Multilayer Perceptron Network for Automatic Stenosis Grades Detected of Coronary Artery Diseases in Cardiac CT Scanner

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Abstract

This paper deals with who to automatic detected the lesion and stenosis grades (calcification type) of body arteries specifically coronary arteries which was blood supply the heart muscles. It was divided to eight levels (1-2 mild stages, 3-5 intermediate stages and 6-8 complex stages) which lead to help the physician to determine the time interval of therapy, type of drakes and catheterization decision. The perceptron algorithms designed in flexible way to allow the physician to choose the thresholds conditions of cardiac CT parameters (LAS, MDS and EAS) according to his opinion and experience. The experimental data get it from 64 slice cardiac system in Medicine City in Baghdad and it's trained by using Matlab 7.7 program.

Keywords: Multilayer Perceptron Algorithm, Measurements in Coronary Analysis, Parameters of Cardiac CT Scanner System and MATLAB 7.7 M-File.

الخلاصة

هذا البحث يتناول طريقة الكشف التلقائي لتدرجات التضيق و الضرر (تصلب الشراين) لكافة شراين الجسم وخاصة شريان التاجي والذي يغذي عضلة القلب بالدم. حيث تم تقسيم درجات الضرر في هذا البحث الى ثمانية مستويات (1–2 مستوى بسيط, 3–5 مستوى متوسط و 6–8 مستوى معقد) مما يساعد الطبيب لتحديد طول فترة العلاج ونوع الدواء المستخدم وكذلك قرار استخدام قسطرة القلب. حيث ان برنامج بيرسبترون متعدد الطبقات صمم بطريقة مرنة يسمح من خلالها للطبيب تغير الشروط العليا والحرجة لكل قراءة موجودة ضمن قياسات جهاز مفراس القلب (LAS, MDS and EAS) اعتمادا على رأيه الطبي وخبرته العملية. علما ان القراءات تم اخذها من جهاز مفراس القلب متعدد الطبقات (64 طبقة) من مدينة الطب في بغداد وتم تحليلها وتدريب الشبكة عليها باستخدام برنامج ال MatLab.

1. Introduction

Coronary vessel and its branches is very important vessel where was supply the cardiac muscles by blood which lead to heart contraction and relaxation phases to feeder the whole body. Any clotting or calcification (according to grades levels) inside it may be cause Muscle Angina (MI) which leads to death of some muscles or heart failure [Donald and Martin 2004].

Multidetector computer tomography (CT scan) throughout the past decade have provided clinicians with a non- invasive way to comprehensively evaluate the coronary arteries such as (End Systolic Volume (ESV), End Diastolic Volume (EDV), Cardiac Output (CO), Ejection Fraction (EF), coronary CTA analysis and general vascular analysis, etc). The non-invasive method help the physician to early diagnose about 80% for many vessels and muscles artifacts without make the diagnostic catheterization (invasive method). Now the challenge is who to use the engineering sense to enhancement and developed the algorithms for early and more accuracy diseases diagnose by computer aid detected (CAD) [Dalager and Norrgren 2010].

Neural network algorithms used to clattering the input then to determine the desire output. In this paper the multilayer perceptron algorithm used three normalized CT parameter (Lumen Area Stenosis (LAS), Minimum Diameter Stenosis (MDS) and Efficient Area Stenosis (EAS)) as inputs with multi neurons and according to the values of these inputs get on desired eight output levels which help the physician to determine exactly the grades of lesion inside coronary artery.

2. Measurement in Coronary Analysis:

On the straightened vessel there are three vertical lines: Red – the line which indicates the stenosis location Yellow - the line which indicates the proximal reference location Green - the line which indicates the distal reference location as shown in fig. (1) [Philips Healthcare 2010]:

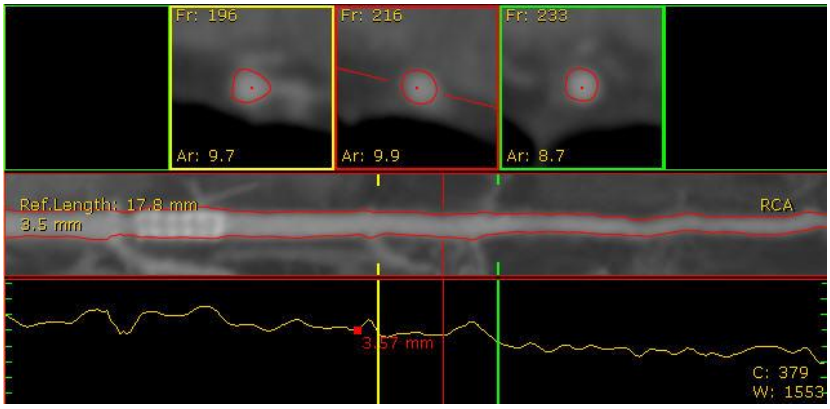
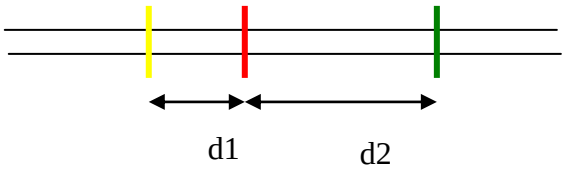


Fig. (1) Show the Straight Coronary vessel with its Flags Lines.

