Checklist for Adult Sponsor (1)

This completed form is required for ALL projects.

To be completed by the Adult Sponsor in collaboration with the student researcher(s):

Student's Name(s): Aditya Kendre

Project Title: Employing Adversarial Machine Learning and Computer Audition for Smartphone-Based Real-Time Arrhythmia Classification in Heart Sounds

1. ☑ I have reviewed the ISEF Rules and Guidelines.

2. ☑ I have reviewed the student's completed Student Checklist (1A) and Research Plan/Project Summary.

3. ☑ I have worked with the student and we have discussed the possible risks involved in the project.

4. ☐ The project involves one or more of the following and requires prior approval by an SRC, IRB, IACUC or IBC:
   - ☐ Humans
   - ☐ Vertebrate Animals
   - ☐ Potentially Hazardous Biological Agents
   - ☐ Microorganisms ☐ rDNA ☐ Tissues

5. ☑ Items to be completed for **ALL PROJECTS**
   - ☑ Adult Sponsor Checklist (1)
   - ☑ Student Checklist (1A)
   - ☑ Research Plan/Project Summary
   - ☑ Approval Form (1B)
   - ☐ Regulated Research Institutional/Industrial Setting Form (1C) (when applicable; after completed experiment)
   - ☑ Continuation/Research Progression Form (7) (when applicable)

Additional forms required if the project includes the use of one or more of the following (check all that apply):

- ☐ **Humans,** including student designed inventions/prototypes. (Requires prior approval by an Institutional Review Board (IRB); see full text of the rules.)
  - ☐ Human Participants Form (4) or appropriate Institutional IRB documentation
  - ☐ Sample of Informed Consent Form (when applicable and/or required by the IRB)
  - ☐ Qualified Scientist Form (2) (when applicable and/or required by the IRB)

- ☐ **Vertebrate Animals** (Requires prior approval, see full text of the rules.)
  - ☐ Vertebrate Animal Form (5A) - for projects conducted in a school/home/field research site (SRC prior approval required.)
  - ☐ Vertebrate Animal Form (5B) - for projects conducted at a Regulated Research Institution. (Institutional Animal Care and Use Committee (IACUC) approval required prior experimentation.)
  - ☐ Qualified Scientist Form (2) (Required for all vertebrate animal projects at a regulated research site or when applicable)

- ☐ **Potentially Hazardous Biological Agents** (Requires prior approval by SRC, IACUC or IBC, see full text of the rules.)
  - ☐ Potentially Hazardous Biological Agents Risk Assessment Form (6A)
  - ☐ Human and Vertebrate Animal Tissue Form (6B) - to be completed in addition to Form 6A when project involves the use of fresh or frozen tissue, primary cell cultures, blood, blood products and body fluids.
  - ☐ Qualified Scientist Form (2) (when applicable)
  - ☐ The following are exempt from prior review but require a Risk Assessment Form 3: projects involving protists, archae and similar microorganisms, for projects using manure for composting, fuel production or other non-culturing experiments, projects using color change coliform water test kits, microbial fuel cells, and projects involving decomposing vertebrate organisms.

- ☐ **Hazardous Chemicals, Activities and Devices** (No SRC prior approval required, see full text of the rules.)
  - ☐ Risk Assessment Form (3)
  - ☐ Qualified Scientist Form (2) (required for projects involving DEA-controlled substances or when applicable)

- ☐ **Other**
  - ☐ Risk Assessment Form (3)

Mike Floreck

Adult Sponsor's Printed Name | Signature | Date of Review (mm/dd/yy)

(717) 506-3413 | mfloreck@cvschools.org

Phone | Email

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:

   Employing Adversarial Machine Learning and Computer Audition for Smartphone-Based Real-Time Arrhythmia Classification in Heart Sounds

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)

   4/19/21 — End Date: (mm/dd/yy)

8. Where will you conduct your experimentation? (check all that apply)

   ☐ Research Institution ☐ School ☐ Field ☐ Home ☐ Other: _____

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.**

Research Plan/Project Summary Instructions

A complete Research Plan/Project Summary is required for ALL projects and must accompany Student Checklist (1A).

- All projects must have a Research Plan/Project Summary
  a. Written prior to experimentation following the instructions below to detail the rationale, research question(s), methodology, and risk assessment of the proposed research.
  b. If changes are made during the research, such changes can be added to the original research plan as an addendum, recognizing that some changes may require returning to the IRB or SRC for appropriate review and approvals. If no additional approvals are required, this addendum serves as a project summary to explain research that was conducted.
  c. If no changes are made from the original research plan, no project summary is required.

- Some studies, such as an engineering design or mathematics projects, will be less detailed in the initial project plan and will change through the course of research. If such changes occur, a project summary that explains what was done is required and can be appended to the original research plan.

- The Research Plan/Project Summary should include the following:
  a. **RATIONALE:** Include a brief synopsis of the background that supports your research problem and explain why this research is important and if applicable, explain any societal impact of your research.
  b. **RESEARCH QUESTION(S), HYPOTHESIS(ES), ENGINEERING GOAL(S), EXPECTED OUTCOMES:** How is this based on the rationale described above?
  c. Describe the following in detail:
- **Procedures:** Detail all procedures and experimental design including methods for data collection, and when applicable, the source of data used. Describe only your project. Do not include work done by mentor or others.
- **Risk and Safety:** Identify any potential risks and safety precautions needed.
- **Data Analysis:** Describe the procedures you will use to analyze the data/results.
  d. **BIBLIOGRAPHY:** List major references (e.g. science journal articles, books, internet sites) from your literature review. If you plan to use vertebrate animals, one of these references must be an animal care reference.

