ABNORMALITY DETECTION USING HEART SOUNDS

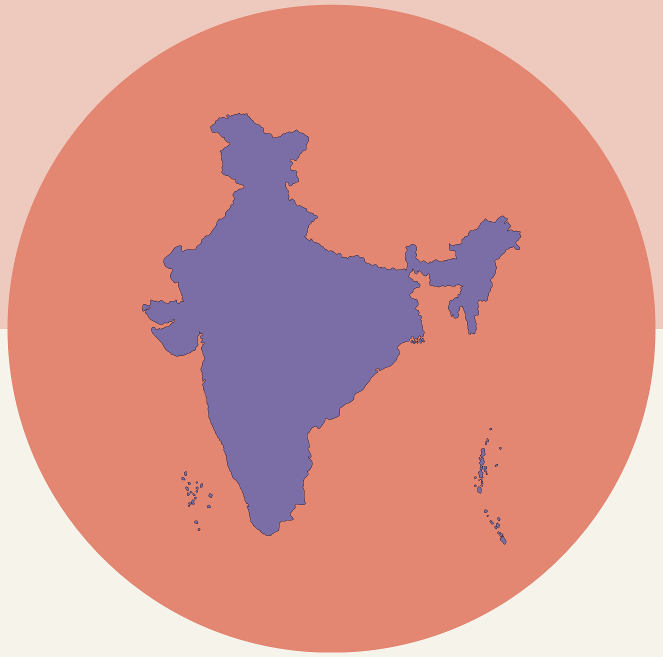
Angad Singh, Malhar Bhise, Suhani Jain, Yuvna Jain

RELEVANCE OF PROBLEM

Cardio Vascular Disease took

20.5 MILLION

lives in 2023

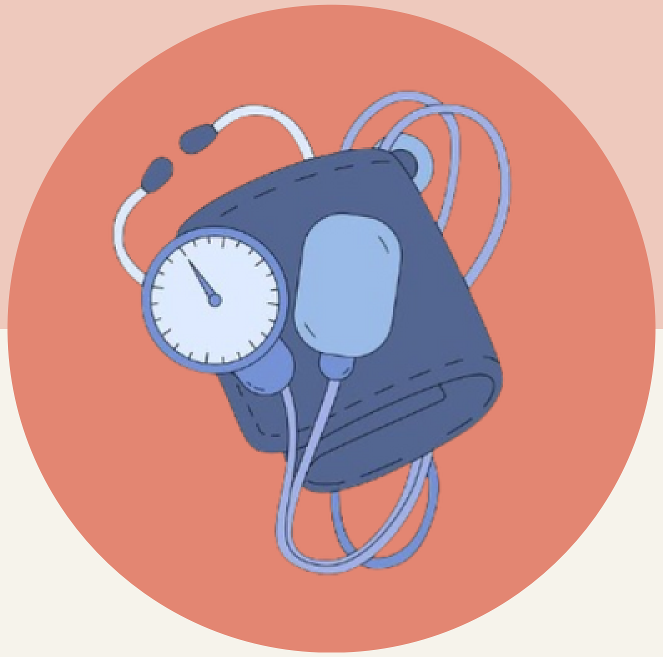


Cardio Vascular Disease death rate of

272 per 100000

population in India which is much higher than that of global average of 235.

CVDs strike Indians a decade earlier than the western population.



27.9% were aware of their hypertension status.

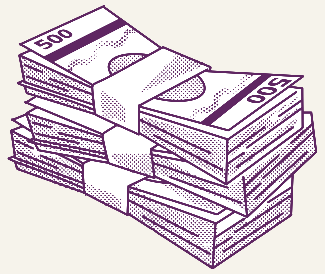
14.5% were under treatment for hypertension.

12.6% had their blood pressure under control.

PROBLEM STATEMENT

Our objective is to employ machine learning for the analysis of heart sounds collected via devices such as a digital stethoscope, to facilitate the early identification of cardiac abnormalities such as murmurs.

We aim to expand this feature to smartphones, where people can easily check their heart health and seek medical advice if necessary.



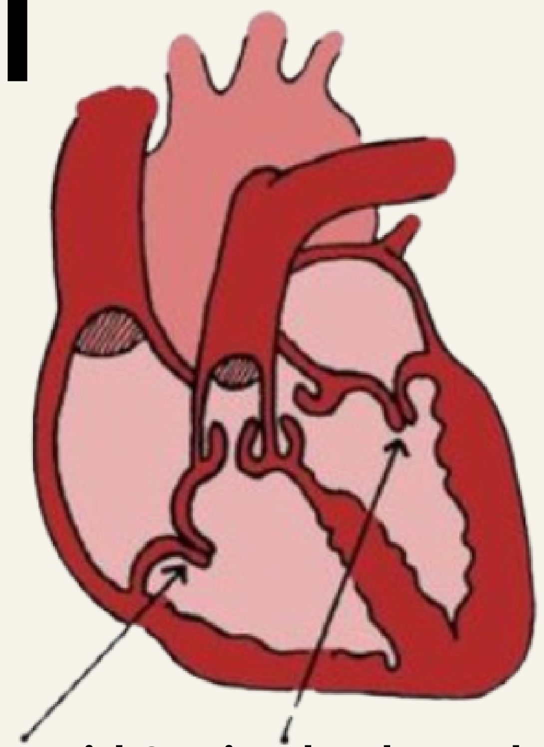
Cost Efficienct

Timely intervention leads to better management and treatment outcomes

By deploying this solution globally, especially in low-resource settings, there could be a significant improvement in global health outcomes related to heart diseases

LITERATURE REVIEW I

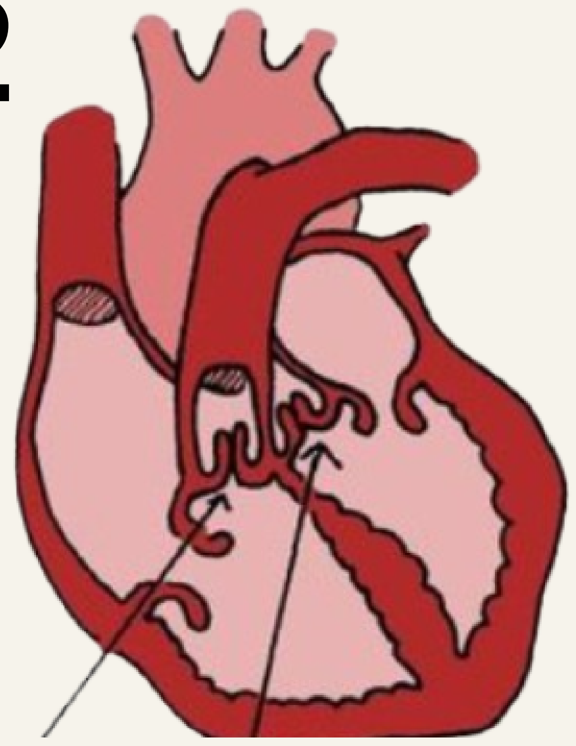
S1



Tricuspid & Mitral valves close

‘Lub’

S2



Aortic & Pulmonic valves close

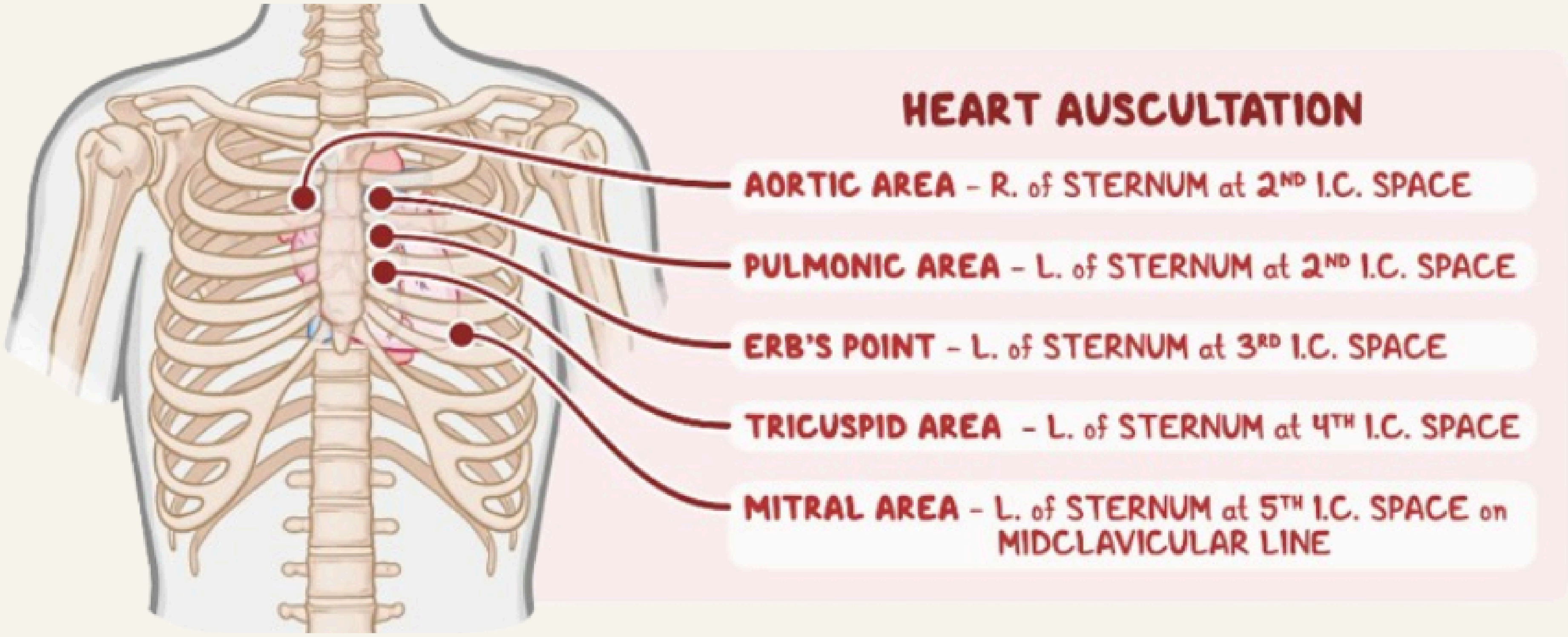
‘Dub’

S3: Ventricular Gallop

- May be normal at times
- Can be a sign of systolic congestive HF

S4: Atrial Gallop

- Almost always abnormal
- Can be a sign of diastolic congestive HF



LITERATURE REVIEW II THE MODEL

PRE- PROCESSING

FEATURE EXTRACTION

CLASSIFICATION

PRE-PROCESSING

Step 1

Basic Denoising

Butterworth high Pass filter
Below 30Hz
Removes breathing and other background

Sampling Rate Reduction
Original -> 2000 Hz
Processing time is saved

Step 2

Advanced Denoising

Traditional and most popular - DWT
Decomposes into individual frequencies.

Recently popular - SVD
Breaks into 3 matrixes, identifies “low singular values”.

Chorba, J. S., Shapiro, A. M., Le, L., Maidens, J., Prince, J. T., Pham, S., Kanzawa, M. M., Barbosa, D. N., Currie, C., Brooks, C., White, B., Huskin, A., Paek, J., Geocaris, J., Elnathan, D., Ronquillo, R., Kim, R., Alam, Z., Mahadevan, V. S., . . . Thomas, J. D. (2021). Deep learning algorithm for automated cardiac murmur detection via a digital stethoscope platform. Journal of the American Heart Association, 10(9). https://doi.org/10.1161/jaha.120.019905

FEATURES EXTRACTED

- Short-time Fourier Transform **(STFT)**

Decompose the signal into its frequency components over time.
Which frequencies? - dominant frequency information
When they are present? - temporal information
Analyses how the frequency content of a signal changes over time.

- Mel Spectrogram

A visual representation of the spectrum of frequencies of a signal as it varies with time.

- Mel-Frequency Cepstral Coefficients **(MFCC)**

Coefficients extracted from Mel Spectrogram - represent the spectral characteristics of an audio signal.

