A Radiomics-Based Machine Learning Approach for Coronary Stenosis Assessment from Coronary Computed Tomography Angiography

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Abstract

Coronary Artery Disease (CAD) is a leading cause of mortality worldwide. This study aims to improve CAD diagnosis and facilitate tailored treatment strategies by implementing a radiomics-based machine learning algorithm for the automated evaluation of stenosis from coronary computed tomography angiography (CCTA).

The study population included 220 patients undergoing CCTA for suspected CAD. Multiplanar Reconstruction images at 45° of rotation were obtained for each of the three primary coronary arteries, resulting in a total of 343 coronary artery segments. Each patient was assigned to: non-obstructive (0% stenosis), sub-obstructive (stenosis<50%) or obstructive (stenosis>50%) class. After radiomic features extraction and selection, a gradient boosting model was trained using a cascade approach, which subdivided the CAD-RADS scoring task into two easier sub-tasks: (A) no CAD vs. CAD and (B) nonobstructive vs. obstructive CAD. The dataset was divided into training and test sets (80-20%) and 5-fold cross-validation was applied to the training set to determine optimal hyperparameters.

A balanced accuracy of 80% and AUC-ROC of 84% were achieved on the test set. These preliminary results are promising for automatic stenosis assessment, potentially useful in optimizing CAD management.

1. Introduction

Coronary Artery Disease (CAD) represents one of the leading causes of morbidity and mortality worldwide, accounting for 8.9 million annual deaths [1]. Coronary plaque progression may determine coronary lumen stenosis and impairing blood supply to the myocardium, thus potentially causing major adverse cardiac events (MACE) [2]. Grading coronary artery stenosis is a crucial step in the diagnosis of patients with suspected CAD, enabling tailored therapeutic interventions and clinical decision-making. Based on the Coronary Artery Disease-Reporting and Data System (CAD-RADS), a CCTA-based stenosis severity scoring, different treatment strategies can be planned depending on plaques presenting non-obstructive (CAD-RADS 0, 0% stenosis), sub-obstructive (CAD-RADS 1-2, stenosis<50%) or obstructive (CAD-RADS 3-4-5, stenosis>50%) stenosis. However, stenosis grading is manual and requires a high-level of expertise from radiologists, thus being subjected to interobserver variability, and high time-consumption [3]. While several deep learning models have been proposed to automate stenosis scoring [4]–[10], only three radiomic models [11]–[13] were developed for the prediction of stenosis grading, and only one reported significant results [11].

The aim of the present study is to develop a radiomics-based machine learning pipeline for the automated evaluation of stenosis from coronary computed tomography angiography (CCTA) multiplanar reconstruction (MPR) images obtained by rotating images 45° around the vessel centerline.

2. Materials and Methods

2.1. Patient and image dataset

The study population included 220 patients who underwent CCTA at IRCCS Centro Cardiologico Monzino (Milan, Italy) between 2016 and 2018 for suspected CAD. The study was approved by the institutional review board and all patients signed the informed consent. CCTA scans were acquired using Discovery CT 750 HD or Revolution CT (GE Healthcare, Milwaukee, IL) following the Society of Cardiovascular Computed Tomography guidelines[14].

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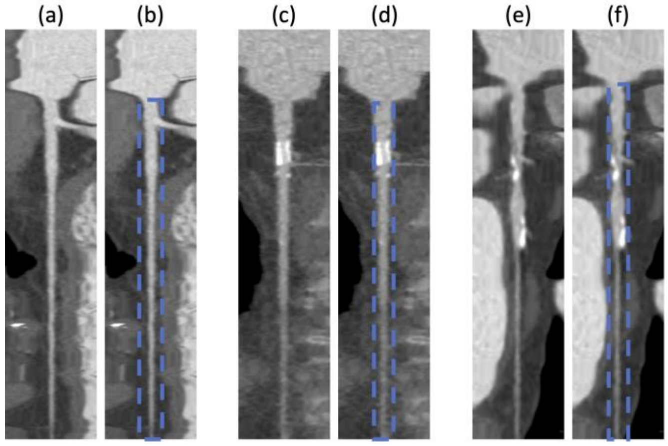

Figure 1. Example of Multiplanar Reconstruction image for a patient of (a) non-obstructive, (c) sub-obstructive and (e) obstructive class with the corresponding ROI delineation in blue (b), (d), (f).