Items 1–4 below are subject-specific guidelines for additional items to be included in your research plan/project summary as applicable.

1. **Human participants research:**
   a. **Participants:** Describe age range, gender, racial/ethnic composition of participants. Identify vulnerable populations (minors, pregnant women, prisoners, mentally disabled or economically disadvantaged).
   b. **Recruitment:** Where will you find your participants? How will they be invited to participate?
   c. **Methods:** What will participants be asked to do? Will you use any surveys, questionnaires or tests? If yes and not your own, how did you obtain? Did it require permissions? If so, explain. What is the frequency and length of time involved for each subject?
   d. **Risk Assessment:** What are the risks or potential discomforts (physical, psychological, time involved, social, legal, etc.) to participants? How will you minimize risks? List any benefits to society or participants.
   e. **Protection of Privacy:** Will identifiable information (e.g., names, telephone numbers, birth dates, email addresses) be collected? Will data be confidential/anonymous? If anonymous, describe how the data will be collected. If not anonymous, what procedures are in place for safeguarding confidentiality? Where will data be stored? Who will have access to the data? What will you do with the data after the study?
   f. **Informed Consent Process:** Describe how you will inform participants about the purpose of the study, what they will be asked to do, that their participation is voluntary and they have the right to stop at any time.

2. **Vertebrate animal research:**
   a. Discuss potential ALTERNATIVES to vertebrate animal use and present justification for use of vertebrates.
   b. Explain potential impact or contribution of this research.
   c. Detail all procedures to be used, including methods used to minimize potential discomfort, distress, pain and injury to the animals and detailed chemical concentrations and drug dosages.
   d. Detail animal numbers, species, strain, sex, age, source, etc., include justification of the numbers planned.
   e. Describe housing and oversight of daily care.
   f. Discuss disposition of the animals at the end of the study.

- **Potentially hazardous biological agents research:**
  a. Give source of the organism and describe BSL assessment process and BSL determination.
  b. Detail safety precautions and discuss methods of disposal.

4. **Hazardous chemicals, activities & devices:**
   - Describe Risk Assessment process, supervision, safety precautions and methods of disposal.
   - Material Safety Data Sheets are not necessary to submit with paperwork.

ISEF Sample Abstract & Certification

Employing Adversarial Machine Learning and Computer Audition for Smartphone-Based Real-Time Arrhythmia Classification in Heart Sounds

Aditya Kendre

Cumberland Valley High School, Mechanicsburg, PA, USA, Cumberland County

We propose a novel approach to detect arrhythmias in Phonocardiograms (PCGs). Typically, many arrhythmia conditions are unknown until a patient is suggested an ECG/EKG test. 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 is comprised of two subsystems; one is based on the relationship between Electrocardiograms (ECGs) and PCGs, and the other between PCGs and arrhythmias. The first subsystem uses a Generative Adversarial Networks (GAN), in which both generated and real PCG signals are fed into the discriminator for classification. In subsystem two, ECG spectrograms are dimensionally reduced, then constructed into PCG spectrograms using a transGAN. These constructed PCG spectrograms, when converted back into time series, should be identical to the ground truth. This would allow the transGAN to convert ECG datasets into PCG datasets, providing subsystem one to train on both ECG and PCG datasets. After testing, the GAN model (subsystem one) should achieve an accuracy of 86.02%, a specificity of 77.81%, and a sensitivity of 94.24% on the testing set. Furthermore, the transGAN should show promising results, in that the transGAN discriminator should be able to construct the PCG spectrogram accurately. With this data, we should be able to use subsystem one to create a smartphone-based app to detect arrhythmias in heart sound recordings. Our proposed method should accomplish exemplary statistics in abnormalities detection and show promising results in increased arrhythmia construction.

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

- [ ] Animal Sciences
- [ ] Behavioral and Social Sciences
- [ ] Biochemistry
- [ ] Biomedical and Health Sciences
- [x] 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.
   [x] yes [ ] no

3. I/We worked or used equipment in a regulated research institution or industrial setting.
   [ ] yes [x] no

4. This project is a continuation of previous research.
   [x] yes [ ] no

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

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

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Employing Adversarial Machine Learning and Computer Audition for Smartphone-Based Real-Time Arrhythmia Classification in Heart Sounds

Aditya Kendre
Cumberland Valley High School
Mechanicsburg, PA, USA

March 16, 2021

Abstract

We propose a novel approach to detect arrhythmias in Phonocardiograms (PCGs). Typically, many arrhythmia conditions are unknown until a patient is suggested an ECG/EKG test. 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 is comprised of two subsystems; one is based on the relationship between Electrocardiograms (ECGs) and PCGs, and the other between PCGs and arrhythmias. The first subsystem uses a Generative Adversarial Networks (GAN), in which both generated and real PCG signals are fed into the discriminator for classification. In subsystem two, ECG spectrograms are dimensionally reduced, then constructed into PCG spectrograms using a transGAN. These constructed PCG spectrograms, when converted back into time series, should be identical to the ground truth. This would allow the transGAN to convert ECG datasets into PCG datasets, providing subsystem one to train on both ECG and PCG datasets. After testing, the GAN model (subsystem one) should achieve an accuracy of 86.02%, a specificity of 77.81%, and a sensitivity of 94.24% on the testing set. Furthermore, the transGAN should show promising results, in that the transGAN discriminator should be able to construct the PCG spectrogram accurately. With this data, we should be able to use subsystem one to create a smartphone-based app to detect arrhythmias in heart sound recordings. Our proposed method should accomplish exemplary statistics in abnormalities detection and show promising results in increased arrhythmia construction.

