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A Generative Adversarial Network Based Approach for Synthesis of Deep Fake Electrocardiograms

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Abstract— Analyzing the data from an electrocardiogram (ECG) can reveal important details about a patient's heart health. A key component of modern medicine is the use of AI and ML-based computer-aided diagnosis tools to aid in making life-or-death decisions. It is common practice to use them in cardiology for the automatic early diagnosis of a variety of potentially fatal illnesses. The machine learning algorithm's need for a large amount of training data to build the learning model is an empirical challenge in the medical domain. To address this challenge, study into methods for creating synthetic patient data has blossomed. There is a higher risk of privacy invasion due to the need for massive amounts of training data for deep learning automated medical diagnostic systems that may help assess the state of the heart from this signal. To combat this issue, researchers have tried to create artificial ECG readings by analyzing only the statistical distributions of the accessible authentic training data.The primary goal of this study is to learn how generative adversarial networks can be used to create artificial ECG signals for use as training data in a classification task. In this study, we used both GAN and WGAN for generation of artificial ECG signals.

Keywords- Artificial Intelligence, Generative Adversarial Networks, Semi-supervised learning.

I. INTRODUCTION

Arrhythmias are a type of the diseases that can cause anything from a small annoyance or discomfort to a potentially fatal problem. Heart arrhythmias occur when the heart's electrical impulses are disrupted in some way. The heartbeat could be too sluggish, too fast, or otherwise abnormal. The electrical activity of the heart can be measured with an electrocardiogram (ECG), which is a useful diagnostic instrument for detecting arrhythmias. The P wave, the T wave and the QRS complex (with its R peak), make up the three principal components of a typical ECG signal that span a full cardiac cycle [1]. The P wave is associated with atrial depolarization, which triggers atrial muscular contraction. When the ventricles depolarize, the QRS complex appears, and when they repolarize, the T wave does, too. The ECG signal that

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electrodes collect is tainted by many types of noise. Therefore, using an ECG's visual assessment to detect any heart abnormalities may not be very accurate.

Many individuals have died in recent years from cardiovascular diseases [2]. Research into early identification and the development of an automatic diagnosis has received considerable attention in recent years [3]. Artificial neural networks (ANN) have recently proven themselves adept at solving complex problems, making them the go-to method for a wide variety of uses, from those requiring only rudimentary classification or regression to those that previously defied the state of the art. Deep learning approaches including attention processes have demonstrated great performance on both images and sequential data [4].

The present methods for ECG classification rely heavily on the application of classic supervised machine learning techniques. Support Vector Machine [5], convolutional neural networks [6], are just some of the classifiers that have been attempted. Recently, the recurrent neural network (RNN) has been applied to the classification of ECG rhythms, and its use is investigated in [7] and [8].

Although there is rising interest in deep learning algorithms for e-health, the tasks still present a difficulty and need for large or big datasets in order to learn the most crucial elements that will boost the accuracy of prediction or diagnosis. Semi-supervised learning try to imitate newer artificial or synthetic data by first learning the pattern from proper training data. The Generative Adversarial Network (GAN) [9] is a well-known example of generative modelling that is often used to generate time-series data and images. GANs are used in many applications including in health care [10], sequence creation [11], image processing [12], satellite applications [13] etc. we teach deep learning models with synthetic ECG signals representing different arrhythmias.

In this work, we investigate how Generative Adversarial Networks are used for the creation of artificial realistic ECG signals. Section II deals with the architecture of GANs and WGAN and section III briefs about the evaluation metrics used and section IV describes datasets and simulation results.

II. Architecture

A. Generative Adversarial Networks

Game-theoretic zero-sum games between two players (where one player wins precisely as much as the other loses) serve as a structural inspiration for GANs [6]. It prepares a pair of game elements—a generator and a discriminator—for each player. The purpose of the generator is to learn from the real data samples, capture their potential distribution, and then generate new data samples. The goal of the Discriminator, a type of binary classifier, is to identify if the input data comes from the real data or a generator. Each participant needs to steadily increase their capacity to generate and discriminate in order to succeed. Therefore, the best way to learn is a minimax game challenge. The generator's goal is to predict the distribution of data samples by reaching a Nash equilibrium between the two sides.

