Heartbeat Sound Classification Using Deep Learning

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The Problem

- Cardiovascular diseases, such as heartbeat irregularities, are a leading cause of death globally [1]
- Heartbeat irregularities often do not cause visible symptoms, but can evolve into very serious conditions if left untreated and undetected
- Huge strain is placed on medical professionals to correctly analyze thousands of heartbeats

Our Solution

- Traditional approaches require medical professionals to accurately analyze thousands of heartbeat sounds

- **Solution:** Utilize deep learning and other machine learning methods to classify heartbeats and detect irregularities
    - ML can solve this problem better than traditional approaches as heartbeat detection is essentially a classification problem
    - **Challenges:** There are many more normal cases than non-normal!

Prior Work

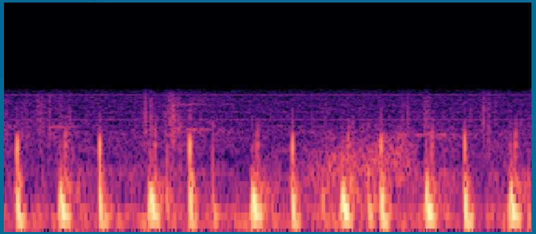
- Prior work has addressed the heartbeat classification problem using multiple ML and DL practices
- Raza et. al [3] proposed a Long Short-Term Memory (LSTM) model to classify heartbeat sounds as an initial step in diagnosing heart disease
- Li et. al [4] described a Convolutional Neural Network (CNN) framework that utilized global average pooling and multiple feature extraction techniques in the time and energy domain to classify such sound
- Kedir-Talha and Ould-Slimane [5] utilized SVMs to propose a diagnostic system for modeling and classification of a heartbeat

Dataset

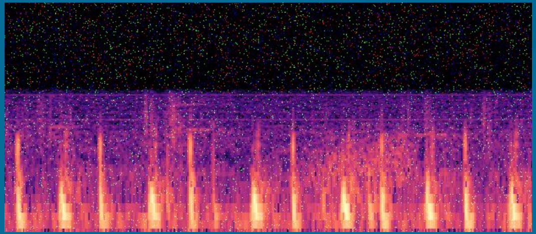
- **Dataset:** Heartbeat Sounds dataset from Kaggle
- **Data Format:** 435 .wav files
- **Classes:**
  - *Normal:* 231
  - *Artifact:* 40
  - *Extrasystole:* 64
  - *Murmur:* 100
- **Data Source:** Heartbeats were recorded using the iStethoscope Pro iPhone app and a digital stethoscope DigiScope in a clinical trial

Dataset

- Generated spectrograms for each .wav file
  - Individual image size: 271 x 624 x 4
- Addressed class imbalance by generating synthetic data for less represented classes
  - 435 spectrograms to 876 spectrograms
  - This is done by adding Gaussian noise to the existing spectrograms



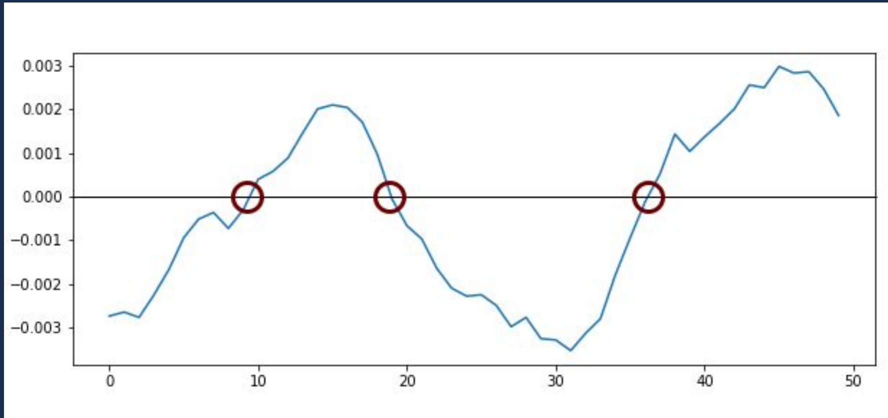
Original Extrasystole Spectrogram



Noisy Extrasystole Spectrogram

Feature Extraction

- Zero Crossing Rate
  - Rate of sign changes along a signal
- Spectral Centroid
  - Center of mass for a sound
- Mel-Frequency Cepstral Coefficients
  - Describes the overall shape of a signal



➔ New size: 271 x 627 x 4

Model Architectures - Custom CNN Model

- Preliminary Models
  - ResNet22-v1: Too deep, very slow, bad test accuracy
  - VGG-like: Overparameterized, slow, bad test accuracy

- Custom CNN Model
  - Shallower than ResNet22-v1
  - Less parameters than both VGG and ResNet22-v1
  - Much faster than the other models

Model Architectures

DenseNet:

- CNN model where each layer is connected to every layer deeper than it
- Newer model