Keywords Arrhythmias · Phonocardiograms · Electrocardiograms · Biomarkers

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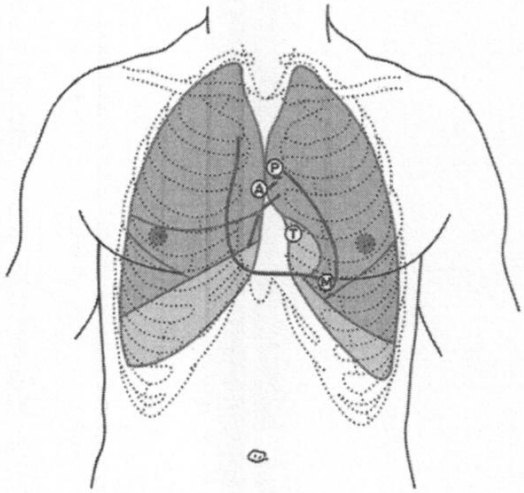

Figure 1: Representation of heart sound recording positions.

1 Rationale

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

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.

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.

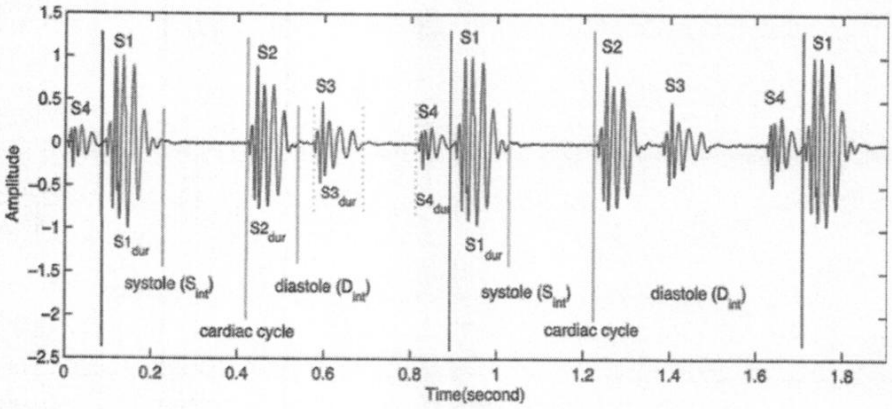

Figure 2: Illustrates the S1, S2, S3, and S4 biomarkers of heart sounds.

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 (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.

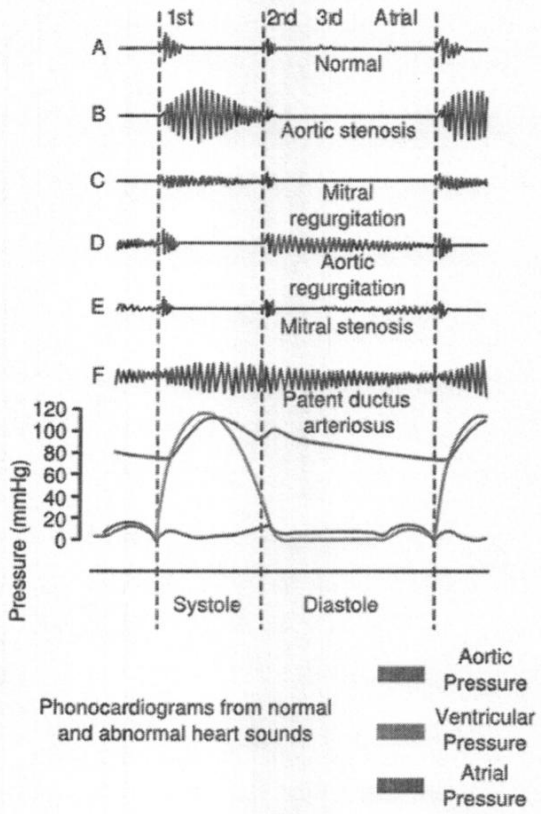

Figure 3: Representation of different abnormalities in sound and pressure.

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.

