A Comparative Study of GAN Methods for Physiological Signal Generation

Nour Neifar[1], Achraf Ben-Hamadou[2], Afef Mdhaffar[1], Mohamed Jmaiel[1] and Bernd Freisleben[3]
[1] *ReDCAD Lab, ENIS, University of Sfax, Tunisia*
[2] *Centre de Recherche en Numérique de Sfax, Laboratory of Signals, Systems, Artificial Intelligence and Networks, Technopôle de Sfax, Sfax, Tunisia*
[3] *Department of Mathematics and Computer Science, Philipps-Universität Marburg, Germany*

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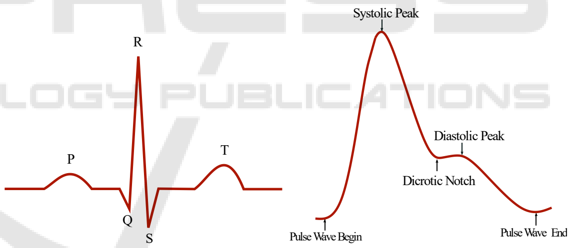
Abstract: Due to medical data scarcity and complex dynamics of physiological signals, different solutions based on generative adversarial networks (GANs) have been proposed to generate physiological signals, such as electrocardiograms (ECG) and photoplethysmograms (PPG). In this paper, we present a comparative study of existing methods for ECG and PPG signal generation. The competing methods are evaluated on the MIT-BIH arrhythmia and the PPG-BP datasets. Experimental results demonstrate the benefits of incorporating prior knowledge in the generation process and the robustness of these methods for the synthesis of realistic ECG and PPG signals.

1 INTRODUCTION

Clinical reference tests such as electrocardiograms (ECG) and photoplethysmograms (PPG) are frequently used for continuous health monitoring (Lanza, 2007; Kamaruddin et al., 2012; Song et al., 2011; Ave et al., 2015). Since cardiovascular diseases (CVDs) are reported to be the leading causes of deaths worldwide (Deaton et al., 2011; Mensah et al., 2019), several machine learning methods have been proposed in recent years with the aim of preventing, detecting, and classifying CVDs. However, the performance of these solutions is limited by the lack of the available annotated training data. Medical data collection is challenging either because of ethical issues and data privacy laws or the limitations of acquiring pathological data during critical situations (*i.e.,* strokes and seizures). Therefore, several medical data generation techniques have recently been developed to address these issues. Generative Adversarial Networks (GANs) (Goodfellow et al., 2014) represent one of the most efficient solutions for data synthesis. Over the past few years, GANs have proven their ability to synthesize high-quality data in various domains. Their effects have mainly been observed in the medical field, such as physiological time series generation. Beyond realistic data generation, one expected benefit of developing GAN-based methods on physiological signals is to leverage synthetic data for improving clinical applications, particularly in cases of low-volume of datasets. In this paper, we conduct a comparative study of GAN-based methods for physiological signal generation, namely ECG and PPG, which play crucial roles in diagnosing various cardiac diseases. ECG and PPG represent the electrical and hemodynamic activity of the heart, respectively. Each signal has its specific waveform and main features. An ECG signal is a sequence of cardiac cycles (*i.e.,* heartbeats), where each cycle is represented by a succession of waves. A typical heartbeat consists of a P wave, a QRS complex, and a



(a) (b)

Figure 1: Illustration of ECG heartbeat (a) and PPG pulse waves (b).

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T wave, each defined by specific pattern (see Figure 1a), while PPG is a series of pulses where every pulse is defined by two peaks (systolic and diastolic peaks) and a dicrotic notch (see Figure 1b).

Most existing methods for ECG and PPG signal generation (Wang et al., 2020; Hazra and Byun, 2020; Kiyasseh et al., 2020) are based on using the standard GAN architecture, which does not consider the complex properties and dynamic nature of these signals. However, recent attempts were proposed to leverage customized prior knowledge about ECG and PPG dynamics in the generation process to synthesize more realistic data (Golany and Radinsky, 2019; Golany et al., 2021; Kang et al., 2022).

