Classification of Cardiac Conditions using MPI Images

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Abstract

This paper presents a deep learning-based system for classifying cardiac conditions using Myocardial Perfusion Imaging (MPI). The proposed approach employs a ResNet-18[1] model with an attention mechanism to analyze both rest and stress phase images, enabling accurate differentiation between normal, ischemia, and infarction cases. The model is trained and evaluated on a proprietary dataset of 97 patients, with data augmentation and focal loss techniques used to address class imbalance. Experimental results demonstrate high classification accuracy and provide interpretability through attention weight analysis, highlighting the clinical importance of specific image types. This work demonstrates the potential of AI-driven tools to enhance cardiac diagnosis and support clinical decision-making[2], [3].

I. Introduction

Heart disease is a major health problem around the world. Doctors need to find heart problems quickly to help patients get better. Myocardial Perfusion Imaging (MPI) is a safe way to take pictures of the heart and see how blood flows through it [4], [5]. This project creates a computer system that can look at these heart pictures and tell if there are any problems.

The system looks at two types of heart pictures: one taken when the patient is resting and another taken when the heart is working harder. It can identify three main conditions: normal heart function, reduced blood flow (ischemia), and heart muscle damage (infarction). By using computers to help analyze these pictures, doctors can make faster and more accurate decisions about patient care [6], [7].

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A. *Challenges*

Despite advancements in cardiac imaging and machine learning, several obstacles remain in analyzing perfusion studies and generating automated reports[8]:

- **Incomplete and Inconsistent Data:**
  - Cases like 661 (Ischemia) and 3078 (Normal) lack critical Rest QGS or entire QGS datasets
- **Data Heterogeneity:**
  - Mixed conditions (Normal, Ischemia, Infarction) require careful stratification
  - Multiple file types per case (AC/NAC Display, QPS, QGS) need uniform preprocessing[9]
- **Algorithmic Limitations:**
  - Images suffer from attenuation artifacts and low resolution[10]
  - Small proprietary datasets limit model generalizability (vs. public datasets like MIMIC-CXR)
- **Clinical Validation:**
  - Only 97 samples (some incomplete) may be insufficient for robust training[11]

II. Related Works

A. *Deep Learning-Based CAD Classification using RGB-SPECT Images*

Papandrianos et al. proposed a convolutional neural network (CNN) tailored for coronary artery disease (CAD) classification using RGB-converted SPECT myocardial perfusion images [12]. The model, developed from scratch, was trained on augmented datasets and evaluated using 10-fold cross-validation. It achieved an accuracy of 91.86%, surpassing pre-trained networks like VGG-16 and DenseNet-121. This work highlights the potential of customized CNNs over generic models for domain-specific medical imaging tasks[13].

