Enhancing the Prediction of Ablation Outcomes Using Transfer Learning on Residual Network via Spectrogram in Persistent Atrial Fibrillation

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Abstract

***Introduction**: Ablation of persistent atrial fibrillation targets using dominant frequency (DF), rotors, and complex fractionated atrial electrograms has been disappointing. A transfer learning applied to electrogram (EGM) spectrograms may be a promising tool for predicting ablation outcomes. **Methods**: 3206 non-contact EGMs were collected before and after ablating 51 high DF locations of 10 patients. Two categories of data were labelled: 1490 EGMs had positive ablation responses (AF termination or AF cycle length (AFCL) increased (≥10msec)), whereas 1716 EGMs had negative responses (AFCL increase (<10msec)) to catheter ablation. After QRST subtraction, EGMs were converted to spectrograms. The residual network, equipped with a 50-layer pre-trained model, was utilized to extract features for training and testing the transferred fully connected layers. The model performance was evaluated using a leave-one-patient-out 10-fold cross-validation (CV). **Results**: The 10-fold CV accuracy, balanced accuracy, F1_score, AUC-ROC, sensitivity, specificity, and precision were 60.2%, 60.0%, 55.0%, 0.64, 51.5%, 67.8% and 58.2% respectively. **Conclusions**: A transfer learning applied to spectrograms might be useful in predicting the local atrial tissue responses to ablation and their effect on terminating AF and changes in CL.*

1. Introduction

Atrial fibrillation (AF) is the most common arrhythmia, affecting around 1-2% of the population. The risk of stroke is increased by around 5-fold in AF patients [1]. Pulmonary vein isolation (PVI) is the cornerstone of ablation protocols for various types of AF. Ablation strategies of persistent AF are more complicated and require ablation of additional sites in the atria responsible for AF drivers. Several classical methods have been used to target the AF drivers, including dominant frequency (DF) [2], rotors [3], and complex fractionated atrial electrograms (CFAEs) [4]. The ablation outcomes using these methods have been suboptimal in patients with persistent AF. Analysis of EGM signals has been used as a method to detect the AF drivers that are responsible for the initiation and perpetuation of AF. Spectral analysis has been widely used to find features relevant to the EGM signal characteristics of AF and non-AF (e.g., DF [2], organization index (OI) [5]). In the same context, temporal analysis of EGMs has also been considered to guide catheter ablation of AF targets (e.g., recurrence plot analysis (RQA) [6]. Power spectral density has also played a role in characterizing the EGMs for treating AF [7, 8]. Spectrograms contain information related to the frequency, time, and power of the signals. Therefore, in this work, spectrograms generated from EGM signals were used as input to a residual neural network via transfer learning techniques to classify the EGM responses to catheter ablation in terms of AF termination and changing the AF cycle length.

2. Materials and Methods

The complete framework for the proposed method is shown in Figure 1, indicating the method for the prediction of EGM responses to catheter ablation (positive and negative).

2.1. Dataset Collection and Labeling

A total of 3206 non-contact EGMs were collected using a mapping catheter (Ensite array, Abbot, USA). These signals were collected by ablating 51 locations identified as high dominant frequency (HDF) regions in the left atrium of 10 persistent AF (persAF) patients to guide the catheter during the ablation procedure. The EGM signals for 4 seconds duration were collected pre- and post-ablations. The EGM signals were labeled by cardiologists from the Leicester Glenfield Hospital into two classes: a positive response to catheter ablation (AF termination or AF cycle length increasing by >=10ms), and negative responses (AFCL increasing <10ms) [9]. Four out of ten patients had AF termination (3 flutter and

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one sinus rhythm) before the following PVI procedure.

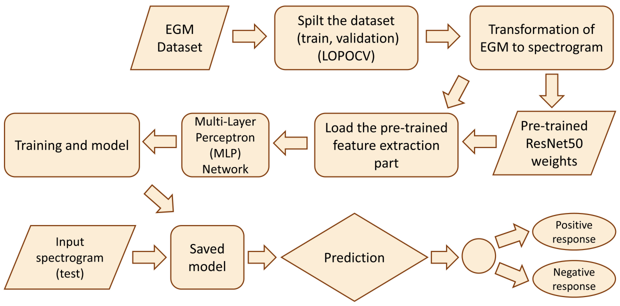

Figure 1: The framework of the proposed method; starting from the electrogram data as inputs, splitting them into train and test sets, then generating the spectrograms from each signal, loading the ResNet50 model to extract 2048 features, and finally using transferred fully connected layers to classify the EGM responses.