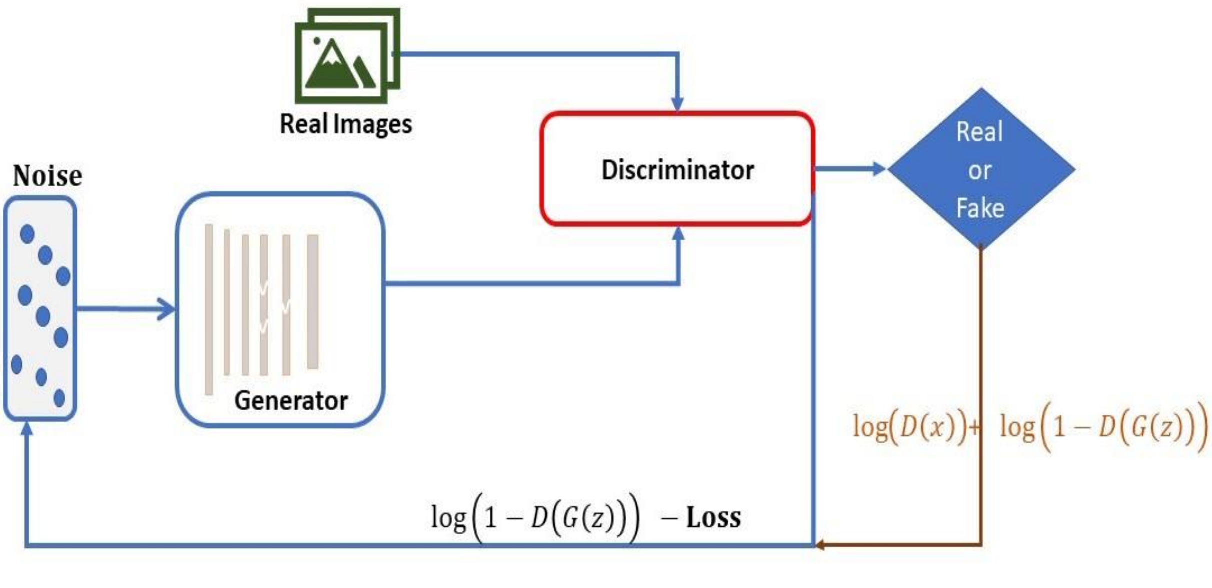

Figure 2. High level GAN Architecture

$$min_G max_D \mathrm{V(D,G)} = E_x \log(D(x)) + E_z \log\left(1 - D\left(G(z)\right)\right) \quad (1)$$

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Since GANs' generator and discriminator can be represented by any differentiable function, the generator and discriminator can use a deep neural network. Discriminators (represented by differentiable functions D) and generators (represented by differentiable functions G) take in actual data (x) and a random variable (z), respectively. Generated by G, G(z) follows the same distribution as actual data. The discriminator outputs a One if its input is derived from the original data. The incoming sample is labelled as Zero if it is G(z).D's objective is to arrive at a correct binary classification of data sources, either true (based on the distribution classification of real data x) or false (based on the fake data G(z) of the generator), while G's objective is to have the self-generated false data G(z) perform as well on D(x) as the real data x does. The method can be used to iteratively optimize the performance of both D and G.

B. *Wasserstein -GAN*

The foundational teaching procedure of D AND G is carried over to WGAN(Wasserstein GAN GAN). In WGAN, the difference between genuine and fake data can be obtained by replacing JS divergence in GAN with EM distance. The uniformity of the EM distance makes it a useful source of gradient for the generator.

Since the structural similarity measure (SSIM) has proven to be more accurate than other distance metrics, including the traditional Euclidean metric, it was chosen as main metric of choice for this paper.

III. EVALUATION METRICS

A. *Structural Similarity Index (SSIM)*

The SSIM index is a metric for assessing how good digital pictures and motion pictures really are [15]. Incorporating key perceptual phenomena like luminance blurring and contrast masking, SSIM treats picture degradation as a perceptual shift in structural information. Consider two images x and y, SSIM is calculated as shown in below equation.

$$SSIM(x,y) = \frac{(2\cdot\mu_x\mu_y + c_1).(2.\sigma_{xy} + c_2)}{({c_1}^2+{\mu_x}^2+{\mu_y}^2).({c_2}^2+{\sigma_x}^2+{\sigma_y}^2)} \quad (2)$$

σ_{xy} - covariance of x and y.
${\sigma_x}^2$- variance of x.
${\sigma_y}^2$- variance of y.
μ_x- mean of x.
μ_y- mean of y.

B. *Cross correlation Coeffiecient*

Cross-correlation analysis is a method for deriving information from two signals by comparing how close they are to one another [16].

C. *Mean Squared Error*

The mean squared error (MSE) measures how far off the generated image is from the source. The smaller the MSE, the less severe the mistake.

IV. RESULTS

The suggested architecture was developed using Tensor Flow framework in Python 3.7.

