# AUTOMATING THE DETECTION & CLASSIFICATION OF CORONARY STENOSIS USING DEEP LEARNING

Coronary arteries are major blood vessels in your body, supplying blood to your heart. They make it possible for your heart to beat and pump blood throughout your body. So, any blockage in these arteries will most probably lead to heart failure or at least a heart stroke. Non-invasive imaging techniques, specifically Coronary CT angiography (CCTA), are usually preferred as the safest way to visualize the coronaries vasculature and assess stenosis. In this work, we propose a fully automated workflow that finds the centerline of the arteries, then using these points we straighten the arteries to have a clear region of interest which gives us the ability to detect the stenosis regions and classify their types,

## INTRODUCTION

Investigating stenosis location and sizes in coronary arteries to detect coronary artery disease from CCTA is a complicated task that requires a considerable amount of experience. Therefore, doing this task manually is prone to subjective image interpretation and it's also time consuming.

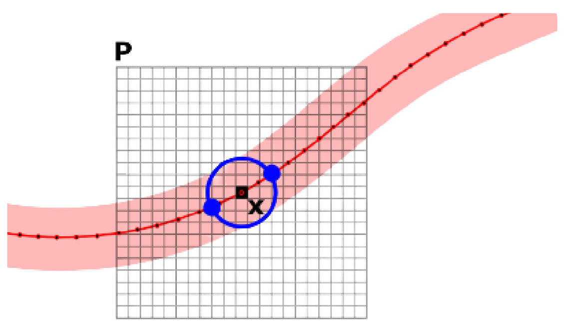
Several methods have been proposed to automate the detection and quantification of stenosis. While few methods use image features and pattern recognition, the latest accomplishments helped in stenosis detection by accurate lumen segmentation and centerline extraction. However nobody succeeded in classifying the types of stenosis or even its size. Our approach is to find the centerline of the arteries using a CNN model, then using these points we straighten the arteries using image processing techniques and curved multiplanar reconstruction. Having the input of straightened arteries, the developed RCNN will be able to detect the stenosis regions and classify their types.

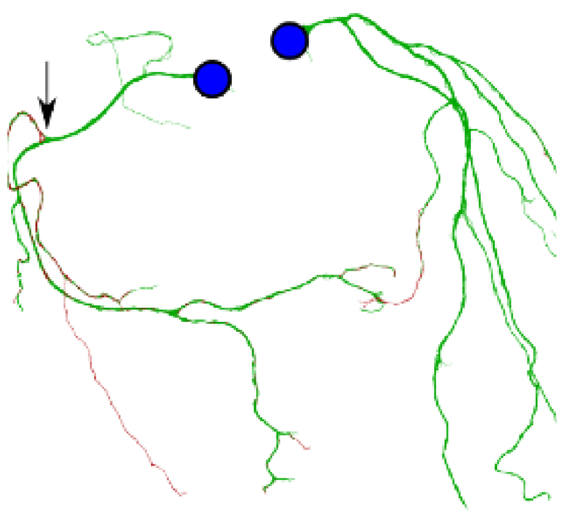
## OBJECTIVE

Centerline Extraction and detecting Stenosis types.

