Anomaly Detection of ECG with Wavelet Decomposition and Reinforcement Learning

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***Abstract*— Many heart health problems can be detected with ECG (Electrocardiogram). Today, there are many devices which can collect your Heartbeat such as Fitbits and Apple Watch amongst the category of Smartwatches. Accordingly, it would be prudent to incorporate a Reinforcement Learning model in these devices that learns your Heartbeat patterns so that it is later able to recognize if your ECG is abnormal thus signaling a timely medical intervention. In this project, we work with 16 seconds of ECG to train a Reinforcement Learning model. Wavelet Decomposition and Savitzky-Golay Filter were both leveraged to denoise and smooth the signals. Due to limited data, we chose to focus on learning the distribution of normal data. Hence, our model only determines if the data is normal or abnormal. Now, whenever the difference between the predicted and actual Heartbeats differs by being greater than a certain threshold (Mean + 3xStandardDeviation), then a flag is raised alerting of an abnormal ECG. It is our hope that such a Reinforcement Learning model is incorporated into small mobile devices, hence, we are mindful of using small training time, data, and memory.**

***Keywords* —ECG, Forecasting, Wavelet Decomposition, Savitzky-Golay Filter, Reinforcement Learning**

I. Introduction

With ECG (Electrocardiogram) we are able to determine if someone is experiencing an “arrhythmia” which means an abnormal rate or rhythm of the Heartbeat indicating diseases such as heart defect, coronary artery, heart valve, and enlarged heart. In 2020 [1], an estimated 53,000 Canadians died of heart disease making it the second cause of death after cancer. In comparison, during that same period, around 16,000 people died of COVID-19. In our world today, smart devices are ubiquitous. Many already have the ability to collect Heartbeat information such as Fitbits and Apple Watch. Accordingly, it would be beneficial to go one step further by using these devices to monitor and detect abnormal Heartbeats.

In this project, we train a Reinforcement Learning model to learn the normal patterns of Heartbeats. The data set consists of normal data from the ECG-ID Database [2]. This data is also transformed to the frequency domain using Wavelet Decomposition to remove noise. Thus, our Reinforcement Learning model will learn the patterns of normal Heartbeats. If the difference between the forecast and the actual results are above a threshold (Mean + 3xStandardDeviation), then it will be considered, an anomaly and the user will be alerted. This value means the data falls at the extremes of a normal distribution thus indicating that it is of low occurrence. Percentage wise, if a result is above this threshold, then it is equivalent to having an occurrence of 0.27%. If the condition is severe enough, we propose that the device could automatically alert 911.

The use of devices for medical purposes is becoming more prevalent. Just recently [3], Apple has patented AirPods that are able to monitor brain activity whereby strokes may be detected amongst other things. There is a large potential and public good to work with these easy to collect bio signals. Thus, our project has great potential to help people who unwittingly have some sort of heart disease.

II. Related Works

We investigated several papers ranging from 2016 to 2023 with most falling into 2021 and up. Additionally, we participated in McGill University’s McMedHacks [4] that focused on Artificial Intelligence in Medicine. Overall, we found that there were various solutions for Anomaly Detection of ECG. Our search was for the Wavelet Decomposition and Reinforcement Learning methodologies. Wavelet Decomposition was used in a couple of articles to filter noise. Reinforcement Learning was also used. However, it was of the Deep Reinforcement Learning version which incorporates a Neural Network instead of a table as is done in our project. We chose our methodology because we want it to be applicable in mobile devices. Hence, we seek simplicity, ease of use, and, also, being lightweight.

In [5], they used Deep Reinforcement Learning in order to analyze ECG. Plus, they combined an age parameter. In [6] they also performed Deep Reinforcement Learning combining it with SVM (Support Vector Machine). In addition, they trained the model using 11 subjects for 6 days. In [7], they use a Deep CNN Reinforcement Learning model.