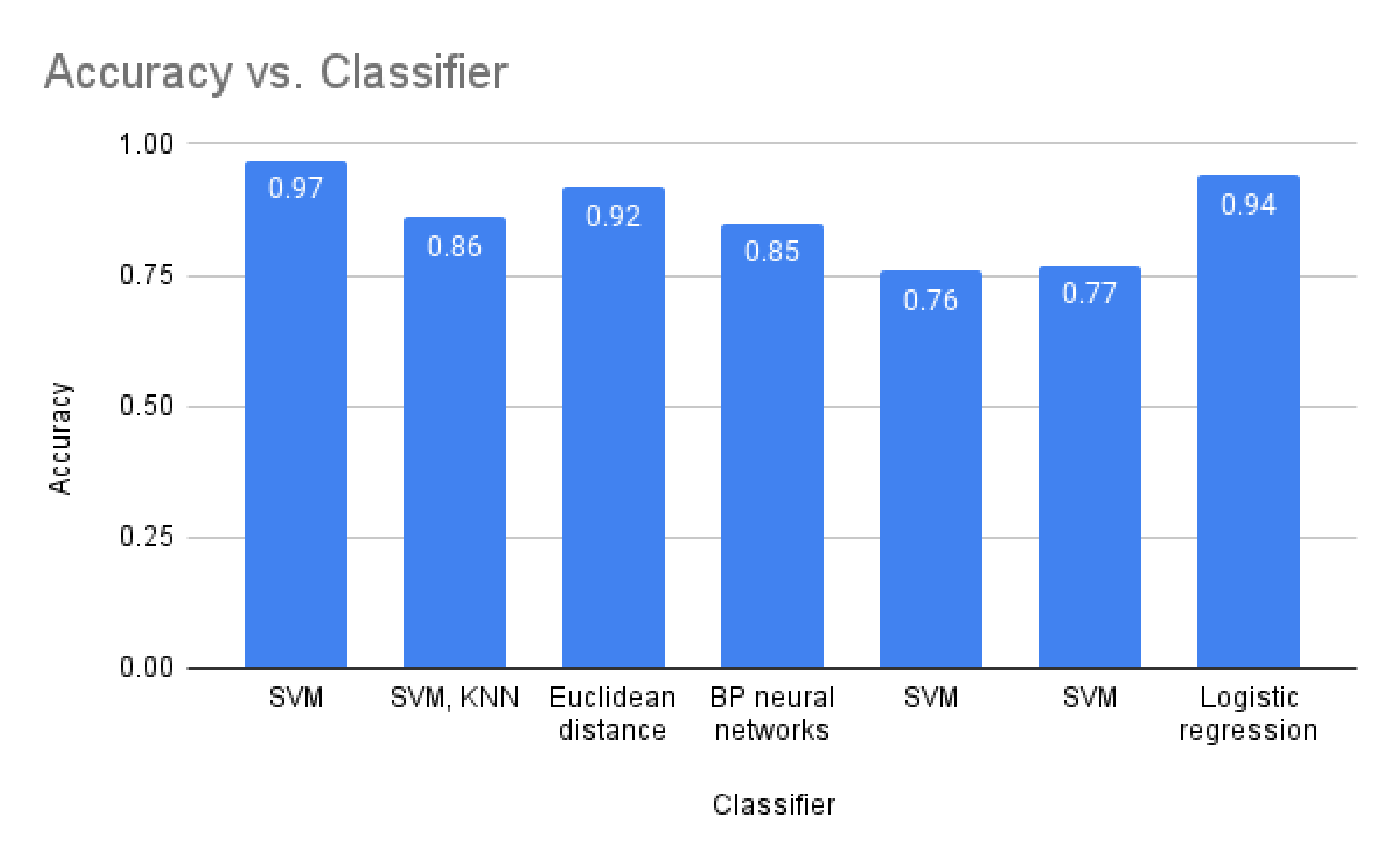
Li, S., Li, F., Tang, S., & Xiong, W. (2020). A review of Computer-Aided Heart Sound Detection Techniques. BioMed Research International, 2020, 1–10. https://doi.org/10.1155/2020/5846191

CLASSIFICATION

- The goal of classification is to present the qualitative results of the detection, dividing the heart sound signals into the normal or abnormal.

- Support Vector Machine (SVM), Artificial Neural Networks (ANN), k-Nearest Neighbor (kNN), Euclidean distance, etc. .

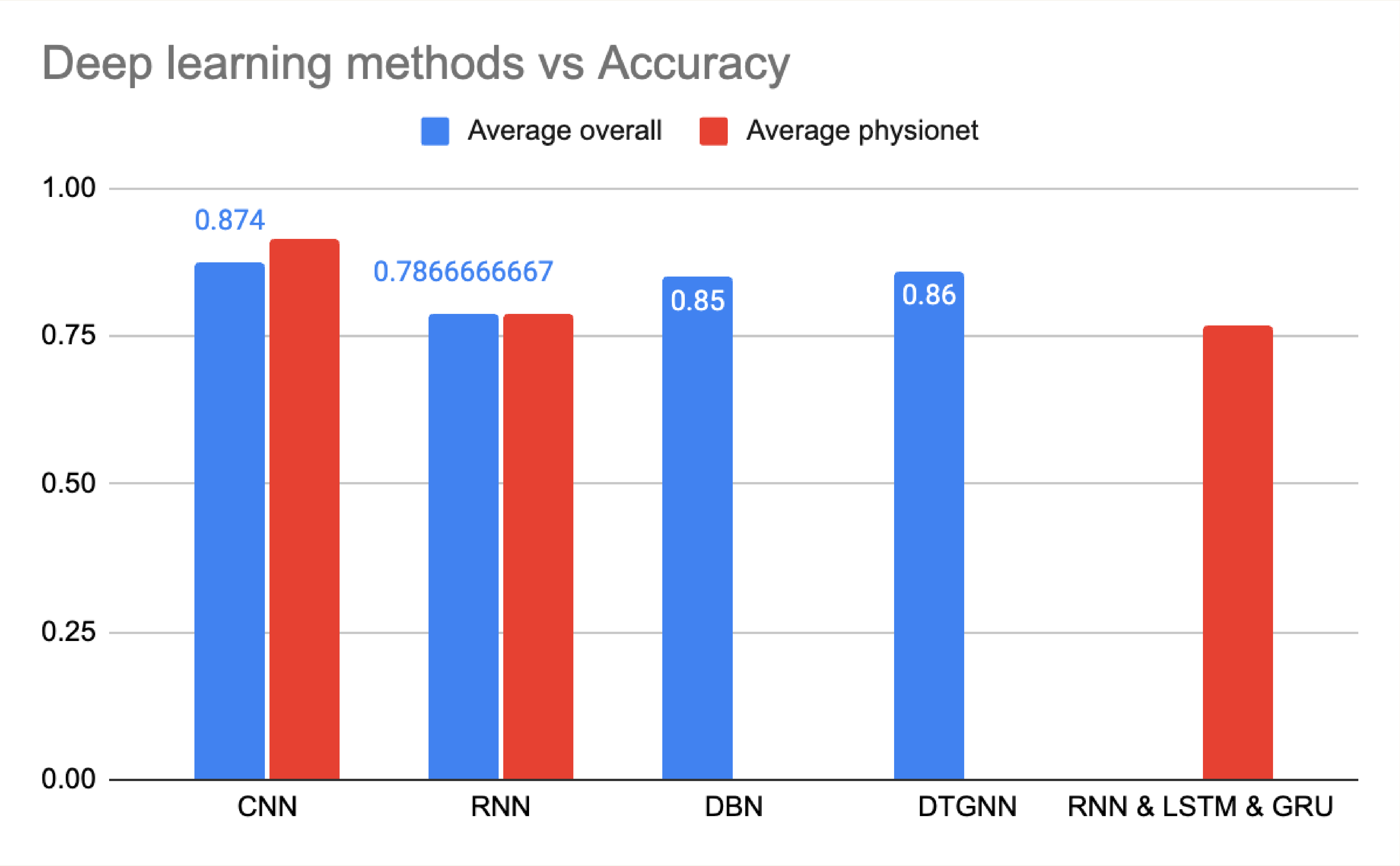
- **Most popular and accurate - SVM**



Mean of MAcc calculated where available.

CLASSIFICATION: DEEP LEARNING MODELS

- Most popular - CNN
- CNN suited for spectral and temporal data / DNN general purpose
- CNN's - Highest accuracy



Malik, H., Bashir, U., & Ahmad, A. (2022). Multi-classification neural network model for detection of abnormal heartbeat audio signals. Biomedical Engineering Advances, 4, 100048. https://doi.org/10.1016/j.bea.2022.100048

DRAWBACKS AND OUR IMPROVEMENTS

Challenges

- Black-box models (interpretability)
- Data availability
- Research vs. real-world gap, stakes are too high.

Solutions

- Data improvement and tweaking for specific use-cases.
- Catering it to a specific relatively low-stakes problem - At home detection using phones.

LITERATURE REVIEW: PHYSIONET CHALLENGE

Performance metrics of the winners

Team	Cost	Weighted accuracy
CUED_Acousitcs	11144	0.821
prna	11403	0.8
Melbourne_Kangas	11735	0.755

Some methods used by the top ten winners:

Preprocessing:
- Downsampling (100Hz, 2000 Hz)
- Butterworth filter (25 Hz - 400 Hz)
- MFCC of 3/10 second segments
- Cutout, cutmix, mixup

Features:
- STFT, Mel spectogram
- Time domain embedding vector

Model:
- CNN
- Light CNN
- Vision transformer

The PhysioNet Challenge description paper: Reyna, M. A., Kiarashi, Y., Elola, A., Oliveira, J., Renna, F., Gu, A., Perez-Alday, E. A., Sadr, N., Sharma, A., Mattos, S., Coimbra, M. T., Sameni, R., Rad, A. B., Clifford, G. D. (2022). Heart murmur detection from phonocardiogram recordings: The George B. Moody PhysioNet Challenge 2022. medRxiv, doi: 10.1101/2022.08.11.22278688

DATASET: CIRCOR DIGISCOPE PHONOCARDIOGRAM DATASET V1.0.3

Collection and Ethics

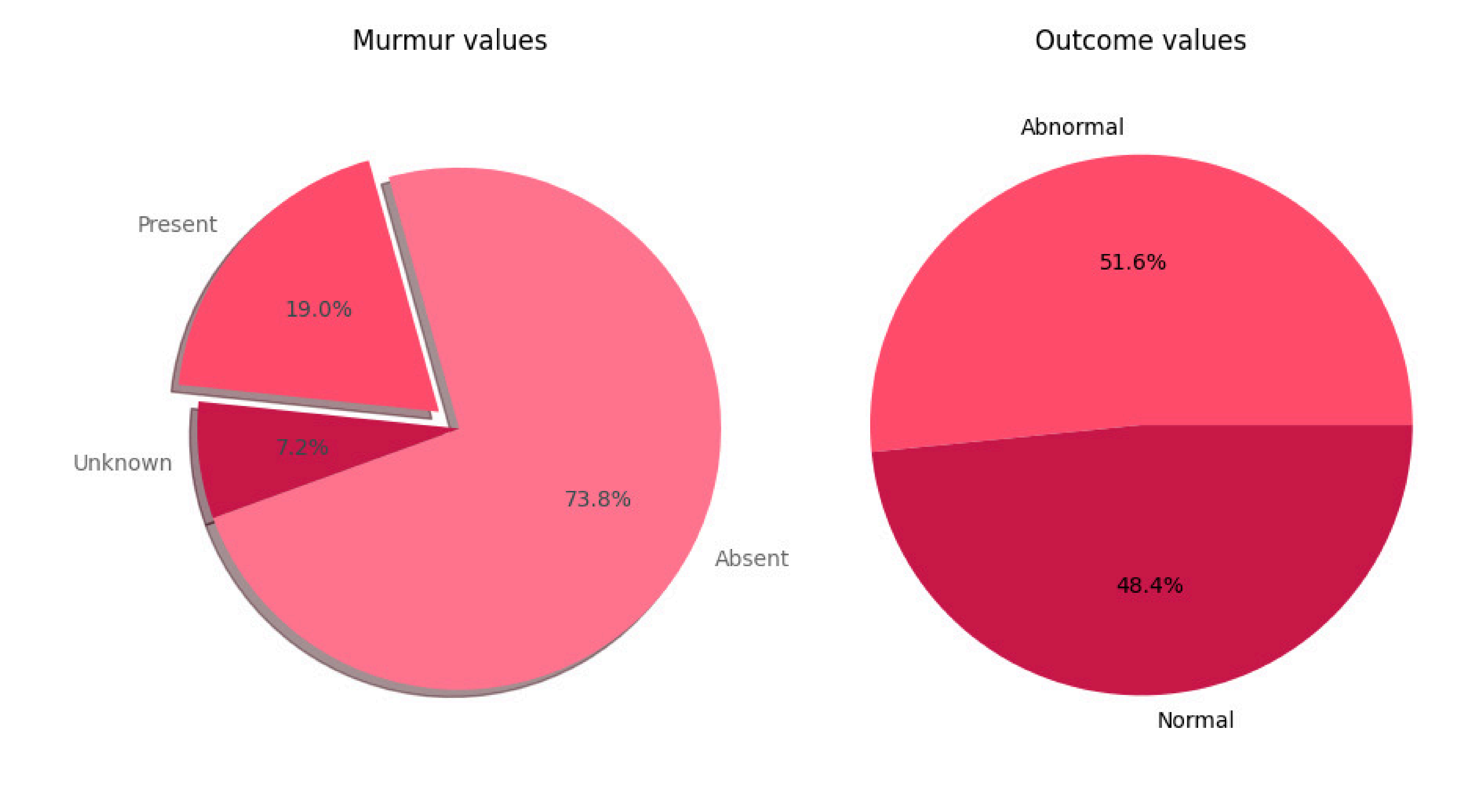
- Pediatric population **(0 - 21)**
- Mass screening campaigns - Northeast **Brazil**.
- Parental **permission obtained.**

