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ECG Waveform Segmentation for P-QRS-T Detection Using Deep Learning Based on Fourier Synchrosqueezed Transform

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1. Introduction

The electrocardiograph (ECG) is a method that is used to record the electrical activity of the heart. It can be used to diagnose different heart conditions such as heart disease. Heart disease, or cardiovascular disease, is the leading cause of death for men, women, and people of most racial and ethnic groups in the United States, with heart disease responsible for 1 in every 5 deaths in the United States in 2021 [1]. From 2018-19, the Unites States spent $239.9 billion in health care services, medicines, and lost productivity due to death [2]. It is estimated that around 17.9 million lives are lost worldwide due to heart disease/cardiovascular disease [3]. Understanding the condition of the heart using ECG signals is not new, however, ECG produces a waveform which generates a large amount of data that is difficult to process. Deep learning can be used to expedite this task and in turn, potentially help save lives. Some study demonstrate the efficacy of employing signal preprocessing techniques and time-frequency analysis to enhance LSTM segmentation performance [4]. Specifically, it employs the Fourier synchrosqueezed transform to capture the nonstationary characteristics of the ECG signal.

The electrocardiogram (ECG) depicts the dynamic changes in electrical activity corresponding to the flow of ions, triggering contraction and relaxation of cardiac fibers [5]. Surface ECG is derived from the potential difference recorded between two skin-surface electrodes. Each normal ECG cycle comprises a P wave (atrial depolarization), a QRS complex (ventricular depolarization), and a T wave (ventricular repolarization), synchronizing with each heartbeat. Segmenting these waveform regions facilitates measurements crucial for evaluating cardiac health and identifying abnormalities [6]. Manual annotation of ECG segments is laborious and time-intensive. Signal processing and deep learning techniques offer promising avenues to automate and expedite this annotation process.

2. Proposed Methods

MATLAB 2023b is used to implement the design with the following packages installed for deep learning, digital signal processing, image processing, parallel computing, and statistics. They include the Communications Toolbox, the Deep Learning HDL Toolbox, Deep Learning Toolbox, Deep Learning Toolbox Converter for TensorFlow models, DSP System Toolbox, Image Processing Toolbox, Parallel Computing Toolbox, Signal Processing Toolbox, and Statistics and Machine Learning Toolbox.

With the packages installed and using appropriate computer hardware; the MathWorks code only runs on computers with 8 processing cores (8 CPU processors), or else errors occur. We attempted to run the code with a 6-core processor, but errors prevented the code from fully executing. A 12-core processor was also tested however, the code did not run past halfway without errors occurring. An 8-core CPU is required for this code. The PC used was equipped with an AMD 5800X3D CPU, 32 GB of RAM, and a 3080ti GPU and completed a full pass of the code in roughly 25 minutes.

The MathWorks code has three separate data training sections. The dataset is comprised of 225,000 ECG samples. The dataset is then split into training and testing datasets with a 70-30 split, respectively. A preview of the first 1000 samples of unprocessed data is shown in Figure 1.

