Eurographics Workshop on Visual Computing for Biology and Medicine (2024)
L. Garrison and D. Jönsson (Editors)

Short Paper

Workflow for AI-Supported Stenosis Prediction in X-Ray Coronary Angiography for SYNTAX Score Calculation

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Abstract

X-ray coronary angiography is the primary imaging modality for evaluating coronary artery disease. The visual assessment of angiography videos in clinical routines is time-consuming, requires expert experience and lacks standardization. This complicates the calculation of the SYNTAX score, a recommended instrument for therapy decision making. In this work we propose an end-to-end pipeline for segment-wise stenosis prediction in multi-view angiography videos to facilitate the calculation of the SYNTAX score. While recent approaches mainly focus on stenosis detection on frame- or video-level, our method is developed and evaluated for stenosis prediction on patient-level. The pipeline is composed as follows: (1) Selection of frames showing arteries filled with contrast medium using a convolutional neural network, (2) Stenosis detection and segment labelling on selected frames using a region-based convolutional neural network for object detection, (3) Linkage of detected regions showing the same stenosis by tracking the optical flow of the detections in the angiography video, (4) Segment assignment to the detected and tracked stenosis to predict stenotic segments on patient-level. The workflow is adjusted and evaluated using the image data and diagnostic annotations of 219 patients with multi-vessel coronary artery disease from the German Heart Center of the Charité University Hospital (DHZC), Berlin. To fine-tune the models, we used manually flagged frames for the frame classification model and bounding box annotations provided by a cardiac expert for the stenosis detection model. For the segment-wise prediction of all patients, we achieved a total sensitivity of 56.41*, specificity of* 85.88*, precision of* 52.81 *and F1 score of* 54.55 *with varying results for the 25 coronary segments. The established workflow can facilitate visual assessment of CAD in angiography videos and increase accuracy and precision in clinical diagnostics.*

CCS Concepts

• ***Applied computing*** → ***Health informatics; Life and medical sciences;***

1. Introduction

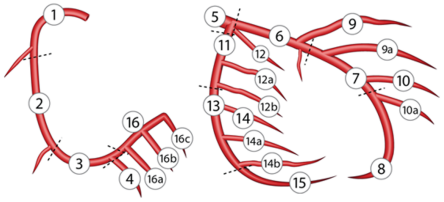
Coronary artery disease (CAD), the leading cause of death worldwide [WNAB16], is caused by atherosclerotic plaque resulting in pathological narrowing of the coronary vessels. This leads to reduced blood flow followed by insufficient supply of the heart muscles and increases the risk of ischaemia [LT05]. In clinical environments treatment options for patients with complex CAD are discussed in meetings of cardiac experts, known as heart teams, with the aim of identifying the optimal treatment strategy [HRZM13]. X-ray coronary angiography (XCA) can visualize coronary arteries filled with contrast agent in video sequences and is the gold standard imaging modality for CAD assessment [RGZ21]. The interpretation of XCA depends on visual assessment by the physician, which is poorly reproducible, highly variable and bias prone.

As recommended in the ESC/EACTS Guidelines on Myocardial Revascularization [NSUA*19], the anatomical SYNTAX score quantifies the extent and the complexity of CAD and stratifies the risk between the two common revascularization strategies: percutaneous coronary intervention (PCI) and coronary artery bypass graft (CABG). The score is calculated with the help of an interface that asks sequential and interactive questions about left-right dominance, segments involved per stenosis and adverse characteristics [Off22]. Stenoses identified in proximal segments of the coronary tree are scored higher than stenoses in distal segments (Fig. 1).

However, there is a significant concern about bias and inter-individual variability in calculating the SYNTAX score. An ever-increasing amount of patient data, therapeutic options, complex metrics and image-based disease classifications, new research studies, and the patient's personal preferences all add to the complexity of decision making. (Partially) automating the CAD assessment

DOI: 10.2312/vcbm.20241188

process could facilitate guideline-compliant decision making, reduce inappropriate use of revascularization methods and improve overall patient outcomes.



