The Application of Deep Convolutional Networks for the Classification of ECG Signal

Edward Mina
Advisor: Professor Byron Wallace Ph.D.
Northeastern University College of Engineering
Boston MA

Abstract:

Electrocardiograms or ECG are signals that assess an individual's cardiac rhythm as signal. This is a result of the depolarization and repolarization of the hearts' chambers that can be interpreted voltage over time. The premise of this paper is the application of supervised deep learning to identify illustrations of labeled rhythmic aberrations. The proposed technique uses a series of single dimensional convolutions paired with a multilayered perceptron to classify five common arrhythmia's. The model was trained with 75% of the data which was sampled with equal class counts per batch but tested on the data's natural distribution. After implementation, the accuracy of the model proved to be 97.5 $\pm$ .0044 % over five iterations with per class metrics higher than 85% across all classes. Future improvements include different processing techniques as well as slight adjustment to model architecture.

Introduction:

Electrocardiograms are heart monitoring devices that measure a hearts' sinus rhythm. Biologically speaking, cardiac muscles generate a wave pattern through depolarization and repolarization of each chamber. As such, ECG measurements are often recorded by the placement of up to 12 electrodes on the body that can measure the overall magnitude of the heart's potential. A single heart beat voltage signal can be examined with a P wave which represents the depolarization of the atria; the QRS complex which illustrates ventricle depolarization; and finally the T wave, which indicates ventricle repolarization[1] (Figure A).

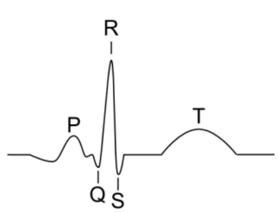

Figure A: An illustration of standard normal heart rhythm structure consisting a P wave, QRS complex, and T wave where R is the signal peak.

ECG's can also record instances of arrhythmia as well. This includes cases of premature beats where the either the atria or the ventricles pump an extra rhythm. This often causes feelings of a "flutter" or effectively a skipped beat in patient[2]. Likewise, fusion, a case where electrical impulses from different sources act upon the same region of the heart at the same time, can also be dangerous[3]. Instances of anomalous heart rhythm may indicate the onset of a potential cardiac infarction or heart attack. According to the Journal of the American Medical Association, nearly 25% of patients that experience heart failure return within 30 days costing patients, hospitals, and medical insurance companies billions annually. This minor percentage translates to millions of readmissions and thousands of deaths if it is too late[4]. As such, there exists an unmet need for the detection of these rhythmic aberrations to alarm patients, doctors, and nurses of potential arising cardiac conditions.

Data:

The data used in experimentation will be from the MIT-BIH Arrhythmia Database. The following database, collecting data from as far as 1975 has 30 minute (360 samples/sec) ECG recordings of 48 patients at Beth-Israel Hospital. Twenty-three recordings are randomly selected from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%). The remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample[5]. A sample illustration of the signal and labelled R peaks can be seen below.

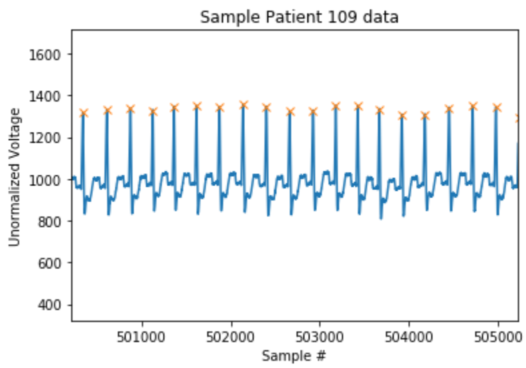

Figure B: Raw ECG data for patient 109 with labelled peaks with respect to sample number and raw unnormalized voltage recording.

Methodology:

Firstly, raw signal data was normalized from 0 to 1 using the equation below.

$$z_i = \frac{x_i - min(x)}{max(x) - min(x)}$$

Equation 1: 0_1 Norm Function

Afterwards, a moving average and a Butterworth low pass signal filter was implemented with a cutoff frequency of 20Hz out of the range of 60Hz. This however was later discovered to not have much impact on the model and was thus left independent of training.

