AI to identify arrhythmogenic sources in the heart from patient ECG

As part of the King's Undergraduate Research Fellowship (KURF)

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Background

Atrial Fibrillation (AF) is a heart condition which affects 2% of the UK population and causes adverse health problems such as increased risk of stroke and overall mortality. AF is caused by abnormal sources of electrical activity in the Left Atria (LA). Current treatment procedures involve burning the area of abnormal electrical activity using catheter ablation or cryoablation techniques [1] (Figure 1). Currently, the procedure uses a probabilistic approach, where most likely areas for the source to be are burnt first and then checked if this has influenced the fibrillations. This approach leads to problems such as recurrent AF, as the true abnormal source may not be fully treated. If we could identify exactly where the abnormal source was initiating using time-series data from patient ECG and burn directly, this would minimise the time of the procedure and lower the risk of recurrent AF, greatly improving patient outcome and hospital efficiency.

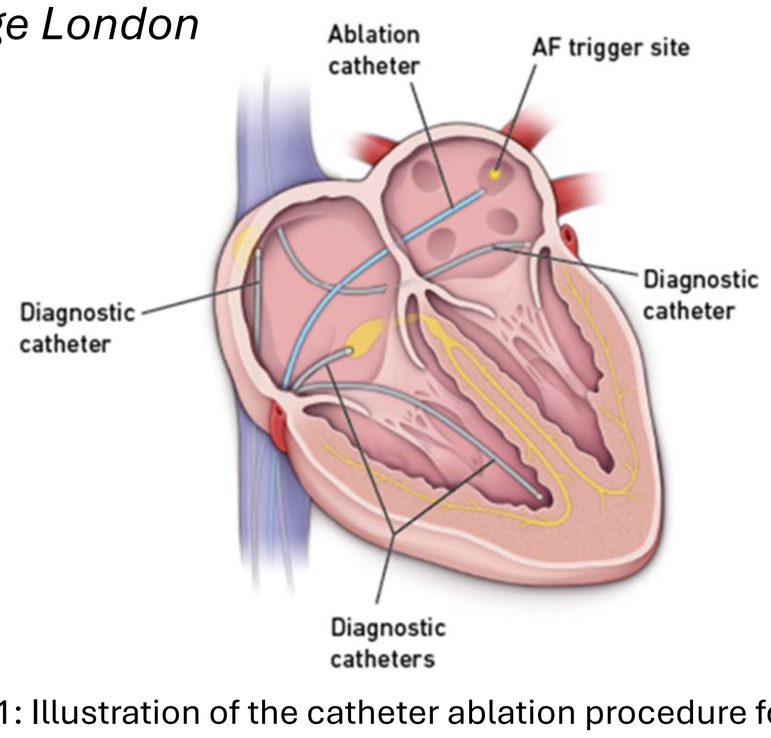

Figure 1: Illustration of the catheter ablation procedure for AF

Objectives and Methods

This project had 3 main tasks:

1) Simulate AF computationally in a 2D (100 by 100) tissue grid on Spyder IDE. This was done by solving the FitzHugh-Nagumo equations [2] using Euler's method for the Laplacian and Central Difference method for the derivative. The abnormal sources could be Rotor (Figure 2) points or Focal points.

2) Generate synthetic ECGs from the simulations in 1). Sources of abnormal activity were computationally 'initiated' at different points in the 2D grid and ECGs were computed based on the measured electrical activity at different heights which imitated electrode lead placements. These simulations correspond to the P-wave in the ECG (Figure 3).

3) Develop deep learning algorithms to classify location of the abnormal activity and the type of abnormal activity (Rotor or Focal point) from synthetic ECG. The network architecture consisted of 3 1D convolutional layers [3] with a ReLu and Sigmoid activation function (Figure 4). The number of outputs expected in the final layer was varied according to the type of classification wanted (location or type of abnormal source). The models were programmed and trained in Google Colab (Figure 6).

