An Open Access Database for Evaluating the Algorithms of Electrocardiogram Rhythm and Morphology Abnormality Detection

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Over the past few decades, methods for classification and detection of rhythm or morphology abnormalities in ECG signals have been widely studied. However, it lacks the comprehensive performance evaluation on an open database. This paper presents a detailed introduction for the database used for the 1st China Physiological Signal Challenge 2018 (CPSC 2018), which will be run as a special section during the ICBEB 2018. CPSC 2018 aims to encourage the development of algorithms to identify the rhythm/morphology abnormalities from 12-lead ECGs. The data used in CPSC 2018 include one normal ECG type and eight abnormal types. This paper details the data source, recording information, patients’ clinical baseline parameters as age, gender and so on. Meanwhile, it also presents the commonly used detection/classification methods for the abovementioned abnormal ECG types. We hope this paper could be a guide reference for the CPSC 2018, to facilitate the researchers familiar with the data and the related research advances.

Keywords: Electrocardiogram (ECG), Database, Rhythm and Morphology Abnormal, CPSC.

1. INTRODUCTION
Cardiovascular diseases (CVDs) continue to be the leading cause of morbidity and mortality worldwide.¹ An estimated 17.5 million people died from CVDs in 2012, representing 31% of all global deaths (WHO 2015).² Electrocardiogram (ECG) signal is the expression of the myocardium electrical activity on the body’s surface. It can provide important information about the status of cardiac activity³ and is commonly used to detect rhythm/morphology abnormalities. The standard 12 lead ECGs has been an important tool for clinicians to diagnose heart diseases.

Over the past few decades, methods for classification and detection of rhythm or morphology abnormalities in ECG signals have been widely studied. Many methods have demonstrated potential to accurately detect pathologies in clinical applications.¹ Unfortunately, the current works lack comprehensive comparisons performed on as many as heart abnormal types. Existing

 Works focus on single or a few combination, such as atrial fibrillation,⁴,⁵ while some studied ST changes.⁶,⁷ The China Physiological Signal Challenge (CPSC) 2018 (http://www.icbeb.org/Challenge.html) attempts to address this issue by contributing a more comprehensive database. The signals of this database (9,831 records from 9458 patients with a time length of 7–60 min) came from 11 hospitals, containing nine types: one normal ECG type and eight abnormal types. The purpose of this paper is to provide a detailed description for the challenge data and a concise introduction for the existing methods, to help researchers familiar with the data and the related research advances.

2. BRIEF REVIEW ON THE RHYTHM/ MORPHOLOGY ABNORMALITIES CLASSIFICATION METHODS

2.1. Atrial Fibrillation
Atrial fibrillation (AF) is a serious cardiovascular disease with the phenomenon of beating irregularly. In 2003, the European
Society of Cardiovascular Diseases and North American Association of Pacing and Electrophysiology Arrhythmia divided atrial fibrillation into paroxysmal atrial fibrillation, persistent atrial fibrillation and permanent atrial fibrillation based on the time of atrial fibrillation episode. There are many well-known schools and institutions that have established large-capacity, multi-category, and well-annotated databases for AF studying work, such as the MIT-BIH database,10 the AHA database,11 and the ST-T ECG database.12 The automatic AF detection is divided into two major categories: one based on the characteristics of atrial activity; one atrial fibrillation based on the characteristics of the RR interval. The success of the PhysioNet/Computing in Cardiology Challenge 2017 of “AF Classification from a short single lead ECG recording” significantly promotes the process of AF detection research.12

In 2000, Andrikopoulos et al. defined the square of the P-wave standard deviation in ECG signals as P-wave variability. This value could represent the changes of atrial activity characteristics in atrial fibrillation process. Using 12-lead ECG data from 60 normal subjects and 50 AF subjects to verify the performance, 88% sensitivity and 75% specificity were obtained.13 Lepage et al.14 used wavelet transform and Hidden Markov Models (HMM) to extract the P waves from 63 normal and 82 AF patient records. Specificity and sensitivity obtained were 65% and 70%, respectively. Maji et al.4 presented a method of automatic detection of AF by using higher order statistical moments of ECG signal in Empirical Mode Decomposition (EMD) domain. The performance of this method was tested on the MIT-BIH arrhythmia database with Sensitivity of 96% and Specificity of 93%. Teijeiro et al.15 employed a Convolutional Neural Network (CNN) with one fully connected layer to learn the time-domain features. Then the proposed CNN-based feature learning mechanism was integrated with the other standard classifiers to improve the accuracy. The results demonstrated that the integration of CNN structure as a feature extractor with the other conventional classifier can improve the resulting classification performance.

