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Training the Machine Learning Programs to Measure the Arterial Phase and Identify the Types of Coronary Flow

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ABSTRACT

Coronary artery disease (CAD) is one of the most common and severe medical conditions worldwide. The current research focused on investigating the mechanisms and prevention of the detrimental effects of CAD. Recently, the principles and practices of fluid mechanics were used to explain the formation of CAD with the help of a new angiographic recording and reviewing technique. This new method focused on identifying the types of blood flows and their effects on the intima. To automate the process, an Artificial Intelligence program was utilized to support the investigators in reviewing coronary flow. This paper analyzes AI methods that assisted physician investigators in the measurement of the arterial phase and in the identification of the types of coronary flows.

KEYWORDS Artificial intelligence; deep learning, coronary artery disease; coronary flow

INTRODUCTION

Coronary artery disease (CAD) is an extremely common illness today and a leading cause of death for over 17.9 million people (WHO 2019 statistics) [1]. Due to the failure of conventional research elucidating the mechanism of formation and growth of coronary plaques, a radical shift in strategy in which hydraulic and fluid mechanics principles and practice were recently used to investigate the mechanism of atherosclerosis [2]-[4]. As a result, a new angiographic recording and review technique was designed and reprogrammed for the investigators to accurately identify the shape, directions, and movements of blood flow [5]. The preliminary results showed that the turbulent flow with high kinetic disturbance triggered plaque development, while laminar flow protected the intima from the atherosclerotic process [6]. Even though the new reviewing technique was quite effective, it required time and concentration from the reviewers. How could artificial intelligence (AI) programs assist in improving the accuracy of the results while shaving the reading time?

In the last decade, Deep Learning programs provided a big jump in the practice of AI and computer sciences [7], [8]. At the same time, new technologies were invented and used in the evaluation, management, and follow-up of patients with CAD. As a result, AI was widely applied in the fields of clinical imaging, electronic health records, and quantitative analysis [9]-[12].

In order to facilitate research on coronary lesions and flows, systemize the protocol for angiographic interpretation, and shorten the time required for manual review of imaging, the authors/investigators of this group extensively used Deep Learning (DL) programs in its operations. This article explains how we trained a model based on DL architecture to evaluate the coronary flow dynamics, especially by measuring the duration of the arterial phase and identifying the types of blood flow.

DEEP LEARNING PROGRAM

With the new angiographic technique, the goals of today's invasive and interventional cardiology were to: identify the type of blood flow (laminar or turbulent), direction (antegrade or retrograde) (Figure 1), assess the stenosis (comparing with the results from the Quantitative Coronary Analysis (QCA)

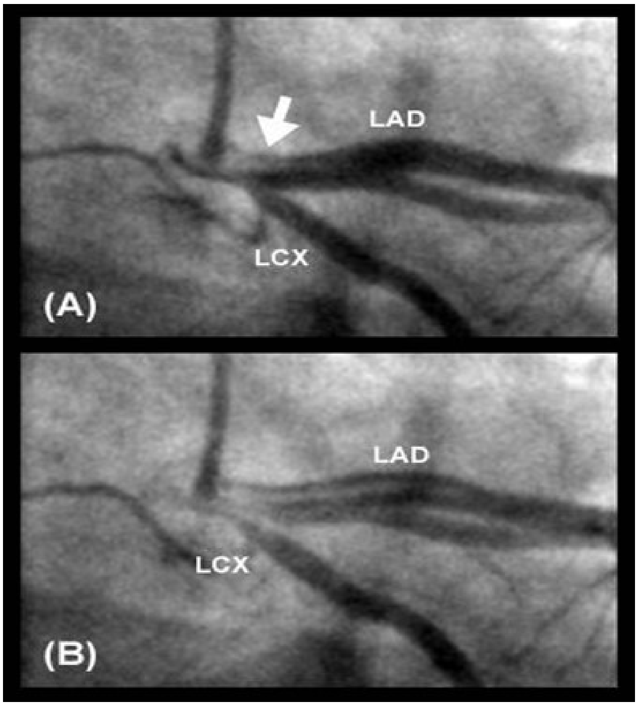

FIGURE 1. The coronary artery was filled with contrast. (A) The blood in white color moved in and displaced the contrast in black color at Left main, (B) Laminar flow with the pointed tip at LAD

