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A Deep Learning based approach for Diagnosing Coronary Inflammation with Multi-Scale Coronary Response Dynamic Balloon Tracking (MSCAR-DBT) based artery Segmentation in Coronary Computed Tomography Angiography (CCTA)

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ABSTRACT

Coronary inflammation plays a vital role in causing the myocardial infarction commonly known as heart attack. Therefore it is very difficult to predict and classify the coronary inflammation to prevent the heart attack as early as possible. Fat attenuation Index (FAI) is an imaging biomarker quantifies the inflamed coronary artery and is clinically obtained using non-invasive Coronary Computed Tomography Angiography (CCTA) test. In this work, a Deep Learning (DL) based network is being used to diagnose the prognostic value of FAI using anatomical information obtained from CCTA of the coronary arteries. The Recurrent Convolutional Neural Network (RCNN) is proposed for train the model on a CCTA categorical and anatomical image datasets of coronary artery to classify the cardiac mortality by diagnosing the inflamed coronary of the heart. The trained model uses Deeper Convolutional Neural Network's (CNNs) Residual Network (ResNet) as image reconstruction method for denoising the cardiac artifacts. The most adverse cardiac event occurs in the proximal side of Right Coronary Artery. So, the network utilizes a Multi scale Coronary Response Dynamic Balloon Tracking Method (MSCAR-DBT) method for heart region enhancement and also to segment the RCA vessel from the arteries. Later, the features that are extracted are aggregated by Recurrent Convolutional Neural Network (RCNN) which performs single task classification. The system trained and tested using UCI repository datasets. To validate the networks performance Mann-Whitney U test is employed and the evaluated result is visualized in Receiver Operating Characteristics (ROC) curve. The experimental results demonstrate that automatic analysis of the coronary inflammation in a single task RCNN can produce better sensitivity, specificity and accuracy rate. This might helps the medical practitioner to diagnose the future heart attack and prevent patients from taking further non-invasive tests unnecessarily.

Keywords
Deep Learning, Recurrent Convolutional Neural Network, Coronary inflammation, Coronary Artery Segmentation

Introduction

Coronary Artery Disease (CAD) is the main cause for mortality rate in the world. It happens due to the plaque build-up inside the coronary artery wall. This becomes narrowing in the coronary artery lumen which limits the blood flow to the heart. Narrowing of the arteries is known as Stenosis. The entire blockage in the artery potentially leads the Myocardial Infarction (MI) commonly known as heart attack [1]. These coronary plaques diffuse the fat content to the proximal side wall to the vessel and it causes the coronary inflammation. This kind of inflammation is leading cause for heart attack.

Present biomarkers suitable for predicting the heart disease only after it happens. It is a challenging task to diagnose heart attack as early as it happens. Recently, a new biomarker Fat Attenuation Index (FAI) proposed by the medical practitioners of Centre of Research Excellence, British Heart Foundation, Oxford, UK for diagnosing future fatal heart attack many years before it happens.

According to the mixture of different substances the atherosclerotic plaque can be classified into three. They are calcified, non-calcified and mixed plaque based on its composition [2]. Formation of these plaques and its rupture leads to the acute coronary syndrome and it causes to the Myocardial Infarction (MI) i.e heart attack [3],[4]. Coronary artery Stenosis is narrowing of the arteries. A severe blockage of arteries may cause heart attack [1]. Coronary artery calcium score (CACS) is one of the best tool for identifying coronary artery stenosis. The predictive value of CACS is used to know the existence and harshness of CAD in patients. Although it is not exactly predicts all the reasons for affecting disease and cardiac death.

Vascular inflammation in the arteries enables timely exploitation of measures to prevent future heart attacks. A new imaging biomarker called Fat Attenuation Index (FAI) around Coronary Artery is used to diagnose coronary inflammation and also it identifies individuals at risk of cardiac mortality. FAI captures fat attenuation of perivascular and it detects vascular inflammation at an early with routine Coronary Computed Tomography Angiography CCTA [1].