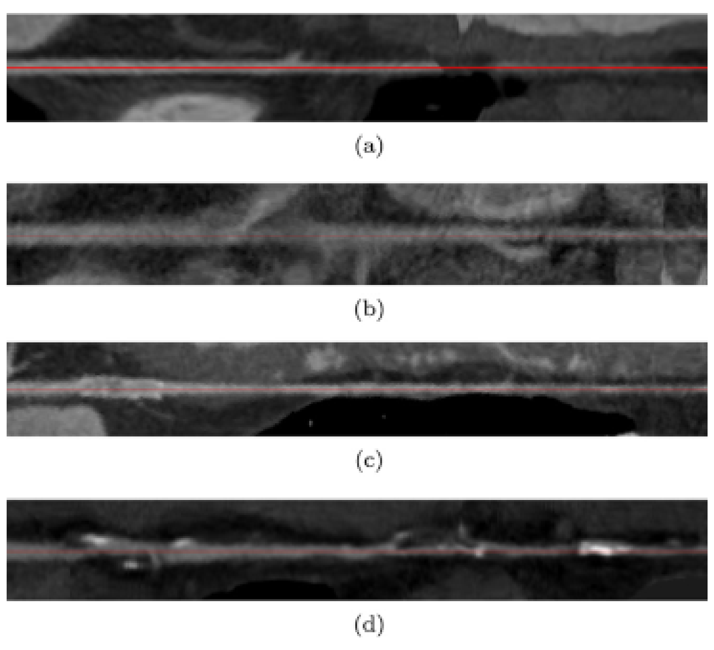
## METHODOLOGY

### CENTERLINE EXTRACTION

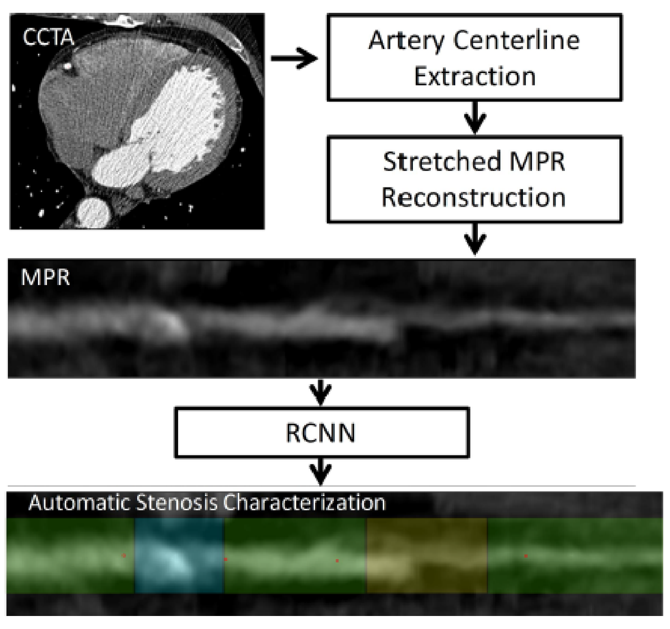


### MULTIPLANAR RECONSTRUCTION




### STENOSIS DETECTION & CLASSIFICATION

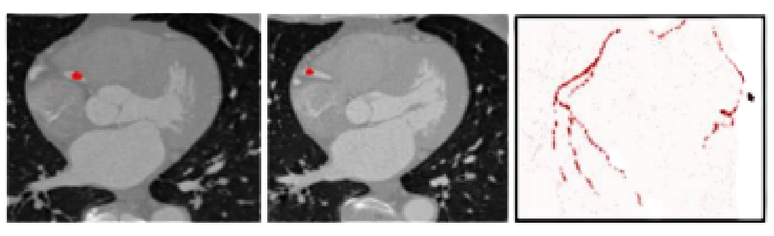



### WANT TO KNOW MORE?

## CENTERLINE EXTRACTION

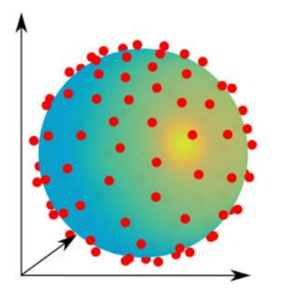
### PRE-PROCESSING OF THE DATA

- Convert Points from mm to pixels
- Dataset resampling
- Centerline resampling
- Volume truncation



