized to

minimize the discriminant accuracy [11]. Long Short Term Memory Recurrent Neural Network (LSTM) is a kind of special Recurrent Neural Network (RNN). Its cellular state is more complex than that of the ordinary RNN [12]. LSTM stores information in gated units that can store, write, or read information [13].

In this paper, we propose a GAN-based framework (called CAB) to **C**lassify **A**rrhythmias (N, S, V, F, and Q) based on im**B**alanced ECG sensor data. In CAB, we design a GAN to generate data for the heartbeat categories with sparse samples. In addition, we develop a stacked Bidirectional Long Short Term Memory Recurrent Neural Network (Bi-LSTM) to classify heartbeats. Our main contributions are as follows:

• design a GAN-based data augmentation algorithm for augmenting ECG data. The algorithm can effectively capture the characteristics of ECG data to generate high-quality ECG data. Then it generates enough heartbeat data for classes with sparse samples to train the classification model.

• propose a deep neural network based on stacked Bi-LSTM. The network is trained by the original data and the data augmented by GAN. CAB classifies heartbeats based on the morphology of heartbeats. It can extract timing features, thus improving the accuracy of heartbeat classification based on a small set of labeled samples.

• conduct comprehensive experiments to evaluate CAB by comparing it with state-of-the-art methods. The overall classification accuracy is 99.71%. The F1- scores of classifying N, S, V, F, and Q heartbeats are 99.86%, 97.66%, 99.05%, 98.57%, and 99.88%, respectively.

The rest structure of this paper is: Section 2 introduces related work Section 3 introduces CAB; Section4 describes experiments and results, and Section 5 concludes this paper.

2. Related Work

2.1 Arrhythmia Heartbeat Classification Methods

2.1.1 Machine Learning Classification Methods

Elhaj et al. [14] proposed a classification method combining Bayesian algorithm with Extreme Learning Machine (ELM), which can avoid the problem of overfitting. Mondéjar-Guerra et al. [15] proposed a multi-support vector machines-based classification method. This method uses the time intervals and the morphology of heartbeats as features. Shi et al. [16] developed a classification method using the weighted extreme gradient boosting. Garcia et al. [17] proposed a new ECG representation based on an ECG vector, called Temporal VectorCardioGram (TVCG). The classification method uses Support Vector Machines (SVMs) as a classifier and performs feature selection with a Particle Swarm Optimization (PSO) algorithm. Alfaras et al. [18] proposed an automatic and fast ECG arrhythmia classifier based on a brain-inspired machine learning method called Echo State Networks. Houssein et al. [19] proposed a heartbeat classification method based on Twin Support Vector Machines (TWSVM) and Particle Swarm Optimization (PSOGSA). Empirical Mode Decomposition (EMD) is applied to ECG noise removal and feature extraction. PSOGSA is used to find the optimal parameters of TWSVM to improve the classification process.

2.1.2 Deep Learning Classification Methods

Jiang et al. [20] proposed a sequence-to-sequence (seq2seq) model based on LSTM with Convolutional Neural Network (CNN)-based embedding. Specifically, local channel-wise attention is used to highlight more discriminative features. Li et al. [21] developed a DNN based on the residual network. Chazal et al. [22] used the ECG morphology, heartbeat interval,

and RR interval to select the optimal classifier configuration. Niu et al. [23] designed a heartbeat classification framework based on Multi-Perspective CNN. This method automatically learns features and classifies heartbeats based on the symbolic representation of heartbeat. Hannun et al. [24] proposed a deep neural network (DNN) that can classify 12 kinds of ECG signals, including 10 arrhythmias, one sinus rhythm, and one noise. Saadatnejad et al. [25] proposed a heartbeat classification framework composed of wavelet transform and multiple LSTM. Lu et al. [26] proposed a hybrid ECG classification model based on LSTM and CNN. The model can learn the structural features of ECG signals and mine the time correlation between ECG signal points.