2.1 Lumen Area Parameter:

2.1.1 Reference Area:

a. If you only check one of the reference lines (distal or proximal) the reference area is the area at the location of the reference line (if it is proximal it is the left CS image, if it is distal it is the right CS image).
b. If you check both of the reference lines the reference diameter is the weighted average between the diameters:



d1 – the distance between the stenosis location and the proximal reference location.
d2- the distance between the stenosis location and the distal reference location.

$$reference\ \ area = \frac{[(distal reference area) * d1 + (proximal reference area) * d2]}{(d1 + d2)} \qquad (1)$$

2.1.1 Lesion Area:

The area of the cross-section at the lesion line location (red line) – the middle cross-section as shown in fig. (2):

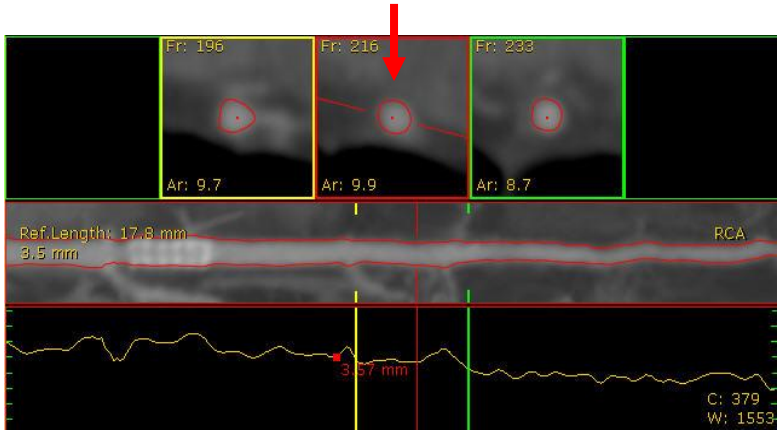


Fig. (2) Show the Middle Cross Section Area and its Flags Lines.

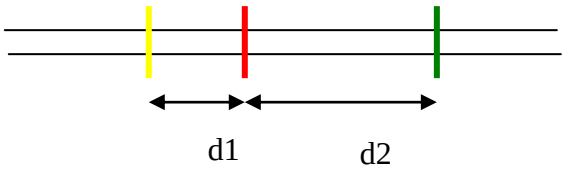
$$\%\ Stenosis\ (Lumen\ \ Area) = \frac{referenace\ \ area - lesion\ area}{reference\ \ area} \qquad (2)$$

2.2 Minimum Diameter Parameter:

2.2.1 Minimum Reference Diameter:

A- If you only check one of the reference lines (distal or proximal) the reference diameter is the diameter at the location of the reference line.

B - If you check both of the reference lines the reference diameter is the **weighted average** between the diameters:



d1 – the distance between the stenosis location and the proximal reference location.

d2- the distance between the stenosis location and the distal reference location.

$$reference\ \ diameter = \frac{[(distal\ ref.diameter) * d1 + (proximal\ ref.\ diameter) * d2]}{(d1 + d2)} \qquad (3)$$

2.2.2 Minimum Lesion Diameter:

The diameter on the current image at the stenosis location (white line) as shown in fig (3):

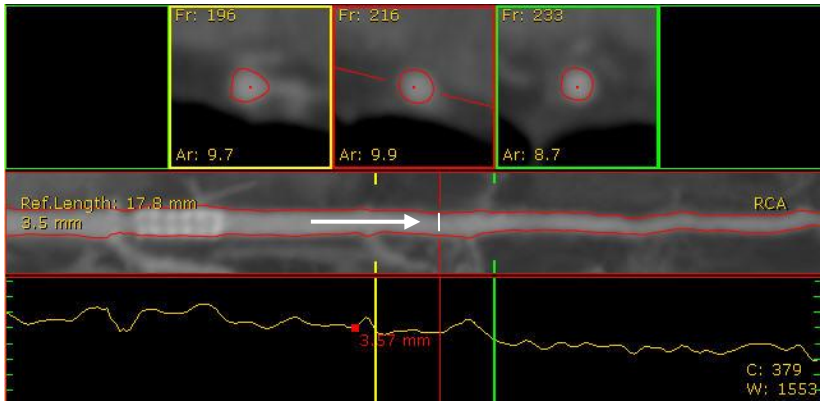


Fig. (3) Show the Straight Coronary vessel with Minimum Stenosis Diameter.

