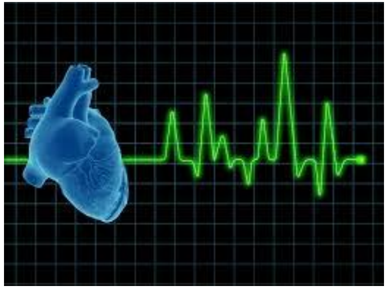
VIDYAVARDHAKA COLLEGE OF ENGINEERING
GOKULAM III STAGE, MYSURU 570 002

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

FINAL YEAR PROJECT PRESENTATION

Detection of Cardiac Arrhythmia Using Machine Learning



Under the Guidance of
Dr. K Paramesha
Professor, CS&E
VVCE, Mysuru

Contents

Introduction

- Certain circumstances cause the heart to beat in an irregular rhythm, these are medically known as arrhythmias.
- The heart rhythm is regulated by a node at the top of the head, known as sinus node which activates an electrical signal travelling through the heart causing the heart to beat and to pump blood in the body.
- Surplus electrical activity in the upper or lower portion of the heart indicates the heart is not pumping well.
- Symptoms of Cardiac Arrhythmia are increasing heartbeat called tachycardia and decreasing heartbeat called bradycardia. Few of the other symptoms are anxiety, fatigue, chest pain, dizziness, sweating and fainting.

Problem Statement

Cardiac Arrhythmia refers to a group of conditions that causes the heart to beat too slow or too fast. During initial stages of Cardiac Arrhythmia, doctors need to carefully examine the heartbeats precisely from different locations of the body. Manually evaluating these fundamental heart sounds (FHSs) for each and every patient is time consuming. Thus automating the procedure by using Machine Learning techniques to classify heart sound recordings would help in overcoming this problem.

Approach

- We have come up with a new approach where we will be using phonocardiogram (PCG) to classify heartbeat.
- The basic idea is to classify heartbeat using sound recording of heartbeat. Firstly we will convert heart sound recording (wav file) to spectrogram images and then we will use these spectogramic images to train the model.
- We are using convolutional neural networks to train the model. After training, our model will be able to predict the given PCG recording as normal or abnormal.
- One of the method is to build a multilayer neural network and based on accuracy, precision, recall, loss and f-beta score evaluate the model.
- Another way is to train the images to custom model based on VGG16 model architecture from scratch to obtain better results.

Literature Survey

- Heart Arrhythmia is one of the principal ailments that we have come over in the cardiology field. Its examination and recognition assumes a significant job and to cure the patients.
- The dataset considered for the assessment is taken from MIT-BIH arrhythmia database which had ECG chronicles as a noticeable factor which was taken care of as a contribution to the model to assess the outcome.
- Heart rhythm abnormality detection from PCG signal, in the initial step performed Signal Quality Evaluation and Component Extraction in which we investigate numerous data models to identify the connection between the functionality and the outcomes, producing low performance.
- Arrhythmia classification on ECG using Deep Learning, is an approach to signal classification based on intelligent electrocardiograms (ECG) using Deep Learning (DL) is being developed. They use Deep Learning algorithms to identify different forms of arrhythmia. Here they use the Convolutional Neural Network (CNN). A DL algorithm that is effective in signal detection and has 93.6 percent accuracy.
- Using a Logistic Regression-HSMM, audio files are segmented into Systolic and Diastolic phases during the second stage. These systems and diastoles segments are then analysed individually, and the extraction of individual features is carried out. A ton of de-noising is often performed in the segmentation process eliminating the surrounding sounds. This strategy provides 79 percent precision.

