Combining Deep Learning with Traditional Machine Learning to Improve Phonocardiography Classification Accuracy

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Key Topics for Discussion

- Introduction of Deep Hybrid Learning.
- Advantages and limitations of conventional Machine Learning and Deep Learning.
- Advantages of Deep Hybrid Learning over conventional Machine Learning and Deep Learning.
- Case study on Phonocardiography (PCG) signals to detect early stage heart diseases.

Deep Hybrid Learning

- An approach to combine a conventional Deep Learning model with other Machine Learning models.
- DL is used to extract meaningful features from signals.
- ML is used to classify signals.

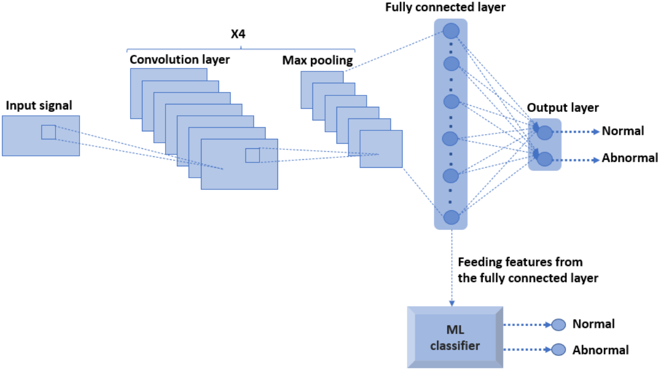

Figure: A deep hybrid model architecture.

Classical Machine Learning

- Advantages:
  - Classical ML algorithms can give very good accuracy with less data as compared to DL.
  - ML algorithms require less computational resources than DL.
  - ML algorithms perform better with structured data.
- Limitations:
  - Classical ML algorithms require manual feature engineering.
  - ML algorithms perform poor with raw/unstructured data like images, test, audio signals.

Conventional Deep Learning

- Advantages:
  - Conventional DL algorithms don't require manual feature engineering.
  - DL can extract meaningful features from raw/unstructured data like images, test, audio signals.
  - DL usually perform better compared to ML for solving complex problems such as image classification, natural language processing, and speech recognition.
  - Perform very well when large amount of data is present.
- Limitations:
  - DL can be prone to overfitting or underfitting if insufficient amount of data is used to train the model.
  - Computationally expensive compared to ML algorithms.
  - Can't work well with less amount of data.

DHL- A Fusion of Benefits of Conventional Approaches

- DHL is better in most cases than individual DL and ML approaches.
- DHL combines the benefits of ML and DL techniques and overcome their limitations.
- DHL performs auto feature extraction using DL methods.
- DHL performs well where less data is available, example: Medical data.
- DHL is less computationally expensive and have less time complexity compared to traditional DL algorithms.

Early Detection of Heart Diseases using PCG and DHL

- Heart disease is the leading cause of death.
- About 655,000 Americans die from heart disease each year.
- Continuous remote monitoring of heart using PCG signal and DHL can detect heart diseases in the initial stage.
- Patients can know the condition of their heart continuously and they can consult with cardiologist instantly if any anomaly occurs.

Review of the Phonocardiogram Signal

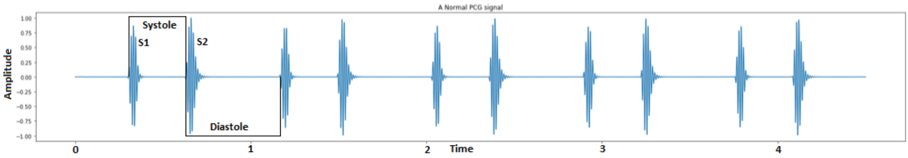

Figure: A PCG signal of normal heart sound with systole and diastole intervals with reference to S1 and S2.

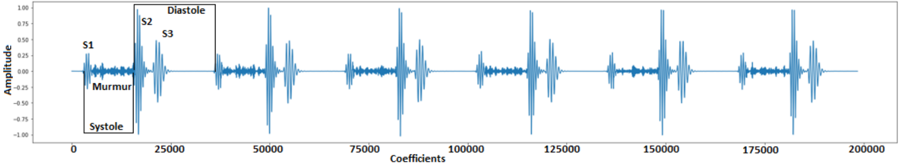

Figure: A pathological PCG signal with murmurs and S3.

