Generated ECG signal feasibility evaluation for classification

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Abstract

Nowadays, Electrocardiogram (ECG) signals can be measured using wearable devices, such as smart watches. In this study, 12-lead ECG signals were generated from lead I and their feasibility was tested to obtain more details. The 12-lead ECG signals were generated using a U-net-based generative adversarial network (GAN) that was trained on ECG data obtained from the Asan Medical Center. Subsequently, unseen PTB-XL PhysioNet data were used to produce real 12-lead ECG signals for classification.

The generated and real 12-lead ECG signals were then compared using a ResNet classification model; and the normal, atrial fibrillation (A-fib), left bundle branch block (LBBB), right bundle branch block (RBBB), left ventricular hypertrophy (LVH), and right ventricular hypertrophy (RVH) were classified. The mean precision, recall, and f1-score for the real 12-lead ECG signals are 0.70, 0.72, and 0.70, and that for the generated 12-lead ECG signals are 0.82, 0.80, and 0.81, respectively.

The generated 12-lead ECG signals perform better than real 12-lead ECG signals. In this study, the 12-lead generative model was evaluated by classifying the 6 diagnostic classes, and the results showed that generated 12-lead ECG signals can be used to diagnose cardiac diseases.

1. Introduction

Cardiovascular diseases (CVDs) comprise a series of heart blood-vessel abnormalities, which are one of leading reasons for deaths worldwide. ECG signals are typically used in the early prediction and general diagnosis of abnormal heart rhythms. Typically, 12-lead ECG signals are used to diagnose cardiac diseases [1]. Heart diseases often cause an irregularity in the heart called arrhythmia, wherein A-fib is the most common cardiac arrhythmia. However, real-time ECG measurement is required for early diagnoses.

In this regard, wearable ECG measurement devices are currently in use, with more being developed. Holter ECG devices were developed for long-term ECG monitoring [2]; however, owing to their limitations, ECG monitoring devices, such as patches and watches, were developed. These methods can be used to only measure one of the 12 leads. It is now possible to monitor the patient’s ECG from their bedside. These ECG monitoring devices are less complex and expensive compared to conventional methods. However, wearable devices, such as patches and smart watches, have a critical limitation; they can only measure lead I. Generally, lead I can be representative of limb leads but not precordial leads. Therefore, abnormal cardiac diseases, such as RBBB, LBBB, RVH, and LVH, cannot be diagnosed [3]. Although single-lead devices are widely used, they are rarely used for diagnoses owing to their lack of information and difficulty in application for medical use [4].

2. Methods

In this study, the ECG generation model was based on that in our previous study [5]. The pix2pix GAN model was trained using MUSE data on patients who had visited the Seoul Asan Medical Center Hospital between January 01, 2001, and February 28, 2022. For classification, the PTB-XL database was used as external data, and evaluation was based on the F1-score, precision, recall, and accuracy. The overview of this study is illustrated in Figure 1.

2.1. Datasets and Preprocessing

The 12-lead ECG data used in this study were obtained from the MUSE and PTB-XL databases [6]. The PTB-XL dataset contains 21,837 records obtained from 18,885 patients, and the MUSE database comprises 400 million records obtained from the Asan Medical Center Hospital. The experimental protocols in the data were approved by the Institutional Review Board (IRB) at the Asan Medical Center Hospital, under the approval number IRB No. 2022-0781.