2.2. Block

In the process of cardiac electrical activation, abnormal electrical conduction occurs, so that the heart cannot normally contract and pump blood, which is called conduction block. It mainly divided into intro-atrial block, atrioventricular block (AVB) and bundle branch block (BBB). At present, automatic detection methods focused on BBB.

In 2007, Ilic16 employed the Continuous Wavelet Transform (CWT) to detect the normal and left BBB (LBBB). In 2011, Ceylan et al.17 proposed wavelet neural network (WNN) with Morlet and Mexican hat wavelet functions as activation function in hidden layer to classify LBBB, right BBB (RBBB) and normal types, achieving accuracies of 97.9% and 99.2% respectively. In 2014, Kora and Kalva18 proposed a hybrid technique: Bacterial Foraging-Particle Swarm Optimization (BFPSSO) for the feature selection and used the Levenberg-Marquardt neural network to classify LBBB, RBBB and normal types. This work achieved the results with 98.2% (LBBB), 98.15 (RBBB) and 98.1% (Normal). Huang et al.19 proposed a heartbeat classification method through a combination of three different types of classifiers: a minimum distance classifier, a weighted linear discriminant classifier and support vector machine (SVM). The results showed a sensitivity of 91.4% and a positive predictive value of 37.3% for LBBB and a sensitivity of 92.8% and a positive predictive value of 88.8% for RBBB. In 2005, Yukel and Bekir20 proposed a new neural network structure based on fuzzy clustering (FCNN) for BBB classification the results showed that FCNN method gave better recognition rates for mixed classification.

2.3. Ventricular Premature Contraction

Before the sinus node impulse has reached the ventricle, an electrical impulse is caused by an electrical impulse in advance of any site in the ventricle or the ectopic rhythm of the interventricular septum, causing ventricular depolarization, known as premature ventricular contraction (PVC). It has a high incidence in adults and can cause other diseases. Frequent PVC can be complicated by syncope, angina, and heart failure, which poses a great health threat to the elderly. There are many researchers dedicated to the automatic detection of PVC. SVM, neural network, wavelet analysis, Gaussian mixture model, decision trees, multi-domain feature extraction, etc., were commonly used.

Benali et al.21 used the supervised classifiers and efficient features to detect PVC automatically, and the accuracy achieved about 97.14%. Saibal et al.22 proposed a model with a feature extractor based on cross-correlation approach and an Artificial Neural Network (ANN) classifier to detect PVC with an accuracy of 95.24%. Vessela et al.23 developed a three processing stages-based method, including preprocessing filtration, heartbeat detection and heartbeat classification by estimation of the interbeat differences of the RR intervals and the QRS morphological descriptors, and obtained sensitivity of 92.2% and specificity of 96%. Using fuzzy C-means clustering algorithm, Sutar et al.24 develop an classifier to use the features of informational entropy and mean Teager energy, and achieved sensitivity of 97.78% and PPV of 97.28%.

2.4. Premature Atrial Contraction

Premature atrial contraction (PAC) occurs at a high rate, commonly followed by PVC. Its main manifestations are palpitation, chest distress, uncomfortable dizziness in the precordial area and intermittent pulse.

Vessela et al.25 proposed a method for PAC detection based on QRS morphological descriptors and the RR-interval information, achieving a sensitivity of 88%. Khazaei et al.25 proposed a power spectral-based hybrid genetic algorithm-SVM (SVMGA) method and achieved sensitivity of 98.93% sensitivity, specificity of 99.42% and PPV of 97.56%. In Ref. [26], two-layered Hidden Markov Models (HMMs) were employed to classify normal, PVC and PAC, obtaining a sensitivity of 99.21% and PPV of 95.57% for PAC beats.

2.5. Heartbeat Classification

Sections 2.1–2.4 mainly described the detection methods for one arrhythmia type. In fact, more papers have been focused on the multiple classification.