- 943 patients-3163 recordings (60%)
- Segmented Data file provided
- 4 auscultation locations, demographic data.
  - **Murmur presence/absence** (by expert annotator)
  - **Clinical outcomes** (normal/abnormal)

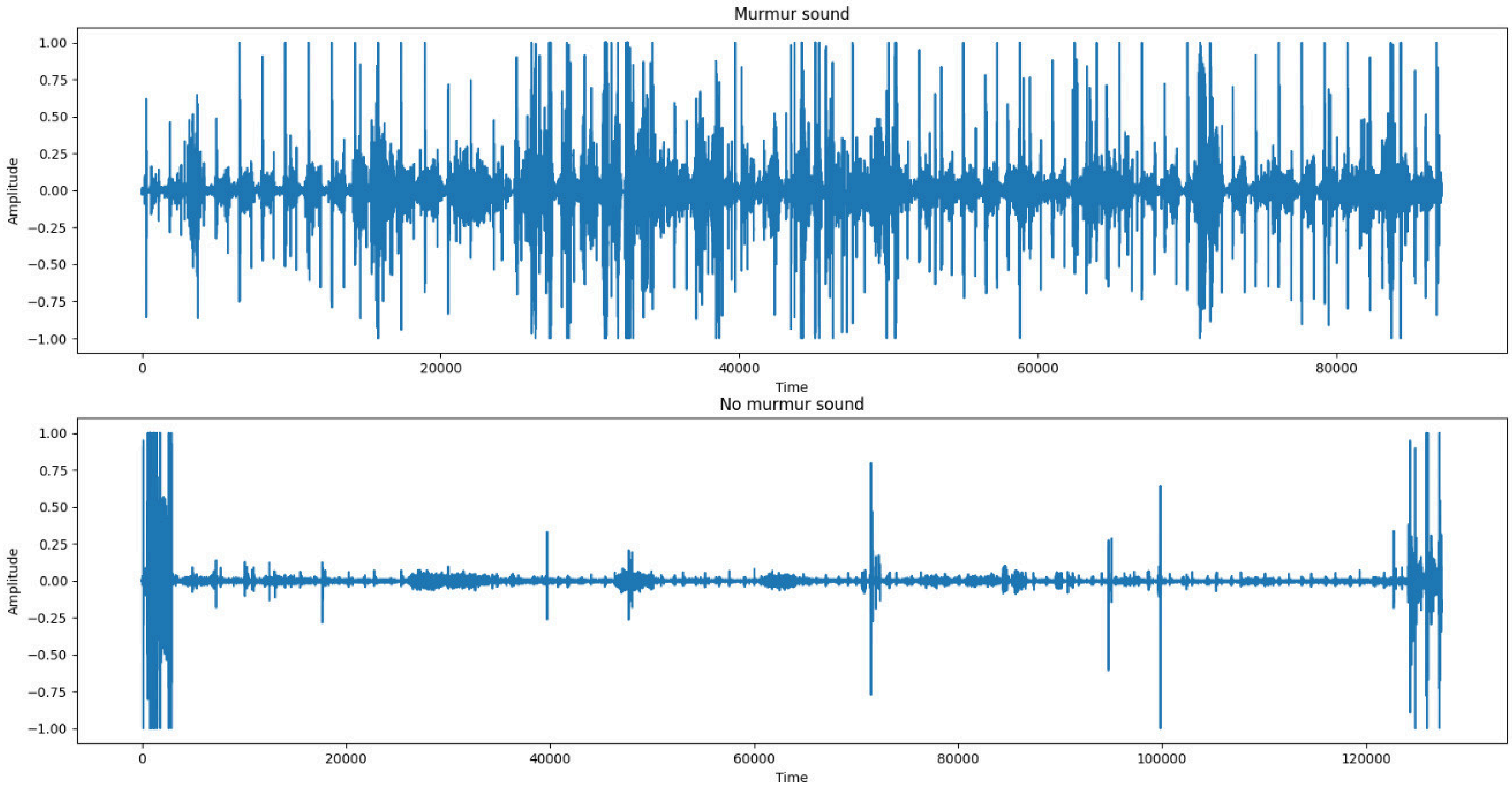
Why we chose it

- **Largest dataset available** for raw audio data. (3000 datapoints)
- Extensive **labelling by medical** professionals.
- **4 auscultation locations** - helps with phone irregularity.
- Pre-segmented data for start and end of S1 and S2.
  - Segmentation is a non-trivial problem.
  - Other dataset's we will try to segment in order to integrate.

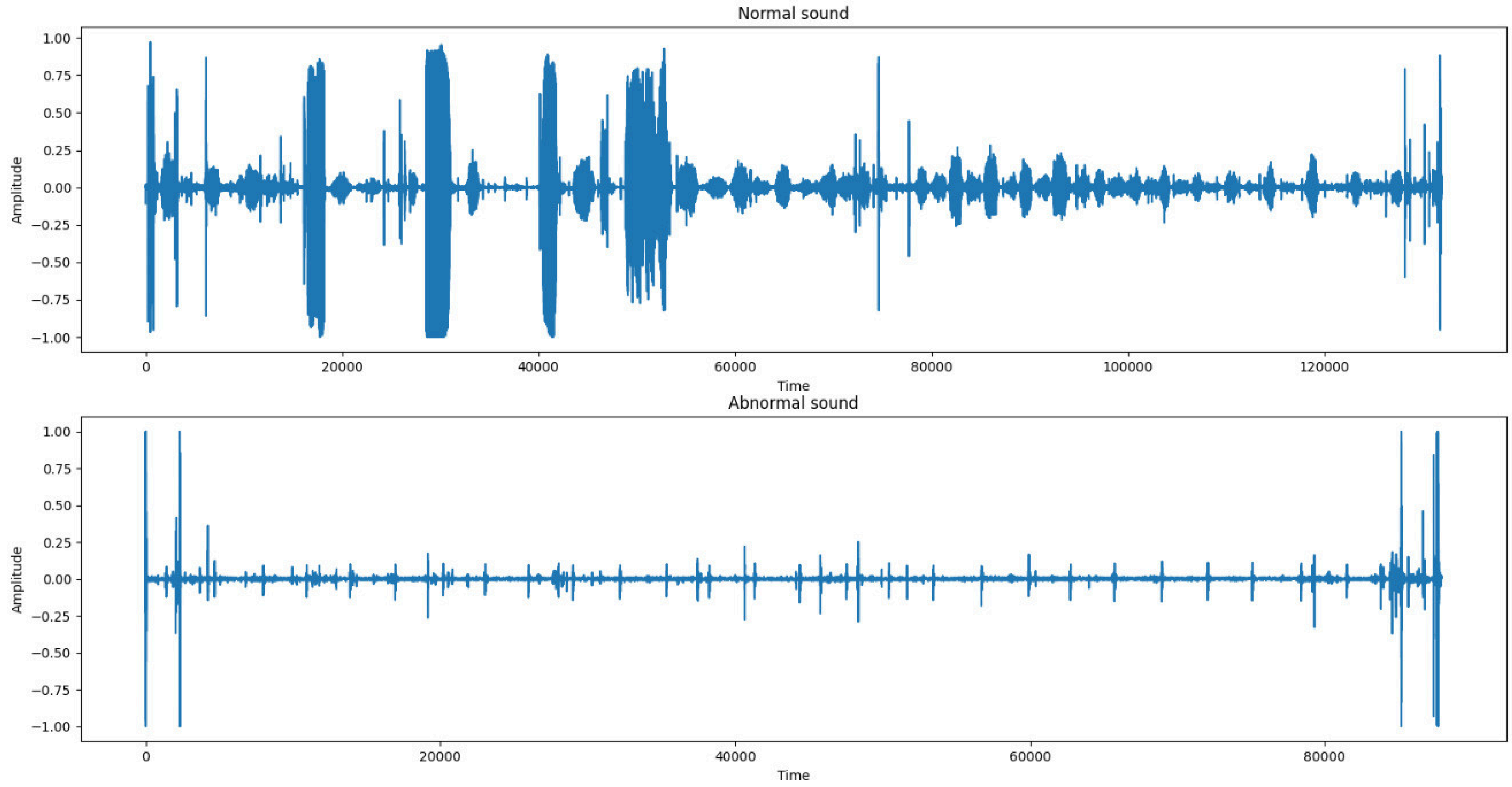
DATASET: CIRCOR DIGISCOPE PHONOCARDIOGRAM DATASET V1.0.3



PHYSIONET : MURMER V/S NO MURMER



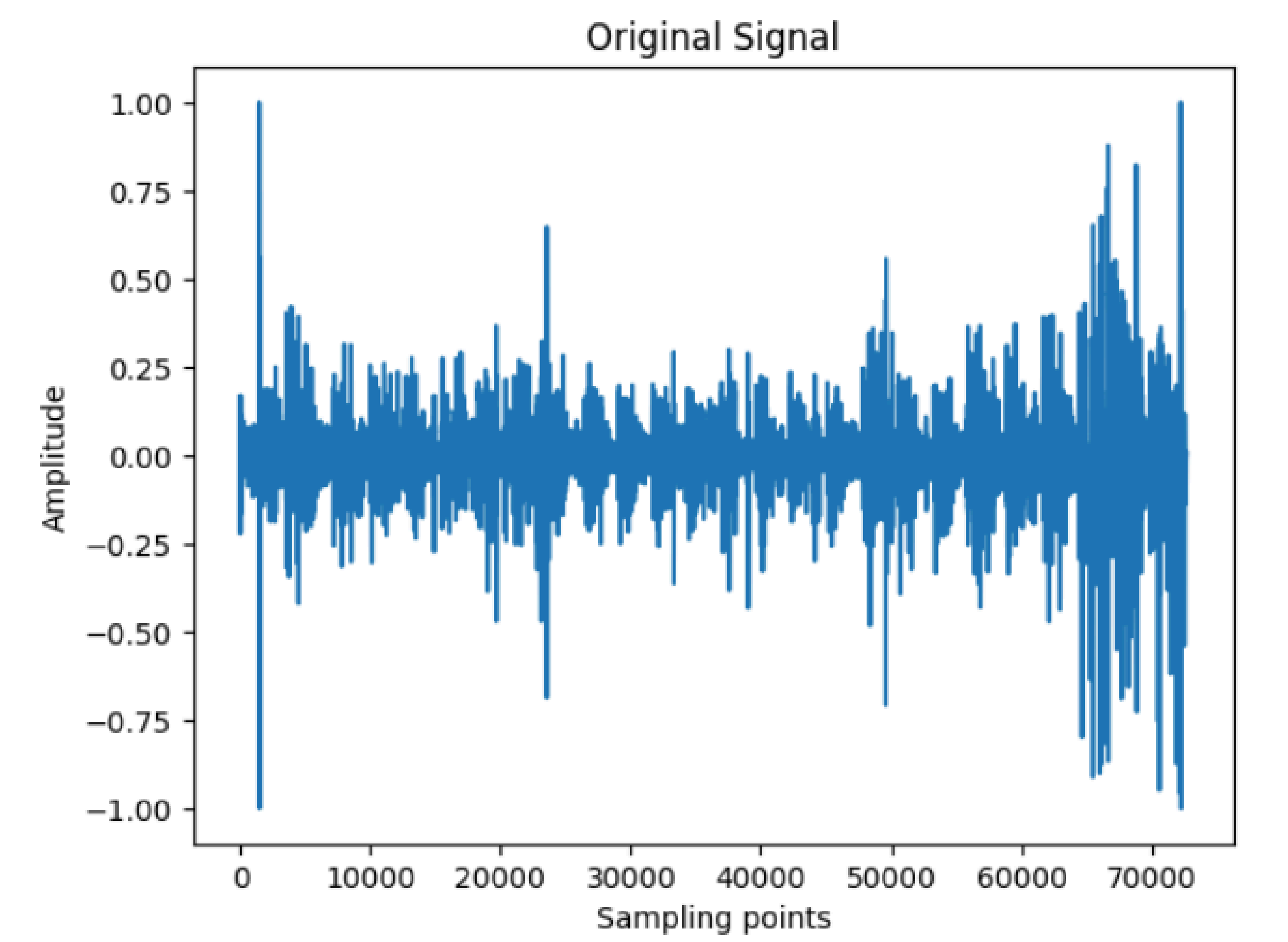
PHYSIONET : CLINICAL OUTCOME TIME V/S AMPLITUDE

