DREXEL UNIVERSITY
College of Computing & Informatics

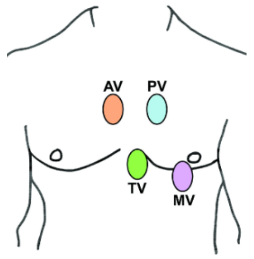
Deep Learning for Heart Disease Prediction

Instructor: Dr.Milad Toutounchian
Team members: Ziao You, Weijie Chen, Yixuan Song, Kan Kim, Xiao Fang

CardioWave Forecaster

Introduction

Heart disease is a prevalent health issue, and early detection can significantly improve patient outcomes. Our project aims to develop a deep learning system for predicting heart disease from heart sound recordings. Traditional imaging techniques like MRI and CT scans can be time-consuming and resource-intensive. Our project leverages the power of deep learning to analyze heart sound recordings, providing a faster and more accessible alternative for initial screening.



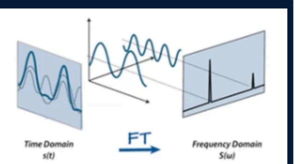
Methodology

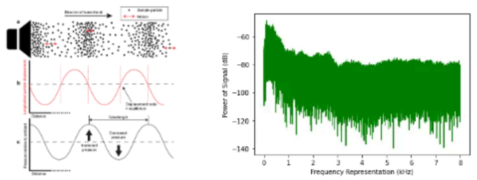
Our methodology involves three main components: data preprocessing, conventional machine learning, and deep learning experiments. The dataset used is the CirCor DigiScope Phonocardiogram dataset, which contains totaling 33.5 hours of audio data. We employed various techniques to preprocess the data, including filtering, thresholding, and data augmentation. For conventional ML, we explored algorithms like Logistic Regression, and SVM, trained on audio features and patient metadata.

Preprocessing

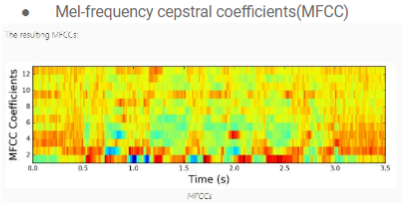
There are several preprocess together with data transformation. Pre-filtering involved removing portions of the audio that did not contain heartbeats. Cutting off frequencies above 450Hz to focus on the relevant frequency range. Subseting of the audio with different durations can increase the diversity of the training data.

- Fourier Transforms



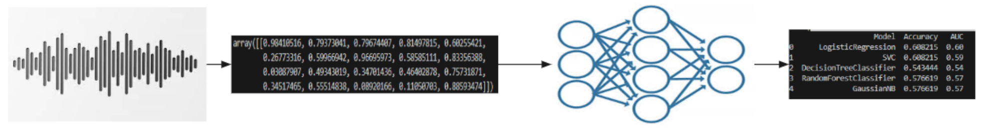


- Mel-frequency cepstral coefficients(MFCC)



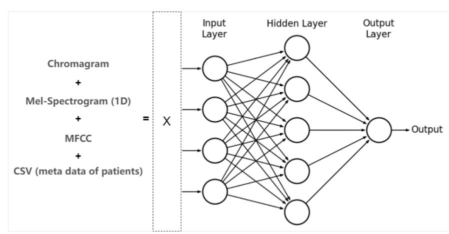
Conventional ML

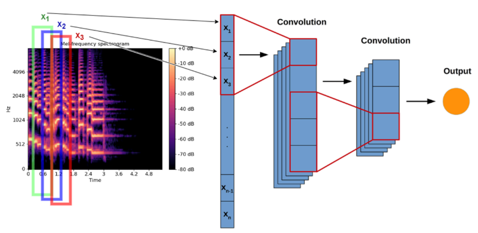
Conventional ML approaches were explored as a baseline for heart disease prediction. We trained models like Logistic Regression, Support Vector Machines, and Random Forests on a combination of audio features and patient metadata. These features included Mel-Frequency Cepstral Coefficients (MFCCs), chromatograms, mel-spectrograms, and patient demographics.