$$\%Stenosis(Minimum\ diameter)=\frac{(Min.\ reference\ diameter - Min.\ lesion\ diameter)}{Min.\ reference\ diameter} \quad (4)$$

2.3 Effective Area Parameter (Ideal Circular):

Let the cross section of the irregular vessel is a perfect circle.

$$Area = pi*radius\ \hat{}\ 2 \quad \Rightarrow \quad A=pi*(\frac{diameter}{2})\hat{}\ 2 \quad (5)$$

Out of this equation we extract the effective diameter. Meaning:

$$Effective\ Diamter=2*sqrt(A/\ pi) \quad (6)$$

2.3.1 Effective Lesion Area:

The effective Area measured at lesion area.

$$\%Stenosis(Effective\ Area) = \frac{effec.\ refer.\ area - effec.\ lesion\ area}{effective\ reference\ area} \quad (7)$$

3. Artificial Neural Network System:

Artificial neural network can be defined as a computational system consisting of a set of highly interconnected processing elements, called neurons, which process information as a response to external stimuli. An artificial neuron is a simplistic representation that emulates the signal integration and threshold firing behavior of biological neurons by means of mathematical equations. Like their biological counterpart, artificial neurons are bound together by connections that determine the flow of information between peer neurons. Stimuli are transmitted from one processing element to another via synapses or interconnections, which can be excitatory or inhibitory. If the input to a neuron is excitatory, it is more likely that this neuron will transmit an excitatory signal to the other neurons connected to it as shown in fig (4) [Norsarini 2002].

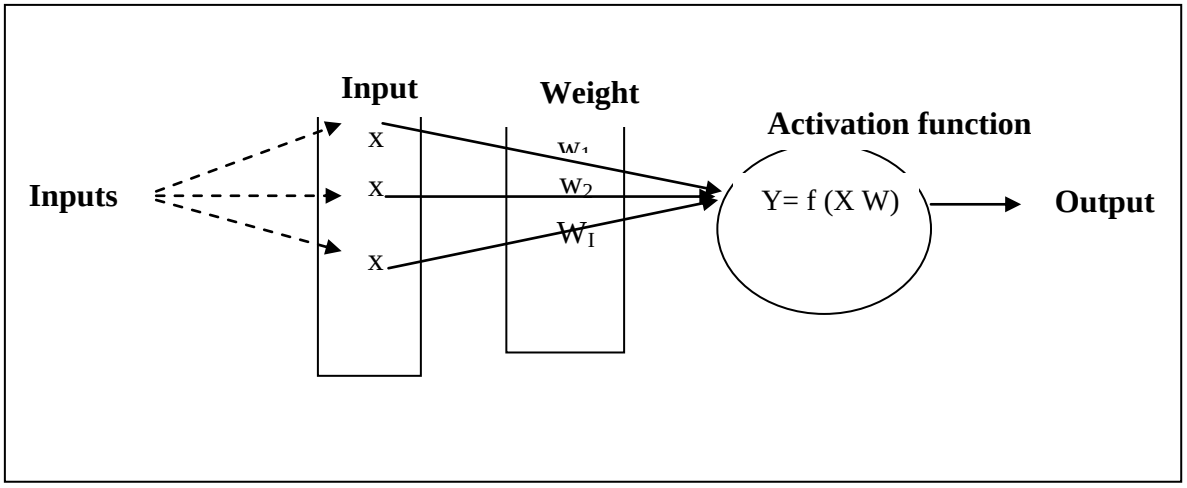


Fig. (4) Basic Model of a Single Neuron

3.1 Multilayer Perceptron Algorithm:

Multilayer perceptrons have been applied successfully to solve some difficult and diverse problems by training the network in a supervised manner with a highly popular algorithm known as the error back propagation algorithm. This algorithm is based on the error-correction learning rule and it may be viewed as its generalization. Basically, error backpropagation learning consists of two phases performed through the different layers of the network: a forward pass and a backward pass.

3.1.1: Feedforward Algorithm:

In the forward pass, a training sample (input data vector) is applied to the input nodes of the network, and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward phase, the synaptic weights of the network are all fixed [Mano and Charles 2004, Veelenturf 1995].

Step 1. Initialize weights (w) and bias (b).
(For simplicity, set weights and bias to zero.)
Set learning rate α ($0 < \alpha \leq 1$).
(For simplicity, α can be set to 1).

Step 2. While stopping condition is false, do Steps 2-6.

Step 3. For each training pair x: t, do Steps 3-5. Where (x) is input data and (t) is a desired output.