We evaluate the effectiveness of the methodology and prototype with data from the PTB and MIT-BIH databases [17]. The MIT-BIH arrhythmia database and PTB diagnostic database is a freely accessible dataset that includes common research materials for identifying cardiac arrhythmia. 549 records representing 290 individuals are present in the PTB diagnostic database. Each record contains 15 signals with a resolution of 16 bits that were measured at the same time. This database includes 148 records of myocardial infarction, 14 records of Dysrhythmia, 4 records of myocarditis, 7 records of Myocardial hypertrophy and 52 healthy controls etc.

A. *Simulation Results*

Figure 3, Figure 4, Figure 5 shows the real and synthesized or adversarial ECG signals generated from real signals for ventricular tachyarrhythmia, Atrial Fibrillation and Apnea respectively.

Method	Cross Correlation Coefficient	SSIM	MSE
GAN	0.9532	0.9621	0.00316
WGAN	0.9601	0.9695	0.00279

Table 1. Similarity results between Real and Adversarial or synthesized images.

V. CONCLUSION

There are a number of factors why it could be challenging to collect massive amounts of patient data. The synthesis of realistic data has surfaced as an exciting new field of study in medicine. The purpose of this field of study is to improve the efficiency of supervised machine learning classifiers applied to datasets. This research makes use of Generative Adversarial Networks that have a high degree of structural resemblance in order to produce electrocardiogram (ECG) signals. Synthetic ECG data was created using GAN and WGAN, and the Abnormal ECG data was selected from the Physio Net database, including atrial fibrillation, ventricular tachyarrhythmia, and apnea. The generated or adversarial ECG signals show a good structural similarity and cross correlation coefficient of 0.9621 and 0.9532 respectively.

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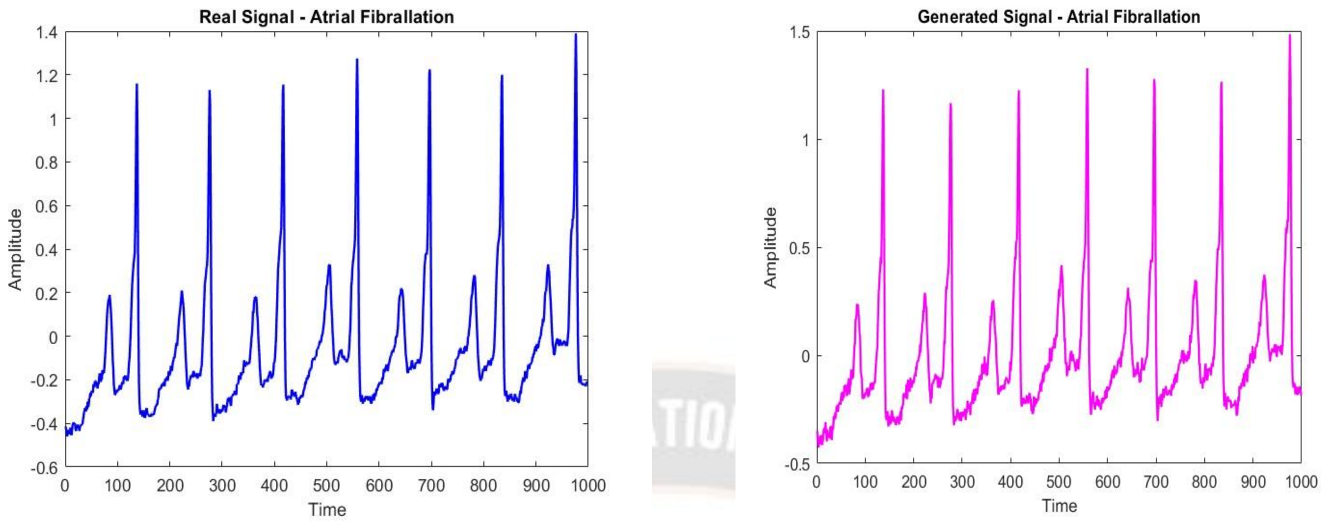

