Improving Cloud-based ECG Monitoring, Detection, and Classification using GAN

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Abstract

Internet of Things (IoT) based healthcare applications have grown exponentially over the past decade. With the increasing number of fatalities due to cardiovascular diseases (CVD), it is the need of the hour to detect any signs of cardiac abnormalities as early as possible. This calls for automation in the detection and classification of said cardiac abnormalities by physicians. The problem here is that there is not enough data to train Deep Learning models to classify ECG signals accurately because of the sensitive nature of data and the rarity of certain cases involved in CVDs. In this paper, we propose a framework that involves Generative Adversarial Networks (GAN) to create synthetic training data for the classes with fewer data points to improve the performance of Deep Learning models trained with the dataset. With data being input from sensors via the cloud and this model to classify the ECG signals, we expect the framework to be functional, accurate, and efficient.

Keywords: Internet of Things (IoT); Generative Adversarial Networks (GAN); Deep Learning; ECG Classification; Convolution Neural Networks

1. Introduction

Heart attacks and cardiovascular diseases account for over 15 million deaths globally. The interval between the primary indication of a cardiac abnormality and the distress call for emergency services varies greatly for different patients and can prove fatal. Timely detection and curing of such cardiac abnormalities have better chances of reducing the associated fatality risk than providing care post-hospitalization. Therefore, novel methods are required for the early detection of cardiac abnormalities. [1]

Internet of things (IoT) is a part of the solution here. IoT, in essence, is the interconnection of sensors and the internet in order to obtain, transfer, pool, and analyze all kinds of data. One of the most essential and appealing applications of IoT in healthcare would enable the remote monitoring and treatment of patients at risk rather than having them go to hospitals. For example, Sensors can collect and transmit continuous recording of Electrocardiogram (ECG) signals which can be used to detect and identify cardiac abnormalities, which may not be possible with short-term ECG recordings.

An ECG is a common, non-invasive tool that measures the heart's electrical activity and follow-up of anomalies, functional disorders, and cardiac arrhythmias. The cardiac cycle is composed of electrical depolarization

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patterns and presents the change in the heart's electrical activity over time. The standard method of obtaining ECG signals requires placing a number of electrodes in certain places of the human body like the chest, arms, and neck. These electrodes detect electrical changes in the heart. The signal thus obtained has certain distinct components: P wave, QRS complex, and T wave.

Each component corresponds to atrial contraction, ventricular contractions, and repolarization, respectively. Heartbeats and their corresponding ECG signals may be classified into one of five categories: Normal beats, Supraventricular ectopic beats, Ventricular ectopic beats, Fusion beats, and Unknown beats. A fusion beat is a bit different from the others as it occurs simultaneously between a supraventricular beat and a ventricular beat. Cardiac arrhythmias are mostly either Supraventricular ectopic beat (S) or Ventricular ectopic beat (V).

Medical data is sensitive in nature, and publication and access to medical datasets are tightly regulated. There are not many medical datasets, and this is also the case for ECG data. Usually, data for software testing and training needs to be anonymized [2]. This anonymization is done using certain de-identification methods; however, even these methods do not guarantee the security of data as it has been shown that re-identification is possible by linkage of data from other sources. This has led to a shortage of biomedical data.

Deep learning models show promising results for ECG classification but require a large number of training examples per class. These examples are difficult to get as most life-threatening arrhythmias are extremely rare, limiting the amount available to train deep learning models. Consequently, the available datasets usually have a class imbalance problem wherein one class is over-represented, and some classes are not represented enough. In this case, the over-represented class would be common cardiac abnormalities, whereas rare CVDs would be sparsely represented. This would result in the deep learning models being biased towards one class, and in the field of biomedicine, the misclassification of minor classes could cost a life.

One solution to the above problems is the synthesis of ECG signals using GAN. GANs are a class of deep learning algorithms implemented using two deep networks, a generator, and a discriminator. These two networks compete against each other, with the generator trying to fool the discriminator, hence the term 'Adversarial.' The generator attempts to learn a latent representation of some distribution so that the discriminator network which is trained to discriminate between instances from the true data distribution and the ones produced by the generator, has a high gloss. We attempt to generate synthetic heartbeats as similar to real heartbeats as possible using GANs. [3]

In this paper, we propose a framework to improve the existing cloud-based ECG classification system by introducing GAN to reduce misclassification and provide real-time and reliable solutions to physicians. We discuss the efficient cloud-based system and methodology to improve the accuracy and efficiency.

The rest of the paper is organized as follows: section 2 discusses and reviews similar work. The methodology and framework are discussed in section 3. Section 4 consists of the evaluation of the models and the results. The final section, section 5, concludes the paper.