Mathematical Model

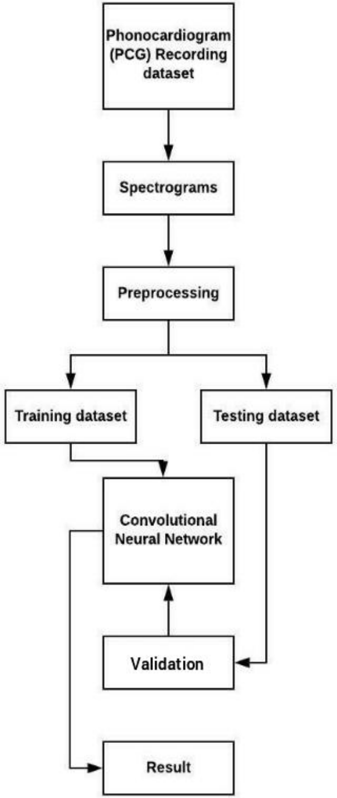
- Categorical cross entropy is the metric used to determine the model's performance on the entire dataset which is logarithmic loss. The formulae for this is given below.

$$\text{log-loss} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij}\log\left(p_{ij}\right)$$

- Since the dataset is imbalanced as the numbers of abnormal samples is less than that of normal samples in the training dataset, accuracy is not only the metric we considered. Hence the model was evaluated on accuracy, precision, recall, loss and f-beta score.

Metric	Formula
True positive rate, recall	$\frac{\text{TP}}{\text{TP+FN}}$
False positive rate	$\frac{\text{FP}}{\text{FP+TN}}$
Precision	$\frac{\text{TP}}{\text{TP+FP}}$
Accuracy	$\frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$
F-measure	$\frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$

System Design



Implementation

The dataset used for this project is freely available as part of the PhysioNet in Cardiology Challenge 2016 which focuses on automatic classification of normal or abnormal phonocardiogram (PCG) recording.

- Load the .wav files into memory.
- Process all the recordings and header files and parse them for file names and class labels and store them in separate lists.Once we have all the class labels and file names, we use scipy's wavfile class to get the sample rate and data of the wav file.
- The length of the windowing segments and sampling frequency for the spectrograms will be 256. Matplotlib spectrogram() function computes and plot a spectrogram of data. It takes minimum 3 parameters:

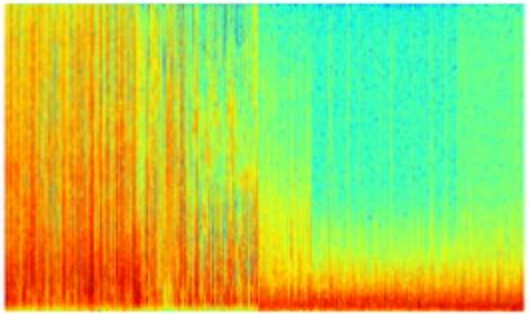
- x: Array or sequence containing the data or data of wav file

- Fs: The sampling frequency or the samples per time unit which is used to calculate Fourier frequencies.

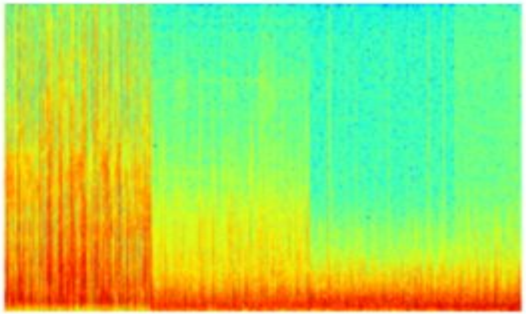
- NFFT: The number of data points used in each block for the FFT.

- The spectrogram is then plotted as a colormap.
- Finally, using the list of class labels we separate the spectrograms into individual classes. This way we can easily feed the images directly into our model using Keras' inbuilt ImageData Generator class as shown in the notebook.

