## Abstract

Heart disease is the leading cause of death in the United States. With the COVID-19 pandemic, there is a lack of access to medical infrastructure and a reduced ability to identify patients who may be at high risk for heart disease. Using data from the 2016 Physionet challenge and the YAMnet neural network, I created a classifier for abnormal heart rhythms as well as an open-source, web-based application for community involvement. The classifier was used against test datasets and also audio files collected using different mobile phones.

# Introduction

Heart disease is the leading cause of mortality in the United States with approximately 660,000 people dying each year of heat-related illnesses[2]. Additionally, research has shown that the novel 2019 coronavirus (COVID-19) has a strong involvement with the cardiovascular system. Assessments of COVID-19 patients have found that the risk of several cerebrovascular disorders, dysrhythmias, and thromboembolic disease increased significantly following even nonsymptomatic cases[2,9]. Despite an increasing incidence of heart disease, there is a lack of surveillance methods for patients at risk. Additionally, with the COVID-19 pandemic, patients have been staying at home and attending medical appointments virtually. Due to this lack of contact, doctors may be at a higher risk of missing important signs of early-stage heart disease.

In the past, people have used ECG (electrocardiogram) recordings to create classifiers that can detect specific heart diseases[3,5,6]. However, due to increased accessibility and portability, audio files have become a prominent data source in recent times. With the rise of audio recordings as a primary data source, there is a growing interest in using machine learning to classify abnormal heart rhythms[7,8]. In short, a neural network is a series of algorithms that find similarities and relationships in a set of data in a way similar to the human brain. This paper will describe one type of neural network: a Convolutional Neural Network (CNN). In this project, we used a CNN to classify irregular heartbeats.

# Methods

## Data

Our primary dataset was derived from the 2016 Physionet challenge. We segmented our data into 2 sets: 1) heart sounds of people with a regular heartbeat and no heart problems and 2) heart sounds of people with an abnormal heart rhythm. In total, 3,126 recordings, ranging from 5 to 120 seconds, were included from 4 cardiovascular locations: The Aorta, Pulmonic region, tricuspid valve, and mitral valve. For the abnormal rhythms, sound clips were from patients with heart valve defects and coronary artery diseases. The data included patients aged 5 - 68 and each individual contributed anywhere from 1 to 6 recordings. Along with acquiring this data, we needed to create a csv(comma separated values) file which contained the file number, its class, and a fold value which determines if the audio is training data test, test data, or validation data.

## Pre-processing

Prior to analyzing the audio, we re-sampled all the data at 1000 Hz. Yamnet works by splitting the audio into frames that are 0.96 seconds long, taken every 0.48 seconds. Each frame is then converted into a Mel spectrogram which is finally passed into the network. Mel spectrograms are similar to regular spectrograms but are on the Mel scale and they also show time, frequency, and amplitude(figure 1). Having all 3 of those values is essential for the network because it is able to train in a much more accurate way.

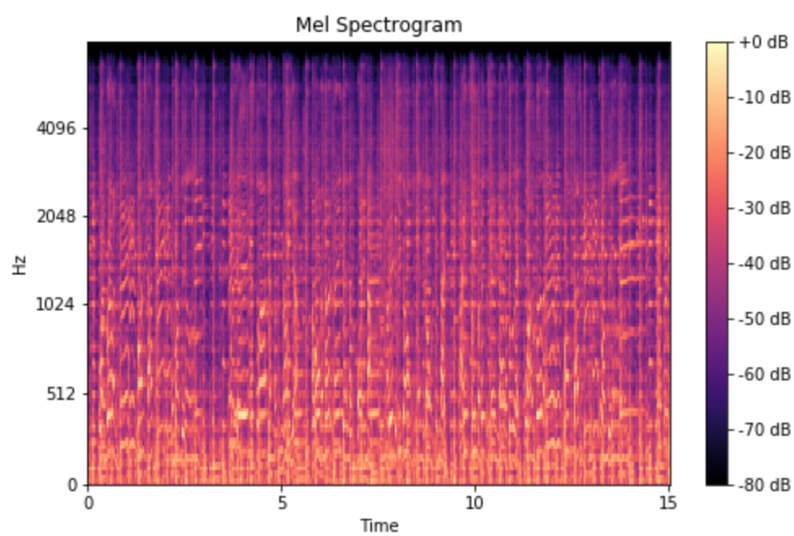


*Figure 1: Depiction of a Mel Spectrogram*

## Model Architecture and Training

YAMnet is a 86 layer CNN. The network has 27 convolutional layers and 1 fully connected layer(figure 2). The convolution layers extract features from the Mel spectrogram while the fully connected layer will process and map the extracted features to a class. For training the model we kept the batch size to 32 and experimented with different amounts of epochs ranging from 20 to 25.