2.2. AF Signal Processing

The collected signals were sampled at a rate of 2038.5 Hz and then resampled at 512 Hz to reduce processing time and memory allocation. A QRST complex subtraction process was applied to remove far-field activity resulting from ventricular activity, which can distort the true AF characteristics [10]. Lead I was used as a reference lead in the QRST removal process (Figure 2).

2.3. AF Electrogram Analysis

After removing the QRST effect from the EGM signals, a spectrogram was generated. The 2-dimensional spectrogram image of electrogram signals can reflect the dynamic changes in the energy, frequency, and time components of these signals. This provides additional information about the characteristics of EGM signals. The process to construct the spectrogram using short time Fourier transform (STFT) is shown in the Figure 3. A spectrogram was constructed using equations 1 and 2, and a Hanning window was used as an anti-leakage window function with a length (NFFT) of 512 samples (1 second), and an overlap length between the successive windows of 128 samples (0.5 second).

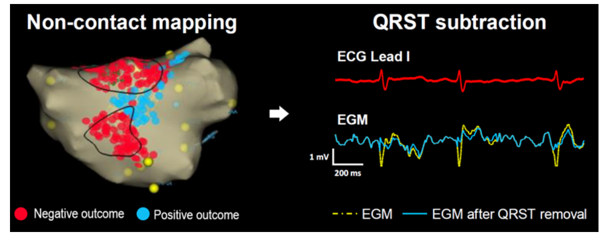

Figure 2: The QRST subtracting process (A) the EGM signals collected from the left atrium and their labelled (positive and negative) responses to ablation and (B) the QRST subtraction process using Lead I ECG as reference.

$$X(\tau,\omega) = \sum_{n=-\infty}^{\infty} x[n]w[n-m]e^{-j\omega t} \qquad 1$$

$$|X(\tau,\omega)|^2 \qquad 2$$

Where $x[n]$ is the original EGM signal being analyzed, $w[n-m]$ is the Hanning window function centered at time m, and $|X(\tau,\omega)|^2$ is the spectrogram (power/frequency content over time).

2.4. ResNet50 using Transfer Learning

The Residual Neural Network 50 (ResNet50) model has been considered one of the well-known models used in computer vision. This deep learning model is trained on large and diverse categories of datasets. This pre-trained model can be used to solve different computer vision problems using the transfer learning technique. Feature extraction layers were frozen in the ResNet50 model, and the pre-trained weights were used to extract features from the spectrograms. The classifier part of the Resnet50 model was adapted to the new task for predicting the ablation outcomes. Figure 4 shows the feature extraction and transferred layer classifier parts used in this work. The input image size for the ResNet50 model is 224 × 224 × 3 for color images. We resized all spectrogram images to 224 × 224-pixel resolution to match the size of the input layer in the ResNet50 model. The model architecture comprises a series of convolutional layers and fully connected layers. The first convolution layer consists of 64 different kernels of size 7 × 7 and a stride size of 3 × 3, followed by a max pooling

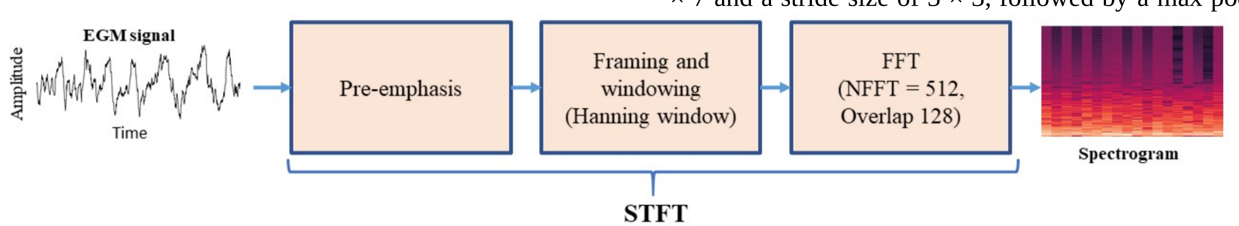

Figure 3: The process of converting the EGM signal to a spectrogram using a Hanning window of size 512 samples (1 second) with an overlap of 128 samples (50%) between windows.

