Texture Feature Extraction from Intracoronary OCT Images and Atherosclerosis Detection using Deep Neural Network

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Abstract- A coronary atherosclerotic plaque's morphological structure and tissue composition evaluate its stability, this could be investigated using intracoronary optical coherence tomography (OCT) imaging. The objective of this research is to extract intensity features from OCT images utilising Histograms of Oriented Gradients (HOG) as well as Local Binary Patterns (LBP) bag-of-words (BOW). The approach is concentrated on Twopath Convolution Neural Network(CNN),an unique CNN architecture. This proposed technique is reliable and durable in the detection of atherosclerosis OCT imaging, and per the evaluation. The accuracy of the Twopath CNN architecture is significantly higher than that of conventional CNN methodologies as well as machine learning approaches. This method seems to have a better efficiency of 98.5 %, suggesting that it could be a suitable diagnostic tool for detecting atherosclerosis.

Keywords-CNN, HOG, atherosclerosis

I INTRODUCTION

Coronary artery disease was the supremesource of temporality as well as morbidity in the world. Intravascular optical coherence tomography (IVOCT) is a new imaging methodology that could being used to diagnose coronary atherosclerosis. This review summarises the main methods for detecting and segmenting blood vessel lumen boundaries, as well as plaque segmentation and classification [1].

At the point in time, artificial intelligence (AI) had been practised in cardiovascular imaging, discussed the incorporation of multiple areas from plaque component evaluation to risk prediction [2]. Current AI [3] assisted image processing, extraction of features, plaque recognition and characterization, and the have been using of AI-assisted computer aided diagnosis (CAD) to recognize and classify atherosclerotic plaques, which would include their high-risk features characterising plaques [3].

Manual identification as well as characterization of plaques necessitates expertise and a significant amount of time. It is also affected by speckle noise empowered CAD systems for automated image processing along both invasive or rather noninvasive image displays [4,5]. The organisation is as follows: section 2 defines relevant studies, section 3 clarifies the suggested framework, section 4 demonstrates the findings, and section 5 describes the conclusion.

II RELATED WORKS

Cheimariotis et al. [6] developed a novel automatic method that used CNN for classification and included arterial wall segmentation as well as an OCT-specific transformation. According to Kolluru et al. [7], the utilisation of OCT includes the compilation of a huge portion of imaging data, the assessment of which requires a significant amount of time and effort from a skilled medical specialist. Rico-Jimenez et al. [8] used least-square optimization to model every axial line in IVOCT data as a combination of several profiles, and they classified the tissue kinds relying on their morphological attributes.

Deep learning associated with Conditional Random Fields has been utilised by Kolluru et al. [9] to obtain 83.16 % in the identical task. Ali et al. [10] suggested a novel, holistic, yet realistic algorithm that includes both morphological and ischemic specifications and intends to deliver a systematic strategy to assess complete revascularization. Cavallo et al. [11] postulated an Ensemble Machine Learning (EML) score with 60% accuracy for obtaining radiomic attributes distinguishing among patients even with an antiquity of hypertension.

Jin et al.[12] and Zreik et al.[13] recommended utilising a CNN to extract features from the coronary artery, with the gradient-boosting decision tree (GBDT) achieving the ideal efficiency in stenosis grading and the highest AUC. Erdal et al. [14] and Demirer et al. [15] presented deep learning relied systems as well as machine learning approaches that permit training data to be upgraded on a continuous basis with latest examples.

III PROPOSED SYSTEM

This section describes the system's three principal phases: preprocessing to eliminate noise as well as artefacts, feature extraction and disease detection. Fig.1 depicts framework.

3.1 Preprocessing: Convert the image's coordinates to polar coordinates. The pixels are transferred from circle to line upon the

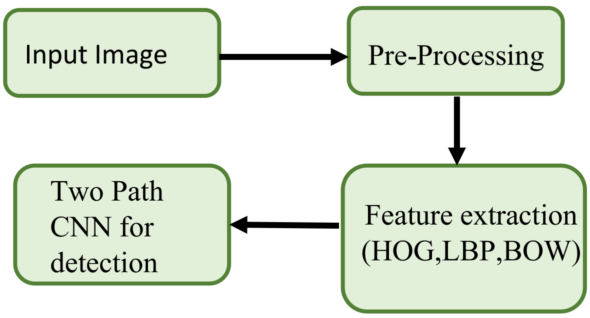

Fig.1 Proposed System's Framework

transformation. Other artefacts can be removed by eliminating the black sector induced by occlusion.

