NEURAL NETWORK APPROACH TO DIAGNOSIS OF CORONARY ARTERY DISEASE IN NUCLEAR MEDICINE

H. Bagher-Ebadian [1,2,3], H. Soltanian-Zadeh [3,4], S. Setayeshi [1]

[1] Department of Physics, Amir-Kabir University of Technology, Tehran, Iran

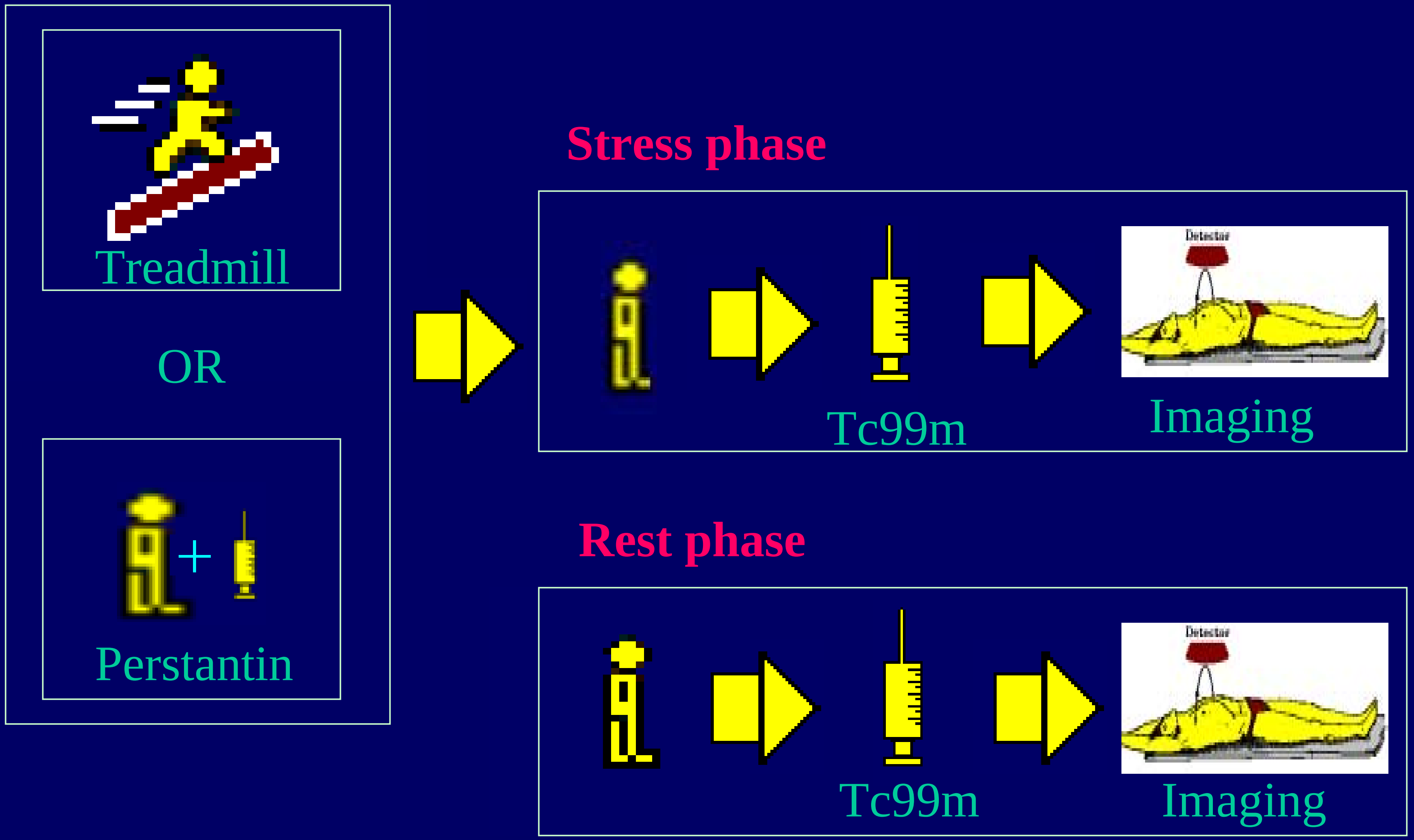
[2] Research Institute of Nuclear Medicine, Shariati Hospital, Tehran, Iran

[3] Radiology Image Analysis Lab, Henry Ford Health System, Detroit, MI 48202, USA

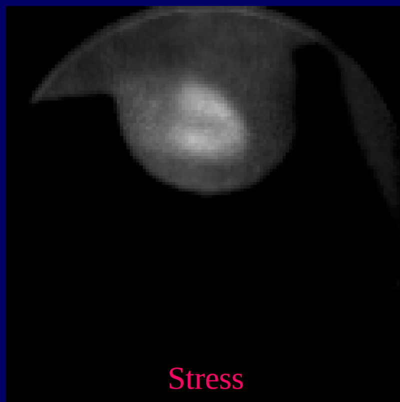
[4] Department of Electrical and Computer Engineering, Tehran University, Tehran 14399, Iran