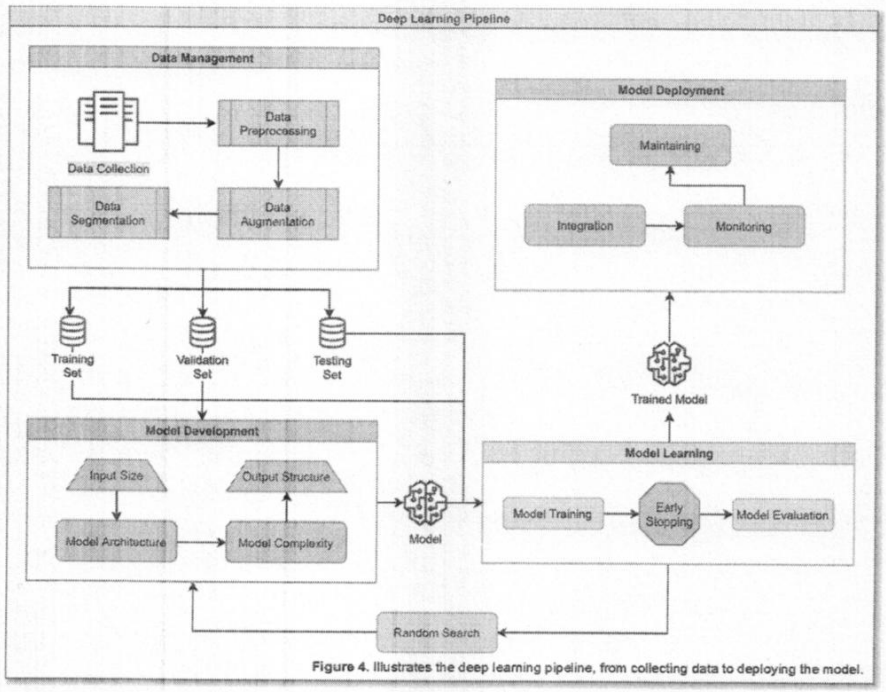

Figure 4: Illustrates the deep learning pipeline, from collecting data to deploying the model.

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

2 Objectives

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

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.

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.

Expected Outcomes 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.

3 Data Management

3.1 Data Collection

Although PCG signals are analyzed less often than ECG signals, these signals are rather analyzed in real-time by physicians and healthcare workers. Preliminary studies were done on PCG segmentation and classification primarily used private datasets. Hence, there existed no publicly available datasets until recently. Since then, many public datasets have been developed aiding researchers in their studies and creating open benchmarks for researchers to use in comparing similar findings. However, these datasets are still limited by the number of classes that are collected, when compared to ECG datasets.

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. These datasets are all anonymized and de-identified for the safety of their subjects, and thus includes no personal information such as name, income, age, etc.

The PhysioNet Classification of Heart Sound Recording Challenge dataset was produced as a part of the 2016 PhyisoNet Computing in Cardiology Challenge. The heart sounds were collected from both clinical and non-clinical environments (in-home visits). The challenge focused on creating an accurate dataset of normal and abnormal heart sound recordings, especially in real-world (extremely noisy and low signal quality) scenarios. These recordings were sourced from nine independent databases and in total, contain 4,593 heart sound recordings from 1072 subjects, lasting from 5-120 seconds. Of which, 409 recordings that were collected from 121 patients contain one PCG lead and one simultaneously recorded ECG. Though, all recordings were resampled to 2,000 Hz using an anti-alias filter. Furthermore, the dataset is comprised of 3 classes: normal, abnormal, and unsure (this is due to poor recording quality), and have the following proportion respectively: 77.1%, 12,0%, 10.9%.

The PASCAL Classifying Heart Sounds Challenge dataset was released to the general public in 2011. The challenge consisted of two sub-challenges: heart sound segmentation, and heart sounds classification; these sub-challenges corresponded with dataset A, and dataset B respectively. Both datasets have recordings of varying lengths, between 1 second and 30 seconds. Dataset A was collected via the iSethoscope Pro iPhone app, and contained 176 heart sound recordings. 124 of which are divided into four classes: Normal (31 recordings), Murmur (34 recordings), Extra heart sound (19 recordings), and Artifact (40 recordings); the rest of the records are unlabeled for testing purposes. Dataset B was collected using a DigiScope (a digital stethoscope), and included 656 heart sounds. All except 370 were separated into three classes: Normal (320 recordings), Murmur (95 recordings), and Extra-systole (46 recordings). Both datasets A and B vary in sound recordings between lengths of 1 second and 30 seconds.

More than 300 million ECG recordings are analyzed yearly, and thus create an exceptional tool for arrhythmia classification. Coupled with the recent surge in research interest in 2015, many massive publicly available datasets have been published, notable by PhysioNet - the moniker of the Research Resource for Complex Physiologic Signals. Numerous, datasets ECG exist, however, many are limited to few classes (Normal and Abnormal). At present, three public datasets exist that have more than 4 classes: AF Classification Challenge 2017, PTB Diagnostic ECG, and PTB-XL dataset. Additionally, iRhythm Technologies have developed a semi-public dataset, that is available upon request, that contains 12 classes.

The PTB-XL is the largest publicly available dataset for ECGs and contains 21,837 clinical 12-lead ECG recordings from 18,885 patients of 10 second length. These recordings are separated into 5 super-classes: Normal, Myocardial Infraction, Hypertrophy, ST/T-Change, and Conduction Disturbance. These super-classes are further split into 71 sub-classes that range from AV Block to Posterior Myocardial Infraction. The raw signal data were downsampled to 100 Hz and annotated by up to two cardiologists, who assigned potentially multiple ECG statements to each record. iRhythm Technologies developed a large, 12 classes ECG dataset using raw single-lead ECG inputs. The 12 classes include Atrial fibrillation and flutter, AVB, Bigeminy, EAR, IVR, Junctional rhythm, Noise, Sinus rhythm, SVT, Trigeminy, Ventricular tachycardia, and Wenckebach. The dataset consists of 91,232 ECG recordings from 53,549 patients. This training dataset is available upon request under license from iRhythm Technologies, Inc. The publicly available test dataset contains 328 records collected from 328 unique patients, split between 6 classes. Both datasets were recorded using a Zio monitor, which monitors the heart through a single-lead sensor at 200 Hz. The annotation was done by a consensus committee of expert cardiologists.

