Student Checklist (1A)

This form is required for ALL projects.

1. a. Student/Team Leader: Aditya Kendre Grade: 12

   Email: kendreaditya@gmail.com Phone: (717) 622-1281

   b. Team Member: _____ c. Team Member: _____

2. Title of Project:

   Generative Adversarial Networks for PCG Arrhythmia Detection

3. School: Cumberland Valley High School School Phone: (717) 506-3413

   School Address: 6746 Carlisle Pike
   Mechanicsburg, PA 17050

4. Adult Sponsor: Mike Floreck Phone/Email: mfloreck@cvschools.org

5. Does this project need SRC/IRB/IACUC or other pre-approval? ☐ Yes ☒ No Tentative start date: _____

6. Is this a continuation/progression from a previous year? ☒ Yes ☐ No
   If Yes:
   a. Attach the previous year's ☑ Abstract **and** ☑ Research Plan/Project Summary
   b. Explain how this project is new and different from previous years on
   ☑ Continuation/Research Progression Form (7)

7. This year's laboratory experiment/data collection:

   10/30/20 (Actual Start Date: (mm/dd/yy)) 03/01/21 (End Date: (mm/dd/yy))

8. Source of Data:

   ☐ Collected self/mentor ☑ Other Describe/url: Physionet Database

9. List name and address of all non-home and non-school work site(s):

Name:		
Address:		
Phone/ email		

10. **Complete a Research Plan/Project Summary following the Research Plan/Project Summary instructions and attach to this form.**

11. **An abstract is required for all projects after experimentation.**

ISEF Sample Abstract & Certification

Generative Adversarial Networks for PCG Arrhythmia Detection

Aditya Kendre

Cumberland Valley HS, Mechanicsburg, PA, USA

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 accurately recognize cardiac illnesses. PCGs provide ease of access to everyone who has a device capable of recording audio, 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 are generated, and preexisting ECG datasets are recreated into PCG signals (using subsystem one). These signals are fed into a classifier that detects if an arrhythmia is present. This proposed system's advantage is that PCG data is more readily available than ECG data; hence, more heart diagnostics can be made.

Category
Pick one only--
mark an "X"
in box at right

- Animal Sciences ☐
- Behavioral and Social Sciences ☐
- Biochemistry ☐
- Biomedical and Health Sciences ☐
- Biomedical Engineering ☐
- Cellular & Molecular Biology ☐
- Chemistry ☐
- Computational Biology and Bioinformatics ☑
- Earth & Environmental Sciences ☐
- Embedded Systems ☐
- Energy: Sustainable Materials and Design ☐
- Engineering Mechanics ☐
- Environmental Engineering ☐
- Materials Science ☐
- Mathematics ☐
- Microbiology ☐
- Physics and Astronomy ☐
- Plant Sciences ☐
- Robotics & Intelligent Machines ☐
- Systems Software ☐
- Translational Medical Science ☐

1. As a part of this research project, the student directly handled, manipulated, or interacted with (check all that apply):

   ☐ human participants ☐ potentially hazardous biological agents
   ☐ vertebrate animals ☐ microorganisms ☐ rDNA ☐ tissue

2. This abstract describes only procedures performed by me/us, reflects my/our own independent research, and represents one year's work only.
   ☑ yes ☐ no

3. I/We worked or used equipment in a regulated research institution or industrial setting.
   ☐ yes ☑ no

4. This project is a continuation of previous research.
   ☑ yes ☑ no

5. My display board includes non-published photographs/visual depictions of humans (other than myself):
   ☑ yes ☐ no

6. I/We hereby certify that the abstract and responses to the above statements are correct and properly reflect my/our own work.
   ☑ yes ☐ no

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GENERATIVE ADVERSARIAL NETWORKS FOR PCG ARRHYTHMIA DETECTION

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Mechanicsburg, PA 17050

January 3, 2021

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 accurately recognize cardiac illnesses (Rajpurkar et al., 2017). PCGs, however, provide ease of access to everyone who has a device capable of recording audio, 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 are generated, and preexisting ECG datasets are recreated into PCG signals (using subsystem one). These signals are fed into a classifier that detects if an arrhythmia is present. This proposed system's advantage is that PCG data is more readily available than ECG data; hence, more heart diagnostics can be made.

1 Introduction

Problem Statement. Every physical examination done with a stethoscope should aim to diagnose any arrhythmias present within a patient.

Question. Is it possible to create a model capable of surpassing the accuracy of Cardiologists in identifying heart arrhythmias in Phonocardiograms?