- Myocardial Imaging in Nuclear Medicine
- Myocardial Projections
- Myocardial Perfusion
- Patient Population
- Angiogram As a Gold Standatrd for Training of ANN
- Myocardial Segmentation Using Fuzzy Clustering Approach
- Polar Transform
- Feature Extraction
- ANN As an Observer
- Validation and Testing
- ROC Analysis
- Summary and Conclusion
- Future Works

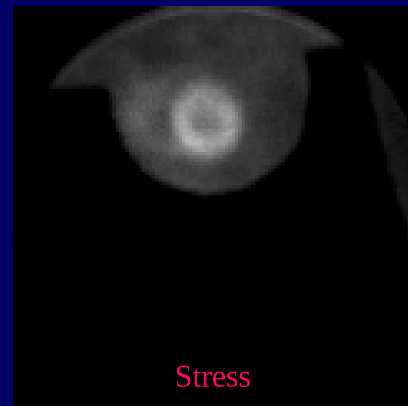
Myocardial Imaging in Nuclear Medicine



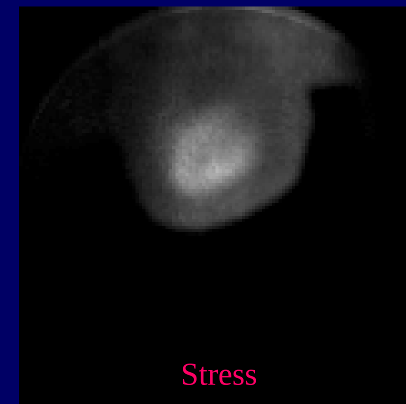
Three Projections in Stress and Rest Phases



