Segmentation of Coronary Arteries from CTA axial slices using Deep Learning techniques

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***Abstract*—Coronary Artery disease (CAD) is a type of Cardio Vascular disease caused due to disorders in blood vessels of the heart. Stenosis is sudden narrowing or blockage in coronary arteries and this happens because of cholesterol formation, fatty deposition, and damages in blood cells. In order to detect stenosis in Computed Tomography Angiography (CTA) images, the segmentation of the coronary artery is essential. In this paper, we propose a deep learning based model to segment the coronary arteries from 2D slices of CTA heart images and reconstruct them into 3D coronary artery. The coronary arteries may not present in all the 2D slices, so a combination of Convolutional Neural Network and Recurrent Neural Network (CNN-RNN) model is used to identify the presence of coronary arteries in the 2D slices. The identified coronary arteries are then segmented using the U-Net model. The segmented coronary arteries are then reconstructed into 3D images using the Maximum Intensity Projection (MIP) reconstruction algorithm in order to analyze the presence of stenosis. The proposed system was evaluated for segmentation using IOU (Intersection Over Union) and for reconstruction using Structure Similarity Index metric (SSIM) for the CTA images obtained from Bilroth hospitals, Chennai.**

***Index Terms*—Segmentation, Coronary artery, Deep learning, Convolutional Layer, Recurrent Neural Network**

I. Introduction

Stenosis is a type of Coronary Artery Disease (CAD) caused by the formation of plaque inside the arteries due to the deposition of cholesterol, calcium, fatty, and other substances. When the plaque builds up it clogs up the artery and reduces the amount of oxygen-rich blood getting in to the heart which can be fatal. This condition of narrowing or clogging up of vessel is called stenosis and the severity depends on the percentage of the blockage. Thus, early diagnosis of stenosis is very important.

Several imaging techniques are used to diagnose CAD, among them Computed Tomography Angiography (CTA) image is considered to the best imaging modality for coronary arteries of the heart [10]. CTA is less invasive and uses advanced CT technology along with contrast material (dye) which generates several cross-sectional slices of the heart. Analysis of stenosis in each slice manually is a tedious process, lead to inter-observer and intra-observer variability and may lead to inaccurate estimation of lesion severity [6]. So an automated system is required for detection of stenosis which may act as a first level filter for the experts. Automatic detection of stenosis from CTA images requires accurate segmentation and analysis of arteries.

Each 2D slice of CTA image contains coronary and non-coronary arteries namely aorta, pulmonary artery, and veins. As the information present in a 2D-slice is insufficient to analyze the presence of stenosis, 3D reconstruction of coronary artery may help in accurate analysis and diagnosis. But reconstruction done without segmenting the coronary arteries produce entire heart with coronary and non-coronary arteries which can be a hindrance for further analysis. Thus reconstructing the segmented arteries is needed and helpful for coronary artery analysis.

Segmenting the coronary arteries is a tedious process due to inhomogeneity of the arteries and complex anatomy of vessels. Most of the algorithms in literature use image processing techniques such as thresholding, region growing approaches ([15], [27]), level set methods ([4], [22]), vesselness based methods ([12], [18]) and learning based methods ([2], [21]) for segmentation of coronary arteries. The connected component labeling is applied to the vessel enhanced image using frangi vesselness filter was proposed in [16] to segment the coronary arteries. An automatic method for vessel segmentation was proposed in [14] which uses greyscale and spatial information for segmentation and this system perfectly segments larger vessels. Extracting of coronary arterial tree in angiography images using Starlet wavelet transform was performed in [24] after de-noising and sharpen the angiogram images. A machine learning based interactive coronary artery segmentation method for 3D computed tomography angiography images was proposed in [5]. A framework for image segmentation was proposed where each propagation is formulated as an optimal labeling problem that was solved using the graph-cut algorithm in [28]. End-to-end learning based method was proposed which learns using sparse annotation and segments a 3D volume [3]. Among them, a machine learning based approach produces better results than other approaches. Even though machine learning based approaches produce a better result, the accuracy of the system is based on factors like feature engineering and experts knowledge [9], [19]. The quantification of pathology is purely based on the accurate segmentation of coronary arteries. Coronary artery lumen segmentation has been investigated using 3D

U-net convolutional neural networks in [11]. Left Ventricle myocardium is segmented using a multiscale convolutional neural network (CNN) was proposed in [29]. A fully convolutional network which outperforms the prior best method with a modified structure like contracting and expanding path suitable for biomedical segmentation was proposed in [20]. The deep learning based models are automatic features learner. The algorithms try to learn multiple levels of abstraction, representation, and information automatically from a large set of images that exhibit the desired behavior of data [19]. So we have proposed a deep learning based segmentation of coronary arteries where the model learns the required features from the input images in order to segment the arteries.

