



Heart Monitoring System for Personalized Arrhythmia Detection

Elise Donkor, Tinoosh Mohsenin, Ph.D

Department of Computer Science and Electrical Engineering, University of Maryland, Baltimore County

Abstract

The purpose of this work is to build accurate algorithms to detect abnormalities in ECG signals from patients suffering from arrhythmia. ECG signals were obtained from the MIT-BIH arrhythmia database and relevant arrhythmia annotations. The signals were then detected using artificial neural networks, a biology-inspired machine-learning algorithm. The results ultimately yielded an arrhythmia detection accuracy of over 97%.

Background

What is Arrhythmia?

Arrhythmia is an irregularity with the rate or rhythm of the heartbeat. During arrhythmia, the heart can beat too fast, too slow, or with an irregular rhythm.

Why is it important to study?

There are over 3 million U.S. cases of arrhythmia per year. These irregularities can be indicators of diseases such as diabetes and precursors to on-setting heart attacks.

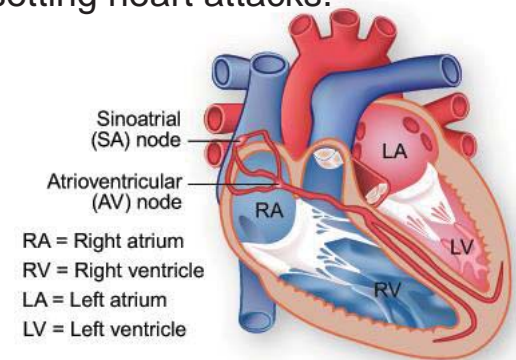


Figure 1 Heart Chambers (Texas Heart Institute)

Premature Atrial Contractions

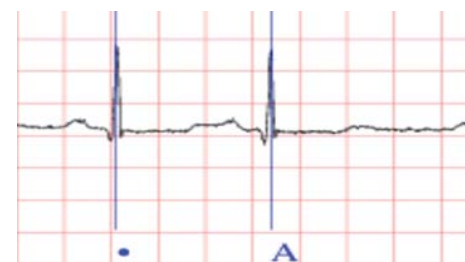


Figure 2 Premature heartbeats from atria (MIT-BIH)

Premature Ventricular Contractions

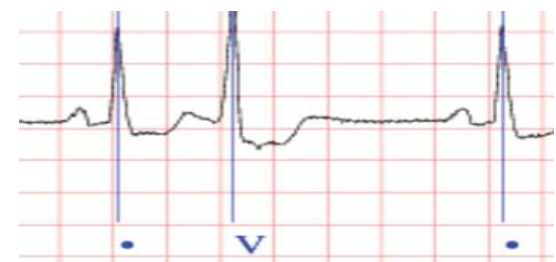


Figure 3 Abnormal heartbeats originating from ventricles (MIT-BIH)

Left Bundle Branch Block

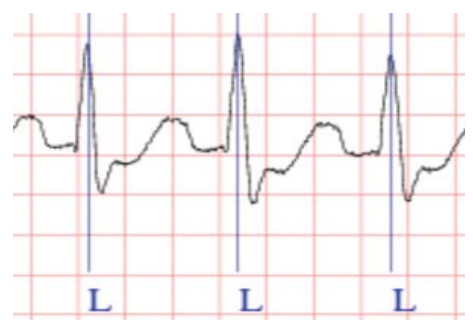


Figure 4 Left ventricle activation delayed (MIT-BIH)

Right Bundle Branch Block

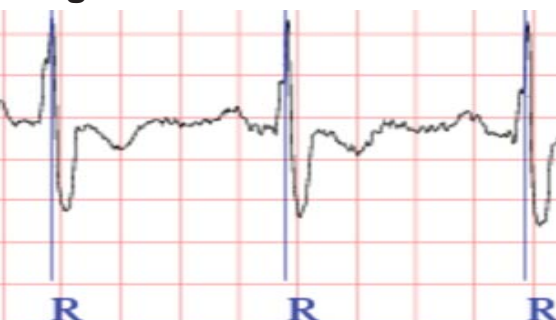


Figure 5 Conduction blockage through right ventricle (MIT-BIH)

Methodology

Patient Data Acquisition

Boston's Beth Israel Hospital (now Beth Israel Deaconess Medical Center) at the Massachusetts Institute of Technology (MIT-BIH) Arrhythmia Database contains 48 half-hour excerpts and annotations of ambulatory ECG recordings. All 48 Recordings were used for training.

Machine Learning – Artificial Neural Networks (ANN)

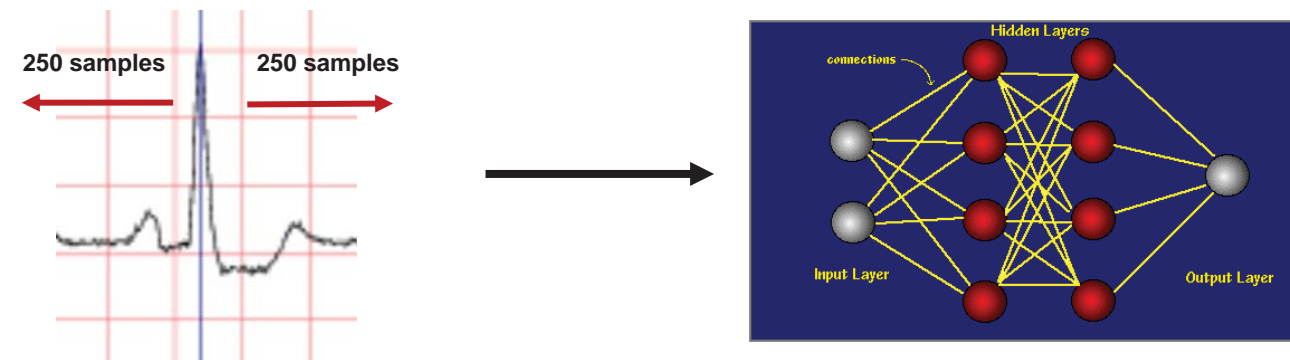


Figure 6 Signal Entering Artificial Neural Network (MIT-BIH, cs.wiscnson.edu)