Anterior



Left-Anterior Oblique 45



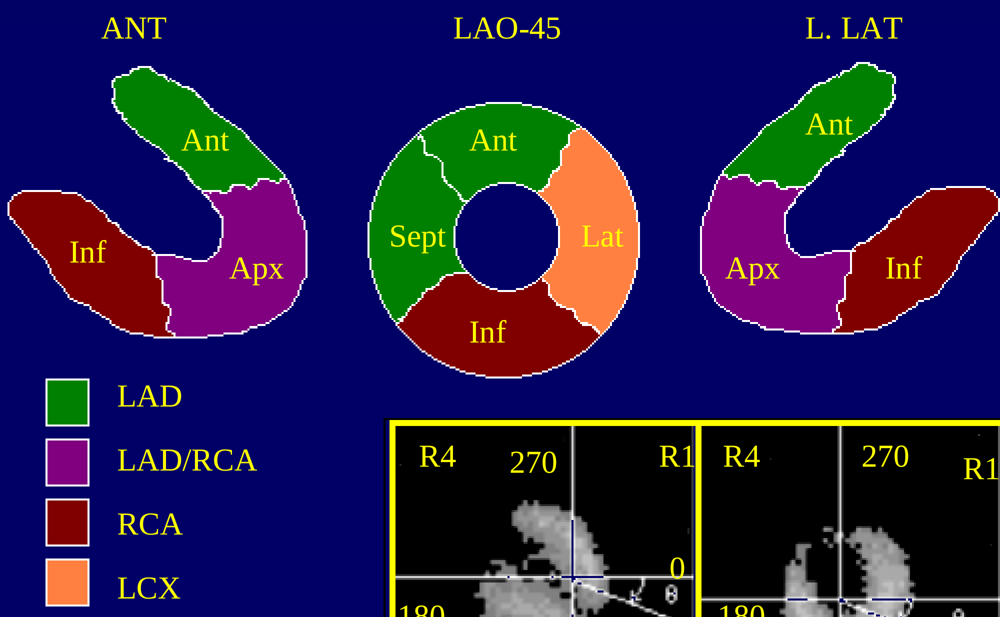
Left-Lateral

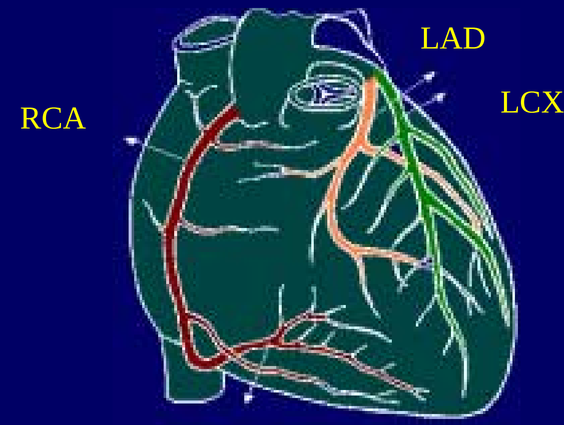
Anterior

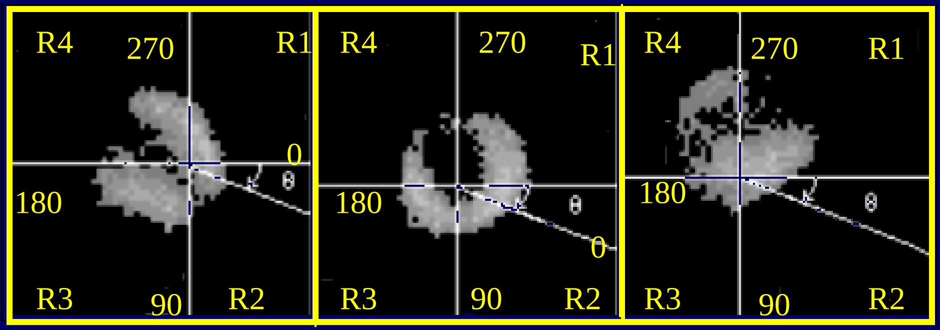
Left-Anterior Oblique 45

Left-Lateral

Myocardial Perfusion Regarding Three Major Coronary Arteries: LAD-RCA-LCX







Projection	Region 1	Region 2	Region 3	Region 4
Anterior	Antero-Apical	Apex	Inferior	Base
Left Anterior Oblique 45	Antero-Lateral	Infero-Lateral	Infero-Spetal	Antero-Spetal
Left Lateral	Infero- Basal	Inferior	Infero-Apical	Anterior

Patient Population and Diagnosis of Physicians Ward (Positive Or Negative) Regarding Their Angiograms

	True-Positive	True-Negative	False-Positive	False-Negative
Male	10	6	8	6
Female	12	4	7	5
Total	22	10	15	11

Table 1

Training Diagram for Neural Network

Rest Three Projections

Stress Three Projections

Myocardial Segmentation and Noise Reduction Using Fuzzy Clustering Approach

Feature Extractor

Artificial Neural Network

Angiogram as a gold standard

Myocardial Segmentation

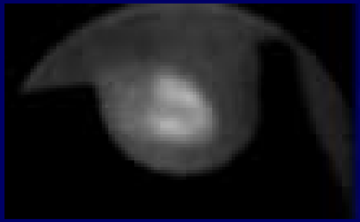
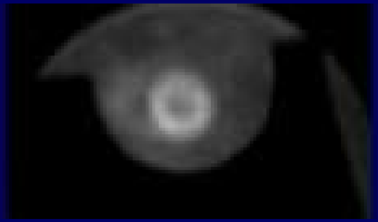
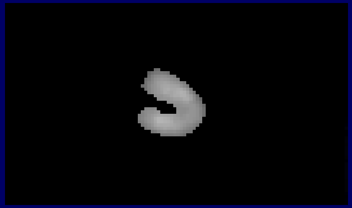
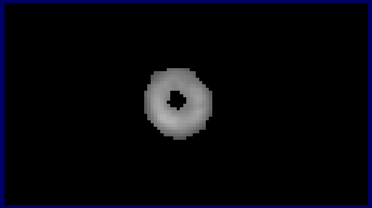
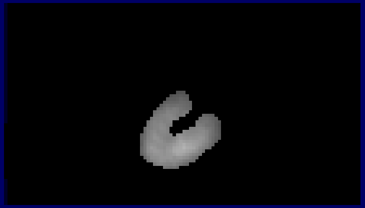
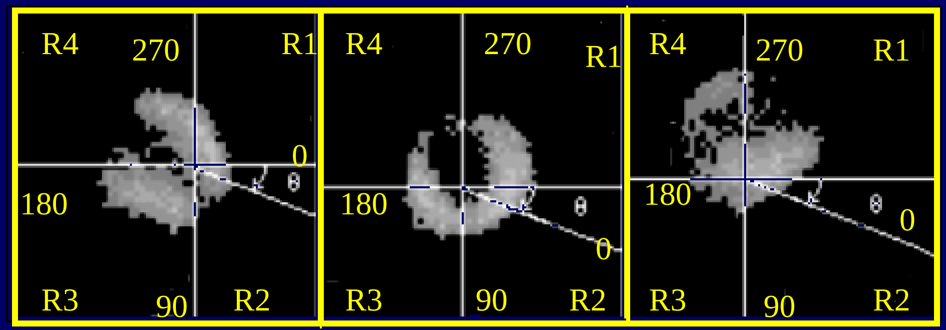
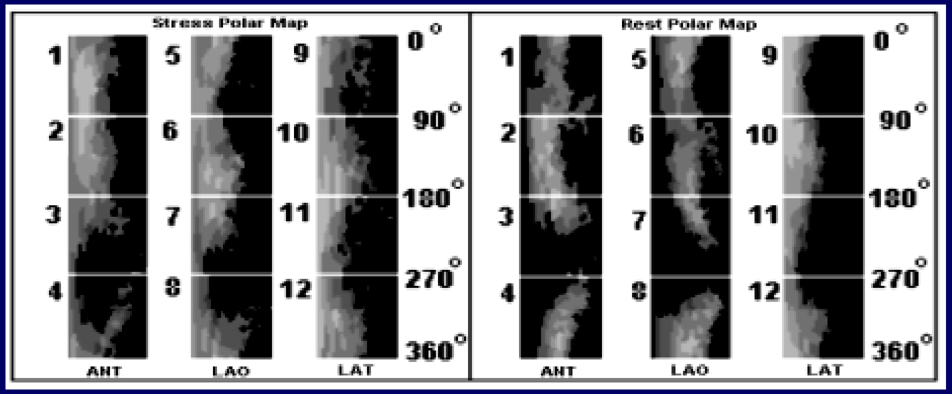
  

Image Segmentation Using Fuzzy Clustering Approach



Polar Transform Around The Center Of Mass



Feature Extraction

$\vec{\mu}_p = [\mu_p^1, \mu_p^2, \mu_p^3 .... \mu_p^{12}]$ denotes the mean vector obtained from phase *p* (stress or rest).