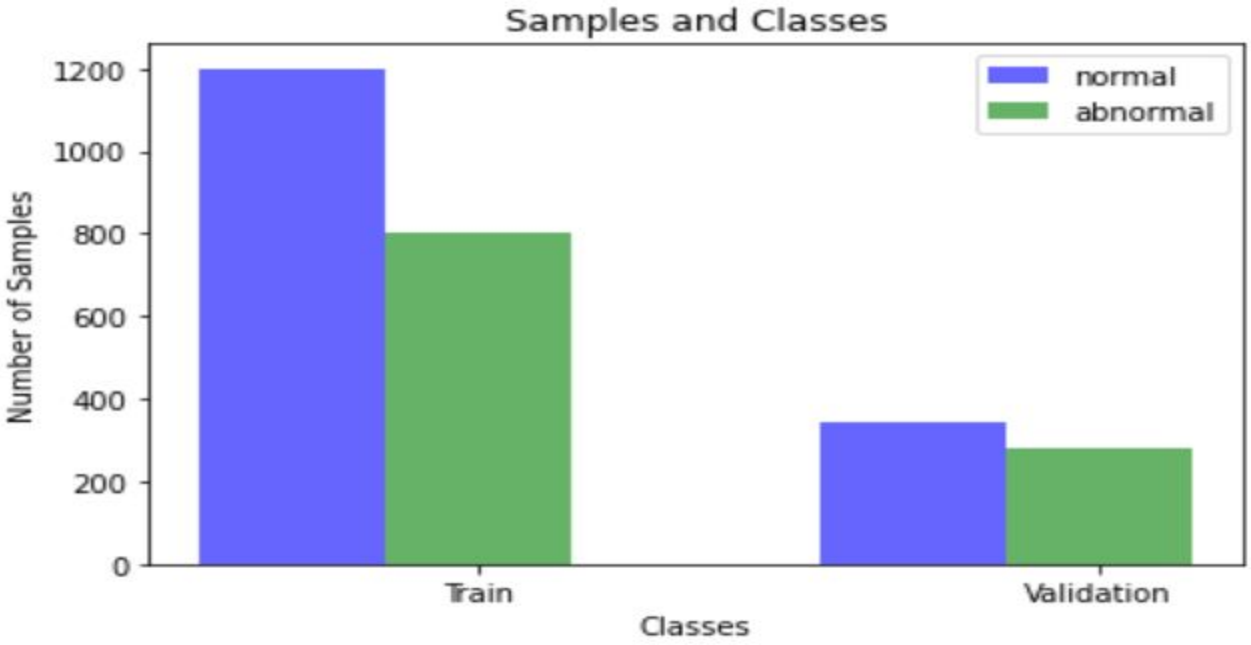
An abnormal heartbeat



A normal heartbeat



The image below shows the number of samples for each class in training and validation set.



DATA PRE-PROCESSING

For this project, the following data augmentation techniques were applied:

• Resizing: All the images in the dataset were resized to 150x150x3 (width = height = 150 ; colour channel = 3) before feeding into the CNN.