Training the Network

Tool: MATLAB Machine Learning Toolbox (Pattern Recognition and Classification)

Data Division: Random

Training: Scaled Conjugate Gradient

Performance: Cross-Entropy

Calculations: MEX

ANN Data Division

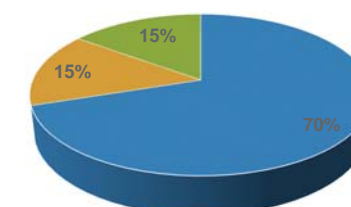


Figure 7 Artificial Neural Network Data Division

Results

Classification

5 Different beat types were classified using annotations in the MIT-BIH database: Normal, Premature Atrial Contraction (PAC), Premature Ventricular Contraction (PVC), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB)

Number of Hidden Layers

The detection accuracy increased as the number of hidden layers increased but plateaued around 16 hidden layers (Fig 8).

Confusion Matrix

A confusion matrix is a table that shows the performance of a classification model with 16 hidden layers. Accuracy was roughly 98% (Fig 9)

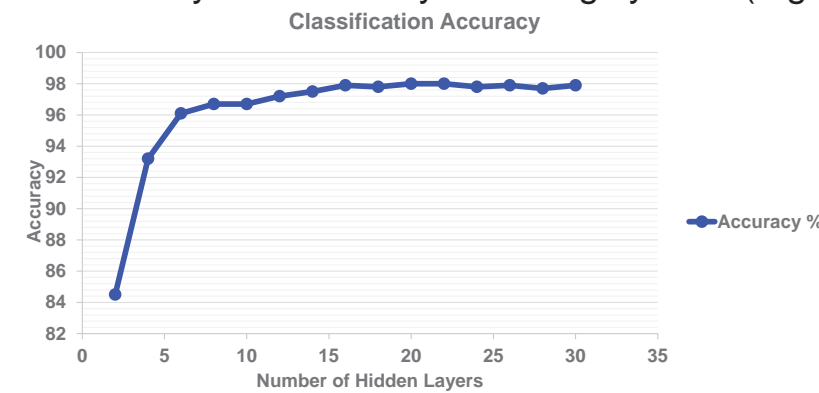


Figure 8

Output Class	1	2	3	4	5	
1	11043 74.2%	74 0.5%	67 0.5%	23 0.2%	7 0.0%	98.5% 1.5%
2	21 0.1%	280 1.9%	5 0.0%	0 0.0%	8 0.1%	89.2% 10.8%
3	48 0.3%	4 0.0%	952 6.4%	2 0.0%	3 0.0%	94.4% 5.6%
4	26 0.2%	7 0.0%	8 0.1%	1242 8.4%	0 0.0%	96.8% 3.2%
5	7 0.0%	12 0.1%	8 0.1%	0 0.0%	1026 6.9%	97.4% 2.6%
	99.1% 0.9%	74.3% 25.7%	91.5% 8.5%	98.0% 2.0%	98.3% 1.7%	97.8% 2.2%

Figure 9 Target Class

Class Number	Arrhythmia Type
1	Normal
2	PAC
3	PVC
4	LBBB
5	RBBB

Table 1

Results

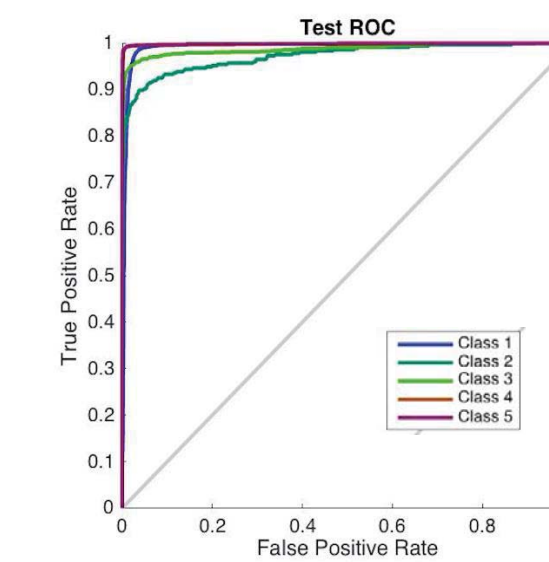


Figure 10

Receiver Operating Characteristic

- The ROC Graph represents the true positive rate or sensitivity vs the false positive rate.
- Ideally, a great algorithm should show points in the upper left corner, far from the diagonal, with 100% specificity and sensitivity.
- This graph shows all lines in the upper left hand corner

Conclusions

Neural Networks as a Classifier

- 250 samples before and after beat and ANN is a strong technique for Arrhythmia detection.
- No filtering or pre-processing has to be done in order for high accuracy to be achieved.
- Gives the possibility for low powered devices, since very little processing has to be done.

These algorithms pave the way for energy efficient wearable biomedical devices to monitor ECG heart signals. Heart monitoring systems can be implemented through smart phones that can send alerts to a care-giver whenever arrhythmia occurs.



Figure 11 Example of ECG Device (Fitbit)



Figure 12 Mobile Phone (Apple)

Acknowledgments

This project was supported by UMBC's Undergraduate Research Award and conducted under the guidance of Dr. Tinoosh Mohsenin in the Energy Efficient High Performance Computing Laboratory.