### INPUT

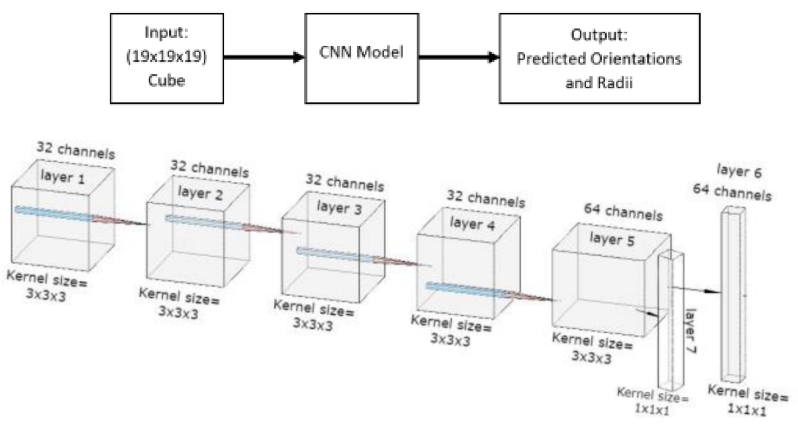
The doctor puts a point on the artery requirement: get consequent points
Only one point --> infinite number of directions to travel to --> this is represented by points on a sphere.
Solution: get discrete directions to span this sphere and make it a classification problem where you have a point and a cube around this point representing the volume plus, definite number of directions and radius from a point to another



J. M. Wolterink, R. W. van Hamersvelt, M. A. Viergever, T. Leiner, and I. Išgum, "Coronary artery centerline extraction in cardiac CT angiography using a CNN-based orientation classifier.," Med. Image Anal., vol. 51, pp. 46–60, Jan. 2019

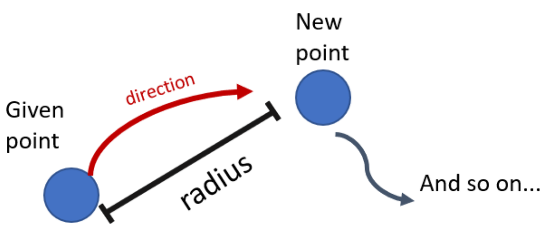
### CNN ARCHITECTURE

| Layer | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Kernel width | 3 | 3 | 3 | 3 | 3 | 1 | 1 |
| Dilation | 1 | 1 | 2 | 4 | 1 | 1 | 1 |
| Channels | 32 | 64 | 64 | 64 | 64 | 180 | $\|D\|+1$ |
| Field width | 3 | 5 | 9 | 17 | 19 | 19 | 19 |



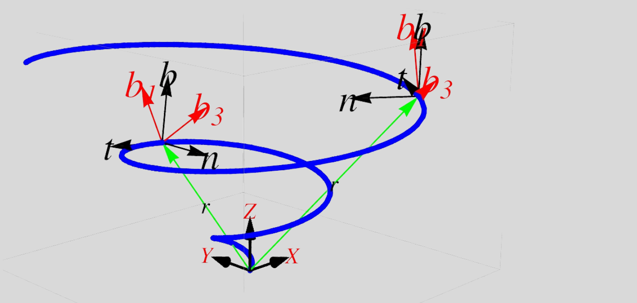

### OUTPUT

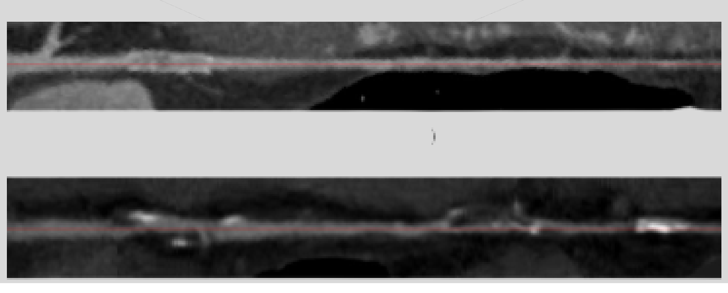
The output during testing is posterior probability distribution over directions. A workflow of centerline tracking begins from this point, where we determine the most probable direction that accompany the given point, the CNN also predicted the radius so now we have a direction to the new point and the distance taken to this point.