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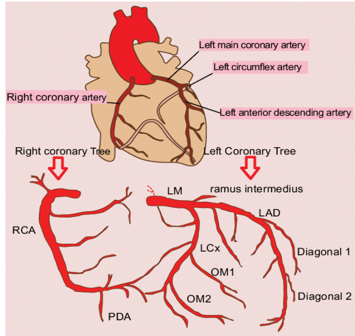

Figure 1. Heart and coronary arteries

There are many invasive and non invasive tests or procedures available to detect the heart disease. CCTA is an image test tool that supports in finding the plaque build-up has lessened the coronary arteries. It is a sensitive and widely used diagnostic tool for the diagnosing coronary CAD [5]. It also helps the doctors to know the details about the luminal plaque along with plaque composition.

Literature Review

Perivascular FAT attenuation mapped around all the three arteries Left anterior Descending Artery (LAD), Right Coronary Artery (RCA), Left Circumflex (LCX). Nevertheless, Perivascular FAI value around RCA is the most common for diagnosing global coronary inflammation. Perivascular FAT validated with the prognostic value index over and the higher than the existence of stenosis and plaque calcification. High values of the FAI around RCA can be used to quantify adverse events. There are various methods available to assess the prognostic value of FAI. In this work, Multivariate regression model is used for assessing the prognostic value of FAI.

Usually these tasks are done by first removing cardiac motion noises in the RCA of coronary artery by doing image reconstruction process to the CCTA. Image reconstruction refers to recovering the original clean CCTA image from the corruption arises from the motion blur, low resolution, image noise refers to the variations in colour, brightness or imperfect camera sensor [6-8].

The fundamental impact of image reconstruction is image quality and therefore on radiation dose. The main purpose of doing reconstructions is to improve image quality [9]. It is difficult task to eradicate noises and errors completely with conventional denoising methods. The block-matching 3D (BM3D) method has provides strong evidence in image restoration for various noise/error types and also several CT image related problems [10], [11]. It has been improved denoising computation with a local artifacts level estimation [12]. Non Local Means (NLM) low-dose CT restoration with same means [13-16] considered for image noise reduction process. According to an idea of sparse representation [17] adapted K-Singular Value Decomposition (K-SVD) to work with low-dose CT scan image[18].

This study uses Deeper CNNs ResNet, which are widely used DL methodology and became best solution for denoising an image data [19]. One of the most promising network architecture is ResNet. This is recently used for image processing. The noises/errors present in the training model are exactly identified by the ResNet [20-22].

Next step is segmenting arteries and tracking of heart of coronary artery tree in CCTA [23]. MSCAR-DBT method is suitable for heart region enhancement as well as segmentation. This method uses 3D dynamic balloon tracking method for constructing coronary artery tree. There are three major vessels in myocardium namely RCA, LDA, and LCX. Furthermore, there are totally 17 major arterial segments considered in clinical significant. Although in this work the most prominent artery for the cardiac mortality prediction is Proximal RCA. GUI shows the coronary artery rendered in 3D volume.

The RCNN is proposed to classify the cardiac mortality on diagnosing the vascular inflammation present along with the high risk prognostic index value of FAI. The Network utilizes the proximal cross sectional view of RCA. The distance from the radial to the diameter of the outer line artery is considered to show the coronary inflammation thickness.

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Dataset

This study collects data from UCI Heart Disease Database. The Multivariate categorical data is gathered from Cleveland Clinic Foundation and Hungarian Institute of Cardiology of UCI source. Each database contains 76 attributes and both are in the same instance format. Number of instances of Cleveland and Hungarian is 303 and 294 respectively. Both categorical and CCTA image datasets have been established to train and test the system proposed. For statistical analysis Cohort demographics and clinical characteristics data's are considered from derivation and validation cohorts [2]. Mainly, segmented RCA image of CCTA scan is employed for classifying the presence of FAT inflammation. Consecutively the prognostic value of FAI index is acquired from the two cohort samples [23] during the Mann-Whitney process to evaluate the significance of the network in the prediction of cardiac mortality.