A method for coronary artery registration in CTA and angiography modalities was proposed in [25] to obtain the 3D position of the stenosis lesion. 3D models of stenotic coronary arteries were reconstructed directly from 2D coronary images using 3D centerline extraction, 3D luminal contour generation, and control points adjustment in order to analysis the severity of contour [7]. In [13] a semi-automated methodology for three-dimensional (3D) reconstruction of coronary arteries and their plaque morphology using CTA images was proposed using level set method and surface reconstruction. A method based on the variation intensity in the X-Ray Coronary Angiography (XCA) image sequence using enhancement and thresholding algorithms were proposed in [26] and the performance of the methods was evaluated.

In this paper, a deep learning based method has been proposed to identify and segment the coronary arteries from the 2D CTA images of the heart. Since the detection of stenosis in a single slice of the coronary artery is impossible, a 3D view of the coronary artery is constructed from the resulting images for further analysis and treatment.

II. Proposed System

For a patient, about 150 to 200 axial slices were generated by CTA imaging technology. Some of the axial slices may not contain coronary artery information. In rest of the slices, the information about the coronary artery appears continuous. The coronary artery information can be extracted by RNN as it produces good results for seq-to-seq information. We have proposed an deep learning model which uses a CNN-RNN to identify the presence of coronary arteries in the slices based on the sequence information. The CNN extracts the feature map of the input image which is given to the RNN which to process the sequence information. The model performs a classification to select only those slices which might be a part of the coronary artery. This method leverages the similarity between subsequent axial slices of the heart and enhances the accuracy of the segmentation model. The shape of coronary arteries also varies from slice to slice so we have proposed an U-Net based architecture to segment the coronary arteries from the identified slices. Since each slice depicts only a small portion of the coronary artery, a single 2D segmented image is insufficient to detect the stenosis. Multiple segmented images of the patient are gathered, and a 3D view of the coronary artery is constructed using a 3D reconstruction algorithm. 2D projection images from the 3D structure have been obtained using different rotation angles which can be used further used for analysis of stenosis. The architecture of the proposed system is depicted in Figure.1. The different processing steps of the proposed system involve Data preparation, Identification of Coronary Arteries, Segmentation of Coronary Arteries and Reconstruction of 3D model.

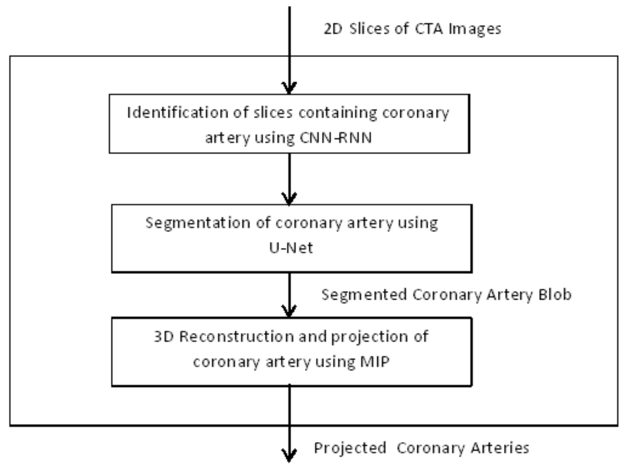

Fig. 1. System architecture

A. Data Preparation

In the proposed work, we have automated the ground truth preparation of coronary artery blobs which helps the deep learning model to learn during the training process. It involves obtaining multiple 2D heart slices and creating the mask of coronary artery for each slice to distinguish the coronary artery from a non-coronary artery. To facilitate extraction of coronary artery blobs from input axial slices, we have created a tool using Python and OpenCV. Contour detection method has been used to find all the contours in each slice and coronary artery blobs are identified and extracted using point polygon test with the help of expert guidance. The mask obtained by this process contains only the coronary artery portion of the corresponding slice in a black background. This is used by the subsequent models to learn the location, size, intensity and other parameters about the coronary artery which is the part of the input slice.

