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# DETECTION OF PLAQUES IN ARTERY WALL USING INTRAVASCULAR ULTRASOUND IMAGES FOR DIAGNOSIS OF CORONARY ARTERY DISEASES

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**ABSTRACT**

In past two decades, the Intra Vascular Ultrasound (IVUS) imaging technique is utilized for detecting the calcified plaque in the coronary artery aided with deep learning techniques. However, the existing approaches fall on computational complexity, time consumption and poor accuracy of plaque localization. In this paper, a deep CNN based plaque detection framework is proposed to tackle the issues in the existing approaches. Initially, the region between lumen and media contour is segmented with the terminus sector segmenting approach based on pixel concentration divergence and the texture features. Then the discriminative features are extracted through the meticulous feature extraction approach via construction of contraction path in multi-scale CNN. Finally, the location of the plaque has been identified with unambiguous detection and localization approach, whereas the expansion path is constructed for plaque detection. The experimental result shows the effectiveness of the proposed framework and the results are compared with other existing approaches.

**Keywords:** *Intravascular Ultrasound (IVUS) Images, Plaque, Deep Learning, Coronary Artery, Segmentation, Multi-Scale Deep CNN.*

## 1. INTRODUCTION:

Plaque builds up within the arteries of blood vessels, causing atherosclerosis. Fat, cholesterol, calcium, and other substances present in the blood makes up plaque. The deposited plaque hardens and narrows the arteries over the time. The supply of oxygen-rich blood to organs and other parts of the human body is hampered as a result [1]. Intravascular Ultrasound (IVUS) images show the lumen's cross-sectional detail, which can be used to calculate the volume of blood vessels by measuring the diameter and length of the lumen. They also provide details about the plaque components, which aids in the diagnosis of coronary heart disease and the delivery of appropriate interventional therapy [2].

Coronary angiography is a widely used medical imaging technique for detecting and diagnosing coronary heart disease. [3] Angiogram technology does not offer information about the heart artery layer and vessel wall for diagnostic purposes. The plaque layer boundary, which is responsible for partial or complete artery obstruction, is often overlooked. [4] Intravascular Ultrasound has recently been implemented as an alternative to angiography diagnostics, with the aim of providing more precise imaging of coronary atherosclerosis.

Intravascular Ultrasound is a catheter-based imaging technology that allows doctors to see through an artery. It has become the most powerful imaging modality for detecting cardiovascular diseases. IVUS images are obtained by inserting the catheter into the artery and continuously pulling back the ultrasound transducer in the catheter [5]. The arteries are usually divided into two parts by two distinct boundaries. The lumen boundary that connects the lumen to the wall and the media to the adventitia [6].

The first step in determining the morphology of a vessel and recognizing potential atherosclerotic lesions is segmenting the lumen and media in IVUS images [7]. Several works have been done for segmentation of lumen and media adventitia border in artery. [8] Presented the method for segmentation of lumen with the use of k-means algorithm and mean roundness. But it requires a greater number of parameters for clustering algorithm. [9] addresses multi-label segmentation of the wall and lumen areas. Similarly, [10] detected the lumen, media and surrounding tissues using support vector machines and random forest method. Moreover, these techniques require additional steps called post-processing for segmentation, which leads to the computational complexity.

As well as various methods has been implemented for detecting plaque in artery wall. A fully automated deep learning algorithm implemented in [11], which uses recurrent neural network and long-term memory for detecting coronary artery calcium. Similarly, a convolutional neural network based with temporal constraint across X-ray angiographic sequences is proposed in [12]. But background structures with inhomogeneous intensities overlap in a complex way. As well as deep learning-based methods are used for detecting plaques in artery [13], where the localization efficiency of plaque might be reduced due to the deeper structure of convolutional neural networks (CNN) [14].

A Lipid-Rich Plaque (LRP) rupture is responsible for nearly two-thirds of all adverse coronary events, including myocardial infarction and death. [15-16] On the basis of absorption patterns of near-infrared light by cholesterol molecules, Near-Infrared Spectroscopy (NIRS) will detect LRP. NIRS intravascular ultrasound (NIRS-IVUS) imaging is a dual-modality intravascular imaging device that incorporates NIRS and IVUS to determine plaque morphology while also providing information on cholesterol content in the arterial wall [17-19].

Through evaluating the above-mentioned investigation, the detection of plaque in artery wall using IVUS images faces challenges in segmentation, feature extraction and plaque localization. To cope up such issues, a novel Plaque detection framework using IVUS images has been proposed to obtain efficient detection of plaque in artery. The main contribution of the proposed framework is presented below,

- Initially, the lumen and media border is segmented using terminus sector segmenting approach, where the segmentation is performed based on the pixel concentration divergence.
- Then the feature extraction is performed through the meticulous feature extraction approach in which the construction of contraction path in CNN is developed.
- To increase the plaque localization accuracy, unambiguous detection and localization approach is incorporated with the construction of expansion path.
- The proposed plaque detection framework is implemented in MATLAB platform then the performance of the proposed framework is compared with the existing techniques.

The structure of the paper is as follows: section 2 explains the existing approaches in the field of plaque detection; section 3 presents the novel plaque detection framework; section 4 discusses the results of the proposed work and the comparison analysis; section 5 concludes the paper.

## 2. LITERATURE SURVEY:

Liu, et al [20] presented an optimized framework for automatic detection and quantification of calcified plaque in coronary artery using IVUS images. Calcified lesions were identified by training a supported vector classifier per IVUS A-line on manually annotated IVUS images, then uses regional information in post-processing through conditional random field. It achieves ~ 0.9 as accuracy by comparing the evaluated IVUS calcium score (ICS) with the manually calculated ICS. Moreover, it requires an addition steps like post-processing which leads to time complexity of process.