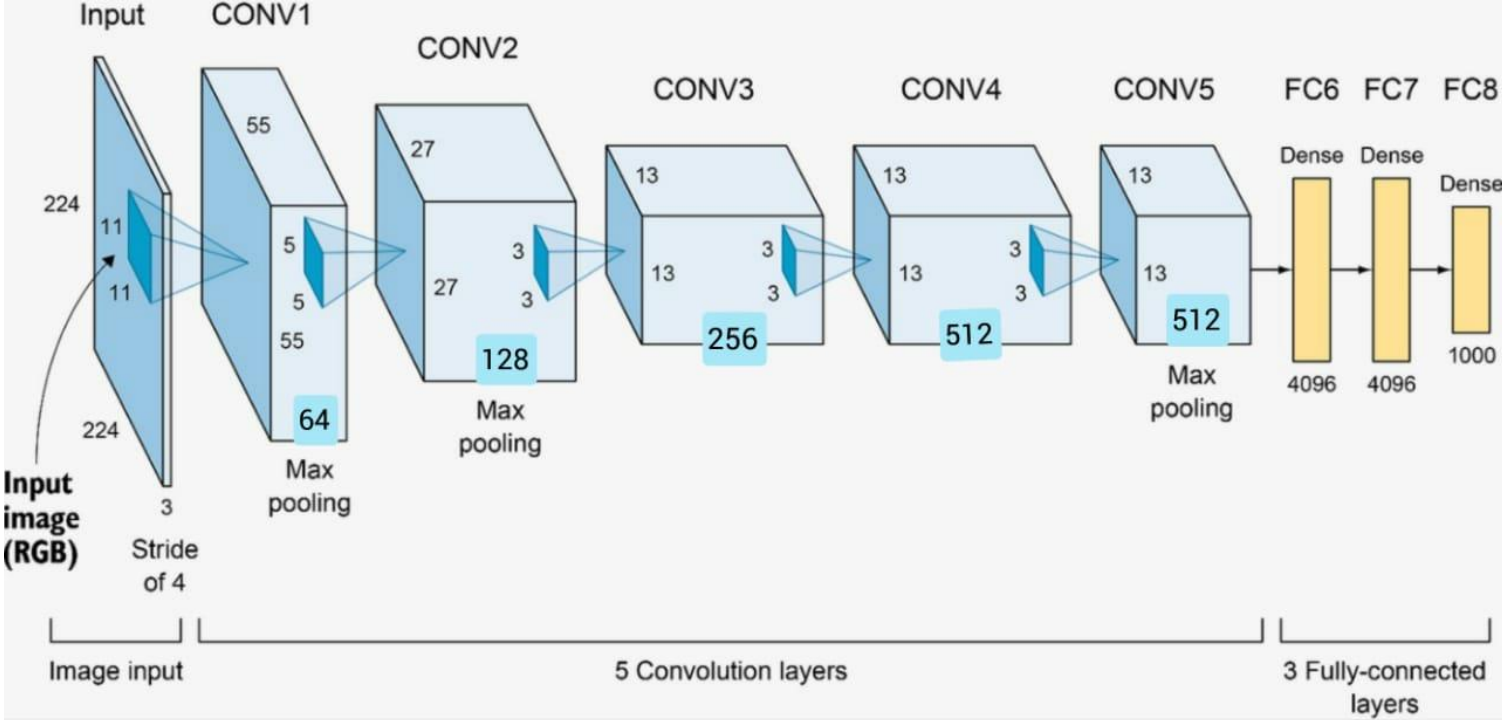
• Normalize: Pixel values for all images were normalized between 0 and 1. This was done by subtracting the minimum pixel (i.e. 0) and dividing by maximum pixel value (i.e. 255). In Keras, this was done by setting the rescale attribute to 1/.255.

• Shear Transformation: Shear Transformation was applied to control the shear intensity of the input images. It was set to 0.2 using the shear-range attribute.

• Zooming: Randomly zooming inside images by setting zoom-range attribute to 0.2

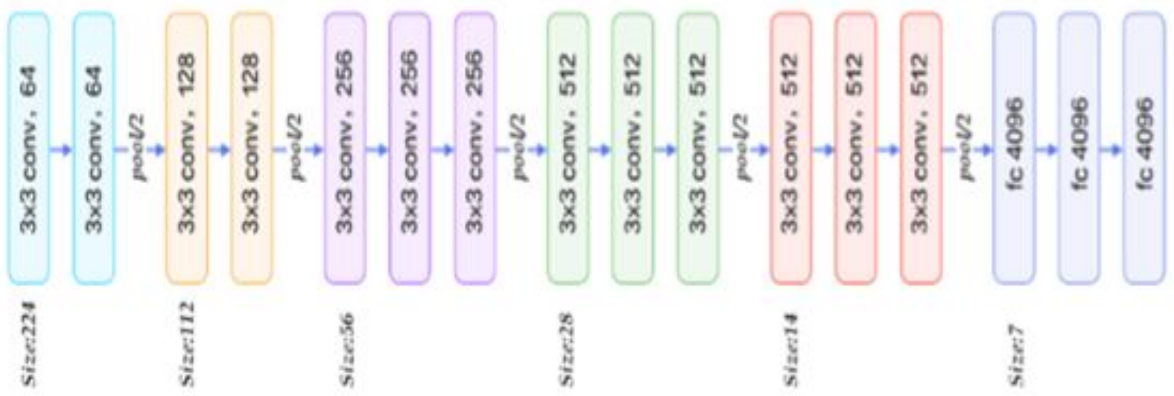
• Flipping: Half of the training inputs were randomly flipped horizontally using the horizontal-flip attribute.