Yeh et al.26 proposed a cluster analysis (CA) method and obtained sensitivity of 95.59%, 91.32%, 90.50%, 94.51% and 93.77% for normal, LBBB, RBBB, PVC, and PAC respectively, with a total classification accuracy of 94.30%. Teijeiro et al.15 proposed a novel knowledge-based approach to classify five beat classes in the MIT-BIH arrhythmia and obtained a sensitivity of 94.63% and PPV of 96.79% for multiple classification. In 2017, Rajpurkar et al.28 built a dataset with of 64,121 ECG
records from 29,163 patients and trained 34-layer CNN to detect 14 rhythm classes. The database was much larger than other datasets, such as MIT/BIH. The model outperformed the average cardiologist performance on most rhythms, noticeably outperforming the cardiologists in the AV block set of arrhythmias which includes Mobitz I (Wenckebach), Mobitz II (AVB Type2) and complete heart block (CHB).

2.6. Ischemic Disease
Ischemic disease is an important cause of death worldwide, responsible for more than 8 million deaths globally every year. If persistent, ischemia will lead to cell death and permanent damage to the heart muscle causing a myocardial infarction (MI). The main characteristics in ECGs are ST segment elevation or depression, T wave abnormality, the development of pathological Q waves. ST-segment deviation is the most widely used feature for ischemic disease and MI detection. In 1984, Gallino et al.30 analyzed the ST-segment deviation of 2-lead ECGs on 24 hour Holter monitor tapes. Concurrently, Mitchell31 and Sun32 used Karhunen-Loeve transform (KLT) to analyze the ST-segment changes. Then, principal component analysis (PCA) was applied. Diamantaras33 proposed a nonlinear PCA method to the extracted ST segment. Recently, various advanced methods are used to identify ischemic disease and MI detection. In 2008, Gharaviri34 proposed an adaptive neuro-fuzzy interface system (ANFIS) classifier to classify the ST segment elevation and depression, which obtained a sensitivity of 88.62% and a specificity of 99.65%. In 2012, Arif et al.35 used $K$-nearest neighbor (KNN) to develop an automatic method for MI localization, using the features of T wave amplitude, Q wave amplitude and ST deviation measure and achieving overall classification accuracy of 98.3%. Sun et al.36 proposed the latent variable multiple instance learning method to build a totally automatic ECG classification procedure, which achieved a good performance on recognition of ECGs related to MI. In 2015, Murthy and Meenakshi37 provided the comparison of performance of ANN, SVM and KNN models for cardiac ischemia classification. In 2016, Padhy and Dandapat38 employed a third-order tensor structure to represent the multi-lead ECG signals and used the modern singular values and normalized multiscale wavelet energy as the input features. This work achieved the detection accuracy of 95.30%, with sensitivity and specificity of 94.6% and 96.0%, respectively. There are many published papers on automatic diagnosis of myocardial ischemic and myocardial infarction. Literature gives a detailed overview and the readers can refer to this article.

3. DESCRIPTION OF THE 2018 CHINA PHYSIOLOGICAL SIGNAL CHALLENGE

3.1. Main Aim
The China Physiological Signal Challenge (CPSC) 2018 is the 1st China Physiological Signal Challenge, aiming to provide a platform for the open-source data and algorithms for the physiological signal analysis, and thus to promote the open-source research pattern for the cardiovascular disease detection and prediction in China. The practical objective is to identify the rhythm/morphology abnormalities from 12-lead ECGs, lasting several seconds to tens of seconds.

A number of studies have investigated the performances of different detection/classification methods for the abnormal ECG types. However, many studies are generally limited in applicability because (1) the classification of normal and only one single abnormality was performed; (2) the data were not sufficient without the use of a separate out of sample test dataset and only a small number of subjects were used, almost certainly resulting in over-fitting of the model and inflated statistics; (3) failure to post the data (and any code to process the data) publicly so others may compare their results directly. Therefore, this challenge contributes a more comprehensive database to address these issues, including one normal type and eight abnormal types, which are detailed as:

(1) Atrial fibrillation (AF)
(2) First-degree atrioventricular block (I-AVB)
(3) Left bundle branch block (LBBB)
(4) Right bundle branch block (RBBB)