The PhysioNet AF Classification database, presented in 2017 for the Computing in Cardiology Challenge, contains 8,528 ECG recordings, divided into 4 classes: Normal (5154 recordings), Atrial Fibrillation (771 recordings), Other arrhythmias (2557 recordings), and Noisy (46 recordings). The single-lead recordings last from 9 - 61 seconds, with a mean of 32.5 seconds and a standard deviation of 10.9 seconds. The ECG recordings were sampled to 300 Hz and provided in MATLAB V4 WFDB-compliant format.

3.2 Data Preprocessing

PCG recordings often are recording in non-ideal environments that are filled with unwanted background noise and interference. Data preprocessing is the process of altering the data in the signal, often by denoising, normalizing, standardizing, and transforming the signal. These steps are crucial for automatic localization and classification tasks. Preprocessing the data allows a model to extract meaning features efficiently and reveals the physiological structure of the heart sounds [Latif et al.]. Furthermore, preprocessing helps ensure that the data that is fed into the model is always in the same domain. This allows the model to generalize more easily.

We first resample the data to 500 Hz, to decrease the spatial resolution of the heart sound recordings, but still retain important features. Thus, helping the model to converge faster. The resampled data is standardized using the standard score equation. This scales the mean of the distribution to 0, artificially scaling all data into similar ranges, thus, helping combat the exploding gradient problem.

The standardized data is then fed into a CycleGAN that has learned to denoise data. The CycleGAN is fed synthetically noised PCG signal and attempts to construct the denoised data from the noisy data. This synthetic noise consists of white noise, pink noise, and real background noise collected from audio recordings. The noise is added to each PCG signal recording and then treated as the input to the CycleGAN. The CycleGAN's output is compared to the original, non-noise, PCG recording. In this way, the CycleGAN eventually learns to denoise PCG recordings.

3.3 Data Segmentation

Data segmentation refers to the process of creating cross-validation datasets. This process assists in validating if the model is overfitting to the dataset. These datasets include the training set, validation set, and testing set. Typically, the training set is 70%-80% of the dataset, the reset of the dataset is split among the validation set and testing set. Here, we split the data 80% training, 10% validation, and 10% testing.

3.4 Data Augmentation

Data augmentation is a strategy that enables a significant increase in the diversity of data available while training a model, without actually collecting new data. Data augmentation techniques aim to slightly alter existing data to a point where the model cannot recognize the augmented data as one it has trained on before, but still retains the characteristics of the data's category. This helps in reinforcing important features within the data and is only done during the training portion of the workflow.

A common misconception arises when comparing preprocessing and augmentation. To be clear, preprocessing aims to clean the data of unwanted artifacts that are not meant for classification and is done in place. Augmentation, on the other hand, is solely done for expanding the dataset's size, often to combat overfitting. Augmenting the data before preprocessing further obscures the data unrealistically, and beyond classification.

We use to resample the heart sound recordings to different frequencies to simulate slower and faster beats per minute (bpm). The normal bpm for a human is between 60-100 bpm. Thus, measuring the sample distance between the first S1 (the start of systole) and the second S1, we calculate the bps and resample accordingly.

Furthermore, we use noise injection directly to preprocessed PCG recordings [Messner et al.]. This process is identical to the process of synthetically adding noise to PCG recordings described in the preprocessing step. A variety of noises, like white noise, is added to the signal to increase the sample of recordings per class. This method is extremely beneficial for training on small datasets, like the PASCAL dataset.

4 Model Development

4.1 Model Architecture

Here we propose using Generative Adversarial Networks (GANs) for increased success in PCG heart sound detection. GANs pose a unique advantage over traditional machine learning and deep learning methods, in that a model learns to

mimic a dataset by creating its own data, and tries to fool a discriminator into thinking the generated data is real. In a supervised approach, a GAN consists of two parts, a generator and a discriminator. The generator is responsible for creating fake heart sound data, while the discriminator tries to predict where the incoming data is fake or real. In a semi-supervised approach, however, the is fed data from a real dataset and the generator. Here, the discriminator tries to classify the generator's fake data, as well as predict the classes form the real dataset.

4.2 Model Complexity

Traditionally, generators are dense layers that slowly increase the dimensionality of the generated data to match that of the real dataset. Discriminators, on the other hand, are commonly CNNs because the majority of their applications work with images. However, it is possible to use a wide variety of architectures; such as LSTMs, RNNs, SVMs, DNNs, ANNs, Transformers. As mentioned previously, there are many types of model architecture, some are used for classification, and others for feature extraction. Optimizing the combination of feature extraction layers and classification layers is extremely time-consuming and computationally taxing. This is because there exist many combinations of hyperparameters, thus making it difficult to optimize each parameter. To optimize hyperparameters, we used hyperparameter sweeps to make the optimization process more efficient. This method involves using one of three methods: grid search, random search, and Bayesian search. Grid search computes each possible combination of all hyperparameters and tests them all. Although this is very effective, it can be computationally costly. Random search selects a new combination at random, provided a distribution of values. This method is surprisingly effective and scales very well. Bayesian search creates a probabilistic model of metrics and suggests parameters that have a high probability of improving metrics. This works well for small-scale projects, but scales poorly as the complexity of parameter relationships increases. Here, we used a random search to optimize our hyperparameters.