CNN MODEL



Input
CONV1
CONV2
CONV3
CONV4
CONV5
FC6
FC7
FC8
224
11
11
224
3
55
5
5
55
64
27
27
3
3
128
13
13
3
3
256
13
13
3
3
512
13
13
512
Dense
Dense
Dense
4096
4096
1000
Max pooling
Max pooling
Max pooling
Input image (RGB)
Stride of 4
Image input
5 Convolution layers
3 Fully-connected layers

TRANSFER LEARNING MODEL (VGG16 Architecture)



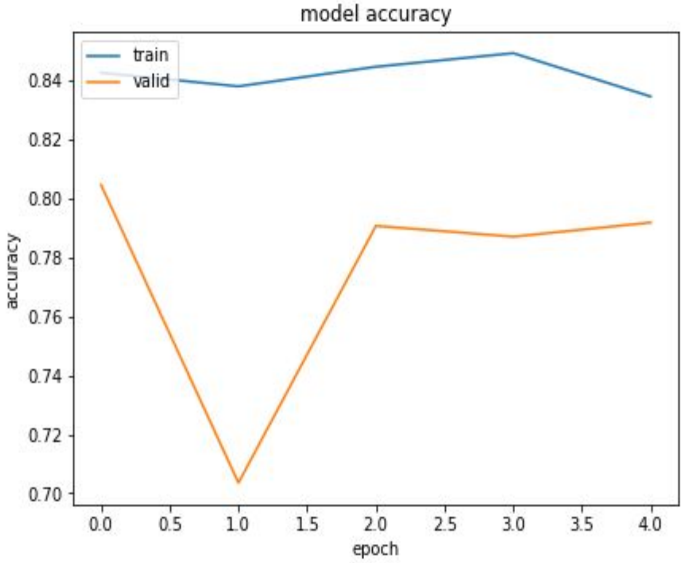
The architecture for this model is as follows: Each block is stacked with convolution layers and at the end of every block a pooling layer to reduce spatial dimension is applied. The output dimensions are increased by a factor of 2 every block. It should also be noted that zero padding is applied before every convolution layer in each block since it is not shown in the figure. The last three fully connected layers were removed as discussed above.

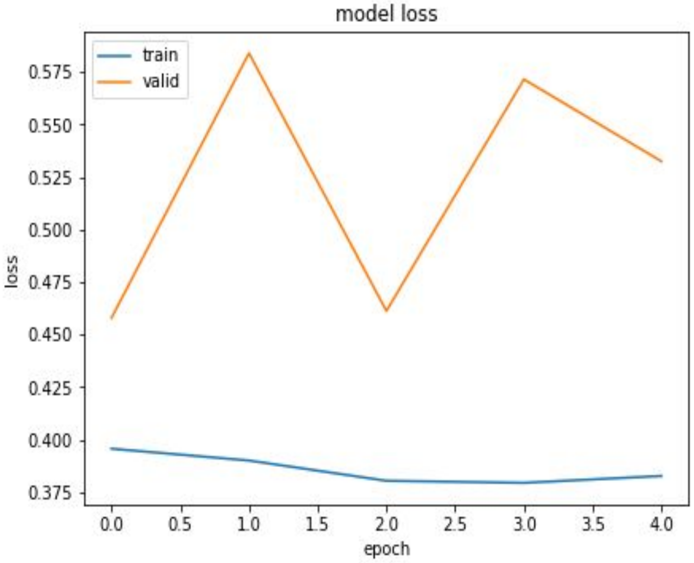
Results

We evaluate our models based on the measures taken like accuracy, recall, precision, loss and F-beta score. We try to minimize the loss function in all the models to achieve better accuracy. Overall, we get a whole simulated model to find the abnormal and normal spectrograms. We ran tests for the machine learning model built using ReLU, ELU, Tanh activation function and the transfer learning model and obtained results for the following measures as shown in the table below.