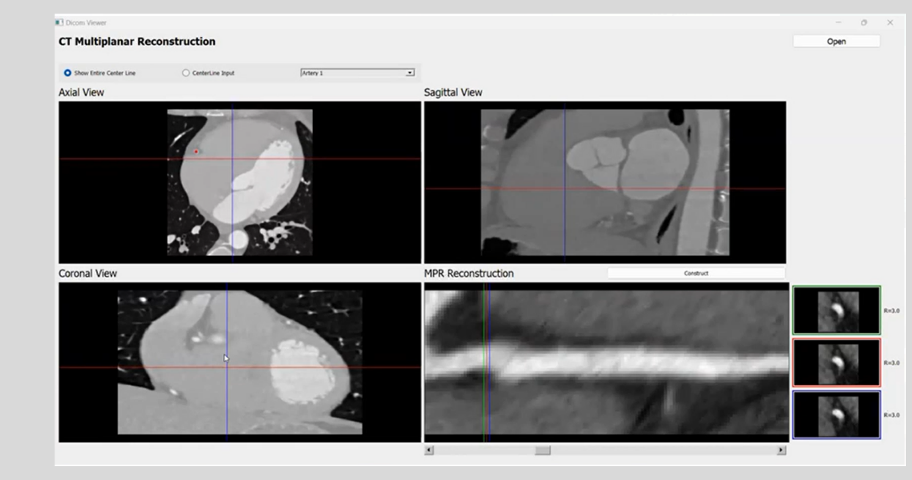

## MULTIPLANAR RECONSTRUCTION

After being able to reslice the volume from different directions to achieve the different views and to trace the centerline itself, we wanted to be able to straighten the artery to be able to easily detect stenosis regions using the model that will be developed in the next phase . To do so we had to follow the curved MPR technique to obtain the normal, binormal, tangent vectors to be able to straighten the vessel. This technique is similar to a camera movement that tracks an object so these three vectors are needed to track the vessel as we change slices as the vessel is curved not straight and needs these vectors to determine the path of movement. After doing so and combining all the tasks assigned above we were able to construct a straightened vessel in different views to be able to detect stenosis easily