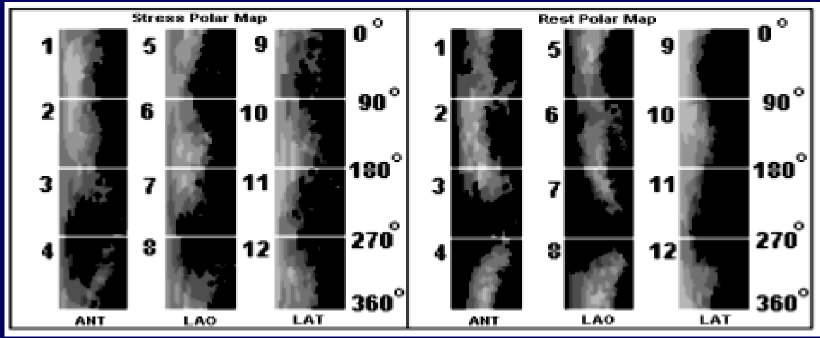
$$\mu_p^m = \frac{1}{A_p^m} \sum_i \sum_j H_p^m(i,j) \quad , \qquad 1 \le m \le 12$$

$\vec{H}_p(i,j)$ points out to the amount of count in position *(i,j)* in polar image for phase *p*

$$A_p^m = \sum_i \sum_j I_p^m(i,j)$$

$$I_p^m(i,j) = \begin{cases} 1, & H_p^m(i,j) \neq 0 \\ 0, & H_p^m(i,j) = 0 \end{cases}$$

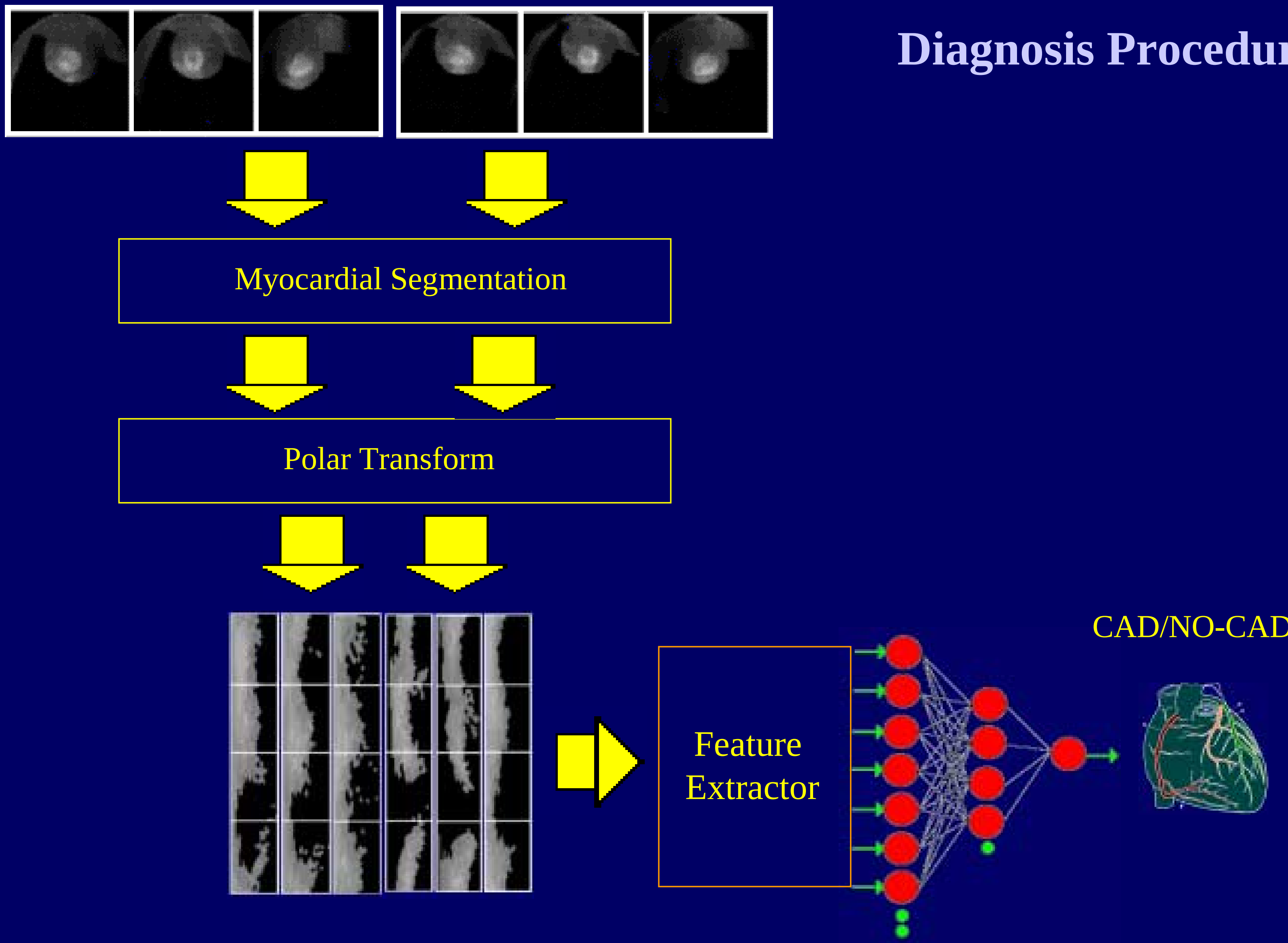
$$\Sigma_p^m = \frac{1}{A_p^m} \sum_i \sum_j [H_p^m(i,j) - \mu_p^m]^2 \quad , \qquad 1 \le m \le 12$$



