International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-7 Issue-6C, April 2019

Different Approaches of ANN for Detection of Cancer

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Abstract: Lung cancer is a very serious disease in current time. If cancer is detect its early stage, and then survival rate of patient is increase. Here a system is designed for detecting lung cancer in early stage .this system is consist of two major phases first is digital image processing techniques for enhance the quality and appearance of the image and the second one is apply neural network techniques for classifications of cancer. The system works as. First image is enhanced using image enhancement techniques, then suspected region for tumor part is detected using various region growing algorithms, when the suspected region is detected then based on that region 25 features is calculated using GLCM. Then classify them using back propagation and radial bias neural network approaches. Comparison of both the Ann techniques for classification radial bias gives better accuracy.

Index Terms: About four key words or phrases in alphabetical order, separated by commas.

I. INTRODUCTION

Digital image processing is a very good technique to just for prediction of tumor part.it consists of many operations and function by which image clarity is good and further operation on images will effective. Neural network architecture is having decision capability same as human brain and that is same as nervous system **.**larger number of neurons highly interconnected to perform a task. Tasks are depends upon classification and estimtions.to create a system using with Ann have some mathematical model and programming concepts. This study motivates us to find early stages tumor to increases survival rate of patient. This CAD system is efficient because it take minimum time to detect weather the patient has cancer or not. This paper presents a system for find the suspected reign for lung cancer using CT images. Image processing and ANN algorithms are used for this purpose. Mainly two ANN approaches are used. BPNN and Radial Bias Function NN. This method is further applied for different cancer detection. in this methods gray level image is used but in future color images be considered.

II. LITRATURE REVIEW

Cinar Murat et al **(**2009) study for design a classifier of early diagnosis of cancer without biopsy. There are 300 samples were collected. Various feature are (weight, height, age, volume, density, pulse and gleason score) calculated. For classification following classifier was used: SCG, Broyden-Fletcher Glodfarb Shannon and Levenberg Marquardt training algorithms for neural network works and linear, polynomial and Radial Based Kernel method of SVM. The proposed system gives best performance with radial basis kernel function with 79% accuracy.

Abinav Vishwa (2011) proposed a two classification method algorithm for detection of lung cancer that is FFNN and BPN. In this methodology is form of 0 and 1, if the patient has cancer then input is taken 1 otherwise 0.transfer function is sigmoid.

TAN Shanjun et al (2012) proposed a CAD system by using an ANN combine with tumor markers with some clinic methods. A total of 140 samples are obtained. Neural network with BP algorithms were performed. The model was developed by NN was implemented by sigmoidal method. The 5 tumor values were then used as ANN input data. Throughput of ANN and detrimental analysis among all samples of the test group was 95.5 % and 73.3%, respectively. ANN is a better choice than the traditional method for differentiating hepatic carcinoma.

Vijay Gajdhane and Deshpandey (2014) proposed CAD system for detection of lung cancer containing some image enhancement approaches. As enhancement and segmentation techniques for classification SVM is used. Three features are extracted, that gives basic idea about size of tumor. The result shows tumor is different dimensions, based on dimension tumor size can be calculated.

III. PROPOSED WORK

A. Data Acquisition: for the analysis of system here i use 500 images. Which i have taken from different source

B. Preprocessing: Median Filter Is Preferred Because It Give Better Result In Sharpening Of Edges, Image Enhancement Techniques Is Using For Enhance The Quality Of Image. After that Segmentation is processed.

C. Extraction of ROI: using region growing algorithms detects the suspected region for tumor from the image.

D. Feature extraction: from the ROI part detect some feature using GLCM approaches. For the purpose of classification. Larger number of features also needs high computations. Analysis of feature and its extraction is highly required sides of machine task.