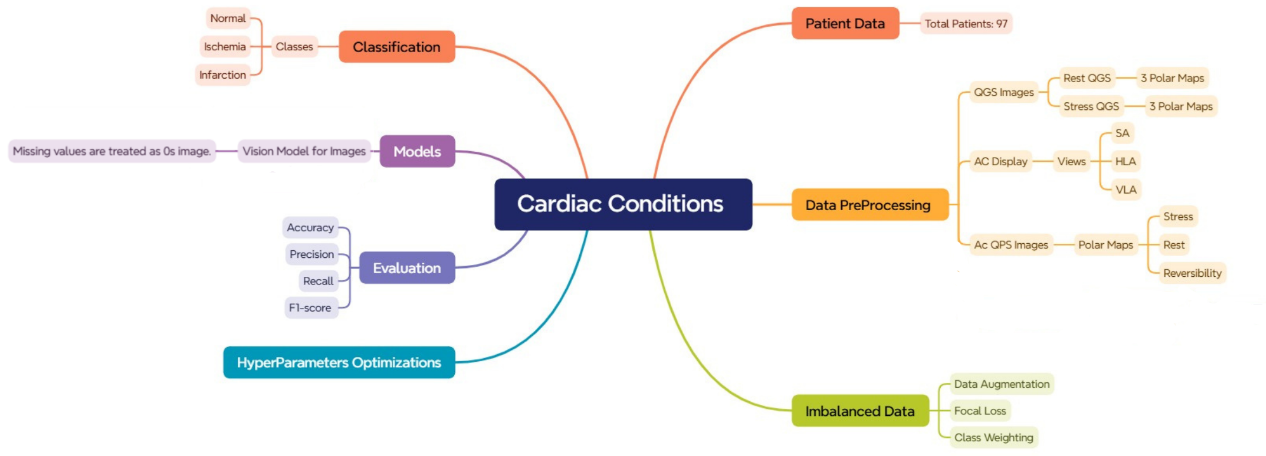

Fig. 1: Cardiac Conditions Pipeline

B. *Explainable AI for Coronary Artery Disease Diagnosis*

Liu et al. integrated the ResNet-34 architecture with Gradient-weighted Class Activation Mapping (Grad-CAM) to diagnose CAD from SPECT MPI scans while offering visual explanations [6]. The proposed method achieved an AUC of 0.872, outperforming traditional quantitative analysis. The incorporation of Grad-CAM enabled clinicians to better understand and validate model predictions, emphasizing the importance of interpretability in clinical settings[14].

C. *Radiomic Feature Extraction and Ensemble Learning for Risk Stratification*

Arsanjani et al. utilized radiomic features extracted from SPECT MPI images combined with clinical variables to stratify patients into different CAD risk categories [4]. Using a LogitBoost ensemble learning model, they achieved an accuracy of 87.3% and an AUC of 0.94. This study illustrates how combining imaging data with clinical features can enhance predictive modeling for cardiac risk assessment[15].

III. METHODOLOGY

In this section, we explain how our system works to classify heart conditions from MPI images. Our approach uses a deep learning model that can analyze both rest and stress phase images to make accurate predictions[16].

A. ***Proposed Method***

Our system uses a special type of neural network called ResNet-18 with an attention mechanism[1]. This helps the computer focus on the most important parts of the heart images. The system works in three main steps:

1) First, it looks at the heart images and extracts important features
2) Then, it uses attention to decide which parts of the images are most important[17]
3) Finally, it makes a prediction about the heart condition

B. ***Model Architecture***

Our model has three main parts:

1) ***Feature Extractor***:

- Uses ResNet-18 to look at the heart images[1]
- Takes both rest and stress phase images[16]
- Finds important patterns in the images

2) ***Attention Module***:

- Helps the model focus on important areas[17]
- Weights different parts of the images[9]
- Combines information from both rest and stress phases

3) ***Classifier***:

- Takes the processed information
- Makes the final decision about the heart condition
- Outputs one of three possible conditions: Normal, Ischemia, or Infarction[18]

C. *Training Process*

To make the model work well, we use several techniques:

1) Focal Loss to handle the imbalance between different conditions
2) Data augmentation to create more training examples[19]
3) Early stopping to prevent overfitting
4) Split the data into training, validation, and test sets
5) AdamW optimizer with learning rate scheduling

IV. EXPERIMENTS

A. *Datasets, Evaluation metrics, and Settings*

In our evaluation, we used a dataset of 97 MPI images from 97 patients, with each patient having both rest and stress phase images. The dataset was split into training (57 patients), validation (20 patients), and test (20 patients) sets, maintaining class distribution across splits. We evaluated our model's performance using standard classification metrics including accuracy, precision, recall, and F1-score [17]. Additionally, we analyzed the attention weights to understand which image phases (rest vs stress) were most important for different cardiac conditions[9].

*1) **Preprocessing**:* For our MPI image classification model, preprocessing involved:

- Resizing images to 224×224 pixels
- Normalizing pixel values
- Converting images to 2-channel format (rest and stress phases)[16]
- Applying data augmentation techniques:
  - Color jittering (brightness and contrast adjustments)
  - Small translations (±5% of image size)
  - Slight scaling (95-105% of original size)
  - Random zoom-in (95-100% of original size)

*2) **Experimental Settings**:* For the MPI classification model, we trained on a Tesla P100 GPU. The training configuration included:

- Model: ResNet-18 backbone with attention mechanism[1], [9]
- Input: 2-channel MPI polar maps (rest and stress)[20]
- Image size: 224×224 pixels
- Batch size: 6
- Optimizer: AdamW with learning rate 0.0001 and weight decay 10^{-5}
- Loss function: Focal Loss with $\gamma = 1.5$ and class weights
- Learning rate scheduling: ReduceLROnPlateau with patience=3 and factor=0.5
- Early stopping: Patience=10 epochs

B. *Main Results*

Our model demonstrated strong performance in classifying cardiac conditions from MPI images[2]. The key results include:

- Training accuracy: 94.59%
- Validation accuracy: 95.00%
- Best validation loss: 0.0106 (achieved at epoch 4)
- Training stopped at epoch 17 due to early stopping

The attention mechanism provided valuable insights into the model's decision-making process [21]:

- Higher attention weights were assigned to stress phase images for Ischemia and Infarction cases[16]
- Normal cases showed more balanced attention between rest and stress phases
- The attention weights helped validate clinical knowledge about the importance of stress phase imaging in detecting pathological conditions[9]

*1) **Confusion Matrix**:* The confusion matrix for the test set (20 patients) is shown in Table I. The model shows high accuracy in classifying Normal cases and good performance in identifying Ischemia cases. The small number of Infarction cases in the test set makes it challenging to fully evaluate performance on this class[18].

