Cardiovascular Abnormality Recognition using Heart Signal Segmentation and Deep Learning

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under the guidance of

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IT5712 Project-1

PROGRESS THROUGH KNOWLEDGE

Problem Statement

- The focus of existing literature on heart sound classification has been on image processing, rather than feature extraction.
- The goal is to develop an efficient model for extracting features from heart sound signals (PCG and ECG) with high sensitivity and specificity.
- Two hybrid methodologies are employed: a PCG-ECG technique and a matrix combining Mel-Spectrogram image features and wave-based features from PCG signals.
- Various feature selection techniques and algorithms for classification are used for comparitive analysis
- Transfer learning and unsupervised learning techniques, including neural networks and pixel-based clustering, are employed for classification of spectrogram images. A comparison is made between traditional and deep architecture approaches

Literature Survey

S. No	Title of the paper	Year	Methodologies / Approach used	Pros	Cons
1	Cardiovascular Disease Recognition Based on Heartbeat Segmentation and Selection Process. (International Journal of Environmental Research and Public Health)	2021	• PASCAL and PhysioNet dataset is used • CNN model is used for classification • IIR filtering is used for noise filtering • Segments are selected using clustering (Mixture Gaussian Model)	• Classification with an overall accuracy of 97% for the PhysioNet dataset	• Due to the fact that abnormality detection should be extremely accurate, the PASCAL dataset only had an 87% accuracy
2	The CirCor DigiScope Dataset: From Murmur Detection to Murmur Classification (IEEE Journal of Bioinformatics)	2022	• Literature review of all datasets • Made use of the CirCor Dataset - 1568 Participants • Automatic segmentation of audio samples using Hidden Semi Markov Model, Logistic Regression-HSMM, Deep-CNN	• Audio dataset along with textual dataset • Extensive segmentation algorithms used	• Not much predictive analytics done with the textual dataset

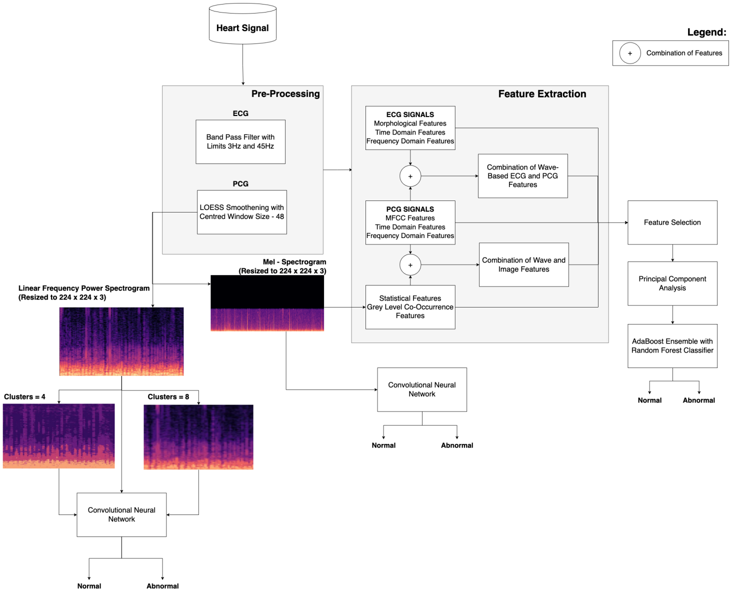
Literature Survey (Contd.)

S. No	Title of the paper	Year	Methodologies / Approach used	Pros	Cons
3	Detection of heartbeat abnormalities from phonocardiography using machine learning (11th International Conference on Cloud Computing, Data Science and Engineering)	2021	• Use of PhysioNet database • Detecting heartbeat anomalies from PCG abnormalities and performs segmentation • Algorithm to analyse and differentiate noise from heartbeat sounds used	• Authors use a mobile application and stethoscope with mic to perform detection • Accuracy of normal and abnormal cardiac sound segmentation is 93%	• Only used 400 PCG data • Lack of transparency of models used and optimization methods
4	Classification of normal/abnormal heart sound recordings: The PhysioNet/Computing in Cardiology Challenge 2016 (Computing in Cardiology; 42:609-612)	2016	• Makes use of the PhysioNet/CinC Dataset • Manual review performed on each data instance to correct segmentation mistakes • Classification for “Normal”, “Abnormal” or “Unsure”	• Has a review of the top submissions to the challenge • Top submission had a sensitivity score of 0.94	• Only 472 abnormal recordings • Lack of classification of dataset in terms of age group, pregnancy, gender

Literature Survey (Contd.)

