

SEVERE CONGESTIVE HEART FAILURE DETECTION USING 'HeartGAN': A DEEP LEARNING APPROACH

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ABSTRACT

The proliferating mortality rate due to Congestive Heart Failure (CHF) has become an area of concern worldwide. The triumph to detect CHF at the earliest possible stage has witnessed various detection methods since its breakthrough. Moreover, Artificial Intelligence has played a pivotal role in the detection process through the boon of technology. Various methods involving statistical, machine, and deep learning have already been discovered, capable of performing accurately. Nevertheless, all the existing methods require the user to perform some manual tasks for processing, or they may not function properly under the deficit of a large dataset. To tide over the problem, we have developed 'HeartGAN'. The 1-Dimensional time series electrocardiogram signal (ECG) has been converted to a 2-Dimensional spectrogram to enhance the model's performance. Those spectrograms are fed into the unsupervised Generative Adversarial Network (GAN), which was self-tailored to augment the dataset up to 30 times with an enormous accuracy of 95.532%. The augmented dataset was then used for autonomous detection of severe CHF with an accuracy of 94.114%. The capability to perform accurately, with minimal data and manual involvement, marks the excellence of our proposed model. Our study can be of immense use to the medical community for severe CHF detection during an emergency. Furthermore, our study can act as a resource to the researchers in the Computational Sciences, Biomedical, and medical arenas, for developing similar technical tools that can aid in saving lives.

Keywords: Congestive Heart failure, electrooculogram signal, Generative Adversarial Network, Deep Convolution Neural Network, Spectrogram analysis

1. INTRODUCTION

Heart failure (HF) is a syndrome with more detailed clinical presentations than a disease. Heart failure can be caused by various factors, including anatomical and functional abnormalities in the heart. It occurs due to a failure in the body's blood-pumping action, which prevents complete blood circulation. Patients with heart failure will experience several symptoms, including trouble breathing, ankle swelling, and physical exhaustion. It may also show jugular venous pressure elevation, lung fissure, and peripheral edema due to anomalies in cardiac or non-cardiac tissues [1]. Congestive heart failure is a frequent heart condition in which the heart cannot transport enough oxygen-rich blood to other tissues and organs due to structural or functional heart problems. Simultaneously, the ventricle's poor pumping function leads to blood and bodily fluid leaking to the lungs and body, causing respiratory discomfort and systemic edema [2]. Heart disease is a

deadly disease on the rise in both developed and developing countries. According to the World Health Organization (WHO), 17.90 million people died from cardiovascular disease in 2016. Every year, nearly 26 million people contract CHF all around the world. Nearly half of the patients will die every five years [3]. These patients' symptoms are determined by the severity of their Congestive Heart Failure (CHF).

Electrocardiography is a vital technical tool for detecting cardiac conditions. In the electrocardiogram (ECG) analysis, the heart rhythm is governed by the cooperation of sympathetic and parasympathetic nerves, two branches of the autonomic nervous system, in normal physiological states, and illnesses disrupt this coordination and balance. Heart Rate Variability (HRV) analysis can quantify such rhythmical events. HRV analysis is also known as a time sequence of an RR interval, which is composed of continuous R-wave intervals recovered from ECG data. It is frequently used in disease detection [4,5]. And prognosis [6,7].

Cardiologists commonly use ECG to diagnose human arrhythmias because computerized approaches have such a high error rate. A machine learning system must recognize the numerous arrhythmia wave types and their diverse morphologies to diagnose this medical condition using ECG. Algorithms for detecting CHF using ECG data have been studied and demonstrated to be successful in recent decades. They typically use feature extraction-based machine learning techniques, in which the extracted features include morphological characteristics, temporal and frequency domain features, and many more. The retrieved features are then selected and entered into the classifier for diagnosis. The model must be trained using a combination of feature parameters to improve classification results. Convolutional Neural Networks (CNN) was employed to address the above-noted restrictions, considering the difficulty and relevance of incorporating spatial information into ECG analysis. The problem is putting up a dataset that can be utilized to train a neural network model quickly. To address this issue, we suggested an architecture that uses a Generative Adversarial Network (GAN) [8] to augment a tiny or standard-sized dataset with a substantially larger dataset to train a neural network model accurately. This proposed architecture, named 'HeartGAN,' can increase the dataset by 30 times with an accuracy of 95.532%. The enlarged dataset was then utilized to detect the presence of CHF using a classifier model autonomously. The overall accuracy of the model is 94.114%. 'HeartGAN' has successfully augmented a dataset comprising just 15 Holter monitor recordings to 450 ECG signals. This massive augmentation power with such a classifier model of this architecture may be a foundation stone for much future research in this domain.