2. Related Work

A considerable amount of work has been done on ECG classification due to demand in the healthcare industry. Much of it has been done by utilizing various machine learning techniques for efficient identification and classification. Heuristic-based methods [4], statistical methods [5], support vector machines (SVMs) [6], wavelet transform, and artificial neural networks (ANNs) [7] are some of the most common methods. Deep Learning was also successfully applied in this domain. Recurrent Neural Networks Classifiers with Eigen vector-based feature extraction, Random Forest Tree classifier, Parallel K Nearest Neighbour classifier, and 1D Convolutional Neural Networks [8] were some of the deep learning methods proposed for ECG classification.

The conventional approach involves developing an algorithm for the extraction of essential features from the ECG signal and choosing a suitable classifier to classify the processed signal. Most such studies have acceptable results, but again, when such models are used in the industry, they need to be extremely reliable, considering that any misclassification could prove fatal. Not only that, there are several disadvantages to such conventional methods as well. These require the creation of a feature extractor which reduces the extracted features to a set of ideal features, which are then fed to the classifier model. This additional step often results in low performance

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and overfitting. A unique solution to this was explored by creating synthetic training data by calculating the Z score from the base dataset and varying the mean and standard deviation [9]. This achieved better results in comparison to training the model without the augmented data. The proposed framework in this paper will utilize GAN to generate additional instances for each class and to classify ECG signals into their respective categories, which were discussed previously.

3. Methodology

The proposed framework is described in this section. The following figure shows the flow of information through the system and describes the components involved.

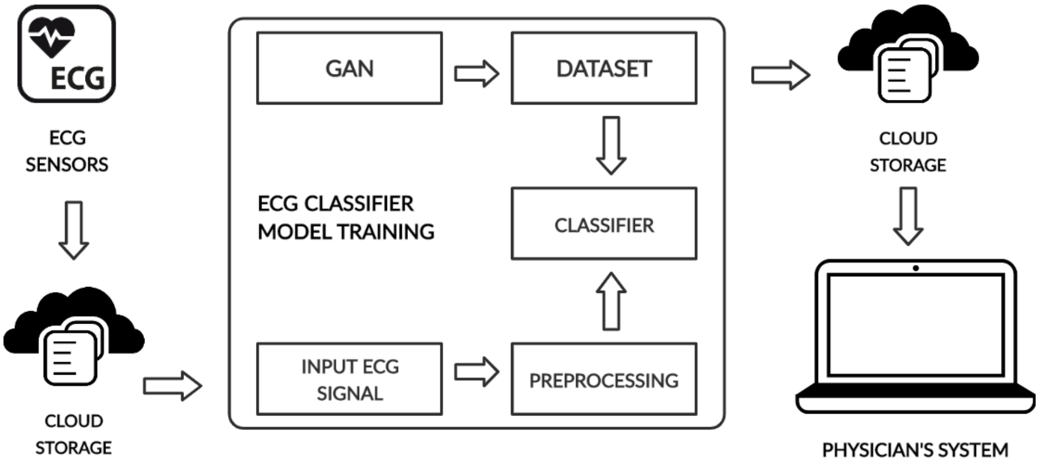

Figure 1: Proposed Framework

3.1 About the Dataset

The MIT-BIH Arrhythmia dataset contains 48 two-leads ambulatory ECG records from 47 patients (22 females and 25 males). Each record is approximately 30 minutes in length. These recordings were originally digitized at 360Hz. ECG lead II signal of the records in the dataset has been re-sampled to a frequency of 125Hz, which has been used as the input. Annotations present in the dataset were used to create the five different categories shown in the table below.

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Table 1: Categories of ECG signals and the corresponding problems

CATEGORY	ANNOTATIONS
N	Normal, Left/Right bundle branch block, Atrial escape, Nodal escape
S	Atrial premature, Aberrant atrial premature, Nodal premature, Supra-ventricular premature
V	Premature ventricular contraction, Ventricular escape
F	Fusion of ventricular and normal
Q	Paced, Fusion of paced and normal, Unclassifiable

3.2 Pre-processing

The pre-processing step cleans the data and makes it more usable. The continuous ECG signals in the dataset are split into the 10-second window and selected. There are 13964 samples overall, with 187 values per sample. These values for each sample are normalized. The number of values per sample is the same for all samples. The status of the ECG signal in the pre-processing stage is shown in the figure below. [10]

