Classification of Cardiovascular Arrhythmia using ECG Signals

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Introduction

An arrhythmia is an abnormal heart rate resulting from a cardiovascular problem. Approximately 5% of the US population develops an arrhythmia every year, and a new University of Pennsylvania study suggests that COVID-19 positive patients are 10 times more likely to develop arrhythmias than those without. In this project, we aim to accurately classify normal heartbeats from four different types of arrhythmias.

Dataset

MIT-BIH arrhythmia database[2] (downsampled and cropped signals with a sample rate of 125 Hz)
-87,554 training examples
-21,892 validation examples

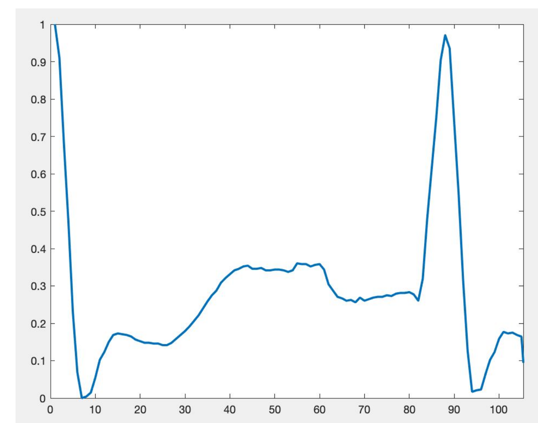
[2]Mohammad Kachuee, Shayan Fazeli, and Majid Sarrafzadeh. "ECG Heartbeat Classification: A Deep Transferable Representation." *arXiv preprint arXiv:1805.00794 (2018)*.
https://www.kaggle.com/shayanfazeli/heartbeat?select=mitbih_train.csv

Class Label	Arrhythmia Class	Distribution
0	Normal (N)	82.76%
1	Supraventricular premature beat (S)	2.54%
2	Premature ventricular contraction (V)	6.61%
3	Fusion of ventricular and normal beat (F)	0.74%
4	Unclassifiable beat (Q)	7.35%