Figure 3. Real and Generated ECG Signals for Atrial Fibrillation

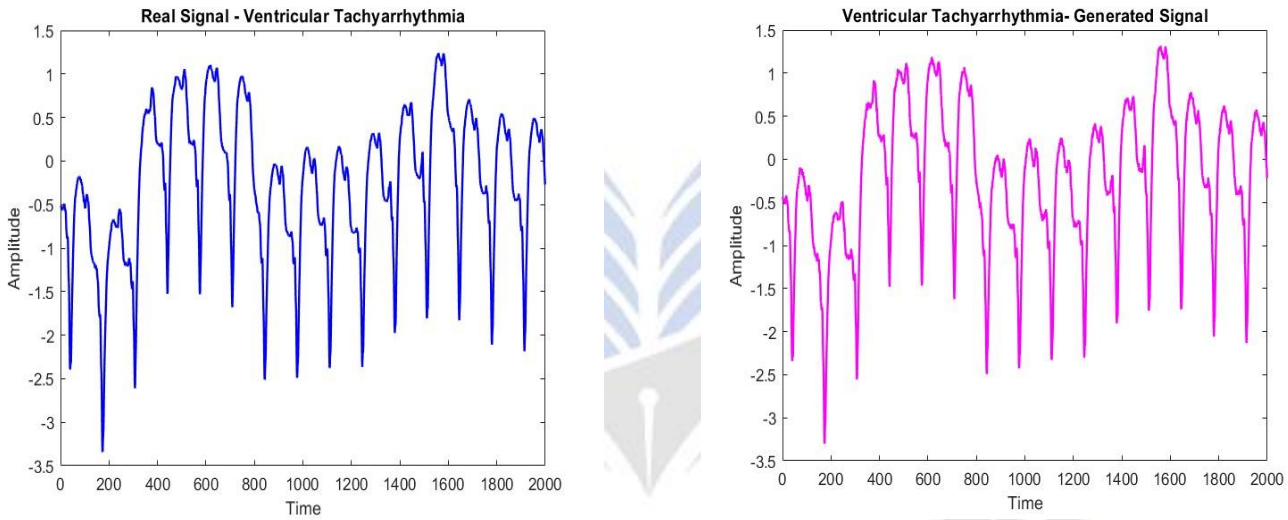

Figure 4**.** Real and Generated ECG Signals for Ventricular Tachyarrhythmia.

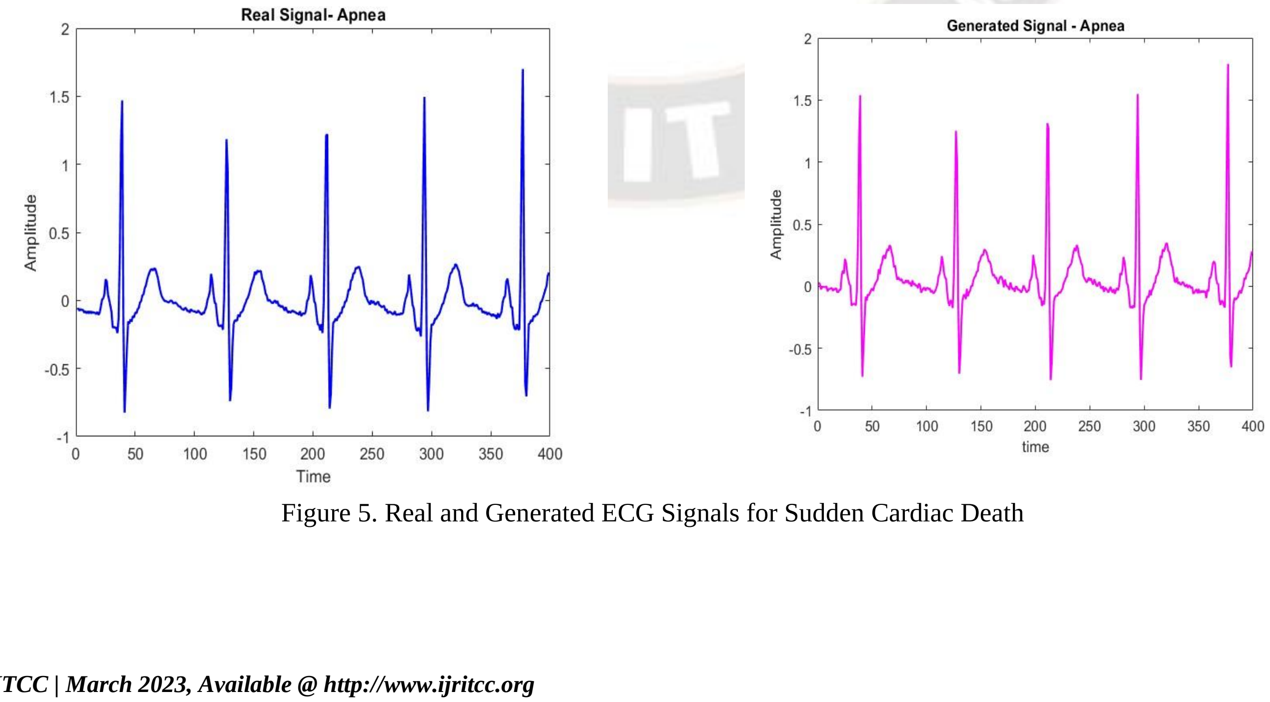

Figure 5. Real and Generated ECG Signals for Sudden Cardiac Death

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