The methodology has been described in section 2, followed by results and discussion in section 3, and concluding our study in section 4.

2. METHODS AND MATERIALS:

2.1. DATASET COLLECTION:

The dataset considered in our study has been downloaded from Physio Net. The collection contains long-term ECG recordings from 15 patients with severe congestive heart failure (NYHA class 3–4) (11 males, ages 22 to 71, and 4 women, ages 54 to 63). This group of people as part of a larger trial that received traditional medical treatment before receiving milrinone, an oral inotropic drug. Each recording lasts roughly 20 hours and contains two ECG signals recorded at 250 samples per second with 12-bit resolution over a 10-millivolt range. The first analog recordings were made using ambulatory ECG recorders with a typical recording bandwidth of around 0.1 Hz to 40 Hz at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Center). Annotation files were generated by an automatic detector and were not manually corrected [9].

2.2. DATA PRE-PROCESSING:

The time-series signal was converted to spectrograms after reshaping to a uniform length. The conversion was done in order to facilitate the process of applying 2-Dimensional convolution in our architecture.

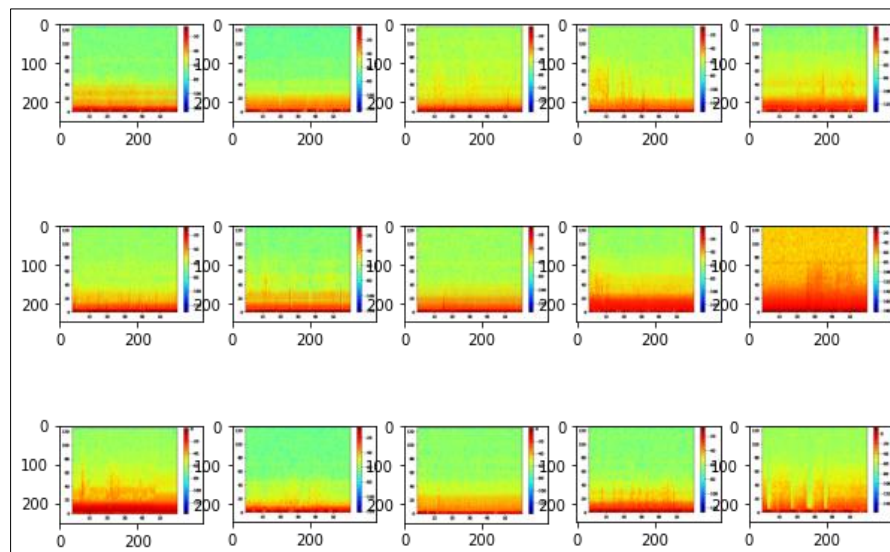


Figure 1: The spectrograms used as the training dataset

2.3. METHODOLOGY:

The ECG recordings obtained from the mentioned dataset are initially visualized to understand the pattern of the ECG in the patients suffering from severe CHF. From several observations [Figure-1], it has been re-confirmed that the patients suffering from CHF have an irregular heartbeat.