In [8], they used 3D Discrete Wavelet Transform and SVM. The Wavelet was used to preprocess the data by removing noise. This was a classification problem whereby the SVM categorized the ECG into nine different heartbeats.

In [9], they leveraged the AWS (Amazon Web Service) cloud machine learning services and storage. They perform multi-class classification using a deep LSTM (Long Short-Term Memory) auto-encoder with 98% accuracy.

In [10], they used neural networks to detect the QRS interval. Heartbeats follow a distinctive pattern called the PQRST (see Fig. 2). Their conclusion is that most of the anomalies occur at this junction.

In [11], they created Deep Learning "ECG-AAE" which consists of autoencoder, discriminator, and outlier detection. A significant characteristic is that they only used normal ECG data. Thus, if a data does not fit this model, it is considered an anomaly.

In [12], they combine wavelet scattering feature extraction with a Neural Network and SVM achieving good results that are capable of classifying heart issues such into the categories of arrhythmia, congestive heart failure, and also normal sinus rhythm.

In [13], they use LSTM-RNN with Reinforcement Learning in order to predict missing data. Missing data may be a result of poor conduction of the ECG probs or a recording error.

In [14], they highlight the potential of AI-ECG (Artificial Intelligence based ECG). Indeed, such tools could significantly improve clinical care. They present the great potential of this field. In [15], they highlight the growing importance and use of devices capable of measuring physiological signals. They highlight the use of LSTM with wavelet scattering. In [16], the goal is similar – to present a review of the potential of the use of Artificial Intelligence with ECG in order to monitor and diagnose cardiovascular diseases.

In [17], they perform both Discrete Wavelet Transform and Continuous Wavelet Transform in order to detect two types of disease: cardiac and congestive heart failure. They combine this with a CNN (Convolutional Neural Network). In [18], they also combine Wavelet Transform with CNN in order to classify into nine kinds of signals.

In [19], they use ECG to determine stress levels of the patient. Their model is a multi-kernel SVM that is combined with three optimization techniques: Genetic Algorithm, Artificial Bee Colony, and Particle Swarm Optimization.

In [20], they use Reinforcement Learning with a Q-Table in order to detect the "R" component of the ECG signal. The reason is that the irregularity of the "R" component is prevalent in many heart diseases.

In [21], they use an ensemble of ESN (Echo State Network) which is able to determine the VEB+ and SVEB+ classes. These are special groupings based on morphological features.

In [22], they use a Deep Reinforcement Learning architecture in order to learn the different classifications of heart disease.

Literature presents many successful stories. The main difference with ours is that we incorporate Wavelet Decomposition with a Q-Table based Reinforcement Learning. Plus, our training dataset is small, only 16 seconds. Our goal is to successfully detect anomalies while at the same time being small enough to fit in a Smartwatch device and fast enough to use. In this paper, we provide our proof of concept.

III. Methodology

This project consists of two major components. The first is the collection of data, preprocessing, and transforming it from a time-series to the frequency domain using Wavelet Decomposition, then we return to the time domain. Next, we train a Reinforcement Learning model to learn the dataset to make predictions of what the future values should be. Finally, we find the difference between the actual and predicted values. If this difference is above a threshold (mean + 3xStandardDeviation), we flag it as an anomaly, hence, an arrhythmia. Heartbeat anomalies tend to follow a pattern. As they have a frequency and are, thus, different from regular noise and outliers. The anomalies were manually generated to test our system. Additionally, we would like to state that we leveraged ChatGPT.

A. *Dataset*

The dataset used is from ECG-ID [2] published on March 6, 2014. It consists of 310 normal ECG recordings from 90 people. The readings are all for 20 seconds measured with a period of 0.002 seconds which is equivalent to a frequency of 500 Hz. It is from 44 men and 46 women of the ages 13 to 75 years old. The number of records per participant is from 2 (for one day) to 20 (over 6 months). In Fig. 1., a sample patient ECG is presented. For this project, we will only consider one 20 second sequence (10,000 steps) from the first patient. The reason is that our goal is for the Smartwatch to be able to quickly train a small 16 second baseline live. Additionally, we will split this 80%-20% meaning 16 seconds (8000 steps) is for training with 4 seconds (2000 steps) for testing. Additionally, the mean and standard deviation from these 16 seconds is calculated to be used as the anomaly threshold. Below, is a visual of the ECG patterns of the first patient.