Li et al. [27] proposed a heartbeat classification model based on the Bi-LSTM and Bi-LSTM Attention algorithm. Wang et al. [28] proposed a classification method based on semantic coding, and Bi-LSTM is used as the classification model. The model uses a Stack Denoising AutoEncoder (SDAE) as the encoder to automatically learn the semantic encoding of the heartbeat. Yildirim [29] proposed a wavelet sequence classification model called DBLSTM-WS based on a deep Bi-LSTM network. This model divides the ECG signal into sub-bands of different scales based on wavelets and inputs them into the LSTM network. Wu et al. [30] proposed an ECG signal analysis method based on residual network and Bi-LSTM. This method uses the statistical time domain, frequency domain, nonlinear domain, and deep features of the ECG signal to distinguish basic heart diseases. The combination of residual network and Bi-LSTM can better pay attention to the sequence information contained in the ECG signal. Li et al. [31] proposed a heartbeat classification method based on General CNN.

Li et al. [32] proposed a customizable CNN-based automatic patient-specific classification method and a channel-wise attention module to selectively emphasize the information features. Zhai and Tin [33] proposed a CNN-based classifier. According to the change of heart rate, the single-channel ECG signal is divided into beats and the beat value is converted into a two-beat coupling matrix. The coupling matrix input into the CNN classifier can not only obtain the morphology of beats in ECG but also the correlation of beats to beats. Xia et al. [34] proposed a sparse constraint SDAE to learn ECG features. Mousavi and Afghah [35] developed an automatic heartbeat classification method using deep CNN and sequence-to-sequence models for unbalanced datasets. Xu et al. [36] proposed a signal alignment method based on deep learning and a feature extraction method using DNN. Wang et al. [37] proposed an improved CNN for accurate classification. Each convolution layer of CNN uses cores of different sizes, making full use of the characteristics of different scales.

2.2 Data Augmentation Methods

Shaker et al. [38] proposed two methods: (1) an end-to-end deep learning method, (2) a two-stage hierarchical learning method based on deep CNNs. The designed GAN for the balance of the dataset is based on fully connected layers. Wang et al. [39] proposed a classification method using stacked residual networks and LSTM. They used an Auxiliary Classifier Generative Adversarial Network (ACGAN) for data augmentation. Zhou et al. [40] proposed an arrhythmia classification system based on GAN. The generator of GAN is used for data augmentation. The discriminator is used as the arrhythmia classifier. Golany et al. [41] proposed an Ordinary Differential Equation (ODE) system. The ODE system uses GAN to generate ECG data. Golany and Radinsky [42] proposed a patient-specific ECG classification method using semi-supervised approach . A GAN-based augmentation model is designed to learn and synthesize patient-specific ECG signals.

Acharya et al. [43] designed a 9-layer CNN to classify heartbeat and a method based on Z-score normalization to augment data. Rajesh and Dhuli [9] proposed a nonstationary nonlinear decomposition method to extract features. The AdaBoost integrated classifier is used for heartbeat classification. Besides, Re-sampling, SMOTE, and Distribution based data sampling are used for data augmentation. Sellami and Hwang [44] proposed a new deep CNN for heartbeat classification. A batch weighted loss function is proposed to quantify the loss to overcome the problem of data imbalance. Romdhane et al. [45] proposed a CNN-based method and an optimized loss function for data augmentation. Nazi et al. [46] proposed a classification framework based on the dot Residual LSTM network. Conditional Variational AutoEncoder (CVAE) and LSTM network are used to increase training samples to solve data imbalance.

2.3 Abnormal Heartbeat Detection

Atrial Fibrillation (AF) is the most common arrhythmia, and the incidence of AF increases with age. To prevent atrial fibrillation from affecting people's health, it must be diagnosed and treated as soon as possible. Many studies are devoted to the detection of AF. These studies can screen out AF. Zhou et al. [47] proposed an algorithm based on GAN called BeatGAN for detecting abnormal heartbeats. Lai et al. [48] proposed a lightweight CNN to automatically identify AF, using representative rhythmic features of AF. Shen et al. [49] developed a 50-layer CNN to detect AF. Fan et al. [50] proposed a Multi-Scale deep CNN (MS-CNN) fusion algorithm. MS-CNN uses double-stream convolutional network architecture with filters of different sizes to capture features of different scales. Zhao et al. [51] proposed a Bayesian spectral time representation method for ECG signals based on the state-space model and Kalman filter. A dense CNN is used as a classifier.