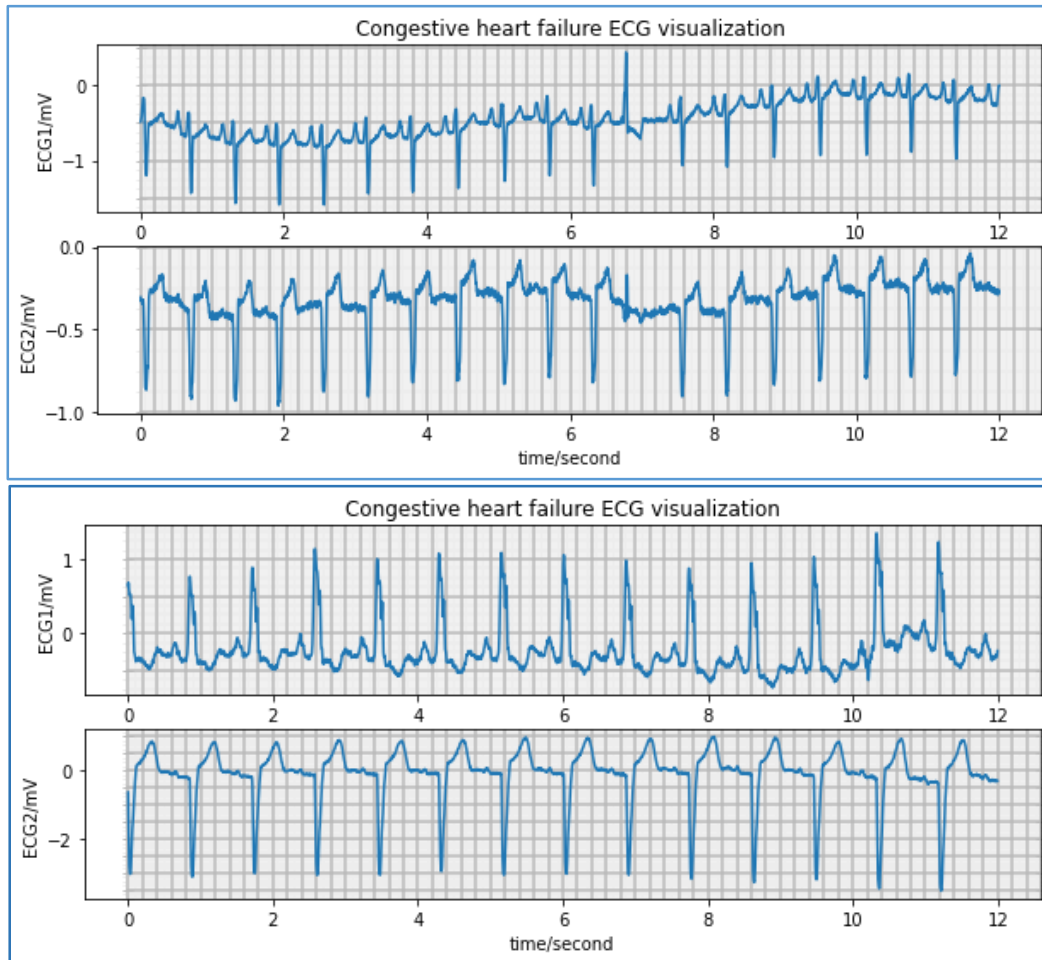


Figure 2: Two ECG recordings have been visualized from the original dataset

To enhance the feature extraction process, the 1-Dimensional ECG signal was converted to a 2-Dimensional spectrogram. The spectrogram was then fed to the 'HeartGAN' for augmentation [Figure-2]. The proposed architecture takes its inspiration from DC-GAN [10] and performs remarkably well in specificity and accuracy. The deep layers of Convolution Networks can augment the dataset up to 30 times. The GAN model was based on the concept of using stridden convolution layers. Each layer or stack of layers was activated using Leaky ReLu activation. Downsampling has been done with each convolution layer to maintain the computing capacity without compromising any feature loss with zero padding. After that batch, normalization was performed, and the models were optimized using the Adam optimizer. The model was a sequential model, with one input and a single output, performed in an unsupervised approach. Furthermore, 2-Dimensional convolution has been used in each layer to enhance feature learning capability over the 1-Dimensional convolution technique.