Methodology

Image Denoising

The original CCTA image has cardiac motion artifacts due to the several reasons. The first and foremost step is to perform removal of cardiac motion artifacts in the RCA. It is done by doing image reconstruction process to the CCTA. Image reconstruction refers to recovering the original clean CCTA image from the corruption arises from the motion blur, low resolution, image noise refers to the variations in colour, brightness or imperfect camera sensor [24-26].

The fundamental impact of image reconstruction is image quality and therefore on radiation dose. The main purpose of doing reconstructions is to improve image quality [27]. Sometimes the low radiation dose degrades the original image quality. Deep Convolutional Neural network considers the low dose CT image for noise reduction and produces normal-dose CT image patch by patch. It is very tough to remove all noises fully with the conventional denoising methods [28].

The block-matching 3D (BM3D) algorithm has been suggested as a fine method for image restoration [29]. It has been enhanced with performing denoising in a local noise level estimation [30]. Non Local Means (NLM) low-dose CT image restoration with similar means [31][32] considered for image noise reduction process. Sparse representation technique has been adapted with K-Singular Value Decomposition (K-SVD) to face the low-dose CT images.

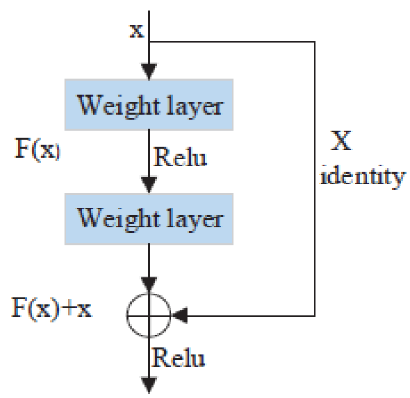

Figure 2. Residual Network: a building block

This work uses Deeper CNNs ResNet, which is used DL method for image denoising. Mostly deep network play vital role in image classification. Additionally, it has responsible to other visual recognition and benefits over image processing. Especially deep network can be used for exploding gradients. One of the popular network architecture in deep neural network is ResNet. This network is recently used for image processing. The total number of errors are available in the training framework are exactly identified by the ResNet [32]. ResNet contains many blocks where x is represented as an input and f denoted as an activation function. The residual block is determined by f(x) + x. There are many valuable reasons for accepting and using ResNet.

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Primary reason for using ResNet is it focuses on the height rather than the width of an image. It also takes the responsibility to control the various parameters very effectively and it brings the solution to overcome the over fitting problem. Second, it uses very less pooling layers and does more down sampling tasks to enhance the efficiency of the transmission. As a result ResNet decreases the error up to 3.57% on the CCTA image set.

Coronary Artery Segmentation

The improved quality CCTA image is needed to achieve further feature extraction. Fat inflammation diffuses around all the vessels of the arteries. Moreover, the inflamed artery which scatters the adipogenesis around the wall of the vessels. There are three major vessels in myocardium namely RCA, LDA, and LCX. Furthermore, there are totally 17 major arterial segments considered in clinical significant. The most adverse event happens due to the attenuation happens in the proximal side of the Right coronary Artery (RCA) vessel. This ruptures the vessel tube along with acute risk factor in all cause and cardiac mortality and inhibits the blood flow inside the heart. So in this work first major coronary artery segmentation happens subsequently one of the major levels of myocardium RCA.

Image segmentation of CCTA is essential to visualize the vessel lumen clearly for assessing the disease and it is predominantly helpful for the researcher to quantify the inflammation. The artery segmentation and tracking of heart's coronary artery tree with several methods in CCTA have been mentioned in [31]. MSCAR-DBT method is suitable for heart region enhancement as well as segmentation.