In this paper, we conduct a comparative study by comparing the quality of the generated physiological signals and assessing the impact of using existing data generation approaches in improving the performance of baseline classification approaches. The obtained results demonstrate that augmenting the training data with synthetic data systematically improves ECG arrhythmia and PPG hypertension classifications. In particular, the synthetic data generated by the competing advanced GAN-based methods can significantly enhance the performance of the state-of-art classification baselines compared to standard GAN architecture. Furthermore, the various tested setups on ECG and PPG datasets show that advanced generation methods can synthesize realistic data even in the case of relatively small datasets.

The remainder of this paper is organized as follows. In Section 2, we provide an overview of GANs. We discuss the generation methods selected for this comparison and the used datasets for their training. In Section 3, we present the conducted experiments and discuss our obtained results of this comparison. Section 4 summarizes our findings and concludes our paper with some suggestions for future research.

2 METHODS AND MATERIALS

This section starts with a brief introduction to GANs. Then, we introduce the competing methods for comparison as well as the training datasets.

2.1 Generative Adversarial Networks

Generative Adversarial Networks (Goodfellow et al., 2014) are made up of a pair of models called the generator and the discriminator. Competing with its adversary, the generative model tries to synthesize data similar to real data, while the discriminator learns to determine whether a sample is from the generator or from the training data (Figure 2). The whole framework corresponds to a two-player minimax game, where the generator tries to minimize its loss function and the discriminator tries to maximize its loss function.

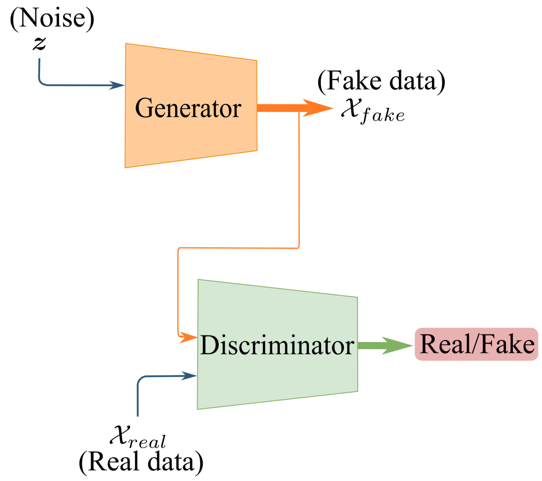

Figure 2: Training architecture of generative adversarial networks.

2.2 Methods

The majority of existing ECG and PPG signal generation methods are based on the adaptation of standard GAN architectures (Wang et al., 2020; Hazra and Byun, 2020; Kiyasseh et al., 2020). However, recent solutions argue that due to the complexity of ECG and PPG signals, their generation remains a challenging task (Golany and Radinsky, 2019; Golany et al., 2021; Kang et al., 2022). For this purpose, advanced solutions have been proposed to incorporate prior knowledge about ECG and PPG dynamics into the generation networks.

We consider three different methods in this comparative study. The first one is based on standard GAN architecture for reference (Goodfellow et al., 2014). The second one (Neifar et al., 2022b) and the third one (Neifar et al., 2022a) are recent approaches that incorporate shape priors to the generation networks. The architecture of the generator and the discriminator networks in (Goodfellow et al., 2014) is based on multilayer perceptron layers. The generator directly outputs the synthetic signal from an input noise vector.

Neifar *et al.* proposed to incorporate ECG shape prior in the generation process by defining a number of ECG shape clusters called anchors (Neifar et al., 2022b). The generator is designed to only learn to synthesize a range of variations relative to anchors. In this work, the authors also proposed disentangling the temporal and amplitude dynamics (*i.e.,* variations) of ECG signals leading to 1-D pattern dynamics modeling.

Furthermore, Neifar *et al.* introduced leveraging 2-D statistical shape prior about the ECG signals patterns into the generation process (Neifar et al., 2022a). The statistical shape modeling provides prior knowledge about the global shape of ECG signal clusters as well as the range of possible shape variations inside a single ECG signal cluster. In this way, the generator learns to generate a realistic combination of variations relative to the average shape obtained from a semantically similar ECG signal set.

2.3 Datasets

2.3.1 MIT-BIH Arrhythmia Dataset

The MIT-BIH arrhythmia dataset is the most widely used dataset for arrhythmia detection and classification. 48 half-hour ECG recordings from patients who were examined at the BIH Arrhythmia laboratory between 1975 and 1979 are included in this dataset. Each record consists of two 30-minutes ECG lead signals that have been digitally recorded at 360 samples per second and annotated by cardiologists. The dataset contains over 100,000 heartbeats, most of them are representing the normal class. Three classes of heartbeats are typically considered for the generation of ECG: the normal beats (class N), the premature ventricular contraction beats (class V), and fusion beats (class F).

