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Computer-aided Detection of Lesions from Coronary Angiograms Based on Contrast Learning Technique

Poulomi Pal[1], Sumagna Dey[2], and Manjunatha Mahadevappa[1], *Senior Member, IEEE*

Abstract— **Coronary artery disease is one of the prevalent cardiovascular diseases in the world. Clinically, coronary artery angiography (CAG) is the most efficient diagnostic tool for detecting the stenosis caused by the presence of coronary lesions. Here, we proposed a simple but efficient methodology for predicting the coronary arterial block. The technique of classifying the angiograms collected from 369 patients is implemented using the contrast learning approach. ResNet 152 V2 is used as the deep network. Region of interest (ROI) is found for the diseased arteries for deciding the type of treatment procedure. Four different losses were implemented in this two-level classification technique. This framework achieved an accuracy of 0.81 recall of 0.76, precision of 0.86, specificity of 0.87, and F-score of 0.80. A comparative study with the state-of-the-art is carried out to establish the advantage of the proposed method. This computer-aided approach could be implemented by clinicians quite easily.**

Clinical relevance—**An easy, simple, and fast technique of detecting and deciding treatment of coronary artery stenosis was studied using contrast learning and ROI. A computerised model was designed which can draw conclusion from CAGs even in the absence of clinical annotations.**

I. INTRODUCTION

According to health statistics, in US 18.2 million adults have coronary artery disease (CAD), and 2 out of 10 die, among patients who are less than 65 years [1]. In 2016, an estimated 2.8 million Indians died from CAD constituting 18% of all deaths in India [2]. CAD is a type of heart disease, which occurs due to arteriosclerosis. The diseased artery becomes stiff and uneven, different from healthy arteries, which are elastic and smooth by nature. These abnormalities in the arteries are caused by the atheromatous plaque called a lesion. This plaque gets built up by the deposition of fat, cholesterol, collagen, elastin, or other substance. Eventually, the arterial wall gets thicker and the inner circumference gets narrowed, leading to blockage of blood circulation. The restriction in blood flow inside coronary arteries is termed stenosis and it may lead to heart failure. To diagnose unhealthy coronary arteries, cardiologists use a medical imaging technique known as coronary artery angiography (CAG). In CAG, the arteries and veins of the heart are visualized minutely. This procedure is conducted by injecting a dye (which is made of a radio-opaque contrasting agent) in the blood vessels and observing its flow using the X-ray imaging modality known as fluoroscopy. This interventional method produces a film or an image of the inner blood vessels known as angiography or an angiogram. The cardiologists decide the treatment for blocked arteries based on the degree of stenosis. Percutaneous coronary intervention (PCI) or angioplasty is an effective technique when a stent has to be placed after cleaning the clogged artery for re-vascularization. PCI is opted if the degree of stenosis is 60% to 80% in either one or two arteries. Coronary artery bypass grafting surgery (CABG) is referred to if more than two arteries get obstructed by 80%- 100%. In CABG surgery the blocked coronary artery is replaced with a vein from leg or an artery from chest to restore smooth blood flow. The manual annotation of CAG images for deciding treatment is done by cardiologists. A computer-aided diagnosis can come to rescue in making such decisions. This can give more accurate results, within less time, even in absence of cardiologists.

Several works are carried out for detecting CAD using angiograms with different computational techniques. Majd et al. used the convolution neural network and a recurrent neural network comprising GRUs on angiograms of 163 patients for identifying the coronary artery plaques. In another work Tao et al. [2] implemented a framework comprising enhancement, skeletonization, match measurement, and identification for the classification of 143 patients' angiograms [3]. Detection of stenosis was also conducted by Chao et al. using LSTM and Inception-Net on 194 patients' CAG reports [4]. Viacheslav et al. predicted coronary lesions or stenosis using a region-based fully convoluted network (RFCN) with ResNet [5] with 100 CAG patients' data. In all these previous studies the size of data samples was limited. Moreover, all the methods incorporated were complex. In our work, we used the data set comprising 369 patient information. We used a simple and latest technique of contrast learning which has a good amount of advantage over those from literature. Using three different losses (max-margin loss, dual pair loss, and Cosine similarity loss) we formed Level 1 classification, where patients with and without stenosis were segregated. In Level 2 classification, region of interest (ROI) was evaluated and contrast loss was used in deciding the type of treatment required to cure the patients with stenosis. This two-step classification method was used to study the patient conditions and develop the proposed computerized framework.