5 Model Learning

5.1 Model Training

During the training phase, the model is trained using backpropagation in conjunction with a cost function. Backpropagation attempts to calculate the gradient of the cost function with respect to the weight and biases of the model. This process involves an optimizer, which optimizes the model's parameters and a cost function that measure the correctness or incorrectness of the model. The goal of the optimizer is to minimize the cost function's error by adjusting the parameters to the given label. In this study, we used the Adam optimizer in union with Cross-Entropy Loss. The Adam optimizer uses a hyperparameter that dictated the change in the model's parameters on each backpropagation step, this is called the learning rate. Here we choose a learning rate of 0.0001.

The model is only trained on the training set; thus, backpropagation only occurs on the training set. Additionally, for each step in the training set, the optimizer backpropagates and optimizes the parameters and calculates metrics to further evaluate the model. The amount of steps in the training set is dictated by the batch size, the number of signals the model is trained on, in a single forward pass. Here we use a batch size of 32, meaning that the model is fed 32 signals per input. This significantly speeds up the process of training as more signals are passed through the model every time the model is optimized. A full pass of the training set is called an Epoch, here we train the model on 100 Epochs.

5.2 Model Training

To ensure the model is not overfitting, but generalizing to the training set, we use a validation set to track the metrics of the model. In theory, the metrics on the training set equal to that of the validation set. In practicality, after many epochs of training the metrics of the validation set become static, but the metrics of the training set still increase. This suggests that the model is overfitting. Thus, we stop training the model on the training set and test it as a testing set.

5.3 Model Evaluation/Data Analysis

Testing sets or hold-out sets are used to validate the metrics of the model, this is because both the validation set and the testing set have been tested by the model; thus, the model has developed a latent bias to both sets. Therefore, a third set is needed to assess the model's ability to generalize on an independent dataset. The metrics calculated on the testing set include the Accuracy, Sensitivity, Specificity, and ROC/AUC (and MSELoss in the case of the VQGAN).

6 Model Deployment

Model Deployment is one of the last stages of any machine learning project and involves releasing the model to the public.

6.1 Integration

Integration consists of implementing the model in a system, whether it happens on the client-side or the backend. The most popular backend model integration tools involve Flask, Azure, and FastAPI. These tools create APIs that encapsulate the model prediction, given a GET request with the desired input.

6.2 Monitoring & Maintaining

Following model integration and deployment, we move onto the next phase, monitoring and maintaining the system. As more and more data passes through the model, it increases the opportunity for the model to learn from a more generalized dataset. Though such data would be unsupervised, we could use unsupervised techniques to categories the data. Based on the improvement of the model, the model and be reintegrated and deployed. In essence, looping the whole process from data management to model learning.

6.3 Potential Problems

6.4 Risk and Safety

The equipment used in this research include mobile devices such as phones and laptops, these devices pose no risk.

6.5 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.

6.6 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.

6.7 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 discriminator model will run on a single GPU, while the generator will run on another GPU.

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Approval Form (1B)

A completed form is required for each student, including all team members.

1. To Be Completed by Student and Parent

a. **Student Acknowledgment:**

- I understand the risks and possible dangers to me of the proposed research plan.
- I have read the ISEF Rules and Guidelines and will adhere to all International Rules when conducting this research.
- I have read and will abide by the following Ethics statement

Student researchers are expected to maintain the highest standards of honesty and integrity. Scientific fraud and misconduct are not condoned at any level of research or competition. Such practices include but are not limited to plagiarism, forgery, use or presentation of other researcher's work as one's own, and fabrication of data. Fraudulent projects will fail to qualify for competition in affiliated fairs and ISEF.

Aditya Kendre _____ 3/14/21

Student's Printed Name | Signature | Date Acknowledged (mm/dd/yy) (Must be prior to experimentation.)

b. **Parent/Guardian Approval:** I have read and understand the risks and possible dangers involved in the **Research Plan/Project Summary**. I consent to my child participating in this research.

Nivrutti Kendre _____ 3/14/21

Parent/Guardian's Printed Name | Signature | Date Acknowledged (mm/dd/yy) (Must be prior to experimentation.)

2. To be completed by the local or affiliated Fair SRC

(Required for projects requiring prior SRC/IRB APPROVAL. Sign 2a or 2b as appropriate.)

a. **Required for projects that need prior SRC/IRB approval BEFORE experimentation** (humans, vertebrates or potentially hazardous biological agents).

The SRC/IRB has carefully studied this project's **Research Plan/ Project Summary** and all the required forms are included. My signature indicates approval of the **Research Plan/Project Summary** before the student begins experimentation.

Mike Floreck

SRC/IRB Chair's Printed Name

Signature | Date of Approval (mm/dd/yy) (Must be prior to experimentation.)

OR

b. **Required for research conducted at all Regulated Research Institutions with no prior fair SRC/IRB approval.**

This project was conducted at a regulated research institution (**not home or high school, etc.**), was reviewed and approved by the proper institutional board before experimentation and complies with the ISEF Rules. **Attach (1C) and any required institutional approvals (e.g. IACUC, IRB).**

SRC Chair's Printed Name

Signature | Date of Signature (mm/dd/yy) (May be after experimentation)

3. Final ISEF Affiliated Fair SRC Approval (Required for ALL Projects)

SRC Approval After Experimentation and Before Competition at Regional/State/National Fair

I certify that this project adheres to the approved **Research Plan/Project Summary** and complies with all ISEF Rules.

Regional SRC Chair's Printed Name | Signature | Date of Approval (mm/dd/yy)

State/National SRC Chair's Printed Name *(where applicable)* | Signature | Date of Approval (mm/dd/yy)

Qualified Scientist Form (2)

May be required for research involving human participants, vertebrate animals, potentially hazardous biological agents, and hazardous substances and devices. Must be completed and signed before the start of student experimentation.