Segment Points		Segment Points	
1	+1	12	+1
2	+1	12a	+1
3	+1	12b	+1
4	+1	13	+0.5/+1.5
5	+5/+6	14	+0.5/+1
6	+3.5	14a	+0.5/+1
7	+2.5	14b	+0.5/+1
8	+1	15	+1
9	+1	16	+0.5
9a	+1	16a	+0.5
10	+0.5	16b	+0.5
10a	+0.5	16c	+0.5
11	+1.5/+2.5		

Figure 1: *Vessel segments of the right coronary artery (RCA) and left coronary artery (LCA) in the SYNTAX score scheme [Off22]: (1) RCA proximal, (2) RCA mid, (3) RCA distal, (4) Posterior descending, (5) Left main, (6) LAD proximal, (7) LAD mid, (8) LAD apical, (9) First diagonal, (9a) Add. first diagonal, (10) Second diagonal, (10a) Add. second diagonal, (11) LCX proximal, (12) Intermediate, (12a) Obtuse marginal, (12b) Obtuse marginal, (13) LCX distal circumflex, (14) Left posterolateral, (14a) Left posterolateral, (14b) Left posterolateral, (15) Posterior descending. Weighting factors for the corresponding coronary segments [SMKM05].*

Earlier approaches apply convolutional neural networks (CNNs) to XCA images for vessel segmentation prior to stenosis classification by finding locations along the extracted centerline with decreased diameter [ZGS*21]. Recent studies investigated direct stenosis detection using region-based CNNs and achieved reliable results [DKG*21, LCG*23]. Typically, clinicians inspect the entire XCA video sequences since the visibility of coronary arteries and stenoses varies with the diastolic and systolic phase of the heart. Only few stenosis detection methods include temporal information [PAF*21, CKdV*23]. However, the calculation of the SYNTAX score requires information about the affected coronary segments. A recently published dataset includes segmented and labelled coronary segments in XCA images according to the SYNTAX score scheme, which allows for training multi-class segmentation models [PAZ*24]. A multi-step AI workflow for coronary stenosis detection, segment assignment and prediction of the stenosis degree in XCA videos has been published recently with reliable performance of the described components [LCT*24]. But the method excludes segments with poor visibility and is evaluated only on video-level, thus, lacks patient-level evaluation considering multiple projection angles. To tackle the difficult task of segment assignment the pipeline includes a multi-class vessel segmentation algorithm reaching a Dice score of 74% which could potentially be improved.

The visibility of segments and stenoses in the XCA video relies on the location in the coronary tree and the viewing angle, since arteries can overlap or appear oblique in the complex 3D tree structure. In clinical practice multiple videos with different projection angles are recorded with the aim to capture all stenoses in the patient [RGZ21]. Therefore, evaluation on patient-level is indispensable, and has been conducted in more recent works which still lack separate segment prediction [CKdV*23, PAH*24].

In this work we present a four-step end-to-end workflow to predict stenotic segments in multiple XCA video sequences captured with different viewing angles to facilitate the calculation of the SYNTAX score. Standing out from recent works, the pipeline was developed to predict coronary stenoses for each of the 25 coronary segments respectively, and is evaluated on patient-level using a clinical dataset of multi-vessel CAD patients. The dataset includes multi-view XCA videos and information about the segment-wise presence of stenoses for each patient. To evade the difficult task of multi-class vessel segmentation our pipeline includes a detection model which directly classifies the affected coronary segment for stenoses detected in XCA frames. For model training a dataset was created by annotating selected frames with bounding boxes and the corresponding segment. Another novelty in our approach is the usage of optical flow to combine detections showing the same stenosis in one video by tracking the movement of detected stenoses over all frames.

2. Material and Methods

Our workflow for automated stenosis detection includes four steps and processes XCA videos recorded with multiple projection angles (Fig. 2). First, a classification model is used to select frames with sufficient vessel lumen visibility in each XCA video. A stenosis detection model is applied to the selected frames to find regions likely to show a stenosis and predict the corresponding coronary segment. Subsequently, a movement tracking algorithm is used to follow the movement of a detected region and link detected bounding boxes showing the same stenosis in different frames. The segment of a set of linked bounding boxes is predicted through majority voting. A graphical user interface was developed to show the projection videos of a patient and display the detected and linked boxes along with the predicted segments.

2.1. Material

The dataset for model training and patient-level evaluation was collected from two cohorts of CAD patients from the German Heart Center of the Charité University Hospital (DHZC), Berlin. The first cohort consisted of 126 patients with complex triple vessel disease and high SYNTAX scores who were being prepared to receive CABG surgery. The second cohort included 93 patients with moderate SYNTAX scores and primarily LAD stenoses, who were eligible for hybrid procedures (PCI and CABG). The average age of all patients was 70.0 ± 10.1 years old. 23.4% were identified as female and 76.6% as male. The number of stenoses per segment is visualized in Figure 3. The XCA videos were exported directly from a clinical system without pre-selection and show the right coronary arteries, left coronary arteries, the aorta or the catheter track. In total, 1137 of 5165 coronary segments are marked with stenosis, of which 832 have a stenotic degree of $> 75\%$ and require treatment. Several minor stenoses were not marked in the dataset.