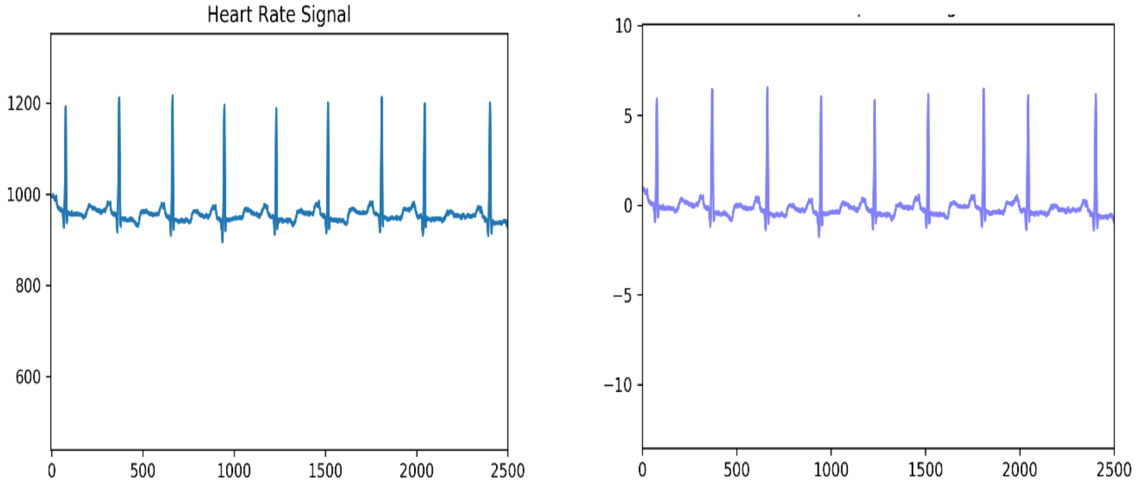

Figure 2: Pre-processing stage of ECG signal. The figure on the left shows the original signal, and the one on the right shows a normalized ECG signal.

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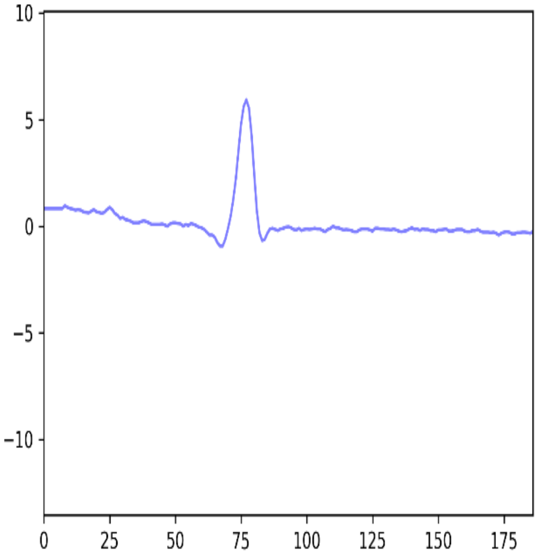

Figure 3: The final output of the pre-processing stage, which contains the segmented heartbeat

3.3 Synthesis using GAN

GAN or Generative Adversarial Networks was originally proposed by [11]. Given a real dataset, the generator network G tries to synthesize fake data that is as similar to the genuine data as possible, while the discriminator network, D, gets the data from either the real dataset or from the generator network and tries to label the difference. The process is simplified in the figure below.

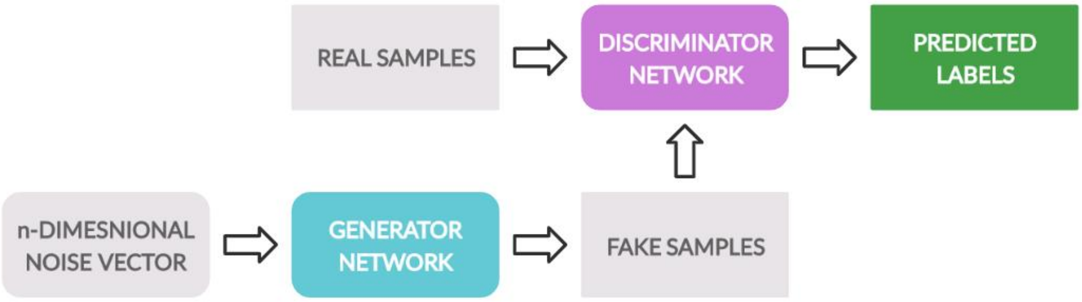

Figure 4: Simple GAN architecture

The synthetic samples are obtained by training the GAN using heartbeats from each class. The dominant class, the N class, is avoided, as adding more samples to class N would only make the classifier training biased towards class N.