Student's Name(s) Aditya Kendre

Title of Project Employing Adversarial Machine Learning and Computer Audition for Smartphone-Based Real-Time Arrhythmia Classification in Heart Sounds

To be completed by the Qualified Scientist:

Scientist Name: Lifang He

Educational Background: Machine Learning/Deep Learning/Biomedical Informatics Degree(s): B.S., Computational Mathematics; Ph.D., Computer Science

Experience/Training as relates to the student's area of research: Biomedical Engineering in Machine Learning

Assistant Professor
Position:

Lehigh University
Institution:

BC 327, 113 Research Drive, Bethlehem, PA 18015
Address:

lih319@lehigh.edu
Email/Phone:

1. Have you reviewed the ISEF rules relevant to this project? ☑ Yes ☐ No
2. Will any of the following be used?
   a. Human participants ☐ Yes ☑ No
   b. Vertebrate animals ☐ Yes ☑ No
   c. Potentially hazardous biological agents (microorganisms, rDNA and tissues, including blood and blood products) ☐ Yes ☑ No
   d. Hazardous substances and devices ☐ Yes ☑ No
3. Will this study be a sub-set of a larger study? ☐ Yes ☑ No
4. Will you directly supervise the student? ☑ Yes ☐ No
   a. If no, who will directly supervise and serve as the Designated Supervisor? _____
   b. Experience/Training of the Designated Supervisor:
   Assistant Professor at Lehigh University

To be completed by the Qualified Scientist:

I certify that I have reviewed and approved the Research Plan/Project Summary prior to the start of the experimentation. If the student or Designated Supervisor is not trained in the necessary procedures, I will ensure her/his training. I will provide advice and supervision during the research. I have a working knowledge of the techniques to be used by the student in the Research Plan/Project Summary. I understand that a Designated Supervisor is required when the student is not conducting experimentation under my direct supervision.

Lifang He
Qualified Scientist's Printed Name

Lifang He
Signature

04/14/21
Date of Approval (mm/dd/yy)

To be completed by the Designated Supervisor when the Qualified Scientist cannot directly supervise.

I certify that I have reviewed the Research Plan/Project Summary and have been trained in the techniques to be used by this student, and I will provide direct supervision.

Mike Floreck
Designated Supervisor's Printed Name

Signature

04/14/21
Date of Approval (mm/dd/yy)

(717) 506-3413
Phone

mfloreck@cvschools.org
Email

Risk Assessment Form (3)

Must be completed before experimentation.

Student's Name(s) Aditya Kendre

Title of Project Employing Adversarial Machine Learning and Computer Audition for Smartphone-Based Real-Time Arrhythmia Classification in Heart Sounds

To be completed by the Student Researcher(s) in collaboration with Designated Supervisor/Qualified Scientist:
(All questions must be answered; additional page(s) may be attached.)

1. List all hazardous chemicals, activities, or devices that will be used; identify microorganisms exempt from pre-approval (see Potentially Hazardous Biological Agent rules).

   Mobile devices such as phones and laptops.

2. Identify and assess the risks involved in this project.

   N/A

3. Describe the safety precautions and procedures that will be used to reduce the risks.

   N/A

4. Describe the disposal procedures that will be used (when applicable).

   N/A

5. List the source(s) of safety information.

   Mushroor, S., Haque, S., & Amir, R. A. (2019). The impact of smart phones and mobile devices on human health and life. International Journal Of Community Medicine And Public Health, 7(1), 9. https://doi.org/10.18203/2394-6040.ijcmph20195825

To be completed and signed by the Designated Supervisor (or Qualified Scientist, when applicable):
I agree with the risk assessment and safety precautions and procedures described above. I certify that I have reviewed the Research Plan/Project Summary and will provide direct supervision.

Mike Floreck

Designated Supervisor's Printed Name | Signature | Date of Review (mm/dd/yy)

Admin

Position & Institution

(717) 506-3413

Phone or email contact information

Experience/Training as relates to the student's area of research

Continuation/Research Progression Projects Form (7)

Required for projects that are a continuation/progression in the same field of study as a previous project.
This form must be accompanied by the previous year's abstract and Research Plan/Project Summary.

Student's Name(s) Aditya Kendre

To be completed by Student Researcher: List all components of the current project that make it new and different from previous research. The information must be on the form; use an additional form for previous year and earlier projects.

Components	Current Research Project	Previous Research Project: Year: 19-20
1. Title	Employing Adversarial Machine Learning and Computer Audition for Smartphone-Based Real-Time Arrhythmia Classification in Heart Sounds	ECG-Based Abnormal Heartbeat Classification: A Deep Learning Approach for Arrhythmia Detection
2. Change in goal/ purpose/objective	To create a lightweight, precise, and accurate model for predicting heart arrhythmias in Phonocardiograms using a Generative Adversarial Network capable of accurate diagnosis.	To create a model capable of surpassing the accuracy of Cardiologists in identifying heart arrhythmias in Electrocardiograms.
3. Changes in methodology	A Generative Adversarial Networks comprises of two models: a generator model and a classifier model (which contains a Convolutional Neural Network). The generator creates artificial PCG data to deceive the classifier into predicting the data is a real PCG signal while simultaneously being fed true PCG data from a dataset.	A Convolutional Neural Network extracts latent features from an electrocardiogram database following a fully-connected Linear layer that predicts whether an arrhythmia is present within the electrocardiogram, based upon the features extracted by the CNN.
4. Variable studied	Manipulated variables include: Learning Rate, Batch size, Number of Epochs, Hidden Layers, Hidden Units, Activations Functions, and level of Data Augmentation. Responding variables include: Loss, Accuracy, Recall, Precision, F-Beta Score, F1 Score, and ROC and AUC.	Manipulated variables include: Number of layers, Hidden Units, and the level of Data Augmentation. Responding variables include: Loss and Accuracy.
5. Additional changes	Conversion between ECG and PCG signals using an transGANs.	ECG signal with a one-dimensional CNN.