Selected frames were annotated by a cardiac expert using a customized annotation tool which shows regions which were already detected by a trained stenosis detection model, fine-tuned on a public dataset [DKG*21] and allows to verify correct detections, insert missed stenotic regions and annotate the corresponding segments [PAH*24]. Not every stenosis visible in a labelled frame was annotated as such, resulting in an incompletely labelled dataset.

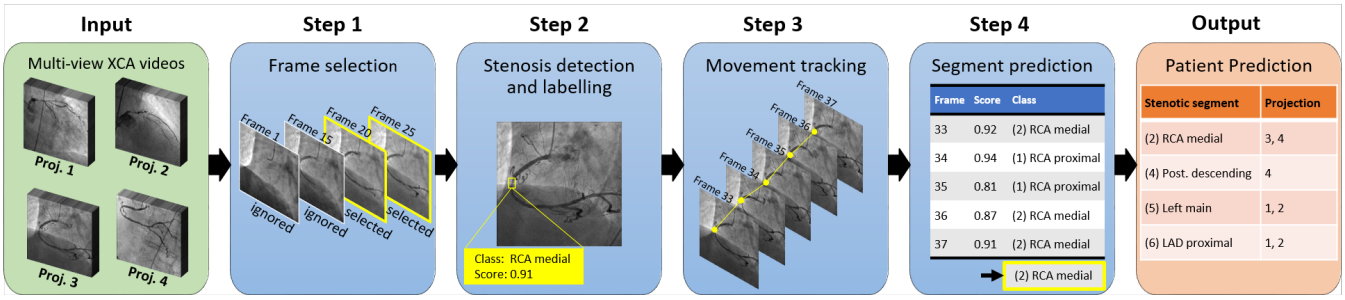


Figure 2: *Stenosis prediction pipeline. Input: Several XCA videos of the same patient with different projection angles. Four steps: (1) Selection of frames with sufficient contrast agent to show the coronary vessels, (2) Detection of stenotic regions with confidence score* > 0.8 *and classification of the corresponding coronary segment on selected frames, (3) Tracking of the detected regions in all frames of one sequence to combine detections showing the same stenosis, (4) Segment prediction by majority voting of the predicted classes in a set of linked stenoses. Output: Segment-wise stenosis prediction at the patient-level after processing all XCA projections through the pipeline.*

2.2. Methods

Frame selection: For the selection of frames with sufficient vessel lumen visibility we used *Inception-v3*, a basic and computationally cheap CNN-based classification model to enable fast inference [SVI*]. In order to create a training dataset for this task, the first two frames of selected XCA videos were labelled as inappropriate, and the two mid frames which typically show high contrast were labelled as suitable resulting in 4462 labelled frames. The model was initialized with *ImageNet* weights and trained for 10 epochs with the initial learning rate $1e^{-4}$, batch size 8 and binary cross entropy loss function.

Stenosis detection: For stenosis detection, we used the pre-trained *Faster R-CNN ResNet-101 V2*, as it achieves the highest accuracy in detecting stenotic regions among multiple object detection networks [DKG*21]. The network consists of a CNN for object detection, including a region proposal network which shares full-image convolutional features with the detection network [RHGS15]. One prediction consists of the bounding box, the confidence score and the estimated class among 25 classes for the coronary segments according to the SYNTAX score scheme. The model was initialized with *COCO* weights [LMB*14] and fine-tuned over 10^5 iterations using the weighted smooth L1 loss for localization, the weighted focal loss for classification and a gradually decreasing learning rate of initially $1e^{-4}$. Detections with a confidence score of > 0.8 were considered for further processing. The threshold was chosen after evaluation of the model using different thresholds.

Region tracking: To combine the detected regions showing the same stenosis on different frames, we applied a stenosis tracking algorithm. The RAFT model is a pre-trained deep network architecture to measure optical flow by calculating the correlation of all pixel-pairs based on per-pixel features and iteratively updating a flow field through a recurrent unit [TD20]. In order to define one flow vector per detection, we calculated the average vector of all optical flow vectors in the vessel region within the detected bounding boxes. The vessels were segmented using the Frangi vesselness filter [FNVV98]. Detected boxes with a minimum overlap rate of 0.1 were linked to the tracked stenosis.

Segment prediction: A set of detections, showing the same stenosis in one video, is assigned with the coronary segment which was predicted most frequently. Single detections not associated with a set were rejected. Coronary segments with at least one assigned set of detections in the available projection videos were marked as stenotic, resulting in a segment-wise prediction per-patient.