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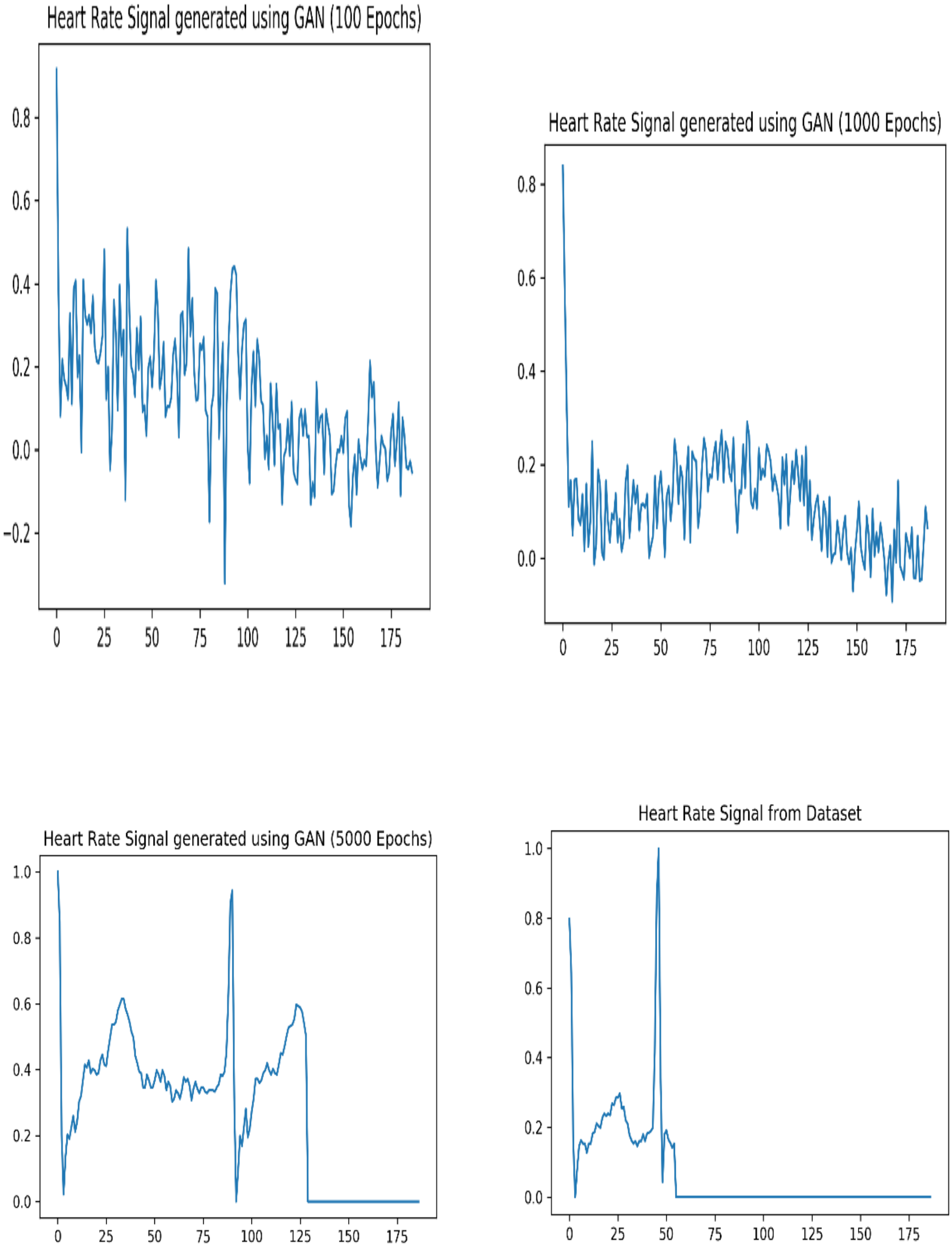
Heart Rate Signal generated using GAN (100 Epochs)

Heart Rate Signal generated using GAN (1000 Epochs)

Heart Rate Signal generated using GAN (5000 Epochs)

Heart Rate Signal from Dataset

Figure 5: The figures show the signals generated throughout the training of GAN as well as the final signal at 5000 epochs compared to a signal from the dataset.

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4. Results

In this section, we present our results. These results include the performance of Generated Adversarial Networks to synthesize new training data for each class. This section also compares the classification performance before and after the addition of the synthetic data to certain classes which had very few samples compared to the dominant class, that is, Class N of ECG signals, which is used to avoid any class imbalance. To evaluate the performance of the proposed model on the base dataset and adding samples generated using GAN, Precision, Recall, F1 Score, and Accuracy metrics have been used. All these can be calculated using true positive, true negative, false positive, and false negative values, which are obtained from the confusion matrix.

Table 2: Results comparing both cases are presented below

Metrics	**Base Dataset**	**Base Dataset + GAN generated samples**
Accuracy	94.243%	97.994%
F1 Score	78.794%	89.465%
Precision	72.009%	92.057%
Recall	94.409%	87.299%

5. Conclusion

In this paper, we consider the existing cloud-based ECG classification system and discuss the problems related to the system. We propose a better framework that involves improved classification accuracy to avoid misclassification as much as possible. This framework involved the use of Generated Adversarial Networks to generate synthetic training data, which are similar to the actual ECG signals and counter the class imbalance present in the MIT-BIH arrhythmia dataset. From the results, the model clearly works better when there are additional samples for each class.

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