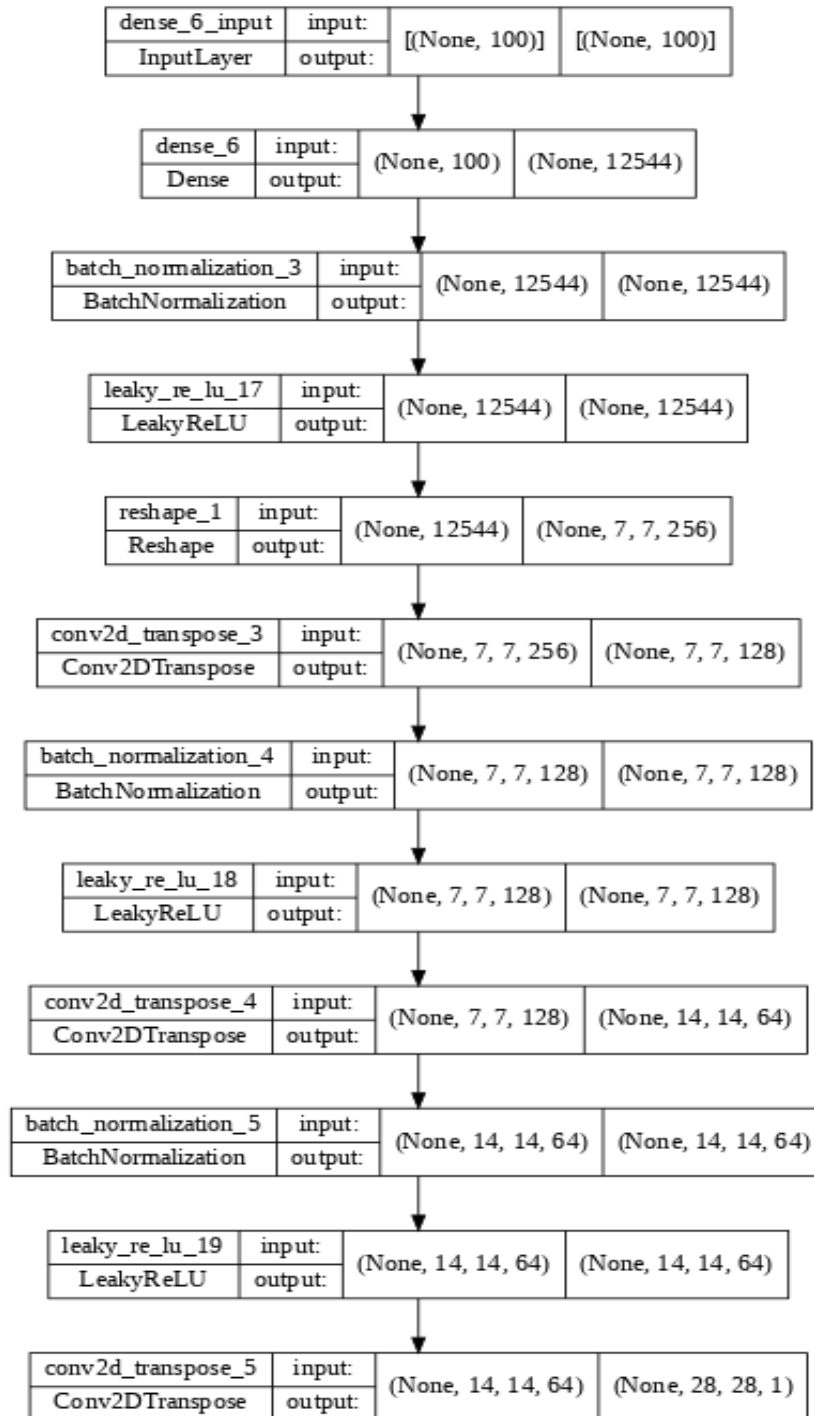


Figure 3: Model summary of the Generator architecture

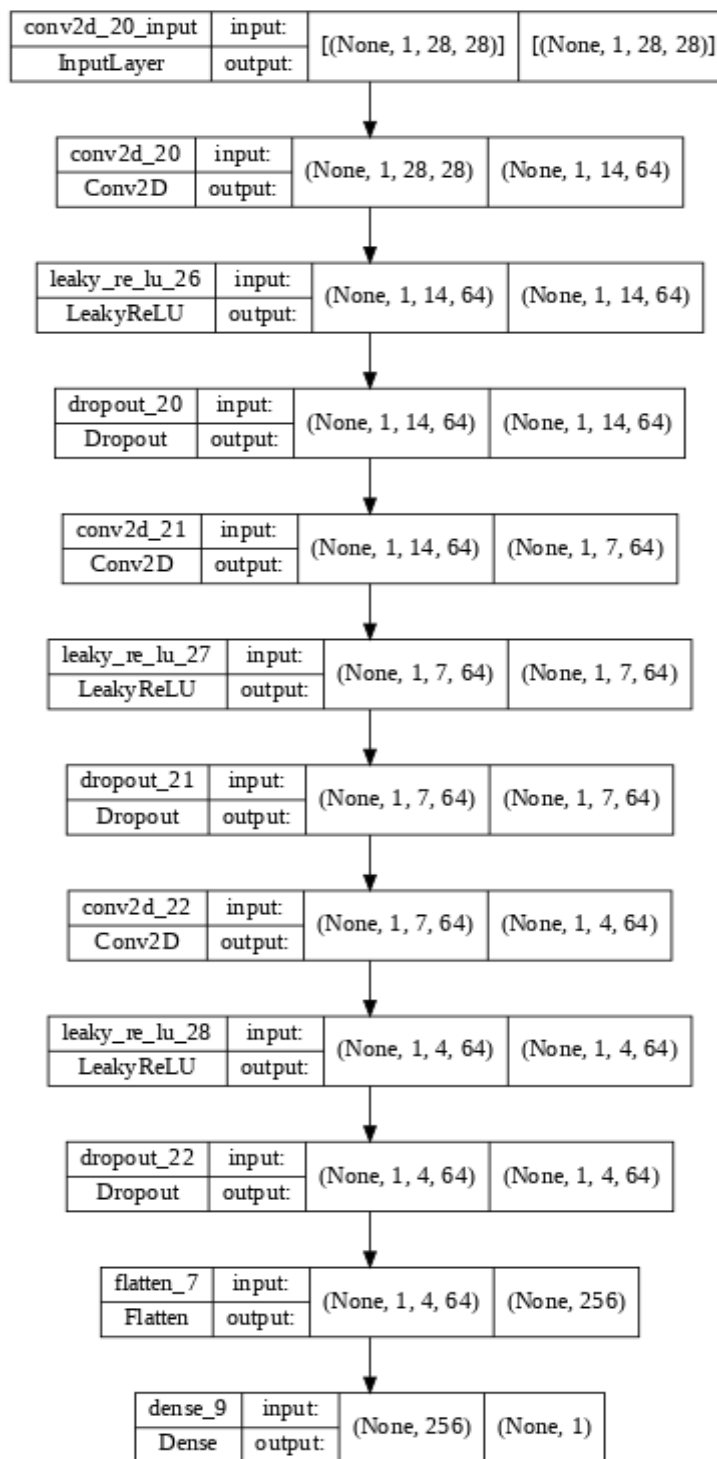


Figure 4: Discriminator architecture

After augmentation, the generated dataset was used in the self-tailored classifier model. The model's overall accuracy turned out to be 94.114%, thus marking its remarkable capability. The GAN model was run on 60 epochs to gain a better feature extraction to predict the presence of the disease.

3. RESULTS AND DISCUSSIONS :

The data visualization and pre-processing involved the incorporation of detecting the R-R peaks as they are crucial in understanding the condition of the heart. The QRS complex has been figured out and rectified before further processing to visualize those intervals. [Figure-5].