Hypothesis. It is possible to exceed the accuracy of Cardiologists when compared to that of a Generative Adversarial Network's, to identify heart arrhythmias in Phonocardiograms.

Materials List. Computer.

Electrocardiograms have created a profound impact in the field of cardiology, specifically in recognizing heart arrhythmias, a problem with the rhythm of one's heartbeat. Noninvasive arrhythmia analysis is based on multiple electrodes that reflect the electrical activity on ECGs. However, with the recent surge of heart-related medical cases, it is getting difficult to diagnose heart conditions at an early stage. As most treatments rely on detecting the disease in it's infancy stages. Traditionally, arrhythmias are diagnosed by cardiologists by analyzing ECG recordings (Jordaens, 2018). Some clinics have adopted a new technique in which ECG and PCG signals are simultaneously recorded and then computationally analyzed. This, however, still requires an instrument capable of recording ECG data. Such instruments are only available during scheduled appointments, often which are recommended by physicians. If a physician fails to detect symptoms of arrhythmia, a patient may never receive a diagnosis. One study found 44% of cardiologists were not able to detect common cardiac events with stethoscopes (Mangione et al., 1993); in another study, delays in cardiac-related illness diagnosis and treatment impacted procedural success rates by as much as 24% (Bunch et al., 2013). We propose a method where it is now possible to accurately detect arrhythmias with only PCG recordings. This provides an opportunity for physicians to check for potential developments of cardiac arrhythmias at every physical exam accurately.

Current PCG arrhythmia diagnosis methods only recognize between Normal and Abnormal (binary classification), providing minimal information about what is present within the PCG signal (Aziz et al., 2020). This is because no PCG datasets exist that include more than 3 classes of arrhythmia. Therefore, it is necessary to transform pre-existing ECG datasets with multiple classes to PCG signals. This enables models to detect a larger range of arrhythmia without explicitly collecting new PCG recordings. Currently, no technology attempts to construct PCG signals from existing ECG data.