Data Acquisition (PCG Signals)

- The University of Michigan Heart Sound and Murmur database.
- The 2016 PhysioNet Computing in Cardiology Challenge database.
- Total 3240 PCG signals sampled at 2000 hz, with 5 to 120 seconds duration.
- Imbalance ratio 4:1 (Normal:Abnormal).
- We used the Synthetic Minority Oversampling technique (SMOTE) to make the dataset balanced.
- 10-fold cross validation technique to test the performance of deep hybrid models.

Data Preprocessing

- The features of the Mel-scaled power spectrogram and the MFCC are biologically inspired and resemble the resolution of the human auditory system, which (features) are proven to be more efficient to discriminate between two different sound signals.

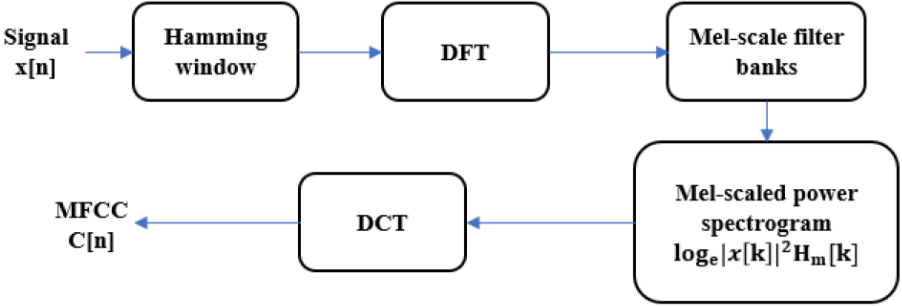

Figure: Preprocessing of PCG signals.

Mel-scaled Power Spectrogram

- Mel-scaled Power spectrogram:
  1. Simulate human ear properties.
  2. By applying mel-scaled filters to the power spectrum of a signal.
  3. More filters in the low-frequency and fewer filters in the high-frequency region.

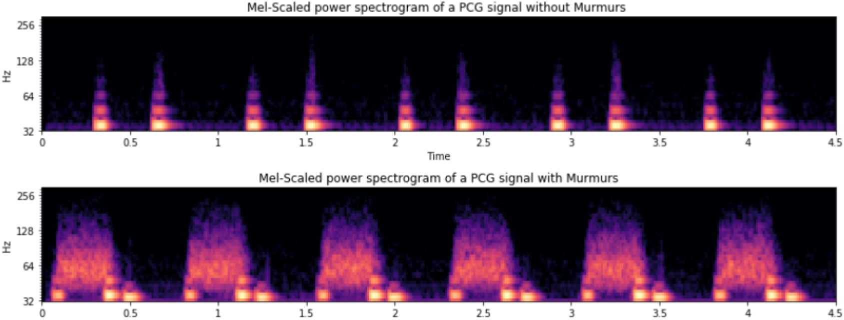

Figure: Mel Scaled Power Spectrogram of normal and abnormal PCG signals.

Mel-Frequency Cepstral Coefficients

- Mel-Frequency Cepstral Coefficients:
  1. Compressed representation of the mel-scaled power spectrogram.
  2. Small set of features (usually about 10-20) which concisely describe the overall shape of mel-scaled power spectrogram.
  3. By taking the discrete cosine transform of a log power spectrum.

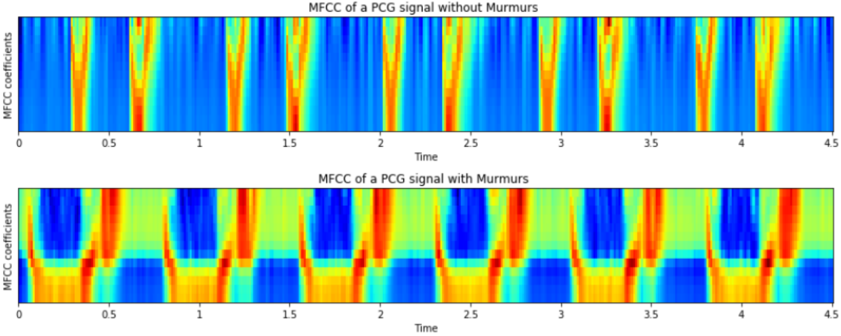

Figure: MFCC of of normal and abnormal PCG signals.