Step 4. Compute response of output unit:

$$y_{i\,in} = b_i + \sum_i x_i \; w_{ij} \qquad (8)$$

$$output_i = f(y_{i\,in}) = hard\lim(y_{i\,in}) = \begin{cases} 1 & if \; y_{i\,in} \rangle \theta \\ 0 & if \; -\theta \leq y_{i\,in} \leq \theta \\ -1 & if \; y_{i\,in} \langle -\theta \end{cases} \qquad (9)$$

3.1.2: Backward Algorithm:

Step 5. Update weights and bias if an error (e) occurred for this pattern.

$$if \quad output_i \neq t_i$$

$$e_i = output_i - t_i \tag{10}$$

$$w_{i\ j(new)} = w_{i\ j(old)} + \alpha e_i\ x_i \tag{11}$$

$$b_i\,(new) = b_i\ (old) + \alpha\ e_i \tag{12}$$

Step 6. Test stopping condition:

If no weights changed in Step 2, step; else, continue.

4. Experimental Results:

4.1 CT Image Analysis:

All image analysis was performed using an advanced cardiac CT application (comprehensive cardiac analysis (CCA)). CCA provides no-click coronary segmentation which enable automatic extraction and visualization of the entire coronary tree. Each artery and subsequent side branches can be selected for analysis. A quick measurement of the luminal stenosis in both diameter and area is available using coronary analysis where the vessel and lumen contours are calculated and displayed.

A new multineurons feature of CCA is CT plaque analysis, which provides the ability to quantify and characterize coronary arterial stenosis grades from CT exam. Once the coronary arteries have been identified and centerline automatically detected, the application then performs a complete coronary stenosis or plaque assessment using a simplified workflow with detection of findings along the vessel wall performed via a multineurons perceptron algorithm [Roland and Thomas 2006].

4.2 Multineurons Perceptron Algorithm for Coronary Stenosis Detected:

This paper used multineurons supervised perceptron algorithm, it consist of three inputs, three hidden and three output neurons so it was give eight output results which represented the grades of coronary stenosis according to our desired. The network description and structure are mention bellow.

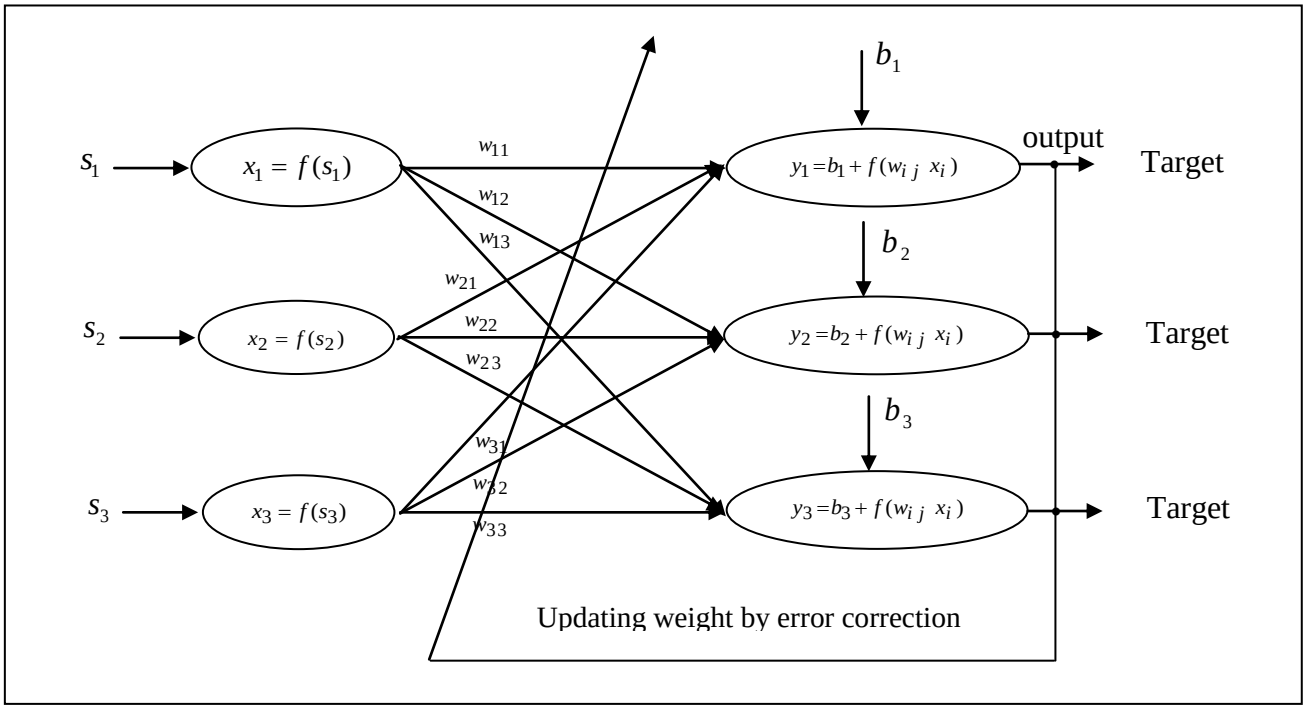


Fig. (5) Show the Multineuorns Perceptron Algorithm used to Detecting the Coronary Grades Stenosis.