## GUI

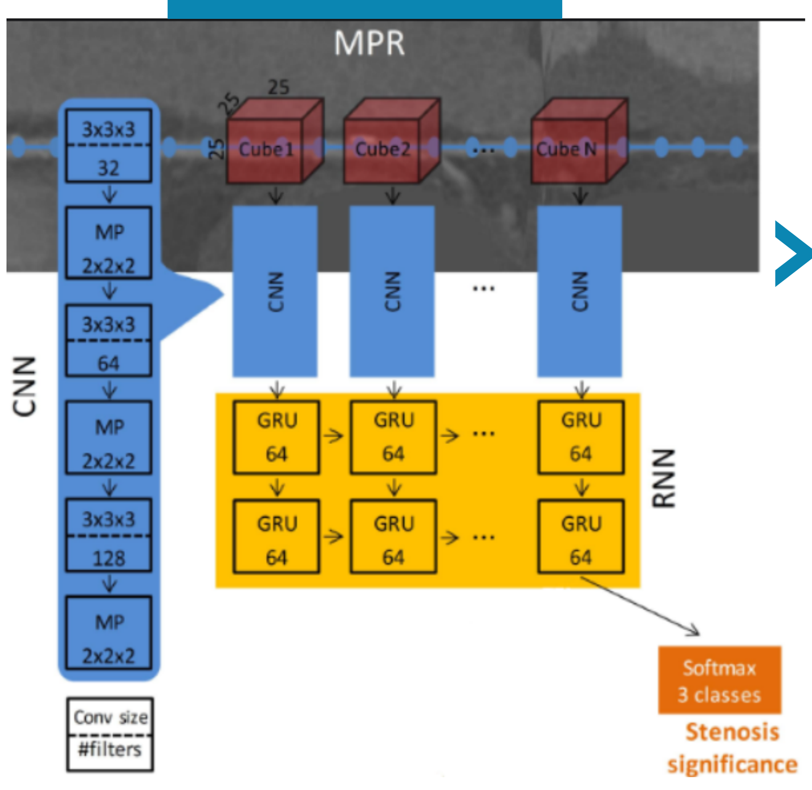



## STENOSIS DETECTION & CLASSIFICATION

### INPUT

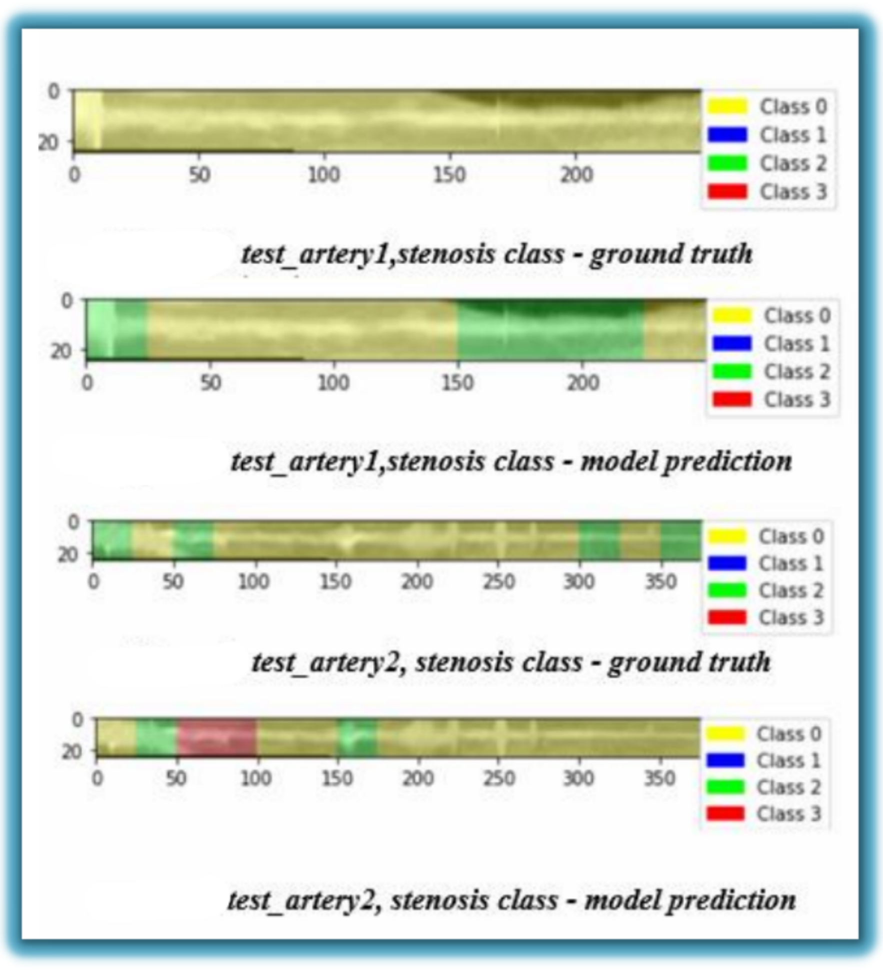
Each patient dataset contains Dicom frames along with reference files containing information about the segments, segments are combined into arteries using the reference files. Center points along the artery vessels are resampled using cubic spline interpolation and used to create an MPR which is then divided into segments. Each segment contains a set of 10 cubes, each cube if formed from 25 MPR Dicom frame of size 25x25. Segments formed from all the patients are then combined to have a final dataset of shape 234x10x25x25x25