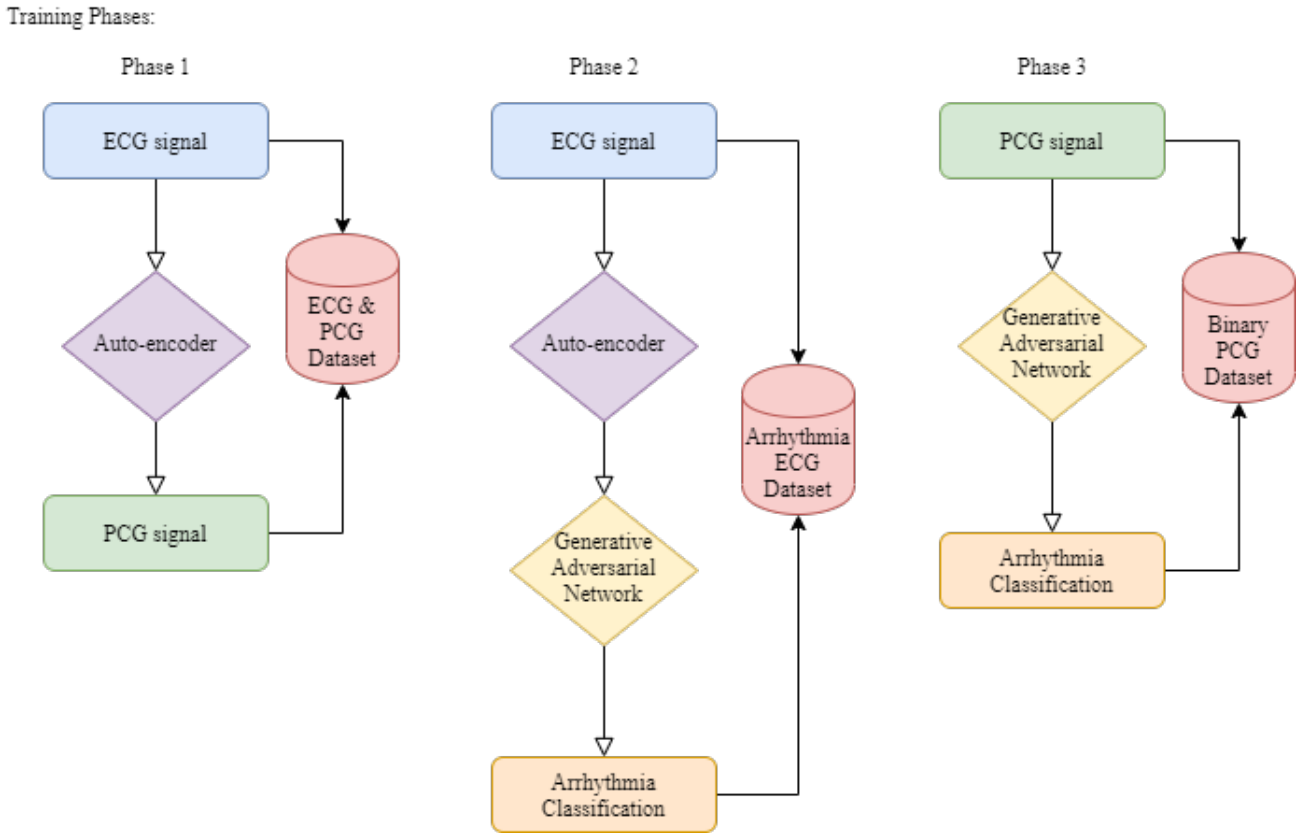
2 Methodology

2.1 Approach

The model contains two sub-models, an Autoencoder (AE), and a Generative Adversarial Network (GAN). The AE is responsible for extracting relevant features from an ECG signal and constructing a PCG signal from the latent features. The GAN is responsible for extracting relevant features and classifying the PCG signals.

The training phase involves 3 stages: AE training, AE+GAN training, and GAN fine-tuning. During training phases, all datasets will follow the following split: 70% - training, 15% - validation, 15% - testing; this cross-validation step validates that both models are not overfitting during the training phase. The first stage involves training the AE with a supervised dataset of ECG and PCG signals (Liu et al, 2016). The second stage involves training both the AE and the

GAN with a supervised dataset of arrhythmias within ECGs (Goldberger et al., 2017). During the training process, the AE model will be frozen (the weights and biases of the AE model won't be trained) as this process is already done in the preceding stage. The last stage is fine-tuning the GAN on a binary supervised dataset of PCG signals (Normal vs Abnormal). This validates the model's metrics in the previous step.



2.2 Data Analysis

While testing and training, the model will be validated against with metrics such as recall, precision, accuracy, loss, FBeta, F1 score, and ROC/AUC score. These tests will ensure that the model is accurately predicting the classes, and identifying important features within the datasets. Each step in the training phase will represent a milestone and an accuracy of 97% will mark the completion criteria.

2.3 Potential Problems

Overfitting: One of the largest problems in Deep Learning overall, which possesses a threat to our model is overfitting. Overfitting typically happens when the model metrics of the training and validation set diverge. This suggests that the model is not generalizing, but rather memorizing the training dataset. To combat overfitting, researchers typically implement data argumentation techniques to reinforce important features in a dataset.

Domain Shift: A domain shift occurs when a source dataset performs well but on a different dataset distribution, the performance drastically decreases. Typically, domain adaptation is often used to improve performance on target datasets. This is done by training the model itself on multiple datasets to improve the model's capacity to generalize.

Traning Time: With large multi-model architectures, it becomes tough to train models on a single GPU. This can happen for a number of reasons, but the main reason is because the model takes up too much memory of the GPU. Generally, parallel processing is used to split tasks and assign them to different GPUs. For instance, the AE model will run on a single GPU, while the GAN will run on another GPU.

References

[1] Jordaens, L. (2018). Aclinical approach to arrhythmias revisited in 2018. Netherlands Heart Journal. doi:10.1007/s12471-018-1089-1

[2] Mangione, S. (1993). The Teaching and Practice of Cardiac Auscultation during Internal Medicine and Cardiology Training: A Nationwide Survey. Annals of Internal Medicine, 119(1), 47. doi:10.7326/0003-4819-119-1-199307010-00009

[3] Bunch, T. J., May, H. T., Bair, T. L., Johnson, D. L., Weiss, J. P., Crandall, B. G., … Day, J. D. (2013). Increasing time between first diagnosis of atrial fibrillation and catheter ablation adversely affects long-term outcomes. Heart Rhythm, 10(9), 1257–1262. doi:10.1016/j.hrthm.2013.05.013

[4] Aziz, S., Khan, M. U., Alhaisoni, M., Akram, T., Altaf, M. (2020). Phonocardiogram Signal Processing for Automatic Diagnosis of Congenital Heart Disorders through Fusion of Temporal and Cepstral Features. Sensors, 20(13), 3790. doi:10.3390/s20133790

[5] Felipe Alonso "Detection of life threatening arrhythmias using feature selection andsupport vector machines", IEEE Transactions on Biomedical Engineering,Vol 61No.3,pp.832-840,March 2014.