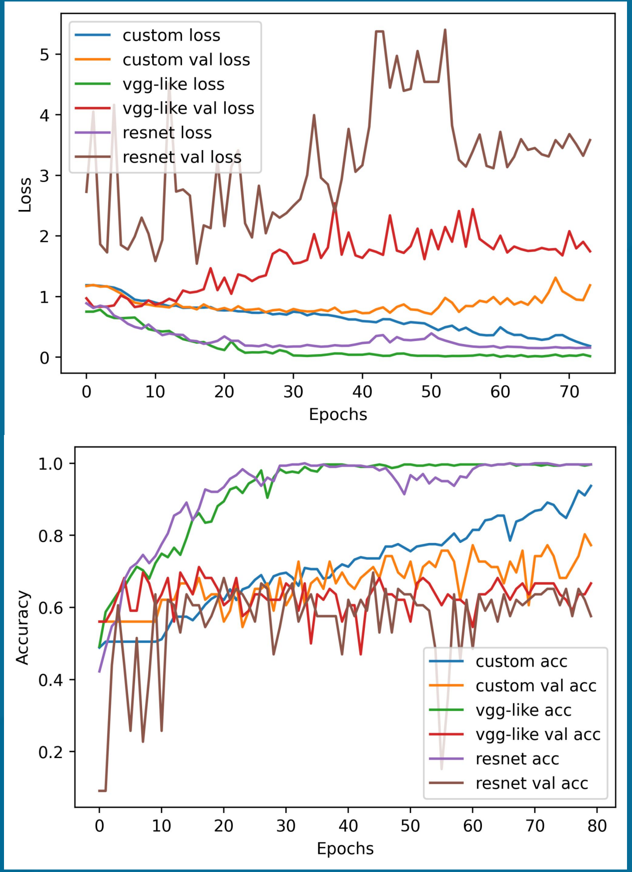
Support Vector Machine (SVM):

- Supervised learning machine method used for classification
- Used scikit-learn’s implementation to train using spectrograms

Results - Custom Model

- Preliminary models overfit
- Custom model has better validation accuracy than preliminary models

Model	Test Acc (%)	# of Parameters	Training Time Per Sample
Custom Model	77.27	73k	2ms
VGG-like	68.18	35M	10ms
ResNet22-v1	66.67	313k	23ms

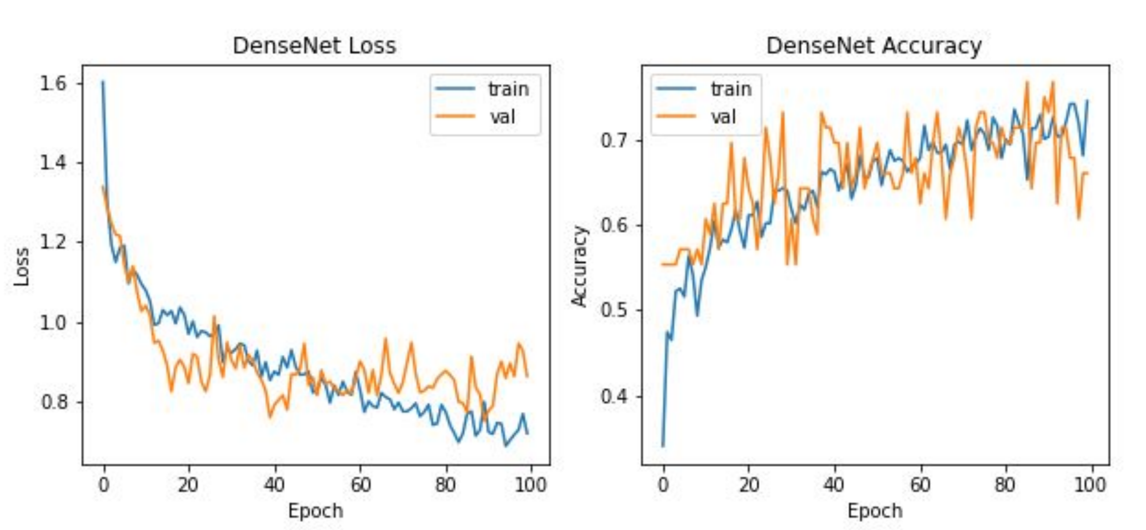


Results - DenseNet

- Highest test accuracy out of all models

Test Acc (%)	# of Parameters	Training Time Per Sample
78.89	7M	23ms

- Since each layer is connected to every layer deeper than it, maximum information flow occurs



Results - SVM

- With no hyperparameter tuning, we were able to achieve 61% accuracy

- We are still experimenting with SVM

Final Experiments

- Try different hyperparameters on DenseNet model
- Run models on noisy dataset
- Continue experimentation with SVM

References

[1] McNamara, Kevin et al. "Cardiovascular disease as a leading cause of death: how are pharmacists getting involved?." Integrated pharmacy research & practice vol. 8 1-11. 4 Feb. 2019, doi:10.2147/IPRP.S133088

[2] Shenda Hong, Yuxi Zhou, Junyuan Shang, Cao Xiao, Jimeng Sun, Opportunities and challenges of deep learning methods for electrocardiogram data: A systematic review, Computers in Biology and Medicine, Volume 122, 2020, 103801, ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2020.103801.

[3] Ali Raza et al. "Heartbeat Sound Signal Classification Using Deep Learning". In:Sensors19.21 (2019).issn: 1424-8220.doi:10.3390/s19214819.url:https://www.mdpi.com/1424-8220/19/21/4819.

[4] Fan Li et al. "Classification of Heart Sounds Using Convolutional Neural Network". In:Applied Sciences10 (June 2020), p. 3956.doi:10.3390/app10113956.

[5] M. Kedir-Talha and S. Ould-Slimane, "Neural networks and SVM for heartbeat classification," 2012 11th International Conference on Information Science, Signal Processing and their Applications (ISSPA), 2012, pp. 830-835, doi: 10.1109/ISSPA.2012.6310668.

[6] Wang Chao Ng. "Listen to Your Heart: Feature Extraction and Classification Methods for Heart Sounds". In: ()