operation with a stride size of 2. The following convolution blocks (Conv Block and Identity Block) are made of three convolution layers (1 × 1 × 64 kernels), (3 × 3 × 64 kernels), and (1 × 1 × 256 kernels). These are repeated 3 times as shown in Figure 4. Following the same procedure, convolution layers (1 × 1 × 128 kernels), (3 × 3 × 128 kernels) and (1 × 1 × 512 kernels) are repeated 4 times; followed by three convolution layers (1 × 1 × 256 kernels), (3 × 3 × 256 kernels) and (1 × 1 × 1024 kernels) repeated six times and lastly three convolution layers (1 × 1 × 512 kernels), (3 × 3 × 512 kernels) and (1 × 1 × 2048 kernels) repeated 3 times. Then, global average pooling is applied to generate 2048 features from each spectrogram image. These features were used as input to a ResNet50 fine-tuning classifier to classify the EGM responses to catheter ablation. Four fully connected layers with nodes (2048, 1024, 512, 256) were used to build the classifier part, followed by batch normalization after each layer. We used halving patterns in layer sizes to enable the network to progressively compress and abstract the information. The batch normalization process makes training faster, more stable, and less sensitive to initialization. Figure 4 shows the architecture of the ResNet50 model, showing the name, size, and operations of each of the 50 layers.

3. Experimental Results and Discussion

The transfer learning technique was applied using the ResNet50 pretrained model via the spectrogram images for predicting the catheter ablation outcomes. A leave-one-patient-out 10-fold cross-validation (LOPOCV) technique was used to split the train and test sets to prevent any data leakage from training to the testing set of data, where electrograms from 9 patients were used to train the model, and the remaining patient was used for testing. This process was repeated 10 times, and an average was taken for evaluating the model for seven evaluation metrics (overall accuracy, balanced accuracy, sensitivity, Specificity, precision, F1_score, and area under the receiver operating characteristic curve (AUROC)). The proposed model was trained for 50 epochs. In each epoch during the training and validation, the accuracy and loss were calculated. We used the Adam optimizer with a learning rate of 0.0001, beta_1=0.9, beta_2=0.999, and epsilon=1e-07. We used a cross-entropy loss and a batch size of 512, which is the number of spectrograms that passed through the network simultaneously during the training process. The 10-fold CV accuracy, balanced accuracy, F1_score, AUC-ROC, sensitivity, specificity, and precision were 60.2%, 60.0%, 55.0%, 0.64, 51.5%, 67.8% and 58.2%, respectively, using the testing dataset. Figure 5A shows the confusion matrix, which shows the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values for the 10 EGM patients. The ROC and the AUC for the proposed transfer learning approach are shown in Figure 5B. It can be seen that the model predicts EGM negative responses to ablation more accurately than positive response signals (Figure 5A). The spectrogram transforms

