

DEEP LEARNING MODEL FOR DETECTION OF CARDIAC ARRHYTHMIAS FROM ECG SIGNALS

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BACKGROUND

Cardiac arrhythmias account for the largest percentage of premature deaths in the United States. These are heart conditions characterized by uncoordinated electrical pulses in the heart. These pulses can be read through ECG readings and a medical professional can diagnose different forms of arrhythmias by analyzing the ECG data. However, the intermittent nature of some arrhythmias make it challenging to detect in short ECG readings. My goal is to develop a machine learning model that can accurately diagnose cardiac arrhythmias despite their intermittent and random symptoms. This model also must overcome the challenge of noisy ECG signals.

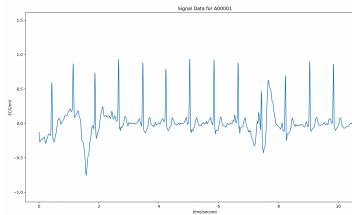


Figure 1: ECG signal sample plot from signal in PhysioNet database [3]

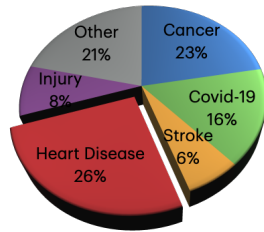


Figure 2: Leading cause of Death in the USA pie chart according to ...[1]

MODEL: 1D CNN FOR MULTICLASS CLASSIFICATION

- 1D Convolutional Neural Networks are good at learning and extracting important features from the dataset.
- Effective for identifying patterns such as normal vs irregular rhythms in a heartbeat
- Convolutional layers apply a filter for feature extraction while pooling layers help reduce dimensionality of the model.



Figure 3: Experimental Model - 1D CNN Architecture

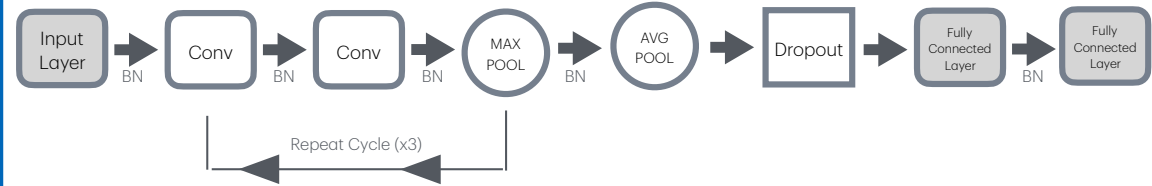


Figure 4: Baseline Model - 1D CNN Architecture [2]

*BN = Batch Normalization

RESEARCH & METHODS

Data

- To train and test the data I used a sample of 9,050 ECGs from the PhysioNet database [3] of 45,152 patient ECGs.
- 12-lead ECG readings no longer than 10 seconds
- Less frequent types of cardiac arrhythmias (Less than 1000 samples per category)

Pre-Processing

- I first wrote a program to sort the entirety of the .mat files into their respective classification folders according to the "ConditionNames_SNOMED-CT" (a reference .csv file) containing 43 classifications of different forms of cardiac arrhythmia, along with their abbreviations and header file code names).
- After the data had been categorized in their respective folders the program then selects the less common arrhythmias. I then conducted a 80/20 split for training and testing sets respectively.

Designing Pipeline/Model

- Comparing performance between two 1D-CNN model architectures.
- Implemented Hyper-parameter tuning
- Experimented with different DataFrame styles

DISCUSSION & RESULTS

The results from the 1D CNN for multi-class classification were very promising. Through experimentation with data formatting and implementation of hyper-parameter tuning I was able to achieve the performance metrics seen below. While these results varied slightly depending on how the data was randomized between training and test sets the performance seen below represents the overall performance of the model fairly well.



Figure 5: Experimental CNN Training and Validation Loss Graph.

NEXT STEPS: HYBRID QUANTUM CONVOLUTIONAL NEURAL NETWORK

Quantum Neural Networks are known to produce effective predictive models with excellent generalization performance even when provided with only a small amount of training data. My goal is to apply the best quantum convolutional layers and pooling layers to yield the best test results using a hybrid model design. I plan to experiment with different quantum encoding methods when transforming classical data to quantum bits. I plan to implement a quantum neural network layer using the PennyLane framework to encode the data and use its quantum circuit simulation to design a quantum neural network. With this I hope to improve performance in the classes that were harder for the model to classify as well as with noisy ECG signal samples.

REFERENCES & NOTES

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