### Table I. Data profile for the training and testing sets.

<table>
<thead>
<tr>
<th>Challenge set</th>
<th>Type</th>
<th># recording of each hospital</th>
<th># total recording</th>
<th>Time length (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>Normal</td>
<td>73 90 73 70 90 77 76 78 77 140</td>
<td>918</td>
<td>15.43 7.81 10.00 13.00 60.00</td>
</tr>
<tr>
<td></td>
<td>AF</td>
<td>45 184 28 26 138 155 280 104 27 47 64</td>
<td>1098</td>
<td>15.01 8.39 9.00 11.00 60.00</td>
</tr>
<tr>
<td></td>
<td>I-AVB</td>
<td>39 71 0 8 150 129 212 19 15 27 34</td>
<td>704</td>
<td>14.32 7.21 10.00 11.27 60.00</td>
</tr>
<tr>
<td></td>
<td>LBBB</td>
<td>7 12 7 2 41 30 51 13 9 18 17</td>
<td>207</td>
<td>14.92 8.09 9.00 12.00 60.00</td>
</tr>
<tr>
<td></td>
<td>RBBB</td>
<td>79 272 29 30 423 205 401 140 26 30 60</td>
<td>1695</td>
<td>14.42 7.60 10.00 11.19 60.00</td>
</tr>
<tr>
<td></td>
<td>PAC</td>
<td>57 147 4 8 105 24 111 50 2 57 9</td>
<td>574</td>
<td>19.46 12.36 9.00 14.00 60.00</td>
</tr>
<tr>
<td></td>
<td>PVC</td>
<td>76 111 3 21 150 80 132 13 18 32 17</td>
<td>653</td>
<td>20.21 12.85 6.00 15.00 60.00</td>
</tr>
<tr>
<td></td>
<td>STD</td>
<td>117 117 22 32 525 36 52 1 28</td>
<td>15</td>
<td>826</td>
</tr>
<tr>
<td></td>
<td>STE</td>
<td>3 90 6 7 38 12</td>
<td>16 0 22</td>
<td>0 8</td>
</tr>
<tr>
<td>Total/Average</td>
<td>Normal</td>
<td>490 980 169 202 1645 762 1338 416 223 288 364</td>
<td>6877</td>
<td>15.79 9.04 6.00 12.00 60.00</td>
</tr>
<tr>
<td></td>
<td>AF</td>
<td>31 38 32</td>
<td>32 30 38 33 33 34 33</td>
<td>360</td>
</tr>
<tr>
<td></td>
<td>I-AVB</td>
<td>19 79 12</td>
<td>11 59 66 120 44 11</td>
<td>20 28</td>
</tr>
<tr>
<td></td>
<td>LBBB</td>
<td>17 30</td>
<td>0 3</td>
<td>64 56 91</td>
</tr>
<tr>
<td></td>
<td>RBBB</td>
<td>5 3 5</td>
<td>3 1</td>
<td>18 13 22</td>
</tr>
<tr>
<td></td>
<td>PAC</td>
<td>34 116</td>
<td>13 13 181</td>
<td>88 173 61</td>
</tr>
<tr>
<td></td>
<td>PVC</td>
<td>23 65</td>
<td>1 3 45</td>
<td>12 48 32</td>
</tr>
<tr>
<td></td>
<td>STD</td>
<td>30 49</td>
<td>2</td>
<td>10 65 33 56</td>
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<tr>
<td></td>
<td>STE</td>
<td>50</td>
<td>0 9</td>
<td>14 225</td>
</tr>
<tr>
<td>Total/Average</td>
<td>209 420</td>
<td>74</td>
<td>90 703</td>
<td>327 573 179</td>
</tr>
</tbody>
</table>
(5) Premature atrial contraction (PAC)
(6) Premature ventricular contraction (PVC)
(7) ST-segment depression (STD)
(8) ST-segment elevated (STE).

3.2. Challenge Data
The challenge ECG recordings were collected from 11 hospitals and were generously donated for this Challenge. In order to protect the privacy of patients, the hospital names are not disclosed here. 11 hospitals are represented by A–K 11 letters. All data from 11 hospitals were combined to constitute the challenge database. The database was divided into both training and test sets with a random 70–30 training-test split. The training set contains 6,877 (female: 3178; male: 3699) 12 leads ECG recordings lasting from 6 s to just 60 s and the test set contains 2,954 (female: 1416; male: 1538) ECG recordings with the similar lengths. Table I shows the details of these two data sets, including the data source, recording information. Figure 1 illustrates the patients’ age distribution and so on. The test set is unavailable to the public and will remain private.