### R-CNN MODEL

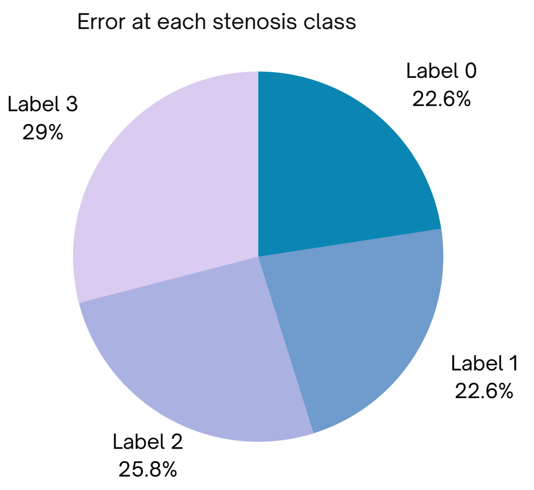


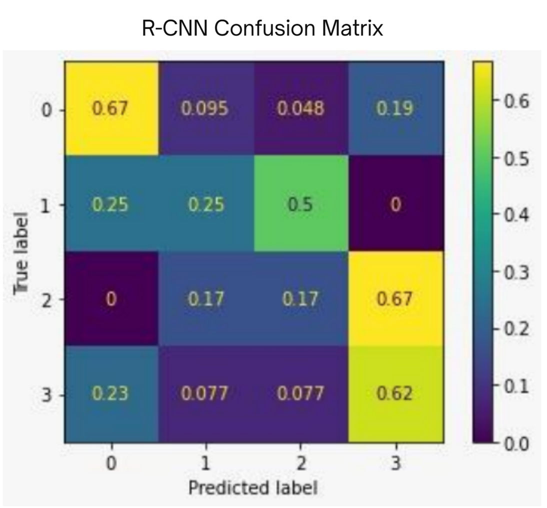

### OUTPUT

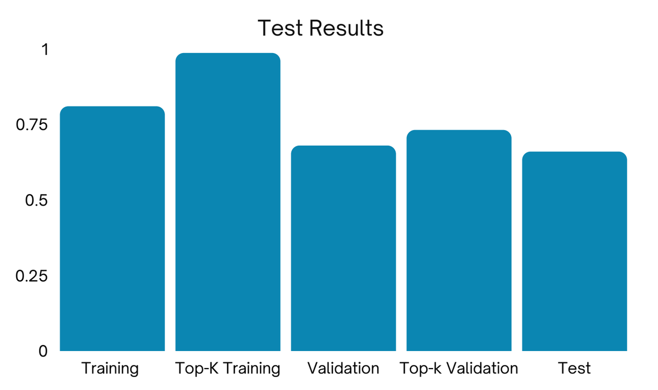
After training the model, we calculated the error for each class by getting the indices of ground truth representing a certain class. After that we subtract that class from the values of the prediction in these indices. We also used the Top-K category metric which computes how often targets are in the top K predictions where k is equal to 2 categories
We then tested the model's ability to label an artery according to our 4 classes and compared it with the ground truth and these were the results:




## RESULTS AND STATISTICS




## CONCLUSION

A method for automatic detection and characterization of the anatomical significance of the coronary artery stenosis was presented. The method employs a RCNN that analyzes an MPR view of a coronary artery extracted from a CT scan using the coronary artery centerline. proposed method requires only the coronary artery centerline as an input along with the CT volume. Since manual annotation is burdensome, we developed a CNN model to automatically compute the centerline without the doctors' annotations. We have constructed a good infrastructure where future improvements can be made to enable an automated triage of patients to those without coronary stenosis and those who with stenosis in need for further cardiovascular investigation

**Team Members**

Ahmed Mahmoud Fawzi
asemidamail@gmail.com

Adham Ashraf Khater
adhamkhaterr@gmail.com

Amira Ahmad Noaman
amira.noaman21@gmail.com

Rawda Ahmed Rumaieh
rawda.rumaieh99@eng-st.cu.edu.eg

**Supervised By:**
**Dr. Ahmed Abdelfadeel**
Research Associate in
National Institute of Health (NIH)