GENERATIVE ADVERSARIAL NETWORKS FOR PCG ARRHYTHMIA DETECTION

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ABSTRACT

With the rapid growth of computational power and complex algorithms, we propose a novel approach to detect arrhythmias in Phonocardiograms (PCGs). Typically, Electrocardiograms are used to diagnose arrhythmias, requiring medical-grade equipment to recognize cardiac illnesses accurately. However, PCGs provide ease of access to everyone who has a device capable of recording audio, leading to early diagnosis and allowing medical professionals to treat arrhythmias in the developmental stages. The new design comprises two subsystems; one is based on the relationship between Electrocardiograms (ECGs) and PCGs, and the other between PCGs and arrhythmias. The association between ECGs and PCGs is amended to translate from one space to another, where ECGs become dimensionally reduced, then reconstructed into a PCG signal. The second subsystem uses a Generative Adversarial Networks (GAN), in which both arbitrary PCG signals and generated signals are fed into a discriminator that detects if an arrhythmia is present (normal and abnormal) or if the signal is false (generated).

***K*eywords** Arrhythmias · Phonocardiograms · Electrocardiograms · Biomarkers

Problem Current detection methods have limited performance in pathologies and lack real-time classification capabilities.

Motivation To create a fast and accurate model capable of detecting Cardiovascular modalities, specifically a variety arrhythmia's in heart sound recordings (PCGs) without the need for specialized equipment.

Question Is it possible to use Generative Adversarial Networks (GANs) to accurately detect arrhythmias in PCGs and surpass previous methods in detection tasks?

Hypothesis If a Generative Adversarial Network is used to create spurious data, then the model will outperform previous state-of-the-art methods in classification, because the specious data will aid the model in extracting significant features from a ground truth dataset.

Solution The new semi-supervised approach is composed of two subsystems; the first subsystem uses a discriminator, in which PCG signals are classified into categories based on arrhythmias in the signal. The second subsystem – a generator, aims to generate data such that, when fed into the discriminator, the discriminator will classify the generated data as abnormal or normal. While the discriminator aims to simultaneously classify the generated data as fake and classify the real PCG signals to their respective categories. This adversarial approach allows the discriminator to not only extract PCG signal specific features, but also introduces the discriminator potential noisy signals that should not be classified.

Engineering Goals

1. **Develop a System for End-to-End Heart Sound Arrhythmia Detection** — Create a system that is able to record and analyze heart sounds for Cardiovascular modalities. The system should implement an adversarial model that is both time and space-efficient, and accurate.

2. **Increase the Number of Cardiovascular Pathologies** — Develop a model to construct heart sounds from pre-existing data.
3. **Real-World Testing** — Test the end-to-end system in a real-world environment to ensure practicality and generality of the system.

Constraints Constraints include a time complexity complexity of O(n) and an accuracy above 90%. These constraints are to ensure that the model is comparable to the current state-of-the-art performance and has computationally efficient for real-world use.

1 Introduction

An estimated three million cases of arrhythmia occur in the United States yearly (Mayo Clinic), with 300,000 sudden deaths per year – an incidence rather higher than stroke, lung cancer, or breast cancer (American Heart Association). Traditionally, non-invasive arrhythmia analysis is based on multiple electrodes that reflect the electrical activity on ECGs. This method, despite being accurate, limits the use case to hospitals and clinics with specialized equipment; thus, limiting the portability of diagnosing, let alone classification of the type of pathology.

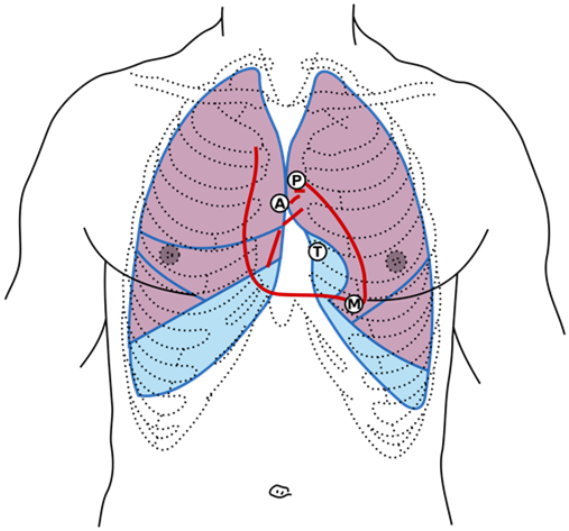

Figure 1: Representation of heart sound recording positions.

Phonocardiograms (PCGs) are sounds that are created by the mechanical movement of the heart. This physical movement produces four distinct sounds: S1, S2, S3, S4, and murmurs. S1 and S2 are sounds created by a healthy heart; whereas, S3, S4, and murmurs refer to diseases or anomalies.The first heat sound, S1, marks the start of Systole. Systole occurs when the heart muscle contracts and pumps blood from the chambers into the arteries. The second heart sound, S2, marks the end of Systole and the start of Diastole. Diastole is a phase of the heartbeat when the heart muscle relaxes and allows the chambers to fill with blood.