There are also some studies that classify ECG records. Dang et al. [52] proposed a model based on Bi-LSTM and CNN for AF heartbeat detection. Wu et al. [53] used the feature of the wavelet coefficient matrix based on the continuous wavelet transform. And a CNN with a specific structure is used as a detection model. Limam and Precioso [54] designed a classification network using Convolutional Recurrent Neural Network (CRNN). The network is composed of two independent CNNs, one RNN, and an SVM. Zabihi et al. [55] selected the ECG signal features from time, frequency, time-frequency domains, and phase space reconstruction. Finally, a random forest classifier is used to classify the selected features.

Many studies have used the MIT-BIH dataset to classify the heartbeats of N, S, V, F, and Q. Li et al. [27] developed a Bi-LSTM network for heartbeat classification. Chen et al. [56] proposed an SVM algorithm to classify heartbeats. Wang et al. [57] developed a two-layer classifier. Each layer contains two independent fully connected networks. Acharya et al. [43] designed a nine-layer CNN for classification. Wang et al. [37] developed an improved CNN, where the kernel sizes of convolution layers are different from each other. Experiment results show that CAB performs better than the classification models in [27] [37][43] [56][57][59][60] (see Section 4).
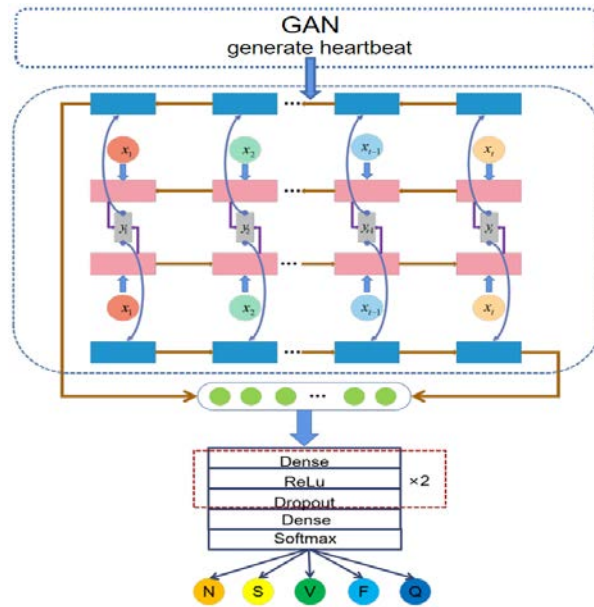
Fig. 2. Structure of CAB framework.

3. The Proposed Framework for Heartbeat Classification

CAB consists of two parts: (1) a GAN for generating data to solve the problem of class imbalance; and (2) a stacked Bi-LSTM for heartbeat classification. The framework of CAB is shown in **Fig. 2**. The GAN generates data for the classes with small samples. And then the generated data combined with the original data are used to train the classification model.
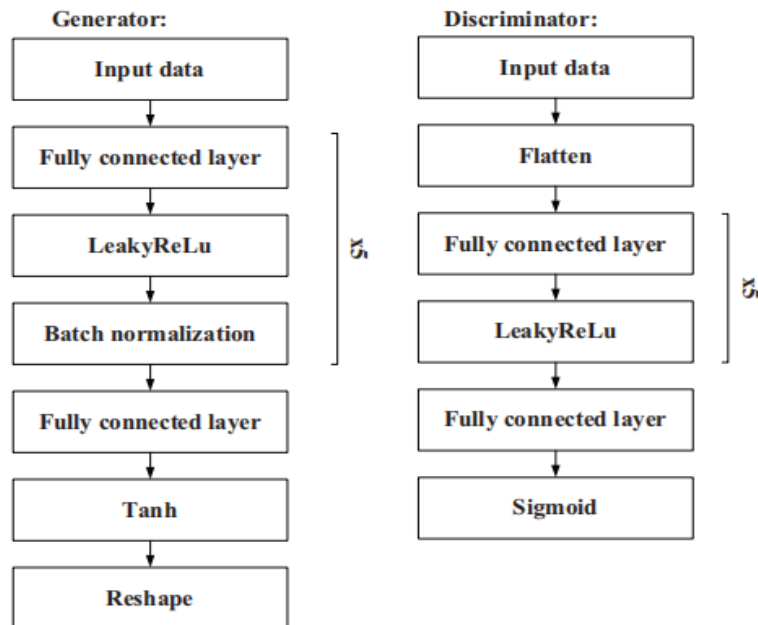
3.1 GAN for Data Augmentation