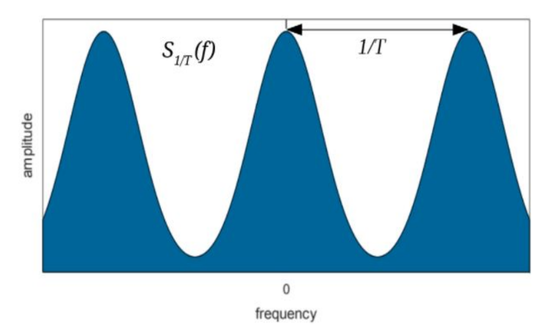
Features

1-D Features

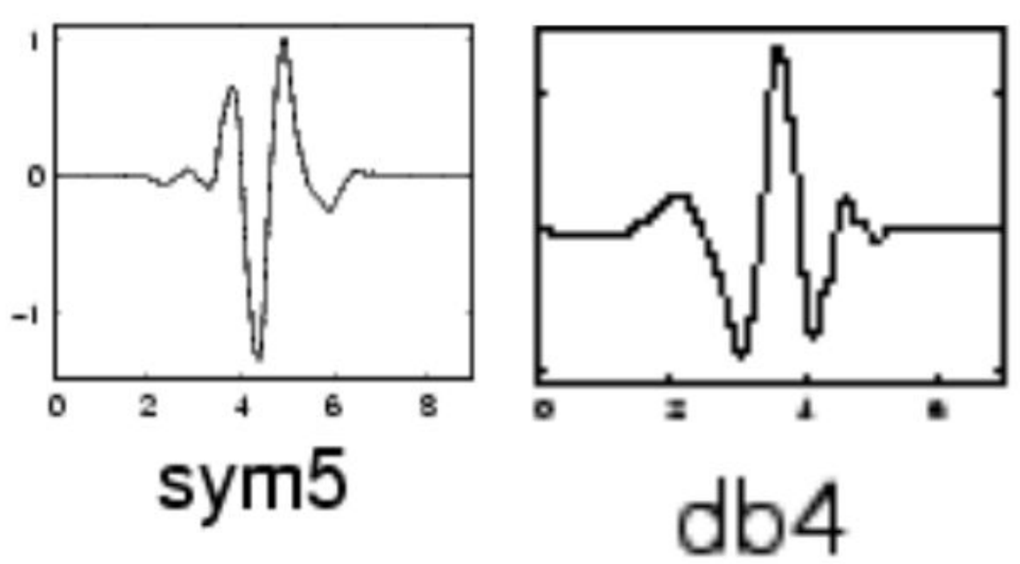
Raw Signal



DFT Magnitude

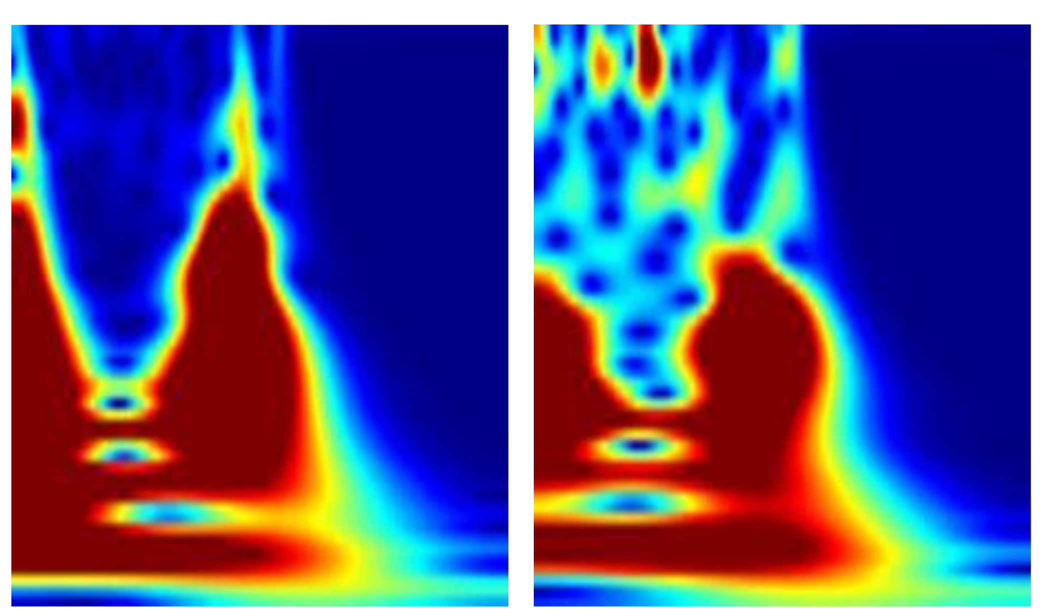


Discrete Wavelet Transform (DWT)