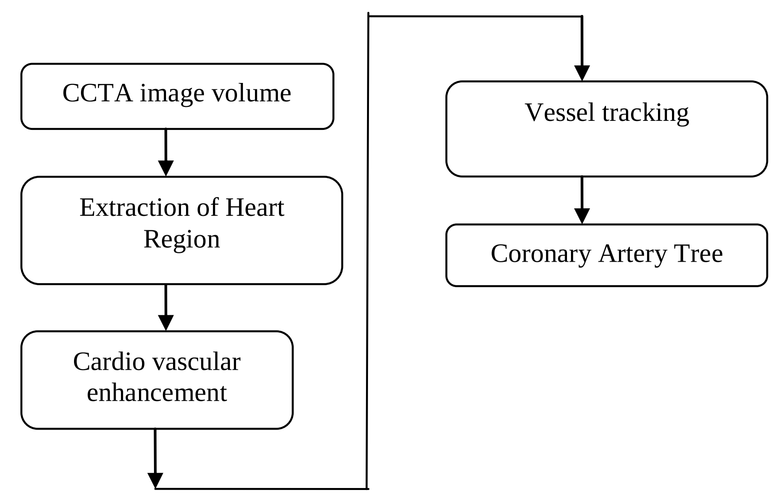

Figure 3. Coronary Arteries extraction using MSCAR-DBT method

This method uses 3D-DBT method for construction coronary artery tree. GUI illustrates the coronary artery provided in 3D volume. The figure 2 shows the schematic diagram of coronary artery extraction using MSCAR-DBT. First the morphological operation is applied to the heart to extract all the regions of heart and the maximum likelihood is found by using Expectation-Maximization (EM) [32] estimation. During this process chest wall, the pulmonary vessel structures and outer region of heart were extracted. Subsequently, the heart's boundary is enhanced and get segmented using MSCAR-DBT. After segmenting of vascular structures, the intended RCA is tracked using 3D DBT method. This method initiates its tracking process at the origin seed points of RCA that is identified manually.

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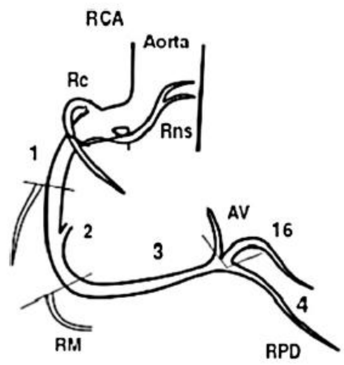

Figure 4. Major Coronary artery Segmentation - Proximal RCA

There are totally 17 major coronary arterial segments presents in the clinical significant. Some of the coronary arterial segments are shown in the above figure. From these segments the left and right coronary vessels alone exactly separated by the MSCAR-DBT method. Sample illustrations of the left and right vessel of coronary extraction are shown in the figure 3.

RCNN Network Design

The sequence of CCTA image cubes from Residual Network (ResNet) is considered as an input to the proposed RCNN network. To perform the automatic analysis on the coronary inflammation, a single task RCNN is used to assess the vicinity along the extracted artery vessel in a ResNet image and to classify the coronary inflammation induced by the attenuation FAT prognostic index value. The predominant task of the network is to diagnose the cardiac mortality by classifying the coronary inflammation presence and absence around the proximal side of the Right Coronary Artery (RCA). It analyses the ResNet artery defined as smaller cubes along the artery centreline. This definition facilitates the RCNN constructed from CNN and RNN to extract the RCA image features from the smaller cubes apart from the artery length and then it aggregates all the features of the coronary artery.