II. DATASET

The CAG reports of the patients undergoing angiography were obtained from the catheterization laboratory (cath lab) of the Department of Cardiology in Medical College and

[1] Poulomi Pal and Manjunatha Mahadevappa[1] are with the School of Medical Science and Technology, Indian Institute of Technology Kharagpur, INDIA poulomipal77@gmail.com, mmaha2@smst.iitkgp.ac.in

[2] Sumagna Dey is with the Computer Science and Engineering Department, Meghnad Saha Institute of Technology, Kolkata, INDIA sumagna.dey@gmail.com

TABLE I: Baseline Characteristics of Patients

Clinical parameters	Patients - PCI	Patients - CABG	Patients without stenosis
Gender (M/F)	138/62	58/29	67/15
Age (yrs)	52.11±8.2	59.34±6.1	55.08±3.4
Height (cm)	163.87±9.6	162.70±9.4	163.16±7.5
Weight (kg)	67.42±13.1	68.57±8.9	64.99±4.2
SBP (mm-Hg)	131.62±5.2	138.55±2.1	119.87±3.9
DBP (mm-Hg)	90.99±7.1	88.63±3.1	84.65±2.6
HR (bpm)	77.32±1.4	75.59±2.5	74.01±5.6

Hospital, Kolkata. This lab was dedicated to examining and visualizing the coronary arteries for detecting stenosis and localizing lesions. The Institutional Ethical Clearance (IEC) was obtained from the Indian Institute of Technology, Kharagpur vide reference no.:IIT/ SRIC/DR/2019, dated 6-11-2019. The IEC was also obtained from Medical College and Hospital, Kolkata vide reference No.: MC/Kol/IEC/Non-spon/139/09-2018, dated 10-11-2018. As per IEC rules, consent forms were authorized by the patients before collecting their CAG reports. The patient clinical details who were involved in the cohort study are shown in Table 1. Angiography was performed by the cardiologists and other experts using Siemens Axiom Artis Zee (floor). The images of CAG were collected from the console room attached to the cath lab. These images were used for the study without revealing the patient details as per the ethical rules. Two CAG images are shown in Fig. 1 who had a coronary lesion in their coronary arteries.

III. METHODOLOGY

We used RadiAnt DICOM viewer to create the required input dataset from hospital CAG images. From 369 collected images only 287 were selected for analysis, after data cleaning. Only prominent and relevant images were targeted for study. All the 287 images were resized to 256 x 256 pixels. Decision-Based Untrimmed Median filter and Laplacian filter were used for noise removal (correcting corrupted pixels) and smoothening (edge detection). Image augmentation (4 types) was carried out by employing translating, flipping, shearing, and rotating. The final input comprised 1148 (287x4) images. The data were divided into training: validation: testing set in the ratio of 60:20:20. Cardiologists manually annotated these processed angiograms which were considered as the *gold standard* information. Two-step classification was performed to fulfill the desired objective (Fig. 2).