B. Segmentation of Coronary Arteries

The proposed automated system helps in segmenting the coronary arteries from the 2D slices of the heart by removing the non-aortic regions using the deep learning architecture U-Net. The U-Net architecture is built on the Fully Convolutional Neural Network (FCNN) and modified in a way that it yields better segmentation for medical imaging [19]. For this model to attain good segmentation results, we have fed only the slices with coronary artery as input by identifying corresponding slices using CNN-RNN architecture.

1) CNN-RNN Model: In the 2D slices of a patient, coronary artery is not found in every slice. The part of the coronary artery present in each subsequent slice have structures with a specific shape or appearance which changes minimally from slice to slice. The proposed model is used to identify the slices containing the coronary artery from among the 200 axial slices of the CTA images of a patient. The model consists of combination CNN and RNN architecture. The hybrid network consists of a CNN and a Long Short Term Memory (LSTM) connected in series. LSTM is a type of RNN which is best suited for learning long term dependencies in sequential data [23]. The short term memory and the vanishing back propagation problem of RNN has been replaced by LSTM [8]. LSTM when applied to temporal sequences, neural networks recurrence relationship is mapped to the time axis of the input sequence but when applied to image classification, LSTM networks treat each dimension of the image similar to a temporal axis and combine the outputs [1].

CNN is proved to be successful in extracting features of image. The input images are fed into the CNN and the feature maps are extracted. Coronary arteries which spread across consecutive 2D axial slices have been tracked sequentially with the help of the LSTM, which is capable of processing sequential data. Due to its recurrent structure, the LSTM is able to generate a temporal correlation between successive slices [1]. Thus the CNN and LSTM are combined to process the sequential image information of the slices. The image features have been extracted by the CNN where the sequential information has been aggregated by the LSTM and the information passed on to the fully-connected layers which perform binary classification. The proposed model thus classifies the given slice contains the coronary artery or not. With the help of the model, the proposed system can detect the starting and ending slices which contain coronary arteries. The proposed model for identification of coronary arteries slices consists of sequence of CNN layers followed by RNN layer and fully-connected layers. The architecture diagram of the model is depicted in Figure. 2.

1) The CNN part has four 3x3 convolution layers followed by 2x2 max pooling layers. The four convolutional layers have 32, 64, 128 and 256 filters respectively. This layer takes the slices as input and extracts the feature maps of the image at each layer.
2) A 3x3 ConvLSTM2D layer is then added, where the input transformations and recurrent transformations are both convolution. This layer is able to generate a temporal correlation between successive slices.
3) This is followed by a flattening layer which flattens the input.
4) The final fully-connected layers which act as a classifier has four dropout layers, each dropout followed by a dense layer having 256, 128, 64 and 1 filters respectively. The last layer provides binary output ’0’ or ’1’.

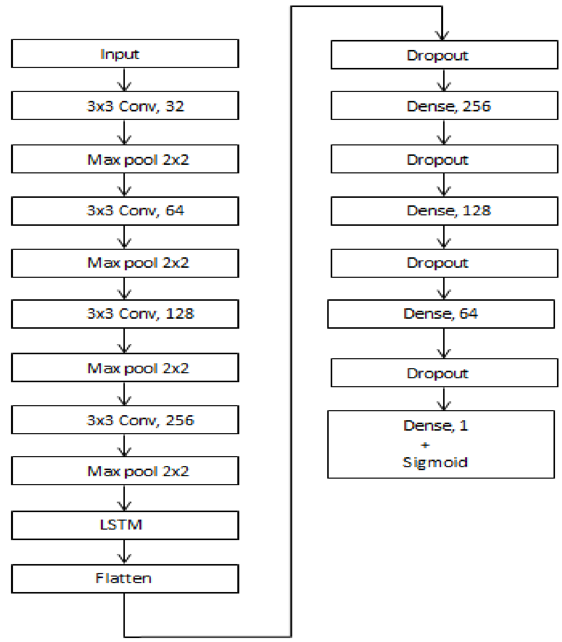

Fig. 2. CNN-RNN architecture

During training, the model takes all the slices of the patient and corresponding labels as input. Labels 0 or 1 denotes the absence or presence of coronary artery blob. The information of the slices are converted into numpy array and their corresponding labels which are encoded as one hot vector were taken as input. Labels are assigned automatically with the help of ground truth tool. If the mask of the slice is completely black, label 0 is assigned when the mask has grey values due to the presence of coronary artery, label 1 is assigned. For the test images of a patient, the model predicts whether the slice contains coronary artery or not based on the learning attained during the training phase.The sample input output obtained using the CNN-RNN model is depicted in Figure 3.