Olender, et al [21] presented a post-hoc image-based tissue characterization method for evaluating diseased vessels that can be applied to entire acquisition sequences. Using only gray scale IVUS images, the pixel-based approach uses domain knowledge of arterial pathology and physiology, as well as technical developments in convolutional neural networks, to segment diseased vessel walls into the same tissue groups as virtual histology. The system was trained and validated on patches collected from VH-IVUS images obtained from a variety of patients, and it achieved a 93.5 percent overall accuracy for all segmented tissue. To achieve high efficiency, domain awareness was used to impose physically specific spatial constraints. Although caution must be exercised in considering and communicating assumptions.

Dong, et al [22] developed a fully automated approach using 8-layer U-Net to segment the lumen of a coronary artery and the region bounded by an external elastic membrane (EEM), i.e. the cross section area (EEM-CSA). The database contains IVUS data from a single vendor and at a single frequency. In particular, the proposed Mesh Grid data augmentation combined with flip and rotation processes is introduced, resulting in improved model performance without the need for pre- or post-processing of the raw IVUS images. The lumen and EEM-CSA had Mean Intersection of Union (MIoU) of 0.937 and 0.804, respectively, which outperformed the clinician's manual labeling accuracy. However, in order to train a more robust model, the case data, which includes calcified plaque, will need to be strengthened in the future.

Cui, et al [23] designed a supervised machine learning method for coronary artery lumen segmentation with a high degree of precision and low user interaction. The completely discriminative lumen segmentation method is developed by jointly learning a classifier on which poor learners depend on the classifier's features. The theoretical underpinnings of the Gradient Boosting method used in this research paper as well as its quadratic approximation are also presented. The proposed algorithm is evaluated on public datasets for lumen boundary detection in the IVUS challenge, which was held at MICCAI 2011, and achieves a higher average Jaccard similarity of 96.8% and a lower mean error distance of 0.55 (in Cartesian coordinates), demonstrating higher accuracy than current learning-based approaches. But, it has the computation complexity.

Hartman, et al [24] demonstrated Lipid-Rich Plaque (LRP) co-localization using Near-Infrared Spectroscopy (NIRS) and a large Wall Shear Stress (WSS). Fifty-three patients with acute coronary syndrome had a non-culprit coronary artery imaged using NIRS-Intravascular-Ultrasound (NIRS-IVUS). WSS was measured using WSS profiling in 3D coronary artery reconstructions based on the fusion of IVUS-segmented lumen and CT-derived 3D-centerline.LRP sectors were more often co-localized with high WSS than non-LRP sectors, as determined by NIRS. Furthermore, lipid content and high WSS exposure had a dose-dependent relationship. Further research is required to show how high time-averaged WSS (TAWSS) affects the production and destabilization of lipid-rich plaques.

From the above analysis, it is clear that [20] had the time complexity due to the additional processes; [21] needs more caution to implement; [22] presented model needs to been strengthen to achieve the high efficiency; [23] had computation complexity; and [24] requires further improvement for plaque segmentation. Thus, a novel plaque detection framework is proposed to tackle the issues in detection of plaque in artery wall.

## 3. DEEP CNN BASED PLAQUE DETECTION FRAMEWORK:

IVUS can provide high-resolution cross-section images of coronary arteries, revealing specific details about the vascular lumen, artery wall, and athermanous plaques, which is useful for detecting or identifying early atherosclerotic plaques. The arteries have two distinct borders: the lumen border and the media-adventitia border. The first step in determining the morphology of a vessel and identifying atherosclerotic plaques is to segment the lumen and media in IVUS images. The existing segmentation process are widely depending on the labeling of each pixel to be lumen, media or background, which requires more additional steps for segmentation. This might be an effective method, but it falls on computational complexity of processing which leads to increase the latency. Thus it requires an effective segmentation process with reduced complexity. After that, the required features related to plaque need to be extracted from the given IVUS images with the assist of deep learning. In medical image processing with deep learning, as CNN structure goes deeper, it requires more training samples. This increases the number of parameters in exponential rate, which leads to more time consumption. Therefore, an efficient CNN structure for feature extraction is needed with the reduced number of parameters. Feature maps are resulted from the feature extraction process, which are getting much smaller in size due to CNN layers operation. This leads to the lacking of detecting plaque’s localization.

Deep learning applications in the medical image processing solve a wide range of issues, from disease diagnosis to personalized treatment recommendations. Thus an efficient novel deep learning based plaque detection framework is being proposed for plaque detection in artery walls which is depicted in figure 1. Initially, the Region of Interest (ROI) for plaque detection is the region between lumen border and media-adventitia border in IVUS images, which is segmented with the adoption of terminus sector segmenting approach. This is implemented by computing the concentrations of each pixel in IVUS images, where pixels evolving brighter to darker from outer as media-adventitia contour and pixels

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evolving darker to brighter from the center of image as lumen contour were segmented with reduced complexity. After the segmentation of ROI, the important features are extracted from the segmented IVUS images through meticulous feature extraction approach. Here, the features are extracted through the construction of contraction path based on CNN which includes convolution, activation and max pooling layers. In this way, the receptive field can be expanded to obtain the feature maps, without increasing the number of parameters, thus it diminishes the time consumption. Feature extraction process produces the smaller size of feature map, which reduces the plaque localization accuracy. This can be tackled by incorporating, unambiguous detection and localization approach. This introduces a transpose convolution layer with the construction of expansion path. This can increase the scale of feature map to retrieve the location of plaque in artery wall. Finally, the resulted feature maps from contraction path and expansion paths were fused to obtain the feature map for training which can detect the plaque and its position.