A. Contrast Learning

Contrast learning is SELF-supervised learning where a model can be trained with a dataset lacking labels or annotations [6]. Contrast learning derives a functional mapping between higher dimensional information (images I) and lower-dimensional details (data features). The features differentiating the inputs from each other are encoded using a deep neural network. Initially, random correlated versions of the input data were created using two synthesizing techniques (scaling and wrapping). Thus, n input images became $2n$ using these augmentation techniques. Here, we used ResNet152-V2 as an encoder $E(\cdot)$ for mapping the parameters from input data to general but powerful representational vectors. ResNet was trained using Adam optimizer with minibatch 30 for 150 epochs, initial learning rate=0.001 for 60 epochs and remaining 90 epochs with Cosine decay learning rate, and momentum=0.9. In this work, Pytorch with CUDA was utilized to run the code. ASUS TUF FX504, with Intel i5 (8th gen) processor having 8GB RAM is used to execute the code. Its GPU was made of NVIDIA Geforce GTX, 1050 Ti with a memory of 4GB. During training, at each epoch, image features were derived per minibatch. This learned mapping to latent space is propagated forward through the network layers. The projection heads $H(\cdot)$ transformed these representational spaces to compute either a similarity or dissimilarity metric embedding depending on specific choices. This step comprised two thick layers of a non-linear multilayer perceptron (containing 2048 units) that functionally distinguished the inputs. We used trilinear interpolation for upsampling the final feature maps to a hybrid ones. In this junction max-margin loss (L_{mm}) [9], dual-class loss (L_{dc}) [9], and Cosine similarity loss (L_{cs}) [9] were used on the L2 normalized output of projection heads to find the deviation among the two different images. Computation of L_{mm}, L_{dc}, and L_{cs} loses are shown in (1), (2), and (3), respectively [9].

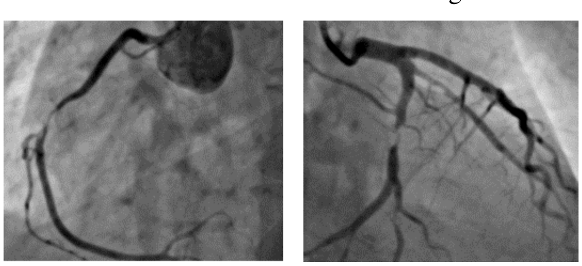

Fig. 1: Angiogram reports showing coronary lesions.

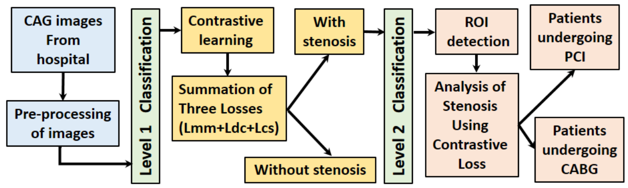

Fig. 2: Schematic diagram.

$$L_{mm}(v_a, v_b) = \mathbb{E}_{I_a=I_b} \|v_a - v_b\|_2^2 + \mathbb{E}_{I_a \neq I_b} max(0, m - \|v_a - v_b\|_2)^2 \quad (1)$$

L_{mm} is the max margin loss function, where $\mathbb{E}$ is the Euclidean distance, I_a and I_b are the inputs, m is the margin parameter which imposed lower limit during deviation calculation, and v_a and v_b are the embedding vectors generated from the proposed neural network.

$$L_{dc}(I_i, I_j) = log(1 + \sum_{k=1}^{2N} \mathbb{E}_{k \neq i} exp(I_i I_j - I_j I_k) \quad (2)$$

L_{dc} is the dual class loss function, where two pairs of images are taken; I_i and I_j as one pair and I_j and I_k another pair.

$$L_{cs}(I_1, I_2, y) = \left\{ \begin{array}{c} max(0, cs(I_1, I_2) - m), \\ if(y == 1) \\ 1 - cs(I_1, I_2), if(y == -1) \end{array} \right\} \quad (3)$$

$$cs = \frac{x.y}{\|x\| \, \|y\|} \tag{4}$$

$$\|x\| = \sqrt{\sum_{i=1}^{n} (x_i^2)} \tag{5}$$

$$x.y = \sum_{i}^{n} x_i y_i \tag{6}$$

L_{cs} is the Cosine similarity loss function, where loss values differ on the basis of similarity ($y == 1$) and dissimilarity ($y == 1$) of the input images I_1 and I_2, and cs is Cosine similarity value calculated using (5) and (6).

