Pulmonary Vein Detection Using a 1D Convolutional Neural Network Classification Model for Pulmonary Vein Isolation Treatment

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INTRODUCTION

- When treating atrial fibrillation, radiofrequency ablation (RFA) therapy requires pulmonary vein isolation (PVI).
- The correct identification of the junction between the left atrium and the pulmonary vein is critical to the success of PVI.

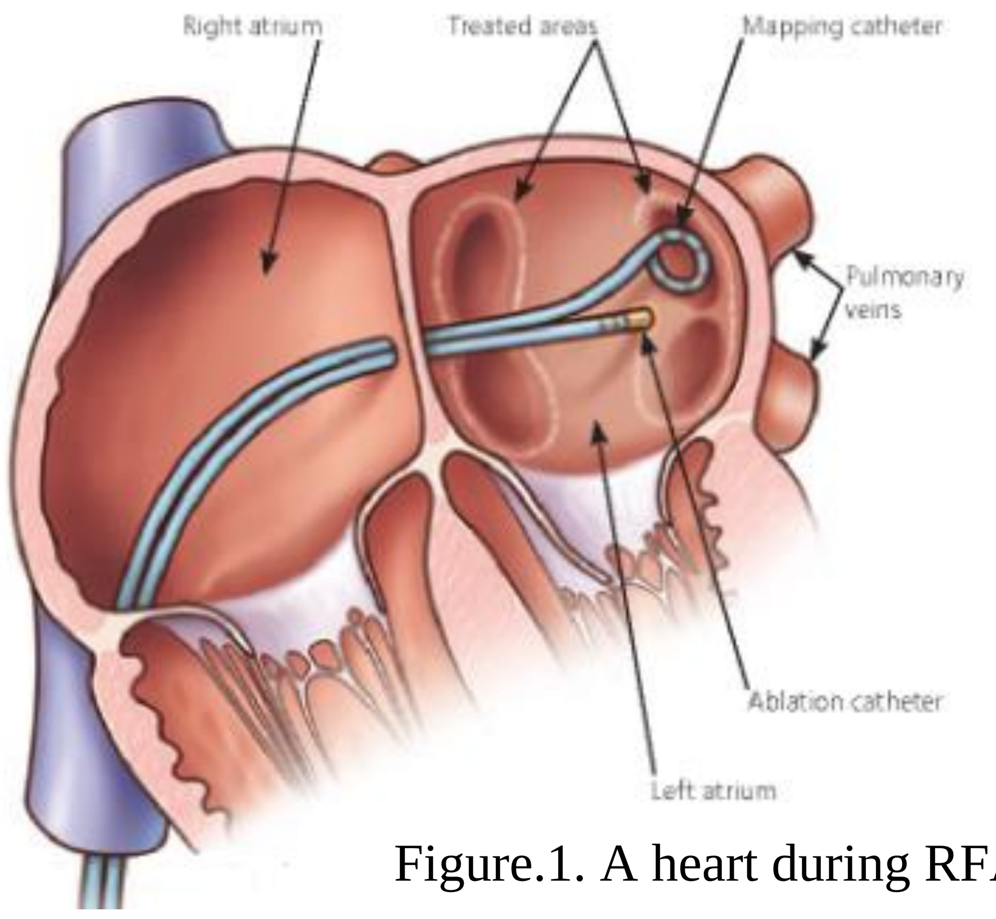

Figure.1. A heart during RFA treatment

- The study proposes using deep learning, specifically CNNs, for better pulmonary vein identification.
- Utilizes near-infrared spectroscopy (NIRS) data for improved precision.