E. CLASSIFICATION: Two algorithms BP neural network and radial bias NN algorithms were used

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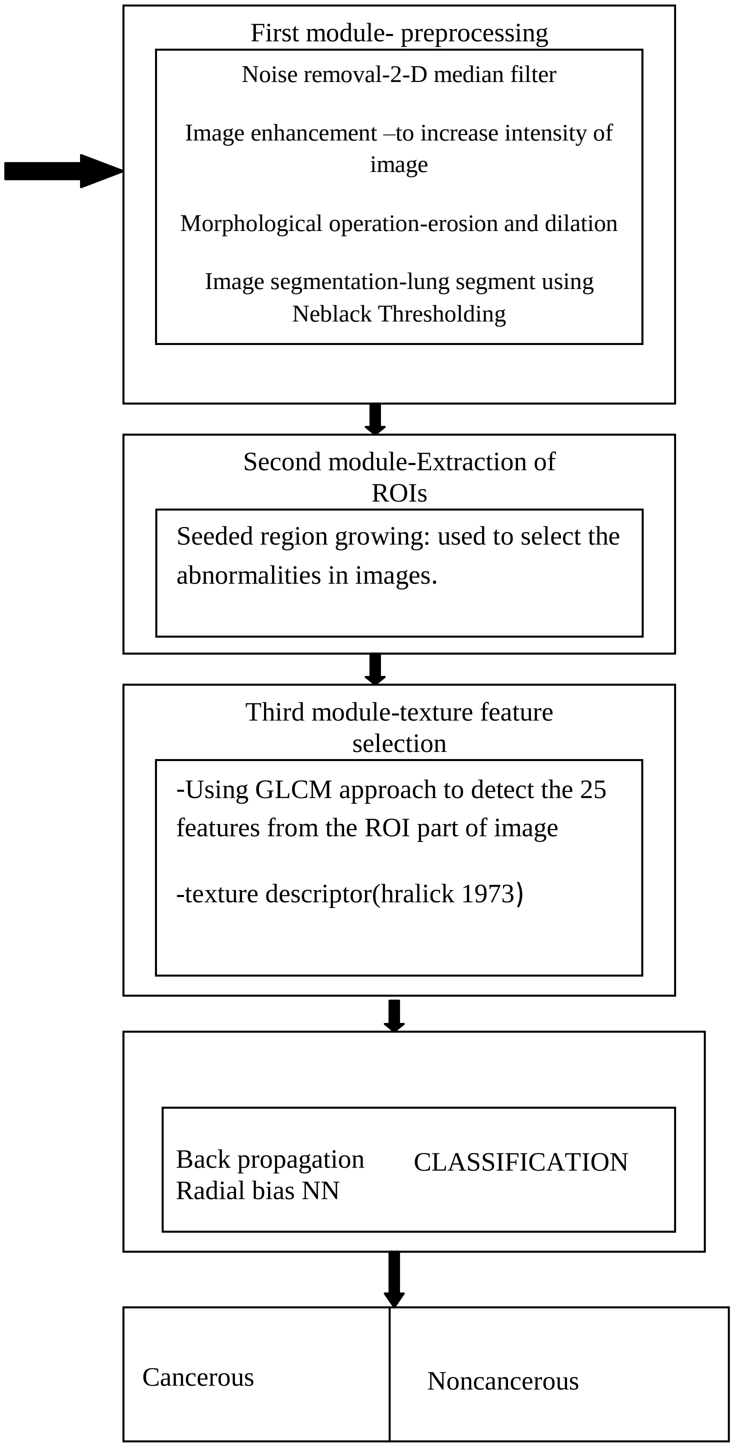

Fig. 1 Proposed work

Table1: Data source

Data source	Cancerous samples	Noncancerous samples	Total database
PGI Chandigarh, India	120	180	300
University of medical college,Srinagar,UK,INDIA	155	45	200
Total samples	275	225	500

GLCM (Gray level covariance Matrix) is used for extract the features. There are some features which calculate as:

Table2: Features Calculation

S.N	Features calculated	Formulas
1	Area	Total no of white pixals in ROI
2	Standard deviation	$\sigma_x = \sum_i \sum_j (i-\mu_x)^2 . p(i,j)$ $\sigma_y = \sum_i \sum_j (j-\mu_y)^2 . p(i,j)$
3	Auto correlation	$\sum_i \sum_j (ij) p(i,j)$
4	contrast	$\sum_{n=0}^{N_g-1} n^2 \{\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j), \lvert i-j\rvert = n\}$
5	correlation	$\sum_i \sum_j \frac{(i,j)p(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$
6	Correlation: MATLAB	$\sum_{i,j} \frac{(i-\mu_x)(j-\mu_y)p(i,j)}{\sigma_x\sigma_y}$
7	Cluster Prominence	$\sum_i \sum_j (i+j-\mu_x-\mu_y)4\, p(i,j)$
8	Cluster shade	$\sum_i \sum_j (i+j-\mu_x-\mu_y)3\, p(i,j)$
9	Dissimilarity	$\sum_i \sum_j \lvert i-j\rvert . p(i,j)$
10	Energy	$\sum_i \sum_j \{p(i,j)^2\}$
11	Entropy	$\sum_i \sum_j p(i,j) log(p(i,j))$
12	Homogeneity	$\sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j)$
13	Homogeneity: MATLAB	$\sum_{i,j} \frac{p(i,j)}{1+\lvert i-j\rvert}$
14	Maximum probability	$MAXP(i,j)$
15	Sum of squares: variances	$\sum_i \sum_j (i-\mu)^2 p(i,j)$
16	Sum average	$\sum_{i=2}^{2N_g} i p_{x+y}(i)$
17	Sum variance	$\sum_{i=2}^{2N_g} (i-S_{ent})^2 p_{x+y}(i)$
18	Sum entropy	$-\sum_{i=2}^{2N_g} p_{x+y}(i) log\{p_{x+y}(i)\} = S_{ent}$
19	Difference variance	$\sum_{i=0}^{N_g-1} i^2 p_{x-y}(i)$
20	Difference entropy	
21	Information measure of correlation1	$\frac{HXY-HXY1}{max\{HX,HY\}}$
22	Information measure of correlation2	$(1-exp[-2(HXY2-HXY)]^{1/2}$
24	Inverse difference normalized (INN)	$\sum \frac{c(i,j)}{1+\lvert i-j\rvert}$ where c(I,j) is cooccurance probability between gray level(I and j) define as: $c(i,j) = \frac{p(i,j)}{\sum_{i,j=1}^{G} p(i,j)}$
25	Inverse difference moment normalized	$\sum \frac{C_{ij}}{1+\lvert i-j\rvert}$

IV. PERFORMANCE EVOLUTION

These are the factors by which performance is calculated.

Table3: Performance Matrices

Performance measure	Definitions
TP	Images are cancerous by a biopsy, which is also classified as cancerous by the system.
TN	Images are noncancerous by a biopsy, which is also classified as noncancerous by the system.
FP	Images are cancerous by a biopsy, which is classified as noncancerous by the system.
FN	Images are non-cancerous by a biopsy, which is classified as cancerous by the system.

V. EXPERIMENTAL RESULT

These are the results of system for single image.

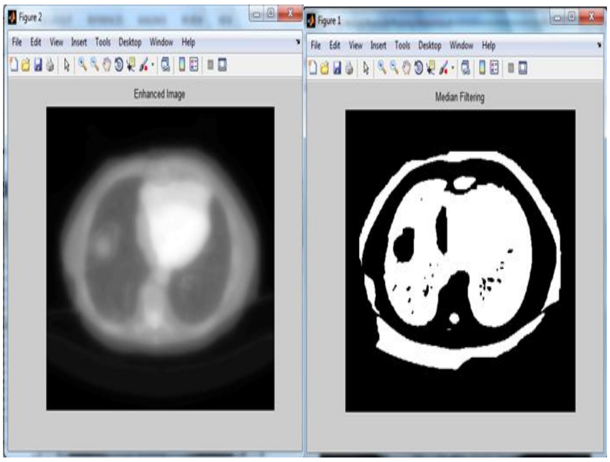

Fig. 2 (a) and (b)

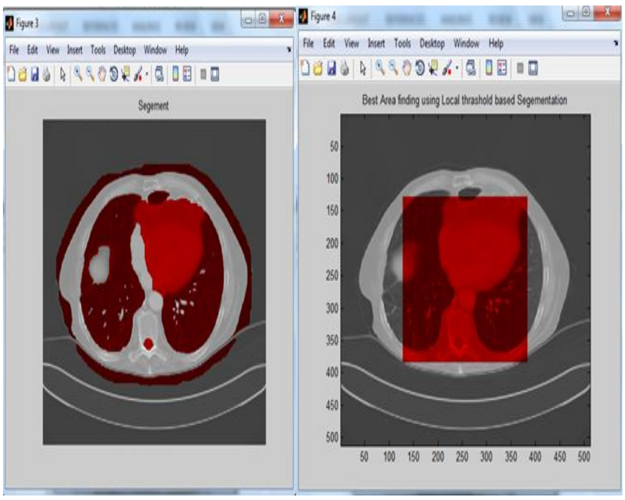

Fig. 2 (c) and (d)

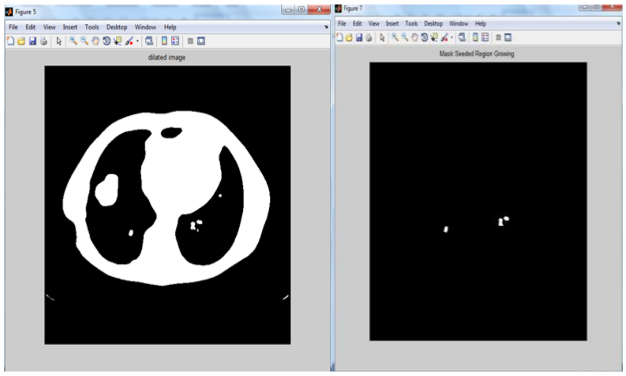

Fig. 2 (e) and (f)