2) U-Net: The slices which contain coronary arteries are identified using the above proposed CNN-RNN architecture. The coronary artery portions exhibit specific inter-structure topology that constraints their neighboring relations. This property helps in accurate segmentation of the series of 2D serial-sectioned heart images using an U-Net architecture [20]. It is basically a CNN where the fully connected layers are replaced with a convolutional layer with large receptive field to get high resolution image. It also consists of 2 symmetric parts the contracting or downsampling path and the expansive or upsampling path. The contracting path which captures the context of the input image enables to do segmentation. The coarse information will be transferred to the upsampling path by means of skip connections. The purpose of the expanding path is to enable precise localization combined with contextual information from the contracting path.

The proposed U-Net model consists of residual blocks. Each residual block contains a 1x1 convolution layer, followed by

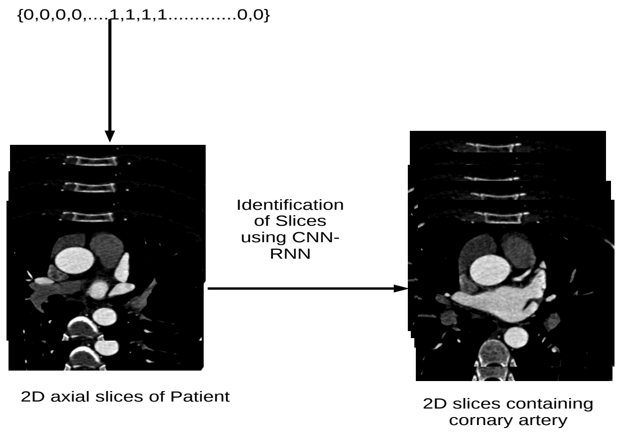

Fig. 3. Sample input output from CNN-RNN

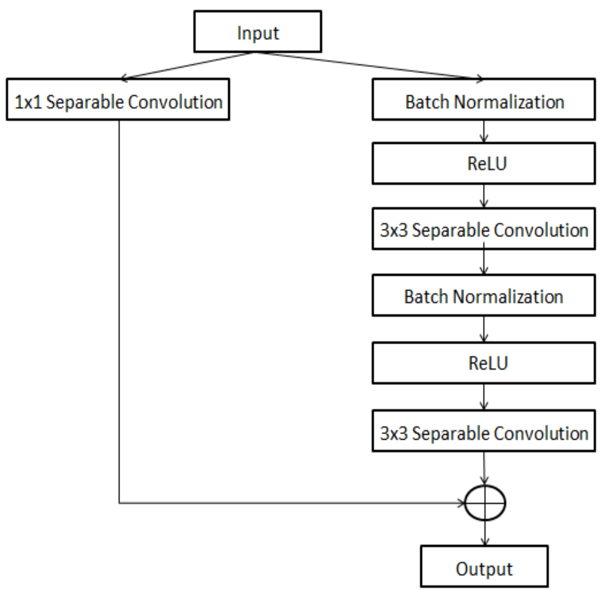

Fig. 4. Residual block

a sequence of batch normalization, ReLU activation function and a SeparableConv2D layer. This sequence is repeated twice in each block. The architecture of the residual block is given in Figure 4.

The model consists of repeating sequence of residual blocks with the following layers:

1) The contracting path has six Residual blocks, each followed by a 2x2 max pooling. The six residual blocks have 32, 64, 96,128, 256 and 512 filters respectively.
2) A dropout layer is then added to generalize the model and to prevent overfitting. This is followed by a residual block of 512 filters.
3) The expansive path has six 2x2 up-sampling layers, each followed by a residual block. The six residual blocks have 512, 256, 128, 96, 64 and 32 filters respectively.
4) A dropout layer followed by a 1x1 convolution layer with sigmoid activation function.

The overall U-Net architecture of the proposed system is depicted in Figure 5.