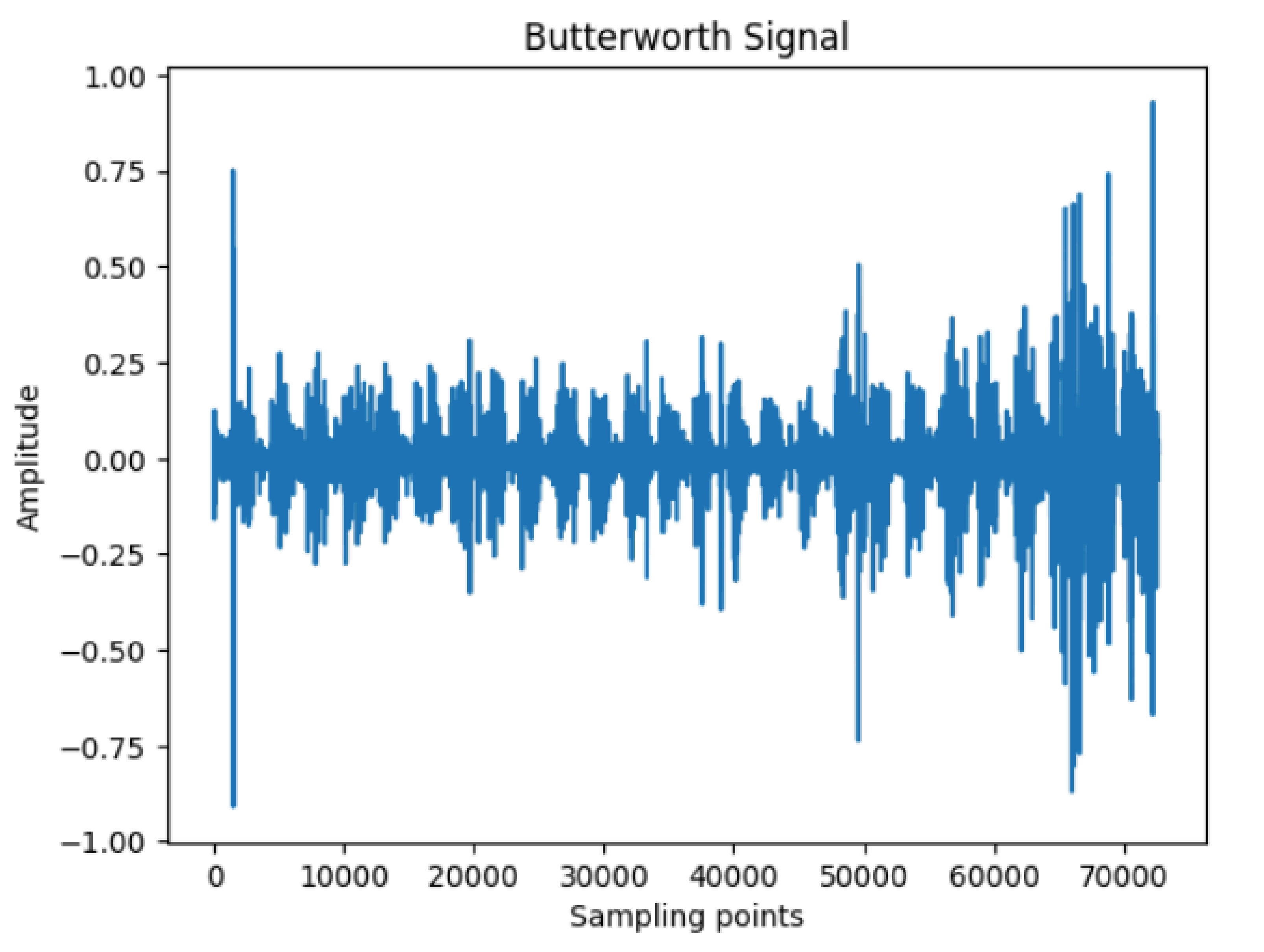


PRE-PROCESSING

Signal processing filter: Butterworth bandpass filter

25 Hz, 450 Hz





PRE-PROCESSING

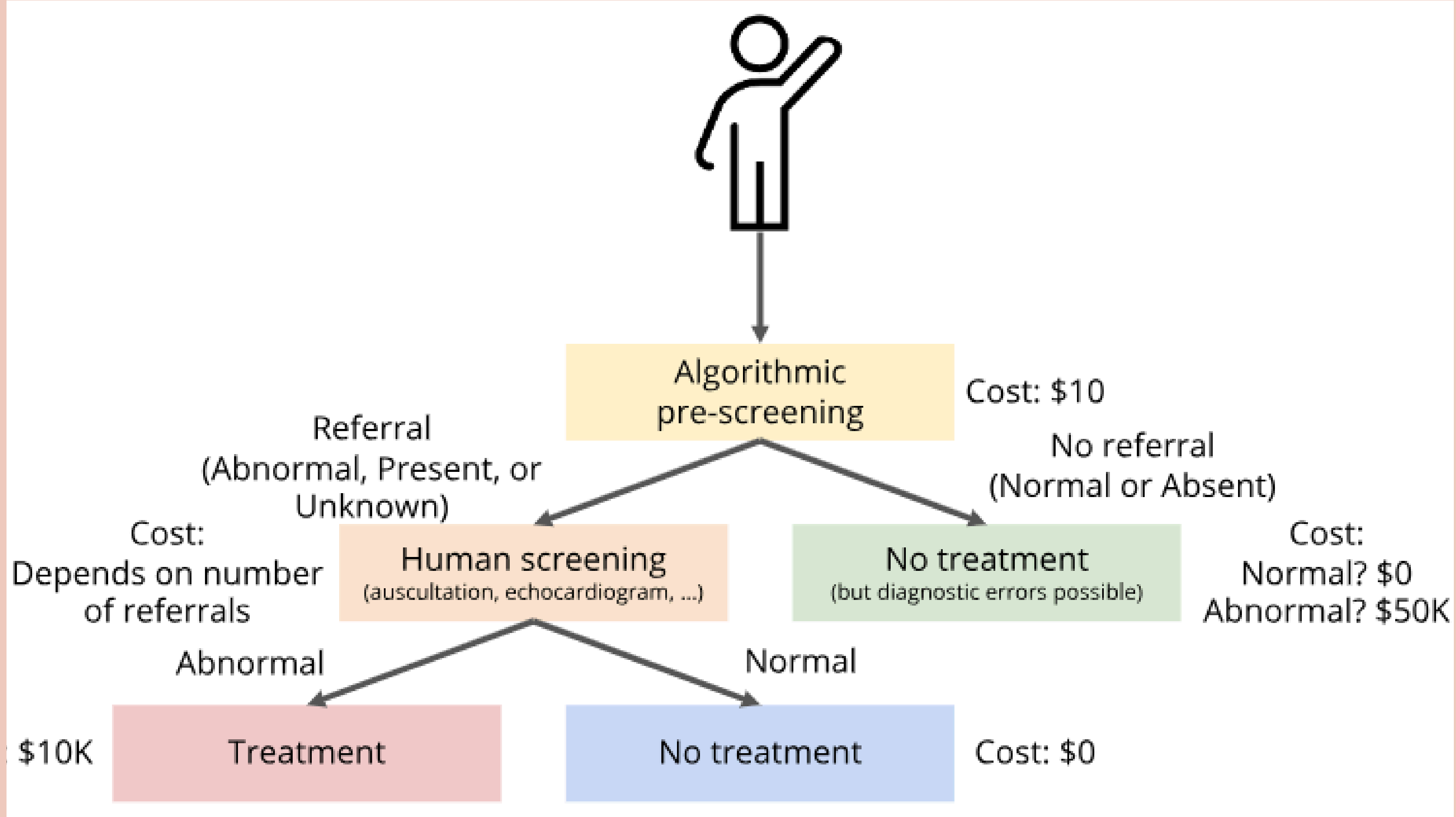
Sampling rate

Physionet data sampling rate: 4000 Hz
Resampled to 2000 Hz

- The sampling rate is the number of samples taken per second
- Consistency across datasets
- Lowers computational demands without losing key information.

PHYSIONET: EVALUATION METRIC

COST FUNCTION



WEIGHTED ACCURACY

Places more importance or weight on patients with murmurs and abnormal outcomes

		Outcome Expert	
		Abnormal	**Normal**
Outcome Classifier	**Abnormal**	n_{TP}	n_{FP}
	Normal	n_{FN}	n_{TN}

$$s_{\text{outcome}} = \frac{5n_{\text{TP}} + n_{\text{TN}}}{5(n_{\text{TP}} + n_{\text{FN}}) + (n_{\text{FP}} + n_{\text{TN}})}$$