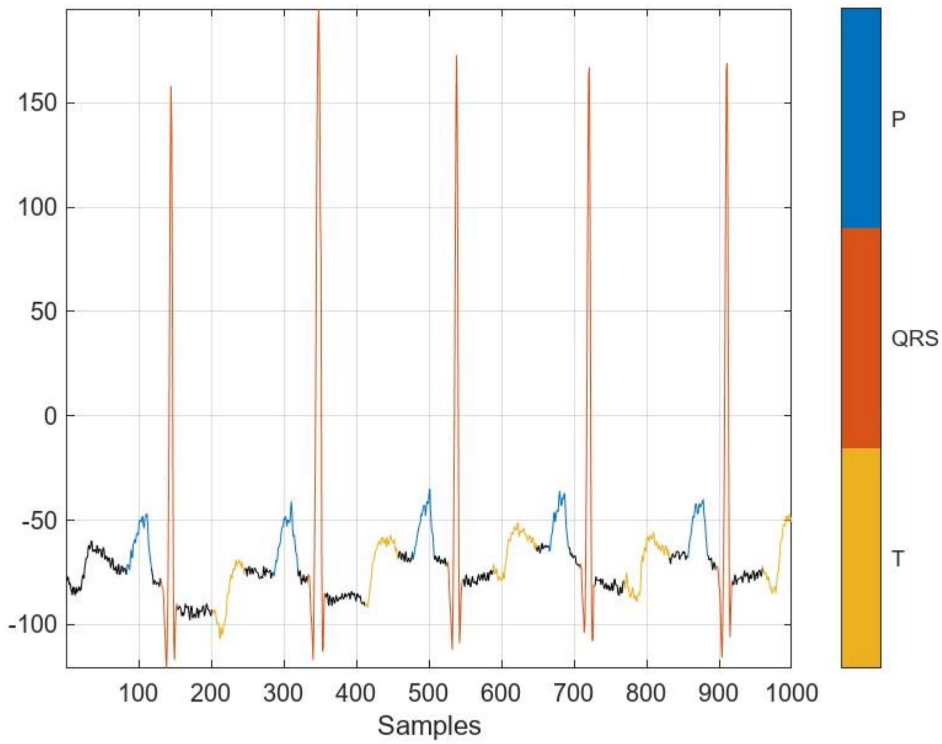

Figure 1: ECG sample of first 1000 signals, initial classification without any training/testing

First, the deep-learning network is fed the raw ECG signals and then begins the first training, on our PC the first training took just over 5 minutes. Then the ECG signals are filtered, a low and high pass filter to eliminate the participants breathing and any other high frequence noises. The deep-learning network is retrained with the filtered ECG signals data. The second training took just under 6 minutes. After, the filtered ECG signals are then converted into a time-frequency representation of the ECG signals using a Fourier Synchrosqueezed Transform (FSST). The FSST data is then fed into the deep-learning network and trained for the final time. The third training took almost 8 minutes to complete.

With our PC, the total time from start to finish for this was roughly 20 minutes to do multiple training phases and testing.

3. Experimental Results

The first training was conducted with the raw ECG signals and the accuracy can be seen below in Figure 2.

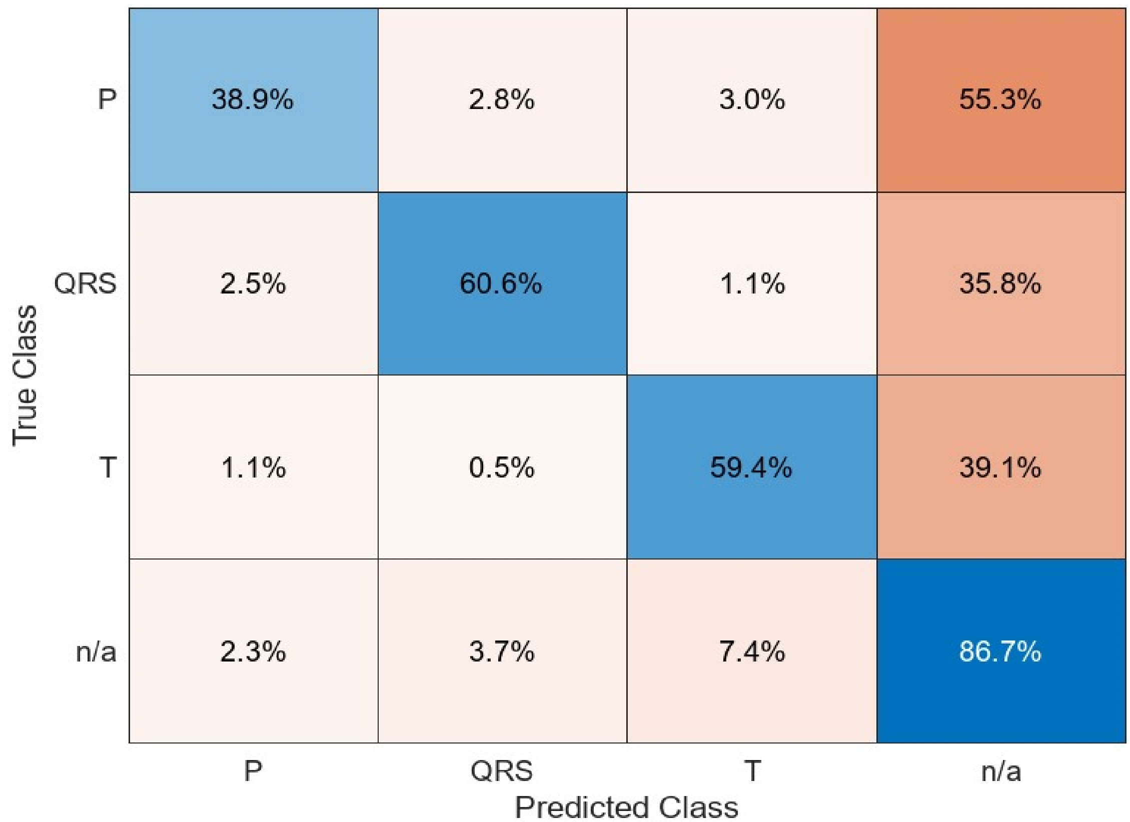

Figure 2: Training Accuracy after 1st training with raw ECG signals

Utilizing the raw ECG signal as input to the deep learning network resulted in approximately 60% accuracy for T-wave samples, 40% accuracy for P-wave samples, and 60% accuracy for QRS-complex samples. A bandpass filter was used to remove frequencies below 0.5hz and above 40hz. The then filtered ECG signals were fed back into the deep-learning network and retrained. Results of the retraining are seen in Figure 3.