Initially set the weights to zero.

$$W_{ij} = \begin{vmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{vmatrix} \quad \Rightarrow \quad W_{ij} = \begin{vmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{vmatrix}$$

Initially set the bias to one.

$$b_i = \begin{vmatrix} b_1 \\ b_2 \\ b_3 \end{vmatrix} \quad \Rightarrow \quad b_i = \begin{vmatrix} 1 \\ 1 \\ 1 \end{vmatrix}$$

Set the desired target according to the level of our design

$$(\text{Target})\, t_1 = \begin{vmatrix} 0 \\ 0 \\ 0 \end{vmatrix},\ t_2 = \begin{vmatrix} 0 \\ 0 \\ 1 \end{vmatrix},\ t_3 = \begin{vmatrix} 0 \\ 1 \\ 0 \end{vmatrix},\ t_4 = \begin{vmatrix} 0 \\ 1 \\ 1 \end{vmatrix},\ t_5 = \begin{vmatrix} 1 \\ 0 \\ 0 \end{vmatrix},\ t_6 = \begin{vmatrix} 1 \\ 0 \\ 1 \end{vmatrix},\ t_7 = \begin{vmatrix} 1 \\ 1 \\ 0 \end{vmatrix},\ t_8 = \begin{vmatrix} 1 \\ 1 \\ 1 \end{vmatrix}$$

Set the input according to the real values of cardiac CT measurement.

$$s_i\,(real\ \ input) = \begin{vmatrix} s_1 \\ s_2 \\ s_3 \end{vmatrix}$$

Set the thresholds of each input parameters (s) depend on the physician opinion.

$$\theta\ \ (threshold) = \begin{vmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{vmatrix} \quad \Rightarrow\ \theta = \begin{vmatrix} 0.35 \\ 0.25 \\ 0.2 \end{vmatrix}$$

The above threshold come from the data will illustrate bellow for many patients and for multi-Grades coronary lesion.

4.3 Standard Weights and Bias Learning Results:

Input data and desired output probability of coronary stenosis grades can be dividing to the eight classes:-

$$Class1:\left\{ x_1 = \begin{bmatrix} -1 \\ -1 \\ -1 \end{bmatrix},\ t_1 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \right\}, \qquad Class2:\left\{ x_2 = \begin{bmatrix} -1 \\ 1 \\ -1 \end{bmatrix},\ t_2 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\},$$

$$Class3:\left\{ x_3 = \begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix},\ t_3 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \right\}, \qquad Class4:\left\{ x_4 = \begin{bmatrix} 1 \\ -1 \\ -1 \end{bmatrix},\ t_3 = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \right\},$$

$$Class5:\left\{ x_5 = \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix},\ t_5 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \right\}, \qquad Class6:\left\{ x_6 = \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix},\ t_6 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \right\},$$

$$Class7:\left\{ x_7 = \begin{bmatrix} 1 \\ -1 \\ -1 \end{bmatrix},\ t_7 = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \right\}, \qquad Class8:\left\{ x_8 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix},\ t_8 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \right\},$$

The input binary values come from the compares between the real data input from cardiac CT parameters and the thresholds of each parameter according to opinion of the cardiologist.

According to use the symmetrical hard limit activation function to normalize the input from real values between [0-1] to binary values [-1 and 1]:

$$x=\begin{cases} -1, & if\ s \geq \theta \\ 1, & otherwise \end{cases} \quad where\,(s)\ is\ real input\ and\ (x)\ is\ normalize input$$

$$if\ s_1=\begin{bmatrix} 0.48 \\ 0.20 \\ 0.7 \end{bmatrix}\ compare\ with\ \theta=\begin{bmatrix} 0.25 \\ 0.25 \\ 0.55 \end{bmatrix} \Rightarrow \quad x=\begin{bmatrix} -1 \\ 1 \\ -1 \end{bmatrix}$$

Now make network training for all of coronary stenosis grades to update and get the suitable weights and the bias values by using error correction back way.

After first train of first epoch get:

$$W_1=\begin{vmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{vmatrix}, \quad b_1=\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \quad e_1=\begin{bmatrix} -1 \\ -1 \\ -1 \end{bmatrix}$$

After second train of first epoch get:

$$W_2=\begin{vmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 0 & 2 & 0 \end{vmatrix}, \quad b_2=\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \quad e_2=\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

After third train of first epoch get:

$$W_3=\begin{vmatrix} 1 & 1 & 1 \\ 0 & 0 & 2 \\ 0 & 2 & 0 \end{vmatrix}, \quad b_3=\begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}, \quad e_3=\begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

After fourth train of first epoch get:

$$W_4=\begin{vmatrix} 1 & 1 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & -1 \end{vmatrix}, \quad b_2=\begin{bmatrix} 0 \\ 2 \\ 2 \end{bmatrix}, \quad e_2=\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