THE NAIVE APPROACH – KNN/SVM

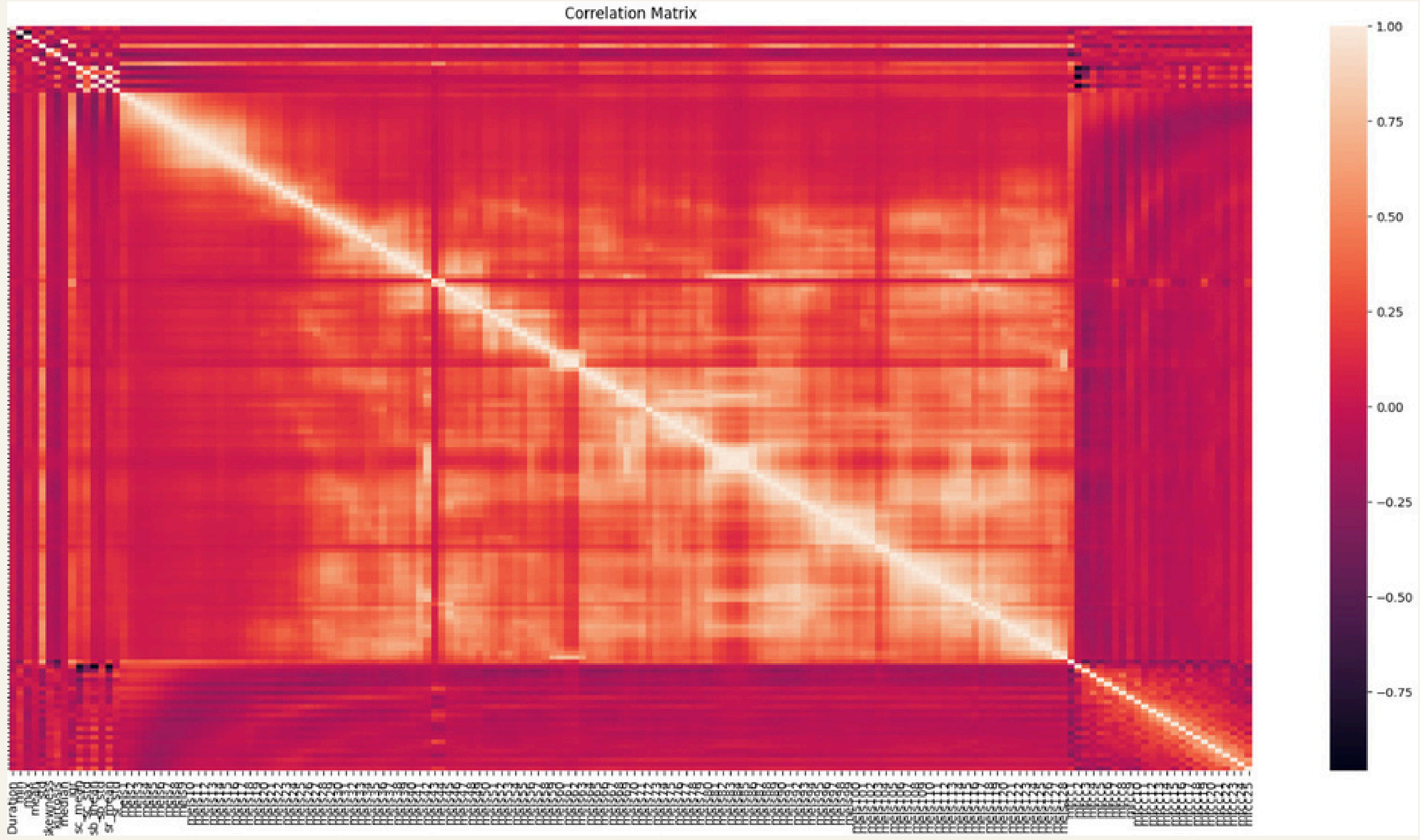
NAIVE APPROACH- FEATURE EXTRACTION

1. **Audio**

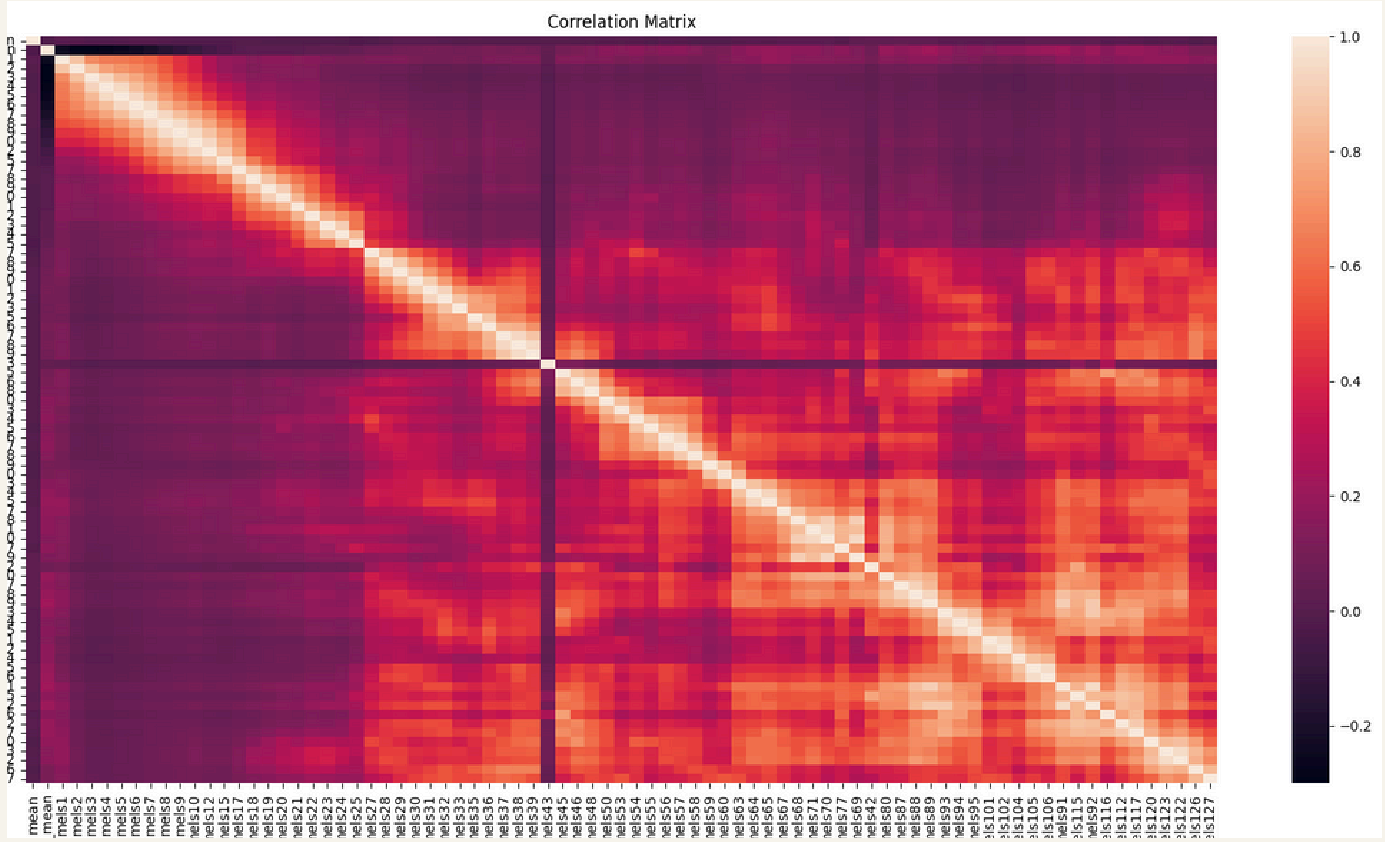
2. Resample to 2000 Hz
   Butterworth filter (25 Hz, 450 Hz)

3.
   - Mean of MFCC's
   - Time domain features (mean, median, standard deviation)
   - Spectral features (Centroid, Roll off, Bandwidth)