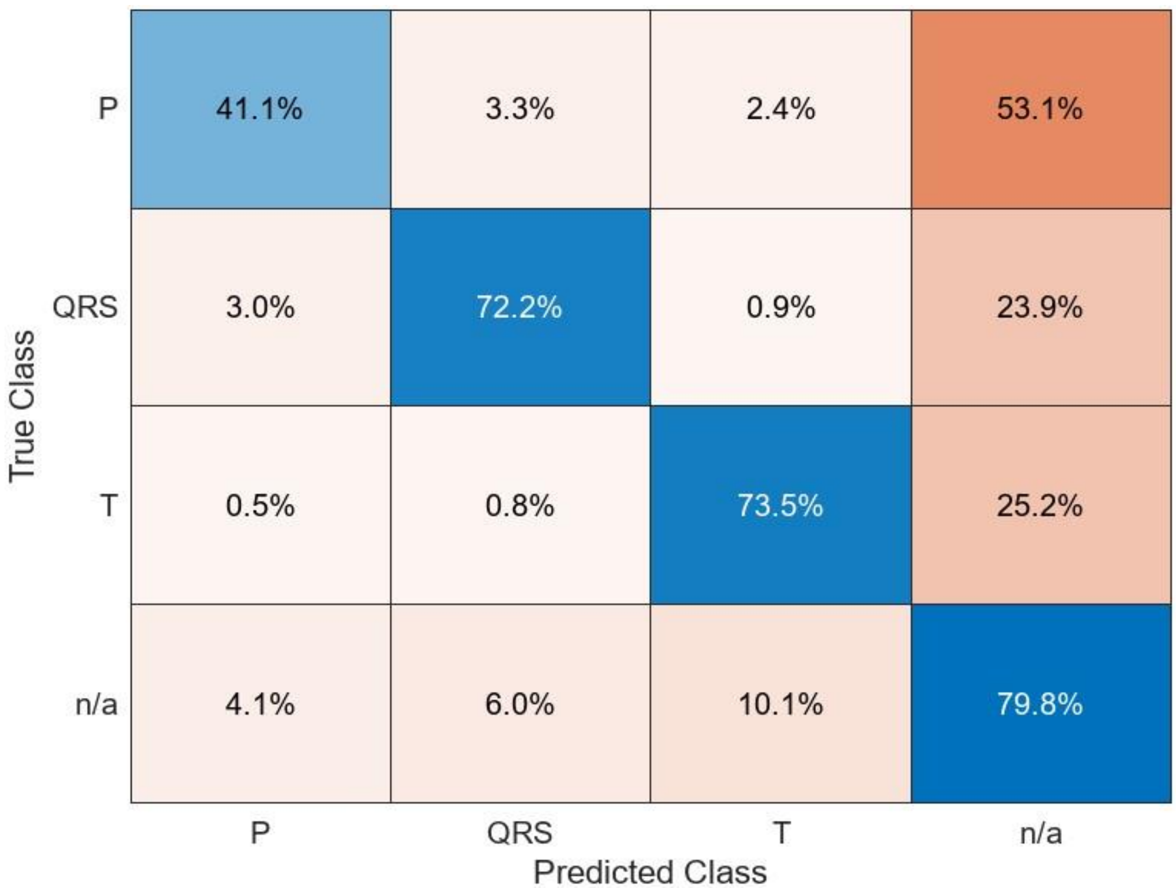

Figure 3: Training Accuracy after 2nd training with filtered ECG signals

With the filtered ECG signals, the accuracy has improved by about 15% for the T-wave, from 59% to 73%, and 10% for the QRS-complex and the P-wave respectively. Next, the filtered data was fed into the FSST, and the deep-learning network was trained for the final time as seen in Figure 4.

Employing a time-frequency representation enhances T-wave classification by approximately 25%, P-wave classification by around 40%, and QRS-complex classification by 30% compared to the results obtained using the raw ECG signal.