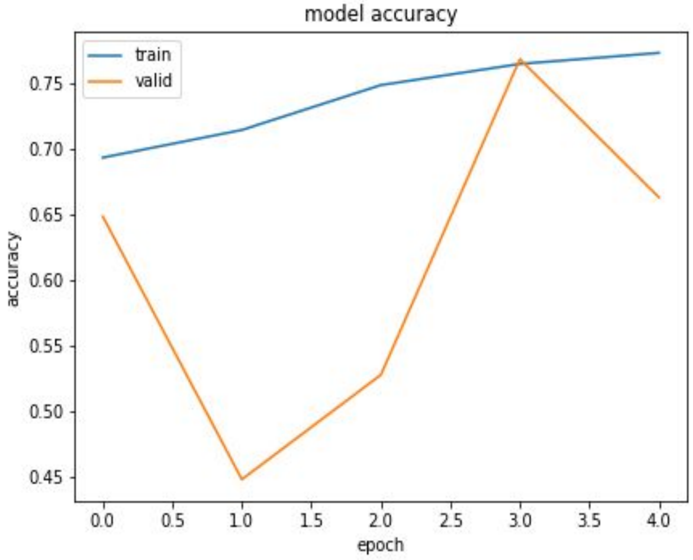
ML Model	Accuracy	Precision	Recall	F-beta Score	Loss
Model 1 (ReLU)	0.8006	0.7862	0.9175	0.8418	0.5545
Model 2 (ELU)	0.7326	0.6852	0.8875	0.7814	0.6328
Model 3 (tanh)	0.7689	0.7112	0.8913	0.8018	0.6113
Model 4 (Transfer Learning)	0.8119	0.8012	0.9375	0.8651	0.5118