4. Feature selection using correlation matrix
   70 features selected

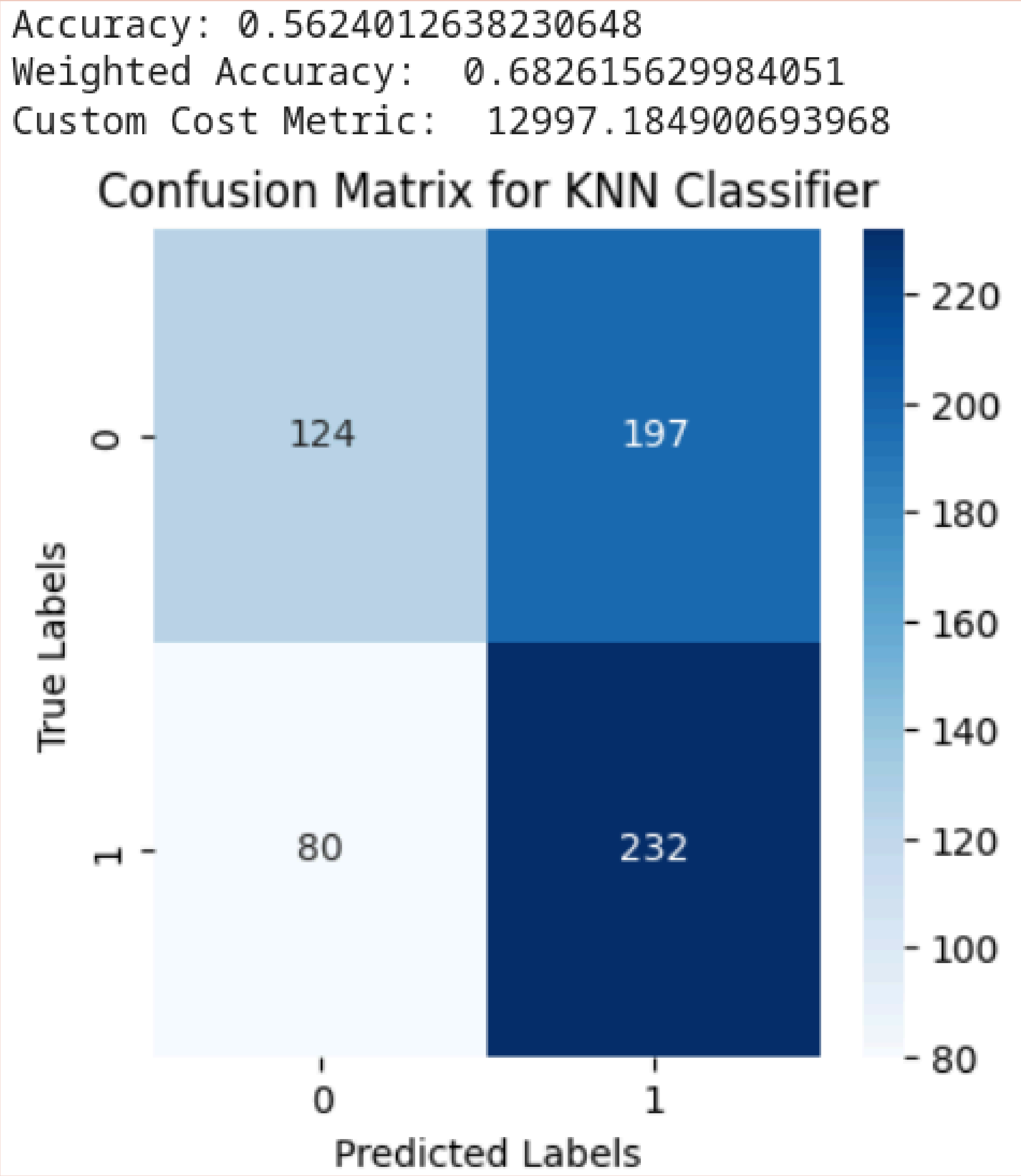


Initial correlation matrix



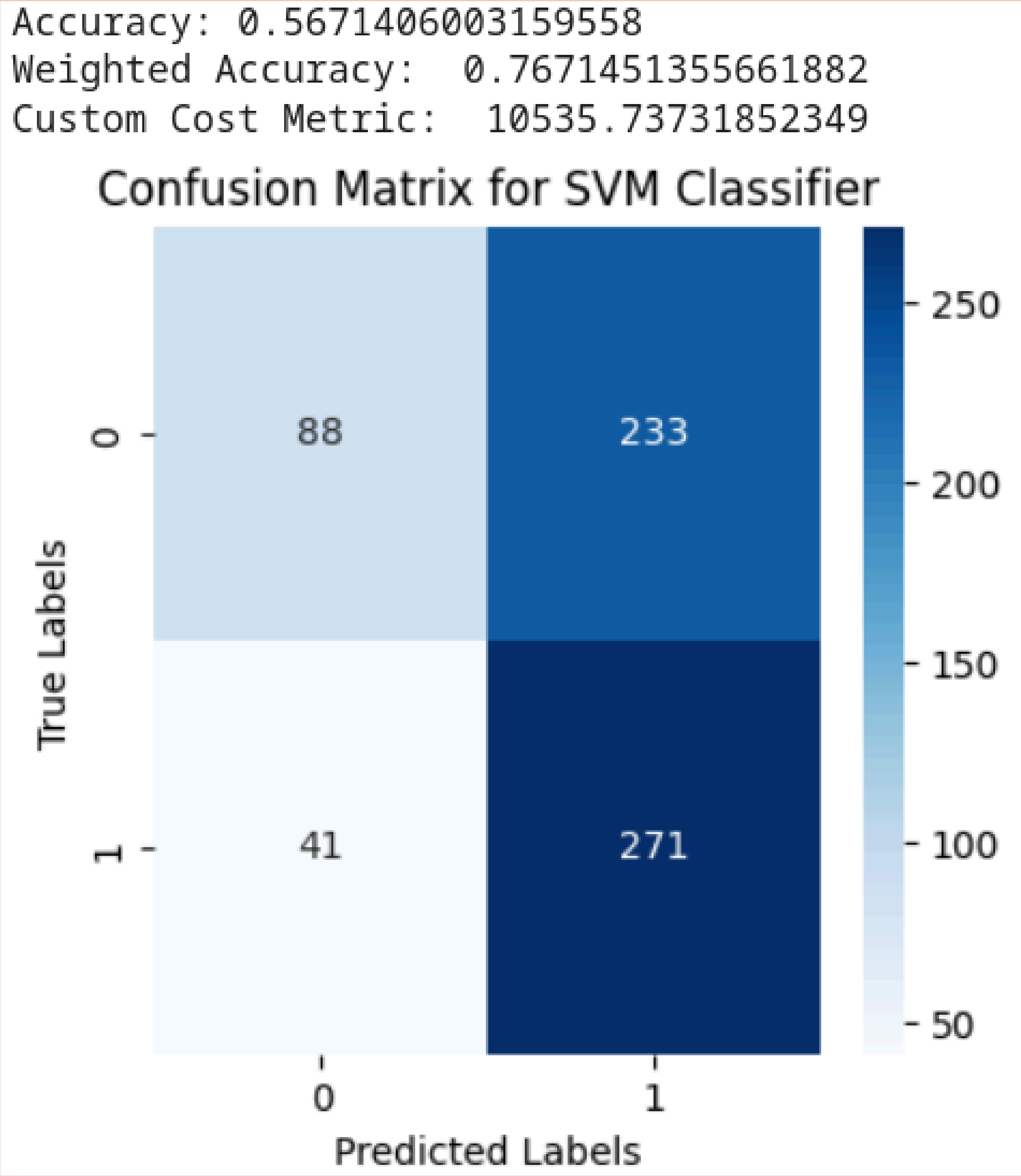
Final correlation matrix

KNN



ABNORMAL - 1, NORMAL - 0

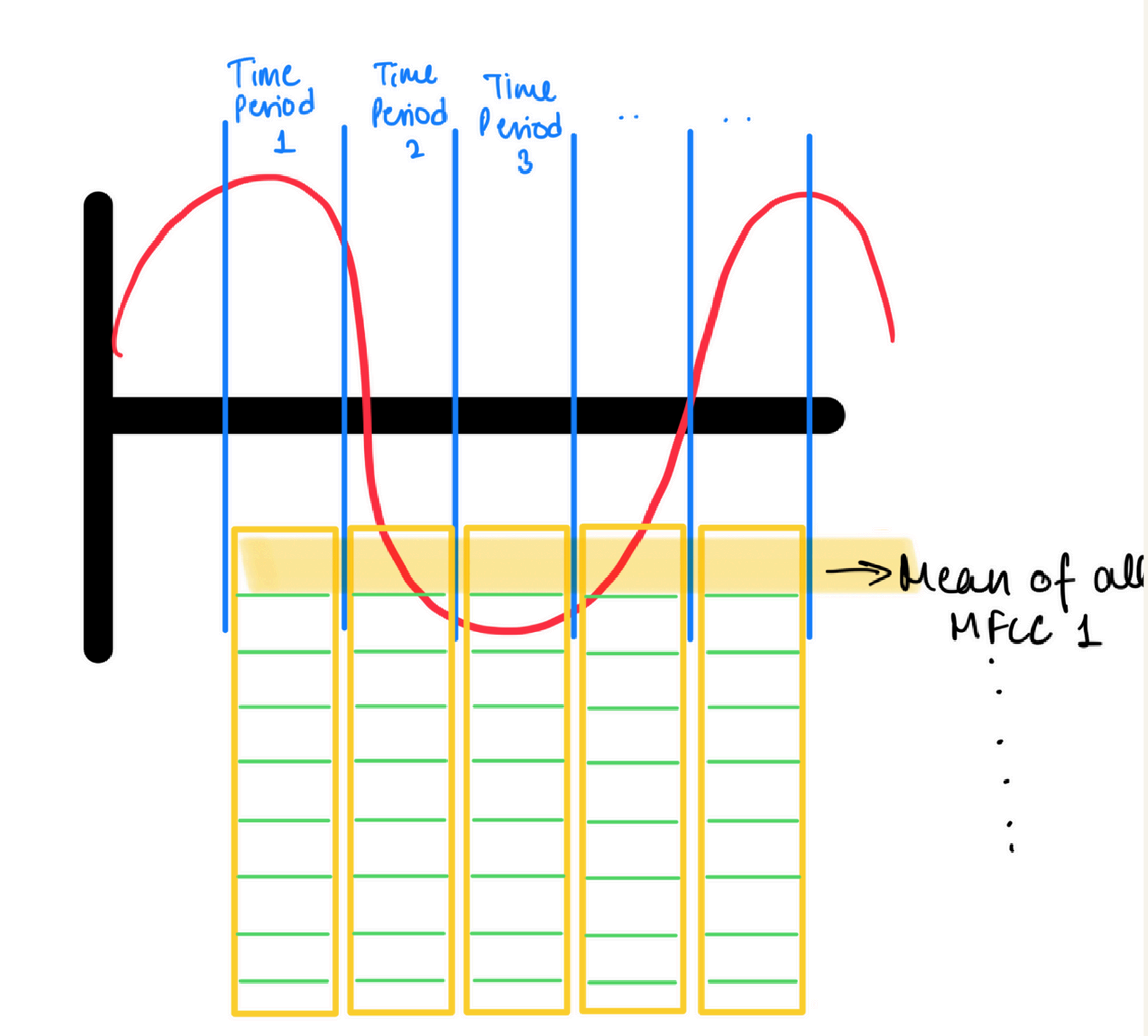
SVM



ABNORMAL - 1, NORMAL - 0

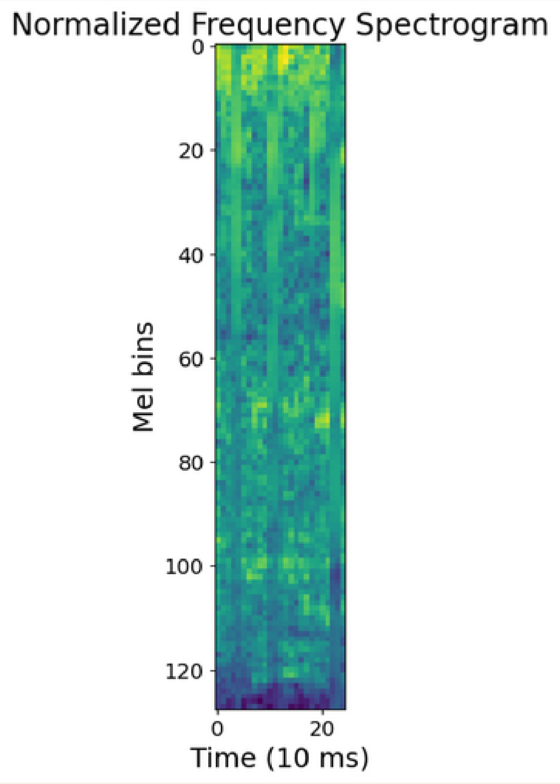
NAIVE APPROACH-DRAWBACKS

- Originally, we took a mean of features from all time windows.
- This led to information loss.
- Did not account for temporal features of our dataset.



FINAL APPROACH – CNN/LSTM

THE MODEL



1 **Audio**

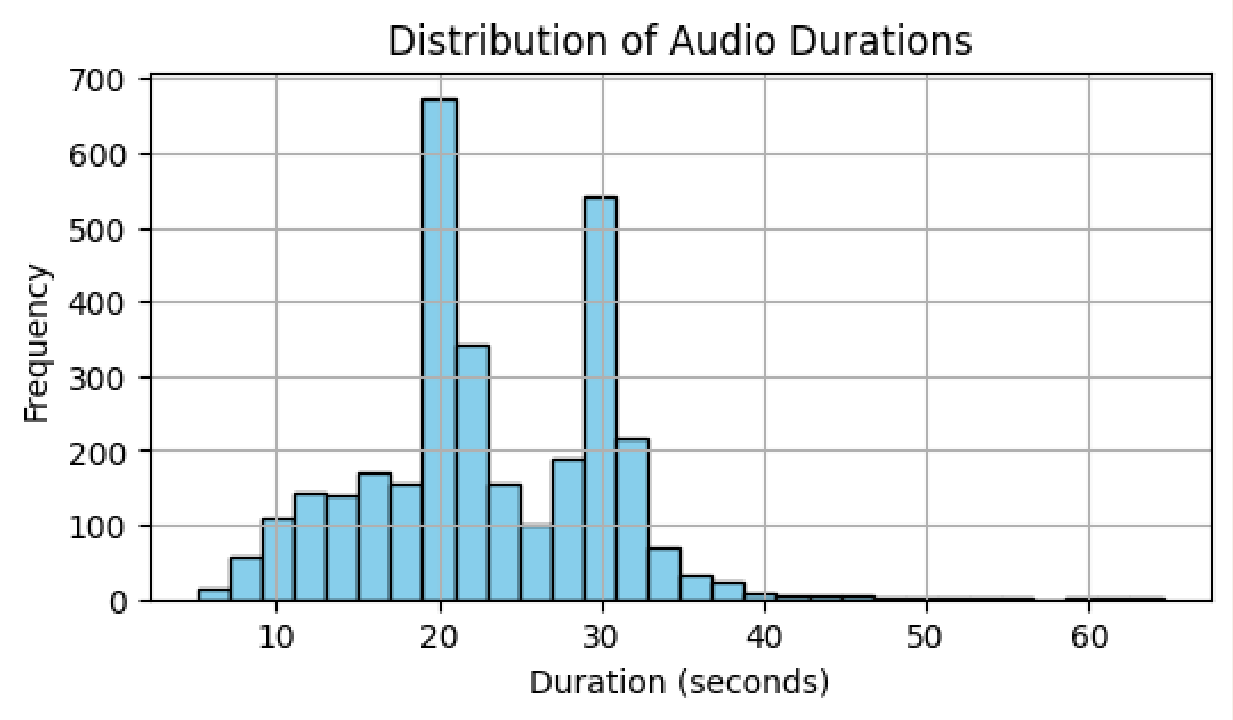
2
- Clipped into 10s segments
- Resampled to 2000 Hz
- Butterworth filter (25 Hz, 450 Hz)