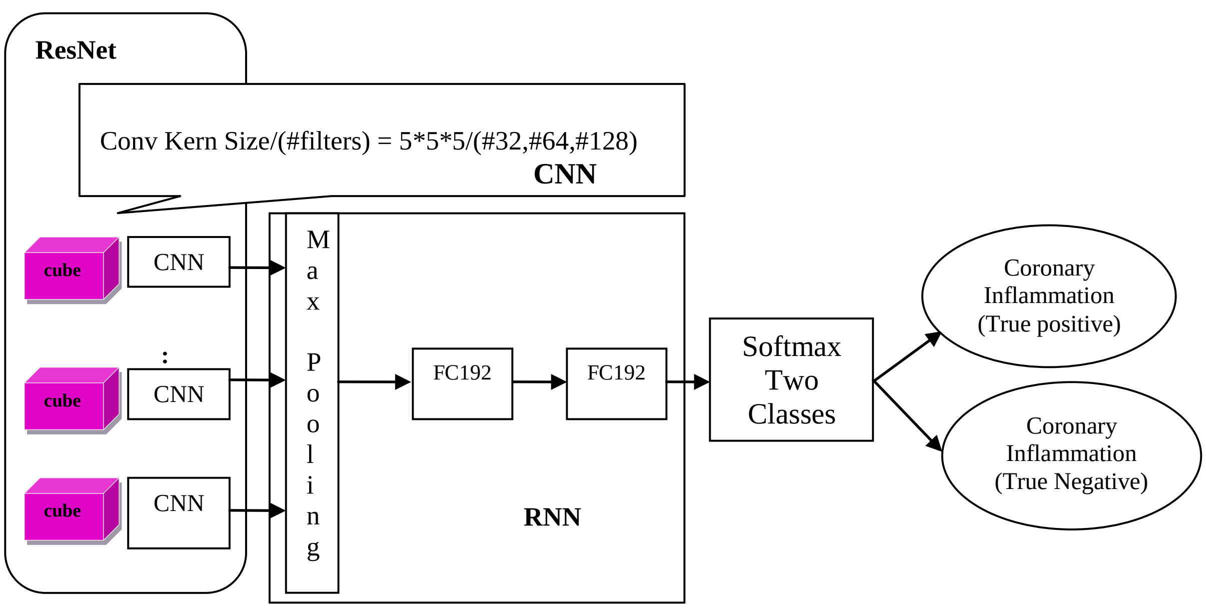

Figure 5. Workflow of the proposed network

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To detect and characterize the presence and absence of coronary inflammation using Perivascular FAI, a RCNN is designed. Usually, RCNN is a popular deep learning method for video recognition and description [33-35] object recognition [35], speech modelling [36], and in medical image analysis [37-40]. The proposed method connects a CNN with RNN together to analyze the given sequential input [1]. Right coronary artery image feature is extracted by ResNet of CNN for each and every element of the sequence separately. Later the aggregation of all the features that are extracted fed into the proposed RNN framework which analyzes the cardiac risk factor with the relevant sequential dependencies of the inflamed artery.

Impact of the RCNN architecture

In this work a supplementary method is applied for tryout with an equal CNN architecture for establishing the value of recurrent nature of the proposed model. The RNN is substituted by Fully Connected (FC) layers. To evaluate diverse length of the sequence and to combine the extracted features by the CNN into one sequence, a max pooling layer is established after the CNN. Consequently, this layer is connected to two Fully Connected layers instead of the Gated Recurrent Units present in RNN. The number of units may get varies in each of the FC layers with respective to the trainable parameters. The proposed RCNN network is trained with a set of images, the same data are used to validate and test the model.

Results

Network Validation

The prognostic value of FAI is tested to validate the robustness of the network. Many statistical analysis tests are available for validating the system. In this work, Mann-Whitney U test is used to test the Prognostic value of FAI along with the categorical variables of two groups. It is a non-parametric test to the independent sample t-test. Usually it compares two sample means that is taken from the same population. It is also used to test whether two sample means are equal or not. Usually, the Mann-Whitney U test is used when the data is ordinal.

There are many instances employed [2] for their study. Among which, the proposed system considers only four attributes that are predominantly helps in validating the network in the sequence of diagnosing the disease rate to the validation process are mentioned below

Table 1. Four major attributes considered for the validation process

Demographics	Risk factors	Cardiac CT	Degree of Stenosis
		Total Coronary Calcium Score	
Patients in original Statistics	Hypertension	0	<25% luminal Narrowing
Eligible patients included in study	Hypercholesterolaemia	1-10	>75% luminal Narrowing
Age (years)	Diabetes mellitus	11-100	-
Men	Smoking	101-400	-
Women	-	>400	-

Performance Evaluation

To evaluate the proposed model there are three performance metrics are applied. They are accuracy, sensitivity, Positive Predictivity. These metrics are calculated using 4 measures True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

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$$Accuracy = \left(\frac{(TP + TN)}{(TP + TN + FP + FN)}\right) * 100$$