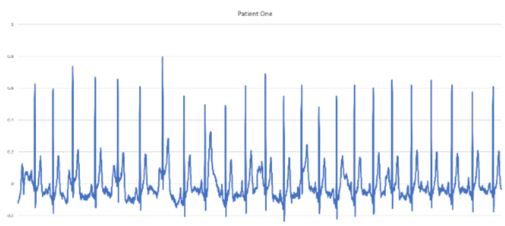

Fig. 1. Sample ECG data for Patient One

The ECG has a periodic appearance with a distinctive pattern that is repeated. In medical terminology, the ECG signal is called a PQRST signal. In the following image, an example period is presented.

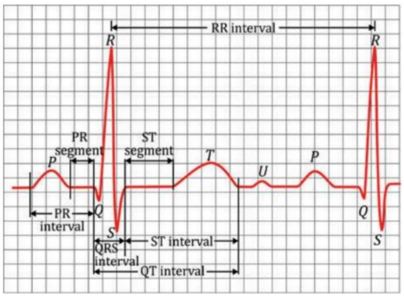

Fig. 2. ECG PQRST Sequence for one Cycle, Source [10]

Abnormalities occur when the height and frequency does not conform to this pattern. Additionally, it is possible for too early or too late distortion of the signal. It is these disparities from the normal PQRST that we will classify as being an anomaly. It is also important to know that Heart anomalies occur in distinct patterns (they have a frequency), hence, these anomalies are different from random noise and outliers.

B. Wavelet Decomposition

The original data is in the time domain. Thus, we will convert it to the frequency domain by using Wavelet Decomposition. Then, the data will be converted back to the time domain. The reason for this is because it is very easy to remove noise from the frequency domain instead of the time domain. The equation is as follows:

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\, \varphi^{*} \frac{(t-b)}{a} dt$$

a: Scale (dilation) parameter, b: Location of wavelet,
φ: $Wavelet\ function$, x: Signal

Fig. 3. Continuous Wavelet Transform

In our project, this Wavelet Decomposition was performed twice. First, it is to remove noise from the original signal. Next, it is to remove noise from the forecasted signal.

C. Reinforcement Learning

Reinforcement Learning is a way to train a model that is based on how humans learn. Essentially, there is an agent that moves in an environment. He takes actions according to the current state. These actions may lead to rewards thus emphasizing that the paths with the biggest rewards are the best options. The following figure captures this architecture.

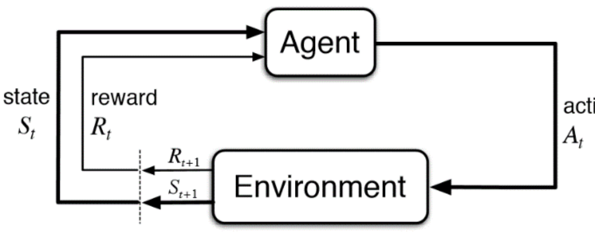

Fig. 4. Reinforcement Learning architecture. Source [8]

In our experiment, actions are based on epsilon (the epsilon-greedy policy) being 0.3 with the reward as the inverse of the distance between a predicted and actual action. Thus, if the distance is close the award would be high and if the distance is large the award would be low. Additionally, we have set our state to be a window of the past 5-time steps which is equal to 0.1 seconds.