Fig. 3. Structure of the generator and discriminator of CAB.

Fig. 3 shows the GAN structure of CAB. The input of the discriminator is a heartbeat sequence $X_i = \{x_1, x_2, \cdots, x_t\}$, where $x_j (j \in [1, \cdots t])$ is an ECG signal value at the j_{th} time tick. The input of the generator is a sequence of noise signals $Z_i = \{z_1, z_2, \cdots, z_t\}$. Z is a random noise satisfying the Gaussian distribution. Finally, GAN outputs the generated ECG sequence $X_i' = \{x_0', x_1', \cdots, x_t'\}$. The target function of the GAN is represented by (1).

$$V(D, G) = E_{X_i \sim p_{data}(X_i)}[\log D(X_i)] + E_{Z_i \sim p_{Z_i}(Z_i)}\left[\log\left(10D(G(Z_i))\right)\right] \tag{1}$$

Both the discriminator and generator are implemented on a full-connection basis. The generator adds the Batch Normalization to process the data, and the discriminator uses the Flatten layer to transform multi-dimensional inputs into one-dimensional data. The generator has five repeated blocks. Each block has a fully connected layer, a LeakyReLu layer, and a Batch Normalization. The discriminator has five repeated blocks too. Each block consists of a fully connected layer and a LeakyReLu layer.

3.2 Stacked Bi-LSTM for Classification

Our classification model combines the stacked Bi-LSTM with the fully connected layer. It also adds several dropout layers to prevent overfitting. ReLu is used as the activation function. After using GAN to generate enough data, we integrate the generated data with the original data (represented by $X_i'' = \{x_1'', x_2'', \cdots, x_t''\}$). X_i'' is input to the Stacked Bi-LSTM. At last, the classification model outputs the probability of each type of heartbeat. The type with the highest probability is the type of the input heartbeat.

In each LSTM cell, the forgotten gate determines the discarding of information. Equation (2) is the activation function of the forgotten gate. The input of the t_{th} forgotten gate is x_t and the output of cell h_{t-1}. The input gate adds useful new information to the cellular state. Equation (3) decides which information needs to be updated. Equation (4) determines the alternate content to be updated. And $\tilde{C}_t$ is optional for updating. Equation (5) adds new information to the cell state C_t to replace the old state C_{t-1}. The output gate selects important information from the current state as the output of the cellular state, (6) determines o_t, i.e., the output information. Equation (7) transforms o_t to the final output h_t.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t''] + b_f\right) \tag{2}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t''] + b_i) \tag{3}$$

$$\tilde{C}_t = tanh(W_c \cdot [h_{t-1}, x_t''] + b_c) \tag{4}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{5}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t''] + b_o) \tag{6}$$

$$h_t = o_t * tanh(C_t) \tag{7}$$

CAB uses the Bi-LSTM network, whose output result is determined by both the previous input and the later input. The forward LSTM combining with the backward LSTM forms Bi-LSTM. Besides, a stacked structure is used to deepen the depth of the model. The Bi-LSTM uses the Adam gradient descent algorithm and the spars categorical cross-entropy loss function. The parameter settings of the Stacked Bi-LSTM are shown in **Table 1**.