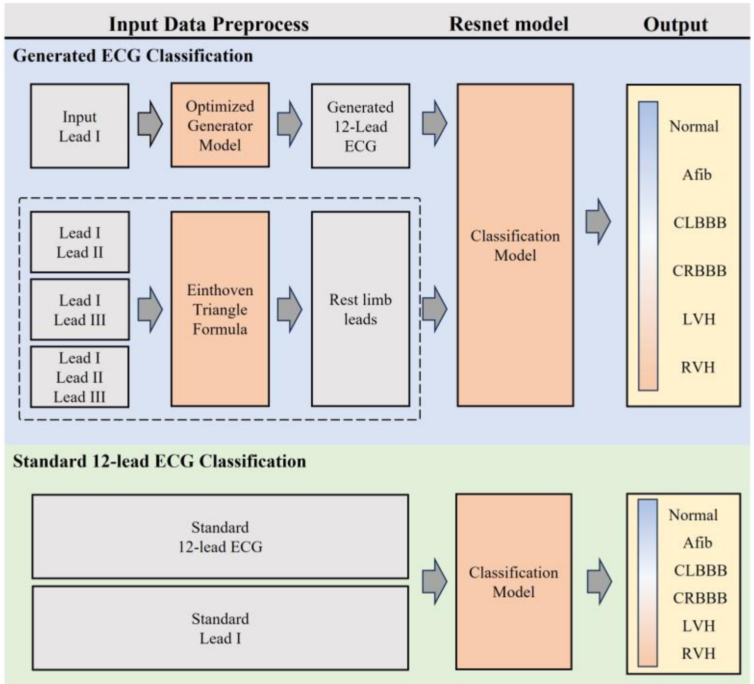

Figure 1. Overview of the proposed method. Generated ECG and real ECG signals are equally preprocessed, trained, and classified using the same ResNet model. The output of the classification model is normal, A-fib, CLBBB, CRBBB, LVH, and RVH.

2.2. GAN Architecture

GAN consists of two main networks: a generator and discriminator [7]. The basis of GAN is a minimax game between the generator and discriminator. In this study, the generator considers lead I as the input and synthesizes the remaining leads; and the discriminator distinguishes the generated signals from the real ones. Figure 1 depicts the overall architecture of the proposed model. The proposed model follows the main objective of conditional GAN, which can be expressed as shown in (1). Conditional GANs [8] learn mapping based on the relationship between the signal x and random noise vectors z and y [9].

$$\mathcal{L}_{cGAN}(G,D) = \mathbb{E}_{x,y}[logD(x,y)] + \mathbb{E}_{x,z}[\log(1 - D(x,G(x,z))], \quad (1)$$

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x,y,z}[\|y - G(x,z)\|], \quad (2)$$

where G tries to minimize the objective of GAN against D, which tries to maximize it (1). Moreover, L1 loss was used (2); thus, the final objective of GAN was represented as follows:

$$G^* = arg\min_G \max_D \mathcal{L}_{cGAN}(G,D) + \lambda\mathcal{L}_{L1}(G). \quad (3)$$

2.3. Evaluation Method

The classification of the generated 12-lead ECG signals was performed using the ResNet model. The normal ECG, RBBB, LBBB, LVH, RVH, and A-fib values were then used to evaluate the classification classes. The A-fib and normal ECG were used because most out-of-hospital wearable devices are used to detect AF, and both normal ECG and AF can be classified using single-lead ECG measurement [10]. By contrast, RBBB, LBBB, LVH, and RVH were diagnosed using the precordial leads. To test the feasibility of the 12-lead ECG generated from lead I, 5 different methods were compared. First, the classification results of the generated 12-lead ECG and real lead-I ECG signals were compared. To verify the disadvantages of single-lead measurement, the classification performances of the generated 12-lead ECG and real lead-I were compared. Second, the classification results of the generated 12-lead and real 12-lead ECG signals was compared. The Einthoven triangle formula [11] was then applied to the generated 12-lead ECG signals to conduct the ablation study. Therefore, three different groups of leads were used in the experiment: input lead I and generated lead II, input lead I and generated lead III, and input lead I and generated lead II, III. The groups were separately evaluated to determine the best outcome results and differences in the number of generated leads.

All the five different sets of methods were evaluated based on their precision, recall and f1-score values; and PTB-XL external data were used to train and evaluate each classification method.

Table 1 Evaluation of the Performance Score of the Generated ECG signals

	Generated 12-Lead			Lead II by GAN			Lead III by GAN			Lead II, III by GAN		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Normal	**0.89**	**0.92**	**0.91**	0.88	0.82	0.85	**0.92**	0.81	0.86	0.79	0.93	0.8[illegible]
Afib	**0.96**	0.76	0.84	0.94	0.72	0.81	0.92	0.88	**0.9**	0.85	**0.91**	0.8[illegible]
CLBBB	**1**	**0.96**	**0.98**	1	0.95	0.97	1	0.94	0.97	1	0.92	0.9[illegible]
CRBBB	0.87	0.77	0.82	0.89	0.78	0.83	**0.89**	**0.85**	**0.87**	0.84	0.81	0.8[illegible]
LVH	**0.82**	**0.94**	**0.87**	0.77	0.96	0.85	0.81	0.93	0.87	0.91	0.80	0.8[illegible]
RVH	0.38	0.47	0.42	0.49	0.31	0.38	**0.52**	**0.51**	**0.51**	0.42	0.19	0.2[illegible]

Table 2 Evaluation of the Performance Score of Real ECG signals

	Real Lead I			Real 12-Lead ECG		
	Precision	Recall	F1-score	Precision	Recall	F1-score
Normal	0.63	0.77	0.69	0.72	0.84	0.78
Afib	0.66	0.69	0.67	0.70	0.88	0.78
CLBBB	0.78	0.73	0.75	0.81	0.85	0.83
CRBBB	0.64	0.71	0.67	0.70	0.71	0.70
LVH	0.68	0.56	0.62	0.87	0.61	0.72
RVH	0.25	0.16	0.20	0.40	0.43	0.41

3. Results

In this section, the generated signals from the PTB-XL database and their evaluation scores are presented and compared. The evaluation of the generation model performance was performed in our previous study [5]. The evaluation scores for all five results are shown in Table 1 and Table 2.