Feature Extractor

$$\Delta\vec{\mu} = [\mu_R^1 - \mu_S^1, \mu_R^2 - \mu_S^2, \mu_p^3 .... \mu_R^{12} - \mu_S^{12}]$$

Diagnosis Procedure



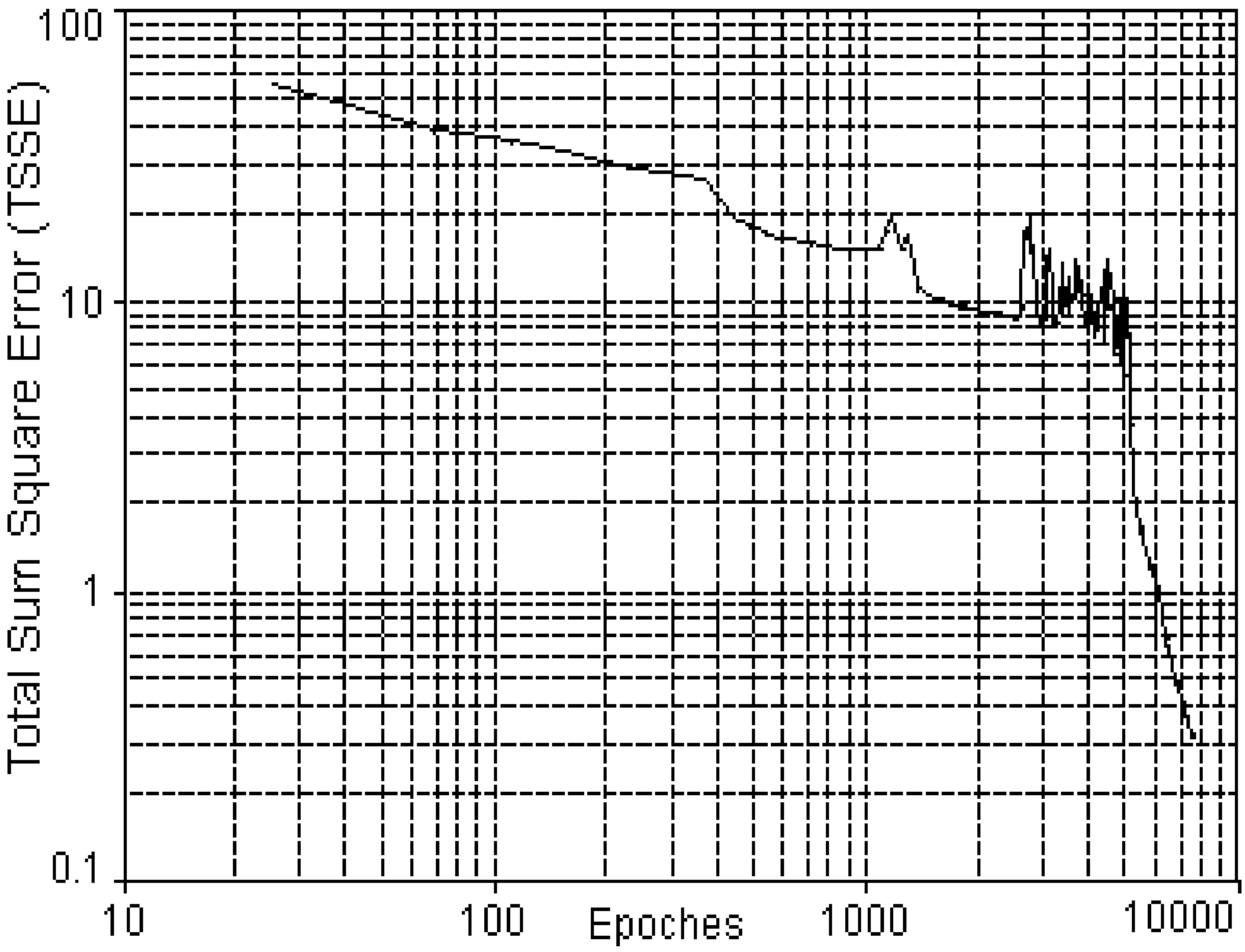


Figure 1. Total Sum Square Error Versus Epoches (13:5:1).