Based on CCTA image evaluation by a group of ten expert radiologists and cardiologists, each patient was assigned to one of these three classes: no CAD (0% stenosis, n=40), nonobstructive CAD (stenosis<50%, n=80) and obstructive CAD (stenosis≥50%, n=100).

The dataset comprises CCTA longitudinal sections of the three main coronary arteries: left anterior descending, left circumflex, and right coronary artery. Multiple images (i.e., from 2 to 8 images) were captured from various angles around the longitudinal axis of each artery. Multiplanar Reconstruction (MPR) images were obtained for each segment, allowing visualization of the entire course of the vessel in 2D. Finally, the study considered a total of 343 coronary artery segments and 2548 MPR images.

2.2. Image segmentation, radiomic feature extraction

A semi-automatic method was adopted to extract a rectangular, 40-pixel wide region of interest (ROI), centered along the straightened coronary centerline (Fig. 1). ROI delineation was performed on a single view of a patient's coronary artery and then applied to all the images of the same vessel.
A total of four-hundred sixty-five 2D radiomic features, encompassing textural and first-order characteristics, were extracted from both the original and filtered version of the images (Wavelet transformation) using Pyradiomics 3.0.

2.3. Machine learning pipeline

The image dataset was partitioned into training set (80%) and test set (20%), using a patient-stratified split. This resulted in 176 patients, 270 coronary arteries, and 2012 images in the training set, while the test set contained 44 patients, 73 coronary arteries, and 536 images.

During the training phase, a 5-fold cross-validation was applied, in which feature scaling and selection, and data balancing (by using Synthetic Minority Over-sampling TEchnique algorithm) were applied. Features selection encompassed three steps: (i) non-redundancy, (ii) significance and (iii) maximum relevance-minimum redundancy. Gradient boosting classifiers were chosen as the best performing models during preliminary attempts, and within the 5-fold cross-validation, they were trained, and the optimal number of selected features was determined based on the performance metrics on the validation set. Finally, a gradient boosting classifier was trained with the optimal number of features on the entire training set, and then applied on the test set.

A cascade machine learning pipeline was developed to achieve the final 3-class stratification through two simpler sub-tasks: (A) no CAD *vs.* CAD and (B) nonobstructive *vs.* obstructive CAD.

Each patient image was independently classified, and the final patient classification was based on majority voting criterion.

3. Results

The feature selection step identified 17 features for the sub-task A and 23 features for the sub-task B. In particular, for both sub-tasks, all the selected features concerned texture information extracted either from the original image or from its Wavelet transform (majority of the selected features).

Table 1 presents the classification performance metrics of the validation, in the two sub-tasks (A, B).

Table 1. Classification metrics for sub-tasks A (no CAD *vs.* CAD) and B (nonobstructive *vs.* obstructive CAD)

Task	Sensitivity	Specificity	AUC	Bal. Acc
A	89% ±5%	79% ±15%	95% ±2%	84% ±7%
B	70% ±7%	69% ±12%	81% ±3%	69% ±4%