3. Results

To evaluate the frame selection of step 1 and the stenosis detection of step 2, we divided the CAD patients of our clinical dataset (Sec. 2.1) into five subsets for five-fold cross-validation with a 4:1 split for training and testing of the models. Due to the low incidence of some stenotic coronary segments (Fig. 3) we did not use a completely separate test set to evaluate the workflow. The resulting five frame selection models achieved a mean accuracy, sensitivity, specificity and F1 score of 95.67, 93.79, 97.56, and 95.60 on the classified frames across the folds. The five stenosis detection models achieved a mean sensitivity, precision and F1 score of 27.9, 55.04 and 46.64 for region detection and a mean accuracy of 59.71 for segment classification on the 5664 annotated frames. Additionally, the fine-tuned detection models were evaluated using the part of the external ARCADE dataset which consisted of XCA frames annotated with bounding boxes [PAZ*24] and achieved a mean sensitivity, precision and F1 score of 18.90, 58.07 and 35.00. The five fine-tuned models of steps 1 and 2 were applied to the frames of all XCA videos of the patients in the respective test set to predict stenotic regions for further processing in pipeline steps 3 and 4. For evaluation of the total pipeline we compare the segment-wise labels from the physician with the segment-wise predictions of our workflow.

647 out of 1137 stenotic segments in the clinical dataset were successfully predicted as stenotic by the model, resulting in a sensitivity of 56.41. 3411 out of 3901 healthy segments were not predicted as stenotic, resulting in a specificity of 85.88. 647 out of 1350 predictions correctly show a stenosis resulting in a precision

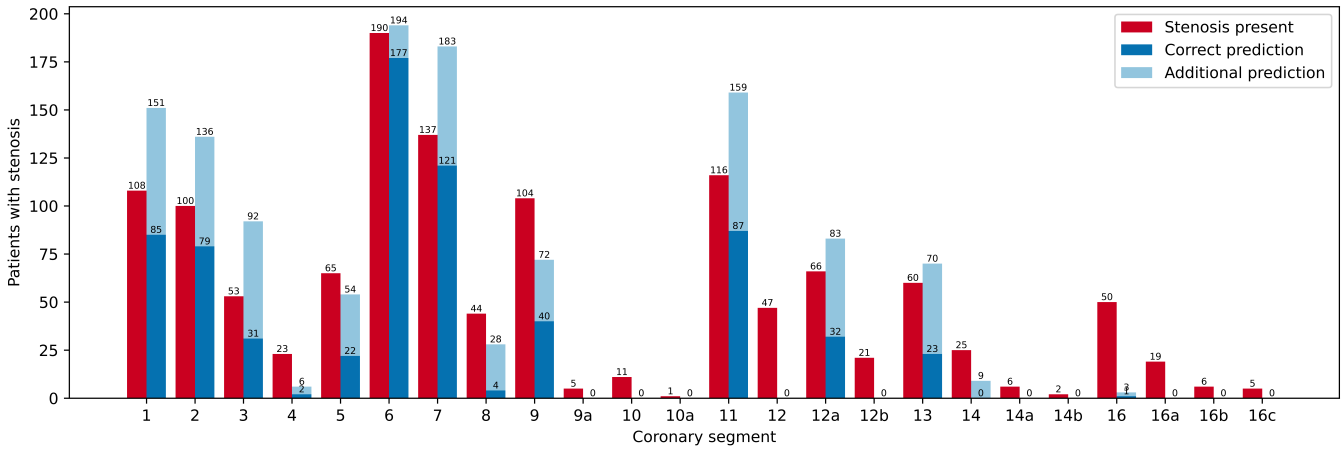


Figure 3: *Number of patients who actually have a stenosis in the segment (red bar). Number of patients for whom the stenosis in the respective segment was successfully predicted by the model (dark blue bar) and the number of patients for whom a stenosis in the respective segment was predicted despite no stenosis was labelled for the patient (light blue bar).*

of 52.81. The total F1 score was 54.55. Figure 3 shows the number of patients with a present stenosis in the respective segment and the number of patients for whom the present stenosis was correctly detected by the workflow. The figure also shows additional predictions that partially correspond to unlabelled stenoses (stenotic degree $< 50\%$). These unlabelled stenoses were counted as false positives in our metrics. Segment 15 (left posterior descending) was left out for evaluation because stenoses in this segment were not labelled by the clinicians.