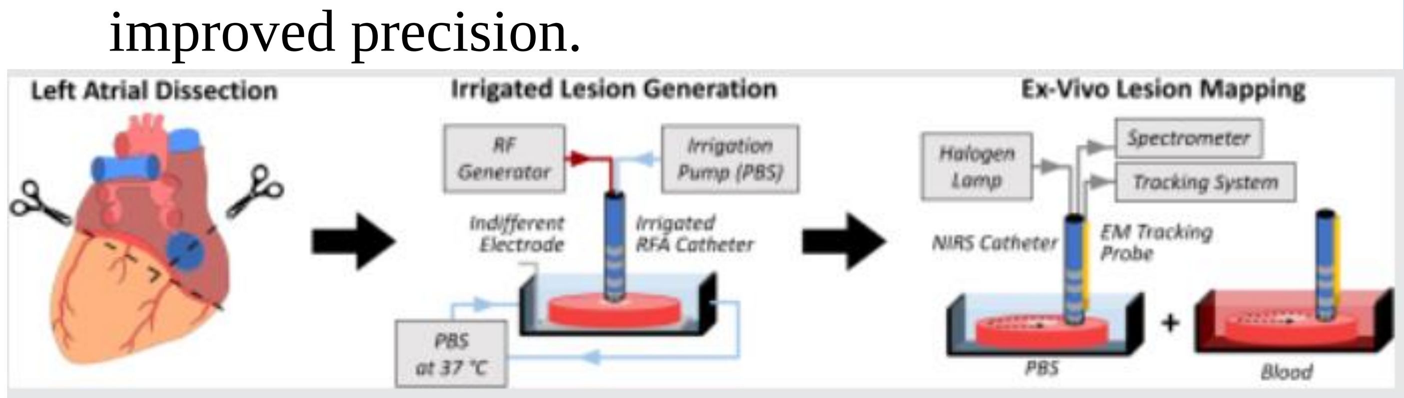

Figure.2 The procedure of how the NIRS catheter collected the data

- Dataset: 22 swine hearts with spectra at 1024 wavelengths (500-1100 nm).

The data is categorized into three classes:

- normal myocardium (0),
- lesions (1)
- pulmonary veins (3).

OBJECTIVE

This study aims to develop a 1D convolutional neural network (CNN) model to improve the accuracy and specificity of pulmonary vein detection using near-infrared spectroscopy (NIRS) data.

METHODS

- **Dataset Preparation**:
- Derived from 22 swine hearts.
- NIRS measurements were calibrated, and absolute reflectance spectra were converted into relative reflectance spectra. NIRS reflectance measurements were taken at 1024 wavelengths (500-1100 nanometers).
- Data was preprocessed for CNN training:
  - Dataset divided into training, validation, and test sets based on heart numbers to ensure no overlap.
  - Specific cardiac indices assigned to test and validation sets to guarantee data integrity.

CNN Model Architecture:

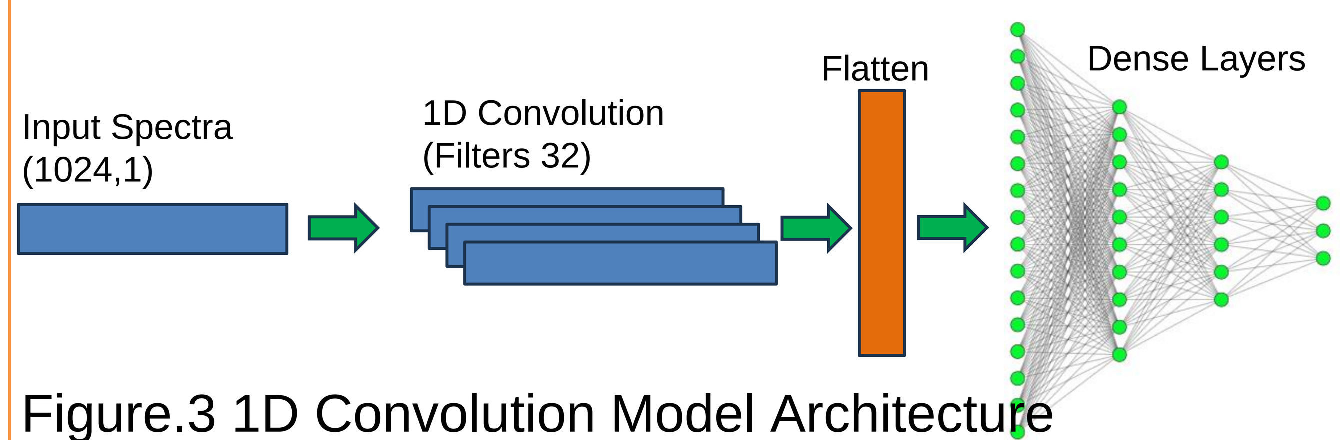

Figure.3 1D Convolution Model Architecture

Designed to capture complex patterns in the NIRS data.

- Included several layers:
  - Input layer accepted data in the shape (1024, 1).
  - Flattening layer to convert 3D data into a 1D vector.
  - Three dense layers with 128, 64, and 32 neurons, each using 'relu' activation functions.
  - Final dense layer with softmax activation to classify data into predefined categories (normal myocardium, RFA lesions, pulmonary veins).
- **Training and Validation**:
- Split dataset using an 80-20 ratio training and validation sets using train_test_split from sklearn.model_selction.

RESULTS

The AUC value of 0.94 suggests that the model has a high ability to distinguish class 2 (PV) from the other classes. This is the highest AUC among the three classes, indicating that the model performs very well in identifying PV instances.

Metrics	Training	Validation	Test
Accuracy	0.7494	0.7272	0.7487
AUC	0.9072	0.9066	0.8299
Loss	0.5683	0.6023	0.5912
Precision	0.7940	0.7444	.0.7833
Specificity	0.8373	0.8200	0.8250
Recall	09000	0.8900	0.9013

Figure.4 A table of the CNN model's metric results

The ROC (Receiver Operating Characteristic) curve results illustrate the performance of the classification model for each of the three classes: Normal Myocardium (class 0), Lesion (class 1), and PV (class 2).