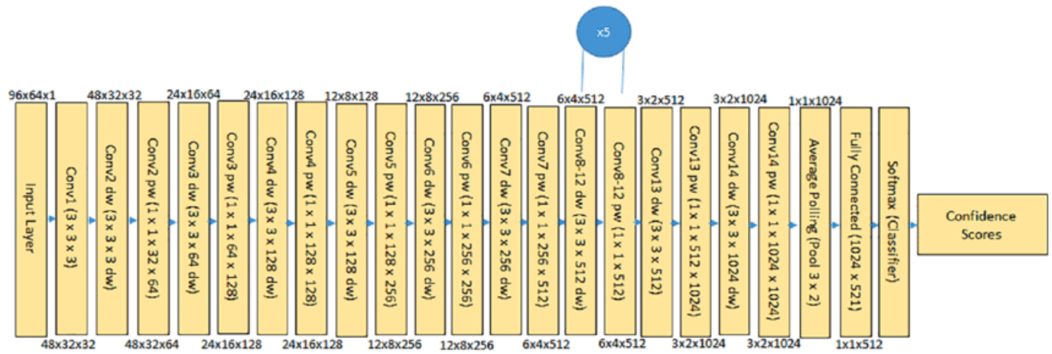


*Figure 2: Structure of YAMnets convolutional layers*

## Results

Over the course of this project, we managed to increase the accuracy of our classifier using many different methods. The very first model we created achieved a training accuracy of 91% and a test accuracy of 86%. This was done with a 16KHz resample rate, 20 epochs, and a batch size of 32. As we decreased the resample rate all the way down to 1KHz and increased the epochs to 25, by the end we achieved a training accuracy of 99% and a test of 88.7%.

Along the way, besides the test dataset, we tested our models on recordings of my heart taken with an iphone 11 and an Android Pixel 3 device  to understand how microphone quality and ambient noise would affect the classification. The recordings taken from the phones almost always worked with the classifier unless there was too much (deliberate) background noise. It achieved just as high a classification accuracy on the phone recorded files as on any other file we gave it.

We also tested the usability of the website from the mobile devices. Users can record heart audio on the phone , save the file on the phone and upload to the classification website from the phone.

## Discussion

With heart disease being the leading cause of death in the U.S yearly and the lack of access to medical infrastructure due to Covid-19, there is a critical need to create new screening methods for the early detection of heart disease. The development of a highly accessible screening method could help doctors recognize heart disease prior to harmful health events. In this project, we describe an accurate deep learning model that is easily accessible through a web-based design.

In the past, there have been multiple attempts to use machine learning to identify abnormal heartbeats. Miquel Alfaras et al created a model that only required a single lead ECG to make a classification[9]. However, in recent times, applications of machine learning in the classification of abnormal heartbeats have been focused on the use of heart audio because of convenience and cost. For example, the Physionet challenge in 2016 was centered around creating a neural network to classify normal vs. abnormal heartbeats[5].

Arman Kilic wrote a review paper about multiple models that were made for classification on ECGs[4]. From this paper, I was able to get a deeper understanding on the basics of classifying abnormal heart rhythms. I was able to increase my overall background knowledge a lot through this paper. Arooshi Taneja et al. researched how well different types of models perform on heart audio classification[7]. From this paper I was able to make the decision that a CNN would be the most fitting type of neural network for this project. It gave very clear evidence that a CNN would achieve some of the highest accuracies for heart audio classification. Tanachat Nilanon et al. were participants in the 2016 Physionet challenge who created a CNN for heart audio classification[5]. They had used the strategy of converting the audio files into Mel spectrograms which I found to be beneficial. I decided to incorporate the same method into my model, converting each frame taken into a Mel spectrogram instead of the entire audio recording as one.

For limitations, as I trained and tested the model we came across a small problem. Specifically, I noticed that there was a slight bias towards the normal class meaning that a majority of inaccurate cases were abnormal heart rhythms that were classified as normal. I believe this is due to the imbalance in data, where there are more than double the amount of normal files in the training dataset, compared to abnormal. With the addition of a greater variety of data in the future, the classifier will correct this bias.

## Next Steps

There are still many improvements to be made to this system. Currently, it is just a simple screening system that gives people a warning. In the future, I would like to improve the accuracy of the classifier along with tolerating more background noise. I would also like to allow it to classify more diseases and put them into classes instead of just saying if something was abnormal or not. Finally another important improvement that we could make to understand this classifier better is to use a saliency map. A saliency map shows what part of an image a CNN is weighing heavily, to make a classification. If we are able to use that for our sound data it can help us improve the model a lot and get much more accurate results.

In thinking about future applications, I believe that this system has lots of room to be taken even further. It can be brought to hospitals in need of a system like this, maybe because they do not have full-time physicians or fully trained ones. This concept of recording a heartbeat and classifying it as abnormal can also be applied to prenatal detection. Finally, in the future, a simple and small digital stethoscope that can be plugged into a mobile device would allow people to get much more clear and better recordings which would potentially result in higher accuracies.

## Conclusion

I was able to create an open-source classifier with easy access through a web-based application. The website has a section where people are able to upload their own heart recordings and check if it is abnormal or not. Although this system is still just a basic screening method, in the future if we keep improving this system, it can be taken much farther then just a quick screening.


## Acknowledgement

I would like to give a special thanks to researcher Jonathan Rubin. He was a participant in the 2016 Physionet challenge and also has a Ph.D. in computer science. I was able to get in contact with him and get advice from him. With his advice, we were able to make the classifier more efficient resulting in a 9% and 3% increase in our training and test accuracies respectively.

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