3.2 Feature Extraction: In this research, HOG, LBP and BOW features are utilised to represent OCT images. The HOG operator for capturing information of edge, and the LBP for descriptors of texture. To reduce dimensionality, employ principal component analysis (PCA) and retain the top 95% of energy.LBP-BOW feature extracts LBP feature and uses it to represent each image (BOW). The image is represented by a BOW by the frequency of the words. The HOG -BOW feature extracts the HOG feature and quantifies it with the assist of the HOG-BOW.

3.3Proposed Two path CNN for detection:

As a result, the CNN model's input was M M patches of various types. CNN was able to extract complex features by employing a series of convolutional layers. ReLU was used as an activation function to extract non-linear features from the input. After the activation function, a normalisation process is incorporated respectively. The following formula can be used to summarise the normalisation process:

$$x_n = \frac{x-\mu}{\sqrt{\sigma^2+t}} \quad (1)$$

In (1) ,x_n and x represent the feature maps and μ and σ^2 were the mean as well as variance of the feature maps. t symbolises a minimal constant. When the fully connected layer is replaced with a convolutional output layer, the number of kernels in the layer constitutes the amount of labels. The kernel output, which can be normalised using the $SoftMax$ function as follow:

$$Softmax\ (a) = \frac{\exp\ (a)}{\sum_i \exp\ (a_i)} \quad (2)$$

In (2), $a$is the output vector. Each element of $w = SoftMax(a)$ and the sum equals to 1. Following the convolution process, a concatenation layer blended the feature maps again from two streams. The prediction of labels in this infrastructure can be impacted by two attributes: the graphical specifics of the area and the overall features.

IV RESULTS AND DISCUSSION

The proposed system is evaluated using a four-fold cross-validation process. One subset is used as a testing set each time, while the others are utilised as training sets. Four outcome are mentioned with accuracy value. The LBP and HOG are features that are a jumble of words. The single features as well as feature combinations (I+HOG,I+LBP, I+LBP+HOG and LBP+HOG) were analysed.

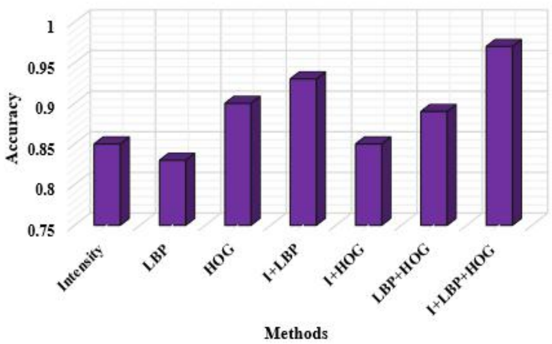

Fig.2 Accuracy for Proposed Methodology

It could indeed be noticed that the accuracy values for all feature configurations are greater than 0.80. Intensity provides the ideal performance for a single feature. One cause could be that intensity is a global feature, whereas LBP and HOG seem to be local features. In terms of feature combination,Intensity+LBP+HOG performs better, but Intensity + LBP results are comparable to the three feature combination results. Fig.3 compares the ROC curves of the methods

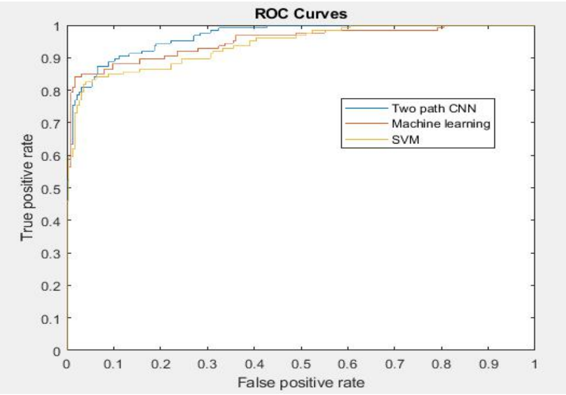

Fig.3 Comparision of Methods

V CONCLUSION:

To represent the OCT images, this research extracted intensity features employing HOG, LBP and BOW. The approach is premised on TwopathCNN, that is used in a cascaded structure. This suggested procedure is effective and robust in the detection of atherosclerosis OCT imaging, according to the evaluation. The accuracy of the Twopath CNN architecture is significantly higher than that of conventional CNN methods. This method have 98.5 %r efficiency indicating that it could be a favourable screening tool for detecting atherosclerosis.

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