3 Extract MFCC's
25 MFCC's in 40 time windows

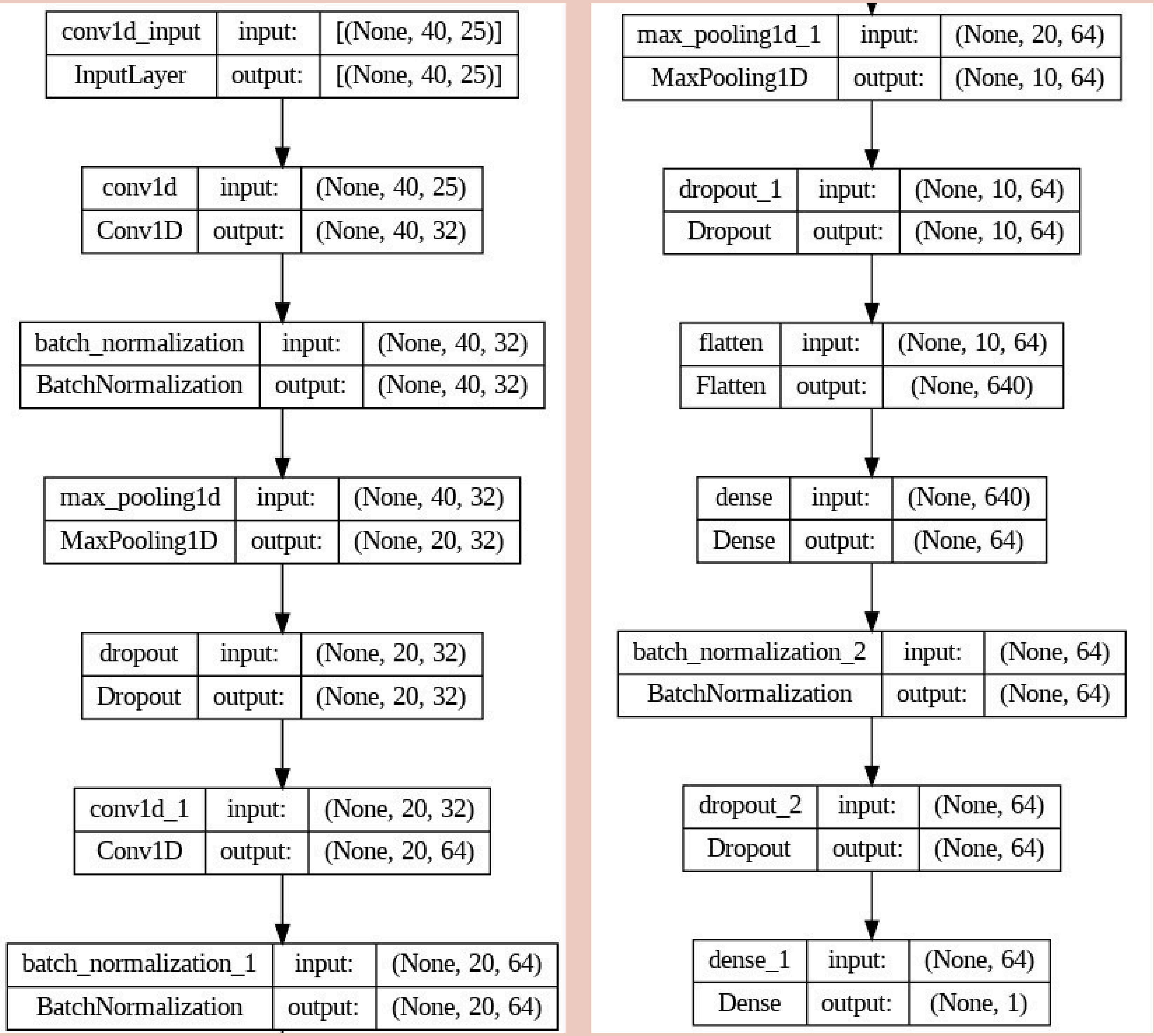
CNN 1D

CNN 2D

LSTM

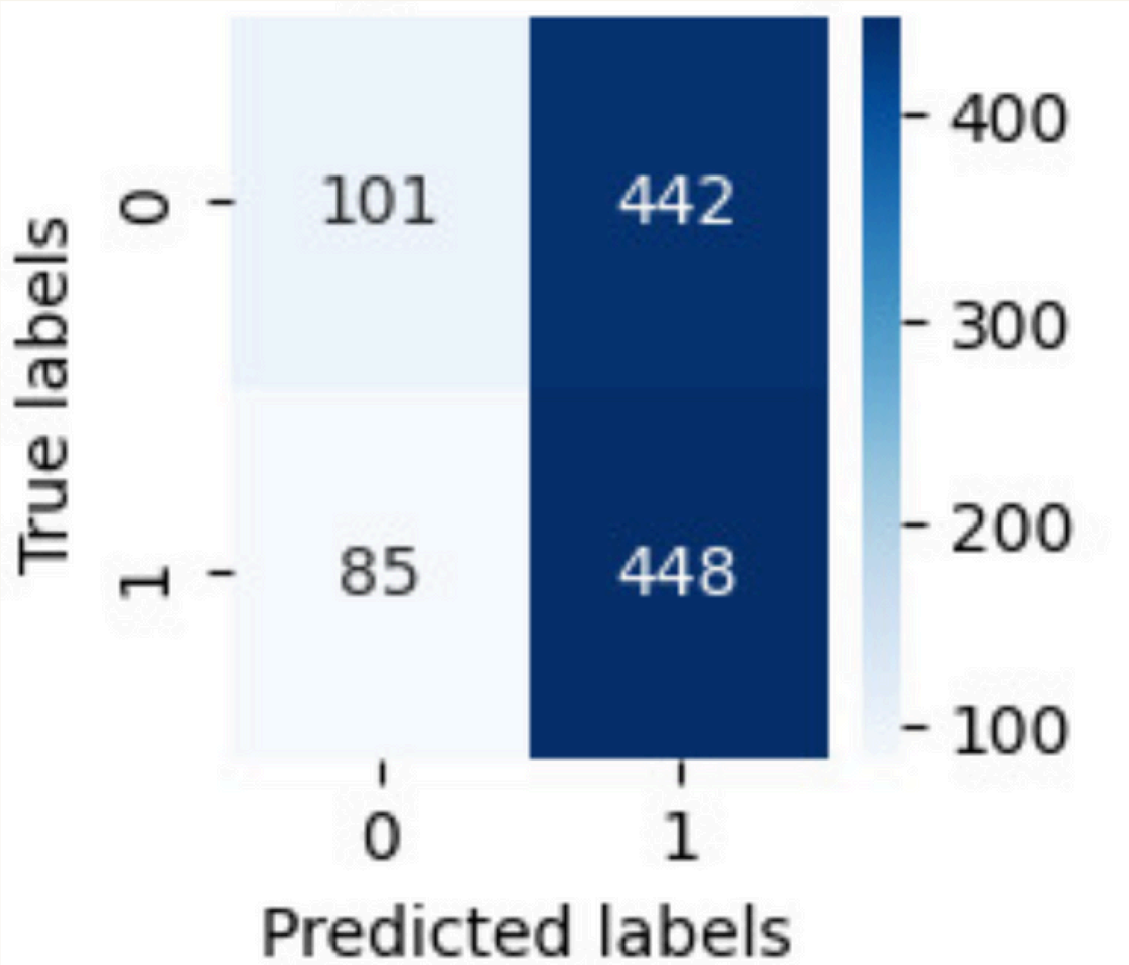


CNN - 1D



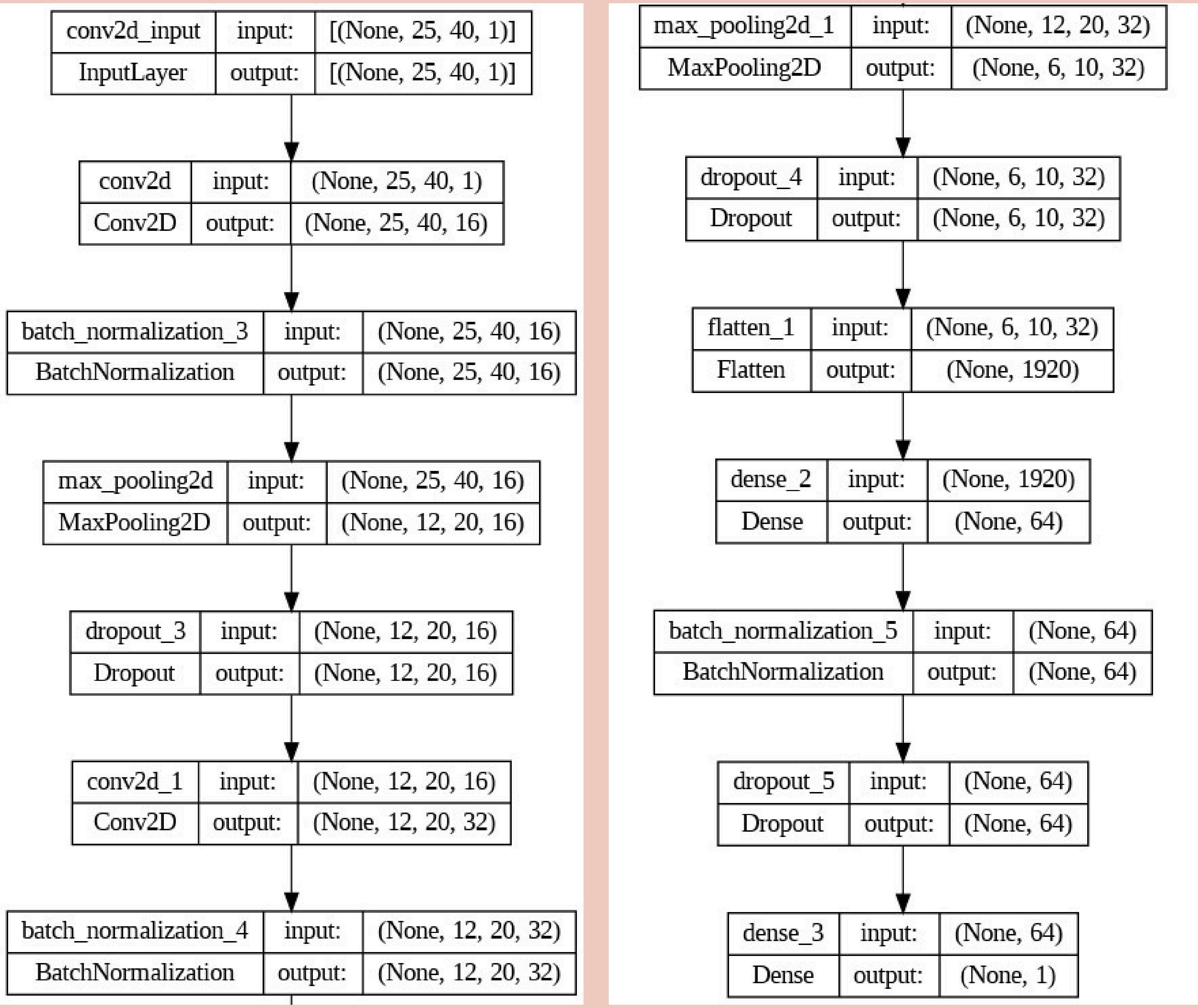
RESULTS

- **Accuracy: 0.510**
- **F1 Score: 0.629**
- **Recall: 0.840**
- **Weighted Accuracy: 0.716**
- **Cost: 8388.654**



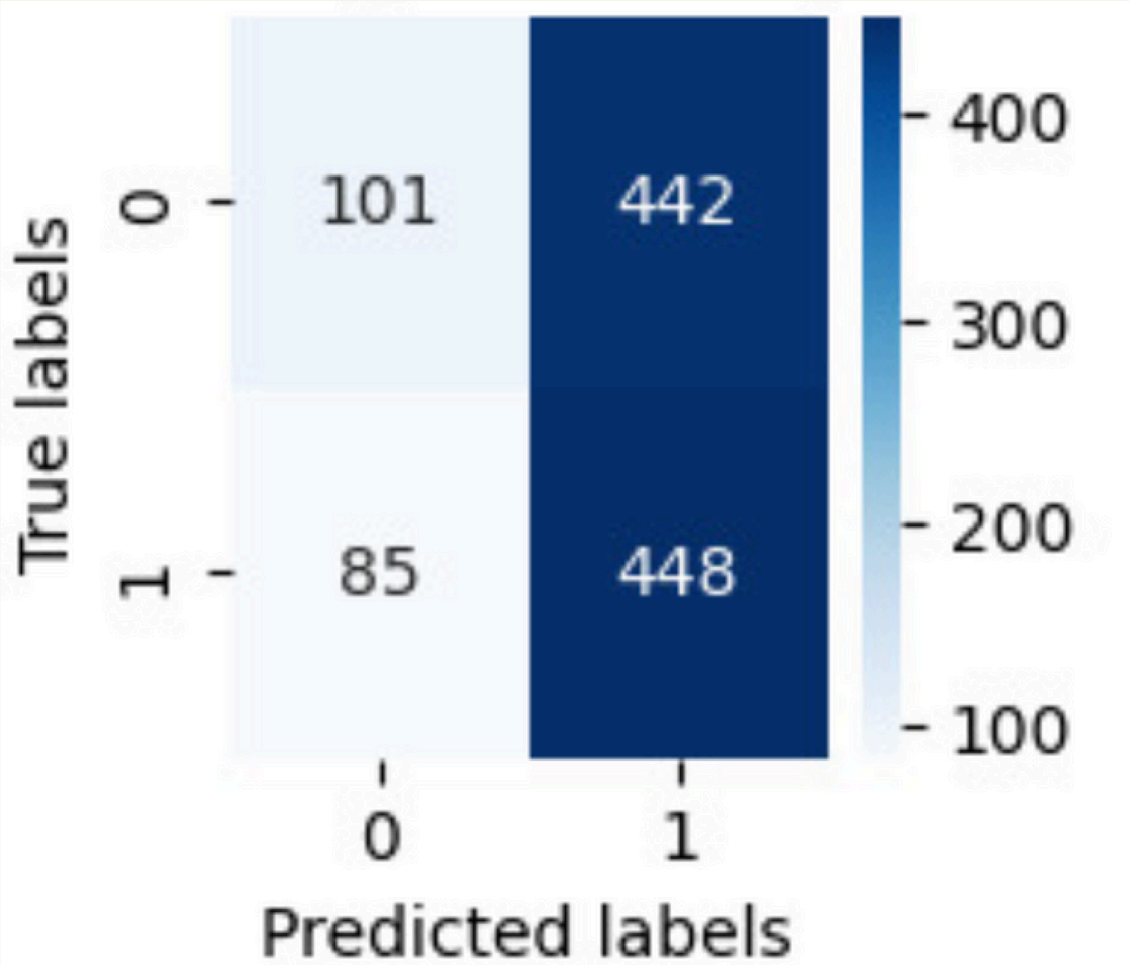
1- Abnormal (Positive)
0- Normal (Negative)

CNN - 2D



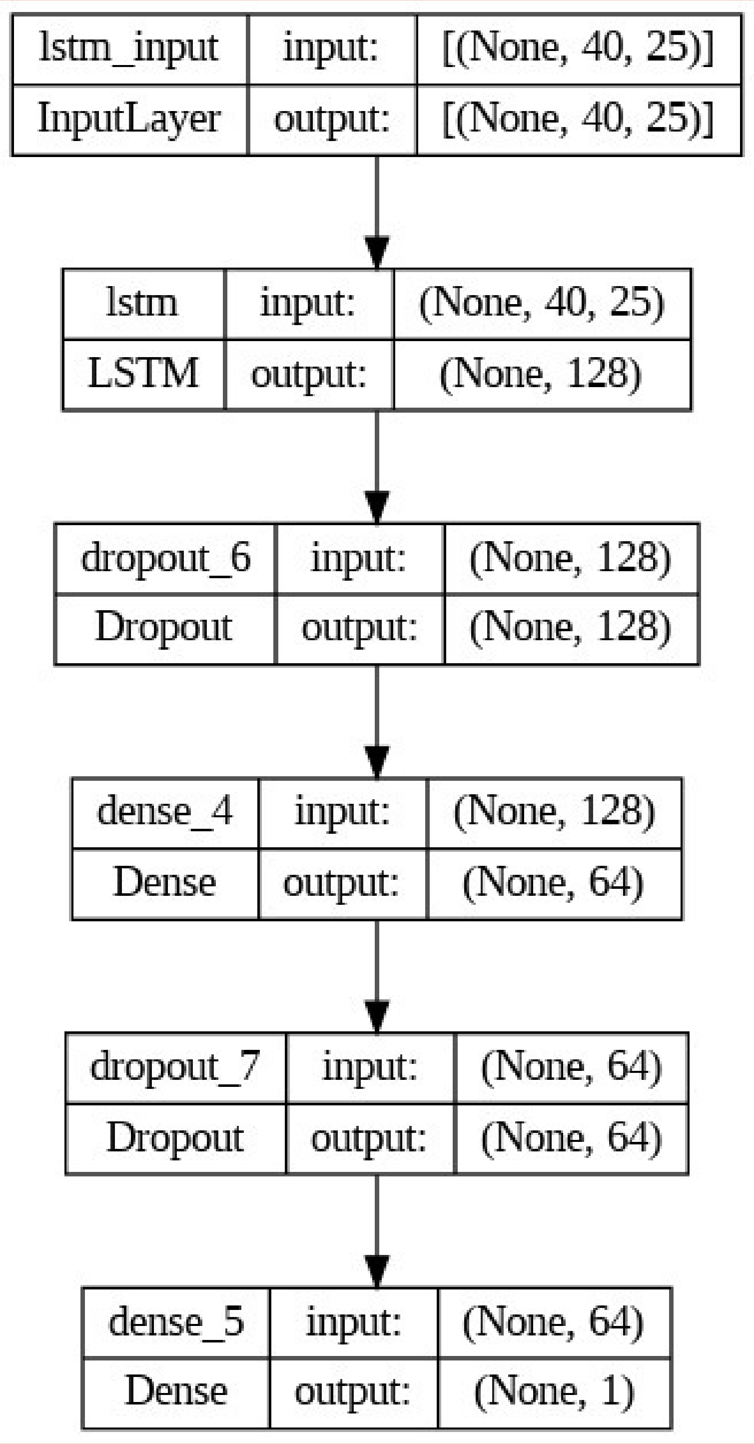
RESULTS

- **Accuracy: 0.531**
- **F1 Score: 0.618**
- **Recall: 0.765**
- **Weighted Accuracy: 0.653**
- **Cost: 10285.358**