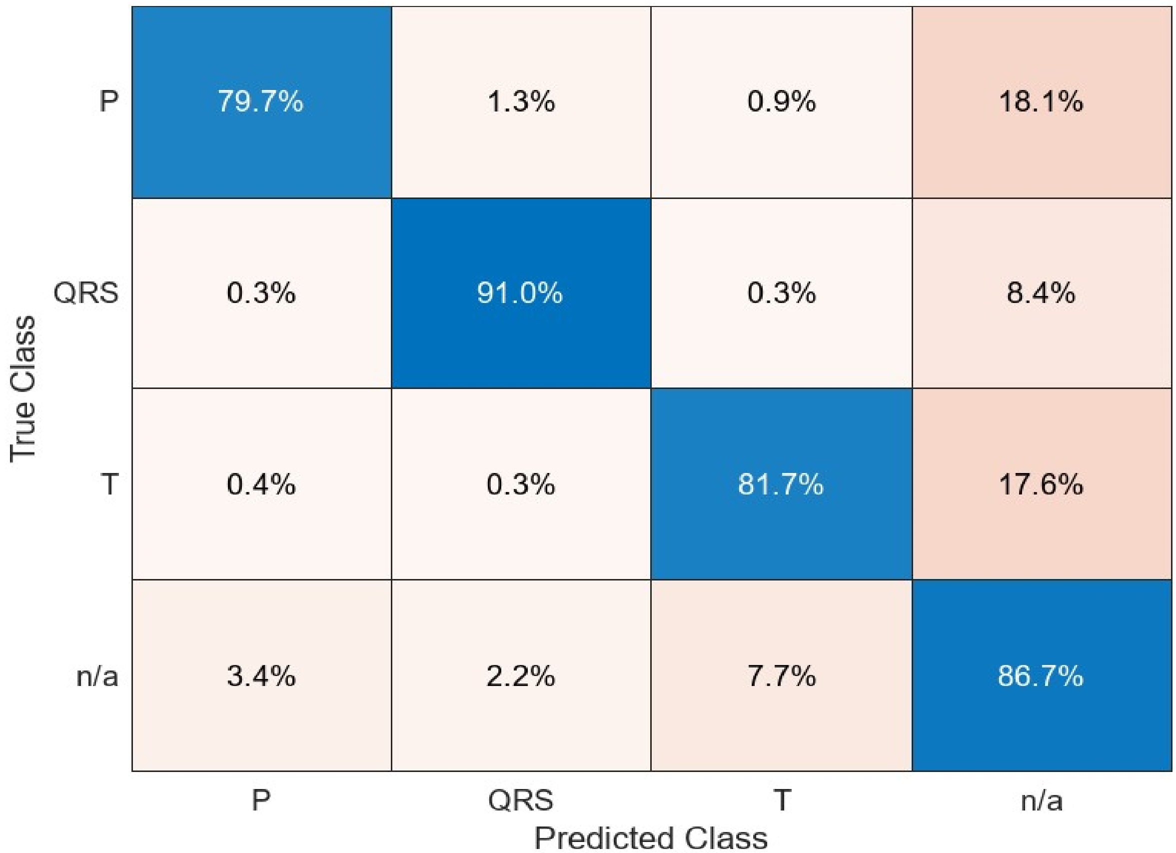

Figure 4: Training Accuracy after 3rd training with FSST data

4. Conclusions

In a span of roughly 20 minutes, a dataset compromising 225,000 raw ECG signals was split into 70:30 training and testing datasets. With the deep-learning network, the test dataset, which is 67,500 raw ECG signals, was first shown to accurately 60% of T-wave samples, 40% of P-wave samples, and 60% of QRS-complex samples in only 5 minutes. In roughly 6 minutes, the deep-learning network was retrained with filtered data and accuracy improved by about 15% for the T-wave, from 59% to 73%, and 10% for the QRS-complex and the P-wave respectively. In another additional 8 minutes, the accuracy improved to almost 80% for P-waves samples, 91% for QRS-complex, and almost 82% for T-wave samples. This deep-learning network is able to rapidly and accurately predict the types of ECG signals from the heart. Once this deep-learning network is properly set up, and with the necessary PC hardware, doctors/nurses will be able to quickly determine how a patient’s ECG signals from their heart is behaving. If there is something out of the ordinary, the doctors and nurses can be aware within minutes of gathering ECG signals.

As mentioned, the hospital or clinic will have to have the deep-learning network already set up and ready for use and preferably further trained with ECG signals. As an initial proof of concept, the deep-learning network shows promise. However, the P-wave & T-wave accuracy must be improved and further training with larger datasets can help improve accuracy. Hospitals/clinics will also need to have the raw ECG signals from patients filtered and then fed into the deep-learning network with FSST to get the most accurate results. The process of getting the ECG signal classification must be streamlined and simplified before hospitals/clinics can implement them since doctors or nurses may not have the necessary skillsets to troubleshoot code in MATLAB.

Acknowledgment

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