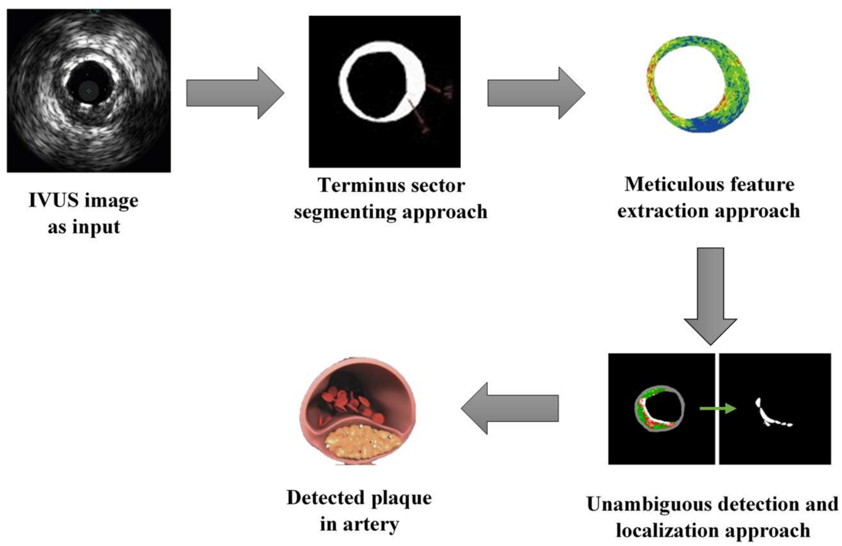


*Figure 1: Schematic Representation Of The Proposed Plaque Detection Framework*

The following subsections presents the detailed explanation of each process in the detection of plaque in artery wall in IVUS images using deep learning model.

**3.1 Terminus Sector Segmenting Approach:**

Image acquisition is the initial stage in deep learning image processing. The IVUS images are utilized as an input for identifying plaques in coronary artery walls in this research. For coronary artery disease, Intravascular Ultrasound (IVUS) is a frequently used imaging technique. It uses a catheter with an ultrasound probe to obtain real-time cross-sectional pictures of the arteries and gives information such as lumen size, plaque rupture, and plaque components. This information is crucial for determining how to treat a lesion before angioplasty, since each patient requires a different therapy depending on the kind of lesion. It can also be used to monitor the prognosis following the therapy. Further it is used to detect a susceptible plaque that could lead to a stroke or heart attack. Figure 2 illustrates an intravascular ultrasound image. Several IVUS images are acquired in this manner, and the plaques in the artery wall are recognized employing deep learning.

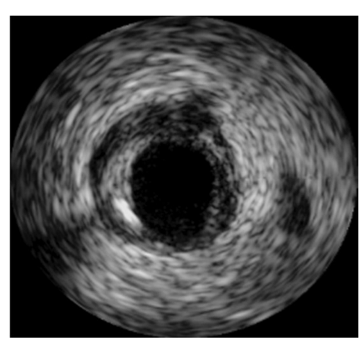

*Figure 2: IVUS Image*

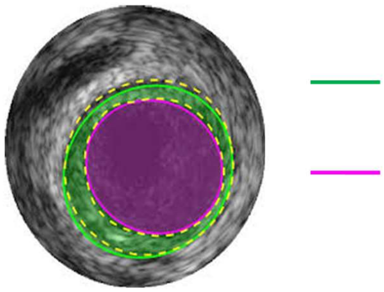


*Figure 3: Contour REPRESENTED Ivus IMAGE*

Segmentation is then performed in plaque detection, in which the Region of Interest (RoI) is segmented from the IVUS images. The region of interest for plaque detection is the region between lumen and media-adventitia, since the plaque is developed in this region, which is illustrated in figure 3. The existing techniques for segmentation approaches are depending on the labeling of each pixel which increases the computational complexity as well as the latency. To overcome the issues in the existing technique, the proposed work utilizes the intensity of each pixel as well as the texture features for segmentation of lumen-media border. This approach performs through calculating the concentration of each pixel in IVUS images where pixels evolving brighter to darker from outer as media-adventitia contour and pixels evolving darker to brighter from the center of image as lumen contour were segmented. In addition to this, the texture based features are computed to segment pixel by pixel such as, mean, global mean, standard deviation, smoothness, uniformity, entropy, skewness, correlation. These features are considered as the first order statistics, which analyzes the original image with the gray-scale value of each pixel. The texture features as well as their computing formula are described below.

***Mean:***

Mean value is the sum of pixel values divided by the total number of pixel values. Pixel values of each pixel that represents an image stored inside a computer has a pixel value which describes how bright that pixel is, and/or what color it should be. The formula for finding mean is given in equation 1.

$$M_n(z) = \sum_{i=0}^{L-1}(z_i - m)^n p(z_i) \tag{1}$$

Where, $m = \sum_{i=0}^{L-1} z_i p(z_i)$

$z_i$ - Random variables related to the intensity range of the image

$p(z_i)$ - Number of pixels in the image that have a gray level equal to $z_i$

***Global Mean:***

To reduce the interactions between different distributions and to estimate the global parameters of the image robustly, we estimate the means of different pixel classes by the global peaks of the histogram distribution. The formula for determining the global mean is given in equation 2.

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

***Standard Deviation:***

A low variance or standard deviation indicates that the pixel intensity is close to the average, while a high variance indicates that the pixel intensity is far from the average. In an image with a high standard deviation value, the contrast is high. In fact, specifying the standard deviation of pixel values in an image is a way to quantify contrast. The standard deviation formula is as shown in the equation 3.