The total loss (L_T) is summation of L_{mm}, L_{dc}, and L_{cs}.

$$L_T = L_{mm} + L_{dc} + L_{cs} \tag{7}$$

L_{mm} is good for binary classification. Here, predictions were made on the basis of target's sign (positive for same group images and negative for different). In case of L_{dc} margin value gets increased between samples of identical labelled images and that value gets decreased when the samples non-identical labelled images. L_{cs} improves feature similarity points from images of selfsame class and reduces those points from two images of separate classes. We tried to use these three losses to make the model a robust and discriminative model.

B. Region of interest (ROI)

After distinguishing the images I we found the ROI for locating the lesion of the diseased artery we want to concentrate on. This step is initiated for analyzing the stenosis part deeply. ROI marking allowed us to study the degree of block in that coronary artery. Thus, the blocked part of the artery is extracted and further studied.

Algorithm 1 Pseudocode to find ROI

```
IMAGES = gray-scale (angiograms with stenosis)
images = GaussianBlur (IMAGES)
for i in images do
    darkPixel = 255
    for pixel in i do
        if darkPixel ≥min(pixel) then
            darkPixel = min(pixel)
            roi = matrixSize(i)
            for row in length(roi) do
                for col in length(row) do
                    if i[row][col] ≤ darkPixel + 5 then
                        roi[row][col] = i[row][col]
                    else if roi[row][col] = 255 then
                    end if
                end for
            end for
        end if
    end for
end for
```

Before finding ROI, I were converted to gray-scale version (**IMAGES**), and Gaussian blurring was used to perform smoothening on them (**images**). The ROI was evaluated by creating a binary mask using the pseudo-code shown in Algorithm 1. In the angiograms, the arteries were darkest because of the flowing radioactive dye. So, if only the deep black part of the images could be focused, it was easy to extract the artery. Here, we considered pixels of each image (i) from the dataset ($images$). The variable $darkPixel$ was initialized with a value of 255. The algorithm was designed to set the dark portions as 1 and the remaining pixels to 0. We stored the size of each image ($matrixSize$) in roi variable. The information of pixels values present in the rows and columns of i was checked, whether it was less than equal to the sum of $darkPixel$ and 5. The ROI of the image in i was extracted and stored in roi. The remaining pixels were set to white. In this way, the target pixel values were extracted by checking all the pixel values in the entire image. Focusing on these ROIs, we implemented the contrast learning concept again. The entire framework of the network was the same except for the type of loss. Instead of L_T, we used the contrastive loss L_{CL} here, as shown in (8).

$$L_{CL}(W, Y, \overrightarrow{I_p}, \overrightarrow{I_q}) = (1 - Y)\frac{1}{2}(D_W)^2 + (Y)\frac{1}{2}\{max(0, m - (D_W))\}^2 \tag{8}$$

L_{CL} is the contrast loss function, where $Y = 0$ if images I_p and I_q are similar and $Y = 1$ if they are dissimilar. Usually, Dw is the Euclidean distance between any two inputs, but here it is the output of the proposed neural network with respective input images. Final results were derived keeping all the other computational specifications similar.

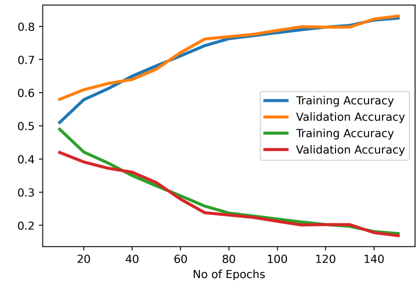

Fig. 3: Result in terms of accuracy and loss curves.

IV. Results and Discussion

The performance of the proposed network was evaluated on the prepared angiogram dataset after performing five-fold cross-validation. The training and validation curves in terms of accuracy and loss with changing epochs are shown in Fig. 3. The results were obtained after overcoming the overfitting issues. They are accuracy=0.81, recall=0.76, precision=0.86, specificity=0.87, F-score=0.80, and CSI(Critical success index)=0.67.