Table 1. The numbers of cells in different layers

Layer	The number of cells
1st LSTM	320
2nd LSTM	320
1st Dense	64
2nd Dense	32

4. Experiment

The experimernt is based on the MIT-BIH arrhythmia database. It is performed on a computer with a GPU of NVIDIA GeForce GTX 950M and 3049 MB memory.

4.1 Arrhythmia Dataset

The MIT-BIH arrhythmia database contains 48 two-channel ECG recordings from Beth Israel hospital. The duration of each record is half an hour. The ECG signals are from 47 patients. And they are digitized at a rate of 360 samples per second per channel, with an 11-bit resolution of more than 10 mV. In addition, two or more experts annotated each record to iron out their differences [59].

4.2 Experimental Setup

The experiment includes the following steps: (1) heartbeat segmentation; (2) data generation; (3) training, testing, and validation dataset partition; and (4) model training and evaluation.
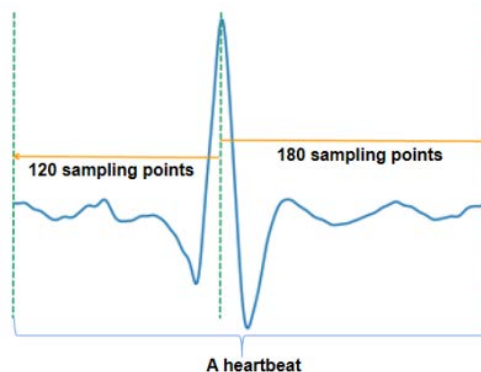
4.2.1 Heartbeats Segmentation

Fig. 4. Heartbeat segmentation.

The procedure of heartbeat segmentation refers to the method of [47]. At first, we de-noise ECG signals and locate the R peak. An ECG record is divided by taking 140-time ticks in front of R peaks and 180-time ticks behind R peaks. Therefore, a heartbeat contains a total of 320-time ticks. **Fig. 4** shows the heartbeat segmentation. According to AAMI [8], the signals in the recordings named 102, 104, 107, and 218 are of poor quality, so we do not extract the signals in these four recordings. Finally, the number of extracted heartbeats of each type is shown in **Table 2**.

Table 2. Heartbeat distributions in MIT-BIH arrhythmia dataset

Heartbeat class	The number of heartbeat
N	86717
S	3026
V	7008
F	802
Q	15

4.2.2 Data Generation

As can be seen from **Table 2**, the numbers of different types of heartbeat vary greatly. The heartbeat numbers of F and Q are much fewer than the numbers of the other three types. To solve this class imbalance problem, we use GAN to respectively expand the samples of F and Q to 2500.

4.2.3 Training, Testing, and Validation Dataset Partition

We first partition the original dataset as 90% for training and 10% for testing. And then we partition the training dataset as 80% for training and 20% for validating. Figure 1 shows that each category contains several subclasses. To make the subclasses evenly distributed in the dataset, data are shuffled before partitioning the data set. We divide all the ECG sequences into ten equal portions, one portion for testing, and the other nine portions for training. This operation is repeated ten times by shifting the testing portion. Each time the evaluation metrics are evaluated. Finally, the average performance of CAB is calculated.

4.2.4 Model Training

Table 3. The important parameter settings of classification model

Parameter	Value
Optimizer	Adam
Loss function	Sparse categorical crossentropy
Dropout rate	0.3
Epoch	100
Validation rate	0.2

Before the training, we shuffle the training set again to effectively avoid the occurrence of overfitting. The settings of important parameters are shown in **Table 3**. The classification model uses Adam [60] as the optimizer. The loss function is the sparse categorical cross-entropy. Equation (8) expresses the cross-entropy.