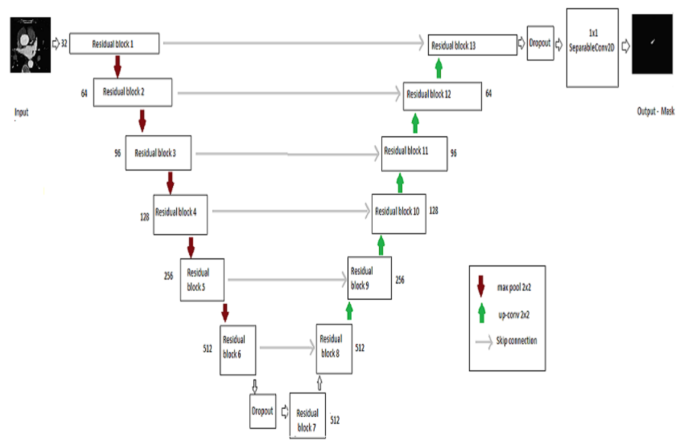

Fig. 5. U-Net architecture

The slices which contain coronary arteries which have been filtered by the previous CNN-RNN model act as input to the module along with the masks created by the ground truth tool. For each input slice, the corresponding mask of the coronary arteries was taken as input. The U-Net model combines the location information of coronary arteries from the downsampling path with the contextual information such as size, the intensity in the upsampling path to obtain general information in order to predict a good segmentation map. During the training phase, the architecture learns to discriminate the coronary arteries and the non-coronary arteries using the mask fed into them. In Figure. 6 sample input and output obtained from the U-Net model for segmentation of coronary arteries is depicted.

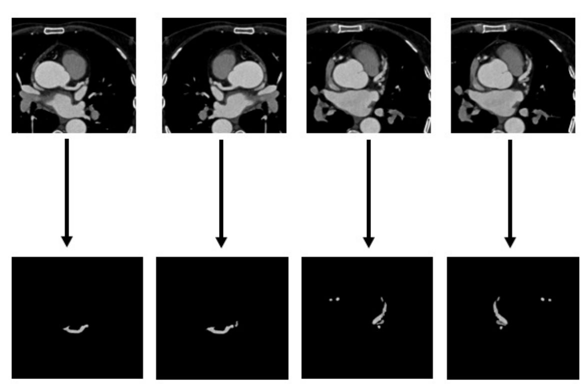

Fig. 6. Input and output from U-Net

C. Reconstruction of 3D model

Due to the complexity involved in the analysis of stenosis in an axial 2D axial image, a 3D view is constructed from the segmented images using Maximum Intensity Projection (MIP) algorithm [17]. MIP uses volume rendering technique to obtain the 3D reconstruction images. The algorithm projects the maximal intensity value along the line perpendicular to the view angle selected. The 2D projection images are created for every 10 degree rotation of the 3D image, resulting in 36 projection images for every patient. The absence of aortic and other irrelevant regions gives a better processing time for detection and analysis of stenosis.

The input for 3D reconstruction is the segmented axial slices containing the coronary artery. The resultant coronary artery masks from the U-Net model are binary images. Bitwise AND operation is applied between with the original image and the binary images to get the segmented portion. During 3D reconstruction, the segmented images are stacked to form a 3-dimensional view of the coronary artery. The 3D reconstructed coronary artery obtained from segmented coronary artery images is depicted in Figure.7.

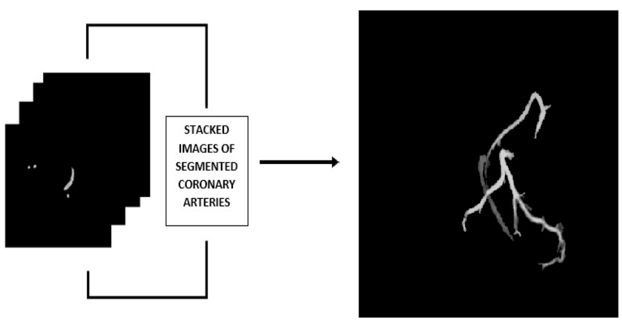

Fig. 7. 3D reconstruction from segmented images using MIP

III. Experiments and Results

The research work utilizes 2D axial slices of CTA images and creates projection images of the coronary artery by performing the 3D reconstruction. 2D axial slices of the heart have been used for classification and segmentation of the coronary artery. The 2-dimensional axial CTA images of the heart are collected from 50 patients. Each patient has about 200-250 axial slices depicting the internal structure of the heart and arteries. The slices are collected from Billroth Hospital, Chennai. The images are obtained in DICOM format from the CTA scanner. They are converted to Tag Image File Format (TIFF) format by MicroDicom tool. Each image is resized to 512x512 dimensions. To ascertain the performance of our proposed system, the following experiments were conducted.

- Experiment 1 - Identification of coronary artery slices.
- Experiment 2 - Segmentation of coronary artery from 2D axial slices.
- Experiment 3 - Reconstruction of coronary arteries.