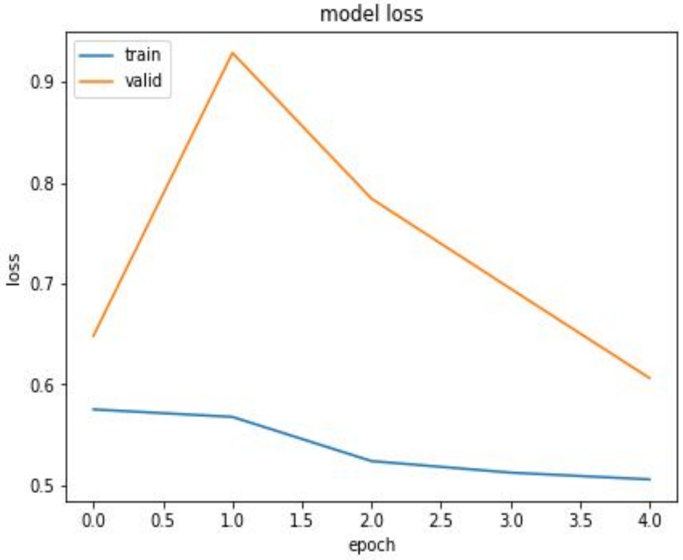
Graph of ReLU Activation Function



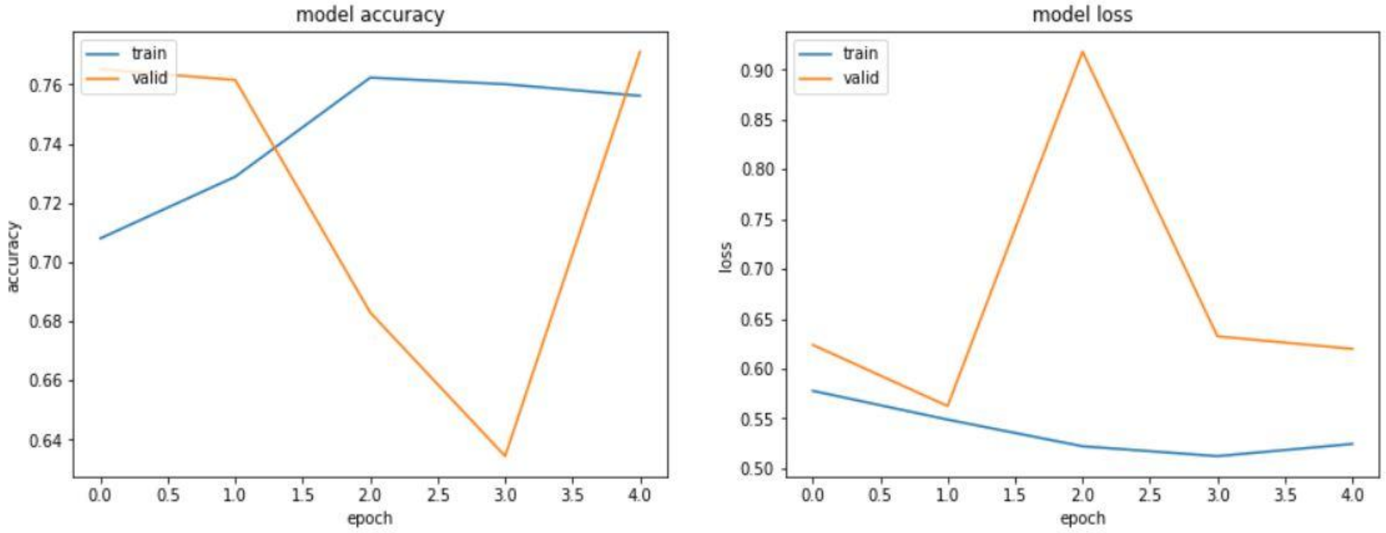


Graph of ELU Activation Function

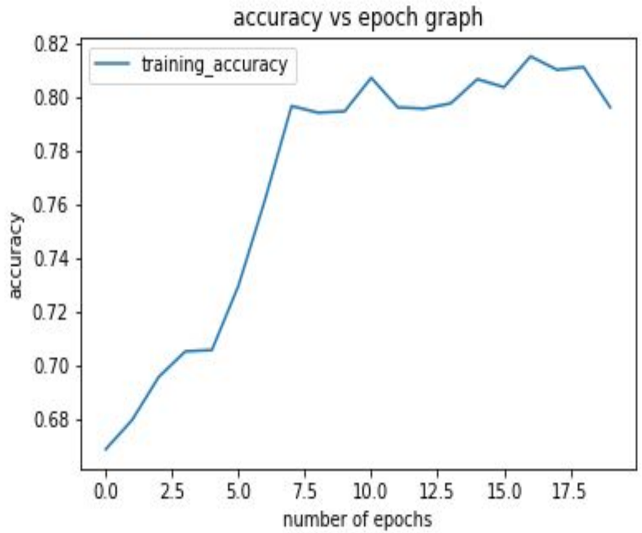


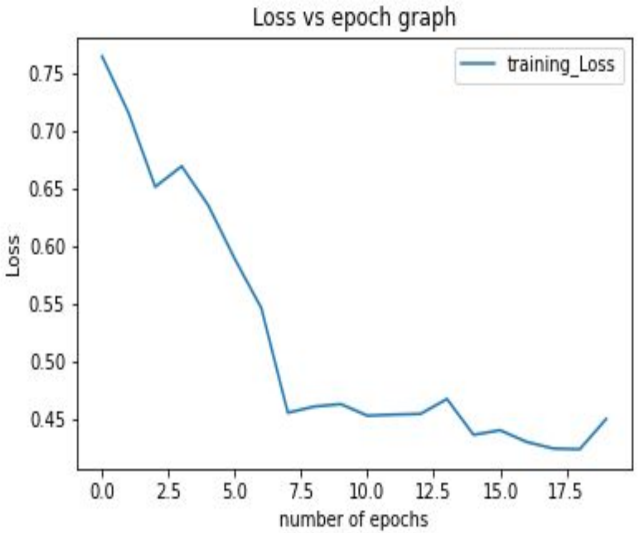


Graph of Tanh Activation Function

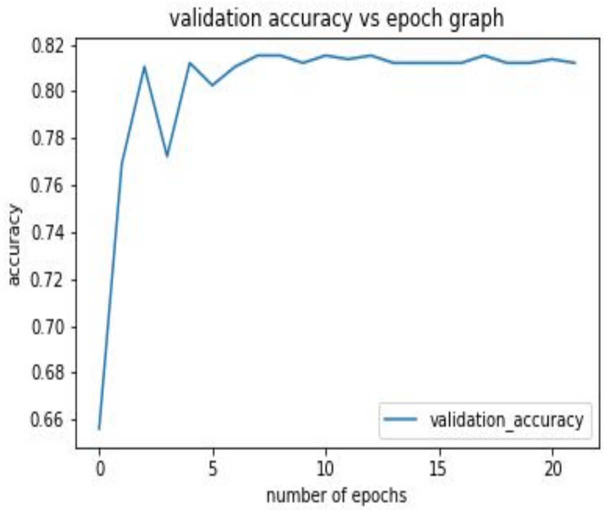


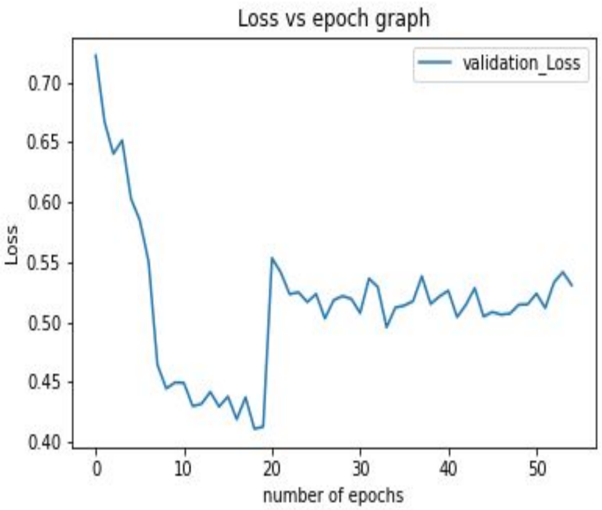
Graph of Transfer Learning Model (Training)





Graph of Transfer Learning Model (Validation)





Conclusion

The heartbeat given as an input to the machine learning model and to classify it as normal or abnormal. We made use of the dataset which was available as a part of Physio-Net 2016 Cardio challenge. During the training phase of the machine learning models we made use of keras an open-source neural network library written in python and its activation functions such as ReLU (Rectified Linear Unit), ELU (Exponential Linear Unit) and Tanh (Hyperbolic Tangent) and proposed a model to compare their accuracy and precision based on the validation set. Along with this we also implemented, Transfer Learning method to predict the result using the VGG16 architecture which allowed us to use the pre-trained models trained on datasets with millions of images. Based on the observations made and results obtained we got an accuracy of 80% from ReLU network of Keras model which is the highest among them and an accuracy of 81.19% from transfer learning model implementation of VGG-16 architecture but when compared with loss VGG-16 performed well than the ReLU network.

Future Enhancements

One of the simplest ways to improve upon the existing model is to use more data. Due to non-availability of data, high computational cost, time and memory constraints we were only able to use a small subset of the complete dataset consisting of 2000 samples for training and 700 for validation. The dataset also had a lot of noise since the heart recordings consisted of people talking and breathing heavily and due to high computational cost it was not possible to do so. Collecting dataset by ourself and conducting the experiment would provide more accuracy. We have built four different models and experimenting like this with other different parameters and cnn models might also yield a better result.

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Thank You

- Presented by:

1.	Avani H S	4VV16CS016
2.	Madhu S	4VV16CS051
3.	Manoj Athreya A	4VV16CS055
4.	Pooja	4VV14CS064