2.3.2 PPG-BP Dataset

The PPG-BP dataset (Liang et al., 2018a) is widely used for the non-invasive detection of cardiovascular disease. It contains 657 data segments from 219 patients with hypertension and/or diabetes aged from 8 to 22 years. The records were sampled at a rate of 1 kHz, and each patient record contains three 2.1-second PPG segments. This dataset provides four diagnosis classes of hypertension including normotension (N), prehypertension (P), stage 1 hypertension (H1), and stage 2 hypertension (H2).

3 EXPERIMENTS AND RESULTS

Two types of experiments were performed to compare the performance of the competing generation methods. First, a quantitative evaluation is carried out to assess the impact of adding synthetic signals to the real training sets on different baseline arrhythmia and hypertension classifiers. On the other hand, a qualitative evaluation is carried out by visually inspecting the generated signals for incoherence and artifacts.

3.1 Training Settings

Our evaluation is conducted following four settings of training baseline classifiers for both ECG and PPG signals. These different settings are as follows:

Setting 1: the models are trained with only real training set without any additional synthetic (*i.e.,* generated) data.

Setting 2: the classification models are trained using a combination of real data and synthetic data generated by the standard GAN (Goodfellow et al., 2014).

Setting 3: similar to setting 2, but the synthetic data are generated by (Neifar et al., 2022b).

Setting 4: similar to the setting 3, but the synthetic data are generated using (Neifar et al., 2022a).

3.2 Quantitative Evaluation

Experiments were conducted separately for ECG and PPG signals.

3.2.1 Experiments on ECG Signals

In addition to comparing the performance of the competing generation approaches, we are particularly interested in highlighting their generation ability in the case of relatively small data volumes. To this end, we propose two evaluation dataset setups built from the MIT-BIH dataset:

- Setup 1: the entire MIT-BIH dataset (N, V ,and F classes) is considered.
- Setup 2: a reduced MIT-BIH dataset is considered where the number of samples in the dataset is down sampled to 10 %.

Classification Baselines: Before discussing the experimental results, we present the used classification baselines, In these experiments, four classification baselines are used.

The classifier model introduced by Kachuee et al. (Kachuee et al., 2018) includes a 1-D convolutional layer, five residual convolution sets, two fully connected (FC) layers and a softmax layer to output

Table 1: Performance of our classification baseline model for ECG classification with the entire MIT-BIH (setup 1).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.98	0.90	0.92	0.91
Setting 2	0.98	0.94	0.95	0.93
Setting 3	0.99	0.96	0.95	0.95
Setting 4	**0.99**	**0.98**	**0.96**	**0.96**

Table 2: Performance of (Kachuee et al., 2018) model for ECG classification with the entire MIT-BIH (setup 1).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.96	0.87	0.74	0.77
Setting 2	0.97	0.87	0.79	0.82
Setting 3	0.99	0.96	0.95	0.95
Setting 4	**0.99**	**0.96**	**0.96**	**0.96**

Table 3: Performance of (Kumar et al., 2019) model for ECG classification with the entire MIT-BIH (setup 1).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.98	0.87	0.82	0.84
Setting 2	0.98	0.93	0.91	0.92
Setting 3	0.98	0.96	0.94	0.95
Setting 4	**0.99**	**0.97**	**0.95**	**0.96**

Table 4: Performance of (Acharya et al., 2017) model for ECG classification with the entire MIT-BIH (setup 1).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.97	0.93	0.89	0.91
Setting 2	0.98	0.94	0.91	0.92
Setting 3	0.98	0.95	0.93	**0.94**
Setting 4	**0.99**	**0.97**	**0.95**	**0.94**

Table 5: Performance of our classification baseline model for ECG classification with the reduced MIT-BIH (setup 2).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.67	0.75	0.72	0.59
Setting 2	0.88	0.84	0.90	0.84
Setting 3	0.98	0.98	**0.99**	0.98
Setting 4	**0.99**	**0.99**	**0.99**	**0.99**