Fig. 1. The age distribution of training and test set.

Fig. 2. Example of a 12-lead ECG waveforms (AF and RBBB).
for the purpose of scoring. ECG recordings were sampled as 500 Hz. All data are provided in MATLAB format (each recording is a .mat file containing the ECG data, as well as the patient sex and age information).

In both training and test sets, ECG signal recordings were divided into 9 types. For the most data, each recording has only one label. While, some recordings have two or three labels because the patient who provided the signals suffers from multiple diseases simultaneously. There are 477 and 203 subjects of this multi-label type in the training and test sets respectively. Figure 2 illustrates an example of the 12-lead ECG waveforms with AF and RBBB. For this multi-label situation, as long as the result provided by the contestant is consistent with one of the labels, we consider this to be a correct result.

### 3.3. Scoring Mechanism

The overall score is computed based on the number of recordings classified as nine types. The scoring for CPSC2018 uses a $F_1$ measure, which is an average of the nine $F_1$ values from each classification type. The counting rules for the numbers of the variables are defined in Table II.

For each of the nine types, $F_1$ is defined as:

\[
F_1 = \frac{2 \times N_{x_1} \times N_{x_2}}{N_{x_1} + N_{x_2}}
\]

Table II. Counting rules for the numbers of the variables.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Normal</th>
<th>AF</th>
<th>I-AVB</th>
<th>LBBB</th>
<th>RBBB</th>
<th>PAC</th>
<th>PVC</th>
<th>STD</th>
<th>STE</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>$N_{x_1}$</td>
<td>$N_{x_2}$</td>
<td>$N_{x_3}$</td>
<td>$N_{x_4}$</td>
<td>$N_{x_5}$</td>
<td>$N_{x_6}$</td>
<td>$N_{x_7}$</td>
<td>$N_{x_8}$</td>
<td>$N_{x_9}$</td>
<td></td>
</tr>
<tr>
<td>AF</td>
<td>$N_{x_1}$</td>
<td>$N_{x_2}$</td>
<td>$N_{x_3}$</td>
<td>$N_{x_4}$</td>
<td>$N_{x_5}$</td>
<td>$N_{x_6}$</td>
<td>$N_{x_7}$</td>
<td>$N_{x_8}$</td>
<td>$N_{x_9}$</td>
<td></td>
</tr>
<tr>
<td>I-AVB</td>
<td>$N_{x_1}$</td>
<td>$N_{x_2}$</td>
<td>$N_{x_3}$</td>
<td>$N_{x_4}$</td>
<td>$N_{x_5}$</td>
<td>$N_{x_6}$</td>
<td>$N_{x_7}$</td>
<td>$N_{x_8}$</td>
<td>$N_{x_9}$</td>
<td></td>
</tr>
<tr>
<td>LBBB</td>
<td>$N_{x_1}$</td>
<td>$N_{x_2}$</td>
<td>$N_{x_3}$</td>
<td>$N_{x_4}$</td>
<td>$N_{x_5}$</td>
<td>$N_{x_6}$</td>
<td>$N_{x_7}$</td>
<td>$N_{x_8}$</td>
<td>$N_{x_9}$</td>
<td></td>
</tr>
<tr>
<td>RBBB</td>
<td>$N_{x_1}$</td>
<td>$N_{x_2}$</td>
<td>$N_{x_3}$</td>
<td>$N_{x_4}$</td>
<td>$N_{x_5}$</td>
<td>$N_{x_6}$</td>
<td>$N_{x_7}$</td>
<td>$N_{x_8}$</td>
<td>$N_{x_9}$</td>
<td></td>
</tr>
<tr>
<td>PAC</td>
<td>$N_{x_1}$</td>
<td>$N_{x_2}$</td>
<td>$N_{x_3}$</td>
<td>$N_{x_4}$</td>
<td>$N_{x_5}$</td>
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<td>$N_{x_8}$</td>
<td>$N_{x_9}$</td>
<td></td>
</tr>
<tr>
<td>PVC</td>
<td>$N_{x_1}$</td>
<td>$N_{x_2}$</td>
<td>$N_{x_3}$</td>
<td>$N_{x_4}$</td>
<td>$N_{x_5}$</td>
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<td>$N_{x_7}$</td>
<td>$N_{x_8}$</td>
<td>$N_{x_9}$</td>
<td></td>
</tr>
<tr>
<td>STD</td>
<td>$N_{x_1}$</td>
<td>$N_{x_2}$</td>
<td>$N_{x_3}$</td>
<td>$N_{x_4}$</td>
<td>$N_{x_5}$</td>
<td>$N_{x_6}$</td>
<td>$N_{x_7}$</td>
<td>$N_{x_8}$</td>
<td>$N_{x_9}$</td>
<td></td>
</tr>
<tr>
<td>STE</td>
<td>$N_{x_1}$</td>
<td>$N_{x_2}$</td>
<td>$N_{x_3}$</td>
<td>$N_{x_4}$</td>
<td>$N_{x_5}$</td>
<td>$N_{x_6}$</td>
<td>$N_{x_7}$</td>
<td>$N_{x_8}$</td>
<td>$N_{x_9}$</td>
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<tr>
<td>Total</td>
<td>$N_{x_1}$</td>
<td>$N_{x_2}$</td>
<td>$N_{x_3}$</td>
<td>$N_{x_4}$</td>
<td>$N_{x_5}$</td>
<td>$N_{x_6}$</td>
<td>$N_{x_7}$</td>
<td>$N_{x_8}$</td>
<td>$N_{x_9}$</td>
<td></td>
</tr>
</tbody>
</table>