The precision, recall, and f1-score values of the generated 12-lead ECG signals and classification performance results of real lead-I are shown in Table 1, where the best results are highlighted in bold. The generated 12-lead ECG signals exhibited the best results followed by the generated lead II. This shows that multi-lead ECG classification is more accurate. Particularly, the classification results of the abnormal ECG signals that are typically diagnosed at the precordial lead show a significant difference. The classification performance of all real 12-leads is shown in Table 2, where real lead exhibited poor results using both the 12-lead ECG and single lead I signals. Therefore, generating only Lead II or Lead III and calculating the rest of limb leads using the Einthoven formula reduces both the model complexity and time.

4. Discussion

This study demonstrates that generated ECG signals are capable of diagnosing CVDs. To the best of our knowledge, no previous studies have explored the generation of all 12-lead ECG signals and compared their classification performance. Previous and related studies have only focused on data augmentations.

Single-lead ECG signals can be better classified by implementing the proposed method to classify CVDs, which improves the disadvantages of single-lead ECG signals. This method enables the real-time analysis of ECG signals through single-lead ECG measurement, thereby allowing the use of single-lead ECG measurement devices, such as smart watches, on both patients and the public. Therefore, the proposed method can be used to alert users and patients of potential danger. Additionally, single-lead measurement, which is a more comfortable method, can be adopted in hospitals instead of 12-lead standard ECG measurement.

This study presented the feasibility of generated ECG signals for use in diagnosis. The obtained results were better than those of real ECG signals, which can be implemented in single lead devices. The accuracies, precisions, and F1 scores of the generated 12-lead ECG are shown in Table 1 and Table 2. The normal class values are 0.89, 0.92, and 0.91; the A-fib class values are 0.96, 0,76, and 0.84; the LBBB values are 1, 0.96, and 0.98; the RBBB results are 0.87, 0.77, and 0.82; the LVH results are 0.82, 0.94, and 0.87; and the RVH values are 0.38, 0.47, and 0.42, respectively. The proposed method can also be used to provide insights into various pathological cardiac diagnoses features. This will allow the monitoring of personalized ECG signals during in- and out-of-hospital care, where the cardiologist keeps patient records over a long time. Moreover, further assessment can be made by the cardiologist when a remarkable CVD is detected during the patient's daily life.

Most of all, the novelty of our study is:
(1) A large dataset of over 400 million data is used to train the generative model.
(2) No other study has investigated the use of generated ECG signals for diagnosis.
(3) Generated ECG classification exhibits a better performance than reference single-lead ECG classification, indicating that the information obtained from the precordial leads are crucial.

As shown in Table 1 and Table 2, the proposed method produces a better performance than real ECG classification. However, a few limitations exist in this study. First, 6 CVD types containing both precordial and limb leads were classified. Nonetheless, there are various of types of CVDs, such as acute MI (AMI), that are life-threatening. Certain MI, such as ST elevation, are fairly classified using DL (deep learning) [12] [13] [14]. However, there are very few AMI record data available owing to its high mortality rate. In the future, more focus should be placed on critical CVDs, which can require out-of-hospital care. Second, for the lead I ECG signals, the input in the proposed method was based on standard 12-lead ECG records. No open data were measured using both the single-lead device and standard 12-lead ECG.

5. Conclusion

This study presents a method for generating 12-lead ECG signals that can be used to classify CVDs using DL. ECG data obtained from the Asan medical center and containing 400 million records was used. External data from the PTB-XL database were also used to classify 6 types of cardiac diseases present in the limb and precordial leads. Additionally, the performance of the classification results was compared with those of real and generated ECGs. Consequently, the proposed method exhibited outstanding results during classification, which can be applied in real-life ECG monitoring. Single-lead ECG devices are simple and comfortable to wear; however, owing to the lack of lead information, rhythm features are mainly used to detect abnormal ECG. This approach can be used to solve for the disadvantages of single-lead ECG devices, thereby helping in out-of-hospital CVD detection, which is a crucial step in personalized medicine.

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