A. Identification of coronary artery slices using CNN-RNN

This step involves identification of slices which has a portion of coronary artery in them. This is preferred to facilitate the segmentation process to have only relevant slices for further processing. This step accepts the input as the set of 2D axial slices obtained from CTA. The model classifies the input slices by identifying if it contains a portion of coronary artery in them. This information is then used to identify the starting and ending slice which has the coronary artery.

The model is trained for 70 epochs with Binary Cross Entropy loss function and Adam optimizer for the training data set with batch size as 4. About 80% of the patient images were used for training and remaining 20% were used for testing. For each paient about 220 slices were considered. The accuracy obtained with Binary Cross Entropy as loss function from the validation data was 0.9835. The overall loss value was found to be 0.0389.

To evaluate the performance of the model, we have used precision, accuracy and recall as the performance metrics. The CNN-RNN model has achieved a recall of 95.9%, precision of 97.9% and an accuracy of 96.1% using the test data. This shows that all coronary arteries are detected and only few non-coronary arteries are misclassified as coronary arteries. This misclassification is due to variation in position and size of the heart and difference in imaging quality, which makes it difficult in distinguishing the coronary from non-coronary arteries.

B. Segmentation of coronary artery from 2D axial slices using U-Net architecture

The previous model returns the starting and ending slice to consider for segmentation process. Based on that values, only those slices which are within the range are selected for processing.The segmentation model is based on U-Net architecture. The U-Net model understands to segment the artery by learning the images and the respective masks. The output of this model is the set of masks corresponding to the input images.

The model is trained for 80 epochs for 40 patients with Mean Squared Error (MSE) loss function and Adam optimizer for the training data set with batch size as 4. The accuracy obtained from the validation data was 0.9992 and the loss obtained was 0.00065.

The model was tested with 2D CTA slices of 10 patients to produce the corresponding masks. The performance of the model is evaluated by Insertion Over Union (IOU) metric.It can be observed that the overall IOU score is 0.8436. This indicates that there is a 84.36% overlap between the ground truth and the predicted masks on an average. Though our model produces good results, few coronary arteries were missed due to smaller presence of the arteries in the slices and a few of the non-coronary artery parts were also segmented by the model, due to their size and shape being very similar to coronary arteries.

C. Reconstruction of Coronary Arteries

After segmenting the coronary arteries, the segmented coronary arteries are reconstructed using MIP algorithm and different 2D projection images were created for every 10 degree rotation of the 3D image. Even though the proposed system produces projection angle for every 10 degree we have compared the test images with ground truth of rotation angle $(60, 120, 180, 240, 300)$ using Structure Similarity Index Metrics (SSIM). SSIM is a quality assessment index based on the computation of three terms, namely the luminance term, the contrast term and the structural term between the input image and reference image. The SSIM value for different rotation angles have been listed in Table I

TABLE I
RESULTS OF RECONSTRUCTION MODEL

P.No	R1	R2	R3	R4	R5
1	.8502	.8756	.8801	.8323	.8476
2	.8702	.8506	.8991	.9123	.8589
3	.9008	.8917	.8853	.8605	.9217
4	.8407	.8547	.8024	.8256	.8125
5	.8536	.8415	.8469	.8107	.8639
6	.8401	.8057	.8234	.7959	.8001
7	.8316	.8281	. 7827	.8158	.8589
8	.8067	.8429	.7986	.8279	.8423
9	.8123	.8845	.8350	.8450	.8500
10	.8767	.8986	.8332	.8530	.8751

The system produces an average of 83% to 85% of SSIM values for all rotation angles. The value can fruther be improved by attaing more IOU metric value.

CONCLUSION

In this research work, we have proposed automated method using deep learning models for detecting the coronary artery from 2D axial slices of CTA images and also we have used U-Net architecture to segment the coronary arteries. The segmented coronary arteries is then reconstructed into 3D coronary artery tree using MIP which helps in stenosis analysis. The system has been evaluated using different metrics at each level. The system attained a overall accuracy of 96% in identification of coronary artery slices using CNN-RNN architecture, IOU of 84% during segmentation process using U-Net architecture. The system attained average SSIM values of $0.84829, 0.85739, 0.83857, 0.8459, .8531$ for different rotation angles $60, 120, 180, 240, 300$. This system can further be extended to do analysis and measure the severity of stenosis.

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