Table 6: Performance of (Kachuee et al., 2018) model for ECG classification with the reduced MIT-BIH (setup 2).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.57	0.55	0.57	0.51
Setting 2	0.64	0.57	0.59	0.57
Setting 3	0.66	0.58	0.60	0.58
Setting 4	**0.75**	**0.62**	**0.61**	**0.60**

Table 7: Performance of (Kumar et al., 2019) model for ECG classification with the reduced MIT-BIH (setup 2).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.62	0.58	0.61	0.57
Setting 2	0.73	0.78	0.78	0.72
Setting 3	0.93	0.88	0.95	0.90
Setting 4	**0.97**	**0.98**	**0.98**	**0.97**

Table 8: Performance of (Acharya et al., 2017) model for ECG classification with the reduced MIT-BIH (setup 2).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.56	0.74	0.64	0.46
Setting 2	0.79	0.79	0.83	0.74
Setting 3	**0.98**	0.98	0.96	**0.97**
Setting 4	**0.98**	**0.99**	**0.97**	**0.97**

the class probabilities. In every residual block, two 1-D convolution layers, two ReLU activation layers, a residual skip connection, and finally a pooling layer are used.

The architecture of the model proposed by Acharya et al. (Acharya et al., 2017) is made up of three 1-D convolution layers and three FC layers. Each convolution layer is succeeded by a max-pooling layer. A softmax function is applied to the last output to generate classification scores.

Kumar et al. (Kumar et al., 2019) proposed a classifier model composed of four blocks, each contains a FC layer followed by both a batch normalization layer and ReLU activation function. A FC layer with a softmax activation function is used after the last block.

In addition to these baselines, we propose our classification model based on ResNet34 (He et al., 2016) and transformer (Vaswani et al., 2017) networks in which we take advantage of transformer benefits to capture the temporal information present in the signals. In this model, extracted features from the ResNet blocks are passed to the transformer encoder before being finally fed to the classification layer.

Results. Tables 1, 2, 3, and 4 show the performance metrics of the four state-of-art classification methods for dataset setup 1 (*i.e.,* the entire MIT-BIH) in the different training settings described above. We can observe that adding synthetic heartbeats from generative models definitely improves the classification performance for all generation approaches. In particular, the performance of classifiers in settings 3 and 4 is superior to classifiers performance in setting 2. We can confirm so that leveraging shape prior in the advanced generation approaches (*i.e.,* training settings 3 and 4) has a significant impact on the quality of the generated data. For example, Acharya et al. (Acharya et al.,

Table 9: Performance of our classification baseline model for PPG 3 classes classification (setup 1).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.42	0.42	0.39	0.39
Setting 2	0.46	0.45	0.46	0.45
Setting 3	0.49	0.51	0.46	0.47
Setting 4	**0.53**	**0.54**	**0.50**	**0.50**

Table 10: Performance of (Wang et al., 2017) model for PPG 3 classes classification (setup 1).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.37	0.25	0.41	0.31
Setting 2	0.40	0.39	0.42	0.38
Setting 3	0.45	0.47	0.44	0.39
Setting 4	**0.46**	**0.50**	**0.45**	**0.40**

Table 11: Performance of (Liu et al., 2020) model for PPG 3 classes classification (setup 1).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.35	0.23	0.30	0.26
Setting 2	0.40	0.41	0.37	0.37
Setting 3	0.44	0.44	0.45	0.44
Setting 4	**0.46**	**0.45**	**0.47**	**0.46**

Table 12: Performance of our classification baseline model for PPG 2 classes classification (setup 2).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.64	0.58	0.60	0.58
Setting 2	0.65	0.60	0.64	0.60
Setting 3	0.75	0.66	**0.66**	**0.66**
Setting 4	**0.79**	**0.71**	**0.66**	**0.66**

Table 13: Performance of (Wang et al., 2017) model for PPG 2 classes classification (setup2).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.57	0.56	0.54	0.53
Setting 2	0.63	0.56	0.57	0.55
Setting 3	0.64	0.57	0.58	0.56
Setting 4	**0.64**	**0.57**	**0.59**	**0.57**

Table 14: Performance of (Liu et al., 2020) model for PPG 2 classes classification (setup 2).