Sensitivity: This indicates the percentage of true case that was correctly detected by the algorithm.

$$\text{Sensitivity}(\%) = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Positive Predictivity: It gives the percentage of disease detection which are reality to the true case.

$$\text{Positive predictive}(\%) = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$Detection\ error\ rate\,(\%) = \left(\frac{FP + FN}{Total\ \ number\ of\ QRS\ complex}\right)$$

Where, TP=Number of true positive beat detected
FP= Number of false positive
FN= Number of false negative
TN=Number of true negative

Based on these Performance measures the proposed RCNN model with FAI is calculated and the result is visualized in Receiver Operating Characteristics (ROC) curve.

Discussions

Classification of cardiac mortality of RCNNFAI index value is validated against the RCNNFFR. Only four attributes of the clinical characteristics from both cohorts [2] are considered for testing the network performance. The four attributes are Demographics, Risk factors, Maximum stenosis, Total coronary calcium score.

Total number of records in both the cohorts is 4239. Among all the eligible patients included in the study [2] is 3912. Nevertheless, to validate the proposed network dataset of 125 patients are taken into account for validation. Out off 125 datasets, 80 of them are used for training and 45 of them used for testing. Totally 125 numbers of record details are considered for this task.. The experimental result of the proposed work is compared with the previous work of detecting the Functional Flow Reserve by using the same network RCNNN [41]. The proposed method RCNN using FAI index value gives better performance over RCNNFFR.
The result of the comparison is shown in the below table,

Table 2. Diagnostic parameters in Right Coronary Vessel (N = 125)

Performance Metric	$RCNN_{FFR}$	$RCNN_{FAI}$
True Positive No.	31	31
False Positive No.	14	14
True Negative No	73	73
False Negative No.	7	7
Sensitivity %	77	80
Specificity %	71	76
Accuracy%	76	81

The obtained result is visualized below using Receiver Operating Characteristics (ROC) curve for better understanding of the proposed RCNN with FAI and the FFR based RCNN.

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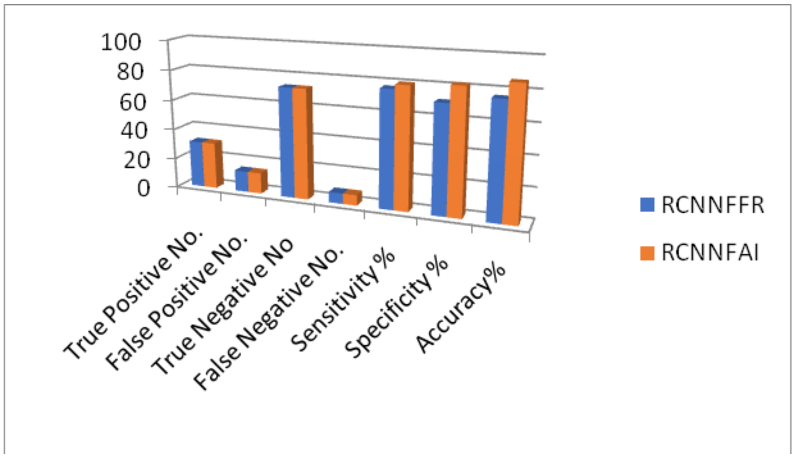

Figure 6. ROC curve of comparison of $RCNN_{FFR}$ and $RCNN_{FAI}$

Conclusion

Cardiac diseases are harmful to the human society which increases the mortality rate. Its very much necessary to detect and prevent as early as possible. Maximum of existing technologies are able to diagnose the heart related disease. Particularly heart attack once after it happens. The proposed system give better result in diagnosing future fatal heart attack many years before it happens. The experimental result is also more accurate since it uses FAI biomarker for the prediction. Furthermore, it uses 3D Dynamic Balloon Tracking Method for denoising and deep NN for the image segmentation for better input to the classification network RCNN. Nevertheless, the error propagate rate is minimized because of this deep learning approach. It helps the medical practitioners to predict heart attack earlier so that patients no need to go for further non invasive tests.

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