After fifth, sixth, seventh and eighth trains of first epoch get:

$$W_8=\begin{vmatrix}1 & 1 & 1\\ 2 & -2 & 2\\ 2 & 2 & -2\end{vmatrix}, \quad b_5=\begin{bmatrix}0\\1\\1\end{bmatrix}, \quad e_5=\begin{bmatrix}0\\1\\1\end{bmatrix}$$

After first train of second epoch get:

$$W_1=\begin{vmatrix}1 & 1 & 1\\ 2 & -2 & 2\\ 2 & 2 & -2\end{vmatrix}, \quad b_1=\begin{bmatrix}0\\1\\1\end{bmatrix}, \quad e_1=\begin{bmatrix}0\\0\\0\end{bmatrix}$$

$$\begin{matrix}\cdot & \cdot & \cdot\\ \cdot & \cdot & \cdot\\ \cdot & \cdot & \cdot\end{matrix}$$

After seven train of second epoch get:

$$W_1=\begin{vmatrix}1 & 1 & 1\\ 2 & -2 & 2\\ 2 & 2 & -2\end{vmatrix}, \quad b_1=\begin{bmatrix}0\\1\\1\end{bmatrix}, \quad e_1=\begin{bmatrix}0\\0\\-1\end{bmatrix}$$

The training will be stop when the error corrections become zeros and there is no difference between real outputs and the desired outputs. These cases get it at eight trains in the second epoch of the recent algorithm and the final updated and suitable weights and biases become as mention bellow:

After eighth train of second epoch get:

$$W_1=\begin{vmatrix}1 & 1 & 1\\ 2 & -2 & 2\\ 2 & 2 & -2\end{vmatrix}, \quad b_1=\begin{bmatrix}0\\1\\1\end{bmatrix}, \quad e_1=\begin{bmatrix}0\\0\\0\end{bmatrix}$$

Ant the time of processing is 0.488458 second.

4.4 Case Studies:

Case 1 (Intermediate Grade):-

A 64-year-old female presented at the emergency room with chest pain and prior medical history.

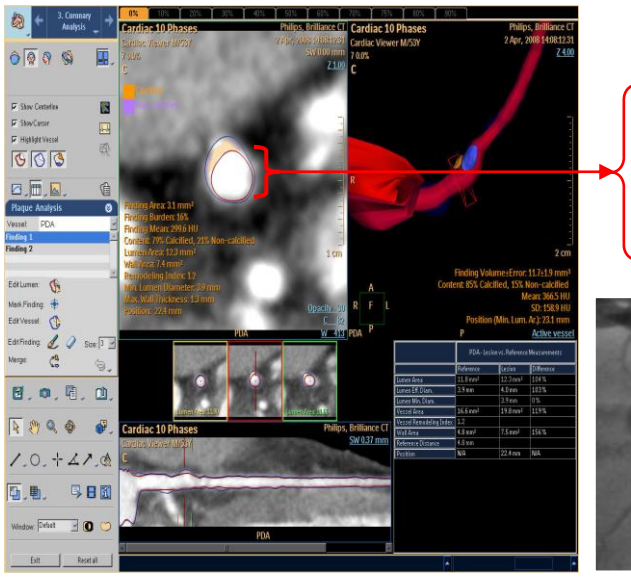


Fig (6a) Coronary Image from Cardiac CT

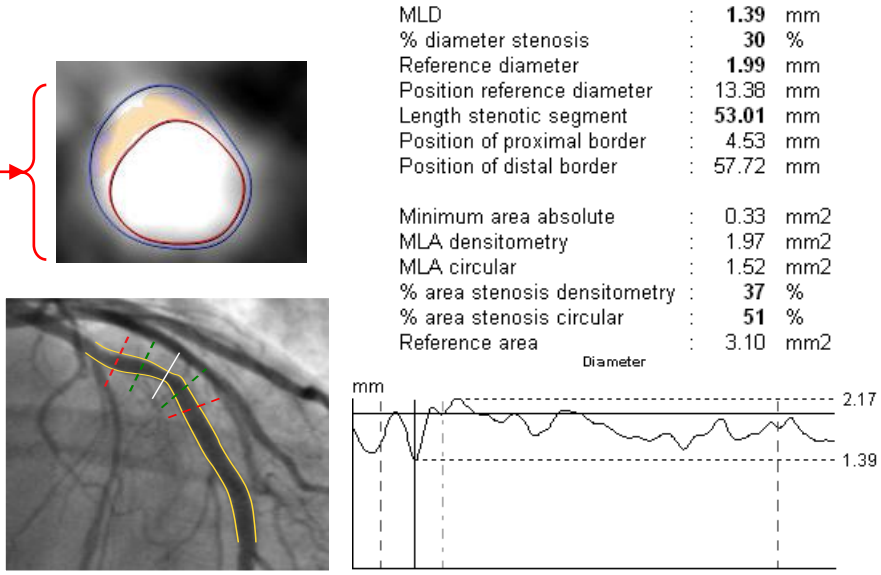


Fig (6b) Measurements of CT Parameters

From the measurements above can be calculating the stenosis parameters as follow:-