$$C = -\frac{1}{n}\sum [y \ln a + (1-y)\ln(1-a)]$$

(8)

where, n is the number of categories, y is the desired output, a is the actual output of the neuron, and x is the input.
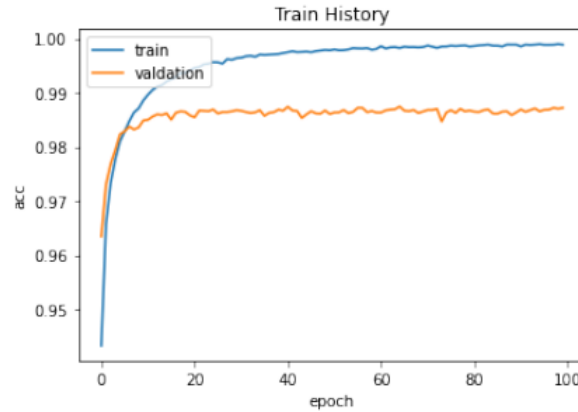

Fig. 5. The train history of training set.

4.2.5 Evaluation Metrics

Four metrics are used to evaluate the performance of CAB, which are the accuracy(ACC), precision (PRE), recall (REC), and f1 score (F1) (see (9)-(12)).

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

$$PRE = \frac{TP}{TP + FP} \tag{10}$$

$$REC = \frac{TP}{TP + FN} \tag{11}$$

$$F_1 = \frac{2 * PRE * REC}{PRE + REC} \tag{12}$$

where, TP, FP, TN and FN represent the true positives, false positives, true negatives and false negatives respectively.

4.3   Results

4.3.1 Training

The average ACC, PRE, REC, and F1 of CAB based on the training set are 99.71%, 99.30%, 98.73%, and 99.01% respectively (see **Fig. 6**). The ACCs of training and validation for 100 epochs are shown in **Fig. 5**. We can see that the ACCs increase when the epoch number increases.
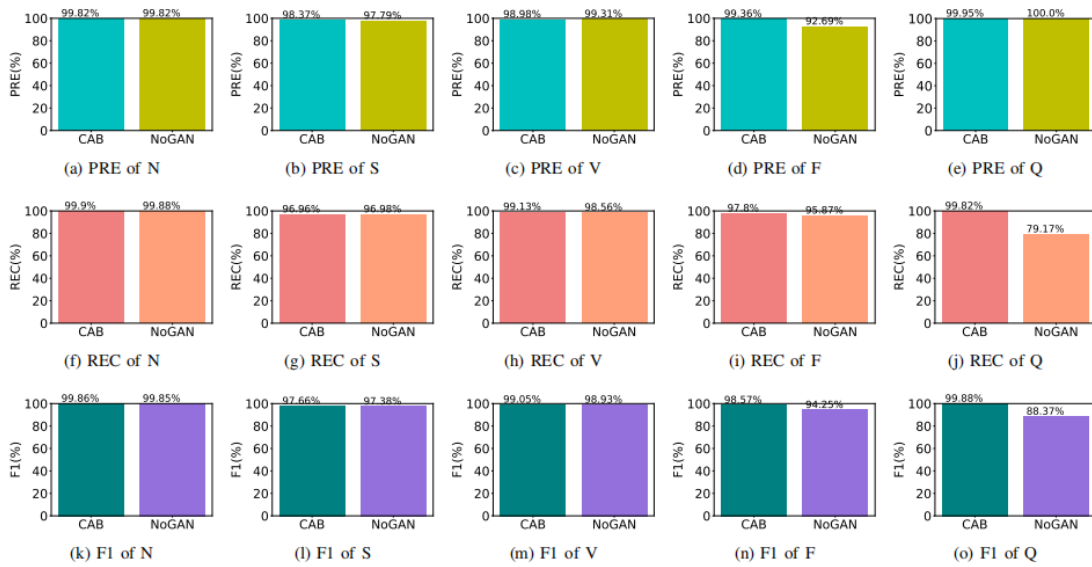
Fig. 6. The classification PRE, REC, and F1 of CAB and No-GAN basedon the training set.
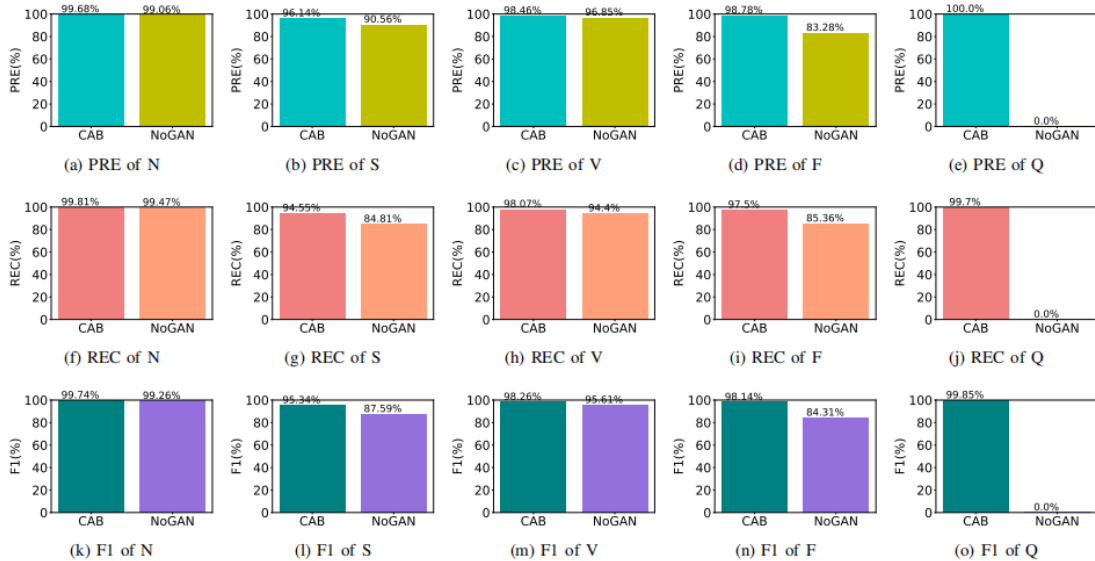