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n} x_i^2 - \mu^2 \tag{3}$$

***Smoothness:***

In statistics and image processing, the smoothing of the data set creates an approximate function that attempts to capture important patterns in the data while eliminating noise or other small-scale structures/fast events. They change in such a way that the individual points above the neighboring points decrease (presumably due to noise), and the points below the neighboring points increase, resulting in a smoother signal. By being able to extract more information from the data under appropriate smoothing assumptions, and provide flexible and reliable analysis. The smoothness formula is as shown in the equation 4.

$$\boldsymbol{Smoothness} = \sum_{i=0}^{L-1}(z_i - m)^2 p(z_i) \quad \text{…. (4)}$$

***Uniformity:***

Uniformity measures radiance (reducing light at the edges of the image) and other irregularities in the image. For example, you can measure the uniformity of a flash illumination or the uniformity of a flatbed scanner. In Uniformity, you can also analyze color cast (blemishes), hot pixels and dead pixels, view pixel-level histograms, raster (fan-shaped) graphs, and detailed images to view defects (i.e. sensor noise). The formula for the uniformity is as shown in the equation 5.

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$$\boldsymbol{Uniformity} = \left(\mathbf{1} - \frac{\sigma^2}{\tau}\right) \times \mathbf{100\%} \quad .... (5)$$

Where, $\boldsymbol{\tau} = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{L_i}$

$\boldsymbol{L}$ – Measured radiance or luminance

***Entropy:***

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. In image processing, entropy can be used to classify textures, because certain patterns are roughly repeated in a certain way, so a texture can have entropy. In the context of this work, low entropy means very small disturbances, and the low variance of the component. A component with low entropy is more homogenous than a component with high entropy, which they use in combination with the smoothness criterion to classify the components. The formula for entropy is as shown in the equation 6.

$$\boldsymbol{Entropy} = \sum_{i=0}^{L-1} \boldsymbol{p(z_i)} \log_2 \boldsymbol{p(z_i)} \quad .... (6)$$

***Skewness:***

Skewness refers to the distortion or skewness that deviates from a symmetric bell curve or normal distribution in the data set. If the curve moves to the left or right, it is called skewed. In terms of digital image processing, darker and glossier surfaces tend to be more positively skewed than lighter and matte surfaces. Hence we can use skewness in making decisions about image surfaces. This is because skewness measures how "lopsided" the distribution of pixel values are. The formula for the Skewness is as shown in the equation 7.

$$\boldsymbol{Skewness} = \sum_{i=0}^{L-1} (\boldsymbol{z_i} - \boldsymbol{m})^3 \boldsymbol{p(z_i)} \quad .... (7)$$

***Correlation:***

Correlation involves moving a filter (often called a kernel) on the image and calculating the sum of the products of each position. In other words, the first correlation value corresponds to a filter offset of zero; the second value corresponds to the unit of the offset, and so on. The formula of the correlation is as shown in the equation 8.

$$\boldsymbol{Correlation} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}(i-\mu_x)(j-\mu_y)p(i,j)}{\sigma_x \sigma_y} \quad ..... (8)$$

As mentioned above, the proposed framework segments the lumen-media contour as a region of interest for plaque detection in coronary artery wall. The above segmented region is used to visualize the properties of the IVUS image contours (lumens and medium). These regions are used to obtain the information about the lumen and media because both the regions evolve from dark surfaces with brighter boundaries. This method can reduce the complexity as well as latency. Then this work involves, extracting the discriminative features from the segmented region for plaque detection which is explained in the forthcoming section.

**3.2 Meticulous Feature Extraction Approach:**

Once the lumen-media contour of the IVUS image is segmented, then the plaque related features extraction is done with the assist of deep learning model. In medical image processing with deep learning, as CNN structure goes deeper, it requires more training samples. This increases the number of parameters in exponential rate, which leads to more time consumption. Therefore, an efficient CNN structure for feature extraction is needed with the reduced number of parameters. For this purpose, the proposed framework designed the Multi-Scale deep CNN network for feature extraction process. Multi-scale CNN structure generates features with different scales through construction of contraction path based convolutional neural network.

Generating feature maps with different scales can reduces the number of parameters as well as increases the receptive field. Multi-scale networks can extract more abstract features, local features, and overall aspects of fibrous plaques in this way, therefore increasing the receptive field size. A contraction path based on convolutional neural networks is developed to collect the abstract characteristics and context information of the fibrous plaques from the image and to gain a wider receptive field. The constructed contraction path based CNN is depicted in figure 4.

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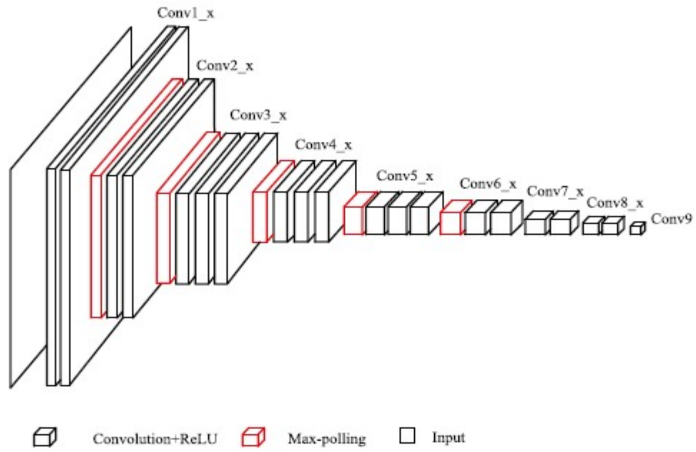


*Figure 4: Contraction Path Based Convolutional Neural Network*

A 20-layer multi-scale deep convolutional neural network is built using the shrinking route. The convolutional layer, the activation layer, and the pooling layer make up the network structure. Instead of employing a larger convolution kernel (5x5 or 7x7), the contraction approach comprises multiple applications of 3x3 convolution, which resolves nonlinearity in the convolution procedure. The parameters are decreased while the receptive field size is kept the same. The activation function is set to ReLU, while the pooling layer is set to max-pooling. The max-pooling and convolution processes minimize the size of the feature map, resulting in a multi-scale feature map.