	Accuracy	Precision	Recall	F1 score
Setting 1	0.56	0.56	0.59	0.53
Setting 2	0.61	0.57	0.60	0.56
Setting 3	0.62	0.59	0.62	0.57
Setting 4	**0.66**	**0.59**	**0.62**	**0.59**

2017) achieve (Accuracy, Recall, Precision, F1 score) = (0.98, 0.95,0.93, and 0.94) and (0.99, 0.97, 0.95, and 0.94) in training settings 3 and 4, respectively vs. (0.98, 0.94, 0.91, and 0.92) in setting 2. The obtained results also show that the classification performance of all classifiers in setting 4 were slightly higher than in setting 3, where synthetic data from Neifar et al. (Neifar et al., 2022b) were used for additional training, which demonstrates that Neifar et al..'s approach (Neifar et al., 2022a) is more efficient than Neifar et al.'s (Neifar et al., 2022b) in generating more realistic ECG heartbeats.

The performance results of the classifiers models for dataset setup 2 (*i.e.,* reduced MIT-BIH) are shown in Tables 5, 6, 7, and 8. The obtained results demonstrate that augmenting the real training set with generated heartbeats obtained from (Goodfellow et al., 2014; Neifar et al., 2022b; Neifar et al., 2022a) trained with small a volume dataset has improved the classifiers' performance. In particular, classifiers trained with added synthetic ECG heartbeats generated by the advanced GAN approaches (Neifar et al., 2022b; Neifar et al., 2022a) outperform the standard GAN.

3.2.2 Experiments on PPG Signals

For PPG experiments, different dataset setups were used in comparison to the ECG experiments because the PPG-BP dataset has a relatively small data volume. However, following the state of the art methods (Liang et al., 2018b; Sannino et al., 2020), we defined two dataset setups for hypertension classification:

- Setup 1: three classes classification, where the class H1 and H2 are considered as one class.
- Setup 2: two classes classification, where the classes (H1 and H2) and (N and P) are considered as one class, respectively.

Classification Baselines: Three classification baselines were used in these experiments. Liu *et al.* (Liu et al., 2020) used a classifier based on the traditional VGG19 model (Simonyan and Zisserman, 2014) with a unique one change in the last FC output layer. The time series classification model proposed by Wang et al. (Wang et al., 2017) is composed of three FC layers with the ReLU activation, each followed by a dropout layer. The final layer is a FC with softmax function.

We also tested our classification approach, previously used for ECG signals, as a competing method for PPG signals classification.

Results: Tables (9, 10, 11) and (12, 13, 14) summarize the obtained performance values for PPG