Another important variable updated is the Q-Table whose Q-Values are governed by the Bellman Equation with a discount factor of 0.95 and a learning rate of 0.1. The Q-Table is a lookup that determines what is the next best action given the current state. Generally, a Q-Table takes up less space than a Deep Neural Network, hence, our choice to use a Q-Table. The following is the Bellman Equation.

$$Q(s,a) = \sum_{s',r} p(s',r|s,a)[r + \gamma max_{a'} Q(s',a')]$$

$r\ is\ the\ immediate\ reward\ for\ taking\ action\ a\ in\ state\ s$

$\gamma\ is\ the\ discount\ factor$

$Q(s,a)\ is\ the\ Q-value\ for\ state\ s\ and\ action\ a$

$p(s',r|s,a)\ is\ the\ probability\ to\ s'and\ with\ r\ when\ a\ \&\ s$

$s'is\ the\ next\ state, a'is\ the\ next\ action$

Fig. 5. Q-Value Bellman Equation

To test if Reinforcement Learning is working, we will calculate the MAPE (Mean Absolute Percentage Error) which is the distance between Actual and Forecasted as presented next.

$$MAPE = \frac{1}{n} \times \sum \left| \frac{actual\ value - forecast\ value}{actual\ value} \right|$$

Fig. 6. MAPE Equation

The MAPE score indicates the average distance between the predictions and the actual values, expressed as a percentage of the actual value.

D. Anomaly Detection

Once we have a Reinforcement Learning model that has learned the normal distribution of ECG data, we are now ready to perform anomaly detection. Here, we use a simple distance namely to determine if the distance between actual and predicted is above a certain threshold. We have set this threshold to be (Mean + 3xStandardDeviation). Thus, if the distance is above this, then we have an anomaly. Below, is the equation of the threshold.

$$Anomaly\ if\ |predicted - actual| > (\mu + 3 \times \sigma)$$

Fig. 7. Anomaly Detection Equation

To test we synthetically produce anomalies.

E. Savitzky-Golay Filter

This is a procedure used in signal processing to remove noise but preserve the important features of the time series. It works with a polynomial and window to determine how and where to put the smoothed values. The equation is as follows:

$$y_i = \sum_{j=-n}^{n} c_j \cdot x_{i+j}$$

$$y_i: estimated\ smoothed\ value\ at\ i$$

$$x_{i+y}: data\ in\ the\ moving\ window$$

$$n: \frac{1}{2}\ width\ of\ moving\ window$$

$$c_j: coefficient\ of\ polynomial\ fit$$

Fig. 8. Savitzkey-Golay Equation

First forecasting is done followed by Wavelet Decomposition to remove noise. Finally, this is sent to a Savitzky-Golay Filter to perform the final smoothing of the forecast.

IV. Experimental Results

Our project demonstrates that it is possible to build a functioning Reinforcement Learning model to predict normal patterns, hence, also the ability to predict abnormalities. We demonstrated that we only needed 16 seconds worth of normal data in order to train a working prediction model. The reason that 16 seconds is good is because of the repetitive nature of ECG and the fast frequency this is repeated. Plus, if this functionality is incorporated into a Smartwatch, we have to be mindful of memory size and processing time. Which is what we have accomplished.

Our process is to take an ECG signal, do Wavelet Decomposition to remove noise, then revert to the time domain and align the second R peak to time zero. A Reinforcement Learning model is then trained being mindful of spikes in the data and also having a reward that awards small distances between predicted and actuals and also penalized large distances between predicted and actuals. This was achieved by using the inverse of the distance as the reward. Once the signal is forecasted, it is again sent to a Wavelet Decomposition to remove added noise. Additionally, it is finally smoothed by using the Savitzky-Golay Filter. The following figure plots the original compared with the forecasted.