S. No.	Title of the paper	Year	Methodologies / Approach used	Pros	Cons
5	Automatic heart sound classification from segmented/unsegmented phonocardiogram signals using time and frequency features (IOP Science, Physiological Measurement)	2020	• Classification algorithms (KNN, Decision Tree, Ensemble Classifier, ANN, LSTM) are used • Feature extraction of time and frequency features of the distinct states of the PCG signal • Uses different techniques for un-segmented and segmented signals	-Compares unsegmented data classification results with segmented data classification -Detailed Literature survey with previous work done from 2009 with PCG data	-Does not take into account other factors such as age, sex, pregnancy -Uses 2016 challenge data (3000 recordings) rather than updated data (5000+ recordings)
6	Logistic Regression-HSMM-Based Heart Sound Segmentation (IEEE Transactions on Biomedical Engineering)	2016	• Accurate segmentation of first and second heart sound within noisy PCG recording using LR-HSMM • Implements Viterbi algorithm to decode most likely sequence of states	-Proposes modification to the HSMM model to allow greater discrimination between states	-Uses 405 PCG, ECG recording from small population (all adult)

Technical Architecture



Datasets

Table: Dataset Analysis

Dataset	**File Type**	**Training Samples**	**Signal**	**Labels**
PhysioNet/CinC-2016	.wav	3240	PCG	Normal Abnormal
PhysioNet/CinC-2016	.dat	409	ECG	Normal Abnormal
PhysioNet/CinC-2017	.mat	8528	ECG	Normal Abnormal(AF)

PCG Signals - Features

Table: PCG Wavelet Features

#	Feature
1-39	MFCCs (Mel Frequency Cepstral Coefficients)
40	Occupied Bandwidth
41	Zero Cross Rate
42	Peak Magnitude to RMS Ratio
43	Maximum to Minimum Difference
44	Median Frequency
45	Power Bandwidth
46	Equivalent Noise Bandwidth
47	Mean Frequency
48	Band Power
49	Root Sum of Squares

ECG Signals - Features : Full Waveform Features

Table: Full Waveform Features

Stationary Wavelet Transform Decomposition	Coefficients
Level 1 Level 2 Level 3 Level 4	Approximation Coefficient Detail Coefficient

Table: Power Spectral Density Ratios & Additional Features

Spectral Density	Frequency Band
Low	03 - 10 Hz
Med	10 - 30 Hz
High	30 - 45 Hz
Log Entropy Higuchi Fractal Dimensions	

ECG Signals - Features : R-R Interval Features

Table: R-R Interval Features

Max	pNN01	pNN50	pNN100
Min	pNN10	pNN60	pNN200
Median	pNN20	pNN70	pNN400
Mean	pNN30	pNN80	pNN600
Standard Deviation	pNN0	pNN90	pNN800

PCG Signals - Wave Feature Classification

- The project identified 49 features from PCG signals.
- The MFCC features were extracted by converting the heartbeat sound into multiple windows and applying Discrete Fourier Transformation to convert the signal from the time domain to the frequency domain.
- The Mel-frequency cepstral coefficients were extracted by applying the Mel() function to the frequencies obtained from DFT using a mel filter bank, applying a logarithm function, and applying Inverse Discrete Fourier Transformation.
- From each window, 39 unique MFCC features were obtained and the mean was calculated for each feature across all the windows to obtain a total of 39 features for a particular PCG signal.
- Feature selection algorithms used - Relief, Kruskal Wallis

ECG Signals - Wave Feature Classification

- ECG signals were filtered and normalized using Min-Max normalization.
- Morphological features of R to R Intervals, and full waveform features with spectral density and fractal dimensions were extracted.
- Principal Component Analysis was done to construct new axes.
- This was performed for both the 2016 (.dat format) and the 2017 (.mat) challenge data.
- The performance of the machine learning classifier was compared before and after the application of these techniques.