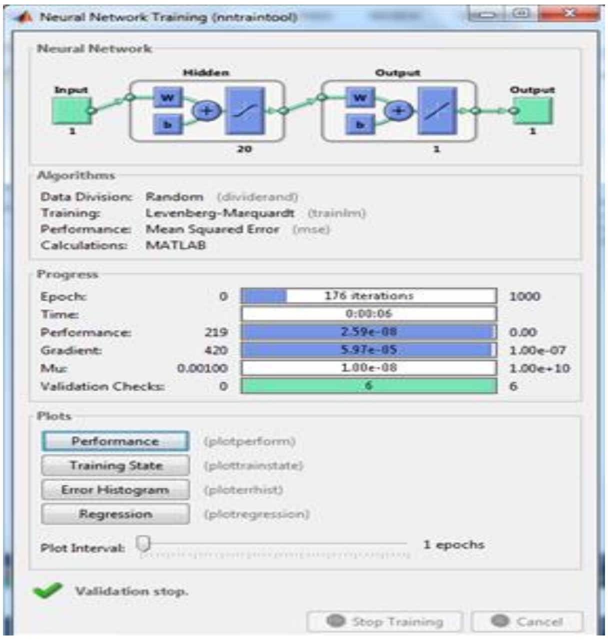

Fig. 2(g)

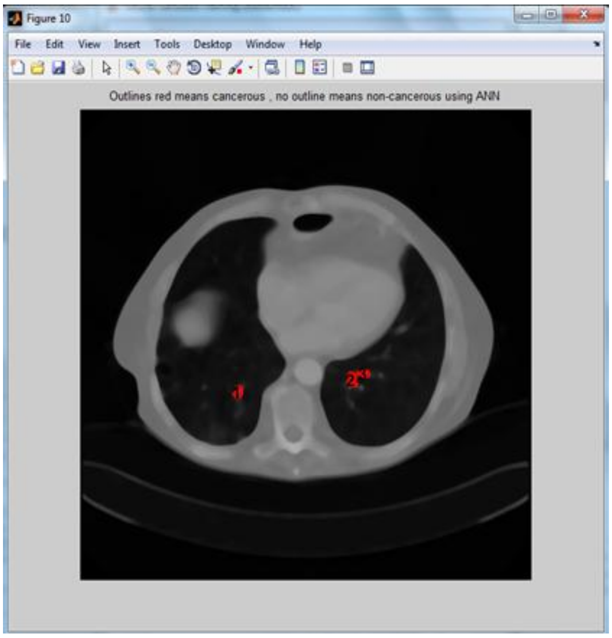

Fig. 2(h)

Fig. 2 Results of system for single image (a-h)