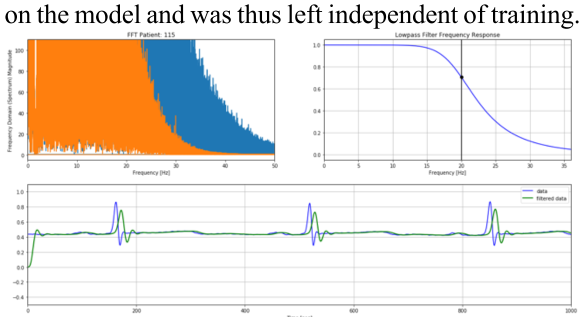

Figure C: Simple signal processing library was designed to examine the properties of the signal. Above is an illustration of a low pass filters effect with a cutoff= 20Hz within the frequency domain. The top right subplot is an illustration of the fast Fourier transform before (blue) and after filtering (orange).

In the final states of processing, an isolation algorithm was based on a R wave peak finder algorithm, such as a Christov Segmenter, to identify peaks. The MIT database has already labelled all peak instances and thus a segmenter will only be used in future application. The R peaks also provide the opportunity to compute the average patient heart beat. Every heart beat was isolated as follows:

$$Beat_i = \text{signal}\left[p_i - \frac{p_i - p_{i-1}}{2} : p_i + \frac{p_{i+1} - p_i}{2}\right], where\ p = peak$$