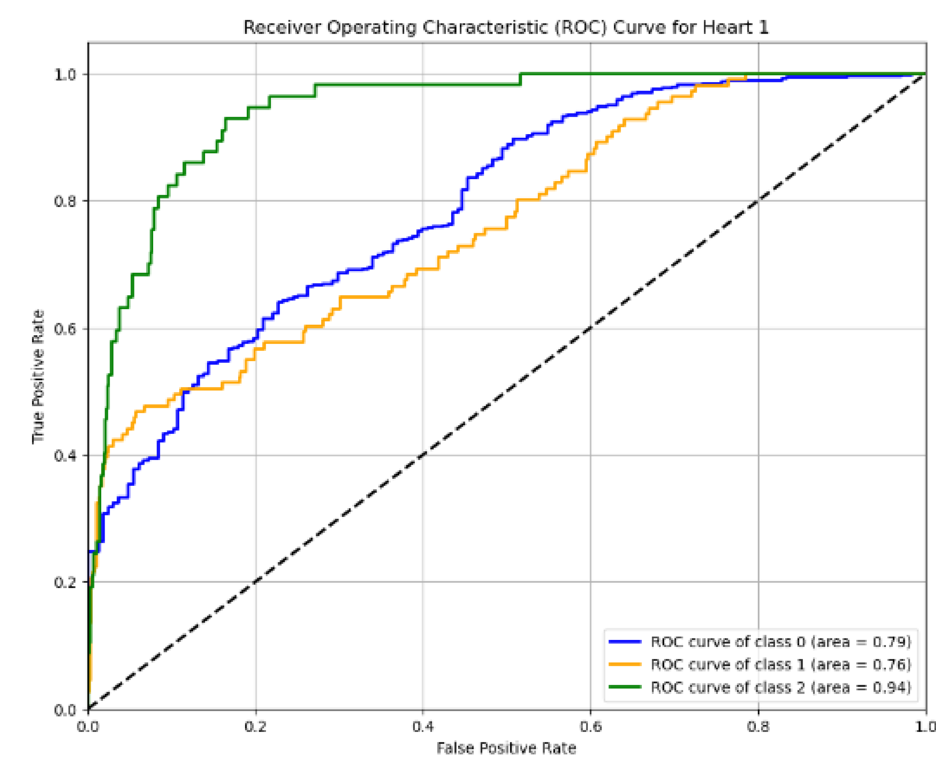

Figure.5 The ROC graph chart

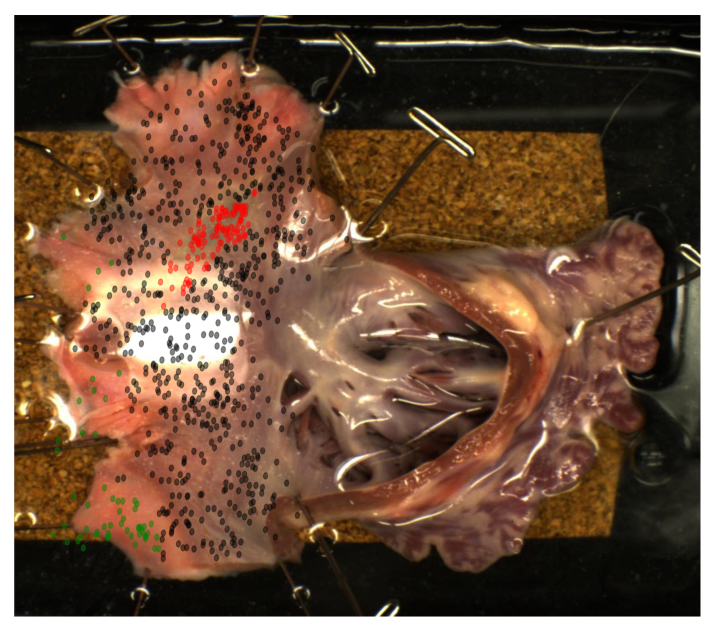

Figure.6 The True Labels

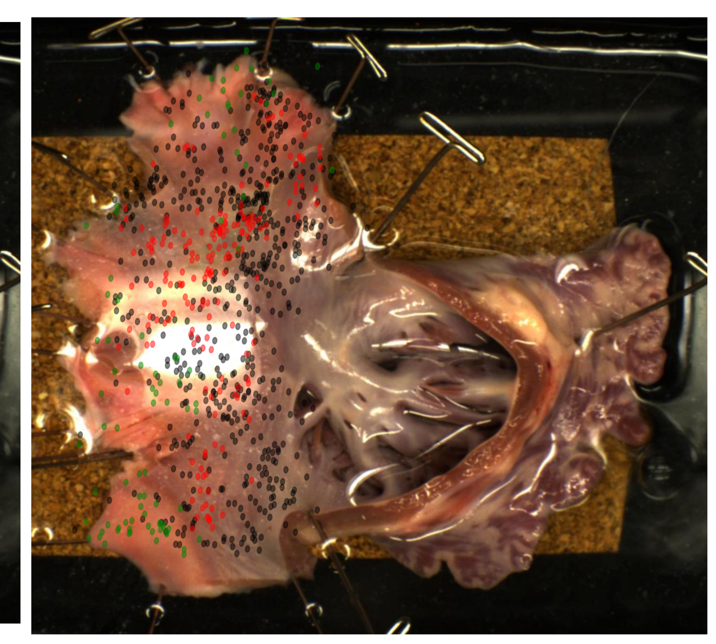

Figure.7 CNN predicted labels

DISCUSSION

- Potential for improving vein detection in clinical settings
- These could help doctors reduce complications in PVI treatments

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REFERENCES

Haiqiu Yang, Jonah A. Majumder, Ziyi Huang, Deepak Saluja, Kenneth Laurita, Andrew M. Rollins, Christine P. Hendon, "Robust, high-density lesion mapping in the left atrium with near-infrared spectroscopy," J. Biomed. Opt. 29(2) 028001 (28 February 2024) https://doi.org/10.1117/1.JBO.29.2.028001