**** MDS Parameter:-***

- MLD (Minimum Lumen Diameter = Minimum Lesion Diameter) = 1.39 mm.
- RD (Reference Diameter) = 1.99 mm.
- MDS (Minimum Diameter Stenosis) = (1.99 – 1.39) /1.99 *100% = 30 %

**** LAS Parameter:-***

- MLA (Minimum Lumen Area Densitometry = Min. Lesion Diameter) = 1.97 mm^2.
- RA (Reference Area) = 3.10 mm^2.
- MDS (Minimum Diameter Stenosis) = (3.10 – 1.97)/3.10 *100% = 37 %

**** EAS Parameter:-***

- MLA (Minimum Lumen Area Circular = Min. Lesion Area Circular) = 1.52 mm^2.
- RA (Reference Area) = 3.10 mm^2.
- EAS (Effective Area Stenosis) = (3.10 – 1.52)/3.10 *100% = 51 %

That is mean the real inputs s_i of the above case are $\begin{bmatrix} 0.37 \\ 0.30 \\ 0.51 \end{bmatrix}$

And if compare with the thresholds $\theta = \begin{bmatrix} 0.25 \\ 0.25 \\ 0.55 \end{bmatrix}$ $\Rightarrow$ $x_1 = \begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix}$

Then the patient case is intermediate coronary grade according to our designed categories of stenosis mention in the table bellow:-

Table (1) Show the Levels of Grades Coronary Stenosis or Diseases.

Parameters	Lumen Area Ste. LAS	Min. Diameter Ste. MDS	Effective Area Ste. EAS	Target
Threshold separating between Mild and Complex Stage	$\theta 1$ Depend on Doctor	$\theta 2$ Depend on Doctor	$\theta 3$ Depend on Doctor	
Input Normalize (-1,1) -1 = abnormal 1 = normal	$x_1 = \begin{cases} -1 \ if \ s_1 \geq \theta 1 \\ 1 \ if \ s_1 < \theta 1 \end{cases}$	$x_2 = \begin{cases} -1 \ if \ s_2 \geq \theta 2 \\ 1 \ if \ s_2 < \theta 2 \end{cases}$	$x_3 = \begin{cases} -1 \ if \ s_3 \geq \theta 3 \\ 1 \ if \ s_3 < \theta 3 \end{cases}$	$target = \begin{cases} 1 \ if \ net \geq 0 \\ 0 \ if \ net < 0 \end{cases}$
Probability of desired Results (Level of Stenosis Grades)				
Grade 1	-1	-1	-1	0 0 0
Grade 2	-1	1	-1	0 0 1
Grade 3	-1	-1	1	0 1 0
Grade 4	1	-1	-1	0 1 1
Grade 5	-1	1	1	1 0 0
Grade 6	1	1	-1	1 0 1
Grade 7	1	-1	1	1 1 0
Grade 8	1	1	1	1 1 1

- Yellow Color means Mild Stage
- Brown Color means Intermediate stage
- Red Color means Complex stage

Note: Grades categories can be change according to physician opinion depend on its experiences, for example (level 1 is Mild grade, levels 2-4 are Intermediate grades and levels 5-8 are Complex grades)

Case 2 (Detected as Mild Grade):-

A 56-year-old male presented at the emergency room with chest pain and no prior medical history.

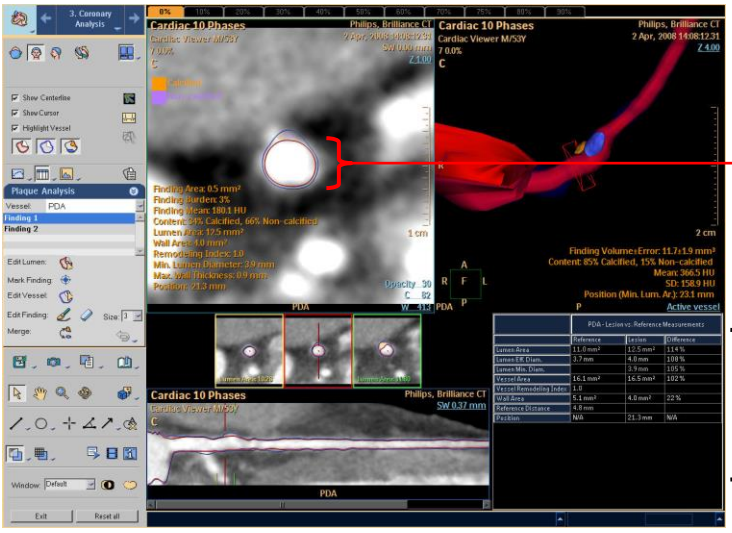
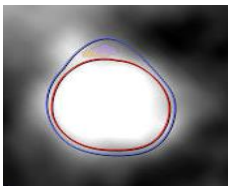