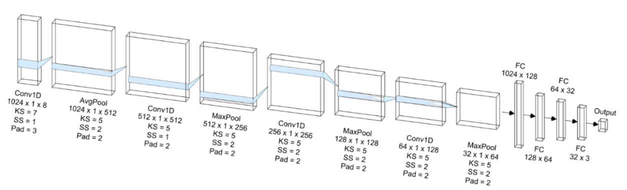


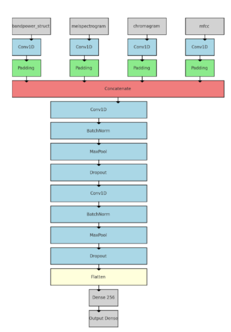
DL Experiments

Deep learning techniques were extensively explored for this project, including Multilayer Perceptrons (MLPs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and ensemble models. We experimented with various architectures and input representations, such as 1D-CNNs on MFCCs, MLPs, and CNNs on concatenated features (chromatograms, mel-spectrograms, MFCCs, and patient data), and 2D-CNNs on mel-spectrograms. Additionally, we investigated advanced models like multiscale CNNs and Conv-RNNs, which combine the strengths of convolutional and recurrent layers for analyzing sequential data.



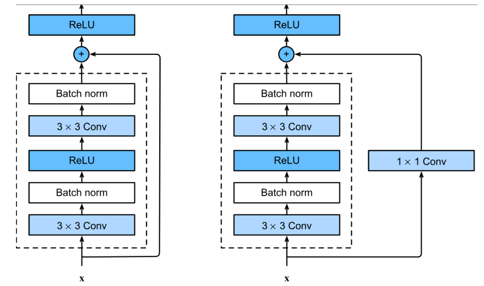


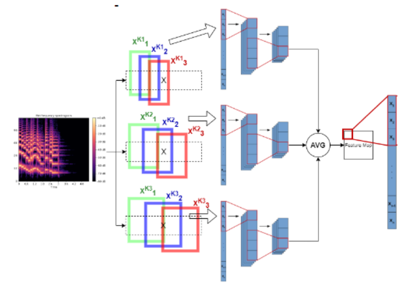




Advanced Models

To further enhance the performance of our heart disease prediction system, we explored advanced deep learning architectures like Residual Networks (RESNETs) and Multiscale CNN. RESNETs allow more effective training of deeper models. Multiscale CNN enhance the model's ability to learn relevant patterns in the heart sound data.





Results

The best-performing model was an ensemble approach that combined multiple MLPs trained on different feature representations, achieving a test accuracy of around 66%. Also, a CNN model trained on concatenated features achieved a test accuracy of 64.22%.

Model	Feature									Normalization	Test Set (%)			Train Set (%)		
	Chromagram	1D Mel-Spec	2D Mel-Spec	MFCC	Bandpower Struct	Opensmile	NMF	CSV	Time Series		Accuracy	F1	AUC	Accuracy	F1	AUC
Single MLP	☑	☑	☐	☑	☐	☑	☐	☑	☑	Raw	66.46	67.28	66.45	100	100	100
2D CNN	☐	☐	☑	☐	☐	☐	☐	☐	☐	Raw	56.01	49.64	56.05	79.82	77.88	80.31
Multiscale 2D CNN	☐	☐	☑	☐	☐	☐	☐	☐	☐	Scaled	58.23	66.5	58.15	60.98	68.63	60.08
1D CNN	☐	☐	☐	☐	☑	☐	☐	☑	☐		68.95	54.33	67.07			
1D CNN	☐	☑	☐	☐	☐	☐	☐	☐	☐		67.65	53.74	65.83			
concat-cnn	☑	☑	☐	☑	☑	☐	☐	☑	☐		64.22	54.28	63.94			
conv-rnn	☑	☐	☐	☐	☐	☐	☐	☑	☐		64.38	50	64.87			
ResNet	☐	☐	☑	☐	☐	☐	☐	☐	☐	MinMax	55.22					
Concat-MLP	☑	☑	☐	☑	☑	☐	☐	☐	☐	Raw	59.11			61.82		
LSTM	☐	☐	☐	☐	☐	☐	☐	☐	☑	Raw	53.85			51.33		
RNN	☐	☐	☐	☐	☐	☐	☐	☐	☑	Raw	50			51.53		

Future Works

There are several avenues for further improvement and future work. One key area is the exploration of alternative feature representations, such as the Wavelet Scattering Transform (WST), which has shown potential for better representation of time-series data like heart sound recordings.

Additionally, we plan to conduct more extensive hyperparameter tuning and optimization for our DL models.