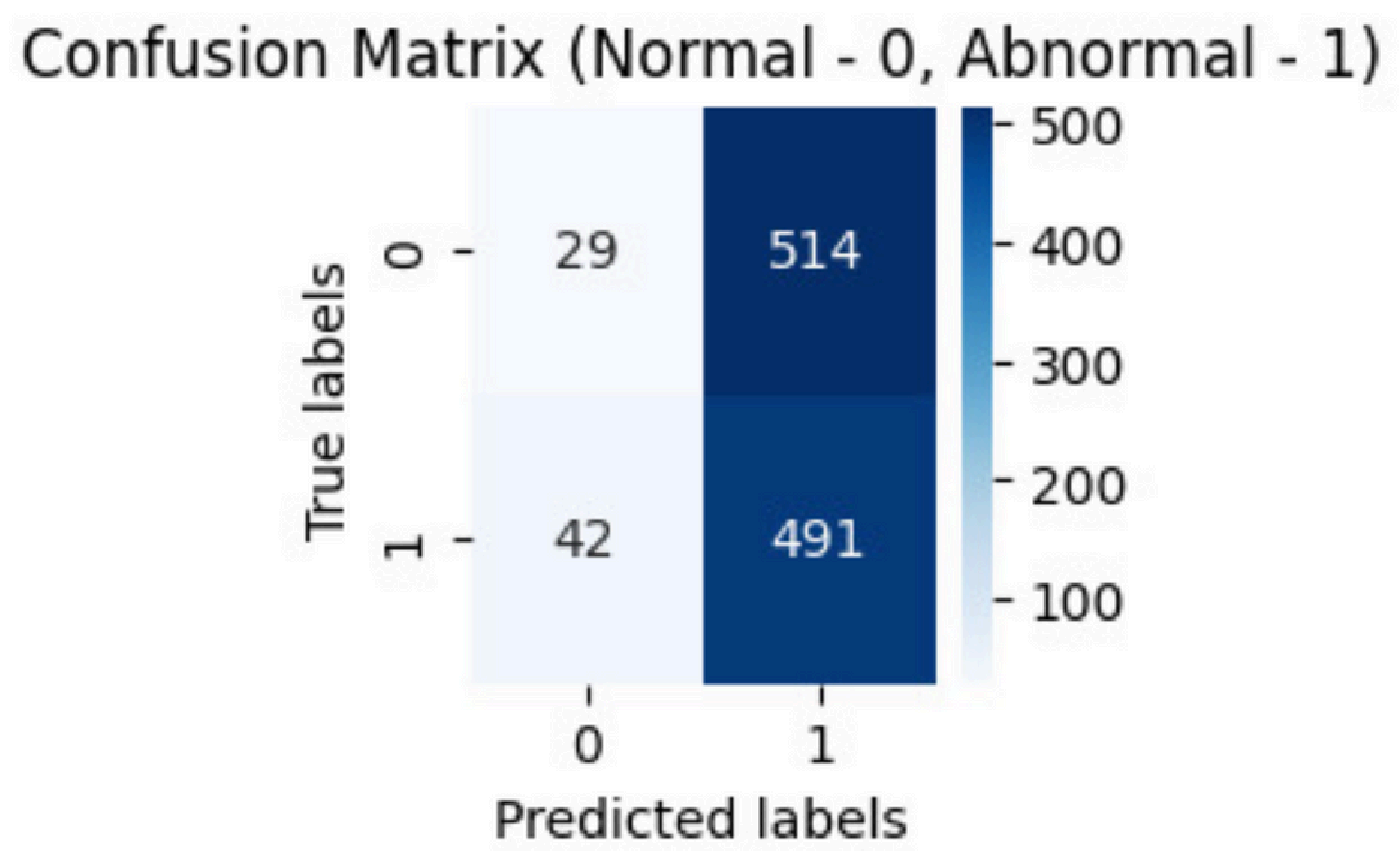
1- Abnormal (Positive)
0- Normal (Negative)

LSTM



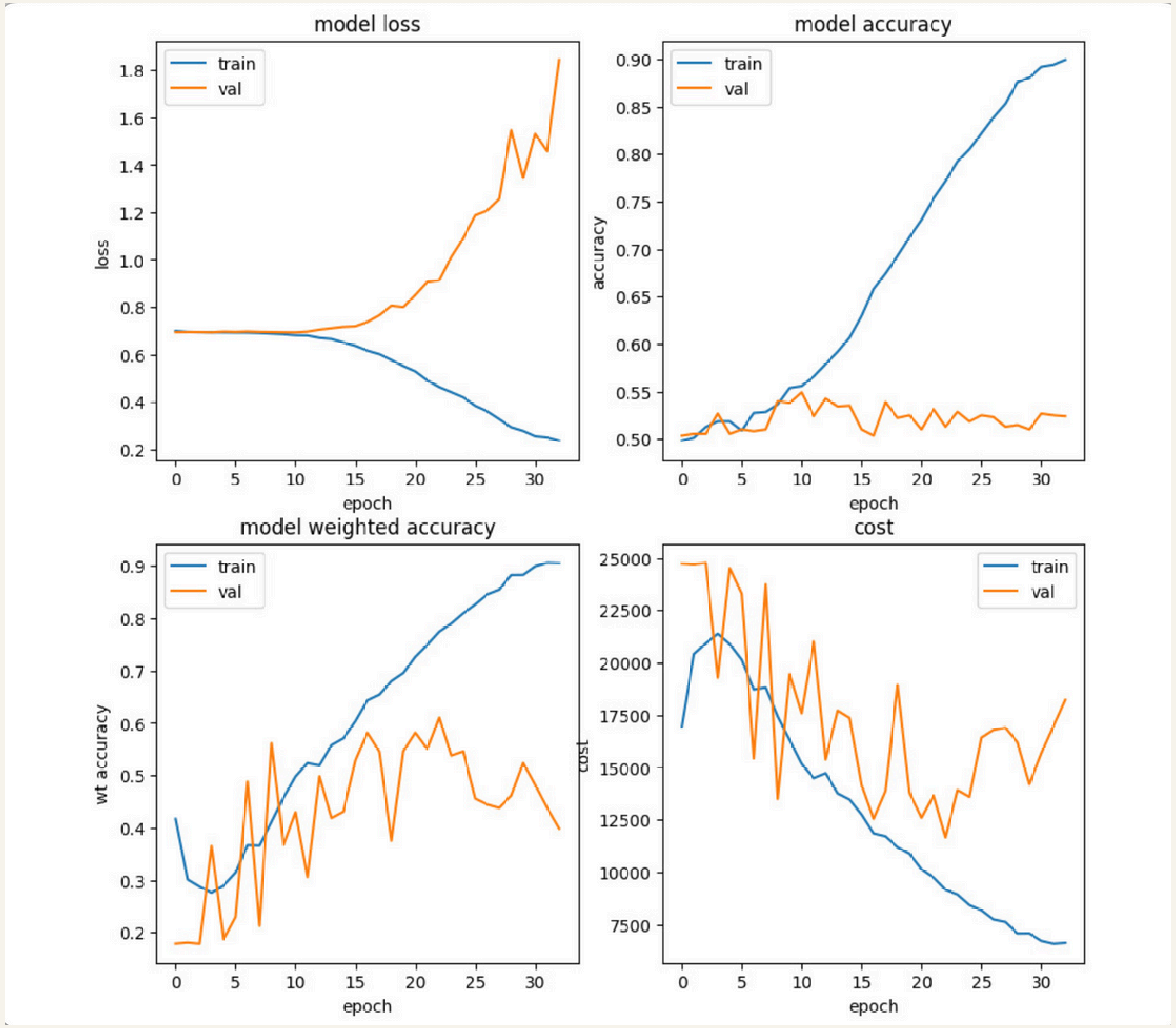
RESULTS

- **Accuracy: 0.483**
- **F1 Score: 0.638**
- **Recall: 0.921**
- **Weighted Accuracy: 0.787**
- **Cost: 6270.975**

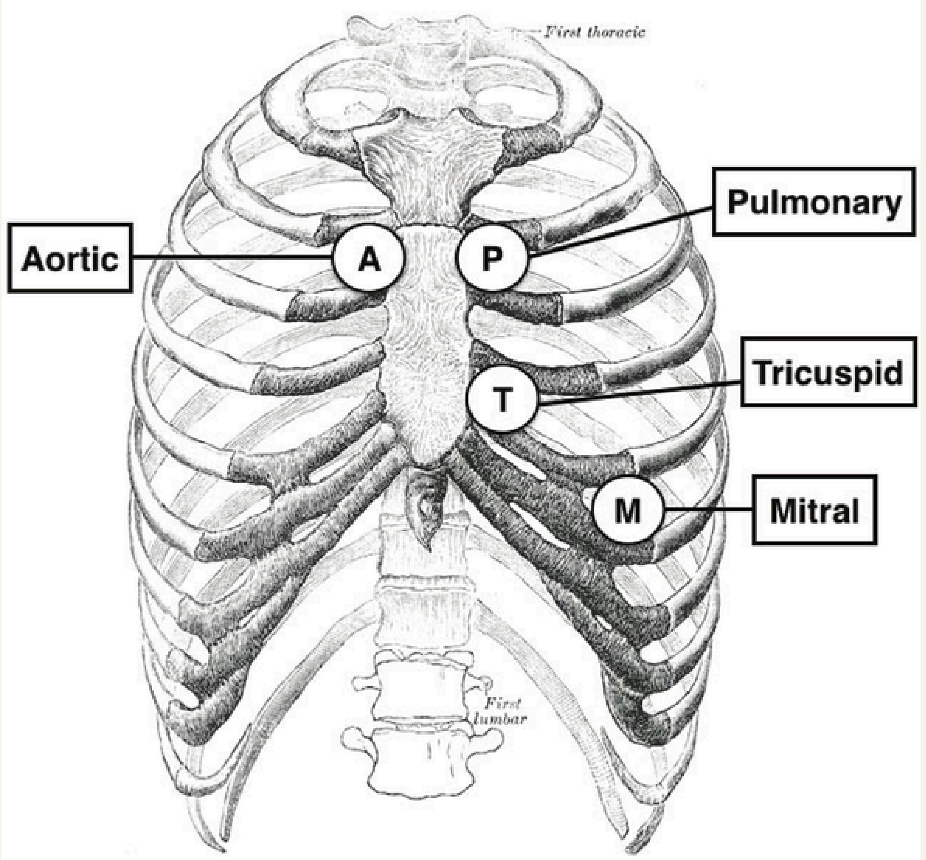


1- Abnormal (Positive)
0- Normal (Negative)

OVERFITTING



DEPLOYMENT: ABNORMALITY DETECTION USING SMARTPHONES



Recording heartbeat sounds at the ausculation points
Ascultation site: Pulmonary (most clear sound)
Software used to record: Garage band -> converted to wave file

Manual diagnosis of heartbeat sound by Dr. Amrit Kaur
Heart beat sounds of 15 students were recorded and diagnosed manually using GarageBand.

Accuracy: 0.714
Weighted accuracy: 0.777
Cost: 733.64 Dollars (not enough people with abnormalities)

- Not representative of our model
- Requires more testing data and data with enough variation

Results after testing on CNN 1D model

[redacted]

CHALLENGES AND DRAWBACKS

Segmentation data unavailable:
The task of segmentation between S1 and S2 was beyond the scope of this project. This could have affected accuracy.

Limited abnormal data:
The data we collected at Plaksha, limiting our ability to test accuracy of abnormal detection.

Model trained without phone data:
Training dataset contained no phone recordings, limiting accuracy in deployment.

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