Fig (7a) Coronary Image from Cardiac CT

Fig (7c) cross section of mild coronary stenosis



	PDA - Lesion vs. Reference Measurements		
	Reference	Lesion	Difference
Lumen Area	11.0 mm²	12.5 mm²	114 %
Lumen Eff. Diam.	3.7 mm	4.0 mm	108 %
Lumen Min. Diam.		3.9 mm	105 %
Vessel Area	16.1 mm²	16.5 mm²	102 %
Vessel Remodeling Index	1.0		
Wall Area	5.1 mm²	4.0 mm²	22 %
Reference Distance	4.8 mm		
Position	N/A	21.3 mm	N/A

Fig (7b) Measurements of Input Parameters

Case 3 (Detected as Complex Grade):-

A 59-year-old male was hospitalized due to several attacks of severe chest pain over a three-week period.

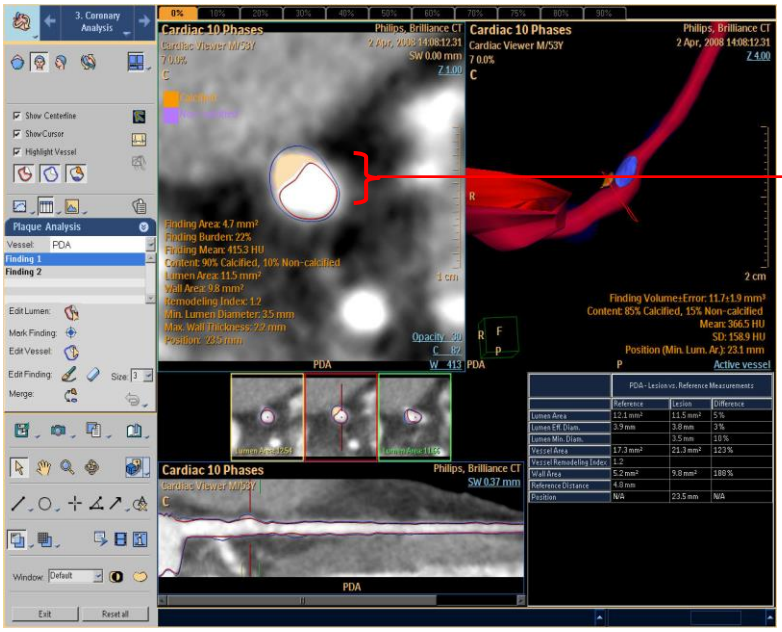
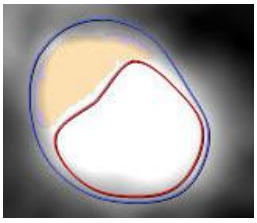


Fig (8a) Coronary Image from Cardiac CT

Fig (8c) cross section of Complex coronary stenosis



	PDA - Lesion vs. Reference Measurements		
	Reference	Lesion	Difference
Lumen Area	12.1 mm²	11.5 mm²	5 %
Lumen Eff. Diam.	3.9 mm	3.8 mm	3 %
Lumen Min. Diam.		3.5 mm	10 %
Vessel Area	17.3 mm²	21.3 mm²	123 %
Vessel Remodeling Index	1.2		
Wall Area	5.2 mm²	9.8 mm²	188 %
Reference Distance	4.8 mm		
Position	N/A	23.5 mm	N/A

Fig (8b) Measurements of Input Parameters

5. Discussions

The multineurons preceptron algorithm of accuracy (93%), with its simplified workflow, provides physician with plaque (stenosis) information, including the location and morphology. As the case studies demonstrate, CT based stenosis indices agree with the finding of coronary stenosis grades. This type of information could potentially be useful in risk stratifying patients with sub-clinical cardiovascular disease and may guide preventive treatment. However, the clinical values of these

new tools with have to be confirmed by randomized trials proving a prognostic value of such early risk stratification. Consequently, they must still be regarded as experimental at this stage.

In addition, these tools may enable the evaluation of different therapeutic strategies to prevent future development of sub-clinical disease. For research purpose, MPA in cardiac CT provides an excellent way to standardize the evaluation of different coronary stenosis type.

6. Conclusions

From the results obtain if we want to increase the accuracy of results, increase the parameters of algorithm input (CT measurements) like patient symptoms (pain, age and history …etc). This algorithm help in future understanding the morphology and the underlying composition of significant and non-significant stenosis lesions. These lesions can be interrogated to provide additional information on the entire disease state of the patient, and may guide further prevention and treatment options, which will hopefully prevent future adverse cardiovascular events.

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