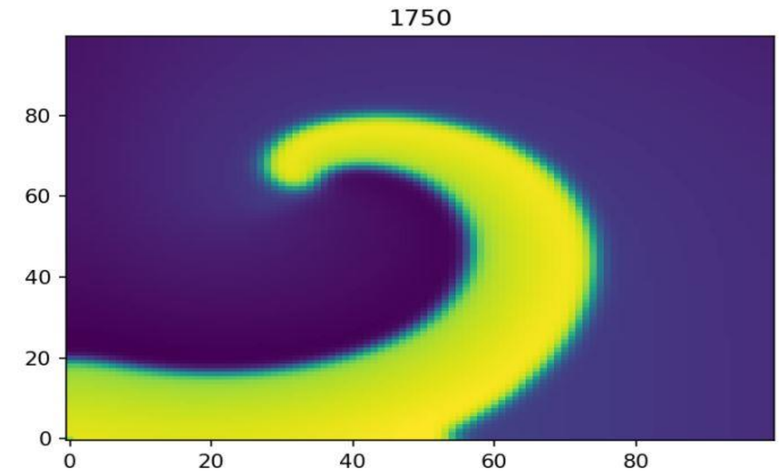

Figure 2: Rotor point simulation on Spyder IDE

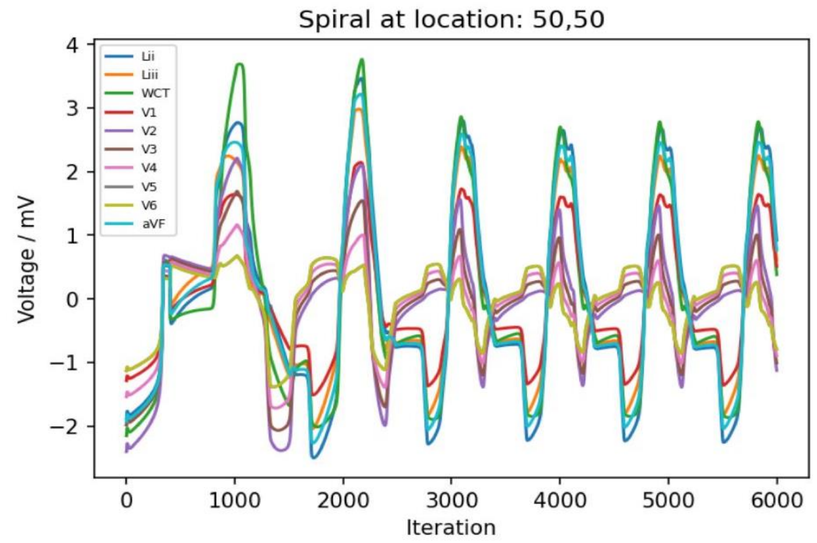

Figure 3: ECG simulated for Rotor at location (50,50)

Results

The Rotor/Focal point simulations and the resultant synthetic ECGs were collected for 50 cases. Initially, the ECG datasets was considered for 2 cardiac tissue patches surrounding [30,30] and [70,70] and sustaining rotors. Once the CNN architecture had been completed for classification of these 2 patches, more points were chosen and ECGs were collected for rotors around these points (Figure 5), Focal initiations were also simulated at the same points to have a complete dataset of Rotor and Focal points for all 9 initiation points. Accuracy was evaluated on 5 K-fold cross validation and with a test set of ECGs from outside training area.

There were 3 main classification tasks for this project:

1) CNN for **binary** classification for 2 initiation points :

- K-fold accuracy 96%, test set accuracy 94%

2) Rotor vs Spiral **binary** classification

- K-fold accuracy 98%, test set accuracy 96%

3) Rotor classification initiated at **various locations**:

- K-fold accuracy 92%, test set accuracy 91%

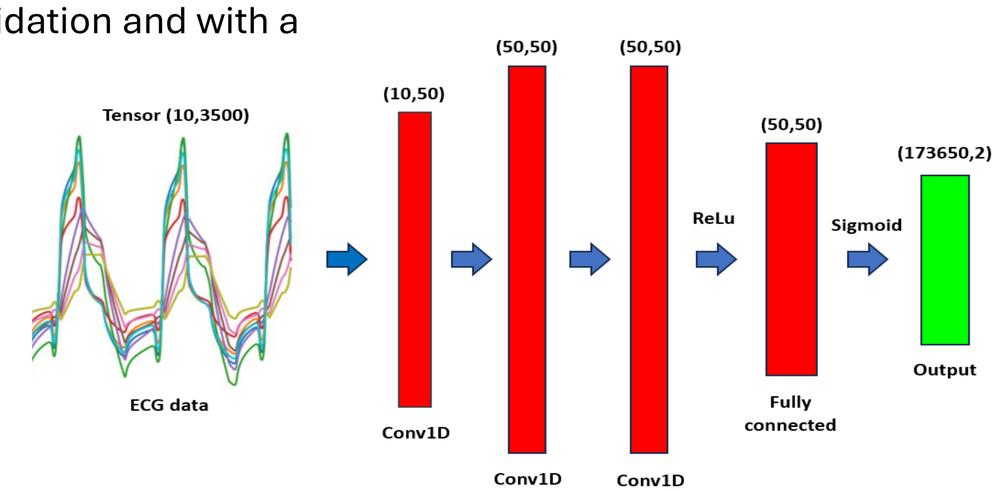

Figure 4: Network architecture for classification model

Conclusion and Future Work

This project shows that this approach could be very effective in locating arrhythmogenic sources in the left atria from patient ECG. However, this model is highly simplified and there are likely many factors which would affect the accuracy of this approach in the real heart. Further work is needed in higher domains (3D) with a more accurate model representing the heart and its variables before determining whether this approach would be as effective on real patient ECG.

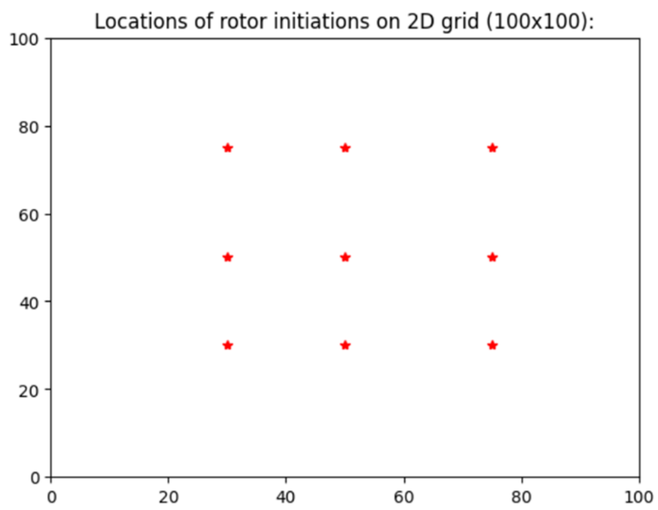

Figure 5: Initiation points for arrhythmogenic sources

```
[ ]  # Create class for image classifier:
     # fully connected layer
     # hyperparameter tuning
     class ImageClassifier(nn.Module):
         def __init__(self):
             super().__init__()
             self.model = nn.Sequential(
                 nn.Conv1d(10, 50, 10),
                 nn.ReLU(),
                 nn.Conv1d(50, 50, 10),
                 nn.ReLU(),
                 nn.Conv1d(50, 50, 10),
                 nn.ReLU(),
                 nn.Flatten(),
                 #nn.Linear(20*(10-6)*(3500-6), 2)
                 nn.Linear(173650, 9),
                 nn.Sigmoid()
             )

         def forward(self, x):
           x = self.model(x)
           return x
```

Figure 6: Google Colab code for CNN

References

1) James L. Cox, MD, Thomas E. Canavan, MD, Richard B. Schuessler Et al, The surgical treatment of atrial fibrillation

2) Rose T. Faghih Ketan Savla Munther Et al, The FitzHugh-Nagumo Model: Firing Modes with Time-varying Parameters & Parameter Estimation

3) Dan Li, Jianxin Zhang*, Qiang Zhang Et al, Classification of ECG Signals Based on 1D Convolution Neural Network