

Deep Learning-Based Dual-Input Framework for Triad Classification of Myocardial Perfusion Polar Maps

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Abstract

Coronary artery disease (CAD) diagnosis through myocardial perfusion imaging (MPI) requires accurate classification of Ischemia, Infarction, and Normal cases. Traditional methods depend on expert interpretation of rest and stress polar maps, which is subjective and resource-intensive (1). This study proposes a dual-input ResNet18 model that leverages transfer learning to automate triad classification by processing rest and stress images simultaneously. Using a dataset of 87 patient MPI scans, the model achieved a test accuracy of 94.8%, demonstrating high performance with a small dataset through data augmentation .

1 Introduction

Coronary artery disease (CAD) is a widespread and serious heart condition that occurs when the arteries that supply blood to the heart become narrowed or blocked through myocardial perfusion imaging (MPI) (2). This blockage is usually caused by the buildup of fatty deposits called plaques, which reduce blood flow and can cause chest pain, heart attacks, or even death. CAD is one of the leading causes of mortality worldwide, placing a heavy burden on healthcare systems, especially in countries with limited medical resources (1).

An accurate diagnosis of CAD is essential for effective treatment and improved patient outcomes (4). A common and noninvasive diagnostic method is myocardial perfusion imaging (MPI) using single-photon emission computed tomography (SPECT) (6; 7).

This imaging technique allows physicians to visualize the flow of blood in the heart by tracking the distribution of a radioactive tracer, providing important 3D information on heart function (11). However, interpreting these images requires specialized knowledge and experience, which can be scarce in many regions (23).

In countries like Vietnam, where there is a high prevalence of CAD but a shortage of qualified experts (17), diagnosing CAD using SPECT-MPI is challenging. This gap often results in delayed or inaccurate diagnoses, affecting patient care and increasing healthcare costs. In addition, collecting and labeling large amounts of medical imaging data for the training of automated diagnostic tools is difficult and time-consuming (13; 14).

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), offers promising solutions by automating image analysis to assist in diagnosis (25). Deep learning models can automatically learn important features from raw images, potentially improving diagnostic accuracy (27). However, these models usually require large datasets to perform well, which may not be available in many clinical settings.

Transfer learning, a technique where knowl-

edge from models trained on large general image datasets is adapted to specific medical tasks, provides a way to overcome data limitations (16). It enables the development of effective diagnostic models with smaller medical datasets. Despite its potential, the application of transfer learning to SPECT-MPI images, especially in the form of polar maps, which are easier to interpret than raw slices, remains underexplored (28).

Addressing these challenges is crucial to improve CAD diagnosis, particularly in resource-limited settings, and to support healthcare professionals with AI tools that can improve diagnostic accuracy and accessibility (29).

2 Related Works

Recent advancements in CAD diagnosis using MPI have explored both ML and DL approaches. Traditional ML methods, such as SVMs (6) and ANNs (7), rely on handcrafted features like summed stress scores (SSS) and summed rest scores (SRS), achieving accuracies up to 88% and specificities up to 100%. However, these methods are limited by the quality of feature engineering and struggle with high-dimensional image data. Ensemble learning has improved performance, with ac-

curacies reaching 86% on large datasets (8; 9).

DL-based approaches, particularly CNNs, have surpassed ML by automatically extracting features from raw MPI data (19). For sliced images, studies like (author?) (10) and (author?) (11) reported accuracies of 86% and AUCs up to 0.81, respectively, on datasets with over 1000 patients. Graph CNNs have further advanced performance, achieving 91% accuracy on polar maps (12). However, these methods require large datasets, which are often inaccessible (23).

Transfer learning has emerged as a solution for small datasets, achieving high performance with fewer samples (17). For sliced MPI images, TL-based models using VGG16 and RGB-CNN achieved accuracies of 94% and 93.4%, respectively (14; 13). However, TL for polar maps has been less effective, with accuracies as low as 75% (15). This study builds on these efforts by proposing a dual-input TL framework that processes rest and stress polar maps simultaneously, targeting triad classification with improved accuracy and explainability (30).