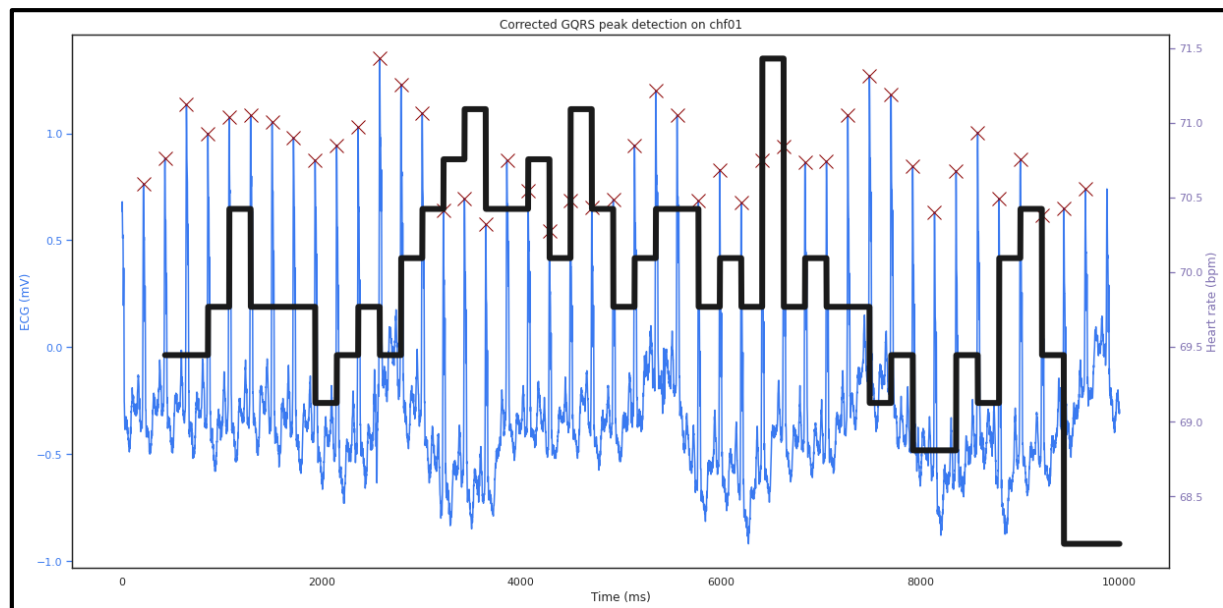


Figure 5: Example of a data being visualized with the marking of R-R peaks and corrected QRS peak detection

From the observation, it has been realized that patients suffering from CHF have irregular Heart Rate Variability (HRV). Then, the converted spectrograms were directly fed into the HeartGAN, which could successfully augment the dataset up to 30 times with a specificity of 93.118% and an accuracy of 95.532% [Figure-4]. The loss graph during training of the generator and discriminator models was plotted [Figure-6]. From the graph, it is observable that both the plots are in equilibrium, thus accounting for the stability of the HeartGAN.

