Cardiac Dysrhythmia Detection with GPU-Accelerated Neural Networks

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Abstract

Cardiac dysrhythmia is responsible for over half a million deaths in the United States annually. Many of these deaths can be prevented with proper early diagnosis. In this work, we evaluate the performance of neural networks on classifying electrocardiogram (ECG) sequences as normal or abnormal (arrhythmia). Using both hand-crafted features and features contained in the dataset, we explain our model's performance and discuss hyperparameters we selected. Comparing the results of our model to those of popular models such as SVMs, random forests, and logistic regression, we find that our neural network outperforms these other algorithms in the binary classification case and achieves an accuracy of 78.5%. The use of GPUs accelerates the neural network training process by an order of magnitude.

Background

What is Dysrhythmia?

Cardiac dysrhythmia (or arrhythmia) occurs when the electrical activity of the heart is irregular, sometimes causing 100 beats per minute even at rest. Effects of arrhythmia range from discomfort to cardiac arrest.

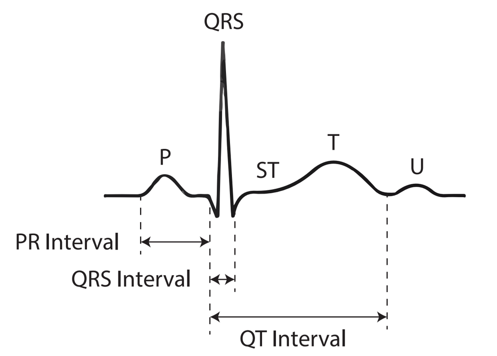

Figure 1: ECG measurement with common components used by physicians

Arrhythmia is responsible for about 500,000 deaths in the US, annually. Early detection and treatment of arrhythmia can reduce the number of deaths by 25% [1].

The simplest way to detect arrhythmia is through electrocardiograms (ECG). ECGs are time series measurements of electrical activity in the heart (see Figure 1). In this project, our goal is to detect and classify arrhythmia given ECG sensor readings.

Data & Features

We use the arrhythmia dataset found in the UCI Machine Learning Repository [2]. We describe the dataset below:

- **452 records with 279 attributes per record**
- Some records are missing one or more attributes
  - We imputed the data (mean) to fill missing attributes
- **16 unique class labels**
  - Label = 1: Normal ECG pattern
  - Label = 2 to 16: Arrhythmia is present (different labels denote a specific type of arrhythmia)

We used several features including:

- Patient characteristics: age, sex, height, and weight
- Average duration of the QRS complex (see Figure 1)
- Average heart rate of the patient
- First five principal componenets

Methods & Models

Why use GPUs?

Deep neural networks often require a large number of parameters for neuron weights and computation for backpropagation. Each neuron at each layer is identical and lends itself nicely to parallel computation. It has been shown that using GPUs for neural networks improves training speed by 11x-14x [4].

Additionally, with the rise of elastic compute architecture (i.e. the cloud), it is now possible to use GPU farms for training without owning the physical hardware.

In this work, we train a multi-layer neural network on a single GPU. Special code modifications must be made to leverage multiple GPU training.

Experimental Design

- Our training size is 272 records
- We use a hold out test set consisting of 180 records
- All test set results are from this hold out test set
- We use a GeForce GTX 750 Ti (640 CUDA cores)

We use the following models in our experiment:

1. Support Vector Machines
2. Random Forests
3. Logistic Regression
4. Neural Networks

A one-vs-all classifier is used for the multi-class case.

Our neural network uses two hidden layers and 2 and 16 output nodes for binary and multi-class classification, respectively. Hyperparameters are listed in the discussion section. Additional features are fed into the network with the original features.