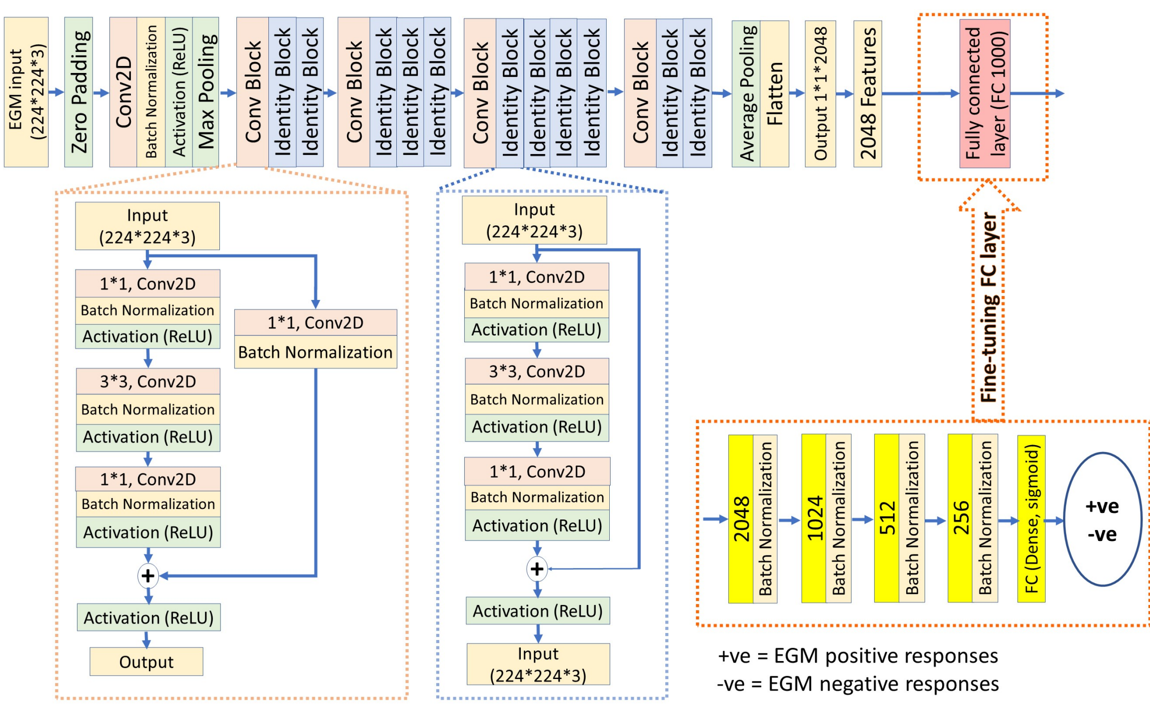

Figure 4: Transfer learning using the ResNet50 model. It shows the layers used to extract 2048 features from spectrogram images with size (224 × 224 × 3). Also shows the process of freezing the classifier layers (red block) and replacing them with 4 layers (yellow blocks) for predicting the ablation outcomes.

the electrogram signals into the time-frequency domain, revealing several parameters such as the DF content [2], repetitive patterns, fractionation [11], and temporal variability that have been used in characterizing EGM signals for predicting ablation outcomes [12]. Therefore, representing the EGM signal in the time-frequency domain helped in classifying the positive and negative responses of these signals to the ablation procedure.

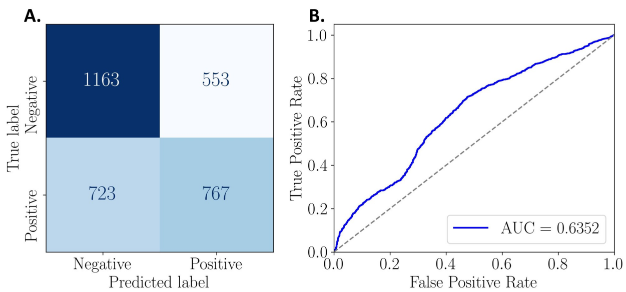

Figure 5: (A) Confusion matrix (CM), and (B) the ROC for the proposed method

4. Conclusions

Spectrograms, with the help of the transfer learning technique using the ResNet50 model, played a role in predicting the responses of ablating the EGMs and their effect on AF termination and CL changes. The model achieved a 10-fold CV overall accuracy of 60.2%, balanced accuracy of 60%, F1_score of 55%, AUC-ROC of 0.64, sensitivity of 51.5%, specificity of 67.8% and precision of 58.2% by evaluating the proposed model on the test (unseen) dataset. This is an indication that the time-frequency representation of the EGM signals might be helpful for discriminating the EGM responses to catheter ablation.

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References

[1] M. J. Singleton, M. Imtiaz-Ahmad, H. Kamel, W. T. O'Neal, S. E. Judd, V. J. Howard, G. Howard, E. Z. Soliman, and P. D. Bhave, "Association of atrial fibrillation without cardiovascular comorbidities and stroke risk: from the REGARDS study," *Journal of the American Heart Association*, vol. 9, no. 12, pp. 1-10, Jun 16, 2020.