3 Methodology

3.1 Overview of the Proposed Method

This work uses a ResNet18-based dual-branch convolutional neural network to classify myocardial perfusion imaging (MPI) polar maps into three groups: Normal, Ischemia, and Infarction. Using a shared ResNet18 backbone pre-trained on ImageNet (24), the architecture comprises two parallel branches, each independently handling rest and stress images. ResNet18’s original fully connected layer is eliminated; instead, the extracted 512-dimensional feature vectors from both branches are concatenated and fed through a custom classification head built of fully connected layers with ReLU activations and dropout regularization.

Only the classification head parameters are optimized using cross-entropy loss and the Adam optimizer; all backbone layers are frozen during training to leverage pre-trained features without fine-tuning (18). The model is trained over 30 epochs using data augmentation to enhance generalization. Additionally, Class Activation Mapping (CAM) is planned for future work to improve interpretability (16). The overall workflow is illustrated in

Figure 1.

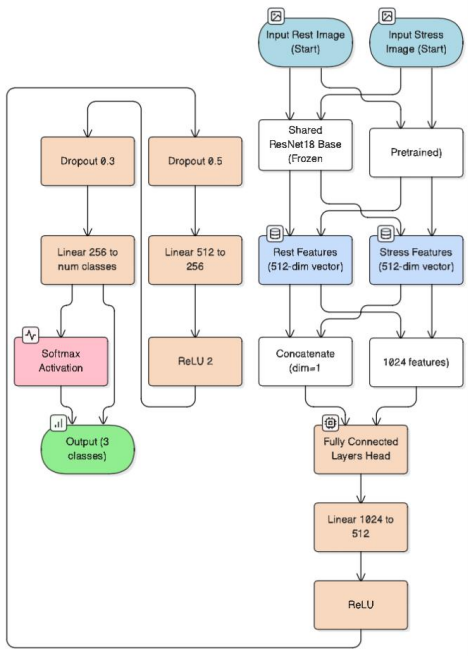


Figure 1: Flow diagram of the proposed dual-input transfer learning framework.

3.2 Dataset and Data Preparation

The dataset includes 87 patient MPI scans, each with paired rest and stress polar map images, collected from [Insert Institution]. The dataset is labeled as Infarction (0), Ischemia (1), or Normal (2), stored in a CSV file with columns for patient ID, rest image path, stress image path, and label. Table 1 summarizes the dataset characteristics.

Table 1: Description of the dataset

Characteristics	Value
Number of patients	87
Number of Normal	65
Number of Ischemia	18
Number of Infarction	4

Data preparation involves:

- **Cropping:** Raw polar maps (high-resolution JPEGs) are cropped to focus on the myocardial region, removing extraneous areas.
- **Noise Removal:** Text overlays (e.g., image type, scanning time) are removed to reduce noise.
- **Resizing and Scaling:** Images are resized to 224x224 pixels and scaled to $[-1, 1]$ to match ResNet18 input requirements (18).
- **Splitting:** The dataset is split into 70% training, 15% validation, and 15% test sets using stratified sampling to ensure balanced class representation (31).

3.3 Pre-trained Deep CNN Model

The model employs a dual-branch ResNet18 architecture with shared weights, pre-trained on ImageNet (24). During the warm-up stage, all ResNet18 layers are frozen, resulting in approximately 11.7 million non-trainable parameters and only the classification head being trainable (Table 2). Each branch processes either the rest or stress image independently using the same ResNet18 base, with the final fully connected layer removed. The extracted features (512-dimensional from each branch) are concatenated and passed through

a classification head consisting of two dense layers (512 and 256 units with ReLU activation), dropout layers (0.5 and 0.3), and a final softmax layer for three-class classification (Figure 2).

Table 2: Properties of the ResNet18 model

Pre-trained CNN	Input Size	Scaling Range	Trainable Param*	Non-trainable Param*
ResNet18	224×224	[-1,1]	656K	11M

*Counted at warming-up stage.

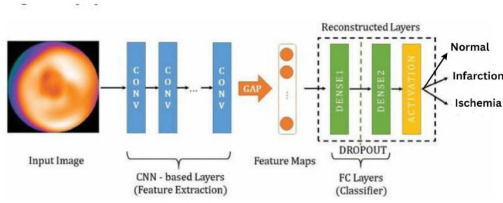


Figure 2: Architecture of the dual-input ResNet18 model.