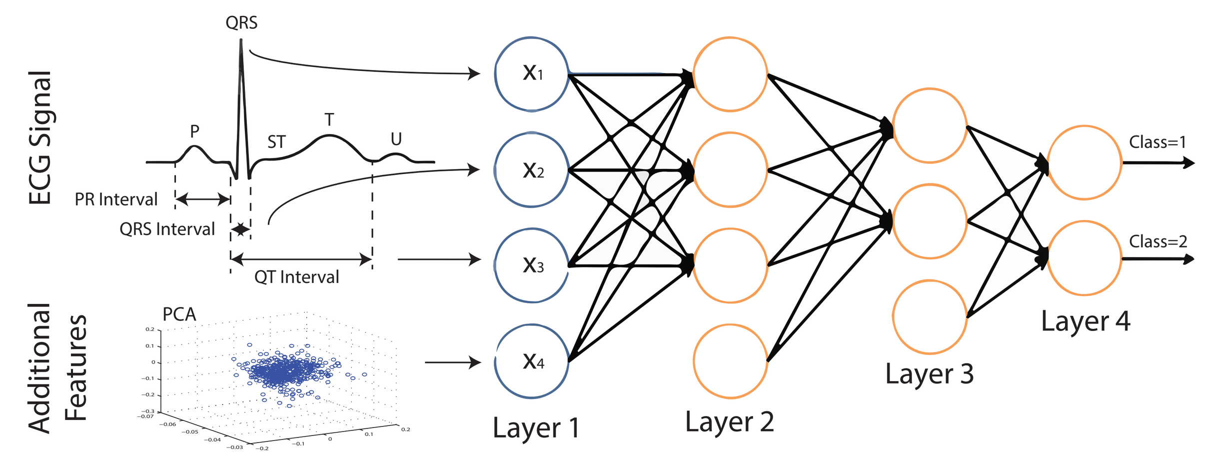

Figure 2: End-to-end illustration from feature extraction to prediction

Results

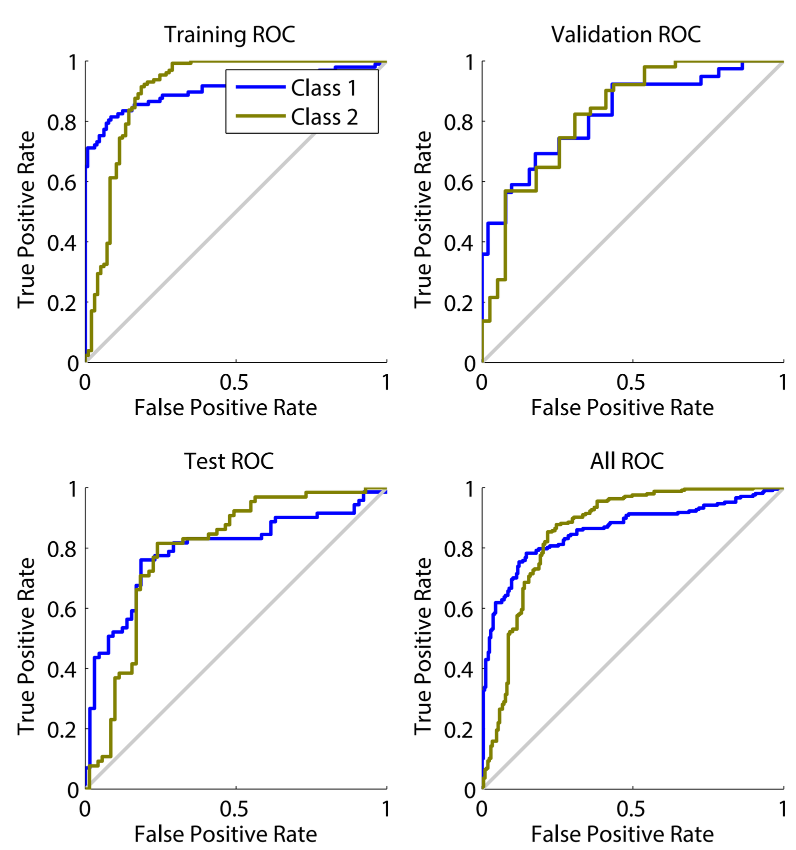

Figure 3: ROC curves for neural network (binary)

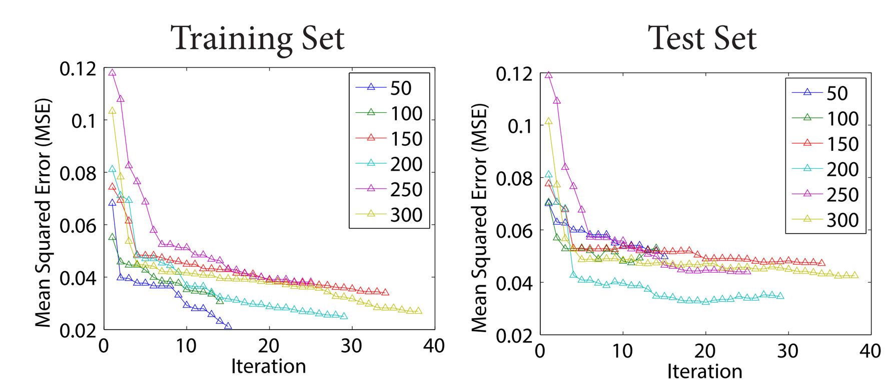

Figure 4: Training set size vs MSE for neural network (multi-class)

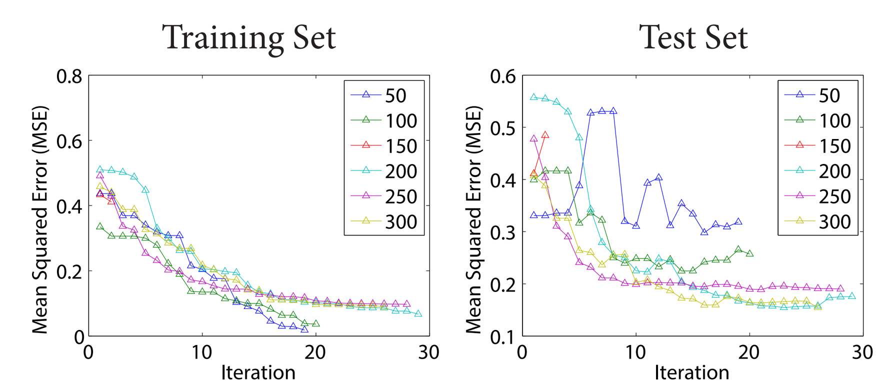

Figure 5: Training set size vs MSE for neural network (binary)