[2] P. Sanders, O. Berenfeld, M. Hocini, P. Jais, R. Vaidyanathan, L. F. Hsu, S. Garrigue, Y. Takahashi, M. Rotter, F. Sacher, C. Scavee, R. Ploutz-Snyder, J. Jalife, and M. Haissaguerre, "Spectral analysis identifies sites of high-frequency activity maintaining atrial fibrillation in humans," *Circulation*, vol. 112, no. 6, pp. 789-97, Aug 9, 2005.

[3] J. Jalife, O. Berenfeld, and M. Mansour, "Mother rotors and fibrillatory conduction: a mechanism of atrial fibrillation," *Cardiovascular Research*, vol. 54, no. 2, pp. 204-216, 2002.

[4] K. Nademanee, J. McKenzie, E. Kosar, M. Schwab, B. Sunsaneewitayakul, T. Vasavakul, C. Khunnawat, and T. Ngarmukos, "A new approach for catheter ablation of atrial fibrillation: mapping of the electrophysiologic substrate," *Journal of the American Colleage of Cardiology*, vol. 43, no. 11, pp. 2044-53, Jun 2, 2004.

[5] Y. Takahashi, P. Sanders, P. Jais, M. Hocini, R. Dubois, M. Rotter, T. Rostock, C. J. Nalliah, F. Sacher, J. Clementy, and M. Haissaguerre, "Organization of frequency spectra of atrial fibrillation: relevance to radiofrequency catheter ablation," *Journal of Cardiovascular Electrophysiology*, vol. 17, no. 4, pp. 382-8, Apr, 2006.

[6] T. P. Almeida, F. S. Schlindwein, J. Salinet, X. Li, G. S. Chu, J. H. Tuan, P. J. Stafford, G. Andre Ng, and D. C. Soriano, "Characterization of human persistent atrial fibrillation electrograms using recurrence quantification analysis," *Chaos*, vol. 28, no. 8, pp. 1-12, Aug, 2018.

[7] L. Y. Di Marco, D. Raine, J. P. Bourke, and P. Langley, "Atrial fibrillation type characterization and catheter ablation acute outcome prediction: comparative analysis of spectral and nonlinear indices from right atrium electrograms.", *Computing in Cardiology Conference*, pp. 817-820, 2014.

[8] N. Qaqos, X. Li, and G. A. Ng, "Po-04-077 Electrogram strength at 10 Hz unveiled as accurate predictor of regional catheter ablation success in persistent atrial fibrillation," *Heart Rhythm*, vol. 21, no. 5, pp. S486-S487, 2024.

[9] T. P. Almeida, X. Li, B. Sidhu, A. S. Bezerra, M. Ehnesh, I. Anton, I. A. Nasser, G. S. Chu, P. J. Stafford, and T. Yoneyama, G. A. Ng, and F. S. Schlindwein, "Dominant frequency and organization index for substrate identification of persistent atrial fibrillation,", *Computing in Cardiology Conference*, 2021.

[10] J. L. Salinet, Jr., J. P. Madeiro, P. C. Cortez, P. J. Stafford, G. A. Ng, and F. S. Schlindwein, "Analysis of QRS-T subtraction in unipolar atrial fibrillation electrograms," *Medical and Biological Engineering and Computing*, vol. 51, no. 12, pp. 1381-1391, Dec, 2013.

[11] K. Nademanee, J. McKenzie, E. Kosar, M. Schwab, B. Sunsaneewitayakul, T. Vasavakul, C. Khunnawat, and T. Ngarmukos, "A new approach for catheter ablation of atrial fibrillation: mapping of the electrophysiologic substrate," *Journal of the American College of Cardiology*, vol. 43, no. 11, pp. 2044-2053, 2004.

[12] P. Escribano, J. Ródenas, M. A. Arias, P. Langley, J. J. Rieta, and R. Alcaraz, "Catheter ablation outcome prediction with advanced time-frequency features of the fibrillatory waves from patients in persistent atrial fibrillation." *Computing in Cardiology Conference*, pp. 1-4, 2020.

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