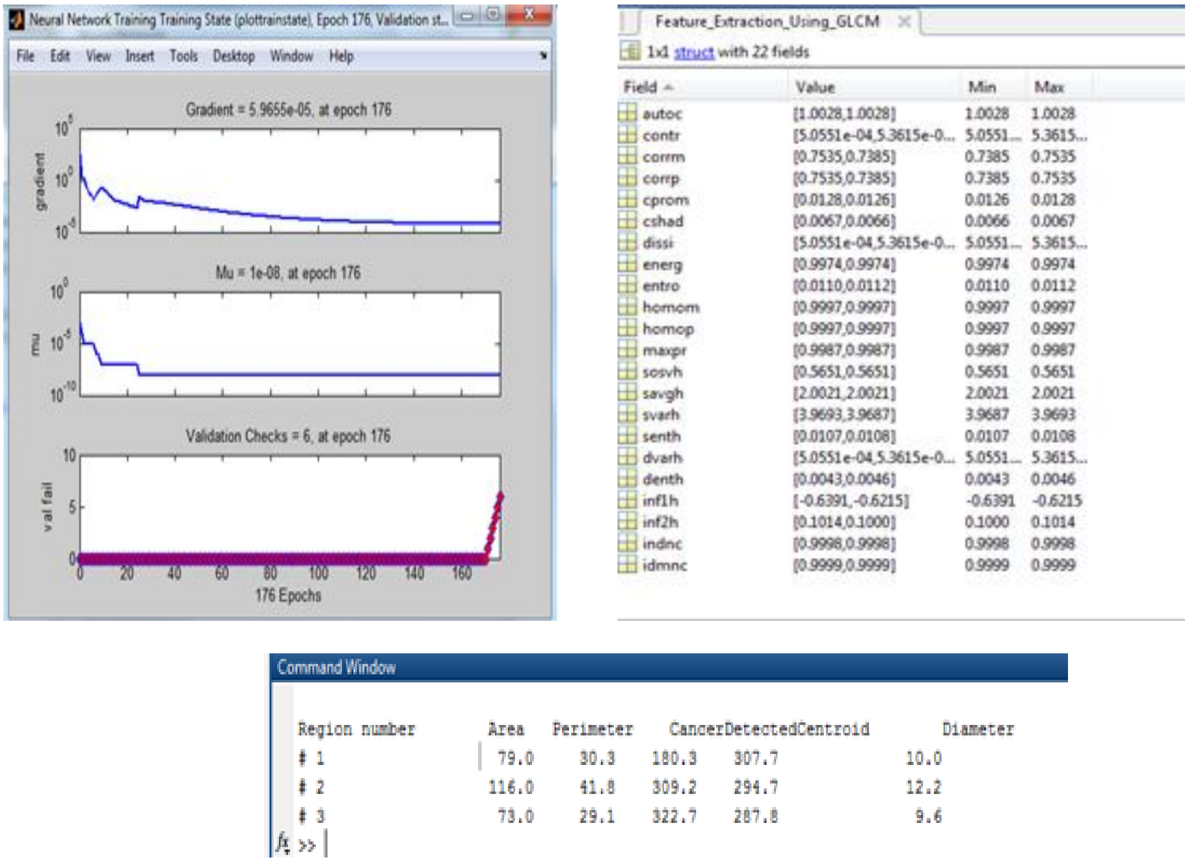

Fig.3 Different images for Classification (MATLAB implementation)

These are the images details which show test result and accurate results.

Table 4: Classifications of results with actual results

Patients1	Diagnosis Results	Classification
Image1	cancerous	Cancerous
Image2	noncancerous	Noncancerous
Image3	cancerous	Cancerous
Image4	noncancerous	Cancerous
Image5	cancerous	Cancerous
Image6	cancerous	Noncancerous
Image7	noncancerous	Noncancerous
Image8	cancerous	Cancerous
Image9	noncancerous	Noncancerous
Image10	cancerous	Noncancerous

Table 5: Comparisons of performance matrices for patient 1(10 images)

Performance matrices	**Formulas**	**BPNN classification**	**RBNFF classification**
TPs	True cancerous classified	3	6
TNs	True noncancerous classified	4	2
FPs	False cancerous identified	1	2
FNs	False noncancerous identified	2	0
Accuracy	TP+TN/TP+FP+TN+FP	70%	**80%**
Sensitivity	TP/TP+FN	0.60%	**100%**
Specificity	TN/TN+FP	0.8%	**80%**
Quality	TP/FN+FP+TP	0.50%	**100%**
correctness	TP/TP+FP	0.75%	**80%**

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Table 6: Comparisons of performance matrices

Performance matrices	Formulas	Base paper (1)	Base paper (2)	BPNN classification	RBFNN classification
TPs	True cancerous classified	-	34	215	252
TNs	True noncancerous classified	-	24	204	220
FPs	False cancerous identified	-	3	21	5
FNs	False noncancerous identified	-	2	60	23
Accuracy	TP+TN/TP+FP+TN+FP	81.25%	80	83.80%	94%
Sensitivity	TP/TP+FN	82%	81.6	76.19%	91%
Specificity	TN/TN+FP	82.65%	76.9	90.66%	97%
Quality	TP/FN+FP+TP	-	0.62	0.7263%	90%
correctness	TP/TP+FP	-	0.918	0.9110%	98%

VI. CONCLUSION AND FUTURE WORK

The experiment is performed on dataset of 70 patients containing 500 Lung cancer CT scan images. The neural network classifier gives accurate diagnosis for detection of lung cancer. The performance matrices for both the algorithms are Accuracy, Sensitivity, Specificity and Correctness. For Back Propagation the matrices values are 84%, 76%, 90% and 91% and for Radial Bias Neural Network are 94%, 91%,97%, and 98%.it is clearly shown that radial bias gives better accuracy for lung cancer classification.

Application of this system in future will be the followings:

- MRI or PET scan lung cancer images can be used.
- Features set can be extended.
- To improve accuracy another feature extraction and analysis approaches will be used.

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