Equation 2: Heart Beat Isolation

Furthermore, in an effort to avoid instances of extreme class imbalance, categories were further grouped within each other based on relevance as seen in the table below. Thus, main classes included Normal Beats, All forms of premature beat, Ventricular Contraction, Fusion Beats, and the remainder grouped as unclassifiable.

```
For class: N (Normal beat)
  (N) Normal beat
  (L) Left bundle branch block beat
  (R) Right bundle branch block beat
  (e) Atrial escape beat
  (j) Nodal (junctional) escape beat
For class: S (Supraventricular premature beat)
  (S) Supraventricular premature beat
  (A) Atrial premature beat
  (a) Aberrated atrial premature beat
  (J) Nodal (junctional) premature beat
For class: V (Premature ventricular contraction)
  (V) Premature ventricular contraction
  (E) Ventricular escape beat
For class: F (Fusion of ventricular and normal beat)
  (F) Fusion of ventricular and normal beat
For class: Q (Unclassifiable beat)
  (/) Paced beat
  (Q) Unclassifiable beat
  (f) Fusion of paced and normal beat
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Table A: Heart Beat Classification Grouping Reference

After beat isolation and labelling, the data was zero padded to the maximum heart beat sample length and then resampled from 360Hz to125Hz. This was done to reduce the amount of data while preserving signal integrity. The data was then batched with a size of 512 and fed into a deep one dimensional convolutional network model shown in Figure E. It is important to note that training batch instances contained equal number of data points per class. This was done by using a weight based sampling method where each class weight was equal to the reciprocal of its count. This however was only done the training data whereas validation and test sets where evaluated with their true distribution. Since all patients did not have all classes, the testing data was isolated randomly per class as opposed generally across the entire data set.

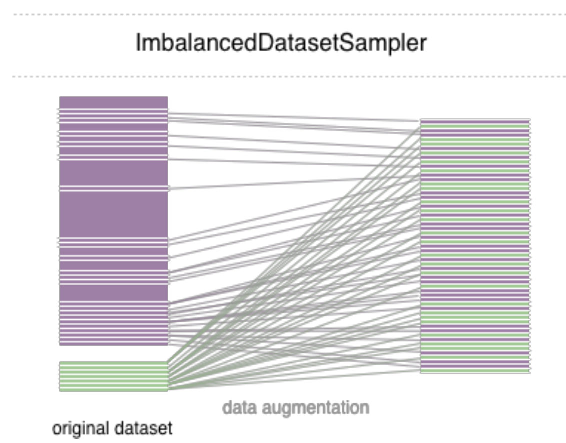

Figure D: Batch Sampling Methodology

A 1D CNN is very effective when examining features from shorter (fixed-length) segments of the overall data set and where the location of the feature within the segment is not of high relevance[6]. The model effectively relies on 4 blocks where each consisted of two 32 x 5 x 1 kernel convolutions and a final max pooling layer with a kernel size of 5 and stride of 2. The convoluted output is then fed into a dense fully connected series of layers with a ReLU activation function only after the first dense layer. The final dense layer output is equal to the number of classes (5) and activated with a Log SoftMax function. The model loss criteria was determined by the Pytorch's negative log loss and the model was optimized by a Adam optimizer with default decay beta values of .9 and .999 respectively along with a learning rate of .001 and epsilon of 1 x 10^{-8}.

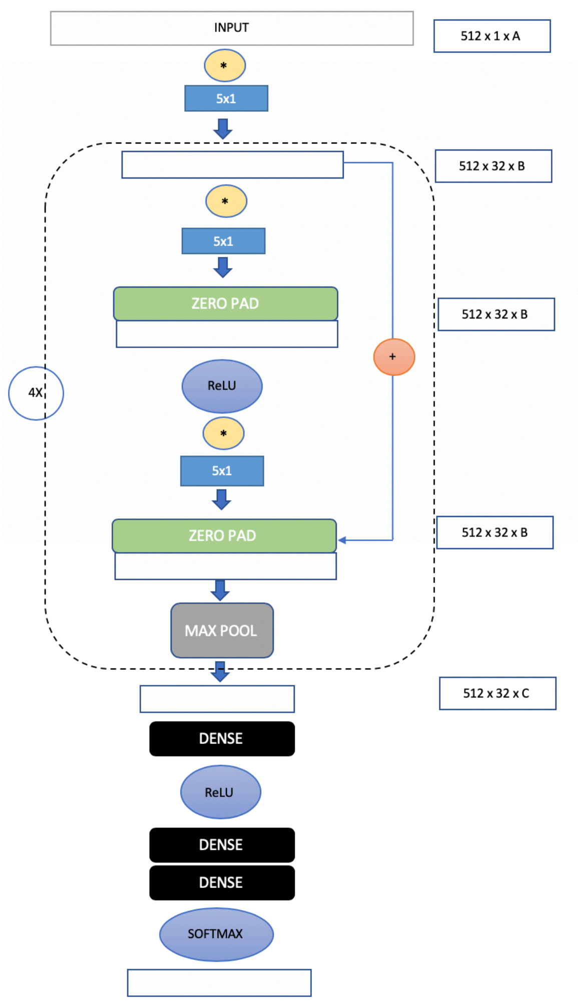

Figure E: 1D Convolutional Network Architecture

Results and Discussion:

In terms of signal processing, the average heart rate of all patients was 80.61 bpm with an average length of 283 and max length of 539 samples. This was later resampled to 187 with over 100,000 heart beat instances. The distributions were as follows: 89696 cases of Normal beats, 2388 cases of Supraventricular premature beats, 6827 cases of Premature ventricular contraction, 8028 cases of Unclassifiable beat, and 787 cases of Fusion of ventricular and normal beats. There were 163 training batches, 8 validation batches, and 43 test batches. The average model accuracy over 100 epochs and five iterations was 97.5 $\pm$ .0044 %. More specifically the model at 99% accuracy for Normal Beat, 90% for Supraventricular premature beats, 98% for Premature ventricular contraction, 87% for Unclassifiable beat and 99% for Fusion of ventricular and normal beat classification. Likewise, the macro average score for precision, recall, and f1-score were all .98, and .89, .94, and .92 for the micro average respectively. Loss at the first epoch was 151.74 and dropped to lower than 3.70 after the 90^{th} epoch. The unbalanced sampling method saw an 80% increase on average in the model per each class metrics. As such the premise for the high success rate relies on the normalization methodology and unbalanced sampling methods. Using an equal pooling and filter kernels sizes also is very suggestive of the nature of ECG signal, especially in cases of abbreviated time series data for classification.

Conclusion:

In the paper, a common approach for time series analysis was applied in a novel way for the classification and detection of anomalous heart beat data collected from Beth Isreal Hospital. The model relies on repeated single dimensional convolutions paired with relu activation functions and a max pooling layer and terminating with a simple fully connected, multilayer, perceptron. The model was very successful with an overall accuracy of 97% and greater than 85% accuracy across all class metrics. Applications of this model can be used in hospitals and smart medical devices to reduce the rate of re-hospitalization due to cardiac issues or examine improvement in a patient's conditions over time. Future applications of this model include improved signal processing techniques including different cutoff thresholds and normalization methodology as well as different heat beat segmentation and class categorization techniques.

Citations:

[1] Beatty, Graydon Ernest, Jeffrey Robert Budd, and John Anderson Hauck. "Method for measuring heart electrophysiology." U.S. Patent No. 7,189,208. 13 Mar. 2007.

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[4] Hernandez, Adrian F., et al. "Relationship between early physician follow-up and 30-day readmission among Medicare beneficiaries hospitalized for heart failure." *Jama* (2010): 1716-1722.

[5] G.B. Moody, R.G. Mark, and A.L. Goldberger, "PhysioNet: A web-based resource for study of physiologic signals," IEEE

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