As mentioned above, the discriminative plaque features are extracted with the multi-scale deep CNN network. This reduces the number parameters, thus reducing the time consumption. Whereas, the size of the resulted feature map is smaller as much possible. This introduces the challenge in accurate localization of plaque in artery wall which can be handled in the next section.

### 3.3 Unambiguous Detection and Localization Approach:

Through the utilization of contraction path construction in multi-scale deep CNN network, the discriminative features are extracted efficiently. However, the network gets deeper, and the feature maps get smaller and smaller due to the CNN layers operation, resulting in the plaque's poor location decision, despite the network's vast receptive field and abstract characteristics. To solve this issue and increase the accuracy of plaque detection and localization, the scale of the feature map should be increased as the size of input image.

There are two types of methods can develop the size of the feature map to a bigger feature map for better reading, studying and identifying the plaque formation in the coronary artery between the lumen and the media-adventitia border. The first one is using the near infrared (NIR) spectroscopy. In near-infrared spectroscopy, unknown substances are illuminated by a broad spectrum (many wavelengths or frequencies) of near-infrared light, which can be absorbed, transmitted, reflected or scattered by the sample being examined. The visible band in NIR is usually very wide, which makes the spectrum more difficult to interpret than FTIR spectrum. Assigning specific properties to certain chemical components can be a challenge. Near-infrared analysis methods require careful design of a set of calibration samples and the use of multivariate calibration methods. However, NIR excitation may cause desensitization. Similarly, NIR lasers usually have beam characteristics (such as beam width and divergence) that are very unsuitable for microscope use. As a result, the spatial resolution may be reduced, so the achievable results may not match the theoretical predictions.

Thus the proposed method utilizes the transpose convolution layer often named as deconvolution layer with the construction of expansion path followed by the contraction path based multi-scale deep CNN which is depicted in figure 5. As this method consumes less time, it is easy to process and gives high level of output than the NIRS. A transposed convolutional layer attempts to reconstruct the spatial dimensions of

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the convolutional layer and reverses the down sampling and up sampling techniques applied to it. Since the deconvolution can increase the scale of feature map and regain the position information of the plaque. After creating the contraction path, we recommend expanding the feature map at different scales to obtain a feature map with abstract features and location information.

Since the feature map of the advanced feature extraction network contains a large amount of semantic information, the last five scale feature maps are selected during the process from compression to expansion, and the feature map corresponding to the map scale is generated. Construct an element extraction network on the restoration path to extract abstract elements, local elements and common board elements and restore positions Information about the plaque.

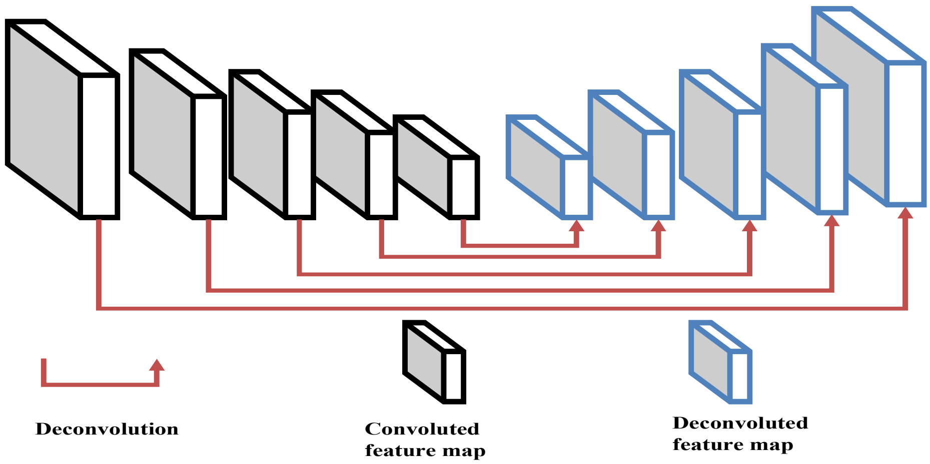


*Figure 5: Deconvolution Process Of Feature Map*

Finally, we have got a bigger and high resolution of the feature map to analyze, study and to find the plaque in the segmented part of the coronary artery. Since the deconvolution method is very easy and does not need any type of repeated or complex process it is faster and efficient method to find the plaque in the coronary artery using IVUS images. Because the contraction path and expansion path feature maps each have their own benefits, the feature maps of the same size in the contraction path and expansion path are fused to create a multi-scale feature map. Thus the deconvoluted feature map identify the location of the plaque in coronary artery wall more efficiently.

As a whole, the novel deep CNN based plaque detection framework segments the lumen-media contour as region of interest more efficiently. And the multi-scale deep CNN based model can extract the discriminative features with the construction of contraction path and the plaque location can be accurately identified with the construction of expansion path. Thus the proposed framework detects the plaque in artery walls using IVUS images. The implementation and the results are discussed in the following section.

## 4. RESULTS AND DISCUSSION:

This section provides a detailed description of the implementation results as well as the performance of our proposed framework, as well as a comparison analysis to ensure that our proposed framework outperforms the existing techniques in plaque detection.

### 4.1 System Specifications:

The proposed plaque detection framework has been implemented in MATLAB platform with the system specifications are listed below.