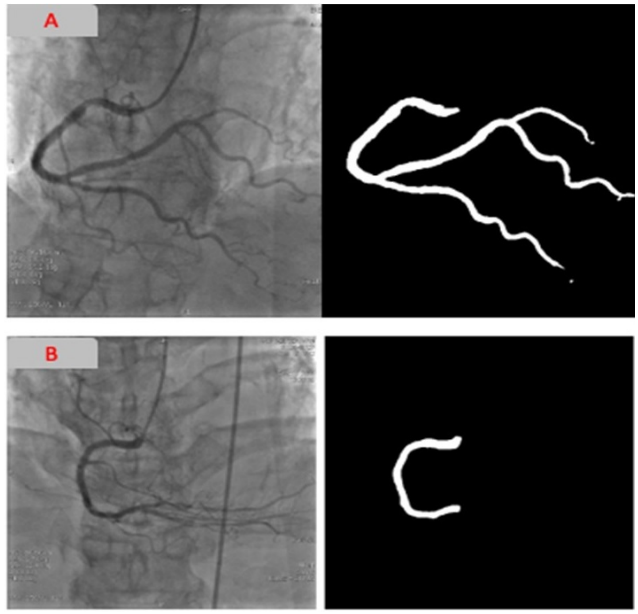

FIGURE 2. A: Segmentation of the whole RCA system, B: the segmentation of major vessel was set from the ostium to the far distal bifurcation.

technique), and measuring the duration of the arterial phase (AP) or calculating the Fractional Flow Reverse (FFR) with and without the FloWire (Phillips Healthcare, Andover, MA, USA) [12]-[17]. In all of these measurements, the application of AI and DL was possible; however more complex because of the many steps in the protocol.

General Protocol

Like human investigators, computers must first learn how to recognize a coronary artery. To begin this process, the data was extracted from the Picture Archiving and Communication System (PACS) with Digital Imaging and Communications in Medicine (DICOM) format. The DICOM images were semi-automatically or manually labeled for training the segmentation model. Subsequently, the relevant features of the coronary arteries were edited and used to create a dataset for building the classification model or calculation of the index. In the end, each model was built separately depending on the aim of the study [10].

Labeling the Coronary Images

The coronary angiogram is a continuous series of images saved in the electronic medical record system and could be converted into videos for cardiologists to review. The first step in creating the DL model was to label the series image of a coronary angiogram. If the system was programmed only to detect stenosis or the feature on the main vessel segmentation, the labeling method, e.g., the right coronary artery, was labeled from the ostium to the distal bifurcation (Figure 2) [18]. This method proved high accuracy and helped better analyze the characteristics of major vessels. Based on the purpose of each project, either complete labeling of the whole image or partial labeling of just the main vessel was performed. At the end of this first stage, data for training the segmentation model would have included images and labeled images.

Segmentation Model

After finishing the labeling process, the consecutive step was to perform the medical image segmentation with U-net. This step was more efficient when combining the U-net with other Deep Learning Networks such as ResNet101, DenseNet121, or InceptionResNet-v2 [19]. In our laboratory, combining U-net with the DenseNet-121 model produced the best results, which were found to be highly accurate (Figure 3) [20].

Calculation of the Arterial Phase

With the new coronary angiogram technique, we can calculate the new index of the arterial phase (AP), which is defined as the time from blood began to move in and replace the contrast to washed out of contrast. It was calculated autonomically based on the following protocol, which was designed to identify the first and last frames. (1) The first frame was identified when the blood began to move in, and (2) the ending frame was identified when all contrast was completely washed out from the distal vasculature (Figure 4).

At first, the catheter guide (CG) was used as the landmark for detecting the ostium of the coronary artery, so the segmentation model was built to identify the CG. Based on the CG segmentation, the ostium of the coronary artery was

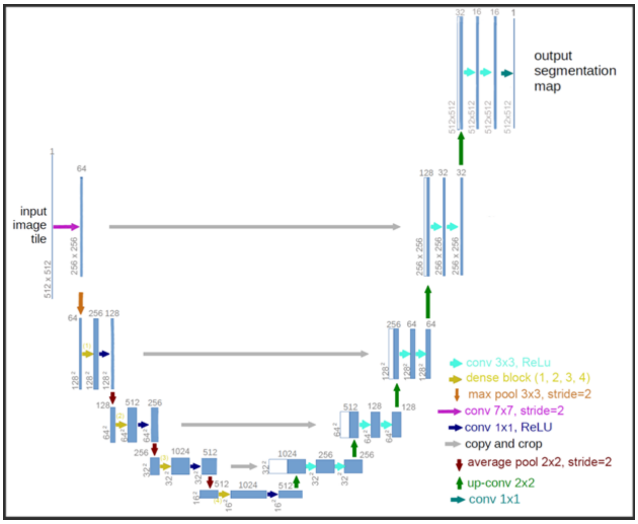

FIGURE 3. **Unet combined with DeseNet-121 architecture.**

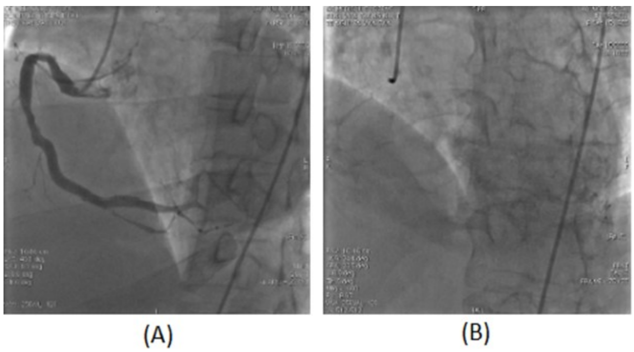

FIGURE 4. **Beginning and Ending frame of AP.** (A) full of contrast-beginning of AP, (B) washed out frame (ending frame of AP)

extracted. Next, the beginning of the AP (seen as blood in white moved in) was classified by the Convolutional Neural Network model with pixel shift at the coronary ostium. Finally, the ending frame was detected by the segmentation model. The whole angiographic videos were segmented to identify the frame without a coronary artery. The first black image in a series of segmented angiographic images identified the end of the AP [18].