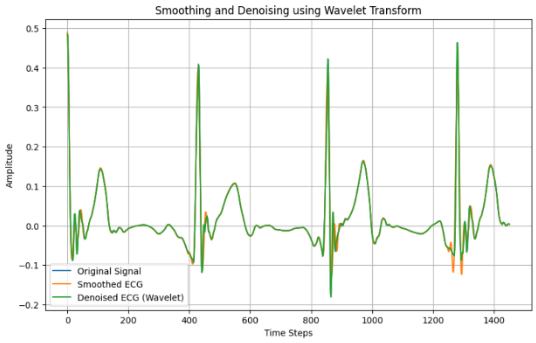

Fig. 9. Reconstructed Signal (Normal-Original with forecasted)

Our MAPE score measures how successful our forecasting is, and it achieves a value of 69.66%. Although this value is relatively high, we can see from the plot that it does forecast very well. Additionally, as is later stated, even with this MAPE score, we achieved a very high accuracy of 95%.

Next, to test if our Anomaly Detection works, we use the same 4 second test sample as input to be forecasted. Again, it is denoised with Wavelet Decomposition. When returned to the time-domain, we add periodic values (to model cardiac anomalies) that are way above the anomaly threshold of (Mean + 3xStandardDdeviation). We then pass this to the Reinforcement Learning model. In the chart below, predicted values (green) correspond to the forecasted patterns we saw in the previous figure.

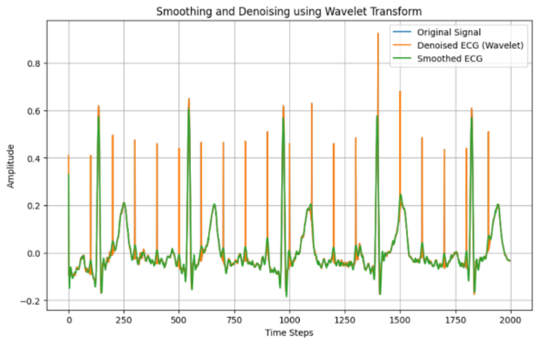

Fig. 10. Anomaly Dection (Anomaly-Original with Forecasted)

Accordingly, the Accuracy is 95% where we had deliberately added 20 anomalies. Hence, 19 anomalies were captured.

V. Discussions

In our project, we were able to successfully determine if a Heartbeat is an anomaly (arrythmia). This was accomplished, first, by preprocessing the data into the frequency domain using Wavelet Decomposition and denoising. Then a Reinforcement Learning model learned the normal distribution with a Q-Table. Next, the forecasted results are again denoised with Wavelet Decomposition and further smoothed with Savitzky-Golay Filter. Now, if the distances are above a threshold (Mean + 3xStandardDeviation), it is categorized as an ECG anomaly.

It would be interesting to determine what type of arrythmia is found at a greater granularity than just determining if it is normal or abnormal. This could be easily accomplished if we had more data of the anomalies to train a model. However, this procedure would most likely be better achieved if CNN is used instead of Reinforcement Learning. Additionally, our MAPE scare was relatively high and relies on further denoising and smoothing. This could be further explored by improving the parameters of the Reinforcement Learning model as well as having longer training data. However, if we would like for our architecture to fit in a Smartwatch, we must be mindful of size and speed. Given that we achieved a high accuracy value, it means that this MAPE score is good enough.

VI. Conclusions

In conclusion, we were able to create a Reinforcement Learning model with Q-Table that was able to learn the statistical distribution of normal ECG patterns. This was accomplished by first transforming the data into the frequency domain with Wavelet Decomposition for denoising. Then training the Reinforcement Learning model on this. After a forecasting is completed, it is further denoised and has Savitzky-Golay Filter smoothing. Once the normal distribution has been learned, the distance of predicted and actual values was calculated to determine an anomaly which is a value above a certain threshold. We strived to use the most minimal and fastest technologies in order to be feasible in a mobile device setting. First, our training set is based on only 16 seconds of data. Plus, the Reinforcement Learning model is lightweight given it is a Q-Table and not a Deep Neural Network. Overall, we have met the goals of our project.

Keeping up with the spirit of reproducible research, all our models, dataset, and code can be accessed through the repository at: https://github.com/marciahon29/Anomaly-Detection-of-ECG-with-Wavelet-Decomposition-and-Reinforcement-Learning .

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