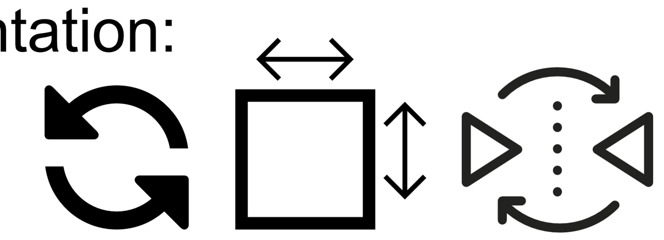


2-D Features

Continuous Wavelet Transform



Data Augmentation:
- Rotation
- Scaling
- Reflection

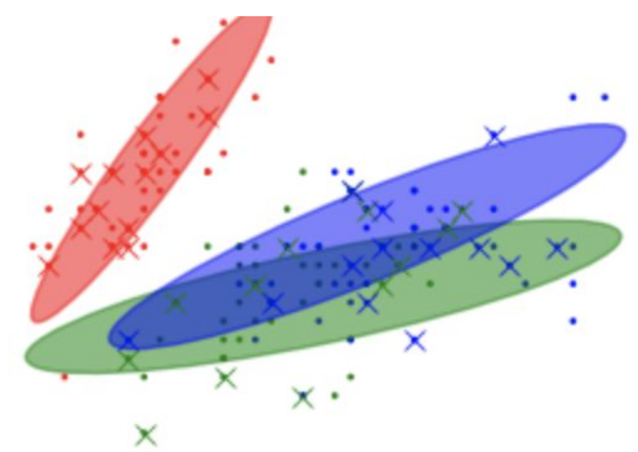


Models

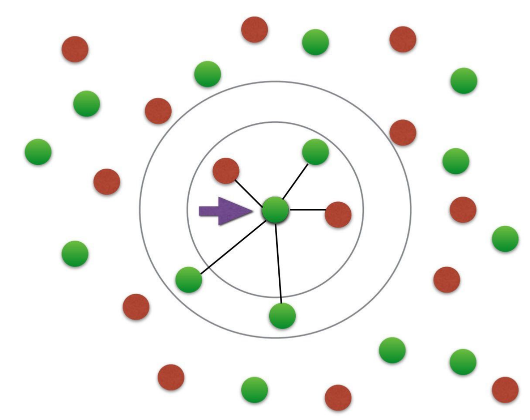
1-D Feature Classifiers

Naive Bayes $P(A|B) = \frac{P(B|A)P(A)}{P(B)}$

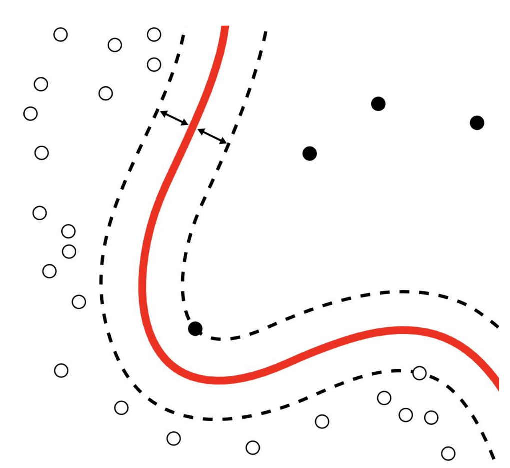
GMM



KNN

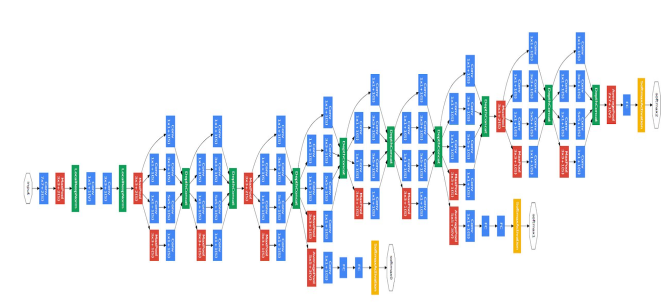


SVM

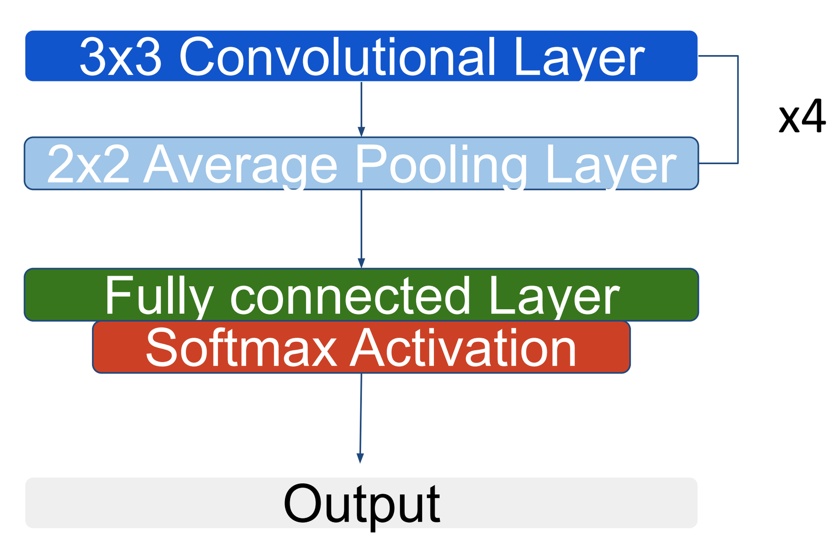


2-D Feature Classifiers

GoogleNet



Custom CNN



Results

1-D Classifiers

	Naïve Bayes	GMM (w/ PCA, max of number of components)	KNN (max of k=1,3,5)	Linear SVM	Quadratic SVM	Cubic SVM	RBF SVM
Raw ECG	41.95%	82.73% (1 component)	97.73% (k=1, normalized)	92.16%	97.08%	97.73%	81.40%
DFT Magnitude	47.75%	82.76% (same for 1, 2, 5, 15)	97.12% (k=3)	89.26%	93.79%	96.22%	82.76%
DWT Coefficients (max of db4 or sym5)	42.91% (db4)	82.76% (sym5, same for 1, 2)	**Best model: 97.76% (k=3, sym5)**	91.88% (same)	97.02% (sym5)	97.67% (sym5)	82.76% (same)
Raw + DWT (max of db4 or sym5)	-	-	97.76% (k=1, db4)	-	-	25.11% (sym5)	-

2-D Classifiers (Deep Models)

Model	Accuracy
GoogleNet + CWT images (224x224x3) Adam optimizer, 5e-3 learning rate, batch size = 128	69.32%
Custom CNN+ CWT images (32x32x3), No augmentation Adam optimizer, 1e-3 learning rate, batch size = 400	70.93%
Custom CNN + CWT images (32x32x3), with data augmentation SGDM optimizer, 1e-3 learning rate, batch size = 2800	82.76%

Conclusions

- The best classifier was KNN (k=3) with sym5 DWT features. The top classifiers were KNN and cubic SVM (with PCA) for raw waveform and DWT features.
- Raw and wavelet features led to better classifier performance than DFT features (i.e. time or time + frequency localization yielded better performance than frequency-only localization).
- Custom CNN performed better overall than GoogleNet with smaller CWT image size, most likely because parameters were trained from scratch. Smaller size helped save time and memory.
- As expected, CWT image data augmentation improved results for custom CNN.

Future Work

With more time and resources, we would:
1) Using known biological models, create custom wavelets designed to match features of ECG signals (e.g. QRS complexes, arrhythmic waveforms, etc.),
2) Use known characteristic features of the signals (i.e. QRS complex, P Wave, R-R segment, etc.),
3) With the above features, compare effectiveness of KNN and Cubic SVM classifiers,
4) Use GAN models for data augmentation, and
5) Hire ECG technicians to classify data set and compare human accuracy and model accuracy.