Classification - Hybrid Wave Features (PCG+ECG)

- Wave features combined from PCG and ECG
- Total number of features - 135
- Classification attempted by combining PCA features, and without the same

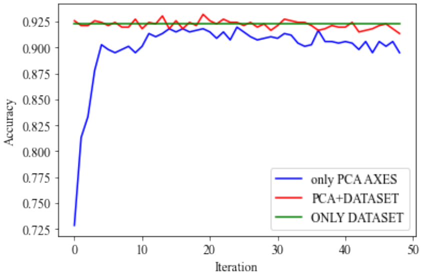


Figure: Accuracy verses Number of Axes/Iterations for the Normalized ECG-PCG Hybrid Set

PCG Signals - Image Feature Classification

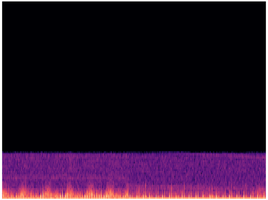
Statistical Features	Gray Level Co-Occurence Features
Energy	Autocorrelation
Statistical Energy	Cluster prominence
Kurtosis	Cluster shade
Maximum	Cluster tendency
Minimum	Contrast
Mean	Correlation
Mean Deviation	Difference entropy
Median	Dissimilarity
Image Range	GLCM energy
RMS	GLCM entropy
Skewness	Homogeneity
Standard Deviation	IMC1
Variance	IMC2
Entropy	IDMN
Uniformity	IDN
	Inverse variance
	Maximum probability
	Sum Average
	Sum Entropy
	Variance

Classification - Hybrid Image+Wave Features

- This hybrid approach involves converting the PCG audio into Mel spectrograms.
- The PCG wave features extracted for the same subject are combined with the features extracted from the spectrograms to create a hybrid feature matrix.
- The hybrid feature matrix consists of a total of 85 features.

Spectrograms

- Two types of Spectrograms are made use of - Mel Spectrogram and Linear Frequency Power Spectrograms
- Linear Frequency Power Spectrograms pick out higher frequencies than Mel Spectrograms
- In a linear frequency power spectrogram, the x axis typically represents time and the y axis represents frequency. In a mel spectrogram, the x axis again represents time and the y axis represents frequency, but the frequency scale is on the mel scale rather than a linear scale.



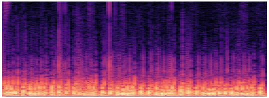


Figure: Left - Mel Spectrogram; Right - Linear Power Spectrogram

Deep Learning - Spectrograms

- Classification of heart sounds using CNNs
- Input for the CNNs is the spectrograms of the heart sounds (mel spectrograms or linear frequency power spectrograms)
- Pre-trained deep network architectures with transfer learning are used to predict normal or abnormal heart beats
- At least 85 iterations (5 epochs) were run and results were obtained

Clustered Spectrograms (Elbow Method)

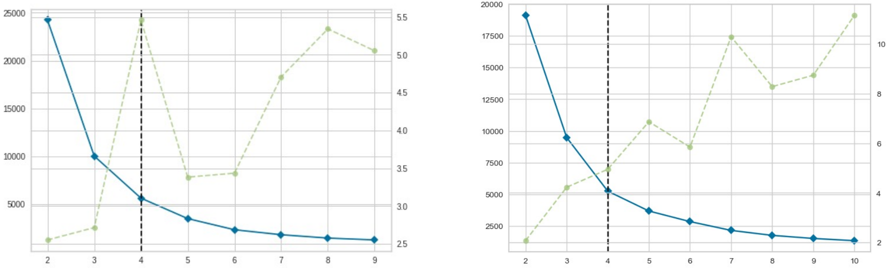


Figure: Distortion vs Clusters graphs, Blue: Distortion Score, Green: Time

Clustering (Linear Frequency Power Spectrograms)

Figure: Spectrogram for Subject a0007

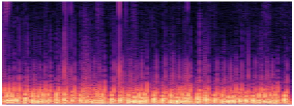


Figure: Spectrogram Clustered into 4 Clusters

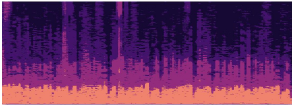
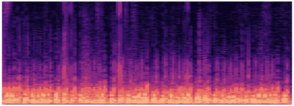