Although heart sound databases do exist, these datasets are still limited by the number of pathologies that are collected, often having to divide the dataset into two categories: normal and abnormal. Currently, only three major supervised PCG datasets exist: PhysioNet Classification of Heart Sound Recording Challenge dataset, PASCAL Heart Sound Challenge dataset, and the Heart Sound and Murmur Library. The presently available PCG datasets have a limited number of samples and do not cover the complete range of pathologies that are likely to be encountered in clinical settings.

In diagnosing heart sounds, two major challenges arise: localization and classification. Localization aims to find the position of the aforementioned biomarkers in heart sounds. By doing this, heart sounds can be segmented into signals containing a single heart sound. Furthermore, classification attempts to categorize heart sounds into normal and abnormal groups by exploiting the information extracted from localization. Conventional heart sound localization and classification methods involve time, frequency, or both, and are typically dependent on machine learning algorithms to enhance the results. These algorithms typically include artificial neural networks (ANNs), support vector machines

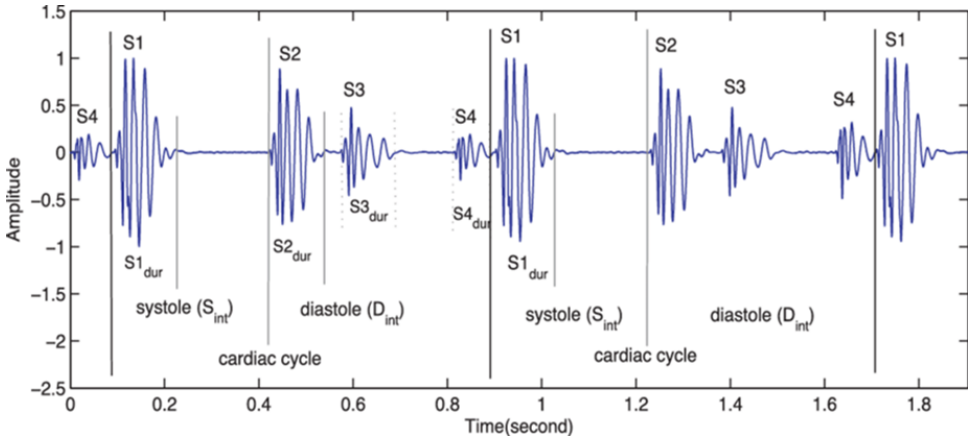

Figure 2: Illustrates the S1, S2, S3, and S4 biomarkers of heart sounds.

(SVMs), self-organizing maps (SOMs), and are limited to the number of samples and pathologies covered in a given dataset. This leads to a surface-level analysis of the heart sounds.

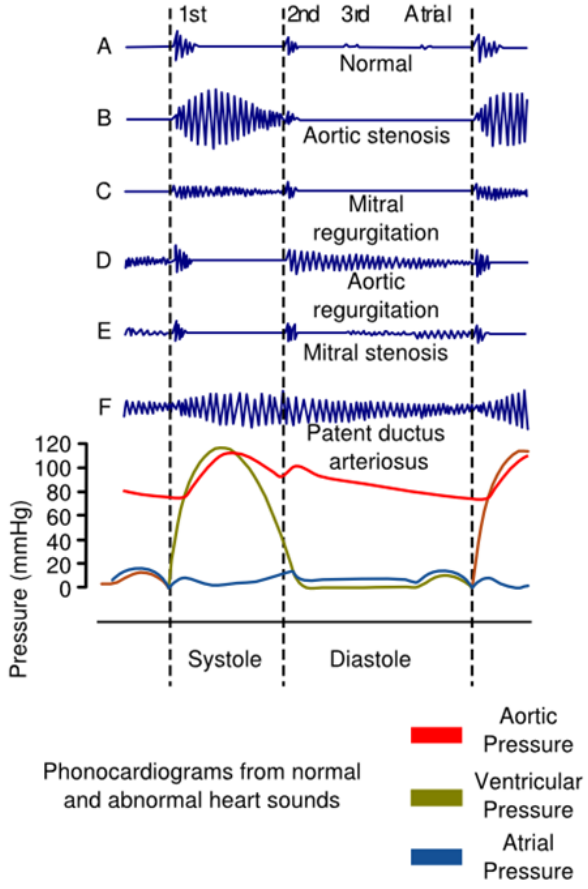

Figure 3: Representation of different abnormalities in sound and pressure.

The main challenge of ineffective heart sound detection stems from an analysis of noisy heartbeats, e.g., background noise. For clean datasets, e.g., the PhysioNet Challenge dataset, a varieties time and frequency of methods converged on

localization accuracy of 96.9% (Fernando et al.) and 86.02% classification accuracy (Potes et al.). From the viewpoint of practical applications, the development of computationally efficient solutions is extremely important to the success of a model's deployment. Many studies have negated to comment on the practicality of their proposed methods. From our research, we have concluded only two studies have noted their time efficiency, (Fernando et al.) and (Messner et al.). The fastest model processed 1000 heart state classifications in 56.88 seconds (Fernando et al.), suggesting the model can process 18 bps. Thus, current models need severe optimization to achieve near to real-time analysis. These results are excluding the classification of heart arrhythmias.

Thus, the problem of computationally efficient and accurate classification of noisy heartbeats, especially with datasets with a variety of pathologies still remains a problem.