Proposed CNN Model to Classify PCG Signals

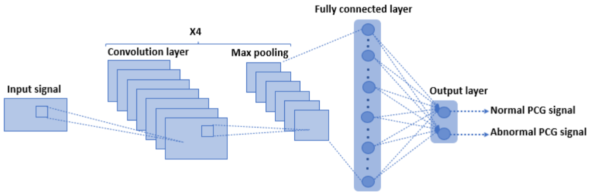

Figure: Proposed CNN model to classify PCG signals.

1. 4 hidden layers with 256, 512, 1024, and 2048 filters.
2. Kernel size in convolution layer and Max-pooling layer: 2.
3. Number of epochs: 100.
4. Learning rate: 0.0001.
5. Activation function: ReLU and Sigmoid.
6. Optimizer: Adam.
7. Regularization technique: Dropout.

Proposed Deep Hybrid Model Architecture

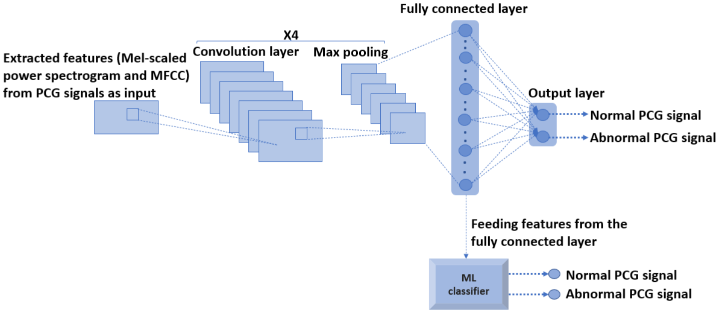

Figure: Proposed deep hybrid model architecture.

Performance of the Proposed Deep Hybrid Model

Table. Comparison of the proposed deep hybrid models with ML and DL classification models implemented separately

Model	Sensitivity	Specificity	Accuracy
CNN	87.69%	93.44%	92.00%
LR	72.33%	66.25%	67.50%
CNN-LR	94.58%	92.27%	92.70%
RF	75.48%	85.35%	83.33%
CNN-RF	92.03%	94.83%	94.30%
KNN	75.19%	80.12%	79.10%
CNN-KNN	95.33%	90.79%	91.72%
DT	78.19%	76.42%	76.79%
CNN-DT	92.03%	92.47%	92.37%
NB	70.22%	67.30%	75.33%
CNN-NB	97.00%	90.17%	91.60%
SVM	77.29%	80.15%	79.56%
CNN-SVM	93.30%	91.80%	92.10%
AB	74.14%	81.13%	79.70%
CNN-AB	94.14%	92.23%	92.62%

Table. Comparing the performance of the proposed CNN-RF deep hybrid model with previous models

Model	Sensitivity	Specificity	Accuracy
Potes et al., (2016) [8]	94.24%	77.81%	86.02%
Nassralla et al., (2017) [9]	78.00%	98.00%	92.00%
Whitaker et al., (2017) [10]	90.00%	88.45%	89.26%
Langley et al., (2017) [7]	77.00%	80.00%	79.00%
Han et al., (2018) [14]	98.33%	84.67%	91.50%
Tang et al., (2018) [11]	88.00%	87.00%	88.00%
Sotaquirá et al., (2018) [6]	91.30%	93.80%	92.60%
Singh et al., (2019) [12]	93.00%	90.00%	90.00%
Sing et al., (2020) [12]	94.08%	91.95%	92.47%
Nogueira et al., (2019) [15]	90.45%	85.25%	87.85%
Krishnan et al., (2020) [13]	86.73%	84.75%	85.65%
CNN-RF Model	**92.03%**	**94.83%**	**94.30%**

Conclusions and Future Works

- We have combined the advantages of Machine Learning and Deep Learning to build deep hybrid models.
- Significant improvements in the classification accuracy can be achieved by using deep hybrid models compared to traditional Machine Learning models.
- We have also shown that some hybrid models performed better than the single Deep Learning model in classifying PCG signals.
- Check with other advanced Deep Learning models.

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