Figure: Spectrogram Clustered into 8 Clusters



Algorithms

Algorithm 1 Relief Algorithm

$A := A_1, A_2, ..., An$
$W[A] := 0.0$
for $i = 1$ to K **do**
    $A_x \in A$
    $H := NearestHitFromA_x, N := NearestMissFromA_x$
    for $A := 1$ to n **do**
        $W[A] := W[A] - diff(A, A_i, H)/K + diff(A, A_i, M)/K$
    end for
end for

Algorithms

Algorithm 2 Adaboost Algorithm

$D_1(i) = 1/m$
for $t := 1$ to T **do**
    $H_t = RandomForestClassifier(D_t)$
    $Error = e_t$
    $a_t = 0.5log(\frac{1-e_t}{e_t})$
    $D_t(i) := updatedWeights(D_t(i))$
    $D_{t+1}(i) = \frac{D_t(i)}{Z_t}$
end for
$H = signum(\sum_{t=1}^{T} a_t h_t)$

Results and Discussions

The proposed models are evaluated using three parameters - Sensitivity, Specificity and Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

Table: Performance of Models on PhysioNet/CinC 2016 for PCG

Methodology	**Selection**	**Classification**	**Accuracy**	**Sensitivity**	**Specificity**
36 Features	Relief	AdaBoost Ensemble	92%	89.2%	92.8%
Z-Score PCA (20)	-	AdaBoost Ensemble	**93.2%**	**93.6%**	91.2%

Results and Discussions (Continued)

Table: Performance of Models on “training-a” of PhysioNet/CinC 2016

Data + #Features	Selection	Classification	Accuracy	Specificity	Sensitivity
PCG +ECG (135)	ReliefF	Cubic SVM	86.6%	79.2%	94.1%
PCG +ECG (137)	No	AdaBoost Ensemble (Decision Tree Classifier Base model)	86.1%	82.3%	89.4%
PCG +ECG (90)	ReliefF	ANN	81.9%	86.7%	78.2%
PCG +ECG (93 PCA)	No	AdaBoost Ensemble with Random Forest Classifier	**91.37%**	87.03%	**95.16%**

Results and Discussions (Continued)

Table: PhysioNet/CinC 2016 - ECG Data (Training-A): Experiments Conducted on Normalized Data for Random Forest Classifier

Feature Selection	**Factorial Analysis**	**Assessment**	**Accuracy**	**Specificity**	**Sensitivity**
-	-	Cross Validation (3 Folds)	66.42%	73.96%	47.86%
Fisher Filtering (x-best = 55)	PCA (15 axes &all extracted features)	Cross Validation (3 fold)	68.64%	75.35%	52.14%
-	PCA (21 axes)	Cross Validation (3 fold)	86.42%	89.24%	79.49%
-	**PCA (21 axes all extracted features)**	**Cross Validation (3 fold)**	**87.16%**	**89.58%**	**81.20%**

Results and Discussions (Continued)

Table: PhysioNet/CinC 2017 - ECG Data: Experiments Conducted

Selection	Factorial Analysis	Classifier	Assessment	Accuracy	Specificity	Sensitivity
Fisher Filtering (p-value = 0.001)	-	Random Forest	Cross Validation (3 Folds)	78.89%	82.67%	72.92%
Fisher Filtering (p-value = 0.001)	-	Random Forest	Cross Validation (3 fold)	79.25%	83.52%	72.48%
	PCA (16 axis)	Random Forest (Boosting)	Cross Validation (3 folds)	79.26%	85.19%	69.88%
	PCA (16 axis + all features)	Random Forest (Boosting)	Cross Validation (3 folds)	85.13%	90.81%	76.14%

Results and Discussions (Continued)

Table: Experiments conducted with Image Features

Model	Features	Accuracy	Sensitivity	Specificity
Boosting (Random Forest Classifier)	36 Features	89.01%	62.58%	95.27%
Boosting (Random Forest Classifier)	36 PCA Components	89.50%	65.95%	96.05%
Boosting (Random Forest Classifier)	**72 (36 PCA + Image Features)**	**90.27%**	**68.79%**	**96.25%**

Results and Discussions (Continued)

Table: Experiments conducted with Hybrid PCG Wave - Image Features

Model	Features	Accuracy	Sensitivity	Specificity
Boosting (Random Forest Classifier)	87 Features	92.80%	84.30%	78.30%
Boosting (Random Forest Classifier)	Only 13 Features (PCA Axes)	92.40%	75.90%	83.50%
Boosting (Random Forest Classifier)	100 Features (PCA + Wave/Image Features)	92.80%	81.40%	82.30%
Boosting (Random Forest Classifier)	93 Features (PCA + Wave/Image Features)	94.10%	95.03%	90.32%