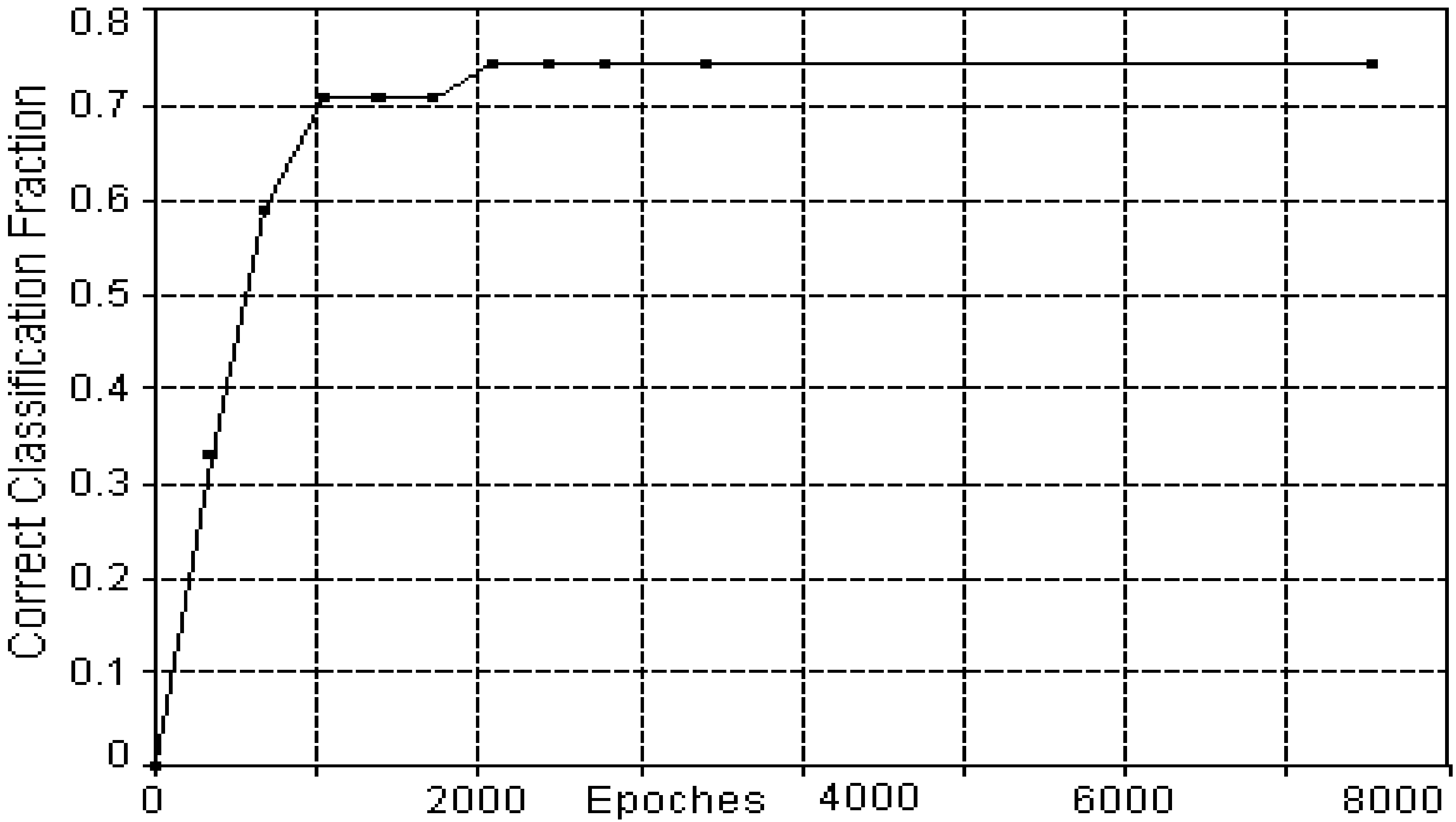


Figure 2. Correct Classification Fraction Versus Epoches for Optimal ANN (13:5:1)