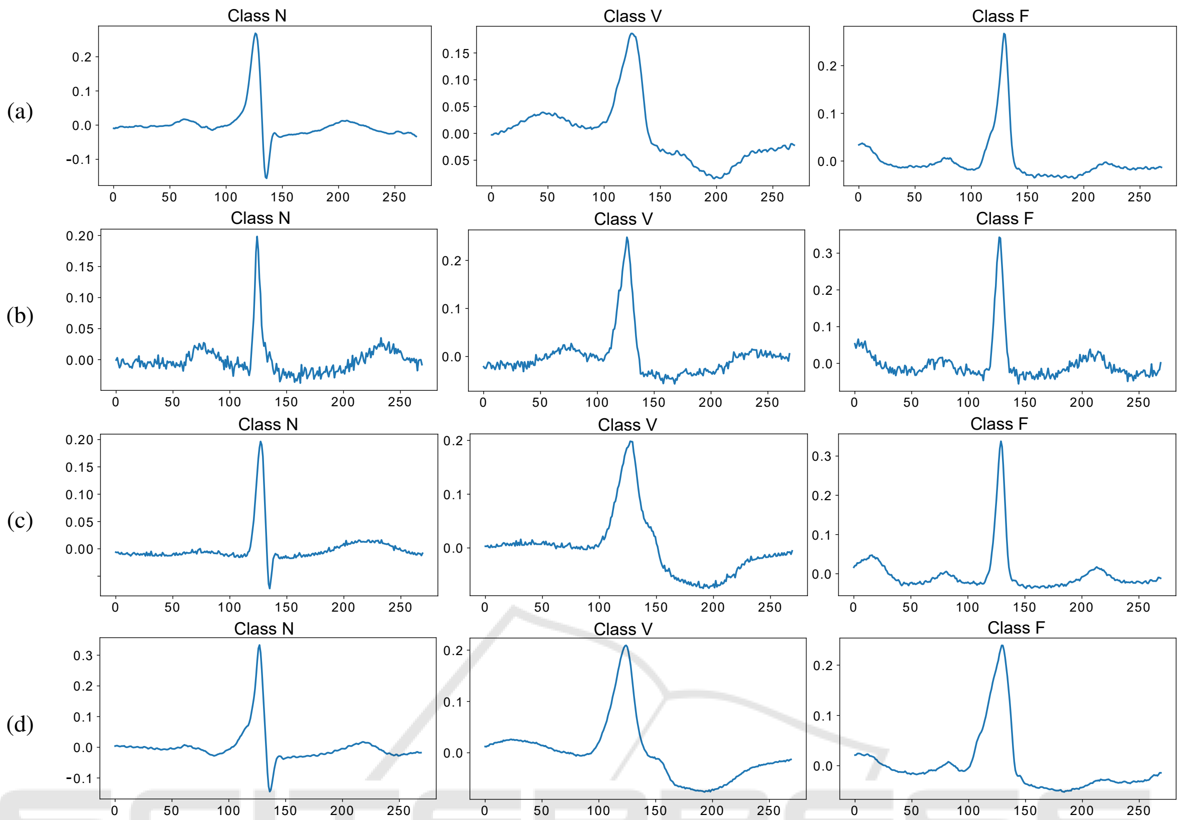

Figure 3: (a) Examples of real heartbeats from the classes (N, V, and F) taken from the training dataset. (b) Examples of synthetic heartbeats from the classes (N, V, and F) generated by the standard GAN (Goodfellow et al., 2014). (c) Examples of synthetic heartbeats from the classes (N, V, and F) generated by (Neifar et al., 2022b). (d) Examples of synthetic heartbeats from the the classes (N, V, and F) generated by (Neifar et al., 2022a).

classification for dataset setups 1 and 2, respectively. It is obvious that the performance of the three baseline classifiers in the training settings, where the training dataset is augmented by synthetic data, is higher than setting 1. In particular, the performance has been improved with additional synthetic data generated by (Neifar et al., 2022b; Neifar et al., 2022a). For example, our classification baseline achieves for dataset setup 1 (Accuracy, Recall, Precision, F1 score) = (0.49, 0.51, 0.46, and 0.47) and (0.53, 0.54, 0.50, and 0.50) in training settings 3 and 4, respectively vs (0.46, 0.45, 0.46, and 0.45) in training setting 2. On the other hand, for dataset setup 2, it achieves (Accuracy, Recall, Precision, F1 score) = (0.75, 0.66, 0.66, and 0.66) and (0.79,0.71, 0.66, and 0.66) in setting 3 and 4 ,respectively vs. (0.65, 0.60, 0.64, and 0.60) in setting 2.

Neifar et al. (Neifar et al., 2022b), (Neifar et al., 2022b) have clearly demonstrated robustness in generating realistic PPG signals, resulting in better classification performance even in low-volume datasets. The results also show an improvement of the performance between the training settings 3 and 4. For instance, the accuracy of Wang et al. (Wang et al., 2017) has increased by 2% for dataset setup 1 and 4% for dataset setup 2. This confirms that the advanced generation method based on modeling the temporal and amplitude variations as 2-D shapes is more efficient in dealing with the complicated dynamics of ECG and PPG patterns.

3.3 Qualitative Evaluation

Figure 3 shows examples of real heartbeats and synthetic heartbeats generated by the three studied generation approaches from classes N, V and F, respectively. We can observe that the heartbeats generated by Neifar et al. (Neifar et al., 2022a) (Figure 3d) and Neifar et al. (Neifar et al., 2022b) (Figure 3c) maintain realistic shapes similar to real heartbeats (Figure 3a). The synthetic heartbeats obtained by the standard GAN (Figures 3b), on the other hand, do not always follow the full ECG morphology. We can also notice that the heartbeats generated by the standard GAN (Goodfellow et al., 2014) contains significantly more artifacts. On the