TABLE II: Ablation studies with different types of Losses

Level 1	Level 2	Acc
MaxMargin+Cosine similarity	Contrast Loss	0.77
Dual class loss + MaxMargin	Contrast Loss	0.73
Cosine similarity+Dual class loss	Contrast Loss	0.79
MaxMargin+Dual class loss+Cosine similarity	Contrast Loss	0.81

TABLE III: Comparative studies using state-of-art

	Accuracy	Recall	Precision	Specificity
Majd et al. [3]	0.78	0.79	0.77	0.78
Tao et al. [4]	0.80	0.76	0.84	0.83
Chao et al. [5]	0.75	0.74	0.73	0.76
Viacheslav et al. [6]	0.78	0.77	0.79	0.78
Proposed work	0.81	0.76	0.86	0.87

A. Ablation studies with different types of Losses

The decision of using the summation of three losses was taken after studying the performance of the entire network with various combinations of losses. As shown in Table 2, the loss in Level 2 classification, contrast learning , was kept constant. Different combinations of losses in Level 1 classification yielded different accuracy values. The first three rows showed that accuracy was changing with two losses. Accuracy of 0.77, 0.73, and 0.79 was obtained by using $L_{mm} + L_{cs}$, $L_{mm} + L_{dc}$, and $L_{cs} + L_{dc}$, respectively. The highest accuracy of 0.81 was obtained when the sum of all three losses was applied (L_T).

B. Comparison with the state-of-art

Experiments were conducted to compare the present work with previous studies which is tabulated in Table 2. In this work, we implemented the concept of contrast learning with ResNet-152 V2. With the same dataset and hyperparameter settings, we executed CNN, RNN, LSTM, RFCN, InceptionNet, and ResNet to compare the values of performance metrics. Using the methods of Majd et al. the accuracy, recall, precision, and specificity were obtained as 0.78, 0.79, 0.77, and 0.78. The techniques used by Tao et al. produced accuracy of 0.80, recall of 0.76, precision of 0.84, and specificity of 0.83. After implementing the procedures by Chao et al. and Viacheslav et al. the resulting metric values shown by the third and fourth row are obtained. It can be seen from Table 2 that the proposed work showed a better accuracy(0.81) recall(0.76), precision(0.86), and specificity(0.87).

The receiver operating characteristic curve (ROC) and precision-recall characteristic (PRC) curves were studied in Fig. 4 and Fig. 5, respectively. The values of the area under the ROC curve (AUC) and area under the PRC curve (AP) are exhibited along with the ROC and PRC curves. The highest value of AUC(0.87) and AP(0.63) were obtained for the proposed network.

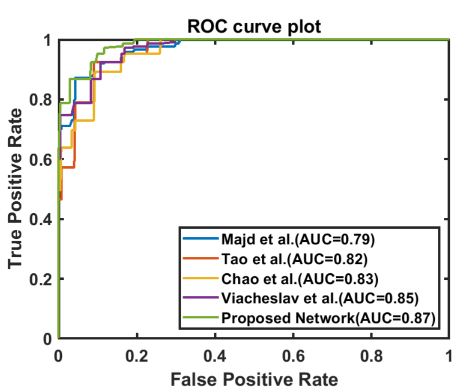

Fig. 4: Receiver Operating Characteristic curve Plot

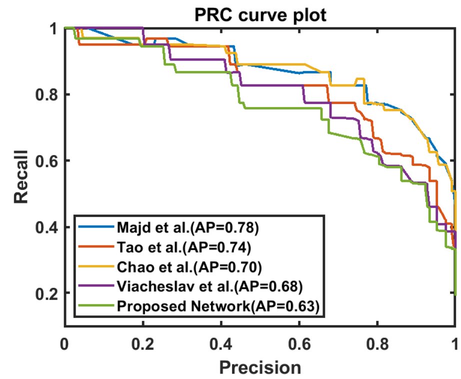

Fig. 5: Precision Recall Curve Plot

V. Conclusion

The most efficient diagnostic tool for diagnosing CAD patients is CAG. The CAG was performed by the cardiologists using instruments, but the final decision of treatment was taken manually by them. This manual step of identification and annotation could be replaced by our proposed computational method. We utilized the concept of contrast learning and performed classification in two levels. With the help of different loss functions and ROI computation, we built the framework for determining the type of treatment for patients with coronary lesions.

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