Fig. 7. The classification PRE, REC, and F1 on testing set of CAB and No-GAN.

Fig. 6 also shows the training results based on the raw unbalanced data, i.e. without using the GAN to balance classes (called No-GAN). The average ACC, PRE, REC, and F1 of No-GAN based on the training set are 97.92%, 97.92%, 94.09%, and 95.76% respectively. We can see from **Fig. 6** that the average performance of CAB is better than the average performance of No-GAN. No-GAN performs as well as CAB in terms of classifying N, S, and V heartbeats. However, CAB performs much better than No-GAN for classifying F and Q heartbeats. The average PRE, REC, and F1 of CAB are 2%, 5%, and 3% higher than those of No-GAN respectively.

4.3.2 Testing

Table 4. Compare CAB with State of the Art

Work	Over all ACC (%)	N (%)	S (%)	V (%)	F (%)	Q (%)
CAB	99.71	PRE = 99.82 REC = 99.90 F1 = 99.86	PRE = 98.37 REC = 96.96 F1 = 97.66	PRE = 98.98 REC = 99.13 F1 = 99.05	PRE = 99.36 REC = 97.80 F1 = 98.57	PRE = 99.95 REC= 99.82 F1 = 99.88
No-GAN	99.48	PRE = 99.82 REC = 99.88 F1 = 99.85	PRE = 97.79 REC = 96.98 F1 = 97.38	PRE = 99.31 REC = 98.56 F1 = 98.93	PRE = 92.69 REC = 95.87 F1 = 94.25	PRE = 100.0 REC= 79.17 F1 = 88.37
Li et al. [27]	99.49	PRE = 99.67 REC = 99.86 F1 = 99.76	PRE = 97.08 REC = 92.09 F1 = 94.52	PRE = 98.10 REC = 98.47 F1 = 98.28	-	-
Chen et al. [56]	93.1	PRE = 95.4 REC = 98.4 F1 = 96.9	PRE = 38.4 REC = 29.5 F1 = 33.37	PRE = 85.1 REC = 93.1 F1 = 91.3	-	-
Wang et al. [57]	93.4	PRE = 98.3 REC = 93.4 F1 = 95.8	PRE = 43.5 REC = 92.1 F1 = 59.1	PRE = 89.5 REC = 93.1 F1 = 91.3	PRE = 89.9 REC = 62.1 F1 = 73.5	-
Acharya et al. [43]	94.03	PRE = 89.68 REC = 88.41 F1 = 89.04	PRE = 95.78 REC = 84.21 F1 = 89.62	PRE = 97.27 REC = 91.67 F1 = 94.39	PRE = 96.50 REC = 88.53 F1 = 92.34	PRE = 98.83 REC= 95.63 F1 = 97.20
Wang et al. [37]	99.06	PRE = 98.89 REC = 99.81 F1 = 99.35	PRE = 96.56 REC = 77.07 F1 = 85.72	PRE = 97.09 REC = 95.37 F1 = 96.22	PRE = 91.02 REC = 73.32 F1 = 81.22	-