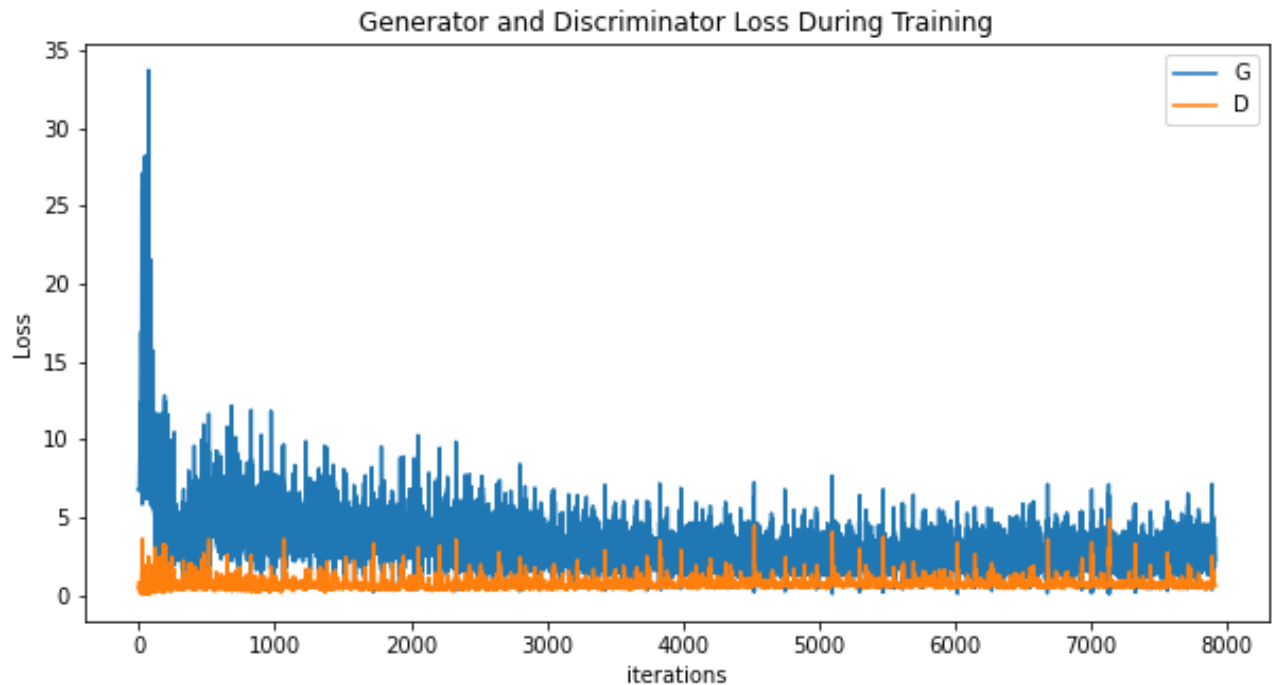


Figure 6: Loss Graph of HEART-GAN discriminator model

After that, the conventional classifier model involved performed significantly, begetting an accuracy of 94.114%. The sequential model of the HeartGAN aids in computation in less time so that our study can be used during medical emergencies, where each second turns out to be crucial in saving a life.

Author	Methods	Accuracy	Classification Result
Wenlong Ning[3]	Hybrid Deep Learning Algorithm	99.93%	ECG signal-based CHF detection approach with a hybrid deep learning algorithm that can recognize CHF patients clinically
David J. Cornforth[11]	Detection of Congestive Heart Failure using Renyi Entropy	87.9	CHF was detected using brief 3-lead ECG recordings, implying that Renyi entropy can improve the effectiveness of automated diagnostic methods over time-domain measurements alone.
A. A. Bhurane[12]	frequency localized filter	99.66	Five distinct features were recovered from the wavelet decomposition of ECG segments using frequency localized filter banks.
Z. Masetic[13]	random forest classifier	NA	It is useful in presenting facts relevant to medicine and plays an important role in identifying congestive heart failure (CHF).
Our proposed method	Implementation of GAN	94.5	It has been discovered that CHF patients have irregular Heart Rate Variability (HRV)

The comparison table indicates the superiority of our study over the existing works. Our model could not only autonomously detect the anomaly but could also synthesize data of its own, thus making it feasible to learn rare symptoms. The stability indicated by the loss graph and the obtained accuracy make our model reliable, feasible, and accessible at the time of need without investing much time figuring out the available data.

4. CONCLUSION :

The results and discussion show that non-invasive methods to detect CHF accurately are hard to find. Moreover, our study has tided over the deficit of not being able to perform well if there is insufficient data. The integral focus of our study was centered on the

amount of data and the accuracy of the results. Methods involving statistical methods, machine learning methods, and deep learning have already been discovered, capable of performing accurately. However, all the existing methods either require the user to perform some manual tasks for processing, or they may not function properly under the deficit of a large dataset. To tide over the problem, we have developed 'HeartGAN'. To enhance the model's performance, the 1-Dimensional time series electrocardiogram signal (ECG) has been converted to a 2-Dimensional spectrogram. Those spectrograms are fed into the Generative Adversarial Network (GAN), which was self-tailored to augment the dataset up to 30 times with an enormous accuracy of 95.532%. The augmented dataset was then used for autonomous detection of severe CHF with an accuracy of 94.114%. The capability of performing accurately, with a minimal amount of data and manual involvement, marks the excellence of our proposed model.

Moreover, designing an unsupervised GAN is a novel approach, as most of the existing studies are based on either supervised or semi-supervised GAN. Our study can be of immense use to the medical community for severe CHF detection during an emergency. Most of the existing studies focus on the early detection of CHF, whereas our study focuses on the detection of severe CHF. This purpose is to provide relief to the patients undergoing any critical circumstance requiring medical attention. However, somehow, their medical history is not accessible for some cause. HeartGAN can act as a boon in such cases but alarm the medical practitioners about the condition of cardiac arrhythmia at the right time, thus taking a step toward saving a precious life. Furthermore, our study can act as a resource to the researchers in the domain of Computational Sciences, Biomedical and medical arenas for developing similar technical tools that can aid in saving lives.

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