Results and Discussions (Continued)

Table: Experiments conducted with Pre-trained Deep learning architectures in PCG Spectrograms

Model	Validation Accuracy
DarkNet-53	92%
SqueezeNet	79.45%
AlexNet	79.45%
GoogleNet	79.45%

No. of Epochs- 10
Number of Iterations per Epoch - 17
Learning Rate - 0.01
Hardware Resource - Single CPU
Validation Frequency - 50 iterations

Results and Discussions (Continued)

Figure: Results of Clustered Spectrograms with Deep Learning Models

Model	**Spectrogram**	**Accuracy**	**Specificity**	**Sensitivity**
VGG-16	Full Spectrogram	**90.37%**	54.12%	83.68%
	4 Clusters	83.14%	**63.43%**	**86.29%**
	8 Clusters	84.50%	42.90%	80.50%
SqueezeNet	Full Spectrogram	**87.19%**	**73.14%**	90.00%
	4 Clusters	82.10%	57.00%	87.70%
	8 Clusters	87.04%	65.80%	**93.71%**

Results and Discussions (Continued)

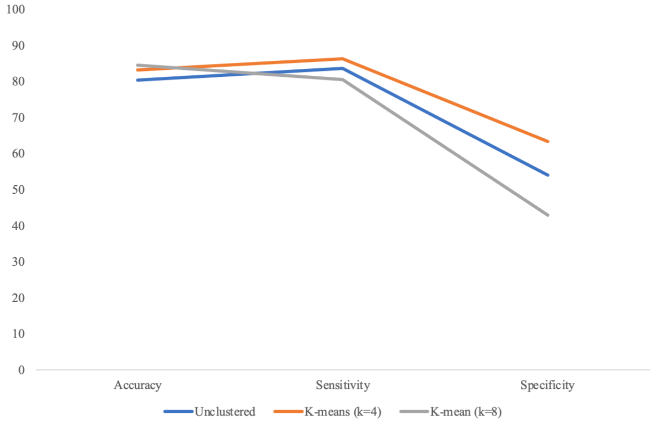


Figure: Performance of VGG16 on Linear Frequency Power Spectrograms

Results and Discussions (Continued)

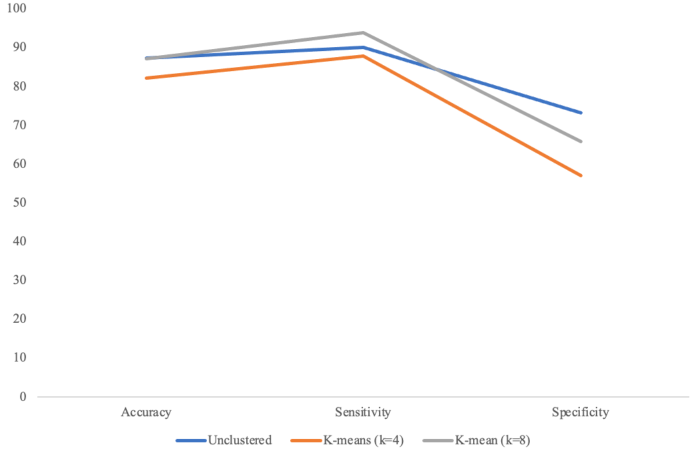


Figure: Performance of SqueezeNet on Linear Frequency Power Spectrograms

Results and Discussions (Continued)

- Best results obtained were from the Wave+Image hybrid feature matrix with Principal Component Analysis as well as a pure-PCG feature model with 20 PCA components added into it. A high sensitivity of 95.03% and accuracy of 94.10% was noted in the hybrid approach.
- In Boulares et. Al, a maximum sensitivity of 94.6% was achieved using the PhysioNet/CinC 2016 dataset. However, our hybrid model enhances the sensitivity score by 2%.
- In attempting segmentation using image unsupervised clustering of similar pixels, the newly generated clustered spectrograms were used to try various pre-trained architectures.
- The highest accuracy achieved using the Convolutional Neural Networks is 93.71%.
- Comparing the results obtained from various workflows followed, the highest metrics obtained followed the PCG Wave-Image Hybrid approach.

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