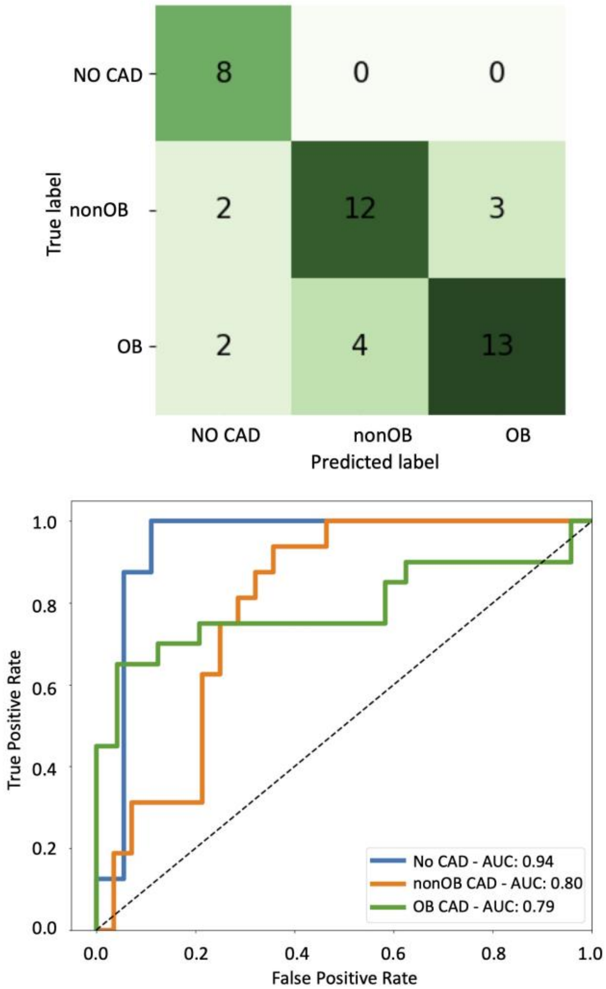

Figure 2. Top panel: Confusion matrix of the test set. Bottom panel: Receiving operating characteristic (ROC) curves for the test set. No CAD: no Coronary Artery Disease. nonOB: non-obstructive, OB: obstructive. AUC: area under the curve.

Good performances were achieved also on test set, with a macro-sensitivity of 80%, a macro-specificity 87% and a balanced accuracy of 80% (computed as the average across all classes of the proportion of true positives over the total number of actual instances for each class). The confusion matrix is shown in Figure 2, where it can be noted that all patients with non-obstructive plaques have been correctly classified. The receiving operating characteristic (ROC) curve for the test set is shown Figure 2, macro-AUC-ROC was 80%.

4. Discussion and Conclusions

Herein we proposed a novel radiomics-based machine learning pipeline for automated coronary artery stenosis scoring from CCTA-based MPR images. By strategically dividing the classification task into easier sub-tasks, the model achieved good stratification performances on the test set. The 3-class stratification, non-obstructive, sub-obstructive and obstructive coronary stenosis, is clinically relevant as it may drive therapeutic strategy decision. Accordingly, an automated tool is of utmost importance for effective decision support.

Several deep learning models have been developed so far, that demonstrated comparable stenosis grading performances [4]–[10]. However, deep learning methods often rely on complex and scarcely interpretable "black box" models. Differently, radiomic features are more understandable and can be related to aspects of the coronary artery lesion, as the shape or tissue heterogeneity. Notably, our model primarily relied on texture-based features suggesting that plaque composition may also play an important role in accurately classifying stenosis severity. As a result, radiomics-based machine learning models hold the potential to be transferrable into clinics.

Despite several CCTA-based radiomic models have been developed for the detection of vulnerable plaques [15]–[18], the prediction of coronary plaque stenosis grading has been poorly investigated through radiomic approaches [19]. Hu et al. [12] and Li et al. [13] developed a radiomic model for the identification of significant ischemic plaques, reporting an AUC of 67% [12] (on the training set) and of 77% [13] (on the validation set), respectively. Our study outperformed these results, suggesting that radiomics is a potential tool for automated plaque stenosis grading. Our results are in line with those reported by Jin et al. [11], achieving an AUC of 91% on the test set. However, while the aforementioned radiomic studies [11]–[13] applied radiomics on the CCTA-segmented plaque volume, our analysis was based on MPR images of the whole coronary artery, without the need to 3D plaque segmentation. This further facilitates its application into clinics, by removing cumbersome segmentation steps.

Considering all the above, the proposed algorithm has the potential to provide a promising support system to reduce interobserver variability in coronary artery stenosis assessment and potentially helping in optimizing CAD management.

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