**Platform** : Matlab 2019.a
**OS** : Windows 8
**Processor** : Intel Core i5
**RAM** : 8GB RAM

### 4.2 Evaluation Metrics:

The performance of the proposed framework has been evaluated with the related evaluation metrics such as accuracy, precision, recall, sensitivity, F1 score, Predictive positivity value.

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***4.2.1 Accuracy:***

Accuracy is the ratio of the number of correct predictions of plaque to the total samples. Thus, the formula to calculate the accuracy is given by:

$$Accuracy = \frac{True\ Positive + Tru\ \ Negative}{All\ samples} \quad .... (9)$$

***4.2.2 Sensitivity:***

Sensitivity is the ability to detect the plaque in IVUS image correctly. That is the ratio of correctly predicted samples to the total samples.

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad .... (10)$$

***4.2.3 F1-Score:***

F1-Score provides a way to combine both precision and recall into a single measure that captures both properties.

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

$$F1 - Score = \frac{2 \times True\ Positive}{2 \times True\ Positive + False\ Positive + False\ Negative} \quad .... (11)$$

***4.2.4 Specificity:***

Specificity is the ability to determine the location of plaque correctly. The specificity is the number of true negative results divided by the sum of the numbers of true negative plus false-positive results.

$$Specificity = \frac{True\ Negative}{True\ Negative + Fals\ \ Positive} \quad .... (12)$$

***4.2.5 Precision:***

Precision evaluates the fraction of correctly predicted instances or samples among the ones predicted as positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{True\ Positive}{True\ Positive + Fals\ \ Positive} \quad .... (13)$$

***4.2.6 Recall:***

The recall is defined as the ratio of pertinent data that are recovered successfully. Thus, the formula to calculate the recall is given by:

$$Recall = \frac{True\ Positive}{True\ Positive + Fa\ \ \ Negative} \quad .... (14)$$

**4.3 Simulation Output:**

This section discusses the implementation results of the proposed framework. It starts from the IVUS images as input then the segmentation process takes place and the features are extracted from the segmented image finally the plaque has been located in the IVUS image.

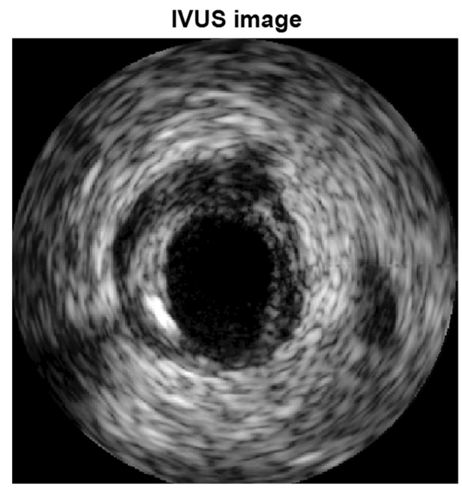


*Figure 6: Input IVUS Image*

The proposed plaque detection framework utilizes the intravascular ultrasound images as the input for plaque detection. IVUS images provide the cross-sectional view of coronary artery wall. The input IVUS image has been depicted in the figure 6.

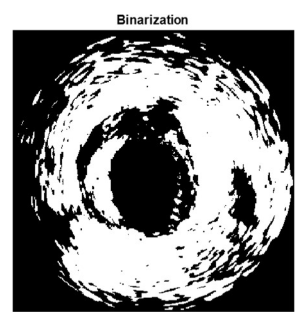


*Figure 7: Binarized Image*

For segmenting the region between the lumen and media contour as region of interest, the concentration of each pixel is calculated. For this purpose, the input image is binarized, that is the binary value 0 is depicted for the black pixels and binary value 1 is depicted for the white pixels. The IVUS image binarization is illustrated in figure 7.

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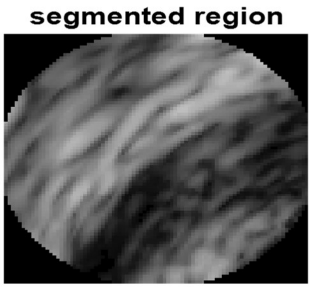
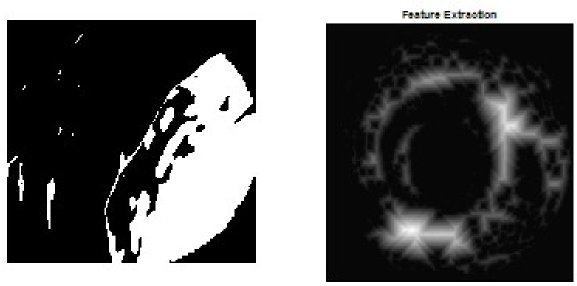



*Figure 8: Segmented Region From IVUS Image*

The Region of Interest is segmented through intensity divergence of pixels and based on the texture features. The segmented region of IVUS image is shown in figure 8.




**(a)** **(b)**

*Figure 9: Feature Extraction*

Then the features are extracted using multi-scale deep CNN network. The extracted features from the overall IVUS images is depicted in figure 9a. Whereas, the extracted features from the segmented features for plaque detection is presented in figure 9b.

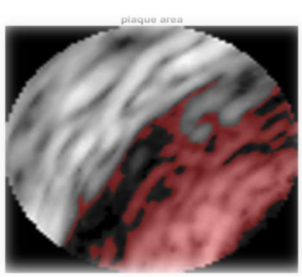


*Figure 10: Plaque Detection*

Figure 10 shows the final output of plaque detection in coronary artery wall using IVUS images. From the features extracted in the segmented region, the location of the plaque is identified using the transpose convolution layer processing. In the figure 10 the plaque area is exhibited as the colored region.