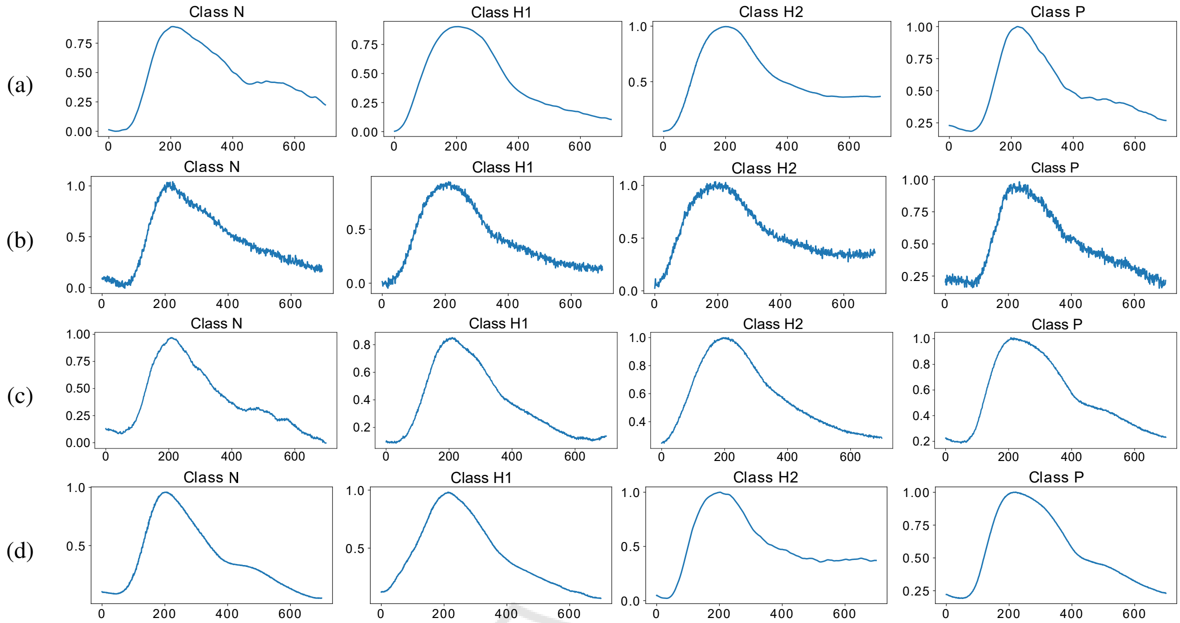

Figure 4: (a) Examples of real PPG pulses from the classes (N, H1, H2, P) taken from the training dataset. (b) Examples of synthetic PPG pulses from the classes (N, H1, H2, P) generated by the standard GAN. (c) Examples of synthetic PPG pulses from the classes (N, H1, H2, P) generated by (Neifar et al., 2022b). (d) Examples of synthetic PPG pulses from the classes (N, H1, H2, P) generated by (Neifar et al., 2022a).

other hand, the generated heartbeats by Neifar et al. (Neifar et al., 2022b) are slightly noisy than the real and synthesized heartbeats obtained by Neifar et al. (Neifar et al., 2022a).

Figure 4 depicts examples of real pulses and synthetic pulses obtained by the three studied generation approaches from classes (N, H1, H2, and P). As ECG heartbeats, the PPG pulses generated by the approach of Neifar et al. (Neifar et al., 2022a) (Figure 4d) and generated by the approach of Neifar et al. (Neifar et al., 2022b) (Figure 4c) maintain also realistic morphology. For example, the generated pulses from normal class in Figures 4c and 4d contain the total waves: the systolic peak, the diastolic peak, and the dicrotic notch. For the synthetic PPG pulse of the normal class in Figure 4b obtained from the standard GAN, the morphology is not complete, where the diastolic peak has not been respected.

4 CONCLUSION

We presented a comparison of three GAN-based methods for generating ECG and PPG signals. The obtained results demonstrated that augmenting the training data with synthetic data systematically improves ECG arrhythmia and PPG hypertension classifications. In particular, the synthetic data generated by the competing advanced GAN-based methods significantly enhanced the performance of the state-of-art classification baselines compared to standard GAN architecture. Furthermore, the various tested setups on ECG and PPG datasets demonstrated that advanced generation methods can synthesize realistic data even in the case of relatively small datasets. We propose three axes of extension of this study as future work. We intend to expand the study to include other competing generation methods. We would like to cover more physiological signal types and representations.

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