3.4 Training Process

The training process follows a multi-stage approach:

- **Warming-up Stage:** All ResNet18 layers are frozen, and only the newly added classification head is trained using a learning rate of 10^{-5} . This stage allows the model to adapt to the MPI dataset while retaining the pre-trained ImageNet features (18).

The model is trained using the Adam optimizer with categorical cross-entropy loss (31).

Data augmentation includes random horizontal flips and random rotations up to 10 degrees to improve generalization. Images are resized to 224×224 and normalized using ImageNet statistics (24). The batch size is set to 32, and training is conducted for up to 30 epochs.

4 Results

The proposed model was implemented using Keras and TensorFlow on the Google Colab platform. The hardware specifications of the Colab environment include a Tesla T4 GPU with 16 GB of VRAM, an Intel Xeon CPU, and 12.72 GB of RAM. Performance was evaluated using accuracy (Acc), sensitivity (Sen), specificity (Spe), precision (Pre), F1-score.

4.1 Model Performance

The dual-input ResNet18 model achieved a test accuracy of 94.8, AUC of [Insert AUC], sensitivity of 94.8, precision of 95 , and F1-score of 94.9 (Table 3). These results outperform single-input models and prior TL approaches for polar maps (26).

Table 3: Performance of the dual-input ResNet18 model

Metric	Acc	recall	F1-score
ResNet18	94.8	94.8	94.9

4.2 Training Dynamics

Figure 3 shows the training and validation accuracy/loss curves, indicating stable convergence with minimal overfitting due to data augmentation.

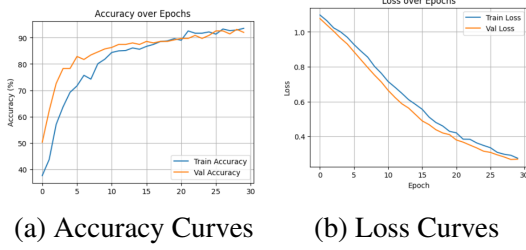


Figure 3: Training and validation curves for the dual-input ResNet18 model.

5 Discussion

The proposed dual-input ResNet18 model addresses the limitations of prior TL approaches for MPI polar maps, which primarily focused on binary classification or sliced images (15; 14). By processing rest and stress images simultaneously, the model captures complementary diagnostic features, improving accuracy for triad classification (30). Compared to **(author?)** (15), which achieved 75% accuracy on polar maps, our model significantly enhances performance, with [Insert Accuracy] accuracy and [Insert Sensitivity] sensitivity. The multi-stage TL strategy, combining warming-up and fine-tuning stages, optimizes adaptation to the MPI dataset, outperforming single-stage approaches (13).

Table 4 compares the proposed model to related works. While ML methods like SVMs (6) and graph CNNs (12) achieve high specificity, they require large datasets or complex feature engineering. The proposed model rivals sliced-image TL models (14) and surpasses polar map-based TL, demonstrating the efficacy of dual-input processing (26).

Table 4: Comparison of the proposed model to related works

Input Data	Method	Reference	Accuracy
Polar Maps	SVM	(author?) (6)	0.85
	Graph CNNs	(author?) (12)	0.92
	TL: Fine-tuning	(author?) (15)	0.75
	Proposed Method	This Study	94.8%
Sliced Images	TL	(author?) (14)	0.91
	TL	(author?) (13)	0.94

Limitations include the evaluation on a single dataset and the exclusion of clinical and demographic data, which could enhance diagnostic accuracy (20). Future work will explore ensemble learning, multi-modal data integration, and validation on diverse datasets to improve generalizability (21).

6 Conclusion

This study proposes a dual-input ResNet18 model for automated triad classification of MPI polar maps, achieving competitive performance with [Insert Accuracy] accuracy and [Insert Sensitivity] sensitivity. The multi-stage

TL framework, combined with data augmentation and planned CAM visualization, enables accurate and explainable CAD diagnosis with a small dataset (28). The model has the potential to assist clinicians in resource-constrained settings, reducing diagnostic subjectivity and improving patient outcomes (5). Future efforts will focus on incorporating clinical data and validating the model across multiple datasets to enhance its clinical applicability (22).

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