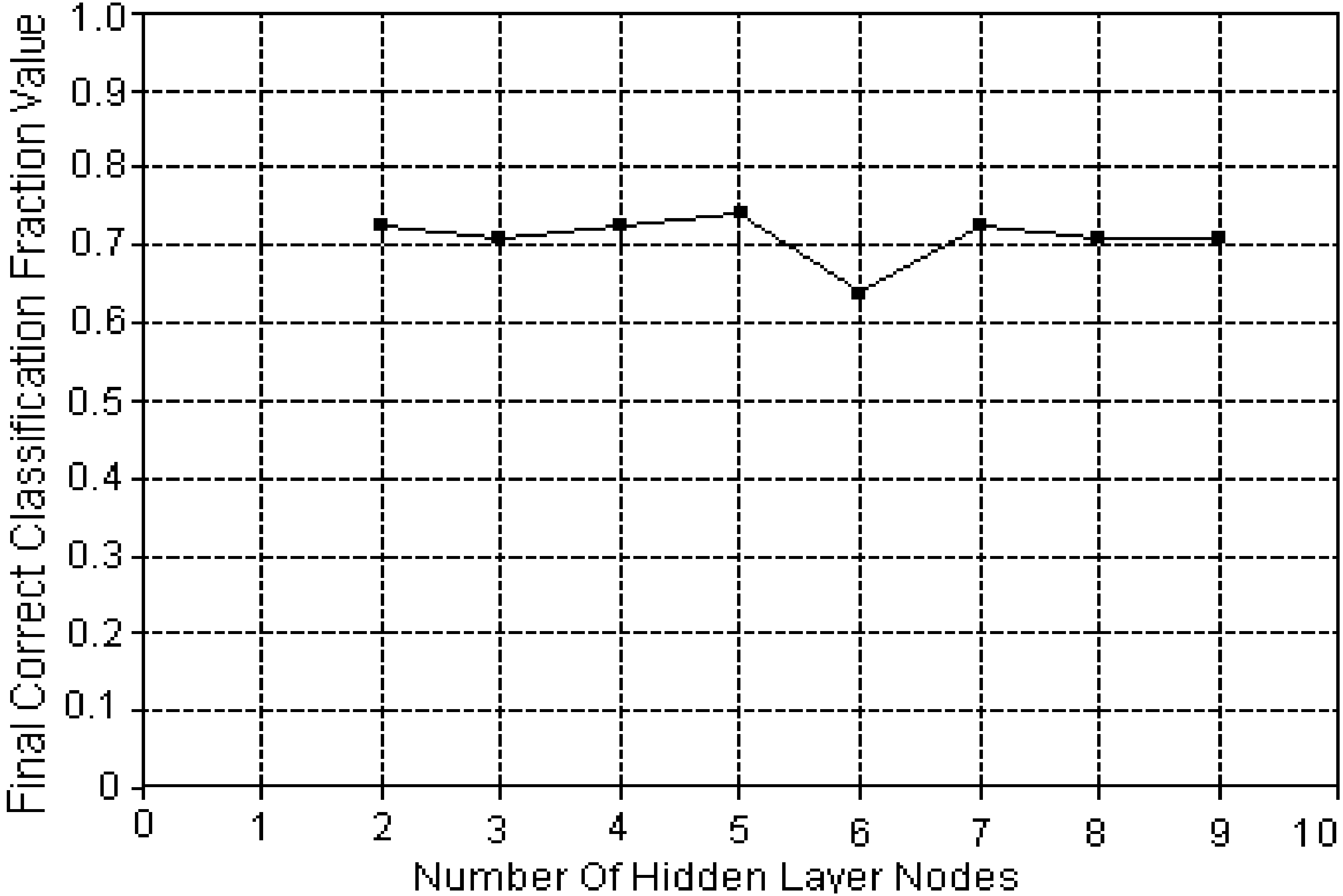


Figure 3. Hidden Layer Node Optimization Using Final Correct Classification Value.

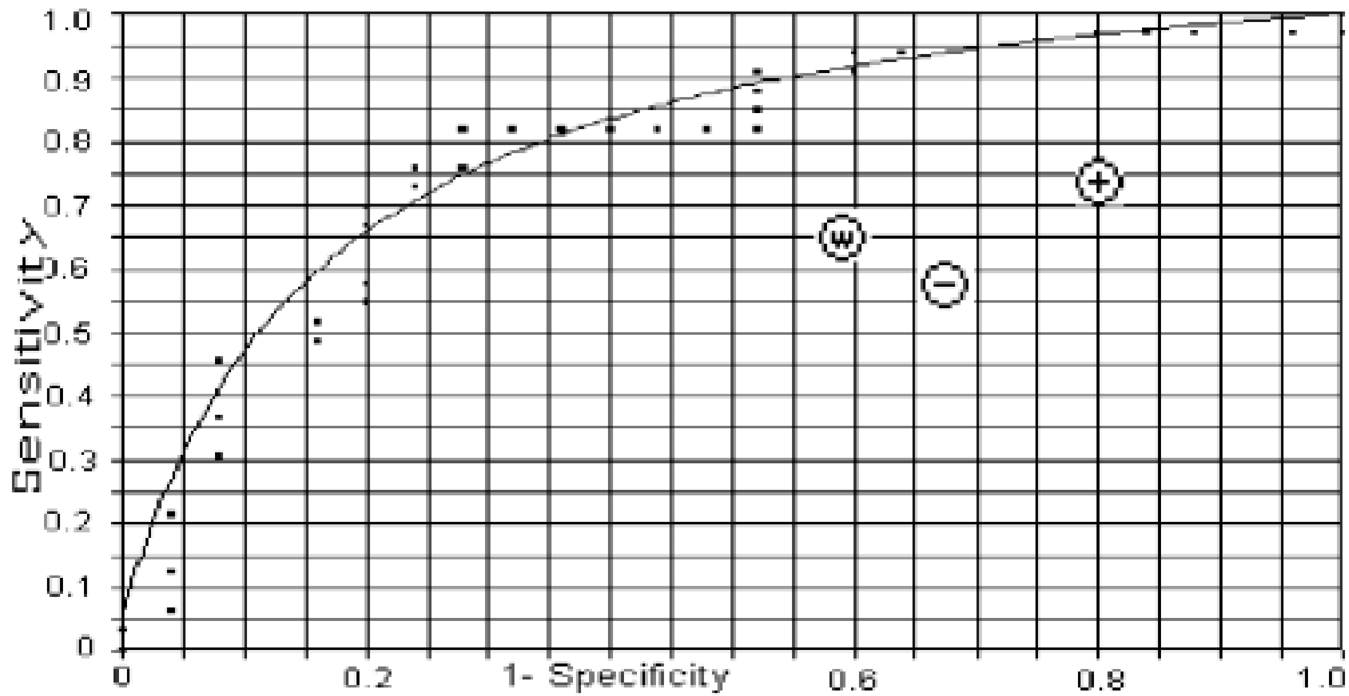


Figure 4 . Receiver Operator Characteristic curve for the optimal ANN, with points representing the physician's performance.