Predicted \ True Label	0 (Normal)	1 (Arrhythmia)
0	81 35.8%	5 2.2%
1	15 6.6%	125 55.3%

Figure 6: Confusion Matrix (NN, Binary, Training)

Predicted \ True Label	0 (Normal)	1 (Arrhythmia)
0	65 35.9%	16 8.8%
1	23 12.7%	77 42.5%

Figure 7: Confusion Matrix (NN, Binary, Test)

Table 1: Binary Classification (Test Set)

Model	Precision	Recall	Accuracy
Neural Network	80.2%	73.9%	78.5%
SVM	75.0%	74.0%	73.6%
Random Forest	72.0%	72.0%	72.0%
Logistic Regression	82.1%	71.0%	77.6%

Table 2: Multi-Class Classification (Test Set)

Model	Precision	Recall	Accuracy
Neural Network	N/A	N/A	47.6%
SVM	62.0%	65.0%	65.1%
Random Forest	69.0%	76.0%	76.0%
Logistic Regression	68.0%	70.0%	69.0%

Discussion

General Comments

Table 1 and Table 2 show results of our neural network when compared to other models. Our neural network achieves an accuracy of 78.5% and a false negative rate of 8.8% (Figure 7) in the binary classification case. SVMs are the second best model which achieve an accuracy of 73.6%.

Because of the limited training size and large number of class labels (16 labels), our neural network's performance suffers greatly (Table 2). Our network is unable to correctly learn weights for classes with few training examples (see Figure 8).

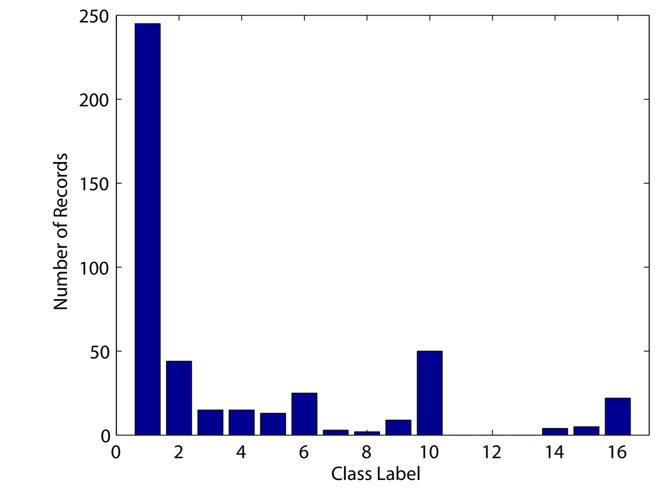

Figure 8: Dataset Class Distribution

Hyperparameter Tuning

Neural networks are parameter rich and have many options for training. To select the hyperparameters for our network, we manually tuned the parameters and iteratively improved performance. Our hyperparameter selections are below (binary classifier):

- Hidden layers: 3
- Neurons per layer: 300, 100, 100
- Regularization parameter: 0.01
- Learning rate: 0.01

Figure 9 (right) shows one of our analyses used to determine the optimal hyperparameters. Additional neurons at each layer does not necessarily increase performance.

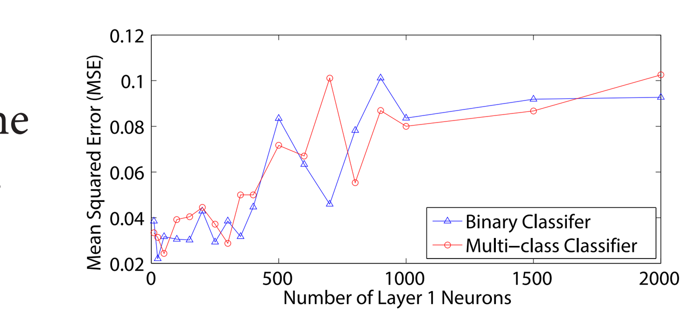

Figure 9: Number of neurons vs MSE

Future Work

Due to the time-series nature of ECG data, future work can explore recurrent and autoregressive neural networks [3]. These networks are well suited for predicting future time series and can be applied to ECG signals. Additionally, as with any learning problem, more (training) data would benefit our research.

References

[1] Heart Disease: Arrhythmia: A Patient Guide. HealthCentral.com - Remedy Health Media.
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[4] Brown, L. Accelerate Machine Learning with the cuDNN Deep Neural Network Library. nVidia Developer Zone. Sep 2014.