4. Discussion

We proposed a four-step workflow for segment-wise stenosis prediction in multi-view XCA video sequences, which can be used to facilitate the calculation of the SYNTAX score. For evaluation on patient-level we used a clinical dataset of multi-vessel CAD patients with marked stenotic segments and XCA video data. Considering the stenoses present in the clinical dataset, most stenoses occurred in the main branches or proximal segments (1, 2, 6, 7, 9, 11) (Fig. 3). Descending arteries contained less stenoses (4, 9a-10a, 14-15, 16a-c). Considering the detection performance, the system succeeded well in predicting stenoses in the main branches of the RCA (1,2,3) and proximal segments of the LCA (6,7,11) which are visualized with more contrast in XCA compared to smaller and distal vessels. The increased visibility facilitates automated prediction equivalently to visual diagnosis (Fig. 4, top left).

The system had difficulties with detecting stenoses occurring in smaller vessels and distal regions (4, 8, 9a, 10, 10a, 12, 12b, 14a, 14b, 16a-c). This can can be explained by lower segment class representation in the training data, lower contrast and increased vessel overlay due to the branched structure in the distal regions (Fig. 4, top right). The system was able to predict stenoses disregardful of the stenotic degree. Since many stenoses with low degree ($< 50\%$) were not marked in the dataset by the clinicians (Sec. 2.1), some low degree stenoses predicted by the system were mistakenly counted as false positives, which had a negative impact on sensitivity and specificity (Fig. 4, bottom left). Thus, the evaluated performance is a pessimistic estimate that could possibly be improved if the ground truth labels of all stenoses were available.

Correct detections, particularly in the side branches, were often classified with the wrong segment, which increases the number of missed stenoses and of false predictions (Fig. 4, bottom right). This leads to the assumption that the topology of the coronary tree was difficult to identify for the model in distal regions. Furthermore, some stenotic regions were left out by the clinician when annotating frames with the annotation tool. These incompletely labelled frames complicated the training process of the detection model.

Compared to the approach of Labrecque Langlais et al. [LCT*24], which included the classification of detected regions based on prior segmentation of coronary segments, our approach could not reach their sensitivity of 70.72, but clearly outperformed their method in terms of specificity, (87.43 over 76.71), precision (47.93 over 39.42) and F1 score (54.55 over 51.15). Considering that we included all segments and used a different cohort of multi-vessel CAD patients, our results are satisfactory and encourage further development and model fine-tuning.

Next steps include further improvement of the proposed workflow, such as fine-tuning the CNN models used, separating RCA and LCA, investigating different segment prediction schemes and focusing more on under-represented segment classes. Completing the annotation of the dataset (Sec. 2.1) is likely to improve the performance in two ways: by making XCA frames with annotations for all visible stenoses available for training and by correcting the false positive rate. Future enhancements could comprise the consideration of typical projection angles for certain segments or the prediction of the stenotic degree and calcification type based on image features. The automated assessment and quantification of CAD can facilitate the calculation of the SYNTAX score and improve clinical decision-making in heart team discussions.

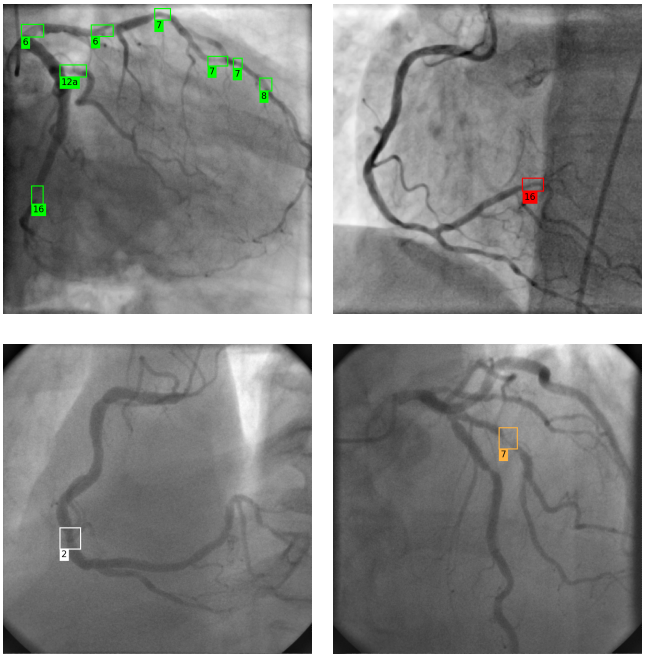


Figure 4: *Cases of successful successful prediction (top left) and unsuccessful prediction: Missed stenosis (top right), false prediction (bottom left), false segment classification (bottom right).*

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