Ⓦ Nuclear Medicine Ward: TPF: 0.66, FPF: 0.60

⊕ Expert (Physicien) No.1: TPF: 0.75, FPF: 0.80

⊖ Expert (Physicien) No.2: TPF: 0.60, FPF: 0.68

- Sensitivity measures how frequently the test is positive in the population with disease
- Specificity measures how frequently the test is negative in the population without the disease
- Prevalence is the pro-portion of the population with disease

$$Sensitivity = P(T+ \mid D+) = TPF = \frac{TP}{TP + FN}$$

* The Disease is present: designated D+
* The Disease is absent: designated D-
* The Test is positive: designated T+
* The Test is negative: designated T-

$$Specificity = P(T- \mid D-) = TNF = \frac{TN}{TN + FP}$$

$$\text{Prevalence} = P(D+) = \frac{TP + FN}{TP + FP + TN + FN}$$

- Using the rules for inverting probability, we can compute the probability of disease or non-disease under conditions of various test outcomes to determine the test’s predictive value

$$\mathrm{P(D+\,|\,T+)} = \text{Positive Predictive Value} = \frac{TP}{TP+FP} = \frac{P(T+\,|\,D+)P(D+)}{P(T+\,|\,D+)P(D+)+P(T+\,|\,D-)P(D-)}$$

$$\text{PPV(Positive Predictive Value)} = \frac{(Sensitivity)(\text{Prevalence})}{(Sensitivity)(\text{Prevalence})+(1-Sensitivity)(1-\text{Prevalence})}$$

$$\mathrm{P(D-\,|\,T-)} = \text{Negative Predictive Value} = \frac{TN}{TN+FN} = \frac{P(T-\,|\,D-)P(D-)}{P(T-\,|\,D-)P(D-)+P(T-\,|\,D+)P(D-)}$$

$$\text{NPV(Negative Predictive Value)} = \frac{(Specificity)(1-\text{Prevalence})}{(Specificity)(1-\text{Prevalence})+(1-Sensitivity)(\text{Prevalence})}$$

Positive Predictive Values and Negative Predictive Values for Nuclear Medicine Ward, Expert #1, Expert #2 at Prevalence of 0.568 corresponding Sensitivity and Specificities.

	Specificity	**Sensitivity**	**Positive Prediction Value**	**Negative Prediction Value**
Ward	**0.40**	**0.66**	**59%**	**60%**
ANN-Ward	**0.40**	**0.92**	**67%**	**80%**
Expert #1	**0.20**	**0.75**	**55%**	**70%**
ANN-Expert #1	**0.20**	**0.97**	**52%**	**84%**
Expert #2	**0.32**	**0.6**	**54%**	**53%**
ANN-Expert #2	**0.32**	**0.95**	**65%**	**83%**
ANN-Optimum	**0.72**	**0.72**	**80%**	**68%**

Table 2

Summary and Conclusions

- **Our attempt to apply neural network for CAD detection in nuclear medicine has been quite successful in acute phase of myocardial infarction.**
- **The proposed approach is more appropriate than the optimal detection theory because the complexity of anatomical structures and noise for nuclear medicine images makes the estimation of probability density functions of the two classes of images extremely difficult.**
- **The ANN proved to be capable of extracting essential characteristics from noisy images and learning from angiograms.**
- **The recognition performance of the optimal ANN is superior to that of the experienced physicians (see Table 3).**
- **As shown in Table 3, the ANN detects CAD in myocardial planar images more accurately than the expert physicians and nuclear medicine ward.**

	Specificity	Sensitivity
ANN-Ward	0.40	0.92
ANN-Expert #1	0.20	0.97
ANN-Expert #2	0.32	0.95
ANN-Optimum	0.72	0.72

Table 3

Future works.

- This method may be applied to SPECT images using three spot views (ANT, LAO45, Lt. LAT) from series of images in each phase and liver patterns may be separated from each spot by manual or semi-automated methods.

- The six spot views should be selected based on LV-orientation using manual or semi-automated methods. Sets of the six views in the rest and stress can be used as the input of the proposed method for pre-diagnosis of CAD.

- The proposed method deals with the basic aspects for pre-diagnosis of either CAD or no-CAD in nuclear medicine images and it can be adapted for the analysis of SPECT images to create an ideal observer. By ideal observer, we mean a neural-network-assisted system to help physicians improve their diagnosis.

- Accurate determination of the location and amount of the disease using the techniques developed in this paper may be considered as a direction for future work.

- Another direction can be finding of the optimal set of myocardium segments, which are more sensitive compared to the other sets for detection of CAD. This optimization can be done for offset location and number of myocardium segments.