The average ACC, PRE, REC, and F1 of CAB based on the testing set are 99.48%, 98.81%, 97.93%, and 98.27% respectively (see Fig. 7). The average ACC, PRE, REC, and F1 of No-GAN based on the testing set are 98.52%, 73.95%, 72.81%, and 73.41% respectively. The average PRE, REC, and F1 of CAB are 15%, 15%, and 15% higher than those of No-GAN respectively.

We compare CAB with five state-of-the-art arrhythmia classification models based on the MIT-BIH dataset: Li et al. [27], Chen et al. [56], Wang et al. [57], Acharya et al. [43], and Wang et al. [37]. The comparison results are shown in Table IV. The average ACC of CAB is higher than the ACCs of the other work. It is 7%, 6% and 6% higher than the average ACCs of [56], [57], and [43] respectively. For 'N' classification, the F1 of CAB is around 10% higher than the F1's of [56], [57] and [43] respectively. For 'S' classification, the F1 of CAB is around 60%, 30%, 10% and 15% higher than the F1's of [56], [57] [43] and [37] respectively. For 'V' classification, the F1 of CAB is around 30%, 10% and 6% higher than [56], [57] and [43] respectively. And for 'F' classification, the F1 of CAB is around 25%, 6%, and 17% higher than [57] [43] and [37] respectively.

Overall, CAB performs better than No-GAN and the classification models in [27] [37] [43][56][57][59][60] on average. The experiment results show that it is efficient to use GAN to solve the data unbalance problem for heartbeat classifications.

5. Conclusion

In this paper, we propose CAB, a heartbeat classification framework for arrhythmia detection based on the morphology of heartbeats. CAB solves the class imbalance problem by using a GAN to generate samples for the heartbeat categories with sparse samples. We design a heartbeat classification model based on Bi-LSTM to capture information between time series. Using the ECG data augmented by GAN to train the classification model can improve the accuracy of heartbeat classification. Experiment results show that CAB performs better than the state-of-the-art heartbeat classification models. The overall classification accuracy is 99.71%. The F1-scores of classifying N, S, V, F and, Q heartbeats are 99.86%, 97.66%, 99.05%, 98.57%, and 99.88%, respectively. CAB realizes the intelligent classification of a heartbeat. It automatically classifies the received ECG data and analyzes the type of arrhythmia in time. This can save the energy of cardiologists and effectively prevent the occurrence of various complications. CAB helps cardiologists make a timely diagnosis and promotes the development of telemedicine. It can bring convenience to patients and doctors, save time and medical resources. Besides, CAB can continuously monitor people's heart health, reduce the prevalence of heart diseases, and vigorously promote physical health. In the future, we will further design a general classification model with more arrhythmia data sets for testing. And we plan to extract the information of the frequency domain and the time domain using the wavelet transform. The accurate classification of finer-grained arrhythmia heartbeats will be also explored.

Acknowledgement

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