**4.4 Comparison Analysis:**

In this section, the performance of the proposed framework is compared with the other existing works done in the detection of plaque in coronary artery walls.

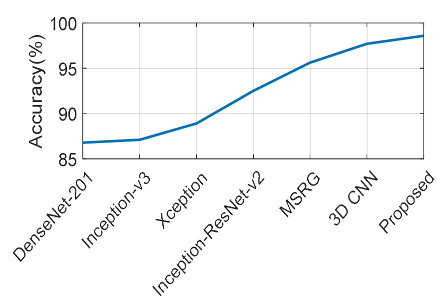



*Figure 11: Comparison Of Accuracy*

The plaque detection accuracy of the proposed model is compared with the existing detection models such as DenseNet-201, Inception-v3, Xception, Inception-ResNet-v2, MSRG, and 3D CNN. The accuracy of the proposed model achieves 98.8% which outperforms the other models. Whereas, the accuracy of the 3D CNN attains 97.7%, anyhow, the proposed model has 1% higher accuracy than 3D CNN and 11% higher accuracy than DenseNet-201 model.

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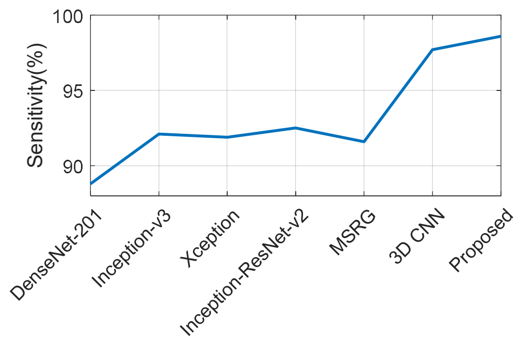


*Figure 12: Comparison Of Sensitivity*

The sensitivity of the proposed model achieves 98.6% which is 0.9% higher than 3D CNN and 10% higher than DenseNet-201 model.

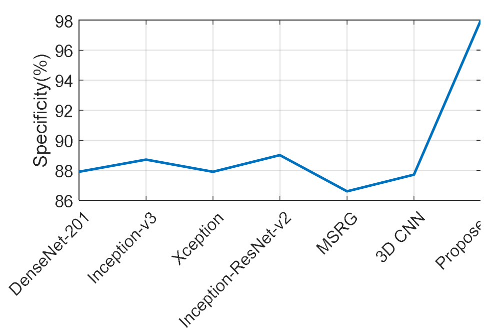


*Figure 13: Comparison Of Specificity*

The specificity of the proposed model achieves 98%, which is 9% higher than the Inception-ResNet-v2.

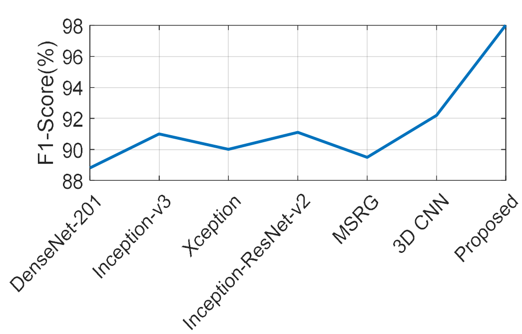


*Figure 14: Comparison Of F1-Score*

The F1-Score of the proposed model achieves 98% which is 6% higher than 3D CNN and 9% higher than DenseNet-201 model.

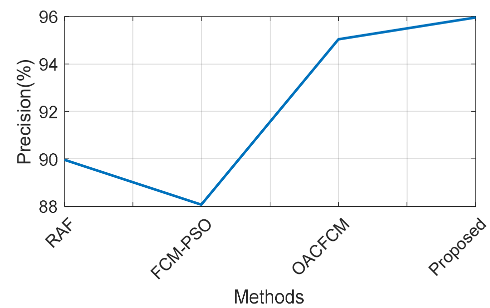


*Figure 15: Comparison Of Precision*

From the figure 15, it is clear that, the precision of the proposed framework is 96%, in which the existing classifier attains 95.2% as precision.

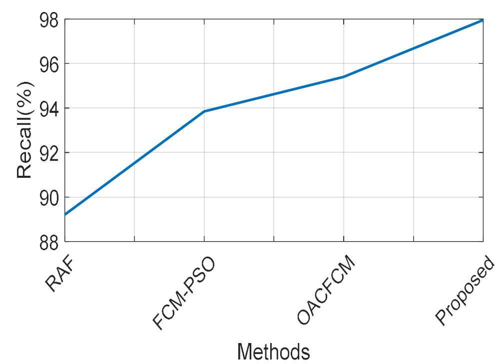


*Figure 16: Comparison Of Recall*

The recall of the segmentation process is compared with the existing classifiers like RAF, FCM-PSO, and OACFCM. From the graph, it is clear that, the recall of the proposed framework has achieved 98%, in which the existing classifier attains 95.5% as recall.

## 5. CONCLUSION:

In medical sector, clinicians find difficult to manually detect the plaques in coronary artery walls. In this paper, an efficient deep CNN based plaque detection framework is proposed and implemented which addresses the issues in the existing approaches. In this framework, the lumen-media contour is segmented with the terminus sector segmenting approach then the plaque features are extracted with the multi-scale deep CNN model with the construction of contraction path through meticulous feature extraction approach. Finally, the plaque in the artery wall detected via unambiguous detection and localization approach with the construction of

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expansion path. The experimental result shows the performance of the proposed framework with the accuracy of 98.8%, sensitivity of 98.6%, specificity and F1-Score of 98%. From the comparison analysis, the proposed model outperforms the other existing models.

**REFERENCES:**

[1] Shioi, Atsushi, and Yuji Ikari. Plaque calcification during atherosclerosis progression and regression. *Journal of atherosclerosis and thrombosis* 2017: RV17020.