Attached are:
☑ Abstract and Research Plan/Project Summary, Year 19-20

I hereby certify that the above information is correct and that the current year Abstract & Certification and project display board properly reflect work done only in the current year.

Aditya Kendre — Student's Printed Name(s)
Signature
3/14/21 — Date of Signature (mm/dd/yy)

OFFICIAL ABSTRACT and CERTIFICATION

A Deep Learning Approach for Arrhythmia Detection

Aditya Kendre
Cumberland Valley High School, Mechanicsburg PA, Adams County

Early detection of cardiac arrhythmia has the potential to prevent the millions of moralities that the disease causes globally. However, there are few automated systems to identify arrhythmia. A significant impediment in achieving successful methods include the lack of a large training dataset. Despite this difficulty, processes like data augmentation allow for anincreased amount and diversity of data. Here, the electrocardiogram (ECG) datasets were obtained from the PhysioNet database. The dataset was used to train a Convolutional Neural Network (CNN) on classifying cardiac arrhythmia. Experimental results illustrate advantages such as better responsiveness and higher accuracy of deep learning-based models when compared to the traditional analysis on ECGs.

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

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

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. I/we worked or used equipment in a regulated research institution or industrial setting: ☐ Yes ■ No

3. This project is a continuation of previous research. ☐ Yes ■ No

4. My display board includes non-published photographs/visual depictions of humans (other than myself): ☐ Yes ■ No

5. This abstract describes only procedures performed by me/us, reflects my/our own independent research, and represents one year's work only ■ 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

This stamp or embossed seal attests that this project is in compliance with all federal and state laws and regulations and that all appropriate reviews and approvals have been obtained including the final clearance by the Scientific Review Committee.

ECG-Based Abnormal Heartbeat Classification: A Deep Learning Approach for Arrhythmia Detection

Aditya Kendre

Cumberland Valley High School

Rationale

Electrocardiograms (ECG) have created a profound impact in the field of cardiology, specify in recognizing of heart arrhythmias. Non-invasive arrhythmia analysis is based on 10 electrodes that reflect the electrical activity on ECGs. An estimated three million cases of arrhythmia occur in the United States yearly (Mayo Clinic). Diagnosing this disease early is the key to one's wellness, yet 18% of cardiologists misinterpreted ECGs containing atrial fibrillation (Anh et al, 2006). With the recent advancements in technology, Machine Learning algorithms such as Deep Neural Networks (DNNs), allow a computer to learn features and identify patterns within a given dataset. On the basic level, DNNs receive input data, and through a series of weights and biases, outputs a confidence value in all possible labels of the dataset, similar to a human's neural network. Furtherance in the accuracy of abnormal heartbeat classification will allow cardiologists to accurately, and efficiently recognizing arrhythmia before becoming prevalent in one's wellbeing.

Research

Research Question: This research project will examine whether a classifier will be able to accurately identify abnormal heartbeat in ECGs.

Hypothesis: If an image classifier received a supervised dataset of heart arrhythmia of ECGs, then the image classifier will allow an accurate identification of arrhythmia.

Expectation: The image classifier should reach an accuracy of above 82%.

Procedure:

1. Gather a dataset of annotated ECGs
2. Determine type of classifier used to learn dataset features
3. Analyze results using Gradient Decent and Mean Loss function

Risks and Safety:

This research project involves no risks or safety concerns.

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May 3-6 2021

Participation Agreement Form

Failure to comply with guidelines dictated in this may result in the student forfeiting the CASEF Grand Champion cash award. Therefore, the following agreement must be signed by a parent/guardian, sponsor, and school administration. Please return this to Valerie Knowles, Fair Director by ***March 19, 2021*** *director@casef.org*

I Aditya Kendre (student) agree to participate in the judging and events of the Virtual 2021 ISEF program. As a representative of the Capital Area Science and Engineering Fair (CASEF) I agree to meet the deadlines and complete the registration process, prepare my project for judging and participate in the Regeneron 2021 ISEF competition.

The CASEF Grand Champion Finalists may need to be excused from regular school day activities and provided with access to participate in the events and judging of the ISEF program. The sponsor/school administration/parent agree to provide student access to participate.

CASEF will award the grand champion cash award at the completing of ISEF participation. The signatures on this form recognize and agree that the award will be forfeited if the finalists fails to meet the registration requirements, deadlines and/or does not participate in the virtual event.

Students who fail to participate will be asked to reimburse CASEF the registration fees ($180) and forfeit the cash award.

I understand and agree to the participation requirement for the dispensing of the cash award and the reimbursement responsibility for failure to participate.

Student Signature: aditya Date: 3/12/2021

Parent/Guardian's Signature: [signature] Date: 3/12/2021

Sponsor/Teacher Signature: _____ Date: _____

Building Administrator Signature: _____ Date: _____