Confusion Matrix			
	Predicted		
Actual	Normal	Ischemia	Infarction
Normal	13	1	0
Ischemia	2	3	0
Infarction	0	1	1

TABLE I: Confusion matrix for the test set showing the distribution of predictions across the three classes.

2) ***Attention Weight Analysis:*** The attention mechanism provided valuable insights into the model's decision-making process[21]. Figure 2 shows the average attention weights assigned to each image type for the three cardiac condition classes (Normal, Ischemia, Infarction).

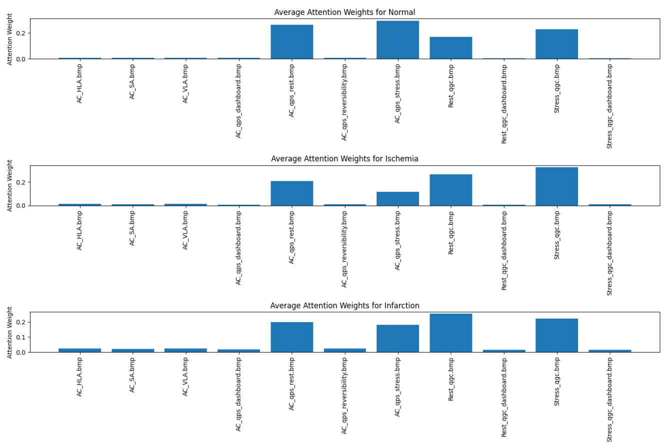

Fig. 2: Average attention weights across different cardiac conditions.

Key observations from the attention weight analysis:

- For all classes, the model assigns the highest attention weights to a subset of image types, particularly `AC_qps_rest.bmp`, `AC_qps_stress.bmp`, `Rest_qgc.bmp`, and `Stress_qgc.bmp`[20].
- In the Ischemia and Infarction classes, the attention is more strongly focused on the stress-phase images (`AC_qps_stress.bmp`, `Stress_qgc.bmp`), which aligns with clinical expectations that stress images are more informative for detecting pathological conditions [22], [3].
- For the Normal class, the attention is more evenly distributed between rest and stress images, but still highlights the same key image types.
- Other image types (e.g., `AC_H-LA.bmp`, `AC_S-SA.bmp`, `AC_V-LA.bmp`, and dashboard images) receive consistently low attention weights across all classes, indicating they are less informative for the classification task.

This analysis demonstrates that the model learns to focus on clinically relevant image types for each cardiac condition, providing interpretability and supporting the reliability of the classification results [23], [14].

Class imbalance was effectively handled through:

- Class weights: Normal (0.055), Ischemia (0.175), Infarction (0.770)
- Focal Loss with $\gamma = 1.5$ to focus on hard examples
- Data augmentation to increase minority class samples[19]

V. Conclusion

Our system successfully demonstrates the potential of deep learning in analyzing MPI images for cardiac condition classification [12], [4], [2]. The model achieves high accuracy in distinguishing between Normal, Ischemia, and Infarction cases, with particular attention to the stress phase images for detecting pathological conditions. The attention mechanism provides interpretability by showing which image phases are most important for different conditions, aligning with clinical knowledge[14], [9].

Future work could focus on expanding the dataset size to improve generalization[19], incorporating clinical metadata to enhance classification accuracy[7], and exploring different attention mechanisms to further improve interpretability[17]. Additionally, deployment in clinical settings could provide valuable feedback for model refinement and validation[8].

VI. Limitations

While our system shows promising results, there are several limitations to consider:

- Limited dataset size (97 patients) may affect model generalization[11]
- Class imbalance between conditions (70 Normal, 22 Ischemia, 5 Infarction cases)
- Need for validation on larger, more diverse datasets[19]
- Computational requirements for training the attention-based model[17]
- Potential need for fine-tuning based on specific clinical requirements[8]

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