Identification of Types of Flows

In order to identify and classify the flow patterns in coronary arteries, the first task was to build a dataset with typical flow features. They included the laminar flow with a pointed tip (Figure 1.A-B), the stagnant flow with an internal boundary layer (Figure 5), and the turbulent flow with the chaotic area of disorganized flow (Figure 6).

In the case of the laminar flow with the pointed tip, the laminar flow was best recognized when the blood entered the ostial segment of an artery and displaced the contrast. The images could be collected from the angiogram and fed into a Convolutional Neural Network (CNN) model to train and classify other flows based on the above-mentioned characteristics. In a coronary angiogram (Figure 1), we could see that the pointed tip was moving in at the ostium of the coronary artery. Using a small part to focus on the ostium of the coronary artery would make the classification much better.

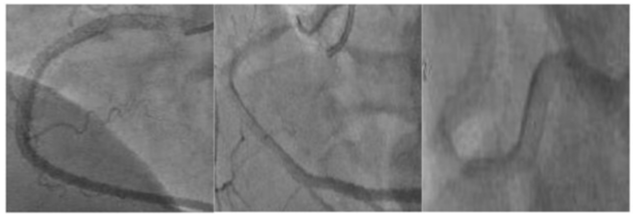

FIGURE 5. **Stagnant flow at the middle segment of right coronary artery.**

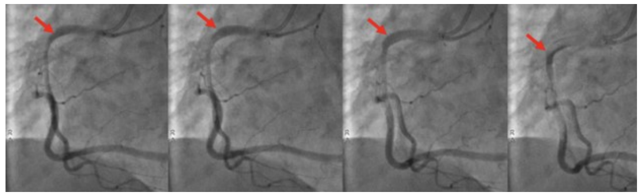

FIGURE 6. **Turbulence flow is the chaotic area (antegrade flow in diastole and retrograde flow in systole); most dynamics area is at red arrow.**

In the case of stagnant flow, after segmentation, the flow characteristics were extracted for classification. The challenge in detecting the flow was that the segmentation was only good when the blood vessels were full of contrast. Which was the best method of detection of the stagnant flow? (Figure 5). The unclear images would give incorrect data. Therefore, the output of segmentation was to be re-classified. One extra step was performed as the frame with unclear images was deleted based on the original images and the segmented images. From the segmented images, although there were broken vascular shapes, we could accurately position the blood vessels across the upper, lower, right, and left boundaries (white pixels) in the segmented images (Figure 7) [21]. As all images after cropping had different sizes, so the image dataset was re-sized before training. Finally, the classification model was ready to be trained to identify the angiographic images with or without stagnant flow.

The greatest challenge was in classifying turbulent flow. The main problem was that turbulent flow did not have a specific shape, and its location changed from frame to frame. Several ideas have been proposed based on the coronary artery reconstruction and the centerline of the coronary artery over each cardiac cycle [22]. Then the chaotic, turbulent flow was calculated based on changes in pixel values.

Limitations and future potential

In the early stages, the classification of flow characteristics faced many difficulties because of limited data collected by new angiographic techniques. Moreover, the efficiency of artificial intelligence models was not as high as expected

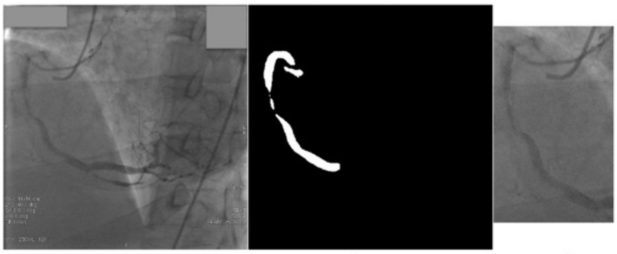

FIGURE 7. Processing data for classification model. A original frame extracted from Angiogram videos, B Segmented image uncovered all vessels because the contrast was low. C Cropping image based on the boundaries

and needed further optimization by ML algorithms. Ongoing studies will need to streamline the process of collecting, evaluating, and creating the perfect data set for future AI models.

CONCLUSION

The existing Machine Learning programs had a few limitations in identifying complex flows such as turbulent and reverse flows. Many methods of reconstructing the circuit structures are suggested to improve the results and shorten the performance time in future applications.

CONFLICTS OF INTEREST

None of the authors have conflicts of interest to declare

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