[2] Shammas, Nicolas W, et al. The role of precise imaging with intravascular ultrasound in coronary and peripheral interventions. *Vascular health and risk management* 2019; 15: 283.

[3] Lemkes, Jorrit S, et al. Coronary angiography after cardiac arrest without ST-segment elevation. *New England Journal of Medicine* 2019; 380(15): 1397-1407.

[4] Shlofmitz, Evan, Bo Zhu, and Nauman Khalid. Intravascular ultrasound (IVUS). *StatPearls [Internet]* 2019.

[5] Ma, Teng, et al. Multi-frequency intravascular ultrasound (IVUS) imaging. *IEEE transactions on ultrasonics, ferroelectrics, and frequency control* 2015; 62(1): 97-107.

[6] Gholipour, Alireza, Mergen Ghayesh H, and Anthony Zander. Nonlinear biomechanics of bifurcated atherosclerotic coronary arteries. *International Journal of Engineering Science* 2018; 133: 60-83.

[7] Hafiane, Anouar. Vulnerable plaque, characteristics, detection, and potential therapies. *Journal of cardiovascular development and disease* 2019; 6(3): 26.

[8] Jodas, Danilo Samuel, Aledir Silveira Pereira, and João Manuel Tavares RS. Automatic segmentation of the lumen region in intravascular images of the coronary artery. *Medical image analysis* 2017; 40: 60-79.

[9] Kim, Sekeun, et al. Fully automatic segmentation of coronary arteries based on deep neural network in intravascular ultrasound images. *Intravascular Imaging and Computer Assisted Stenting and Large-Scale Annotation of Biomedical Data and Expert Label Synthesis*. Springer, Cham 2018: 161-168.

[10] Vercio, Lucas Lo, Mariana Del Fresno, and Ignacio Larrabide. Lumen-intima and media-adventitia segmentation in IVUS images using supervised classifications of arterial layers and morphological structures. *Computer methods and programs in biomedicine* 2019; 177: 113-121.

[11] Fischer, Andreas M, et al. Accuracy of an artificial intelligence deep learning algorithm implementing a recurrent neural network with long short-term memory for the automated detection of calcified plaques from coronary computed tomography angiography. *Journal of thoracic imaging* 2020; 35: S49-S57.

[12] Wu, Wei, et al. Automatic detection of coronary artery stenosis by convolutional neural network with temporal constraint. *Computers in biology and medicine* 2020; 118: 103657.

[13] Chen, Meng, et al. Diagnostic performance of deep learning-based vascular extraction and stenosis detection technique for coronary artery disease. *The British journal of radiology* 2020; 93(1113): 20191028.

[14] Wong, Kelvin KL, Giancarlo Fortino, and Derek Abbott. Deep learning-based cardiovascular image diagnosis: a promising challenge. *Future Generation Computer Systems* 2020; 110: 802-811.

[15] Yamaguchi M, et al. Association between near-infrared spectroscopy defined lipid rich plaque and pericoronary adipose tissue inflammation on computed tomography angiography. *European Heart Journal* 2020; 41: ehaa946-0314.

[16] Wilkinson, Stephen E, and Ryan Madder D. Intracoronary near-infrared spectroscopy—role and clinical applications. *Cardiovascular Diagnosis and Therapy* 2020; 10(5): 1508.

[17] Li, Yan, and Zhongping Chen. Intravascular Dual-Modality Imaging (NIRF/IVUS, NIRS/IVUS, IVOCT/NIRF. *Multimodality Imaging: For Intravascular Application* 2019: 173.

[18] Kole, Ayeeshik, et al. Comparative quantification of arterial lipid by intravascular photoacoustic-ultrasound imaging and near-infrared spectroscopy-intravascular ultrasound. *Journal of cardiovascular translational research* 2019; 12(3): 211-220.

[19] Terada, Kosei, et al. NIRS-IVUS for Differentiating Coronary Plaque Rupture, Erosion and Calcified Nodule in Acute Myocardial Infarction. *JACC: Cardiovascular Imaging* 2020.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[20] Liu, Shengnan, et al. Automated Quantitative Assessment of Coronary Calcification Using Intravascular Ultrasound. *Ultrasound in Medicine & Biology* 2020; 46(10): 2801-2809.
[21] Olender, Max L, et al. A Domain Enriched Deep Learning Approach to Classify Atherosclerosis Using Intravascular Ultrasound Imaging. *IEEE Journal of Selected Topics in Signal Processing* 2020; 14(6): 1210-1220.
[22] Dong, Liang, et al. Automatic Segmentation of Coronary Lumen and External Elastic Membrane in IVUS Images Using 8-layer U-Net 2020.
[23] Cui, Hengfei, Yong Xia, and Yanning Zhang. Supervised machine learning for coronary artery lumen segmentation in intravascular ultrasound images. *International journal for numerical methods in biomedical engineering* 2020; 36(7): e3348.
[24] Hartman, Eline MJ, et al. Lipid-rich Plaques Detected by Near-infrared Spectroscopy Are More Frequently Exposed to High Shear Stress. *Journal of Cardiovascular Translational Research* 2020: 1-10.
[25] Yan J, Lv D & Cui Y. A Novel Segmentation Approach for Intravascular Ultrasound Images. *J. Med. Biol. Eng.* 2017; 37: 386–394.
[26] Lee, Ju Hwan, Hwang, Yoo Na, Kim, Ga Young, Sung Min, Kim. Segmentation of the lumen and media-adventitial borders in intravascular ultrasound images using a geometric deformable model. IET Image Processing 2018; 12(10): 1881-1891.