The final challenge score is defined as follows:

\[
F_1 = \frac{F_{11} + F_{12} + F_{13} + F_{14} + F_{15} + F_{16} + F_{17} + F_{18} + F_{19}}{9}
\]

In addition, we also calculate the $F_2$ measures for each of the four sub-abnormal types, i.e., the AF, block, premature contraction and ST-segment change, as follows:

\[
F_{AF} = \frac{2 \times N_{x_2}}{N_{x_1} + N_{x_2}}
\]

\[
F_{Block} = \frac{2 \times (N_{x_1} + N_{x_4} + N_{x_5})}{N_{x_1} + N_{x_3} + N_{x_4} + N_{x_5} + N_{x_6} + N_{x_7} + N_{x_8} + N_{x_9}}
\]

\[
F_{Precontract} = \frac{2 \times (N_{x_4} + N_{x_5})}{N_{x_1} + N_{x_6} + N_{x_7} + N_{x_8} + N_{x_9}}
\]

\[
F_{ST} = \frac{2 \times (N_{x_8} + N_{x_9})}{N_{x_1} + N_{x_3} + N_{x_4} + N_{x_5} + N_{x_6} + N_{x_7} + N_{x_8} + N_{x_9}}
\]

### 4. DISCUSSION

This paper presents an introduction for the database used in CPSC 2018, including the data source, recording information, patients’ clinical baseline parameters (age and gender). Meanwhile, it also presents the common detection/classification methods for the abovementioned abnormal ECG types.

At present, there are various published ECG databases for evaluating the ECG abnormalities classification. MIT-BIH arrhythmia database is the most frequently used one, consisting of 48 records at 360 Hz for approximately 30 min from 47 different patients. This database contains 15 recommended classes of arrhythmia, which are further classified into five super-classes: normal (N), supraventricular ectopic beat (SVEB), ventricular ectopic beat (VEB), fusion beat (F) and unknown beat (Q).

The European ST-T database was the standard for evaluating ST-T changes in ambulatory ECG,11 which consists of 90 records acquired from 79 subjects suffering myocardial ischemia, sampled at 250 Hz. The MIT-BIH Atrial Fibrillation Database includes 25 long-term ECG AF recordings (mostly paroxysmal), providing a database for evaluating AF detection method. These databases contained one disease or one type abnormal. Thus the evaluations focus on only one or a few combination of disease abnormalities, such as AF, ST change, etc.

To address this issue, CPSC 2018 contains more abnormal types (normal type and eight abnormal types). The public release of such a database has many potential benefits to a wide range of users. The data of 9,458 patients were sufficient to use a separate out of sample test dataset. The availability of these data can encourage various researchers to develop innovative algorithms.

**Conflicts of Interest Statement**

There is no conflict of interest to this work.

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References and Notes


