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Automated Stenosis Detection in Coronarography Image Data

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Abstract— **Coronary Artery Disease (CAD) represents a life-threatening condition resulting from the constriction or obstruction of coronary arteries. Timely detection plays a critical role in effective treatment. This paper introduces an innovative machine-learning approach that utilizes the ResNet architecture to automate stenosis identification in coronarography. The proposed method aims to enhance the efficiency and reliability of CAD diagnosis, providing valuable support to medical practitioners. Results emphasize the significance of high-quality training datasets in achieving precise stenosis detection. Discussion is made regarding study limitations, including dataset artifacts, and avenues for future research are proposed. This approach establishes a foundation for advancements in coronary vessel stenosis detection, with potential for classification and additional feature extraction.**

Clinical relevance— **The proposed method aims at the automation of CAD - a world-leading cause of death - diagnosis and personalized treatment suggestions. AI-supported detection and characterization facilitates cardiologist work required for manual data analysis.**

I. INTRODUCTION

Coronary Artery Disease (CAD) is a prevalent and life-threatening condition affecting millions of people with approximately 17.8 million annual deaths worldwide [1]. It results from the narrowing or blockage of coronary arteries, which supply the heart muscle leading to symptoms like chest pain and shortness of breath. Early detection and treatment are essential to mitigate heart attack, heart failure, and other complications. Standard diagnosis methods include coronarography scans. This involves inserting a catheter into a blood vessel and guiding it to the heart using X-ray imaging. A contrast dye is injected through the catheter, enabling detailed X-ray images of coronary arteries to reveal blockages or abnormalities. Cardiologists analyze these images for diagnosis and treatment planning. Machine learning algorithms have gained traction for CAD diagnosis [2], offering potential advantages like speed, reduced invasiveness, and cost-effectiveness compared to conventional approaches. Most prior research focuses on non-invasive techniques, particularly angio CT scans, while our study explores the potential of X-ray scans, which have lower information capacity than 3D CT images, but expose patients to less ionizing radiation, apart from specific medical recommendations for using CT. In [3], authors use a U-Net model for segmentation and stenosis detection based on computed segmentation masks. They rely on the difference between the widest and narrowest points of arterial segments for detection. Another approach is object detection[4], where authors employ RetinaNet on a large dataset of coronarography scans, achieving high F1 scores through extensive data augmentation. A classical approach with interactive algorithms is explored in [5] requiring substantial image preprocessing techniques.

This paper describes an ML-based tool with the potential to become a real-time technique employed during the coronarography procedure. Our primary goal was to develop a method capable of identifying potential stenosis in unseen scans and extracting features relevant to the SyntaxScore. Considering the critical nature of disease detection and the potential consequences of false negatives, the model prioritizes recall over precision. Our aim is to ensure that all stenosis are detected, which is a fundamental assumption guiding the design of our detection model (details in III). This approach minimizes the risk of missing any instances of stenosis, enhancing patient safety and clinical decision-making by offering personalized treatment options based on SyntaxScore. Moreover, it was developed in close collaboration with leading cardiologists to ensure its clinical viability.

II. DATA

A dataset consists of 97 preprocessed coronarography images. Each data element includes:

- Coronarography Scan: A grayscale 8-bit-depth image (512x512 pixels) representing the original coronary vessel X-ray scan.
- Segmentation Mask: A PNG file with a binary vessel segmentation mask, approximating the vessel's location on the image.
- Centerline: A graph representation of the vessel and its branches, derived from the segmentation mask.
- Region Of Interest (ROI): A rectangular field marking the possible stenosis location on the coronary scan image. This ROI may contain additional attributes used to calculate the SYNTAX score.

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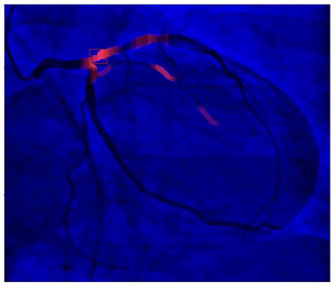

Fig. 1. Heatmap produced by the model as a result of the voting procedure.

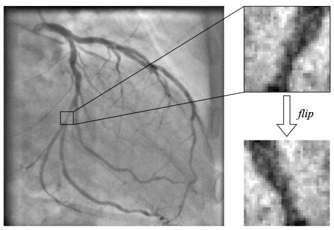

Fig. 2. Example of extracting a single clipping from the coronarography scan and applying augmentation through horizontal flip. The resulting 32 x 32 image is fed to the classifier.

III. PROPOSED SOLUTION

We propose an ML-based method for stenosis detection in coronarography scans. Our approach involves fine-tuning of a pre-trained ResNet model. The data elements are described in **??**. Some images require preprocessing to fit the classification model, some have multiple ROIs marked, and there are no direct negative examples. Aiming to precisely locate stenosis and train the model with the required recall, we extract small clippings along the centerline from the coronarography scan. These clippings are labeled as positive stenosis examples if their center falls within any ROI from the parent scan.

Two key challenges are the limited number of data and an uneven number of negative (healthy vessels) and positive examples. To address this, we employ data augmentation techniques on the clippings, expanding the training dataset and balancing the class ratio. The process includes random rotation, scaling, and horizontal flipping. An example of the latter can be seen in Figure 2.

For training, we selected ResNet-50 initialized with weights pre-trained on ImageNet, and we replaced the final feed-forward layer. Binary cross-entropy loss is used for optimization. We experimented with different positive class weight values to balance precision and recall. Values from 0.4 to 2.0 showed meaningful results. We employed the Stochastic Gradient Descent optimizer with a learning rate of 1e-4, a momentum of 0.9, and a weight decay of 0.1 for 200 epochs. Due to the limited dataset size, aggressive augmentation, and low data quality, training was somewhat unstable, requiring a relatively small learning rate. Data augmentation aimed to generate homogeneous images without black paddings, which negatively affected training.

The classification model operates on individual clippings. To process the entire coronarography scan, we traverse the vessel along centerline nodes, extracting square clippings and classifying each. This allows us to identify stenosis within vessel segments. As a result, each anchor is associated with multiple overlapping classified clippings, leading to multiple classifications (votes) for each anchor. This approach generates a vessel heatmap where hotter sections correspond to anchors accumulating more votes, indicating potential stenosis areas (redundancy). Anchor-level results are aggregated to report stenosis-level evaluations with a per-pixel voting method. This generates a binary image, marking segments considered as stenoses. The connected component algorithm treats each output as an individual stenosis segment.

IV. RESULTS

The validation procedure involved the comparison of ROIs with our output segments, we transformed ROIs into segments using the vessel mask allowing us to compute the Intersection over Union (IoU) between predictions and ROI segments. For a given ROI, if a predicted segment has an IoU above the threshold - true positive, if no segment exists - false negative. For a predicted segment, if no corresponding ROI segment meets this criterion - false positive.

The results are as follows: Precision 51.11%, Recall 45.10%, F1 score 47.92%. Our system, upon input of a coronarography scan, automatically highlights vessel segments suspected of stenosis. The model visualizes detection results in the form of a heatmap (see Figure 1).

V. CONCLUSION

We conducted a practical exploration of ML methods for detecting coronary vessel stenosis. We investigated various techniques, architectures, and datasets, resulting in the development of a network designed and trained to assist medical professionals in automated stenosis detection. We have introduced a straightforward yet effective tool to aid MDs in their work. Future enhancements may involve classifying detected stenoses and extracting additional pertinent features from the provided datasets. Future work includes the integration of external datasets into the classification model's training process, provided segmentation masks and centerline data are available.

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